



Explainable AI Based Credit Risk Prediction for Loan Approval using CIBIL Score

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Abstract

Everyday bank gives loan to many people. Many people pay the loan whereas there are many people who don't pay the loan. So, it is very difficult for bank to understand whom to give the loan. Because they don't know the borrower. They don't know which borrower will be able to pay the loan and which will not. Machine learning can be an alternative for this process but the main problem is that machine learning uses the advanced algorithm which is 'black box'. The main problem is that black box only answers the "yes" or "no". Black box does not give the explanation of why it has rejected or approved the loan

In this project, we tried to solve this problem. We made a credit risk predictor which uses cibil score (we used the loan grade as a cibil score) and also used many financial features. We tested four different types of models in our dataset Logistic Regression, Decision Tree, Random Forest, and XGBoost. In our testing process XGBoost gave the best results.

After that we used a tool called SHAP (SHapley Additive Explanations) to understand why this model was giving the best result. SHAP showed us that there are three most reasons that decide whether to give the person the loan or not, Person Income, Loan Grade and Loan Percent Income are the three most important reasons. This system helps the bank to trust why this model is helpful for the banks and it also helps the customers because it tells them why their loan was approved or rejected.

Keywords: Credit Risk Assessment, Loan Approval Prediction, Machine Learning, Explainable AI (XAI), SHAP, CIBIL Score, Financial Risk Prediction, Loan Default Prediction.

1. Introduction

Giving loan is always a risky business for banks because bank does not have a guarantee that their money will be returned or not. But banks are very important for our economy because they do this job. If they make a mistake, they get bad loans and lose money. In past years bank officers checked the loan application manually. They looked at salary, job history and past record. But this old way is very slow. It also depends completely on the personal choice of the officer. Sometimes two same people get different result just because different officer checked their file and one gets the loan approved and other one gets their loan rejected.

In simple words credit risk checking tries to answer only one question. The question is can this person pay the loan back or not. If the bank makes a wrong decision and gives loan to bad customer then it becomes bad loan which is called non-performing asset (NPA). This decreases the profit of the bank. If the bank

makes another wrong decision and rejects a good customer then the customer goes to another bank and the first bank loses its good customer. Balancing these two things is a very big challenge for the banks today.

From many years this checking is done manually by the bank employee. A bank officer looks at the income, job, past loan, credit record, loan amount and interest rate. Then he decides to approve or reject the loan. Joining ML with XAI has many clear advantages over manual checking. Automated system can check thousands of application very fast a. Manual checking depends on subjective decision making so the correct result is not guaranteed . With SHAP the contribution of each feature is clearly visible It is also a very slow process. It does not work good when bank has to check thousands of application everyday.

From all the things which bank checks CIBIL score is the most important sign. It shows if the person is trustworthy or not. Good CIBIL means the customer pays the EMI and loan amount on time. It is basically a summary of the past financial behaviour of the person. If someone has high CIBIL score it means they paid past money on time. Such people get loan very fast and at low interest rate. If someone has low score it means they missed payment or defaulted in past. They are very risky. Because of this CIBIL score has become the biggest factor today to decide if loan will be approved or rejected.

Checking loans manually with old methods has many limits and it looks too much time. Financial data has many hidden connections which we cannot see just by looking because it is hidden internally. There are many different factors for approval and rejection which depends upon different type of factors. Things like income, job length, loan amount and credit record are connected to each other. A simple manual check can miss these connections and this could result in bad result by system. Also nowadays digital banking is growing very fast. The number of applicants are increasing day by day. If banks use manual checking today then it will take too much time and it is very slow process. To solve this problem banks need a system which can check large data very fast and gives the results correctly.

In the last few years Machine Learning (ML) has been used in almost all the sectors for the prediction and early assessments [1]. ML programs read old financial records and find the hidden connections. A human takes too much time to do this. ML predicts if the person will pay the loan or not. It does not use fixed rules. It learns directly from the data. This makes the prediction very consistent and accurate. It makes the loan approval automatic for the bank. It also reduces the time very much. This is also very helpful for the customers because they get the loan very fast.

Some ML algorithms are already very helpful for credit risk checking. Logistic Regression is famous because it is simple. It works very good when the answer is only yes or no. Decision Tree works just like how a human thinks step by step. So it is very easy for us to understand. Random Forest combines many trees together to make the prediction very strong. It also stops the overfitting problem. XGBoost goes one step ahead. It uses gradient boosting where the model fixes its own mistake when it is training. Every model has its own strength. So it is very important to compare all of them before we choose the best one.

But getting better accuracy also brings a new problem every time. Many advanced models give very correct prediction but they never explain how they got the answer. We call this the black box problem. This system only says approve or reject and gives the answer in yes and no and does not give any explanation. It does

not tell which financial reason is responsible for this decision. In banking this is a very big problem. It creates question on the fairness. Because a loan decision affects the life of the person. If a bank rejects a person then he wants to know the exact reason. Bank also needs to prove that their computer decision is fair and correct.

To solve this problem Explainable Artificial Intelligence (XAI) is very popular nowadays. XAI tries to make the ML models very open and clear. It attaches a proper explanation with every final answer. It tells which input pushed the model to take that decision. This helps the bank and officer to see how different financial values are affecting the loan decision. It gives a way to check that model is working properly and not giving random numbers.

The most famous XAI method is SHAP. SHAP calculates how much every input feature added to the final prediction. It gives an importance value to every financial detail. SHAP shows exactly which value is pushing the decision to approve or reject means on what basis it is making the decision of approval or rejection of loan. Features like loan grade, income, job length and interest rate can be checked easily. We can see how much each feature is pulling the result. This detail helps the banks to explain the loan decision very clearly. It builds more trust in the automated system of customer and banks.

This project builds an Explainable Artificial Intelligence based credit risk prediction system for approval or rejection of loan. It uses CIBIL score and other financial factors which are important. We use four algorithms Logistic Regression, Decision Tree, Random Forest and XGBoost to sort the risky applicant and good applicant. We compare all four using standard measurements. Then the best model is chosen for the final prediction which one to be used for the prediction. After that SHAP is applied on this best model to explain every single prediction. It shows the contribution of every financial feature. The final result is a complete system which gives correct prediction and clear explanation of approval or rejection. This helps in taking better lending decision.

The main goal of this project is to help the banks and financial companies and also the customer . It makes the loan approval process very fast, consistent and reliable. By joining ML with XAI the system does not only say that person is risky or not. It also explains why he is risky and why the loan has been rejected. This openness is very important to build trust in automated lending system. It helps to use AI in a responsible way in the banking sector. In the end this project proves that joining accurate ML models with explainable methods is very good. It makes credit risk checking system fast and clearer while making the correct loan decision.

2. Background Study

Loan approval is the main thing for banks because banks give money for different things like education loan, home loan or business loan and many other loans. Before giving the loan bank has to be sure that the customer will pay the money back in time. If the checking is wrong and bank gives money to risky customer then the bank will face loss. So checking the credit risk is very important job for the bank. In the old days the bank employee checked all the papers manually. They checked the salary slip, bank statement and past loan record to make a decision. This method is working from many years but it takes

too much time and it is not perfect. Two different officer can take two different decision for the same customer depending on their own experience.

The CIBIL score is very important for checking the loan. CIBIL score is between 300 to 900. If the score is higher then the customer is good because in past he has paid all the dues on time and thus he has good score and he gets the loan fast with low interest rate. If the score is low then the customer is risky because he had not paid the dues on time and bank rejects the loan. Bank trusts this score very much because it is a summary of past repayment behaviour of the customer and it is the main factor of loan approval or rejection. But the old method has some problems. Many good customer don't have the past credit history like students or first time borrower. They are able to pay the loan but because they don't have past record bank rejects them. This is not fair for the good customer.

Nowadays digital banking is growing very fast. Bank gets thousands of application everyday. Manual checking is not possible now because it takes too much time. Because of this problem banks are using Machine learning now. Machine learning algorithm learns from old data and predict if the customer is good or bad. Models like Logistic Regression, Decision tree, Random Forest and XGBoost are used because they give good accuracy. ML reduces the manual work and gives fast decision.

But ML model has the black box problem. The model gives the high accuracy but it does not tell why it accepted or rejected the loan. Customer wants to know why his loan is rejected and banks also need to understand their own model.

To solve this problem Explainable AI (XAI) is used. SHAP is the most used method in XAI. SHAP tells which feature is most important for the prediction. So this project uses ML and XAI together to make the loan process faster and easier.

3. Literature Review

Many research are done in the last ten years about credit risk prediction and loan approval system. These studies gives very useful background for our project which we are trying to solve.

Lessmann et al. (2015) Lessmann and his team did a very detailed comparison study [2]. They tested 41 different classification algorithms to check which model is best to predict if customer will pay the money or default. They tested Logistic Regression, Decision Tree, Random Forest and other models. They found that gradient boosting model gives the highest accuracy on most datasets. But the problem was they only focused on accuracy and they did not explain why the model took the decision. This is a big gap because explanation is the most important part of loan why it is accepted or rejected.

Dastile et al. (2020) Dastile and his team read about hundreds of studies about credit scoring and financial risk [3]. They compared old statistical method with new ML algorithms like Random Forest and Neural Networks. They found that machine learning win because they can easily pick the patterns in the financial data of customer. Their main point was that ML is very important for modern bank because it reduces the manual work and speeds up the decision. But they also warned that accuracy alone is not enough for today's world , it should be something more. Bank also needs system which is reliable and easy to understand

Bussmann et al. (2021) Bussmann and his team focused on explainable machine learning for credit risk. They used XGBoost with SHAP analysis to see how different financial feature affect the loan prediction. They found that we can keep high prediction accuracy and also explain every decision of the model [4]. Their conclusion was that explainable AI is very important in finance. Banks need to know why customer is marked risky and they should not use black box model in banking.

Lundberg and Lee (2017) introduced the SHAP method. Now it is the most used XAI method to explain ML models [5]. The main job of SHAP is to measure how much each input feature added to the final prediction. This paper became very famous because it solved the biggest problem of AI which is understanding how complex model reach their answer. In loan approval SHAP explains exactly why application was accepted or rejected.

Nallakuruppan et al. (2024) and his team studied credit risk using XAI for bank decision system. They joined ML model with explainable method to improve performance and clarity together. Their model correctly sorted the risky and good borrowers based on financial history [6]. The explainable layer clearly showed which feature was driving the decision most. Their main point was that bank needs both accuracy and interpretability because decision maker will not trust automated system if they don't understand it.

Berg et al. (2020) and his team looked at a different angle. They explored alternative financial data and digital footprint for credit scoring [7]. Old method uses past loan history but many customer don't have past history. They showed that digital behaviour and online activity can also tell if customer is good or bad by checking their records of past. This is very useful for first time borrower who don't have formal credit record yet.

Kozodoi et al. (2022) with his team studied fairness and transparency in ML model. They checked if these algorithms are creating bias in bank decisions without anyone noticing. They found that complex model can sometimes do bias against some people without meaning to and this creates trust problem in lending. They said bank system should be clear and free from unfair bias and every customer should be treated equally [8]. Our project is not checking fairness directly but this is a good reminder for why responsible AI is important in banking sector.

All these research papers show very clearly that the ML algorithms which are in used are working great for the credit risk prediction and the loan approval. Models like Random Forest and XGBoost always perform much better than the old statistical methods [9]. But at the same time only accuracy is not everything for the modern bank systems they need something more. Being explainable and understanding how the model works and takes the decision is also very important. Our project is also built on this same idea. We are joining the ML credit risk prediction with XAI methods. We are also checking how the CIBIL score details help to take the automated loan approval decisions in the modern banking.

4. Research Gap

In many past research the main focus is only on the accuracy of the prediction model. They don't give attention to explain the reason behind their decision. Another problem is that old loan approval system

depends very much on the past financial record. So the customer who don't have credit history face big problem to get the loan.

Also the advanced ML models have the black box problem with them. SHAP can solve this problem but very few study bring loan approval prediction, credit risk, cibil score analysis and explainable AI together in one complete system. This is the exact gap which we are trying to solve in this project.

5. System Architecture

Figure 1 shows the complete system architecture of our project. It is divided into five layers Input, Preprocessing, Model Training, Evaluation and Output layer.

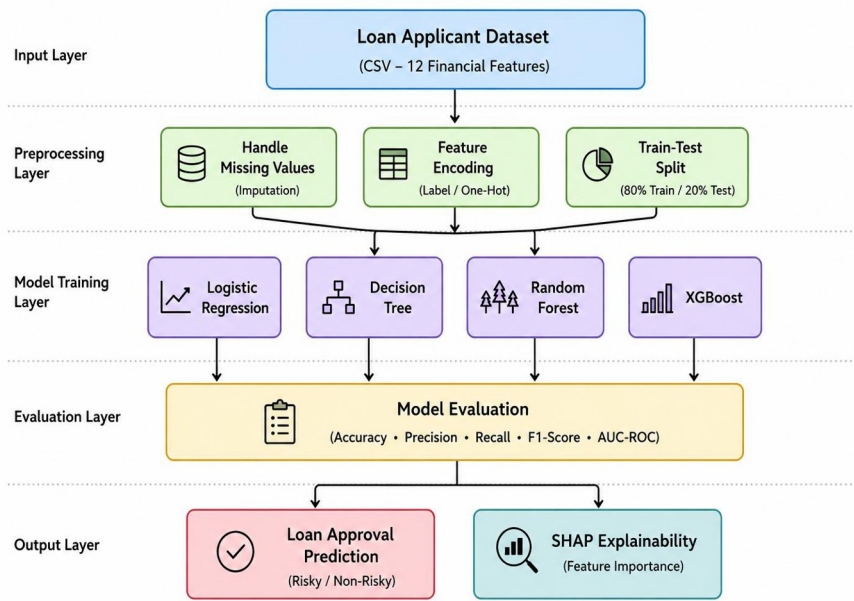


Figure 1: System Architecture of the Proposed Model

6. Methodology

The methodology of this project follows a clear set of steps, shown in Figure 2.

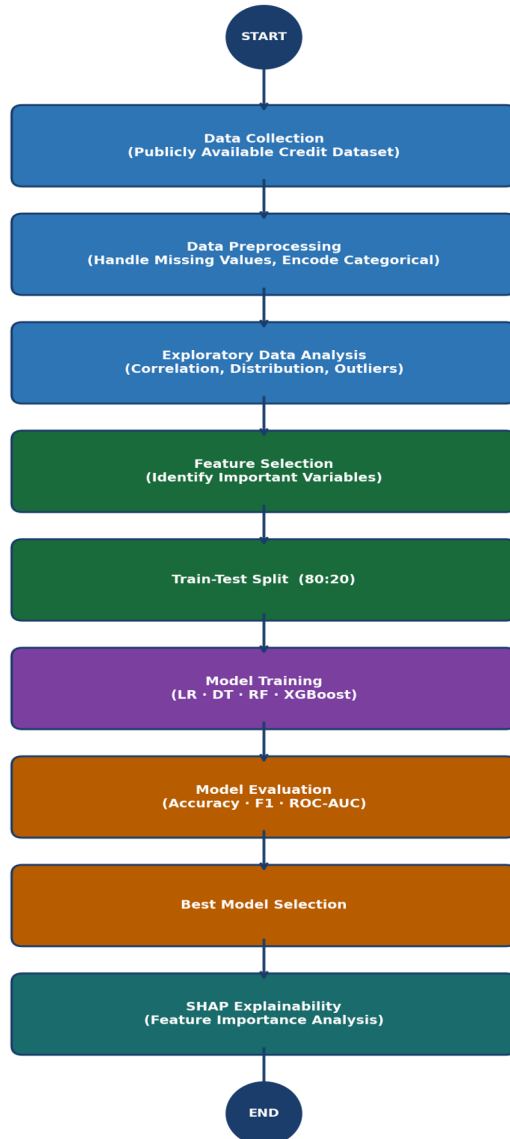


Figure 2 Step-by-Step Methodology Followed in This Project

First of all, the researcher collects the data from a public credit risk dataset. Then, the researchers will do pre-processing to handle the missing values and change the text features into numbers using Label Encoding

and One-Hot Encoding. After that we do Exploratory Data Analysis (EDA) to understand how the data is spread and how different features are related to each other. We also check if there are any outliers hiding in the data.

Then we choose the right features and split the data in 80% for training and 20% for testing . We train four models and compare them using performance measurements. Then the best model is chosen and we calculate SHAP values on it to explain which feature is most important for the prediction . We did all this coding work in Python. We used standard tools like scikit-learn for building the models and we used the SHAP library for the explanation.

Machine Learning Algorithms Used

Machine learning is the main part of this project to study the financial data of applicant and predict the risk. Different algorithm learns patterns from old data in different way. So, we compared four very famous algorithms here Logistic Regression, Decision Tree, Random Forest and XGBoost [10].

We run all four models together so we can compare their accuracy and check their strength and weakness. Then we choose the best model for credit risk prediction. Each model is explained below.

6.1 Logistic Regression

Logistic Regression is very simple and famous algorithm. We use this when the answer is in two groups like Yes or No and Risky or Non-Risky it only has two options. In this project it separates the risky applicant from the good applicant who will pay the loan. It calculates the probability between 0 and 1 using the sigmoid function. Sigmoid function is basically a math formula which makes an S-shape curve. It takes any big or small number and converts it into a value exactly between 0 and 1. If this value is more than 0.5 then the model puts the applicant in the risky group. If the value is less than 0.5 then it puts the applicant in the safe group it basically divides and then check if above 0.5 then good, if below 0.5 then bad. It is very popular because it is simple and fast to run. But it struggles when the data is very complex. It is a good baseline to compare our other models.

6.2 Decision Tree

Decision tree is a supervised algorithm which learns from labelled data. It splits the data in small groups using some condition. These are called branches and the final answer is at the leaf node. For credit risk it groups the applicant by income , loan amount and past default. Each branch checks a condition to see if applicant is financially risky. Its biggest advantage is that it is very easy to understand. The tree looks exactly like human thinking step by step. But the problem is that it can overfit the training data very easily if we don't adjust it. Then it will not work good on new data.

6.3 Random Forest

Random forest uses ensemble learning. It does not rely on one single tree. It makes many trees and combine their output by majority voting to give the final prediction. The idea is that combining many weak tree gives a very strong and stable result. In credit scoring it captures the relation between many financial variables. It performs better than simple model and it stops the overfitting problem of decision tree. It also handles number and text data very well. That is why it is used very much in banking and financial risk.

6.4 XGBoost

XGBoost full form is Extreme Gradient Boosting. It is very strong algorithm for prediction [10]. It uses boosting method. In boosting a chain of weak models are trained and each model fixes the mistake of the previous model. It keeps improving the accuracy step by step in training. It handles large dataset very easily. This is the reason it is used very much in ML competition. In our project we expect XGBoost to perform better than Logistic Regression, Decision tree and Random Forest. Because financial data has complex connection and boosting algorithm is very good to find them.

6.5 Comparison of Algorithms

Every algorithm has some good point and bad point. Logistic Regression is simple and fast but it struggles with complex pattern. Decision tree is easy to read but it overfit easily. Random forest improves the stability by combining many trees and stops overfitting. XGBoost is the best because it fixes its own mistake during training and works very well on large dataset it basically works on itself. We compare all four models side by side to see which one performs best and giving the best result. We use different factors like Accuracy, Precision, Recall, F1 Score and ROC-AUC for checking the results. Then the winning model is chosen for the final prediction and we apply SHAP on it to explain the decision because this method was the winning method.

7. Dataset Acquisition

The dataset has 12 different financial features which describe every applicant what type of applicant they are and where they stand financially. The main columns which we use in this project are shown in Table 1 below. The dataset has 28,634 loan applicants records for these 12 features. It covers personal details, loan information, job history and past credit behaviour. Each feature helps the model to understand the financial condition of applicant and decide if they are risky or good for approval. Each feature is explained below.

7.1. Person Age (person_age)

This tells the age of the applicant in years. We check this because it tells us how mature the person is and what is their earning power will the person will be able to pay or not. A young applicant will have less job experience. An old applicant will have a settled financial background. Both these things change the repayment capacity of the loan.

7.2. Person Income (person_income)

This is the total yearly income of the applicant. It is the strongest sign to check the financial condition because a high income means the person has a good ability to pay back the loan. The bank always compares this income with the loan amount. Because a low-income person will not be able to pay a very big loan on time.

Table 1: Dataset Feature Description

S. No.	Feature Name	Description
1	person_age	Age of the loan applicant in years. Used to check maturity and earning potential.
2	person_income	Yearly income of the applicant. Higher income means better ability to repay.
3	person_home_ownership	Housing status (OWN / MORTGAGE / RENT). Shows financial stability.
4	person_emp_length	Number of years the applicant has been employed. Longer time means more stable income.
5	loan_intent	Purpose of the loan: Personal, Education, Medical, Business, or Home Improvement.
6	loan_grade	Grades A-G showing creditworthiness. Used as a CIBIL Score stand-in in this project.
7	loan_amnt	Amount of money requested. Higher amount means higher lending risk.
8	loan_int_rate	Interest rate charged on the loan. Higher rate is often given to riskier applicants.
9	loan_status	Target column: whether applicant is financially risky (1) or non-risky (0).
10	loan_percent_income	Percentage of yearly income taken up by the loan amount.
11	cb_person_default_on_file	Past default history: Y = defaulted before, N = no default history.
12	cb_person_cred_hist_length	Length of credit history in years. Longer history means easier evaluation by banks.

7.3. Person Home Ownership (person_home_ownership)

This shows the housing status of the applicant. It can be OWN, MORTGAGE or RENT. If a person owns a house it shows they have more financial stability than a person who is renting because if someone had the money then firstly he will built his house and mortgage will firstly pay the loan of his house and will free his house. The bank uses this to check the long-term financial position of the customer.

7.4. Person Employment Length (person_emp_length)

This tells the number of years the applicant is working in their current job. Having a long and stable job means the person gets a regular income and the person is working regularly or not because if the customer is having a permanent job means he is stable enough to repay the loan. This helps the bank to easily decide if the applicant is risky or safe for lending.

7.5. Loan Intent (loan_intent)

This is the main reason for taking the loan, for what purpose the customer wants the loan. It can be Personal, Education, Medical or Business. Every different reason has a different risk level for the bank. For example a business loan is much more risky than an education loan. So the bank checks this reason carefully before giving the money.

7.6. Loan Grade (loan_grade)

This is the loan grade which goes from A to G. Getting Grade A means the customer has low risk and Grade G means they have high risk basically grade A are higher category and G are lower category. In our project we are using this feature as the CIBIL score. Both this grade and the CIBIL score measure how safely the applicant will repay the money to the bank because a good CIBIL represents the customer paid all the previous dues on time that's why customer's cibil is good.

7.7. Loan Amount (loan_amnt)

This is the total money requested by the loan applicant, how much money customer is asking for and for what purpose. Asking for a big amount has more risk for the bank because the repayment burden will be very high and risky whether the customer will be able to pay or not. The bank always checks this amount with the income and past history before doing the approval.

7.8. Loan Interest Rate (loan_int_rate)

This is the interest rate given on the loan CIBIL also helps in lower interest rate as a good cibil person will be given loan on low interest . A risky applicant always gets a higher interest rate from the bank. So we can say that the interest rate shows how much the bank trusts the applicant to pay back the money to the bank.

7.9. Loan Status (loan_status)

This is the target variable which our machine learning model will finally predict. It tells if the applicant is financially risky or not risky. The model learns from all the other 11 features to predict this final answer.

7.10. Loan Percent Income (loan_percent_income)

This shows the loan amount as a percentage of the yearly income of the person. A high percentage means a very big part of their income will go into the loan repayment. This naturally increases the risk for the bank.

7.11. Credit Default History (cb_person_default_on_file)

This shows if the applicant has defaulted in the past or not. Y means yes and N means no. Having a past default is a very big warning sign for the bank that banks should reject the loan. It means they have a history of poor repayment. Because of this the bank becomes very careful before giving any new loan to such applicant as there are very high chances of no repayment .

7.12. Credit History Length (cb_person_cred_hist_length)

This shows how many years of credit history the applicant has on record. Long history gives more information to bank and checking becomes very easy. Short history has more uncertainty for the bank.

8. CIBIL Score and Loan Grade Analysis

In our dataset we don't have the direct CIBIL score column. But we have the loan_grade feature and it works exactly like the CIBIL score to check if customer is good or bad. The grades are from A to G. Grade

A means the customer is very safe and we are assuming it is equal to high CIBIL score of 800 and can be given loan. Grade G means the customer is very risky and we are assuming it is equal to low CIBIL score of 500 and bank should avoid giving loan to that person. We are only doing a guess mapping here so that we can easily understand the risk level of the customer whether bank should approve or reject the loan. Figure 3 shows how the loan grade is connected to the credit risk level.

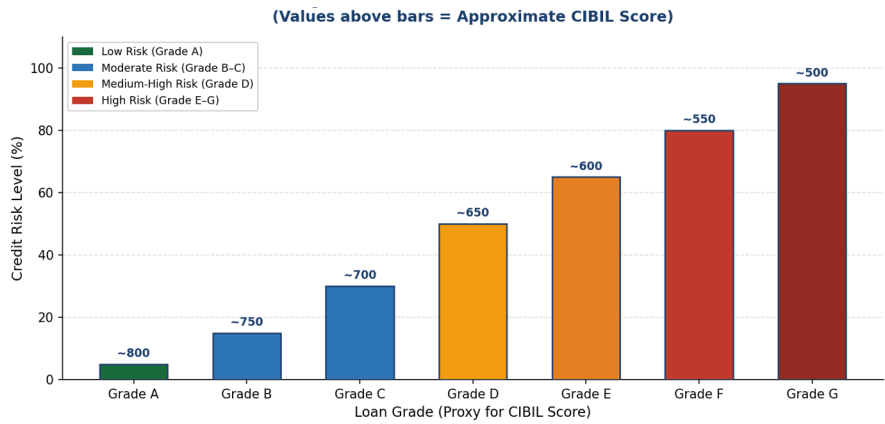


Figure 3: Loan Grade vs. Credit Risk Level (CIBIL Score Proxy Analysis)

As we can see in Figure 3 the Grade A applicants who have CIBIL around 800 are at the lowest risk. Their risk is very low close to 5%. On the other side the Grade G applicants who have CIBIL around 500 are at the highest risk. Their risk is very high close to 95%. This clearly shows that the CIBIL score and loan grade are very important. Both of them carry a lot of weight when bank makes the loan approval decision. If the grade is good bank gives loan and if grade is bad bank rejects the loan.

9. Explainable AI — SHAP Analysis

We use SHAP in this project to understand which feature is most important for the loan approval prediction. Figure 4 shows the SHAP feature importance values from our best model which is XGBoost. It basically shows the average absolute SHAP value for every feature in the dataset.

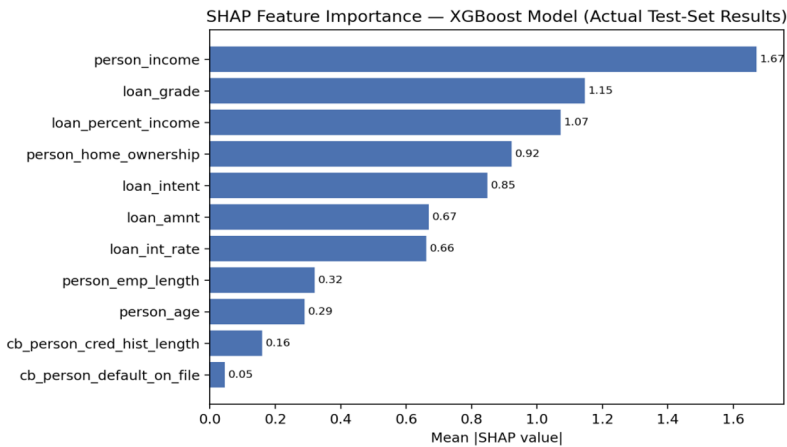


Figure 4: SHAP Feature Importance — XGBoost Model

In the graph we can see that Person Income comes on the top because it is the toppest priority. It has a mean absolute SHAP value of 1.67. This shows that the income of the applicant is the strongest predictor of credit risk in our model. After that Loan Grade which is our CIBIL score proxy is on the second number with 1.15 score. This confirms that loan grade is still at the most important predictors of credit risk. Then Loan Percent Income is on the third number with 1.07 score. Other features like Home Ownership, Loan Intent, Loan Amount and Interest Rate come after these and they have less influence on the final result. These SHAP values are very helpful because they give the banks a solid reason to explain the customer exactly why a particular loan was approved or rejected by the system.

10. Model Performance Comparison

In our project we trained and tested all four types of models. The models which we tested are Logistic Regression, Decision Tree, Random Forest and XGBoost. Figure 5 shows the performance comparison of all these models which we tested.

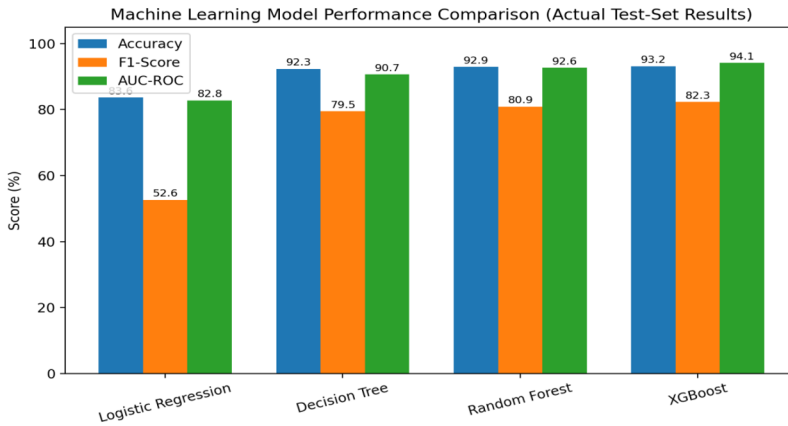


Figure 5: Machine Learning Model Performance Comparison

After checking all the models XGBoost comes on the top. It gives 93.17% Accuracy, 82.35% F1-Score and 94.13% AUC-ROC. Random Forest is on the second number and it is very close with 92.91% Accuracy and 92.65% AUC-ROC. Decision Tree is in the middle and it manages a moderate 92.33% Accuracy. Logistic Regression is at the last and it sits at a baseline of 83.62% Accuracy. Because XGBoost gives the highest numbers in all checking we choose XGBoost model for the final loan approval prediction.

11. Conclusion

This project was started to build an Explainable AI based credit risk prediction system for loan approval. We joined machine learning algorithms with CIBIL score and other financial details of the customer. Our main goal is to give the banks and financial companies a good way to make loan decisions. The decision should be accurate, transparent and reliable. It should be based on the proper reading of the financial condition of the applicant. It is fast and is helpful for both customer and bank as customer gets their loan fast and bank can process the next application of loan

Credit risk assessment is very important for modern banking. Banks need to feel confident that the borrower will pay the money back in the given time. If bank makes a mistake and checking goes wrong then the result is bad loans and financial loss. This increases the non-performing assets of the bank. So a smart computer system which can reliably separate the risky applicants from the non-risky applicants is very useful for the bank.

Our system uses many financial details to work properly. It uses income, employment history, loan amount, interest rate, loan grade, past default and credit history length. Every feature gives a small piece of the financial picture of the applicant. We don't depend only on the manual checking done by the bank officer. We use ML to go through the old data and pick the hidden patterns of the data. This sorts the applicants by

risk level. It speeds up the checking process very much and cuts down the manual work of the bank officer and the customer gets the loan faster as can work on the purpose.

To make this system we run four classification models Logistic Regression, Decision Tree, Random Forest and XGBoost. Every model brings something different. Logistic Regression gives a simple baseline. Decision Tree gives an easy structure just like human thinking. Random Forest improves the reliability by joining many trees and stops the overfitting. XGBoost pushes the performance to the maximum by learning from its own mistakes and finding complex relation between variables. Comparing all four models helped us to choose the best model which is XGBoost.

The most important part of this project is joining Explainable AI with ML to get the best result. Advanced ML models give very correct answers but they work like a black box. They only say yes or no. They never tell the reason behind their answer. In banking this is a very big problem. Bank and customer both need to know why a loan was approved or rejected. If there is no explanation then the customer will lose trust in the computer decision.

SHAP solves this black box problem very easily. It tells exactly how much every input reason changed the final answer. It gives a proper explanation for approval and rejection. Our system does not stop at just giving the prediction. It also shows which financial reason was the most important for the result. This clear answer helps the bank to understand their model. It makes the bank trust the automatic credit checking. Adding the explanation with the prediction makes this system very responsible and clear.

The result of our experiment shows that all financial features do not have equal weight every features has its own value. Person Income is the single most important factor for the loan decision. Loan Grade which is CIBIL score comes right after that as the second most important factor. Better grade means low risk and high chance of loan approval. Loan Percent Income comes right after that. They also play a big role to check the repayment ability. Financial institutions should look at these three factors very carefully.

Joining ML with XAI has many clear advantages over manual checking, which is not everytime correct. Automated system can check thousands of applications very fast and keep the decision consistent at a time. Manual checking depends on the mood of the officer so it is not guaranteed if he is in bad mood he will rejected, it totally depends on the officer not the bank if the officer want to give the loan then he will everything depends on the officer and this is very unfair for the customer. With SHAP the contribution of each feature is clearly visible. This mix type of high accuracy and clear explanation makes this system very practical for real world banking use.

There is also a trust factor here for the customers. When customer gets a clear explanation for why their loan was rejected, they can accept it easily because they think if the reason is given by the system that means it is correct reason of approval or rejection. They will know where they need to improve financially so that their loan can be accepted by system. Bank also gets benefit because decision maker can check that the model is working logically and not doing any bias and also helping them in saving the time. In the end this project proves that joining ML with Explainable AI is a very good way to solve credit risk problem because it does not only give the answer in yes or no and it has a feature of explanation. It helps banks to

lend money faster, accurately and more openly while keeping the risk very low. Explainability should be a core part of all future intelligent banking systems.

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