FACULTY OF SCIENCE & ENGINEERING

DEPARTMENT OF COMPUTER SCIENCE

DEVELOPING A MACHINE LEARNING MODEL TO DETECT AND MITIGATE MOBILE MONEY TRANSACTION FAILURE IN ESWATINI

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KWALUSENI

DECLARATION

I , Mxolisi Lukhele , hereby declare that this research titled " Developing a Machine learning model to detect and mitigate mobile money transaction in Eswatini" is my original work and has not been submitted to any institution for any academic award. All sources used in the preparation of this work have been acknowledged in accordance with standard academic practice.

This project was completed under the supervision of Mr. SM Jahidul Islam

Signed……………………………….. Date ………………………..

Student's Signature

Signed……………………………….. Date ………………………..

Mxolisi Lukhele

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ABSTRACT

Mobile money have significantly transformed financial transactions in developing countries , its offering inclusive and accessible financial solutions. Although these services usually experience transaction failures due to network congestion, system faults and user error. This study proposes a machine learning-based predictive system to detect and mitigate mobile money transaction failures . through the use of an ensemble of five models which are: Artificial Neural Network, Logistic Regression, Random forest ,Gradient Boosting and support Vector Machine. The system analyze the transactions attributes to predict the outcomes . the system was developed using Flask for the backend , MySQL for database and HTML with CSS for user interface . The results from experiments using real-world dataset has demonstrated high accuracy in failure prediction. The system will help to ensure mobile money service reliability and also improve user experience on the financial environment of Eswatini.

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CHAPTER 1

1.1 INTRODUCTION

Mobile money services are a revolution in the Eswatini financial space, offering an easy way of transacting without necessarily requiring to personal visit traditional banking system or Auto Teller machines. Mobile money has brought a significant change on the sector of financial services, it also provided people who are less privileged and lives in rural areas with accessible and affordable financial services thus minimizing poverty and also filling the gap of digital divide (Demirguc-Kunt, Klapper & Van Oudheusden, 2015). However, regardless of the increased usage, transaction failures can be one of the serious challenges that may hamper user experience and trust in financial services, For the users , unsuccessful transaction may result to delays in purchasing essential products and performing financial services like sending and receiving cash. Small business owners who rely on mobile payments can experience losses because of failed transactions ,with mobile money agents risk customer trust result in reduced revenue . Munyua & Muli (2020) noted that to devise effective solutions that limit the impact of such issues, it is to first understand why transaction failures occur. Transaction failures in mobile money services can be broadly categorized into two types: soft declines and hard declines. Soft declines occur when a transaction is temporarily rejected by the issuer, often due to issues that can be resolved, such as insufficient funds or exceeding daily spending limits (Kumar et al., 2021). In contrast, hard declines are permanent rejections resulting from invalid transaction details or forgotten passcode or sim cards. Both types of declines can be frustrating to users and may lead to loss of business for service providers (Aker & Mbiti, 2010).

Several factors contribute to the failure of transactions in mobile money systems. Among these are technical issues, including system downtimes or misconfigurations at the payment gateway level and network traffic congestion during peak hours, that disrupt the processing of transactions (Zhou et al., 2019). User-related errors also contribute significantly to transaction failures, such as incorrect entry of payment information or the use of unsupported payment methods (Khan et al., 2022). In Eswatini, where mobile money usage is prevalent, these challenges are mostly caused by infrastructural limitations, network traffic congestion and varying levels of digital literacy among users (Munyua & Muli, 2020).

With the mentioned issues, there is a real need for creative solutions to such problems using technology for detection and mitigation against failure in transactions. Machine learning models can be implemented to proactively identify patterns associated with failed transactions and allow timely interventions (Bashir et al., 2021). These models, based on historical data about transactions, will contribute to helping service providers understand the root causes of the failures and, as a result, increase the reliability of mobile money services in Eswatini.

In the end, while mobile money services come with great benefits, the failure of transactions is a critical challenge that needs to be resolved if the service is to be continuously successful. By understanding the causes and putting in place advanced detection mechanisms, stakeholders can work toward a more productive mobile financial ecosystem-one that support trust and accessibility for all users.

1.2 BACKGROUND OF THE STUDY

Mobile money has transformed financial transactions in many developing countries more especially in Eswatini, in a way that it provides a simple and cheapest way of banking with limited access to traditional banking or accessing banks Auto Teller Machines (ATMs). Since the traditional way of banking is considered expensive in terms of remoteness of some areas of Eswatini, many Emaswati need to travels long distances to reach ATMs in order to do financial transactions. The introduction of mobile money banking in the country has played a significant role in terms of economic development and the improvement of financial inclusion, it has gained a huge momentum interms of its usage for many e-commerce businesses, bill payments and transaction services. The Mobile Money Banking operates through platforms like MTN mobile money and Eswatini Mobile e-Mali which are services used by many Emaswati to pay bills like electricity, water, many other bills, money transfers. According to the World Bank, mobile money has been essential in increasing financial inclusion rate in Sub-Saharan Africa, with

Eswatini reporting and increase from 50% to approximately 71% between the year 2011 and 2017 due to mobile money adoption, Global Findex Database (2021).

Even though mobile money services have many advantages but the issue of transaction failures continues to be significant barrier, these transaction failures maybe caused by different factors like network problems like traffic congestion, user errors and infrastructure or system failure. Transaction failures , according to studies do not only lead to user dissatisfaction but they also undermine users trust which put a brake on the expansion of mobile money services , (Myeni & Makate, 2020; World Bank Group, 2024).Since many people in Eswatini highly depend on mobile money for basic transactions even the in government DPM office elderly grant is paid through mobile money so it is very important to understand and mitigate these transaction failures in order to improve users satisfaction and promoting e-commerce businesses which in turn promotes economic development.

The Central Bank of Eswatini has noted the significancy of addressing these issues, it also emphasized on the need of regulatory frameworks that will support inter-operability among mobile money providers, this will allow the users to be able to perform transactions across a variety of platforms without any problem, thus improving user experience while reducing the issue of transaction failure, (Kunene,2020). In addition, with the development of machine learning technologies there is a chance of improving transaction data analysis. Through the use of machine learning algorithms stakeholders can be able to identify trends linked to transaction failures and also implements targeted interventions.

According to ResearchGate (2024) prior studies has shown that machine learning can be used to forecast fraudulent activities in mobile money transactions through analyzing transaction history and users' behaviors. This approach does not only assist in fraud detection but also improves the overall strength of mobile economic system.

In the context of Eswatini developing a machine learning model which would be specially designed to detect and mitigate transaction failures and tailored to the local context of Eswatini, could improve user satisfaction and trust in the mobile money services. Through analyzing the historic transactions data, the model will assist in pin pointing the actual cause of the transaction failure and provide a solution.

Inconclusion the integration of machine learning technologies into mobile money operation may be a good improvement and innovation within the sector of technology and e-commerce that may results to improved delivery of service .Since mobile money improves economic development in the country and also promotes financial inclusion , so issues like transaction failures remains a barrier .This research project will try to understand the causes of these failures and employ machine learning model for detection and mitigating these failures.

1.3 PROBLEM STATEMENT

Mobile money has played a significant role in transforming financial transactions in Eswatini, by improving financial inclusion and providing cost effective alternative to traditional banking. However, there is an issue of transaction failures which pose a serious problem on user satisfaction and trust on the mobile money services. These transaction failures are often caused by various factors like network traffic congestions, user errors, and system malfunction or failure which hinders usability and availability of mobile money services. Integrating machine learning technologies to address these issues is critical for improving users experience and promoting the financial inclusion with growth of e-commerce in Eswatini, since a large portion of the population relies on mobile money services for basic transactions and the government uses these services to disburse the elderly grants. This study investigates on how machine learning models can be utilized to predict and mitigate transaction failures on mobile money services in Eswatini.

1.4 AIM AND OBJECTIVES

1.4.1 AIM:

The primary aim of this research is to develop a machine learning model to detect and prevent transaction failures on mobile money services in Eswatini.

1.4.2 OBJECTIVES:

The objectives of the study is to:

1. Study the causes of transaction failures in mobile money services in Eswatini.
2. Develop a machine learning model to detect and mitigate transaction failures.
3. Assess the performance of the proposed model

1.4.3 RESEARCH QUESTIONS:

1. What are the key causes of transaction failures in mobile money service in Eswatini?
2. How can a machine learning model be developed to detect and mitigate transaction failures in mobile money services?
3. How effective is the developed machine learning model in detecting and mitigating transaction failures?

1.5 PROJECT JUSTIFICATION

The creation of a machine learning model aimed at identifying and alleviating failures in mobile money transactions is strongly warranted by the increasing dependence on mobile money services within Eswatini. Services such as MTN Mobile Money and Eswatini Mobile e-Mali have proven essential for advancing financial inclusion, especially in isolated regions where conventional banking systems are scarce. These services are critical in facilitating e-commerce transactions, bill payments, and social welfare disbursements such as the government's elderly grants.

Notwithstanding their advantages, transaction failures have arisen as a considerable impediment, leading to user dissatisfaction, eroding trust, and possibly hindering the uptake and expansion of mobile money services. The origins of these failures are varied, encompassing network congestion, system malfunctions, and user mistakes, thereby underscoring the multifaceted nature of the issue. The Central Bank of Eswatini has acknowledged the critical need to tackle these challenges in order to improve the reliability and interoperability of mobile money platforms (Kunene, 2020).

A potential answer to this problem is the integration of machine learning technologies. Machine learning algorithms can spot trends and anticipate possible problems by examining transaction data from the past. This allows for prompt interventions to stop failures before they happen. The mobile money ecosystem is further strengthened by studies showing that machine learning can also identify fraudulent activity (ResearchGate, 2024). Consequently, this study is characterized by its technological innovation as well as its significant social and economic effects, which correspond with worldwide patterns in financial inclusion and digital transformation (World Bank Group, 2024; Global Findex Database, 2021).

In conclusion, the rationale for
the proposed research is grounded in its capacity to bolster user confidence, mitigate transaction failures, and promote economic advancement in Eswatini. Through the utilization of machine learning, this initiative aims to fill a significant void in mobile money
services, thereby facilitating enhanced financial inclusion and fostering sustainable development.

1.6 PROJECT STRUCTURE

- ***Chapter 1:*** This chapter introduces the study, it backgrounds information, problem statement, aim and objectives, research questions and chapter summary.
- ***Chapter 2:*** Present a comprehensive review of related literature on previous studies on mobile transaction failure money systems and application of machine learning in financial systems.
- ***Chapter 3:*** consist of the research methodology with: data collection methods, data processing using machine learning and the design with the type of models, programming languages, programming tools that will be used.
- ***Chapter 4:*** Focuses on the actual implementation and evaluation of the proposed machine learning model, providing the results and analyses.
- ***Chapter 5:*** Concludes the study by summarizing the findings, discussing the limitations faced during the research and then provide recommendations for future research.

1.7 CHAPTER SUMMARY

Mobile money services in Eswatini have filled significant gaps, both in terms of financial inclusion and economic engagement. However, some of the main setbacks to the successful use of these services include transaction failures. Therefore, this study will seek to address the challenge by developing a machine learning model capable of detecting and hence reduction of transaction failures. The study shall classify the causes of failures, develop a predictive model, and evaluate the performance of such a model in enhancing reliability and user satisfaction by analyzing historical transaction data. This study is justified in light of the fact that it plays a key role in ensuring economic development, whereby there is an urgent need to address challenges that hamper users' confidence in the application of its services. In five clear chapters, the research systematically studies the problem, implements a possible solution, updates the current information about the financial systems in developing countries. The next section will do a critical review of related literature to provide a theoretical framework for the proposed solution.

CHAPTER 2

2.1 INTRODUCTION

The introduction of Mobile money has changed the way financial services used to operate in recent years, more especially in many developing countries like Eswatini, where traditional banking infrastructure remains very limited, many populations is unable to access Automatic Teller Machines (ATMs) to do financial transactions at the traditional banks. This may be due to remoteness of their places interms of distance they travel to reach the ATMs. The high increase in the deployment of mobile money had a good impact on improving financial inclusion through provision of accessible, secure and convenient financial services (GSMA,2022). Since the population who uses mobile money for doing their basic transaction has increased the reliance on mobile money for their everyday transactions like paying water bills, buying electricity and other transactions and even many people's businesses operate using mobile money. So, if the incident of transaction failures keeps on increasing results in the negative effects on the user's experience, trust, adoption rates and that may also affect the business operation which then results in loss thus affecting the national economy. These transaction failures maybe caused by many factors like network issues including network traffic congestion during peak hours, also system malfunctions, human error and fraud all of which pose an issue to the service for reliability and efficiency of operation. (Mothobi & Grzybowski, 2017).
In Eswatini, mobile money has emerged as one of the most accessible and widely adopted forms of digital financial services, playing a crucial role in promoting financial inclusion, especially in rural and underserved communities. With limited access to brick-and-mortar bank branches in many parts of the country, mobile money provides a practical alternative that meets the everyday financial needs of citizens through mobile phones.

The two major mobile money service providers in the country are:

1. MTN MoMo (Mobile Money) – Introduced in 2011 by MTN Eswatini, MoMo has since experienced exponential growth in both its user base and service offerings. Initially launched for basic peer-to-peer money transfers, it has expanded to support a wide range of functions, including:

- ✓ Utility and bill payments (e.g., electricity, water, DSTV)
- ✓ School fee payments for public and private institutions
- ✓ Merchant payments using Momo Pay via QR codes or USSD
- ✓ Mobile-based loans, including the *MoMo Kash* service
- ✓ Cross-border remittances, allowing users to send or receive money from neighboring countries like South Africa.

2. Eswatini Mobile e-Mali – Launched by Eswatini Mobile as a competitor to MoMo, e-Mali offers similar wallet services. It enables:

- ✓ Cash-in and cash-out through a network of mobile money agents
- ✓ Interoperability with local banks, allowing users to link their mobile wallets with savings or current accounts
- ✓ Mobile airtime purchases, loan repayments, and merchant payments.

The Central Bank of Eswatini (CBE) has been instrumental in ensuring a secure and regulated environment for mobile money operations. Through its National Financial Inclusion Strategy (NFIS) and Digital Financial Services policy, the CBE monitors mobile money providers, mandates consumer protection measures, promotes financial literacy, and fosters innovation in financial products. The licensing and supervision of agents, interoperability frameworks, and anti-money laundering (AML) guidelines are part of this oversight.

Recent efforts have focused on integrating mobile money with Point-of-Sale (POS) systems in both urban and peri-urban retail settings. This development has allowed mobile wallets to function beyond peer-to-peer (P2P) transfers, supporting everyday commercial transactions, improving customer convenience, and encouraging broader merchant adoption of digital payments.

Moreover, mobile money has become a catalyst for digital trade, enabling small businesses to sell goods and services online while receiving secure payments. It is also increasingly used for government-to-person (G2P) payments, such as social grant distributions, which reduce leakages and enhance transparency.

According to FinMark Trust (2023) and Finscope Eswatini 2021, mobile money services in Eswatini have contributed significantly to:

- ✓ The formalization of informal businesses, by providing digital records and access to customer payment histories.
- ✓ Greater access to credit, especially microloans based on mobile transaction behavior.
- ✓ Improved saving behaviors, as users store money safely in digital wallets instead of holding physical cash.
- ✓ Women's economic participation, with mobile money giving female entrepreneurs more control over finances and access to digital tools.

Challenges still exist, such as limited smartphone penetration, digital literacy gaps, and inconsistent mobile network coverage in rural areas. However, the growing integration of mobile money with banking, retail, and government systems shows that Eswatini is making steady progress toward a more inclusive and resilient digital economy.

According to The World Global Findex Database (2021) Mobile money accounts have assisted in improving gender equity interms of accounts ownership, in some economies of developing countries like Eswatini. In most developing countries more than 20 percents of adults or elderly people have mobile money accounts, women have equal or higher mobile money ownership than men. the report also stated that age equity has improved for mobile money accounts ownership this helps to improve the developing countries' economies. Many account owners use mobile money for many uses of which large populations use mobile money for daily payments, and receiving payments into their accounts. This includes government payments, private sector wages payments. For example, in Togo almost 40 percent of elderly people who receive government payment receives them on mobile money accounts, just like in Eswatini. The figure below shows on how the adults in Sub-Saharan Africa use mobile money accounts

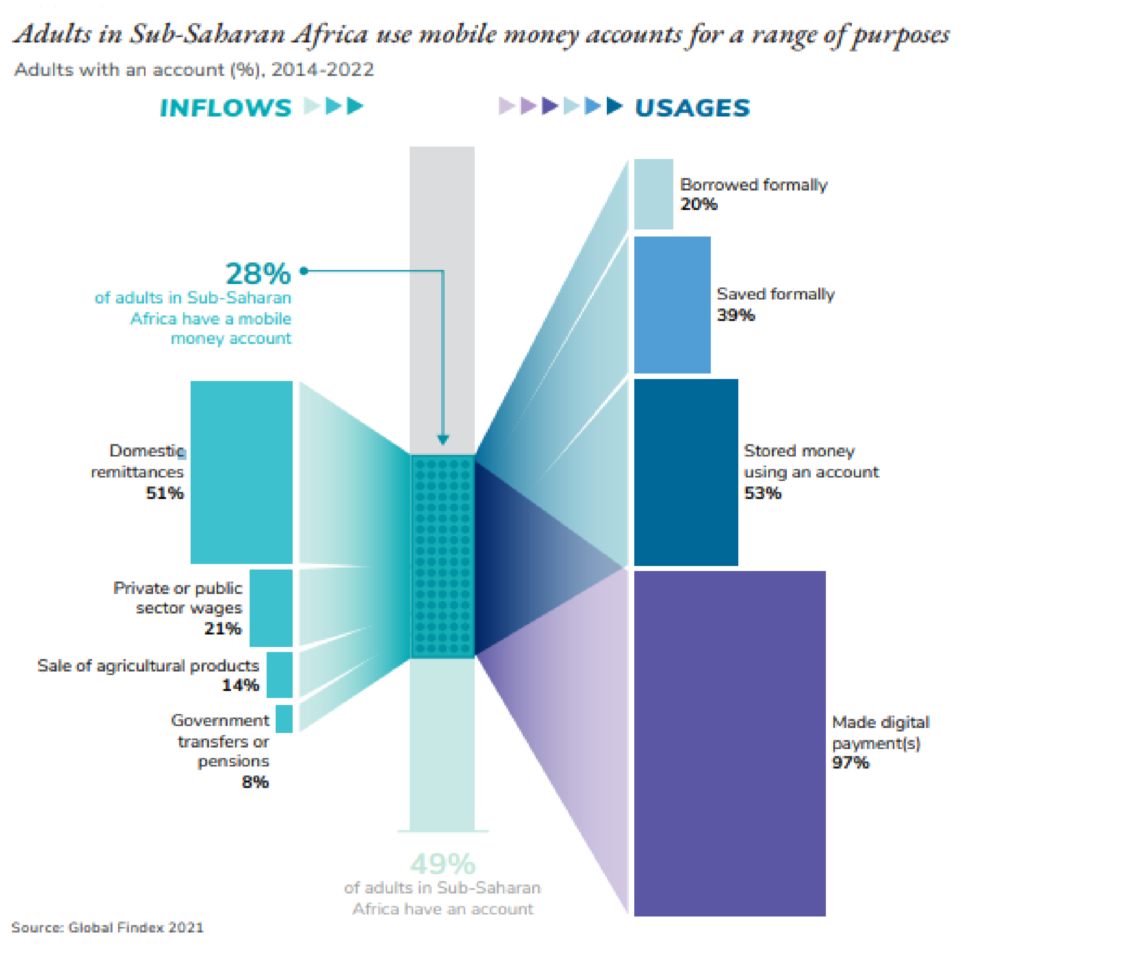


Figure 2.1 Mobile money account range

The above figure proves on the high usage of mobile money services in many African developing countries which shows the need to address any issue which can hinder the operation of mobile money services like the transaction failures.

These challenges have led researchers and practitioners to increasingly consider machine learning as a promising solution. ML techniques offer advanced capabilities in data analysis, pattern recognition, and predictive modeling that enable the development of systems capable of proactive detection, diagnosis, and mitigation of transaction failures (Sharma et al., 2021). ML-based solutions have been developed to provide an improved system performance, reduced failure rate, and enhanced user experience by leveraging a large volume of transaction data (Ali et al., 2019).

In this chapter we will review related studies on the failure in mobile money transactions and the use of ML in solving them. Precisely, this study will seek an overview of mobile money systems, common causes of mobile money transaction failures, the roles of ML in detecting failures, and how ML detects mobile money transaction failures. The review also goes into key contributing research, methodologies, and cases that have been developed around the subject matter, stating various achievements and limitations. Thus, this review synthesizes such insights into laying a foundation for building a robust ML model that best fits the unique challenges of mobile money transactions in Eswatini.

Financial inclusion in mobile money is the process of ensuring that individuals and businesses are able to access affordable and reliable financial services regardless of their location and socioeconomic status. This includes basic services responsible for facilitating payments, savings, credit, and insurance, among others, through mobile technology (World Bank, 2020). The major benefit of mobile money financial inclusion is that it ensures that people in rural and marginalized areas are able to do transactions without need for travelling to traditional banks which may be costly to them (Jack & Suri, 2016).Lastly mobile money provides financial security by reducing risks of handling cash, since the cash is store digitally and can be securely accessed when needed thus reduce theft and loss (GSMA, 2022), Although there is a huge challenge of mobile money fraud which keeps on increasing nowadays in the country.

2.1.1 AN OVERVIEW OF MOBILE MONEY

Mobile money refers to financial services that are performed via a mobile device such as a phone or tablet, allowing users to store, send, and receive money without the need for a traditional bank account. These services are typically offered by mobile network operators (MNOs) in partnership with financial institutions. Mobile money has played a transformative role in promoting financial inclusion, particularly in developing countries where access to formal banking services is limited.

The foundation of mobile money is built on mobile wallets—electronic accounts linked to a user's mobile phone number. Through mobile wallets, users can deposit cash through agents, transfer funds to other users, pay bills, purchase goods and services, and withdraw money. The transactions are authenticated using secure methods such as PIN codes, USSD, or mobile apps (GSMA, 2021).

Mobile money services differ from mobile banking in that they do not necessarily require users to have a bank account. This makes them accessible to a broader population, including those in rural or underserved areas. According to the GSMA (2023), there were over 1.6 billion registered mobile money accounts globally, with Africa accounting for nearly 70% of the total transaction volume. In Sub-Saharan Africa, mobile money is widely used to bridge the financial services gap, especially among low-income populations.

In Eswatini, mobile money services such as MTN Mobile Money (MoMo) and Eswatini Mobile's e-Mali have gained popularity, allowing users to carry out financial transactions with ease. These platforms have also expanded into offering value-added services such as loan disbursements, insurance, savings, and utility payments, thereby deepening financial penetration.

The benefits of mobile money include improved financial inclusion, increased convenience, reduced transaction costs, and enhanced economic participation. However, challenges remain, such as network reliability, fraud, regulatory compliance, and the need for user education (World Bank, 2022).

According to a review by Tavneet Suri, (2017) Mobile money is a digital payment platform which is capable of allowing users to store, transfer and do cash withdrawals through the use of their mobile phones. Mobile money enables mobile phone owners to deposit, transfer, and withdraw funds without owning a bank account which makes it to be different from mobile banking which connects the user to an existing banking account via the mobile phone. Mobile money operates in a software which is installed in the SIM cards by the particular network operator which owns the SIM card. This installed software can run on both regular phones and smartphones since it is being installed on the SIM card. Users can easily do any kind of transactions on their mobile phones through a straightforward menu interface on their mobile devices and they can do: person-to-person payment, bill payments, and government-to-person payment.

Mobile money serves as an electronic wallet, enabling users to store, send, and receive money directly from their mobile devices (GSMA, 2015). To access these services, users must register at a mobile money agent, typically presenting a government-issued ID for identity verification in line with Know Your Customer (KYC) regulations (World Bank, 2014). After registration, clients deposit cash in their accounts through agents, send money to other people using the recipient's mobile phone number, and withdraw their cash through an agent.

The process followed starts with registrations at which people visit a mobile money agent who puts their identifications into his records. Deposit takes place physically to the agent of cash for credit into users accounts as e-money, transferred using only your mobile phone's straightforward menu to ' send money' or 'pay your bill'. While a cash withdrawal requires clients go back to this agent by having the real currency in replacement to the e-money (Jack & Suri 2010).

Over time, mobile money has evolved from just simple transactional services to other financial services. This includes person-to-person payments, where a user can send money to another individual who may or may not have an account. Utility bills and other expenses can be paid directly from the user's mobile money account. Savings and wage payments are also supported by mobile money, which provides users with a secure place to keep money and receive wages from employers or government programs (Bernanke, 2012).

One important ingredient in mobile money systems is the agent network. Agents act predominantly as small businesspeople-for example, food retailers and petroleum stations-accelerating the transaction of cash and maintaining an inventory of e-money and cash on demand to end-users. Agents have also mushroomed in just a few years into the millions globally, thus creating much greater scope in use-the system's reach.

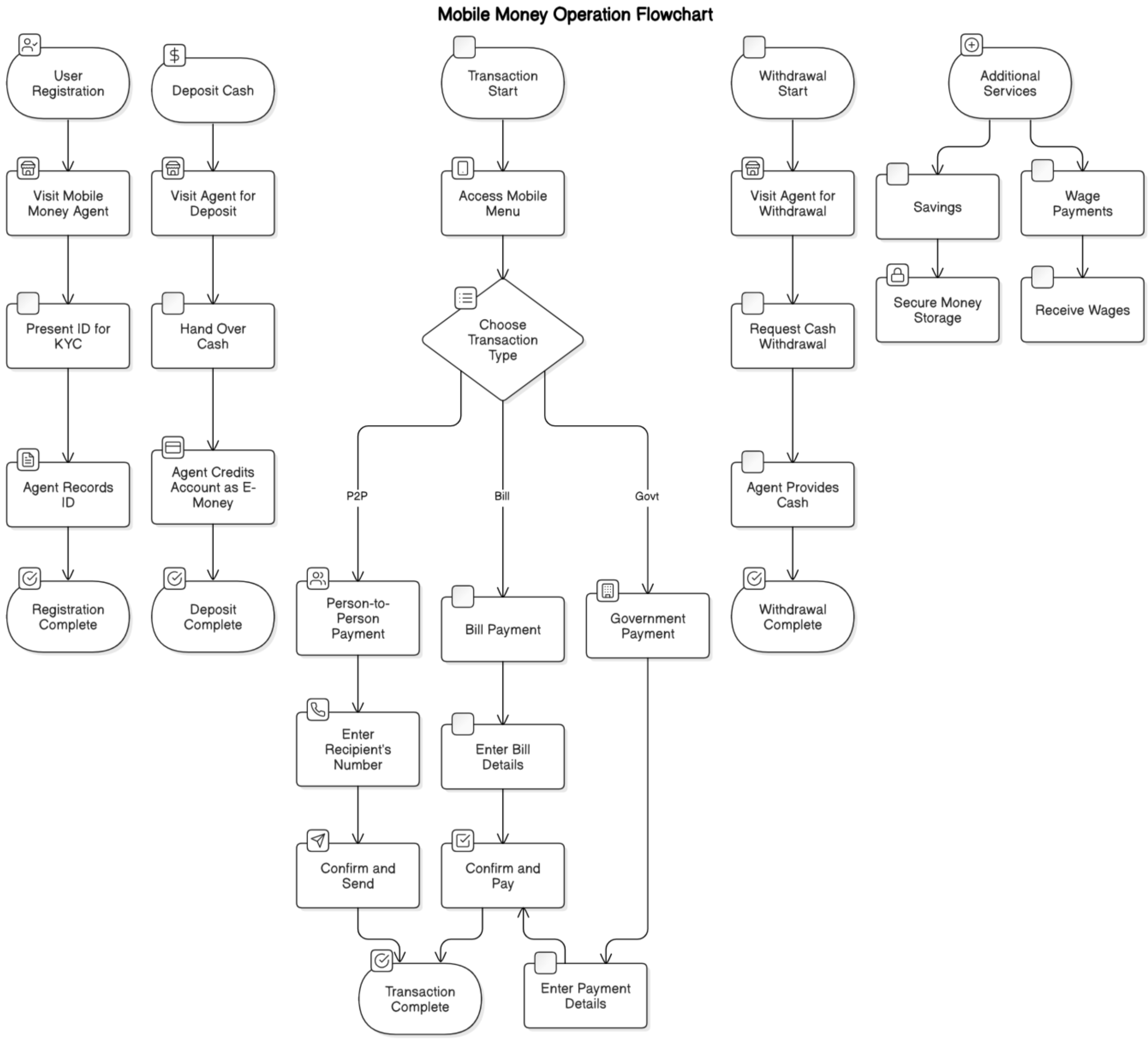


Figure 2.1.1 Mobile money operation

2.1.2 EVOLUTION AND ADOPTION OF MOBILE MONEY

The concept of mobile money emerged in the early 2000s, with Kenya's M-Pesa, launched in 2007 by Safaricom, being the most well-known and widely studied success story. M-Pesa demonstrated that mobile network operators (MNOs) could provide financial services to millions of unbanked people using basic mobile phones and agent networks. This success led to the replication and adaptation of mobile money models in other regions, including South Asia, Latin America, and Sub-Saharan Africa.

Today, over 1.6 billion mobile money accounts are registered globally, with Africa accounting for nearly 70% of global mobile money transaction volume (GSMA, 2023). The convenience, security, and low cost of mobile money have made it a preferred method of conducting everyday financial transactions.

According to GSMA, 2023 The concept of mobile money emerged in the early 2000s as a response to the need for accessible, affordable financial services in regions with limited banking infrastructure. It initially developed as a means to facilitate microfinance repayments and peer-to-peer (P2P) transfers using mobile phone networks. The most iconic and widely studied example is Kenya's M-Pesa, launched in 2007 by Safaricom in partnership with Vodafone. M-Pesa (short for *mobile pesa*, with *pesa* meaning "money" in Swahili) allowed users to deposit, withdraw, and transfer money via a simple menu-based system on feature phones. It also utilized a widespread network of retail agents who functioned as human ATMs, bridging the gap between digital and physical cash.

M-Pesa's groundbreaking success demonstrated that mobile network operators (MNOs)—not just traditional banks—could play a central role in delivering financial services to unbanked populations. Within a few years, M-Pesa reached over 10 million users in Kenya and became deeply embedded in the daily economic life of the country. Its success catalyzed a global movement toward mobile-enabled financial inclusion, leading to the replication and adaptation of similar models across Sub-Saharan Africa, South Asia, Southeast Asia, and Latin America.

Countries like Tanzania, Uganda, Bangladesh (with bKash), Pakistan (Easypaisa), India (Paytm), and the Philippines (GCash) followed suit, each adapting the mobile money model to suit their regulatory environments, user behavior, and technological capabilities. These services have enabled rural and marginalized communities to perform transactions such as remittances, bill payments, school fee payments, merchant purchases, and government-to-person (G2P) disbursements.

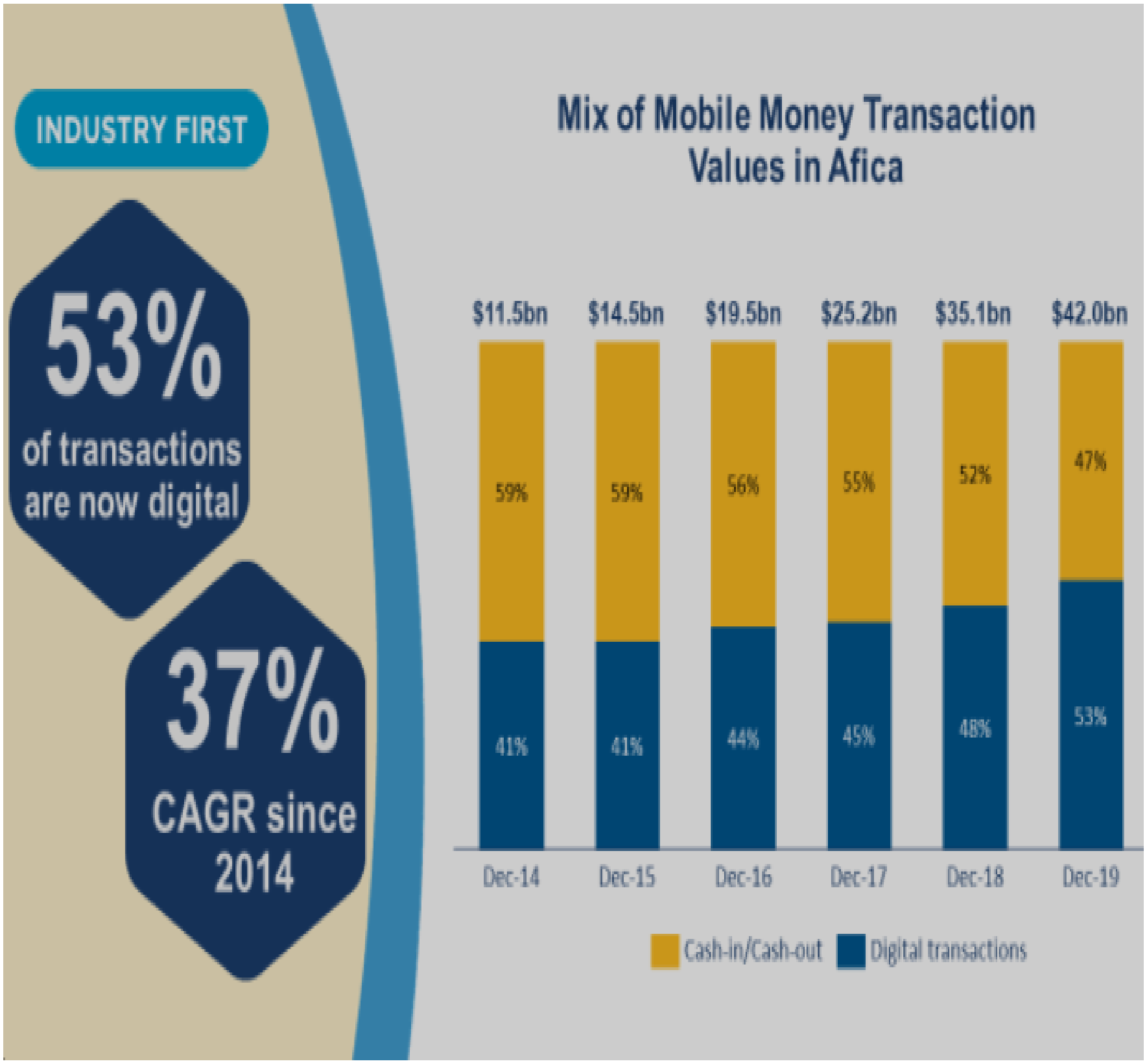
As of 2023, there are over 1.6 billion registered mobile money accounts worldwide, with Africa accounting for nearly 70% of all global mobile money transaction volume (GSMA, 2023). The Sub-Saharan Africa region alone saw mobile money transactions exceeding $836 billion in value in 2022, highlighting the vital role mobile money plays in driving financial access, supporting small businesses, and facilitating economic resilience in areas with limited formal banking infrastructure (GSMA, 2023).

The widespread adoption of mobile money can be attributed to several key factors:

- The ubiquity of mobile phones, even in low-income and rural areas,
- Minimal infrastructure requirements, compared to setting up bank branches,
- Cost-effective service delivery, and
- High levels of trust in mobile operators, especially where banks may not have a strong presence.

Moreover, the COVID-19 pandemic accelerated the digital shift, further reinforcing mobile money's role in enabling contactless transactions and ensuring continued financial activity during lockdowns. Governments and NGOs also used mobile platforms for emergency cash transfers and health campaigns, demonstrating mobile money's broader utility beyond commerce.

In summary, mobile money has transformed from a niche innovation into a core component of financial ecosystems in developing economies. It has not only expanded access to formal financial tools but also paved the way for the development of digital credit, insurance, and savings products tailored for underserved populations.



INDUSTRY FIRST
53%
of transactions are now digital
37%
CAGR since 2014
Mix of Mobile Money Transaction Values in Afica
$11.5bn
$14.5bn
$19.5bn
$25.2bn
$35.1bn
$42.0bn
59%
59%
56%
55%
52%
47%
41%
41%
44%
45%
48%
53%
Dec-14
Dec-15
Dec-16
Dec-17
Dec-18
Dec-19
Cash-in/Cash-out
Digital transactions

2.2 RELATED LITERETURE

2.2.1 Enhancing transaction reliability using predictive models

Bashir et al. (2021) present a study where they used machine learning predictive models in mobile payment systems; the key emphasis of this study is placed on how these predictive models help in enhancing the reliability of transactions. In this respect, the historical datasets from mobile phone payment platforms are used, finding patterns that lead to frequent failures during transactions. The researchers used supervised learning algorithms, namely decision trees and support vector machines (SVM) to classify and predict possible failures of transactions based on input features like time of transaction, user behavior, and network conditions.

The predictive models built by Bashir et al. had high accuracy in detecting transaction failures. The decision tree model gave an accuracy of 87.5%, while the SVM model outperformed the decision tree model, giving an accuracy of 89.2%. Also, the SVM model showed higher precision in identifying failure-prsone transactions, which reduced false positives by 12% compared to a decision tree model. A prototype real-time monitoring system using these models was implemented, and the efficiency of such a system has already been evaluated in a simulated environment. The results demonstrate a reduction of 20% of transaction failures compared to the baseline system without the predictive capabilities in the simulated environment. This result proves the potential for machine learning to improve the reliability and user satisfaction for mobile money systems.

This study is considered relevant for developing countries like Eswatini whose financial inclusion depend only on mobile money services. The predictive analytics and real-time monitoring make the insights applicable to the enhancement of the robustness and reliability of any mobile money platform on handling user daily transactions. This will be much helpful on the designing and implementation of the Machine Learning model for detecting and mitigating Momo transaction failures in Eswatini.

2.2.2 Analyzing Transaction Failure Mechanisms

A study conducted by Kumar et al. (2021) for understanding and mitigating transaction failures in mobile payment systems considering anomaly detection of machine learning. It was conducted in a two-way approach: first, was identification of major causes related to the failure of transactions; second, was developing machine learning techniques to identify and address these anomalies in real time. They used k-nearest neighbors(K-NN) and neural networks to detect abnormalities in the pattern of transactions, they also used a dataset of millions of transaction records, labeled in outcomes of success or failure, and trained their models on these to find out what pattern and anomalies to signals that a transaction is about to fail. This study contributed a lot with it feature engineering process, they found some very important predictors for failures in a transaction, including network latency, insufficient user balances, transaction congestion at peak times, and system integration bugs. The respective models in their inputs are formed around these features that prov ide most of the gain in the accuracy of ML techniques.

This work presented k-NN and neural network models for efficient detection of anomalies and the prediction of impending failures. The performance evaluation of k-NN was 85.4%, but the performance of the neural network outperformed k-NN with an accuracy of 92.1%. Furthermore, the neural network model developed here outperforms k-NN in finding latent anomalies in complex patterns of transaction data; thus, it might be more appropriate for real-time failure prediction.

When applied to a simulated transaction environment, the neural network model reduced the incidence of transaction failures by 25%, compared with a baseline system with no anomaly detection. The study further recorded a 15% decrease in false negatives, referring to missed failures, to ensure an even higher level of system reliability and user trust. This research holds particular significance for mobile money systems in Eswatini, where transaction failures can have severe repercussions, including financial losses and customer dissatisfaction. The proactive framework proposed by Kumar et al. aligns with the need for a robust and scalable mobile money infrastructure in developing regions. By leveraging anomaly detection and real-time prediction, this study provides valuable insights for designing ML-based solutions tailored to Eswatini's unique challenges in mobile money operations.

2.2.3 Fraud Detection and Transaction Failure Reduction

A 2024 ResearchGate publication investigated the double dividends of machine learning on mobile money systems by reducing fraud detection to lower the number of failed transactions. Using advanced techniques in machine learning and deep learning models, the authors developed predictive tools that identify fraud activities likely to cause disruption in transactions.

The research built a dataset including a wide range of transaction metadata and behavioral patterns, such as frequency features, geographic anomalies, and device inconsistencies. The developed features are then used to train deep learning algorithms such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) for classifying transactions into either legitimate or suspicious. In fact, in recognizing disruptions created by fraudulent activities, many examples of failures in transactions resulting from these activities were stopped, such as the freezing of accounts or unauthorized system access.

Results from the study appeared promising. The deep learning models had high accuracy in fraud detection, with the CNN model achieving as high as 94.6% and that of RNN achieving as high as 92.8%. Besides, both have minimized false positives in transactions that are actually legitimate. Apart from fraud detection, these deployed ML models reduced transaction failures by 30%. The system was then able to detect anomalies much earlier and prevent them from causing larger disruptions. The researchers also reported a reduction in system downtime by up to 40%, evidence of efficiency gains brought about by ML-driven monitoring and intervention mechanisms.

The findings of this study are particularly relevant to Eswatini, where mobile money systems serve as a critical component of financial inclusion and economic activity. By integrating fraud detection with transaction failure mitigation, the proposed ML framework addresses two key challenges simultaneously. This dual-purpose approach has the potential to enhance user trust, improve system reliability, and support the growing reliance on mobile money in Eswatini's economy.

2.2.4 Use of Graph Convolution Networks to Identify and Reduce Failures in Mobile Money Transactions

In a 2019 study, Sun et al. investigated how deep learning might be used to identify and stop fraudulent activity and unsuccessful mobile money transactions. An algorithm based on Graph Convolution Networks (GCNs) was used in the study to examine transaction networks and find illegal financial activity. The study showed how machine learning models could greatly increase transaction dependability by anticipating and preventing possible failures and fraudulent actions before they happen by including real-time anomaly detection techniques. In two extensive e-payment datasets, the results demonstrated an accuracy rate of 94.62% and 86.98% in identifying fraudulent accounts, demonstrating the model's efficacy in boosting the security and reliability of mobile money systems.

2.2.5 Real-Time Mobile Financial Risk Scoring

In a study by **Ndulu and Kinyua (2022)**, researchers proposed a real-time risk scoring framework for mobile financial services in East Africa. The system used ensemble machine learning techniques including Random Forests, Gradient Boosting, and Logistic Regression to assign dynamic risk scores to transactions. These scores were based on features such as user history, geospatial movement, transaction size, and behavioral patterns.

The research demonstrated that real-time scoring systems could not only flag high-risk transactions for additional verification but also reduce transaction rejection rates by 18% by enabling smarter, risk-aware approvals. The ensemble model achieved an average accuracy of 90.3% with minimal latency, ensuring timely decisions.

This kind of adaptive, intelligent decision-making system is highly applicable to Eswatini's mobile money platforms, enabling proactive transaction validation without compromising on user experience or processing speed.

2.2.6 Improving Mobile Payment Experience Through User-Centric Modeling

A study by Chen et al. (2023) investigated how user-centric behavior modeling could improve the mobile payment experience and reduce failures due to user errors. They collected interaction logs from a mobile money app and used deep learning models—particularly LSTMs—to predict transaction drop-off points and system-user mismatches (e.g., confusing UI, slow loading).

Their results indicated that over 22% of failed transactions were caused by user behavior, not technical issues. The predictive model, with 91.2% accuracy, helped redesign the app's interface and timing logic. After deploying the optimized version, user success rate increased by 17%, and transaction failures due to timeouts or misclicks dropped by 30%.

For Eswatini, where digital literacy levels vary greatly, this research underlines the need to build user-friendly mobile money platforms that adapt to local user behavior and minimize errors at the source.

2.2.7 Leveraging Ensemble Deep Learning for Transactional Data Integrity

A study by Rahman et al. (2022) explored the use of ensemble deep learning techniques to improve data integrity in mobile financial transactions, especially in low-resource settings like Sub-Saharan Africa. The researchers combined Convolutional Neural Networks (CNN), Long Short-Term Memory networks (LSTM), and Extreme Gradient Boosting (XGBoost) to develop a hybrid model that could analyze historical transaction data and predict abnormalities that commonly precede failure events. The dataset used was sourced from mobile financial service providers operating in rural and semi-urban communities, which included metadata on timestamps, device IDs, transaction amounts, and failure logs.

The study demonstrated that combining deep learning with traditional gradient boosting methods improved the system's performance, achieving an overall prediction accuracy of 95.4%, outperforming standalone CNN and LSTM models. Additionally, the ensemble model reduced false negatives by 19% compared to single-model benchmarks. The authors highlighted how this hybrid system was particularly effective in identifying subtle patterns of data corruption or anomalies that are often missed in basic transaction checks.

This work has high relevance for Eswatini, where mobile money platforms must ensure not only operational reliability but also data integrity due to weak digital infrastructures. Applying ensemble learning to capture multiple layers of data anomalies can significantly enhance system resilience and minimize transaction disruptions caused by data loss

2.3 RESEARCH GAP

There were limited research which focused on mobile money transaction failures in Eswatini where there is a limited infrastructure interms of scalability and poor network operation in some areas. Secondly there is not a single reviewed study was able to integrate machine learning to address both transaction failures and fraud detection in local context. So, this study will bridge the gap by developing a machine learning model made specifically for Eswatini mobile money ecosystem, the model will also integrate machine learning and fraud detection.

2.4 CONTRIBUTION OF THE STUDY

This research will contribute to the field of financial services by designing a machine learning model that discovers and minimizes transaction failures in Eswatini's mobile money services, utilizing a predictive model to reduce failure rates, the study will also enhance user confidence and transaction reliability. It also offers some insights into the main reasons why these transactions in Eswatini failed, this will also assist mobile money providers in trying to prevent the increasing rate of mobile money fraud in Eswatini.

2.5 CHAPTER SUMMARY

This chapter explored on different studies which make use of machine learning to detect and mitigate transaction failures in mobile money services, they also detect fraud on mobile money services. It also identified the existing studies, gaps in the research, and established the need for a localized machine learning model to suit the Eswatini financial environment. The next chapter outlines the methodology used in the research, explaining data collection, techniques used in data processing, and how the development of the model is

CHAPTER 3

3.1 INTRODUCTION

This chapter presents a methodology that will be used to develop the proposed machine learning model for detecting and mitigating transaction failures in mobile money services in Eswatini. This project integrates theoretical and practical approaches in the design ,development , and evaluation of the machine learning model which aims to improve mobile money service reliability .Three methodologies were used which includes design science, system design and implementation and data mining, they were chosen to unsure predictive accuracy and developing a functional artifact.

3.2 RESEARCH METHODOLOGY

3.2.1 Design science research

This is central to the study since the core goal of the project is to develop a functional software system that will solve a real-world problem of failed mobile money transactions. The system is developed iteratively, combining both functional and non-functional requirements based on the user needs and data characteristics.

Key features of Design science research applied in this project:

- **Artefact creation**: here the main artefact is a flask-based web application which is integrated with machine learning models.
- **Relevance:** which is what the system address , a practical issue affecting mobile money users in Eswatini.
- **Rigor:** the machine learning models were trained using a well-structured algorithm and evaluated with performance metrics.
- **Evaluation:** The system will be tested using real transaction data and logging features will be included to evaluate the prediction reliability.

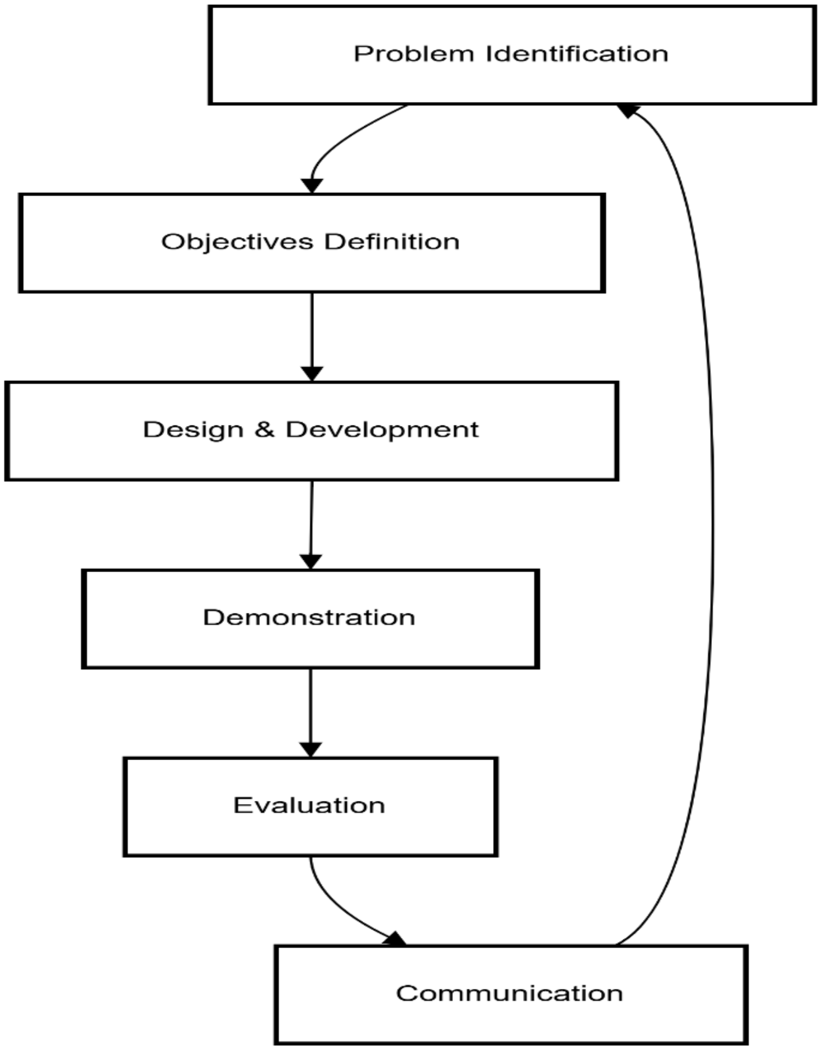


Fig 3.1 Design Science Methodology lifecycle

3.2.2 System Design and Implementation

This methodology focuses on applying software engineering practices to build and then test the working prototype or model. The system was developed using a modular design approach based on the flask framework, with the backend linked to MySQL database and integrated with pre-trained machine learning models.

It followed this process:

- **Reequipments Analysis:** user needs were identified , like predicting transaction success or failure before it occurs ,giving the user the option to continue with the transection or not thus reducing traffic on the network which may also lead to transaction failure.
- **Design:** The system architecture was defined with three layers that is fronted, backend and database.
- **Implementation:** technologies like Flask(Python), HTML, MySQL, and joblib for model serialization.

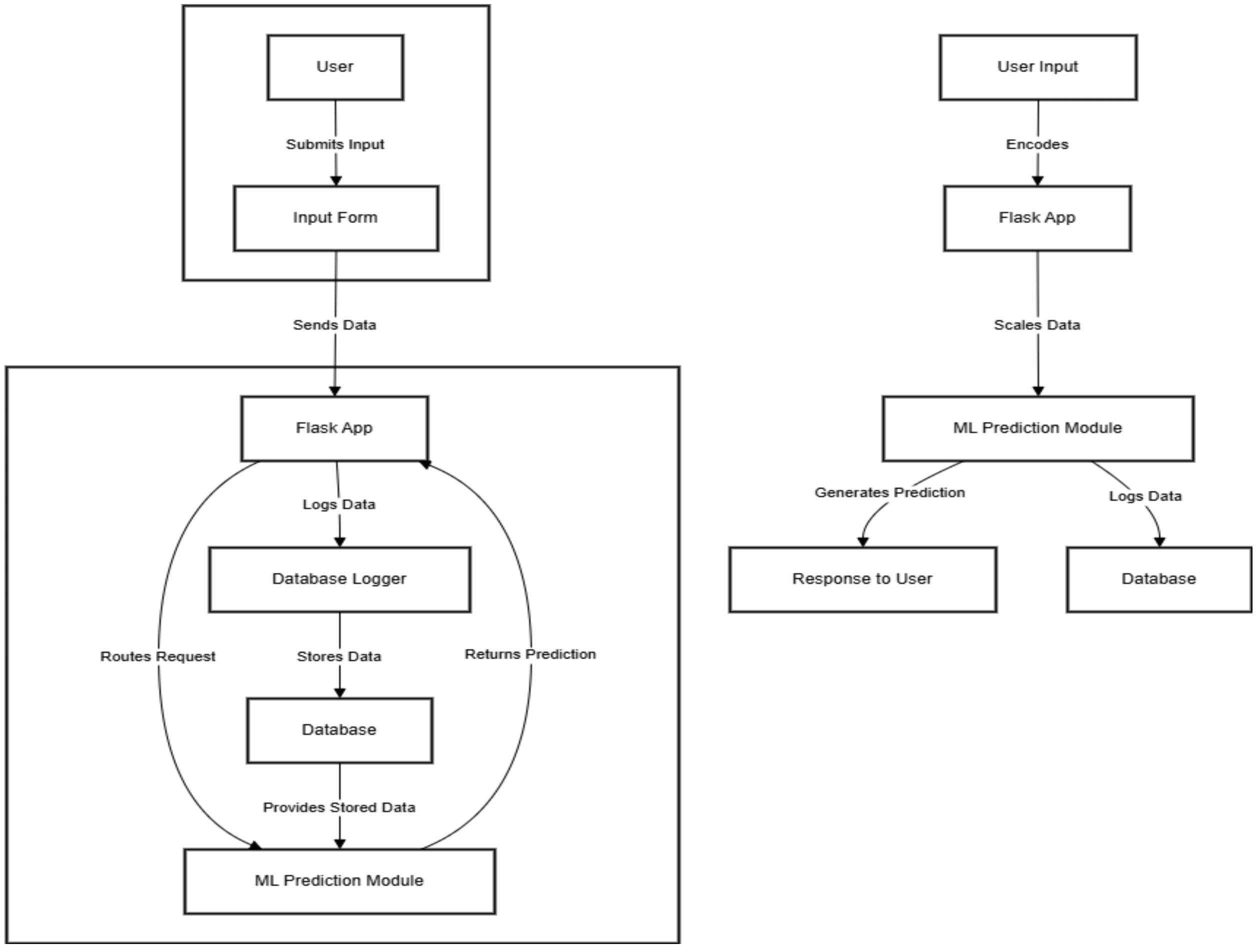


Fig 3.2.2 System Architecture of the Mobile Money Transaction Prediction System

3.2.3 Data mining

The most significant part of the system which is the prediction engine was built upon data mining techniques which includes:

- **Feature Extraction and Engineering:** Extracted features like time of the day, day of the week, transaction amount and sender balance.
- **Model Training:** Historical transaction data will be used to train five models which are : Random Forest,SVM,Gradient Boosting, ANN and Logistic Regression.
- **Anomaly Detection:** This help to improve fault tolerance and prediction accuracy, identifying outliers that may result in transaction failure.

3.3 DATA COLLECTION AND PREPARATION

Due to high increase on the mobile money fraud in Eswatini the transaction data is restricted from access thus the research is going to use online publicly available and relevant datasets to simulate and model transaction behavior. Thus historical mobile money data was sourced from publicly available datasets and cleaned for consistency and quality. Variety of available datasets will identify and used to develop and also test the machine learning model. These datasets include:

- World bank mobile money dataset: this dataset will help to provide statistical data about mobile money transactions that includes transaction failure rates, the actual reasons for failures and fraud trends across multiple countries.
- GSMA Mobile money adoption dataset: they offer understanding about the transaction behaviors , which includes network issues and user behavior patterns that affects mobile money transactions .
- Financial Inclusion Insights(FII) dataset: this dataset consists of survey data on mobile money adoption and transaction failures thus helping in understanding the user behavior and transaction failure rates.
- Kaggle synthetic financial datasets for fraud detection: these are type of synthetic datasets generated by the PaySim mobile money simulator

3.3.1 Data Preprocessing

Data preprocessing is   a crucial initial phase to prepare the datasets for effective analyses; this process will include these steps: We will first import all the needed libraries and load the datasets.

- **Data cleaning**: here transactions with missing data or incomplete fields will be removed, duplicate entries will also be removed in order to avoid redundancy and inaccurate results.
- **Feature engineering**: where new features will be identified and extracted , these are significant variables which contributes to mobile money transaction failures. These features include, transaction times patterns, frequency and recency of transactions and user behavior indicators, Feature selection techniques such as correlation analysis and feature importance from tree-based models will be applied.
- **Data normalization**: after cleaning the data, standardization techniques will be applied to numerical to ensure uniformity across all variables, z-score normalization will be used to ensure that all features equally contribute to the model.
- **Data splitting**: The datasets will be splitted into 80% for training , , and 20 % for testing sets.

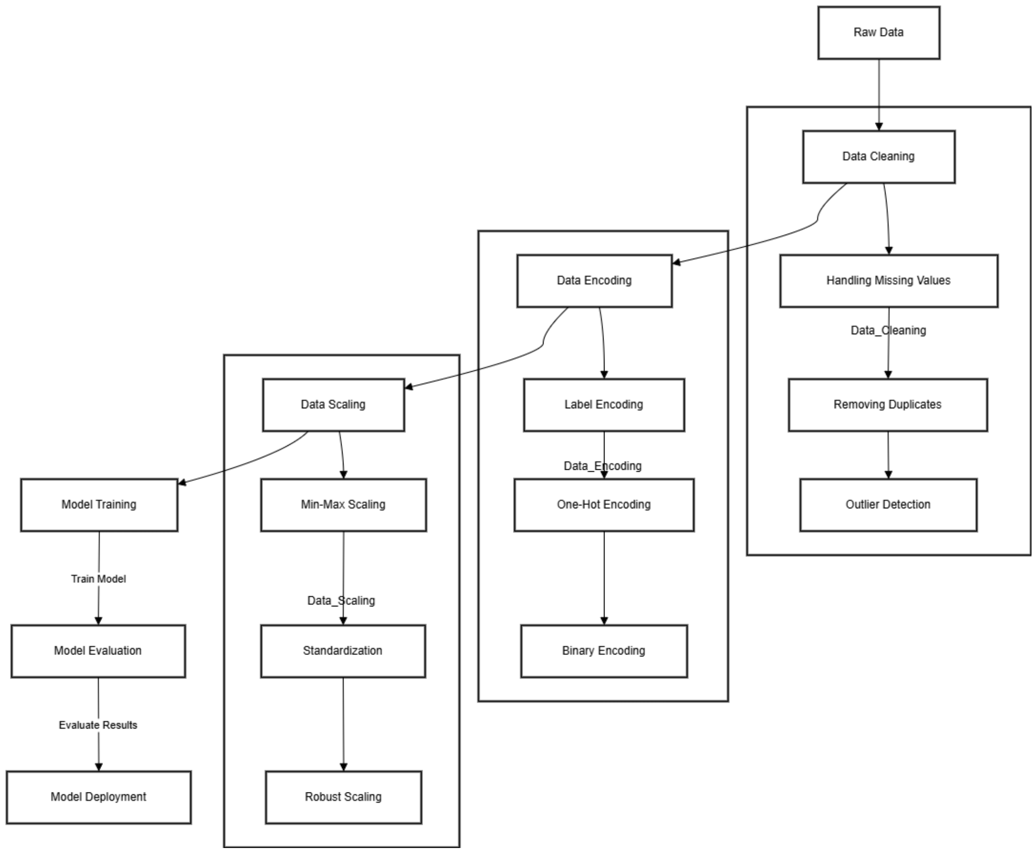


Fig 3.3.1A Data Preprocessing Pipeline

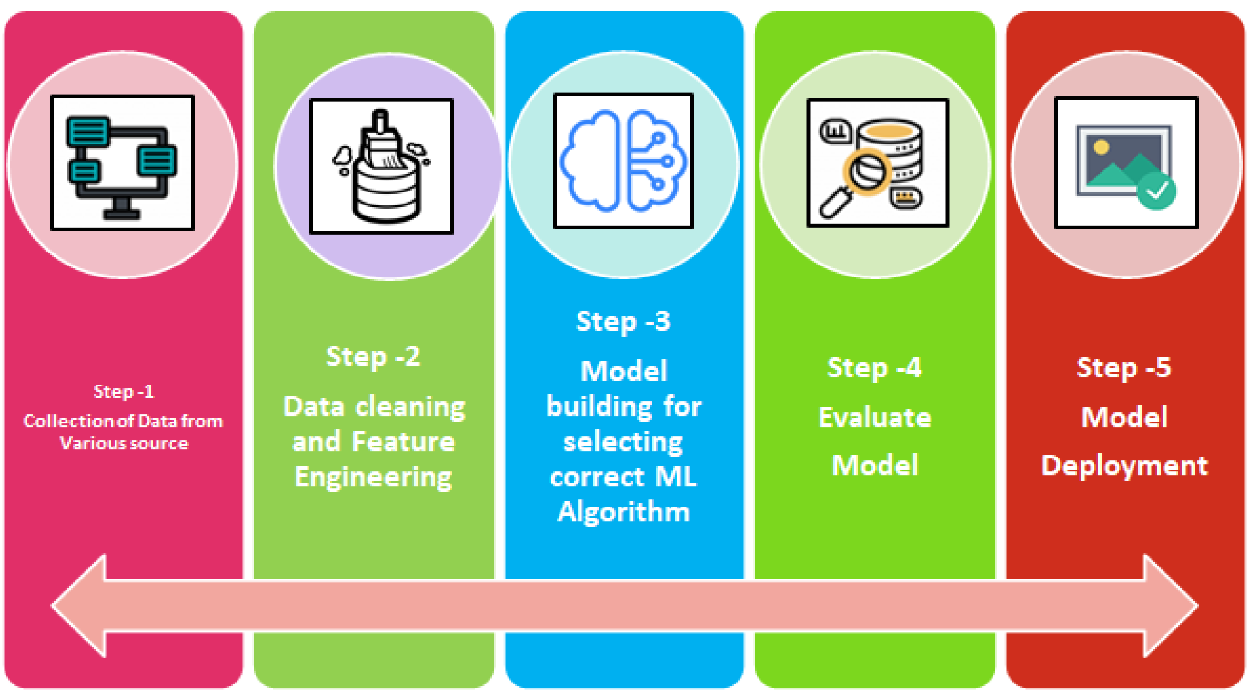


Fig 3.3.1B The entire process of model development

3.3.2 Tools and Technologies to be used:

- **Flask :** Web framework for building the application backend
- **MySQL:** Relational database for storing user and transactional data.
- **Scikit-learn, TensorFlow/Keras**: used for machine learning model development.
- **Joblib:** for serializing trained models.
- **HTML/CSS:** language used to build the user interface.
- **Python:** This is the core language used for backend logic and data processing .

3.4 MODEL EVALUATION:

The following evaluation metrics will be used to measure the effectiveness of the trained models:

- Accuracy: it will be used to measure the overall correctness of predictions done by the models
- Precision and recall: it ensures that the model correctly identifies any failed transactions and also minimizing false positive and false negatives.
- F1-score: it is useful for imbalanced dataset; this will balance between precision and recall .
- Confusion matrix: it will help to analyze classification errors.
- Receiver Operating Characteristic -area Under Curve(AUC-ROC curve): this evaluates model performance in differentiating between successful and failed transactions.

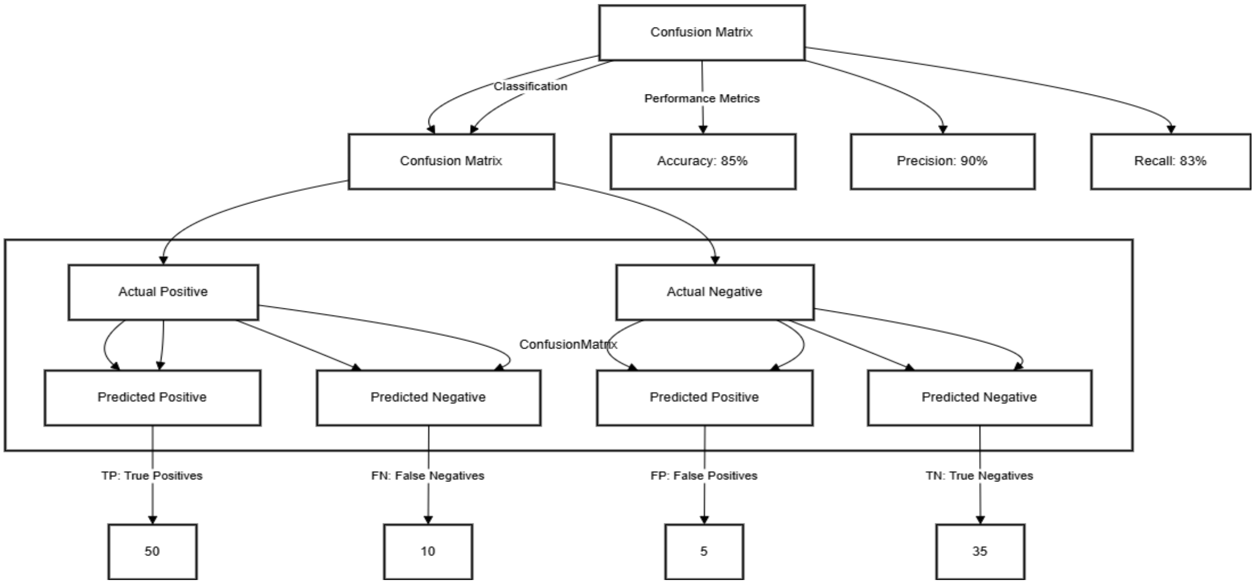


Fig 3.4 Confusion Matrix for Model Evaluation

3.5 Model Deployment and mitigation strategies

- Integration with mobile money platforms: The model will be deployed as an API service which interacts with transaction systems.
- Real-time failure prediction: Alerts for failures before transaction are processed.
- Automated Mitigation: the model will execute a corrective actions like transaction retries, customer notifications , routing transaction trough alternative channels.

3.6 Implementation details

After the model is evaluated, it will be implemented in a prototype system using Python-based frameworks such as:

- Scikit-Learn which is for machine learning development.
- XGBoost and LightGBM which is for gradient boosting.
- TensorFlow/Keras which is used for deep learning approaches.
- Flask/Django used to develop an API for real-time prediction.

3.7 Ethical considerations:

- **Data privacy and security**: Compliance with data protection regulations in Eswatini ensured.

- **Informed consent**: Before data was collected from the data providers and participants permission is obtained .

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3.8 Chapter summary

This chapter has presented the research methodology adopted in detecting and mitigating mobile money transaction failures in Eswatini. The study will use machine learning techniques based on publicly available datasets preprocessed to guarantee data quality. Several machine learning models will be experimented on and compared for the best performance in detecting transaction failure. The implementation will be done with Python, Jupyter Notebook, TensorFlow, and Scikit-learn for rapid development.

The implementation and experimental results of the proposed model will be discussed in the next chapter.

CHAPTER 4

IMPLEMENTATION

4.1 Introduction

This chapter consist of the implementation details of the mobile money machine learning model for detecting and mitigating mobile money transactions in eSwatini. It describe the practical development steps taken based on the methodology presented in chapter three. It entails hardware and software requirements, system architecture diagrams, screenshots of developed components and summary of technologies used in development process.

4.2 Software and Hardware requirements

4.2.1 Software requirements

Software component	**Description**
Python 3.11+	Core programming language
MySQL	Relational database system
Flask	Web framework for backend API
Joblib	Model serialization
Scikit-learn, TensorFlow	ML libraries used for model training
HTML/CSS	Fronted User Interface Design
Visual Studio Code	Development environment

4.2.2 Hardware Requirements

Hardware component	Minimum Specification
Processor	Intel core i5 or equivalent
RAM	8 GB
Storage	500 GB HDD or 256 GB SSD
Internet	Required for deployment and testing

4.3 System Architecture

4.3.1 Overview

The system architecture is based on a client-server model where the user interacts with a web-based frontend that sends requests to flask-based backend .The backend then communicates with a MySQL database and an ensemble of machine Learning Models serialized with joblib. The system uses a classic three-tier client-server architecture with : presentation layer which is a client side, Application layer which is a backend and the data layer which is MySQL relational database.

4.3.2 System Architecture Diagram

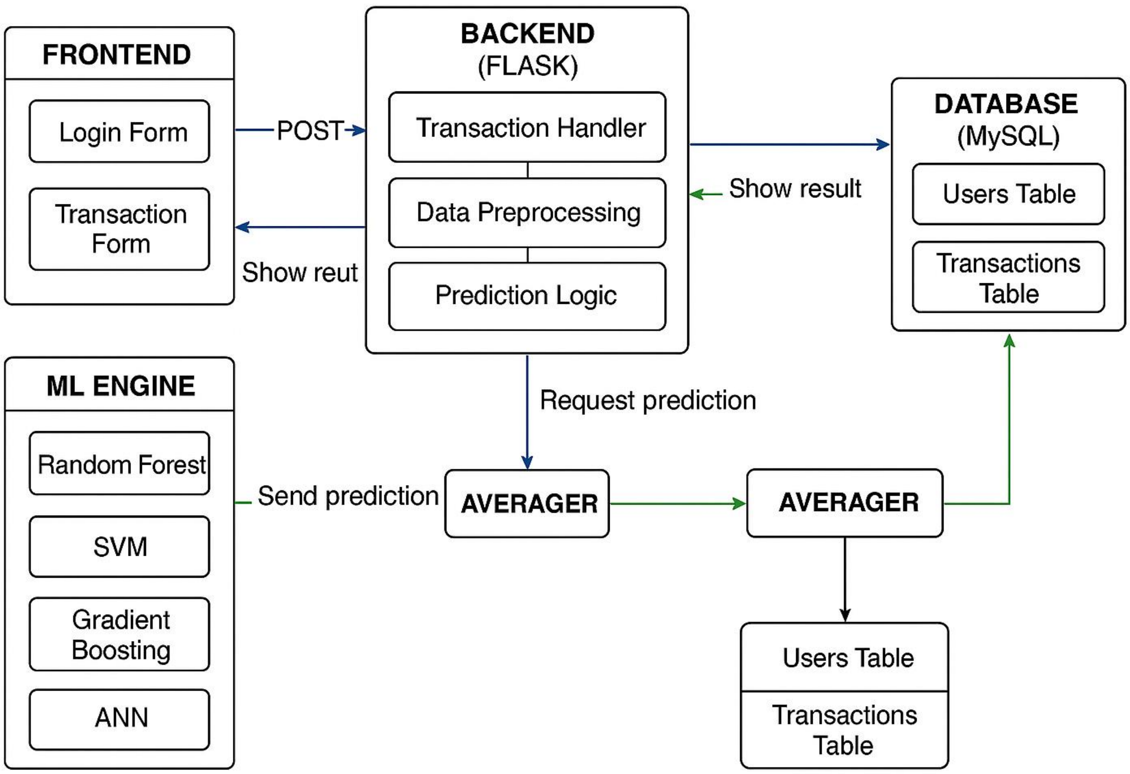
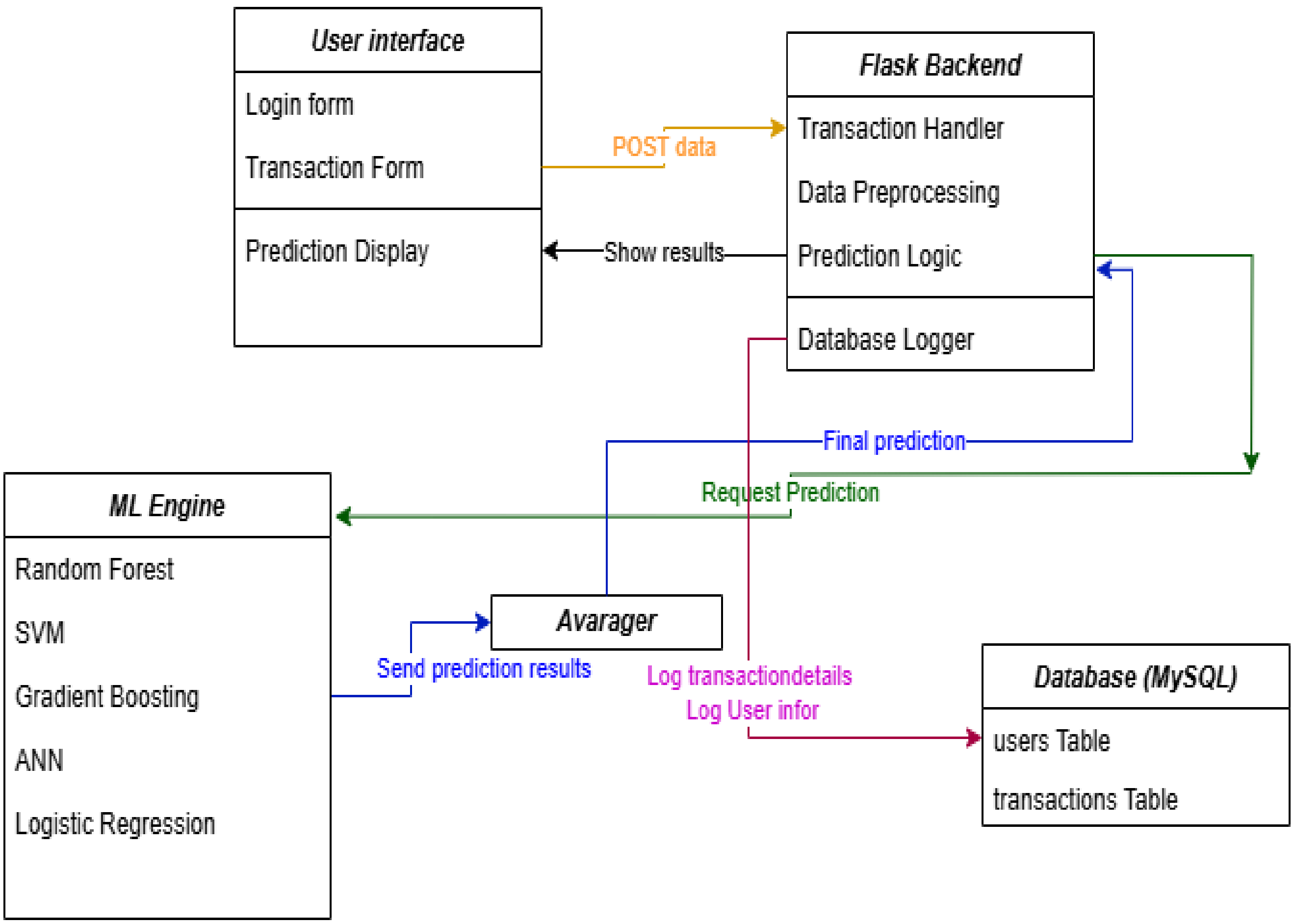


Fig 4.3.2 System architecture diagram

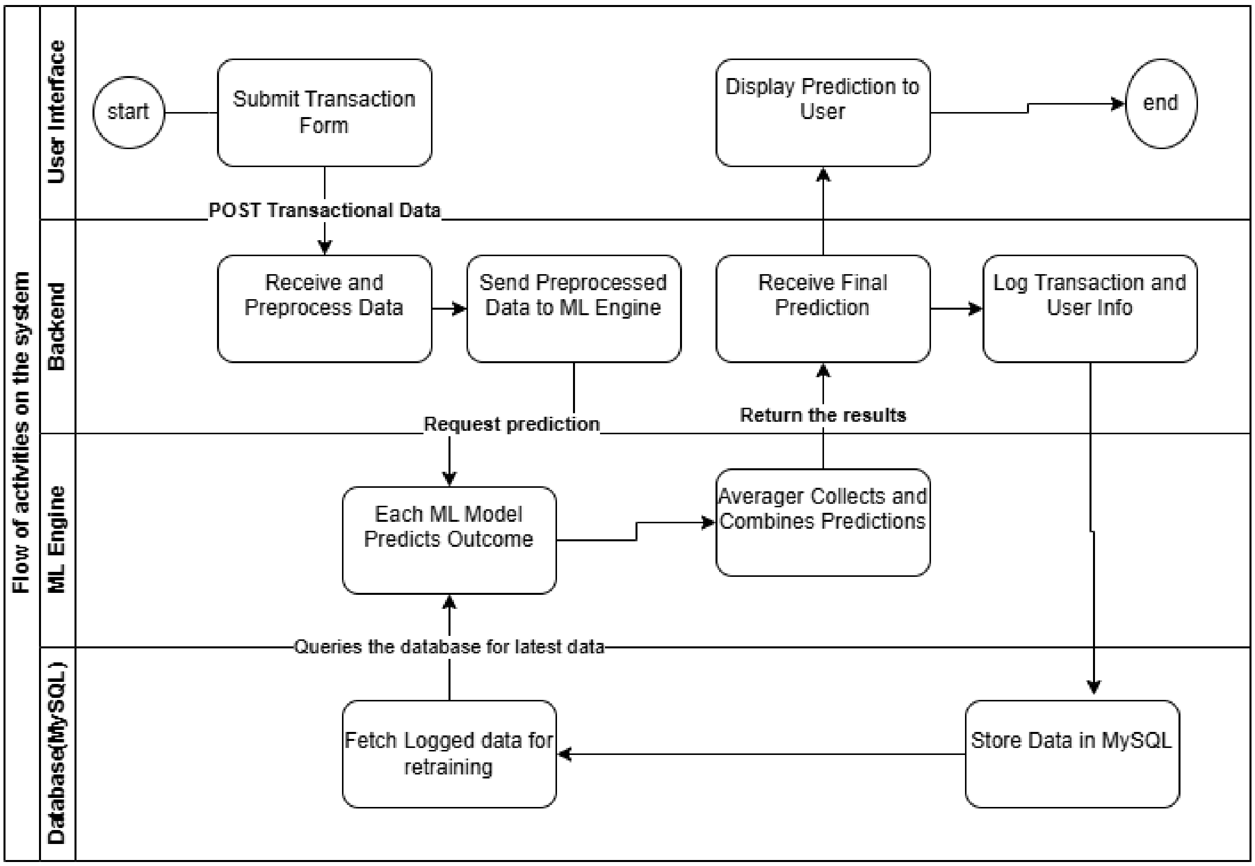
4.4 UML Diagrams

4.4.1 Use case Diagram



4.4.2 Activity Diagram

The Activity diagram which shows the logical flow of activities from when the user submits the transaction details ,to when the system processes the prediction and logs the transaction information into the database.



4.5 Implementation Details

This section outlines detailed implementation of the system, it outlines steps for data preprocessing ,model training ,and evaluation metrics based on the methodology in chapter 3, the screenshots of relevant code for each step are included to ensure clarity.

4.5.1 Data preprocessing

Before training the machine learning models the crucial step of cleaning and data normalization was taken where missing ,duplicates values were handled and scaling numerical features. The data was cleaned and prepared for model training.

```
# Handle missing values
df.fillna("Unknown", inplace=True)

# Encode categorical variables
label_encoders = {}
categorical_columns = ['Network_Provider', 'Day_of_Week', 'Transaction_Type', 'Status']
for col in categorical_columns:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col])
    label_encoders[col] = le

# Convert Time_of_Day to hour
df['Time_of_Day'] = pd.to_datetime(df['Time_of_Day'], format='%H:%M').dt.hour
```

Fig 4.5.1 Code for data Preprocessing

4.5.2 Model training

This is the process of applying machine learning algorithms to the preprocessed data in order to create models which are capable of making prediction, below is the code that train an ensemble of models on the transactional data.

```
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)

# Models
models = {
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "SVM": SVC(kernel='linear', probability=True, random_state=42),  # Enable probability
    "Gradient Boosting": GradientBoostingClassifier(n_estimators=100, random_state=42),
    "ANN": MLPClassifier(hidden_layer_sizes=(100,), max_iter=500, random_state=42),
    "Logistic Regression": LogisticRegression(max_iter=500, random_state=42)
}

# Train models and evaluate performance
for name, model in models.items():
    model.fit(X_train, y_train)
```

Fig 4.5.2 Code for Model training

4.5.3 Model evaluation

After training the models we the assessed its performances using different metrics like accuracy,precision,recall and F1-score and they achieved these results in percentage. The following screenshots show the evaluation results for each model on test data.

```
Random Forest Evaluation Metrics:
Accuracy: 0.8475
Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.61      0.72       127
           1       0.84      0.96      0.90       273

    accuracy                           0.85       400
   macro avg       0.86      0.78      0.81       400
weighted avg       0.85      0.85      0.84       400

Confusion Matrix:
[[ 77  50]
 [ 11 262]]
AUC Score: 0.7860315537480892
```

Fig 4.5.3A evaluation results for Random Forest

```
SVM Evaluation Metrics:
Accuracy: 0.8075
Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.65      0.68       127
           1       0.85      0.88      0.86       273

    accuracy                           0.81       400
   macro avg       0.78      0.77      0.77       400
weighted avg       0.80      0.81      0.81       400

Confusion Matrix:
[[ 83  44]
 [ 33 240]]
AUC Score: 0.7881803236133945
```

Fig 4.5.3B evaluation results for SVM

```
Gradient Boosting Evaluation Metrics:
Accuracy: 0.8350
Classification Report:
              precision    recall  f1-score   support

           0       0.85      0.58      0.69       127
           1       0.83      0.95      0.89       273

    accuracy                           0.83       400
   macro avg       0.84      0.77      0.79       400
weighted avg       0.84      0.83      0.83       400

Confusion Matrix:
[[ 74  53]
 [ 13 260]]
AUC Score: 0.7777248997721439
```

Fig 4.5.3C evaluation results for Gradient Boosting

```
ANN Evaluation Metrics:
Accuracy: 0.8575
Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.61      0.73       127
           1       0.84      0.97      0.90       273

    accuracy                           0.86       400
   macro avg       0.88      0.79      0.82       400
weighted avg       0.87      0.86      0.85       400

Confusion Matrix:
[[ 77  50]
 [  7 266]]
AUC Score: 0.7943237864497708
```

Fig 4.5.3D evaluation results for ANN

```
Logistic Regression Evaluation Metrics:
Accuracy: 0.7950
Classification Report:
              precision    recall  f1-score   support

           0       0.68      0.66      0.67       127
           1       0.84      0.86      0.85       273

    accuracy                           0.80       400
   macro avg       0.76      0.76      0.76       400
weighted avg       0.79      0.80      0.79       400

Confusion Matrix:
[[ 84  43]
 [ 39 234]]
AUC Score: 0.7863344005076288
```

Fig 4.5.3E evaluation results for Logistic Regression

4.5.4 Comparison Summary

Model	**Accuracy**	**Precision (0/1)**	**Recall (0/1)**	**F1-Score (0/1)**
ANN	0.8575	0.92/ 0.84	0.61/ 0.97	0.73/ 0.90
Random Forest	0.8457	0.88/ 0.84	0.61/ 0.96	0.72/ 0.90
Gradient Boosting	0.8350	0.85/ 0.83	0.58/ 0.95	0.69/ 0.89
SVM	0.8075	0.72/ 0.85	0.65/0.88	0.68/ 0.86
Logistic Regression	0.7950	0.68/ 0.84	0.67/0.85	0.76/ 0.79

NB: *class 0 = Failed transactions, class 1 = Successful transactions*

Table 4.5.4 Comparative performance of classification models

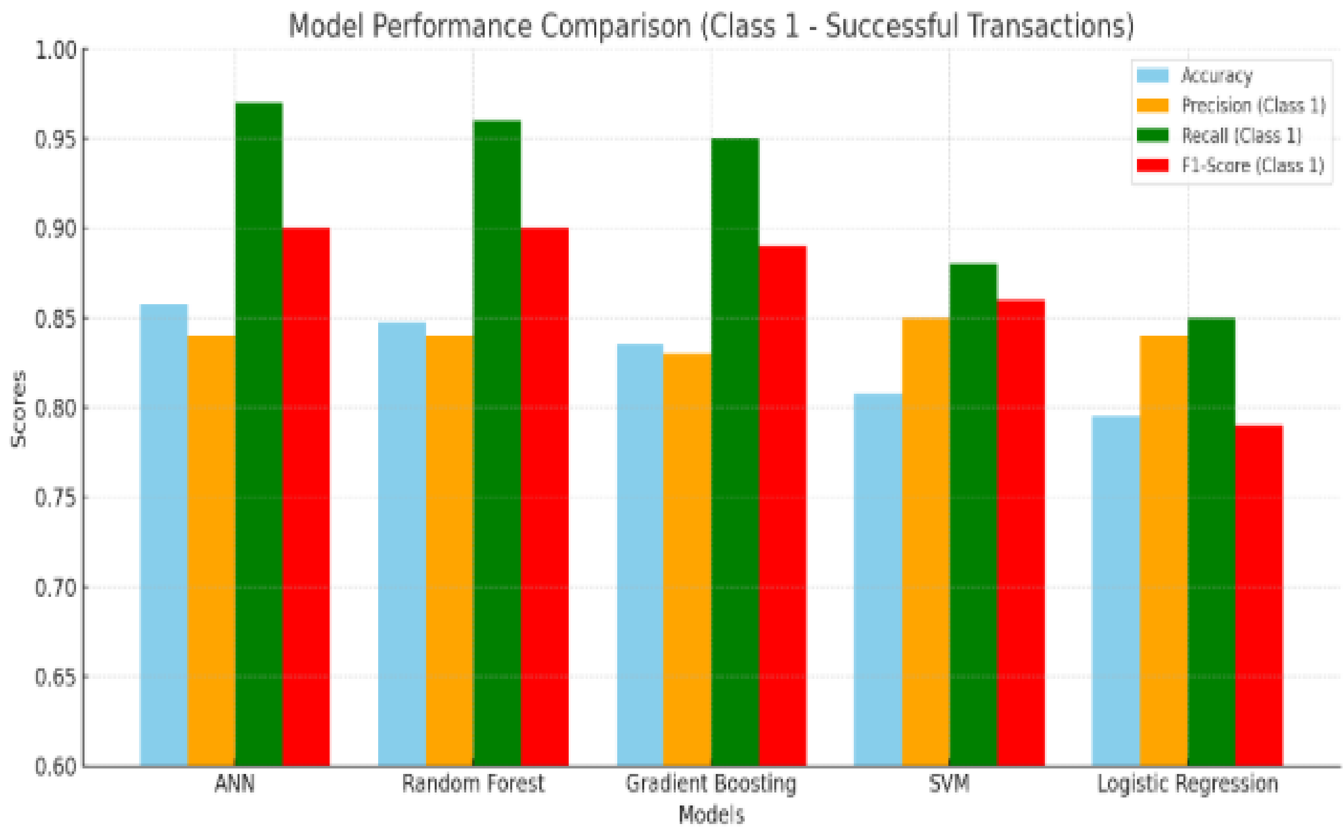


Fig 4.5.5 Graph for model performance comparison

These table and graph provide a comparative overview of the classification performance of the five machine learning models evaluated in the study, where the Artificial Neural Network achieved the highest overall accuracy of 85.75% and the best recall for successful transaction of 0.97 thus making this model to be highly effective at detecting positive transaction outcomes. We then had a Random Forest which followed closely with accuracy of 84.75 % ,Gradient Boosting followed with accuracy of 83.50 % ,SVM with accuracy 80.75 % and the Logistic Regression with 79.50 %.

To enhance the prediction reliability and generalization ,an ensemble learning approach was used by aggregating the outputs of the five classification models. Each of these models was trained and evaluated individually, so to ensure complementary strengths of these classifiers , a soft voting ensemble strategy was applied . Each predicted probability of each model were averaged to determine final class label. This approach helped the system to capitalize on the high recall of

ANN and Random Forest for successful transaction detection, while making use of the precision of all the other models in identifying failed transaction. This method proved effective in reducing false negatives and false positives.

4.5.5 Database Creation

Database called mobile_money_db was created

- ✓ Transaction table:

1	transaction_id	int(11)		No	None	AUTO_INCREMENT
2	user_id	int(11)		No	None	
3	phone_number	varchar(15)	utf8mb4_general_ci	No	None	
4	transaction_type	varchar(50)	utf8mb4_general_ci	No	None	
5	amount	decimal(10,2)		No	None	
6	sender_balance_before	decimal(10,2)		No	None	
7	sender_balance_after	decimal(10,2)		No	None	
8	time_of_transaction	time		No	None	
9	day_of_week	varchar(10)	utf8mb4_general_ci	No	None	
10	status	varchar(20)	utf8mb4_general_ci	No	None	
11	failure_reason	text	utf8mb4_general_ci	Yes	NULL	
12	network_provider	varchar(50)	utf8mb4_general_ci	No	None	
13	prediction_success_probability	decimal(5,2)		No	None	
14	prediction_failure_probability	decimal(5,2)		No	None	

Fig 4.5.5B Transactions table on the database

- ✓ Users table:

#	Name	Type	Collation	Attributes	Null	Default	Comments	Extra	Action
1	id	int(11)			No	*None*		AUTO_INCREMENT	Change Drop More
2	phone_number	varchar(15)	utf8mb4_general_ci		No	*None*			Change Drop More
3	pin	varchar(5)	utf8mb4_general_ci		No	*None*			Change Drop More
4	balance	decimal(10,2)			Yes	0.00			Change Drop More
5	created_at	timestamp			No	current_timestamp()			Change Drop More

Fig 4.5.5C Users table on the database

4.6 System Artifacts

This is a subsection which focuses on the visual and architectural components of the including the user interface ,backend like database. Screenshots of key artifacts like the login page, transaction page and the database schema are provided.

4.6.1 Login page

This is the first point of interaction with the system where the users authenticate themselves. Below is the screenshot

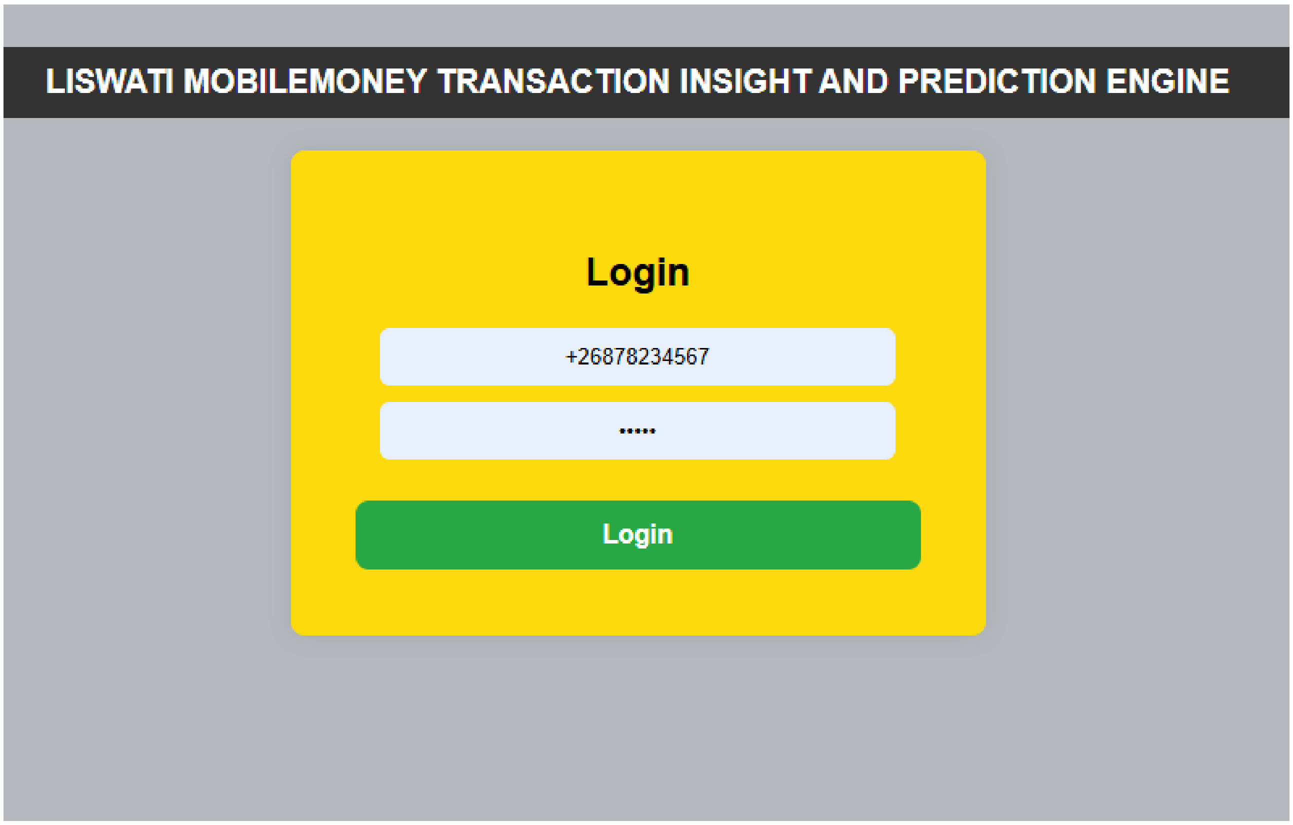


Fig 4.6.1 Screenshot for a login page for the system

4.6.2 Transaction Page

Once the user is logged in ,they can access the transaction page that allows them to submit transaction details for processing, and the page also shows the prediction results. Below is the screenshot of the transaction page.

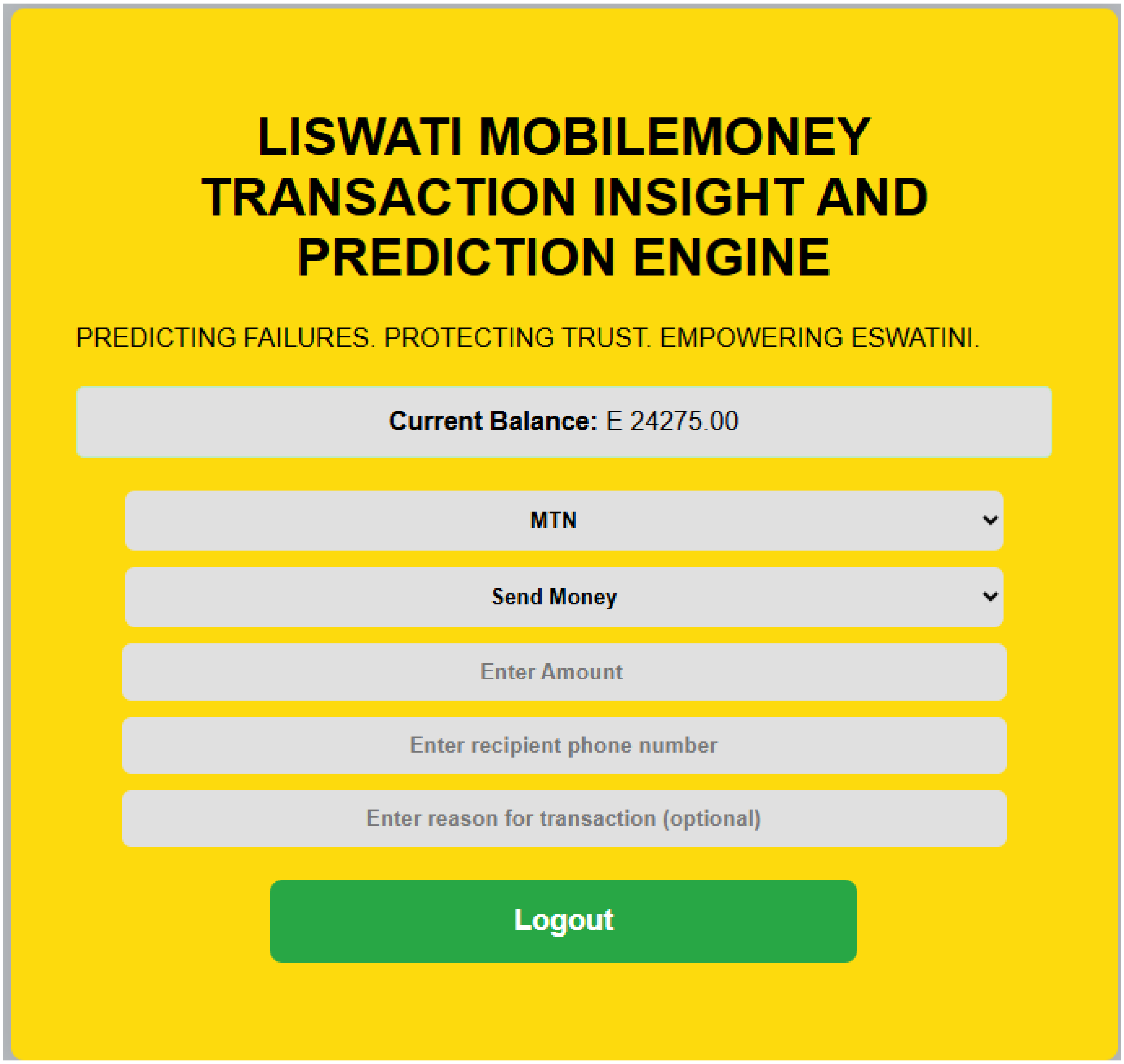


Fig 4.6.2A Transaction page

Transaction page with the prediction results:

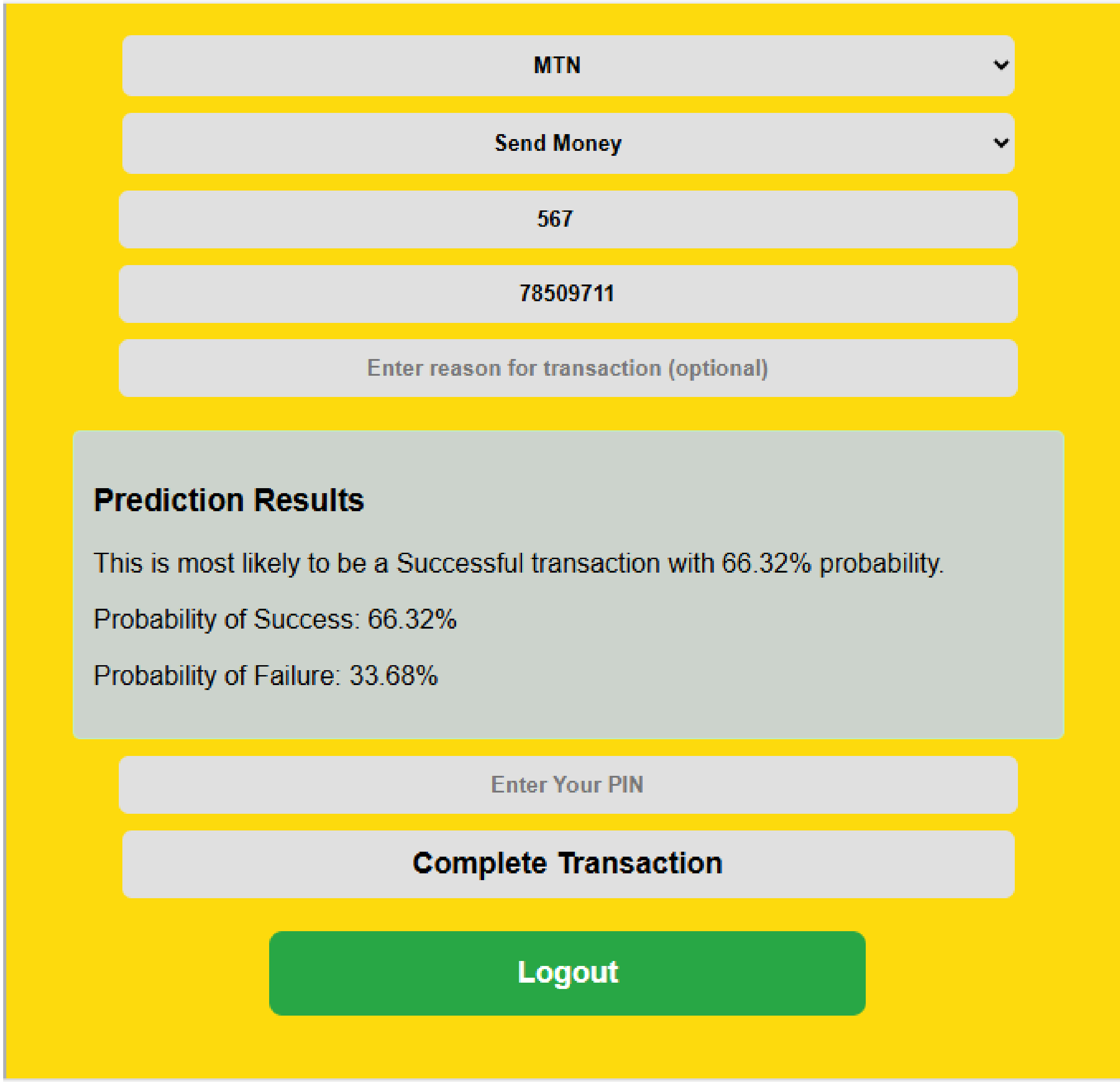


Fig 4.6.2B Transaction page

4.7 Database Schema

The database stores transaction data ,model prediction and other relevant information, Any transaction which occurs is being logged here. below is a screenshot of database schema showing the structure of the table used.

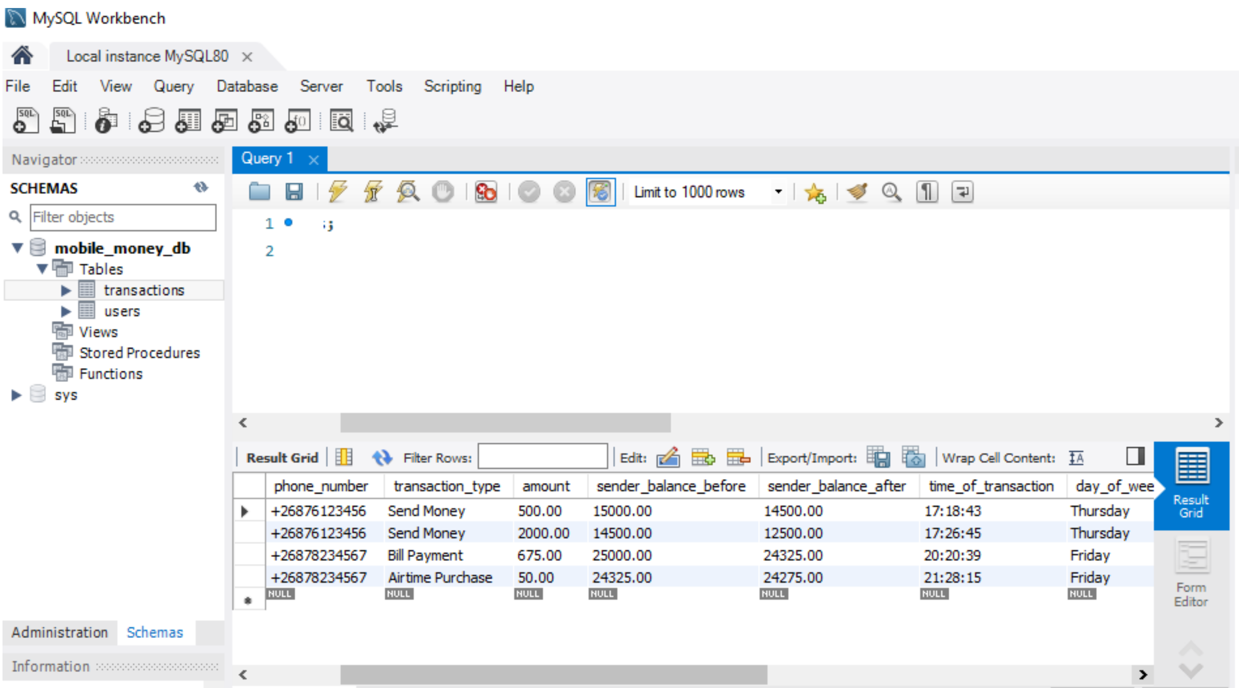


Fig 4.7.1A screenshot for transaction table

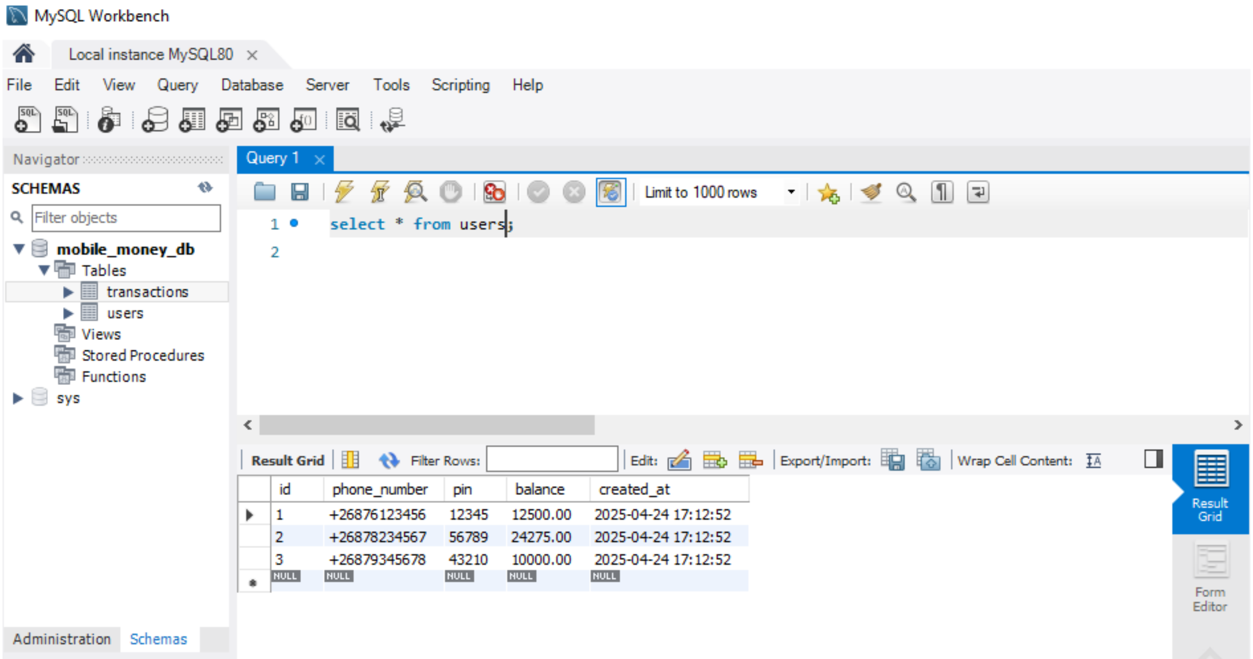


Fig 4.7.1B screenshot for users table

4.8 System deployment

This subsection outlines how the system was deployed in a simulated environment allowing the users to interact with it and also assess its usability and performance . At the current stage the system has been developed and tested locally as a working prototype, although the full system is not deployed in a live environment the important functionalities like machine learning model predictions, data processing and user interface interaction have been verified and in a controlled development setup.

4.8.1 Intended Deployment approach

The prototype is designed to be deployed as a web application using the following stack:

- Frontend: HTML/CSS
- Backend: Flask REST API

- Database: MySQL(which is locally hosted)
- Model Integration: Serialized models using joblib, served through Flask.
- USSD gateway integration: for future phone use.
- SMS notification system: for alerting the of predicted failures .

4.8.2 USSD and SMS integration

These components are planned but not yet implemented in the current prototype since the integration will require third-party API like local Telcom-provided gateways.

- USSD interface: this will allow users who are using the short code manus to do transactions to be able to get transaction prediction.
- SMS alerts: they will provide the user with prediction results , even those who are not using smartphones in rural arears.

4.8.3 Current limitations

- Only web-based interaction has been tested in the prototype
- No real-time USSD or SMS gateway integration due to limited access to local mobile operator APIs.
- Live deployment and telecom partnership are pending to activate these missing components.

4.8.4 Future deployment steps

- Partner with Telcom providers to register USSD codes and SMS short codes.
- Extend the Flask routes and database logic to handle text-based request and responses.
- Try to deploy backend API to cloud platform with endpoint routing for USSD and SMS traffic.

4.9 Chapter Summary

This chapter has presented the actual implementation of mobile money transaction prediction system , a prototype to detect and mitigate transaction failures in Eswatini have been developed. Here there is a detailed software and hardware requirements, system architecture, UML diagrams, model training and evaluation processes and system artifacts like the user interface and database structure.

Tools that were used to develop the system was , Python through VS code, Flask, MySQL and other machine learning libraries, five predictive models were integrated into a unified backend. The prototype function in local development environment since a full deployment strategy has been proposed including plans for the system to support USSD and SMS interfaces in order to accommodate all users. Although some features are pending but the system successfully demonstrates its core functionality and lays the groundwork for future expansion.

CHAPTER 5

LIMITATIONS,CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This chapter presents the key findings of the study, then discusses their significancy in the context of prior chapters and also identifies areas where outcomes stray from expectations and requirements. The chapter concludes by summarizing the contributions made by the research.

5.2 Summary of key findings

The study successfully developed a prototype machine learning model that is capable of predicting and mitigating mobile money transactions failures in Eswatini. Through the use of ensemble of models which are :Random forest, SVM,ANN, Gradient Boosting and Logistic Regression, whereby the system demonstrated high accuracy in identifying potential failed transactions based on historical transactional data.

Key findings:

- The Random Forest and Gradient Boosting models showed the highest performance interms of accuracy and F1-score among the other models .This has proved the models ability to correct and classify both successful and failed transactions making the system to be more effective.
- The system architecture built on Flask and MySQL supports future extensibility and integration. This architecture was chosen for its simplicity ,ease of deployment and its salacity.
- The prototype design consider user inclusivity trough proposed USSD and AMA intergration.This will help to ensure that users without internet access can still benefit from the system's predictive functionalities.
- The proposed system can be utilized an early warning tool for mobile money service provider .By flagging potentially transaction failure before they occur and also before that transaction is executed , thus limiting the traffic and also helping the providers to address issues like backend system congestion.

The above findings have shown consistency to the earlier studies which include that was conducted by Bashir et al. (2021) and Kumar et al.(2021) that highlighted the transformative role of machine learning in improving reliability of financial transactions.

5.3 Limitations of the study

- **Data access:** due to high increased of fraud in the country transactional data was not accessible , so this study relied on publicly available dataset that may not reflect local transaction behaviors accurately.
- **Deployment limitation:** the system is currently a prototype and not deployed on a real-world mobile money platforms, thus real-time prediction and mitigation in production environment remain untested.
- **Incomplete USSD and SMS functionality:** these features are not yet implemented because of lack of access to Internet Service Provider APIs.
- **Evaluation scope :** the fact that the system was evaluated in a controlled environment so broader usability testing involving scalability testing of the users on the system has not been conducted.

5.4 Conclusion

This research set out to address the issue of mobile money transaction failures in Eswatini, where the mobile financial services are a backbone of the economic activities and financial inclusion. The project succefully developed and evaluated a machine learning-based prototype system which is capable of predicting and mitigating mobile transaction failures through the use of an ensemble of five models which are : Artificial Neural Network, Random Forest, Gradient Boosting, Logistic Regression and Support Vector Machine.

The findings has showed that machine learning techniques can accurately detect transaction failures before they occur with the Artificial Neural Network model achieving highest accuracy of 85.75%. The ensemble technique helped to improve the prediction reliability through combining the strengths of each individual model. Regardless of the limitations , the project made use of publicly available datasets and simulated environments which helped for real-world mimic. The architecture has been designed to be able to allow for future integration with USSD and SMS gateway allowing it accessibility to users without internet access

5.5 Recommendations

Data collaboration with ISPs

Internet Service Providers (ISP) and financial institutions in Eswatini should collaborate with researchers and also grant them controlled access to anonymized transaction data in order to improve accuracy of the model and also make it to be localized in the financial environment of Eswatini.

Full Deployment and pilot Testing

Researchers should partner with Mobile money service providers for pilot deployment of the system in a real transaction space, that will help to allow real-time testing ,monitoring and refinement of the system based the user requirements.

USSD and SMS integration

The system should integrate USSD and SMS functionality to serve users who lives in rural areas who do not have internet access, this will help to ensure to fill the digital gap and also ensure that the system is practical nationwide.

Fraud detection integration

The system should be integrated with fraud detection by incorporating deep learning models like CNNs and RNNs , and this can help in preventing both transaction failures and mobile money fraudulent activity.

Admin interface for service providers

An administrative interface should be developed for mobile money service providers, this will assist the service providers to be able to monitor the system performance ,view flagged transactions, generate reports and also take proactive actions based on the system alerts.

User Training and awareness campaigns

Users should be trained and also educated on how the system works and also how to interpret the probability display before a transaction.

Scalability Testing and Cloud deployment

A scalability testing should be conducted to ensure that the system is capable of handling high transaction volumes without affecting its performances

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