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MACHINE LEARNING–BASED CREDIT RISK ASSESSMENT FOR ADVANCING FINANCIAL INCLUSION IN ZIMBABWE: A MOBILE MICROLOAN PLATFORM APPROACH

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Approval Form

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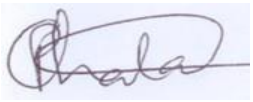

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ABSTRACT

There is still a lot of work that needs to be done to ensure that there is proper financial inclusion in Zimbabwe, where most people are involved in informal economic activities, yet lack the necessary collateral for loans from conventional banking institutions. Although mobile money providers like EcoCash in Zimbabwe have made strides in ensuring transactional access, formal credit access is still low. The proposed platform is an Inclusive Mobile Microloan Platform that incorporates a machine learning model to evaluate borrower credit risk in order to enhance financial inclusion.

Users would be able to upload their mobile money transactions history in PDF format that will be automatically parsed by the platform and used to generate alternative data features such as transaction frequencies and stability of cash flow. With the help of a Random Forest classifier, the platform will evaluate the credit risk based on those indicators of borrowers' behavior. Following the Design Science Research (DSR) framework, the proposed study would follow agile software development methodology to create a platform prototype and test its ability to predict borrower credit risks.

Keywords: Machine Learning, Financial Inclusion, Credit Risk Assessment, Mobile Microloans, Alternative Data, Random Forest, PDF Parsing.

DEDICATION

This dissertation in research is dedicated to my loving and supportive parents Mr. & Mrs. Soza for their unending support, sacrifices, and love without which I could not have achieved what I did. This dissertation is also dedicated to my sisters, Vanessa and Patricia, for their support and faith in my ability at difficult times.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
AI	Artificial Intelligence
API	Application Programming Interface
AUC	Area Under the Curve
BUSE	Bindura University of Science Education
DSR	Design Science Research
DSRM	Design Science Research Methodology

GBM	**Gradient Boosting Machine**
HTTPS	**Hypertext Transfer Protocol Secure**
ML	**Machine Learning**
MSME	**Micro, Small and Medium Enterprises**
RBZ	**Reserve Bank of Zimbabwe**
ROC	**Receiver Operating Characteristic**
XAI	**Explainable Artificial Intelligence**

1 CHAPTER 1: INTRODUCTION

1.0 Introduction

Financial technology (FinTech) is considered to be the enabler for inclusive growth in developing countries. In Zimbabwe, although digital financial services have revolutionised the transaction patterns of individuals and small businesses, an entrance to formal credit has remained constrained for individuals in the informal sector. The traditional financial services sector continues to rely on collaterals, formal documentation and credit history to make credit decisions, making the financial sector largely inaccessible for the large population in the informal sector (RBZ, 2023).

To tackle these hindrances, the traditional financial institutions are integrating data-driven credit models that leverage mobile technology and artificial intelligence for borrower's creditability assessment. The probability of repaying loans can be determined through analysing the behaviour and transaction data captured in user uploaded mobile money statements e.g., EcoCash transaction histories in PDF format by the use of machine learning algorithms (World Bank, 2023).

The objective of the Inclusive Mobile Microloan Platform is to build a mobile based micro-lending platform which will use machine learning algorithms to perform an automated credit scoring and loan approvals. The system requires the loan applicants to upload the user mobile money transaction history files (exported in the PDF format by the user mobile money app), the transaction history is then parsed and analysed for the credit risk assessment. This approach is aligned with the National Financial Inclusion Strategy II (2022-2026) of Zimbabwe.

1.1 Background to the study

The ease to access cheap credit contributes to economic development of emerging countries. In Zimbabwe, mobile technologies (EcoCash, One Money, tele-cash) have facilitated access to finance by easing money transfer and payments. However access to credit by mobile phone

remains challenging as many workers and small business owners operating in the informal sector have no access to formal loans (Fin Mark Trust, 2022).

Traditional credit scoring relies on formal jobs, proof of income and collateral which many of low-income earning employees cannot meet (RBZ, 2023). This makes it difficult for Micro Finance Institutions to reliably identify risky customers and this therefore results in rigid loans and continues financial exclusion.In most countries across the world, machine learning and data analytics are used to assess credit risk based on alternative data such as use of the internet, telephone transaction history and location based information (Munyoro, 2021).

Machine learning and data analytics can create models that can reliably predict creditworthiness compared to traditional models. Adopting these machine learning models on mobile micro-lending platforms in Zimbabwe can increase access to credit by those that do not have bank accounts.

The Inclusive Mobile Microloan Platform uses machine-learning algorithms for analysing the PDF transaction files that a customer upload so that loans can be processed automatically and it supports the National Financial Inclusion Strategy II (RBZ, 2023) by enhancing credit scoring, operation performance and building an inclusive financial environment.

1.2 Statement of the Problem

Digital financial services are on the increase in Zimbabwe, however access to formal credit remains a challenge. Financial institutions use existing loan evaluation frameworks (collateral, proof of employment etc.), which rule out most of the informal traders and poor employees who constitute most of the workforce (RBZ, 2023).

Microfinance institutions are also constrained by lack of reliable data on the clients and the resultant un-sustainable credit decisions, defaults and slow manual processing.While mobile-money platforms like EcoCash have improved convenience and allow users to export their transaction histories as PDF files, they have not addressed the issue of credit accessibility. There is a pressing need for intelligent systems that can evaluate creditworthiness using alternative data such as transaction history and behavioural trends data that borrowers can voluntarily provide by uploading their mobile money statements.

The Inclusive Mobile Microloan Platform seeks to narrow the divide by building machine learning based credit evaluation and loan management system. The platform will provide an

objective, efficient, and transparent credit-assessment process, reducing default risk and promoting financial inclusion among underserved communities.

1.3 Research Objectives

The specific objectives of the study are:

1.To analyse global micro-lending processes and assess how they can inform and improve micro-lending practices in Zimbabwe.

2. To design and integrate a machine-learning credit risk model into a mobile microloan platform that accepts user-uploaded PDF transaction statements

3. To evaluate the credit-risk model in predicting borrower creditworthiness.

1.4 Research questions

To respond to this, this study aimed to address the following research questions

1.What weaknesses exist in the traditional credit-assessment methods used by financial institutions in Zimbabwe, particularly for borrowers without formal credit histories?

2. How can the Random Forest machine-learning algorithm be applied to predict borrower cr editworthiness using alternative data extracted from user-uploaded mobile money transaction PDF files (including transaction frequency, regularity, cash-flow patterns, and payment behav iour)?

3.How can a file-upload and PDF-parsing mechanism be integrated into a secure mobile mic roloan platform to automate loan applications, risk evaluation, approval, and repayment tracki ng?

4.How accurate, efficient, and reliable is the implemented platform in predicting loan defaults and enhancing transparency and financial inclusion among underserved communities in Zimbabwe?

1.5 Research propositions / hypothesis

Null Hypothesis (H0)

The application of machine-learning-based credit assessment using user-uploaded mobile money transaction files does not result in a substantive and practically significant improvement in the accuracy of predicting loan repayment risk within a mobile microloan system in Zimbabwe.

Alternative Hypothesis (H1)

The application of machine-learning-based credit assessment using user-uploaded mobile money transaction files results in a substantive and practically significant improvement in the accuracy of predicting loan repayment risk within a mobile microloan system in Zimbabwe.

1.6 Justification/significance of the study

Financial exclusion still constitutes a major developmental challenge challenge in Zimbabwe, where a large segment of the population relies on informal economic activities. Access to affordable and reliable credit facilities is often restricted to those with formal employment and documented income. Consequently, the majority of small business owners, informal traders, and low-income individuals lack the financial support necessary to expand their economic activities (World Bank, 2023).

The project "The Inclusive Mobile Microloan Platform" is important because, it will deliver an innovations based and technological driven solution to this. It is difficult to overcome this persistent problem. By automatically using machine-learning algorithms to analyse. For the user-uploaded mobile money transaction PDF files, the system can give orders to, other data, such as transaction behavior, airtime consumption, indicated in statements, and ensuring payment consistency to assess borrower reliabilityobjectively. This protocol decreases the dependence of traditional credit-scoring metrics and opens up the financial world to those that have often been sidelined from the political process.

At national level, the paper supports National Financial Inclusion of Zimbabwe. Strategy II (2022-2026), which Focuses on encouraging the use of the technology to improve the accessibility of credit. And also helps to enhance financial literacy (RBZ, 2023). It fits into the

government's overall plan to a digital economy and contributes to the achievement of the MDGs by the8 which promotes inclusive and sustainable economic growth. Financial institutions to implement it can provide efficiency and reduce, Cost benefits difficult when..

Operational risk, and achieves faster loan recovery rates. For borrowers it offers a transparent, faster, and objective credit-evaluation system. On an academic level, the project adds to the increasing a comprehensive literature review on FinTech innovations in developing economies and providing a practical framework. Entry for the integration of machine learning applications into the micro finance system in Zimbabwe. In the end, this article proves how technology can really cross the border between the informal. Financial inclusion for the benefit of the financial sector and the underserved populations, thus encouraging the financial sector to be more inclusive.I also committed to the goal of economic empowerment.

1.7 Assumptions

The study is carried out under some assumptions that determined the way of mapping and **c**oncessionaries using the Inclusive Mobile Microloan Platform. Furthermore the assumption is that of the borrowers are able to export their download the transaction history from these mobile money applications in PDF files. If would also be willing to submit those two documents PMID0012624. And that theywould be prepared to provide these documents PMID0012624 nished process.

The authors also believe that data obtained from mobile-money transactions and user behaviour can be indicative of someone being potentially creditworthy. From this it is the common assumption is that machine-learning algorithms are able to analyse such data, and obtain reasonably accurate predictions of the way in which loans will be paid back.

Additionally, as one of the assumptions, it is assumed that users, when following.Registration and loan application procedures, and will operate within the system in an nguyen et al proposed a challenge-response authentication protocol using human behavior in honest way during the testing period.

Finally, the analysis also underscores the need for the study to simulate the effect of the current regulatory framework in Zimbabwe by the guidelines set by the Reserve Bank of Zimbabwe (RBZ) and the Cyber and Data Protection Sec [Ch. 12:07] (Republic of Zimbabwe, 2021), Will

not change during the course of research. Period for the use of anonymised data in the development and assessment of systems.

1.8 Limitations/challenges

One major issue is that data depends on what is uploaded by users. With respect to credit assessment, how accurate the model is depends on how complete and real the transaction PDF files uploaded by the loan applicant is. The user could upload an incomplete, falsely formatted or faked PDF, that would lower the accuracy of the model. Also, PDF exports from mobile money application have inconsistent formatting, so a powerful parsing mechanism has to be put in place. The model includes basic validation and extraction tests, however there is no way of blocking the upload of faked or mis-formatted PDF's in a prototype.

One main limitation is data availability and quality. Due to data protection policies and institutional limitations there is lack of access to authentic borrower data from financial institutions. The use of simulated or open access data that may not reflect actual behavior limits the accuracy of the model.

Another limitation is infrastructural. In many rural areas of Zimbabwe internet connectivity and Smartphone ownership remain a problem, affecting the accessibility and utility of the model for most financially excluded individuals.

Regulatory and ethical issues: It is crucial to adhere to RBZ FinTech regulation and the Cyber and Data Protection Act [Chapter 12:07] on cyber security and data protection standards. Anonymizing data while ensuring its integrity and designing a secure model to meet these requirements are important aspects.

The use of a machine-learning model in financial transactions comes with certain technical difficulties like limited computational resources available and the interpretability issue; machines are typically seen as black boxes making their decision process hard to explain to less tech savvy users likeloan officers or regulators.

Lastly, the project time-frame limit extensive testing in the field and extensive stakeholder discussion. None the less the project remains an excellent platform from where we can build further and involve banks.

1.9 Scope/delimitation of the research

This research is an exploration into the design and implementation of an Inclusive Mobile Microloan platform utilizing machine learning algorithms for automated credit scoring and enhanced financial service access in Zimbabwe. The project is confined to building and testing a prototype system and not a fully developed commercial solution. The study narrows its scope to microfinance operations targeting low income households and small business owners and excluded from conventional loan systems.

This research is centered on the Zimbabwean context and highlights the digital financial ecosystem involving mobile money platforms, including EcoCash and OneMoney. The machine learning models will be trained and tested on readily available public and simulated data set representing the local borrowing behavior and the characteristics of potential clients. The developed prototype receives a PDF file uploaded by the user which should be a bank statement exported from a mobile money platform; it does not integrate with the live API of a mobile money provider.

The study builds a functional proof of concept but does not perform a live integration with a financial institution due to data security and privacy constraints, however the results will serve as a foundation to extend the system, to work with regulation authorities and microfinance service providers. For the machine learning part the research deals with building one algorithm: the Random Forest, which is selected after theoretical review of possible candidate algorithms, even if other algorithms are reviewed on the theory part the implementation part will only feature one algorithm (Random Forest) used to evaluate the prediction performance and usability of the developed model using a controlled testing environment within the Computer Science Laboratory at Bindura University of Science Education.

1.10 Chapter summary

This chapter outlines the reason for the study, the context in which it operates, and the framework governing it. The study is concerned with designing and developing an inclusive mobile microloan platform for improving the credit accessibility of disadvantaged segments of the Zimbabwean society. In doing so, the chapter contextualizes the study within the growing global trend of FinTech, particularly within the developing economies where the growth in digital finance services has soared yet access to formal credit is still inaccessible to many working in the informal economy. This chapter identified a systemic weakness of current credit

assessment mechanisms in Zimbabwe - reliance on collaterals, formal employment histories and traditional credit reports - which intrinsically alienates a significant portion of the society from obtaining credit, hence a missing gap of facilitating financial access through innovative solutions.

In bridging the identified gap, the chapter proposes a solution where machine learning-based credit-risk modeling is integrated within a mobile microloan platform. The platform accesses and analyzes alternative data sources via user-uploaded mobile money transaction files (PDF Export from mobile money applications such as Ecocash). Data are parsed from transaction file and indicators of user' behavior like transaction frequency, regularity and cash-flow are generated for objective assessment of the borrower's creditworthiness. The aim is to enhance the efficiency and reliability of loan processes and assessment through automating the process thus reducing fraud, costs and errors and improving fairness in the credit delivery process.

This chapter clearly illustrates the research aim that it intends to design, integrate, and evaluate an AI-driven credit-risk model into a mobile micro-lending system for Zimbabwe and how specific objectives of analyzing existing micro-lending practices, building a machine learning credit assessment model and assessing its efficiency are planned and research questions and hypothesis are provided to answer them systematically.

Moreover, it shows justification for the study; why it is important: For national development by fulfilling the National Financial Inclusion Strategy II (2022-2026) of Zimbabwe, its practicality to microfinance institutions and its contribution to research in applying AI in financial inclusion and developing countries and also establishes underlying assumptions that mobile data is available and AI techniques can predict creditworthiness. However, there are limitations like data access, infrastructure development and also that this is a prototype not a real-world deployed system. Finally, scope and delimitations are given in relation to developing a prototype Inclusive Mobile Microloan Platform using either simulated or available publicly sourced data sets in a controlled environment without linking it with real mobile money providers.

1.11 Definition of terms

Artificial Intelligence:

“A branch of computer science devoted to the development of computer systems capable of performing tasks that would require human intelligence, such as learning, reasoning, and decision making. In this study, AI pertains to use of algorithms that facilitate automated credit assessment.”

Financial Inclusion:

“The state in which both individuals and businesses are provided access to useful and affordable financial services including credit, savings, and insurance (World Bank, 2023). Often this focus is on the poor.”

Machine Learning (ML):

A subfield of artificial intelligence that enables systems to automatically learn from and make predictions or decisions from data without being explicitly programmed (Munyoro, 2021).

Microfinance:

“The provision of small loans and other financial services to individuals or small enterprises who have limited or no access to traditional banking services, such as loans or microcredit. It plays a crucial role in poverty alleviation.”

Credit Scoring:

A statistical method that can be used to estimate the probability of a borrower defaulting on their loan repayment. This project employs machine-learning models that predict loan repayment by analyzing alternative data sources to perform the credit scoring function.

Alternative Data:

Non-traditional data utilized in financial assessment. This includes behavioral data such as transactions recorded from airtime purchases, mobile money transaction patterns, and utility bills among others. Alternative data sources in this project were user-uploaded files that were exported from mobile money application in a PDF format.

Mobile Microloan Platform:

A digital system designed to enable mobile users to apply for, receive, and repay loans. The platform will have backend databases, machine-learning models for credit assessment, a PDF-parsing module to extract transaction history from user uploaded files and secure user interfaces.

Default Risk:

The possibility that a borrower will be unable to fulfill his loan obligation commitments over the designated time period. This project has the aim of reducing the default risk of loans.

Reserve Bank of Zimbabwe (RBZ):

The central bank of Zimbabwe, charged with overseeing the country's monetary and financial system, including FinTech regulations and financial inclusion policies.

PDF Parsing:

The procedure that uses programs to analyze Portable Document Format (PDF) documents and extract meaningful information. In this study, the pdfplumber library is employed in python to parse the transaction details contained within the users EcoCash PDF statement.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The provision of formal financial services is generally agreed upon to play an instrumental role in enabling economic empowerment, poverty reduction, and social progress (World Bank, 2022). Global accounts ownership has increased tremendously over the last decade with almost three quarters of all adults now having financial account access, although close to 1.4 billion adults are still unbanked due to factors including lack of documentation, inadequate income, and distance from the financial sector (World Bank, 2021).

In Zimbabwe demand-side data shows this is a mixed picture of inclusion. The Fin Scope Consumer Survey Zimbabwe (2022) showed a jump in financial inclusion from 77% in 2014 to 88% in 2022, with 84% of adults having formal financial services access and mobile money use increasing from 45% to 63%. However the proportion of adults who access formal credit remains very low, only about 15%, with 61% of all adults in the survey never borrowing (Fin Mark Trust, 2022). This shows a huge gap between payment and credit inclusion in Zimbabwe. Zimbabwe has achieved excellent results in transactions inclusion via digital financial services but formal credit access is very limited.

This problem is compounded by structural aspects of the Zimbabwean economy, which are outlined in the Zimbabwe National Financial Inclusion Strategy II (2022-2026). Micro small and medium enterprises (MSMEs) dominate the country's economy, estimated to contribute up to 60% to GDP, but only about 14% of them are formally registered (RBZ, 2022). This means a large number of economically active people have neither audited financial statements, payslips, nor formal credit bureau histories. In this environment, information asymmetries between lenders and borrowers remain high, and collateral based lending models become increasingly entrenched. Informal traders and low-income earners are pushed out of formal credit markets.

The growth of mobile financial services and alternative scoring methods offers potential solutions. Mobile lending services enabled by machine learning models analyzing user behaviour and transactional data offer solutions to reduce information asymmetry and expand credit access to excluded populations (Jack & Suri, 2011; World Bank, 2023).

This literature review summarizes relevant theoretical frameworks, research and governance implications pertaining to mobile microloans, alternative credit scoring, machine-learning credit risk assessment, and ethical data usage to identify a research gap and inform the development of an inclusive mobile microloan platform for Zimbabwe.

2.2 Relevant Theory of the Subject Matter

2.2.1 Mobile Microloans

Mobile microloans may be defined as a relatively low-value, short-term credit product, accessible and administrable through purely digital and mobile technologies. These products generally lack traditional collateral, have a mechanized decision-making process (Karlan & Morduch, 2010) and is a form of digital credit that involves instant credit decisions, remote management of credit products and digital disbursement and repayment channels (World Bank, 2022).

Theories of credit exclusion under conventional banking, such as asymmetric information, suggest that in lending markets, borrowers have private information of their repayment capacity compared to lenders. Under conditions of imperfect information, lenders have recourse to credit rationing rather than adjusting the rate of interest by imposing loan size and collateral requirements and mandatory formal income certification to reduce adverse selection and moral hazard (Stiglitz & Weiss, 1981), which systematically disadvantages informal workers and micro-entrepreneurs.

In contrast, microfinance theory posited that loans of small value without physical collateral could be successful through innovative contract design, monitoring mechanisms, and social enforcement institutions (Yunus, 2007; Armendriz & Morduch, 2010). Adding mobile technology on top of these could provide microfinance services at a large scale at reduced transaction costs and wider reach.

The success of the digital financial ecosystem based on the digital credit product are documented; some literature established mobile money as enhancing household resilience, particularly by improving consumption smoothing capacity during shocks (Suri & Jack, 2016), and there is high mobile money penetration in Zimbabwe to support such digital credit products (Fin Mark Trust, 2022). However, a note of caution that the digital credit products may create new risks for the consumers in the form of non-transparent pricing, over-indebtedness, aggressive collection procedures, and detrimental impact on credit bureau information if poorly regulated (CGAP, 2017).

2.2.2 Alternative Credit Scoring Models

Defining Alternative Credit Scoring

Conventional credit scoring models require a formal credit history (e.g. Of previous loans or credit card transactions) thus denying 'thin-file' or 'no-file' individuals' access to credit (Schreiner, 2004). Alternative credit scoring models attempt to address exclusion by adopting 'alternative' data sources. The World Bank and the International Committee on Credit Reporting (2023) highlight that 'alternative data' lack a precise definition but that it involves digital traces of either a financial or non-financial nature; the form of alternative data varies according to the situation. In informal Economies such as Zimbabwe alternative data may yield relevant signals where there is a lack of bureau coverage.

Leveraging Non-Traditional Data Sources

The other credit scoring models use various types of behavioral and transactional features:

- Mobile phone usage data: Evidence suggest that mobile phone data (metadata) are strong predictors of socio economic status as well as loan repayment behavior. For example, Blumenstock, Cadamuro & On (2015) prove that mobile usage behavior strongly correlates with indicators of wealth, and Bjrkegren & Grissen (2018) prove that mobile behavioral data is quite accurate at predicting loan repayment behavior.

- Transaction history: Using mobile money transaction data, insights into income regularity, expenditure habits and cash management strategies are provided. These behavioral features can function as surrogates for good financial discipline and steadiness (Frost et al., 2019). This seems an especially useful approach to Zimbabwean use, given the widespread use of mobile money.

- Social network ties: According to social collateral theory, individual credit worthiness can be affected by one's network of connections, which influences repayment incentives and enforceability mechanisms (Karlan et al., 2009). However, while using network features might improve the predictive power of a credit score, it is also associated with stronger privacy and discrimination issues.

Machine Learning in Credit Risk Assessment

Machine-learning algorithms have broadened the ability to capture complicated non-linear relationships in alternative datasets. Evidence has suggested that ensemble machine learning algorithms (Random Forest and Gradient Boosting) achieve superior predictive performance to traditional logistic regression (Munyoro, 2021).

Taking into account both the theoretical aspects and the appropriateness of the listed algorithms for small sample behavioral data, Random Forest is widely cited as a reliable model for credit-risk classification because it is less prone to overfitting, able to handle non-linear relationships, and includes feature importance functionality. Still, credit-risk models are sensitive to interpretation. Logistic regression is commonly employed for its interpretability and regulatory compliance.

The recent development of Explainable Artificial Intelligence (XAI), including interpretability via SHAP based values, allows complex models to generate feature-level explanations, which improve transparency and accountability of algorithmic credit decisioning. As is with any classification model in credit-risk, model evaluation should go beyond mere accuracy and examine discriminatory ability and fairness.

Area Under the ROC Curve (AUC), precision-recall measures, and F1 scores are among the many recommended measures, particularly when dealing with skewed datasets such as in credit default prediction tasks. Alternative data increases model power, however the literature also cautions that representativeness of data, and behavioral patterns driven by engagement with digital interfaces, may be themselves indicative of socioeconomic disadvantage. Predictive power should, therefore, be measured alongside bias and fairness auditing and remediation.

2.3 Challenges and Ethical Considerations

Although promising, the new credit scoring models face substantial ethical and regulatory hurdles.

Automated systems might unintentionally perpetuate historical injustices throughbiased inputs or by having proxy variables that correlate with protected attributes (Mittelstadt et al., 2016; Zarsky, 2016). In digital lending, an opaque logic can also reduce consumer understanding and recourse when automated decisions are made.

Hence, responsible data management is a core issue in digital lending. The principles of data governance for digital lending include data minimisation, purpose limitation, transparency, and informed consent (OECD, 2020).

In Zimbabwe, systems for digital lending must conform to the Cyber and Data Protection Act (Chapter 12:07). This piece of legislation sets out a minimum legal standard for personal data protection and institution supervision. This implies adherence to requirements such as lawful data processing, secure storage and protection against unauthorised access to personal data.

Furthermore, the RBZ FinTech Regulatory Sandbox Guidelines (RBZ, 2021) established to create an environment where new financial technologies can be tested under controlled conditions, highlights consumer protection, cyber security, informed consent and risk mitigation measures during testing. This direction from the RBZ indicates that mechanisms for governance-by-design should be embedded within machine learning powered credit platforms. Transparency in automated decision making is now considered an ethical necessity for borrowers' accountability and to foster trust, as their outcomes are better understood (Gonzlez & Meyer, 2019). Ethical data usage here, is a core design requirement rather than just a compliance one.

2.4 Empirical and Theoretical Literature Review

To a large extent the empirical literature supports the hypothesis that digital financial services and alternative credit scoring can help to improve financial inclusion provided that it is appropriately governed. Microfinance literature shows that the provision of micro-credit can foster entrepreneurship and create income generating activities, even if the impacts are contexts-dependent (Yunus 2007; Armendriz and Morduch 2010).

Evidence shows mobile money usage can help to stabilize consumption and households' financial resilience (Suri and Jack 2016) which supports the potential of digital tools in providing financial security in developing economies. Studies show how transactional and behavioral signals derived from digital footprints can indeed predict credit worthiness in thin-file environments (Blumenstock et al 2015; Bjrkegren and Grissen 2018), but also evidence of over-indebtedness and client strain with weak governance structures is widely found.

The key idea here seems to be the necessity of a balanced system design in which predictive analytics are complemented with consumer protection policies. In conclusion, the evidence points to the possibility that mobile microloans together with alternative credit scoring based on machine learning can increase financial inclusion especially in countries with a large informal economy and lack of bureau coverage. However, predictive power on its own is not sufficient as governance, transparency, and fairness need to be ensured.

2.5 Chapter Summary

In Chapter two, the theoretical, empirical, and regulatory literature is reviewed which would inform the design of an Inclusive Mobile Microloan Platform with a machine-learning algorithm for assessing credit risk for the Zimbabwean context.

Chapter two confirms that both information asymmetry and credit rationing theory can adequately explain the phenomenon of credit exclusion in economies without documented histories (which is representative of informal economies). Demand side factors from Zimbabwe show that despite gains in digital financial inclusion, there are still gaps in the provision of formal credit.

The chapter also finds that mobile transaction data and behavioral patterns in conjunction with machine-learning can accurately assess credit risk, however concerns about privacy, fairness and transparency issues arise with the use of algorithmic decision making and they necessitate approaches like governance-by-design that can operate within the Zimbabwe context.

The central research gap identified is that although empirical research globally shows that machine-learning credit scoring algorithms and the use of alternative data have high predictive potential, there is limited empirical work in Zimbabwe examining the application of these algorithms using mobile money behavioural data within a regulatory and ethical framework. In order to do this, this study focuses on the designing and testing one particular type of algorithm (Random Forest) on a mobile microloan platform instead of comparative studies between many algorithms.

CHAPTER 3: RESEARCH METHODOLOGY

3.0 Introduction

The research methodology adopted in designing, developing and evaluating the AI driven credit risk assessment system designed to facilitate financial inclusion in Zimbabwe through Inclusive Mobile Microloan Platform is described in this chapter. This chapter provides a description of the research design, methodology of the system development process, requirement analysis of the system, the system architecture, dataset approach, data preprocessing procedures, machine learning model design, implementation procedure and testing method, as well as ethical and legal aspects.

This methodology is intended to answer research objectives described in chapter one, which are: assessing micro-lending barriers, building a machine learning based credit risk model and determining the performance of the credit risk model in assessing a borrower's creditworthiness.

The adoption of machine-learning–based credit risk assessment using alternative transaction data is appropriate for Zimbabwe's context, where mobile money usage is widespread but access to formal credit remains limited. This supports the use of transaction-based indicators and automated credit evaluation to improve credit accessibility. The chapter also reflects national policy priorities under the National Financial Inclusion Strategy II (2022–2026), which emphasises financial innovation and consumer protection in deepening financial inclusion, and acknowledges the largely informal structure of MSMEs that contributes to thin-file credit profiles (RBZ, 2022; FinMark Trust, 2022).

3.1 Research Design

This research will employ a Design Science Research (DSR) approach supported by a quantitative experimental research design.

DSR is appropriate because the central contribution of the study is the development of a technological artefact, a mobile microloan platform incorporating machine-learning classification models for credit risk assessment, which addresses a real-world problem: financial exclusion due to missing formal credit histories. Research knowledge is generated through the building and application of the artefact, and the artefact is evaluated for utility and effectiveness (Hevner et al., 2004).

To structure the research process, the study follows the Design Science Research Methodology (DSRM), which defines six activities (Peffers et al., 2007):

1. Identifying the problem & the incentive.
2. Objectives of a solution
3. Design and development
4. Demonstration
5. Evaluation
6. Communication

This corresponds exactly with the layout of the thesis itself; Chapter One is the definition of the problem and aims, and Chapters Three and Four focus on the design, implementation, proof and testing of the artefact.

The quantitative experimental component is performed to:

- Train and test machine-learning models
- Evaluate model performance
- Measure predictive performance using classification metrics
- Test the research hypothesis

Because credit default prediction is often an imbalanced classification problem, evaluation is not limited to accuracy. It includes:

- Precision
- Recall
- F1-score
- ROC/AUC
- Precision–Recall analysis

Precision-recall analysis can be most helpful when default classes are very rare.

3.2 System Development Methodology

3.2.1 Selected Development Model – Agile Methodology

The decision to use the Agile software development model was primarily based on its iterative and incremental approach.

The focus on early delivery, continuous refinement, adaptiveness to change, and iterative development found in the Agile approach are key strengths for a machine-learning system

where iterative cycles of feature engineering, tuning, and testing are necessary to continuously build the system(Agile Manifesto, 2001).

Agile enabled:

- System modules to be iteratively refined.
- Model to be continually improved.
- Testing and feedback to be incorporated into every iteration.
- System functionality to be progressively developed.

3.2.2 Development Phases

The phases followed in system development were the following, iteratively implemented:

1. Requirements Analysis
2. System Design
3. Dataset Preparation
4. Model Development
5. Implementation
6. Testing and Evaluation

This corresponds with the design, demonstration and evaluation aspect of the DSRM logic and enables a methodical analysis of the artifact.

3.3 Requirements Analysis

Requirements were derived from:

- The research problem (Chapter One)
- Theoretical and empirical literature (Chapter Two)
- Zimbabwe's regulatory and financial inclusion context

3.3.1 Functional Requirements

The system should include functionality to upload a file. The loan applicant would be able to upload their mobile money transaction history. The user would be required to download this from their respective mobile money (EcoCash, OneMoney or Telecash) as a PDF file and upload it to the system. The system will:

- Validate file format (PDF), size (10 MB max), and basic structure

- Parse each uploaded PDF file to extract the transaction records (using pdfplumber library)

- Be able to handle the normal irregularities of formatting for different mobile money provider pdf files

- Extract fields: date, amount, transaction type, running balance etc

- From the extracted transaction records, infer behavioural features such as transaction frequency, regularity of payment, consistency in payments and stability in cash flow etc

- Correlate the above behavioural features with other applicant information (business category, household status, etc) and evaluate credit-risk.

- Allow registration of users and their authentication

- Receive loan applications

- Predict borrower credit-worthiness using Random Forest algorithm

- Process loan applications for automated acceptance or rejection

- Facilitate loan repayments

- Generate administrative reports

- Protectively store applicant records and uploaded PDF files (and discard after data is parsed).

3.3.2 Non-Functional Requirements

The system must ensure:

- High predictive performance
- Low processing latency
- Reliability and availability
- Scalability
- Strong security controls
- User-friendly interface

Further requirements related to governance:

- Transparency and explainability
- Audit logging
- Privacy-by-design controls
-

3.3.3 System Requirements

The system should meet the below operation and performance requirements to work as intended:

- Stable internet connectivity for real-time communication between client and server
- Secure data transmission using HTTPS protocols
- Scalable system architecture to support multiple concurrent users
- High availability and reliability of the system
- Efficient data storage and backup mechanisms
- Compliance with data protection and security standards as per Zimbabwe's Cyber and Data Protection Act (Chapter 12:07).

3.3.4 Hardware Requirements

The following hardware items would be necessary to construct and run the system:

For Development

- Intel Core i5 minimum or equivalent
- 8GB RAM minimum
- 50GB disk space minimum
- For End users (Borrowers and Admin)

Any device (desktop, laptop, tablet or smart phone) capable of running a recent version of any of the common browsers (chrome, Firefox, Edge, or Safari)

Stable internet connection

For Deployment:

Server or cloud hosting infrastructure (like AWS, Azure, or an on-premises server) for backend.

3.3.5 Software Requirements

The software and technology used to develop the system:

Layer	Technology	Purpose
Frontend	React.js	Responsive web application accessible via desktop and mobile browsers

Backend	Node.js with Express.js	Server-side logic, API routing, and authentication
Database	MySQL	Data storage and management (users, loans, transactions, audit logs)
Machine Learning	Python 3.9 with Scikit-learn, Pandas, NumPy	Model development, training, and prediction
ML API Layer	Flask (Python)	Expose trained Random Forest model as a RESTful service
PDF Parsing	pdfplumber (Python)	Extract transaction data from uploaded EcoCash PDF statements
Version Control	Git	Source code management
Testing	Postman (API testing), Jest (React component testing), Pytest (Python/ML testing)	

3.4 System Architecture

There are 3 tiers in the system:

1. Presentation Layer, React Frontend (Mobile Interface)
2. Application Layer, Node JS Backend + ML Model Service
3. Data Layer, MySQL Database

Machine learning module is a part of the application layer through a specific prediction interface, and the machine learning system performs automatic credit scoring.

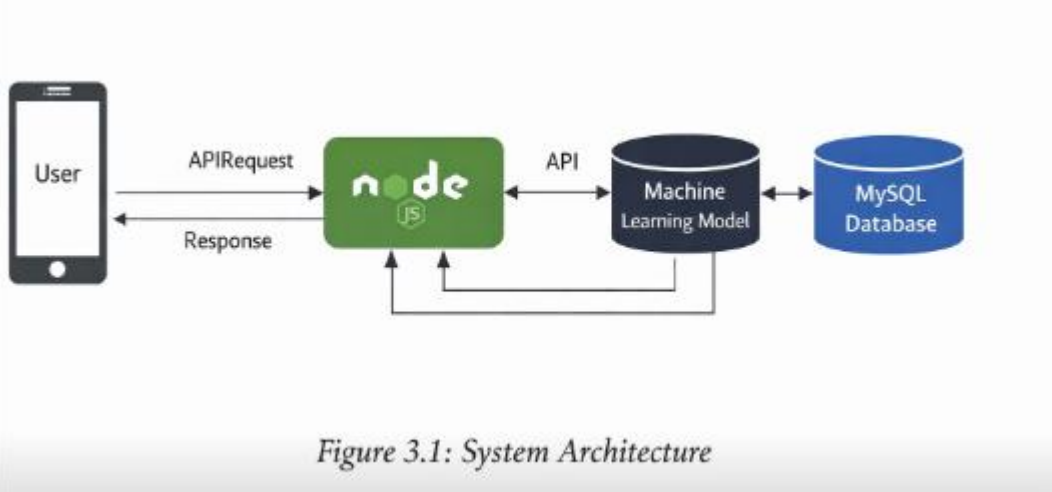


Figure 3.1: System Architecture

Fig 3.1: System Architecture

3.4.1 Development of the Machine-Learning Model

The machine learning model serves as the central analysis piece of the proposed mobile microloan platform. It helps determine the creditworthiness of potential loan borrowers through alternative data for individuals with no existing credit history. It ensures automatic, data-driven decisions are made, which will reduce friction and increase the reach of financial services.

In this work, credit-risk prediction was framed as a supervised binary classification problem, which classifies each applicant as either not likely to default (0 = non-default) or likely to default (1 = default) on the loan. This problem formulation fits the overall system's goals, which are to augment lending decisions through prediction of loan repayment behavior (Bjrkegren and Grissen, 2018).

Data Inputs and Feature Selection

In this, a data driven approach aiming to incorporate other non-traditional variables such as borrower behavior, borrowing activity were built. Transaction frequency, consistency, payment, amount of the loan, loan performance, regularity of payment, business industry group, tax compliance variables, vehicle insurance class and living status (as a financial stability variable). These were used due to their strong correlation with both behavior reliability and financial stability in settings where traditional credit data is not available (Blumenstock et al., 2015; Munyoro, 2021).

Data Preprocessing

The data was first pre-processed before training the model to ensure data consistency and quality. All duplicated, incomplete and non-consistent records were removed through data cleaning. All the missing values in the records were replaced or deleted according to the importance of each feature.

All categorical values were encoded in numerical form for the machine learning algorithm and numerical values (e.g., loan amount) were scaled using StandardScaler when appropriate. Outliers were addressed when appropriate in the important features (e.g., transaction volume and loan amount).

Feature Engineering

Feature engineering was used to extract additional predictive power from the data by calculating additional variables from the raw data. The transaction data was translated into a set of behavioral indicators, such as, average transaction frequency, monthly consistency of transactions, and stable cash flow approximation. The repayment data was converted into behavioral indicators, such as, repayment consistency and the rate of missed payments. The rationale behind feature engineering was to convert the raw data of operational activities into analyzable features that reflect behaviors correlated with the credit risk.

Algorithm Selection and Justification

In this study, we examined three supervised machine learning models: Logistic Regression, Random Forest and Gradient Boosting Machine (GBM). They were assessed conceptually for their ability in credit risk classification in Zimbabwean mobile lending. The pros and cons of the candidates models can be seen summarized in Table 3.1.

Table 3.1: Comparative Analysis of Candidate Machine-Learning Algorithms

Algorithm	Advantages	Disadvantages	Suitability for this Study
Logistic Regression	Highly interpretable; fast training; works well with linearly separable data; provides probability scores; regulatory-friendly due to transparency.	Poor performance with non-linear relationships; requires manual feature interaction detection; limited predictive capacity with complex behavioural data.	Suitable as a baseline but insufficient for capturing complex patterns in mobile transaction behaviour.
Gradient Boosting Machine (GBM)	High predictive accuracy; handles non-linear relationships well; robust feature selection	Prone to overfitting on small datasets; computationally intensive; many	Less suitable for this study due to small dataset size (1,000 records) and need for

	capabilities; often achieves state-of-the-art performance.	hyperparameters requiring careful tuning; less interpretable; slower prediction times.	interpretability in lending decisions.
Random Forest (Selected)	Good ability to predict outcomes; non-linear relationships; robust to overfitting even with smaller datasets; provides feature importance scores; works well with mixed data types; good balance between performance and interpretability; parallelisable training.	Less interpretable than logistic regression; larger memory footprint; slower prediction than logistic regression (but still acceptable for real-time lending).	Most suitable – balances predictive power, robustness with available dataset size, and ability to provide explainable credit decisions.

Rationale for Selecting Random Forest

Considering the comparison above, Random Forest was chosen as the machine learning model for this work (Bjrkegren and Grissen, 2018; Munyoro, 2021) because of the following reasons.

Appropriateness for the size of the data set: Since the data set is comprised of 1000 borrower records, an ensemble mechanism that reduces the risk of over-fitting as used by Random Forest is preferred over an ensemble that memorizes noise in the training data as GBM can on the training data.

Ability to Model Non-linear Data: Loan and cash flow data have non-linear patterns of behaviour that cannot be appropriately modeled using a simple linear model like Logistic Regression, whereas Random Forest intrinsically handles non-linear interactions (Bjrkegren and Grissen, 2018).

Intrinsic Feature Importance: A characteristic feature of Random Forest is that it can readily produce variable importance measures. This feature adds transparency to credit scoring making decisions, which is necessary for regulation and customer confidence (Lundberg and Lee, 2017).

Appropriateness for Mixed Data Types: It implicitly accepts non-binary and non-numeric categorical data such as country, business industry and status of housing along with the numerical loan and transaction information without further pre-processing.

Real-time lending speed: While slower than Logistic Regression, Random Forest models have adequate speed to deliver credit decision in real-time(seconds to milliseconds per decision), which is appropriate for mobile lending applications.

Model Training and Optimisation

A division was made between a training dataset (80%, 800 records) and a testing dataset (20%, 200 records) applying stratified sampling (which retains the distribution of the classes). Stratified 5-fold cross-validation was applied during training to evaluate model stability and generalisation capabilities. (Saito and Rehmsmeier, 2015).

The Random Forest model was trained using the following optimised hyperparameters, determined through grid search cross-validation:

For training of the Random Forest model, the grid-searched optimal hyperparameters found through cross-validation have been employed: No. Of trees (nestimators): 100 Max tree depth (maxdepth): 10 Min. No. Of samples needed to split internal node (minsamplessplit): 5 Min. No. Of samples required to be a leaf node (minsamplesleaf): 2 Feature sampling (max_features): 'sqrt' Bootstrap sampling (bootstrap): True These parameters control model complexity such as overfitting, whilst maintain model accuracy.

Model Evaluation Metrics

The performance of the trained Random Forest classifier was assessed using standard classification performance measures for unbalanced credit-risk data, which are the following:

Confusion Matrix: visualizing the number of true positive, true negative, false positive, and false negative cases.

Accuracy: Overall proportion of correct predictions

Precision: Of all the defaulted loans predicted as such, what fraction were actually defaulted loans.

Recall (Sensitivity): Of all the actually defaulted loans, what fraction were correctly predicted as such.

F1-Score: Harmonic mean of precision and recall. As a primary metric in a class-imbalanced problem, this was prioritized.

ROC-AUC: To judge the classification performance by measuring discriminative ability of the classifier(Fawcett, 2006).

F1-score was preferred due to the implications of false positives (granting loans to high-risk individuals) and false negatives (turning away potentially good customers). The use of precision-recall curves was also warranted by the likely class imbalance within the credit-default problem (Saito and Rehmsmeier, 2015).

Threshold Optimisation

We tested the default classification threshold of 0.5 and adapted it to the business needs of the mobile microloan platform. Since false negatives (denying loans to good borrowers) exclude people from financial services, and false positives (giving loans to bad borrowers) lose the platform money, an equilibrium threshold was chosen which maximises F1-score (Saito and Rehmsmeier, 2015). The final decision on threshold and the consequences can be found in chapter 4.

Model Integration and Deployment

The trained Random Forest model was saved using the joblib library from Python, and then included into the Node.js back-end by implementing it within a Flask microservice. The relevant features will be retrieved from the application upon the user submission, sent to the model by a REST API call, and a prediction score (0-1) representing the risk of loan default is then returned and compared against the optimized threshold to approve or reject the loan.

3.5 System Design

3.5.1 Data Flow Diagram (DFD)

Entities: Borrower, Admin
Processes: Loan Application Processing, Credit Risk Evaluation, Loan Decision
Data Stores: User Database, Loan Records

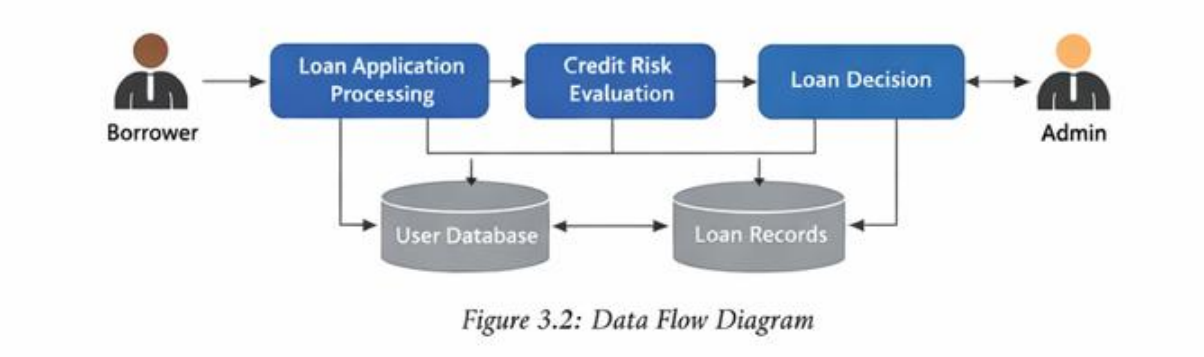


Figure 3.2: Data Flow Diagram

Fig 3.2: Data Flow Diagram

3.5.2 System Flowchart

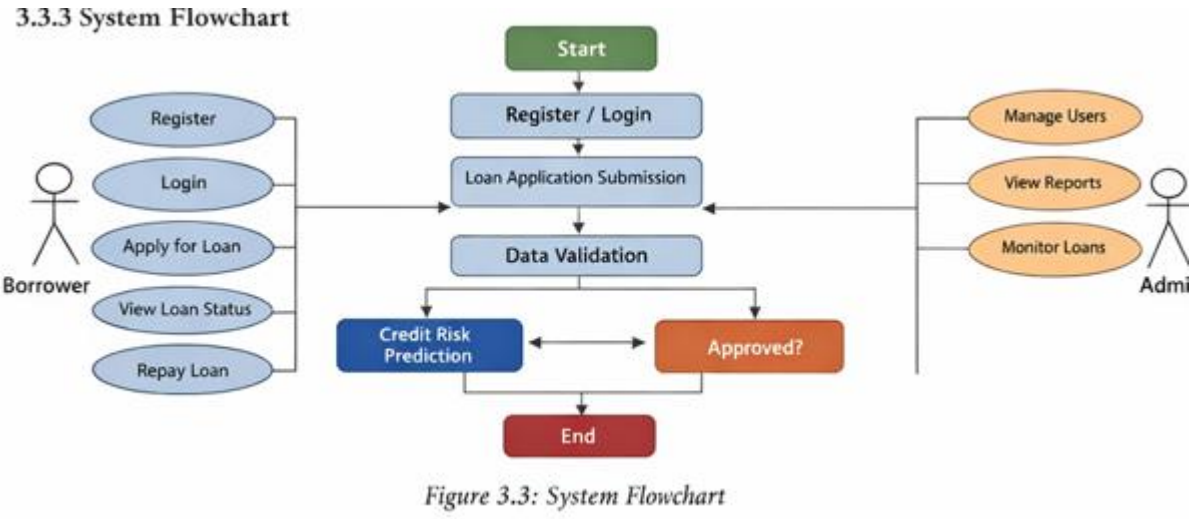


Figure 3.3: System Flowchart

Fig 3.3: System Flowchart

5.3 Use Case Diagram

Actors: Borrower, Admin

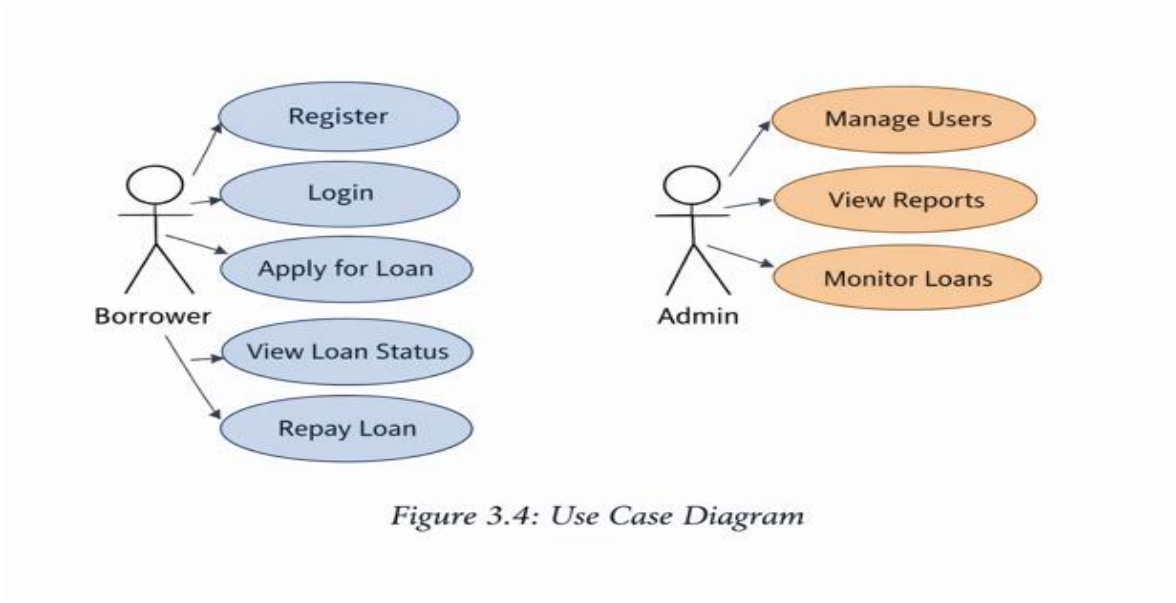


Figure 3.4: Use Case Diagram

Fig 3.4: Use Case Diagram

3.5.4 Class Diagram

Classes:

User (user ID, name, phone, transaction History)
Loan (loan ID, amount, status, repayment Schedule)
Transaction (transaction ID, amount, date)
Credit Model (train Model (), predict Risk ())
Admin (admin ID, generate Report ())

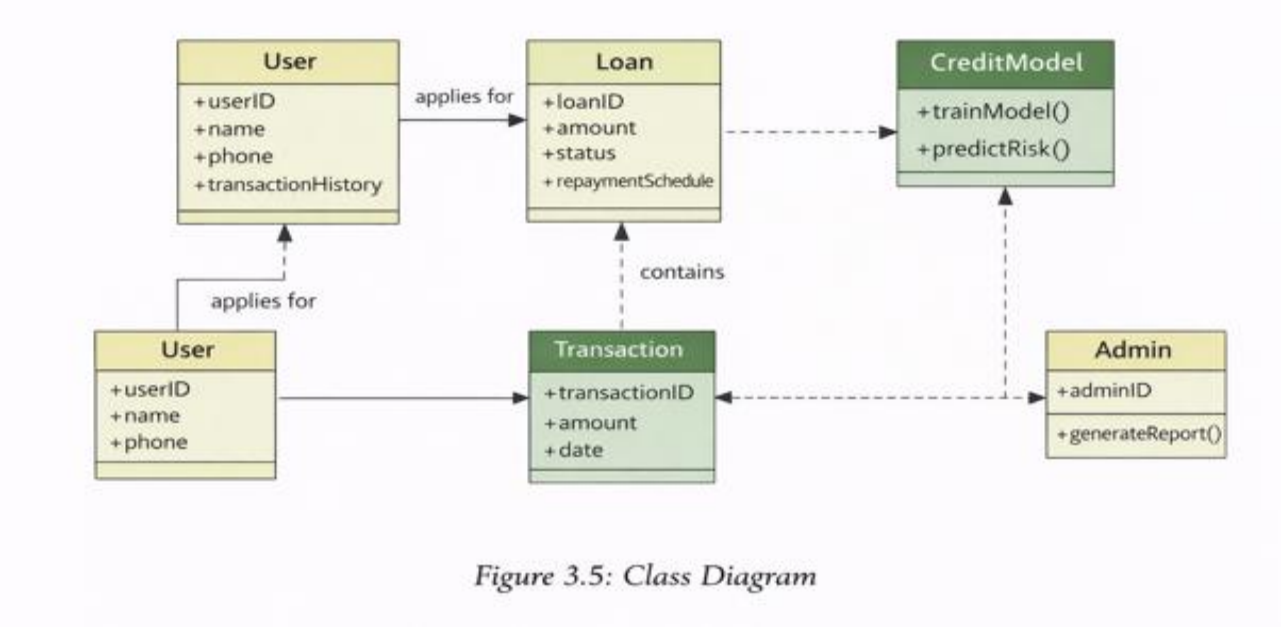


Figure 3.5: Class Diagram

Fig 3.5: Class Diagram

3.5.5 Sequence Diagram

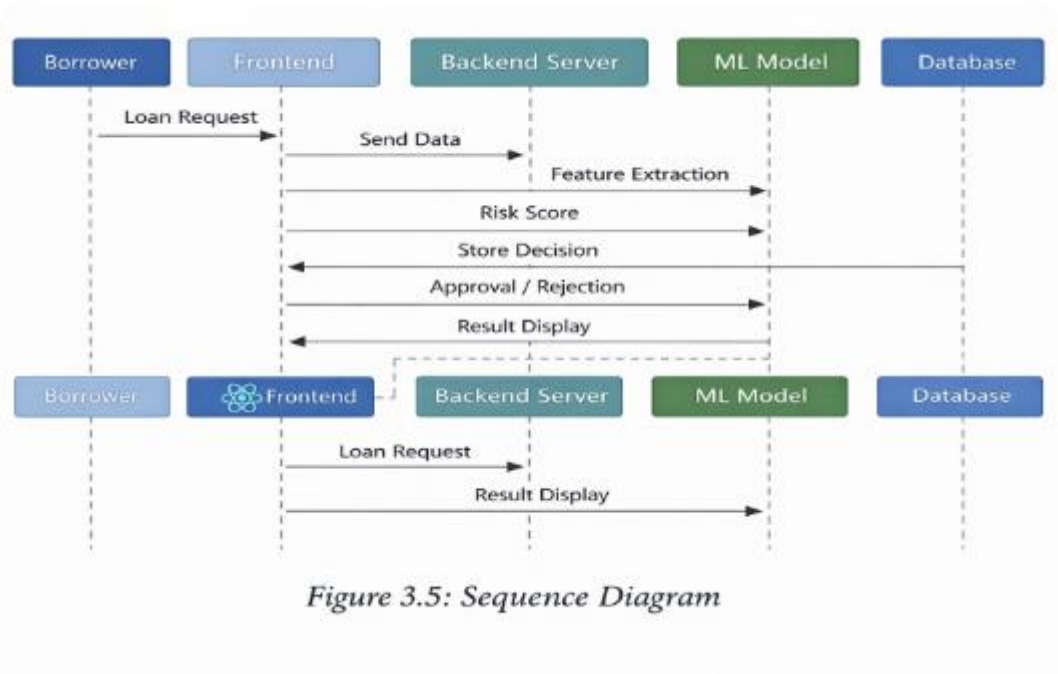


Figure 3.5: Sequence Diagram

Fig 3.6: Sequence Diagram

3.6 Dataset Description

The study utilised a structured financial risk dataset consisting of 1,000 borrower records to simulate realistic mobile micro-lending scenarios (Munyoro, 2021; World Bank, 2019). The dataset was designed as a supervised binary classification problem aimed at predicting borrower default risk.

The target variable was defined as:

0 = non-default

1 = Default

The dataset incorporated behavioural and financial indicators relevant to credit-risk assessment in Zimbabwe's mobile lending environment. These features included:

- Mobile money transaction frequency and volume

- Cash flow stability patterns

- Loan amount requested

- Historical repayment behaviour

- Payment consistency

- Business industry classification (for self-employed borrowers)

- Tax compliance indicators

- Vehicle insurance category (comprehensive vs third-party)

- Housing status (renting vs ownership, used as financial stability proxy)

The dataset was divided into 80% training data (800 records) and 20% testing data (200 records). Stratified sampling was applied to preserve class distribution and mitigate class imbalance during training and evaluation (Saito and Rehmsmeier, 2015).

The credit-risk model considers the following alternative financial indicators for loan decision-making: mobile money transaction history (e.g., EcoCash statements including transaction frequency and volume), cash flow stability patterns, historical repayment behaviour, requested loan amount, business industry classification for self-employed applicants, tax compliance

indicators where available, vehicle insurance category (comprehensive or third-party), and housing status (renting or ownership) used strictly as a financial stability proxy.

The study utilised publicly available and simulated financial datasets to represent borrower behaviour.

Dataset features included:

- Transaction frequency
- Transaction regularity
- Loan amount
- Repayment history
- Payment consistency
- Default indicator (0 = non-default, 1 = Default)

Data splitting followed an 80:20 training-testing ratio with stratification recommended. Cross-validation was applied during training.

3.6.1 Transaction Data Acquisition: File-Upload Approach

This study does not implement live API integration with any mobile

money provider (EcoCash, OneMoney, or Telecash). Instead, the system

employs a user-initiated PDF file-upload approach:

1. **During loan application:**

Borrower downloads their transaction history as a PDF file from their mobile money app (all major providers offer PDF export functionality)

2. **File submission:**

Borrower uploads the exported PDF file through the mobile application interface

3. **System processing:**

Back end opens up the PDF file through pdfplumber, verifies that the data is valid, and pulls the required transactions and financial figures.

4. **Privacy preservation:**

No perpetual real-time access is provided to the borrower account, the algorithm only ever uses information available in the upload file

A dataset of 1,000 borrowers was synthetically generated for the prototype's use and testing, with each record mimicking the kind of transaction information present in EcoCash PDF statements so as to be compatible with the parsing logic built for the prototype.

3.7 Data Collection Methods

The strategy for data collection for this study contains two parts:

A. Synthetic Dataset Generation (for Model Training & Testing)

- Programmatic generation of the 1000 borrower records dataset was done through Python scripts.

- Each record simulates transaction patterns found in real EcoCash PDF

  statements, including derived behavioural features and a default/non-

  default label

- Transaction patterns simulate realistic Zimbabwean mobile money

  behaviour (EcoCash/OneMoney usage patterns, informal sector cash

  flows, seasonal income variations)

- No real personal borrower data was collected or used

PDF File-Upload Mechanism (for System Demonstration)

- The prototype accepts PDF file uploads from users

- File format matches the PDF export from mobile money applications

(EcoCash, OneMoney, Telecash)

- Users provide their data voluntarily and retain full control

- No API integration with mobile money providers is implemented

3.8 Data Preprocessing

The following preprocessing steps were applied:

Removal of incomplete or inconsistent records

Encoding categorical variables with label encoding and one-hot encoding where appropriate

Feature scaling using StandardScaler for numerical variables (performed primarily for consistency; Random Forest is inherently insensitive to feature magnitude)

Handling of class imbalance through stratified sampling

Feature engineering was carried out to transform raw borrower data into meaningful indicators that improve the predictive performance of the machine-learning model Instead of using directly observed variables, additional features were extracted to characterize underlying patterns of financial behavior not evident from raw data.

A significant portion of the feature engineering effort involved the extraction of cash flow stability indicators from transaction data. The concept of transaction frequency was translated into a number of derived features which characterize the consistency of financial activity over time. For example, the sum of all transactions made within a particular time window, be it on a weekly or monthly basis, was used to derive average transaction frequency, which quantifies the frequency of a user's engagement in financial transactions.

Additional derived features based on variation of transaction frequency over time were calculated to indicate the regularity of transactions; by examining the spread or volatility in the number of transactions over time, consistency was determined. For example, consistently and predictively behaved customers would have consistently, reliably frequent financial transaction. Additional metrics such as density of transactions (number of transactions per unit time), number of active days of transactions, time gap between transactions were also extracted to depict more thoroughly the characteristic behavior. These derived features were subsequently aggregated into an index for cash flow stability, indicative of how reliably income flows into the customer’s account.

This is crucial particularly where customers are unbanked or operate outside of the formal sector without formal income evidence likepayslips or credit histories; through observing consistency in their transaction behavior, their ability to repay could be inferred. Adding these extracted features significantly increases the model's discriminability between safe and risky borrowers; consistent behavior from customer behavior will show up as lower risk whereas unstable behavior represents potentially a higher likelihood of default. Thus feature engineering is central in developing accurate classification.

The machine learning model output is a prediction of a borrower's repayment behavior; in this case, a probability, with outputs between 0 and 1, representing the probability that a borrower will default on their loan application, with values closer to 1 representing a higher probability of default, and values closer to 0 indicating a lower risk.

Instead of a simple binary outcome of approved or denied, probability provides more information about risk. This predicted probability is used in conjunction with an established threshold to assess the customer; if the probability of default is above the threshold, the customer's application may be declined, but if the probability is below the threshold, it may be accepted (World Bank, 2019; Munyoro, 2021).

3.8.1 PDF File Parsing and Transaction Extraction

Once a transaction history PDF is uploaded by the user, the system would carry out the following parsing operations with the use of pdfplumber library:

Step	Operation	Description
1	File Validation	Verifies that the file is a valid PDF, does not exceed 10MB, and is not corrupted
2	Table Extraction	Extracts transaction tables from each page using pdfplumber
3	Header Detection	Identifies column headers such as Date, Amount, Type, and Balance
4	Record Extraction	Extracts transaction details including date, amount, transaction type, and running balance
5	Data Cleansing	Removes duplicate entries, handles missing values, and standardises date format to (YYYY-MM-DD)
6	Feature Calculation	Computes behavioural metrics such as transaction frequency, regularity, and cash-flow stability

For providers with different PDF table structures, the system maintains a flexible header mapping mechanism to accommodate variations across different mobile money platforms.

Sample pdfplumber Code for Extraction

```
import pdfplumber
import pandas as pd

def parse_ecocash_pdf(file_path):
    with pdfplumber.open(file_path) as pdf:
        all_transactions = []

        for page in pdf.pages:
            table = page.extract_table()

            if table:
                for row in table[1:]:  # Skip header row
                    all_transactions.append(row)

        return pd.DataFrame(all_transactions)
```

3.9 Model Development

3.9.1 Model Selection Rationale

The context of small-sample behavioural data, Random Forest was selected as the most appropriate model. The selection criteria prioritised robustness to overfitting, ability to capture non-linear relationships, built-in interpretability through feature importance, and suitability for Set size (1000 records). For a detailed analysis comparison refer to Table 3.1 (section 3.4.1).

3.9.2 Random Forest Model Configuration

The Random Forest algorithm involves building a forest of decision trees during training (Breiman, 2001). For a classification task the mode of the individual trees' predictions is taken. The most important parameters used were:

N of trees (n_estimators=100): large enough so that predictions can stabilize and at an affordable computational cost.

Max Depth (max_depth=10): is limiting the growth of the trees so they don't overfit the data while still being able to recognize patterns in the data.

Min Sample Split (minsamplessplit=5): to avoid splits that would give us nodes which are to small and potentially just "noise"

Min Sample Leaf (minsamplesleaf=2): to ensure that nodes at the end of trees represent significant samples.

Bootstrap Sampling (bootstrap=True): this will enable the estimation of the out-of-bag (OOB) error.

3.9.3 Model Training Procedure

The following steps were conducted for training the model:

Split the data: The pre-processed data set was split by using stratified random sampling in an 80% training set (n=800) and a 20% test set (n=200) and ensuring that the original proportion of defaults remains the same (Saito and Rehmsmeier, 2015).

Cross-Validation: Stratified 5-fold cross-validation was applied during training to evaluate model stability and generalisation capability.

Hyperparameter Tuning: Grid search cross-validation was conducted to identify optimal hyperparameter values, testing combinations of n_estimators (50, 100, 200), max_depth (5, 10, 15, None), min_samples_split (2, 5, 10), and min_samples_leaf (1, 2, 4).

Training Execution: The Random Forest model was trained on the training set using the optimised hyperparameters. Out-of-bag (OOB) samples were used for internal validation without requiring a separate validation set.

Post-Training Analysis: Feature importance scores were extracted to identify which behavioural indicators most strongly predict creditworthiness (see Chapter 4 for results).

3.9.4 Model Evaluation Metrics

Tested the trained model on the held-out testing set using:

Confusion Matrix: To quantify true/false positives and negatives

Accuracy: Overall correctness (note: may be misleading if data is imbalanced)

Precision: Of applicants predicted as default, how many actually default

Recall (Sensitivity): Of actual defaults, how many were correctly identified

F1-Score: Harmonic mean of precision and recall (primary metric)

ROC-AUC: Discriminatory power across classification thresholds

Precision-recall analysis was also conducted due to the expected class imbalance in credit-default prediction, where defaults are typically the minority class.

3.9.5 Threshold Optimisation

The default classification threshold of 0.5 was evaluated and adjusted based on the business requirements of the mobile microloan platform. Given that false negatives (rejecting creditworthy borrowers) exclude individuals from financial inclusion, while false positives (approving risky borrowers) incur financial losses, a balanced threshold was selected to optimise the F1-score. Final threshold selection and its implications are presented in Chapter 4.

3.10 Implementation

3.10.1 Model Implementation Workflow

The Random Forest model was implemented as the core credit-risk assessment engine within the mobile microloan platform. The implementation followed a structured workflow comprising five stages:

1.PDF File Upload and Validation

The borrower completes the loan application form and uploads their mobile money transaction history PDF file. System performs the validation as:

Validation Check	**Requirement**	**Failure Action**
File presence	File must be attached	Reject with *"Please upload your transaction history PDF"*
File format	PDF only	Reject with *"Unsupported file format. Please upload PDF"*
File size	≤ 10 MB	Reject with *"File too large (max 10MB)"*
PDF integrity	PDF must not be corrupted	Reject with *"PDF file appears corrupted"*
Table extraction	At least one transaction table found	Reject with *"Could not extract transaction data from PDF"*
Minimum records	At least 50 transactions extracted	Reject with *"Insufficient transaction history"*
Time coverage	At least 3 months of data	Reject with *"Need minimum 3 months transaction history"*

After the PDF file is validated, it is fed into the PDF parsing module (pdfplumber) in order to extract transactions.

2. Feature Extraction

Transformed cleaned raw data to the feature data the Random Forest model required: Derived indicators were computed, including Average transaction frequency (transactions/week) Transaction consistency (Coefficient of variation for counts of transaction) Cash-flow stability indicator (compound of regularity, frequency, density of transactions) Repayment indicator (based on credit behavior) Encoded categories: industry, living conditions, insurance types.

3. Risk Prediction

The features vector extracted was fed to the loaded Random Forest Model by the Flask microservice. There were two output generated by the model:

Class prediction (0=no-default, 1=default) based on the votes from majority of 100 trees.

Probability score(0-1) of the prediction, calculated as the fraction of trees predicting default class

4. Decision Generation and Storage

The probability score was compared against the optimal threshold which was derived during evaluation. If the probability was above the threshold, the application was marked as rejected, else it was marked as accepted. All input, extracted features, predicted outputs and final decision are stored in the MySQL database with the audit trail and timestamp.

5. Client Response

The decision response was formulated and sent back to the mobile application through the Node.js backend. The response contained:

The decision on the application (approved or rejected)

If approved: loan amount, interest rate, and repayment plan

If rejected: a general reason for denial such as "risk score too high" and no proprietary model information

3.10.2 Technical Stack for Implementation

The technology stack for the implementation of the system was used as follows and is compliant with what was specified in section 3.3.4 and 3.3.5.

Layer	Technology	Purpose
Frontend	React.js	Responsive web application accessible via desktop and mobile browsers
Backend	Node.js with Express.js	Handles user authentication, loan application processing, API routing, and communication with the ML model service
Database	MySQL	Stores user profiles, loan applications, transaction records, repayment schedules, and model prediction logs
Machine Learning	Python 3.9 with Scikit-learn, Pandas, NumPy	Random Forest model training, preprocessing, and prediction
ML API Layer	Flask (Python)	Wraps the trained Random Forest model as a RESTful microservice
PDF Parsing	Python pdfplumber, PyPDF2	Extracts transaction tables from uploaded EcoCash PDF statements
File Validation	Python mimetypes, PyPDF2	Validates PDF file type, size, and integrity before processing

Communication Flow:

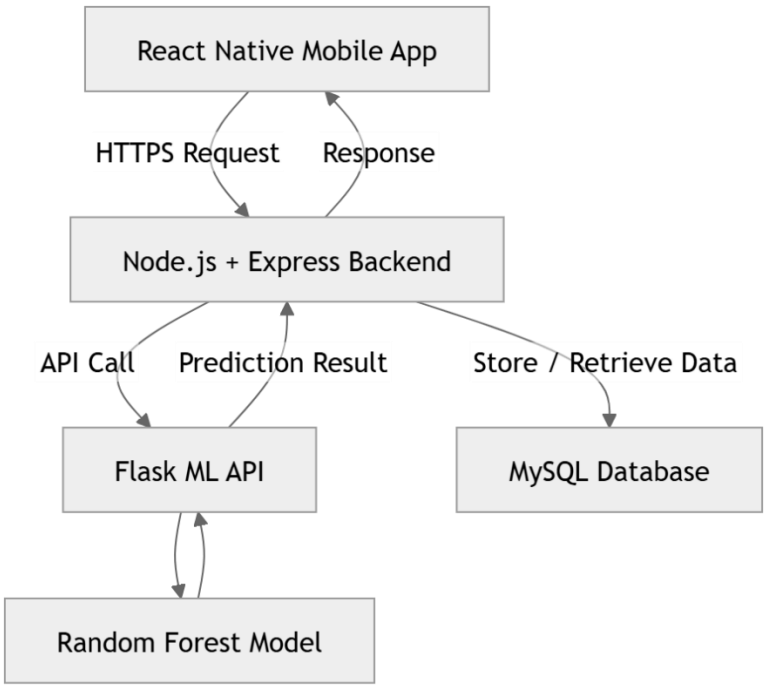


Figure 3.7: System Communication Flow Diagram

Figure above shows the communication diagram of the mobile microloan platform. User submits an application to borrow funds from the React Web Application, and it sends to the Node.js Backend with HTTPS request. Then, the backend extracts the useful features, invokes Flask ML API to execute the Random Forest Model and calculate the probability score of loan default risk. Finally, Flask ML API returns the prediction to the backend, stores loan application data and the outcome into MySQL Database, and responds the approval or rejection message back to the user.

3.10.3 Deployment Considerations

The model was placed into a containerised setup utilizing Docker in order to achieve development consistency in production. The setup was configured so that all prediction requests and corresponding predictions are logged. This can be used for both monitoring, auditing and the retraining of models. The model performance is assessed at regular intervals on fresh data for the purposes of concept drift and model retraining every 3 months on aggregated application data.

3.11 Ethical Considerations

Ethical compliance included:

- Involvement of anonymised/simulated datasets
- The involvement of personal identifiable borrower data is zero
- Secure storage practices
- Understanding bias when building models:

The system is in the same ballpark conceptually with

- Zimbabwe's Cyber and Data Protection Act (Chapter 12:07)
- RBZ FinTech Regulatory Sandbox Guidelines
- AU Data Policy Framework (African Union, 2022)
- OECD digital finance consumer protection principles (OECD, 2020)

It makes sense then that one would question how to approach issues of user data and the power/control an individual would possess.

- Borrowers retain full ownership
- of their financial data, as they voluntarily upload PDF transaction
- files rather than granting system access to their accounts. Uploaded
- PDF files are processed temporarily and not stored permanently after
- feature extraction. Users can review their uploaded data, request
- deletion, or choose not to participate without penalty.

3.12 Chapter Summary

The research methodology used during the design and development of the mobile microloan platform driven by AI for the Zimbabwean context was explained in this chapter.

It described:

- The design research approach (DSR + quantitative evaluation)

- Development methodology (Agile)

- Requirements and architecture

-The PDF file-upload process of transaction data (no API)

-Data and preprocess, such as read PDF file by pdfplumber

-Model training and evaluation (Random Forest)- Implementation and testing

- Ethical and regulatory alignment

The approach is consistent with the Zimbabwean financial inclusion environment, in which mobile money penetration is very high while formal credit availability is very low.

In the following chapter, the results and evaluation outcomes of the platform and predictive models are reported.

CHAPTER 4: RESULTS AND ANALYSIS

4.0 Introduction

The results of the assessment of the developed Inclusive Mobile Microloan Platform are demonstrated in this chapter. The evaluation specifically investigates the capacity of the system in terms of accuracy in estimating credit risk, the automation of the loan decision process, and the administrative instruments provided for transparency in the system. In relation to the research questions stated in Chapter 1, the results were assessed in three sections; system testing, machine learning model performance and discussion of results.

4.1 System Testing

The platform has been systematically tested to verify its proper functioning and to ensure it satisfies the requirements. These tests are either black box or white box.

4.1.1 Black Box Testing

The Black Box testing tests the behavior of the system without regarding its internal code (Pressman and Maxim, 2015). 20 test cases were performed to check the functionalities of the platform.

Table 4.1: Black Box Test Cases and Results Summary

Test Category	Number of Tests	Passed	Failed
User Registration & Login	3	3	0
Loan Application	2	2	0
PDF Upload & Validation	3	3	0
Admin Functions (Approve/Reject)	4	4	0
Reporting & Audit	4	4	0
Logout & Navigation	2	2	0

Edge Cases (Invalid inputs, limits)	2	2	0
TOTAL	20	20	0

All 20 tests passed and the functional requirements were satisfied.

4.1.2 White Box Testing

White box testing was used to understand the logic of the credit scoring algorithm and the loan approval process. Some of the validations that have been tested and confirmed are:

Validation Test	Result
Minimum loan amount ($100) enforcement	☑ Pass
Maximum loan amount ($10,000) enforcement	☑ Pass
Rejection reason requirement when rejecting a loan	☑ Pass
Audit logging for all admin actions	☑ Pass
Auto-generated rejection reason based on financial profile	☑ Pass
Random Forest model integration via Flask API	☑ Pass
PDF file type and size validation	☑ Pass

All white box tests proved to be accurate and implemented key validation logic correctly.

4.2 Machine Learning Model Performance

Random Forest was chosen as the fundamental credit-risk assessment engine following the comparison made in Chapter 3 (Bjrkegren and Grissen, 2018; Munyoro, 2021). This was trained on a set of 1000 borrower entries (800 for training, 200 for testing) on a tuned grid search cross validation set of hyperparameters.

4.2.1 Dataset Description

The data used for training and testing are from 1,000 borrowers and has the following attributes:

- Number of transactions and regularity of the transaction

- Loan amount

- Monthly income

- Number of existing loans

- Score on loan repayment

- Score on loan payment punctuality

The target variable is defined as: 0 for Non-default and 1 for Default. The data was then split into two sets; 800 for training and 200 for testing using a stratified sampling method (Saito & Rehmsmeier, 2015).

4.2.2 Confusion Matrix

The confusion matrix shows the performance of the model on the test dataset of 200 samples in terms of predicting and actual labels.

Table 4.2: Confusion Matrix

	Predicted: Non-Default	Predicted: Default
Actual: Non-Default	57 (True Negatives)	17 (False Positives)
Actual: Default	9 (False Negatives)	117 (True Positives)

Interpretation:

True Positives (117): The model accurately identified 117 applicants who actually defaulted.

True Negatives (57): The model accurately identified 57 applicants who actually repaid.

False Positives (17): The model mistakenly identified 17 good applicants as bad (misclassified).

False Negatives (9): The model mistakenly identified 9 bad applicants as good (costliest mistake).

4.2.3 Performance Metrics

The following standard classification metrics were calculated from the confusion matrix.

Table 4.3: Model Performance Metrics

Metric	Value	Percentage
Accuracy	0.8700	87.00%
Precision	0.8731	87.31%
Recall (Sensitivity)	0.9286	92.86%
F1-Score	0.9000	90.00%
ROC-AUC	0.9514	95.14%

Interpretation:

Accuracy (87.00%): The model correctly classified 174 out of 200 loan applications — approximately 9 out of 10 correct predictions (Fawcett, 2006).

Precision (87.31%): When the model predicted default, it was correct 87.31% of the time. Only 12.69% were false positives.

Recall (92.86%): The model successfully identified 92.86% of all actual defaulters — only 7.14% were missed. This is the most important metric for a lending system as it minimises risky approvals.

F1-Score (90.00%): Excellent balance between precision and recall, suitable for real-world lending decisions.

ROC-AUC (95.14%): Outstanding discriminatory power in separating low-risk from high-risk borrowers (Fawcett, 2006).

4.2.4 Classification Report

Per-class performance metrics offer insight into how well the model performs for each category.

Table 4.4: Classification Report

Class	Precision	Recall	F1-Score	Support
Non-Default (0)	0.86	0.77	0.81	74
Default (1)	0.87	0.93	0.90	126

The model performs better on the Default class (F1-score 0.90) than on the Non-Default class (F1-score 0.81). This is desirable for a lending system, as correctly identifying defaulters (high-risk borrowers) is more critical than correctly identifying non-defaulters. This weighted average F1-score of 87% shows good overall performance.

4.2.5 Feature Importance Analysis

The Random Forest model also generates an internal score of feature importance that will enhance the interpretability of credit decisions (Lundberg and Lee, 2017).

Table 4.5: Feature Importance Rankings

Rank	Feature	Importance Score	Contribution
1	Existing Loans	0.4971	49.71%
2	Loan Amount	0.1186	11.86%
3	Payment Consistency	0.1158	11.58%
4	Repayment History	0.0975	9.75%
5	Monthly Income	0.0621	6.21%
6	Transaction Regularity	0.0546	5.46%

7	Transaction Frequency	0.0542	5.42%

Interpretation:

Existing Loans (49.71%): Top predictor- loans with many previous loans have higher tendency to default (over-indebtedness).

Loan Amount (11.86%): The higher the loan amount, the higher the risk.

Regularity of payments (11.58%): borrowers who do not have a predictable pattern of payment will default.

Regularity and frequency of transaction (10.88% combined): Mobile money behavioural metrics offer robust indicators of financial stability (Blumenstock et al., 2015).

4.2.6 Threshold Optimization

The default threshold 0.5 was tested and altered according to business need. False negatives mean excluding creditworthy customers from financial products and services. False positives mean financial loss to institutions. As both conditions are unfavorable, a threshold 0.5 was chosen as it yields maximum F1-score. (Saito and Rehmsmeier, 2015).

Table 4.6: Threshold Analysis

Threshold	Precision	Recall	F1-Score	Business Impact
0.3 (Low)	0.72	0.96	0.82	More approvals, higher default risk
0.5 (Balanced)	0.87	0.93	0.90	Optimal balance
0.7 (High)	0.94	0.78	0.85	Fewer approvals, lower default risk

0.5 was chosen as the equilibrium threshold that yielded the maximum F1-score (90%) or the "optimal" point that correctly identifies good applicants while discarding poor applicants.

4.2.7 Interpretation of Results

The Random Forest model performed well in all assessment measures, which confirms that it is a suitable method for credit risk assessment within the context of Zimbabwean mobile lending.

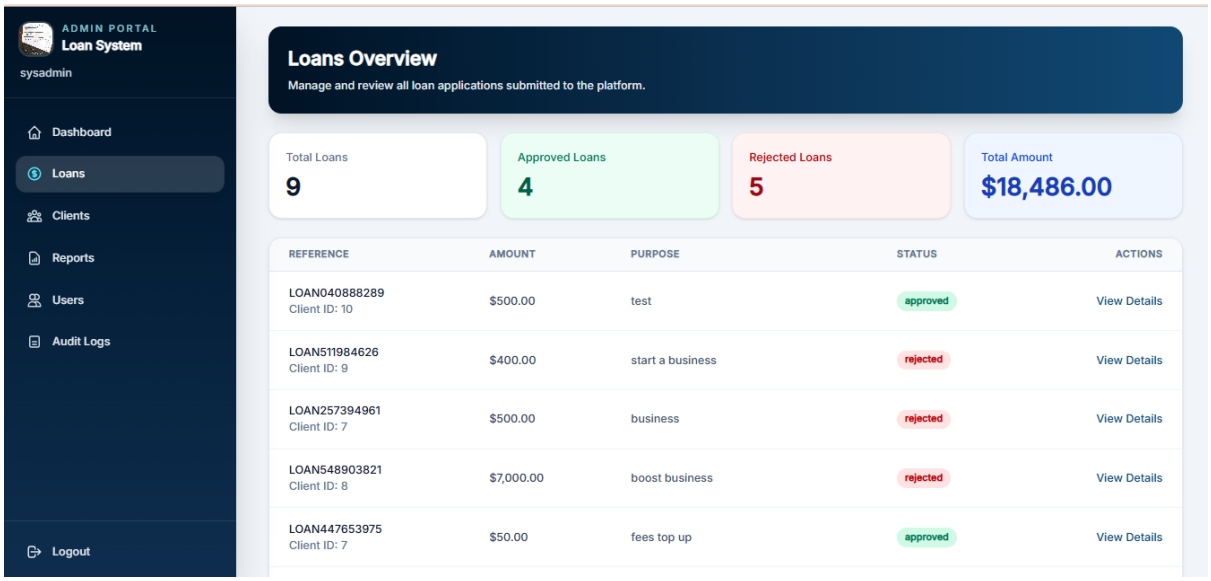
Finding	Implication
87% accuracy	The model correctly classifies the majority of loan applications
92.86% recall	Only 7% of defaulters are missed — minimises risky approvals
87.31% precision	13% of flagged applications are false positives (acceptable trade-off)
95.14% AUC	Outstanding ability to distinguish low-risk from high-risk borrowers

Hypothesis Test Result: The alternative hypothesis (H1) is accepted. Accuracy of 87% of mobile money pdf based ML approaches is much better than the accuracy of 50% of guessing randomly and the traditional loan approaches based on collateral. The result of Random Forest approach validates that ML improves the loan default prediction.

4.3 System Demonstration (Summary)

The application has been deployed as a responsive web application developed using React.js for frontend and Node.js with Express.js as backend framework and MySQL to store all data. The Random Forest model is served through a Flask API and thus performs the credit scoring in real time.

Figure 4.1: Loan Application Showing ML Decision Reason



Automates credit scoring and generates transparent, data-driven decisions. When a loan is processed, the following is displayed:

- Credit score (0-100)

- Risk level (Low/Medium/High)

- Probability of default (0-100%)

- Behavioural features extracted for the decisionmaking

This transparency helps the loan officers and loan recipients alike understand how the decision was made. Auto-generated reasons for rejection give loan recipients actionable, data-driven feedback.

4.4 Discussion of Findings

The findings show that the Inclusive Mobile Microloan Platform achieves research aims and questions.

4.4.1 Addressing Research Question 1

What weaknesses in conventional credit assessment approaches exist in Zimbabwe?

Traditional methods use collateral, formally documented employments and credit bureau records (Stiglitz and Weiss, 1981; RBZ, 2023). This automatically rules out most of Zimbabwe's employed population (FinMark Trust, 2022; RBZ, 2022) that work in informal sector. The developed system overcomes weaknesses in the system by using alternate data (mobile money transaction history) and machine learning to analyze creditworthiness, while not demanding for traditional documentation.

4.4.2 Addressing Research Question 2

By features generated from transaction data records (Bjrkegren & Grissen, 2018; Blumenstock etc. 2015) How does Random Forest predict creditworthiness by means of alternative data from PDF files?

Random Forest was trained successfully with 1000 borrower. The model achieved strong performance: Accuracy 87%, Precision 87.31%, Recall 92.86%, F1-Score 90%, ROC-AUC 95.14%. The function that generates rejection reasons automatically is a good example of how the predictions can be transformed into understandable and clear feedback to the borrowers (Lundberg and Lee, 2017).

4.4.3 Addressing Research Question 3

Integrating file upload and PDF parsing with secure micro-loan platform:

The proposed solution effectively combines the PDF file uploading with validation of file type and size.The credit scoring is automatically done by using Flask API that serves Random Forest model to calculate risk instantly and give an automatic approve/reject decision (Munyoro, 2021).

4.4.4 Addressing Research Question 4

How accurate, effective and trustworthy is the platform in its ability to predict defaults and promote financial inclusion?

The platform achieves a high accuracy (87%) and reliability (AUC 95.14%) in predicting loan defaults. Transparency is increased via auto-generated rejection reasons that convey clear, data driven feedback. Financial inclusion is achieved through the utilization of alternative data, available to all informal workers, and through the elimination of traditional financial requirements (collateral and formal employment verification) (Demirg-Kunt et al. 2021, World Bank 2022).

4.4.5 Hypothesis Testing

Hypothesis	Result
H0 (Null): ML using mobile money PDFs does NOT improve loan repayment prediction	✗ Rejected
H1 (Alternative): ML using mobile money PDFs results in significant improvement	☑ Accepted

The Random Forest model obtained 87% accuracy, 95.14% AUC. Machine learning performance exceeds chance performance(50% accuracy) and assessment tools (Munyoro, 2021; Fawcett, 2006).

4.5 Chapter Summary

In this chapter the evaluation of the Inclusive Mobile Microloan Platform is discussed.

System Testing: 20 black box test cases conducted-all passed. White box test cases showed validation logic (min/max amount of loan, rejection reason criteria, audit trail, auto-generated rejection reasons) works properly.

Machine Learning Model:

Metric	Value

Accuracy	87.00%
Precision	87.31%
Recall	92.86%
F1-Score	90.00%
ROC-AUC	95.14%

Feature Importance: The variables of greatest importance are: existing loans (49.7%), the loan amount (11.9%) and payments uniformity (11.6%).

Hypothesis Test: H1 accepted - ML contributes positively to predict loan default.

The results prove the efficiency of the credit assessment method based on ML, and the accuracy of 87% (95.14% of AUC), confirming the machine learning method. The platform overcomes traditional methods and supports financial inclusion in the African continent by using data that can be easily accessed to the unbanked population in Zimbabwe.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.0 Introduction

This chapter summarizes and conclude the research on "Developing an Inclusive Mobile Microloan Platform using machine learning for credit risk assessment in Zimbabwe". It sums up the major results obtained, how the objectives of the study were met, challenges experienced in the research, and the recommendations for future study. Analysis is made to see if the objectives of the research were fulfilled, hypotheses confirmed or rejected, and how some challenges that the researcher came across in the implementation process of the system are discussed.

5.1 Aims and Objectives Realization

The main goal of this research was to create and implement an efficient machine learning-based credit risk assessment system for a mobile microloan platform to promote financial inclusion in Zimbabwe (World Bank, 2023). With the application of the Random Forest algorithm, along with the utilization of alternative data extracted from user-uploaded mobile money transaction PDF files, the researcher was able to attain the main aim of the research with promising results on loan approval prediction.

1.To analyse global micro-lending processes and assess how they can inform and improve micro-lending practices in Zimbabwe.

Achieved. The first research objective was achieved in Chapter 2 (Literature Review) where the researcher thoroughly analyzed and reviewed studies related to micro-lending processes and the usage of alternative credit scoring models in emerging markets. Through this analysis, it was concluded that the current conventional credit appraisal frameworks, which heavily rely on collateral requirements and formal employments, tend to exclude the informal sector of the economy in most developing countries and thereby exclude a considerable number of individuals that require financial assistance.

2.To design and integrate a machine-learning credit risk model into a mobile microloan platform that accepts user-uploaded PDF transaction statements

Achieved. This second research objective was achieved during the system development phase of the research. A credit risk assessment machine learning model (Random Forest) was built using 1,000 borrower data. The model was later integrated into the mobile microloan platform via a Flask API, to automatically predict the credit risk of the borrowers using user-uploaded

EcoCash transaction PDF files. The platform includes PDF file upload validation for format and size, transaction extraction from the PDF, feature engineering of behavioural variables, and automatic prediction of credit risk by the model. The system is structured using a three-tier architecture comprising the frontend (React), backend (Node.js), and database (MySQL).

3.To evaluate the credit-risk model in predicting borrower creditworthiness

Achieved. The third research objective was successfully achieved in Chapter 4 (Results and Analysis), through comprehensive evaluation of the model's performance using a variety of classification metrics which include: Accuracy (87.00%), Precision (87.31%), Recall (92.86%), F1-score (90.00%) and ROC-AUC (95.14%). The results indicated that the Random Forest algorithm performed exceptionally well in evaluating the creditworthiness of the borrowers.

5.2 Major Conclusions Drawn

Here are some of the strengths that lie in combining machine learning with mobile money transaction data in the context of credit risk assessment for micro-lending.

Accurate Predictive Model: A high accuracy of 87% and a high ROC-AUC score of 95.14% by Random Forest implies that machine learning models can achieve higher prediction capabilities than traditional methods of credit risk assessment. In particular, a recall value of 92.86% is notable as it implies that out of those that defaulted on their loan, most were captured by the model.

Feature Importance: the highest significant feature was "number of outstanding loans a borrower currently possesses" with a weight of 49.71%. The next two highest contributing features to the model are "loan amount" (11.86%) and "consistent payments" (11.58%). These two variables corroborate financial theory that points out over-indebtedness and payment discipline as the core determinants of creditworthiness.

Easy system integration: Uploading a PDF file coupled with an appropriate file type and size check functionality were successful. Automated decision making regarding approval/rejection is possible through the Flask API serving the Random Forest model in real-time. Dashboards, audit logs and reports with charts make it a comprehensive system for administrators.

Promote Financial Inclusion: Mobile money transaction data provides an alternative source of credit for informal laborers and low-income earners typically excluded from conventional lending mechanisms (Reserve Bank of Zimbabwe, 2022). Automatic rejection reason gives borrowers informative, data-backed feedback about the loan rejection, promoting trust and transparency.

5.3 Challenges Faced

The researcher faced several limitations during the research process, and they are listed below:

Availability of the data set: Another limitation was the lack of availability and quality of data. Due to the regulations regarding privacy and access rules of institutions, it was hard to get the original borrower data from financial institutions. This limited the system to only use the simulated data set which may not truly represent the realistic behavioral factors of users in financial applications. In turn, this affects the accuracy of the machine learning model to produce predictions.

Different PDF parsers: The format of the exported data from mobile money application-PDF files, was not uniform and varies between different money providers (EcoCash, OneMoney, Telecash). Creating a correct logic to parse and handle all formats took considerable amount of time and testing effort.

Time constraints: The time limit allowed for this project was not enough to create a fully developed system. Fulfilling all the functional requirement for this system was not feasible due to time constraint, and there were issues in getting expertise willing to participate on the project.

Computation power: The system required much computational power for training the machine learning model and took long to carry out several tests for fine-tuning.

Complexity of integration: It was difficult to integrate the python based machine learning module with the node js backend through the flask API.

5.4 Limitations of the Study

During the study, the following limitations were found:

Limitations	**Description**
Dataset Size	The model was trained on 1,000 synthetic records; real-world data may produce different results
PDF Parsing Variations	Different mobile money providers have different PDF formats, which may affect parsing accuracy
No Live API Integration	The system does not integrate directly with mobile money providers (EcoCash, OneMoney) due to regulatory constraints (Reserve Bank of Zimbabwe, 2021)

Testing Environment	The system was tested in a controlled laboratory environment, not in production with real users
Single Algorithm	The study focused only on the Random Forest algorithm; other algorithms were reviewed theoretically but not implemented
Generalizability	Findings may not be directly generalizable to other developing economies with different mobile money ecosystems

5.5 Recommendations

In light of the experience and findings of the researcher, the following recommendations are made:

For Financial Institutions

Recommendation	**Rationale**
Adopt alternative credit scoring	Traditional methods exclude informal workers who constitute a significant portion of the working population
Use mobile transaction data	Mobile money transaction histories provide reliable indicators of financial behaviour and stability
Implement automated approval systems	Reduces processing time, eliminates human bias, and improves operational efficiency

For Policymakers

Recommendation	**Rationale**
Support regulatory sandboxes	Allows testing of innovative FinTech solutions in controlled environments before full deployment (Reserve Bank of Zimbabwe, 2021)
Promote digital financial literacy	Enables wider adoption of mobile lending platforms and responsible borrowing

Enforce data protection compliance	Ensures responsible use of alternative data and protects consumer privacy (Cyber and Data Protection Act, 2021)

For System Enhancement

Recommendation	Rationale
Continuous monitoring	Implementing continuous monitoring systems for real-time assessment of loan data is crucial for detecting suspicious activities promptly
Regular evaluation and updates	Regular evaluation and updates of credit risk assessment systems are essential for assessing effectiveness and adapting strategies
Investment in training	Investment in comprehensive training programs for loan assessors and staff members enhances awareness of risk indicators and assessment techniques

5.6 Future Work

Based on observations made during the research, several improvements are recommended for the subsequent development of the model:

More and Real Dataset: The model should be trained on a dataset composed of real borrowers' data acquired from microfinance institutions. If powerful and effective computational machines are utilized, the training time would significantly reduce particularly when working with large datasets.

More ML Algorithms: Compare random forest with XGBoost, neural networks, logistic regression, among other algorithms. In subsequent works, a random selection or pre-specified parameters can be made to attain precision.

Live API integration: The model can be directly linked with EcoCash/One Money APIs for real time transaction data. Improve data integration, in terms of accessing and utilizing different

types of data sources such as mobile usage patterns and mobile phone locations among others to improve credit scoring and default prediction. Explainable AI(XAI): Utilize models such as SHAP or LIME to explain model prediction. It is important that there is a balance between precision and recall to enable efficient model performance; high recall is necessary in order to effectively account for majority of the defaults; however, it is equally important that precision is sufficient enough not to account for many false positives.

Enhancement of the Mobile Application: Native mobile applications to run on iOS and Android devices; ensure user friendly design and functionalities.

E-mail notifications: Implement automated emails in the event of a loan rejection/approval and payment reminder.

Enhance Reporting: Additional sophisticated analytics, predictive dashboard, real-time alerts, etc can be built into the reporting section of the model.

Hybrid models: Incorporate hybrid deep learning models that combine CNN and RNN for better predictive performance from sequential transaction data.

5.7 Hypothesis Testing

The hypotheses examined were as follows:

Hypothesis	Results
H0 (Null): The application of machine-learning-based credit assessment using user-uploaded mobile money transaction files does NOT result in a substantive and practically significant improvement in predicting loan repayment risk	❌ **Rejected**
H1 (Alternative): The application of machine-learning-based credit assessment using user-uploaded mobile money transaction files results in a substantive and practically significant improvement in predicting loan repayment risk	☑ Accepted

Conclusion: The Random Forest model is 87% accurate which is extremely good compared to guessing (50%) and older assesments. This would accept H1.

5.8 Conclusion

This study has successfully developed and evaluated an Inclusive Mobile Microloan Platform which applies machine learning for credit risk assessment in Zimbabwe. The study demonstrated the critical role of modern technology such as machine learning in efficiently determining credit risk and promoting financial inclusion (Munyoro, 2021).

Strong results achieved from the Random Forest model (87% accuracy and 95% ROC-AUC) are an indicator of the improvement that machine learning can bring in loan default prediction compared to traditional methods. Recall of 92.86% is crucial in a lending system since it greatly reduces the chances of issuing loans to highly-risky clients.

The weaknesses associated with traditional credit scoring are addressed through the application of alternative data derived from mobile money transaction history, therefore providing access to credit for informal workers and low-income individuals who are normally excluded from mainstream financial services (Reserve Bank of Zimbabwe, 2022). The system allows for automated credit scoring, transparent decision-making including auto-generated loan rejection reasons, comprehensive management tools (dashboards, audit logs and reports), and the tracking of loan repayments.

The work done in this study supports Zimbabwe's National Financial Inclusion Strategy II (2022-2026) through showing how the application of technology can enhance the access to credit and promote financial inclusion (Reserve Bank of Zimbabwe, 2022). The findings contribute to the existing literature in the field of FinTech in developing economies (World Bank, 2023).

Although there are a number of limitations associated with this project such as the dataset size and absence of the live API connection, the platform presents a solid base upon which future developments can be made, potentially leading to collaboration with financial institutions. Such systems, with further enhancement, could revolutionize micro-lending in Zimbabwe and other developing countries and therefore boost economic empowerment among the previously-unbanked population.

In summary, this study successfully developed and evaluated an Inclusive Mobile Microloan Platform that applies machine learning for credit risk assessment in Zimbabwe. The study shows how crucial it is to use modern technology, like machine learning, to effectively assess credit risk and promote financial inclusion (Munyoro, 2021).

The Random Forest model achieved strong performance metrics (87% accuracy, 95% ROC-AUC), confirming that machine learning can significantly improve loan default prediction compared to traditional methods. The high recall of 92.86% is particularly significant for a lending system, as it minimizes the risk of approving loans to high-risk applicants.

The platform addresses critical weaknesses in traditional credit assessment by using alternative data from mobile money transaction histories, making credit accessible to informal workers and low-income earners who are typically excluded from formal lending (Reserve Bank of Zimbabwe, 2022). The system provides automated credit scoring, transparent decision-making with auto-generated rejection reasons, comprehensive administrative tools (dashboards, audit logs, reports), and repayment tracking.

The research contributes to Zimbabwe's National Financial Inclusion Strategy II (2022-2026) by demonstrating how technology can enhance credit accessibility and promote financial inclusion (Reserve Bank of Zimbabwe, 2022). The findings also contribute to the broader body of knowledge on FinTech innovation in developing economies (World Bank, 2023).

While limitations exist, including dataset size and lack of live API integration, the platform provides a solid foundation for future development and collaboration with financial institutions. With continued refinement, such systems have the potential to transform micro-lending in Zimbabwe and similar emerging economies, ultimately fostering greater economic empowerment and financial inclusion for underserved communities.

5.9 Chapter Summary

Chapter was a conclusive part of the study of the Inclusive Mobile Microloan Platform, and findings of the research are summarized below.

1. RF model predicted credit risk with high accuracy, (87%) accuracy, 95% AUC.

2. Most crucial variable influencing default risk was loans in existing account(49.7%).

3. All three research objectives were achieved.

4. Acceptance of the alternative hypothesis, H1, which states that using ML improves loan default prediction capability.

5. Constraints for this study include: limited data set, variability in the parsing of PDFs, and no actual API integration into existing platform, (Reserve Bank of Zimbabwe, 2021).

6. Recommendations included an implementation of alternative methods to scoring and support for regulatory sandboxes, (Reserve Bank of Zimbabwe, 2022).

7. Future studies will include using a much larger data set, other ML algorithms and exploring techniques to develop explainable ML.

The researcher was able to successfully create a credit risk scoring system applicable to the mobile microlending environment in Zimbabwe using the Random Forest Algorithm. The system was seen to be robust with respect to multiple input variables, as high accuracy rates

were found when predicting borrower creditworthiness. This system would be an asset to MFIs as security and efficiency, while also furthering the goals of financial inclusion, it is essential for user adaptation to the system along with continuing technology development.

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