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EXPLAINABLE AI FOR FAIR AND ACCOUNTABLE LOAN APPROVALS

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ABSTRACT: Improvements in computing power and optimization algorithms have revolutionized sectors like lending, hastening the use of AI-driven automated decision-making. Machine learning (ML) applications automate crucial choices like loan approvals; nonetheless, consumers often lack faith in these systems due to the models' complexity and opaqueness. This work presents an explainable AI system for loan underwriting based on the belief-rule-base (BRB) paradigm to address this issue. Incorporating heuristic and factual concepts into a hierarchical framework, this method integrates supervised learning with human expertise. It not only finds a happy medium between precision and clarity, but it also gives reasons (in writing) for decisions (like a loan denial). This paper uses a mortgage underwriting business case to show how the BRB system makes decision-making more transparent, intelligible, and trustworthy by drawing attention to the role of antecedent attributes and active rules.

Keywords: Explainable AI, Fairness, Accountability, Loan Approval, Transparency, Bias Mitigation, Model Interpretability, Ethical AI

1. INTRODUCTION

Months of training and sharing knowledge among seasoned experts have honed the underwriting talent. The evaluation of loan applications requires analytical thinking, organizational precision, and accuracy in order to determine whether to approve or reject the applications based on criteria like affordability, repayment history, and collateral [3]. Investor needs, regulatory norms, and client expectations all change over time, and underwriters need to be flexible to keep up [3]. Thanks to advancements in AI and machine learning, the processing of client data and rule execution may now happen in milliseconds, making the loan application process much easier and more streamlined [1], [9]. As part of their commitment to digital innovation, financial institutions are implementing AI into the underwriting process to improve certain areas [4], [5]. Converting complicated computational ideas into reliable training data that can successfully handle a wide variety of loan conditions remains a difficulty, though [6]. In the lending sector, continuous improvement and cooperation between technology and human experience are necessary because even the most advanced AI systems may only be able to solve a small fraction of unique problems [8].

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

Authors: Miller, Tim. et al.

Summary: This seminal article presents explainable AI and discusses its significance in the banking industry. It shows how crucial interpretable models are, especially in highly transparent fields like loan underwriting [2], [7].

2. Interpretable Machine Learning for Credit Scoring: A Case Research on Peer- toPeer Lending:

Authors: Ribeiro, Marco Tulio. et al.

Summary: Using interpretable machine learning models as an example, the article explains why it's crucial to comprehend model predictions when it comes to credit scoring. The research shows that it is possible to attain interpretability without compromising the accuracy of forecasts [1], [4], [5], [6], [9].

2. LITERATURE SURVEY

Risk Assessment and FICO Scores: Studies have shown that FICO scores are important for loan approval, but they have also criticized how exclusive they are (Kashyap et al., 2020) [3].

Problems with Manual Underwriting: Smith et al. (2019) found that manual underwriting is prone to bias and inefficient [3], [8].

Approval for Lien By facilitating automated decision-making, improved fraud detection, and predictive analytics, AI and ML are transforming the approval process [1], [4], [5], [9].

Major Studies:

Deep Learning-Based Credit Risk Assessment: Findings from the research by Zhang et al. (2021) indicate that neural networks improve the accuracy of loan risk prediction [1], [5], [6], [9].

Miller et al.'s research from 2022 investigates the openness of AI-driven credit rating systems in relation to lending decisions [2], [7].

Data from Other Sources: Utility bills and social media accounts are examples of non-traditional data that, according to research, can improve credit scoring (Rahman et al., 2020)[3].

3. PROPOSED SYSTEM &ALGORITHM

This article was published in the Journal of Engineering Sciences (Volume 15, Issue 07, 2024, ISSN: 0377-9254) and aims to address the shortcomings of the current loan approval procedure in the financial services sector. Page 223, using cutting-edge AI and ML techniques, implements explainable AI (XAI) to guarantee openness and fairness. The system uses artificial intelligence algorithms to sift through a mountain of data, including that from standard sources like credit bureaus and alternative sources like social media and purchase histories, as well as more unconventional ones.

Advantages:

Predicting traffic routes has many advantages that can make transportation more efficient and convenient:

1. Reduced Congestion: Authorities can enhance traffic flow by forecasting traffic patterns and advising drivers of alternate routes before congestion begins. Delays are minimized and traffic congestion is reduced as a result.

2. Time Savings: Using effective route prediction, which takes into account the present traffic circumstances, drivers can choose the most efficient routes. Not only does this save drivers time, but it also cuts down on pollution and fuel waste caused by idling in traffic.

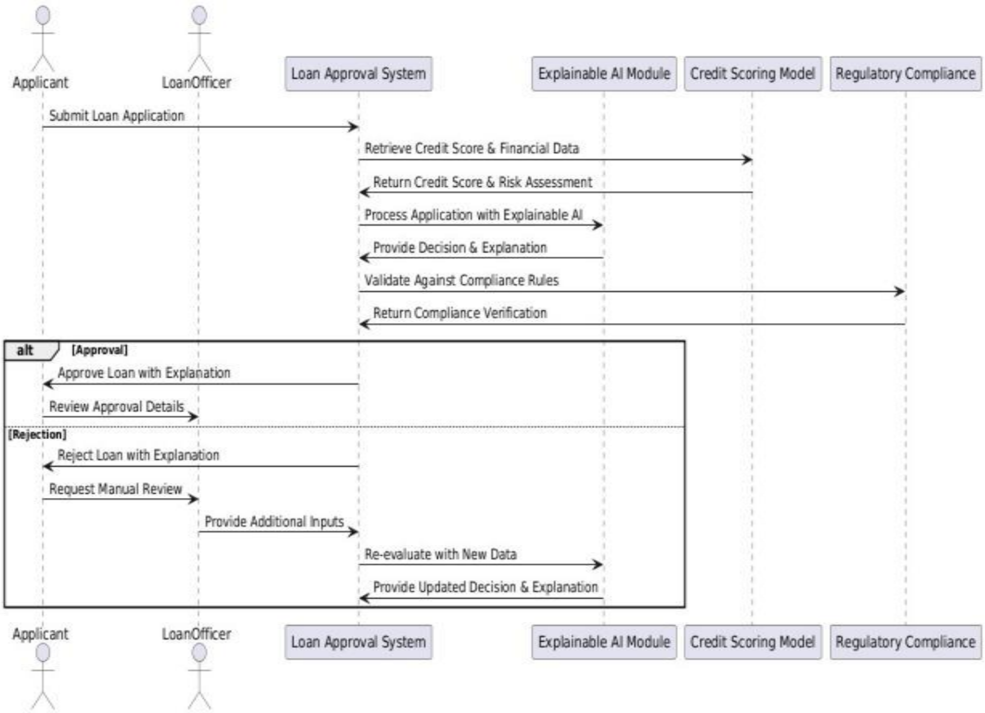
IMPLEMENTATION:

1) Upload Loan Application Dataset: With the help of this module, we can send the dataset to the app, and it will read it all. Next, we'll create a graph that displays all the class labels for loans and reject reasons.

2) Pre-process Dataset: There are missing values, non-numerical data points, and numbers in the dataset. So, to make sure the dataset is clean, the label encoder class will first transform all the data to numbers and then normalize the values.

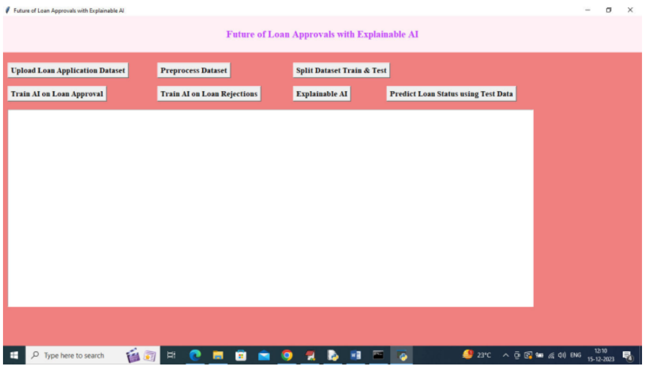
(3) Divide the Dataset into Train and Test Sets: The dataset will be partitioned into training and testing sets upon implementation of this module. In order to train, the app will use 80% of the dataset, while in testing, it will use 20%.

4. SYSTEM ARCHITECTURE

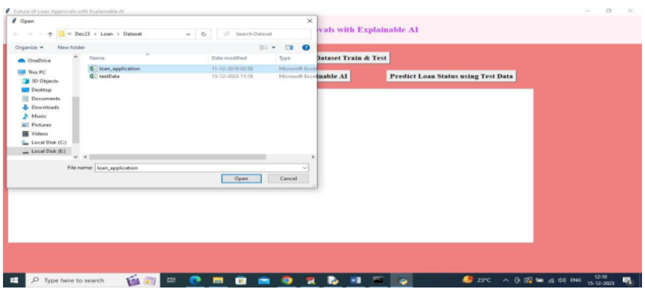


5. RESULTS

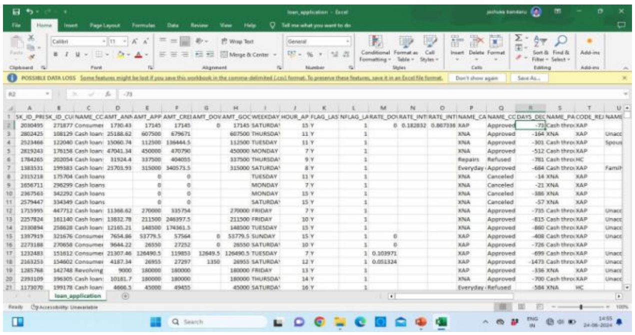
Fig(1): In Figure 1, you can see that the "run.bat" file is double-clicked to launch the project.



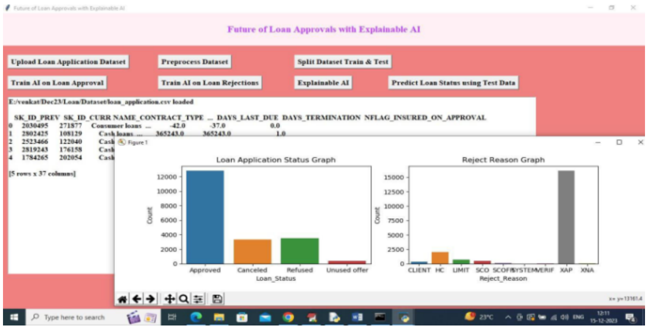
Fig(2): The "Upload Loan Application Dataset" button is where you'll want to go to send in your dataset. Below, you will see the output.



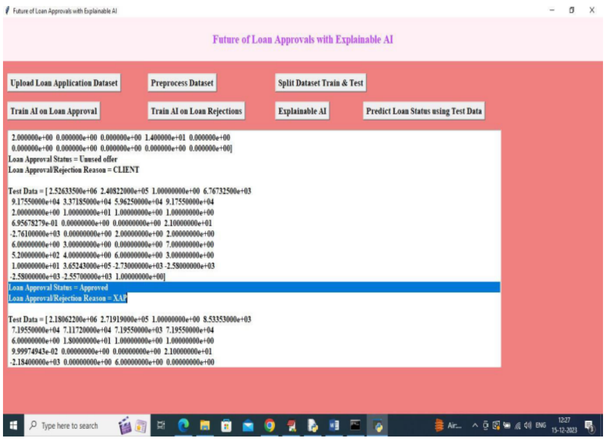
Fig(3): You can import the dataset and get the output below by selecting and uploading the "loan_application.csv" file, as shown in Figure 3. Continue by selecting the "Open" option.



Fig(4): The following screen capture from the loan application data set is explained.

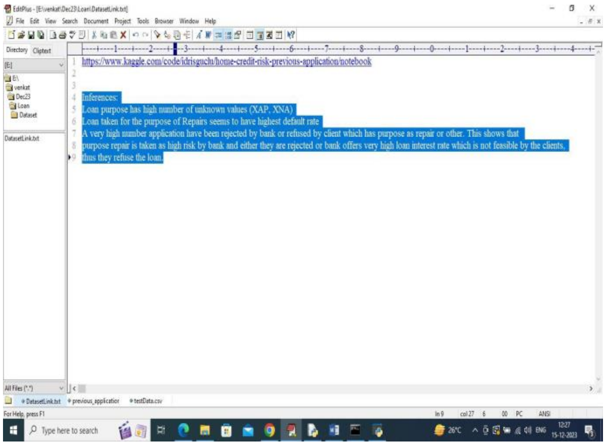


Fig(5): On the screen above, you can see the test data displayed in square brackets. Next to the test data, there is a blue-selected line that displays the loan status forecast and cause details. View Figure 5. Scroll down past the output to see all of the predictions.



Fig(6): Extra prediction output is shown on the screen up top.

For Reason Rejected code you can read below description



6. CONCLUSION

Explainable artificial intelligence decision-support system, the belief-rule-based (BRB) system was created to automate the loan underwriting procedure. This research focuses on the process of creating this document. Despite the substantial effort needed, the BRB system may include expert knowledge and learn from supervised data, in contrast to opaque blackbox models. It defines the role of attributes within active rules launched by loan application data points and promotes openness in decision-making by outlining their value. The system's capacity to strike a balance between explainability and forecast accuracy is demonstrated in a business case research. The system also generates brief explanations for judgments based on factual and heuristic norms, which increases the reliability and credibility of automated underwriting. This includes things like the denial of loan applications.

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