REVOLUTIONIZING LOAN APPROVALS WITH EXPLAINABLE AI

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ABSTRACT

The widespread use of artificial intelligence (AI) for automated decision-making is a result of notable developments in processing capacity and enhancements to optimization techniques, particularly in machine learning (ML). Although complex machine learning models yield good prediction accuracy, their opacity makes them too unreliable to be used in the automation of loan decisions. This research provides an explainable artificial intelligence (AI) decision-support system that uses belief-rule-base (BRB) to automate the loan underwriting process. In addition to accommodating human expertise, this system can use supervised learning to learn from previous data. Both factual and heuristic rules can be accommodated by the hierarchical structure of BRB. The significance of an active rule and the contribution of antecedent qualities in the rule allow the system to explain the series of events that culminate in a judgment regarding a loan application. It is shown through a business case study on automated mortgage underwriting that the BRB system may offer a solid balance between explainability and accuracy. A loan denial could be justified by the textual explanation that results from the regulations being activated. The importance of rules in supplying the choice and the contribution of its antecedent qualities can be used to understand the decision-making process for an application.

Keywords: Loan Approvals , Artificial Intelligence (Ai), Machine Learning (Ml).

1 INTRODUCTION

Underwriting skill is learnt through several months of training and exchange of knowledge by senior underwriters. This task requires underwriters to be fairly analytical, very organized, and accurate to give informed decision to approve or reject a loan application. Underwriters concurrently analyze a large quantity of information to find affordability, repayment history and collateral. Furthermore, sometimes they are required to change the process due to a shift in regulatory and compliance standards, investor requirements, and customer demands (Krovvidy, 2008).

New technology and strong machine learning (ML) algorithms have opened the doors for a straightthrough loan application process. Artificial intelligence (AI) systems can execute rules and process customers‟ information in a few milliseconds. Financial institutions have recognized the benefits of AI and are using it in a different subset of the underwriting process and are keen to test and implement newly introduced digital innovation. AI systems are expected to replicate human decision-making skills. However, even today transformation of various algorithmic concepts into training data could be very challenging to solve every instance of the problem for a range of lending products. It may not be able to solve a tiny subset of the problem (Aggour, Bonissone, Cheetham, & Messmer, 2006).

1. **Explainable AI (XAI) in Financial Decision Making:**

   Authors: Miller, Tim. et al.

   Summary: This seminal work introduces the concept of Explainable AI and its importance in the financial domain. It highlights the need for interpretable models, especially in applications like loan underwriting, where transparency is critical.

2. **Interpretable Machine Learning for Credit Scoring: A Case Study on Peer-to-Peer Lending:**

   Authors: Ribeiro, Marco Tulio. et al.

   Summary: The paper discusses the application of interpretable machine learning models in credit scoring, emphasizing the importance of understanding model predictions. The study showcases how interpretability can be achieved without sacrificing predictive performance.

3 IMPLEMENTATION STUDY

Existing System:

In the current landscape of loan approvals in the financial services industry, traditional methods typically rely on manual review processes and rule-based systems to assess applicants' creditworthiness. These methods often involve subjective assessments by loan officers based on limited information such as credit scores, income levels, and employment history. While these approaches have been effective to some extent, they may suffer from inefficiencies, biases, and lack of scalability. Additionally, the use of manual processes can introduce delays and inconsistencies in decision-making, leading to suboptimal outcomes for both lenders and borrowers. As a result, there is a growing interest in leveraging artificial intelligence (AI) and machine learning (ML) techniques to automate and improve the loan approval process.

Disadvantages:

- Limited Scalability
- Inefficiency
- Lack of Transparency

Proposed System & alogirtham

The proposed system for loan approvals in the financial services industry aims to overcome the limitations of existing methods by leveraging advanced artificial intelligence (AI) and machine learning (ML) techniques, while ensuring transparency and fairness through explainable AI (XAI). The system utilizes AI algorithms to analyze a wide range of data sources, including traditional credit bureau information, alternative data sources, and non-traditional data such as social media activity or transaction history..

Advantages:

Predicting traffic routes offers several advantages that can significantly enhance transportation efficiency and convenience:

1. Reduced Congestion: By predicting traffic patterns, authorities can optimize traffic flow, suggesting alternative routes to drivers before congestion builds up. This reduces overall traffic congestion and minimizes delays.

2. Time Savings: Efficient route prediction helps drivers choose the fastest routes based on real-time traffic conditions. This saves commuters time and reduces fuel consumption and emissions associated with idling in traffic.

IMPLEMENTATION

1) Upload Loan Application Dataset: using this module we will upload dataset to application and then application will read entire dataset and then find all class

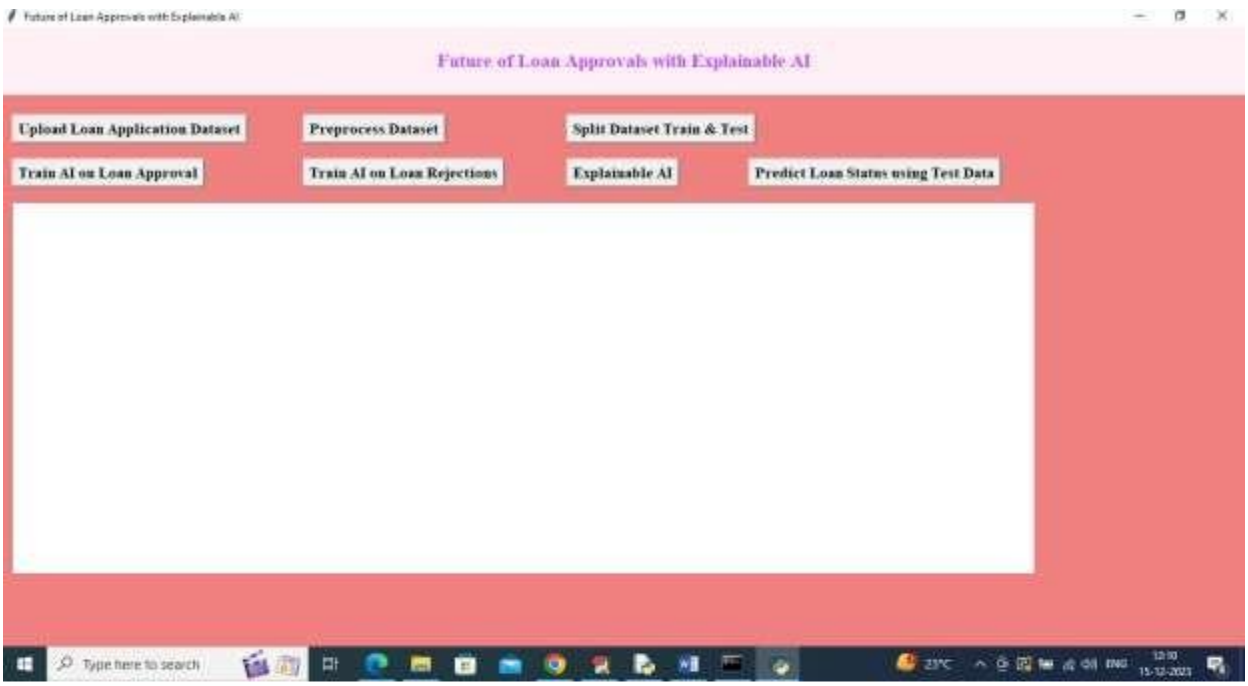
labels for loan and reject reason and plot them in a graph

2) Pre-process Dataset: dataset contains missing value and both numeric and non-numeric data so by employing label encoder class will convert all data into numeric format and then normalized all dataset values to make it clean.
3) Split Dataset Train & Test: using this module will split Dataset in to train and test where application using 80% dataset for training and 20% for testing

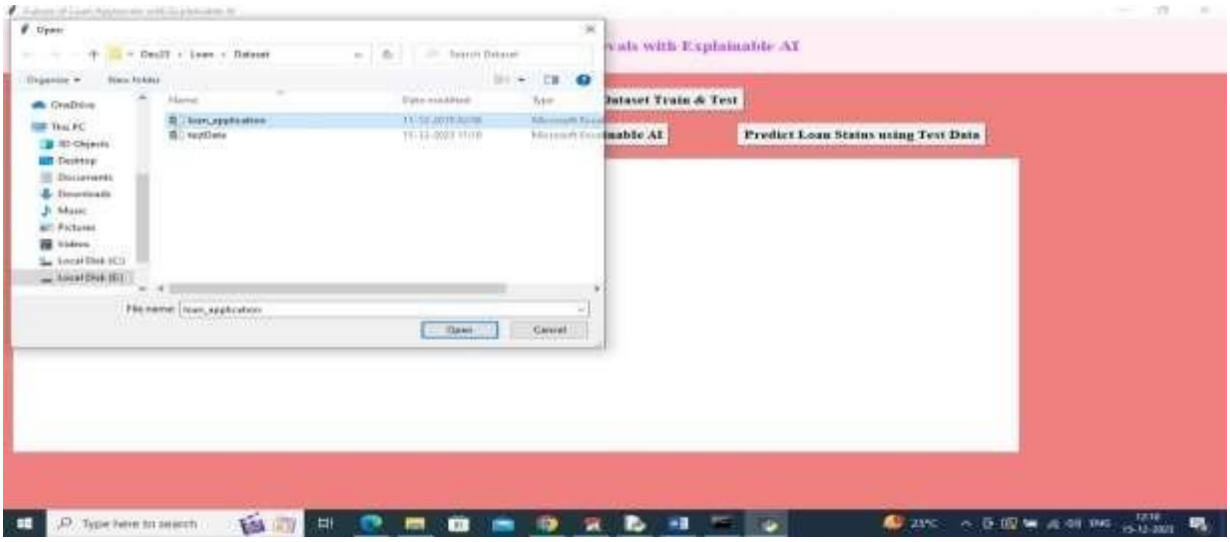
5 RESULTS AND DISCUSSION

1.1 SCREENSHOTS

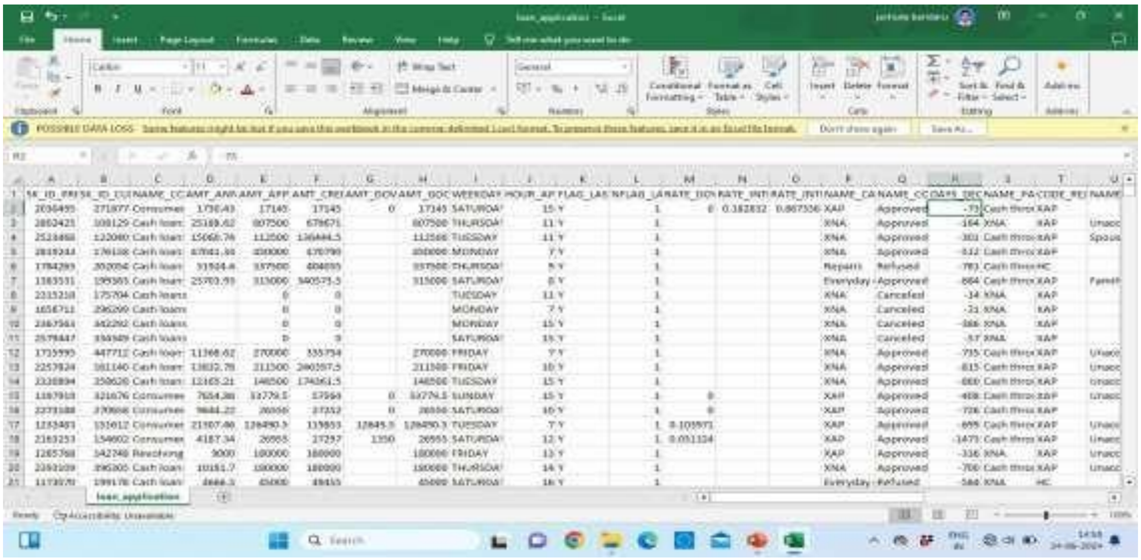
To run project double, click on 'run.bat' file to get below screen



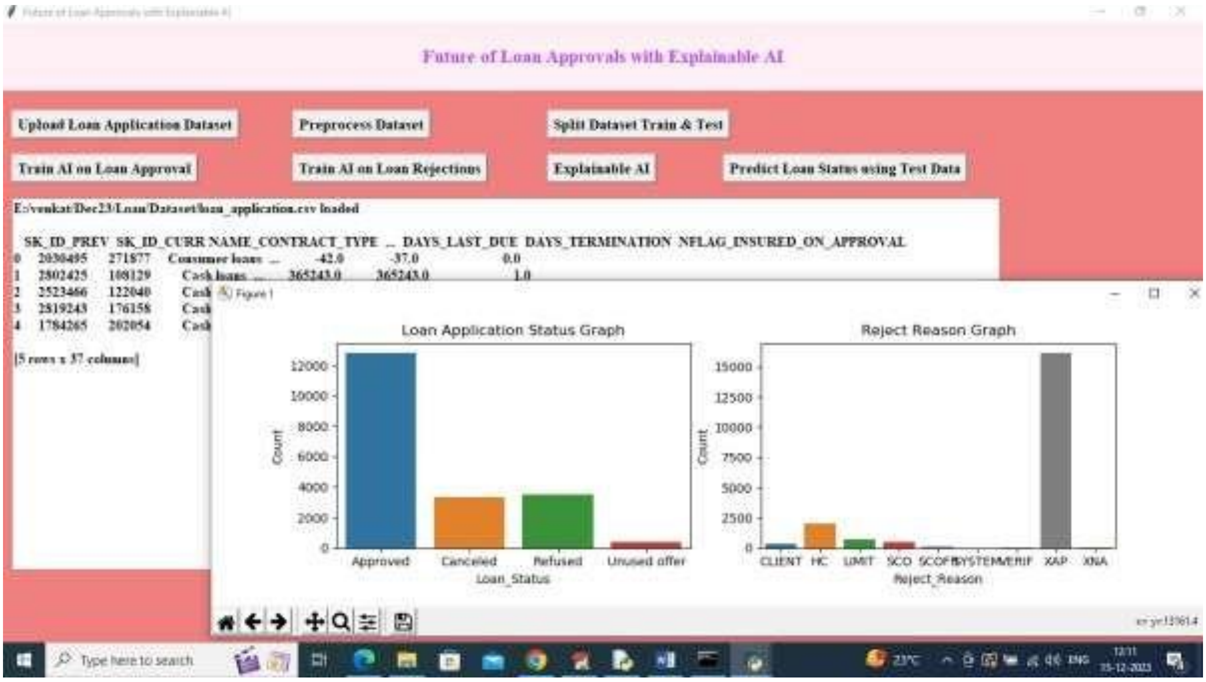
In above screen click on 'Upload Loan Application Dataset' button to upload dataset and then will get below output



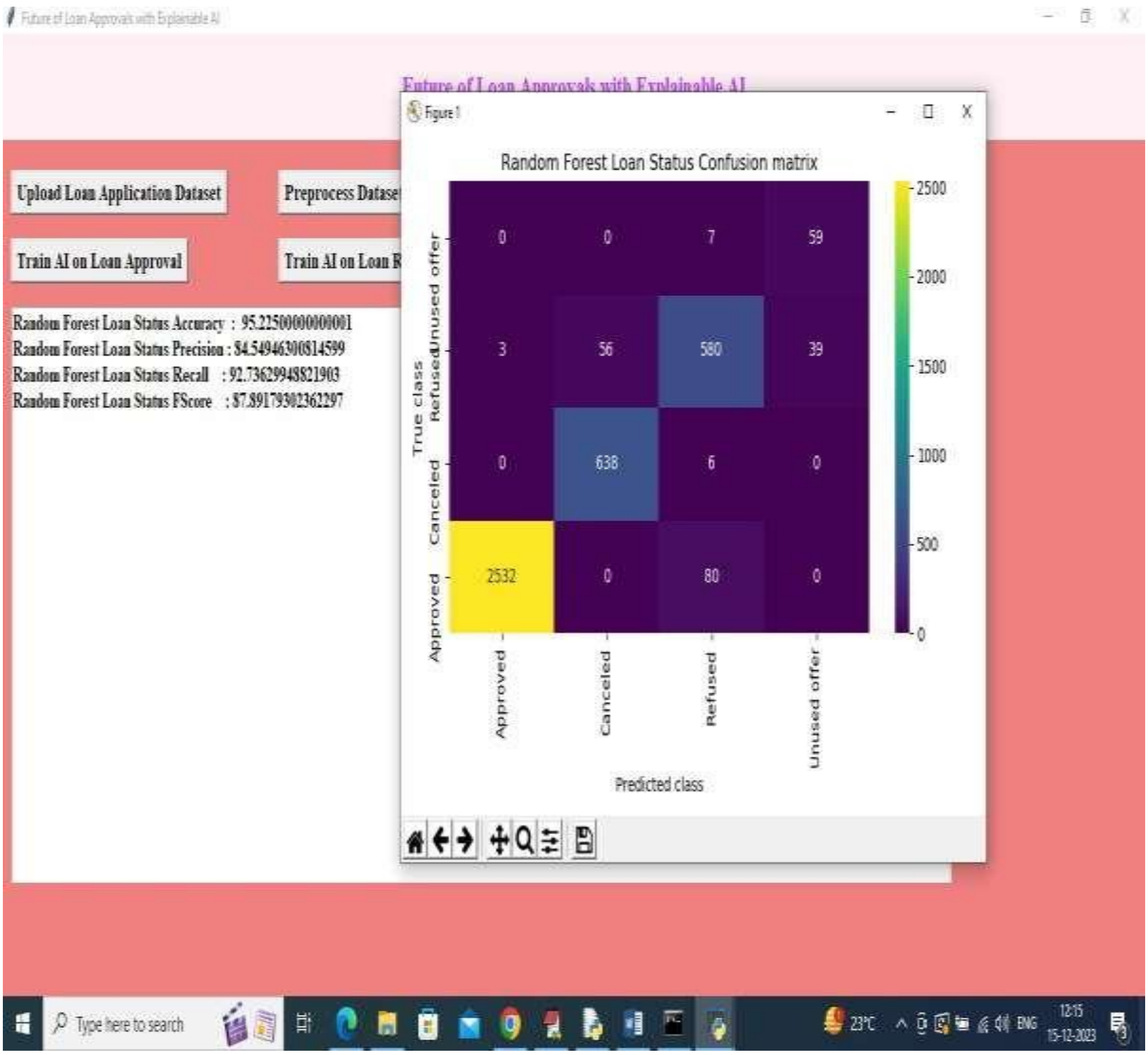
In above screen selecting and uploading 'loan_application.csv' file and then click on 'Open' button to load dataset and get below output



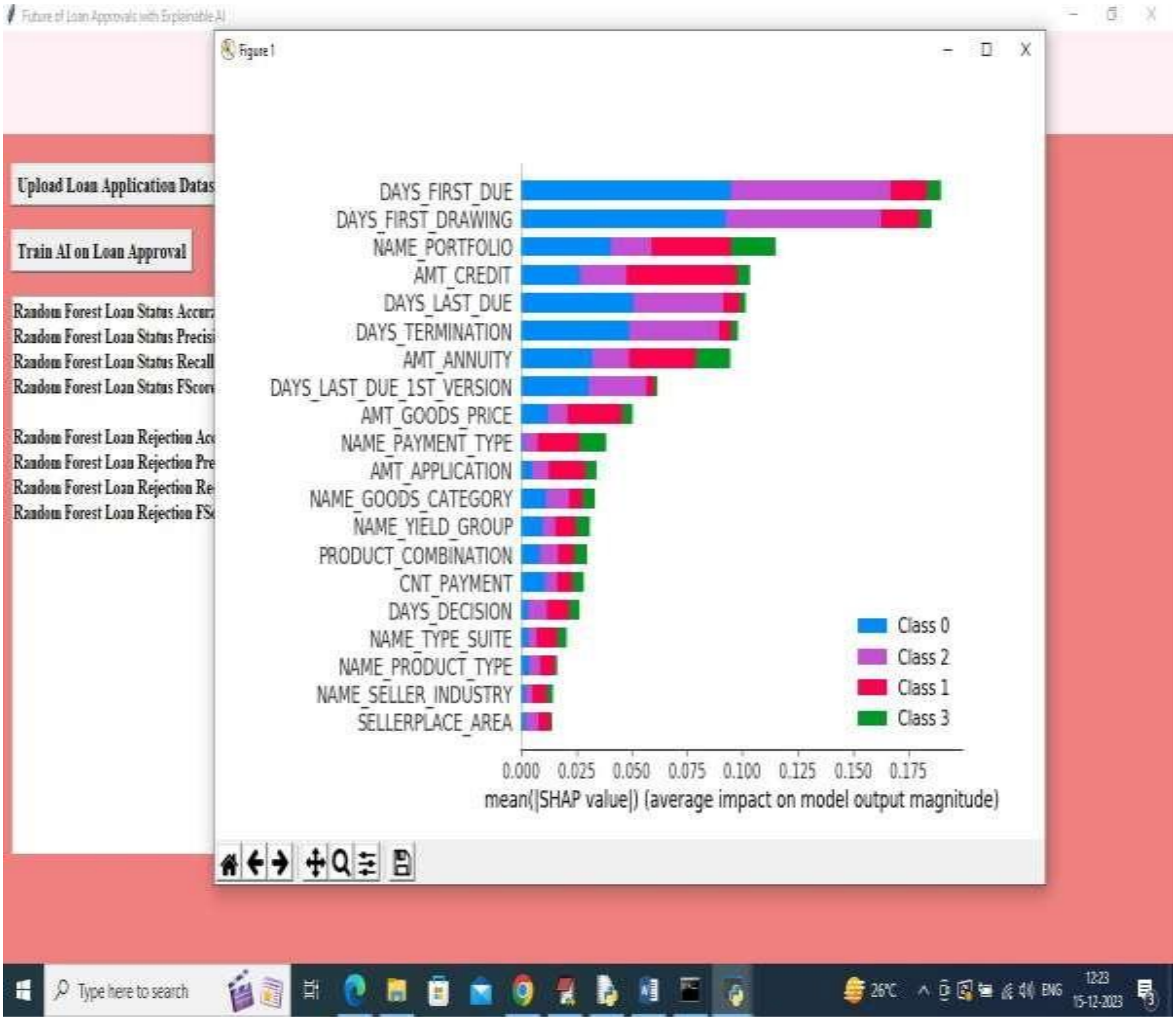
In the above screen explains the what about in loan _application data set.



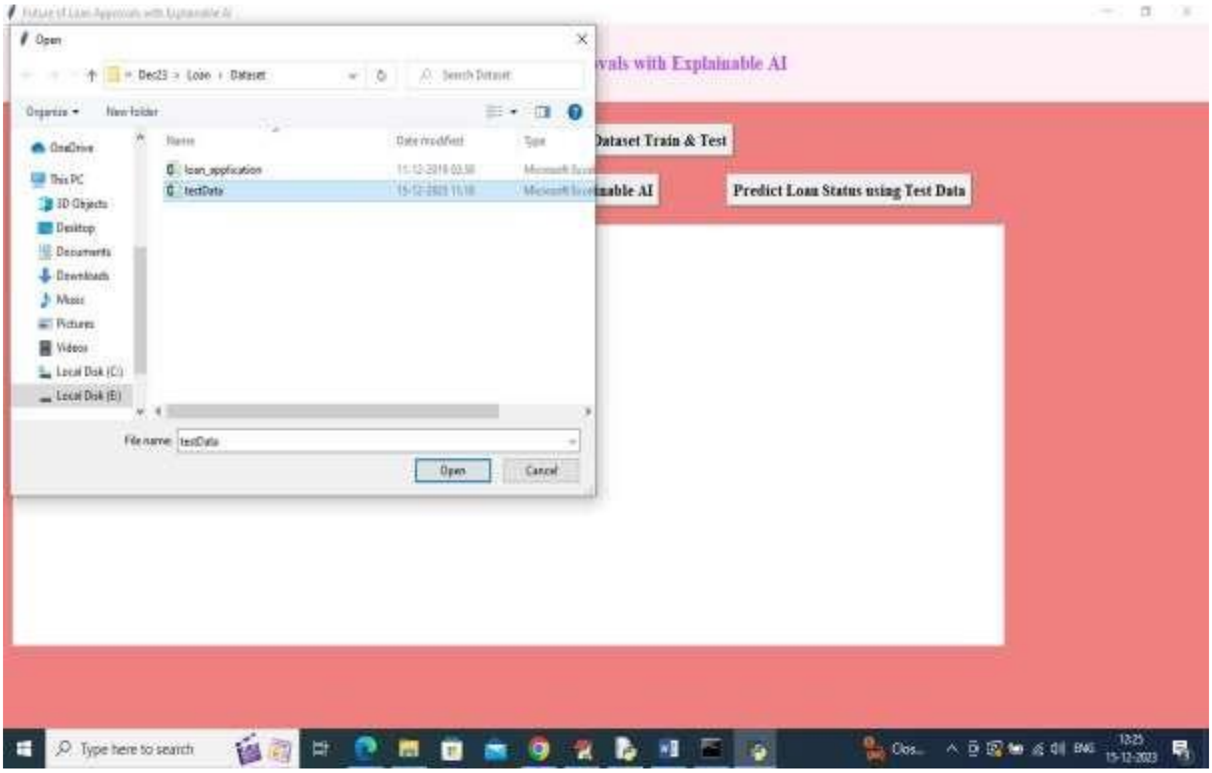
In above screen dataset loaded and in text area can see few records from dataset and in first graph x-axis represents loan status and y-axis represents Number of Records available in that loan status class label. In second graph x-axis represents rejection reason and y-axis represents records size and in dataset we have both numeric and non-numeric values so to convert to numeric data then click on ‘Pre-process Dataset’ button to get below output



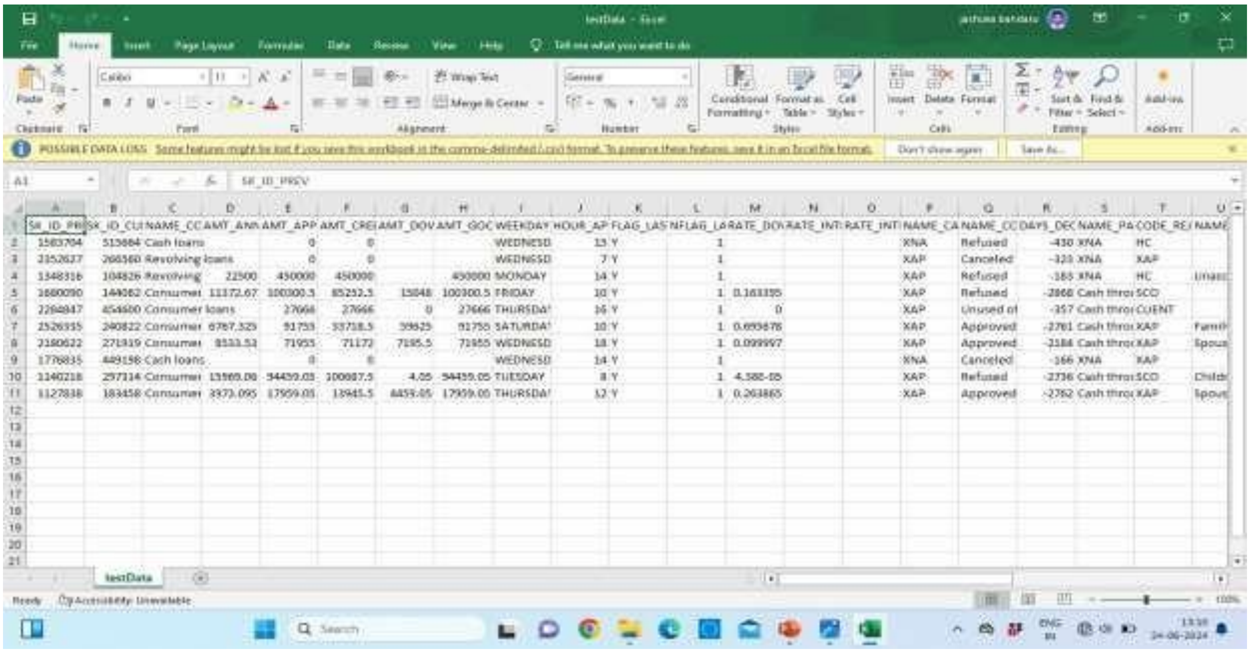
In above screen AI Random Forest got 95% accuracy on Loan STATUS and can see other metrics also. In above confusion matrix graph x-axis represents 'LOAN STATUS Predicted Labels' and y-axis represents TRUE labels and all boxes in diagonal contains correct prediction count and remaining blue boxes contains incorrect prediction count which are very few. Now click on 'Train AI on Loan Rejections' button to train AI on rejection reason and get below output



In above SHAP explanation screen in each bar we can see 4 different colours and each colour represents one class label and based on colour percentage we can say which feature names is contributing how much to predict that class label. Now close above graph and then click on ‘Predict Loan Status using Test Data’ button to upload test data and then will get below prediction



In above screen selecting and uploading testData.csv file and then click on 'Open' button. In the below screen explains the what about in testData.csv



data set.

6. CONCLUSION

In order to automate the loan underwriting process, we described in this work the approach for developing the belief-rule-based (BRB) system as an explainable AI decision-support system. While obtaining expert knowledge might be a labor- and time-intensive process, the BRB system, unlike blackbox models, can explicitly accommodate expert knowledge and learn from data through supervised learning. The significance of rules triggered by a data item that represents a loan application and the contribution of attributes in activated rules can both be used to illustrate the decision-making process in this system. We have shown via a commercial case study that the suggested AI decision-support system offers a reasonable compromise between explainability and forecast accuracy. Understanding the logic behind the choices is made easier by the significance of active rules and their characteristics in the rules. Rejected applicants may receive written justifications for loan denials, extending from the sequence of events in the factual rule basis to the heuristic rule base.

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