

## 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 (MI).

### 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

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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 & algorithm**

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

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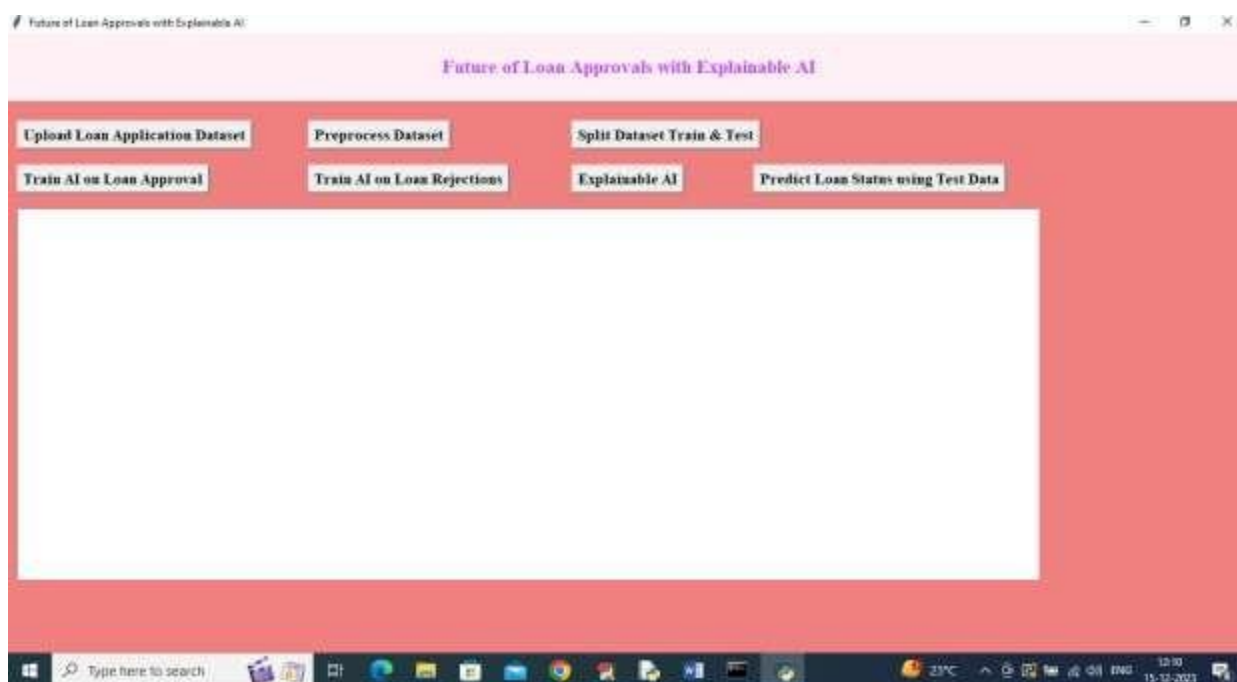
labels for loan and reject reason and plot them in a graph

- 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

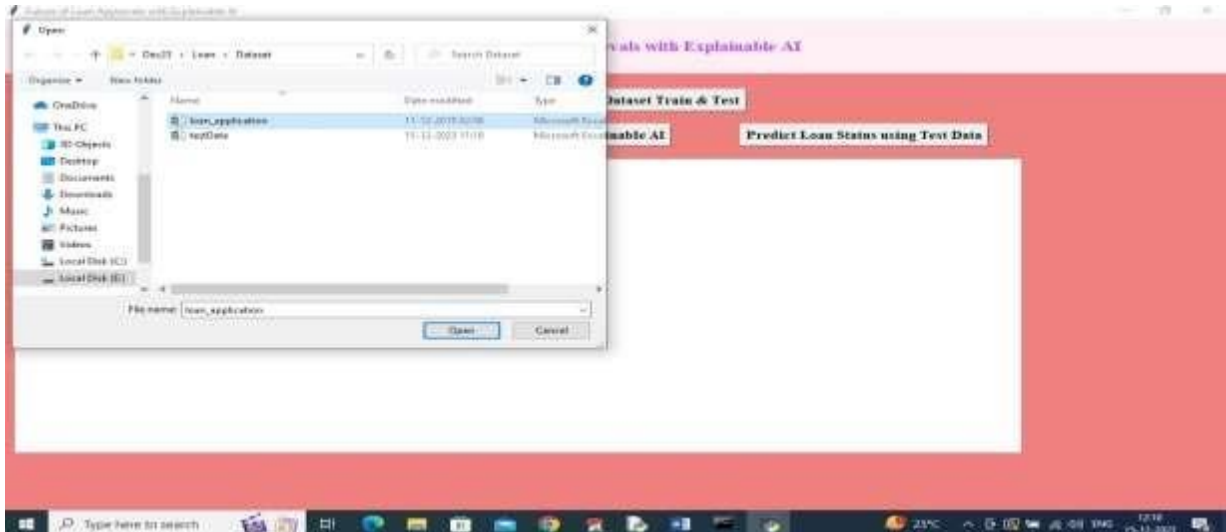
## 5 RESULTS AND DISCUSSION

### 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



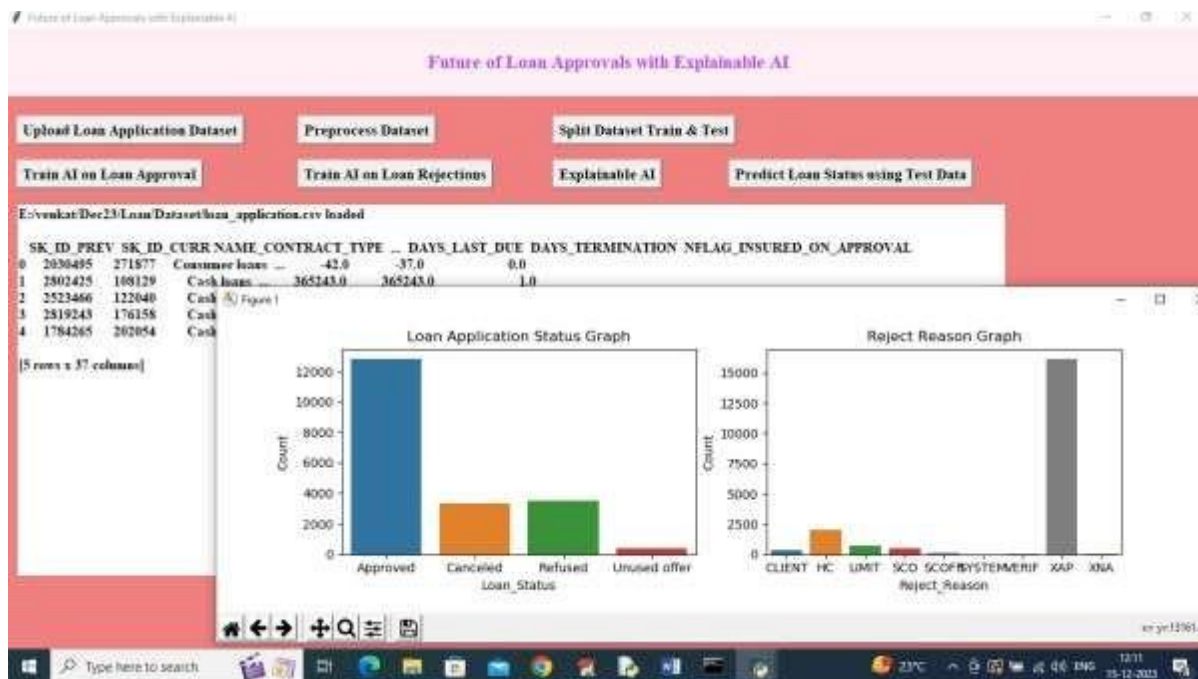
In above screen selecting and uploading 'loan\_application.csv' file and then click on 'Open' button to load dataset and get below output

The screenshot shows an Excel spreadsheet with the following columns: SL\_ID, PRINL\_ID, CUSTNAME, CC\_AMT, ANNUAMT, AFF\_AMT, CRY\_AMT, GOVAMT, DOC\_WEEKDAY, HOUR\_AP, FLAG, LAS\_NFLAG, LARATE, TDN RATE, INTI RATE, JUSTI NAME, CA\_NAME, CC\_CASH, TOC\_NAME, PACTURE, REI\_NAME. The data includes various loan records with their respective amounts, dates, and statuses.

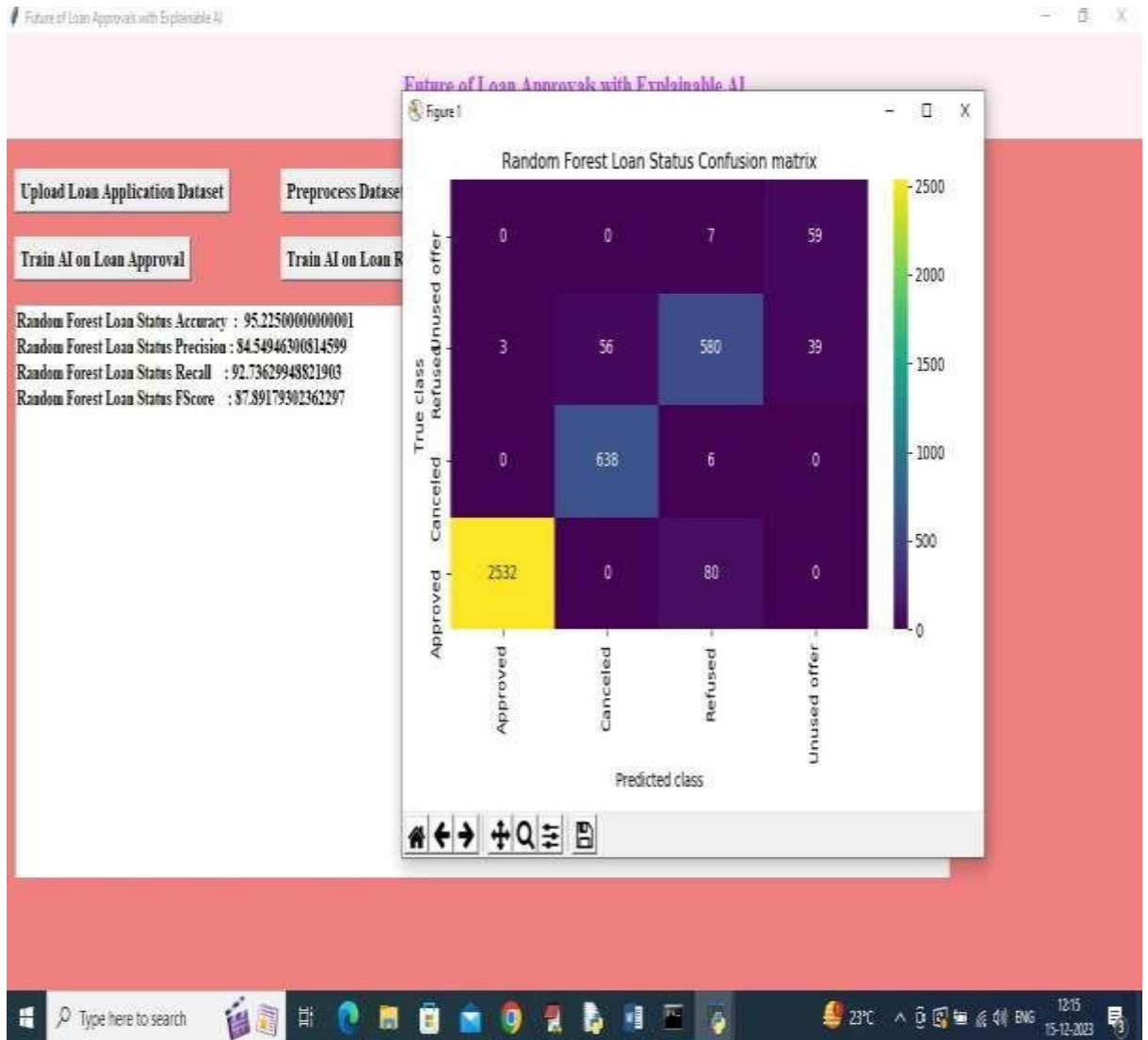
SL_ID	PRINL_ID	CUSTNAME	CC_AMT	ANNUAMT	AFF_AMT	CRY_AMT	GOVAMT	DOC_WEEKDAY	HOUR_AP	FLAG	LAS_NFLAG	LARATE	TDN RATE	INTI RATE	JUSTI NAME	CA_NAME	CC_CASH	TOC_NAME	PACTURE	REI_NAME
2036495	271877	Consumer	1736.43	17145	17145	0	17145	SATURDAY	15	Y	1	0	0.382832	0.867336	XNA	Approved	-73	Cash thro	KAP	Uttac
2852423	308125	Cash loan	25189.62	807500	678671		807500	THURSDAY	11	Y	1				XNA	Approved	-164	XNA	KAP	Uttac
2521888	123080	Cash loan	15066.76	112500	136948.5		112500	TUESDAY	11	Y	1				XNA	Approved	303	Cash thro	KAP	Spous
2818244	278138	Cash loan	81821.84	200000	478799		200000	MONDAY	7	Y	1				XNA	Approved	312	Cash thro	KAP	Uttac
1784289	303004	Cash loan	31504.4	107500	404039		107500	THURSDAY	8	Y	1				Repair	Rejected	793	Cash thro	HC	
1183531	129303	Cash loan	25703.93	113000	340575.5		113000	SATURDAY	8	Y	1				Everyday	Approved	864	Cash thro	KAP	Famil
2038230	175704	Cash loans	0	0	0		0	TUESDAY	11	Y	1				XNA	Cancelled	-14	XNA	KAP	
1658711	296209	Cash loans	0	0	0		0	MONDAY	7	Y	1				XNA	Cancelled	-21	XNA	KAP	
2867541	342262	Cash loans	0	0	0		0	MONDAY	15	Y	1				XNA	Cancelled	-88	XNA	KAP	
2878447	334349	Cash loans	0	0	0		0	SATURDAY	15	Y	1				XNA	Cancelled	-57	XNA	KAP	
1732995	447712	Cash loan	11368.62	270000	555754		270000	FRIDAY	7	Y	1				XNA	Approved	715	Cash thro	KAP	Uttac
2257924	381140	Cash loan	13832.78	111300	240297.5		111300	FRIDAY	10	Y	1				XNA	Approved	815	Cash thro	KAP	Uttac
2328894	358026	Cash loan	12165.21	148500	174961.5		148500	TUESDAY	15	Y	1				XNA	Approved	880	Cash thro	KAP	Uttac
1187913	121676	Consumer	7654.88	10778.8	27564		10778.8	SUNDAY	15	Y	1				XAP	Approved	488	Cash thro	Uttac	
2379188	170668	Consumer	3884.22	20000	27252		20000	SATURDAY	10	Y	1				XAP	Approved	728	Cash thro	KAP	
1253401	135612	Consumer	21807.46	128480.3	135853	128480.3	128480.3	TUESDAY	7	Y	1	0.103973			XAP	Approved	699	Cash thro	KAP	Uttac
2183253	154602	Consumer	4187.34	26955	27257	1350	26955	SATURDAY	12	Y	1	0.031124			XAP	Approved	1473	Cash thro	KAP	Uttac
1285768	342248	Rent/leasg	9000	180000	180000		180000	FRIDAY	13	Y	1				XAP	Approved	-336	XNA	KAP	Uttac
2382039	396205	Cash loan	10181.7	180000	180000		180000	THURSDAY	14	Y	1				XNA	Approved	-700	Cash thro	KAP	Uttac
1173070	198178	Cash loan	4888.3	65000	48435		65000	SATURDAY	18	Y	1				Everyday	Rejected	588	XNA	HC	

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

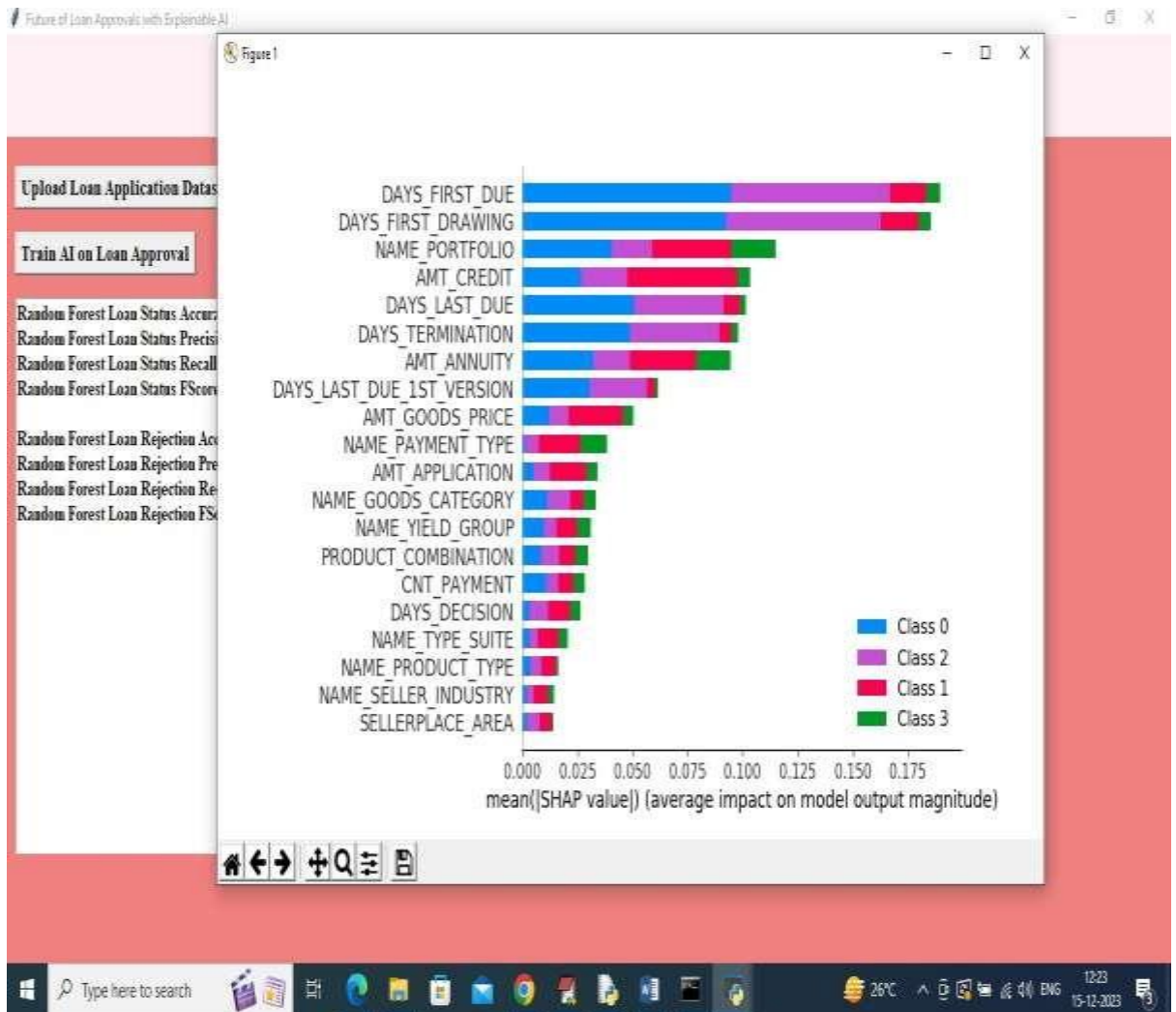
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In above screen dataset loaded and in text area can see few records from dataset and in first graph x-axis represents loan status and y-axis represents Number of Records available in that loan status class label. In second graph x-axis represents rejection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

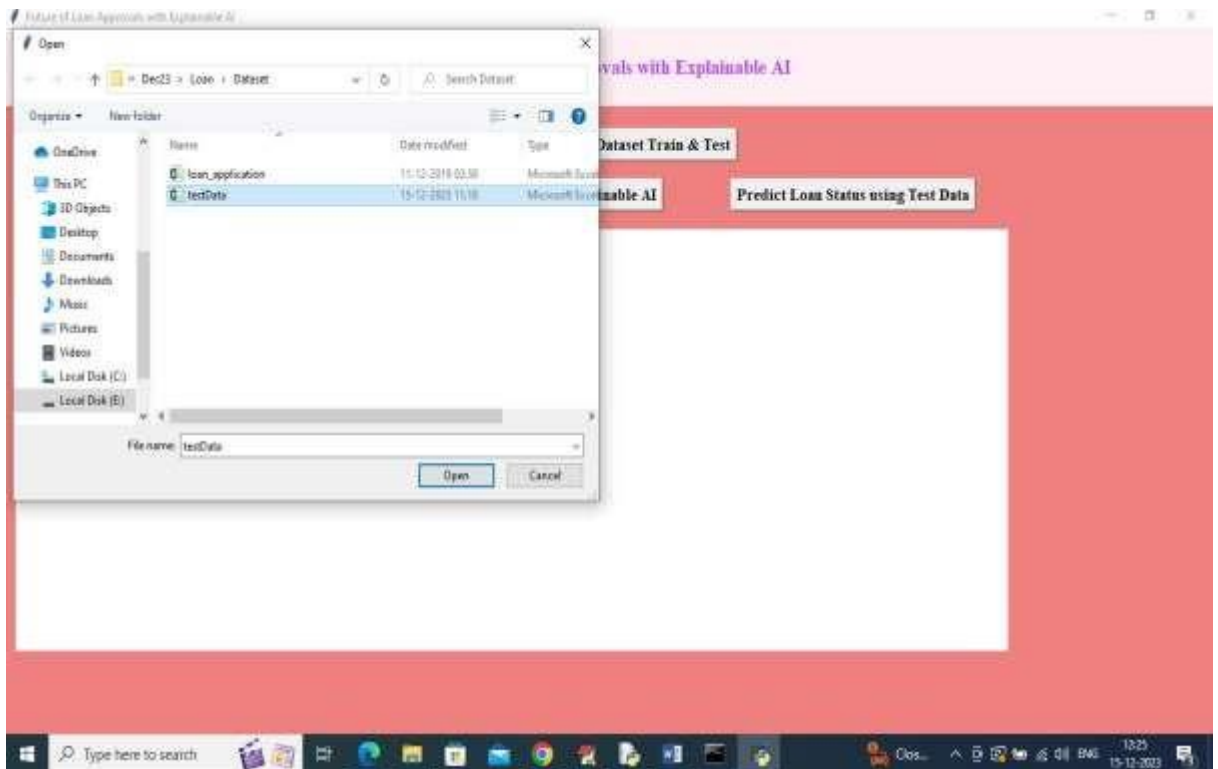


In above screen AI Random Forest got 95% accuracy on Loan STATUS and can see other metrics also. In above confusion matrix graph x-axis represents 'LOAN STATUS Predicted Labels' and y-axis represents TRUE labels and all boxes in diagonal contains correct prediction count and remaining blue boxes contains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

The screenshot shows a Microsoft Excel spreadsheet with the following columns: SR\_ID, PRSK\_ID, CLNAME, CC, AMT, ANN, AMT, APP, AMT, CRE, AMT, DOV, AMT, GOC, WEEKDAY, HOUR, AP, FLAG, LAS, FLAG, LR, RATE, DOV, RATE, INT, RATE, INT, NAME, CA, NAME, CC, DAYS, DEC, NAME, PA, CODE, RE, NAME. The data rows contain various loan details such as loan ID, principal ID, customer name, amount, and status.

SR_ID	PRSK_ID	CLNAME	CC	AMT	ANN	AMT	APP	AMT	CRE	AMT	DOV	AMT	GOC	WEEKDAY	HOUR	AP	FLAG	LAS	FLAG	LR	RATE	DOV	RATE	INT	RATE	INT	NAME	CA	NAME	CC	DAYS	DEC	NAME	PA	CODE	RE	NAME
1583704	513684	Cash loans		0	0									WEDNESD	13	Y					1						XNA	Refused	-430	XNA	HC						
1352637	268560	Revolving loans		0	0									WEDNESD	7	Y					1						XAP	Canceled	-323	XNA	XAP						
1348316	104826	Revolving	22500	450000	450000					400000	MONDAY	14	Y							1						XAP	Refused	-365	XNA	HC					UNRE		
1680090	144862	Consumer	11172.67	100300.3	85232.3	13848	100300.5	FRIDAY	10	Y										1	0.163135					XAP	Refused	-386	Cash thro	SCD							
2294047	454690	Consumer loans	27666	27666		0	27666	THURSDA	16	Y										1	0					XAP	Unused of	-257	Cash thro	COENT							
2526355	240822	Consumer	6787.329	91733	53738.5	39925	91750	SATURDA	10	Y										1	0.699678					XAP	Approved	-2781	Cash thro	XAP					Famil		
2180622	271819	Consumer	8333.53	71925	71177	7195.5	71850	WEDNESD	18	Y										1	0.099997					XAP	Approved	-2184	Cash thro	XAP					Spous		
1778635	449158	Cash loans		0	0									WEDNESD	14	Y					1					XNA	Canceled	-166	XNA	XAP							
1140218	297114	Consumer	13869.08	94430.03	100987.5	-4.05	94430.05	TUESDAY	8	Y										1	4.585-05					XAP	Refused	-2736	Cash thro	SCD					Child		
1127838	183458	Consumer	3973.095	17959.05	18943.5	4453.05	17959.05	THURSDA	12	Y										1	0.263865					XAP	Approved	-2782	Cash thro	XAP					Spous		

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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