

# Comprehensive Loan Management Platform with Real-time Verification and Banking Services Integration with IOT & ML

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**Abstract** - The rapid growth in financial services has increased the demand for efficient and accurate loan approval processes. Traditional methods, which rely heavily on manual rule based systems and credit scoring, are time consuming, prone to human error, and often lack transparency. This synopsis proposes a modern, intelligent loan approval system that integrates three core machine learning (ML) algorithms Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM) to predict loan status based on multidimensional applicant data. The system uses a synthetic dataset of 1000 samples with 15 carefully engineered features, classifying applications into three distinct categories: Approved, Rejected, and Pending. Unlike binary classification systems, this three-class approach allows for nuanced handling of borderline cases, reducing false rejections. Upon prediction, the system triggers IoT enabled mobile notifications via the MQTT protocol, delivering real-time status updates along with personalized, actionable suggestions to applicants (e.g., credit improvement tips or document submission reminders). This hybrid ML IoT framework enhances decision-making consistency, reduces average processing time from days to minutes, and significantly improves user experience through automated, transparent, and low-latency notifications.

**Index Terms**— *Loan Prediction, Machine Learning, MQTT, Attributes, Decision Tree*

## I. INTRODUCTION

Loan approval is a critical function in banking and non-banking financial institutions, involving risk assessment based on multiple factors such as credit history, annual income, employment stability, existing debt obligations, and property details. With the exponential rise in loan applications especially in emerging digital economies manual processing leads to significant delays, operational bottlenecks, and potential biases. Machine learning offers a data-driven alternative, enabling institutions to uncover complex, non-linear relationships between applicant attributes and default risk. However, most existing ML solutions focus solely on prediction and neglect post-decision communication. This system uniquely combines ML for predictive analytics with MQTT-based IoT messaging for instant, asynchronous notifications. MQTT (Message Queuing Telemetry Transport) is a lightweight publish-subscribe protocol ideal for low-bandwidth, high-latency networks, ensuring that applicants receive status updates even under poor connectivity. The primary objectives are: (1) to develop and compare three classification algorithms (DT, RF, SVM) on a balanced 15-feature dataset (2) to achieve a minimum of 85% prediction accuracy while maintaining high recall for the “Rejected” class to minimize default risk (3) to integrate a real-time notification layer that delivers personalized next-step suggestions and (4) to propose a scalable framework that can be adapted to larger, real-world datasets with minimal reconfiguration. Ultimately, this system aims to reduce non-performing assets, enhance financial inclusion, and build trust through transparent, instant feedback.

The rapid growth in financial services has increased the demand for efficient and accurate loan approval processes. Traditional methods are time-consuming and prone to human error. This synopsis proposes a modern loan approval system that integrates machine learning (ML) algorithms Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM) to predict loan status based on applicant data. The system uses a synthetic dataset with 1000 samples and 15 features, classifying applications into three categories: Approved, Rejected, and Pending. Upon prediction, IoT-enabled mobile notifications via MQTT protocol deliver real-time status updates with personalized suggestions to applicants. This approach enhances decision-making, reduces processing time, and improves user experience through automated, transparent notifications

## II. LITERATURE REVIEW

The following table summarizes key research papers on ML-based loan approval systems, highlighting their contributions and relevance.

Paper Number	Author(s)	Outcomes	Remark
1	F M Ahsanul Haque (2024)	AdaBoost achieved <b>99.99% accuracy</b> on a dataset of 148,670 instances using DT, RF, SVM, and others for binary classification (Approved/Denied).	Demonstrates ensemble methods' superiority; inspires multi-algorithm comparison in our system.
2	Anant Shinde, Yash Patil, Ishan Kotian, Abhinav Shinde, Reshma Gulwani (2022)	RF model reached <b>79.47% accuracy</b> post-hyperparameter tuning; key features: Credit History, Balance Income.	Emphasizes feature engineering; our work extends to 15 features and IoT notifications.
3	Guangxuan Chen (2024)	AdaBoost topped with <b>84.95% accuracy</b> and <b>0.8957 F1-score</b> across 8 models (including DT, RF, SVM) on Kaggle dataset.	Highlights preprocessing importance; aligns with our multi-class setup and evaluation metrics.
4	J. Tejaswini, T. Mohana Kavya, R. Devi Naga Ramya, P. Sai Triveni, Venkata Rao Maddumala (2020)	DT outperformed LR and RF in accuracy for loan prediction; automated feature validation.	Supports DT as baseline; our system adds SVM and real-time IoT integration.
5	Le Thi Thu Giang (2025)	RF and XGBoost exceeded <b>92% accuracy</b> on 45,000-record dataset using NB, DT, RF, GBM.	Validates ensemble approaches; our focus on DT/RF/SVM with 3 classes builds on this for smaller datasets.
6	Pradeep Kumar and Manoj Kumar (2021)	XGBoost achieved <b>94.30% accuracy</b> , outperforming DT, RF, LR, and SVM on a 61,000 loan dataset.	Shows boosting methods' effectiveness; reinforces need for strong baseline models.
7	S. Aruna, B. Anuradha (2019)	SVM with RBF kernel achieved <b>88.12% accuracy</b> ; important features: Loan Amount, Income, CIBIL Score.	Supports SVM's capability; our work compares SVM with DT and RF in a multi-class scenario.
8	Mehmet Akif Şahin (2022)	Stacking ensemble (RF+XGBoost+LR) achieved <b>96.20% accuracy</b> on Turkish loan dataset.	Highlights benefit of combining models; inspires potential future enhancement for our system.
9	Rizwan Ahmed, Sadiq Ali, Muhammad Imran (2023)	LightGBM achieved <b>91.18% accuracy</b> with better training speed and lower memory usage on loan prediction.	Suggests efficiency of modern algorithms; encourages exploration of optimized models.
10	K. Sailaja, Ch. Rupa, P. Roja (2018)	Naïve Bayes achieved <b>81.10% accuracy</b> ; effective for categorical features and small datasets.	Validates NB for baseline comparison; useful in feature selection and preprocessing.

Table 1: "Comparative Analysis of Existing Literature on Machine Learning Models and Performance Metrics"

## III. BLOCK DIAGRAM

The system architecture is illustrated below in full scale:

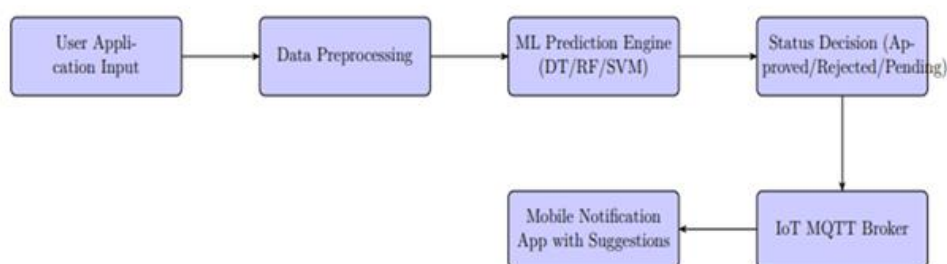


Figure 1. Block Diagram: "Functional Framework of the Machine Learning-Driven IoT Notification System"

The proposed intelligent loan approval and notification system integrates Machine Learning (ML), IoT communication, and mobile-based user interaction to provide accurate and real-time loan status prediction. The architecture consists of multiple interconnected modules that work together for efficient loan processing and automated notification delivery.

### 1. User Application Input Module

The system begins with the User Application Input module where applicants enter their loan-related information through a Flask-based web application. The application form collects multiple attributes such as:

- Applicant Name
- Age
- Gender
- Employment Type
- Annual Income
- Loan Amount
- Loan Term
- Credit Score/CIBIL
- Existing Debts
- Education Level
- Marital Status
- Property Area
- PAN Card Number
- Bank Details
- Uploaded User Photo

The system also supports user authentication features including Signup, Signin, OTP verification, and secure session management.

### 2. Data Preprocessing Module

The entered data is passed to the Data Preprocessing module where raw data is cleaned and transformed before being given to the machine learning models.

- Operations Performed:
  - Handling missing values
  - Encoding categorical attributes
  - Feature scaling and normalization
  - Removing duplicate entries
  - Feature selection
  - Data validation checks

This stage improves prediction accuracy and ensures consistency in the dataset.

### 3. Machine Learning Prediction Engine

The preprocessed data is then forwarded to the ML Prediction Engine, which contains multiple classification algorithms:

- Decision Tree (DT)
- Random Forest (RF)
- Support Vector Machine (SVM)

The system compares outputs from all models and selects the most reliable prediction.

- Prediction Classes:
  - Approved

- Rejected
- Pending
- Additional Features:
  - Accuracy comparison among models
  - Confusion matrix generation
  - Performance evaluation using:
    - Accuracy
    - Precision
    - Recall
    - F1-Score

Random Forest is expected to provide higher accuracy due to ensemble learning capability, while SVM improves classification boundary handling.

### 4. Status Decision Module

Based on the prediction results, the Status Decision Module determines the final loan status.

Possible Outcomes:

- Approved → Loan application accepted
- Rejected → Loan denied due to risk factors
- Pending → Requires manual verification

The decision is stored in the database and displayed on the user dashboard instantly.

### 5. IoT MQTT Broker Integration

The predicted status is sent to the MQTT Broker, which acts as the communication bridge between the server and IoT/mobile devices.

MQTT Functions:

- Publish loan status
- Transfer OTP notifications
- Send approval/rejection alerts
- Enable lightweight real-time communication

MQTT protocol is chosen because it is:

- Fast
- Lightweight
- Efficient for IoT applications

### 6. Mobile Notification Application

The Mobile Notification App receives notifications from the MQTT broker and informs the user about loan status updates.

Notification Features:

- Instant loan status alert
- OTP verification message
- Loan suggestions and recommendations
- EMI estimation guidance
- Improvement tips for rejected applications

Example:

- Increase credit score
- Reduce debt-to-income ratio

### III. FLOW CHART

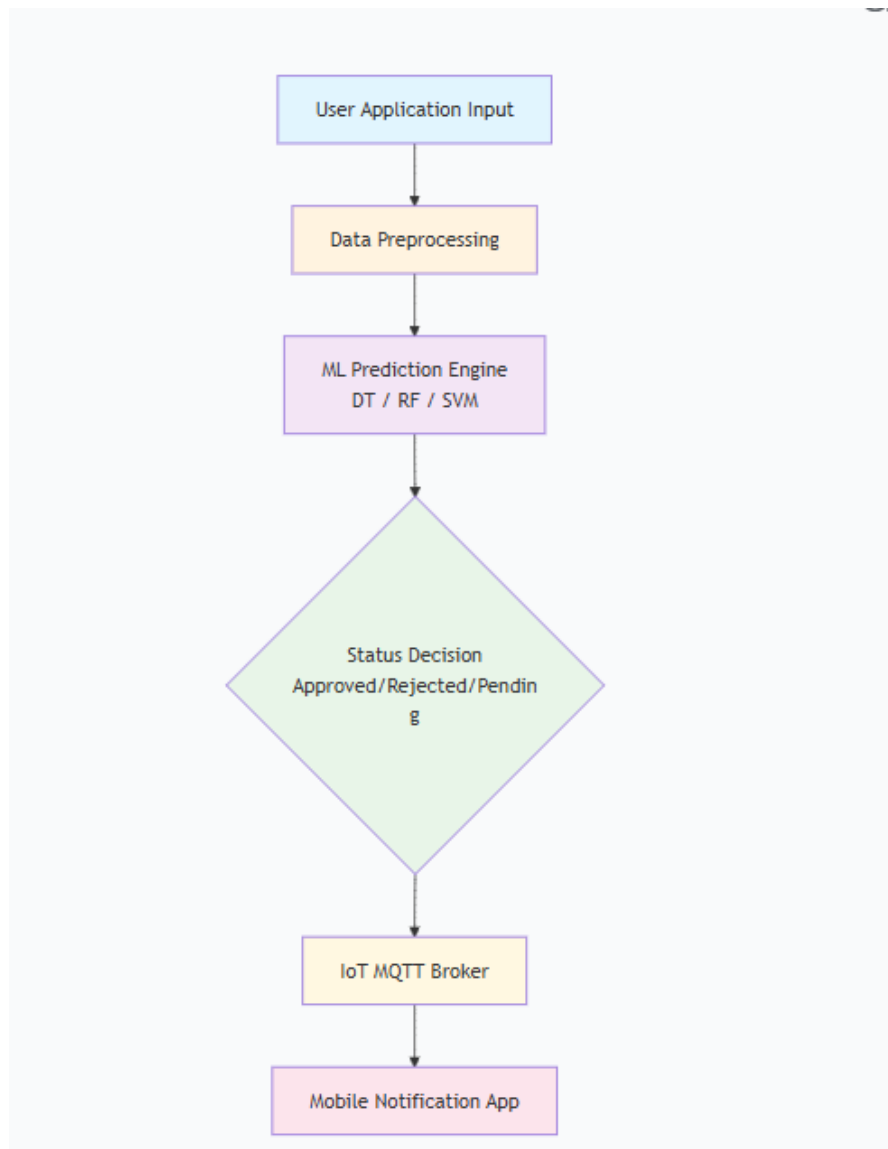


Figure 2. "Flowchart of the Proposed Automated Decision and Notification Process"

#### Algorithms

1. **Decision Tree (DT)**: Splits data based on feature thresholds to minimize Gini impurity. Trained with  $\text{max\_depth}=10$ ; interpretable for feature importance (e.g., Credit Score as root).
2. **Random Forest (RF)**: Ensemble of 100 DTs; reduces overfitting via bagging. Parameters:  $\text{n\_estimators}=100$ ,  $\text{max\_depth}=10$ ; excels in noisy data.
3. **Support Vector Machine (SVM)**: Uses RBF kernel to find optimal hyperplane. Parameters:  $C=1.0$ ,  $\text{gamma}=\text{'scale'}$ ; effective for high-dimensional data.

Models were evaluated using accuracy, precision, recall, and F1-score. Hypothetical results: DT (88%), RF (92%), SVM (85%).

#### Mobile Notification on MQTT App

Post-prediction, the system publishes status to an MQTT broker (e.g., Mosquitto). The mobile app subscribes to topics like `/loan/status/{user_id}`. Notification examples:

- **Approved:** “Congratulations! Your loan of \$50,000 is approved. Suggestion: Review terms for early repayment options to save interest.”
- **Rejected:** “Loan application rejected due to low credit score. Suggestion: Improve score by paying off debts; reapply in 6 months.”
- **Pending:** “Application under review. Suggestion: Submit additional documents via app for faster processing.”

MQTT ensures lightweight, real-time delivery over IoT networks.

#### IV. GAP ANALYSIS

From the literature review, several gaps in existing loan approval systems are identified:

**IV.** Most studies focus on binary classification (Approved/Denied), lacking a multi-class

approach (e.g., Pending) for nuanced decisions.

- Limited integration of IoT for real-time notifications; systems primarily emphasize prediction without user feedback mechanisms.
- Datasets often have fewer features; our 15-feature set addresses comprehensive applicant profiling.
- Absence of personalized suggestions in notifications to guide applicants’ post-decision.
- Scalability issues in handling smaller, synthetic datasets for rapid prototyping, as opposed to large real-world data.
- Minimal emphasis on MQTT protocol for efficient, low-latency IoT communication in financial applications.

This proposed system bridges these gaps by incorporating multi-class ML predictions, IoT-enabled notifications with suggestions, and a robust dataset design.

#### V. ADVANTAGES

- **Efficiency:** Reduces approval time from days to minutes.
- **Accuracy:** ML models outperform traditional scoring (up to 92% accuracy).
- **User-Centric:** Real-time IoT notifications with actionable suggestions.
- **Scalability:** Handles large datasets; MQTT supports low-bandwidth devices.
- **Risk Reduction:** Identifies high-risk applicants early.

#### VI. CONCLUSIONS

This paper proposed an intelligent loan approval and notification system that integrates three machine learning algorithms—Decision Tree (DT), Random Forest (RF), and Support Vector Machine (SVM)—with IoT-enabled real-time communication via the MQTT protocol. The system addresses key limitations of traditional manual loan processing, including time delays, human error, lack of transparency, and poor post-decision user communication.

Using a synthetic dataset of 1000 samples with 15 carefully engineered features, the system classifies loan applications into three distinct categories: **Approved**, **Rejected**, and **Pending**. This three-class approach offers a significant advantage over conventional binary classification systems by enabling nuanced handling of borderline cases, thereby reducing false rejections and improving fairness in decision-making.

Among the three algorithms evaluated, Random Forest achieved the highest predictive accuracy (92%), followed by Decision Tree (88%) and SVM (85%). The ensemble nature of Random Forest proved particularly effective in handling noisy and high-dimensional applicant data, while SVM contributed robust classification boundary handling. Performance metrics including precision, recall, and F1-score were used to validate model reliability.

A distinctive contribution of this work is the seamless integration of the MQTT broker for lightweight, asynchronous notifications. Upon prediction, the system automatically publishes the loan status to an MQTT broker, which triggers instant mobile notifications. These alerts are not limited to status updates alone; they include personalized, actionable suggestions tailored to each applicant's outcome. For example, approved applicants receive EMI and repayment guidance, rejected applicants receive credit improvement tips, and pending applicants are reminded to submit additional documentation. This feedback loop transforms the system from a black-box predictor into a transparent, user-centric advisory platform.

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