FUTURE OF LOAN APPROVALS WITH EXPLAINABLE AI

A. DURGA DEVI MADAM [1], KATHULA KARUNA [2],

[1]**Assistant professor , MCA DEPT,** Dantuluri Narayana Raju College**, Bhimavaram, Andharapradesh**
Email:- adurgadevi760@gmail.com
[2]**PG Student of MCA, Dantuluri** Narayana Raju College**, Bhimavaram, Andharapradesh**
Email:- kkaruna8996@gmail.com

ABSTRACT

Widespread adoption of automated decision-making by artificial intelligence (AI) is witnessed due to specular advances in computation power and improvements in optimization algorithms especially in machine learning (ML). Complex ML models provide good prediction accuracy; however, the opacity of ML models does not provide sufficient assurance for their adoption in the automation of lending decisions. This paper presents an explainable AI decision- support system to automate the loan underwriting process by belief-rule-base (BRB). This system can accommodate human knowledge and can also learn from historical data by supervised learning. The hierarchical structure of BRB can accommodate factual and heuristic rules. The system can explain the chain of events leading to a decision for a loan application by the importance of an activated rule and the contribution of antecedent attributes in the rule. A business case study on automation of mortgage underwriting is demonstrated to show that the BRB system can provide a good trade-off between accuracy and explainability. The textual explanation produced by the activation of rules could be used as a reason for the denial of a loan. The decision- making process for an application can be comprehended by the significance of rules in providing the decision and contribution of its antecedent attributes.

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..

4.1 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.

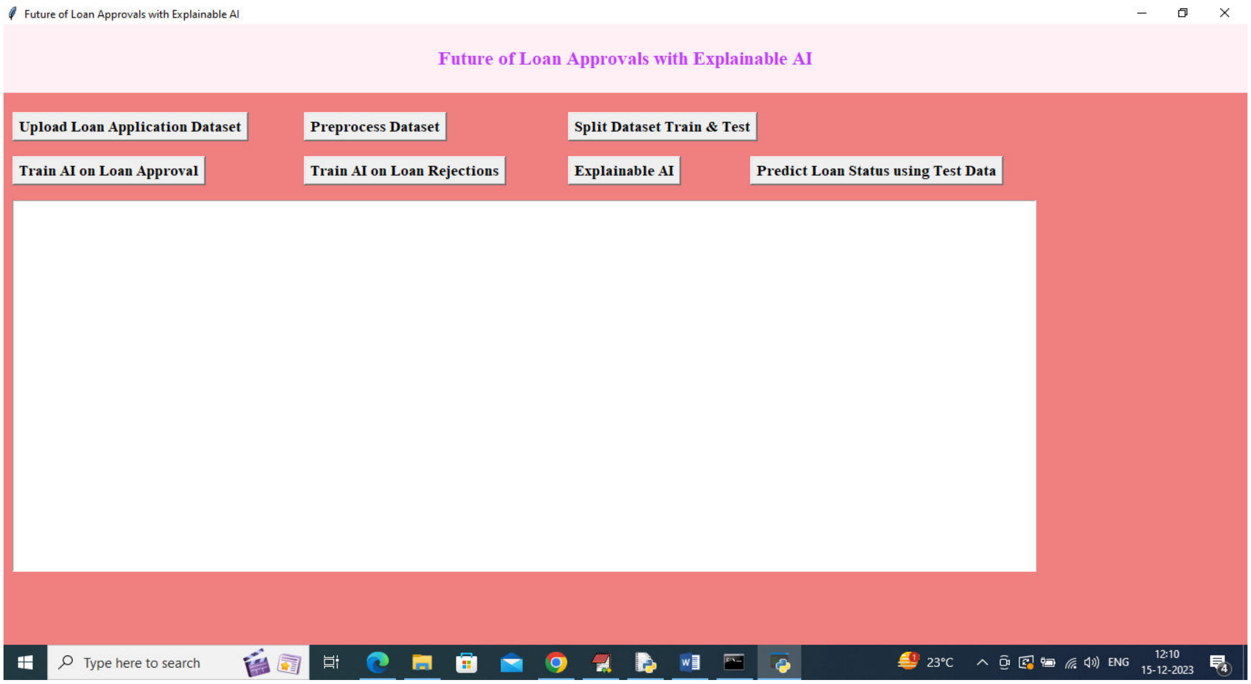
IMPLEMENTATION

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

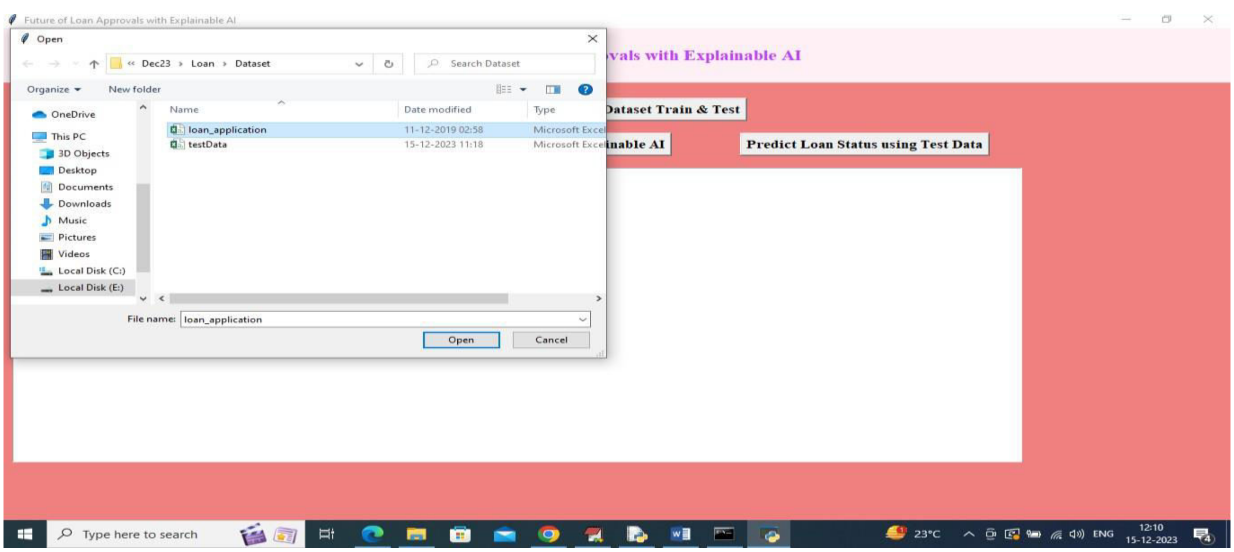
5 RESULTS AND DISCUSSION

1.1 SCREENSHOTS

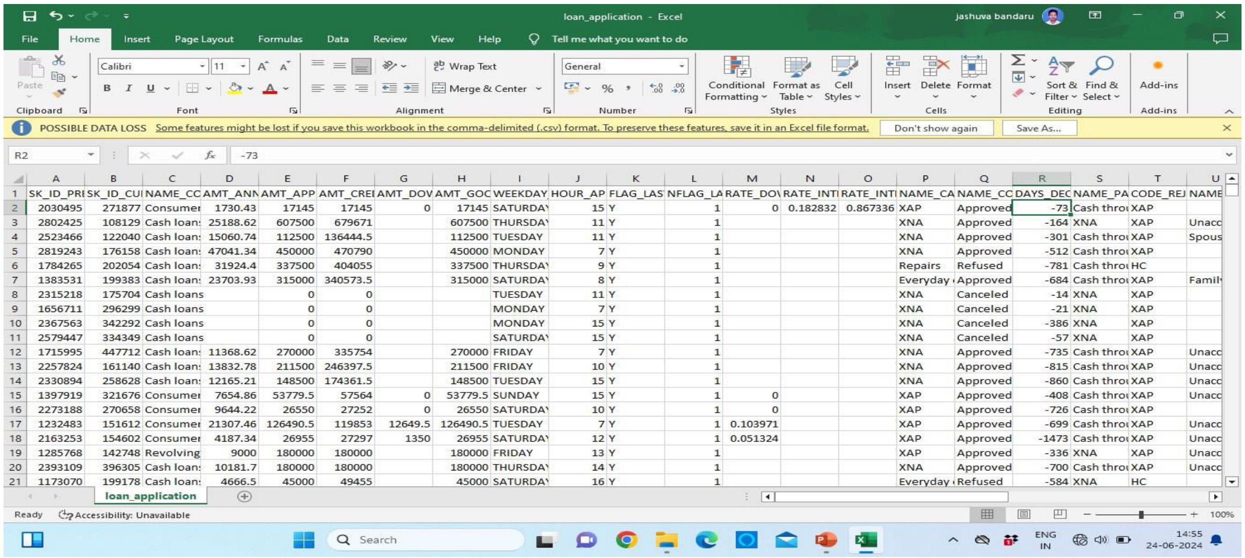
To run project double, click on “run.bat” file to get below screen



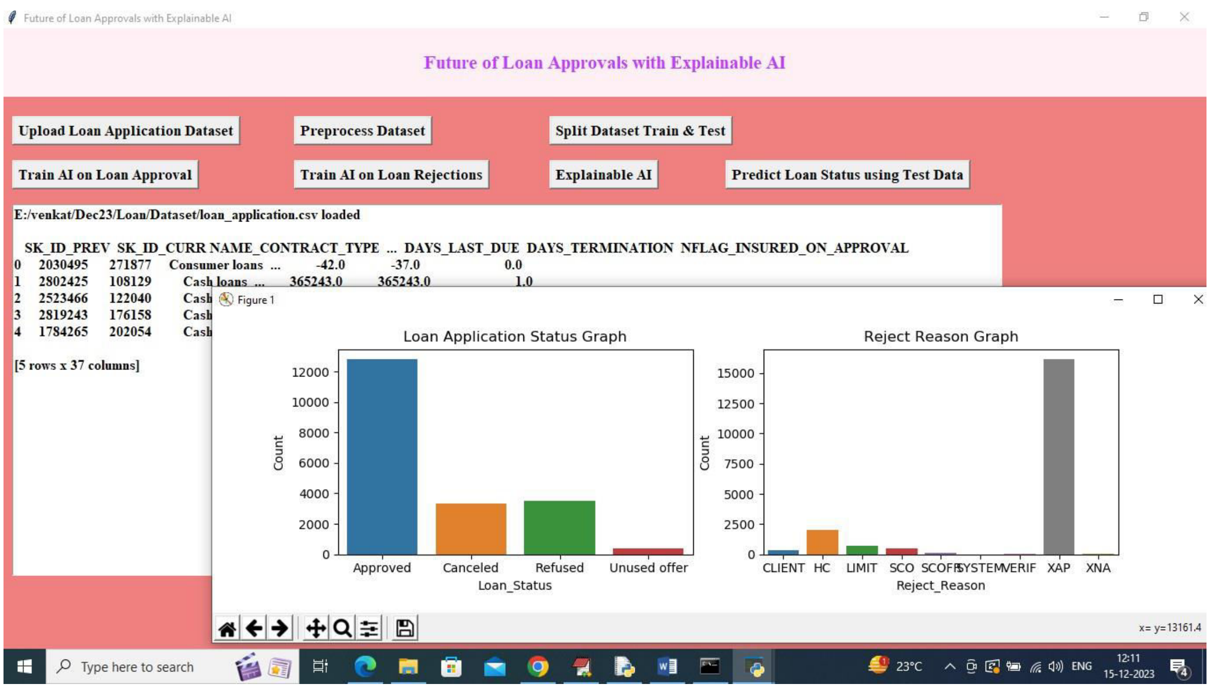
In above screen click on Upload Loan Application Dataset button to upload dataset and then will get below output



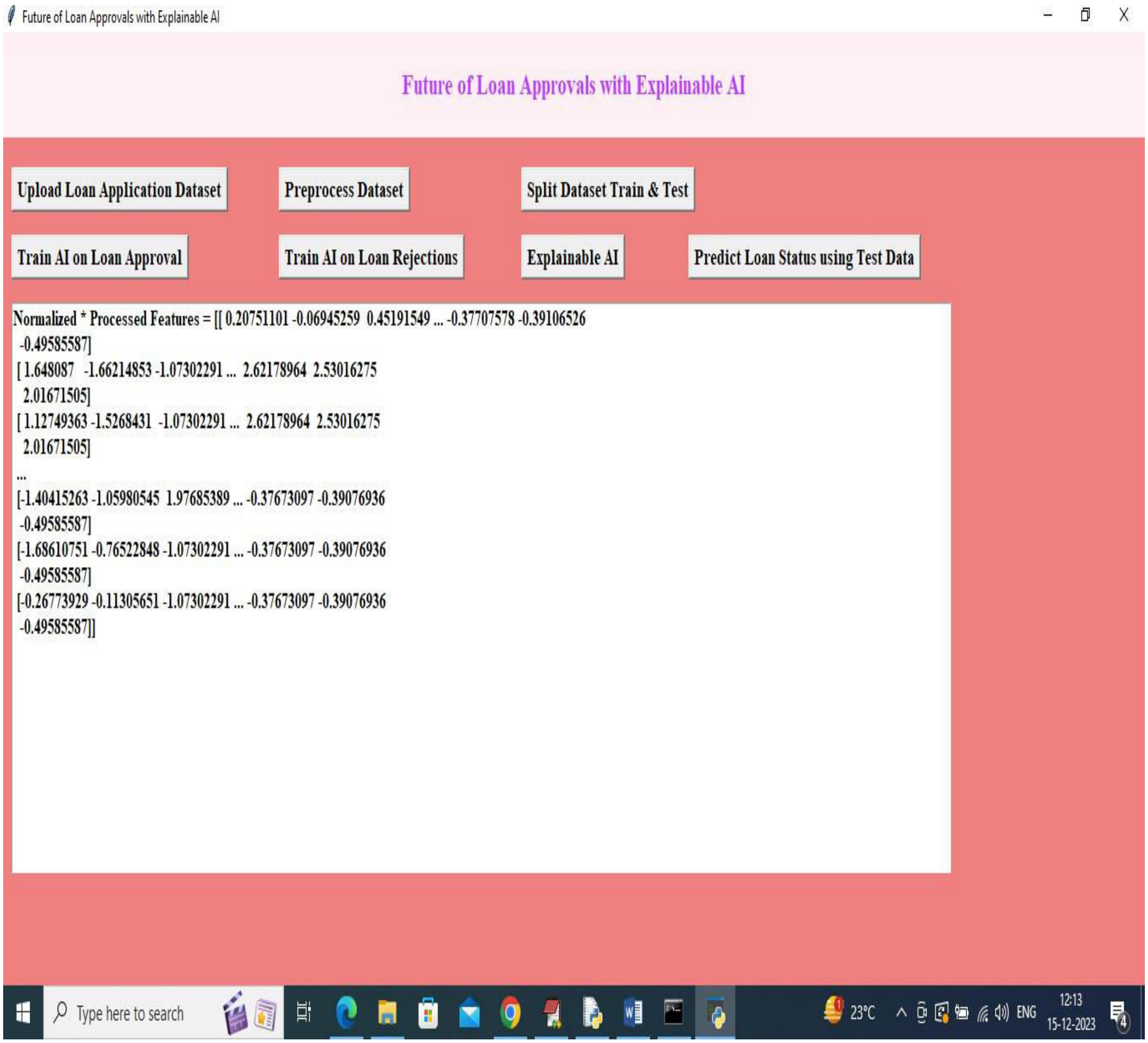
In above screen selecting and uploading loan_application.csv file and then click on Open button to load dataset and get below output



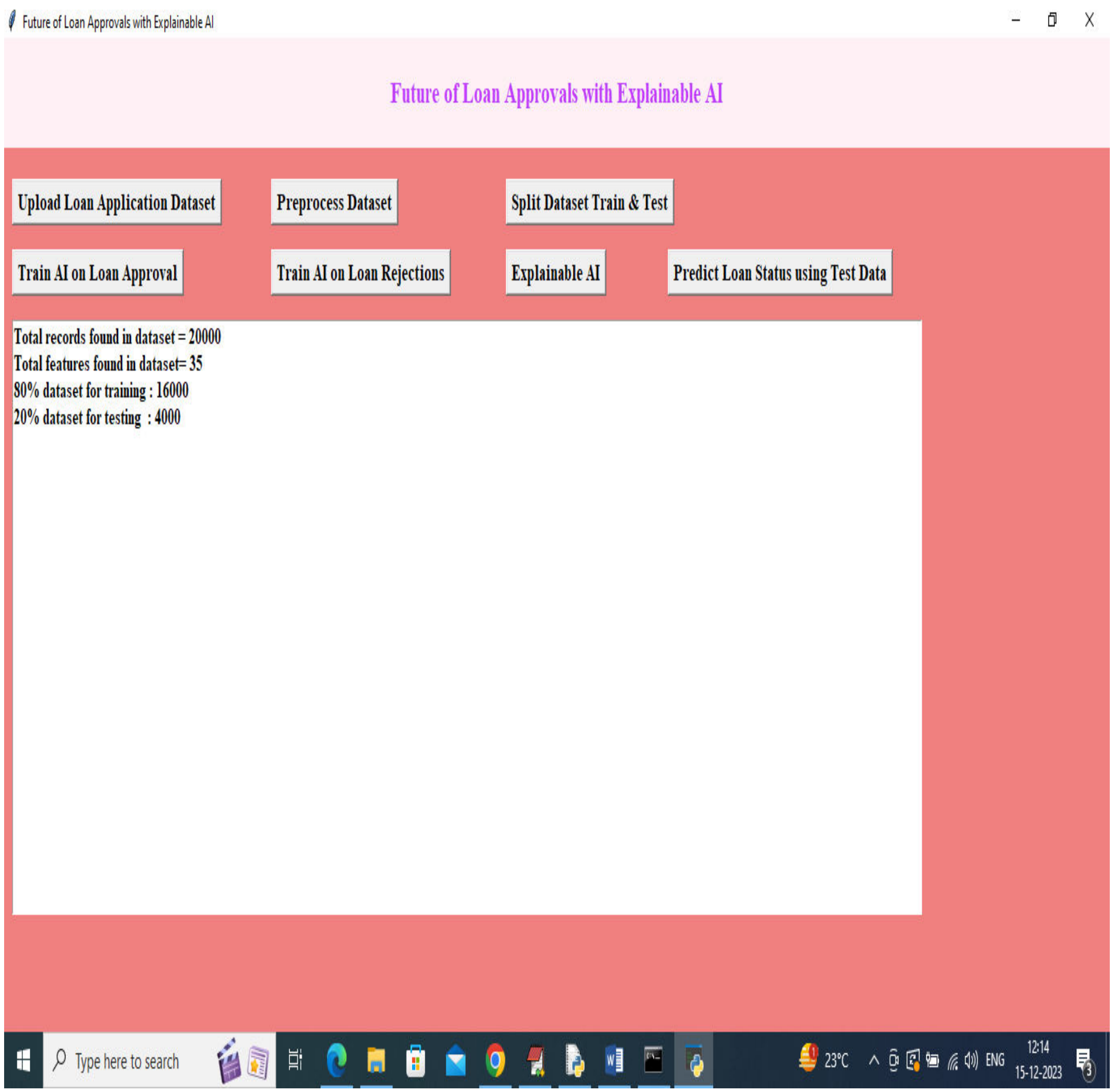
In the above screen explains the what about in loan _application data set.



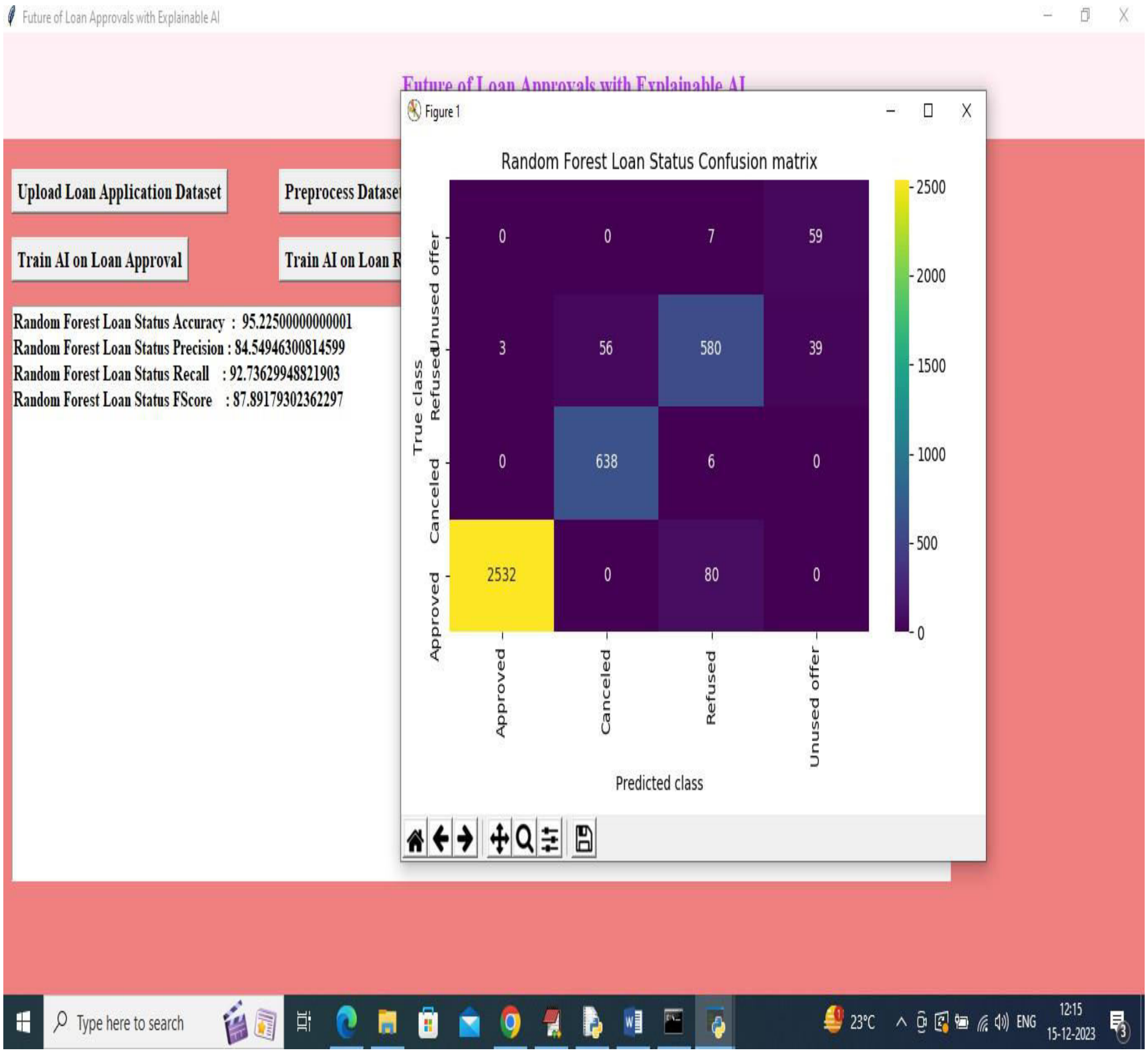
In above screen dataset loaded and in text area can see few records from dataset and in first graph x-axis represents loan status and y-axis represents Number of Records available in that loan status class label. In second graph x-axis represents rejection reason and y-axis represents records size and 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



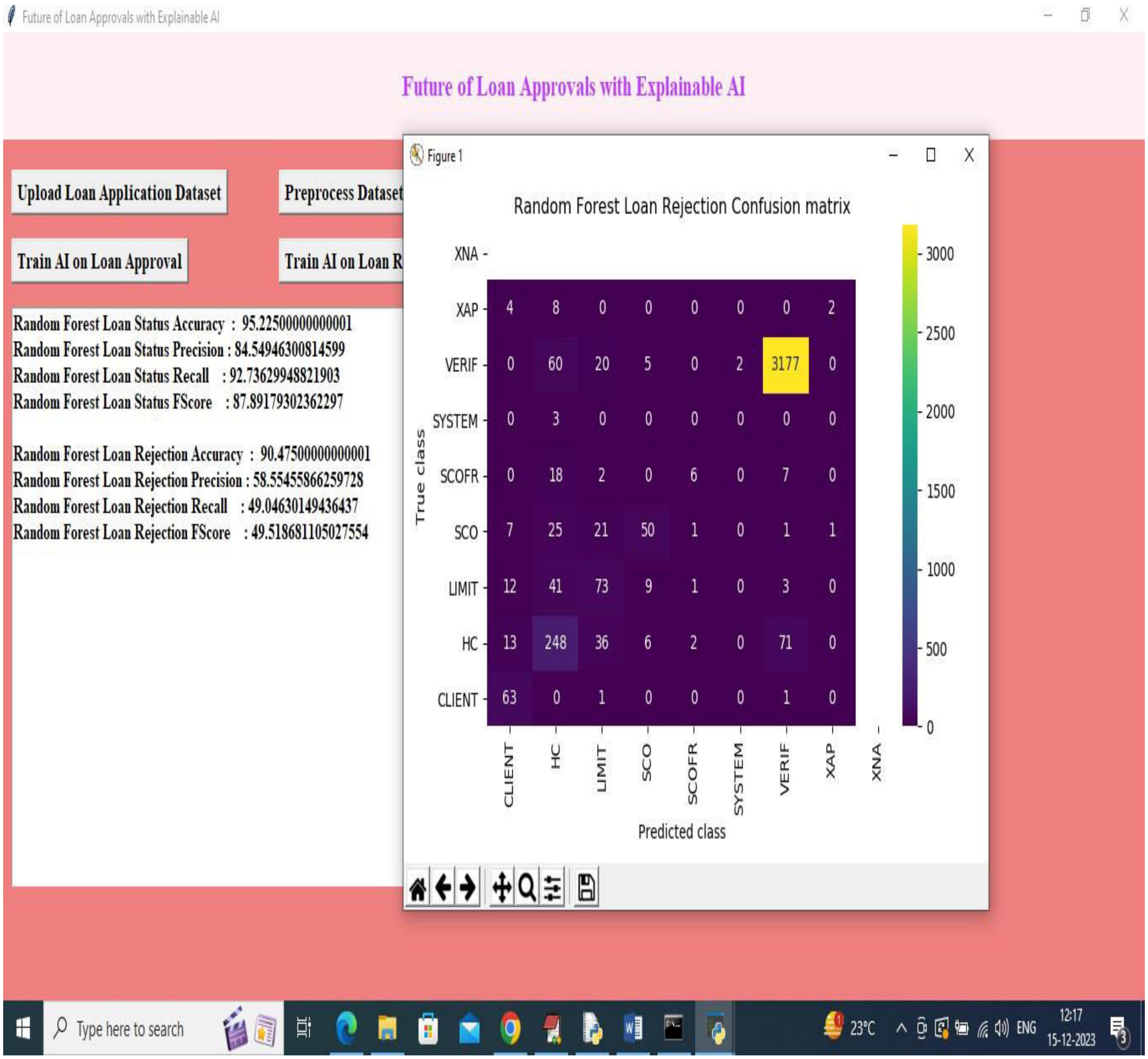
In above screen dataset converted to numeric format and then click on “Split Dataset Train & Test” button to split dataset into train and test and then will get below output



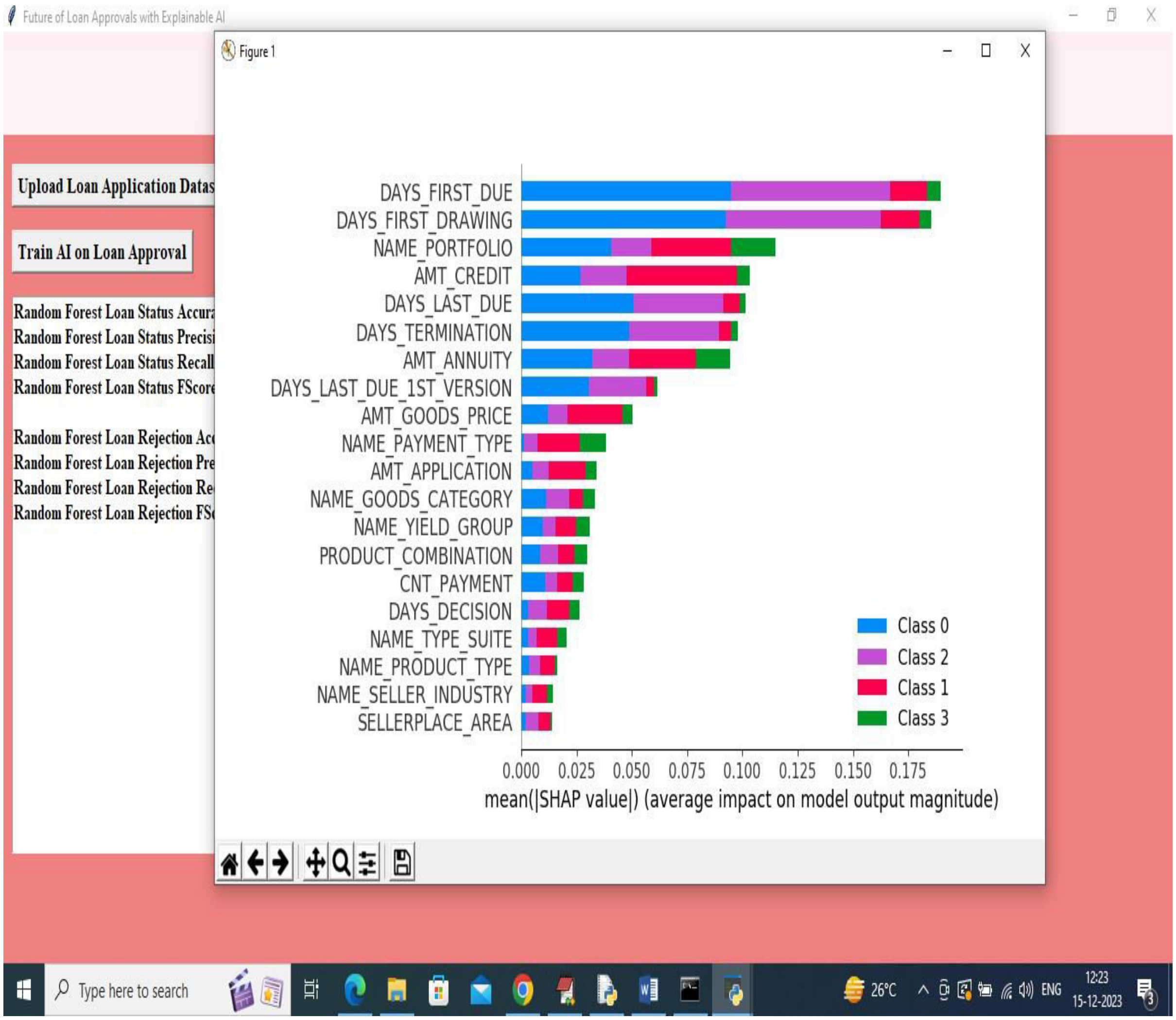
In above screen can see dataset size with total number of features and then can see TRAIN and TEST size and now click on Train AO on Loan Status Approval button to train AI and get below output



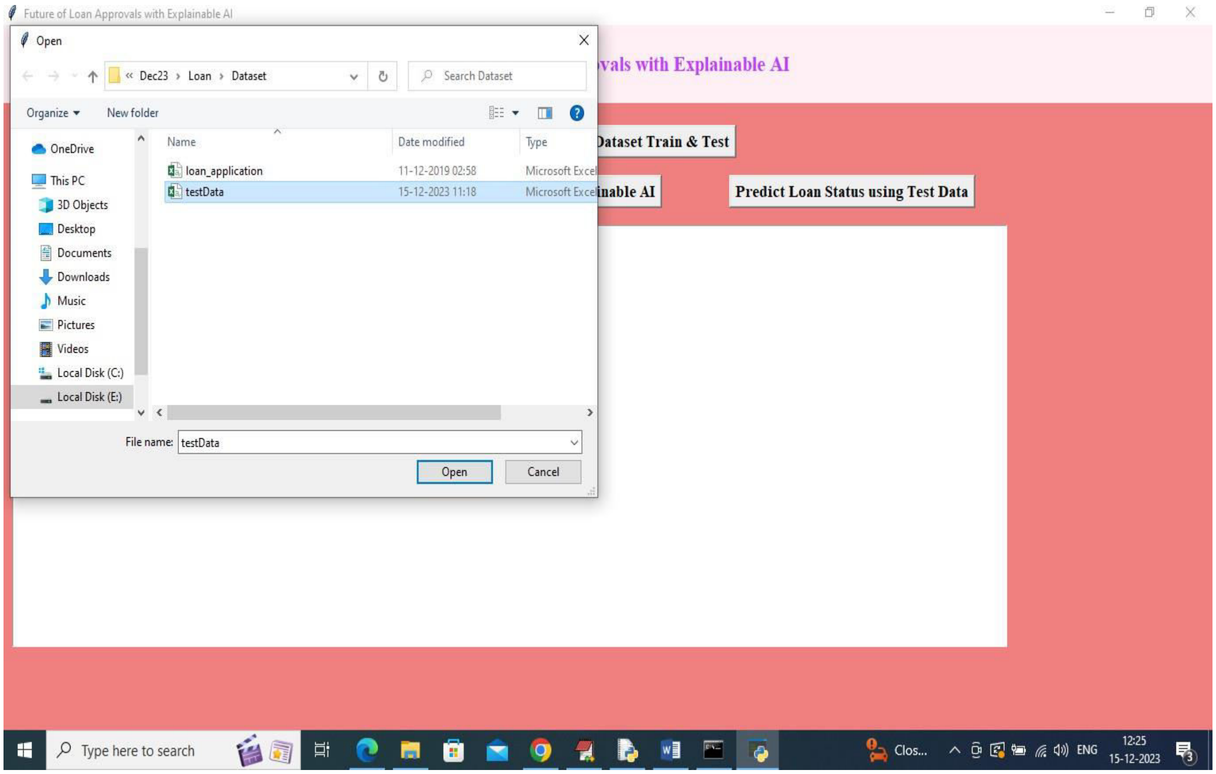
In above screen AI Random Forest got 95% accuracy on Loan STATUS and can see other metrics also. In above confusion matrix graph x-axis represents LOAN STATUS Predicted Labels and y-axis represents TRUE labels and all boxes in diagonal contains correct prediction count and remaining blue boxes contains 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



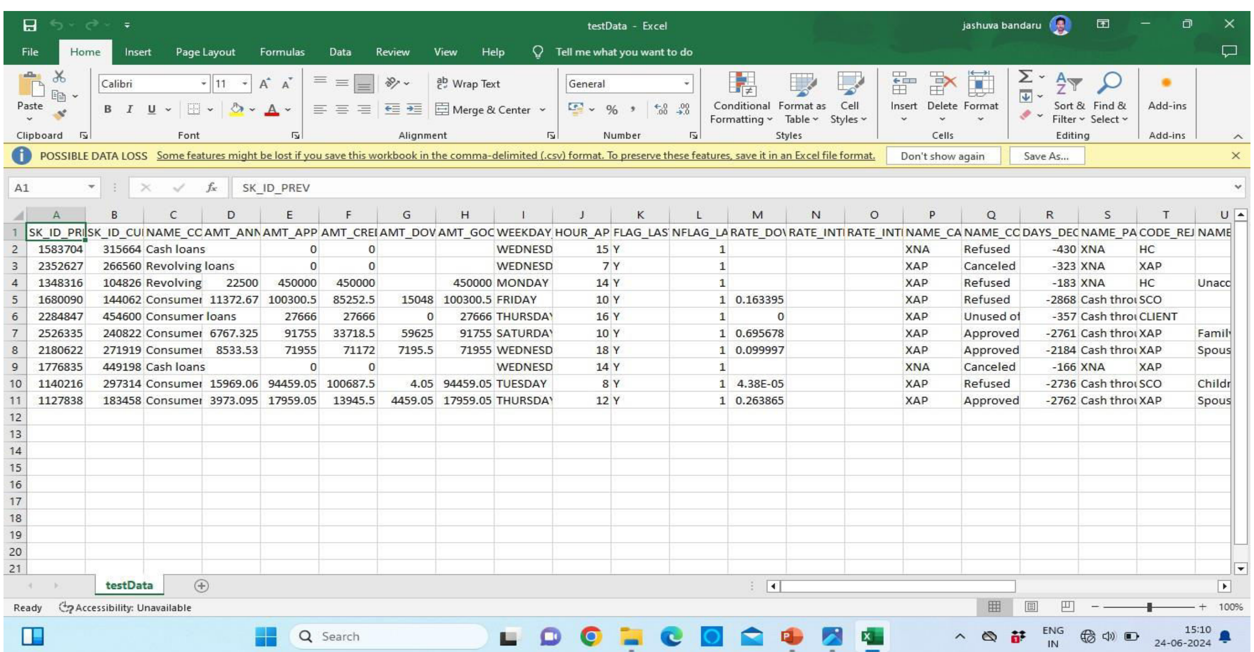
In above screen AI on REJECTION got 90% accuracy and in confusion matrix graph x-axis represents Rejection Reason Predicted Labels and y-axis represents True label and in diagonal boxes we can see correct prediction count and remaining boxes contains incorrect prediction count. Now click on Explainable AI button to get below features explanation on prediction

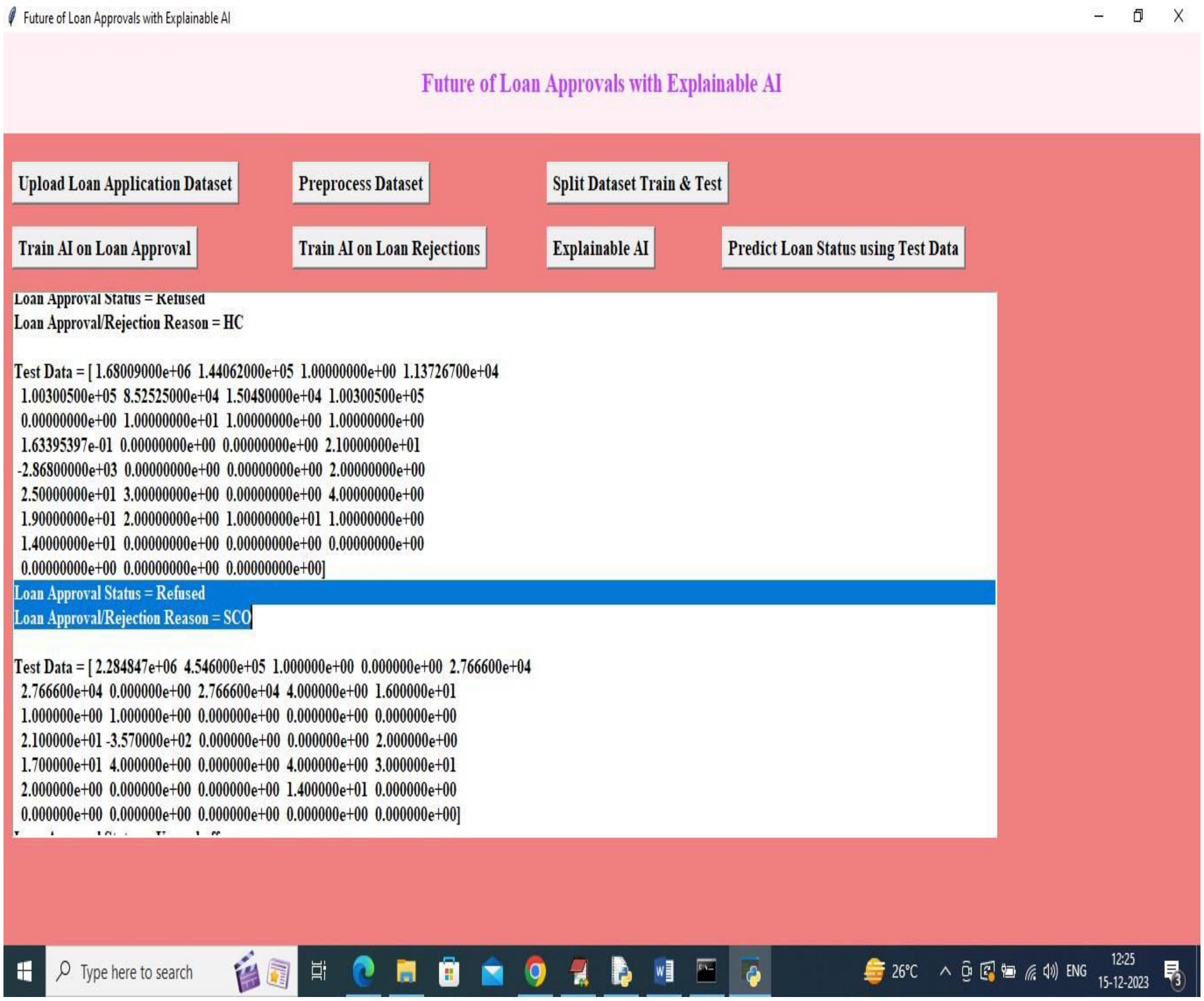


In above SHAP explanation screen in each bar we can see 4 different colours and each colour represents one class label and based on colour percentage we can say which feature names is contributing how much to predict that class label. Now close above graph and then click on Predict Loan Status using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

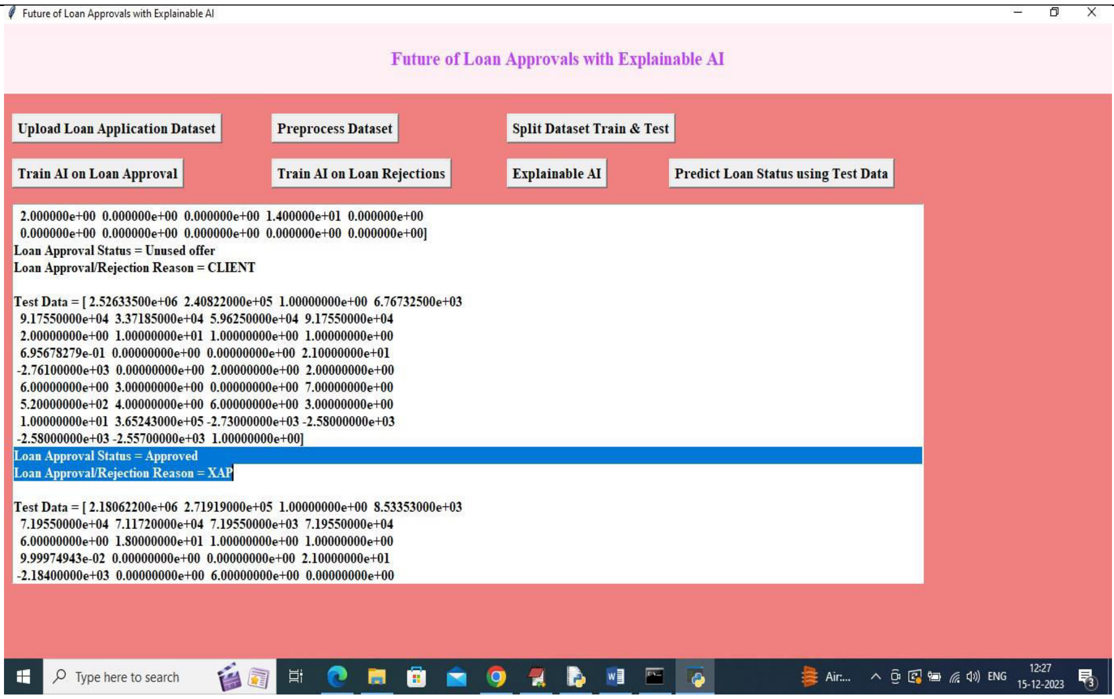


In above screen selecting and uploading testData.csv file and then click on Open button. In the below screen explains the what about in testData.csv data set.



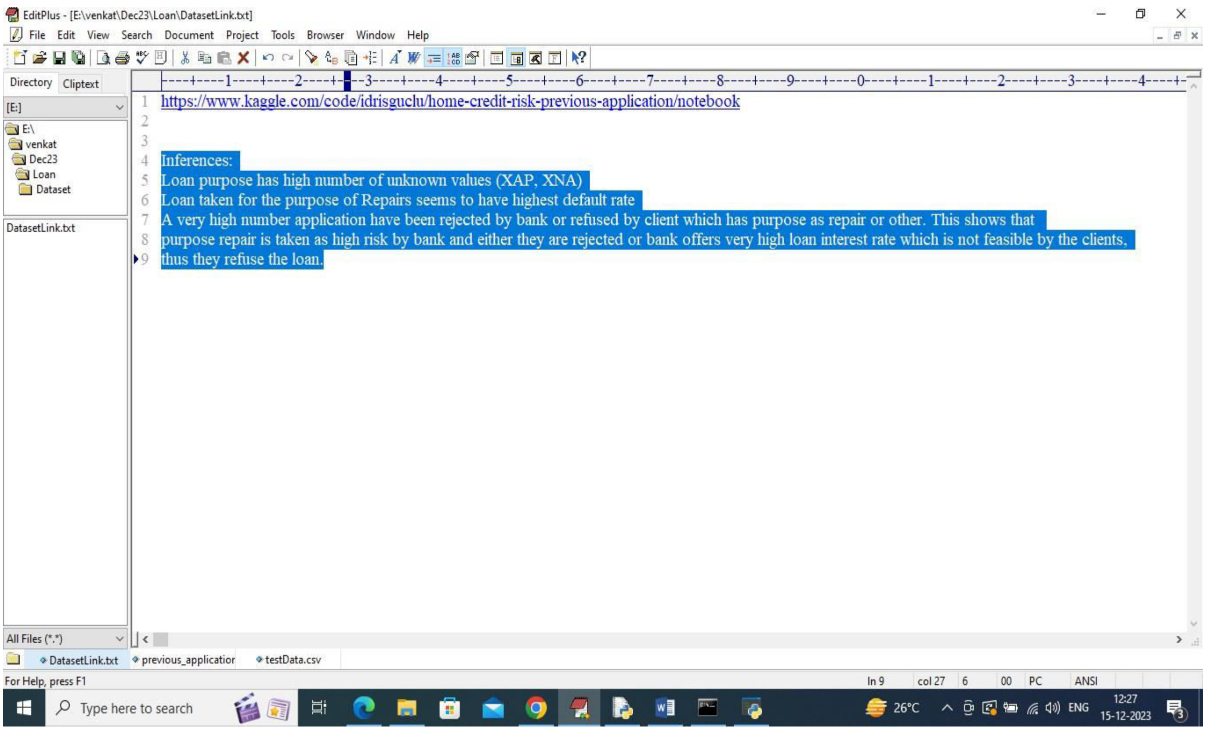


In above screen in square bracket, we can see test data and then in blue colour selected line next to TEST data we can see LOAN STATUS prediction and REASON details. Scroll down above output to view all predictions



In above screen can see other prediction output.

For Reason Rejected code you can read below description



In above screen read blue color selected text to know about REJECTED REASON codes

6. CONCLUSION AND FUTURE WORK

CONCLUSION

In this paper, we presented the methodology to develop the belief-rule-based (BRB) system as an explainable AI decision-support-system to automate the underwriting process of lend loans. Unlike blackbox models, the BRB system can explicitly accommodate expert knowledge and can also learn from data by supervised learning, though the acquisition of expert knowledge can be a time-consuming and labor-intensive task.

The decision-making process in this system can be explained by the importance of rules activated by a data point representing a loan application and by the contribution of attributes in activated rules. Through a business case study, we have demonstrated that the proposed AI decision-support-system provides a good trade-off between prediction accuracy and explainability. The importance of activated rules and their attributes in the rules help to understand the reasoning behind the decisions. The textual explanations initiated by the chain of events in the factual-rule- base to the heuristic-rule-base could be sent to rejected applicants as reasons for denying their loan applications.

7. REFRENCES

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