# BANK LOAN AUTOMATION AND FINANCIAL ANALYTICS

Konga Bhavani dept of CSC MLRITM kongabhavani2004@gmail.com Amandu Akshaya dept of CSC MLRITM amanduakshaya@gmail.com

## **ABSTARCT**

This project focuses on automating the bank loan approval process and analyzing financial data using Power BI. Traditional banking processes are often manual, error-prone, and time-consuming. This project proposes a digital loan management system that allows customers to apply for loans online and enables bank employees to track, approve, or reject loans efficiently. Through interactive dashboards, trends such as approval rates, default patterns, loan amounts, and customer segmentation are analyzed. The system aims to reduce human intervention, improve turnaround time, and enhance data-driven decision-making. Keywords—Phishing, Brute force, Authentication, Graphical Password, cued click points, shoulder surfing

## I. KEY WORDS

Bank Loan, Automation, Power BI, Financial Analytics, Loan Defaults, EMI Trends, Dashboards

#### II.INTRODUCTION

In the digital age, the security of user authentication has In banking systems, processing loans manually leads to inefficiencies and customer dissatisfaction. With the integration of data analytics and automation tools, banks can streamline loan approval processes and manage large volumes of financial data. The objective of this project is to develop a system that handles online loan applications, tracks their progress, and generates financial insights using Power BI. This helps in visualizing metrics like EMI trends, default risks, and approval timelines..

## **II.DEFINITIONS**

**Loan Default**: When a borrower fails to repay a loan on time. **Power BI**: A Microsoft tool for business intelligence and interactive dashboards.

**Loan EMI**: Equated Monthly Installment—a fixed payment amount made by a borrower.

**Financial Analytics**: Data analysis techniques applied to understand financial patterns.

**Dashboard**: A data visualization interface showing KPIs and trends.

## III.BACKGROUND

Traditional banking systems rely heavily on paperwork, face-to-face interactions, and manual verification processes. These outdated methods result in significant delays in loan approvals and introduce a higher probability of human error, data inconsistency, and poor tracking. Loan officers often need to cross-reference multiple files and systems, which further slows down the process and frustrates both staff and customers. Additionally, there is little to no room for

proactive financial analysis or personalized services. Cued Recall Authentication: - Users click one point on each image in a sequence during login.

Recall-Based Authentication: - Users recreate or reselect points chosen during registration.

## IV.EXISTING SYSTEM

The existing semi-digital banking systems are fragmented, lacking seamless integration between essential modules such as customer databases, loan processing engines, and credit risk assessment tools. This disjointed infrastructure results in inefficient workflows and data silos that hinder real-time decision-making. In many cases, banks rely on third-party verification agencies for document validation, credit history checks, and background screening. While this outsourcing may reduce internal workload, it introduces delays due to communication lags, inconsistent service quality, and dependency on external turnaround times

Additionally, customer interaction within these systems is often limited to basic portals or email follow-ups, offering minimal transparency or personalization. There is little room for two-way feedback or proactive issue resolution, leading to dissatisfaction and trust deficits. Analytical dashboards, which are crucial for understanding customer behavior, default risks, and operational bottlenecks, are either completely absent or extremely basic in these systems.

Without advanced visualization and reporting tools, banks cannot perform in-depth analysis or optimize their loan offerings effectively. As a result, they miss out on critical insights that could help in minimizing defaults, enhancing customer experience, and making data-driven lending decisions.

# V. RELATED WORK

Prior research has explored machine learning techniques for credit scoring and risk assessment. Some studies focus on data visualization for financial reporting, while others develop APIs and cloud platforms for online loan applications.

However, few integrate automation and analytics in a unified dashboard. This project fills that gap by using Power BI to visualize loan data and build an interactive dashboard for decision-making.

## VI. METHODOLOGY

The methodology followed in this project begins with data collection, where datasets related to customers and loans were gathered, including fields like income, employment status, loan amount, and repayment history. This data was then cleaned and transformed using Power Query to remove inconsistencies and prepare it for analysis. Relationships were established between various loan-related tables to support accurate data modeling. Once the data was structured, dashboards were developed in Power BI, incorporating various visual elements such as line graphs, pie charts, bar charts, and maps to represent key insights. Finally, these dashboards were published to the Power BI Service, enabling web-based access and secure sharing with stakeholders.

## VII. PROPOSED SYSTEM.

The system maintains records of all submitted applications, enabling better documentation, audit trails, and time-saving workflows compared to traditional methods. One of the core components is the integration of Power BI dashboards, which allow decision-makers to visualize live data on loan volume, application trends, approval rates, and customer demographics. These dashboards are interactive and can filter data by region, time period, or loan type, giving a clear picture of operational performance

Another key feature is EMI trend analysis. The system tracks repayment behavior and highlights accounts with late payments or irregular schedules. This allows early intervention, improved risk assessment, and helps banks categorize customers based on repayment reliability, reducing future defaults..

# VIII . DISCUSSION

The results demonstrate the effectiveness of integrated dashboards in identifying high-risk sectors and optimizing loan offerings. Limitations include lack of real-time external data such as credit bureau scores. However, the system can be extended to integrate third-party data sources. Interactive visualizations helped stakeholders understand complex trends easily.

## IX. CONCLUSION

The project successfully implemented an end-to-end automated system for bank loan processing, significantly improving the speed, accuracy, and transparency of financial operations. By replacing manual workflows with digital processes, the system drastically reduced paperwork, human errors, and processing delays. Customers benefited from a smoother application experience, while bank officials

were equipped with streamlined tools for verification, approval, and monitoring. The integration of Power BI enhanced the analytical capabilities of the system, enabling real-time visualization of key metrics such as loan approvals, repayment behavior, and default trends. These insights empowered decision-makers to assess risks more accurately and tailor lending policies based on data rather than assumptions. Additionally, the system supported strategic planning by revealing hidden patterns in customer segments, loan types, and geographic regions. Overall, the combination of automation and financial analytics provided a scalable and robust framework that not only enhanced operational efficiency but also strengthened customer trust and institutional performance.

## X. RESULT

The Power BI dashboards developed in this project provided valuable insights into various aspects of loan performance. They showcased trends in loan approvals categorized by year and state, allowing the bank to identify regional patterns in disbursement. EMI repayment behavior was analyzed based on customer type, helping to distinguish reliable borrowers from high-risk profiles. The system also included sub-grade-wise default analysis to pinpoint segments with higher default rates. Additionally, the impact of homeownership on repayment behavior was examined, revealing how asset ownership influences financial reliability.

A comparison between verified and non-verified applicants was also conducted to assess the importance of documentation in creditworthiness. These comprehensive dashboards enabled bank officials to identify high-risk sectors and refine their loan approval strategies accordingly.system was scalable, handling user data efficiently using MongoDB Atlas for storage and retrieval of click-point coordinates and image order.

## XI.REFERENCES

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