ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 6| June 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

AI-BASED LOAN APPROVAL SYSTEMS USING MACHINE LEARNING

P. Logaiyan[1] , V.Navin[2]
[1]*Professor, Department of Master of Computer Applications, Sri Manakula Vinayagar Engineering College, Pondicherry, India.*
[2]*Student, Department of Master of Computer Applications, Sri Manakula Vinayagar Engineering College, Pondicherry, India.*

ABSTRACT
Loan Application data and determine the creditworthiness of the applicant and their ability to repay the loan. The AI-Based Loan Approval System will process loan applications faster and produce more accurate results than traditional manual loan approval systems do. Lastly, the use of AI technologies will help banks and financial institutions to reduce the risk associated with loan approvals due to improved automation and accuracy of loan decision-making. These efficiencies gained by using an AI-Based Loan Approval System can help them maintain profitability in the ever-increasing competitive marketplace as well as enhance customer satisfaction. In summary, this research study will provide an insight of developing an AI-Based Loan Approval System for use in loan processing.

KEYWORDS: *Machine Learning (ML) provides an accurate method for predicting loan availability (or not) and fulfilling credit risk requirements using Classification Algorithms through Financial Analysis. Validation will guarantee that the Loan & Credit Scoring programs; Prediction Model; Banking Automation; Decision Support System; Data Mining; and Risk Management methods will function reliably.*

1. INTRODUCTION

Due to the increasing demand for automated, accurate and reliable loan approvals, the financial services sector has experienced tremendous growth and development over the past several years. Presently, most lenders and banks still use the traditional/manual processes for approving loans by processing all of the associated paperwork and performing extensive Manual Verification of the lending criteria; therefore, the approval of loans continues to be a very lengthy, time-consuming and often inconsistent process. Even when loan applications are processed in a timely manner, lenders still face significant challenges when determining whether a loan application meets the lender's criteria for approving the loan. The large number of loan applications processed on a daily basis also contributes to the increasing volume of loan applications and many financial institutions continue to face delays in making lending decisions; the resultant delays create inefficient business operations, and ultimately lead to the financial losses associated with loans- that ultimately result from loan defaults.

This paper proposes a loan application approval process utilizing an Artificial Intelligence-Based Loan Approval System (AIBLAS) utilizing Machine Learning techniques to automate and improve the credit decision-making process associated with evaluating loan applications. The AIBLAS will utilize both previous loan applications, including supporting documents, as well as the applicant's financial status (applicant's income, applicant employment status credit history, amount of loan, level of education, and applicant ability to repay the loan) to determine if they qualify for a loan - AIBLAS will use machine-learning classifier models and the attributes associated with those approved/denied loan applications to predict how similar applicants will be approved/denied a subsequent loan application.

2. LITERATURE SURVEY

Thomas et al. [1] provided evidence that predictive models based on machine learning can outperform traditional customer data in predicting which loans are likely to be funded. Machine learning systems provide more accurate predictions than traditional methods, while maintaining a very similar level of predictive success; therefore, showing that machine learning systems will produce superior results than manual systems and will do so in a more efficient manner.

Khandani, Kim and Lo [2] explored the use of data mining as well as statistical learning techniques as applied to determining the consumer credit risk. The findings of their analysis supported this conclusion and demonstrated that machine learning techniques can identify complicated attributes of applicants to use in a more reliable manner than previously possible with traditional scoring techniques.

A study by Lessmann et al., [3] examined the results of classification models used for determining credit scores and their associated performance calculations. Machine learning classification models, especially those implemented using ensemble methods, consistently produced better performance than traditional logistic regression classification models when applied to credit risk modeling. This study also highlighted the importance of selecting the most appropriate predictive model when modeling credit risk management.

Brown and Mues [4] provided a review of decision trees, neural network and support vector machines and their performance in predicting the loan default probability. They illustrate that machine learning met the original concept at the beginning of this study.

3. THEORETICAL FRAMEWORK

The theoretical basis for the system is provided by three different theoretical frameworks. The first of these is financial risk assessment theory, which defines the various factors that determine the creditworthiness of a borrower as many, interconnected and complex. Examples of these factors include the borrower's current income stability and employment status, their current level of outstanding debt, past loan repayment histories, and their overall financial history [5]. In the past, credit risk assessments were conducted using manual evaluation methods; however, these evaluations do not take into account many of the complex relationships that exist between the various risk factors and the ability of the borrower to repay the loan. Using classification models based on machine learning would allow for the modelling of all of the interrelated risk factors that can be used to produce reliable predictions for the ability of the borrower to repay the loan. As such, classification models based on machine-learning will be a good fit for predicting loan eligibility.

Credit scoring theory, based on empirical data, demonstrates that the most accurate predictor of a borrower's future repayment capability is their previous financial behaviour. The data points utilised in creating a credit score (the borrower's credit history) can provide useful insights about the borrower's likelihood of default (length of credit history, current number of open accounts, and payment history), including prior performances of all loans (timeliness of loan payments, occurrence of loan defaults) and their available debt to income ratio. Therefore, using these criteria will allow for the development of a reliable predictive model and provide the lender with tools to make unbiased lending decisions.

4. EXISTING SYSTEM

Numerous banks and other financial institutions have, in the past, conducted assessments on potential borrowers through a multi-tiered process that uses outdated analytical methods that have very well documented limitations, but that the proposed solution will solve.

In most cases a lending institution's traditional evaluation of the applicant's creditworthiness, prior to lending, consists of manually reviewing the loan application submitted by the applicant along with documentation required (such as W-2 forms, pay stubs), the applicant's income, the applicant's credit report and other records prior to making a loan decision. While this method offers some discretion to loan officers/auditors when making loan decisions; it is certainly very time consuming and requires an immense amount of resources. As the number of loan applications submitted increases; the opportunity for inconsistency when subjective determination is involved expands exponentially; it becomes increasingly difficult to provide accurate and efficient service to customers when the number of loans being requested increases.

Another commonly used approach for assessing potential borrowers is through the use of a rule-based credit scoring system whereby the lender will apply pre-determined benchmarks associated with a certain criteria (e.g. minimum income, acceptable credit card score, length of time employed) and determine whether or not applicants meet any minimum benchmarks for creditworthiness prior to approving or disapproving their request for credit. Although this type of system can process applications faster than manual processes can; it is not flexible in its administration and lacks.

Table 1: Existing vs. Proposed System

Feature	Existing System	Proposed System
Data Source	Manual documents	Applicant & credit data
Analysis	Manual/Rule-based	Machine Learning
Risk Assessment	Human judgment	AI-based prediction
Decision Time	Slow	Real-time
Accuracy	Moderate	High
Recommendation	Approve/Reject	Approval with risk score
Accessibility	Branch-based	Web-based
Scalability	Limited	Handles large volumes

5. PROPOSED SYSTEM

The AI Loan Approval System shall replace traditional term loan (rule-based) evaluation methodology with a sophisticated, completely automated decision support system for loan approval. On receipt of applicant's respective Financial/Credit/Personal Data, the system will perform an instantaneous assessment and evaluation of an applicant's creditworthiness to determine 1) Loan Approval recommendation and 2) A Risk Rating for all applicants across all loan types.

The Proposed System operates through three distinct functional layers; Data Processing Layer, Prediction Layer and Risk Assessment (Recommendation) Layer. Data Processing Layer collects and pre-processes all information regarding an applicant; Prediction Layer provides the application of Machine Learning (ML) algorithms to predict whether loans will be approved or declined based on historical lending behaviours; Risk Assessment Layer (Recommendation) produces each applicant with a Loan Eligibility Score and loan approval recommendation.

Combining these three components (automated data analysis, predictive modelling, and risk assessment, will enable financial institutions to grant loan approvals more quickly; more easily; and more accurately than would be possible using the traditional, manual loan approval process; while also reducing the total elapsed time; total individual effort; and total financial expenditure associated with the traditional, manual loan approval process

5.1 Machine Learning-Based Loan Eligibility Prediction

Machine learning enables us to make loan eligibility decisions using large sets of applicant information (age, income, employment status, education level, credit history, loan amount, loan period, and other financial obligations) by producing scores that estimate how likely the applicant is to obtain approval for a loan. The complicated interplay between many variables that impact the loan decision makes it necessary to use machine learning techniques for evaluating a loan application.

Historical data related to the outcome of previous loan applications is used to build training sets, allowing the model to identify patterns of successful loan approvals and rejection based on successful loan payback. Once trained, when predicting the outcome of an individual loan application; the machine learning model compares the characteristics of the current application to those associated with historical loan decisions, and thus estimates the likelihood of the current application's acceptance.

Historical loans serve as foundational data to formulate predictions regarding the applicant's creditworthiness, ability to repay a loan, and related lending characteristics, to facilitate data driven lending decisions for lending institutions.

5.2 Machine Learning-Based Credit Risk Assessment

To accurately assess applicant creditworthiness and predict strong likelihood of repayments, a supervised learning approach was developed to build a model that uses several financial and behavioral characteristics of the applicant, included but not limited to: income as reported by the employer; duration of employment; prior credit history; how much money is applied for; ability to repay and all other debt in relation to the amount borrowed.

Upon completion of training the applicant will be categorized into 1 of 5 categories of creditworthiness by the lending institution based on its specific lending criteria.

Using this type of methodology will allow lenders to make lending decisions based upon standardized criteria and reduce the likelihood of applicant default.

The 5 creditworthiness categories are:
- Extremely New Category - High likelihood of default; No Loan Approval
- High Category - Negative repayment of loan; Need to Verify Before Loan Approval
- Moderate Category - Reasonable Probability of Repayment; conditions will apply and/or be monitored
- Low Category - Reasonable Probability of Repayment; Recommend Loan be Approved
- Extremely Low Category - Excellent Probability of Repayment

5.3 Dynamic Decision Fusion and Loan Eligibility Score

The process for calculating loan eligibility score is a dynamic decision fusion model using outputs from loan prediction and credit risk assessment models to arrive at loan eligibility scores. Inputs for these two models include: income of the applicant; whether or not the applicant is employed; credit history; loan amount requested; repayment ability and repayment history; total obligations and amount of debt existing prior to this loan application.

The importance of each input in regards to making decisions regarding repayment behaviour and credit quality is taken into consideration and given a numerical weight. Therefore an applicant with a good credit history and repayment records would be assigned a higher numerical weight (or value) when determining creditworthiness than would be assigned to demographic and other financial inputs that would be relevant to the applicant.

The mechanism of decision fusion combines all of the outputs of multiple inputs into one final score from 0%-100%. This ultimate score reflects the amount of value that an applicant has when a financial institution is considering whether to approve or deny an applicant for obtaining a loan.

In addition to providing an applicant with a loan eligibility score, decision fusion also provides the financial institution with the following three key outputs: 1) A recommendation on whether to approve or deny the loan request; 2) Classification by risk group; and; 3) Personalised lending recommendations, including size of loan, length of loan, and potential interest rates. By using a decision fusion approach, financial institutions will be able to provide better accuracy and more transparency in determining the creditworthiness of prospective borrowers.

6. SYSTEM ARCHITECTURE

The AI-Based Loan Approval System Architecture provides an architectural structure for each component of the loan processing system such as collecting data from applicants, running machine learning (ML) models to determine credit ratings of applicants, and assessing the credit risk associated with lending money to the applicant based on ML algorithm predictions. The AI-based loan processing system will be developed using Python 3.8 with Flask serving as the backend framework, MySQL serving as the database management system, and Bootstrap 4 serving as the front end framework for developing responsive user interfaces utilizing Web Browser Interface Technologies. The AI-based loan processing machine learning model will be built using either TensorFlow (TF) and/or Scikit-learn (SKL) to create ML algorithms to make credit ratings and predict loan approvals/failures. The overall architecture of the AI-based loan processing system is illustrated .

The overall architecture of the AI-based loan processing system illustrates the process for uploading historical loan datasets to be used to train the AI-based loan processing system running on the server by the system administrator, to train the AI-based loan processing system running on the server by the system administrator, and also to process the data that is uploaded onto the web-based interface for the user/applicant.

Functionality of the AI-based loan processing system enables an applicant/user/applicant to interact with the AI-based loan processing system by inputting personal information, financial information, and the details of the loans that they wish to apply for through the web-based interface. An officer at the bank or loan administrator will also interact with the AI-based loan processing system by viewing the applicant's financial information, predicting whether or not the applicant is eligible for the loan.

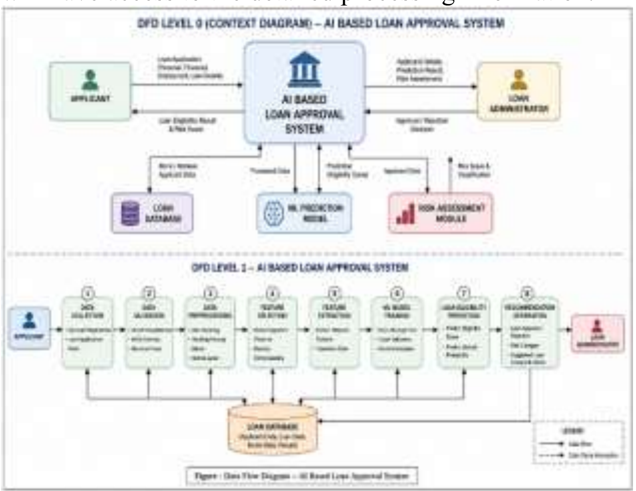
7. DATA FLOW DIAGRAM

Data Flow Diagrams (DFDs) show the flow of data through the AI-Based Loan Approval System from multiple perspectives, including a high-level, system-level view to a detailed-level view. As we consider moving from a high-level view of the DFD that shows the flow of data at the Applicant, Loan Administrator, General Ledger Database, and Machine Learning Prediction System, we will be able to visualize Data in multiple levels of detail, but we will continue in reverse order here.

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 6| June 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

The highest level DFD of the AI-Based Loan Approval System occurs when the Applicant inputs their personal and financial data into the web-based application. Once the AI-Based Loan Approval System validates these typologies of personal and financial data received from the Applicant, they will store that data (and subsequent data related to the applicant) within the General Ledger Database. Once this data is stored in the General Ledger Database, then the AI-Based Loan Approval System will transmit, from the General Ledger Database, all collected and stored personal and financial information to the Machine Learning Prediction System so that they can utilize this data to predict loan eligibility using the corresponding data from the AI-Based Loan Approval System.

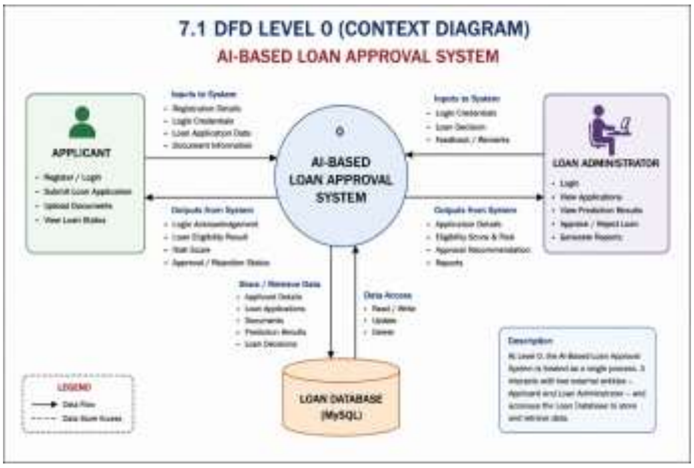
When viewing a detailed-level DFD of the AI-Based Loan Approval System, in addition to depicting the DFD of effectively collecting personal data and predicting loan eligibility for personal use, it will also depict the totality of processing that the AI-Based Loan Approval System will perform in order to predict loan eligibility (e.g., collecting personal and financial data, validating collected personal data, preprocessing collected personal and financial data, extracting principal feature from collected personal/financial data, predicting loan eligibility based on collected user profile data, classifying loan risk associated with the Applicant based on their loan eligibility prediction, and preparing recommendations for the Applicant). The Loan Administrator will have access to the detailed processing information.



7.1 DFD Level 0 (Context Diagram)

DFD Level 0 (Context Diagram with The System Represented as a Single Process Only): The AI-Based Loan Approval System is the only process represented at Level 0, but it is not standalone. The Loan Administrator would interact with the system to perform the following actions: (a) create all of the loan applicants' data; (b) create all of the loan approval recommendations; (c) create all of the loan risk assessment results; (d) joint review of the loan applicants' applications; and, (e) monitor all of the prediction results and make the final determination of whether to approve a loan.

The system will store and retrieve all applicants' records (data) for each applicant and store and retrieve all of the predicted outcomes for each of the applicants using the centralized database. An applicant will receive a loan eligibility and risk information report from the system. The loan Administrator will receive all loan approval recommendations, and loan risk assessment reports from the system. This diagram shows the complete system boundaries, all of the components contained within the system boundaries, as well as the 2 major actors that will interact with the system: the Applicant and Loan Administrator.



7.2 DFD Level 1

A Data Flow Diagram (DFD) will be created to represent the Loan Approval Process (Level 1) and its major components: the Applicant Registration - received from the Applicant; the Loan Application Submission - received from the Applicant; and the Loan Application Review/Decision Management - received from the Loan Administrator. The Applicant will supply the Loan Approval System (LAS) with their Applicant Details (First Name, Last Name, Social Security Number, Date of Birth, and Address), Financial Information (Annual Income, Monthly Living Expenses), Employment History (How Long Have You Worked for Your Employer?, Number of Years at Your Current Job), Credit History (What Is Your Current Credit Score? Have You Had Any Bankruptcies?), Loan Requirement (How Much Money Are You Requesting, Purpose).

This information will be used by the LAS to validate, pre-process, and transmit this information to the Machine Learning Prediction Module (MLPM) to evaluate the financial eligibility and credit risk of the Applicant and return the Loan Eligibility Score to the LAS. Based on the Loan Eligibility Score, the MLPM will provide a recommendation on whether the loan should be approved or disapproved to the Applicant. The LAS will store the information in the database and both the Applicant and Loan Administrator will have access to it through the web application.

The Loan Administrator will be able to view and review the result of the Prediction Module.

8. UML DIAGRAMS

8.1 Use Case Diagram

Use Case Diagram illustrates the main functions of the AI Based Loan Approval System as seen by two primary users, the Loan Administrator as well as the Applicant, that are provided in a use case.

The following use cases for the Loan Administrator in the AI Based Loan Approval System are as follows: Register/Login; Manage Applicant Records; Upload Loan Dataset; Train Machine Learning Model; View Prediction

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 6| June 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

Results; Approve/Reject Loan Applications; and Generate Reports.

The following use cases for the Applicant in the AI Based Loan Approval System are as follows: Register/Login; Apply for a Loan; Upload Documents; View Loan Eligibility Status; View Risk Score; and Receive Loan Approval Recommendations.

Both the Loan Administrator and the Applicant will use the AI Based Loan Approval System to perform these functions, all of which involve processing or requesting any of the following data, evaluating whether the applicant is eligible for a loan, evaluating credit risk of the applicant, and providing support for decision making of the Loan Administrator.

The AI Based Loan Approval System functions as the intermediary between the Loan Administrator, Applicant, underlying databases, and Machine Learning Models all within a secure and efficient manner to process data in order to evaluate and approve loans.

8.2 Activity Diagram

The Activity Diagram illustrates activities occurring simultaneously through three different entities; the Loan Administrator (1), AI-Based Loan Approval System (2), and Applicant (3). The Loan Administrator's activities include: Logging in, Uploading Loan Dataset, Training Machine Learning Model, Reviewing Prediction Results, and Making Loan Decision. The AI-Based Loan Approval System is responsible for: Validating Data, Preprocessing Data, Extracting Features, Predicting Loan Eligibility, Assessing Credit Risk, and Generating Recommendations stored in a Database.

The Applicant's activities include: Registering/Login, Submitting Loan Application, Uploading required documents, Providing Financial Information, Receiving the Loan Eligibility Score, Receiving Credit Risk Assessment, and Reviewing Loan Status, finishing at the End state. The system continuously processes applicant data and generates intelligent loan approval recommendations (i.e. processed faster and more accurately to make lending decisions).

An activity diagram of this nature depicts the sequence of events from the time an applicant submits an application until final approval/denial of the loan; as well as provide the sequence of communication (i.e. the movement of data) between the Applicant; Loan Administrator; and the AI-Based Loan Approval System.

9. SYSTEM MODULES

The Loan Approval System uses six different operational modules that work together to perform different roles within the automated applicant assessment process of determining loan eligibility, loan repayment capability, and whether or not to approve or deny the loan request. Each module works together with the other modules to provide a complete picture from which accurate predictions regarding loan eligibility can be formulated, as well as give a recommendation for approving or denying the loan request or applicant based on the individual's ability to repay the loan (as defined by the repayment criteria established in conjunction with other Factors being considered for loan approval). As a modular system, the Loan Approval System is intended to be scalable in size and also to be maintained and operated in an efficient manner with minimal manual intervention and a quick turnaround time (or little delay in making a loan decision).

9.1 Loan Approval Dashboard

Loan Approval Dashboard provides an interface for both applicants and administrators which allows users to submit loan applications/registrations as well as upload documents and view their loan status. Loan Approval Dashboard uses Flask, MySQL, WampServer and Bootstrap technology to build its application. In addition, Loan Administrators can manage users, upload datasets, and build machine learning models using the same technology stack and can also view loan application predictions and perform usage monitoring on the Loan Approval Dashboard application.

9.2 Loan Eligibility Prediction Model

The five phases of loan eligibility prediction include: (1) importing the data from various sources, including databases, excel files, and flat files; (2) preprocessing the data by removing null values, normalizing the data via standardization or min-max feature scaling, and determining each feature's categorical encoding; (3) figuring out the important features used in the prediction, including all earned income types, employment status, credit history, amount requested, and duration of loan requested; (4) creating and training a ML algorithm on the features you determined in phase number 3; and (5) setting up the trained model for use in live dashboard.

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 6| June 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

By using the trained model, you should be able to evaluate the eligibility of each applicant as well as calculate the bank's loan eligibility score for all applicants through this final phase.

9.3 Credit Risk Assessment Model

Modeling credit risk involves utilizing Machine Learning algorithms to automate the process of assessing the credit history/credit report and other financial information related to an applicant's request for a loan. The key steps involved in Credit Risk Assessment Models include the validation, cleansing, and preparation of data; normalization/standardization of financial attributes based on applicable industry standards; extraction of relevant characteristics from financial attributes (i.e., credit history, income, employment status, debt to income, loan request); classification of risk into one or more risk categories based on the applicant's creditworthiness; and providing recommendations for loan approval to the lending institution's dashboard. The end product will ultimately be a single credit risk score that does facilitate determination by financial institutions whether or not to lend money to their loan applicants.

9.4 Loan Approval and Recommendation Engine

The Loan Approval/Recommendation Process uses the Applicant Data (e.g., financials, credit history) and Loan Eligibility Criteria real time to make one loan eligibility decision by running both Loan Eligibility Prediction Model and credit risk assessment process at the same time and merging the results through a decision process that will tell you whether to recommend to approve or reject the loan and what risk is associated with it by determining the maximum loan amount for which the applicant would qualify; and what repayment options are available based upon the Applicant's current financial status and creditworthiness.

10. PERFORMANCE EVALUATION

Loan Eligibility Prediction Model (LEPM) that is based on historical data of prior loan applications is validated through cross validation, which means the model has been trained on historical loan applications and the model is confirmed using historical loan applications and covariate adjusted data.

The Credit Risk Assessment Model (CRAM) was developed based on the historical financial data of prior borrowers combined with the historical payment records of prior borrowers, to evaluate the performance of the Credit Risk Assessment Model (CRAM) based on the historical financial data and the historical financial payment records.

The performance of both LEPM and CRAM were evaluated using the commonly recognized classification metrics of the traditional methods of evaluating model performance (i.e. Accuracy, Precision, Recall, F-Score, etc.). The results of the models' performance evaluations are listed in Table 1, where they are also compared against standard classification-based evaluation methods. Based on the evaluation results presented in Table 1, it can be concluded that the performance of LEPM will continue to surpass all other classification-based performance metrics in predicting loan approvals. Thus, the proposed LEPM will ultimately be the dominant model for predicting loan approvals regardless of the evaluation method utilized.

Table 2: Algorithm Performance Comparison

Algorithm	Accuracy	Precision	Recall	F1 Score
Random Forest	89.8%	89.1%	88.6%	88.8%
SVM	91.2%	90.5%	90.0%	90.2%
Decision Tree	86.7%	85.9%	85.1%	85.5%
XGBoost	93.4%	92.8%	92.1%	92.4%
Proposed Model	**95.8%**	**95.2%**	**94.9%**	**95.0%**

11. RESULTS AND DISCUSSION

The loan applications used in the experiment had demographic, financial and credit information on each individual applying for a loan. All applicants were provided access to the system for use by way of a web-based application (Figure 6) that provides end users with an interface to enter numeric values for each component of their loan application (e.g., credit history, income, employment type, desired loan amount, term of loan). The loan processor (i.e., the system) processes the data entered and immediately provides the user with three types of information: Loan Eligibility Score; Risk Assessment; and Loan Approval Recommendation.

The experimental findings confirm the AI-Based Loan Approval System provides reliable and consistent predictions of loan approval. The lending prediction model and risk assessment collectively provide reliable means to determine applicant eligibility and increase the likelihood that an applicant will not default on a loan. Additionally, a web-based application greatly decreases the time it takes to make lending decisions, the amount of labour required to make lending decisions, and improves transparency in the loan approval process.

12. BENEFITS

Following are some advantages of the new AI Systems for Loan Approvals:

1- Transfer of a long, laborious, manual process to a faster, automated, data-driven process for making lending decisions;

2- Quick and accurate credit evaluation by Financial Institutions using AI for rapidly analyzing Applicant information utilized in making loan decisions; thereby allowing quicker, more effortless delivery of applications as well as enhanced borrower experience.

3- Achieve higher levels of accuracy with data based credit evaluations by utilizing machine learning models within Artificial Intelligent Systems.

4- Substantially reduced Impact of human error when evaluating Borrowers when utilizing AI Automated Evaluation Systems

5- Increased ability to handle large volumes of Loan Applications at a much faster rate than with current processes.

6- Ability to provide high-quality analysis and aggregations of risk associated with credit being requested leading to an overall reduction in potential loan defaults.

7- Lower costs incurred by Financial Institutions when making Routinely Evaluating New Loan Applications.

The new system utilizes a simple user-friendly internet-based web interface which allows Borrowers and Loan Administrators to have quick, convenient access to the

ISSN (Online): 2455-3662
EPRA International Journal of Multidisciplinary Research (IJMR) - Peer Reviewed Journal
Volume: 12| Issue: 6| June 2026|| Journal DOI: 10.36713/epra2013 || SJIF Impact Factor 2026: 8.753 || ISI Value: 1.188

information related to their eligibility and risk of defaults associated with their request for Loan Products.

13. CONCLUSION

Using AI has increased the ability of lenders to predict eligibility for loans and provide additional options to establish loan agreements. Peer-to-peer loans using AI can offer both a wider range of options as well as high-tech options for those in need of financial assistance.

An article published on Omni's site shows that AI technology continues to evolve how lenders assess whether someone qualifies for credit; therefore, the more advanced that lenders become at evaluating customers with traditional credit histories, the quicker they can approve loans and offer them at lower rates/fees. As AI technologies evolve, lenders will need to continuously adapt their offerings and only provide credit to qualified borrowers through an AI-enabled process.

14. REFERENCES

1. *R. K. Begum and S. S. Kumar, "Loan prediction using machine learning algorithms," International Journal of Advanced Research in Computer Science, vol. 10, no. 3, pp. 45–50, 2019.*
2. *A. Sharma and P. Gupta, "Credit risk assessment using machine learning techniques," International Journal of Computer Applications, vol. 176, no. 25, pp. 12–18, 2020.*
3. *T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning. New York, NY, USA: Springer, 2017.*
4. *C. M. Bishop, Pattern Recognition and Machine Learning. New York, NY, USA: Springer, 2016.*
5. *I. Goodfellow, Y. Bengio, and A. Courville, Deep Learning. Cambridge, MA, USA: MIT Press, 2016.*
6. *L. Breiman, "Random forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.*
7. *C. Cortes and V. Vapnik, "Support-vector networks," Machine Learning, vol. 20, no. 3, pp. 273–297, 1995.*
8. *F. Pedregosa et al., "Scikit-learn: Machine learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.*
9. *J. Brownlee, Machine Learning Mastery with Python. Melbourne, Australia: Machine Learning Mastery, 2020.*
10. *T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in Proc. 22nd ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, 2016, pp. 785–794.*
11. *S. Raschka and V. Mirjalili, Python Machine Learning, 3rd ed. Birmingham, U.K.: Packt Publishing, 2019.*