An Exploratory Study on the Opportunities and Challenges of using Machine Learning in the DHIS2 Ecosystem

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Abstract

Machine Learning (ML) is a rapidly growing subfield of Artificial Intelligence (AI) that involves the development of computer programs that learn by finding patterns in data, without being explicitly programmed. It has been successfully applied in various fields, including agriculture, manufacturing, marketing, finance, and healthcare. In the health sector, ML has been identified as having potential in drug development, clinical diagnosis, disease surveillance, outbreak response, and health systems management, by researchers and development partners such as WHO and USAID.

Although ML has been touted for its potential to improve health outcomes, it has been used to a minimal degree in the DHIS2 ecosystem. Furthermore, recent developments have shown that some private organizations are carrying out the implementations. DHIS2 is a free and open-source digital platform that is used to collect and manage aggregated and patient health data, widely used in developing countries. The opportunities and challenges of using ML in health and developing countries have been studied. Still, none have specifically focused on how to integrate ML into digital health platforms like DHIS2 or the integration opportunities and challenges that developing countries would face where the platform is predominantly used.

To investigate how ML can be integrated with DHIS2 and related opportunities and challenges, I conducted an interview-based study with various stakeholders from the DHIS2 community and used thematic analysis to analyze the data. The results suggest that ML can be integrated with the platform through an app that can be implemented in both standalone and client-server architectures. The opportunities included improved forecasting, disease predictions, and anomaly detections. The challenges included the need for large amounts of data, data quality problems, lack of experts, lack of awareness, inadequate supporting infrastructure, insufficient funding, maintenance costs, risks of project failures, and lack of guidelines for the use and development of ML applications.

Keywords: Machine Learning, District Health Information System, DHIS2, Artificial Intelligence, Digital platform, Architecture, Developing countries.

Acknowledgements

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I am also deeply grateful to Professor Petter Nielsen from UiO for his invaluable advice, feedback, and support throughout my years of study in Norway. I would like to extend my thanks to all the professors who taught me in the various courses, including Magnus Li, Jan Tore Lønning, Kai Olav Ellefsen, Eva Hadler Vihovde, Laszlo Tibor Erdodi, and Amir Taherkordi, for imparting the knowledge I applied in my study and beyond.

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Lastly, I would like to express my profound gratitude to God for His grace.

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List of Acronyms

DHIS2	District Health Information System 2
ML	Machine Learning
AI	Artificial Intelligence
IS	Information Systems
HISP	Health Information System Program
WHO	World Health Organisation
SDG	Sustainable Development Goals
USAID	United States Agency for International Development
HIV	Human Immunodeficiency Virus
HMIS	Health Management Information System
BCG	Bacillus Calmette-Guérin
OECD	Organisation for Economic Co-operation and Development
UNICEF	United Nations International Children's Emergency Fund

Chapter 1

Introduction

In recent years, Artificial Intelligence (AI) has rapidly emerged as a growing field that offers favourable opportunities for humanity. It has been successfully applied in various sectors, such as agriculture, manufacturing, marketing, finance, and healthcare, among others. The growth of this field can be attributed to Machine Learning (ML), a subfield that focuses on the development of algorithms that identify patterns in data and generate rules that can be used to classify new data or predict future data (Panch et al., 2018) (PAHO, 2021). Other contributing factors include the increasing availability of digital data due to digitisation and reduction in the cost of computation (Pugliese et al., 2021).

In health, ML has been identified as having the potential to transform healthcare, public health, and global health by researchers, non-governmental organisations, international development partners, among others. ML has been recognised to have the capacity to help countries achieve universal health coverage by among others assisting with the deployment of different public health interventions, such as disease surveillance, outbreak response, and health systems management (WHO, 2021) (Panch et al., 2018). According to USAID, ML tools in the context of poor resource settings hold the potential in optimising health resources and improve healthcare delivery and outcomes (USAID, 2019) (J. A. Singh, 2019).

DHIS2 is a generic open-source software platform that is used to collect and manage patient and aggregated health data. The platform is widely used in developing countries where it is used by ministries of health and non-governmental organisations, it is estimated that over 100 countries use DHIS2 (Adu-Gyamfi et al., 2019). In these countries, DHIS2 has played a crucial role in digitisation of health data and promotion of evidence-based decision making at individual, facility, and population levels.

Despite the promoted potential of ML technology, it has been used to a limited extent in the DHIS2 ecosystem. Moreover, these implementations have been carried out by private organizations that offer ML as a service for profit, among these include Macro-eyes and BAO systems.

Considering the promoted potential of ML and its limited use with the DHIS2, this thesis explores the opportunities and challenges of using ML with the DHIS2 in the context of developing countries and how ML can be integrated with the DHIS2 digital platform.

1.1 Context

This study was conducted as part of a master program at UiO with the Information System research (IS) group at the department of informatics. The IS group is part of the Health Information System Program (HISP). HISP is a network for action that is composed of various HISP groups, universities, ministries of health, NGOs, global policy makers, global donors, researchers, among others that play different roles around the DHIS2 software (Adu-Gyamfi et al., 2019).

One of the important aspects of DHIS2 is that it is an innovation digital platform. Digital innovation platforms consist of a software-based core or an extensible codebase that provide functionalities that allow third parties to develop complementary applications (de Reuver et al., 2018; Russpatrick, 2020). This enables the platforms to unlock and leverage different innovative ideas in its ecosystem to add value to it, potentially bringing in positive network effects and make them thrive. Thriving in digital platforms influences platform evolution, and Baldwin et al. (2009) argue that one aspect of digital platforms is that they evolve to adapt to unanticipated changes in the external environment. According to Tiwana, (2013), one strategy of evolving digital platforms is increasing the stock of its innovations from the platform owner, app developers, rival platforms among others. External to the DHIS2 ecosystem is ML technology which has found widespread application and has brought different types of innovations to digital platforms. Considering the promoted potential and adoption of ML by some private organisations, it becomes more relevant to study what potential innovations and use cases can ML bring to the DHIS2 ecosystem.

1.2 Motivation

The opportunities and challenges of ML technology and developing countries has been widely studied in health at a broader scope such as (USAID, 2019), and other have focused on diseases such as (Katwesige et al., 2020). However, a systematic exploration of potential use cases and challenges of ML in the context of DHIS2 and developing countries has never been done. Further, how ML can be integrated as an innovation in the DHIS2 digital platform has never been studied. This thesis is an attempt to address this gap.

1.2.1 Research Questions

This thesis aimed to answer the following research questions:

RQ1: How does machine learning fit into the DHIS2 platform ecosystem?

RQ2: What are the opportunities and challenges of using machine learning with DHIS2 in the context of developing countries?

To address these questions, I researched literature on ML and through interviews, engaged in discussions with various stakeholders in DHIS2 community such as data scientists, HISP leaders, implementors, developers among others. The study contributes to the technical knowledge of ML integration architectures with the DHIS2 platform. Secondly, it contributes to the knowledge of opportunities and challenges of ML specific to the DHIS2 digital platform and developing countries. At a broader level, the knowledge contributes to different areas which ML can help strengthen the DHIS2 platform to achieve better health outcomes.

1.3 Thesis Outline

This section presents an outline of how this thesis is structured. The thesis is structured as follows.

Chapter 2: Research context

This section presents the research domain. The first section presents the DHIS2, it focuses on its history of development, architecture, and data analysis tools. The second section discusses ML, focussing on what it is, development history, categories, and commonly used algorithms.

Chapter 3: Literature Review

This section presents previous research related to the use of ML in the domain of health. It focuses on the use of ML in developing countries, the nature of data in DHIS2 implementations and related ML opportunities and challenges, ethical concerns in ML, and recommended ethical guidelines. Further, the ML processes are discussed and its different deployment strategies in IS.

Chapter 4: Methodology

This section presents the research methods which shaped how this study was conducted. This includes the philosophical view, research approach, data collection methods and data analysis.

Chapter 5: Results

The section presents the empirical findings of the study after the data was collected and analysed. It provides potential opportunities of ML and related challenges and potential integration architecture based on the findings.

Chapter 6: Discussion

The section discusses the study’s findings in light of literature and their implications guided by the research questions. It also provides different recommendations to various stakeholder and an outline of the study limitations.

Chapter 7: Conclusion

This section presents a summary of the thesis and recommendations on future work.

Chapter 2

Research Context

This chapter contains background information about the areas under study. In section (2.1), I present the DHIS2. I first discuss its development history, architecture, and its different data analysis features. In section (2.2), I discuss ML focusing on the history of the field, the different categories of ML, and overview of its commonly used algorithms.

2.1 DHIS2

Health Information Systems are a key technological component in making informed decisions and improving health service delivery. There have been great strides in strengthening health systems in developing countries over the years with support from good will global partners such as WHO, UNICEF, GAVI, and the Norwegian Government (Sahay et al., 2020). One of the systems which is playing a fundamental role is the DHIS2, a free and open-source software-based platform for the collection, management, analysis, and use of health data (Karuri et al., 2014).

2.1.1 History of DHIS2

DHIS2 history dates back to 1994 when Norwegian researchers participated in Health System Pilot Project (HISPP) in South Africa. With funding from NORAD and the collaboration of University of Oslo and University of Western Cape, DHIS1 was developed. This was the first version of the system, a standalone system which was based on Microsoft access platform. In 1998 the system was piloted in three districts in Western Cape province in south Africa and by 2001 the system was adopted as a national standard (Adu-Gyamfi et al., 2019). Even though the system was a freeware, it needed a commercial software to run as it was developed to run on the Microsoft excel platform (Krajca, 2010).

The system was a success at a country level and later it was adopted by other countries such as Mozambique and India, but as the project expanded challenges emerged. The system was developed as standalone software, so each health facility that installed it run an independent instance. This made it difficult to maintain the system, as it required travelling to each location to perform updates (Adu-Gyamfi et al., 2019). These challenges led to the development of the second version called DHIS2 and the project's expansion, as other countries adopted the system, led to the establishment of the HISP. HISP is a network of action comprising of universities, ministries of health, global partners like WHO and NORAD and in country HISP groups who provide support in development, fundraising among others (Jørn & Sundeep, 2012).

The second version, DHIS2, was released in 2006 as a successor to DHIS 1.4. It was first used in Kerala, India. The system was developed to run on the web using Java technologies with developers distributed in the HISP network to bring design and development to the users. Over the years the HISP has grown expanding to many countries, it is estimated that more than 100 developing countries use the platform. Among the users are ministries of health and non-governmental organisations (Adu-Gyamfi et al., 2019). At this time of writing, the current version of DHIS2 is v2.38.

2.1.2 The digital platform

The objectives of the second version of DHIS2 were to make the system platform-independent and fully open-source. It was also designed with a modular architecture, dynamic data model, and flexible user interface (Krajca, 2010). The modular architecture makes the DHIS2 an innovation digital platform. Innovation digital platforms enable third parties to develop complementary products or applications extending their functionality (Nicholson et al., 2019). The DHIS2 follows a layered modular architecture with the core component which is similar across the platform and apps which vary to a higher degree. The platform offers a web API which enable apps to interact with the core and external systems, a user interface library and application runtime tools as part of application development toolkit (DHIS2 Developer guide, n.d.). Furthermore, the DHIS2 has an app hub which allows the distribution of apps by various developers across the community (Russpatrick, 2020). The DHIS2 core platform together with the complementary applications constitute the DHIS2 software platform ecosystem. The following figure illustrates the DHIS2 platform ecosystem.

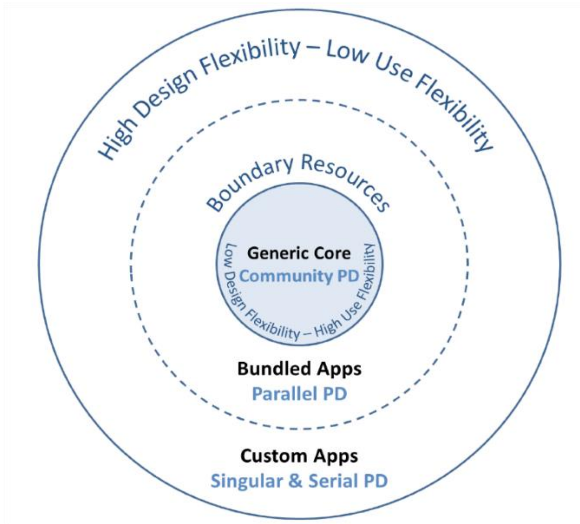


Figure 1: DHIS2 platform ecosystem (source: DHIS Design lab)

2.1.3 Data analysis in DHIS2

The DHIS2 platform offers a lot of features for data entry and analysis for both aggregated data and patient data. Patient data is data which relates to a single patient and aggregated data is consolidated data related to multiple patients used in routine reports, health indicators and strategic planning (DHIS2 Documentation Team, n.d.). The platform offers many data analytics tools such charts, pivot tables, maps and dashboards and predictor.

According to Roy et al. (2022), there are three categories of data analysis techniques: descriptive, predictive, and prescriptive analytics. Descriptive analytics techniques summarize past data to gain insights into what happened in the past, answering questions such as “what happened”, “why it happened”, and “what is happening”. The set of tools for descriptive analytics provides a visual representation of data that makes it easy to read and understand for decision-makers. Examples of the tools used include charts and tables.

Predictive analytics uses statistical modelling, ML techniques, and others to determine what is likely to happen in the future based on past and current data. They answer the questions "what will happen" and "why it will happen".

On the other hand, prescriptive analytics uses algorithms to determine what should be done to affect what will happen in the future, answering questions such as "what should be done", "why will it happen", and "why should we do it".

Charts

DHIS2 contains a Data Visualiser app, the app allows users to create different types of charts which include bar charts, line charts, area charts, pie charts and radar charts. Users can easily create charts by selecting the type of chart and then selecting the data dimensions. The data dimensions include data elements or indicators, period, and organisation units, what constitutes as the "what, when and where" in DHIS2. More features are available when using charts, such as creating favourites, sharing dashboards, downloading the charts in different formats and more. Charts are the most popular way of data summarisation; they offer a visual representation of data and make it easier to compare multiple variables for decision makers. Charts belong to the category of descriptive analytics, as they show what has happened and what is currently happening.

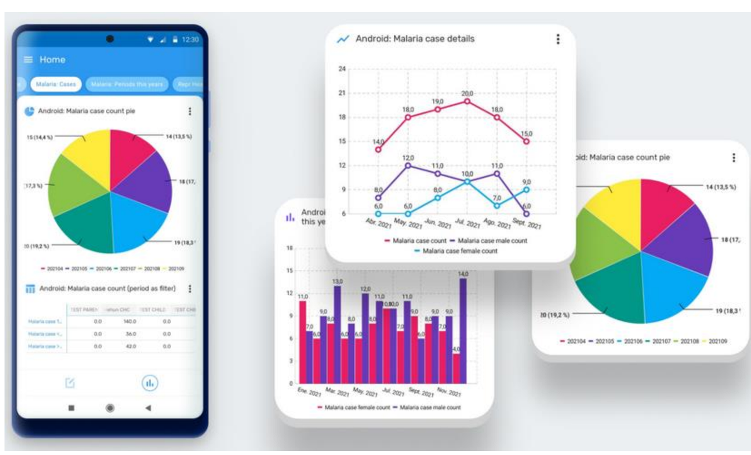
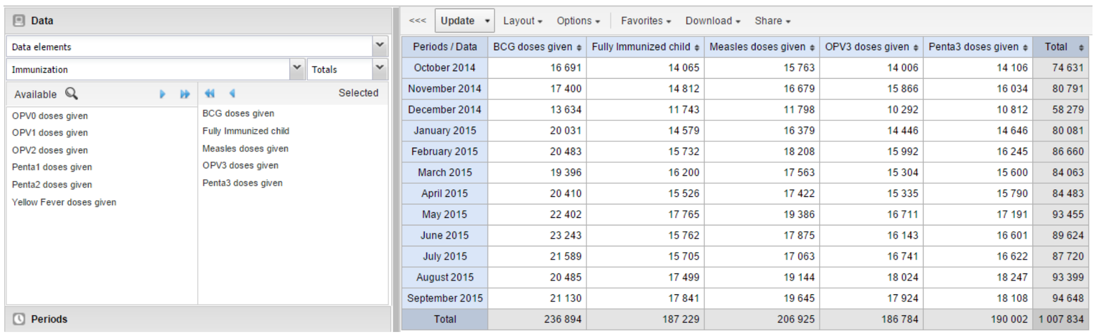


Figure 2: DHIS2 Data Visualisation on android Capture (source: About DHIS2)

Pivot tables

A pivot table is a dynamic tool for data analysis which lets you summarize and arrange data according to its dimensions (DHIS2 Documentation Team, n.d.). The pivot table app allows you to select data dimensions like charts and arrange data on columns, rows, and filters. The pivot table created can be saved to favourites, shared on dashboard, and downloaded in different formats. Pivot tables are easy to create and easily summarise huge amount of data. Pivot tables belong to the category of descriptive analytics, as they show what has happened and what is currently happening.



Periods / Data	BCG doses given	Fully Immunized child	Measles doses given	OPV3 doses given	Penta3 doses given	Total
October 2014	16 691	14 065	15 763	14 006	14 106	74 631
November 2014	17 400	14 812	16 679	15 866	16 034	80 791
December 2014	13 634	11 743	11 798	10 292	10 812	58 279
January 2015	20 031	14 579	16 379	14 446	14 646	80 081
February 2015	20 483	15 732	18 208	15 992	16 245	86 660
March 2015	19 396	16 200	17 563	15 304	15 600	84 063
April 2015	20 410	15 526	17 422	15 335	15 790	84 483
May 2015	22 402	17 765	19 386	16 711	17 191	93 455
June 2015	23 243	15 762	17 875	16 143	16 601	89 624
July 2015	21 589	15 705	17 063	16 741	16 622	87 720
August 2015	20 485	17 499	19 144	18 024	18 247	93 399
September 2015	21 130	17 841	19 645	17 924	18 108	94 648
Total	236 894	187 229	206 925	186 784	190 002	1 007 834

Figure 3 : DHIS2 pivot table (source: DHIS2 Documentation Team)

Maps

The Map app is yet another powerful data analysis tool in the DHIS2 data analysis arsenal, it is capable of displaying thousands of features on the map simultaneously. Maps are powerful as they allow decision makers to see where things are happening and make it possible to understand spatial relationships in public data. The Map app in DHIS2 allow users to create maps with multiple overlays, choose among different base maps, create thematic maps of areas and points, view facilities based on classifications and visualise catchment areas for a health facility (DHIS2 Documentation Team, n.d.). Maps belong to the category of descriptive analytics, as they show what has happened and what is currently happening.

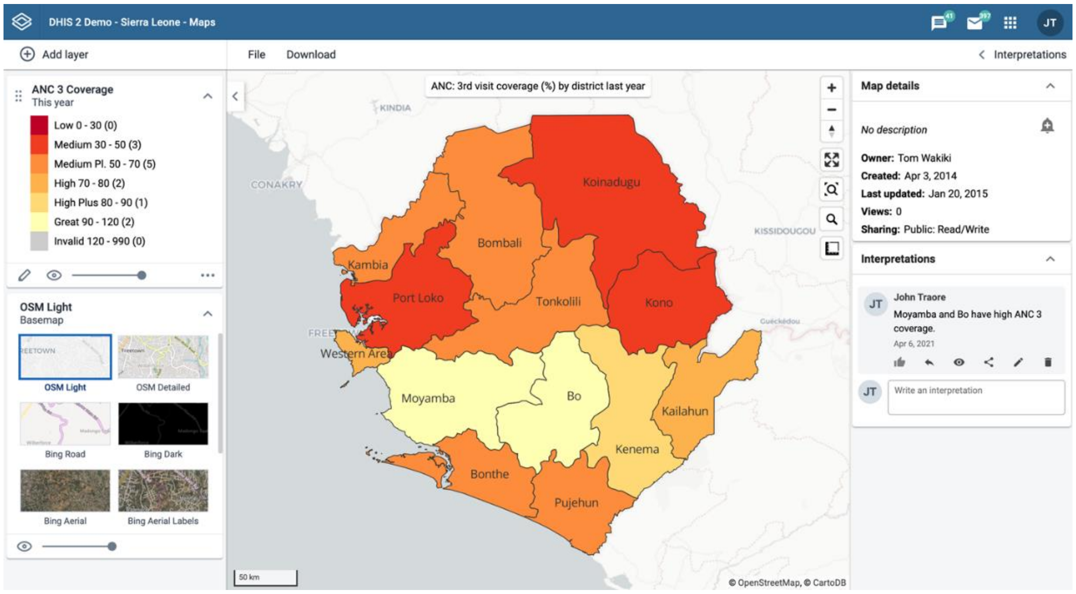


Figure 4: Map in DHIS2 (source: DHIS2 Documentation Team)

Dashboards

Dashboards provide quick access to different analytical objects to an individual user, and they can be shared with other user groups in DHIS2 (DHIS2 Documentation Team, n.d.). This enables users within the same group (for example, users working on the same program) to have access to the dashboard, providing all users with the same analytical information. Dashboards are not analytical techniques; their role is to incorporate different analytical objects that can be easily accessed by users.

Predictor

Predictor is a feature in DHIS2 which provides predictive capabilities to the DHIS2 platform. A predictor generates a data value based on data values from past periods and/or the period of the data value (DHIS2 Documentation Team, n.d.). Predicted values can be in the past, present, or future. This categorizes the Predictor tool as predictive analytics, as it can be used to generate data values that should be expected in the future based on current and past data.

> "… *A more complex use of predictors would be for disease surveillance, to predict what value would be expected in a given week or month of the year, based on previous data values* …" (DHIS2 Documentation Team, n.d. p. 288)

There are various ways to sample past data for predictions, including sequential sampling, sequential skip sampling, annual sampling, and other methods that involve a combination of these methods. When using the Predictor, users need to select the predictor type, which could be weekly, monthly, among others. If sequential sampling is being used, the user must also select the sequential sample count, which determines how many past period values should be used for predictions. For example, if the predictor type is monthly and the sequential sample is 24 months, the Predictor will generate a value for the 25th month based on the sample data from the past 24 months. The following figure illustrates this example.

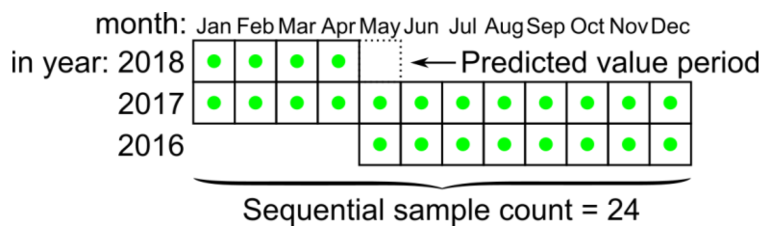


Figure 5: Predictor (source: DHIS2 Documentation Team)

2.2 Machine Learning

It is not easy to talk about ML without talking about its umbrella body AI. There is no distinct definition of AI, rather it is a debatable term within the field of what constitutes *"intelligence"* which is dependent on how it is approached by various researchers such as; acting humanly, thinking rationally and acting rationally (Russel & Norvig, 2009). In simple terms, it is a field which focuses on the development of computer systems which poses abilities which can be described as intelligent, it could be in one aspect or more. The field of AI is large, composed of many subfields which include, Natural Language processing (NLP), Robotics, Evolutionary Computing, Speech Processing, Neural Networks, Computer Vision and Machine Learning (Girasa, 2020). This clearly distinguishes AI from ML. They are not the same thing, with AI being an umbrella term while ML is a subfield. While what constitutes intelligence is wide-ranging, the field of ML focuses on the aspect of "*learning*", i.e., the ability to learn from experience or data. (Géron, 2017).

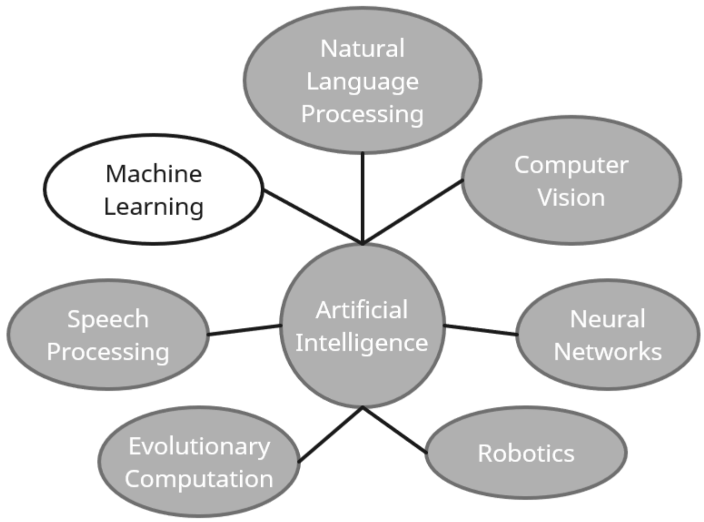


Figure 6: Subfields of AI, Girasa, (2020)

2.2.1 History of Machine Learning

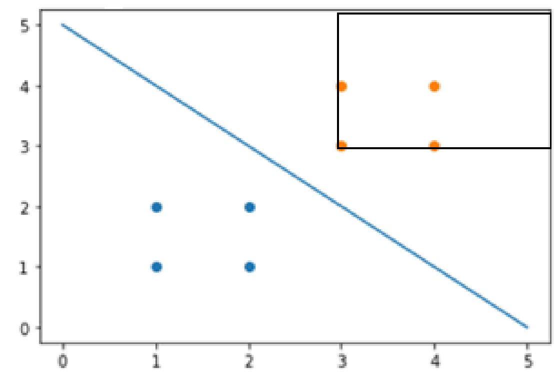
The roots of ML trail back to 1952 when IBM scientist Arthur Samuel developed a program for playing checkers. The program could play against itself and humans. It would remember all the games it had played and use the data to improve over time. Samuel coined the phrase "machine learning" (Samuel, 1988).

The following significant progress was the invention of the perceptron in 1957 by Frank Rosenblatt. The perceptron was a machine which was designed to imitate the working of a brain cell called the *neuron,* based on Hebb's model of 1949 (Rosenblatt, 1958). A neuron is a brain cell that receives electrical input signals from other cells. When it receives these signals, it sums them up. If the sum exceeds a certain threshold, it outputs a spike of electrical signal; otherwise, it does not output anything. In simple terms, a perceptron works using the same principle, however the inputs are numbers instead of electrical signals and the output could be a 1 or 0 resembling a spike or no spike.

I will use the following simple example to explain the perceptron and why ML is referred to as development of programs without explicit programming.

x	y	blue= 0, orange=1
1	1	0
1	2	0
2	1	0
2	2	0
3	3	1
3	4	1
4	3	1
4	4	1

(a)



(b)

Figure 7: The perceptron working principle

Consider the figure 7, (a) is a dataset with features x and y and their labels “blue” or “orange” which have been coded to 0 and 1 respectively. When the dataset is plotted using a scatter plot the output is (b), from the output we can clearly see that there is a pattern. The blue values appear to be on their cluster and so do the orange values. Imagine we have a new data point x = 3.5 and y = 3.5 (the data point falls in the middle of the orange cluster) without a class (blue or orange), using the pattern we have observed, we could predict that that datapoint has the label orange. Now, imagine a programmer has been given a task to write a program to classify a data point given the x and y values, he might come up with the following rules in the code.

> *If x value is greater than or equal to 3 and y value is greater than or equal to 3 then the data point label is orange (region in the rectangle)*
>
> *If the first condition is not met, it is it is blue.*

In that case the programmer is explicitly telling the computer program how to classify the data. It is similar in the development of programs like calculator, for example calculating the average, dividing numbers among others as explicit instructions can be written through programming. But in the example, we can see that those rules will not always work, as some data points that would fall outside the rectangle could be classified to be in the orange class.

The ML approach is different, a perceptron would find a line which separates the two classes as drawn in the (b), and that line would serve as a model for prediction. When a data point is above, it is in orange when it is below it is blue. So, in this case, ML is about using the given data to find a predictive model.

The perceptron has a problem, it can only solve problems which its data is linearly separable because of the way it works, that is finding a line which separates two classes in the data.

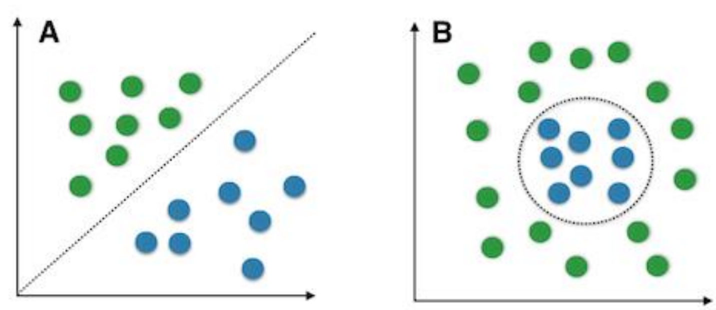


Figure 8: Linear separability

Figure 8 shows two datasets with two features, For the data to the left (a), it is clear that there exists a line which can separate the two classes, the line can be found by the perceptron. The data to the right (b) is not linearly separable as there does not exist a line to separate the two classes, this problem cannot be solved by the perceptron. This was demonstrated by Papert and Minsky in 1969, and they speculated that neuro networks with multiple layers were impossible to implement and this halted ML research for some years and resulted into what is called the first "*AI winter*" (Tappert, 2019) (Marsland, 2014).

Some stubborn scientists continued studying neural networks and it was in 1986 when a breakthrough in the implementation of the multilayer perceptron was found by Rumelhart, Hinton, and McClelland. The breakthrough was the discovery of what is called the backpropagation algorithm (Marsland, 2014; Rumelhart et al., 1986). Multilayer perceptrons are an improvement of the perceptron because they can solve non-linear separable problems such as the one in figure 8 (b). The types of problems which can be solved by multilayer perceptrons include regression, classification, time-series prediction and data compression, some of these will be presented in the algorithms section 2.1.3 (Marsland, 2014). Other uses include in image processing (image classification, objection detection etc), language processing (machine translation, speech recognition etc), self-driving cars and more. However practical results at that time were not impressive. The figure 9 shows diagrammatic presentations of neural networks. x and y represent numbers which are inputs to the networks, for a perceptron there is layer of neurone from which an output is produced. For multilayer perceptron the inputs are connected to hidden neurones which further connect to other neurones from which outputs are produced.

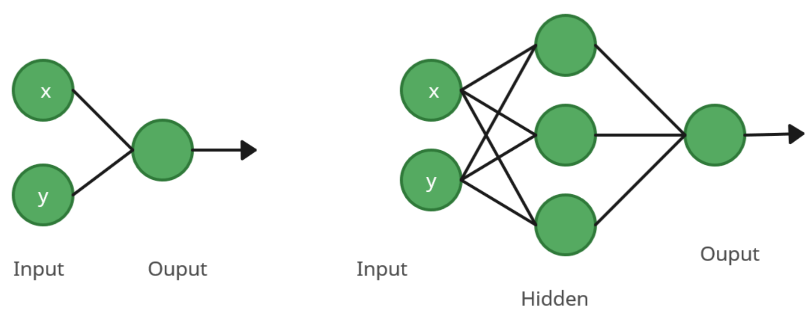


Figure 9 Perceptron (left), multilayer perceptron (right)

Some Scientist continued to do research on neural networks especially networks which can exceed three layers, an area known as *deep learning*. Among these include Hinton, LeCun and Bengio who worked independently and together demonstrated the fundamental breakthroughs in deep learning from which they earned the Turing award in 2018 (Tappert, 2019). Deep learning sparked wide interest in ML research and is responsible for the current advancements in computer vision, speech recognition, natural language processing, and robotics-among other applications (Tappert, 2019).

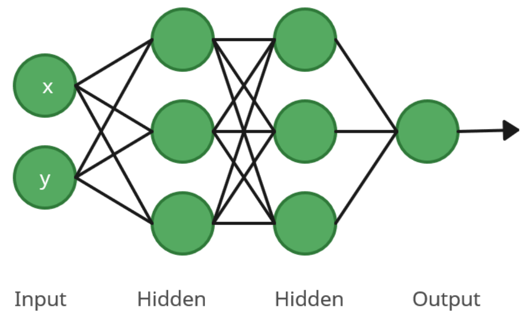


Figure 10 Deep neural network

There are other ML techniques that are not based on neural networks, which were discovered earlier in history and are still relevant today. These include K Nearest Neighbour (KNN) algorithm by Marcello Pelilo in 1967 (Cover & Hart, 1967). Support Vector Machines (SVM) by Corina & Vladimir in 1995 (Cortes & Vapnik, 1995). K-means algorithm by James MacQueen in 1967 (MacQueen, 1967) among others. Some these algorithms will be discussed in section 2.1.3.

2.2.2 Categories of Machine Learning

In this section, I will discuss the four categories of ML, namely, supervised learning, unsupervised learning, semi supervised learning, and re-enforcement learning based on the papers (Sarker, 2021) and (Sah, 2020).

Supervised learning involves the use of training data that has labelled output. This is similar to the typical learning process that occurs in real life. For example, if one wants to teach a toddler how to recognize bananas and apples, a teacher might have pictures of apples and bananas, label the pictures with the correct names of the fruits, and show them to the child. Through the supervision of the teacher, the child eventually learns to distinguish between bananas and apples without the teacher's assistance. In ML, a similar technique is used, where the training data contains features that map to a particular output. For example, when training a model to classify whether an email is spam or not, the training data will include both legitimate emails and spam emails labelled as such. The model learns the patterns in the data, and given an unlabelled email in the future, it will be able to correctly classify it. Supervised learning requires the availability of large amount of data which is labelled which makes it an expensive approach where data is scarce (Sah, 2020).

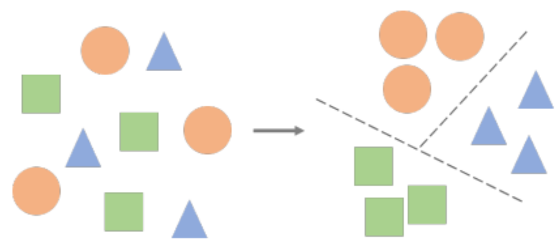


Figure 11: Supervised Learning (source: Sah, 2020)

Two variations of supervised learning exist depending on whether the output is a categorical variable or a continuous variable. These are classification and regression, respectively. In classification, the input data maps into a discrete set of categories. The goal is to learn and predict an input into the right category. Examples include classifying whether an email is spam or not, determining whether a data point is an anomaly or not, classifying whether a medical image is cancerous or not, and more. In regression, the input data maps into a continuous variable, which is a real number. Examples of regression tasks include weather forecasting when temperatures are predicted. Because the target values exist in supervised learning, it is possible to test the accuracy of their predictive models.

Unsupervised learning involves using input data without corresponding output, unlike supervised learning. This is not a typical way of learning, but it is useful. For example, one can be given a bag of balls with different colours and can group them based on their colours into different groups discover some insights. This learning method is used in extracting features, identifying meaningful trends and structure, groupings in results, and for exploratory purposes. Common use cases include clustering, anomaly detection, and others (Sarker, 2021). Since the training data does not contain corresponding output values, it is difficult to evaluate their accuracy.

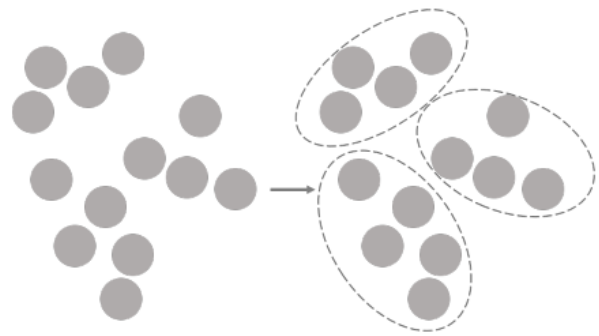


Figure 12: Unsupervised Learning (source: Sah, 2020)

Semi-supervised learning uses both supervised and unsupervised techniques, what we could refer to as a hybrid approach to learning. The learning uses both data which has output labels and data that does not have output labels. Sarker, (2021) argues that labelled data in the real world is rare in some context and unlabelled data are numerous, in these contexts unsupervised learning is useful. He further gives use cases which include machine translation, fraud detection, labelling data, and text classification.

Reinforcement learning uses a different approach to learning compared to the other categories presented so far. Reinforcement learning introduces the concept of an agent, which can be software or a machine, such as a robot. The agent is given a goal, and it must find an optimal way to achieve it given a set of actions it can take and knowledge of the state of its environment. When the agent takes the right actions, it is rewarded, and when it takes wrong actions, it is penalized. This helps the agent learn to take actions that maximize rewards and reduce risks.

A human example of reinforcement learning is how students learn to succeed in their education. They have actions they can take, such as attending classes, sleeping, partying, and missing exams. Taking these actions can lead to rewards and penalties; for example, taking the right actions can lead to passing and rewards like good grades and presents, while taking wrong actions like missing exams can lead to failing with penalties such as bad grades, repeating the year, or even expulsion. By taking different actions, a student learns to take the optimal actions that lead to achieving their goal.

Areas of application for reinforcement learning include computer games, where games can learn how to play against humans, robotics, self-driving vehicles, and others. (Sarker, 2021) (Sah, 2020).

2.2.3 Machine learning Algorithms

In this section I will discuss the common ML algorithms, having knowledge on how general algorithms work helps in identifying application areas. The criteria for selection of the presented algorithms were based on how easy they could be explained to the target audience, as there are many ML algorithms. The underlying mathematical workings have been hidden and simple examples have been used.

Linear Regression

Linear regression is a supervised learning algorithm and one of the common algorithms in statistics and ML. It is used for two purposes; making predictions and determining the causal relationship between the independent and dependent variables (Iqbal, 2020). An independent variable is the variable that affects a dependent variable, in other words an independent variable is used to predict a dependent variable. It works by finding the best line that fits the observed data with minimal errors. Regression models are grouped into two, namely Simple linear regression and Multivariate linear regression. In simple regression, there is one independent variable while in multivariate linear regression there are multiple independent variables (Maulud & Abdulazeez, 2020).

The figure 13 shows an example of the relationship between rainfall and umbrellas sold. We can notice that as the amount or rainfall increases, so does the number of umbrellas sold, this can imply that the amount of rain received influences the number of umbrellas sold. In this case, the amount of rain received can be used to predict umbrellas we can sell. We use linear regression to find the line that best fits the data and that in the future knowing amount rainfall we can predict the number of umbrellas we can sell.

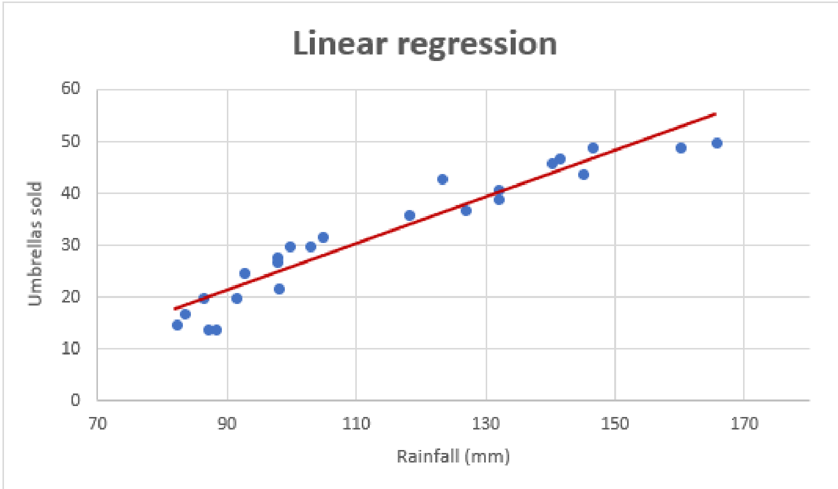


Figure 13: An Example of Linear Regression (source: Cheusheva, 2023)

One advantage of linear regression is that it is easy to use & understand, and one disadvantage is that it assumes there is a linear relationship between the variables which might not be the case sometimes (Iqbal, 2020).

Logistic Regression

Logistic regression is a supervised learning algorithm that is used to model the probability of a discrete outcome given an input variable, in other words it gives the probability of an event occurring (Ray, 2019). While linear regression predicts a continuous value, logistic regression predicts a categorical value which is binary, and it is used for classification tasks. Examples would be predicting whether there is disease or not, an email is spam or not from one or more variables.

Consider the figure 14, imagine we have a dataset consisting of columns for temperature, humidity and a categorical column rain indicating that it rained or not. The data is then plotted on a scatter plot (left), blue indicating rainy day and yellow indicating non rainy day. We can see that there is a pattern, using logistic regression we can be able to create a predictive model (right) that can give us a probability of having a rainy day or not, given the temperature and humidity. The model (right) shows us decision boundaries, if the data point falls in the blue region, then it will predict that it is going to rain, if it will fall in the orange region it is going to predict that it is not going to rain.

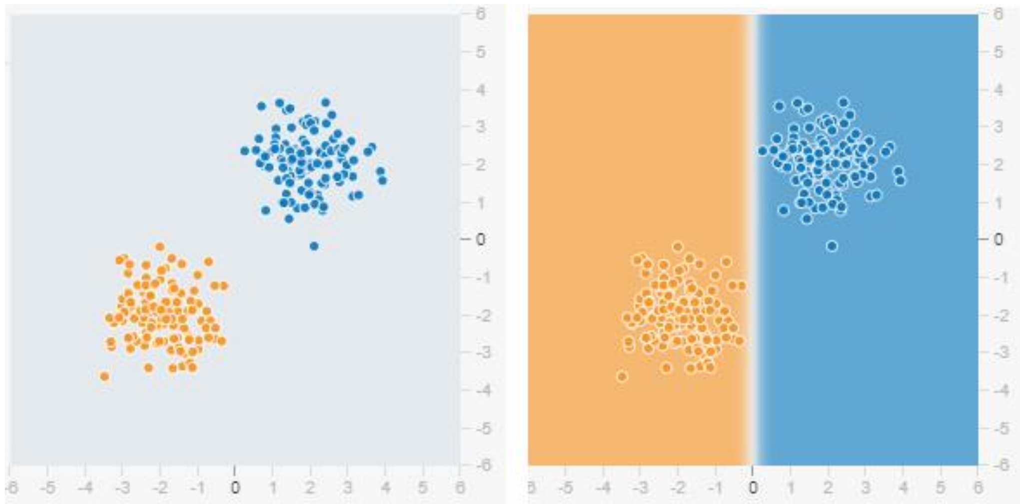


Figure 14: Logistic regression

There are three categories of logistic regression namely binary, multinomial and nominal regression (Ray, 2019). For binary classification the dependent variable can be in two classes only, just like in the example a rainy day or not rainy. In multinomial regression the dependent variable can be in more than two classes in the previous example it could be like predicting the probability that a day could be rainy, cloudy, or sunny. In ordinal regression the dependent variable can be in more than three classes, but the classes have a defined order, for example grading scales from A to F.

One advantage of logistic regression is that it is simple which makes it easy to implement and one disadvantage is its inability to solve non-linear problems as it relies on linear decision boundaries (Ray, 2019).

Decision trees

Decision trees are in the category of supervised learning methods and are used for classification tasks. Decision trees work by asking a series of questions about features associated with items. Each question is contained in a node, and every internal node points to one child node for each possible answer to its question. The questions thereby form a hierarchy, encoded as a tree (Kingsford & Salzberg, 2008). Every internal node has two children which are “True” and “False”, classification is done by answering the questions in the node down to the leaf nodes.

An example is given in figure 15, containing a dataset of animals with their characteristics and a decision tree which is constructed out the dataset. Given the characteristic of an animal, the decision tree can be used to predict what animal it is.

Feathers	Flies	Fins	Animal
True	True	False	Hawk
True	False	False	Pinguin
False	False	True	Dolphin
False	False	False	Bear

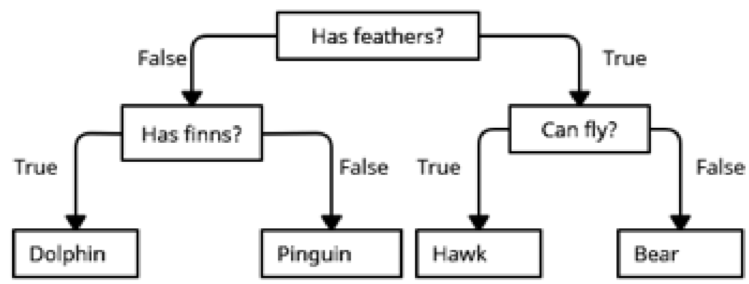


Figure 15: Decision tree

The advantages of decision trees are that they are interpretable classifiers compared to other ML techniques because they combine simple questions about the data in an understandable way (Kingsford & Salzberg, 2008). One disadvantage is that more complex decision trees tend to produce poor decisions (Kotsiantis, 2013).

Artificial Neural Networks (ANNs)

ANN were first presented in the history section of history ML as artificial models of the biological neural network. The perceptron, multilayer neural networks and deep learning are all in the category of ANN’s and they do not present specific algorithms, but they can be configured in different ways to achieve a particular learning task.

The perceptron has one layer of neurons, and it can be used for regression and classification, but it can only learn linear functions. Multi-layer perceptron are limited to two or three layers (input, hidden and output layers), they can learn nonlinear functions and they are used for regression, classification, time-series prediction, data compression, novelty detection and more (Marsland, 2003, 2014). The perceptron and MLP's are referred to as shallow neural networks.

Deep neural networks consist of more than one hidden layer organized in deeply nested network architectures and they are considered as advanced ML in a subfield called deep learning (Janiesch et al., 2021). The human brain consists of billions of neurons (Marsland, 2014). This cannot be matched with an ANN with a one hidden layer, deep learning is a step closer to achieve better complexity. There are many deep learning architectures which include Auto-Encoder (AE), Convolutional Neural Network (CNN), Restricted Boltzmann Machine (RBM), Deep Stacking Network (DSN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU) and Recurrent Neural Network (RNN). I am not going into details into how each one works. They are used in areas such as Natural language processing, document analysis, face recognition, image recognition, video analysis, continuous speech recognition, information retrieval, gesture recognition, handwriting recognition, image captioning, classification, dimensionality reduction, feature learning, regression and more (Dargan et al., 2020).

One strength of deep learning is that they have strong learning ability and use datasets more effectively. One weakness is that they need huge amount of data and require hardware with high performance to train (Dargan et al., 2020). The following diagrams show the complex patterns which deep learning can learn from data. The images to the left show the patterns in data, the images to the right show a learned predictive model indicating the decision boundaries. Any new datapoint falling in the blue region will be predicted to be blue while any datapoint falling in the orange regions will be predicted as orange. Think of the classes to be real world applications like at risk or not, spam or not, anomaly or not etc.

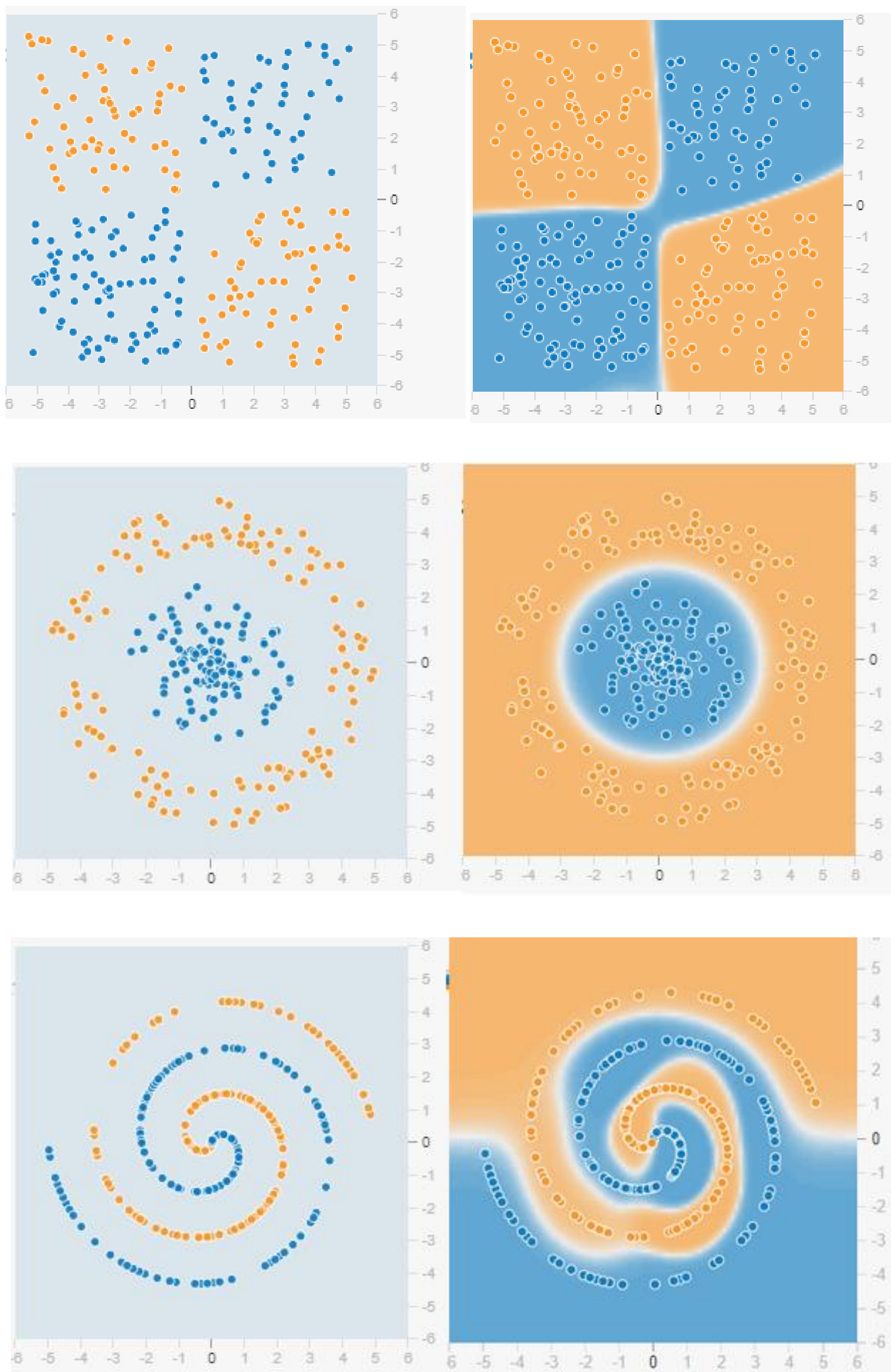


Figure 16: Deep learning models

K Means Clustering Algorithm

It is known that the k-means algorithm is the oldest and popular clustering method, and it has been widely studied with various extensions in the literature and applied in a variety of substantive areas (Sinaga & Yang, 2020). K means is an unsupervised ML algorithm that is used to find clusters in data or discover patterns. The algorithm begins by first initialising ***k***, which is the number of clusters to group the data into. The algorithm then randomly selects ***k*** data points in the dataset as initial centres and assigns each data point to the nearest centre. It then recomputes the centres by calculating the mean in each centre, this may result into other data points becoming close to other centres thus the algorithm continues until there are no changes in the centres.

Figure 17 shows an example. Given a random dataset (left) we can see that there seem to be some clusters in the data, lets initialise k to be 6 (there seem to be 6 clusters). After running the algorithm, it will eventually classify every datapoint and the output might be the figure to the left.

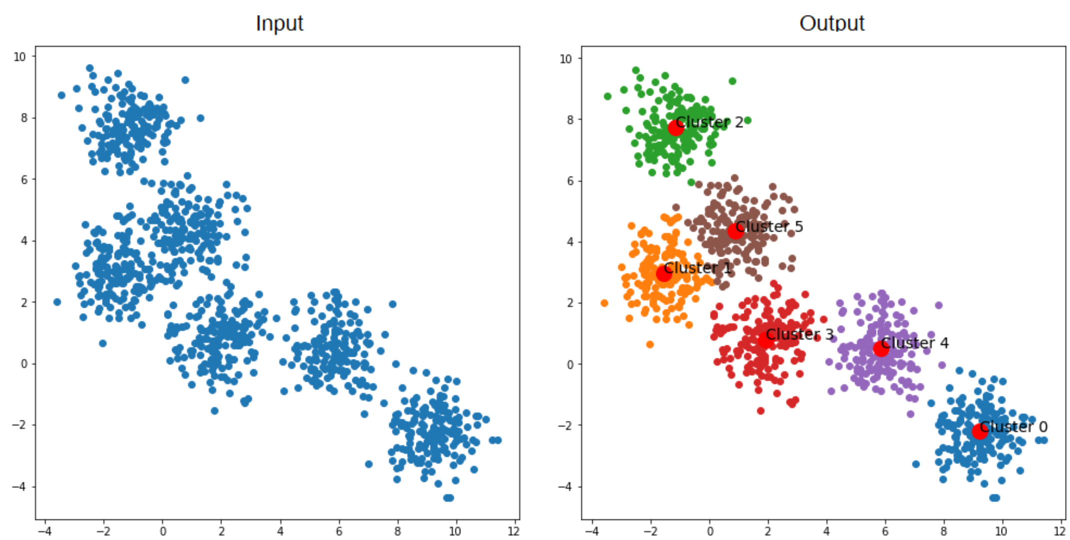


Figure 17: K-means algorithm (source: Tran, 2021)

One advantage of k-means is that it is easy to implement, and one disadvantage is that it is hard to predict the number of k as it is not automatically found by the algorithm (Ray, 2019).

Nearest Neighbours Algorithms (KNN)

K nearest neighbours is a supervised ML method used for classification. It works by comparing the classes of ***k*** data points (called neighbours) which are close to a data point, it then classifies the data point to the classes with many of its neighbours belong. The ***k*** is the number of neighbours, the algorithm knows the ***k*** neighbours by calculating the distance to all the data points in the dataset and sorts the distances to pick ***k*** short distances. Like k-means, ***k*** must be initialised at the beginning to the algorithm.

Figure 18 shows an example. We have datapoints which belong to the blue class "A" and other belonging to the green class "B". We have a new data point "star" which we do not know its class and needs classification. KNN will consider its neighbours, if we set k=3 as in the figure, KNN will consider 3 neighbours, most of the neighbours are green to it will classify it as "B". but if k=6, KNN will consider the 6 closest neighbours, the majority is blues, so KNN will classify it as blue.

One advantage of KNN is that it is easy to implement and well suited for multimodal classification. One disadvantage is that its operation is heavily dependent on ***k***, different values of ***k*** will produce different results.

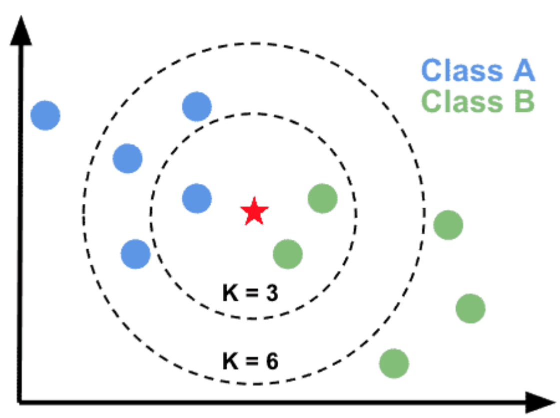


Figure 18: This figure shows how KNN would work (source: Chouinard, 2022)

2.3 Summary

In this section I presented the context of the study focusing on the DHIS2 platform and ML. DHIS2 is a free and open-source software platform for the collection, management, analysis, and use of health data. The roots of DHIS2 dates back into the 1990's when it was developed to be used in South Africa. Following the success, more countries adopted the system and led to the growth of the HISP. Due to design limitations, a new version was developed to be open source, with modularity in mind and using Java web technologies. The second version is a digital platform with a core which can be extended by complementary applications. DHIS2 comes with built in apps for data analysis including data visualiser and pivot tables. The platform also features advanced data analysis tool called predictor for predictive analytics.

ML is a subfield of AI which aims at the development of applications which learn from data and improve overtime. The history of ML dates to 1950's when Arthur Samuel developed a checkers game which would learn from the experience of playing the game overtime. The ML field experienced hiccups in its development and the current growth is attributed to breakthroughs in deep learning. There are several categories of ML which include supervised learning, unsupervised learning, semi supervised learning, and re-enforcement learning. There are many algorithms in ML and among these include linear regression, logistic regression, decision trees, k-means clustering and k-nearest neighbour.

Chapter 3

Literature review

The objective of this section is to provide context for the current study by positioning it in relation to previous research. Specifically, in section (3.1), I discuss the state of ML in developing countries. In section (3.2), I examine the nature of data captured in DHIS2 across different implementations and review the literature on the opportunities and challenges related to this type of data. In section (3.3), I address ethical concerns in the field of ML. Finally, in the last section, I review the processes of ML and deployment architectures in information systems (IS).

3.1 ML in developing countries

Over the past two decades, there have been significant efforts to improve health systems in developing countries. Governments and the international community have collaborated to digitize and strengthen health systems, with the aim of increasing the use of data and promoting informed decision-making to enhance the delivery of health services and plan interventions. DHIS2 has played a crucial role in this effort, as it is the most used HMIS in low- and middle-income countries (Adu-Gyamfi et al., 2019). The growth in the use of digital systems should result in increased availability and use of data, providing more opportunities to maximize data use using ML technologies. In this section, I review studies on the potential of ML in these regions.

Wahl et al., (2018) studied how AI can contribute to health in resource-poor settings. They point out that high income countries are benefiting from integrating AI into their healthcare ecosystems. They give an example of a study that AI could result in approximately $150 billion in saved healthcare costs annually in the US by 2026 alone. They argue that there are many reasons to be optimistic that AI could also prove transformative for public health in resource-poor countries where deployments are still nascent.

De-Arteaga Maria et al., (2018) present ML for the developing world (ML4D), a growing research body with a goal of providing solutions that can effectively contribute towards achieving development objectives through ML solutions. They provide research areas to ML4D that it should relate to improving data reliability, should provide direct solutions to deployed systems and should inform policy making and decision makers. They further argue that while there are limitations on the use of ML in developing regions, they should instead serve as opportunities for research.

J. A. Singh, (2019) believes that AI technologies can accelerate progress on achieving SDG's as well as Mathur et al., (2020) and Owoyemi et al., (2020). SDGs encompass a set of 17 goals which are aspirations set up by the UN to achieve human prosperity and peace. Even though developing countries are behind in adoption of technologies of previous industrial revolution, J. A. Singh, (2019) argues that AI offers opportunities which can help the countries in these regions to leapfrog current methods of health delivery to improve health outcomes. Goal #3 of the SDGs relates to health, and it has 12 indicators which he argues that AI can play a role in achieving all indicators, but the following targets are highlighted.

> "… SDG 3.3. By 2030, end the epidemics of AIDS, tuberculosis, malaria and neglected tropical diseases and combat hepatitis, water-borne diseases and other communicable diseases …" (J. A. Singh, 2019, p. 742)
>
> "… SDG 3.8. Achieve universal health coverage, including financial risk protection, access to quality essential health-care services and access to safe, effective, quality, and affordable essential medicines and vaccines for all …" (J. A. Singh, 2019, p. 743)

While the studies presented so far have concentrated on the potential of AI, the following sections discuss the previous work on areas of opportunities of applying AI and ML and related challenges in the developing countries.

3.1.1 Opportunities of using ML in developing countries

There are many identified use cases of AI in health sector, and it is not feasible to discuss all the uses cases. For example, in a study by two global health donors USAID's Centre for Innovation and Impact (CII) and Rockefeller Foundation, 27 AI use cases were identified grouped into population health, individual health, health systems & pharmacy, and medical technology (USAID, 2019). The use cases discussed are therefore limited to population health and health systems because of the research context, primarily DHIS2 is developed to collect aggregated population data.

(USAID, 2019) identify the following use cases. *Surveillance and protection* in which data from multiple sources can be collected to map how disease spread and use predictive analytics to map future spread. *Population risk management* in which AI and inference generation technologies can be used to understand risk across different populations and stratify groups according to risk levels to enable more accurate projection of medical needs. *Intervention selection* in which AI can analyse certain characteristics of populations and geographic areas can be flagged as high risk and recommend interventions likely to be most effective. *Intervention targeting*, data on disease and risk from surveillance with additional data on population and geography can be used to pinpoint areas where intervention will mostly have highest impact and define who to target, where to target and when to apply.

Owoyemi et al., (2020) presents pilots and test cases of applying ML in Africa, they give examples such as in South Africa where ML is being applied to human resource planning to predict how long health workers might stay in public service and an AI planning application for optimising the scheduling.

3.1.2 Challenges of using ML in developing countries

While there are opportunities, there are several challenges which previous studies have reported in implementation of ML technologies. These include lack of supporting infrastructure, data availability, policy challenges and a set of miscellaneous challenges.

Inadequate supporting infrastructure

AI technologies cannot be developed or used without supporting infrastructure such as network connectivity and electricity, it is estimated that approximately 600 million people do not have access to electricity in sub-Saharan Africa (J. A. Singh, 2019). Further, it was also estimated that 30% of the health facilities in Africa had access to reliable electricity (Owoyemi et al., 2020). In addition to requiring electricity and communication infrastructure, ML processes such as deep learning work with huge amount of data and require considerable powerful computing resources (Owoyemi et al., 2020). It is estimated that training a deep learning model such as GPT-3 requires energy equivalent to annual consumption of 126 Danish homes, even though GPT-3 is a very complex model trained from massive amount of data, the infrastructure required to train AI models incurs addition carbon costs (WHO, 2021).

Data availability and quality challenges

Another set of challenges relate to data availability and quality. AI tools need huge amount of data to create more accurate predictive models appropriate to populations, the geography and populations (USAID, 2019). Reports indicate that developing countries are characterized by data issues, such as the absence of data from vulnerable populations in rural areas, poor quality data, and non-uniformity. (J. A. Singh, 2019) (Haider, 2020). The absence of data for the vulnerable is bad news because the various ML opportunities are geared towards these populations, the absence of such data is critical.

While many countries have made progress in digitization, others are still behind, and not all data is digitised (Owoyemi et al., 2020) (Stankovich, 2021). It is estimated that less than 40% of low middle income countries have adopted EMR and for the countries who have digitised, a few collect and analyse data in real time which is necessary for AI applications (USAID, 2019). The DHIS2 is estimated that it is used in over 100 low middle income countries, which is a big number but still there are about 140 countries in the category of low middle income, according to welcome trust (Adu-Gyamfi et al., 2019) (Wellcome Trust, n.d.). Lack of data for training does not only affect accuracy of the models but inhibits the use of AI models developed in high income countries. Using models developed with data from these countries will show bias in predictions, therefore efforts would be required to be used in context different from where the training data was acquired (USAID, 2019) (Owoyemi et al., 2020).

Legal and policy Issues

Other obstacles in the use of AI technologies are the lack of regulatory frameworks. According to Organisation for Economic Co-operation and Development (OECD) only 69 countries have initiatives on regulatory & legal frameworks on the use of AI and most of these are high income countries (OECD.AI, 2021). It is also reported that other developing countries do not have national health policies or strategy guiding implementation and monitoring of digital health technologies (Owoyemi et al., 2020). National policies on AI do not only foster digital economic development but also regulate ethical use of AI and provide legal implications on irresponsible use. (USAID, 2019) argue that developing countries lack the resources and technologies which they can use to create consistent policies on population health which in turn creates a barrier for AI tools for population health to scale at a national level. The WHO recognises the insufficient regulatory capacity of developing countries in assessing the safety and efficacy of new technologies. They advise these countries to rely on regulatory approval of AI technologies in developed countries or collaborate in registration of regulatory frameworks (WHO, 2021).

Miscellaneous challenges

There are also concerns about data privacy and ethical use. ML requires a lot of data for developing predictive models, since most of the health data is owned by government, there are concerns about allowing them to be used by private companies. The concerns include the fear that data might only profit the companies, might sell the data, and even leak the data. Most countries which have digitised their health systems have regulations on the use of health data, but may countries prohibit private companies taking health data outside their countries (USAID, 2019). This might be difficult to use the data for training in the cloud infrastructure.

Other challenges include the need for AI tools to be consistent with existing health workflows to integrate to existing health system, and lack of standards on what is acceptable accuracy of measuring the performance of AI. Owoyemi et al., (2020) highlights that the costs of deploying AI technologies might be very costly, costs are incurred in the processes of data acquisition, training, and maintenance of the applications (Mathur et al., 2020) (Owoyemi et al., 2020). The limited number of skilled employees is another challenge, J. A. Singh, (2019) argues that will require capacity building of health professional to be widely adopted in these countries.

3.2 DHIS2 Data

To relate opportunities and challenges in DHIS2. It is important to understand the type of data which is captured using the platform. DHIS2 collects aggregate and patient-based data, tailored (but not limited) to integrated health information management activities (Adu-Gyamfi et al., 2019).

The data is organised into three dimensions or building blocks, organisation unit, data element and period. Data element represents what is to be collected, it could be a count like BCG doses given or a property of an individual like HIV test result. Related to Data elements are indicators, indicators are calculated expressions with a numerator and denominator. For example, ART coverage, it is an indicator that is calculated as a percentage of the number of people living with HIV who are receiving treatment (WHO, 2022a). Organisation unit represents organisation structure like health facilities, administrative area, or other geographic area. Period represents the time dimension of data, and it is represented in frequencies like monthly, quarterly etc. This indicates that aggregated data in DHIS2 is time series data. DHIS2 also enables the collection of patient-based data, this is achieved by allowing users to create their own programs through DHIS2 Tracker (Ismanov, 2018).

The aggregated data collected in DHIS2 include the core health indicators. These are indicators specified by the WHO and defined by countries which are prioritised by the global community to provide concise information on the health situation and trends, including responses at national and global levels including agendas such as MDGs (WHO, 2018).

Patient-based data collected is arbitrary, that is it is based on use cases where the platform is implemented. To have an idea on this data, I turned to literature to explore what type of individual data is collected by countries in their DHIS2 implementations and tracker programs.

In Tanzania they use Tracker to collect maternal child health data, drug resistance tuberculosis, HIV care and death registration data (Ayebazibwe et al., 2019) (Sukums et al., 2021). In Zimbabwe Malaria disease data (Fjelstad, 2015), Ebola and covid-19 data in Guinea (Eggers et al., 2022), neonatal data in Malawi (Ismanov, 2018), Covid-19 in Sri Lanka (Kapoor et al., 2020). Cancer patients' data in Sri Lanka (Wijeratne et al., 2020), Cervical and breast cancer in Bangladesh (Khan et al., 2019), maternal and child health in Palestine (Venkateswaran et al., 2022), vaccination data in Nigeria (Shuaib et al., 2020). These are some of the known data collected in various DHIS2 implementations based on literature, but it is possible that there are more.

3.2.1 Related opportunities and challenges

The following section discusses some of the studies on the opportunities of the ML on data like what is collected in DHIS2 implementations.

The first 28 days of a child are considered the most crucial period of a child. Recent reports by WHO says that in 2020 2.4 million children died in their first month (WHO, 2022b). A study in Brazil’s Sao Paulo, researchers trained five ML models to predict risk of mortality using routine data. They found that ML algorithms were able to identify with very high predictive performance in the neonatal mortality risk of new-borns. The limitations of the study were the unavailability of enough predictive variables and researchers were not clear if the model would have the same predictive performance on other cities (Batista et al., 2021).

Time series forecasting are techniques which are used to predict future values from historical time stamped data. In a study in Philippines Alegado & Tumibay, (2020), researchers did a study aimed to find a model to predict vaccines to avoid shortage and oversupply. They used statistical models and multilayer neural networks on BCG coverage data from 2014-2019 and they found that neural networks models were superior because of smaller error values. The following figure shows a summary of their results, the red line shows the data, which was used for training, the blue line shows the forecasted data, and the grey line shows the test data which was used to validate their model. It can be seen that the forecast and test data line approximately match.

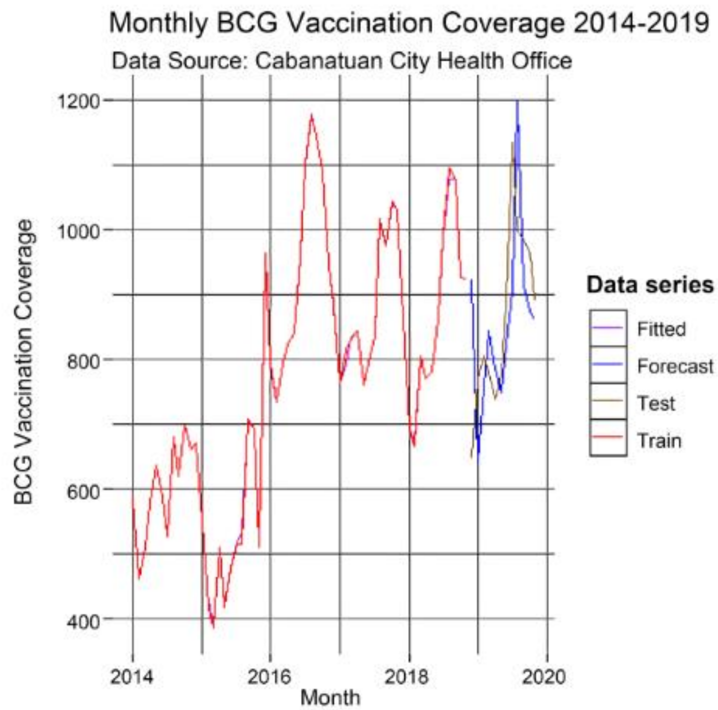


Figure 19: Training results (source: Alegado & Tumibay, 2020)

A similar study was done in Tanzania with the aim of maintaining optimal vaccines in any hospital facility. Their ML approach accurately predicted bi-weekly vaccine utilization at the individual health facility level. They achieved a forecasting fraction error of less than two for about 45% of regional health facilities in Tanzania regions (Hariharan et al., 2020). They concluded that their predictive model to forecast vaccine utilisation can be adapted to many countries and regions.

The need for accurate data is important, as it is the same data that when processed produces information which is used to make informed decisions. McCarthy et al., (2013) worked on developing a set of unsupervised learning algorithms that can aid in detecting and classifying anomalies in health worker data. They argue that probabilistic model approaches are not designed to prevent or catch deliberate falsification or systematic confusion and misunderstanding. They outlined a set of statistical tests that could be implemented by health organisations.

Other studies have involved the use data from various sources combined with data collected from DHIS2 instance. Such studies include one done Katwesige et al., (2020) on integrating Malaria data from DHIS2 and climatic data for predicting Malaria occurrence in Uganda. They used climatic data like rainfall, minimum temperature, maximum temperature, and others to make a model of predicting malaria cases recorded in DHIS2. Their findings were that there was an association between the two, that climatic data seemed to predict malaria cases with a model that had a lag of two weeks proving the best. This means that after the area experiences some rain it would take two weeks to impact malaria cases.

3.3 Ethical concerns in AI

3.3.1 Common Ethical themes

While AI has been studied and found to have the potential achieve developmental outcomes, it can also lead to harmful consequences when it is not appropriately used or developed. AI ethics is an area of study which has emerged as a response to the various individual and societal harms which AI poses due to misapplication, poor design, and development. The ethical issues of AI discussed in this section have been limited to those that relate to ML considering that AI is a wide field, the ethical issues discussed are based on a study by Murphy et al., (2021), these include bias in predictive models, privacy & security concerns, lack of trust, and accountability concerns.

One of the major concerns in the use of ML is the issue of biases in models. Bias in models refers to a phenomenon which happens when predictive models demonstrate some discrimination against a particular group on the data it designed to operate. Murphy et al., (2021) argue that there are two sources of bias: humans and poor data. They argue that humans are fallible creatures that poses different values which are transferred and incorporated in the design of AI systems, as a result the systems simply reflect the societally endemics. Further, they also point out that bias is also manifested in the data which is used to train the models. Data may be inaccurate, incomplete, and underrepresented in attributes such as gender, age, race, sexual orientation (WHO, 2021). Using such data to train models to make generalisation on a wide population will likely read to bias. (USAID, 2019) highlighting the scarcity of data developing countries, if AI systems with models developed in high income countries are to be applied in developing countries, efforts would be required to adjust the models be bias free.

Since ML models are developed from data, there are concerns related to privacy and security on how the data is collected, used, and shared. For ML applications which require individual health data, there are concerns that the data might be used for different purposes, the data might be stollen and that even if consent is offered from the owners, the black box nature of the models make it difficult to trace how the data is used (Murphy et al., 2021) (WHO, 2021).

Other concerns relate to who will be held accountable in cases when the AI applications makes predictive errors, especially in clinical settings to aid in diagnoses (Murphy et al., 2021). ML models work like black boxes which makes it difficult for people to understand and explain the predictions. If predictive errors are made during diagnosis questions arise that who is responsible for the error? On the other hand, reports indicate that clinicians and health care providers have biases and make diagnostic errors. A study in United States found that 5% of adults who seek health advice receive erroneous diagnosis and such errors account for 10% of patient deaths (WHO, 2021). So, while ML models can make errors, but the trail goes back to humans who developed them, and the quality of the data used.

Another issue is trust, trust from the people whom data was collected and trust from the people who are going to use the technologies (Murphy et al., 2021). The questions arise on how do individuals trust that their data is going to be used safely and securely? USAID, (2019) report that in developing countries there are a variety of issues on how health facilities, governments among others think about collecting and using digital data and what companies will do with the data. They further argue that many governments in developing countries and stakeholders at local and national levels hesitate providing data fearing it can be used against them in performance evaluations.

3.3.2 Ethical principles

Realising that ML systems can be wrongly developed and misused, as a response to the ethical concerns various institutions have put efforts in the development of ethical principles in AI. The principles are formulated to act as a guide on what is right to do and what is wrong to do. The institutions include national and international organisations, including governments and non-governmental organisations and research institutes (Zhou et al., 2020).

Some of these include the EU (European Commission, 2018), The United Kingdom (House Of Lords, 2018), standardisation bodies like Institute of Electrical and Electronics Engineers (Chatila & Havens, 2019), the WHO (WHO, 2021), private companies like google, IBM, Microsoft and Intel (Zhou et al., 2020) and others. Furthermore, other researchers have come up with ethical considerations when applying ML in healthcare such as Char et al., (2020), to limit the context, I present the ethical principles stipulated by the WHO, a body responsible for international public health.

WHO came up with ethical principles or guidelines to guide developers, users, and regulators in improving and overseeing the design and use of AI technologies to ensure that AI fulfils its potential and promise. An ethical principle is a statement of a duty or a responsibility in the context of the development, deployment, and continuing assessment of AI technologies for health. The principles state that the technologies should.

> "… Avoid harming others; promote the well-being of others when possible; ensure that all persons are treated fairly, which includes the requirement to ensure that no person or group is subject to discrimination, neglect, manipulation, domination or abuse; deal with persons in ways that respect their interests in making decisions about their lives and their person, including health-care decisions, according to informed understanding of the nature of the choice to be made, its significance, the person's interests and the likely consequences of the alternatives ..." (WHO, 2021, p. 23)

Following the ethical principles lead into development of AI systems which will bring good to humanity, efficiency in operations and promoting equity in access. The WHO also recommends the enactment of data protection laws and policies such as the General Data Protection Regulation (GDPR) of the European Union (EU) which regulate how data is collected and used. Further they recommend the *integration of ethics and human rights standards in design of systems* like the way GDPR mandates privacy in design. One such standard is called “*design for values*”. Design for values promotes consideration of social and moral values in design requirements. It permits the involvement of different stakeholders in design choices of AI systems. The following are the guidelines.

> “… The involvement of all different stakeholders in development of AI technologies, designers and other stakeholders should ensure that AI systems are designed to perform well-defined tasks with accuracy and reliability, designers should ensure that stakeholders have sufficient understanding of the task that an AI system is designed to perform and the conditions necessary to ensure that it can perform that task safely and effectively, the procedures that designers use to ‘design for values’ should be informed and updated by the consensus and continuing education and training programmes should be available to designers and developers to ensure that they integrate evolving ethical considerations into design processes and choices *... ”*(WHO, 2021, p. 68)

3.5 Machine Learning Processes

This section covers several topics related to the development and deployment of ML predictive models. I will review the processes involved in creating these models, discuss different model deployment architectures and how they impact app architectures within platform ecosystems, provide a case study on integrating a model into an HMIS, address challenges associated with deploying ML models, and briefly explore Automated ML.

3.5.1 Model Development

Before gaining insights or making predictions using ML, several processes must take place. There is no standard set of processes for ML, literature presents them in different ways depending on the context of the technology’s application. However, some steps are common in all ML processes. The steps presented in this section are a generalization of those presented by various authors, including Chibani & Coudert, (2020) Bayraktar et al., (2019) and Marsland, (2014). These steps include data gathering, data pre-processing, feature selection, algorithm selection, training, model evaluation, and model deployment.

The first step in ML is data collection. Data can come from one or multiple sources and can be in different formats such as CSV, XML, JSON, among others. It can be downloaded as files or accessed via APIs like REST. The data collected then undergoes a pre-processing phase, during which outliers or missing values are removed or interpolated, depending on the data quality. This is because algorithms cannot work with null values.

Next is feature selection. At this stage, relevant features or attributes for a predictive task are selected. The collected data may contain many attributes or fewer ones. In cases where data is from different sources, the identified features are combined to make a dataset based on the specific use case being implemented.

The next step is the selection of algorithms used train the data. The choice of the algorithm is based on the use case, or the problem being solved, if its supervised learning then appropriate algorithms are selected, if its unsupervised then unsupervised learning algorithms are selected.

The next step in ML is training the selected algorithm with the chosen data. This process can be computationally intensive, depending on the type and amount of data, the algorithm used, and other factors (Ray, 2019). If supervised learning is used, the dataset is typically split into training data and testing data. The training data is used to teach algorithm patterns. Once training is complete, the resulting model is evaluated on the test data, which was set aside for this purpose to see how well the model predicts on data it has not seen before. If the model underperforms, adjustments can be made to the algorithm parameters, feature selection, or different algorithms can be used for the same purpose until satisfactory performance is achieved.

The final step is deploying the model into production for use. The model is the product of the ML process, and when fed with new data, it can make predictions based on the data it was trained on. The model is integrated into a system to make it available for users to make predictions. The following diagram summarises the process.

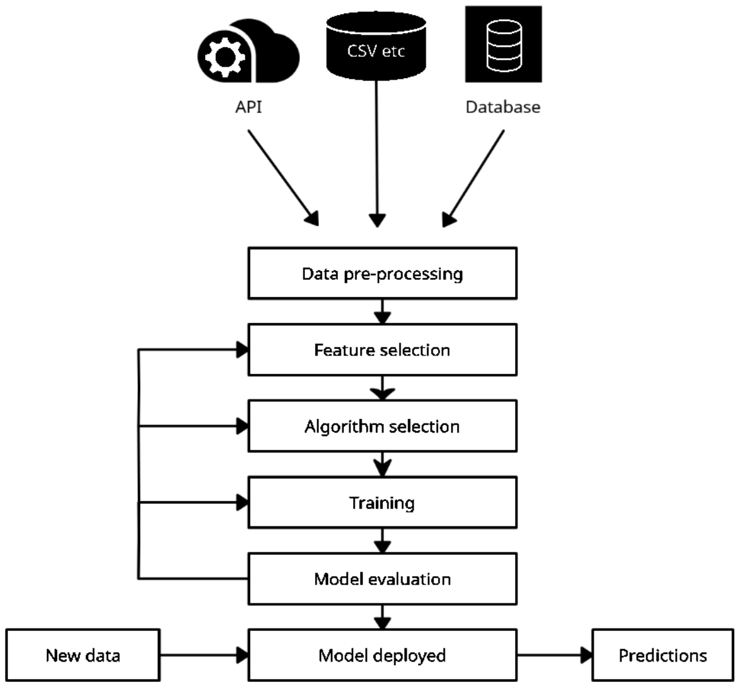


Figure 20: ML model development process

The approach of model development which has been discussed is called offline learning or batch learning (Korstanje, 2022) (Putatunda, 2021). Offline learning requires an entire dataset for training or huge amount of data for training. One of the problems of offline learning is model drift, model drift happens when the model performance degrades below accepted benchmark (P. Singh, 2021). This happens because overtime, the model becomes outdated due to new patterns in data being collected, thus the models need to be evaluated overtime. Another approach is called online learning or incremental learning (Korstanje, 2022). In online learning, the learning process takes place on continuous basis as new data is being generated. This makes the model to be updated all the time and this mitigates the problem of model drift. Online learning is used when streaming data is collected, streaming data refers to data which is captured at high velocity and on a continuous basis (Putatunda, 2021).

3.5.2 Model deployment architectures

As discussed in the previous section, the output of the ML process is a model which is used for making predictions on new data. This section discusses how the models are integrated into digital platforms or software to be accessed by users.

There are multiple ways which ML models are deployed; the deployment architectures align along with application architectures in digital platforms. Platform ecosystems consist of two architectures; the core platform architecture and app architecture (Baldwin & Clark, 2000) (Tiwana, 2013). The core platform provides interfaces to apps on how to extend the platform and it is viewed in the same way to all the apps in the ecosystem. The app architecture describes the design and interaction of the app and the core platform to extend the platform with a new functionality.

There are four functional elements in which influence app architectures. These elements include presentation logic, application logic, data access logic and storage (Tiwana, 2013). The distribution of these elements in an app influences the app architecture, in a way that all elements can be implemented to run on one platform, or several elements can be implemented to run another platform. The partitioning of these elements in apps results into several app architectures which include standalone, cloud, client-based, client-server and peer-to-peer architectures.

ML models are deployed in several ways, among these include integrating the model in an app in *client-side deployment* and serving the model or its predictions through a web service such as REST API in server-side deployments (Ameisen, 2020). The client-side deployment architecture follows the standalone app architectures, and the server-side architecture follows the client-server app architectures. These architectures are illustrated as in the following diagram.

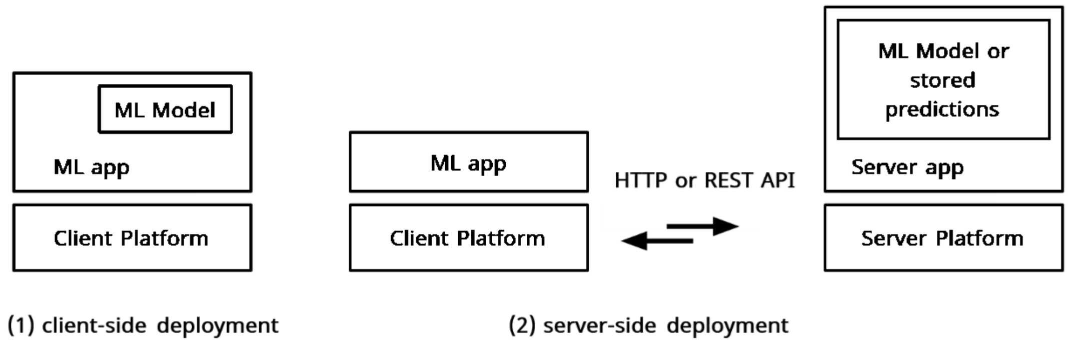


Figure 21: ML deployment architectures

In the client-side deployment, the ML model is embedded in the application, it can be stored in a file or a local database. When the app is published and installed by users, there would be no need for the app to interact with another element outside of the platform ecosystem. The architecture can similarly be implemented in a web application, where the business logic and data access layers reside on the server side. The model is still embedded in the app the only difference being that some functional elements of the app are on the server side.

The advantage of this is that it reduces the need of serving infrastructure and enable the app to run without access to the network which can incur latency while using the app (Ameisen, 2020). The one disadvantage is that the model is tightly coupled with the app, updating the model will result in updating the app, for apps distributed through app stores there would be need for a new update. P. Singh, (2021) presents how this can be done in a web application in which it is described as deployment as web service.

The second deployment architecture is the server-side deployment. In this architecture the model is deployed on another platform which is accessed by apps through a dedicated API (Ameisen, 2020). Users interact with an app which sends request to the server where the model makes predictions or access stored predictions. P. Singh, (2021) describes this as "model as REST service". There are two variations in this deployment based on whether the predictions are made in real time or in batch. If users send requests and the predictions are returned in a request and response fashion it is called online predictions, if predictions are not made instantly that they are available at a later time it called batch prediction (Google Cloud, 2023) (Ameisen, 2020).

In this architecture, instead of the model being tied to the app, an API call is made to a service deployed primary to serve the model or run predictions. The advantage of this is that there is scalability, when more server resources are required due to an increase in the number of users, they can be added. In addition to that, the model is not coupled with the app that updating the model will not require updating the app.

3.5.3 Model Integration in HMIS: Case study

This section reviews an example of how an ML model was integrated as a module in OpenMRS, an open-source HMIS widely used as an Electronic Medical Record (EMR) system in developing countries. The software is recognized as a digital public good, like DHIS2 (Verma et al., 2021). The case is a report on the deployment of ML as a module in OpenMRS to predict interruption in treatment (IIT) among antiretroviral treatment (ART) clients at health facilities in Mozambique with support from the USAID (Stockman et al., n.d.).

The aim of the project was to use ML to identify HIV clients at the greatest risk of IIT, to help health providers direct interventions towards those who are most vulnerable. The models trained using data from OpenMRS showed strong predictive power and outperformed existing techniques. The team developed a software module, which was integrated with the predictive model. OpenMRS uses a modular architecture that allows for additional functionality to be integrated when needed, to enhance the system (Seebregts et al., 2009). In contrast, DHIS2 uses a similar architecture but enables platform extension through the development of apps by third parties (Nicholson et al., 2019).

The deployment process involved the use of a local infrastructure whereby data was pulled from the database through an API for ML training, and the results were written to the local database. This approach was preferred over central deployment that would have pulled data from a central data warehouse due to connectivity concerns. Despite training the model using data from all sites, the module was installed at all facilities and run locally, with the results stored in local databases.

> “*The model was trained on data from all four sites, but it only exists at each site; no outside network connection or data are currently required for the running of the module or the ML model.”* (Stockman et al., n.d. p. 10)

They also report a deployment challenge. Initially, they trained the model in a Python environment and found it difficult to create a workflow that would seamlessly export the model to be used in a Java environment, as the OpenMRS backend is written in Java. They had to retrain the data using a Java framework called Apache Spark.

From the study, it can be seen that the model was integrated through the software module, which was installed at each health facility. In comparison to integration methods in the previous section, they used a standalone implementation architecture. In the maintenance section, they report that updating the model will require manually copying a model file into a folder at all instances across the four facilities.

3.5.4 Challenges in deploying ML models

In section 3.5.1, I presented the various processes involved in the production of predictive models in ML. In the succeeding section, I presented different methods for deploying these models, which can be used by users to yield predictive benefits. It is evident that ML is not necessarily a plug-and-play technology. The development and deployment processes incur many challenges that require careful consideration during implementation.

Sculley et al., (2015) argue that there is technical debt in ML systems, just as there is in software engineering projects. Technical debt in software engineering exists at the code level and involves refactoring code, reducing dependencies, improving tests, documentation, and other aspects. In contrast, they argue that technical debt in ML systems exists at the system level rather than the code level because the code makes up only a small component of ML systems. It is the ML-related processes that incur the costs, such as monitoring, configuration, and serving infrastructure, which may be hidden.

P. Singh, (2021) outlines eight challenges that should be expected when putting ML models into production. The first challenge is the need for coordination between various stakeholders in ML, such as app developers and data scientists. The second challenge is that there might be programming language discrepancies. Singh argues that it helps to use a common language for the app and ML, even though it has become easier to migrate ML models for integration in different languages. The third challenge is model drift. This phenomenon happens when the prediction performance of models degrades below an accepted benchmark. This calls for the requirement of monitoring the performance of the model on a continuous basis. Singh argues that the drift might be due to changes in data and changes in the interpretation of data. The remaining challenges include deployment strategies in the context of cloud or on-premises deployment, considering their pros and cons, model version management, model security, and model ownership.

In their study Baier et al., (2019) reported several deployment challenges. The first challenge is drift in input data also referred to as model drift by P. Singh, (2021), they report that even though tools are available to automatically recognised shifts in data sometimes manual adjustments are done to match the models to the data. The need for documentation on each model update is reported as a daunting. Another challenge is lack of robustness in models when faced with minor data changes or reduction in data quality, there is need for ML models to provide reasonable results is such scenarios. Like P. Singh, (2021), they also report the ongoing process of validating ML solutions a challenge, described as time consuming, unstructured and unstandardised process. The management of deployment infrastructure, the scaling of a model to deployment architectures.

3.5.5 Automated Machine Learning (AutoML)

Even though ML has widely been adopted across different industries, the complexities surrounding the development, deployment of the technology acts a barrier for new users. In particular deep learning requires human experts in selecting the right neural architectures, training procedures and other technical parameters (Hutter et al., 2019). To make ML easy to use by non-experts AutoML has emerged as one of the techniques which automates the various stages on ML processes. Yao et al., (2018) believe that automating the various processes can enable faster deployment in organisations, lead to efficient validation and benchmarking of deployed models, and make experts focus on other areas. The aim of AutoML is to provide a platform for easy integration of ML in different industries and improve better outcomes (Mustafa & Rahimi Azghadi, 2021).

AutoML automates the processes between data collection and model deployment. The processes in between require human interference. According to Mustafa & Rahimi Azghadi, (2021) AutoML automates the processes of data pre-processing, feature engineering, algorithm selection, training, hyperparameter optimisation, and model evaluation. The following figure shows the ML processes when AutoML is used.

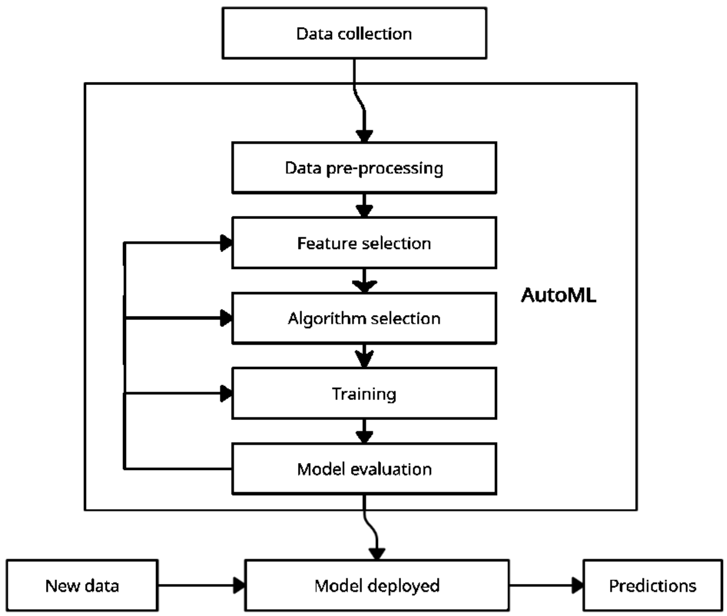


Figure 22: AutoML architecture

While commercial AutoML frameworks are prevalent on the market from google, amazon and Microsoft, there are frameworks from the academia and open-source community (Mustafa & Rahimi Azghadi, 2021) (V. K. Singh & Joshi, 2022).

3.6 Summary

In this section, I have presented literature on the use of ML in developing countries, ML processes, and their integration architectures based on previous studies. The studies report that AI has the potential to reduce healthcare costs and assist countries in achieving developmental goals, such as the SDGs. In the public health sector, AI could be applied in disease surveillance, population risk management, intervention targeting, and more. However, previous studies have also highlighted several challenges that developing countries would face in using ML technologies. These challenges include the lack of supporting infrastructure, quality data, and policies on AI, among others.

The DHIS2 platform is used to collect routine aggregated data and patient-level data related to maternal and child health, drug-resistant tuberculosis, HIV care, malaria, Ebola, COVID-19, neonatal care, vaccination, and more. Other studies have focused on ML opportunities related to this type of data, such as predicting mortality risk in neonates, predicting vaccines to avoid shortages and oversupply, and predicting malaria occurrences. However, these studies did not focus on integrating ML in the HMIS, where the data was collected.

Although AI has the potential to achieve developmental outcomes, it can also lead to harmful consequences when not appropriately used or developed. Previous studies have reported issues of bias in predictive models, discriminatory behaviour, potential breach of privacy when data is shared, lack of trust in algorithms, and accountability concerns when wrong predictions are made. To address ethical concerns, various stakeholders have come up with ethical principles to guide the development of AI solutions that bring good and not harm to humanity.

Developing ML models involves several steps, including data gathering, data pre-processing, feature selection, algorithm selection, training, model evaluation, and model deployment. Once the models are developed, they are integrated into information systems for users to access. The integration architectures align with standalone and client-server architectures, where a predictive model could be embedded in an app or served by a server platform. Studies have also reported challenges in deploying ML models, such as technical debt in maintaining systems and model drift, which requires retraining of the models.

Chapter 4

Methodology

This chapter explains how the research was designed and conducted to answer the research questions. It involved using a combination of philosophy, inquiry strategies, and other research methods. The first section (4.1) discusses the interpretive worldview that shaped the study's perspective. This worldview considers reality as subjective and constructed through human interpretation. The second section (4.2) explains the research approach and strategy, which was inductive and qualitative, using the case study method. The third section (4.3) covers how data was collected through interviews and purposive sampling. The fourth section (4.4) discusses the data analysis method, which involved identifying themes in the collected data. Lastly, section (4.5) talks about ethical considerations that were taken to ensure that the study respected human dignity and upheld the study's reliability.

The methodology outline is based on the research onion model by Saunders et al., (2007) which illustrates and compares the different stages of research design to the process of peeling an onion. I used the onion model as a framework to identify the elements that should constitute the design of a standard empirical study. These elements include philosophies, approaches, strategies, choice of methods, time horizons, and procedures for data collection and analysis. This is illustrated in Figure 23.

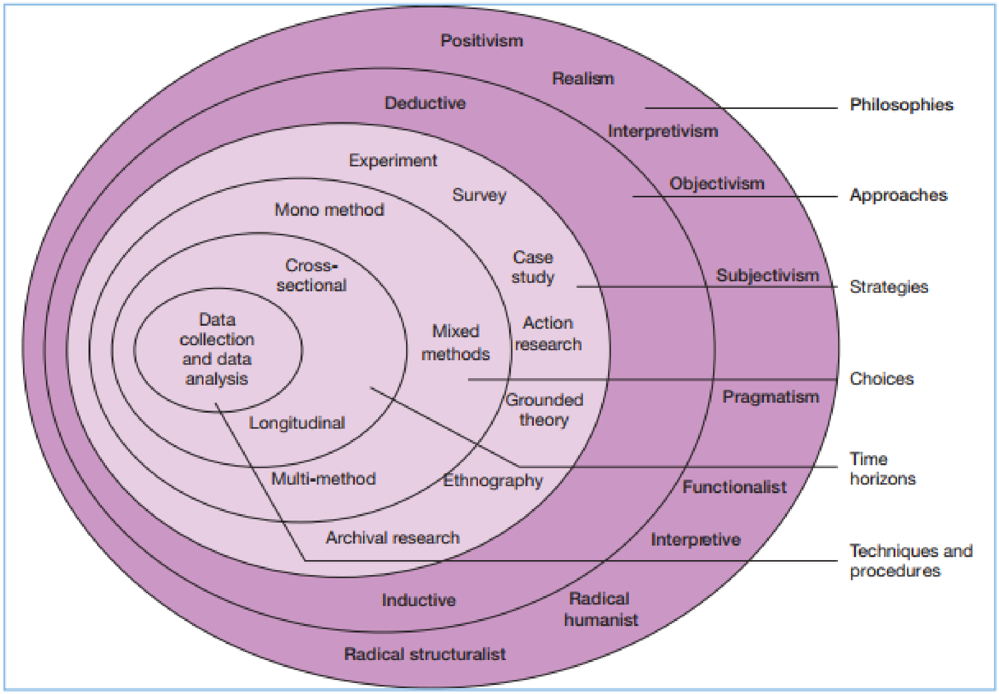


Figure 23 : Research onion (source: Saunders Et al. 2000)

4.1 Philosophical worldview

Worldviews are a set of beliefs that guide action (Creswell, 2009). In epistemology (study of knowledge) and the field of research (search of knowledge), worldviews encompass assumptions which a researcher holds of reality or understanding of the world. The assumptions adopted are fundamental as they influence the research strategy and the methods used in the study. Orlikowski & Baroudi, (1991) categorises research in information technology into three epistemologies, positivist, interpretive, and critical studies. This research adopted the interpretive worldview.

Interpretive research methods are based on the position that our knowledge as well as reality are social constructions by human actors (Walsham, 2006). It asserts that reality is subjective and not objective, that is formed through human interpretation. Researchers aim to understand the constructions rather than measure and quantify it as objective reality. Creswell elaborates more by saying that "… individuals develop subjective meanings of their experience's meanings directed toward certain objects or things, and that these meanings of their experiences lead the researcher to look for the complexity of views rather than narrowing meanings into a few categories or ideas. The goal of the research is to rely as much as possible on participants views of the situation being studied …" (Creswell, 2009, p 8).

Research in information systems focuses on its social-technical components; technology, people, and processes and their interaction. Orlikowski & Baroudi argue that "… the design and use of information technology in organisations is embedded in social context marked by time locale, politics, and culture. Neglecting these influences can only reveal an incomplete picture of information systems phenomenon …" (Orlikowski & Baroudi, 1991, p 12). In the context of this research, ML is a technology component of a larger information system. Its potential, adoption and use or lack of use in an organisation is influenced by experiences, practices, processes, and views of the people in the organisation. This research thus attempts to understand the potential and challenges of ML in an interpretive way from the perspective of the different participants which were engaged in the study.

4.2 Research Approach and Strategy

Peeling the philosophical view layer, we encounter the research approach layer. Two high level approaches exist, *deductive* and *inductive*. In a deductive approach, a theory or a hypothesis is developed, and the research strategy is designed to test whether it adequately explains a phenomenon or not. In the inductive approach researchers do not begin with a hypothesis but rather collect data which is subjected to analysis and the findings can be "… themes, categories, typologies, concepts, tentative hypotheses, and even theory about a particular aspect of practice …" (Merriam & Tisdell, 2015, p 16). These two approaches are attached to the philosophical world views, "… deduction owes more to positivism and induction to interpretivism …" (M. Saunders et al., 2007, p 117). In this study, the data which was collected through interviews was analysed to find the different themes from the participants, thus the inductive approach was used.

Three strategies of inquiry are used in research: qualitative, quantitative, and mixed. The role of the strategies is to guide researchers on how to carry out a research study. Guided by the inductive approach, this research used the qualitative research strategy. Qualitative research is aimed at exploring and understanding the meanings individuals or groups to a social problem and data is analysed inductively (Creswell, 2009). The strategy was a best because the data which was collected was qualitative in nature inform of views, experiences, understandings, observations, and documents. The study used a qualitative strategy of inquiry, which made it a mono-method study. Mono-method studies rely on a single data collection technique and corresponding data analysis procedures, as opposed to multi-method studies (Saunders et al., 2007). In this case, the study utilized only one type of data, which was qualitative, and one corresponding data analysis method.

While there are many qualitative strategies in qualitative research, this study followed an exploratory *case study* strategy. A case study is an in-depth empirical study of a phenomenon utilising various sources of data. Merriam & Tisdell, (2015) argue that a defining characteristic of a case study is the object of the study “a case” around which are boundaries, it could be an individual, a group of people, a policy and more. The study focused on an IS technology “Machine Learning” which was the case, and its boundaries were the “DHIS2 ecosystem”. Further, the study utilised multiple sources of data including interviews, a document, and meetings, this was important as it allowed for more in-depth study of the case. The exploratory nature of the study was since the phenomenon of ML and DHIS2 has never been researched empirically before.

4.3 Sampling and Data Collection

The last layer of the onion focuses on data collection and data analysis methods; however, the data analysis methods will be discussed in the following section. This section presents how participant were selected to be part of the study and the different data collection methods which were used.

4.3.1 Participants selection

The participants in this study were selected using purposive sampling. Purposive sampling is a non-probability method of sampling which does not involve randomisation in the selection of participants. This method allows the researcher to identify participants who have the qualities that align with the sample requirements of the study. Etikan et al., (2016) argue that the sampling method enables a researcher to select participants who are willing to provide information by virtue of knowledge or experience and participants that are proficient and well-informed with a phenomenon of interest.

In the context of this study, one would think that the qualified participants would be individuals who are knowledgeable in ML, but that would be wrong as there would be a potential influence of bias as the data would be from individuals with one perspective. Purposive sampling has several variations and one of it is called heterogenous sampling or maximum variation sampling (M. Saunders et al., 2007). Heterogenous sampling enables the inclusion of participants with distinctive characteristics and come from diverse backgrounds related to the topic under study (Etikan et al., 2016). In the context of the study the, the participants included individuals who had different background about ML, from people who had minimal knowledge to experts who have the technical knowledge and had a great deal of experience. The diversity in the participants reduced the potential of bias and opened room to capture rich data. While the sampling methods has the mentioned advantages, it is has its weakness. Patton, (2002) argues that for small samples it can be a problem, however the method can be turned into a strength when focus is directed to the common patterns which emerge from the variation. "… Any common patterns that emerge from great variation are of particular interest and value in capturing the core experiences and central, shared dimensions of a setting or phenomenon …" (Patton, 2002, p. 235).

This was applied in the study as the sample of the study was small, In the DHIS2 ecosystem there are a few groups of people with ML experience or well knowledgeable about ML technology. Heterogenous sampling allowed me to identify these people to maximise the minimum available resources. The sampling method also enabled me to have participants who did not have knowledge of ML, but they had experience with DHIS2. This allowed me to collect data from individuals coming from different perspectives and reduced bias which can be introduce in selecting participants in research. Further, the variation was not only applied to knowledge background but also from the organisations which the participants belong, the participants came from ministries of health, HISP groups, universities, and private organisations. Smith & Noble, (2014) argue that one of areas where bias is introduced in research is in participant selection, so the diversity in the participants was one the consideration to counter bias and influence reliability.

The people in the DHIS2 ecosystem which met the sample criteria were identified. During the planning phase of the study, the 2022 DHIS2 annual conference was approaching, I was encouraged to participate and identify participants. The participants were reached through emails, however this approach turned out to be with some difficulties. Some emails were not answered, other potential participants responded and promised to participate, but their promise was never committed. I am also grateful with the support given by my supervisor who assisted me in contacting the participants in some instances, but it did not work out in all scenarios. This had an impact on the number of participants in the study, and only 9 participants accepted.

The appropriate number of participants in a qualitative study to reach saturation is a topic of active discussions in the literature (Vasileiou et al., 2018) (B. Saunders et al., 2018). Morse, (2000) argues that the number of participants in a study is one area in which it is clear that too many factors are involved, and conditions vary too greatly to produce recommendations. Morse presents factors which should be considered when determining the sample size which include the scope of the study, the nature of the topic, the quality of data, study design and the use of overshadowed data. The use or integration of ML in DHIS2 has never been studied before and there are a few experts with knowledge of both technologies, this nature of the study affected the number of participants and out of these some did not participate. The scope of the study was narrow considering the research questions, as they focused on opportunities, challenges and how ML can be integrated with DHIS2. Furthermore, by the time I was conducting the last interview, I noticed that there were no new themes being presented by the participant. Further, I was also convinced that the research questions were answered. Considering these factors, I was convinced that saturation was reached, but I would have loved to have had a larger sample.

4.3.2 Data collection methods

The study primarily used interviews as the data collection method. In addition, secondary data was gathered through observations from meetings attended and a draft grant proposal document. Considering the different data collection methods in qualitative research such as focus groups, surveys and questionnaire, interviews were the best fit and a primary method due to the nature of the data to be collected, the phenomenon under study, the availability of participants and time constraints. Participants included individuals who have knowledge in ML implementations supporting DHIS2 and different stakeholders such as developers and HISP partners scattered across the world. Focus groups were considered not to be feasible as the potential participants work in different organisations around the globe, furthermore some interviews were rescheduled due to some unforeseen circumstances faced by participants, cases like that have a great impact on focus groups. Survey and questionnaires would have required more time, and they cannot capture detailed perspectives.

Interviews are a common data collection method and one of the important data collection tool in IS qualitative research (Myers & Newman, 2007). In an interview a researcher engages in a conversation with a participant about a topic. One advantages of interviews is that rich data can be collected as the questions are mostly open-ended to allow a better understanding of the response and clarification whenever necessary. While interviews are a powerful tool for collecting data, the method has its pitfalls if it is not appropriately used. Myers & Newman, (2007) present a number of these pitfalls in IS research, some of these are the possibility of participants lacking trust, lacking time which may lead to incomplete data collection, there could be ambiguities in language which can result into participants failing to understand the questions and others. Therefore, it was also important for me to put these factors into consideration when the interviews were being conducted, for example by making the participants feel more relaxed and clarifying the questions whenever they did not understand.

There are three categories of interviews namely unstructured, semi-structured and unstructured. In this study, I used semi-structured interviews. This type of interview allows a researcher to have a set of questions which would be asked to participants and can vary from participant to participant. Saunders et al., (2007) further elaborates by arguing that semi-structured interviews give room for omission of some questions based on the organisation context in relation to the research question, gives the flexibility of adding more questions depending on the flow of the conversation and a researcher can vary the order in which the questions are covered.

I prepared two sets of questionnaires, one set for participants with experience using ML technology and one set for stakeholders within HISP who did not have any experience with the technology and others demonstrated intermediate knowledge. This was influenced by the heterogeneity of the sample as discussed in the previous section. Some demonstrated lacking any technical knowledge, some argued to have a good knowledge but without technical experience, some argued to have worked on small projects, some studying it, and some demonstrated expertise. Semi structured interviews allowed me to ask questions based on the knowledge levels of the participants, for the ones with intermediate knowledge in ML I would mix up the questions and let the questions flow along their knowledge.

Some of the interviews were conducted in person as opportunities created it, the participants were in proximity to me. Other interviews were conducted online because the participants were in other parts of the world, this is the reflection of the heterogeneity of the sample and the bounds of the study; the DHIS2 ecosystem.

The interviews were conducted between November 2022 and February 2023, which meant that the study had a cross-sectional time horizon. Cross-sectional studies are commonly used in academic research to study a phenomenon at a specific point in time when time constraints are a factor (Saunders et al., 2007). In this case, the study was part of a master’s program with a thesis due in May 2023, so I had limited time to conduct the study. As a result, I opted for a cross-sectional approach that was feasible within the available period.

The following table summarises the list of participants in the study and the interview schedule. The interviews varied in duration, but on average the length was around 15 minutes, that excludes the introductory remarks. The variations were influenced by the heterogeneity of the sample, interviews with participants which had less knowledge were not taking longer than interview with expertise in the field of ML.

Participant ID	Date	Location	Role
STK01	15.11.22	HISP UiO	MOH Senior Developer
STK02	18.11.22	HISP UiO	HISP Leader
STK03	19.12.22	Online	HISP Implementer
STK04	22.12.22	Online	HISP implementer (PhD)
STK05	08.02.22	HISP UiO	Core Developer
STK06	05.12.22	Online	Head of Data Science
STK07	12.12.22	Online	HISP Engineering Manager
STK08	06.02.23	HISP UiO	Assistant Lecturer
STK09	14.02.23	HISP UiO	DHIS2 Lab Project Manager

Table 1: List of participants

I gathered additional data from two meetings I attended on February 8th and 15th, 2023. These were informal gatherings without a formal agenda or minutes being taken and included both physical and virtual attendees from around the world. The meetings involved various stakeholders from UiO and DHIS2 developers. While I mostly observed, I did contribute once when I was prompted. Since no minutes were taken, I took notes of the discussions. After the meeting, I was added to a slack team and given access to a document that also served as a source of data.

4.4 Data analysis

The interviews were successfully carried out and data was recorded with consent from the participants, guaranteed security, explanation of how the data was going to be used, and when the data was going to be deleted. Consent was obtained when the participants were being invited to participate in the study and I also utilised a consent form (see the appendix

A2). I used an app called Diktafon by University of Oslo which securely records audio data from interviews and the data is uploaded to Nettskjema, a system which is used to collect and store research data.

The transcription process started immediately after each interview, taking note of potential themes and began understanding the data before familiarisation process started. Nettskjema allows playing the interview recordings online for security purposes but also the recordings can be downloaded offline in cases which a researcher wants to use a transcription tool. I did the transcription process manually, I listened to the recordings, playing back and forth, and writing down what participants said. Some difficulties were there as the participants had different ascents and for online interviews poor internet connection resulted in some hiccups in the recordings. But through repeated playing I was eventually getting what the participants were saying. The process took a considerable amount of time especially for longer interviews. In the process, each participant was given an ID for anonymity reasons and the transcripts were stored securely in the cloud through Microsoft office 365. The study data and the transcripts will be deleted at the end of the study by June 30, 2023, and this information was shared with the participants.

Guided by the research philosophy, thematic analysis was used to analyse the data. Thematic analysis was chosen because of its flexibility, Braun & Clarke, (2006) argue that thematic analysis can be used across different epistemologies providing rich and detailed yet complex account of data. They define thematic analysis as a method of identifying, analysing, and reporting patterns (themes) within data. Further they developed a guide for using thematic analysis which I used in the study. The guide consists of six steps which starts with familiarising with data, generating initial codes, searching for themes, reviewing themes, defining & naming themes, and authoring the report. The study had two research questions, thematic analysis gave me the flexibility to use it to find themes answering both questions and furthermore there were no problems using it with data from the interviews, document, and observation.

After the data transcription was complete, I read the transcript repeatedly to clearly understand what the participants said. The next step was to generate initial themes, I loaded the data in NVivo, a qualitative data analysis tool and started to code the data manually. The following table shows how some codes were generated at this stage.

Data extract	**Code**
“issue we are having right now is the data quality” “require a lot of actual training data” “advanced statistical outlier detectors, but we are not” “is data quality, you can’t build analytics” “processes to clean up bad data” “plays a big role when it comes to huge amount of data “ “that we have a lot of data” …	Data
“a lot talk about in the literature around biases of AI” “we need people who are well trained” “techniques to detect bias is their datasets” “they will need capacity to do that” “technical skills of course in terms of the capacity “ …	Technical
“are still struggling with infrastructure” “require substantial number of resources” “so, we lack experts as well as resources “ “you need to have the resources to run them” “spending that much money on the infrastructure “ “need some laptops to collect the data “ …	Resources
Run, select, report, notify, pipeline, output, performance, getting in, push back, combine, pull …	Process

Table 2: Code generation

The next step was grouping the codes into potential themes and collate the coded extracts into the identified themes. This was guided by the research questions. The extracts were examined whether they related to challenges, opportunities, and processes. In this process, I used visual representation of themes using thematic maps, figure 25 shows a thematic map at this stage.

After this, I checked whether the coded extracts were relating well with the initial themes. This prompted me to go back to the data and understand the whole idea which the participant was talking about in the sentence the coded extract was taken. In a case of irrelevance, the extract would then get recoded it to a relevant code. I also used post-it notes to organised larger code extracts by themes and participants as shown in figure 24. The themes were then reviewed and reorganised, an example is on the “lack of resources” theme, it was too broad that it could refer to many things, refinement was needed. In the last step, I produced the final thematic map shown in the figure 26.

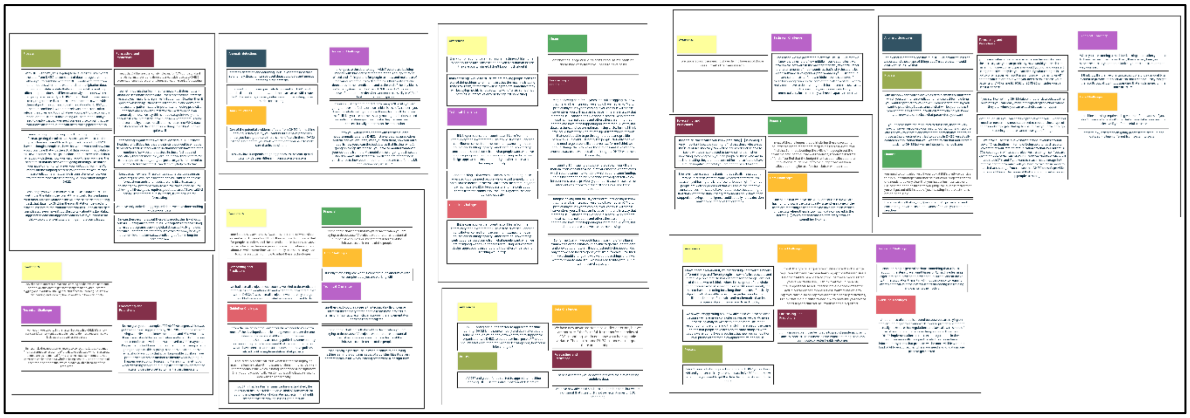


Figure 24: Post-it notes

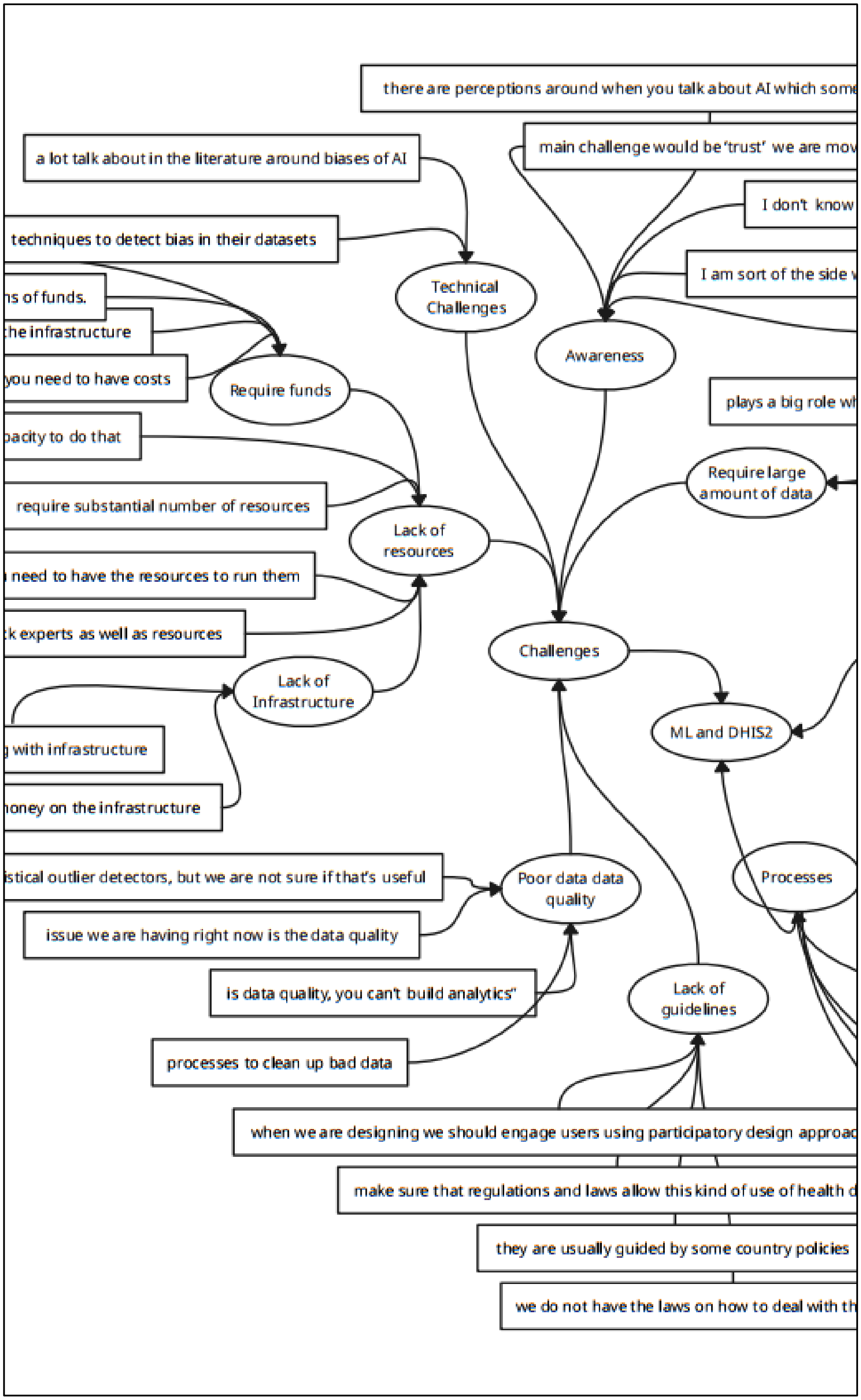


Figure 25: Thematic map in early stages

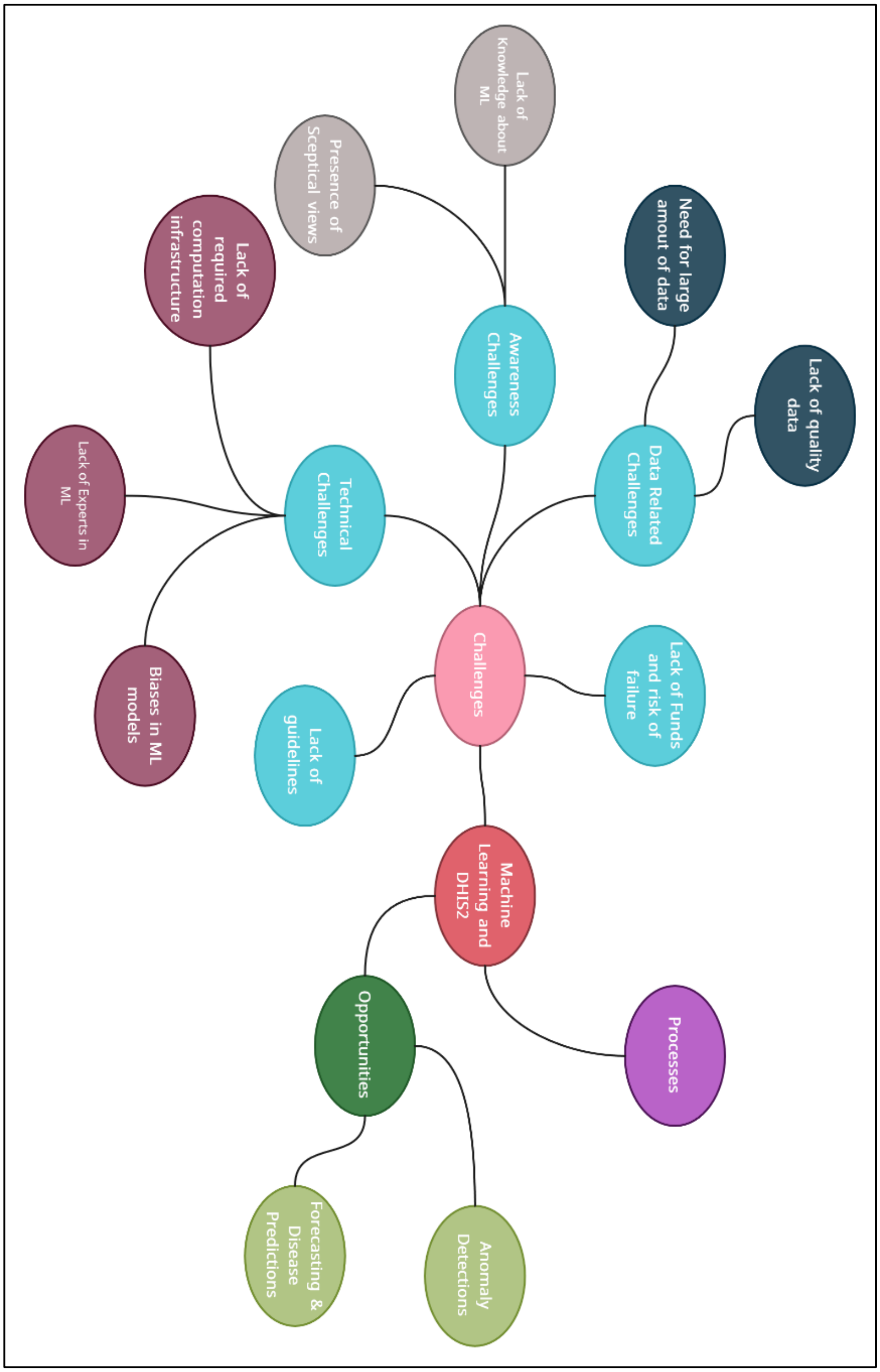


Figure 26: Final thematic map

4.5 Ethical Considerations

Throughout my study, I made sure that I followed research ethical standards. Research ethics relates to how the study was carried out in all the various stages, from the formulation of research questions to the reporting of findings, that all things were done in a moral and responsible way (M. Saunders et al., 2007).

Creswell, (2009) argues that the research problem and the purpose identified should be such that it will benefit individuals participating in the study, or it should be meaningful to other individuals other than the researcher. The research problem and research questions of this study meet this requirement very well. The research questions on opportunities & challenges of ML and how it is used with in DHIS2 platform will not only benefit the participants but the whole DHIS2 ecosystem. Providing information on use cases, pros and cons to organisations considering supporting or integrating DHIS2 with ML.

Another key area of applying ethical standards in research is in data collection and management. M. Saunders et al., (2007) argues that the way you collect data, obtain consent, preserve confidentiality from research participants and the way in which the data is analysed and reported have the capacity to cause harm to participants. To preserve participant's privacy and reliability of the study, verbal and written consent was requested from participants. A written consent was prepared according to a template provided by the Norwegian Centre for Research Data (SND) presented in the appendix, I also obtained a letter from the head of the Information System research group to accredit me as a student at University of Oslo and that I should be assisted in data collection. The participants were clearly told about what data was to be collected & its purpose, that the anonymity of them & the organisations they presented was to be preserved and that the data collected was to be deleted at the end of the study.

On data collection, the university of Oslo provides guidelines and tools on how to handle diverse types of data collected during research to both its employees and students. I followed the guidelines by using Nettskjema and an App called Diktafon to securely collect data and upload it to the cloud, the data can only be accessed online not on the mobile device used to collect the data.

4.6 Summary

In this chapter I presented the methodology of the study; the research philosophy, strategy, sampling technique, data collection, data analysis and ethical considerations which were used in the study. In the study, I adopted the interpretive philosophical view to capture the different views and experiences about ML and DHIS2 as interpreted by the participants. The world view shaped the research approach, I used an inductive approach in which data is collected and analysed to find patterns and theorize. The research strategy was qualitative, a strategy shaped by the nature of the data, which was collected, encompassing views and experiences of the participants, data which cannot be quantified. Purposive sampling technique was used as a sampling method, the technique was selected because it allowed me to target the participants which were relevant to the study. Interviews were the primary data collection method, together with observation data which I collected in meetings which I attended and data from one document-based source which I was given access. The data was analysed using thematic analysis because of its flexibility of being used across different strategies. I followed ethical standards in research from the formulation of research problem and its questions, data collection, data analysis and reporting.

Chapter 5

Results

This section presents the findings from the study after the data was collected and analysed according to the methods presented in the previous chapter. The results show that ML is not being widely used in the DHIS2 ecosystem and there are few organisations which are working on integrating the platform with ML technology. This is presented in section (5.1). The results also show that ML can be integrated with a DHIS2 through an App following the client server microarchitecture. The app would be implemented in DHIS2 and run on top of the core, but the business logic is deployed on another system as an ML service which interacts with the app, that is presented in section (5.2). The results also reveal the opportunities of using ML with DHIS2 which include anomaly detections, forecasting and disease outbreak predictions. The associated challenges include lack of data quality, the requirement of large amount of data, lack of knowledge about ML, presence of sceptical views about ML, lack of required computation infrastructure, lack of experts in the field of ML, issues of biases in ML model, lack of guidelines and funds & risk of failure in ML projects.

5.1 Current use of ML in DHIS2

This section presents the results of the study on the current use of ML in the DHIS2 ecosystem. The results show that there are only a few organisations who have worked on implementing ML related solutions with DHIS2. Participants from these organisations shared information based on their implementational experiences, as they have tested and evaluated the pros and cons of ML through their projects.

From the core development team of DHIS2, findings from the data collected early in the study indicated that there were no initiatives around the support of using ML, this is deduced from what the following participants said.

"*I am not aware of nor have heard of… that is a big sort of thing for developers working on [...] and long-term plans of the DHIS2 platform itself, I don't have a good overview of that hearing anything about DHIS2 machine learning …*" - HISP implementer (PhD)

"*.. we do not know what to do to support the organisations, is DHIS2 to support or incorporate? The app shell was not developed for machine learning apps, how could it be changed? …"* - Core Developer

However, along the study, there were other developments which indicate initiatives aimed to support integration of DHIS2 and ML. I attended two meetings on the agenda "ML opportunities", the discussions were about climate health and ML opportunities. After the meetings I was also given access to a draft grant proposal on the strengthening of the DHIS2 platform and supporting various activities around it. The discussions in the meetings and data in the grant proposal showed that there are interest to support DHIS2 with ML integrations in areas such as streamlining integration with big data analytics tools and incorporation of ML to improve DHIS2's capacity to identify trends and predict future events such as epidemics and stock availability. The discussions were prospects of the future when grants will be available to support the integration. Many ideas were proposed and among these include the development of an extension to extract data from DHIS2 for ML predictions that could solve specific challenges in a particular country as a starting point.

Most of the participants said that they have not implemented ML related solutions with DHIS2, however they expressed optimism, that it should be the direction which countries are supposed to be heading.

"*…there is a lot of data which has been accumulated over time, we have a lot of systems with a lot of data, and I think it has reached a point where now most of the analysis are only using part of the data, and we cannot get a lot of insights from the past. So, I see there is an opportunity to use ML to learn from the data but also to include some predictive capabilities that AI machine learning offers…"* DHIS2 Lab Project Manager

“*… we only use information systems not with machine learning. But that is where we are going because now people are doing machine learning research…”* Assistant Lecturer

“*… for me I think we should change the way we do these things and if we want to promote data use… we need also to integrate DHIS2 with these AI capacity…”* - MOH Senior Developer

The few implementations, initiatives of support from the core team, and optimism from different organisations indicate that the use of ML is in the nascent phase, and it is expected to grow in future.

5.2 Potential ML architecture

This section presents the findings of the study on how ML is used. Innovation platforms usually consist of two architectures: the platform architecture and the application architecture also called the *microarchitecture* (Tiwana, 2013). Microarchitecture defines the structure of the subsystems which comprise the app and how they interact within the app and the platform to fulfil their purpose, the platform architecture entails the subsystems within a digital platform. The microarchitecture of an app may differ from one app to another while the platform architecture is static or is viewed as the same across the different apps. From what the participants said, I focused on understanding how they use ML to establish whether they integrated the technology into the platform architecture or app architecture.

One observed aspect of how ML is used with DHIS2 is that the processing or the *business logic* is executed on another process external to the platform. A core developer said “*UNICEF and global funds started to approach machine learning. DHIS2 is the source mostly and destination of data*”. This means that data flows between these independent systems back and forth. The reason ML processing must be done on another service is due to performance requirements. ML processes and its algorithms are known to demand significant computation resources. DHIS2 is typically implemented to support numerous users concurrently, and not for the high processing demands. One participant explained their experience with regards to this.

> "*…you need to have the resources to run them, they are very heavy on server resources you need to look at your architecture and the way you host it and what's the performance of both of those as I said we tried to do this in DHIS2 …we wanted to run that and insert it back into DHIS2 but we run into performance issues*" - HISP Engineering Manager

The process of using ML starts with exporting data relevant to what the user wants to apply a ML use case, the selected data is sent to an ML process. STK07 explains that this begins with an app in DHIS2 which allows a user to select what data elements users want to predict and how long into the future they would like to forecast based on current trends:

> *"… with an app where you select which data elements or indicators which you want to run prediction on and select for how long you want to predict say you have 10 years of data and say you want to predict say 3 years ahead what will be your values 3 years ahead if you continue your current trend so you know you can select what parameters you want"* - HISP Engineering Manager

This approach only utilises data coming from DHIS2 alone but, in addition to that, the data from DHIS2 can be combined with data from other sources to boost prediction capability. Two participants reflect on how this could be done in DHIS2:

> "*… with DHIS2 the way this is going to be successful is to export the data from DHIS2 to some sort of data storage area, that allows you to combine with that DHIS2 data with data from other sources whether its weather data, precipitation data, geographic data or data that could be useful for making different predictions or different anomaly detections which is not going to be currently in DHIS2. I don't think it makes sense to try to get those data into DHIS2 so in order to work with these algorithms you need to get the data out of DHIS2 you need to combine it with other relevant predictors, other relevant features and tools whatever you want to use to build a model… you need to deploy that so you need some service to pull that, so the workflow can continue and you need those pipelines setup …"* - Head of Data Science

> *"… if you start combining DHIS2 data with other data sets weather or rainfall you can really make appropriate predictions where they are, where you can expect diseases to happen …*" - HISP Engineering Manager

The next step in the process is that the data is passed to a ML process or service. This process or service is based on a program running on a server or servers taking advantage of the required available computational resources. I did not dwell on the inner workings or pipeline of the program such as algorithm selection and more, but it uses the similar ML algorithms presented in section 2.2.3, or those encompassing forecasting or others. The results of the process are fed back as a response to the app in DHIS2 and provide forecasts or predictions.

> *"… into python and run the predictions and pull the data back into DHIS2 or insert that predictive data into DHIS2 and basically show some graphics on the app the predicted values*" - HISP Engineering Manager

> "*… so basically, you have DHIS2 coming out, combining with other data, you have got some sort of ML process/ predictive analytics process which probably creates […] you have either two, all the different analysis happens outside DHIS2 the presentation, the alerts or whatever or you need to pull that data back to DHIS2. I think if you want predictions, if you want anomaly detection alerts to be available to the front line, you want that back to DHIS2 you might then push the predicted values back to DHIS2 or the alerts you know the zero or one this is anomaly or this is an outlier or not you push them back to DHIS2 and then in DHIS2 you have reports or something like that a lot of people see those values.."* - Head of Data Science

During the discussions of this process, I observed that the participants were mentioning and comparing predictors in DHIS2 and ML techniques. One argued that they find problems with DHIS2 predictors when it comes to selection of algorithms and the accuracy of the techniques. STK06 argued that in comparison to ML techniques, predictors "*…require a lot of knowledge and require a lot of specific implementations something like that..."*

"…our work in DHIS2 is basically relate to predictive analytics just to be able to use algorithms just for prediction of what we have in DHIS2, the problem that we find with that module (predictor) is that you have to choose your algorithm upfront and it applies that to all the data in the selection that you like to predict forward to and that doesn't always work when the facilities have different sort of data profiles and the historic data is not necessarily following that algorithm… so it's essentially (ML app) providing similar predictive functionality at a much more high level and the formula that is applied is that you don't have to select the algorithm, if the data is linear it's going to use a linear prediction, if the data is logarithmic it will use that type of prediction for the lower level and obviously… once up in DHIS2 through analytics then you get more accurate predictions" - HISP Engineering Manager

"… predictor was an interesting tool upfront at the beginning trying to solve that, people have sort of forecasting and anomaly detection but the options for doing these types of predictions are so great that you cannot state which one is necessarily going to work for which application so these automated ML tools are specifically setup to identify what's the best predictors overall …" - Head of Data Science

5.2.1 Summary

From the findings the way ML may be implemented in the context of DHIS2 as described by the participants follows the client-server microarchitecture. There would to be an app running on DHIS2 core with an interface for presentation, users would interact with the app and send data to an ML process which would then processes the data for predictions and provide feedback to the app to display the results, generate reports or send notifications. This is visualised in the following diagram.

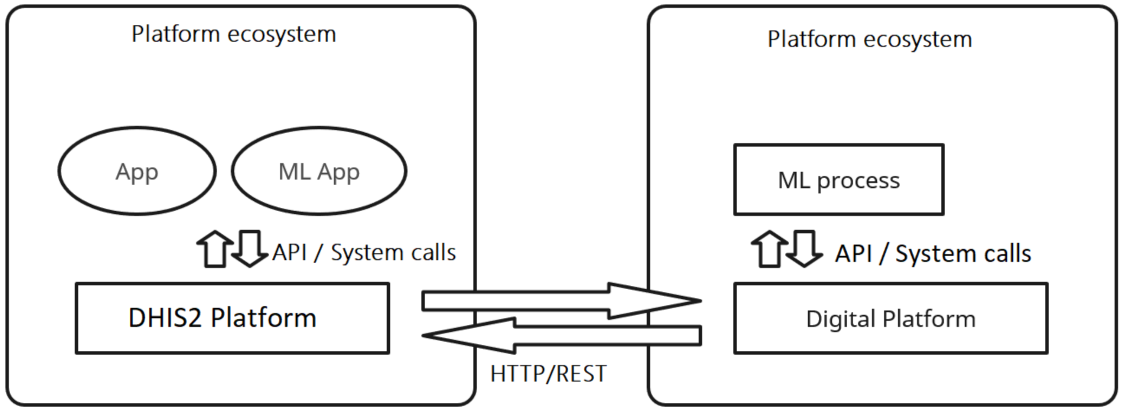


Figure 27: Conceptual ML application architecture

The findings also shed light on the computation resource needs of ML algorithms, as evidenced by the need to run the ML process on a different server. However, as described by the participants there are benefits out of it in terms of ease of use, more functionality and accuracy of predictions compared to DHIS2 predictors.

5.3 Opportunities of ML

This section presents the findings of the study that relates to the opportunities using ML algorithms in DHIS2. The themes which relate to this category include forecasting, disease and outbreak predictions, and anomaly detections.

5.3.1 Forecasting and disease predictions

The primary data which is collected in DHIS2 implementations is aggregate population data, but the platform has the capability of collecting individual data. On what type of data has the potential for ML use cases, the participants said that both aggregated and individual data has the potential to be used for ML use cases. One participant said, "*We have only looked at aggregated data, we have done nothing with tracker data*" while another responded, "*we are looking at both*" and another *"… yes both have the potential to be used…*". The most used type of data is aggregated data, for forecasting. One participant said.

> "*… areas that I think are particularly relevant for AI/ML and standard statistical methods… and those are areas with respect to DHIS2 systems are anomaly detection and forecasting … time series forecasting …*" - Head of Data Science

Time series forecasting was the major use case which the implementers mentioned. Time series forecasting is the process of making predictions of expected values over a given period from historical data which contains timestamps. Aggregated data in DHIS2 contains the "what, where and when" elements representing indicators or data elements, organisation unit and period respectively. For example, you can have data about 1st ANC visit from a certain facility from January to December collected on fortnight or monthly basis. Areas where the implementers see opportunities of forecasting include forecasting health personnel resource demands, logistics, and vaccines.

> "*… in forecasting organisations which collect data in DHIS2 these healthcare facilities, healthcare districts they need to know what the demand for their services will be so that they can have the right number of services and doctors in those facilities and potentially they can move them around if need they need to for*

resource purposes, budgeting purposes organisations need to be able to forecast and AI can definitely help to do that ..." - Head of Data Science

The participant went further to explain what impact this can have on health outcomes such as SDG's and UHC's.

"*... because achieving all these things require scarce resources which require resource allocation and as I said being able to forecast demands and needs are all critical to actually balancing how programs work to achieve those goals ..."* - Head of Data Science

Another participant presented a forecasting use case which can be used in programs to make predictions whether targets can be attained from the current trends or not. The participant said that if a target is to reduce the number of patients of ART by 2030, (SDG target year) forecasting can help to give insights whether the goal can be reached or not based on the trend of data collected over time. This can in turn aid in direction of interventions or a change in policy.

"*... you have a value of how many patients you have on ART over the last 10 years you can predict by 2030 would you reach the millennium development goals or would you not and you start using predictive analytics you can identify what changes in like policy or whatever will result in an increase in patients on ART so then you can clear out what you need to do increase your patients on ART or line 90-90-90 or 95-95-95 principles you can use it a lot here ..."* - HISP Engineering Manager

Similar forecasting use case and a perceived benefit was presented by another participant on 90 90 90 HIV targets. The targets were set by the UN for countries to achieve, that by 2020, 90% of all people with HIV in all counties know their status, 90% of those who know their status should be on ART and 90% of those on ART should achieve suppression of the virus. The participant argued that the ability to forecast can help to know what to do in order to reach the targets.

"*... let me give you an example of 90-90-90-90 targets which was put by UN it was supposed to by 2020, 90% of people who are living with HIV should know their* *status and 90% who know their status should be on medication and so on. But this one could not be achieved, and it was moved to 2030 maybe [….] proper methods of knowing or controlling what is going to happen this is going to be possible or not possible, what should we do so that it can be possible […] if we have proper mechanism or method to identify what is going to happen prediction or forecasting it is easy to […] method or whatever thing should be put in place for the government or stakeholders involved so to me it is very important ..."*– Assistant Lecturer

More similar views on forecasting and helping in interventions.

"*… you are able to understand relationships between data you can understand patterns you can interpret that data gain insights and then make better decisions around not just what is happening now but also what will happen in the future and what should happen in the future and even direct your interactions or your interventions… saying this is what I need to do in order to reach I want to be ...*" - HISP Engineering Manager

"*…. we should have had an AI/ML to predict maybe in 5 years coming if you continue with these interventions, you will have an increase in malaria in a way that it notifies us…. other things like some diseases like in neonatal deaths, maternal deaths, and others these are thing that happen and have been happening for more than 20 years, but data are there, and we are not maximising …*" - MOH Senior Developer

Other areas which forecasting use cases can be applied as said by the participants include the following.

"... logistics, you can predict when you need to reorder, how much you need to reorder those type of things and aggregate that up to ensure that you have enough stock in your stores ..." - HISP Engineering Manager

"... we have a use case but we haven't done it yet it's around covid-19 vaccinations in terms of being able to reach a certain coverage at your rate of immunization say that your target is 70% coverage in [country] at a project we are doing… so if you

are giving an idea of the rate of your current vaccinations when will you reach 70% and if you want to reach that coverage in 6 months period how much will you have to escalate in order to reach that coverage. You can see that DHIS2 doesn't provide that kind of blue at the moment that's where the value comes in to help people to manage …" - HISP Engineering Manager

"… in country […] I'm seeing already where this can work like in malaria it can contribute a lot, in malaria they have same cases which require same interventions which require same funding, so it's the same thing even machine learning can tell which interventions to use, previously you had 10 cases these are the interventions it took to reduce 10 cases you used these interventions…" - MOH Senior Developer

Other type of predictions which the participants also mentioned include those related to individual data which is captured using tracker. This includes prediction of individuals defaulting health care programs and tracking non-communicable diseases like hypertension.

"*… there are examples out there of… predict the risk of drop out of HIV program so default in HIV programs and other long term care programs tracking global diseases like High blood pressure… so there are definitely use cases for applying AL/ML to patient level tracker data…*" - Head of Data Science

Participants also mentioned that the data in DHIS2 can be combined with climatic data to predict diseases outbreaks.

"… if you start combining DHIS2 data with other data sets weather or rainfall you can really make appropriate predictions where they are, where you can expect diseases to happen" - HISP Engineering Manager

"… we had a small project in our country we tried to do prediction of malaria using weather data and we tried to incorporate that within DHIS2. It was a small project; it was not really a large project but were able to do what we were supposed to do …" - DHIS2 Lab Project Manager

On disease outbreaks predictions, one participant argued the that having a mechanism which can give a clue of a scenario of which is to happen will make people prepared for it and reduce negative consequences. The participant went on and presented an example of an outbreak which is being experienced (2022) in a country close to the participant.

> "*… I can give you an example recently there was an announcement of Ebola outbreak in Kampala we found that these neighbouring countries surrounding Uganda they have preparing themselves to tackle that if at all Ebola comes to their country. But I am telling you right now with a lot of preparation that have been done, a lot of measures that have been taken into place [..] if they have declared they are going to remove all the restrictions related to Ebola that it is no longer much of the threat letters will come… we have seen that coming and they took on measures to make some preparations. So, you can see… if there was an intelligence that was helping to tell Uganda that now there is this kind of situation that is happening or it's expected to happen maybe Kampala or Uganda could have made some preparations… it could not have taken a lot of much destruction compared to the way that it has been right now because they could have prepared expecting this could have happened so that you might find that even those unnecessary movements could have been stopped so having an intelligence could actually help a decision maker to be ahead of the outbreak …"* - HISP Implementer

5.3.2 Anomaly detections

The most recurring theme in the interviews was around data quality. One of the requirements of using ML is that the data which is to be used for prediction purposes is that it should be of good quality in terms of completeness and consistency. Participants presented data quality problems in different forms such as having gaps in data, lack of variation in data, seasonality of data and unusual figures which are referred to as anomalies or outliers.

> "*.. the data in some DHIS2 instances is not good, there are a lot of gaps …*" - Core Developer

> "*One of the potential problems of data from DHIS2 for machine learning is data quality, you can't build analytics processes unless you have good data there is a lot*

of data in these DHIS2 instances but before you work with the data you have to make sure that its consistent ..." - Head of Data Science

"*…right now, the main challenge we are having is to promote data quality and data use…"* - HISP Leader

One participant mentioned that data quality is a problem they are currently experiencing in their country and that they are working towards improving situation. What they experience is that some of the data which users enter sometimes falls outside of the expected thresholds.

"*One of it is [challenges] that we have the DHIS2 one of the issue we are having right now is the data quality issue where some of the users are reporting cases that maybe have not been verified … the data where there is too much data compared to the normal … you might find that it is a data entry error or something like that …. for example, there has been a certain threshold that whatever facility maybe report a certain kind of disease like maybe cholera or yellow fever or flaccid paralysis we need to go to that particular facility to check if that actually has happened if not, we need to rectify that kind of information. Because you may find that some of the information is sensitive ….*" - HISP Implementer

There are ongoing initiatives to improve data quality through the WHO Data Quality Review (DQR) framework (WHO, 2022a). This framework consists of procedures for routine data checks and metrics for HMIS which DHIS2 implements. One participant argued that the metrics in DQR framework uses z-scores to determine outliers. z-scores determine outliers based on how far a datapoint is from the mean in data. The participant argued that ML presents an opportunity in detecting anomalies in a unique way by considering relationships between indicators and deseasonalisation of data which is missing in the DQR framework metrics.

"… there are ongoing processes for improvement like the WHO data quality framework… it is based on z-score trends or something like that… we are trying to look at relationships between different indicators and these are all things that

> *AI/ML can do quite well… somethings missing from that framework… it does not talk about de-seasonalising the data… there are seasonal patterns like every year malaria is high like in September, October then it goes down then up.. there is this trend of up and down and that seasonal pattern is very important when doing predictive analytics and a powerful test whether a datapoint is an anomaly or not… we say this is a bad datapoint every time because it's the highest we have ever seen when there is trend and seasonality… deseasonalisation is not part of WHO data quality framework these things are things that AI/ML can do quite well …"* - Head of Data Science

When asked about outlier detections another participant argued differently saying that the DQR framework metrics in DHIS2 are enough but only acknowledged that ML has the potential of detecting outliers.

> "*Yeah, I think that is definitely possible but DHIS2 is advanced in using z-scores and those type of things but I'm sure that… it could deal with issues like that …*" - HISP Engineering Manager

Another participant argued that DHIS2 has been updated with advanced statistical outlier detection techniques but expressed uncertainty on the effectiveness of the tools. The participant further testified of organisations working on using ML to detect fraudulent data or cooked data in DHIS2 in immunisation service programs in one country. Cooked data is data which has been manipulated by data entry clerks, a problem experienced in some countries where DHIS2 is used (Hausenkamph et al., n.d.).

> *"… there is a company called […] with the aim of finding fraudulent data. There are seasonal trends in data and lack of variant data…We have new advanced statistical outlier detectors, but we are not sure if that's useful. It's not perfects, it relies of CDC smoothing, we do not know what acceptable variance is ..."* - Core Developer

The findings indicate that data quality is a prevalent challenge experienced by many participants, but they have different views on the problem. One category considered that the DQR framework toolkit metrics implemented in DHIS2 offers comprehensive input validations but the problem being where data is collected and how it is entered into the system (data collection & data entry). The other category argues that patterns and relationships of the data need to be considered whether determining that a datapoint is an anomaly or not and view that ML can be able to do more validations.

> "*…detecting unusual changes in pattern … so anomaly detection can be used detect bad data and unusual changes in the patterns…"* - Head of Data Science

5.3.4 Summary

The findings show that the perceived opportunities of using DHIS2 with ML is that it can give users the ability to forecast what could expected in the future based on data which they have collected and help in change for better policies and interventions. Another use case is that when DHIS2 diseases data is integrated with climate data it could enable for predictions of disease outbreaks. The findings also indicate that there are data quality challenges, while ML is not a solution, but it can be able in validating data through anomaly detections. Further, the findings indicate that ML can help decision makers in planning, informing which interventions and policy to use and enforce quality data.

Opportunity	**Areas of Application**	**Benefits**
Forecasting	• Forecast in 90-90-90, 95-95-95 targets and similar initiatives • Forecast demands of resources at health facility level • Forecast stockouts and orders according to trends • Forecast vaccine demand according to trends	• Assist in direction of interventions • Aid in change for better policies • Prudent resource allocation
Disease predictions	Predictions of diseases influenced by climate conditions	Aid in planning for outbreak interventions
Anomaly detections	Detection of outliers, anomalies in trends and triangulation across facilities	Good data

Table 3: Summary of Opportunities

5.4 Challenges of using ML in DHIS2

This section presents the findings of the study that relates to the challenges of using ML algorithms in DHIS2. The themes which relate to this category include data challenges, awareness & perspectives challenges, technical challenges, guideline challenges and financial challenges.

5.4.1 Data related challenges

One of the challenges presented by the participants relate to data. The data challenges are in the form of data quality and the need for large amount of data.

Data quality challenges were introduced in the section 5.3.2 where anomaly detection was presented as an ML opportunity which can assist in improving data quality. Most participants presented data quality problems in the forms of data containing gaps, lacking variance, and containing outliers. Data quality challenges do not only affect ML opportunities in DHIS2, but it is a general problem as far as data use is concerned. It is the same data which is used for decision making inconsiderate of what data analysis tools which are being used. Whether pivot tables, maps or charts are beings used, if the input data is bad there is no way you are going to get useful information out of it, the same applies for ML processes. However, in ML data quality is critical to make reliable projections considering extra resources are invested. To emphasize the challenge some participants said the following.

> "*I think that would be a big challenge because you need to have a good dataset to actually train those models if you want to be able to improve data quality or disease predictions, I think that's a big thing to begin with because you sort of need a good dataset so I think that's a big effort*." - HISP implementer (PhD)

> "*One of the potential problems of data from DHIS2 for machine learning is data quality, you can't build analytics processes unless you have good data there is a lot of data in these DHIS2 instances but before you work with the data you have to make sure that its consistent…"* - Head of Data Science

> "*It's very low, it depends on going processes to clean up bad data, so it's been different from system to system*" - Head of Data Science

Another challenge encompasses the need for large amount of data. The participants highlighted that to successfully use ML you need a lot of data, this would be good news for those who have been using DHIS2 for a prolonged period, but for those who have recently adopted the platform this is unwelcome news.

> "*I think the typical aggregate routine data the challenge […] a lot these machine learning approaches require a lot of actual training data to produce these models that you can actually use…"* - HISP implementer (PhD)

> "*… machine learning requires a big volume of data and so if you don't have a lot of data, it's not that successful so you need to be selective if you find useful use case there is value in it"* - HISP Engineering Manager

> *"... it really plays a big role when it comes to huge amount of data or complex data you are working with."* - DHIS2 Lab Project Manager

This is one of the contextual challenge, other participants indicated that they have been using DHIS2 for a long time, so data availability is not a challenge to them.

> *"... In the last 10 years we have been working on strengthening information systems, having systems functional country wide, strengthening the data quality. But now what we are missing is using the data… you know using these artificial intelligence…"* - MOH Senior Developer

> "*…we have a platform right now that is it collects data and we some basic analytics, but the main thing is that we have a lot of data, I have been using it for at least 10 years across different programs, so machine learning and AI is the next step…*" - HISP Leader

5.4.2 Awareness and perspectives challenges

Participants also expressed challenges related to their understanding and attitudes towards ML. One of the knowledge gaps is how ML is integrated with DHIS2. One participant expressed the dilemma on whether the technology can be integrated into the core of DHIS2 or what changes would be there to the core, in short how the technology works.

> "*We do not know what to do to support the organisations, is DHIS2 to support or incorporate? The app shell was not developed for machine learning apps, how could it be changed?*" - Core Developer

Other forms of lacking knowledge were in the form of what ML is about, what the technology does and lack of knowledge in terms of use cases.

> "*It is a combination of data that helps a machine act like human to contribute or take some action or even alert human in case they are overwhelmed. I don't know much about it …*" MOH Senior Developer

> "*… we understood the need, but we didn't have a solid use case [...] that's the main reason …*" - HISP Leader

Another participant said that there is lack of knowledge in the community on what AI technology can do and its limitations. The participant viewed this as a potential barrier to the adoption of the technology and that it may lead to scepticism and recommended the need for education about ML.

> *"… one [challenge] I could say is awareness. Awareness in terms of what AI can do and what AI cannot do, I think there is need for more of that for people to understand the potential the limitations because usually because there are perceptions around when you talk about AI which sometimes are not really true so this may lead to some skepticism on how to adapt these technologies. I think there is need to further education …"* - DHIS2 Lab Project Manager

One participant expressed a sceptical standpoint about AI and ML in general. His scepticism is on how the technology is being glorified today. The participant argued that the technology is being exaggerated in terms of technological breakthrough because what is considered AI today are algorithms that are able to recognise patterns and are basically based on mathematics and statistics. The participant believes that this has been around it is only that we (humans) have only progressed technologically in terms computation resources.

"*... it's a tricky subject because it means different things to different people it's sort of a broad scope and different people refer to it as different sort of things I am sort of the side where I think I'm sceptical of the whole thing because a lot of people think what AI is […] have been doing for a long time in terms of basically algorithms that are able to recognise patterns and something like this. It's more of statistics and mathematics than its intelligence algorithms we refer to as AI today […] we always exaggerating a bit how advanced we have become, because we have more computer resources, we can do more processing analysis we are able to do more like image recognition on the phone and that stuff there sort of the same things that people have been doing same things as what people were doing 5 years ago just that now you can do it on your phone rather than a computer the size of a house*" - HISP implementer (PhD)

5.4.3 Technical challenges

Another category of challenges relates to technical aspects of ML. The challenges are in the form of algorithm biases, lack of experts and lack of infrastructure.

Bias in ML applications is one of the well-known challenges (Mehrabi et al., 2021), and I was asking participants on how they deal with it and some participants raised it as a potential challenge. Biases are incorporated into the models during development, it is not necessarily the algorithms, which are generic and work on data provided. Biases in models simply means that the models are discriminatory, that it favours one group than another on the data which it is designed to operate. One participant argued that if the ML models developed in US and Europe are deployed in Africa or Asia there would be need to retrain them before use.

"*Another thing is general perhaps something that a lot talk about in the literature around biases of AI machine learning algorithms that have been developed in Europe and in the US with the population there it might not be so easy to reuse for example for Africa or Asia without sort of redoing the training and changing the models*" - HISP implementer (PhD)

Related to this I asked one participant from the implementation group whether it is possible to use a model from one country in another country.

> "*…it really depends on the scenario, and I would say that you can never assume that a model can be used to generalise in another country, you have test that."* - Head of Data Science

The participant further argued that it would be necessary to test the models with data collected where the model would be deployed to test their performance for bias or combine the data used to train the original model with the data from the different group to get rid of any biases.

> "*… they can be transferable using specific populations if there are key differences between two populations you are talking about… the relationship between cancer and the it's not going to work it depends on how similar the scenarios are, how similar the populations are if you want to take a model that's built on one population but it could be a good place to start if you had a model that was built some population and you have some data that would allow you to train on another population you can start by running the model and seeing how predictions do, does it predict well as the original or not and so then you have an out of sample performance […] if you have no training data then maybe that model is the best you are going to get […] the decision about whether or not it can be applied is a policy decision what are the consequences, what are the possible bad outcomes of using those […] you can look at data and try to understand how the predictions are doing in what programs to use those models […] but alternately if you get the point where it looks like the model works for both then you can join both datasets together and have a model that is trained across …*" - Head of Data Science

The participant further argued that bias in predictive models originate from data, the models produced from data which is biased simply reflect the biases in the data.

> *"… a lot goes to the data to begin with if people are building models with bias datasets then the models are going to be biased and it's important for people to know and make use of the various techniques to detect bias is there datasets and*

> *detect bias in their predictions and at the end of the day bias is sort of in systems that don't use AI/ML as well it's a concern in the use of data to make decisions and not necessarily in AI/ML I think in public health spaces …"* - Head of Data Science

It shows that dealing with bias requires good technical knowledge and procedures. However, bias issues exist when working with individual data and not in aggregated data. Since the participants highlighted that the ML has the potential for both individual and routine data, for the use cases which work with individual data, procedures would be needed to mitigate the risks of bias. For the use cases which work with population data, such as forecasting, outbreak predictions and anomaly detections as presented by the participants, bias would not be a big concern.

> "*… if you are just trying to predict how many ANC visits you are going to have in a facility or district bias is less of a concern you have the whole history of data in theory for the all districts all the facilities you are not necessarily making predictions based on individual demographics…*" - Head of Data Science

Another challenge is that ML algorithms require considerable computation power, however this is based on the amount of data in use. But in the data availability challenges it was found that in order to yield benefits out of it you need a lot of data and the more data, the more the computation resources needed. This does not only impact the costs of servers and related computation hardware and electricity costs, but also it counters the sustainability goals when it comes to carbon emissions.

> "*When you are running a machine learning application you need to have the resources to run them, they are very heavy on server resources you need to look at your architecture and the way you host it…"* - HISP Engineering Manager

Another participant argued that even though countries are making progress towards digitisation others are still struggling when it comes to infrastructure in their DHIS2 implementations, definitely they would face challenges.

> "*… some of countries are still struggling with infrastructure in terms of the hosting and others sometimes you may find these heavy queries… with the current*

infrastructure may there would be a need to separate the production system with the machine learning server…" - MOH Senior Developer

".. they need some laptops to collect the data […] people are using manual forms to collect data sometimes it's not correct so we find the data which is being sent to DHIS2 at the end of the time is not the actual which is not available because of the resources …" – Assistant Lecturer

"… some of the challenges that might be faced when you are trying to do because AI projects would require substantial number of resources or investments in terms of the infrastructure …" - DHIS2 Lab Project Manager

However, organisations do not need to have all the infrastructure for ML, other options include using cloud infrastructure services. One participant said that they can rent their infrastructure to those who need it to make ML affordable to those who lack server resources.

"…*I think it will either be one can get sort of a pricing model to a system to provide it as a service so that it can be… they can get the results out of it without spending that much money on the infrastructure…*" - HISP Engineering Manager

ML implementations require expertise, when I asked participants if they have implemented ML in their DHIS2 instances many participants declined, they only presented AI use cases which were not related to ML. On the challenges which developing countries would face implementing ML technologies, one participant said DHIS2 is developed to meet the needs of these countries that they do not need software developers, just installation and customisation. ML would be beyond the threshold of these countries. If the solutions would be part of the DHIS2 platform core then everyone would benefit, if not then the countries would need capacity to do that.

"*One reason we are promoting platforms like DHIS2 is that we know the threshold of low-middle income countries […] we develop the software in the most generic way which will meet the requirements of most countries that's why the countries don't need software developers or programmers you just set it up and customise it… for low middle income countries if these technologies are in the core of the platform* *of DHIS2 they really don't have to do anything much for most of the use cases but in time to come if they are sophisticated very contextual very local then they will need capacity to do that*" - HISP Leader

Another participant argued similarly that there would be need for training to build the capacity in the community for people to use and contribute to tools.

"…*another thing is that when it comes to maintaining these advanced tools, we need people who are well trained […] If it is open source then countries will learn from the community that is what made DHIS2 to be successful and the contribution comes from the community […] making it open source and building capacity …*" - MOH Senior Developer

"… *we need more experts in this area. Because this AI/ML it's a new concept it's a new topic so people need to do more research so we lack experts as well as resources* …" Assistant Lecturer

"… *another gap I could also see is the technical skills of course in terms of the capacity of the people to do these projects* …" - DHIS2 Lab Project Manager

5.4.4 Guideline challenges

Another category of challenges mentioned by the participants relate to lack of policies and procedures around the implementation of ML projects. One participant argued that in the global south, many countries do not have policies around the use AI compared to the developed world where the technology is part of their economic and technological development. When the governments take the lead in implementing it becomes easier for the public and private sector in implementing such policies.

"*… from the policy point of view of course […] most of the developed countries the governments are the ones who are leading most of these […] country wide implementations. So, they are usually guided by some country policies […] so one of the gap or what I have seen is that most countries don't have policies related to AI or implementation of AI projects […] at least in […] the ministry of health established an AI kind of framework for guiding implementation of AI related* *projects in the health sector, so we are moving in the right direction …"* - DHIS2 Lab Project Manager

Another argued from the experience point of view that the use of data for ML would require the enactment of laws and regulations because in some countries the laws are designed for case-based information systems.

"*.. because you are relying on data around regulatory framework it would probably needed to actually make sure that regulations and laws allow this kind of use of health data that's something we see in the current DHIS2 implementations in the current regulations in these countries are really designed for electronic case based information systems that problem will be more visible with this kind of AI type approaches where you need a lot of data in one place to get started ..*" - HISP implementer (PhD)

When one participant was asked about how they deal with issues on bias of ML models, the participant said that they do not have laws or regulations on how to deal with those technical issues.

"*… that is really a practical issue when it comes to deploying machine learning algorithms issues of algorithm bias it's a very contemporary issue which is being researched a lot right now. In my country specifically we do not have the laws on how to deal with this specifically …*" - DHIS2 Lab Project Manager

Another participant talked about the need for procedures in the development of ML applications. The participant believes the involvement of users through participatory design methodology would allow users to specify areas which would help and further enforce the responsible use of the technology.

"*… when we are designing, we should engage users using participatory design approach…users should tell you where machine learning would help …"*- MOH Senior Developer

5.4.5 Lack of funds and financial risk

The last category of challenges which participants brought up pertains to finances. The challenges encompass lack of funds, expensiveness of ML projects, the need for maintenance costs and risk of failure.

In section 5.1 I presented that the current use of ML is minimal, when one participant was asked why they have not worked on such solutions responded that they do not get enough funding to work on innovative solutions.

> "*… most of the challenges that is hindering these developing countries to not to meet there targets it's the resources. You find that I am not doubting the skills of the people, but the problems have been due lack of resources, resources in terms of funds. You find that the budget that has been allocated to an innovation is much smaller to the budget that has been allocated to maybe to a football club or whatever team …"* - HISP Implementer

One participant of the implementation group said that ML projects are expensive and there is need to approach them with a lot of considerations. The participant was speaking from experience of implementing projects with an in-house data scientist team and infrastructure. The participant went on to state that most ML projects are expensive and result in failure, presenting a financial risk if considerations are not followed.

> "*… you need to do it selectively if you look at it it's pretty expensive to run ML technologies and there is a lot of ML projects that fail one needs to be very clear that you have a business case or a use case for it and ensure that you judge the success factor that you will get out of it instead of just investing in a project that is not going to scale… there is a study that says 70% or more of ML projects fail and considering they can costs thousands of dollars you need to be selective …*" - HISP Engineering Manager

Another participant talked about maintenance costs which would be the result of running the necessary infrastructure.

> "*… another challenge would be funds because maintaining these kinds of systems you need to have costs …"*- MOH Senior Developer

5.4.5 Summary

Despite the potential opportunities which ML presents to the DHIS2 ecosystem, there is a wide array of challenges which would need to be considered to reap benefits from the technology. These include the need for quality data, awareness campaigns on how ML works, where and how it can be used and its limitations, the need for infrastructure and experts, enactment of policies and regulations on the development and use of ML technologies and the need for funds to maintain the systems. The challenges are summarized in the following table 3.

Challenge	**Description**
Lack of data quality and the need for large amount of data	ML requires extra resources for predictive analysis, there is need for good data, using bad data will be a waste of resources. ML requires a lot of data to benefit from of it
Lack of knowledge about ML and the presence of sceptical views about ML	There is lack of understanding of ML and skepticisms
Lack of experts in the field, lack of required computation infrastructure and issues of biases in ML models	ML requires experts in the field to develop and maintain the systems. ML requires extra computation resources apart from the ones running DHIS2
Lack of guidelines in the development of ML systems	AI and ML require policies and regulations to govern their development and use.
Lack of funds & risk of failure in ML projects	ML projects are expensive, they need to be approached with considerations because many projects fail posing a financial risk.

Table 4: Challenges Summary

Chapter 6

Discussion

This chapter discusses the findings of the study presented in the previous chapter, along with related literature. The first section (6.1) discusses the findings in the context of research questions and literature, while section (6.2) focuses on recommendations for various stakeholders, including ministries of health and HISP developers. Finally, section (6.3) presents the limitations of the study.

6.1 Analysis

The study included two research questions; therefore, the analysis of the findings is guided by the order in which the research questions were presented in chapter 1.

6.1.1 Research Question 1

The first research question was as follows:

> **How does machine learning fit into the DHIS2 platform ecosystem?**

Using ML for predictive analysis involves several steps, including data collection, data pre-processing, feature engineering, algorithm selection, model training, and model evaluation (Marsland, 2014). The product of these processes is a predictive model, which is utilized for predictive analysis. To make the predictive model accessible to users within an information system, it must be integrated or deployed within the software. Various methods can accomplish this, such as embedding the model in an app (Stockman et al., n.d.) or hosting it on another platform, with apps accessing it through an API such as REST (P. Singh, 2021).

The potential integration architecture from the results of the study follows the client-server architecture. In this integration there would be an app running in DHIS2, which users interact with and send data to a server platform through an API to run predictions. The results would then be sent back to the DHIS2 for users to utilise or they may be stored in the database, or they may be returned as a notification.

There are two deployment variations in the client server architectures based on how predictions are made, namely offline (batch) and online predictions (Google Cloud, 2023) (Ameisen, 2020). In online prediction deployments, a user interacting with an app sends data to the model for predictions and the predictions are returned to the user in real time.

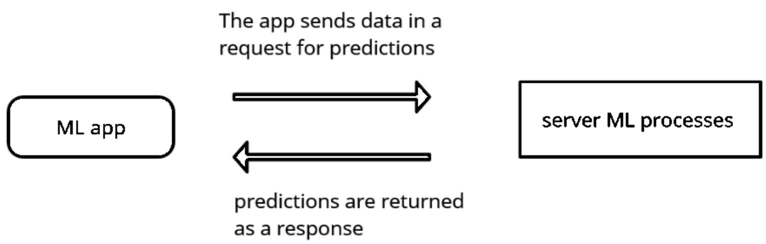


Figure 28: Synchronous predictions

This can happen synchronously or asynchronously. In synchronous method, the user sends a request for predictions and the model sends back a prediction as a response right away this is illustrated in figure 28. In asynchronous method, predictions are triggered by some event or schedule without the need for user request. There are two variations of asynchronous predictions: push and pull. In the push method, a model generates predictions and sends them directly to an app or sends a notification to a user. Google Cloud, (2023) give an example of its application, fraud detection; where predictive models detect potential fraudulent transaction, the predictions can be sent to notify users or to the app as push notifications.

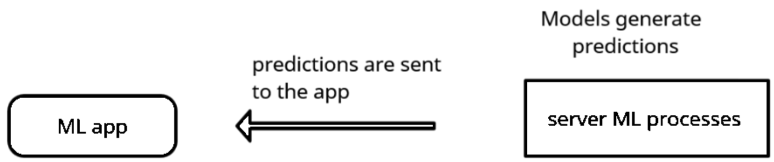


Figure 29: Push asynchronous predictions

In the pull method, the model generates predictions that are stored in a data store, an app periodically checks for new predictions and updates itself. An example of this is the weather widget on a mobile phone, it periodically checks for new predictions, it pulls the predictions and updates itself.

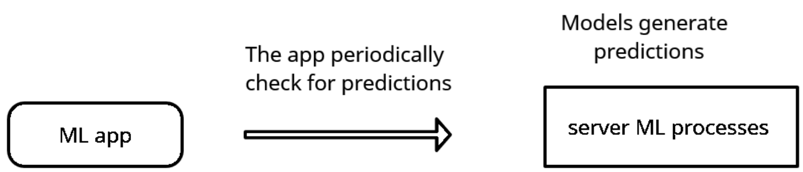


Figure 30: Pull asynchronous predictions

In offline predictions, real-time predictions are not made. Instead, data is selected on which predictions will be made and ML processes are run as a scheduled task, the predictions are stored and accessed by the users at later time. An example of this is in demand forecasting, where data would be selected and pulled from a data store to run predictions at a scheduled time, and the predictions will be made available when the task is complete (Google Cloud, 2023). Offline predictions are also referred to as batch predictions (Ameisen, 2020). It should also be mentioned that AutoML can be incorporated into the deployment architectures to automate ML processes in producing and updating models (Mustafa & Rahimi Azghadi, 2021).

It can be noted that aside from the client-server deployment architecture from the findings of the study, there is a standalone deployment architecture in which a model is embedded inside an app. An example of this deployment was reviewed in the literature section in a case where a predictive model was added to OpenMRS by integrating it into a software module that was installed in four instances of OpenMRS at four health facilities. The advantage of this deployment is that it does not require interaction with ML processes outside the platforms and it is easy to implement, the disadvantage is that ML models need updating over time due to problems like model drift, so the architecture requires updating the whole app to update the model (P. Singh, 2021).

In the context of DHIS2 the standalone architecture would be advantageous only in simplicity and lacking the need of network connectivity, that an app can be developed and run on a local instance or facility without requiring network connection. However, as ML models require updating there would need to be updating the whole app whenever a new model is available.

The client-server architectures would require data movement from a DHIS2 instance to other servers running ML processes through an API. The DHIS2 platform already has a web component API which makes it possible for external systems to access and manipulate data in a DHIS2 instance (DHIS2 Developer guide, n.d.). If applied to DHIS2, the client-server architecture opens various deployments possibilities.

The asynchronous push model deployment can be applied in anomaly or fraudulent data detection. In this architecture, data captured by users for example in a health program would be checked by a model for anomalies, if certain data is flagged as a potential anomaly a notification could be sent to an app or user about an anomaly. The asynchronous pull model deployment could be used in surveillance scenarios, a deployed model would be making predictions which would be stored in some datastore, a real time surveillance app would periodically be checking the datastore for predictions.

The advantage of this architecture is that it offers scalability if a model is hosted as a microservice, because server resources can easily be increased. P. Singh, (2021) discusses a typical deployment using Docker, a platform which enables microservices deployment. Microservices are small independent programs which communicate through a defined API. When using AutoML to automate various processes, including training, one advantage is that the ML processes can run on a platform with proper computational resources. This is especially useful for training, which can require significant computational resources depending on the amount and type of data, algorithms used, and other factors (Ray, 2019).

Predictive analytics processes, including those in DHIS2, require considerable computational resources due to their mathematical calculations. Even DHIS2's predictors demand significant computational resources. In a presentation about predictors, Scott, one of DHIS2 developers, advises against running predictors during peak server usage, when users are experiencing server issues, or when server resources such as storage, CPUs, and RAM are limited (Scott, 2021). Deep learning using artificial neural networks would require even more computational resources. Running ML processes on separate server platforms would increase efficiency and decouple the app code and predictive models.

In conclusion, the findings answer the research question but there are also other deployment architectures with different configurations. What architecture to use in an ML app will depend on the use case and how predictions should be made available to the users.

6.1.2 Research Question 2

The following section presents an analysis on the finding related to the second research question which was:

> **What are the opportunities and challenges of using machine learning with DHIS2 in the context of low and middle-income countries?**

The results showed that there are two areas in which ML could be applied in DHIS2: forecasting & predicting diseases, and anomaly detections. However, several challenges must be overcome to implement ML in these areas. These challenges include poor data quality, the need for large amounts of data, lack of knowledge about ML, scepticism about ML, insufficient computation infrastructure, shortage of experts in the field of ML, issues of bias in ML models, lack of development guidelines, and shortage of funds and the risk of failure in ML projects.

Opportunities

Forecasting & disease predictions

Forecasting involves making predictions using either qualitative methods, such as informed opinion, or quantitative methods that use mathematical techniques. Quantitative forecasting techniques use time series data, which is a set of observations taken sequentially in time (Joseph, 2022). Forecasting has been applied in various fields, such as weather forecasting, stock price prediction, and resource planning. While statistical methods have traditionally dominated forecasting, ML methods have gained attention in recent years (Nielsen, 2019). DHIS2 has a feature called “predictor” which generates a data value based on past data values using statistical methods (DHIS2 Documentation Team, n.d.).

One study found that statistical forecasting methods outperformed ML methods, and that ML methods had greater computational requirements (Makridakis et al., 2018). However, another study countered these results, arguing that ML predictive performance improved as the sample of the data grew (Cerqueira et al., 2019). A more recent study by Makridakis et al. again, found that deep learning forecasting methods outperformed standard statistical and ML methods for monthly series and long-term forecasts (Makridakis et al., 2022). Contrasting between the two methods A. Nielsen, 2019 states that the advantages of statistical forecasting methods is that they are simple, understandable, and work well on small datasets. Their disadvantages is that their performance does not always scale with large amounts of data, and they do work well in data with nonlinear relationships. This shows that ML techniques better statistical techniques when there is vast amounts of data and the ability to learn complex patterns in data.

In the context of DHIS2 some countries have been using the system for a long time relative to others, this means that some countries have much data which makes the use of the ML methods relevant. Another important thing to note is that the digitisation process is continuous, more and more data is going to be collected along the way opening opportunities for ML methods. So, in context where there is less data, statistical forecasting methods are more relevant because of their simplicity, less computation costs and explainability. On the other hand, in context where there is more data, ML methods are more relevant at a cost of more computation resources.

Forecasting plays an important role in planning and achieving goals. A forecast provides estimates of what is to be expected which can be compared with a goal and inform planning. While DHIS2 has predictor for predictive analytics, the functionality is not sophisticated compared to the use cases which the participants argued could be achieved by ML. For example, predicting whether a goal could be reached or not based on previous and current trends in data, if a goal will not be reached what interventions should be applied and how much? The use cases belong into the prescriptive analytics as discussed in section 2.1.3. These use cases have also been reported in other studies such as USAID, (2019) in which they report intervention targeting and intervention selection ML use cases. In these use cases they report that data from multiple sources can be combined to make models to identify the right actions to achieve set goals. For example, they report that geographic and disease data can be used to create models to recommend who to target, where to target and what interventions to apply.

Previous studies have on the use of ML to make forecast and prediction of diseases have been done and have shown promising results. These include prediction of neonatal mortality risk of new-borns (Batista et al., 2021), prediction of vaccines to avoid shortage and oversupply (Alegado & Tumibay, 2020) (Hariharan et al., 2020) and integration of DHIS2 routine data and climatic data to predict malaria (Katwesige et al., 2020).

Anomaly detection

Another opportunity of applying ML in DHIS2 is anomaly detection. Anomalies also referred to as outliers, are data points which deviate from the normal distribution of data and the process of finding them is called outlier detection (Braei & Wagner, 2020). Some researchers have described them as patterns in data that do not conform to well-defined normal behaviour (Chandola et al., 2009), while others have referred to them as corruption in data (Günnemann et al., 2014).

In health information systems, accurate and reliable data are critical in decision-making, but it has been reported that data in HMIS often lack quality, and some users end up not trusting the data (WHO, 2022a). Consistent with the findings of this study, there are data quality challenges in HMIS in developing countries, such as missing values, bias, measurement errors, human errors during data entry and computation (WHO, 2022a). Furthermore, (Hausenkamph et al., n.d.) report that data is sometimes deliberately manipulated by health community workers in some countries where DHIS2 operates. They report that data is vulnerable to falsification to increase their pay in pay for performance schemes (P4P). They also report that in some instances operating partners in some countries have been known to manipulate data indicators and entries to satisfy donors to secure more funding.

Health authorities from different countries and development partners developed a Data Quality Review (DQR) toolkit to aid improving data quality. The DQR toolkit contains guidelines and tools which can be used to make data assessments, part of the toolkit are statistical based metrics which are implemented in HMIS to validate data and detect outliers. Olaniyan & Owoseni, (2022) argue that AI and ML presents a better approach to DQR, they did a study using HIV/AIDS data to evaluate DQR toolkit and an ML model. They found that their anomaly detection model was more reliable in assessing health data quality. (Hausenkamph et al., n.d.) while acknowledging the existence of statistical methods in HMIS, they believe that ML offers opportunities in checking variations in data and evaluate likelihood of fraudulent data as part of combating data manipulation schemes.

> "*This means that there are opportunities to use AI and machine learning (ML) to detect fraudulent or 'cooked' data entries by comparing datasets from similar districts. AI and ML can be used to predict the likelihood of a particular pattern of data and trigger alerts in case of outliers or suspected fraudulent data. Statistical tools to capture outliers already exist, but machine learning could check the natural variations in a dataset and evaluate the likelihood of poor or false entries*" (Hausenkamph et al., n.d., p. 21)

Other studies include (McCarthy et al., 2013) in which they worked on developing a set of unsupervised learning algorithms that can aid in detecting and classifying anomalies in health worker data.

The findings of the study on ML having the opportunity to aid in data quality through anomaly detections are consistent with previous studies. However, it does not imply that it provides an absolute solution. Although DHIS2 has advanced statistical methods aiding in outlier detections, if the available tools fall short and data quality problems are critical, such as data falsification, ML offers advanced opportunities to improve data quality.

Challenges

Data related challenges

The findings revealed that there are data quality challenges, and that ML applications require a large amount of data to perform effectively. Data quality challenges have been partly discussed in the anomaly detection section. In the context of developing countries, previous studies have reported the same challenges. (J. A. Singh, 2019) argues that there is absence of data, inadequate quality data and non-uniform datasets. (USAID, 2019) reported that there is lack of weather pattern and population demographic data which is required in some ML tools. (Stankovich, 2021) report that data is not always digitised and not easily accessible. In the DHIS2 ecosystem previous studies also reported data quality challenges, (Dehnavieh et al., 2019) reviewed articles on DHIS2 operation challenges and experiences of 11 countries and one finding they reported is that there was lack of adequate reporting data and high-quality data but differing in extremity from one country to another. Data quality challenges where DHIS2 is used have also been reported by (Karuri et al., 2014) and (Hagel et al., 2020).

The need for good data is a necessity in information processing. The data collected, when processed, is useful in making informed decisions. The information produced is used in planning interventions, monitoring programs, resource allocation, and more. Bad data can lead to inaccurate decisions that do not reflect the actions that are supposed to be taken. The use of ML involves more resources compared to other data analysis methods, so using ML on poor data will not render any magic; wrong predictions will be made. This can lead to losses and tarnish the image of ML. Therefore, the presence of decent quality data is a requirement in any data analysis application, including ML.

The need for a large amount of data for ML is another challenge. As discussed in the forecasting opportunity section, ML methods, especially deep learning, perform well when there is a huge amount of data. Countries have been implementing DHIS2 at various stages over the years, from pilots to nationwide implementations, and the data could be from different programs initiated at different points in time. It is not feasible to estimate the amount of data where DHIS2 is used, but the availability of a large amount of data is a necessity for ML applications, especially deep learning.

Technical Challenges

A set of challenges were found which relate to technical aspects of ML which include lack of supporting technology infrastructure, the lack of experts in the field and biases in models. Most digital technologies require electricity, network connectivity and computation infrastructure. However, these supporting resources are usually limited in developing countries. Estimates show that 600 million people do not have electricity access in Africa and approximately 30% of health facilities have access to electricity (J. A. Singh, 2019) (Owoyemi et al., 2020).

On challenges experienced in deploying and using DHIS2, lack of effective communication infrastructure has been reported in some countries, citing limitations in internet connectivity and computers (Dehnavieh et al., 2019) (Karuri et al., 2014) (Kariuki et al., 2016) (Reynolds et al., 2022). However, other deployment experiences report success in country wide deployment due to improved countrywide internet connectivity such as the case of Kenya (Manya et al., 2012).

The findings of this study agree with previous research that highlights infrastructure challenges in developing countries. While progress has been made in some countries, many still struggle with limited access to electricity, network connectivity, and computational resources. The training of ML models requires significant computational resources, and additional server resources would be necessary for local or cloud-based deployments. In client-server architectures, network connectivity is also necessary. Given these challenges, the use of ML in countries with infrastructure problems may be difficult.

One of the reasons why AI is identified as potential technology to address challenges in public health and clinical setting in developing countries is because there are significant gaps in health care services (WHO, 2021). Shortages of human resources, medical resources, and elevated levels of disease burden and recurrent disease outbreaks are prevalent (J. A. Singh, 2019) (Owoyemi et al., 2020). While ML has the potential for resource allocation, disease predictions, and other applications, there is a shortage of skilled employees who can initiate such projects in developing countries, and most successful AI projects are from developed countries (J. A. Singh, 2019). Previous studies in the DHIS2 ecosystem have shown that developing countries lack the human capacity to leverage opensource health information systems in innovations, and capacity-building efforts have mostly focused on end-user capacity (Msiska & Nielsen, 2017). If countries lack the capacity to extend health digital platforms, it is not feasible for them to think of integrating DHIS2 with advanced technologies like ML. Therefore, for countries to leverage opensource platforms like DHIS2 through ML technologies, greater capacity building efforts would be required focusing on innovating on the platforms.

Another technical challenge concern bias in predictive models. Bias in models is a result of human errors in design of ML applications and poor data quality (Murphy et al., 2021). People who develop the systems are humans and fallible, different societal values may be incorporated in the design and development of the systems which may result demonstrating bias in their predictions. The most discussed source of bias in literature is poor training data (WHO, 2021) (J. A. Singh, 2019) (USAID, 2019). Bias in the models may result from under-representation in the data used for training, such as gender, age, race, sexual orientation, and other attributes. When models are trained using such data, they merely reflect the systematic bias in the data.

Bias in models is often reported when data from individuals is used. However, the opportunities for ML identified in the study such as forecasting, anomaly detection, and disease predictions do not involve predictions that are sensitive to bias, and the data sources are mostly population data rather than individual data. If individual data were to be used for ML applications, ethical guidelines and principles would be critical, as well as the involvement of experts and relevant stakeholders.

Guideline challenges

Another challenge identified in the study relates to the lack of guidelines and policies regarding the use and development of ML technologies in developing countries. Due to the ethical concerns surrounding AI, such as data privacy breaches, bias in predictive models, and accountability issues when errors occur, it is essential for governments to establish guidelines for the ethical use of AI and for regulatory bodies to oversee AI applications.

According to (OECD.AI, 2021) only 69 countries have AI related policies and most of these are developed countries. OECD observes policies by countries to help countries monitor the development of trustworthy AI systems that is beneficial to the society (WHO, 2021). In developed countries, governments have taken the initial steps in developing AI strategies and policies to promote research, development, and adoption of AI for economic development, as discussed by Murphy et al., (2021) regarding Canada. If governments in developing countries were to take steps to implement strategies and policies around these digital technologies, such as addressing infrastructural challenges and implementing regulatory frameworks, it could open doors for other sectors to adopt these technologies.

Lack of awareness and different perspectives

Another challenge is the lack of awareness of how ML works and the various areas where this technology can be applied. In the context of the DHIS2 ecosystem, this is not a surprise and is a general problem. The field of ML has been around for many years, but its current popularity and growth are due to recent breakthroughs in deep learning discovered in the last decade (Tappert, 2019). Since then, the technology has found use cases in many areas, such as virtual assistants, language translation, autonomous vehicles, and language models like ChatGPT. The DHIS2 community consists of stakeholders from diverse backgrounds, such as NGOs, global donors, researchers, students, universities, ministries of health, policy makers, developers, etc. (Adu-Gyamfi et al., 2019). Many of these people do not have a background in AI, and although some may have heard of the technology, they may not be able to relate to its use cases in DHIS2. Therefore, the lack of awareness should not be a surprise.

Distinct perspective exists toward AI in many people from diverse backgrounds. Ambartsoumean & Yampolskiy, (2023) explored different schools of thought regarding AI, including those who believe that AI poses a threat to our existence and those who believe that AI holds great promise for humanity. They presented various interesting arguments from different sides, but now, neither side can be proven right or wrong. While the most scepticism relate to AI risk to humans, the study found that other scepticism are about doubts of its potential. The presence of sceptical views about the use of ML in the DHIS2 community is normal because we all have different worldviews that are shaped by our experiences, attitudes, and knowledge. These views should be respected.

Lack of funds and financial risks

One of the critical challenges relates to limited financial resources. Most of the digitisation projects in the health sector in developing countries are funded by development partners, such as DHIS2 nationwide rollouts in Tanzania (Sukums et al., 2021) and Uganda (Kiberu et al., 2014). Even when the system is successfully implemented, studies indicate that some countries find difficulties in strengthening the system through innovations, data quality improvement efforts, and other areas due to inadequate financial support from ministries of health. This lack of financial support affects capacity-building efforts, leading to staff retention issues at a larger scale (Kintu, 2012). These findings align with previous studies that highlighting financial difficulties. It is not feasible for countries in such scenarios to work on developing advanced ML-related innovations since more computational resources and expertise are required. Furthermore, the initiation of ML projects in some countries is donor-funded, such as the prediction of the risk of interruption in ART programs in Mozambique (Stockman et al., n.d.).

Due to the hype of the technology in recent years, a lot of organisations get entangled into integrating the technology into their information systems. But the reality is that ML projects are attributed with a great deal of risk, surveys report that 70% of ML implementations result in no or minimal impact and 87% of AI projects fail, that is they do not reach deployment (Weiner, 2021) (Westenberger et al., 2022). Just like software engineering can projects fail, the same fate may befall ML projects if there is poor planning. Some of the factors which contribute to the failures include "over hype" , poor data and inadequate data.

6.2 Recommendations

This section suggests recommendation to the different stakeholders based on the findings of the study with the regards to the use of ML with DHIS2, these include the ministries of health and developers in the DHIS2 ecosystem.

6.2.1 Ministries of Health

The study's findings show that ML can be used with DHIS2 to improve health outcomes in areas such as forecasting, disease prediction and anomaly detections which can make contributions to better health outcomes. Nevertheless, to fully realize the potential benefits of this technology, certain considerations and challenges need to be carefully addressed.

Apply ML to address problems it can uniquely solve

First, it is important to apply ML to address problems that can be uniquely solved by the technology. The popularity of ML does not render statistical methods irrelevant. As discussed earlier, studies have shown that for small datasets, statistical methods perform better than ML methods. However, it is when dealing with large amounts of data that ML methods demonstrate their prowess. Use cases like forecasting and anomaly detections, there are statistical methods which can be used achieve predictive and prescriptive analytics. For instance, DHIS2 has advanced methods for detecting outliers using statistical methods. This is because ML offers a much more expensive way of solving problems than their statistical counterparts. But for extreme cases such as detecting fraudulent data, applying ML methods may be necessary when available methods do not solve the problems at hand. On the other hand, ML offers the flexibility of solving diverse types of problems and they can work with diverse types of data such numbers, text, images, audio, among others.

Perform a cost-effectiveness analysis of ML projects

The study found that there are costs associated with the use of ML applications, such as the need for additional computational infrastructure and human resources to maintain the models, among others. However, as the study has also shown, these resources are scarce in developing countries. Therefore, it makes sense to integrate ML with DHIS2, focusing on use cases that can yield benefits. This approach can help to avoid some of the pitfalls associated with ML systems, such as the implementation of use cases that may not have any impact. Some use cases which were presented in the findings can easily be assessed to be crucial and have the potential to influence development outcomes than others. Among these include predicting whether targets would be reached or not, if not what should be done to change the predicted outcome or what intervention should be selected. So, conducting the cost and benefits analysis is critical.

Developing an enabling context

The various challenges found in the study need to be resolved to create an enabling context. I recommend continued efforts in improving data quality and digitization to make more data available. Some use cases require data from multiple sources, such as meteorology and geography. Governments should work on implementing strategies and policies around the use of AI technologies, like those in developed countries, that can address issues of ethical use, accountability, data access, and privacy. Efforts have been made in formulating guiding principles by international organizations such as WHO and PAHO, but having country-specific policies is important. Awareness campaigns on how the technology works, the problems it can solve, and what it cannot solve would be important to avoid misconceptions. Lastly, there is a need to empower existing statisticians and data analysts with ML knowledge and integrate them into development teams to aid in identifying potential use cases and their implementations.

6.2.2 Developers in DHIS2 ecosystem

ML powered applications work different from most applications that they cannot be incorporated into the core as it features components which are more generic to meet the needs of many countries. ML require training of data, a step which requires computational resources which can exhaust server resources; thus, it would not be recommended to use ML that way. ML models can be developed separately and integrate into apps in a standalone architecture or served using a microservice accessible through an API. However, those deployment methods involve manually training, monitoring, and updating of the predictive models.

A much feasible way of integrating ML with DHIS2 is through automated machine learning tools. AutoML tools automate the processes of ML making it easy for people without data science background to use ML. Data can be pulled from DHIS2 using available API, run AutoML to produce models which can be served or make predictions which can be pushed into the DHIS2 database to be accessed by the users through apps or send notifications. Open-source tools have been developed which can be tested with DHIS2 data or custom tools can be developed by the community to meet the specific predictive needs in the DHIS2. I would recommend the developer community to test these tools and assess their potential. The following table shows some of these tools.

Name	**Licence**	**Link**
H2O.ai	Apache License 2.0	https://github.com/h2oai/h2o-3
Prophet	MIT License	https://github.com/facebook/prophet
Autokeras	Apache License 2.0	https://github.com/keras-team/autokeras
Autosklearn	BSD license	https://automl.github.io/auto-sklearn/master/
AutoPytorch	Apache License 2.0	https://github.com/automl/Auto-PyTorch

Table 5: Automated ML tools

6.3. Limitations of the study

There are two main limitations to the study that should be considered in future studies. The first limitation was that some challenges of using ML are contextual, developing countries are at various levels of progress, some are ahead in some areas than others. For example, digitisation efforts in the use of HIS have been initiated at different points in time, which might reflect data availability. This implies that countries that rolled out DHIS2 a long time ago should have more data available than countries which have rolled out DHIS2 recently, this also applies to supporting infrastructure such as computation, internet connectivity and electricity.

The second limitation is the number of participants in the study. The use ML with DHIS2 is an emerging phenomenon in the community, finding the relevant stakeholders who were willing to participate was a challenge. In addition to that, some who promised to participate withdrew their interest at last minute.

Chapter 7

Conclusion

In this thesis, I explored the opportunities and challenges of using ML with the DHIS2 platform in its ecosystem. The aim of the study was to understand how ML could be integrated with the DHIS2 platform and the challenges and opportunities that developing countries, where the system is used, would face in using this technology. An interview-based study was conducted with various stakeholders in the ecosystem.

The results suggest that ML can be integrated with the platform through an App in both standalone and client-server architectures. In a standalone architecture, an ML model would be developed separately and integrated into the App. In a client-server architecture, a model would be developed and deployed as a microservice accessible through an API. Furthermore, the client-server architecture opens doors for various configurations, such as integration with AutoML tools.

There are several general opportunities, including forecasting, disease predictions, and anomaly detections. However, there are also challenges which developing countries are experiencing that need to be addressed to create headroom for integration. ML requires a significant amount of data, and there are issues with data quality, lack of experts, inadequate supporting infrastructure, insufficient funding, maintenance costs, risks of project failures, and lack of guidelines for the use and development of ML applications.

The study contributes to the technical knowledge of ML integration architectures with the DHIS2 platform and the knowledge of opportunities and challenges specific to the DHIS2 digital platform and developing countries.

7.1 Suggested future work

To advance this research further, I propose that focus should be shifted towards practical assessments by initiating a research project where a potential use case can be implemented. The project could serve as a case study that can provide practical knowledge and create opportunities for conducting tangible impact assessments.

Appendix A

A.1 Interview guides

Interview Guide 1

First of all, thank you for taking the time to participate in this interview. As I already introduced myself, I am a master's student at University of Oslo and I am currently working on a master's thesis in on *Machine Learning and DHIS2: Exploring opportunities and Challenges in DHIS2 ecosystem*. The aim of this interview is to gain more insight into the benefits, opportunities, challenges of using AI/ML techniques to support DHIS2.

The interview audio will be recorded for transcription purposes. I will be using an app called Nettskjema Diktafon, the app encrypts the recording on the phone. The data which will be collected will be anonymised.

Warmup Questions

- Could you please tell me about your profession?
- What is your role and responsibilities?
- How do you understand the field of Artificial Intelligence specifically subfields machine learning and deep learning?
- What is your experience working with machine learning?

Benefits

- What role does machine learning play in data analysis?
- Are you aware of any use of machine learning related to DHIS2
- Are you aware of any other digital platforms for public health in developing countries using machine learning

- What benefits do you think machine learning brings to an organisation using DHIS2?
- For organisations using DHIS2, does the use of machine learning bring an upper hand to the organisation's decision-making process?
- Do you think it is worth investing into the use machine learning for organisations using DHIS2 in terms of the costs and the benefits?
- DHIS2 is mostly used in used in low- and middle-income countries do you believe that these countries have the capacity to afford machine learning solutions?
- Do you think that using machine learning in DHIS2 can contribute to the achievements of millennium development goals in the health sector and universal health coverage?
- Is it possible that machine learning models from one group be shared and be relevant in another group with similar uses case?

Potential

- Do both routine and individual data have the potential to be used in machine learning?
- In your experience with DHIS2 what are the use cases you have implemented or what are the possible use cases?
- In addition to your listed potential, do you think machine learning can be used in the following areas? Skip if already mentioned.
    - *Assist in data quality* (finding fraudulent data and detecting anomalies)
    - *Forecasting*
    - *Predicting pandemics and surveillance*
    - *Predicting risk in individual's health status*
    - *Logistics*
    - *management*
- What do you think about the quality of DHIS2 data which you have used in your implementations of machine learning?

- What would be the minimal infrastructure for a ministry to do machine learning with (a)routine data (b) individual data

Procedures

Research shows that there are ethical concerns in the use of machine learning, what are your approaches to the following issues?

- Bias in algorithms
- Accuracy of algorithms
- Privacy of data

Challenges

- Are there any challenges in the development and deployment of machine learning applications in DHIS2?
- Is there any gap in support from the DHIS2 core team? Do you think that they have a role to play to enhance machine learning in DHIS2 community? If yes, in what way?
- What challenges do you think low-middle income countries using DHIS2 have when it comes to implementing machine learning solutions?

Interview Guide 2

- Could you please tell me about your profession?
- What is your role and responsibilities?
- Have you ever heard of AI/ML?
- Do you have any AI/ML implementations in any of your DHIS2 implementations? If not, why?
- Literature shows that AI/ML have the potential of strengthening and improving health
- outcomes and can help countries achieve universal health coverage. It can be used in areas such as improving data quality, forecasting vaccines, predicting pandemics

and surveillance, predicting risk in individual's health status etc. Do you think this would be crucial in supporting decision making?

- Literature shows that developing countries are yielding the benefits of AI/ML, what challenges do you think low-middle-come income countries would face in implementing such technologies?

A.2 Consent form

Are you interested in taking part in the research project

"Machine Learning and DHIS2: *Exploring opportunities and challenges in DHIS2 community*"

This is an inquiry about participation in a research project where the main purpose is to explore the potential of Machine Learning (ML) in DHIS2. In this letter we will give you information about the purpose of the project and what your participation will involve.

Purpose of the project
DHIS2 is a software platform that is used to collect routine aggregated data which is used to make informed decisions. The platform heavily uses descriptive and exploratory data analysis tools such as charts, tables etc to summarise the data for decision making. There has been a growth in the use of ML algorithms which are used to find patterns and create models for predictive analysis. A preliminary study in DHIS2 shows that there are partners using ML techniques, pioneers of the technology in the context of DHIS2. Not much is known about ML, its potential benefits, use cases, challenges in DHIS2. This research aims to explore machine learning and DHIS2 through answering the following research question.

RQ: *What are the perceived opportunities, challenges, and limitations of using machine learning in DHIS2?*

Who is responsible for the research project?
This research is being conducted at HISP UiO under the Information Systems Research group at the department of Informatics at University of Oslo.

The research will be carried out by Davie Munthali a student studying a master's degree in informatics: *programming & system architecture* and it is being supervised by associate professor Petter Nielsen who is currently the head of Information System Research group at the department of informatics.

Why are you being asked to participate?
The sample has been selected using purposive sampling technique. Purposive sampling allows researchers to select participants based on how relevant they are to the study. You have been chosen have experience with ML and DHIS2, data scientist, developer, or a user in the community.

What does participation involve for you?
Data will be collected through interviews. Considering that the researcher may not manage to travel to your proximity, online digital meetings may be used. The interview session will be recorded for thorough data collection and recordings will solely be used for this research purpose.

No information related to your organisation will be collected, the information to be collected will relate to how you understand ML, how you use the technology, how it complements DHIS2, example of use cases in DHIS2, limitations, challenges and from other stakeholders their views on the technology.

Participation is voluntary
Participation in the project is voluntary. If you chose to participate, you can withdraw your consent at

any time without giving a reason. All information about you will then be made anonymous. There will be no negative consequences for you if you chose not to participate or later decide to withdraw.

Your personal privacy – how we will store and use your personal data
We will only use the data for the purpose(s) specified in this information letter. We will process your data confidentially and in accordance with data protection legislation (the General Data Protection Regulation and Personal Data Act).

What will happen to your personal data at the end of the research project?
The project is scheduled to end on 30th June 2023 when I finish my studies. The data will be stored for verification, follow-up studies, archiving for future research. The data will be stored securely on University of Oslo Nettskjema, the shortest period of keeping data is 1 year.

Your rights
So long as you can be identified in the collected data, you have the right to:

- access the personal data that is being processed about you
- request that your personal data is deleted
- request that incorrect personal data about you is corrected/rectified
- receive a copy of your personal data (data portability), and
- send a complaint to the Data Protection Officer or The Norwegian Data Protection Authority regarding the processing of your personal data

What gives us the right to process your personal data?
We will process your personal data based on your consent.

Based on an agreement with University of Oslo. Data Protection Services has assessed that the processing of personal data in this project is in accordance with data protection legislation.

Where can I find out more?
If you have questions about the project, or want to exercise your rights, contact:

- Davie Munthali
  Email: daviem@ifi.uio.no
- Petter Nielsen (supervisor)
  Email: pnielsen@ifi.uio.no

Yours sincerely,

Davie Munthali
(Researcher)

Consent form

I have received and understood information about the *project Machine Learning and DHIS2: Exploring opportunities and challenges in DHIS2 community* and have been given the opportunity to ask questions. I give consent:

☐ to participate in an interview
☐ for my personal data to be stored after the end of the project for follow-up studies

I give consent for my personal data to be processed until the end date of the project, 30th June 2023.

(Signed by participant, date)

A.3 Letter of support

UiO University of Oslo
Department of Informatics

To: Whom it may concern

Date: 29 June 2022

Letter of Research Report for Mr Davie Munthali
This letter is to confirm that Mr. Davie Munthali from Malawi is a student at the University of Oslo in Norway. He is pursuing an MSc degree in Informatics: programming and system architecture under my supervision.

Davie Munthali is planning to collect data in connection with his master's thesis: "Machine Learning and DHIS2: Exploring implementations, opportunities, challenges, and support needs" which is a mandatory part of the program.

Any assistance to him will be highly appreciated. Please contact me if you need any further clarifications.

Sincerely yours,

Petter Nielsen
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