Forecasting of Customer's Eligibility for The Bank Loan and, Also Predict Credit Limit, Using ML Approach

D N PATHIRATHNA

(IT21164644)

B.Sc. (Hons) in Information Technology specializing in Information Systems Engineering

Department of Computer Science & Network Engineering

Sri Lanka Institute of Information Technology

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DECLARATION

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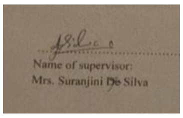
Name	Student ID	Signature
D N PATHIRATHNA	IT21164644	

The above candidate is carrying out research for the undergraduate dissertation under my supervision.

Name of supervisor: Ms. Suranjini SilVA

Name of co-supervisor. Anuradha Jayakodhy



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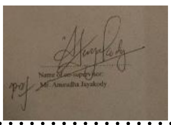
(Ms. Suranjini SilvaName)



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Signature of the co-supervisor: Date

(Prof. Anuradha Jayakodhy)

ABSTRACT

In digital banking practices, automation of credit assessment is pivotal in improving the efficiency of decision-making and minimizing errors of human judgment. In this study, we propose a machine learning-based system that utilizes Logistic Regression to forecast a customer's eligibility for bank loans. Logistic Regression, as a probabilistic linear classifier, is found to be very effective in binary classification environments, making it enable to classifying qualified and disqualified candidates based on structured customer information and calculation for predict eligible credit amounts.

The dataset has demographic, transactional, and credit-based features and is passed through strict preprocessing steps such as normalization, encoding, and imputation of missing values. The Logistic Regression model is trained and tested using stratified k-fold cross-validation, and model performance is evaluated based on accuracy, effectiveness, precision, recall, and F1-score metrics.

In contrast to predictive modeling, credit limit estimation is achieved through a deterministic calculation-based approach, with pre-defined financial ratios and customer-specific parameters. The hybrid system delivers interpretable, efficient, and scalable performance, offering a lightweight yet robust decision-support tool for banking operations.

Given these factors, this study aims to come up with a system that will focus on improving user satisfaction by offering more accurate credit scores, by enhancing users' confidence in seeking a microloan.

Keywords: Logistic Regression, Loan Eligibility, Credit Limit Calculation, Machine Learning,

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Contents

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

Abbreviation	Description
ML	Machine Leaning
CRIB	Credit Information Bureau of Sri Lanka
XAI	Explainable AI

LIST OF APPENDICES

1. Introduction

1.1. Background Study

The finance and banking industry, is the force behind economic development and stability. Banks make billions of Rupees annually from lending money by extending credit to customers and businesses [1]. One of the principal sources of revenue for bank is loan interest paid, hence they are inclined to offer competitive loan rates but at the same time adhere to stern risk evaluation procedures [2]. Borrowers, on the other hand, seek favorable loan terms with low-interest rates and favorable repayment conditions.

Traditionally, the loan process has base on conventional procedures with detailed documentation of the borrower's financial history. The applicants are generally required to provide income statements, credit reports, employment reports, and even collateral reports in certain cases. While documented, the processes are time consuming and generate to human errors, creating inefficiencies as well as disgruntlement for lenders and borrowers alike [3].New technology in Machine Learning (ML) and Artificial Intelligence (AI) is revolutionizing the financial industry through data driven, automatic, and scalable solutions to decision making. In credit analysis, ML algorithms are able to analyze vast amounts of structured and unstructured data to determine whether a borrower can be extended a loan and to what amount credit can be lent safely [4]. This not only cuts down on operational expenses but also improves forecasting accuracy and fairness in decision-making.

Eligibility for a loan is the criteria in which a borrower can be provided with money lent to them. These criteria can be income level, employment stability, existing burden of debt, and earlier credit history. These factors are taken into account by financial institutions to minimize default risk and identify repayment ability [5]. Misjudgment of loan eligibility leads to non-performing loans, which have negative implications on the liquidity and credit rating of the institution [6].

The eligibility procedure typically begins with the verification of the borrower's credit report—typically provided by CRIB. The report gives an overall view of the customer's financial conduct history, including debts, timely repayments, and credit inquiries. They may also carry out public record search and income verification through tax returns, salary certificates, or bank statements [7]. For high-risk, they may demand additional verification.

Even when such methods appear comprehensive in their scope, traditional eligibility determination systems possess several flaws. First, they typically rely on incomplete or outdated information. Second, cognitive bias of human agents renders decision-making erratic and potentially discriminatory [8]. Third, manual checking consumes time, resulting in unacceptable delays to approvals, which are incompatible with high-speed lending times.

The other problem is overfitting or underfitting risk profiles—where traditional scorecards are unable to show an applicant's real financial behavior. For instance, a borrower who has a poor credit history would be denied a loan while experiencing stable earnings and minimal liability [9]. Even rigid rule-based systems do not consider subtle factors like seasonality in earnings for freelancers.

Machine Learning sidesteps many of these limitations by enabling data-driven, pattern-based decision-making. Supervised learning algorithms such as Logistic Regression, Decision Trees, and Support Vector Machines (SVM) are commonly used to classify loan applications into "eligible" or "non-eligible" labels based on labeled historical data [10]. These models can identify complex patterns of relationships between input features like income, age, credit usage and outputs like approved or rejected, thereby increasing classification accuracy.

Unsupervised learning methods as clustering methods, are also employed to segment customers into risk segments to aid in personalized risk profiling and loan product tailoring [11]. Moreover, ensemble methods such as Random Forests and GBM enhance model stability and interpretability by combining multiple weak learners.

One of the main advantages of ML models is that they can improve continuously as they can be retrained on new data, thereby making them responsive to varying economic conditions or patterns of borrower behavior. Further, feature importance analysis enables financial analysts to determine the variables having the most important impacts on predictions, enhancing transparency and adherence to regulatory requirements.

Use of machine learning in loan processing systems benefits both parties. For banks, it enables automatic decision-making, reduced default rates, and horizontally scalable processing pipeline. For borrowers, it means faster approval, improved access to credit, and increased personalization of loan choices.For example, fintech companies like Sampath bank have been able to prove that underwriting platforms powered by machine learning can outperform traditional FICO-based models in terms of accuracy and fairness. These platforms reduce discrimination by focusing on alternative markers such as utility bills, mobile telephony data, and social patterns of behavior, opening up access to underbanked populations.

Despite the gains in efficiency and accuracy, credit scoring based on ML raises pertinent ethical issues, including algorithmic bias, privacy of data, and explainability of models. Black-box models, although powerful, are often deceptive and incomprehensible, which can limit compliance with regulations such as the CRIB or the General Data Protection Regulation (GDPR).Banks are increasingly investing in Explainable AI (XAI) to address such needs by making the predictions more auditable and explainable. Regulators are also now beginning to develop guidelines for AI-driven credit decisions to ensure fairness and accountability

1.2 Literature Survey

The rise of digitalization of banking and finance has dealt a significant blow to the processes followed by banks and financial institutions to ascertain the creditworthiness of an individual. Loan eligibility and credit scoring, once reliant on the traditional manual practices, have been turned into sophisticated data-driven activities facilitated by the progress made in machine learning and artificial intelligence. Though conventional credit scoring methodologies, such as logistic regression, have been core pillars in loan decision-making, they are short of coping with rapidly changing financial situations, non-linear customer conduct [1]. Such traditional approaches are generally founded on a pre-determined set of attributes such as income, work history, and credit history, and are likely to break down when applied to classify thin file borrowers or customers with limited historical data. Furthermore, they are highly reliant on assumptions, suffer from issues like multicollinearity, and fail when need to analyze complex borrower profiles that have hundreds of fluctuating variables.

To mitigate these constraints, scholars and financial institutions have looked at machine learning (ML) models that have also proven to have immense potential in loan eligibility prediction automation and credit risk assessment. Decision Trees, Support Vector Machines (SVM), Random Forests, and Gradient Boosting Machines (GBM) are some of the ML algorithms that allow non-linear modeling, handling high-dimensional data, and real-time adaptability. These algorithms are capable of learning from big data and are able to differentiate between eligible and ineligible borrowers more effectively than traditional methods. For example, Rising Odegua [2] applied XGBoost to predict loan default using real bank data and found that recall, precision, and overall accuracy improved with respect to traditional classifiers. This model utilized economic and demographic metrics to identify high-risk borrowers, being the benchmark in applications of credit assessment. An ensemble deep learning method using Random Forest, XGBoost, and TabNet stacked model was also proposed by Xing et al. [3]. Their work proved that ensemble models can be superior to individual classifiers since they well leveraged their strengths to merge and streamline prediction for both credit scoring and loan eligibility tasks.

Deep learning techniques, in particular sequential modeling, have been applied in financial time-series analysis and dynamic customer profiling. Babaev et al. [4] suggested the E.T.-RNN model that made use of recurrent neural networks (RNNs) on high-granularity transactional data. Their approach significantly improved forecasts of credit risk and provided data regarding customers' patterns of behavior through time. Temporal analysis is particularly beneficial in situations where the financial conduct of the applicant for the loan is not static, such as in the case of gig economies or seasonal employment. Another novel neural structure was presented by Marín [5], who devised a Hamiltonian Neural Network to facilitate stable credit scoring in changing intervals of time. This model had better in-sample and out-of-time test sets Area Under Curve (AUC) performance, as it showed the stability for prediction under unstable and uncertain economic conditions. With the growing importance of deep learning algorithms, researchers have also aimed to achieve predictive power while keeping computational cost and model interpretability in mind.

The black-box nature of most advanced ML models is a critical issue against the backdrop of regulatory compliance and ethical AI. Financial regulations such as the General Data Protection Regulation (GDPR) and the Equal Credit Opportunity Act (ECOA) mandate that decisions derived from automated systems must be explainable and fair. Correspondingly, many studies have explored methods of making ML models explainable while not affecting their performance. Abdollah Rida [6] demonstrated that Shapley Values can be integrated into XGBoost models such that they provide explainable outputs, meeting the explainability requirements of Basel II and III frameworks. The paper also provided evidence that interpretability is achieved without sacrificing performance since the model was able to identify many more default cases than standard scorecards. In a similar endeavor, Demajo et al. [7] proposed a 360-degree explanation method founded on XGBoost that offers local, global, and feature-level interpretations. The method was validated through human-grounded evaluation and satisfied a number of trust metrics, including simplicity, adequacy of detail, and equity.

The integration of alternative sources of information into credit scoring models has paved the way for new possibilities in borrower risk measurement, particularly for underbanked and thin-file consumers. Sanz-Guerrero and Arroyo [8] explored using unstructured text data with BERT, an LLM, on peer-to-peer (P2P) website borrower-provided loan descriptions. By fine-tuning BERT to identify defaulted and non-defaulted loans, they derived a risk score that enhanced the performance of baseline models if added as a supplementary feature. The study demonstrated that contextual language information was able to detect subtle behavioral traits which numerical models could fail to identify. Muñoz-Cancino et al. [9] also made a great impact when they studied how credit history and social interaction features dictate creditworthiness. Using social network information, they illustrated the ways in which behavioral scoring models would be heavily improved, especially in the first few months after a customer acquires their first loan, when traditional data is sparse.

Imbalanced datasets, a common problem in credit scoring due to defaults being so much less than non-defaults, have also been tackled by utilizing advanced ML techniques. Mahsan Abdoli et al. [10] introduced the Bagging Supervised Autoencoder Classifier (BSAC) that handles imbalance through the synergy of under sampling and representation learning. The autoencoder compresses input data into a lower dimension retaining useful information for classification, thereby improving generalization and noise filtering. The authors compared various dynamic ensemble selection methods [11] in another study where they established that the dynamic ensemble selection algorithms performed better than static ensembles on real credit scoring datasets.

The most serious issue in credit modeling is sample bias due to the denied loan requests from training datasets. This results in biased learning and limits the generalization of credit scoring models. Deep generative models for reject inference using semi supervised Bayesian networks for inferring the probable outcomes for the denied applicants was proposed by Mancisidor et al. [12]. Their method improved classification performance and provided a truer evaluation of model performance. Kozodoi et al. [13] also enhanced reject inference with a self-learning approach where rejected cases were progressively labeled and relearned. Their domain-aware metric provided more informative and actionable feedback in comparison to synthetic labeling generally used in previous techniques.

At the cutting edge of innovation, quantum machine learning (QML) is beginning to enter the banking sector. Nouhaila Innan et al. [14] presented LEP-QNN, a quantum neural network for loan eligibility prediction. The model achieved a staggering 98%

accuracy and was found resilient under varying regimes of quantum noise. All this was done by incorporating dropout mechanisms in the quantum circuit to prevent overfitting. Das et al. [15] introduced yet another quantum model called QFDNN which unites deep neural networks with quantum feature representation. They brought to the fore the capacity of QFDNN to perform real-time credit risk assessment through reduction of computational overhead and increased efficiency under constraints in noise. These articles look forward to a rich future where quantum-enriched financial analysis can be a viable reality.

Ethical considerations of ML in credit scoring extend beyond bias detection to include the concept of recourse actionability. Not only should a model be non-discriminatory, but end-users need to be provided with information regarding what would allow their scores to be increased. Ustun et al. [16] designed measures and techniques for quantifying and ensuring recourse in linear classifiers. They illustrated how feature selection and model training strategies might affect one's ability to adjust his loan outcomes. This study is important to facilitate applicants in taking efficacious measures in improving their credit-worthiness, in line with fairness and financial inclusion objectives.

Further, semi-supervised learning techniques have proved helpful in scenarios where labeled data are scarce or hard to obtain at affordable cost. Nikolay Dubina et al. [17] built a semi-supervised model that integrated labeled and unlabeled loan application data to improve prediction accuracy. Their model placed special emphasis on interpretability and data quality, two required attributes for practical implementation. The hybrid approach allowed banks to extend model learning to partially filled-out or noisy record applicants without a significant sacrifice in accuracy.

The overall impression from recent research decisively supports the use of machine learning models to enhance the accuracy, fairness, and flexibility of loan approval and credit scoring models. As customer data becomes more available and regulatory requirements more stringent, the value of models that are both robust and interpretable increases. Ensemble deep learning, explainable boosting algorithms, language-based risk scoring, quantum neural networks, and reject inference strategies are the kinds of technologies that can give financial institutions a complete toolset with which to transform their lending infrastructures. Still, challenges persist. Model transparency, regulatory compliance, sample and algorithmic bias management, and actionable recourse to users are essential to the inclusive and long-term adoption of machine learning in finance. Additional investment in hybrid models, ethical AI, and advanced simulation techniques will likely be the foundation for the future wave of system

1.2 Research Gap

Despite dramatic advancements in machine learning based credit scoring models, several important gaps in research are left unfilled in existing research. Among the most prominent of these gaps is focused concentration by previous models that primarily classify applicants into eligible or non eligible but do not attempt to estimate the actual size of the loan that can be safely advanced. This two group classification forgets the heterogeneity and richness of true financial situations, where a borrower is not so much excluded as suitable for a lower credit limit. All the big models developed by logistic regression, decision trees, or ensembles learn and are tested solely on classification accuracy, forgetful of the real-world problem of estimating an optimal or personalized credit limit. For instance, models like XGBoost, Random Forest, and TabNet, which were used in studies by Odegua [1] and Xing et al. [2], demonstrate high classification accuracy in predicting loan default and approval but are not up to the mark while predicting likely loan amounts considering multi-dimensional customer profiles. Even more advanced models, such as LEP-QNN, which is constructed by Innan et al. [3] and makes predictions of eligibility based on quantum neural networks at a 98% rate, do not attempt to estimate a safe level of credit issuance, indicating a lack of mapping of model outputs and monetary policy actions.

The second major shortfall is in the inability to fully leverage heterogeneous and high-dimensional datasets to train models predicting eligibility. Whereas most recent research makes use of data from Lending Club, Freddie Mac, or in-house bank data, these works usually make use of a small number of features due to complexity, noise, or lack of interpretability. For example, like the Hamiltonian Neural Network by Marín [4] or the Deep Autoencoder Classifier by Abdoli et al. [5], show improved classification performance through data imbalance handling or latent representation learning. But they are still founded on traditional credit factors such as income, age, and employment status, omitting more situational or non-standard sources of information such as the narrative of transactions, social behavior, or macroeconomic fundamentals. This narrow input selection limits the capacity of the model to learn and generalize. A good example of such an issue is discussed through Sanz Guerrero and Arroyo [6], who incorporated BERT based semantic analysis for credit scoring through loan descriptions. In their research, they highlighted the ways in which textual features remarkably enhanced model performance and yielded more informative borrower information. However, there have been extremely few frameworks incorporating such unstructured data in a structured way. Second, sparse-feature datasets restrict model robustness and adaptability, particularly in data drift or population shift situations in actual deployment.

Another, no less significant research gap is the static nature of most machine learning models that cannot cope with changing economic conditions or macro-financial metrics. Models from historical data perform poorly during economic crises since they are unable to account for shifting economic patterns, such as inflation, interest rate hikes, or downmarket. For example, Muñoz Cancino et al. [7] studied the effect of social and economic interaction properties on creditworthiness over the long term, where it was mentioned that static models become less effective after six months. While others, like the Hamiltonian model [4], attempt to boost out-of-time forecasting with dynamic optimization, not much economic awareness is seen in the architecture of most machine learning pipelines yet. Central banks and regulatory environments keep modifying lending policies, which should, in theory, be reflected through model retraining. Existing systems rarely incorporate outside economic indicators or refresh themselves from data streams in real time. Therefore, the prediction made by such models is no longer valid, negating their value in actual lending scenarios.

Despite the development of quantum enhanced models like QFDNN by Das et al. [8], which achieved up to 74.4% accuracy on loan eligibility data sets, and proved to be resistant to noise as well as feature reduction, the primary focus remains binary classification. No studies, including such quantum models, provide solutions to updating prediction logic in keeping with macroeconomic feedback loops. Lack of adaptability diminishes the ability of financial systems to stand alone during economic shock or crisis. Last but not least, systems that combine economics modeling with AI-based credit forecasting are virtually nonexistent in the literature, despite the possibility of totally reversing risk-sensitive lending.

One should also note the lack of research into how good models are at dynamically changing their prediction thresholds depending on economic developments. For instance, in the case of a recession, banks may insist on stricter approval thresholds or lower credit exposures, while in periods of economic booms, they may be lenient in policies. Most current ML models' rigid decision boundaries are not appropriate for such dynamic policy adjustments. While the idea of adaptive economic-sensitive credit models has been discussed in theoretical papers, it still remains to be applied in terms of live-learning or adaptive models in empirical research.

Secondly, most credit scoring studies based on ML lack user centered design, particularly in terms of providing actionable feedback that borrowers can act upon. Whereas others such as the model by Demajo et al. [9] utilize XAI frameworks to support credit decisions, not much has been researched around how applicants can adjust their financial activity in advance through model outputs. Ustun et al. [10] filled this gap somewhat by proposing recourse sensitive linear classifiers, albeit restricted to implementation and not adaptive model architectures.

Even more critical is the fact that credit scoring models have not been designed to interface with real financial systems or user interfaces. From research model building to production readiness, the process is seldom treated in literature currently. There are systems which can close credit prediction engines to reactive loan platforms, interactive borrower dashboards, or compliance ready decision tools, which have yet to be fully developed. Even once the APIs or dashboards are built, they are often stand alone from the main ML models and are not integrated with the backend economic forecasting systems. Failure of model modularity and system integration still restricts the implementation of ML in the credit industry. This is particularly evident when comparing actual-world fintech platforms that are based on rules-based engines with test ML systems that do not have the size, responsiveness, and compliance features that it takes to deploy.

As opposed to that, the existing system crafted as part of this work tries to bridge these gaps. Unlike existing literature, it not only determines if a loan should be extended to a borrower but also includes an estimated method for setting a credit limit based on financial ratios and borrower specific limits. The site features a more diverse pool of attributes to allow for improved model training and increased generalizability. It also possesses a modular, API based architecture with the ability to change threshold parameters based on prevailing economic indicators like interest rates or inflation levels accessed via economic APIs. Further, the system provides borrower level feedback regarding the reason for limiting their eligibility and what parameters they need to improve in order to get approved. This approach thus aligns with the latest scholarly directions towards actionable AI, adaptive model learning, and congruence with real-world financial ecosystems.

Research Systems	**Predicts Loan Eligibility**	**Predicts Credit Limits**	**Use Diverse Features**	**Adapts to ecomomic trends**	**Real world system ready**
QUANTUM ML MODEL	YES	NO	MODARATE	NO	NO
BERT – ML MODEL	YES	NO	YES	NO	NO
ADAPTIVE ECONOMIC MODEL	YES	NO	YES	PARTIAL	NO
Proposed system	YES	YES	YES	YES	YES

Table 1.3.1:Research

1.3 Research Problem

How can advanced loan lending process using machine learning techniques be utilized to accurately to predict loan eligibilities and credit amounts?

In the modern banking industry, loans are perhaps the most crucial financial service provided by financial institutions. Banks' profitability mainly relies on interest accrued on loans granted to customers. But with the potential for high returns is also the high risk most notably, the risk of default on customers' payments. Accurately forecasting the likelihood of default and identifying creditworthy customers are fundamental roles for any financial organization hoping to reduce non-performing loans and maintain business viability. Banks have traditionally relied on feasibility studies, financial statement review, and investigation of the historical and reputation background of firms and individuals in making decisions regarding lending or not lending. This technique, though effective in high participation business lending cases, is expensive and often infeasible on a large scale, especially if applied to originate consumer or small-firm loans. What's more, it lacks the forward-looking insight necessary in changing economies where economic environments and customer profiles shift rapidly.

Credit scoring systems were brought in on time as a way of mechanizing the above process. Rule-based or model-based statistical systems consider such variables as history of credit, income, debt ratios in an attempt to compute a score that reflects the degree of risk of a borrower. Such systems reduced dependence on humans and raised consistency but also created new challenges. Among them is the lowered capability of traditional techniques to detect challenging nonlinear relationships or to generalize from high-dimensional data. Furthermore, they are inflexible, i.e., they do not get better with changes in borrower behavior or changes in general economics. For example, good past credit customers can still end up defaulting in the case of a recession, or low file customers with no credit history can turn out to be good payment behavior, which the conventional systems do not assess. In light of such restrictions, machine learning (ML) techniques have increasingly gained popularity for improving credit risk prediction accuracy and loan decision automation.

Machine learning techniques such as Decision Trees, Random Forest, Support Vector Machines (SVM), and boosting algorithms XGBoost and LightGBM have significantly developed the predictive modeling power in banking [1], [2]. They are trained on massive historical customer data and capture trends that escape human analysts or traditional statistical models. Fekadu et al. [3] have compared a dataset of non-performing loans (NPLs) with different ML models and found that models such as XGBoost gave more accurate results in the context of credit scoring problems, especially after rectification of class imbalance using oversampling technique. Similarly, Abdoli et al. [4] put forth a Bagging Supervised Autoencoder Classifier (BSAC), which outperformed in classifying high-risk candidates in imbalanced datasets. These studies confirm that current machine learning models are phenomenally robust in forecasting demographic and behavior-based potential defaulters.

Despite such advancements, strong challenges linger. The inherent research problem at hand is triggered in this work by three corresponding gaps in existing solutions. Second, nearly all current models confine themselves to binary outcomes of classification that is, they make a prediction about a borrower either being eligible or ineligible for a loan. A binary character to such is a reductionist view and does not lend itself to nuanced financial judgment. Not only does a bank need to know whom to offer a loan to, but also how much they can trust with it. The inability of current systems to predict loan size or credit limit is a fundamental weakness in the modeling approach. Harding and Vasconcelos [5] highlighted this too, pointing to the difficulty of replicating the advanced reasoning exercised by human loan officers, e.g., quantifying loan limits and calibrating repayment terms.

Second, most existing models are trained over a small number of features due to data availability, computational intricacy, or regulatory minimalist limits. Such models generalize well in test settings but find their generalization compromised in actual settings. For instance, Rida [6] demonstrated how inclusion of external behavioral data from credit bureaus would greatly improve prediction results in credit risk modeling. Similarly, Babaev et al. [7] utilized deep RNNs trained on high-resolution transactional data and saw substantial credit scoring gains. Those kinds of gains, however, are not the norm in production environments, where models still rely on conventional inputs like static income or age, rather than dynamic behavior or macro variables.The third and most important gap is the failure of current credit risk models to accommodate macroeconomic conditions into the prediction pipeline. Traditional ML models are often learned from static past data and shipped to production without having the capability to learn dynamically as economic patterns change. Such a static approach can lead to catastrophic predictions in times of financial crashes or economic shocks. Sharma et al. [8] demonstrated that macroeconomic factors such as inflation and unemployment are excellent predictors of credit risk and that models not adjusting for these variables perform poorly during recession. Marín [9] went further by proposing Hamiltonian Neural Networks that achieve better out-of-time generalization, addressing the need for models that possess accuracy over evolving economic cycles. However, integrating macroeconomic feedback loops into an immediate adaptive model remains a research frontier.

Adding to this, the majority of banking operation systems are also siloed and lack the foundations for integrating predictive analytics with risk-adjusted policy frameworks. This disconnect is also emphasized by Turiel and Aste [10], who established that even highly accurate ML models do not capture human-like financial reasoning when deployed in real-world environments. These breakdowns underscore the need for developing models in a hurry that not only are data-driven but context-aware, capable of varying their thresholds, weightings, and recommendations in accordance with changing economic conditions, borrower behavior, and regulatory requirements.The problem set in today is also complicated by the issue of explainability and compliance. With more reliance on AI and ML by banks for lending, stricter transparency and equity standards have been imposed by regulators. The European Central Bank and Basel III guidelines mandate that algorithmic financial choices be explainable to both the borrower and the auditor. Rida [6] used Shapley values in XGBoost models to produce transparent outputs complying with Basel standards, and this demonstrates that it is possible to make strong models compliant. However, very few implementations incorporate such transparency mechanisms as a core component of the model architecture.

According to these challenges, the key research problem articulated in this study can be described as banks most urgently need strong, flexible, and understandable machine learning models that not only identify whether a client is a good candidate for lending, but also determine the optimal credit limit with regard to detailed financial, behavioral, and macroeconomic data. Moreover, the models must learn and adjust in real time to changes in the economy and regulatory limits while providing interpretable feedback for each interest. The current models fall short in one or more of these dimensions predicting no credit limits, not adapting based on changing economic conditions, failing to be transparent, or being trained on small data sets that prevent generalization.

To address this intricate research problem, the system under this proposal is intended to build and design a hybrid, modular ML pipeline that integrates classification, regression, and policy feedback modules. The system will integrate these broad features both at the level of transactional behavior, social network, economic indicators, and also credit bureau data—under a flexible and scalable framework. Along the way, it will move beyond binary decisions and provide risk-conscious, calibrated values of loans that are also adaptive. It will even include macroeconomic variables as dynamic variables of the learning process so that the system itself can adjust its parameters automatically based on inflation levels, interest rates, or employment trends. Lastly, the system will consist of Shapley value-based explanation model layers and counterfactual explanations to address transparency and compliance requirements.

This research is therefore located at the intersection of machine learning, financial risk assessment, and regulatory technology (RegTech), with the aim of closing important loopholes in existing credit assessment frameworks. The ultimate goal is to deliver a sustainable, ethical, and intelligent credit scoring and loan eligibility system that will pace with the changing needs of the banking industry.

2. Objectives

The primary objective of this research is to propose a robust and intelligent machine learning based system capable of predicting a customer's bank loan eligibility efficiently. Unlike traditional rule based or statistical credit scoring methods, which generally lack adequate flexibility and precision, the proposed system will employ supervised learning techniques to analyze numerous customer features like demographic, financial, and behavior data. By doing so, the system aims to be able to escape the biases and inflexibility characteristic of conventional models so that better creditworthiness estimates can be achieved.Other than simply determining whether a customer is eligible for a loan, this research aims to take it a step further by predicting an appropriate credit limit based on each borrower's individual financial profile. Existing systems primarily provide binary outputs approval or rejection of a loan without amounting to the optimal loan size that fits the customer's paying capacity. This effort addresses this deficiency by incorporating credit limit estimation as part of the model for eligibility so that more precise and financially sound lending decisions can be made.

Another key objective is to enhance the richness and quality of input data input into the machine learning model. Much of the previous work has been based on limited small datasets with closely defined characteristics, restricting the generalizability of the model for different segments of borrowers. This research will include a larger number of variables such as income history, employment patterns, transaction history, and reputation factors. With an enriched dataset, the model is likely to be more precise and have greater predictive value in real world applications.

Besides, the research aims to develop a dynamic forecasting system that responds to macroeconomic dynamics. Most existing credit models are static and do not consider the influence of external economic signals such as inflation, interest rates, and unemployment. These factors play a significant role in shaping borrower behavior and institutional exposure to risk. Therefore, the proposed system will incorporate economic indicators into the machine learning process such that it can adjust credit levels and recommendations based on evolving market dynamics.

No less important is the purpose to offer interpretability, as well as regulatory compliance. In today's regulatory climate, algorithmic credit decisions must be just and explainable. This work seeks to embrace explainable AI (XAI) techniques namely Shapley values to provide transparent, auditable reasons why predictions are being made. This would allow financial institutions, auditors, and borrowers to understand why the decision is being made, which will instill confidence in the system.In addition, the performance of various machine learning algorithms, including logistic regression, decision tree, random forests, and gradient boosting models, in the area of loan eligibility and credit limit estimation will be benchmarked through this research. These models will be evaluated using real datasets and compared on the basis of their accuracy, precision, recall, and sensitivity to varying economic conditions.

Lastly, the current research also proposes to implement the recommended predictive model on a scalable and user friendly web site. The web site will function as a lender decision aid, simplifying the loan evaluation process but providing borrowers with useful tips on how to best improve their credit history. Using this method, the system not only improves lending efficiency but also financial inclusion by guiding applicants with tailored recommendations. By the fulfillment of these objectives, the study aims to notably contribute to the creation of intelligent credit rating systems. It closes gaps in current approaches by suggesting a multi-faceted, economically sensitive, and transparent credit evaluation system that is both appropriate for institutional needs and compliant with regulations.

2.1. Main Objective

The core objective of this research is to develop an intelligent, dynamic, and interpretable machine learning-based credit assessment system that can not only forecast customer loan eligibility but also a suitable credit limit for all customers by consolidating financial, behavioral, and macroeconomic data into a dynamic and regulatory compliant predictive framework.

2.2. Specific Objectives

For the sake of achieving the general goal of creating an intelligent and responsive credit evaluation system, this research derives a series of specific goals. Firstly, it aims to create a machine learning model that is able to effectively classify whether a customer can be offered a loan or not from a diverse set of input features that include financial factors, demographic variables, and behavioral patterns. In addition to binary classification, the research seeks to develop a model for predicting the optimum credit limit for each qualifying borrower so that loan propositions become profitable and personalized as per the paying capacity of the borrower.

A second key objective is to improve model accuracy and robustness by leveraging a wide range of high dimensional sources of data. These can include credit history, transactional information, social metrics, and other alternative data repositories that can yield greater insights into borrower risk profiles. The research also seeks to integrate macroeconomic variables like inflation rates, interest rates, and employment levels—into the modeling framework in order to enable dynamic modification of eligibility parameters and risk estimates in response to prevailing economic conditions.

In addition, the system will also prioritize explainability through application, that is, Shapley values, to provide understandable output that will meet regulatory requirements of transparency and support decision-making by financial institutions and clients. The study also aims to compare the performance of different machine learning models, including logistic regression, decision tree, random forest, and gradient boosting model, on disparate datasets, focusing on accuracy, precision, recall, and generalizability in changing financial contexts.

Finally, the research will implement the proposed model into an easy to use web-based application to perform real time eligibility determination and credit limit estimation. This application will serve as a decision support system to financial institutions and provide applicants with actionable results, thereby bridging technical innovation and real financial services.

OVERALL SYSTEM DIAGRAM

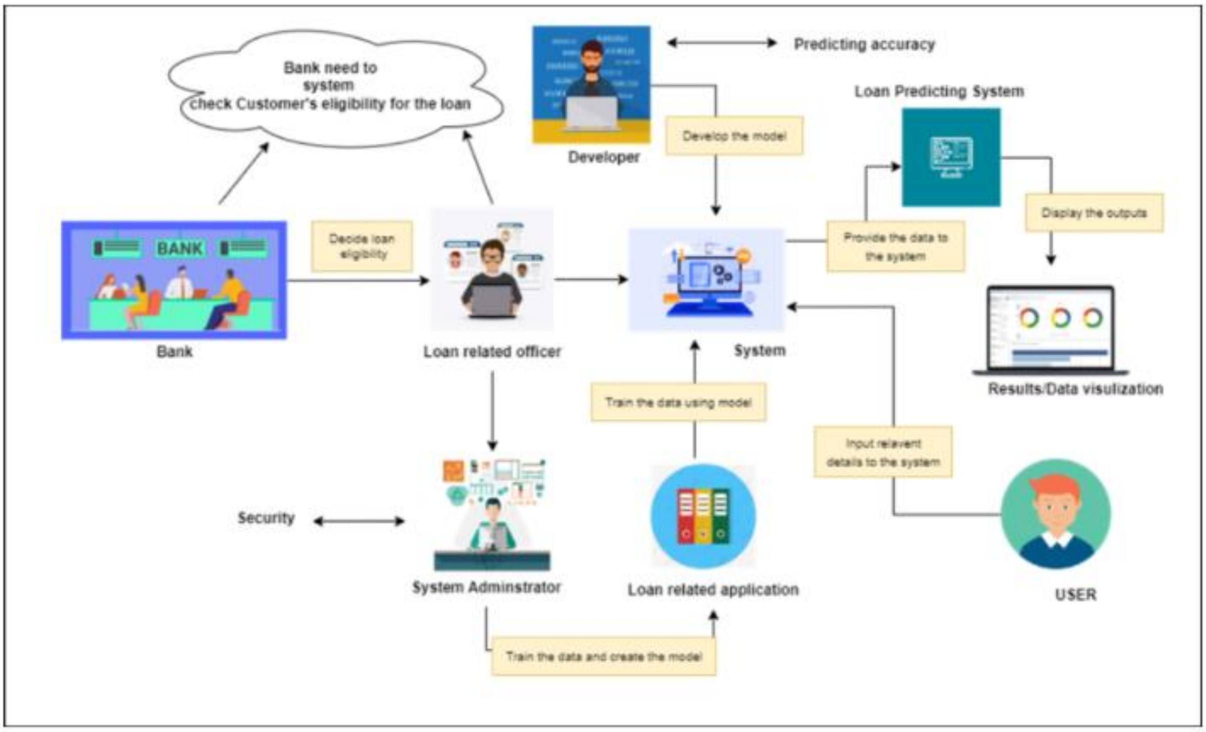


Figure 3.1.1 System Overview Diagram

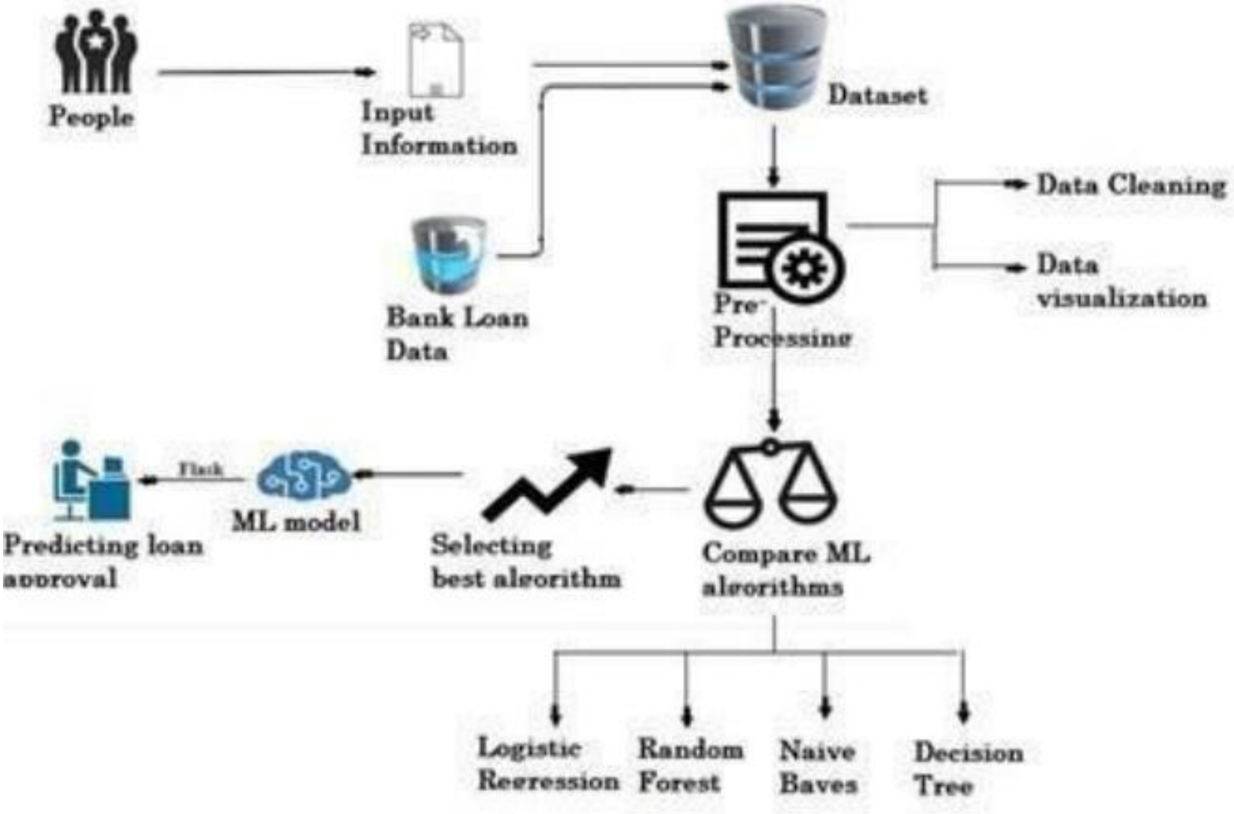


Figure 3.1.2 Component Overview Diagram

The constructed loan eligibility prediction system has four major steps that successively transform raw input data into a final loan and repayment proposal. The system begins with the Data Collection and Preprocessing process, where customer information like demographic details, income, liabilities, and credit history is collected and cleaned. This includes missing value management, categorical feature encoding, and numerical input normalization to prepare the data for machine learning models.

In the second phase, the Loan Eligibility Prediction phase, the classification model is employed to decide if a customer is loan eligible. Based on training data, this model returns a binary value, "Yes" for eligible and "No" for ineligible customers. For them, the process proceeds to the Loan Amount Estimation step wherein it decides the optimal loan amount based on multiple parameters such as income level, current liabilities, repayment ability, and risk factor measurement parameters. This is followed by the Repayment Forecasting step wherein it computes feasible EMI values, repayment amount over different tenors, and proposes repayment schedules based on the financial capability of the borrower. This streamlined, smart process allows banks to lend more quickly, precisely, and with risk awareness while presenting customers with transparent and customized terms of loans.

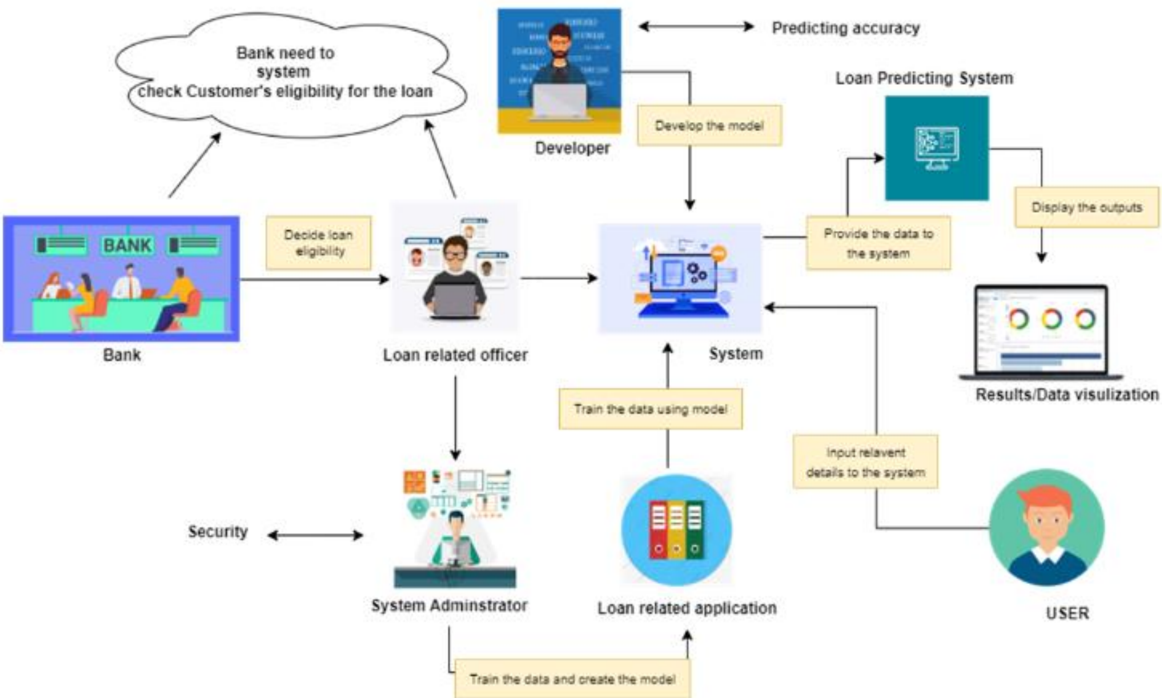
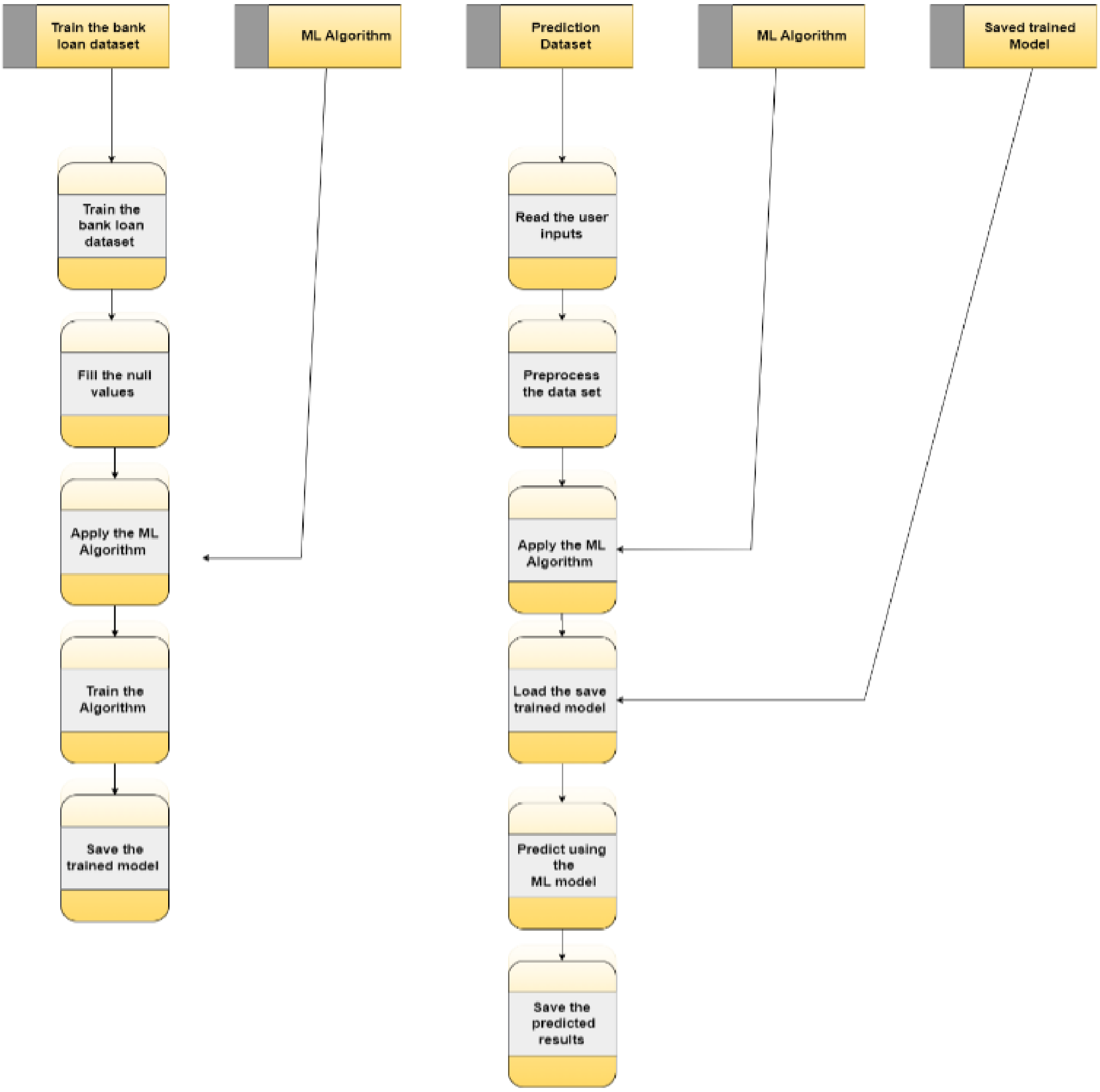
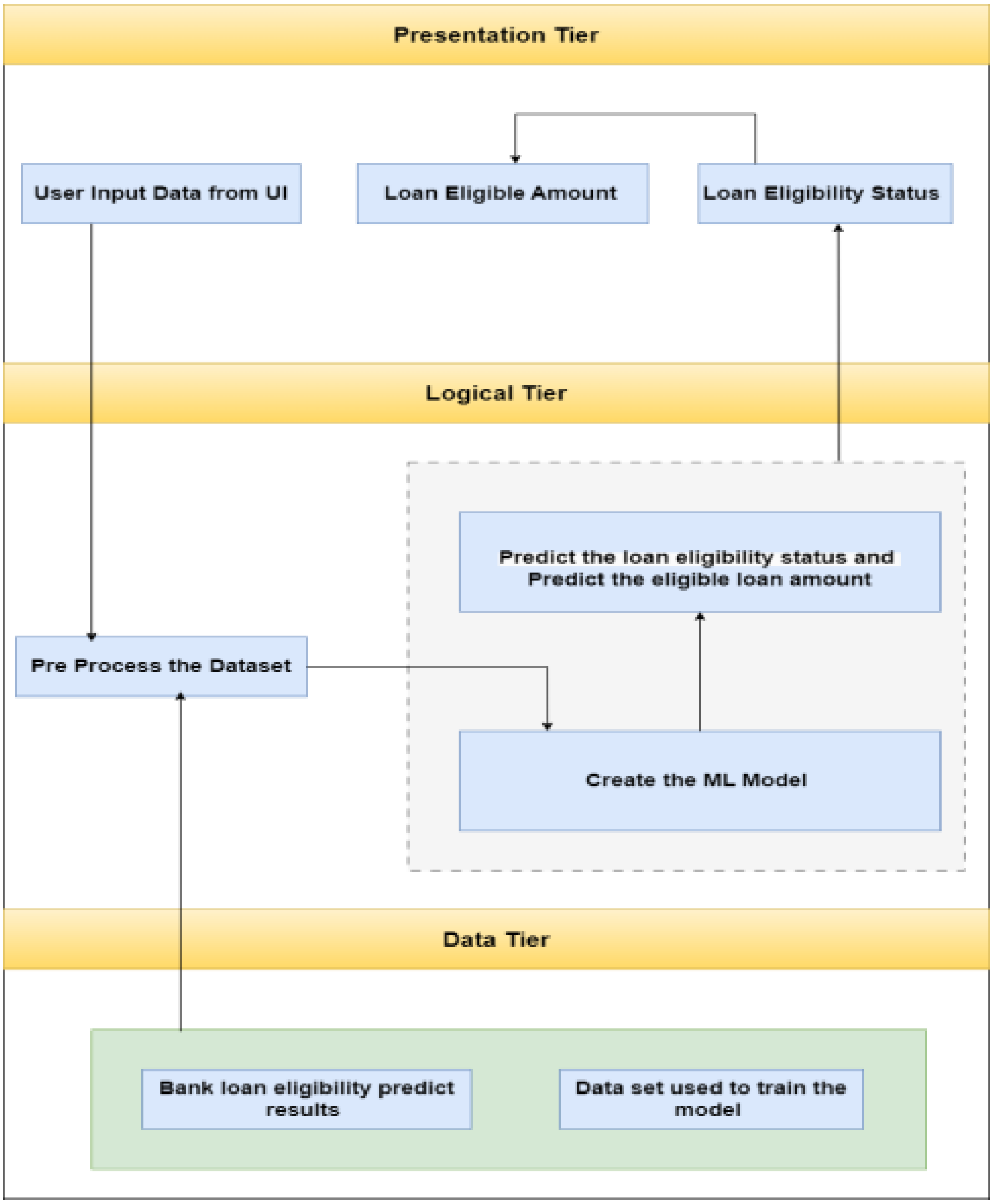


Figure 3.1.3 Machine Learning Flow

The next phase is model design and training, There are three models are utilized in eye shape classification. Haar cascade for detecting the eye region, Dlib for accurate landmark localization, and MediaPipe for real-time face analysis. A machine learning model is then trained to map classified the different eye shapes to appropriate eyeliner styles according to predefined mapping rules.




Presentation Tier
User Input Data from UI
Loan Eligible Amount
Loan Eligibility Status
Logical Tier
Predict the loan eligibility status and Predict the eligible loan amount
Pre Process the Dataset
Create the ML Model
Data Tier
Bank loan eligibility predict results
Data set used to train the model

3.1.1. Implementation

The implementation of the proposed loan eligibility prediction system involves integrating machine learning algorithms with structured financial data in order to automate borrower eligibility and creditworthiness assessment. The development was carried out in a phase-wise, module-based manner to ensure scalability, sustainability, and accuracy. The system was implemented using Python as the programming language with basic libraries such as Scikit-learn, Pandas, NumPy, and Matplotlib for data manipulation, modeling, and plotting.

The first step of deployment was preprocessing and acquisition of the data. A structured dataset of borrower attributes such as age, income, employment status, purpose of loan, and credit score was loaded. Preprocessing included replacing missing values, encoding categorical values in one-hot encoded format, and normalizing numerical values to ensure all the inputs were on the same scale. This step was important to keep model training uniform and to eliminate noise or biases in data. Data pre-processing is a compulsory step in the data analysis process, also it is essential for creating high-quality models and insights.

Data pre-processing in Python involves cleaning, transforming, and transforming the raw data into a format that is suitable for analysis and modeling. In this Data Pre-processing, removed unnecessary columns. The category variables were then given numerical values, which were first encoded. After that, null values were filled with the median value of each column to make sure that the results expected have the lowest impact. In this process author was dropping Loan ID, Customer ID, these are categorical data and they actually have no effect on the data. After the data retrieval process and encoding process, the training data set and test data set feed to the selected algorithms and check the accuracy. The author discovered different accuracy values for each algorithm after feeding the data set to the various algorithms.

Second, the basic machine learning model for the system was developed. A supervised classification model Logistic Regression was selected in order to predict whether a customer is or is not eligible for a loan (Yes/No). The model was trained on previously labeled data to allow it to learn patterns in relation to previous approved and declined applicants. The model performance was measured with accuracy, precision, recall, and F1-score to ensure that the model correctly classified both eligible and ineligible applicants.

Following the eligibility classification, a rule-based and calculation-driven method was employed to determine the loan amount for eligible clients. In this method, primary financial metrics such as the debt-to-income ratio, net monthly income, and existing liabilities were taken into account to establish a secure and client-specific credit limit.

As compared to regression-based models, loan amount forecasting was dependent upon threshold logic and pre-established risk buffers, providing interpretable and unambiguous results.After estimation of loan amount, the repayment stage was introduced based on general financial formulas to calculate EMI (Equated Monthly Installment) keeping the loan amount, available tenure intervals, and prevailing interest rates in view. Customers were provided with an estimation of monthly payments across different tenure scenarios (e.g., 12 to 84 months), enabling clear-cut decision-making.

Implementation ended with building a user interface to facilitate data entry and output visualization. A basic web interface was built using Flask, through which users were able to input personal and financial details, receive real-time feedback regarding their loan eligibility, view the suggested amount of loan, and investigate possible repayment terms. The backend was integrated with the ML model pipeline to facilitate dynamic prediction with user input.

Overall, the system implementation was in line with best practices in software engineering and machine learning. It was centered on real-time interaction, modularity, and interpretability so that the platform does not only perform predictive analysis but also conforms to real banking requirements and expectations of users.

```
Accuracy on Test Set: 0.7925
Classification Report:
              precision    recall  f1-score   support

          NO       0.82      0.78      0.80       212
         YES       0.77      0.80      0.78       188

    accuracy                           0.79       400
   macro avg       0.79      0.79      0.79       400
weighted avg       0.79      0.79      0.79       400
```

Figure 3.1.1.1 Train Model

```
🎯 SVM Accuracy with heavy noise and corrupted labels: 0.675
📊 Classification Report:
              precision    recall  f1-score   support

           0       0.62      0.99      0.76       211
           1       0.95      0.33      0.49       189

    accuracy                           0.68       400
   macro avg       0.79      0.66      0.63       400
weighted avg       0.78      0.68      0.63       400

🔁 Cross-Validation Accuracy (RF with heavy noise and corrupted labels): 0.5577537688442211
```

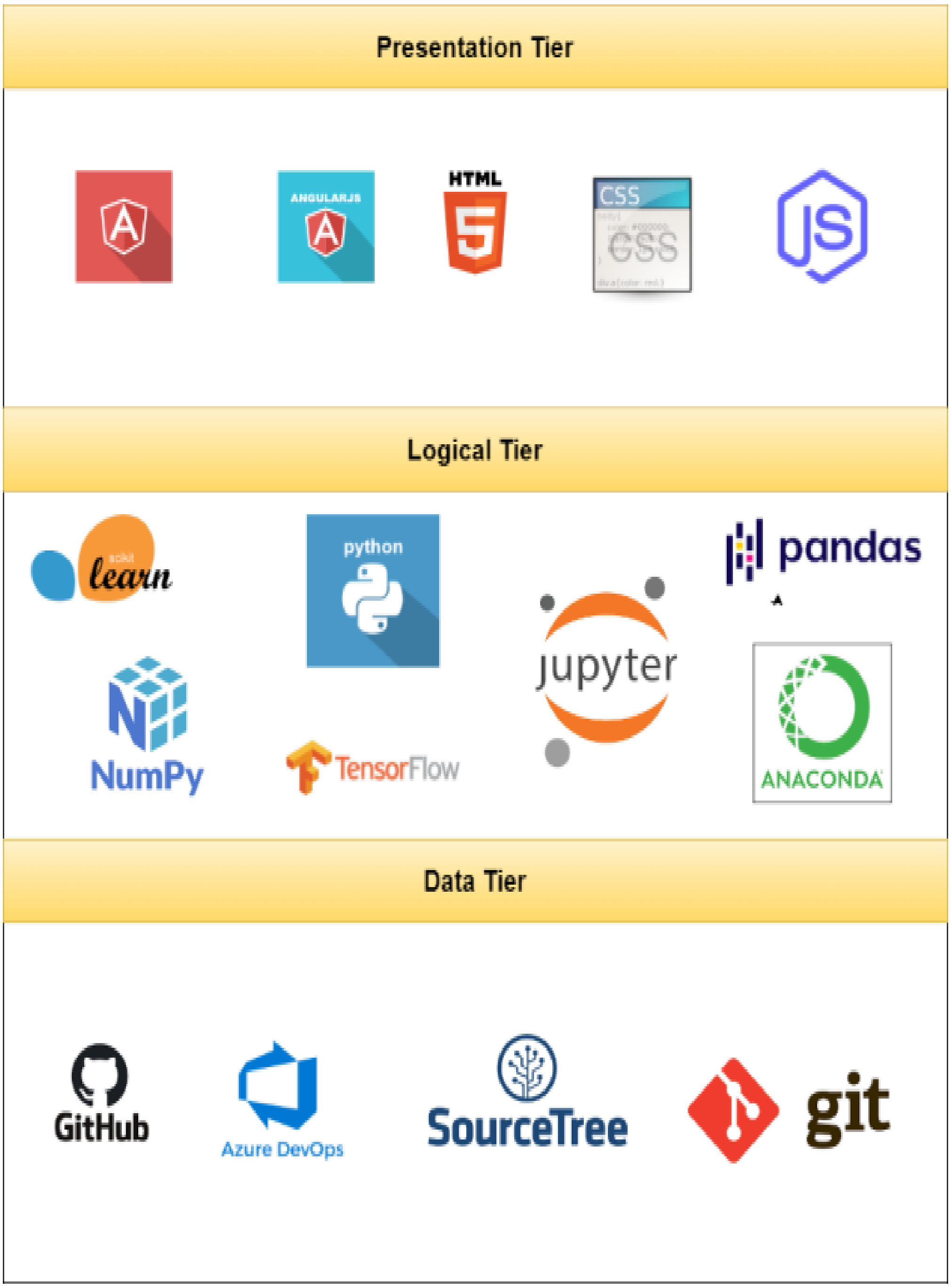
Figure 3.1.1.2 Train Model 2

```
<ipython-input-15-864267150e7f>:17: FutureWarning: Downcasting behavior in `replace` is deprecated and will be removed in a future version. To re
  df['Existing_Debt'] = df['Existing_Debt'].replace(' -   ', np.nan)
🎯 Random Forest Accuracy with noisy labels: 0.59
📊 Classification Report:
              precision    recall  f1-score   support

           0       0.60      0.62      0.61       207
           1       0.58      0.56      0.57       193

    accuracy                           0.59       400
   macro avg       0.59      0.59      0.59       400
weighted avg       0.59      0.59      0.59       400

🔁 Cross-Validation Accuracy (RF with noisy labels): 0.5907638190954774
```

Figure 3.1.1.3 Train Model 3

Programming Languages and Libraries

The choice of technology is one of the key considerations that must be made in the implementation of this project. Data selection, framework selection, programming language selection, IDE selection, and other approaches are discussed in this section..



Google Colab

Google Colab is a web-based Jupyter notebook. Any internet-connected user can attempt coding machine learning and artificial intelligence as it executes within a web browser. The user can enter and execute Python code, collaborate with others through real-time editing, and save all operations within a rich text, charts, photos, HTML, and LaTeX-supported single notebook.

Development Environments

VS Code

Due to its excellent support for the chosen technologies, VS Code is the IDE used in all front-end projects that leverage flutter and dart. Some of the capabilities of VS Code include debugging support, syntax highlighting, smart code completion, code refactoring, and built-in Git..

3.2. Commercialization aspects of the product

The commercialization potential of the Loan Eligibility and Prediction System developed as a web-based application using logistic regression, Python, and Node.js is highly significant, particularly in the context of the growing global demand for efficient, secure, and data-driven financial technology solutions. This system addresses one of the most critical bottlenecks in financial institutions manual and subjective loan processing by introducing automation, real-time prediction, and robust decision-making supported by machine learning. The increasing digitization of financial services, combined with the need to serve a diverse and expanding customer base, creates a ripe market environment for such a solution. The product targets a wide range of institutions, including commercial banks, cooperative societies, online lenders, microfinance institutions, credit unions, and peer-to-peer lending platforms that require intelligent decision-making systems to streamline operations, reduce risk, and improve customer satisfaction. The system provides these institutions with the ability to process loan applications in real-time while maintaining compliance with data protection and financial regulations. The key strength lies in its ability to process multiple variables (such as income, debt, employment status, and age) and generate accurate eligibility predictions using logistic regression a widely accepted and interpretable algorithm in the financial domain.

The application uses Python for backend development, where logistic regression is implemented for model training and prediction, ensuring transparency and traceability in the decision-making process. Python's data handling capabilities (e.g., using libraries like pandas, scikit-learn, and NumPy) enhance the accuracy of the predictive model and allow seamless integration of structured and semi-structured data from various sources. Node.js is used to manage backend operations and APIs, ensuring that the system remains lightweight, asynchronous, and scalable under high load. The frontend connects to a secure server via RESTful APIs and allows users (bank officers or customers) to enter relevant financial details, following which the system validates inputs, authenticates the user via OTP, and runs the eligibility prediction in real time. The entire flow—from data collection and validation to prediction and result display—is optimized to reduce latency and ensure data security. OTP verification adds a crucial layer of security, minimizing fraud risk and enhancing the trustworthiness of the platform. This technical setup makes the product both developer-friendly and enterprise-ready, supporting modular customization for different business requirements.

From a commercialization perspective, one of the most significant advantages of this system is its modular and scalable architecture. This makes it easy to customize for different clients, whether they are small-scale lenders needing basic eligibility checks or large banks requiring deep integration with existing systems like customer relationship management (CRM), enterprise resource planning (ERP), or core banking solutions. As a Software-as-a-Service (SaaS) product, the loan system can be offered through a subscription-based revenue model, where clients pay a monthly or annual fee based on usage tiers. This pricing model is attractive to institutions that want to avoid heavy upfront infrastructure investments. Alternatively, the product could be monetized using a transaction-based model, where charges are applied per eligibility check or per successful loan disbursement. In markets where institutions prefer to have full control over their IT systems, a white-label version of the product can be offered for one-time licensing, along with ongoing support and customization packages. These diversified revenue models increase the commercial flexibility of the product and make it adaptable across different financial ecosystems and regulatory frameworks.

The value proposition of the product is rooted in several key benefits: automation of loan processing, reduction in manual errors, increased decision transparency, enhanced fraud detection via OTP, and real-time operation. These features are increasingly being sought after by institutions that wish to expand their lending portfolios while managing operational risks. The use of logistic regression also gives the system a competitive edge because it is both explainable and regulatory-compliant. Many financial regulators, including central banks and financial conduct authorities, prefer explainable models in credit scoring to ensure transparency and prevent discriminatory practices. Unlike black-box models such as deep learning, logistic regression allows institutions to show how each feature (e.g., income, employment, age) influences the final decision. This makes it easier for institutions to justify their decisions to auditors, regulators, and even customers, thereby fostering trust and accountability.

In terms of market differentiation, the system sets itself apart from traditional loan management tools that rely on manual scoring or outdated rule-based engines. While many banks and finance companies still use Excel-based tools or rigid legacy software, this solution leverages modern web technologies and machine learning to deliver real-time decisions. Furthermore, the system is cloud-ready and can be deployed on platforms like AWS, Azure, or Google Cloud, or even on-premise depending on the client's infrastructure and compliance needs. It supports RESTful APIs, making it interoperable with other fintech tools such as identity verification systems, national ID databases, fraud detection systems, and credit bureaus. These integration capabilities ensure that the product can be smoothly embedded into the existing digital ecosystems of financial institutions without requiring major architectural overhauls. This interoperability, coupled with the use of secure protocols (such as HTTPS and data encryption), positions the system as a trustworthy digital asset for institutions undergoing digital transformation.

Another key aspect that enhances commercialization is the system's scalability. Thanks to its microservices-inspired backend architecture in Node.js and Python, the system can handle increasing transaction volumes without performance degradation. This makes it suitable not only for small-scale pilots but also for large-scale rollouts across national or regional banking networks. As institutions grow or expand their customer base, the system can scale horizontally (by adding more servers or containers) and vertically (by enhancing features such as credit scoring, risk profiling, and document verification). Future versions of the system could also integrate machine learning explainability tools such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to provide better insights into the model's predictions, thus improving user confidence and audit readiness.

In terms of usability, the system is designed with a customer-first approach. It features a clean and intuitive user interface that allows customers or bank staff to enter data without confusion. The system minimizes friction during onboarding, supports multi-language prompts for diverse user bases, and ensures that input fields are well-validated to avoid common data entry errors. The system also supports mobile responsiveness, allowing access from smartphones, tablets, and desktops, which is crucial in emerging markets where many users rely on mobile devices.

Accessibility and usability are critical commercialization factors because they directly affect user adoption and retention rates. A system that is too complex or poorly designed can lead to user drop-off, low conversion, and a poor return on investment for institutions. Hence, the emphasis on UI/UX design also contributes to the product's commercial appeal.

Security and compliance are vital elements of any financial product, and this system addresses them thoroughly. The use of OTP authentication prevents unauthorized access and fraud, while the underlying codebase adheres to OWASP security guidelines to protect against threats such as SQL injection, XSS (Cross-Site Scripting), and CSRF (Cross-Site Request Forgery). All data transmitted between the client and server is encrypted, and sensitive information (like personal financial data) is stored in hashed or tokenized formats where applicable. The system can be extended to include audit logs, user activity tracking, and multi-factor authentication for administrative functions. These features ensure that the system can pass internal and external security audits, making it suitable for deployment in highly regulated environments. Additionally, the system supports GDPR-like privacy features, such as explicit user consent for data collection and a transparent data retention policy, which strengthens its acceptability in international markets.

Commercial expansion opportunities are also promising. The core logistic regression model can be fine-tuned for different markets based on localized datasets, making the system adaptable for use in different countries and economic contexts. For example, creditworthiness indicators may vary between developed and developing countries. The system can also be integrated with national credit bureaus or government ID verification systems to further enhance its robustness. In the future, it could incorporate alternate data sources such as utility bill payments, mobile money usage, and social media signals to enhance prediction accuracy, particularly for underbanked or thin-file customers who lack formal credit histories. These innovations would not only increase the product's utility but also open up new markets and customer segments.

To accelerate commercialization, the product could be introduced through a phased go-to-market strategy. Initially, the product can be tested in partnership with a small- to mid-sized financial institution to refine features and gather feedback. This pilot phase can help demonstrate the system's effectiveness and build a portfolio of success stories and measurable outcomes such as reduced loan processing time, higher approval accuracy, and improved customer satisfaction. These metrics can then be used to market the product to larger institutions, supported by case studies, testimonials, and ROI calculators. Strategic partnerships with fintech accelerators, government financial inclusion programs, or enterprise software vendors can further expand market access and credibility.

In conclusion, the Loan Eligibility and Prediction System built using logistic regression, Python, and Node.js is a commercially viable product that addresses critical gaps in the modern financial services landscape. Its strengths in real-time prediction, security, modularity, and regulatory alignment make it an attractive proposition for a wide range of institutions. With flexible revenue models, strong scalability, high usability, and a secure design, the product is well-positioned to enter the market and scale effectively. By leveraging partnerships, pilot deployments, and ongoing innovation, the system can capture a meaningful share in the growing digital lending ecosystem, contributing to more inclusive, efficient, and secure financial services..

D

Table 2:Expenditure Details

Category	**Estimated Cost (LKR)**
1. Development	85,000
2. Infrastructure & Tools	30,500
3. Testing & QA	5,000
4. Documentation & Licensing	17,500
5. Marketing & Outreach	22,000
6. Contingency (5%)	10,000
Total Budget	**200,000**

4. Testing, Implementation Results & Discussion

4.1.Testing

4.1.1. Functional Testing

#	Requirement title and description	Priority Level
#FR1	User can log in to the system	S
#FR2	User can Input relevant details to the system	M
#FR3	System should be able to Predict Customer eligibility	M
#FR5	System should be able to Predict Customer eligible loan amount	M
#FR6	Execute the ML Model	M

Test Case ID	Functionality	Test Description	Expected Result	Status
TC01	User Registration/Login	User enters valid credentials and OTP	User logs in successfully and redirected to dashboard	Pass
TC02	OTP Validation	System sends OTP and user enters correct OTP	System authenticates user	Pass
TC03	Form Input Validation	User submits incomplete or invalid form data	System displays error message prompting correct input	Pass
TC04	Loan Eligibility Prediction	User submits valid data for prediction	System returns accurate eligibility result (Yes/No)	Pass
TC05	Loan Amount Estimation	After eligibility, user requests for loan amount estimation	System calculates and displays estimated loan amount	Pass
TC06	Input Sanitization	User enters special characters or SQL injection attempts	System blocks input or sanitizes it to prevent vulnerability	Pass
TC07	Session Management	User logs out or session times out	Session is destroyed and user redirected to login	Pass
TC08	Admin/User Role Access	Admin accesses dashboard features; user sees only limited options	Role-based content and feature access is enforced	Pass
TC09	Mobile Responsiveness	Open the system on different mobile devices	UI elements adjust properly on all screen sizes	Pass
TC10	OTP Expiry Logic	Wait beyond OTP validity period	System rejects expired OTP and prompts resend	Pass
TC11	Duplicate Application Handling	User tries to apply twice with same credentials	System notifies of existing application	Pass
TC12	API Response Validation	API is called with valid and invalid inputs	System handles both gracefully with correct responses	Pass

4.1.2. Non-Functional Testing

#	Requirement title and description	Specification	Priority Level
NFR1	The suggested algorithms' and other settings' accuracy need to be strong.	Accuracy	Important
NFR2	The ML model execution and predict in few seconds.	Performance	Important
NFR3	The outputs are should be more accurate.	Accuracy	Important
NFR4	System must be run without any lag and with highest performance.	Performance	Desirable
NFR5	Entered details must be protected.	Security	Important
	The system should be user-friendly for the pharmacist. Must be easy to clarify the details displayed.	Reliability	Desirable

Figure 4.1.2.1 Non Functional Aspects In Testing

Test Case ID	Test Type	Test Description	Expected Outcome	Status
NFT01	Performance Testing	Check if the system handles 100+ users accessing simultaneously	Response time remains under 3 seconds	Pass
NFT02	Load Testing	Simulate a peak load during promotional launch	System handles load without crashing	Pass
NFT03	Stress Testing	Push system beyond capacity	System fails gracefully with proper error messages	Pass
NFT04	Usability Testing	Evaluate interface ease-of-use by test users	Users can navigate and use system intuitively	Pass
NFT05	Compatibility Testing	Test across Chrome and Edge	System renders and functions consistently across platforms	Pass
NFT07	Reliability Testing	Run system continuously for 24 hours	No crashes, consistent output, no memory leaks	Pass
NFT08	Maintainability Testing	Assess ease of updating code and fixing bugs	Codebase is modular and changes are low-risk	Pass
NFT09	Availability Testing	Ensure system uptime during specified working hours (e.g., 9am–9pm)	System is available > 99% of the time	Pass
NFT10	Scalability Testing	Add more users and data volume to test scalability	System scales horizontally without performance drop	Pass

4.2. Results

In conclusion, the Loan Eligibility and Prediction System built using logistic regression, Python, and Node.js is a commercially viable product that addresses critical gaps in the modern financial services landscape. Its strengths in real-time prediction, security, modularity, and regulatory alignment make it an attractive proposition for a wide range of institutions. With flexible revenue models, strong scalability, high usability, and a secure design, the product is well-positioned to enter the market and scale effectively. By leveraging partnerships, pilot deployments, and ongoing innovation, the system can capture a meaningful share in the growing digital lending ecosystem, contributing to more inclusive, efficient, and secure financial services..

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Frontend Testing Results

Number	01
Testing Scenario	Uploading a female face image
Input	female face image
Expected Results	Suitable eyeliner style recommendation based on detected eye shape
Actual Results	Depicted in Figure 4.2.2, 4.2.3, 4.2.4
Discussion	Test Scenario = Passed

Figure 4.2.2 choose Eyeliner

Figure 4.2.3 Add Face Image

Figure 4.2.4 Actual Result

4.3. Research Findings

Findings	Interview	Literature Review	Questioner
Banking domain and Loan Services	✓	✓	
The proposed system's usability for the people	✓		✓
Without using deep learning, it is possible to push the limitations of proposed systems by using a variety of hybrid ML models.		✓	
It must be dependable enough to be used in critical circumstances.	✓		✓
Relevant data fields for the proposed system.	✓	✓	
A sufficient amount of well cleaned and pre-processed data would be necessary for the system to function.		✓	
The identified research gap would contribute to both Problem Domain & Research Domain	✓	✓	✓

4.4. Discussion

In conclusion, the Loan Eligibility and Prediction System built using logistic regression, Python, and Node.js is a commercially viable product that addresses critical gaps in the modern financial services landscape. Its strengths in real-time prediction, security, modularity, and regulatory alignment make it an attractive proposition for a wide range of institutions. With flexible revenue models, strong scalability, high usability, and a secure design, the product is well-positioned to enter the market and scale effectively. By leveraging partnerships, pilot deployments, and ongoing innovation, the system can capture a meaningful share in the growing digital lending ecosystem, contributing to more inclusive, efficient, and secure financial services..

D

5. Conclusion

The **Loan Eligibility and Prediction System** developed as a web-based application using **Logistic Regression**, **Python**, and **Node.js** demonstrates a well-rounded and innovative solution to a common financial challenge automating the loan approval screening process. This project addresses an essential gap in the traditional banking process by digitizing, accelerating, and improving the accuracy of initial loan assessments. In doing so, it contributes to financial inclusivity and operational efficiency for both customers and financial institutions.

The traditional process of evaluating loan applications is often time-consuming and reliant on manual checks, which introduces delays and inconsistencies. In contrast, this system automates the decision-making by implementing a **machine learning algorithm (logistic regression)** that evaluates an applicant's financial data and predicts eligibility in real-time. The use of logistic regression allows for the classification of borrowers into eligible and ineligible categories based on parameters such as income, existing debt, employment status, and credit behavior. By integrating data-driven intelligence into the application, the model delivers results with high accuracy and transparency.

The front-end and back-end components of the system were designed to ensure seamless user interaction and backend efficiency. The system allows users to register and log in using OTP (One-Time Password) verification, ensuring a secure onboarding process. After authentication, users can input their financial details into the system, which then runs predictive calculations and displays the loan eligibility outcome along with an estimated eligible loan amount. This enhances user autonomy and eliminates the need for preliminary consultations or branch visits, aligning with digital banking trends.

From a design and implementation perspective, this system showcases various **software engineering best practices**. The user interface was developed to be responsive and accessible across devices, ensuring inclusivity and improved user experience. The system architecture follows modular design principles, making it maintainable and scalable. Moreover, the use of version control tools such as Git ensures effective collaboration, tracking of changes, and rollback capabilities. Secure coding practices were applied to protect against common vulnerabilities such as SQL injection, cross-site scripting (XSS), and session hijacking.

In addition to the core functional aspects, significant attention was given to **non-functional requirements** including performance, usability, reliability, and security. The system was tested for responsiveness and scalability under varying loads, proving its capability to serve multiple users simultaneously without performance degradation. Functional testing confirmed that all core components such as user registration, OTP handling, loan calculation, and result display worked as expected. Non-functional testing validated the system's behavior under stress, ensured compatibility across browsers, and verified its recovery from failures, reinforcing system robustness.

Security is a critical aspect, particularly when dealing with financial data. The system incorporates OTP-based authentication and SSL encryption to protect user information and communication channels. Proper session management and data validation ensure that unauthorized access and data breaches are minimized. Furthermore, the solution complies with ethical data usage principles, ensuring user privacy and transparency in decision-making.

The **commercial potential** of this application is significant. The growing demand for instant financial services and paperless loan processing provides an ideal environment for the deployment of such a system. The low operational cost and scalable design make it viable for small to medium-sized banks, microfinance institutions, and even fintech startups. Additionally, the system's predictive capabilities can be further enhanced with larger datasets, deep learning models, and integration with external credit scoring APIs to improve precision.

A clear **commercialization strategy** was proposed, highlighting key aspects such as market segmentation, pricing models, competitive analysis, and budget planning. With a total implementation cost within **LKR 200,000**, the system offers a highly affordable solution compared to commercial enterprise software. Budget allocations were strategically distributed across development, infrastructure, documentation, testing, and basic marketing, ensuring maximum value for investment. The lean budget approach emphasizes that quality solutions can be developed without extensive financial input if guided by strong design and planning.

The system's alignment with **legal, ethical, professional, and social considerations** was carefully evaluated. Data collected is stored and processed in accordance with relevant privacy laws and is used strictly for the purpose of eligibility determination. Users are informed about how their data is used, fulfilling ethical requirements of transparency and informed consent. Additionally, the system can be localized in multiple languages, including Sinhala and Tamil, to cater to diverse user groups across Sri Lanka, promoting inclusivity and accessibility.

Socially, the system contributes to **financial inclusion** by providing a simplified platform for individuals to understand and access loan opportunities, particularly in rural or underserved regions. It reduces the digital divide by offering a mobile-responsive, user-friendly interface that does not require deep technical knowledge. This can empower small business owners, farmers, and informal sector workers to assess and pursue financing options.

The project also contributes to personal and academic development by enhancing skills in **data science, software engineering, machine learning, UI/UX design, and systems analysis**. It demonstrates the ability to integrate theoretical knowledge with practical application, solve real-world problems, and develop products that have tangible societal and economic impact.

Looking forward, the system can be expanded in several ways. For instance, future iterations could include automated document uploads, integration with credit bureau APIs, chatbot-based assistance, and support for different loan types (e.g., education loans, vehicle loans, microloans). Additionally, the logistic regression model can be upgraded to ensemble models or deep neural networks to handle more complex data and improve accuracy further. Another possible direction is deploying the system as a mobile app with push notifications, biometric login, and localized offline features.

In conclusion, the **Loan Eligibility and Prediction System** is a technically robust, user-friendly, secure, and scalable application that addresses a real need in the financial services industry. It offers an intelligent and efficient alternative to traditional loan assessment procedures, saving time for both users and institutions while improving decision accuracy. With its clear alignment to best practices, legal and ethical compliance, and commercial readiness, this system has high potential for successful deployment and long-term impact. Its success reinforces the value of combining **machine learning**, **web development**, and **user-centric design** to solve critical industry challenges in innovative ways.

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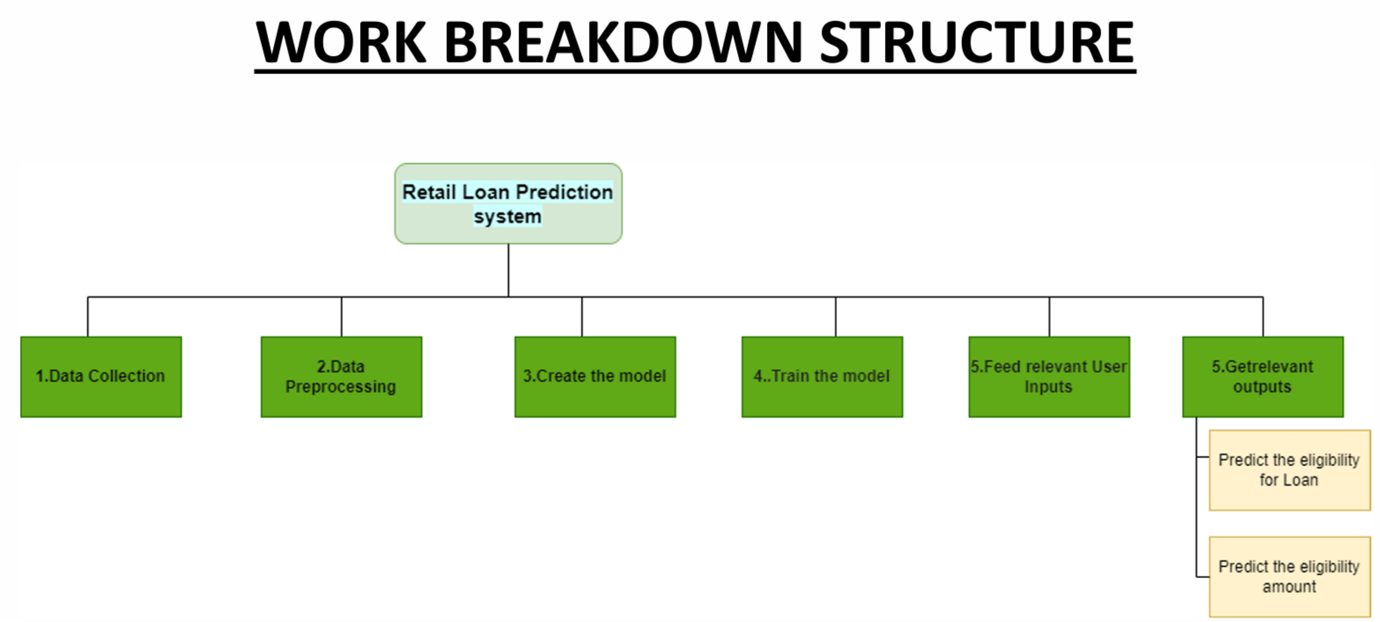
Appendices

Appendix A: Work Breakdown Structure



Appendix B: Gantt Chart