AI MODEL FOR
IMPROVING SOCIAL PROTECTION DELIVERY
IN ZAMBIA

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DECLARATION

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I hereby declare that this final year research project is the result of my own work, except for quotations and summaries which have been duly acknowledged.

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AI MODEL FOR IMPROVING SOCIAL PROTECTION DELIVERY IN ZAMBIA

ABSTRACT

Social Protection programmes in Zambia aim to reduce the levels of poverty and improve the lives of the vulnerable in the communities. However, the two most common challenges in the Social Protection sector in Zambia are fragmented data and poor targeting of beneficiaries. This report describes the development of an AI model prototype for improving Social Protection delivery in Zambia. AI models such as machine learning are discussed in helping solve the fragmented data problem through integration of data from different management information systems as well as improve the targeting challenge using algorithms. The legal, technological and ethical issues in relation to the prototype being developed are also discussed. Furthermore, the report discussed the future works on the enhancements of the model and its functionality.

KEYWORDS: artificial intelligence, social protection, machine learning, targeting

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DEDICATION

I dedicate this paper to my parents, Webster and Elizabeth Muzungaile who are my inspiration, thank you for always believing in me and pushing me to excel in everything I do in life. My good friend Constance Simunji, thanks for your encouragement and support during this academic journey.

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LIST OF ABBREVIATIONS

AI: Artificial Intelligence

ALI: Alternative Livelihood Initiative

CWACs: Community Welfare Assistant Committees

ECT: Emergency Cash Transfer

FSP: Food Security Pack

FSPMIS: Food Security Pack Management Information System

GEWEL: Girl's Education and Women's Empowerment and Livelihoods

INRIS: Integrated National Registration Information System

MCDSS: Ministry of Community Development and Social Services

MIS: Management Information System

ML: Machine Learning

MOHAIS: Ministry of Home Affairs and Internal Security

NAPSA: National Pension Scheme Authority

NRC: National Registration Card

PMT: Proxy Means Testing

PWAS: Public Welfare Assistance Scheme

SCT: Social Cash Transfer

SWL: Supporting Women's Livelihoods

SWLMIS: Supporting Women's Livelihood Management Information System

UK: United Kingdom

ZISPIS: Zambian Integrated Social Protection Information System

1.0 CHAPTER 1 - INTRODUCTION

1.1 Background to the Study

Social Protection in Zambia consists of programmes which aim to reduce the levels of poverty and improve the lives of the vulnerable in the communities. Apart from helping poor and vulnerable families from being stagnant in poverty, Social Protection has greatly contributed to the economic growth by raising labour productivity and enhancing social stability [1].

The Ministry of Community Development and Social Services (MCDSS) is mandated to coordinate the provision of equitable social protection services to communities in order to contribute to sustainable human development [2]. The two main departments at MCDSS that deal with these social protection programmes are the Department of Community Development and the Department of Social Welfare.

The Department of Community Development is mandated to enhance the livelihoods of the poor and vulnerable but viable people, through collective efforts to improve the social, economic and cultural conditions of the communities for sustainability, poverty reduction and national development. Programmes implemented under this department include Food Security Pack (FSP), Supporting Women's Livelihood (SWL), Village Banking, among others [3].

On the other hand, the Department of Social Welfare is responsible for the provision and promotion of quality social welfare services aimed at alleviating poverty, reducing destitution, promoting family values and reducing juvenile delinquency. Programmes implemented under this department include Social Cash Transfer (SCT), Emergency Cash Transfer (ECT), Public Welfare Assistance Scheme (PWAS), Juvenile Welfare, Ending Child Marriage, among others [4].

Statistics provided by MCDSS reveal that, as of 2024, there were 1,311,101 beneficiaries under the SCT programme, 952,570 beneficiaries under ECT, 263,700 beneficiaries under the FSP programme and 139,351 beneficiaries under the SWL programme [5]. These beneficiaries are cut across all the 116 districts in Zambia.

Despite the attempts to enhance Social Protection delivery in Zambia, the country faces lack of integration leading to fragmented data systems and poor targeting of beneficiaries. In order to tackle these existing challenges, the application of Artificial Intelligence (AI) in Social Protection will help to provide solutions via AI models such as machine learning to improve efficiency in the Social Protection sector in Zambia.

1.2 Problem Statement

Firstly, the most common problem in the Social Protection sector in Zambia is the lack of integration of different Social Protection programmes leading to fragmented data systems and overlapping in the implementation of programmes [6]. For instance, the inability to spot out beneficiaries under the main Social Protection floor called the Social Cash Transfer (SCT) programme that are benefiting from other programmes, leads to inefficiencies and gaps in coverage.

In Zambia, the National Registration Cards (NRCs) are issued once a Zambian citizen reaches the age of sixteen (16). The NRCs are used as the unique identifier for beneficiaries to be aligned to Social Protection programmes. However, the challenge is that some of the eligible (targeted) beneficiaries do not possess these NRCs and tend to be excluded from Social Protection programmes that could improve their livelihoods [7].

In addition, other challenging factors that have led to the lack of integration include the legal framework not supporting certain aspects of interoperability [7]. Interoperability requires integration and access to various databases across different departments and ministries. This procedure poses a challenge, as there is lack of coordination and data sharing among departments and ministries [8].

The Management Information Systems (MISs) at MCDSS that support the social protection programmes are; the Supporting Women's Livelihood Management Information System (SWLMIS), the Zambian Integrated Social Protection Information System (ZISPIS) and the Food Security Pack Management Information System (FSPMIS). The three mentioned systems operate in silos and therefore the Social Protection data remains fragmented.

Secondly, the poor targeting of beneficiaries poses as another problem in this sector. The commonly used targeting methods are the "Proxy Means Testing (PMT)" that is used to gather data on the various assets owned by potential beneficiaries and the "Community-based targeting" that involves local community members participating in the selection of programme beneficiaries. However, the challenge with these two methods is that they do not measure poverty with ample accuracy and also the local community members at times choose beneficiaries among their close friends and relatives. Furthermore, lotteries are used by government to target the poorest households. Potential participants are first identified, after which the actual beneficiaries are selected through a simple random draw. This approach is problematic due to the fact that some of the most vulnerable beneficiaries may end up not being drawn and eventually not receiving the benefits [9].

1.3 Aim and Objectives of the Study

The main aim of this project is to develop an AI model prototype for improving Social Protection delivery in Zambia. The specific objectives are as follows:

(i) To review the existing Social Protection delivery systems in Zambia.

(ii) To develop an AI based solution for Zambia's Social Protection programmes.

(iii) To evaluate the performance of the AI model on the efficiency and quality of Social Protection delivery.

1.4 Research Questions

To cover the objectives mentioned in Section 1.3, the following three research questions were formulated:

- **RQ1**: What are the current challenges of the existing Social Protection delivery systems in Zambia?
- **RQ2:** What AI based solution can improve Social Protection delivery in Zambia?
- **RQ3:** Which performance metrics will be used to evaluate the performance of the AI model?

1.5 Scope and Limitation

1.5.1 Scope

The scope of the project will focus on reviewing the existing Social Protection delivery systems in Zambia and identifying any data discrepancies and inefficiencies. The project will analyse how artificial intelligence can address the problems of fragmented data and poor targeting of beneficiaries. It will examine various AI models such as machine learning models and their capability to improve efficiency in the Social Protection sector in Zambia.

1.5.2 Limitation

The following sub-sections explain the limitations in detail. The ethical issues will be discussed in Chapter 3.

1.5.2.1 Legal Issues

The main legal issues that Social Protection systems face are data privacy and protection. Social Protection data is very sensitive as it includes personal, health, financial and social related information for beneficiaries. In order to ensure data privacy, the AI models used in this project adhered to the Data Protection Act of 2021, which included the following principles [10]:

- Lawfulness, fairness and transparency
- Purpose limitation
- Data minimization
- Accuracy
- Storage limitation
- Integrity and confidentiality (security)
- Accountability

1.5.2.2 Technological Issues

The two technological issues to consider are the Data Infrastructure and Quality and Technology Divide in rural setups [7].

In order for AI to be integrated successfully into the Social Protection delivery systems in Zambia, the data infrastructure needs to undergo improvements and standardization. There is usually the case of data being inconsistent or incomplete in the rural areas. Poor quality data can lead to errors in the integration process. Therefore, it is significant to ensure that the data is of high quality, accurate and up-to-date for the adoption of an AI solution into these systems.

The challenges experienced with technology in rural and remote areas is poor internet connectivity, lack of digital skills and devices such as tablets, computers and phones. Recently, the MCDSS had installed Starlink kits in some district offices in Zambia, to improve their access to the internet and daily operations of the Management Information Systems (MISs) that deal with Social Protection data. The Ministry had also introduced Digital Literacy training to help capacity building of non-ICT officers in digital skills. AI is one of the skills that is taught during these trainings and therefore this makes it easier for district personnel to protect themselves from fraud.

1.6 Significance of the Research

According to [11], the problem that developing countries and societies face with Social Protection programmes is financial constraints. As a result, developing countries fail to sponsor large-scale Social Protection programmes on their own without the involvement of multilateral organizations through grants or loan facilities. This financial constraint leads to limited coverage of Social Protection programmes.

Furthermore, poor targeting of beneficiaries and lack of data availability also hinders developing countries progress towards the successful implementation of Social Protection programmes. Zambia is one of the countries which fits the above description, not only with regard to integration and poor targeting but also in regards to limited financial resources as most of its Social Protection programmes are donor-funded.

Therefore, there is need to streamline Social Protection delivery in Zambia so that duplicity and omission of eligible beneficiaries can be avoided. These challenges can be addressed using Artificial Intelligence (AI). Below are the identified AI solutions that make this project significant:

Firstly, AI can improve the targeting process of eligible beneficiaries by using Machine learning algorithms to predict beneficiaries who are eligible or non-eligible. This big data includes socioeconomic data (income, education levels, employment status, housing conditions, health indicators, assets and social status), household characteristics (number of people in the household, their age and gender, educational levels, employment status, income, housing type, assets and access to resources like water and sanitation) and geographical variables (location such as rural or urban, population density, infrastructure, climate and so on. This can help identify beneficiaries who might have been excluded by the traditional targeting methods carried out by MCDSS, such as lotteries [12].

Secondly, AI can also enhance targeting by using machine learning to analyse huge datasets containing the aforementioned socioeconomic, household and geographical data. These algorithms can be trained to collect and process the data from household surveys and from different government institutions that manage population and citizenship registration, social security, revenue administration, vehicle and land registries, farmer registration, and employment agencies to predict which households are most likely to be subject to vulnerability. Thus, helping to improve the accuracy of targeting and reduce errors made during the traditional selection procedure [13].

Lastly, AI can resolve the issue of fragmented data and inconsistencies using integration. It can improve the integration process using machine learning algorithms that can automate the process of cleaning data, alleviating data inconsistences or discrepancies between the various Social Protection programmes MISs [14].

1.7 Preliminary sections of the project report

This project is structured as follows: Chapter 2 will discuss the literature review. The methodology used in this project is described in Chapter 3 and the implementation is discussed in Chapter 4. The results are presented in Chapter 5. Finally, in Chapter 6, the conclusion will be outlined.

1.8 Chapter Summary

This chapter introduced the background to the project. It presented a detailed discussion of the problem statement, aim and objectives, research questions, scope of the project and limitations. It concluded with the significance of the research and the preliminary sections of the project report.

2.0 CHAPTER 2 – LITERATURE REVIEW

2.1 Broad literature review of the topic

2.1.1 Social Protection

Social Protection is a set of programmes and policies by government that provide income or consumption transfers to the poor, protect the vulnerable against livelihood risks and enhance the social status and rights of the excluded; with the overall objective of reducing the economic and social vulnerability of poor and excluded groups.

Social protection can be both contributory and non-contributory. Contributory schemes are defined as plans that require both the employee and their employer to contribute a portion of their income in order to claim their benefits in the future. Non-contributory schemes are those that normally need no direct financial contribution from beneficiaries or their employers as a condition of entitlement to receive benefits. In Zambia, an example of a contributory scheme is the National Pension Scheme Authority (NAPSA) which provides social insurance for formal sector employees in the event of retirement, disability, death of a spouse or parent. Examples of non-contributory schemes are Social Cash Transfer, Food Security Pack which will be discussed in detail in Section 2.1.2. Fig 1 below depicts the structure of these schemes [15].

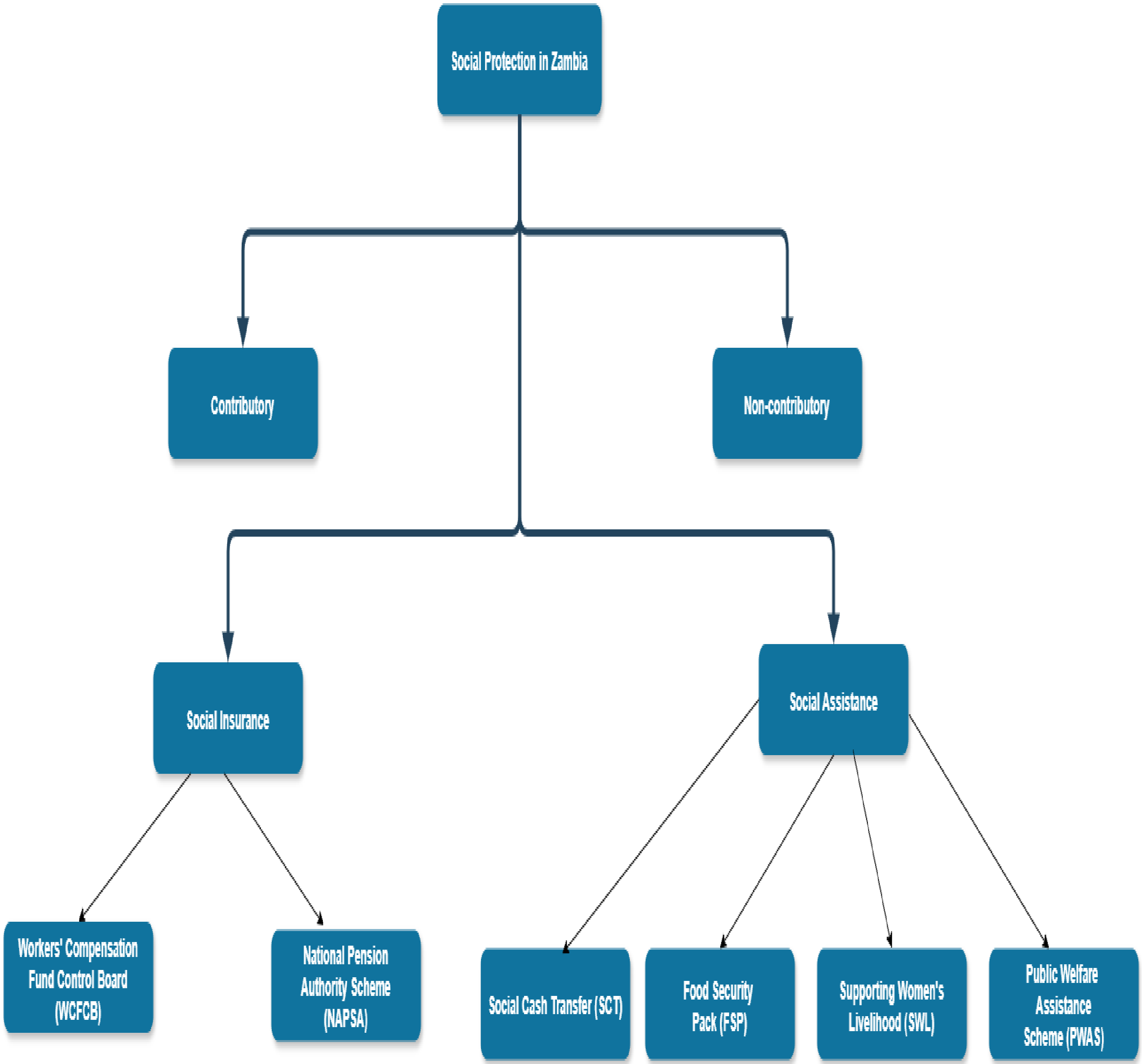
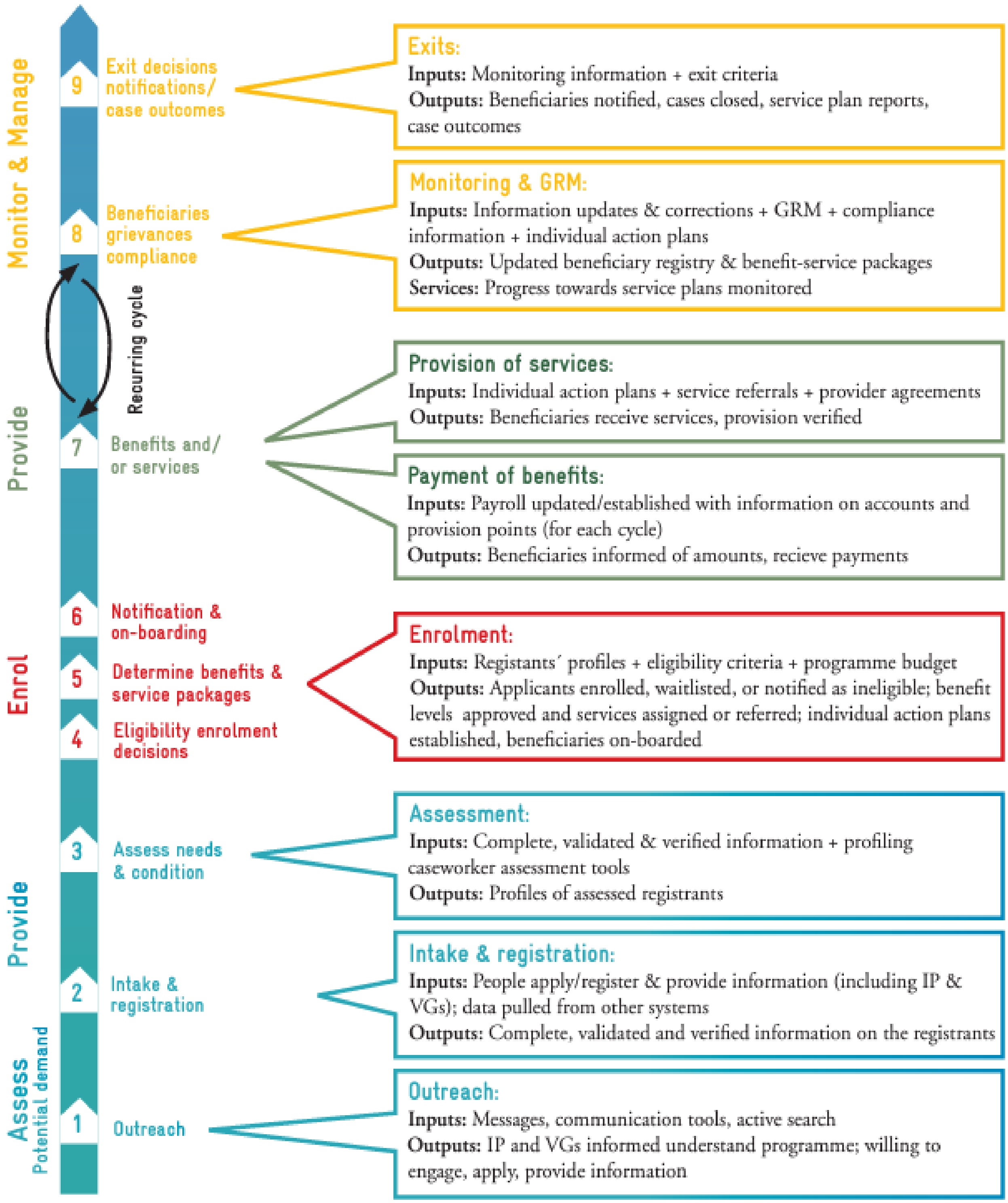


Fig. 1. Contributory and Non-Contributory schemes in Zambia

Fig 2 illustrates the Social Protection delivery chain [16].



Note: IP = intended population; VG = vulnerable groups; GRM = grievance redress mechanism Source: Lindert *et al.* (forthcoming)

Fig. 2. Social Protection Delivery chain

2.1.2 Types of Social Protection Programmes in Zambia

There are many Social Protection programmes that are being implemented in Zambia by both Government and Non-Governmental Organizations (aid agencies and churches). However, the main three non-contributory Social Protection programmes are Social Cash Transfer (SCT), Food Security Pack (FSP) and Supporting Women's Livelihood (SWL) being implemented by the Ministry of Community Development and Social Services (MCDSS).

2.1.2.1 Social Cash Transfer (SCT)

This programme is implemented by MCDSS through the Department of Social Welfare. The objective of the programme is to provide financial support to the poor and vulnerable households in order for them to meet their basic needs, such as health, education, food and shelter. This programme is being implemented in all the 116 districts of Zambia.

In order for beneficiaries to be targeted under this programme, they must meet criterion (a) and any of the other listed below [17]:

a) The household should be resident in the same locality for a continuous period of 6 months or more.

b) They should be female headed households with 3 children or more.

c) Child headed households: This is a household that is headed by a child aged 18 years and below.

d) Households with person(s) who are chronically ill and on palliative care.

e) Households with a person(s) with severe disability.

f) Households with an elderly member aged 65 years and above and confirmed by a green National Registration Card.

g) Proxy Means Testing (PMT) - This is the information on households or individuals' characteristics correlated with their welfare levels which is used in a formal algorithm to proxy household income, welfare or need.

2.1.2.3 Food Security Pack (FSP)

This programme is implemented by MCDSS through the Department of Community Development. The objective of the programme is to empower the poor and vulnerable but viable farmer households with agricultural inputs and livelihood skills to improve their productivity with the ultimate goal of enhancing their food, nutrition and income security for self-sustainability and poverty reduction. FSP has three components namely; Rainfed, Wetland and Alternative Livelihood Initiative (ALI). These components are implemented in all the 116 districts of Zambia.

In order for beneficiaries to be targeted under this programme, they must meet all the primary and at least one secondary criterion as shown below [18]:

(i) **Primary selection criteria**

a) Adequate own labour provided by the household.

b) Access to land of size between ½ and 2 hectares.

c) Household head or breadwinner not in gainful employment.

ii) **Secondary selection criteria**

a) Female headed household

b) Child headed household

c) Disabled headed household

d) Household keeping orphans or abandoned children

e) Household with more than 7 members

f) Household with child or children under 5 years of age

g) Household headed by a terminally ill person

h) Household headed by a person aged 65 years and above

i) Household headed by unemployed (15 – 35 years)

2.1.2.4 Supporting Women's Livelihood (SWL)

This programme is implemented by MCDSS through the Department of Community Development. SWL is a component of the Girl's Education and Women's Empowerment and Livelihoods (GEWEL) project. The objective of SWL is to provide extremely poor women aged between 19 to 64 years with opportunities to increase the productivity of their livelihoods, and their economic empowerment, through training, mentoring, peer support, productivity grants and help with setting up savings clubs. This programme is implemented in 81 districts of Zambia [19].

The targeting process for beneficiaries under this programme is as follows:

(i) **Identification of beneficiaries**

Beneficiaries are selected from the SCT database in the selected Community Welfare Assistant Committees (CWACs). Only households receiving the Social Cash Transfer are eligible. This list is validated through a Self-Registration process and Community Validation.

All the women in SCT households who meet the categorical criteria after self-registration will be considered as potential beneficiaries for SWL.

(ii) **Community Validation and Lottery**

If the number of beneficiaries selected for the SWL programme is more than the allocated number of beneficiaries in a community or CWAC, a lottery will be conducted to select the required number of beneficiaries in a given CWAC. The District will conduct the community validation of the list provided in smaller groups. To allow for full community representation, the list of the potential beneficiaries will be placed at the strategic points in a community for public vetting [20].

2.1.3 Artificial Intelligence

Artificial Intelligence (AI) is a technology that concentrates on building machines capability of executing tasks that are typically thought to require human intelligence. It is able to interpret and sort data at scale, solve complex problems and automate various tasks concurrently, which can save time and fill in operational gaps overlooked by humans.

AI systems operate by using algorithms and data. A large amount of data is collected and applied to algorithms, which utilize the information to recognize patterns and make predictions in a procedure called training. Once algorithms have been trained, they are installed within different applications, where they continuously learn and adapt to new data. This allows AI systems to perform complicated duties such as image recognition, language processing and data analysis with greater accuracy and efficiency over time. AI encompasses a wide variety of models/technologies including Machine Learning and Deep Learning [21].

2.1.4 Types of A.I Models

2.1.4.1 Machine Learning

Machine learning (ML) is a subset of AI that uses algorithms trained on datasets to create self-learning models that are competent at predicting outcomes and organizing information without human intervention. A machine learning algorithm uses statistical techniques to help it "learn" and progressively better at a task, without necessarily having been programmed for that certain task. It uses historical data as input to predict new output values.

There are four types of machine learning namely Supervised Machine Learning, Unsupervised Machine Learning, Semi-Supervised Machine Learning and Reinforcement Learning [22].

2.1.4.2 Supervised Machine Learning

It uses algorithms that are trained on labelled datasets whereby each example has an input and a corresponding output to make predictions on new, unseen data [22].

2.1.4.3 Unsupervised Machine Learning

It uses algorithms that are trained on unlabelled datasets to identify hidden patterns with no guidance [22].

2.1.4.4 Semi-Supervised Machine Learning

It uses algorithms that are trained on both labelled and unlabelled datasets. This technique operates by feeding algorithms a small quantity of labelled data to assist direct their development and then feeds much larger quantities of unlabelled data to complete the algorithm [22].

2.1.4.5 Reinforcement Learning

It uses algorithms that are trained on trial and error basis within an interactive environment. During this process, the algorithms receive feedback in the form of rewards or penalties as they perform actions allowing them to learn and improve performance over time [22].

2.1.4.6 Deep Learning

It is a branch of machine learning that utilizes multi-layered neural networks, known as deep neural networks, to simulate the complex decision-making power of the human brain. Deep neural networks include an input layer, multiple hidden layers, and an output layer. These multiple layers automate the extraction of features from large, unlabelled and unstructured datasets, and make their own predictions about what the data represents. Fig 3 shows the architecture of the deep neutral network [23].

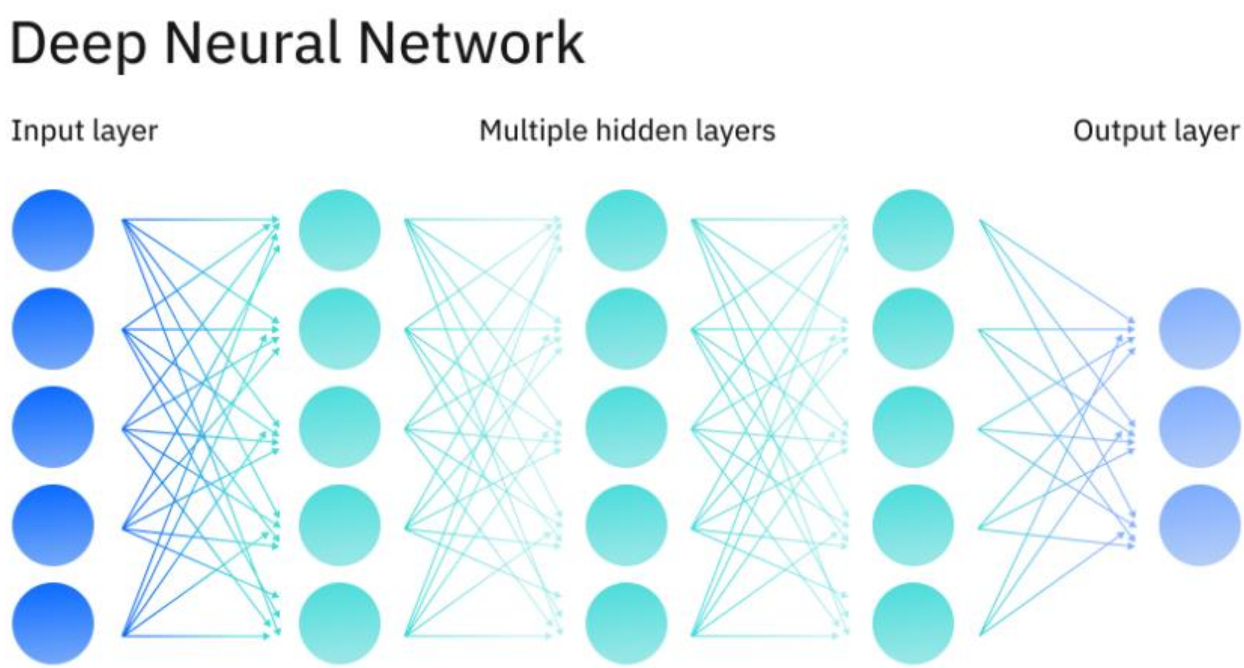


Fig. 3. Deep Neural Network

2.1.5 Benefits of A.I in Social Protection

Table 1 below shows the summary of benefits of AI that can be applied in the Social Protection sector.

Studies	Benefits
[23]	• **Fraud Detection** - Machine learning and deep learning algorithms can analyse transaction patterns and flag anomalies, such as paying beneficiaries who are deceased.
[14]	• **Automation** - AI can improve the integration process using machine learning algorithms that can automate the process of cleaning data, alleviating data inconsistences or discrepancies between the various Social Protection programmes MISs.
[12]	• **Improved Targeting of Beneficiaries** - Machine Learning algorithms can improve the targeting process of beneficiaries by using big data (age, gender, geographic location, etc.) to predict beneficiaries who are eligible or non-eligible.
[13]	• **Enhanced Inclusivity of Vulnerable Groups** - Machine Learning can enhance targeting by analysing huge datasets containing containing the aforementioned socioeconomic, household and geographical data in Chapter 1. These algorithms can be trained to collect and process the data from household surveys to predict which households are most likely to be subject to vulnerability.

Table 1. Benefits of AI in Social Protection

2.2 Critical Review of Related Works

There have been quite a number of studies conducted outside Zambia that utilize AI models to improve Social Protection delivery.

Firstly, [12] conducted a study on 'Leveraging technology and data advances to improve social programme coverage and service delivery'. In her study, she discussed that very few countries have adopted the usage of AI models in the public sector due to ethical and legal concerns. The United Kingdom (UK) Government and the Republic of Korea are the countries mentioned that use AI models to detect fraud in social benefit claims. However, this study presents a knowledge gap in the literature as it does not focus much on the aspect of poor targeting of beneficiaries and the types of AI models used.

Secondly, the study conducted by [16] focuses on 'AI in Social Protection – Exploring Opportunities and Mitigating Risks'. As much as there is evidence in the study on how machine learning algorithms can improve the targeting process, there is a contextual gap due to the fact that the study is not specific to which age groups, gender and vulnerability groups (e.g. people with disabilities, women, children, etc.) these algorithms will assist. The various use cases discussed in this study do not show the integration of existing government systems and databases.

Lastly, [11] conducted a study on 'Machine Learning Based Approach for Sustainable Social Protection Policies in Developing Societies'. Despite extensive research on machine learning, there is a research gap in terms of the lack of application of machine learning in the area of social protection for enhanced targeting of populations who require social protection interventions.

2.3 Comparison with related works and Identified Gaps

Table 2 shows the comparison with related works and identified gaps.

Author(s)	Study	Type of Gap	Identified Gaps
[12]	Leveraging technology and data advances to improve social programme coverage and service delivery	• Knowledge Gap	• The study does not focus much on the aspect of poor targeting of beneficiaries and the types of AI models used.
[16]	AI in Social Protection – Exploring Opportunities and Mitigating Risks	• Contextual Gap	• The study is not specific to which age groups, gender and vulnerability groups (e.g. people with disabilities, women, children, etc.) the machine learning algorithms will assist. • The various use cases discussed in this study do not show the integration of existing government systems and databases.
[11]	Machine Learning Based Approach for Sustainable Social Protection Policies in Developing Societies	• Research Gap	• Lack of application of machine learning in the area for social protection for enhanced targeting of populations who require social protection interventions.

Table 2. Comparisons with related works – Identified Gaps

2.4 Proposed model/system

The proposed model for this study was Supervised Machine Learning.

2.5 Chapter Summary

This chapter reviewed Social Protection and the types of Social Protection programmes in Zambia. It also explored Artificial Intelligence (AI), the various types of AI models, the benefits of AI in Social Protection and it critically reviewed related works with comparisons and identified gaps as well as the proposed model for the study.

3.0 CHAPTER 3 – METHODOLOGY

3.1 Research design

The main research aim was to develop an AI model prototype for improving Social Protection delivery in Zambia. The research design included the data collection methods and the techniques for analysing the collected data.

3.2 Adopted methodology and justification

3.2.1 Agile Methodology

The adopted methodology for this research was the Agile Methodology. According to [24], the agile methodology is a project management architecture that breaks projects down into many dynamic stages called sprints. The following benefits identified by [24,25] make this methodology significant:

This methodology enables collaborative teamwork and breaks down silos as it involves the client from the beginning of the project execution process which is rare in other methodologies.

In addition, agile methods are adaptable. This enables teams to alter techniques without disturbing the flow of a project.

Furthermore, agile methods have an iterative nature. By working in short iterations, the project team is able to learn from its errors and make continuous improvements on each sprint. Fig 4 below shows the structure of the Agile Methodology.

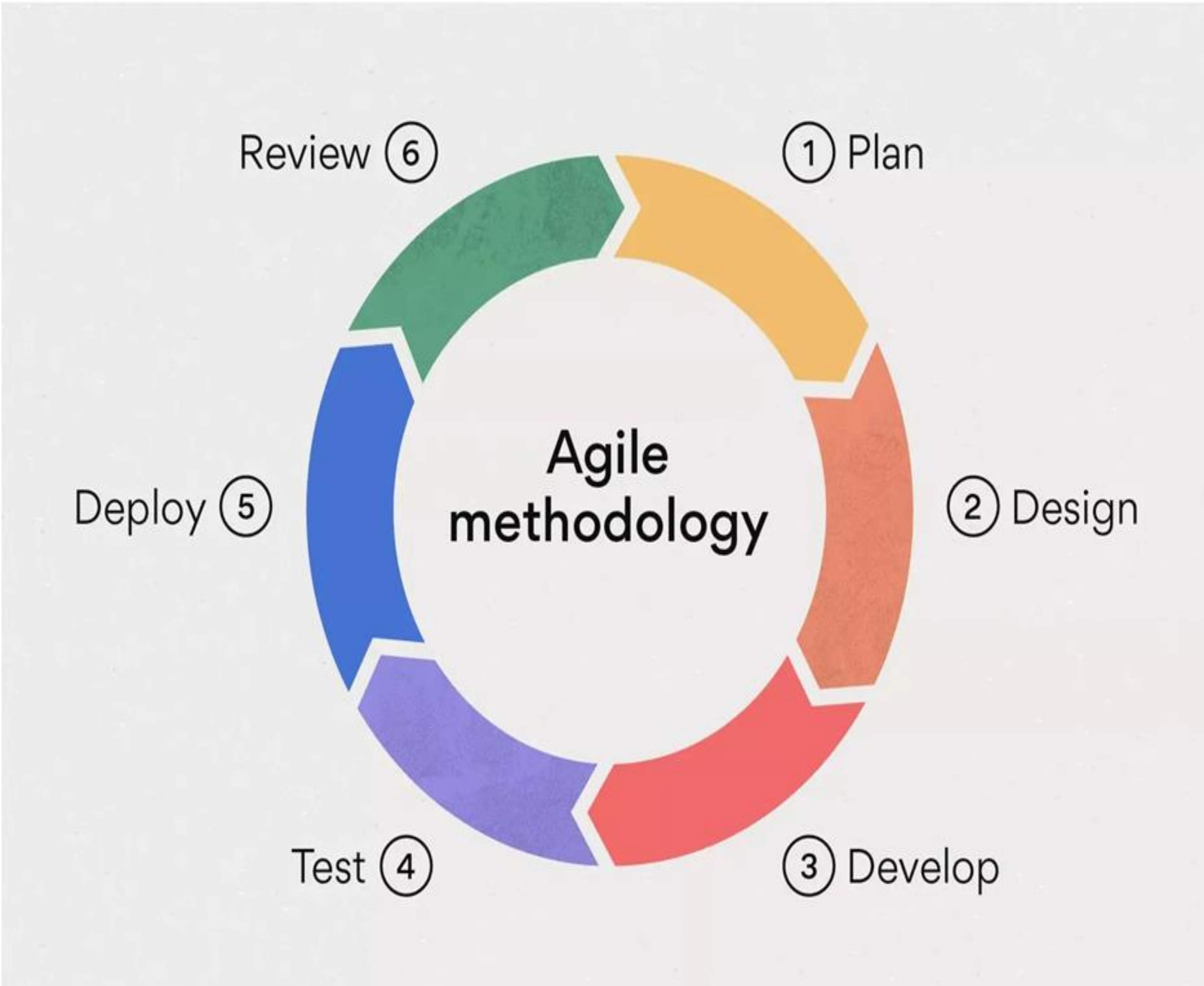


Fig. 4. Agile Methodology

3.3 Association of research method to project

The Agile Methodology is associated with the project in the following ways:

3.3.1 Collaborative teamwork

As mentioned earlier in Chapter 1, the Management Information Systems (MISs) at MCDSS operate in silos leading to fragmented Social Protection data. This methodology encouraged teamwork by breaking down silos allowing the departments at the Ministry to collaborate with each other for the integration task to be achieved by the proposed AI model.

3.3.2 Adaptability

Agile methods are adaptable and they can enable AI models to alter strategies quickly, without disrupting the design of the model.

3.3.3 Iterative nature

Iterative nature of development means that you can go back to a previous phase in the project and change something that was not considered carefully in that particular phase. The Agile Methodology is Iterative, which suits well for Supervised Machine Learning as iterations can improve its performance on targeting eligible beneficiaries as new data or unseen data emerges.

3.4 Research data and datasets

The research data consisted of three datasets with beneficiary data for Chongwe district under MCDSS. The first dataset contained information on Social Cash Transfer (SCT) beneficiaries. The second dataset contained information on Supporting Women's Livelihood (SWL) beneficiaries. The third dataset contained information on Food Security Pack (FSP) beneficiaries.

3.5 Data Collection Methods

There are two types of data collection methods namely; qualitative data and quantitative data [26]. Qualitative data is descriptive and it is expressed in forms of words and languages whereas Quantitative data is defined as any information that can be counted or measured and given a numerical value [27]. The data collection techniques that were used for this research were quantitative data. The data was obtained from the Zambian Government Management Information Systems (MISs) under the Ministry of Community Development and Social Services (MCDSS).

3.5.1 Management Information Systems

Currently, the three Management Information Systems in Zambia that deal with Social Protection programmes at MCDSS are:

- The Zambian Integrated Social Protection Information System (ZISPIS)
- Supporting Women's Livelihood Management Information System (SWLMIS)
- Food Security Pack Management Information System (FSPMIS)

The ZISPIS deals with beneficiaries who are on Social Cash Transfer (SCT), the SWLMIS deals with beneficiaries who receive grants on the SWL and the FSPMIS deals with beneficiaries who receive agricultural inputs such as fertilizer and seed on the FSP programme. The three datasets were downloaded from the three MISs and appeared as Excel sheets in .csv format.

3.6 Data Analysis Techniques

The quantitative data obtained through the MISs was analysed using Supervised Machine Learning. Fig 5 below shows the data analysis process.

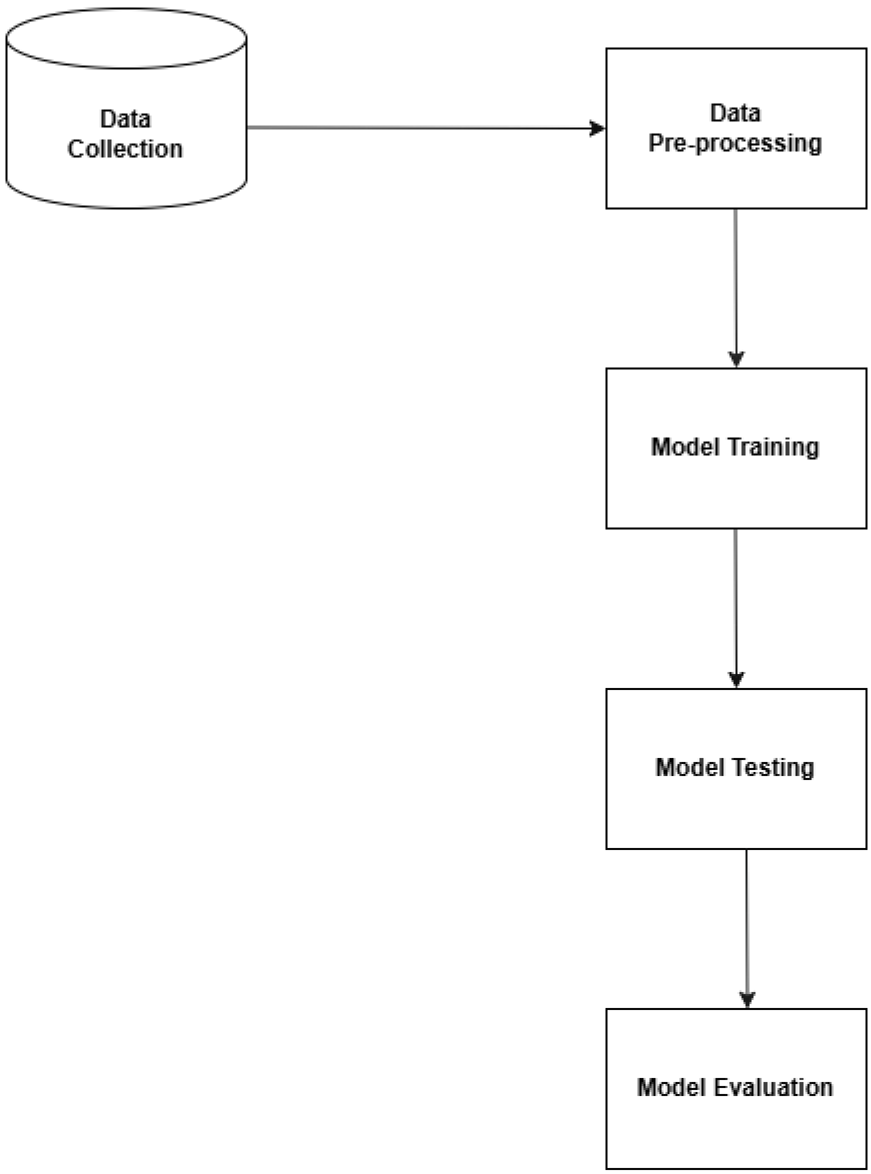


Fig. 5. Data Analysis Process

According to [28], the data analysis process in Fig 5 can be explained as follows:

3.6.1 Data Pre-processing

This technique entailed cleaning and pre-processing the collected data in order to make it suitable for the AI model to undergo training. The cleaning of data involved tasks such as handling missing values by eliminating them.

The data was normalized by formatting it into a single dataset to be used for training and testing the algorithm. The name of the normalized dataset was **Beneficiaries.csv** and it contained the following records:

- FullName
- NRC (Household ID)
- Age
- Gender
- Province
- District
- ProgrammeType (SCT, SWL, FSP)
- Disability
- Eligibility

3.6.2 Model Training and Testing

Supervised machine learning models such as Classification algorithms were trained by analysing the input data and learning to map it to the correct output labels.

Classification depends on an algorithm to assign a class to a categorized dataset. The algorithms were trained with the labelled dataset and the targeting of beneficiaries were classified as "Eligible" or "Not Eligible" based on the integrated data from the government MISs.

3.6.3 Model Evaluation

The AI model was evaluated by performance metrics such as accuracy, precision, recall, F1-score to vizualize how well it performed on the dataset.

3.7 Ethical Concerns

The ethical issues that usually arise in Social Protection systems involve the violation of potential beneficiaries' personal, health, financial and social records, algorithmic bias and discrimination and the impact on employment.

Different departments under the Ministry have different Social Protection data in their systems. AI models can utilize large volumes of social protection data from these departments which would therefore raise privacy and security concerns. These security concerns involve the risk of data being misused, breached from unknown sources. Therefore, the data being collected should also abide by the Data Protection Act of 2021, as mentioned in Section 1.5.2.

Another vital ethical issue to put into consideration is Bias and Discrimination. In this case, AI algorithms are trained on data and the downside to this, is that if the data is biased, then the AI algorithm will be biased too. This could lead to AI algorithms making unsatisfactory or discriminatory decisions towards the targeting of beneficiaries, which would lead to exclusion of beneficiaries who are meant to receive the benefits [29].

The impact on employment is a third ethical issue that needs to be critically addressed. The current rate of unemployment in Zambia is very high and since Machine Learning is able to automate the tasks being conducted by community and social workers, this might cause worries about job losses in the Social Protection sector [29].

3.8 Chapter Summary

This chapter reviewed the research design, the methodology adopted for the research and its relevance. It also explored the data collection and data analysis techniques used in this project, as well as the ethical concerns.

4.0 CHAPTER 4 – DATA, PROTOTYPE & IMPLEMENTATION

4.1 Review of Existing Social Protection Delivery Systems

The first objective of the project was to review the existing Social Protection delivery systems in Zambia. As mentioned earlier in Chapter 1, the main three Social Protection delivery systems in Zambia under the Ministry of Community Development and Social Services (MCDSS) are the Zambian Integrated Social Protection Information System (ZISPIS), Supporting Women's Livelihood Management Information System (SWLMIS) and the Food Security Pack Management Information System (FSPMIS).

4.1.1 ZISPIS

This system deals with the management of Social Cash Transfer for beneficiaries. It can be accessed via this URL – https://www.zispis.gov.zm/. The figure below shows the ZISPIS Home page.

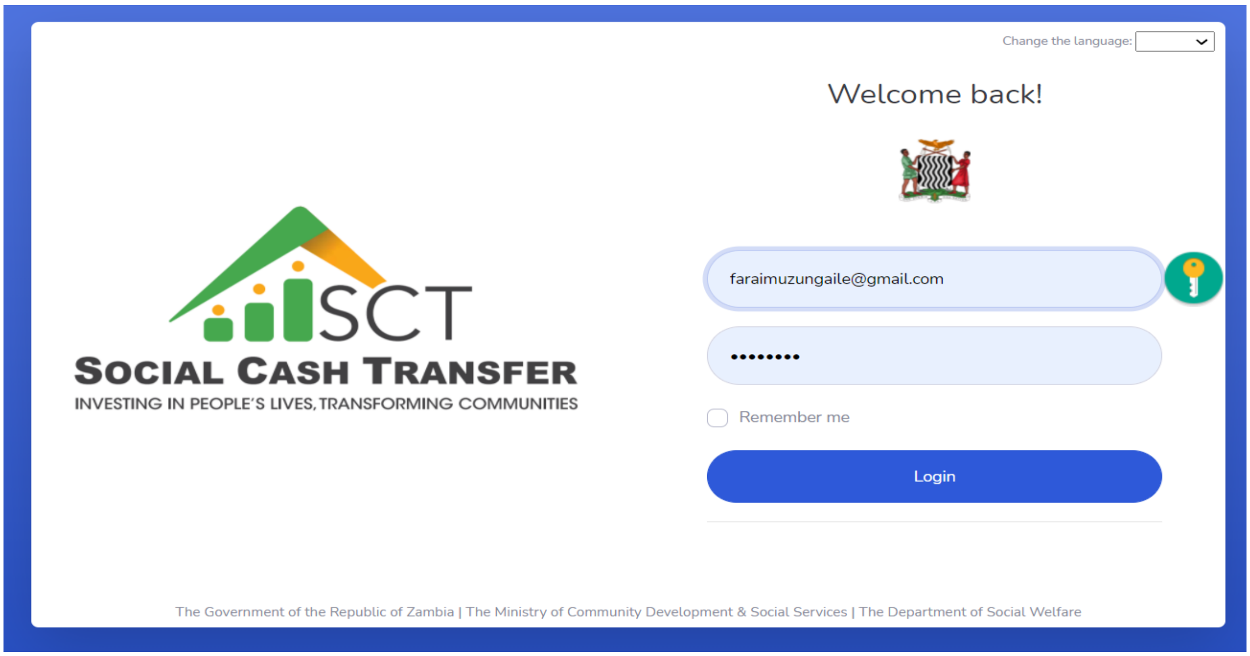


Fig. 6. ZISPIS Homepage

Fig 6 and 7 shows the two-factor authentication required to login to the system. A random code is sent to Google Authenticator app via your mobile phone.

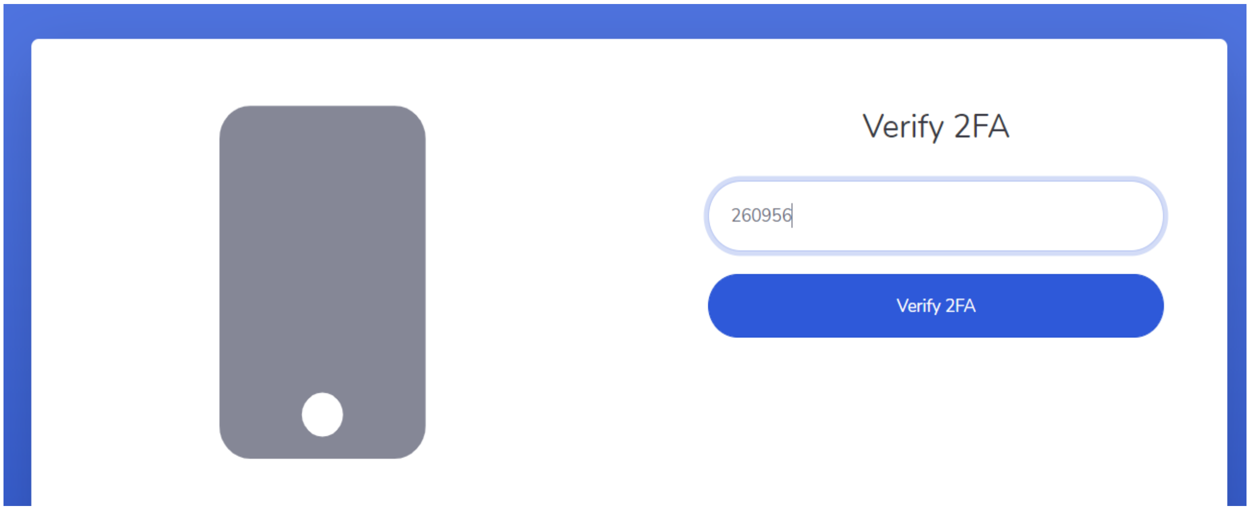


Fig. 7. Two-factor authentication

Fig 8 shows a dashboard with various modules that are available on the ZISPIS.

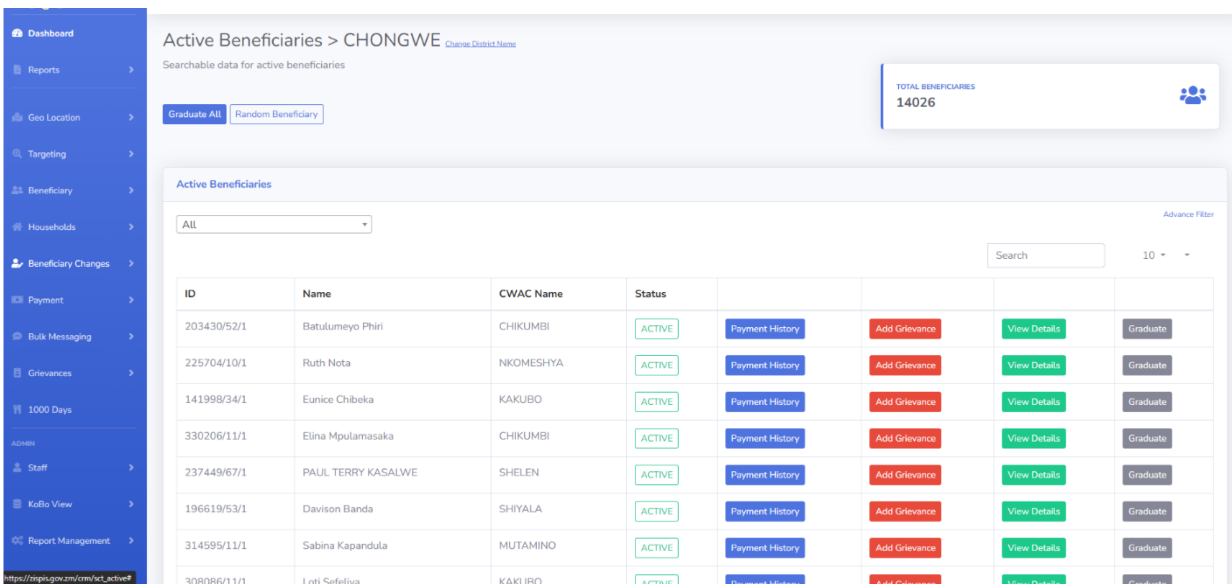


Fig. 8. ZISPIS Dashboard

4.1.2 SWLMIS

This system deals with the management of productivity grants for beneficiaries. It can be accessed via this URL – https://swlmis.mcdss.gov.zm/. The figure below shows the SWLMIS Home page.

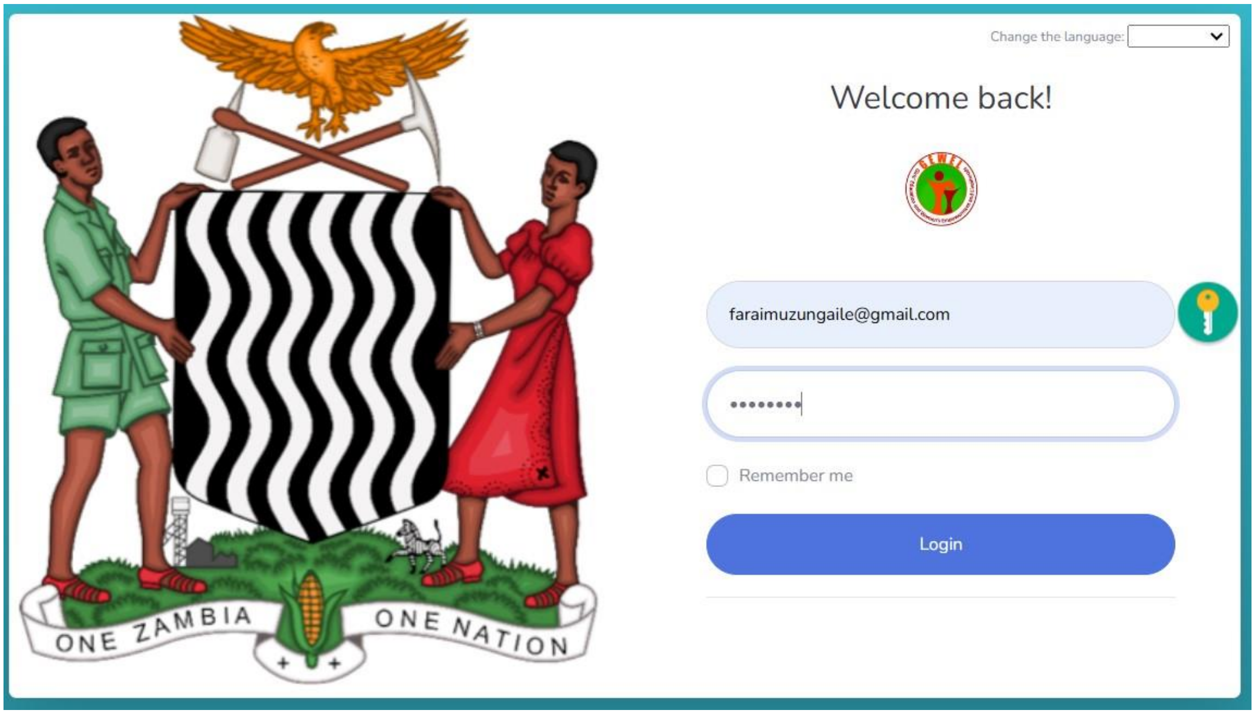


Fig. 9. SWLMIS Homepage

Fig 10 shows a dashboard with various modules that are available on the SWLMIS.

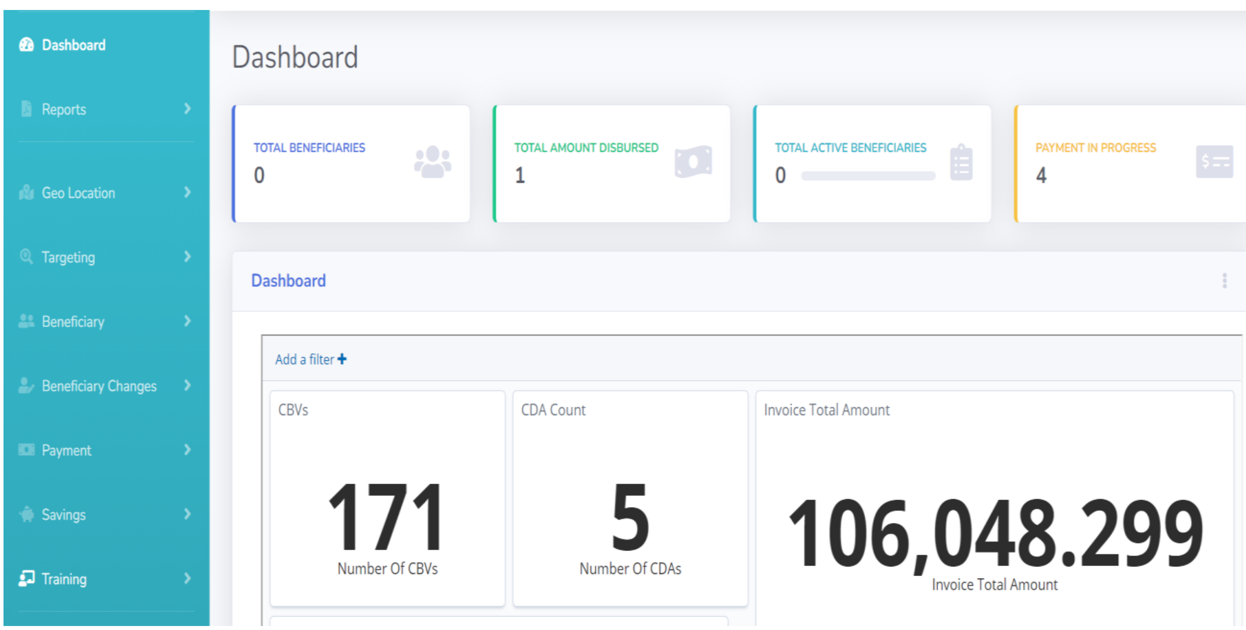


Fig. 10. SWLMIS Dashboard

4.1.3 FSPMIS

This system deals with the management of disbursement of inputs to beneficiaries and tracking of agricultural inputs to targeted farmers. It can be accessed via this URL – https://fspmis.grz.gov.zm/. The figure below shows the FSPMIS Home page.

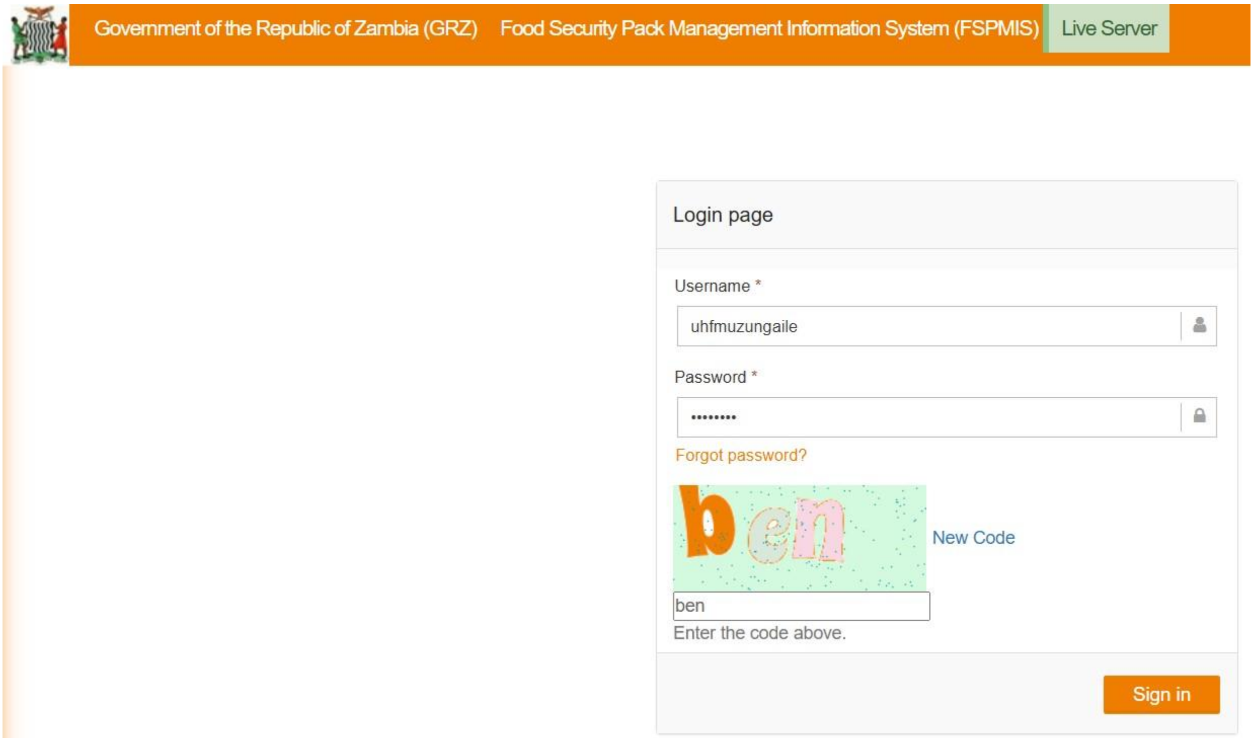


Fig. 11. FSPMIS Homepage

Fig 12 shows a dashboard with various modules that are available on the FSPMIS.

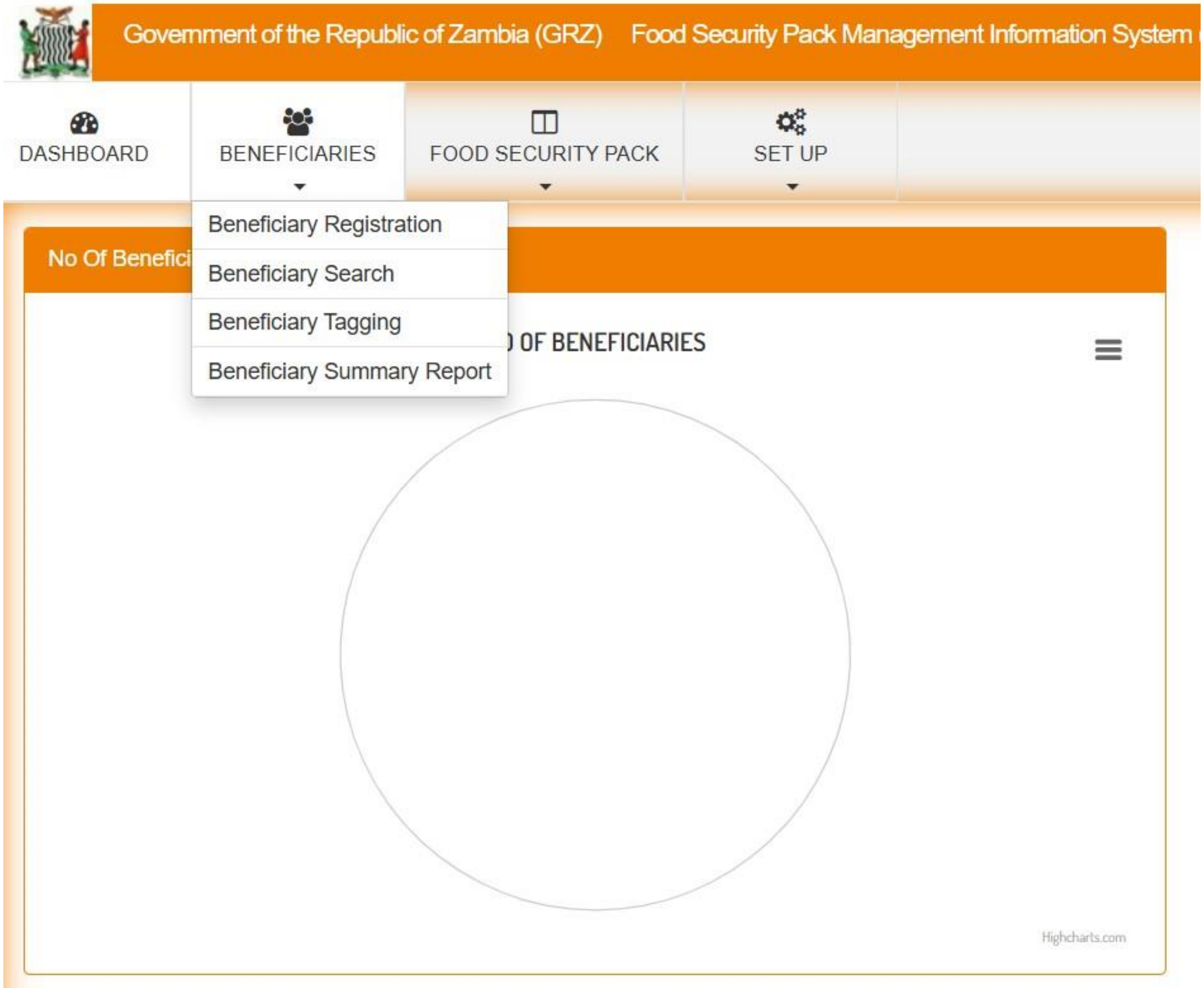


Fig. 12. FSPMIS Dashboard

4.1.4 Comparison of Existing Social Protection Delivery Systems

Table 3 below shows a comparison of each Management Information System (MIS) as well as the answer to the first research question – **RQ1** mentioned in Chapter 1.

MIS	Modules	Challenges
ZISPIS	• Beneficiary Registration • Targeting • Households • Payment • Grievance Redress Mechanism • Reports	• Missing values of NRCs for beneficiaries. • No integration with SWLMIS and FSPMIS.
SWLMIS	• Beneficiary Enrolment • Targeting • Savings • Training • Payment • Reports	• Missing values of NRCs for beneficiaries. • No integration with ZISPIS and FSPMIS.
FSPMIS	• Beneficiaries • Food Security Pack • Set-Up (Administration)	• Missing values of NRCs for beneficiaries. • No integration with ZISPIS and SWLMIS.

Table 3. Comparison of existing Social Protection delivery systems

4.2 Techniques, Algorithms, Mechanisms

The second objective of the project was to develop an AI based solution for Zambia's Social Protection programmes. The following techniques, algorithms, and mechanisms were employed.

4.2.1 Google Colab – Jupyter Notebook

For the implementation of the AI model, Google Colab, a cloud-based Jupyter Notebook environment that allows for writing and executing Python code interactively was used. This platform was used to train, test, and visualize the AI model. Google Colab can be accessed at: https://colab.research.google.com/. Fig 13 below depicts the interface of Google Colab.

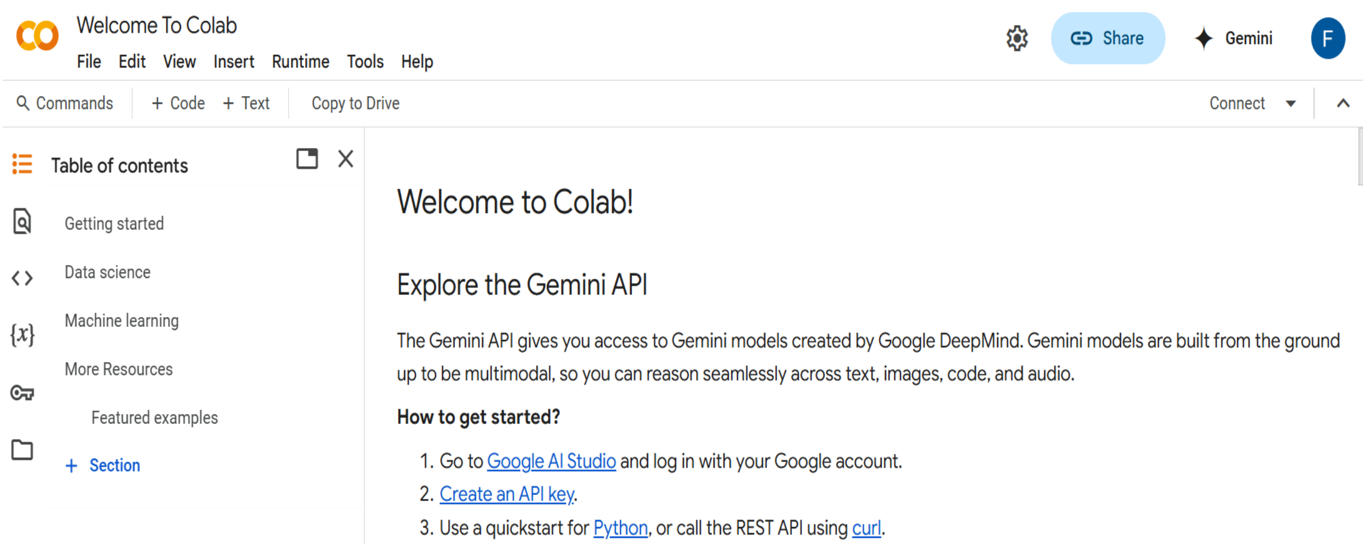


Fig. 13. Google Colab interface

The Jupyter Notebook was created by clicking on the File menu and the selected option ‘New notebook in Drive’ as shown in Fig 14 below.

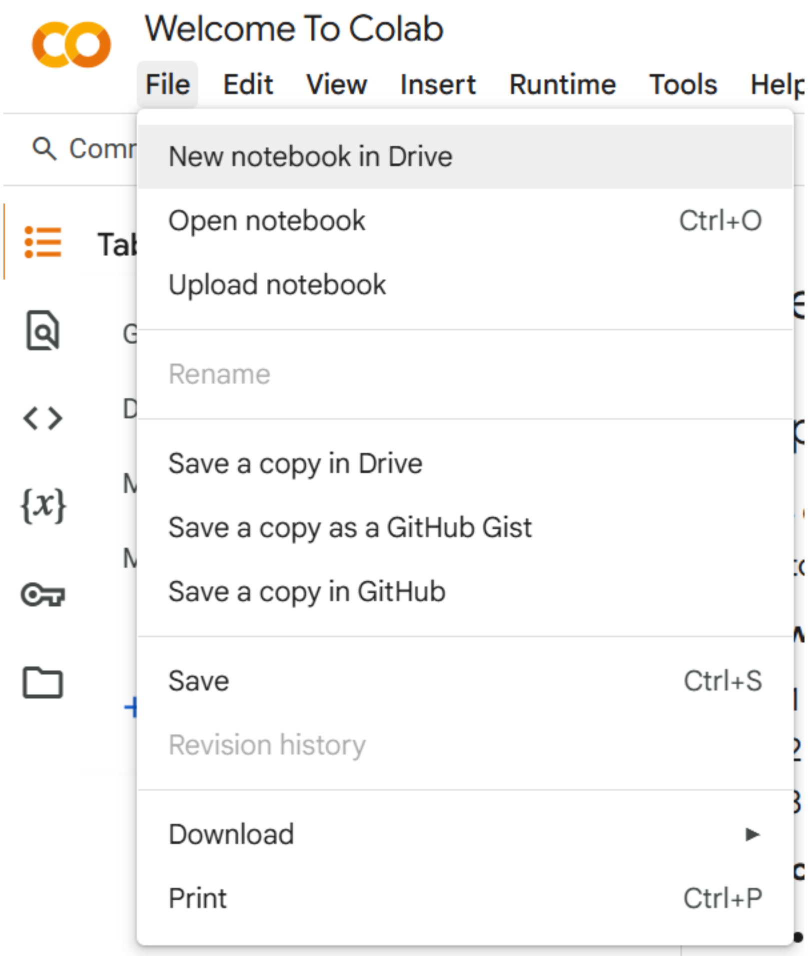


Fig. 14. Creating a Jupyter Notebook

Fig 15 shows the notebook created, titled **"AI Model for Social Protection"**. It can be accessed online at this URL - https://colab.research.google.com/drive/1Fb2pzxgqAHGmeA2-8YBMXBWdkGGWmH7b#scrollTo=rBx1eD3_uRpz

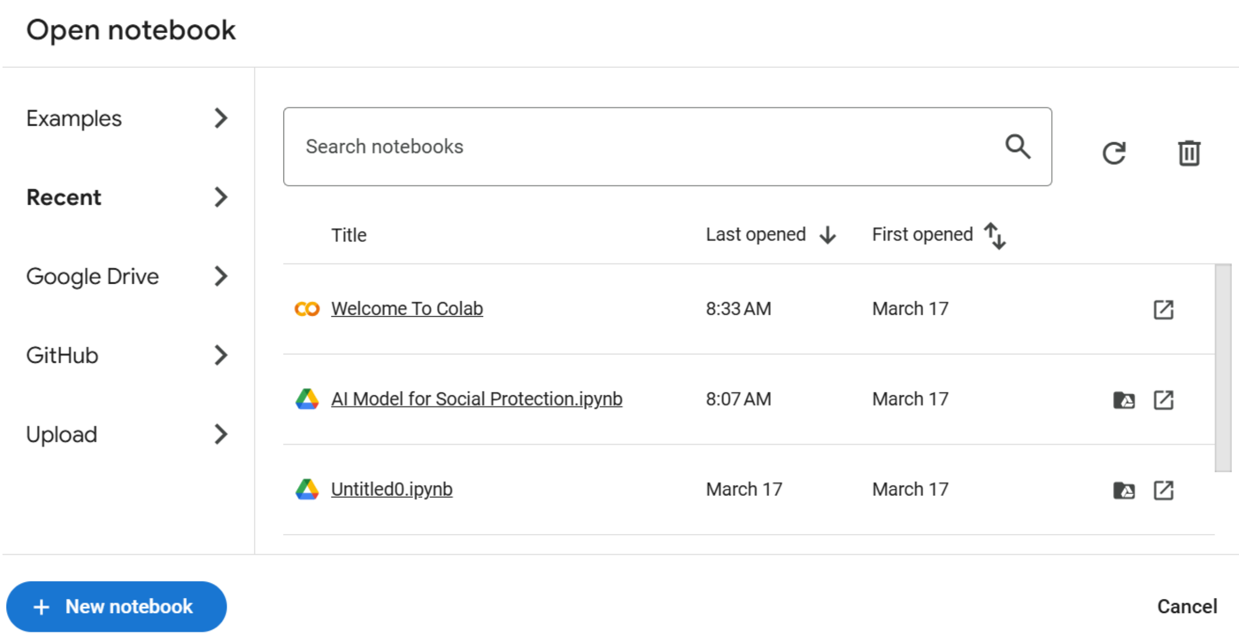


Fig. 15. AI Model for Social Protection

4.2.2 Classification Algorithms

There are various types of Classification Algorithms under Supervised Machine Learning such as Logistic Regression, Decision Trees, Random Forests, Support Vector Machines (SVM), Naïve Bayes and K-Nearest Neighbors (KNN) [30]. The algorithm **'Logistic Regression'** was used for the implementation of the AI model as well as the answer to the second research question – **RQ2** mentioned in Chapter 1.

4.2.2.1 Implementation of Logistic Regression

The implementation of Logistic Regression was conducted in the following six steps below:

(i) Importing the Libraries

(ii) Loading the Dataset

(iii) Data Pre-processing

(iv) Training and Testing the Model

(v) Evaluating the Model

(vi) Visualizing the Confusion Matrix

Section 4.4 will discuss the functionalities of this model.

4.3 Designed Prototype / Model, Framework

Fig 16 below shows the design of the prototype.

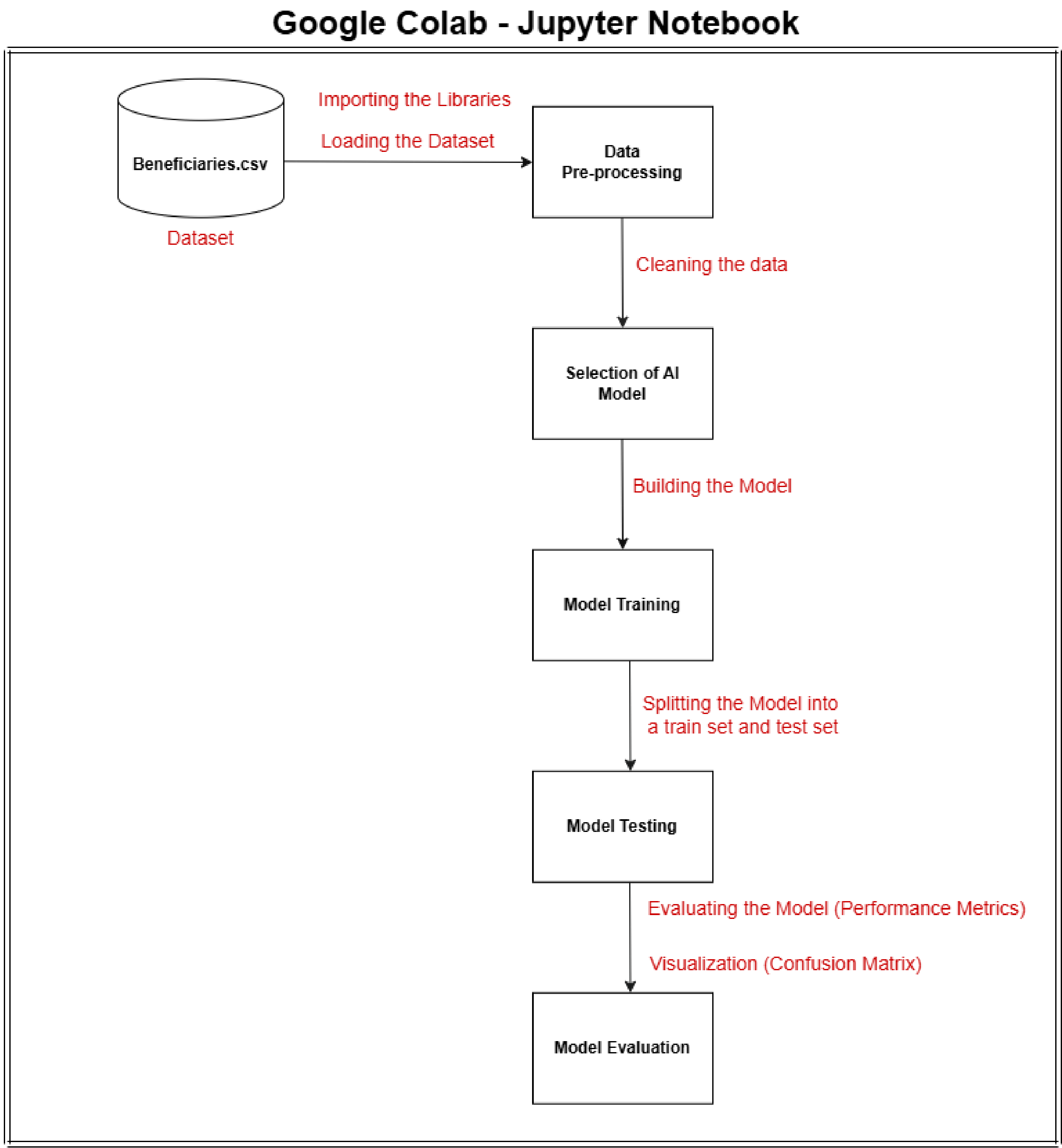


Fig. 16. Prototype Design

4.4 Functions, Models, Framework

4.4.1 Main Functions of the Model

The three research objectives were as follows:

- **Objective 1** – To review the existing Social Protection delivery systems in Zambia.
- **Objective 2** – To develop an AI based solution for Zambia's Social Protection programmes.
- **Objective 3** – To evaluate the performance of the AI model on the efficiency and quality of Social Protection delivery.

Table 4 below shows the functionality of the Model/Prototype in relation to these objectives. The Python code for each Component [31,32,33,34] in Table 4 can be found in Appendix B.

Component	Objective	Function
Importing the Libraries	• Objective 2 • Objective 3	• Import the necessary libraries and modules into Jupyter Notebook (Google Colab) using Python to develop (build) the AI model. • Import the necessary Python libraries and modules to evaluate the model.
Loading the Dataset	• Objective 1	• Loading the **Beneficiaries.csv** dataset by uploading it into Jupyter Notebook (Google Colab).
Data Pre-processing	• Objective 1	• This technique entails cleaning and pre-processing the dataset in order to make it suitable for the AI model to undergo training. • The cleaning of data involves tasks such as handling missing values by eliminating them.

Training and Testing the Model	• Objective 2 • Objective 3	• The dataset will be split into two sets: Train set and Test set. The train set will be used for training the model. Eligible beneficiaries will be represented with a value of **0**, while Non-eligible beneficiaries will be represented with a value of **1**. • The test set will be used to evaluate the performance of the model.
Evaluating the Model	• Objective 3	• Performance metrics such as accuracy, precision, recall, F1-score will be used to evaluate the performance of the model. • The results will be presented in Chapter 5.
Visualizing the Confusion Matrix	• Objective 3	• It is used to visualize model performance by showing the number of correct and incorrect predictions made by the model.

Table 4. Functions of the Prototype/Model

4.5 Chapter Summary

This chapter explored how the three objectives of the project were implemented in full depth using techniques, algorithms, mechanisms. It also focused on the design of the prototype and highlighted the functions of the prototype/model.

5.0 CHAPTER 5 – RESULTS & DISCUSSIONS

5.1 Results Presentation

5.1.1 Confusion Matrix

It was used to visualize model performance by showing the number of correct and incorrect predictions made by the model. Correct predictions are inclusive of true positives and true negatives whereas incorrect predictions are inclusive of false positives and false negatives [35]. With reference to the **AI Model for Social Protection**, the predictions can be identified as follows:

(i) **True Positive (TP) –** A beneficiary who is actually eligible (positive) and is correctly classified by the model as eligible.

(ii) **True Negative (TN) –** A beneficiary who is actually not eligible (negative) and is correctly classified by the model as not eligible.

(iii) **False Positive (FP) –** A beneficiary who is actually not eligible (negative) but is incorrectly classified by the model as eligible.

(iv) **False Negative (FN) –** A beneficiary who is actually eligible (positive) but is incorrectly classified by the model as not eligible.

Fig 17 below shows the results from the Confusion Matrix.

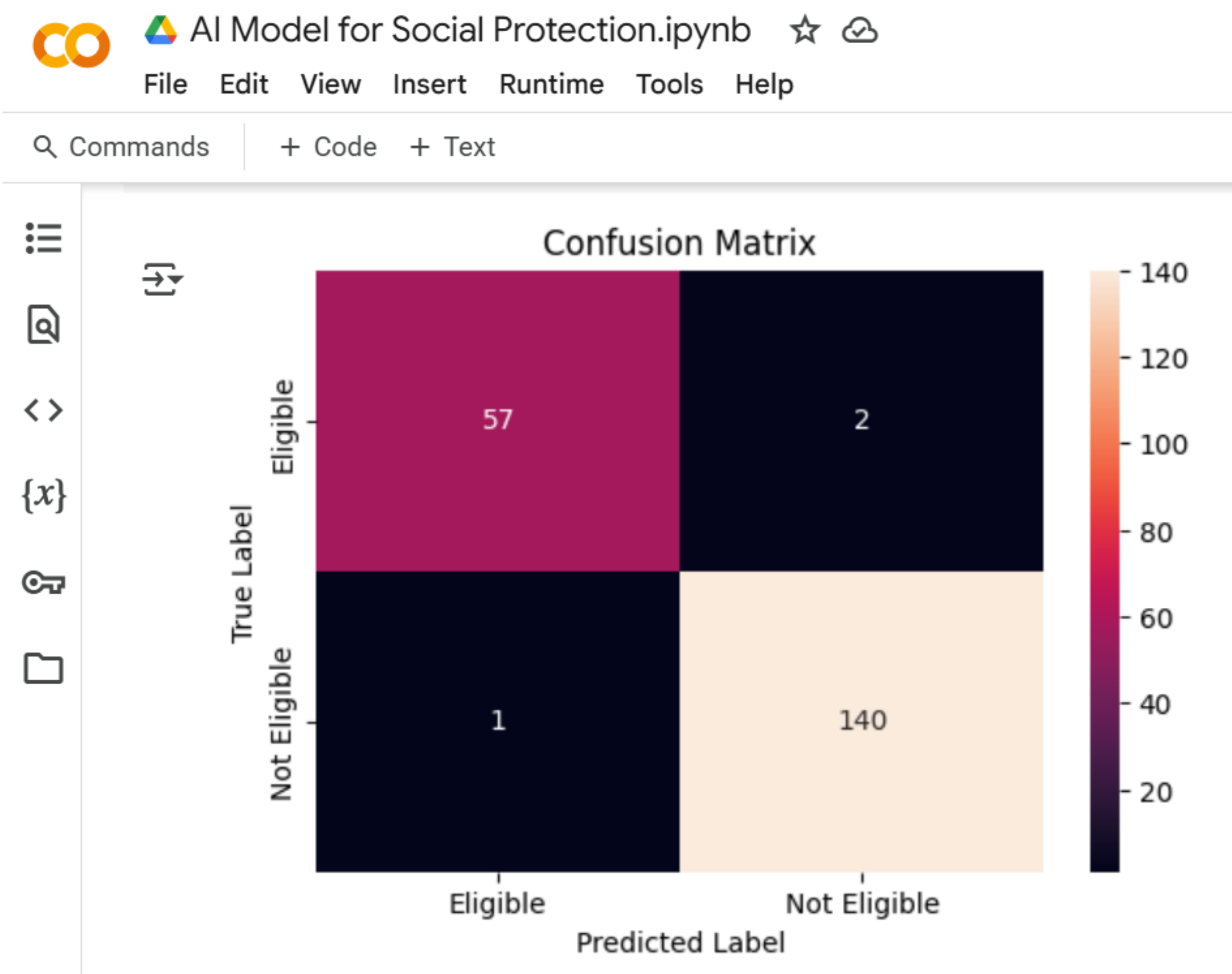


Fig. 17. Confusion Matrix

The value for the true positives - **57** represents the model correctly identifying eligible beneficiaries while the value for the true negatives - **140** represents the model correctly identifying non-eligible beneficiaries, which also contributes to accurate targeting. Although the low false positive value – **1** does not impact the overall effectiveness of the model, the low value of false negatives – **2** is an indication of improved targeting in Social Protection due to the fact that the model is highly accurate at identifying eligible beneficiaries who should receive support.

5.2 Analysis of Results

5.2.1 Performance Metrics

The model was evaluated using the following metrics:

(i) **Accuracy** – It measures how many total predictions (both eligible and not eligible) were correct by the model across the dataset [36].

(ii) **Precision** – It measures the proportion of true positive predictions among all positive predictions made by the model [36].

(iii) **Recall** – It measures the proportion of actual positive cases correctly identified by the model [37].

(iv) **F1 Score** – It is the harmonic mean of precision and recall [38].

The above performance metrics serve as the answer to the third research question – **RQ3** mentioned in Chapter 1. According to [39], the formulas for these 4 metrics were calculated as follows:

Accuracy = (TP + TN) / (TP + FN + TN + FP)

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 Score = 2 * Precision * Recall / (Precision + Recall)

The evaluation using the Logistic Regression classifier reviewed some interesting insights as shown in Fig 18.

```
The accuracy is 0.985
The precision is 0.9859154929577465
The recall is 0.9929078014184397
The F1-Score is 0.9893992932862191
```

Fig. 18. Performance Metrics

5.3 Comparison to Related Work

Various surveys have been published in the past that utilize AI models to improve Social Protection delivery.

Firstly, [40] conducted a study on 'Predicting social assistance beneficiaries'. In this study, the three authors developed a Targeting Assessment framework using AI models namely; Linear Regression and xGBoost to predict poor households in Malawi and Tanzania.

Secondly, [41] conducted a study on 'Machine Learning Application for Classification Prediction of Household's Welfare Status'. In this study, five machine learning techniques namely; Naïve Bayes, Random Forest, Support Vector Machines, K-Nearest Neighbor, and C4.5 Algorithm were used to predict the classifications of social welfare statuses poor in Bengkulu province, Indonesia.

Lastly, [42] conducted a study on 'Harnessing Artificial Intelligence to Deliver Shock-Responsive Social Protection'. In this study, a machine learning method namely; Gradient Boosting Regression was utilized to predict poor households in Togo.

Table 5 shows the comparison to related works with performance metrics.

Author(s)	**Study**	**Countries**	**Performance Metrics**
[40]	Predicting social assistance beneficiaries	• Malawi & Tanzania	• Models - Linear Regression and xGBoost. • Malawi - Accuracy of 81% (xgboost) and 80% (linear regression). • Tanzania - Accuracy of 75% (using both models).
[41]	Machine Learning Application for Classification Prediction of Household's Welfare Status	• Indonesia	• Models - Naïve Bayes, Random Forest, Support Vector Machines, K-Nearest Neighbor, and C4.5 Algorithm.

			• C4.5 Algorithm – Accuracy of 63.65%. • KNN – Accuracy of 64.66%. • Naïve Bayes Classifier – Accuracy of 62.56%. • Random Forest – Accuracy of 72.19%. • Support Vector Machines – Accuracy of 66.37%.
[42]	Harnessing Artificial Intelligence to Deliver Shock-Responsive Social Protection	• Togo	• Models – Gradient Boosting Regression Tree. • Gradient Boosting Regression Tree – Accuracy of 73%.

Table 5. Comparisons to Related work – Performance Metrics

5.4 Implications of Results

The implications of results from the AI model were as follows:

5.4.1 Accuracy

The model was highly accurate at 98.5%, making it reliable and therefore this improves targeting of beneficiaries and reduces inclusion and exclusion errors.

5.4.2 Precision

The model had a precision of 98.6%; this means that when the model predicts the targeting of eligible beneficiaries, it is correct 98.6% of the time.

5.4.3 Recall

The model had a recall of 99.2%; this implies that the model captured a lot of eligible beneficiaries with only a shortfall of 0.8% of beneficiaries who are not eligible.

5.4.4 F1-Score

The model had a f1-score of 98.9%; which means that there was some strong balance between precision and recall.

5.5 Chapter Summary

This chapter discussed the results presentation from the visualization of the confusion matrix and analysis of the results from the performance metrics. It also explored the comparison to related work and implication of the results from the developed model.

6.0 CHAPTER 6 – SUMMARY & CONCLUSION

6.1 Summary of Main Findings

The developed AI model was trained and tested by splitting the dataset into 75% for training and 25% for testing. Predictions were made on the test set to predict beneficiaries that are "Eligible" and those that are "Not Eligible".

Based on the findings from the results (Confusion Matrix), the model predicted **57 beneficiaries**, which were correctly classified as Eligible. This represented **true positives**. It correctly identified **140 beneficiaries** as Not Eligible. These were the **true negatives**. There was **1 beneficiary** that was incorrectly classified by the model as Eligible that was actually Not Eligible. This was a **false positive**. There were **2 beneficiaries** that were incorrectly classified by the model as Not Eligible that were actually Eligible. These were the **false negatives**.

6.2 Discussion and Implications in Relation to Objectives

6.2.1 Objective 1

The first objective was to review the existing Social Protection delivery systems in Zambia. The three Management Information Systems (MISs) under MCDSS were reviewed in Chapter 4 and the comparisons of the challenges faced by the three systems were summarized in Table 3 in the aforementioned chapter.

6.2.2 Objective 2

The second objective was to develop an AI based solution for Zambia's social protection programmes. The AI model was developed using Supervised Machine Learning. The three datasets from the MISs under the Ministry were normalized into one dataset which was used for training and testing. The normalized dataset consisted of 825 records of beneficiary data. The model underwent data pre-processing to remedy data fragmentation. It also utilized a classification algorithm called 'Logistic Regression' to predict eligible and non-eligible beneficiaries for targeting purposes.

6.2.3 Objective 3

The third objective was to evaluate the performance of the AI model on the efficiency and quality of Social Protection delivery. The evaluation of the model presented an accuracy of 98.5% and therefore this improves targeting of beneficiaries and reduces inclusion and exclusion errors.

6.3 Academic contribution to the body of knowledge/Novelty

The empirical evidence from this study confirms that an AI model can improve Social Protection delivery in Zambia. By reviewing the three Management Information Systems under MCDSS that deal with Social Protection beneficiary data, the developed model was able to remedy the challenges of fragmented data and poor targeting of beneficiaries using Supervised Machine Learning.

The integration of this data into the model and the amount of time spent on tasks such as data pre-processing using the model is less as compared to the traditional method and this increases efficiency. The use of performance metrics further strengthens the targeting process, leading to more reliable and efficient results of eligible and non-eligible beneficiaries.

In relation to the iterative nature of the Agile methodology for this study, apart from Chongwe district, the model can be adapted or updated with new data for different districts or provinces (geographical locations) without disrupting the design of the model/prototype. As a result, MCDSS could adopt the AI model to enhance Social Protection delivery in all the 116 districts in Zambia with future works for scaling up of some Social Protection programmes which will be discussed further in Section 6.5.

6.4 Limitations of the system/model/framework

The main limitation of the model was that it was tested using beneficiary data from one geographical location which was Chongwe. The only Social Protection programmes under MCDSS that are implemented in all the 116 districts in Zambia are SCT and FSP, while SWL is only implemented in 81 districts. As a result, not all geographical locations could be tested with the model.

Another limitation was exporting the report in the format of the input data (Full Name, NRC, Age, Gender, ProgrammeType, etc.) of both the predicted eligible and non-eligible beneficiaries.

6.5 Future Works

The system that hosts the National Registration Card (NRC) database in Zambia and is essential for the identification and authentication of beneficiaries, is the Integrated National Registration Information System (INRIS). It is managed by the Ministry of Home Affairs and Internal Security (MOHAIS). The INRIS can be used to validate the NRC details of the beneficiaries to ensure there are no errors, incomplete NRC numbers, inclusion of people that do not exist, validation of eligible beneficiaries, to ensure the right targeted beneficiaries are the ones that receive their benefits and reduce fraud [43]. According to [44], the World Bank recently granted Zambia an amount of $100 to digitize National IDs (NRCs). This financial support can help MOHAIS expedite the validation process in all the 116 districts in the country.

There are future works to scale up the SWL social protection programme under MCDSS from 81 districts to 116 districts which simply means that more beneficiaries will be added to the programme. Once scaled up, the dataset can be expanded for the AI model and INRIS can adopt Supervised Machine Learning techniques to integrate the government databases such as the Civil Registry, which contains the births, deaths, and marriages' records as well as the three Management Information Systems at MCDSS. The AI model can then be retrained to accommodate this newly integrated data. This would prevent fragmentation of Social Protection data as well as avoid paying beneficiaries who are deceased and henceforth improve Social Protection delivery in the long run [45].

6.6 Chapter Summary

This chapter discussed the summary of main findings, implications in relation to the objectives, as well as the academic contribution to the body of knowledge/novelty. It also highlighted the limitations of the model and suggestions on future works for research.

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APPENDICES

APPENDIX A: GANTT CHART

Project: AI Model for Improving Social Protection Delivery in Zambia

Project Start Date: Wednesday, October 30, 2024

Display Week: 1

Farai Muzungaile

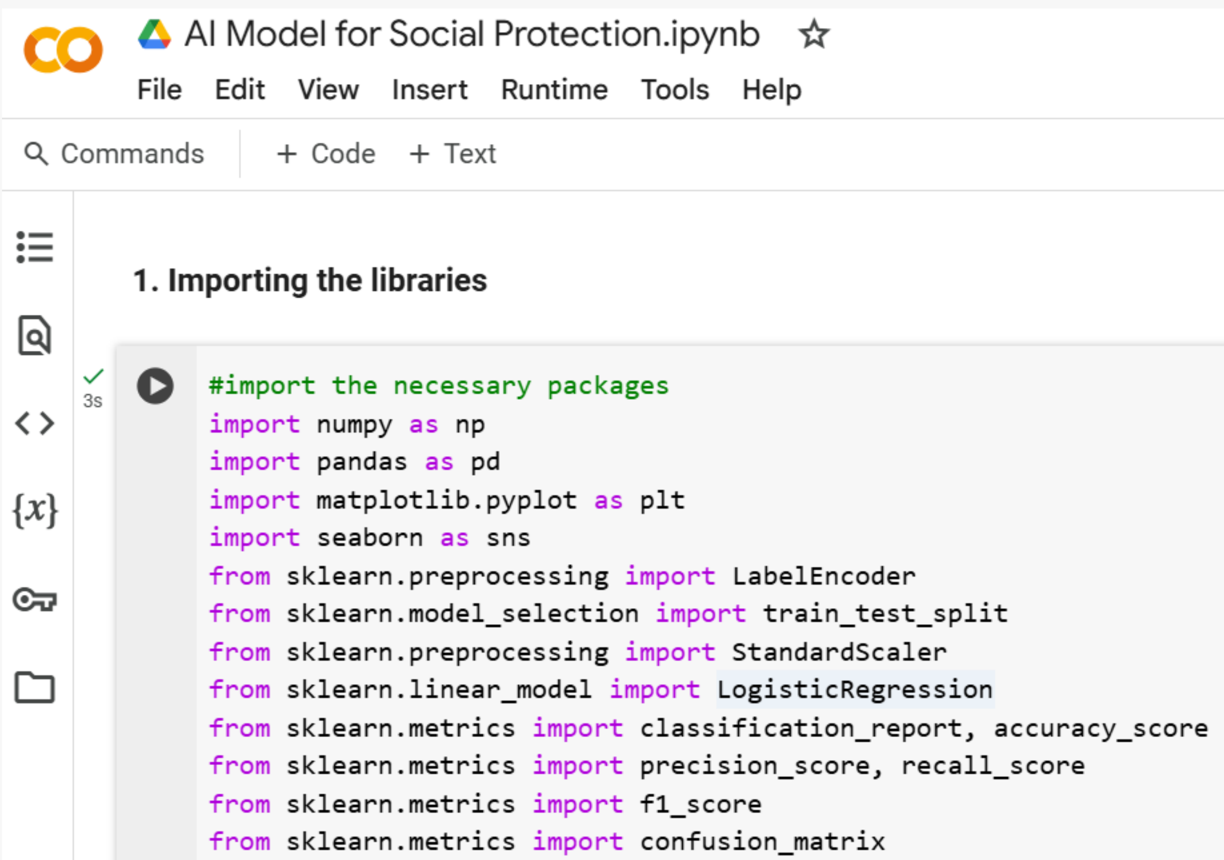
Week 1							Week 2							Week 3						
28 Oct 2024							4 Nov 2024							11 Nov 2024						
28	29	30	31	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
M	T	W	T	F	S	S	M	T	W	T	F	S	S	M	T	W	T	F	S	S

WBS	TASK	LEAD	START	END	DAYS	% DONE	WORK DAYS
1	**Introduction**			-	10		-
1.1	Background to the Study		30 Oct 2024	31 Oct 2024	2	100%	1
1.2	Problem Statement		31 Oct 2024	2 Nov 2024	1	100%	1
1.3	Aim and Objectives		2 Nov 2024	3 Nov 2024	1	100%	1
1.4	Research Questions		3 Nov 2024	4 Nov 2024	1	100%	1
1.5	Scope and Limitation		4 Nov 2024	5 Nov 2024	1	100%	1
1.6	Significance of the Research		5 Nov 2024	8 Nov 2024	3	100%	2
1.7	Preliminary sections of the project report		8 Nov 2024	9 Nov 2024	1	100%	1
2	**Literature Review**			-	19		-
2.1	Broad literature review of the topic		13 Nov 2024	26 Nov 2024	13	100%	12
2.2	Critical review of related works		26 Nov 2024	30 Nov 2024	4	100%	3
2.3	Comparison with related works and Identified Gaps		30 Nov 2024	1 Dec 2024	1	100%	1
2.4	Proposed model/system		1 Dec 2024	2 Dec 2024	1	100%	1
3	**Methodology**			-	16		-
3.1	Research design		5 Dec 2024	7 Dec 2024	2	100%	1
3.2	Adopted methodology and justification		7 Dec 2024	9 Dec 2024	2	100%	1
3.3	Association of research method to project		9 Dec 2024	10 Dec 2024	1	100%	1
3.4	Research data and datasets		10 Dec 2024	11 Dec 2024	1	100%	1
3.5	Data Collection Methods		11 Dec 2024	16 Dec 2024	5	100%	4
3.6	Data Analysis Techniques		16 Dec 2024	19 Dec 2024	3	100%	2
3.7	Ethical Concerns		19 Dec 2024	21 Dec 2024	3	100%	2
4	**Data, Prototype & Implementation**			-	38		-
4.1	Review of the Existing Social Protection Delivery Systems in Zambia		3 Feb 2025	6 Feb 2025	3	100%	2
4.2	Techniques, Algorithms, Mechanisms		6 Feb 2025	23 Feb 2025	17	100%	16
4.3	Designed Prototype, Model/Framework		23 Feb 2025	1 Mar 2025	6	100%	5
4.4	Functions of the Prototype, Model/Framework		1 Mar 2025	13 Mar 2025	12	100%	11
5	**Results & Discussions**			-	25		-
5.1	Results Presentation		16 Mar 2025	23 Mar 2025	7	100%	5
5.2	Analysis of Results/Performance Metrics		23 Mar 2025	5 Apr 2025	12	100%	10
5.3	Comparison to Related Work		5 Apr 2025	8 Apr 2025	3	100%	2
5.4	Implications of Results		8 Apr 2025	11 Apr 2025	3	100%	4
6	**Summary & Conclusion**			-	11		-
6.1	Summary of main Findings		24 Apr 2025	27 Apr 2025	3	100%	2
6.2	Discuss and Implications in Relation to Objectives		27 Apr 2025	29 Apr 2025	2	100%	1
6.3	Academic contribution to the body of knowledge/Novelty		29 Apr 2025	30 Apr 2025	1	100%	1
6.4	Limitations of the system/model/framework		30 Apr 2025	2 May 2025	2	100%	1
6.5	Future works		2 May 2025	5 May 2025	3	100%	2

APPENDIX B: GOOGLE COLAB – JUPYTER NOTEBOOK

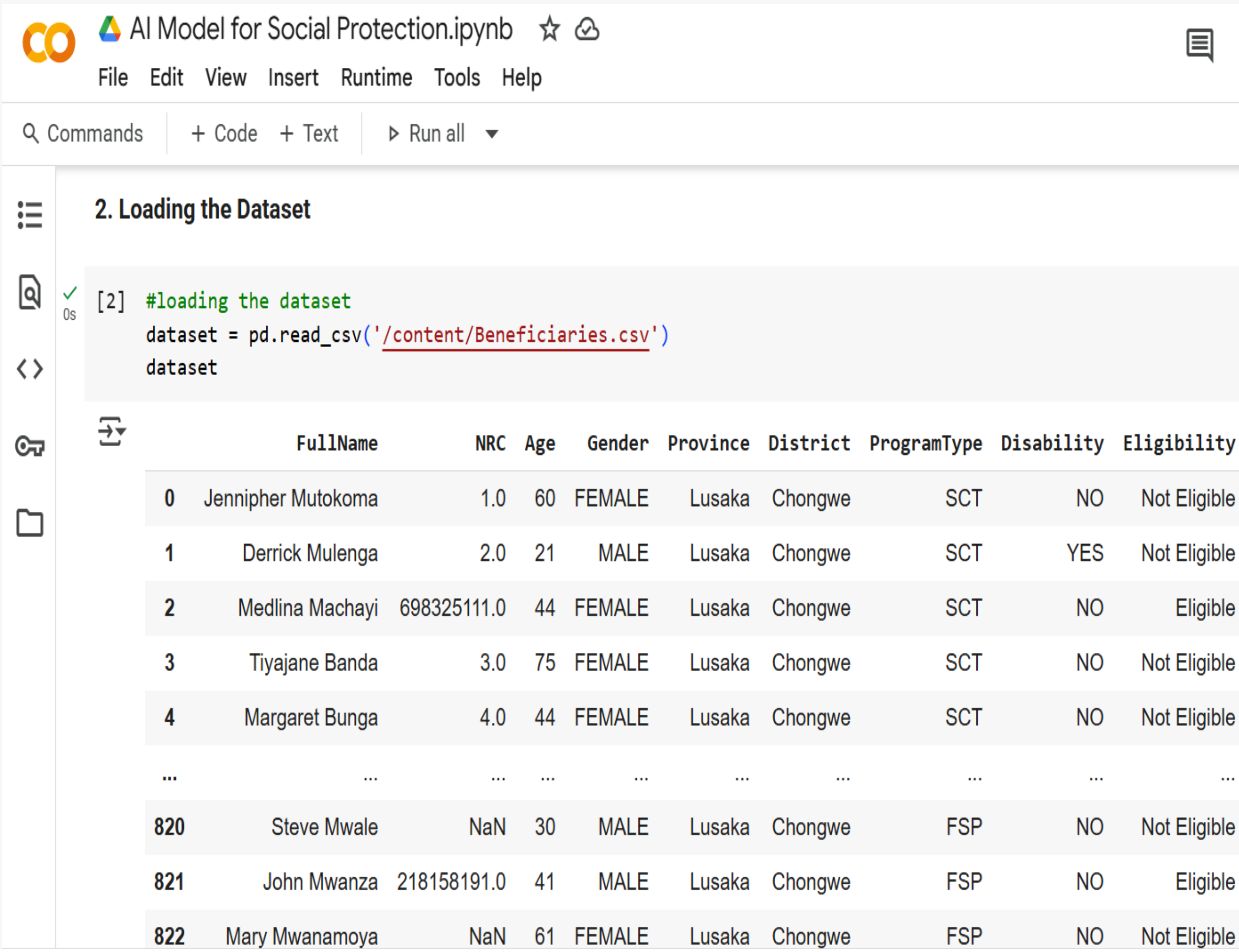
B1: Importing the Libraries

```
#import the necessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score
from sklearn.metrics import precision_score, recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import confusion_matrix
```



B2: Loading the Dataset

```
#loading the dataset
dataset = pd.read_csv('/content/Beneficiaries.csv')
dataset
```




```
[2] #loading the dataset
dataset = pd.read_csv('/content/Beneficiaries.csv')
dataset
```

	FullName	NRC	Age	Gender	Province	District	ProgramType	Disability	Eligibility
0	Jennipher Mutokoma	1.0	60	FEMALE	Lusaka	Chongwe	SCT	NO	Not Eligible
1	Derrick Mulenga	2.0	21	MALE	Lusaka	Chongwe	SCT	YES	Not Eligible
2	Medlina Machayi	698325111.0	44	FEMALE	Lusaka	Chongwe	SCT	NO	Eligible
3	Tiyajane Banda	3.0	75	FEMALE	Lusaka	Chongwe	SCT	NO	Not Eligible
4	Margaret Bunga	4.0	44	FEMALE	Lusaka	Chongwe	SCT	NO	Not Eligible
...	...	...	...	...	...	...	...	...	...
820	Steve Mwale	NaN	30	MALE	Lusaka	Chongwe	FSP	NO	Not Eligible
821	John Mwanza	218158191.0	41	MALE	Lusaka	Chongwe	FSP	NO	Eligible
822	Mary Mwanamoya	NaN	61	FEMALE	Lusaka	Chongwe	FSP	NO	Not Eligible

B3: Data Pre-processing

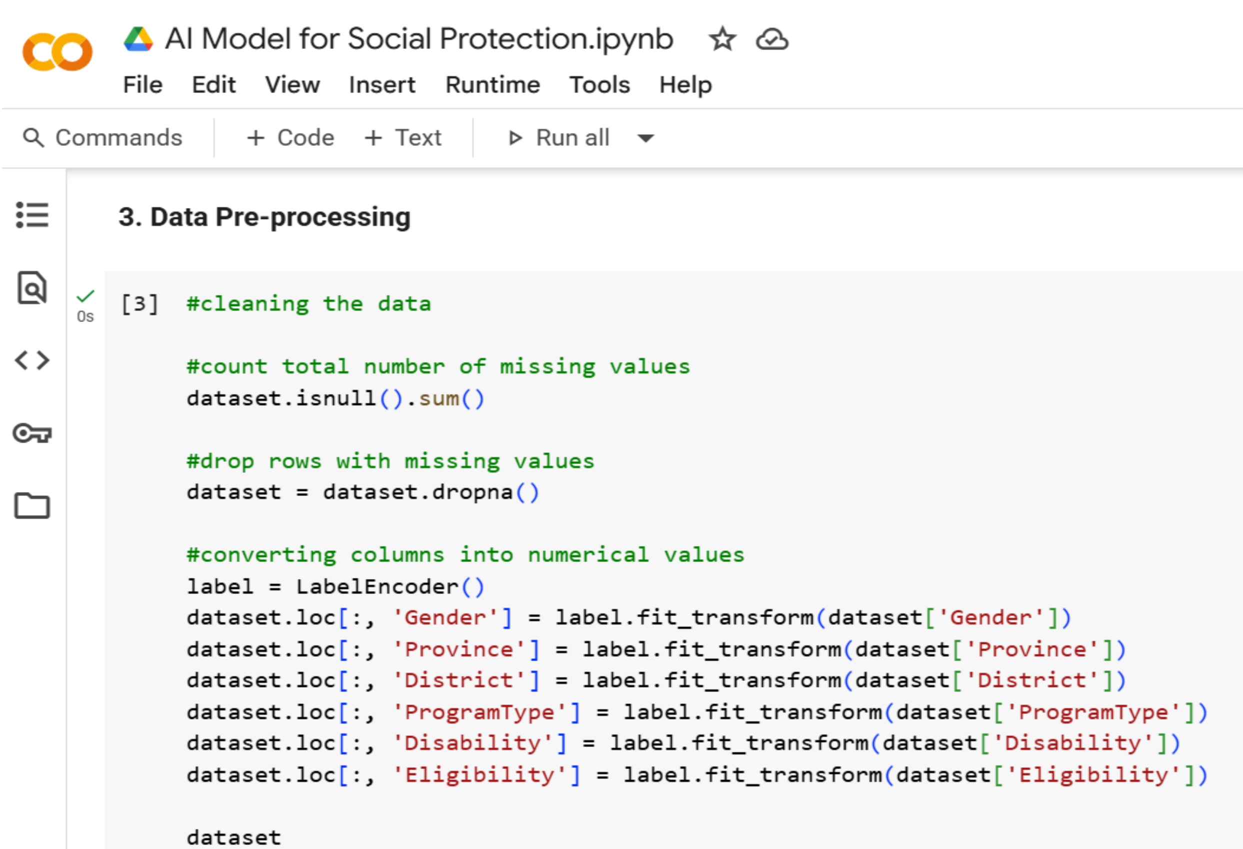
```
#cleaning the data

#count total number of missing values
dataset.isnull().sum()

#drop rows with missing values
dataset = dataset.dropna()

#converting columns into numerical values
label = LabelEncoder()
dataset.loc[:, 'Gender'] = label.fit_transform(dataset['Gender'])
dataset.loc[:, 'Province'] = label.fit_transform(dataset['Province'])
dataset.loc[:, 'District'] = label.fit_transform(dataset['District'])
dataset.loc[:, 'ProgramType'] = label.fit_transform(dataset['ProgramType'])
dataset.loc[:, 'Disability'] = label.fit_transform(dataset['Disability'])
dataset.loc[:, 'Eligibility'] = label.fit_transform(dataset['Eligibility'])

dataset
```



AI Model for Social Protection.ipynb

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	FullName	NRC	Age	Gender	Province	District	ProgramType	Disability	Eligibility
0	Jennipher Mutokoma	1.0	60	0	0	0	1	0	1
1	Derrick Mulenga	2.0	21	1	0	0	1	1	1
2	Medlina Machayi	698325111.0	44	0	0	0	1	0	0
3	Tiyajane Banda	3.0	75	0	0	0	1	0	1
4	Margaret Bunga	4.0	44	0	0	0	1	0	1
...	...	...	...	...	...	...	...	...	...
810	Edson Kamwele	555.0	55	1	0	0	0	0	1
811	Peter Jere	556.0	52	1	0	0	0	0	1
812	Arnold Phiri	218192191.0	47	1	0	0	0	0	0
821	John Mwanza	218158191.0	41	1	0	0	0	0	0
824	Parta Kalumbu	182805191.0	37	1	0	0	0	0	0

800 rows × 9 columns

B4: Training & Testing the Model

```
#split the dataset into features and target variable
x = dataset.drop(['FullName', 'Eligibility'], axis=1)
y = dataset['Eligibility'].values.astype(int) # Convert to integer type

#split the data into training and testing sets (75% for training and 25% for
testing)
xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size = 0.25,
random_state = 0)

#feature scaling
scaler = StandardScaler()
xTrain = scaler.fit_transform(xTrain)
xTest = scaler.transform(xTest)

#building the Logistic Regression model
model = LogisticRegression(random_state = 0)
model.fit(xTrain, yTrain)

#predictions on the test set
yPred = model.predict(xTest)
yPred
```

AI Model for Social Protection.ipynb

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4. Training and Testing the Model

```python
#split the dataset into features and target variable
x = dataset.drop(['FullName', 'Eligibility'], axis=1)
y = dataset['Eligibility'].values.astype(int) # Convert to integer type

#split the data into training and testing sets (75% for training and 25% for testing)
xTrain, xTest, yTrain, yTest = train_test_split(x, y, test_size = 0.25, random_state = 0)

#feature scaling
scaler = StandardScaler()
xTrain = scaler.fit_transform(xTrain)
xTest = scaler.transform(xTest)

#building the Logistic Regression model
model = LogisticRegression(random_state = 0)
model.fit(xTrain, yTrain)

#predictions on the test set
yPred = model.predict(xTest)
yPred
```

AI Model for Social Protection.ipynb

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```
array([0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1,
       0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1,
       1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1])
```

B5: Evaluating the Model

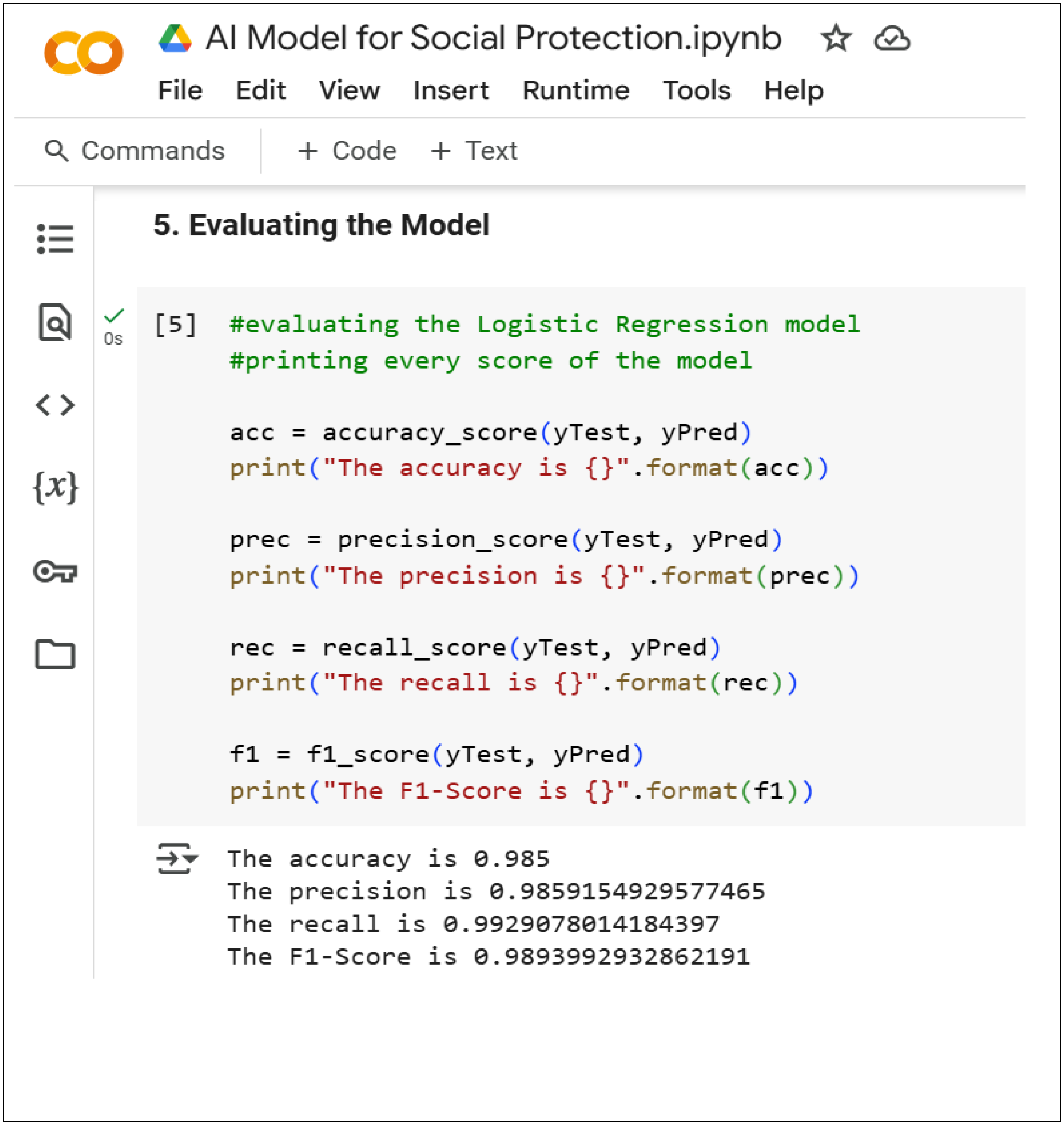
```
#evaluating the Logistic Regression model
#printing every score of the model

acc = accuracy_score(yTest, yPred)
print("The accuracy is {}".format(acc))

prec = precision_score(yTest, yPred)
print("The precision is {}".format(prec))

rec = recall_score(yTest, yPred)
print("The recall is {}".format(rec))

f1 = f1_score(yTest, yPred)
print("The F1-Score is {}".format(f1))
```


AI Model for Social Protection.ipynb
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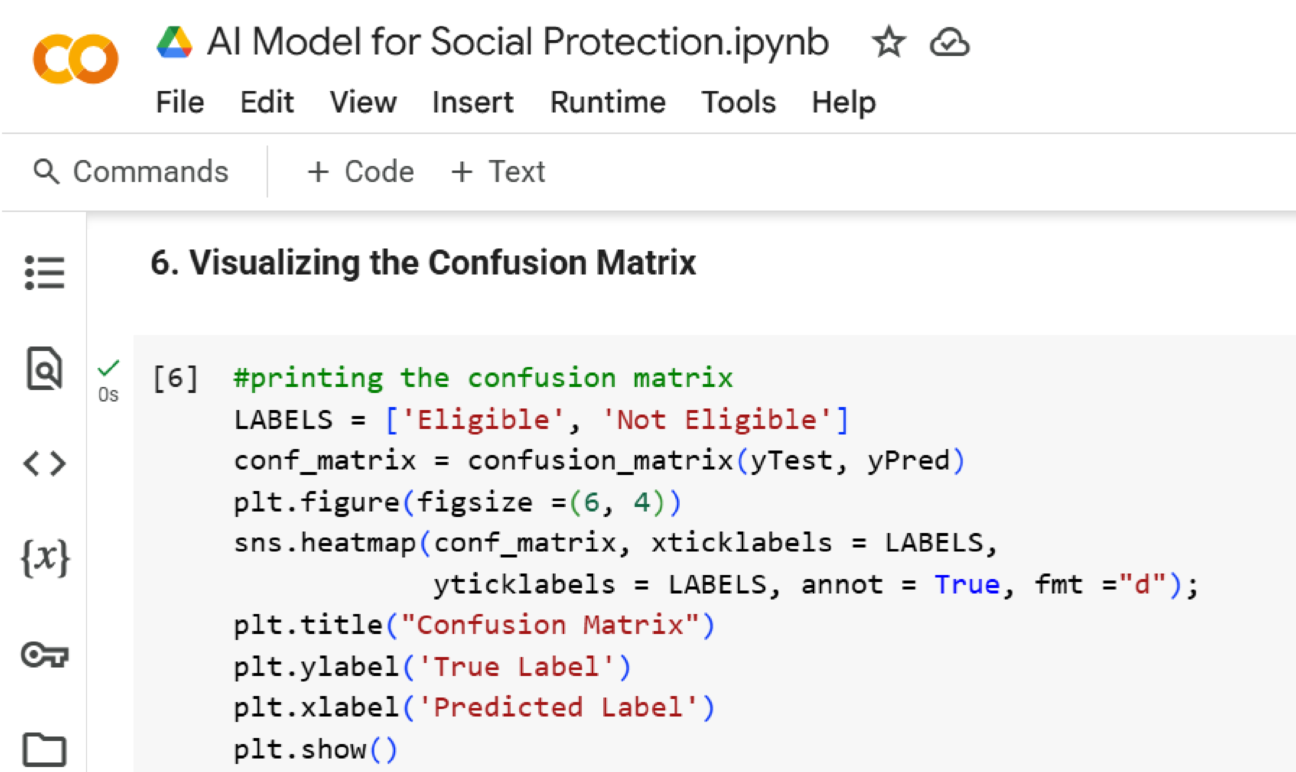
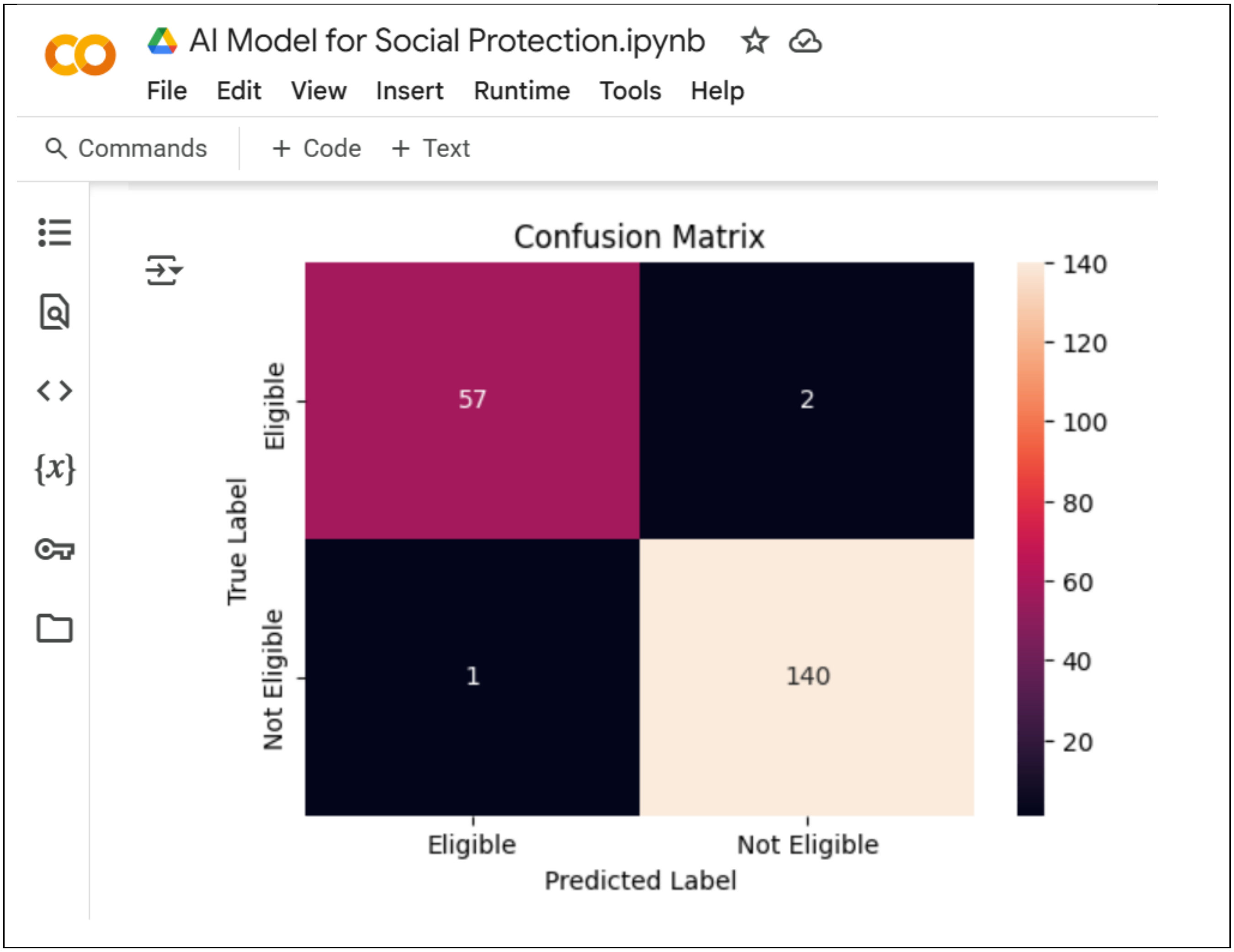
Commands
+ Code + Text
5. Evaluating the Model
0s
[5]
#evaluating the Logistic Regression model
#printing every score of the model
acc = accuracy_score(yTest, yPred)
print("The accuracy is {}".format(acc))
prec = precision_score(yTest, yPred)
print("The precision is {}".format(prec))
rec = recall_score(yTest, yPred)
print("The recall is {}".format(rec))
f1 = f1_score(yTest, yPred)
print("The F1-Score is {}".format(f1))
The accuracy is 0.985
The precision is 0.9859154929577465
The recall is 0.9929078014184397
The F1-Score is 0.9893992932862191

B6: Visualizing the Confusion Matrix

```
#printing the confusion matrix
LABELS = ['Eligible', 'Not Eligible']
conf_matrix = confusion_matrix(yTest, yPred)
plt.figure(figsize =(6, 4))
sns.heatmap(conf_matrix, xticklabels = LABELS,
            yticklabels = LABELS, annot = True, fmt ="d");
plt.title("Confusion Matrix")
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
```

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Confusion Matrix
57
2
1
140
Eligible
Not Eligible
True Label
Eligible
Not Eligible
Predicted Label
140
120
100
80
60
40
20