Bank Loan Eligibility and Credit Limits Prediction Using a Machine Learning Approach

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Abstract*—Loan eligibility assessment based on various eligibility requirements in a financial institution, most typically a bank, is a critically challenging process that often leads to problematic situations, such as delays, inconsistencies, and a lack of transparency in lending decisions. This research presents a web-based machine learning-powered solution for loan eligibility prediction to address these challenges. The software system has been integrated mainly with three components. Firstly, an AI chatbot that makes decisions and provides dynamic responses based on bank-provided documents and user data regarding bank policies, loan agreements, and user-specific loan data. Secondly, a loan eligibility and eligible loan amount prediction module that evaluates identification documents, payslips, and credit information using document analysis mechanisms to determine whether a system user is eligible for a loan on behalf of the financial institution. Lastly, a financial literacy and alternative financing module assists rejected applicants by providing collateral-based loan alternatives in case the salary and bank deposit-based loan application fails. With an accuracy of 79% for the eligibility prediction model and a high-performing alternative financing suggestions model with an R-squared value 0.98 and a mean squared error of approximately 0.0010, this system streamlines the loan application processing to be more effective. It improves the overall transparency of eligibility evaluation practices and enhances financial literacy, introducing a robust solution for modern banking.

***Keywords*—loan eligibility prediction, AI chatbot, OCR-based document analysis, machine learning, collateral-based loan alternatives**

I. Introduction

The financial sector is a crucial player in the world of economics that facilitates means for individuals to safekeep their financial assets and take out loans. Even though the financial sector has become more and more important over time, the traditional methods for loan processing, still being used mainly within banks, are often slow and rely on extensive manual verification, are sometimes subjected to human bias of the assessors, and are inconvenient to both parties in a technically evolving world. Especially in the context of Sri Lanka, applicants frequently experience delays in the loan approval process when it comes to time-consuming document checks, a lack of transparency, and inefficient communication with the financial institutions. Additionally, many applicants also struggle to understand the criteria for loan eligibility and ultimately end up getting rejected.

The system developed in accordance with this research introduces a web-based machine learning-powered system explicitly for predicting loan eligibility with the goal of enhancing loan accessibility, decision-making efficiency, and financial literacy. This system automates the entire loan application process, improves customer engagement, and provides alternative financing solutions when conventional loan applications fail by employing the latest technological developments such as machine learning, artificial intelligence, and optical character recognition (OCR).

When the problem itself is taken into consideration, the current loan approval process in many banks and financial institutions relies on static eligibility criteria, extensive manual processing, and limited customer guidance. This creates the key problems of inefficient loan processing resulting from manual workload, lack of financial literacy, including lack of awareness of terms relevant to loans and alternative collateral-based lending within the common populace, and high rejection rates when customers fail to meet the salary-based eligibility, whereas they could have been approved under asset-based criteria. Thus, there is a need for a computerized solution capable of predicting eligibility and providing customer support to improve the decision-making accuracy, cut back on redundant manual processes, and enhance financial inclusivity.

As a solution, the presented loan eligibility prediction system has utilized the latest technologies to make three critical components available to customers.

1. AI chatbot – A smart chatbot that refers to the pre-provided document and database-based data to answer loan-related queries using a structured knowledge base. The main target of this chatbot is to assist logged-in users with personalized loan insights based on their personal financial history and assist non-registered users with general information regarding eligibility, required documentation, and bank policies.

2. Loan eligibility and lendable loan amount prediction – A component that takes user input in the form of a loan application form and validates attached documents and personal banking information to determine the financial status, so that the user's eligibility for the requested loan can be determined through the formula used within the bank.

3. Financial literacy and alternative financing – A guidance system for rejected applicants that offers personalized advice based on rejection reasons and asset-based financing solutions for those who fail to meet salary-based eligibility.

This study aims to develop an AI-powered chatbot based on the context of Sri Lankan loan eligibility processes, specifically to meet the requirements determined by Ceylan Bank. The goal of this software system lies in enhancing customer engagement and loan-related assistance from a business perspective, and prompting rejected applicants to explore other available alternative financing options. Furthermore, it mainly attempts to improve the loan approval efficiency and reduce the processing delays by incorporating automatic techniques that minimize the need for human intervention.

II. RELATED WORK

A loan refers to the provision of money, assets, or other valuable items by a third party, typically under the agreement that the borrower will repay the amount along with interest. When handled manually, the process of approving loans can be time-consuming, and organizations engaged in lending often encounter challenges in accurately verifying an applicant's eligibility [1]. Determining whether a person qualifies for a loan and calculating the amount they can borrow is a frequent and practical challenge for financial institutions. Automating this approval process can significantly reduce manual effort and enhance the speed and efficiency of service delivery to clients [2]. Not only that, it is seen that automating the processes can also boost the safety of the processes and minimize human error and biased interventions in the long run. It is a step towards preventing fraudulent activities, too. For instance, one of the main priorities in the banking sector is ensuring that loans are provided to trustworthy borrowers. Although banks and financial institutions conduct extensive checks and validations before approving loans, these procedures do not always ensure that the most qualified or suitable applicant is selected [3]. But an automated system evaluates candidates without bias and is transparent about the process, giving every candidate an equal opportunity to obtain a loan.

With the technological advancements in the industry, several countries and individuals have already come up with solutions that computerize at least a part of the eligibility validation process for loans. Most recently, machine learning has emerged as a promising approach for tackling existing inefficiencies, thanks to its ability to independently identify patterns and generate predictions based on data [4]. For example, several studies have assessed the effectiveness of decision tree algorithms, like ID3, CART, CTREE, C4.5, CHAID, QUEST, CRUISE, and GUIDE, by examining factors such as requested loan amount, asset value, age, income, guarantor details, family background, and existing loans. These evaluations aim to determine how suitable machine learning methods are for validating loan eligibility. [5].

Apart from that, new approaches like AI chatbots have already become an important choice for financial decision-making in more than a few use cases. Useful and timely information is critical for financial decision-making. Recent advancements in ML make it possible to extract information from this data quickly and efficiently [6]. The emergence of messaging platforms and mobile technologies in the early 2000s paved the way for businesses to adopt chatbots as part of their customer support strategies. More recently, breakthroughs in artificial intelligence, particularly in deep learning and natural language processing, have enabled chatbots like OpenAI's ChatGPT and IBM Watson Assistant to manage more sophisticated, human-like interactions. As a result, their use has expanded across sectors such as finance, healthcare, and e-commerce [7]. AI-powered chatbots have revolutionized customer service by streamlining operations, replacing outdated manual processes with faster, more efficient automated solutions [8]. Advanced data analytics capabilities in AI chatbots support managers in simplifying customer relationship management while enabling more informed decision-making through comprehensive data insights. These intelligent systems excel at gathering and analyzing vast amounts of information, efficiently monitoring customer interactions, identifying recurring questions and issues, and keeping track of user preferences and feedback [9]. So, from handling routine tasks to forecasting future trends, AI and machine learning provide numerous advantages. In the banking sector, AI-powered chatbots are commonly used to streamline customer support, while machine learning models are applied to identify fraudulent activities and anticipate customer behavior patterns [10].

Deviating from the standard banking and loan application processes, countries all around the world possess different alternative financing solutions, especially in cases where banking loans are not approved due to customer ineligibility. Among these solutions are microfinancing, where financial services are provided to low-income people or people excluded from traditional banking, peer-to-peer lending based on reputational scores and behavioral data rather than hard credit scores, and concepts like Islamic financing. Microfinance approaches, such as the Grameen Bank model, have proven effective within the social and economic settings of Bangladesh and other countries in South Asia. [11], whereas there are several other microfinancing models operating under various regulatory standards in many other countries like South Africa, Peru, Indonesia, Philippines [12]. In addition, most Islamic countries adopt the Islamic financing model that overcomes some common challenges of traditional microfinancing approaches [13]. Peer-to-peer lending has gained significant popularity as an alternative financing method and is widely utilized in various regions, including China, APAC, US, UK, and Europe, particularly for business-related loans [14].

On that note, apart from the main loan application process based on current savings of the customer and their income, there are several other types of loans offered by financial organizations. Collateral is commonly included in credit agreements between businesses and financial institutions, serving as a key mechanism for banks to address information gaps. It helps reduce risks such as low-risk borrowers withdrawing due to high interest rates and also plays a role in resolving credit-rationing issues [15]. In the banking industry, collateral is a standard component of loan agreements, though its application and impact are still not entirely clear or consistently interpreted [16]. So, an opportunity to raise more awareness and proactively suggest available options for collateral-based loans would be ideal to continue the business interactions between banks and customers to provide alternatives where income-based loan applications fail.

Furthermore, even though finance is such a popular domain involved in the world economy, there is an astounding lack of awareness within the general populace, even on basic economics and finance. Findings from an international study suggest that financial literacy varies across different demographic groups. Notably, age-related trends reveal an inverted U-shaped curve, with financial understanding being lowest among younger and older individuals and reaching its highest point during middle age [17]. Although banks and financial institutions provide a wide range of services, many commonly available financial products, such as student loans, credit cards, annuities, mortgages, and pensions, tend to be complicated and challenging for individuals with limited financial knowledge to understand and navigate [18]. This extends to the unawareness regarding alternative financing options, too. Wrong choices in finances are going to ultimately cost a lot, especially for the younger generations if they are not sufficiently financially literate [19]. Therefore, it is important to offer proper guidance and recommendations from an expert perspective to offer the best possible service to help individuals make the best financial decisions from the available options.

III. Methodology

This section encompasses the design and implementation of the loan eligibility and prediction system discussed in this research context by detailing the technologies, processes, and models used in loan assessment, AI chatbot interactions, and financial guidance module implementation. The methodology of this project has followed a structured data-driven approach that integrates machine learning, optical character recognition (OCR), and natural language processing (NLP) to automate the decision-making capabilities and enhance the user engagement with the system.

A. System Architecture

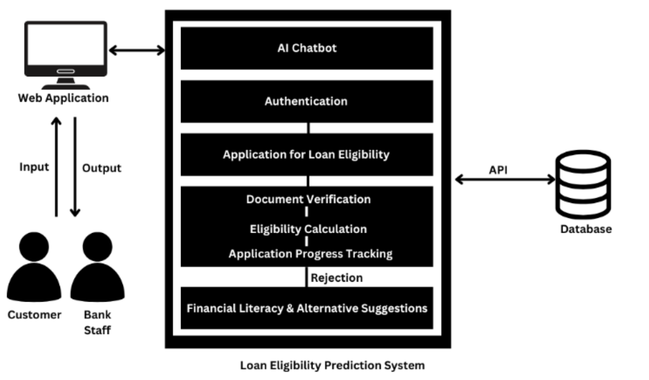


Fig. 1. High-Level Architecture Diagram

Fig. 1 represents a high-level overview of the entire system architecture. The system has been structured into three primary components, namely, the AI chatbot for loan information discussion, the loan eligibility and eligible loan amount prediction component for document analysis and application processing, and the alternative financial guidance module for providing actionable recommendations for rejected applicants. All these models have been hosted on Google Cloud Platform (GCP). The general workflow consists of the following processes;

1. User registration and authentication
2. Loan inquiry via AI chatbot
3. Loan application submission
4. Document analysis
5. Machine-learning based loan eligibility prediction and application processing
6. Financial guidance for rejected applicants

The system caters to the needs of multiple user groups, including new and existing customers, bank staff, and administrative users.

B. AI Chatbot

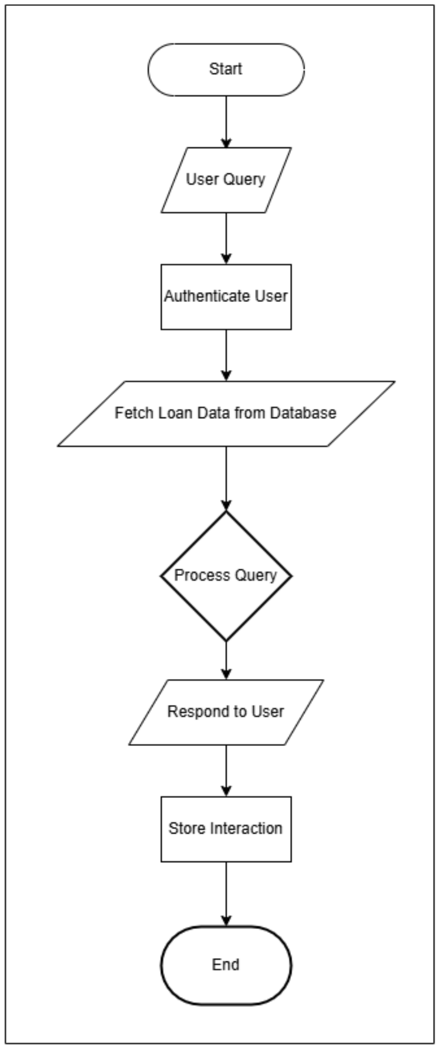


Fig. 2. AI Chatbot Workflow

The AI chatbot has been built by using natural language processing and retrieval-augmented generation (RAG) for generating loan-related answers. In the case of non-registered users, the chatbot provides general loan-related information by retrieving responses from the data fed into the model through properly structured financial documentation, including data related to bank loan policies, eligibility criteria, and required documentation. On the other hand, as Fig. 2 depicts, if the user has already registered and logged into the system, following the login and OTP verification (for newly registered users), the chatbot will act as a personalized inquiry tool that is capable of retrieving loan details from the customer details and answer queries around the up to date information about the user's already existing loans, payment dates, and interest rates. When the user performs a query, the system fetches the personal loan information of the user and stores it in a vector database for efficient retrieval.

Several questions and answers from a typical conversation with the chatbot as a user are presented below.

1. **Scenario 1 (Existing User): Requesting Loan Repayment Schedule**

User: "Can you show me my loan repayment schedule?"

Chatbot: "Here is your repayment schedule:

- April 5, 2025 – LKR 30,000
- May 5, 2025 – LKR 30,000
- June 5, 2025 – LKR 30,000

Would you like a PDF copy emailed to you?"

2. **Scenario 2 (Bank Staff): Retrieving Customer Loan History**

User: "Show me the loan history for Customer ID 7865."

Chatbot: "Customer ID 7865 has:

- Home Loan: LKR 3 Million (Outstanding: LKR 1.5 Million)
- Personal Loan: LKR 500,000 (Fully repaid in 2023)

Would you like details on repayment schedules or late payment records?"

3. **Scenario 3 (Admin Inquiry): Managing Chatbot Responses**

User (Admin): "How many unresolved queries were logged today?"

Chatbot: "There were 15 unresolved queries today. Most of them were related to loan eligibility criteria. Would you like to review them?"

User: "Yes, show me the details."

Chatbot: "Here is a summary:

- 6 inquiries about missing documents for loan applications
- 4 inquiries about delayed loan approvals
- 5 general banking inquiries outside chatbot scope

Would you like to escalate any of these to support?"

The core processes of the AI chatbot follow the architecture depicted in Fig. 3, utilizing the provided documentation to answer user questions.

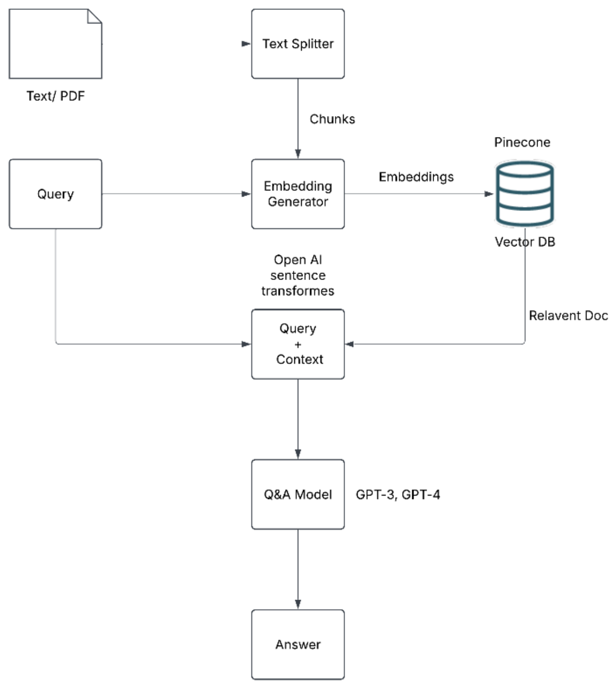


Fig. 3. Query Processing and Answering

If an ambiguous question or a question out of the loan and banking context is asked, the chatbot is configured to reply that the question is out of the range of answerable questions. The answers are data-driven, providing users with accurate loan information using the banking data supplied to the chatbot.

C. Loan Eligibility and Eligible Loan Amount Prediction

The loan eligibility assessment follows a completely data-driven approach that processes the financial data of the user, including OCR-extracted payslip data, CRIB (Credit Information Bureau of Sri Lanka) records, and identification documents. The demographic information (age, employment type), financial information (monthly income, savings, existing debt, other incomes, fixed deposits), credit score (loan repayment history from CRIB verification) are all taken into account and validated with a machine learning model utilizing logistic regression algorithm to perform this binary classification task and determine whether the user is eligible for the requested loan.

The model has been trained using a dataset of approximately 2000 records of loan applications that were securely stored and processed via Google Colab for model development and testing. To ensure model fairness, a balanced dataset has been used. The balance has been ensured by utilizing a well-sanitized, accurate, and inclusive dataset where, for instance, if 1000 applications were those that had been approved, the other 1000 were those that had been rejected.

This follows the workflow graphically represented in Fig. 4.

OCR, Optical Character Recognition technology, has been used in extracting data from national identity cards (NICs), pay slips, and other supporting documents submitted as attachments to the loan application. The text extraction of NICs has been performed with Tesseract OCR. The payslip information has also been cross-checked with customer-provided data, and the salary details have been validated prior to confirming eligibility. If the user is eligible for the loan requested, a machine learning model that utilizes the random forest regression predicts the eligible loan amount.

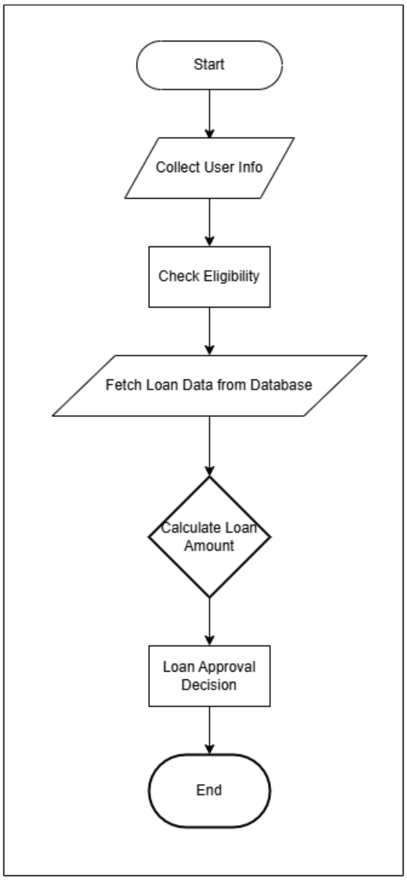


Fig. 4. Loan Eligibility Prediction Workflow

D. Loan Application Status and Approval Workflow

The profile section of the web application allows users to track their loan application status in real time, and the approval process consists of several different steps. These include pending review (initial submission received), personal detail verification (cross-checking the banking information provided with the bank data), attachment analysis (OCR-based document analysis), CRIB verification (assessing the credit score and the past payment behavior), and bank officer verification (manual review for the final approval or rejection by an authorizes bank officer). At any stage, the application can be automatically moved to rejection based on a system-made decision if an issue is detected. In that case, the financial literacy and alternative guidance module provides solutions based on the issue that occurred.

E. Financial Literacy and Alternative Financing Module

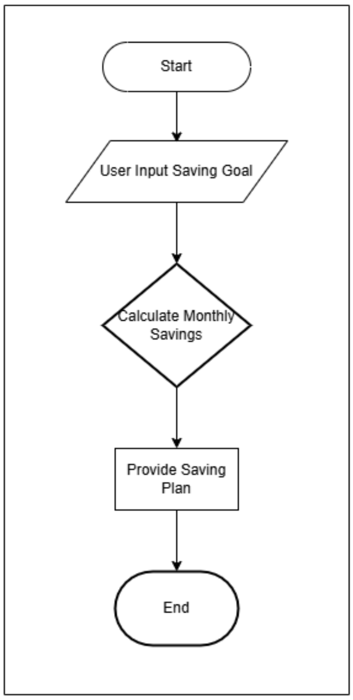


Fig. 5. Saving Plan Recommendation

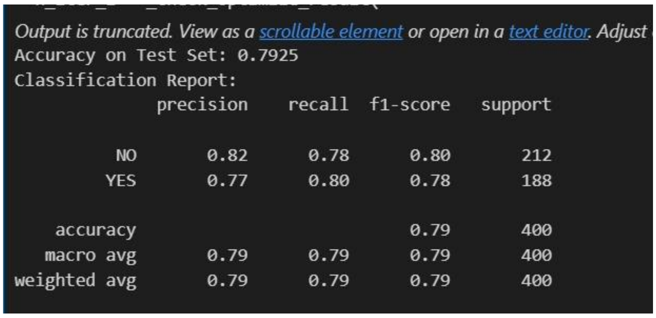
In the case where an application rejection occurs based on the salary and savings-related eligibility criteria, the system offers a collateral-based solution that fits the use case. For instance, the next steps the user can take are suggested, including suggestions such as increasing the bank guarantee by increasing the fixed deposit amount, land revaluations to meet the LTV (Loan-to-Value) threshold for properties, and using vehicles or other assets as collateral. Apart from that, as Fig. 5 shows, a personalized savings plan for loan eligibility can also be suggested through the system.

Altogether, backend technologies like Python (Flask), TensorFlow, scikit-learn, and MySQL, and frontend technologies such as Tailwind CSS and React.js have been used together with AI and NLP technologies such as Hugging Face Transformers (RAG) and Pinecone to develop the software solution.

IV. Results & Discussion

The loan eligibility prediction system has been evaluated based on its accuracy, efficiency, and user engagement across its three core components: AI chatbot, loan eligibility prediction, and financial literacy guidance in realizing the research objectives. The system has been tested against a dummy bank database for evaluating performance against real-world loan application scenarios and synthetic financial data to ensure comprehensive validation.

The AI chatbot's response system has been tested against a set of well-structured documents and a customer database using policy documents, loan agreements, and customer queries. The results have indicated a total of 92% accuracy in correctly answering loan-related questions for non-registered users and 87% accuracy when retrieving loan-specific details of authenticated users, and the response time has been recorded as under 2 seconds, ensuring quality real-time interactions.



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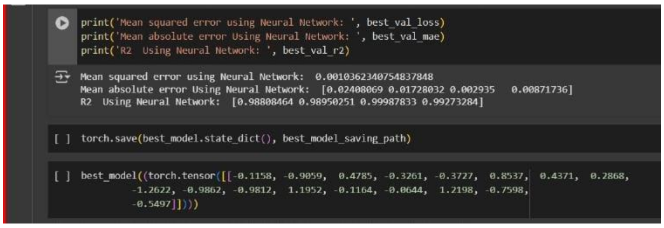
Output is truncated. View as a scrollable element or open in a text editor. Adjust
Accuracy on Test Set: 0.7925
Classification Report:
              precision    recall  f1-score   support

          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
```

Fig. 6. Loan Eligibility Prediction

The loan eligibility prediction component has been evaluated using standard classification metrics on a sample dataset of 2000 loan applicants. It has demonstrated a high accuracy of 79% (Fig. 6) when predicting the eligibility of loan applications after evaluating the personal data, and it later suggests a feasible loan amount based on the data.



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print('Mean squared error using Neural Network: ', best_val_loss)
print('Mean absolute error Using Neural Network: ', best_val_mae)
print('R2  Using Neural Network: ', best_val_r2)

Mean squared error using Neural Network:  0.0010362340754837848
Mean absolute error Using Neural Network:  [0.02408069 0.01728032 0.002935   0.00871736]
R2  Using Neural Network:  [0.98808464 0.98950251 0.99987833 0.99273284]

[ ] torch.save(best_model.state_dict(), best_model_saving_path)

[ ] best_model((torch.tensor([[-0.1158, -0.9059,  0.4785, -0.3261, -0.3727,  0.8537,  0.4371,  0.2868,
        -1.2622, -0.9862, -0.9812,  1.1952, -0.1164, -0.0644,  1.2198, -0.7598,
        -0.5497]])))
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Fig. 7. Collateral-based Alternative Financing Suggestion Model

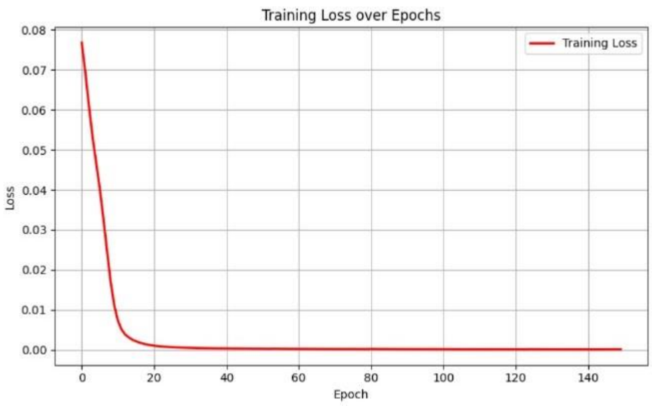

Fig. 8. Training Loss Over Epochs

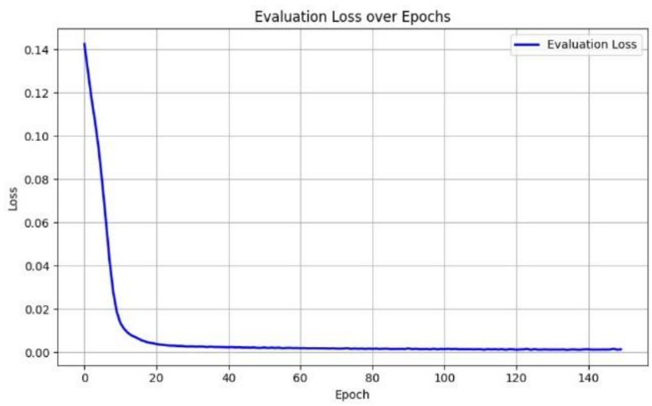

Fig. 9. Evaluation Loss Over Epochs

In the context of rejected applications, it has been seen that the system provides alternative financing suggestions using a model that has achieved a high R-squared value close to 0.98 and a mean squared error (MSE) of around 0.0010 (Fig. 7) for users to opt for collateral-based solutions. Figures 8 and 9 illustrate the training loss and evaluation loss of the model over epochs, respectively, demonstrating its convergence and stability during the learning process. From the data that has been tested against the system, common rejections have been caused due to reasons such as low salary (56%), poor CRIB history (22%), and incomplete documents (15%). 63% of the rejected users have reapplied using collateral of their choice (land, vehicles, etc.) to redo the application process with the suggestions provided through the system.

These results indicate that the system significantly contributes to improving loan accessibility, reducing processing time, and enhancing financial literacy, making it an effective solution for modern banking. This system has been deemed beneficial not just for the customers but also for banking staff, given the ease of use and automated evaluations provided with just a few simple clicks.

V. Conclusion & Future Work

This research has introduced a web-based, machine learning-powered loan eligibility system that has been carefully designed to enhance the loan processing efficiency, transparency, and financial literacy as a whole. The system has utilized AI chatbots, machine learning models, and OCR-based document analysis mechanisms to automate the eligibility assessment processes and provide alternative financing suggestions when applicants fail to meet conventional criteria. It acts as a customer support system for users to understand their loan eligibility and get needed guidance before going through the actual loan application process with a financial institution.

The software system that has been developed has demonstrated an accuracy rate of 92% for non-registered users seeking help with loan-related information in general and an accuracy of 87% in providing personalized responses for personal loan-related inquiries by authenticated users with the AI chatbot component. The loan eligibility prediction model has demonstrated intricate machine learning capabilities with both eligibility prediction and eligible loan amount prediction, going beyond the traditional rule-based systems. Furthermore, the financial guidance module has also played a crucial role in boosting financial literacy in customers, prompting 63% of the rejected applicants to reapply with collateral-based solutions, as suggested by the system.

With the incorporation of the latest technologies, this system has been capable of bridging the gap between applicants and financial institutions, fostering a more inclusive and efficient workflow by addressing common challenges faced with conventional loan processing procedures in the context of Sri Lankan banking systems.

Even though the system has displayed significant performance and success, there are several steps that could improve the functionalities even further to bring the system to the next level. For instance, the data sources can be expanded for dynamic financial data retrieval by integrating real-time banking APIs, the chatbot can be enhanced for multilingual support, and anomaly detection algorithms can be incorporated for potential fraud detection. These future improvements could further increase the potential for the system to grow and become a valuable asset in the financial sector with better accuracy, security, and scalability.

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