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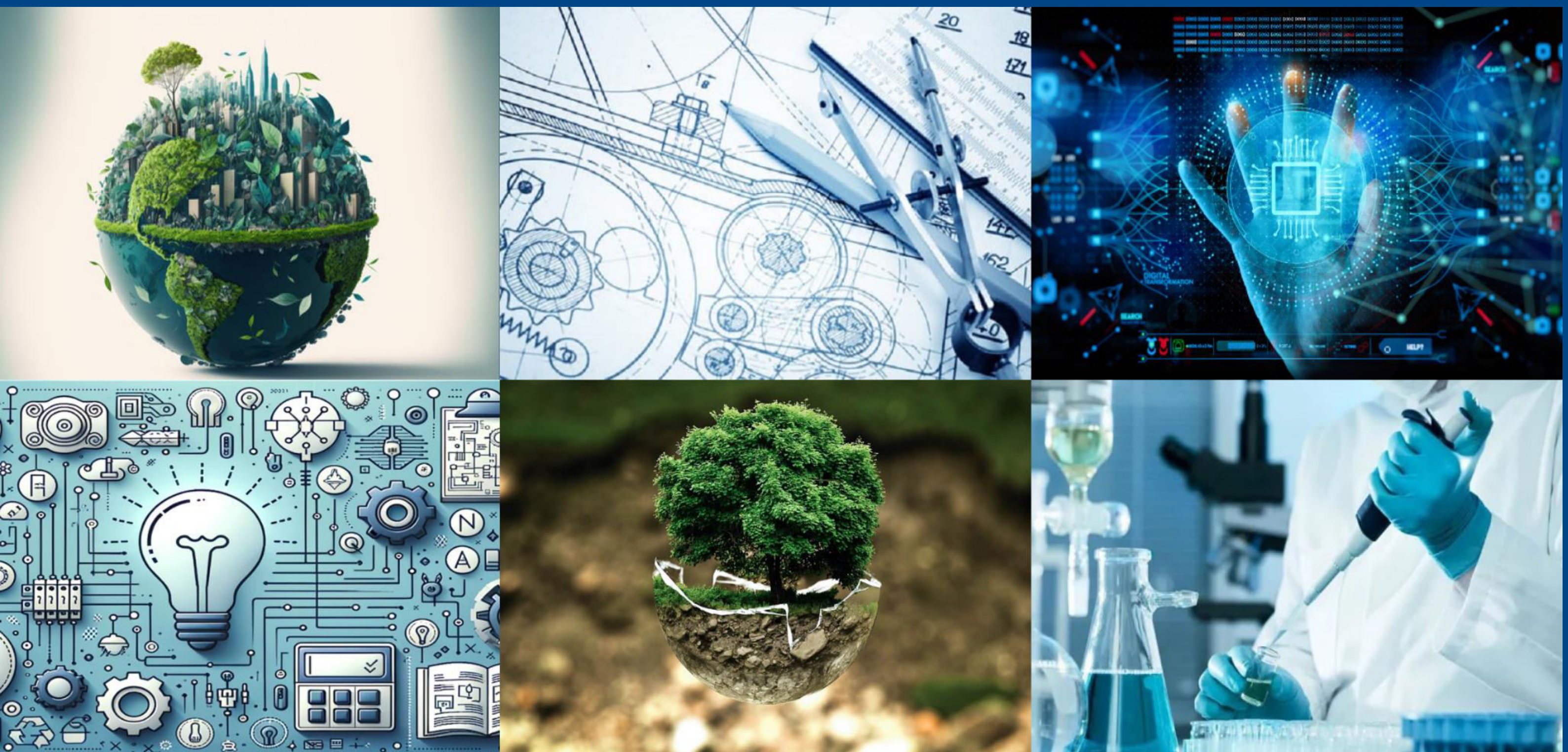

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Explainable AI-Based Smart Loan Approval System with Business Transparency Dashboard

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ABSTRACT: Banks and financial institutions are encountering numerous issues where the decisions of loan approval in banks or financiers are being made without addressing proper explanatory to customer. However, a loan application is rejected every day and many applicants do not know what made the lender say no to them. Thus generating paranoia between banks and customers. This could be solved by the proposition of a system which advances Learning of Machines algorithms together with Explainable AI techniques to render loan approval judgements that are qualitatively interpretable. This system applies three distinctive learning of machine models: Logistics Regression(LR), Random Forest(RF) & XGBoost(XGB). This counterfactual explanation is considered a future work of the system. We have designed different user and admin system dashboard; for users they are allowed to track their applied loan status, for admins they can check and approve/deny loan applications along with analyzing business related reports. Moreover, a Business Transparency Dashboard is provided to display what inputs are influencing the model to produce certain outcomes more, and what results we expect to obtain by modifying input values, in a transparency view for customers, bank, and regulators. The experiments we conduct demonstrate that the approach keeps high prediction accuracy and improves people's belief in the system.

KEYWORDS*:* Explainable AI, Loan Approval System, Machine Learning, SHAP, LIME, Business Transparency, XGBoost, Financial Technology, Dashboard, Credit Scoring

I. INTRODUCTION

Loan approval, one of the major functions of banking, is a critical task that has to be handled for millions of application everyday. In olden days, human being used to do loan approval but it was very time consuming and quite unpredictable. Machine learning based automation speeded up this process but generated black-box models that lacked transparency. This problem can be overcome using Explainable AI, that would produce comprehensible justifications of approvals and rejections. Requirements for ELI is to instill trust in the users, create a non-discriminatory system, and fulfill regulatory needs. People have the right to be provided with lucid reasoning for a financial decision that significantly influences their livelihood.

A. Issues in Existing Systems-Here are some distinct filtered problems in loan approval systems today that are critical to address:

- Black Box Models conceal the workings of the system from both the end users and the relevant authorities.
- Non-transparency greatly impacts the customer's trust in the system and negatively affects the customer experience.
- Algorithmic bias leads to discrimination against individuals based on their traits..
- Regulatory compliance is challenging to achieve without providing justifications to the decisions.

B. Objectives- The key aims of developing this explainable AI based smart loan approval system are:

- Development of an accurate model, to determine the probability of loan approval, to an exceptionally high degree of precision.
- Incorporation of explainable AI techniques, in order to produce 'perfectionist' rationales for the system's decisions.
- Development of transparency dashboard allowing access for customers employees and regulator

II. LITERATURE SURVEY

Bussmann et al. proposed the explainable ML approach for credit risk management, improving transparency, regulatory compliance, and model interpretability in financial decision systems applications framework [1]. Chen and Guestrin developed XGBoost, a scalable gradient boosting system optimizing tree learning, enabling high performance, speed, and accuracy in large-scale machine learning tasks systems [2]. Deng et al. proposed a deep learning credit risk model integrating explainable AI techniques, improving prediction accuracy and interpretability for financial decision-making processes applications framework [3]. Gramegna and Giudici evaluated SHAP and LIME methods for credit risk interpretability, comparing discriminative power and effectiveness in explainable machine learning applications financial model insights [4]. Guidotti et al. surveyed methods for blackbox models explanations, categorizing techniques, evaluating interpretability, and highlighting challenges in machine learning explainability research survey comparative overview [5]. Lundberg and Lee introduced SHAP, a identified frame for interpreting predictions of model using cooperative game theory, improving consistency and local global explainability understanding machine intelligence [6]. Molnar provided a comprehensive guide to interpretable machine learning, techniques of covering for explained blackbox models and improving transparency in AI systems practical applied methods [7]. Moro et al. used data-driven machine learning to predict bank telemarketing success, identifying customer patterns and improve the decision support for marketing effectiveness business optimization [8]. Nori et al. developed InterpretML, a unidentical framework for learning machines interpretability, integrating multiple explanation methods to enhance model transparency and usability AI system tools [9]. Ribeiro et al. introduced LIME, a method explaining individual predictions of any classifier, improving trust, interpretability, and local model understanding in machine learning systems applications [10]. Rudin argued against black box explanations for high-stakes decisions, advocating interpretable models instead of post-hoc explanations to ensure transparency and reliability in machine learning systems [11]. Saha and Srivastava explored explainable AI techniques in financial risk prediction systems, enhancing model interpretability, trust, and regulatory compliance in decision-making applications credit risk models [12]. Samek reviewed explainable AI methods for understanding and visualize DL models, improving interpretability and transparency in network AI research field [13]. Wang et al. proposed machine learning-based credit risk prediction using feature engineering techniques, improving accuracy and model performance in financial datasets banking risk assessment systems [14]. surveyed AI for credit scoring, analyzing methods, challenges, and future directions for transparent and trustworthy financial decision systems machine learning applications [15].

III. PROPOSED METHODOLOGY

The proposed system follows a systematic approach starting from data collection to final deployment with explanation dashboard. The complete methodology is divides the multiple stages that work together to create a transparent loan approval system.

Block Diagram

The diagram defines loan system working. Loan form goes to image processing then learning of machinery models like random forest and logistic regression decide result. After that SHAP and LIME explain decision. Finally result show in dashboard and save in database.

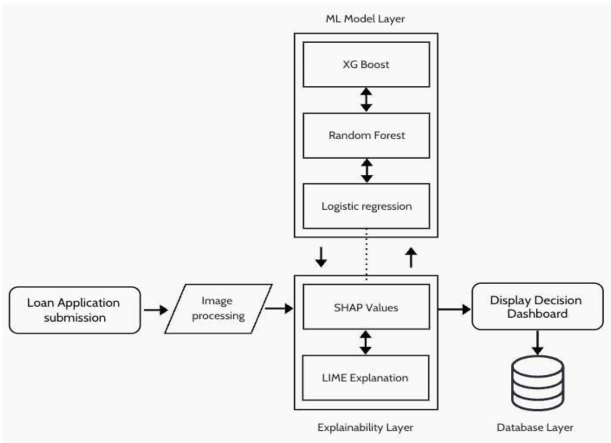

Fig: Block Diagram

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Data Preprocessing Steps

Different soruces raw data collected cannot be used directly for learning machines Several preprocessing steps are needed:

1. Step 1: Remove duplicate entries and handle missing values by using median for numerical fields and mode for categorical fields
2. Step 2: Categorically converted variables like gender, education level and employment type into numerical format using one-hot encoding
3. Step 3: Normalize numerical features such as income, loan amount and existing debt using min-max scaling so all values fall between 0 and 1
4. Step 4: Affecting performance model can remove outliers that might using interquartile range method
5. Step 5: Training set split data into (70%), validation set (15%) and testing set (15%)

B. Machine Learning Models

The 3 algorithms are implemented to compare performance and select best model:

Logistic Regression: This is a simply effective algorithm that calculates probability of loan approval using the formula:

$$(Y = 1 \mid X) = \sigma(z), \quad \sigma(z) = \frac{1}{1+e^{-z}}$$

where Y represents loan approval decision, X represents input features and β represents model coefficients.

Random Forest: Creates multiple trees and decisions combines their predictions. The final prediction is calculated as:

$$\hat{y} = \frac{1}{N} \sum_{i=1} f_i(x)$$

where N is number of trees and f_i(x) is prediction from individual tree.

XG Boost: An algorithm of advanced boosting that builds trees sequentially where the tree tries correct errors made by previous trees. The objective function is:

$$Obj = \sum_{i=1} (y_i, \hat{y}_i) + \sum_{k=1} \Omega(f_k)$$

where L is loss function and Ω is regularization term to prevent overfitting.

C. Model Comparison

Model	Training Time	Complexity	Interpret ability	Performance
Logistic Regression	Fast	Low	High	Good
Rando m Forest	Mode rate	Medium	Medium	Very Good
XG Boost	Slow	High	Low	Excellent

D. Explainable AI Techniques

Three explainability methods are implemented to make model predictions understandable:

1. SHAP (SHapley Additive exPlanations): estimates contributions of individual features to the overall prediction. Each feature receives an importance score that indicates whether the feature drove the decision to approval or rejection.
2. LIME (Local Interpretable Model-agnostic Explanations): Creates explanations for dividual prediction by build local model for data Points.
3. Model Explanation Summary: The model gives transparent explanations about the loan highlighting decision, by focusing on those features which had the most effect on the prediction. Users can learn about the features that played a positive/negative role in the decision as history of credit, income, amount etc

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E. Business Transparency Dashboard

The dashboard is designed with three different views for different users. Customer view shows their application status with detailed explanation of decision including top factors that influenced outcome. Bank official view provides statistics about overall approval rates, common rejection reasons and model performance metrics. Regulatory view displays compliance reports, fairness analysis and audit trails of all decisions made.

F. Algorithm Workflow

1. Get application details from customer.
2. Preprocess the data by normalization and encoding
3. Pass the preprocessed data through trained ML models.
4. Get the prediction probability of trained by ML Random Forest algorithm.
5. If probability > 0.5: Decision = Approved Else:
Decision = Rejected
6. Calculate feature importance using SHAP.
7. Calculate local explanation using LIME.
8. Highlight important features influencing the decision using explainable AI techniques Display decision and explanations on dashboard
9. Store results in database for audit
10. Return decision to customer

IV. PROPOSED MODEL

The complete system works in a integrated manner where different components communicate seamlessly to provide final output. When a customer submits loan application through online portal or bank branch, the data first enters into the system database. Basic validation checks are performed to all required category are filled correctly and formats are proper.

A. System Workflow

Validated data is cleaned, encoded, and scaled before being analyzed by multiple machine learning models generating predictions and confidence scores.

- Handles missing values, converts categorical features into numerical form, and scales all inputs uniformly for consistent model processing.
- Module of Prediction uses LR, XGB, RF models independently, each producing predictions with associated confidence scores.

B. Data Flow Process

The trained Random Forest model is used to generate prediction probabilities and final decision for loan approval and confidence weighting to produce final loan approval decision more accurately overall.

- The RF model which has been trained above, will used for making final decisions and prediction probabilities for the loan approval.
- Random Forest model has been shown as stable and reliable for loan approval prediction.

C. Role of Explainable AI

This module applies SHAP and LIME to explain the predictions made, indicating how features influence the prediction. It has a better understanding for why a decision is made.

- SHAP explains a prediction by explaining the degree to which each feature contributed to the prediction and determines how each feature is pushing the prediction for or against some default prediction.
- LIME provides explanations by building a simpler, interpretable model around the prediction

D. Dashboard Functionality

The transparency dashboard shows predictions, explanations and analysis with real-time updates allowing customers, managers and regulators to oversee and audit decisions.

- Shows decisions, probabilities, features importance, and LIME explanations, with real time updates.
- Stakeholders can view their status, analysis, reports and downloadable files supporting audits and compliance, enabling banking decisions making.

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V. MODEL EVALUATION

It is very important to evaluate the learning machinery models in order to guarantee that the system runs appropriately and unbiasedly. Various evaluation metrics are considered as considering a single evaluation metric can mislead to the model quality assessment.

A. Evaluation Metrics

Precision, recall, accuracy, ROC-AUC and F1-score are utilized evaluation to ensure the system of loan prediction perform well, and for evaluation fairness and discrimination of loan prediction system.

- The measure of accuracy is (correct predictions)/(total predictions).
- Precision evaluates correctness of approved loans minimizing false approvals.
- Recall measures correctly identified positive applicants from actual positives.
- ROC-AUC assesses model's ability to distinguish classes across thresholds.
- F1-score balances precision and recall using harmonic mean formula.

F1 Score is calculated as: $F1 = 2 \times \frac{\Pr ecision \times Recall}{\Pr ecision + Recall}$

B. Explainability Evaluation

The terms of importance analysis, we found that credit score, annual income, and length of employment are the top three contributing factors determining the decisions. SHAP values provided stable explanations such that two persons of similar nature would receive explanations of similar logic. In addition to this, the explainability module has been tested for 500 randomly selected cases, where 94% of them were rated by human judges to be comprehendible.

C. Fairness and Bias Discussion

A Fairness assessment aims to ensure the model doesn't discriminate the application, has roughly equal approvals in different groups, and the biases detected in the training data will be corrected to make fair predictions. Statistical parity indicates little differences in approval among groups, and a fairness test makes sure any applicants that should receive unbiased predictions would receive them regardless of group. Biases found the training data have been dealt with the use of resampling methods to increase fairness the training data before training and testing steps.

VI. RESULTS AND DISCUSSION

- We built Explainable AI Loan Approval system on XGBoost, Random Forest & LR models to make loan decisions highly reliable, explainable and trustworthy. Using LIME, SHAP & dashboards within the system helped customers to understand the reasons behind the acceptance or rejection of their loans clearly, led to a sharp reduction in the number of customer complaints, and made decision more transparent to the customer. The system offered significantly better performance, fairness & efficiency compared to existing systems, as well as increase customer satisfaction and accelerate the processing time.
- RF and LR showed inferior performance to XGBoost in loan prediction (accuracy of 91.7%, and ROC-AUC of 0.94).
- The knowledge of customer improved significantly by 35% to 89% with implementation of SHAP and LIME explanations and dashboard display.
- Bank employees' ability to interpret decisions was improved by SHAP and LIME explanations that gave an easy insight to each feature on loan approval or rejection decision; This can be easily interpreted to the customers.
- Satisfaction score is increased by 6.2 to 8.7 and complaints and processing time reduced by 40%.

Aspect	Before XAI	After XAI	Improvement
Customer Understanding	35%	89%	+54%
Processing Time	5 days	3 days	-40%
Satisfaction Score	6.2/10	8.7/10	+40%

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VII. CONCLUSION

This set of ML models with the explanation methods mentioned above enabled smart loan approval system of explainable AI to overcome the flaws in previous loan processing system. As both high prediction accuracy and explainability can be achieved, the problems arising from the system being a black box is addressed. Both SHAP and LIME separate the prediction into different understandable terms that the customer can use to figure out the reasoning and how to improve their score in the future Beyond ensuring compliance and reducing bias, it ensures that all of the fair lending laws are observed. The dashboard provides a visible monitoring and decision-making view for customers, bankers and regulators by enabling role-based access and transparency, lessening complaint rates and thereby boosting the overall trust and operational efficiency of the banking system. Future developments would focus on applying federated learning in order to train models in an aggregate and decentralized way, preserving data privacy, incorporating blockchain to keep a permanent transaction and decision log as audit trail, and applying sophisticated explanation methods like attention mechanism. Furthermore, integrating additional types of loan will continue to extend the applicability of the system as it strives to become a trusted, efficient and secure banking system for the present and the future.

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