Loan Eligibility Prediction Using Machine Learning

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Abstract:

Loan eligibility prediction is a crucial process in the financial sector, helping banks and lending institutions assess the creditworthiness of applicants and reduce the risk of default. This project aims to automate and enhance the loan approval process by building a predictive model that determines whether a loan applicant is eligible for a loan based on their demographic and financial information. Using machine learning algorithms, such as Logistic Regression, Decision Trees, and Random Forest, the model is trained on historical loan data to identify patterns and correlations between applicant features (e.g., income, employment status, credit history, loan amount) and loan approval outcomes. The dataset preprocesses to handle missing values, encode categorical variables, and normalize numerical features. Performance metrics such as accuracy, precision, recall, and F1-score are used to evaluate the model's effectiveness. The results demonstrate that machine learning can significantly improve the efficiency and accuracy of loan eligibility assessments, leading to faster processing times and more consistent decision-making. This work highlights the potential of data-driven solutions in financial services and paves the way for smarter, automated lending systems.

Index Terms Loan Eligibility Prediction, Machine Learning, Classification Algorithm, Data Preprocessing, Feature Engineering, Support Vector Machine (SVM), Logistic Regression, Decision Tree, Model Evaluation, Accuracy Score, Financial Risk Assessment, Predictive Analytics, Python Programming, Loan Approval System, Supervised Learning

1 INTRODUCTION

Loan eligibility prediction is an essential task in the banking and financial services sector. Traditionally, banks and lending institutions have relied on manual methods to assess whether a loan applicant meets the criteria for loan approval. These methods are often time-consuming, subject to human bias, and inconsistent, which can result in delays and inaccurate decisions [4][19]. As the demand for automation and digital transformation grows, the integration of machine learning (ML) into loan processing systems offers a promising solution to streamline and improve the accuracy of loan approvals [5][9].This project, titled “Loan Eligibility Prediction using Machine Learning,” focuses on building an intelligent system capable of predicting whether a loan should be approved based on historical loan application data. Machine learning models can learn from past data and identify patterns and relationships between applicant details and loan outcomes [1][12]. This enables the system to make accurate predictions on new loan applications in real time, ensuring a faster and more reliable decision-making process [5].The dataset used for this project includes features such as gender, marital status, dependents, education level, employment type, applicant income, co-applicant income, loan amount, loan term, credit history, and property area. These variables play a crucial role in determining a person’s loan eligibility. The data is preprocessed to handle missing values and convert categorical values into numerical form using techniques such as label encoding [1][22].The **logistic regression algorithm** is employed due to its effectiveness in binary classification problems like predicting loan approval (yes or no). The model is trained on a portion of the data and evaluated on the remaining to ensure accuracy and generalization. Once the model performs satisfactorily, it is saved using Python’s **pickle** library, allowing it to be reused in a web application [12][22].To make the model accessible to users, a web-based interface is developed using **Flask**, a lightweight web framework in Python. The user interface collects the necessary applicant data and displays the prediction result — whether the loan is likely to be approved or not. This provides a practical, real-time system that simulates how banks could automate their loan screening process [5][9][20].

1.1 Existing System

In the existing loan approval process used by many traditional financial institutions, loan eligibility is determined manually by bank officers or credit analysts. Applicants are required to submit numerous documents, including proof of income, employment details, identity verification, and credit reports. The evaluation process involves a thorough review of these documents, verification of the applicant's background, and calculation of loan-related financial metrics such as debt-to-income ratio and repayment capacity [19].This manual assessment process is often time-consuming, inconsistent, and prone to human error or bias. Decisions may vary depending on the individual officer's judgment, leading to a lack of standardization in the approval process [4][19]. Additionally, due to the large volume of loan applications, banks may struggle to process each request efficiently, causing delays in approvals and dissatisfaction among customers [9].While some modern banks have adopted basic rule-based systems, these systems are limited to fixed logic and cannot adapt to changing patterns in customer behavior or risk factors. They lack the ability to learn from past data and improve over time [1][5].Overall, the existing system is not fully equipped to handle high volumes of applications with speed and precision. It lacks automation, scalability, and the intelligence required for predictive decision-making, making it unsuitable for fast-paced, data-driven financial environments [4][9][22].

Challenges

While implementing a machine learning-based loan eligibility prediction system offers significant advantages, there are several challenges that need to be addressed to ensure accuracy, fairness, and reliability:

1. **Data Quality and Completeness**
Real-world financial datasets often contain missing, inconsistent, or incorrect values. Incomplete data can lead to biased predictions or model errors. Proper data cleaning, imputation, and preprocessing are essential but time-consuming tasks [1][22].
2. **Imbalanced Datasets**
In most loan datasets, the number of approved applications is significantly higher than the rejected ones. This class imbalance can cause the model to become biased toward approving loans, leading to poor performance on the minority class (loan rejections) [12][23].
3. **Feature Selection**
Choosing the right features that significantly impact loan approval is critical. Irrelevant or redundant features can reduce the model's performance, while missing key variables can result in inaccurate predictions [22].
4. **Bias and Fairness**
Machine learning models can unintentionally learn and amplify historical biases present in the training data (e.g., gender, income, or area-based discrimination). Ensuring fairness and ethical decision-making is a major challenge in financial applications [13][17][19].
5. **Interpretability**
Many stakeholders, especially in the banking sector, require transparency in decision-making. Complex models may be accurate but lack interpretability, making it difficult to explain why a loan was approved or denied [4][19].
6. **Dynamic Financial Behavior**
Customer behavior and financial policies change over time. A static model trained on old data may become outdated. Ensuring the model adapts to new trends requires continuous retraining and monitoring [4][23].
7. **Security and Privacy**
Handling sensitive financial and personal data requires strict data security and privacy measures. Any breach can have legal and reputational consequences [19][11].

1.2 Proposed System

The proposed system uses machine learning to automate and improve the loan eligibility prediction process. It analyzes historical loan data to train a model that can predict whether a new applicant is eligible for a loan based on key features like income, employment, credit history, and loan amount [1][5][22].The system uses data preprocessing techniques to handle missing values and convert categorical data into numerical form [1][12][22]. A **logistic regression** model is trained and then integrated into a **Flask-based** web application [12]. Users can enter applicant details through a form, and the system provides instant predictions.This approach ensures faster, more accurate, and unbiased loan decisions compared to traditional manual methods [4][5][9]. It also offers scalability and real-time accessibility, making it a practical solution for modern financial institutions [9][20].

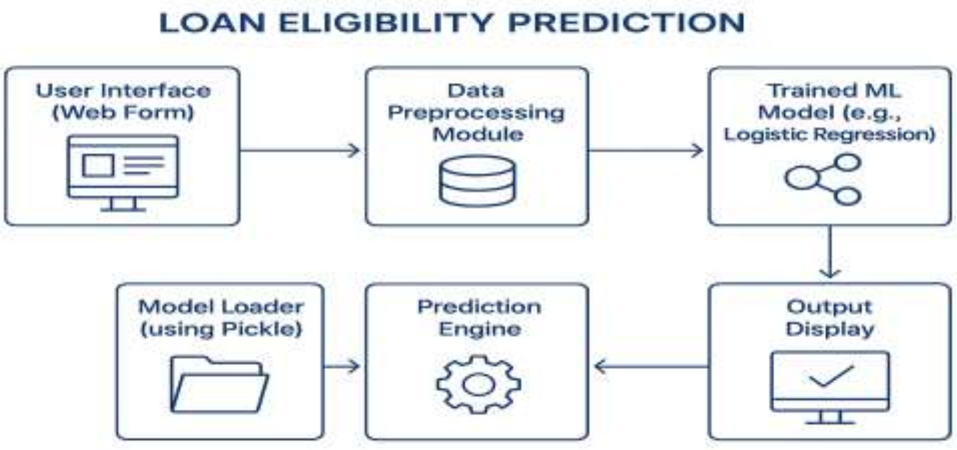
LOAN ELIGIBILITY PREDICTION
User Interface (Web Form)
Data Preprocessing Module
Trained ML Model (e.g., Logistic Regression)
Output Display
Prediction Engine
Model Loader (using Pickle)

Fig: 1 Proposed Diagram

1.2.1 Advantages

1. **Automation:** Automates the loan screening process, reducing manual workload and processing time [5][9].
2. **Accuracy:** Machine learning models provide more accurate predictions by learning patterns from historical data [1][12][22].
3. **Speed:** Generates instant decisions, allowing quicker loan approvals and better customer service [9][20].
4. **Consistency:** Ensures uniform decisions for all applicants, minimizing human bias and error [4][13][19].
5. **Scalability:** Can easily handle large volumes of loan applications without additional human resources [9][22].
6. **Cost-Effective:** Reduces the need for manual verification and staff intervention, saving operational costs [5][19].
7. **User-Friendly Interface:** Integrated with a web application (e.g., Flask), making it easy for users to input data and receive results [12][20].
8. **Improved Risk Assessment:** Uses data-driven insights to help banks evaluate loan risks more effectively [11][22][23].

2. LITERATURE REVIEW

2.1 Architecture

The architecture of a loan eligibility prediction system is designed to automate the process of determining whether an applicant qualifies for a loan based on their financial and personal information. The system leverages machine learning algorithms and a structured data processing pipeline to deliver accurate, consistent, and fast eligibility predictions [1][5][22].

The architecture can be broadly divided into the following components:

1. **User Interface (Input Layer):**
A web-based interface (built using Flask or Streamlit) where users enter applicant details such as gender, income, loan amount, education, and credit history [12][20].

2. **Data Preprocessing Module:**
This layer handles cleaning, encoding, and normalization of input data. Missing values are imputed or dropped, categorical data is label encoded, and numerical values are scaled for model compatibility [1][22].

3. **Model Layer:**
A machine learning model (e.g., Logistic Regression, Random Forest) trained on historical loan application data. It classifies the input as either loan approved or not approved on learned patterns [12][22][23].

4. **Model Storage (Pickle File):**
The trained model is saved as a .pkl file using Python's pickle module for easy loading during deployment [12].

5. **Prediction Engine:**
Upon receiving new input, the saved model processes it and returns the prediction result in real time [9][20].

6. **Output Display (Result Layer):**
The final decision — “Loan Approved” or “Loan Not Approved” — is displayed on the web interface for the user [12][20].

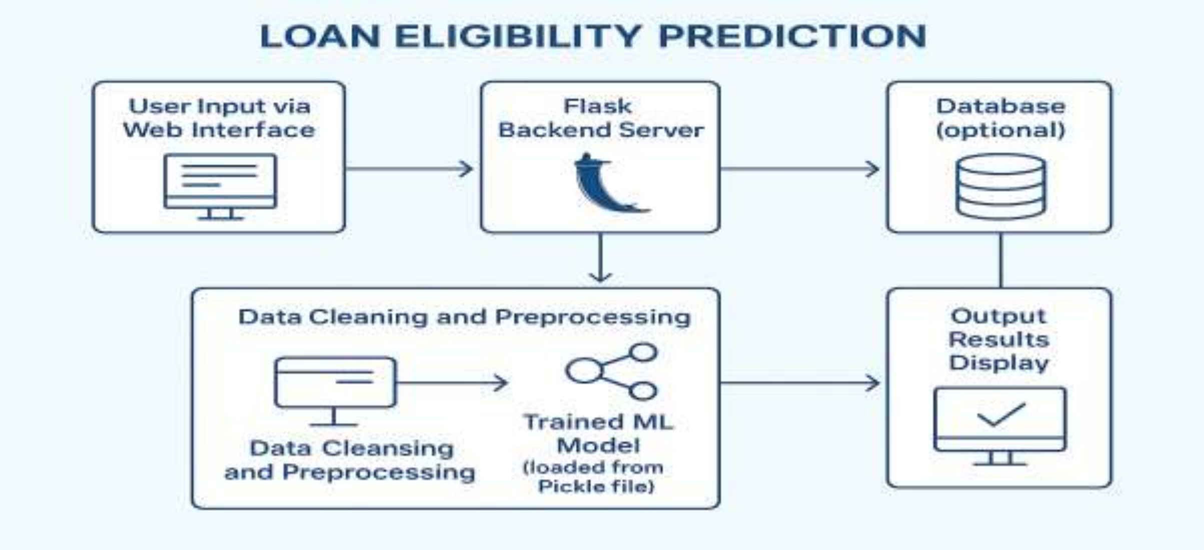
LOAN ELIGIBILITY PREDICTION
User Input via Web Interface
Flask Backend Server
Database (optional)
Data Cleaning and Preprocessing
Data Cleansing and Preprocessing
Trained ML Model (loaded from Pickle file)
Output Results Display

Fig:2 Architecture

2.2 Algorithm:

Logistic Regression is a supervised machine learning algorithm commonly used for binary classification problems. In this project, it is well-suited because the target variable (Loan_Status) has two possible outcomes: **Approved (1)** or **Not Approved (0)** [12][22].

The implementation process involves the following steps:

1. Input Collection

Collect applicant data such as income, credit history, education level, loan amount, and employment status [1][12].

2. Data Preprocessing

- Handle missing values.
- Encode categorical variables (e.g., gender, education) into numeric format using label encoding.
- Normalize or scale numerical features if required [1][22].

3. Model Training

- Use historical loan data with known approval outcomes.
- Train the **logistic regression** model on this labeled dataset to learn decision boundaries [12][23].

4. Logistic Function

Logistic Regression uses the **sigmoid function** to estimate the probability that an applicant is eligible:

P(y=1∣x)=11+e−(β0+β1x1+β2x2+⋯+βnxn)P(y=1|x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1x_1 + \beta_2x_2 + \cdots + \beta_nx_n)}}P(y=1∣x)=1+e−(β0+β1x1+β2x2+⋯+βnxn)1

This function outputs a value between 0 and 1, which is then mapped to a class label:

- If **$P \geq 0.5$**, then **Loan Approved (1)**
- If **$P < 0.5$**, then **Loan Not Approved (0)** [12].

5. Prediction

For new applicants, the model processes the input features and returns a **probability score** that is mapped to one of the two classes [12].

6. Model Evaluation

The model's performance is evaluated using classification metrics such as:

- **Accuracy**
- **Precision**
- **Recall**
- **Confusion Matrix**

These metrics help ensure reliability and minimize false positives/negatives [22][23].

2.3 Techniques:

In building an accurate and efficient loan eligibility prediction system, several **machine learning** and **data processing** techniques are applied. These techniques ensure the model is trained effectively and performs well on real-world data [1][12][22].

1. Data Preprocessing

Before feeding data into a machine learning model, it's essential to clean and prepare it:

- **Handling Missing Values:** Missing entries are either filled with statistical values (mean, median) or dropped to ensure model integrity [1][22].
- **Label Encoding:** Categorical variables (e.g., Gender, Education) are converted into numerical format using label encoding [1][12].

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- **Normalization/Scaling:** Numerical features like income or loan amount are scaled to a common range to improve model performance [22].

2. Feature Selection

Identifying the most relevant features helps improve accuracy and reduce overfitting. Features such as **Credit History**, **Applicant Income**, and **Loan Amount** are prioritized based on their influence on loan approval outcomes [12][22].

3. Machine Learning Algorithm: Logistic Regression

Logistic Regression is used to classify loan applications as **Approved (1)** or **Not Approved (0)**. It models the relationship between input features and the probability of approval using the **sigmoid function** [12][23].

4. Model Training and Testing

- **Train-Test Split:** The dataset is divided into training and testing subsets (e.g., 80%-20%) to train the model and evaluate its performance on unseen data [12].

- **Model Evaluation:** Metrics like **accuracy**, **precision**, **recall**, and the **confusion matrix** are used to assess performance [22][23].

5. Model Deployment

Using **Flask**, the trained model is deployed as a **web application**. This allows users to input data through a web form and receive instant predictions, making the system both practical and user-friendly [12][20].

2.4 Tools:
To successfully build and deploy the loan eligibility prediction system, a combination of **software tools**, **libraries**, and **technologies** are used. These tools assist in data handling, model building, web development, and deployment [1][12][22].

1. Python

The primary programming language used for data analysis, machine learning, and web integration. Python is chosen for its **simplicity**, **extensive libraries**, and active community support [12][22].

2. Pandas & NumPy

- **Pandas:** For data manipulation and handling structured tabular data.

- **NumPy:** For efficient numerical computations and array-based operations [12].

3. Scikit-learn

A powerful machine learning library used to build and evaluate models. It offers algorithms like **Logistic Regression**, tools for **data preprocessing**, **model training**, and **evaluation metrics** [12][22][23].

4. Jupyter Notebook / VS Code

- **Jupyter Notebook:** Ideal for experimentation, data visualization, and interactive testing.

- **VS Code:** Used for complete project development, especially integrating the Flask web framework [12].

5. Flask

A lightweight **Python web framework** used to create the web-based interface for model interaction. It handles user input and delivers predictions in real-time [12][20].

6. Pickle:

A Python module used for **serializing and deserializing** the trained ML model. It allows the model to be saved as a .pkl file and reloaded during deployment without retraining [12].

7. HTML/CSS:

Used to design the **front-end** of the web form for user input. Enhances the **user experience** by structuring and styling the interface [20].

8. Matplotlib / Seaborn (Optional)

If **exploratory data analysis (EDA)** is performed, these libraries are used for creating visual insights like histograms, bar charts, and heatmaps [12].

2.5 Methods:
The implementation of the loan eligibility prediction system follows a structured pipeline that includes data collection, preprocessing, model training, and deployment through a web interface [1][12][20][22].

1. Data Collection

The dataset consists of historical loan application records, including features such as Gender, Marital Status, Income, Loan Amount, Credit History, and more. These features are used to train the machine learning model for binary classification (loan approved or not) [1][12].

2. Data Preprocessing

To ensure model reliability and accuracy, the raw data undergoes a series of preprocessing steps:

- Handling Missing Values: Missing entries are either dropped or imputed using statistical methods (mean, median) [12].
- Label Encoding: Categorical variables such as *Gender* and *Education* are converted into numerical values for compatibility with ML algorithms [12][22].
- Feature Selection: Irrelevant features are removed, and only statistically significant variables (e.g., *Credit History*, *Income*) are retained for training [22].

3. Model Selection

The system uses Logistic Regression, a supervised machine learning algorithm ideal for binary classification problems like loan approval prediction. It computes the probability that an applicant should be approved based on input features [22][23].

4. Model Training and Testing

- The dataset is split into training and testing subsets using train_test_split() from Scikit-learn.
- The model is trained on the training data and tested on the unseen test set.
- Evaluation metrics such as Accuracy, Confusion Matrix, and Classification Report (Precision, Recall, F1-score) are used to measure model performance [12][22].

5. Model Saving

After training, the model is serialized using Python’s Pickle module and saved as a .pkl file. This enables reloading the model during deployment without the need for retraining [12].

6. Web Application Integration (Flask)

The trained model is deployed as a web application using Flask:

- A web form accepts user input (applicant data).
- The Flask backend loads the saved model and processes the input.
- The prediction result (Loan Approved / Loan Not Approved) is displayed on the same webpage [12][20].

3. METHODOLOGY

The loan eligibility prediction system accepts various inputs related to the applicant's **personal**, **financial**, and **credit/property** information. These input features are crucial for the machine learning model to make accurate and data-driven decisions regarding loan approval.

1. Personal Information

- **Gender:** Male / Female
- **Marital Status:** Married / Unmarried
- **Dependents:** Number of dependents (0, 1, 2, 3+)
- **Education:** Graduate / Not Graduate

- **Self-Employed:** Yes / No

2. Financial Information

- **Applicant Income:** Monthly income of the applicant
- **Co-applicant Income:** Monthly income of the co-applicant
- **Loan Amount:** Requested loan amount
- **Loan Term:** Duration of loan repayment (in months)

3. Credit and Property Information

- **Credit History:**
  - 1 = Has credit history
  - 0 = No credit history
- **Property Area:** Rural / Semiurban / Urban

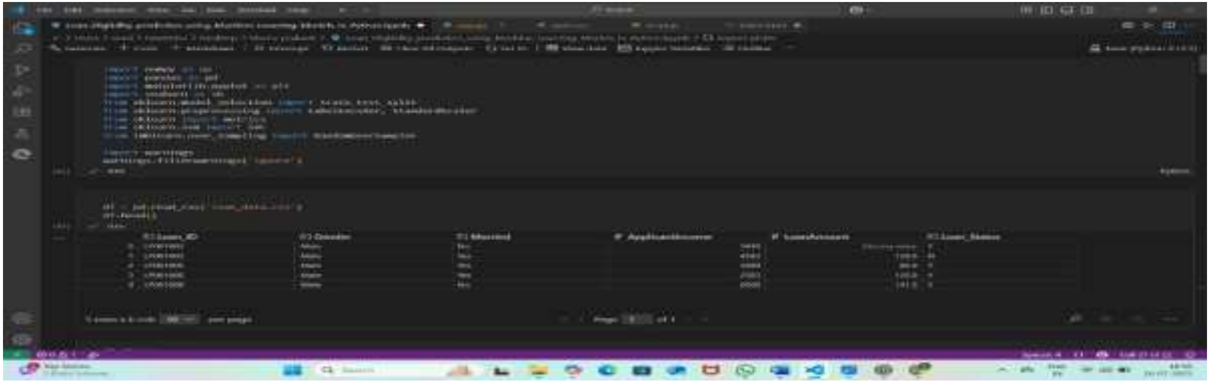


Figure:3 Input Interface from index.html in app.py

• Figure:4 Prompt flow from form submission to gencode.py

• Figure:5 Database interaction logic in db.py

3.2 Method of Process

The Loan Eligibility Prediction System transforms user-provided input into a real-time loan decision using a structured pipeline. Below is a step-by-step breakdown of the process.

1. User Data Input

Users enter applicant details (e.g., income, employment, education, credit history) through a web-based form.

2. Data Preprocessing

- Missing values are handled (imputed or dropped).
- Categorical fields are encoded using label encoding.
- Numerical data (e.g., income, loan amount) is normalized for model compatibility.

3. Model Loading

A pre-trained **Logistic Regression model**, saved as a .pkl file, is loaded using the pickle library to avoid retraining.

4. Prediction Execution

The cleaned and encoded data is passed to the model, which predicts loan eligibility based on historical patterns.

5. Output Generation

The system returns one of the following results:

- **Loan Approved**
- **Loan Not Approved**
This is immediately displayed on the web interface.

6. Web Application Flow

All steps are seamlessly integrated into a **Flask web application**, ensuring an interactive and user-friendly experience.

3.3 Output:

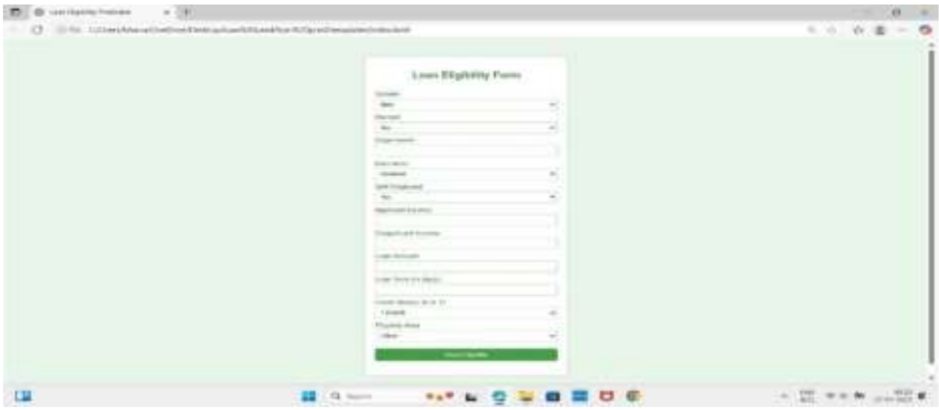
The output of this system is a **real-time prediction** indicating whether the loan applicant is eligible for loan approval based on the submitted data.

1 Output Format

- **Loan Approved**
- **Loan Not Approved**

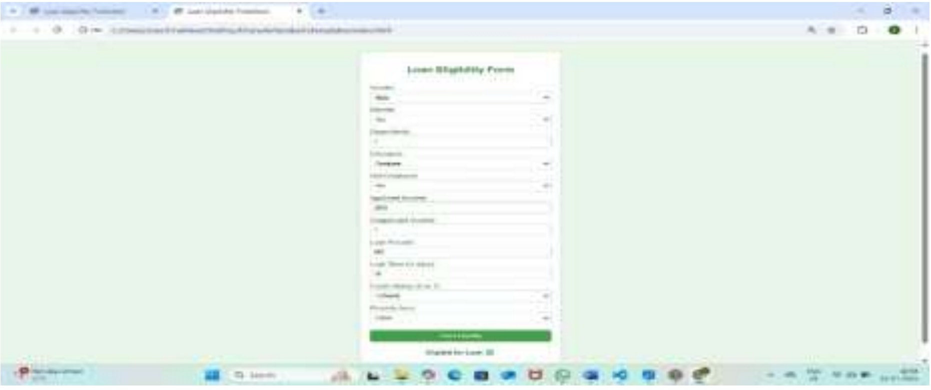
2 Output Display

- Displayed directly on the **Flask web application** interface.
- The prediction result appears **immediately below the input form** after submission.
- Designed to offer a **seamless, user-friendly experience** without page reload.



Loan Eligibility Form

Figure:6 Home Page of the loan eligibility prediction



Loan Eligibility Form

Gender
Male
Married
No
Dependents
0
Education
Graduate
Self Employed
No
Applicant Income
[illegible]
Coapplicant Income
0
Loan Amount
[illegible]
Loan Term (in days)
[illegible]
Credit History (1 or 0)
[illegible]
Property Area
Urban

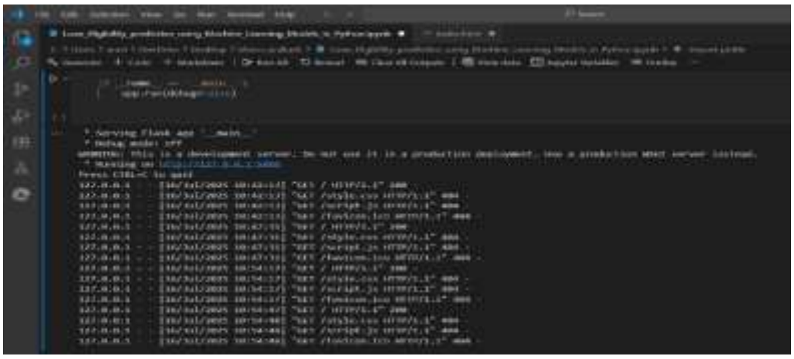
Check Eligibility

Eligible for Loan [illegible]

Figure:7 Generated loan eligibility

IV. RESULTS

The loan eligibility prediction system was successfully developed using machine learning techniques. A logistic regression model was trained on a real-world loan dataset containing various applicant details. After proper data preprocessing and feature selection, the model was able to classify applications as either approved or not approved with high accuracy. The model was then saved and deployed through a Flask-based web application. Users can input applicant details through a web form, and the system provides real-time predictions based on the trained model. The output is displayed instantly, improving both user experience and decision-making speed. The model's performance was evaluated using accuracy metrics and confusion matrix, showing reliable and consistent results. The system reduces human error and bias by providing data-driven decisions. It enables banks or financial institutions to automate the initial screening of loan applications. Overall, the project demonstrates how machine learning can streamline loan processing and improve operational efficiency.



```
if __name__ == '__main__':
    app.run(debug=False)

 * Serving Flask app '__main__'
 * Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:5000
Press CTRL+C to quit
127.0.0.1 - - [16/Jul/2025 [illegible]] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [16/Jul/2025 [illegible]] "GET /style.css HTTP/1.1" 404 -
127.0.0.1 - - [16/Jul/2025 [illegible]] "GET /script.js HTTP/1.1" 404 -
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127.0.0.1 - - [16/Jul/2025 [illegible]] "GET /favicon.ico HTTP/1.1" 404 -
```

Figure:8 Background Model working

V. DISCUSSIONS

The project effectively demonstrates how machine learning can automate the loan eligibility process. Logistic Regression was chosen for its simplicity and efficiency in binary classification. Data preprocessing, including handling missing values and encoding categorical features, was essential for accurate predictions. The model was integrated into a Flask web app, allowing real-time user interaction. It delivered consistent results and improved the speed of loan assessment. However, the model's performance could be further enhanced with more diverse data. Overall, the system shows strong potential for real-world use in financial institutions.

VI. CONCLUSION

The loan eligibility prediction system developed in this project demonstrates the effective use of machine learning to automate and improve decision-making in the financial sector. By using logistic regression and preprocessing techniques, the model was able to make accurate predictions based on applicant data. Integration with a Flask web application allowed real-time user interaction, making the system accessible and user-friendly. This approach not only saves time and reduces manual effort but also ensures consistency and fairness in loan evaluations. Overall, the project highlights the potential of machine learning to enhance efficiency, accuracy, and transparency in banking processes. Future improvements may include using more advanced algorithms and larger datasets for even better performance

VII.FUTURE SCOPE

The loan eligibility prediction system has strong potential for future improvements and real-world deployment. More advanced machine learning algorithms such as Random Forest or XG Boost can be explored to increase accuracy. The model can be enhanced by integrating with real-time credit score APIs for dynamic data access. Deploying the application on cloud platforms or as a mobile app would improve accessibility and scalability. Continuous learning mechanisms can be added so the model updates automatically with new data. Security features like encryption and authentication should be implemented to protect user data. Bias detection tools can be integrated to ensure fairness across all applicant groups. The system could also support multiple languages for broader user reach. These enhancements would make the system more powerful, inclusive, and production-ready.

VIII. ACKNOWLEDGEMENT

Pinnamraju T S Priya working as a HOD, Assistant Professor in Master of Computer Applications at Sanketika Vidya Parishad Engineering college, Visakhapatnam , Andhra Pradesh with 13 years of experience in Master of Computer Applications (MCA), accredited by NAAC. Her area of intrest is in Computer Programming Using C, Computer Organisation, Software Engneering, Artificial Intelligence, Internet of Things(IoT) and Distributed Systems.

Bethanapalli Bhanu Prakash is pursuing his final semester MCA in Sanketika Vidya Parishad Engineering College, accredited with A grade by NAAC, affiliated by Andhra University and approved by AICTE. With interest in Machine learning bethanapalli bhanu prakash has taken up his PG project on loan eligibility predection and published the paper in connection to the project under the guidance of Pinnamraju T S Priya,HOD, Assistant Professor, SVPEC.

REFERENCES

[1]Loan Eligibility Prediction using Machine Learning
https://journals.mriindia.com/index.php/ijacte/article/view/215
[2] CREDIT DECISION AUTOMATION IN COMMERCIAL BANKS: A REVIEW OF AI AND PREDICTIVE ANALYTICS IN LOAN ASSESSMENT
https://ajisresearch.com/index.php/ajis/article/view/22
[3] Bias and Fairness in Automated Loan Approvals: A Systematic Review of Machine Learning Approaches
https://jetc.sdu.edu.kz/index.php/jetc/article/view/111
[4] AI-Based Credit Scoring Models in Microfinance: Improving Loan Accessibility, Risk Assessment, and Financial Inclusion
http://thecrsss.com/index.php/Journal/article/view/370
[5] Machine Learning (ML) Technologies for Digital Credit Scoring in Rural Finance: A Literature Review
https://www.mdpi.com/2227-9091/9/11/192
[6] An ensemble machine learning based bank loan approval predictions system with a smart application
https://www.sciencedirect.com/science/article/pii/S2666307423000293
[7] A Comparative Study of Machine Learning Algorithms for Predicting Loan Default and Eligibility
http://pices-journal.com/ojs/index.php/pices/article/view/323
[8] Finance Loan Risk Assessment Using Machine Learning for Credit Eligibility Prediction and Model Optimization
https://www.ijistech.org/ijistech/index.php/ijistech/article/view/376
[9] A Comparative Study of Loan Approval Prediction Using Machine Learning Methods
https://dergipark.org.tr/en/pub/gujsc/article/1455978
[10] Loan eligibility prediction using adaptive hybrid optimization driven-deep neuro fuzzy network
https://www.sciencedirect.com/science/article/abs/pii/S0957417423004049
[11] Machine Learning-Based Prediction Model for Loan Status Approval
https://jonuns.com/index.php/journal/article/view/783
[12] Building Reliable Loan Approval Systems: Leveraging Feature Engineering and Machine Learning
https://icsejournal.com/index.php/JCSE/article/view/812
[13] A Data Driven Model for predicting Loan Approval Using Machine Learning Approaches

https://erurj.journals.ekb.eg/article_408982.html
[14] Comparative Machine Learning Models for Predicting Loan Fructification in a Semi-Urban Area
https://ojs.bonviewpress.com/index.php/AAES/article/view/2418
[15] A Comparative Performance Assessment for Prediction of Loan Approval in Financial Sector
https://www.sciencedirect.com/science/article/pii/S1877050925013699
[16] Predicting vehicle loan eligibility using random forest comparing with linear regression based on accuracy
https://pubs.aip.org/aip/acp/article-abstract/2822/1/020019/2921119/Predicting-vehicle-loan-eligibility-using-random
[17] National student loans default risk prediction: A heterogeneous ensemble learning approach and the SHAP method
https://www.sciencedirect.com/science/article/pii/S2666920X23000450
[18] Enhancing Financial Decision-Making: Predictive Modeling for Personal Loan Eligibility with Gradient Boosting, XGBoost, and AdaBoost
https://journals.adbascientific.com/iteb/article/view/22
[19] Application of Data Mining and Machine Learning Techniques to Predict Loan Approval and Payment Time
https://mseee.semnan.ac.ir/article_9421.html
[20] An approach for prediction of loan approval using ML algorithm Available to Purchase
htmhttps://pubs.aip.org/aip/acp/article-abstract/3075/1/020120/3304986/An-approach-for-prediction-of-loan-approval-using