K.L.N. COLLEGE OF INFORMATION TECHNOLOGY

POTTAPALAYAM

DEPARTMENT

OF

COMPUTER SCIENCE AND ENGINEERING

SUB.CODE : HX 8001

PROFESSIONAL READINESS FOR INNOVATION, EMPLOYABILITY AND ENTREPRENEURSHIP

PROJECT REPORT

TEAM ID: PNT2022TMID52482

"SMART LENDER - APPLICANT CREDIBILITY PREDICTION FOR LOAN APPROVAL"

SUBMITTED BY,

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GITHUB LINK :-

https://github.com/IBM-EPBL/IBM-Project-17376-1659637497

VIDEO LINK :-

https://drive.google.com/file/d/12Urm7aJmXM4w-yz5JDtUa0eqY2CkRFvt/view?usp=sharing

1. INTRODUCTION

As the data are increasing daily due to digitization in the banking sector, people want to apply for loans through the internet. Artificial intelligence (AI), as a typical method for information investigation, has gotten more consideration increasingly. Individuals of various businesses are utilizing AI calculations to take care of the issues dependent on their industry information. Banks are facing a significant problem in the approval of the loan. Daily there are so many applications that are challenging to manage by the bank employees, and also the chances of some mistakes are high. Most banks earn profit from the loan, but it is risky to choose deserving customers from the number of applications. One mistake can make a massive loss to a bank. Loan distribution is the primary business of almost every bank. This project aims to provide a loan [1, 8] to a deserving applicant out of all applicants. An efficient and non-biased system that reduces the bank's time employs checking every applicant on a priority basis. The bank authorities complete all other customer's other formalities on time, which positively impacts the customers. The best part is that it is efficient for both banks and applicants. This system allows jumping on particular applications that deserve to be https://forms.gle/XLLutHr3c49szVBr6a aproved on a priority basis. There are some features for the prediction like, Gender, Married, Dependents, Education, Self-employed, ApplicantIncome, CoapplicantIncome, LoanAmount, Loan_Amount_Term, Credit_History, Property Area, Loan_Status. Loans have made our life easier, providing us the financial leverage that extends beyond our earnings. Be it Credit Card, Home Loan, Personal Loan or Auto Loan etc. loans are the credit extended to us by lenders on fulfilling certain key parameters. However, getting a loan in India can often be a tedious process for the un-initiated, but not for individuals with a good credit score. Whenever you apply for a loan, banks check your CIBIL Score and Report to evaluate your credit history and credit worthiness. The higher your score the better are the chances of your loan application getting approved.

a) Project Overview

Banks are making major part of profits through loans. Though lot of people are applying for loans. It’s hard to select the genuine applicant, who will repay the loan. While doing the process manually, lot of misconception may happen to select the genuine applicant. Therefore we are developing loan prediction system using machine learning, so the system automatically selects the eligible candidates. This is helpful to both bank staff and applicant. The time period for the sanction of loan will be drastically reduced. In this paper we are predicting the loan data by using some machine learning algorithms that is Decision Tree.

b) **Purpose**

Loan prediction analysis uses specific parameters about a loan application to determine whether or not the loan should get approved. Approved loans usually have a good credit history, decent applicant income, and reliability in other factors.

2. LITERATURE SURVEY

A recent development of machine learning techniques and data mining has led to an interest of implementing these techniques in various fields. The banking sector is no exclusion and the increasing requirements towards financial institutions to have robust risk management has led to an interest of developing current methods of risk estimation. Potentially, the implementation of machine learning techniques could lead to better quantification of the financial risks that banks are exposed to. Within the credit risk area, there has been a continuous development of the Basel accords, which provides frameworks for supervisory standards and risk management techniques as a guideline for banks to manage and quantify their risks. From Basel II, two approaches are presented for quantifying the minimum capital requirement such as the standardized approach and the internal ratings based approach (IRB) . There are different risk measures banks consider in order to estimate the potential loss they may carry in future. One of these measures is the expected loss (EL) a bank would carry in case of a defaulted customer.

One of the components involved in ELestimation is the probability if a certain customer will default or not. Customers in default means that they did not meet their contractual obligations and potentially might not be able to repay their loans . Thus, there is an interest of acquiring a model that can predict defaulted customers. A technique that is widely used for estimating the probability of client default is Logistic Regression . In this thesis, a set of machine learning methods will be investigated and studied in order to test if they can challenge the traditionally applied techniques. A prediction is a statement about what someone thinks will happen in the future. People make predictions all the time. Some are very serious and are based on scientific calculations, but many are just guesses. Prediction helps us in many things to guess what will happen after some time or after a year or after ten years. Predictive analytics is a branch of advanced analytics that uses many techniques from data mining, statistics, modeling, machine learning, and artificial intelligence to analyze current data to make predictions. "Adyan Nur Alfiyatin, Hilman Taufiq and their friends work on the house price prediction. They use regression analysis and Particle Swarm Optimization (PSO) to predict house price". One other similar work on the Mohamed El Mohadab, Belaid Bouikhalene and Said Safi to predict the rank for scientific research paper using supervised learning. Kumar Arun, Garg Ishan and Kaur Sanmeet work on bank loan prediction on how to bank approve a loan. They proposed a model with the help of SVM and Neural networks like machine learning algorithms. This literature review helps us carry out our work and propose a reliable bank loan prediction model. Manjeet et al (2018) there are seven types of variables that may influence consumer loan default; consumer’s annual income, debt-income ratio, occupation, home ownership, work duration and whether or not consumer possesses a saving/checking account. In a work by Steenackers and Goovaerts, the key factors that may influence loan default are borrower’s age, location, resident/work duration, owner of phone, monthly income, loan duration, whether or not applicant works in a public sector, house ownership and loan numbers. Another study by Ali Bangher pour on a large dataset within the period of 2001-2006 indicated that loan age was the most important factor when predicting loan default while market loan-to-value was the most effective factor for mortgage loan applications. In addition to identifying factors that may influence loaned fault, there is also a need to build robust and effective machine learning models that can help capture important patterns in credit data. The choice of model so great importance as the chosen model plays a crucial role in determining accuracy, precision and efficiency of a prediction system. Numerous models have been used for loan default prediction and although there is no one optimal model, some models definitely do better than others. In 2019, Vimala and Sharmili proposed a loan prediction model using and Support Vector Machines(SVM)methods. Naïve Bayes, an independent speculation approach, encompasses probability theory regarding the data classification. On the other hand, SVM uses statistical learning model for classification of predictions. Dataset from UCI repository with 21 attributes was adopted to evaluate the proposed method. Experimentations concluded that, rather than individual performances of classifiers (NB and SVM), the integration of NB and SVM resulted in an efficient classification of loan prediction. In 2019, Jency, Sumathi and Shiva Sri proposed an Exploratory Data Analysis(EDA) regarding the loan prediction procedure based on the client‘s nature and their requirements. The major factors concentrated during the data analysis were annual income versus loan purpose, customer‘s trust, loan tenure versus delinquent months, loan tenure versus credit category, loan tenure versus number of years in the current job, and chances for loan repayment versus the house ownership. Finally, the outcome of the present work was to infer the constraints on the customer who are applying for the loan followed by the prediction regarding the repayment. Further, results showed that, the customers were interested more on availing short-tenure loans rather than longtenure loans. In 2019, Supriya, Pavani, Saisushma, Vimala Kumari and Vikas presented a ML based loan prediction model. Themodulesin the present approach were data collection and pre-processing, applying the ML models, training followed by testing the data. During the preprocessing stage, the detection and removal of outliers and imputation removal processing were carried out. In the present method, SVM, DT, KNN and gradient boosting models were employed to predict the possibilities of current status regarding the loan approval process. The conventional 80:20 rule was adopted to split the dataset into training and testing processes. Experimentation concluded that, DT has significantly higher loan prediction accuracy than the other models. In 2017, Goyal and Kaur presented a loan prediction model using several Machine Learning (ML) algorithms. The dataset with features, namely, gender, marital status, education, number of dependents, employment status, income, co applicant‘s income, loan amount, loan tenure, credit history, existing loan status, and property area, are used for determining the loan eligibility regarding the loan sanctioning process. Various ML models adopted in the present method includes, Linear model, Decision Tree (DT), Neural Network (NN), Random Forest (RF), SVM, Extreme learning machines, Model tree, Multivariate Adaptive Regression Splines, Bagged Cart Model, NB and TGA. When evaluated these models using Environment in five runs, TGA resulted in better loan forecasting performance than the other methods. In 2016, Aboobyda Jafar Hamid and Tarig Mohammed Ahmed presented a loan risk prediction model based on the data mining techniques, such as Decision Tree (J48), Naïve Bayes (NB) and BayseNet approaches. The procedure followed was training set preparation, building the model, Applying the model and finally. Evaluating the accuracy. This approach was implemented using Weka Tool and considered a dataset with eight attributes, namely, gender, job, age, credit amount, credit history, purpose, housing, and class. Evaluating these models on the dataset, experimental results concluded that, J48 based loan prediction approach resulted in better accuracy than the other methods. In 2016, Kacheria, Shivakumar, Sawkar and Gupta suggested a loan sanctioning prediction procedure based on NB approach integrated with K-Nearest

Neighbor (KNN) and binning algorithms. The seven parameters considered were income, age, profession, existing loan with its tenure, amount and approval status. The sub-processes include, Preprocessing (handling the missing values with KNN and data refinement using binning algorithm), Classification using NB approach and Updating the dataset frequently results in appropriate improvement in the loan prediction process. Experimentation put-forth the conclusion that, integration of KNN and binning algorithm with NB resulted in improved prediction of loan sanctioning process. In 2016, Goyal and Kaur suggested an ensemble technique based loan prediction procedure for the customers. The sub processes in the present method includes, data collection, filtering the data, feature extraction, applying the model, and finally analysis the results. The various loan prediction procedures implemented in the present method were Random Forest (RF), SVM and Tree model with Genetic Algorithm (TGA). The parameters considered for evaluating the models were accuracy, Gini Coefficient, Area Under Curve (AUC), Receiver Operating Curve (ROC), Kolmogorov - Smirnov (KS) Chart, Minimum Cost - Weighted Error Rate, Minimum Error Rate, and K-Fold Cross Validation parameters. Experimentation outcome concluded that the integration of three methods (RF, SVM and TGA) resulted in improved loan - prediction results rather than individual method 's prediction. In 2006, Sudhamathy suggested a risk analysis method in sanctioning a loan for the customers using R package. The various modules include data selection, pre-processing, feature extraction and selection, building the model, prediction followed by the evaluation. The dataset used for evaluation in this method was adopted from UCI repository. To fine tune the prediction accuracy, the pre-processing operation includes the following sub-processes: detection, ranking and removal of outliers, removal of imputation, and balancing of dataset by proportional bifurcation regarding testing and training process. Further, feature selection process improves the prediction accuracy. When evaluated, the DT model resulted in 94.3% prediction accuracy. The process of analyzing data from different perspectives and extracting useful knowledge from it. Tithe core of knowledge discovery process. The various steps involved in extracting knowledge from raw data. Different data mining techniques include classification, clustering, association rule mining, prediction and sequential patterns, neural networks, regression etc. Classification is the most commonly applied data mining technique, which employs a set of pre-classified examples to develop a model that can classify the population of records at large. Fraud detection and credit risk applications are particularly well suited to classification technique. This approach frequently employs Decision tree based classification Algorithm. In classification, a training set is used to build the model as the classifier which can classify the data items into its appropriate classes. A test set is used to validate the model.

TITLE 1: Improving Information Quality in Loan Approval Processes for Fair Lending and Fair Pricing

AUTHOR: M. Cary Collins

YEAR: 2013

DESCRIPTION:

Bank data management on loan approval processes has great room for improvements of information quality and data problems prevention especially with regards to fair lending and fair pricing practices. They first reviewed briefly typical data collection protocols deployed at many financial institutions for loan approval and loan pricing. Federal regulations mandate portions of these data protocols. While discussing the data capture and analysis for fair lending, they illustrated some initial key steps currently needed for improving information quality to all parties involved.

TITLE 2: Loan Credibility Prediction System Based on Decision Tree Algorithm

AUTHOR: Sivasree M S, Rekha Sunny T

YEAR: 2015

DESCRIPTION:

Data mining techniques are becoming very popular nowadays because of the wide availability of huge quantity of data and the need for transforming such data into knowledge. Data mining techniques are implemented in various domains such as retail industry, biological data analysis, intrusion detection, telecommunication industry and other scientific applications. Techniques of data mining are also be used in the banking industry which help them compete in the market well equipped. In this paper, they introduced a prediction model for the bankers that will help them predict the credible customers who have applied for a loan. Decision Tree Algorithm is being applied to predict the attributes relevant for credibility. A prototype of the model has been described in this paper which can be used by the organizations for making the right decisions to approve or reject the loan request from the customers.

TITLE 3: Loan Approval Prediction based on Machine Learning Approach

AUTHOR: Kumar Arun, Garg Ishan, Kaur Sanmeet

YEAR: 2016

DESCRIPTION:

With the enhancement in the banking sector, lots of people apply for bank loans but the bank has its limited assets which it grants to only limited people , so finding out to whom the loan can be granted is a typical process for the banks. So, in this paper , they tried to reduce this risk by selecting the safe person so as to save lots of bank efforts and assets. It was done by mining the previous records of the people to whom the loan was granted before and on the basis of these records the machine was trained using the machine learning model which gave the most accurate result. The main goal of this paper is to predict if loan assignment to a specific person will be safe or not. This paper has into four sections (i) Collection of data (ii) Comparing the machine learning models on collected data (iii) Training the system on most promising model (iv) Testing the system.

a) Existing problem

- ✓ Anomaly detection relies on individuals' behaviour profiling and works by detecting any deviation from the norm. When it is used for online banking fraud detection, it suffers from three disadvantages. First, for an individual, the historical behaviour data are often too limited for profiling his/her behaviour pattern. Second, because of the heterogeneous nature of transaction data, there is no uniform treatment to various attribute values, which will become a potential barrier for development of the model and for further usage. Third, the transaction data are highly skewed, and it becomes a challenge for utilizing the label information effectively. Anomaly detection often suffers from poor generalization ability and a very high false alarm rate. We argue that individuals' limited historical data for behaviour profiling and fraud data's highly skewed nature could account for this defect. Since it is straightforward to use information from other similar individuals, similarity measurement itself becomes a great challenge due to heterogeneous nature of attribute values.
- ✓ Bank employees check the details of applicant manually and give the loan to eligible applicant. Checking the details of all

applicants takes lot of time. The artificial neural network model for predict the credit risk of a bank. The Feed- forward back propagation neural network is used to forecast the credit default. The method in which two or more classifiers are combined together to produce a ensemble model for the better prediction. They used the bagging and boosting techniques and then used random forest technique. The process of classifiers is to improve the performance of the data and it gives better efficiency. In this work, the authors describe various ensemble techniques for binary classification and also for multi class classification. The new technique that is described by the authors for ensemble is COB which gives effective performance of classification but it also compromised with noise and outlier data of classification. Finally they concluded that the ensemble based algorithm improves the results for training data set.

b) References

[1] Arun Kumar, Ishan Garg, and Sanmeer Kaur, \"Loan Approval Prediction Using Machine Learning Approach,\" 2018.

[2] K. Hanumantha Rao, G. Srinivas, A. Damodhar, and M. Vikas Krishna at International Journal of Computer Science and Telecommunications published an article titled \"Implementation

of Anomaly Detection Technique Using Machine Learning Algorithms\" (Volume2, Issue3, June 2011).

[3] G. Arutjothi and C. Senthamarai, \"Prediction of loan status in commercial banks using machine learning classifier,\" International Conference on Intelligent Sustainable Systems (ICISS), 2017.

[4] \"AzureML based analysis and prediction of loan applicants creditworthy,\" by Alshouiliy K, Alghamdi A, and Agrawal D P I n 2020, Third International conference on information and computer technologies.

[5] \"Developing prediction model of loan risk in banks using data mining Machine Learning and Applications,\" Hamid A J and Ahmed T M, 2016.

[6] M. Li, A. Mickel, and S. Taylor \"Should this loan be approved or denied?\" published a paper in the Journal of Statistics Education in 2018.

[7] A. Vinayagamoorthy, M. Somasundaram, and C. Sankar, \"Impact of Personal Loans Offered by Banks and Non-Banking Financial Companies in Coimbatore City,\" 2012.

[8] M. Cary Collins, Ph.D., and Frank M. Guess, Ph.D., MIT\'s Information Quality Conference, 2000, \"Improving information quality in loan approval processes for fair lending and fair pricing.\"

[9] Arun Kumar, Ishan Garg, and Sanmeet Kaur, \"Loan approval prediction based on machine learning approach,\" National Conference on Recent Trends in Computer Science and Information Technology, 2016.

[10] Sivasree M S and Rekha Sunny T, \"Loan Credibility Prediction System Using Decision Tree Algorithm,\" International Journal of Engineering Research & Technology (IJERT), Vol. 4 Issue 09, September-2015.

[11] https://machinelearningmastery.com/random-forest-ensembles-with-xgboost/

[12] https://towardsdatascience.com/predict-loan-eligibility-using-machine-learning-models-7a14ef904057

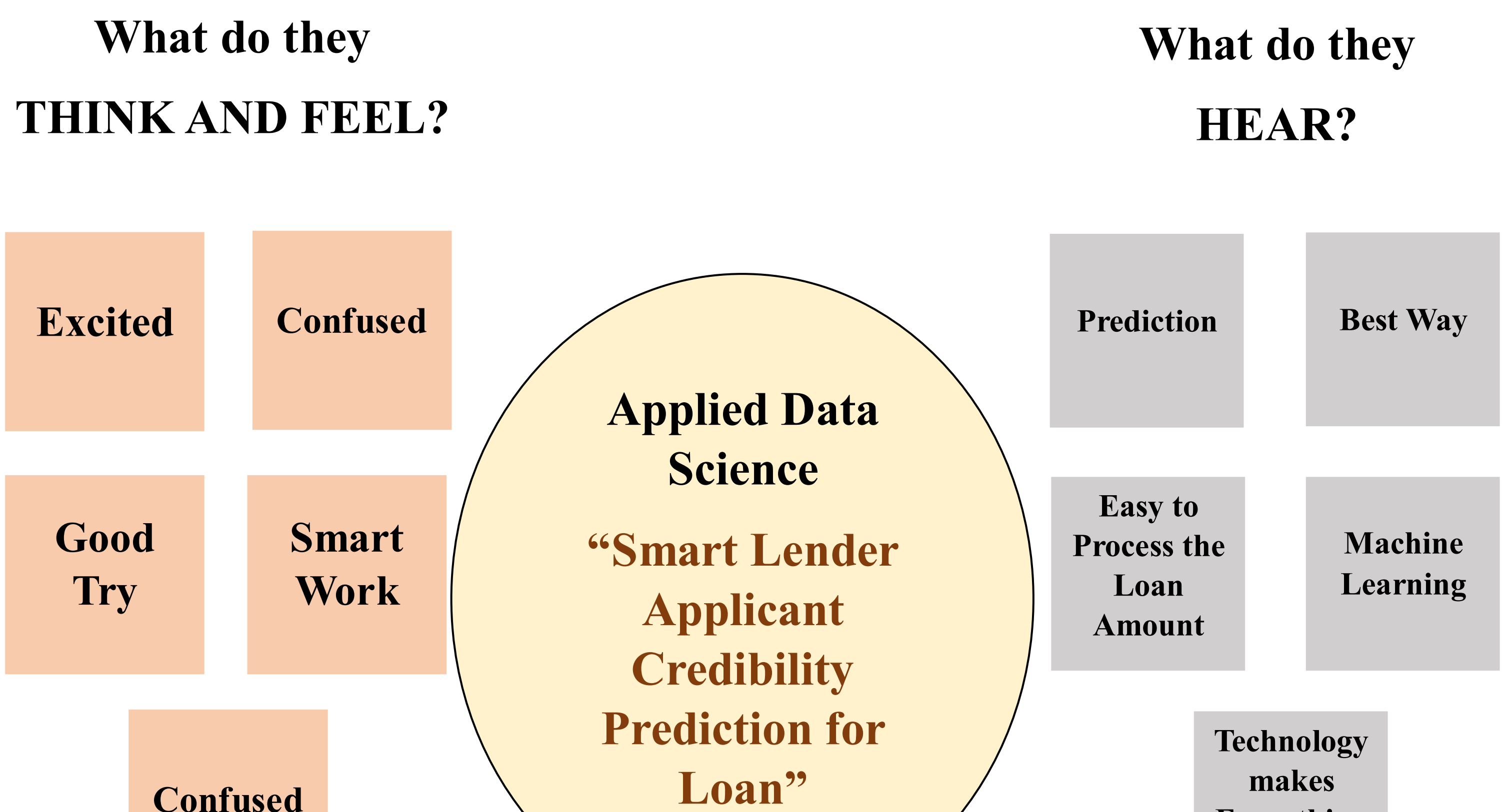
[13] https://machinelearningmastery.com/roc-curves-and-precision-recall-curves-for-classification-in-python

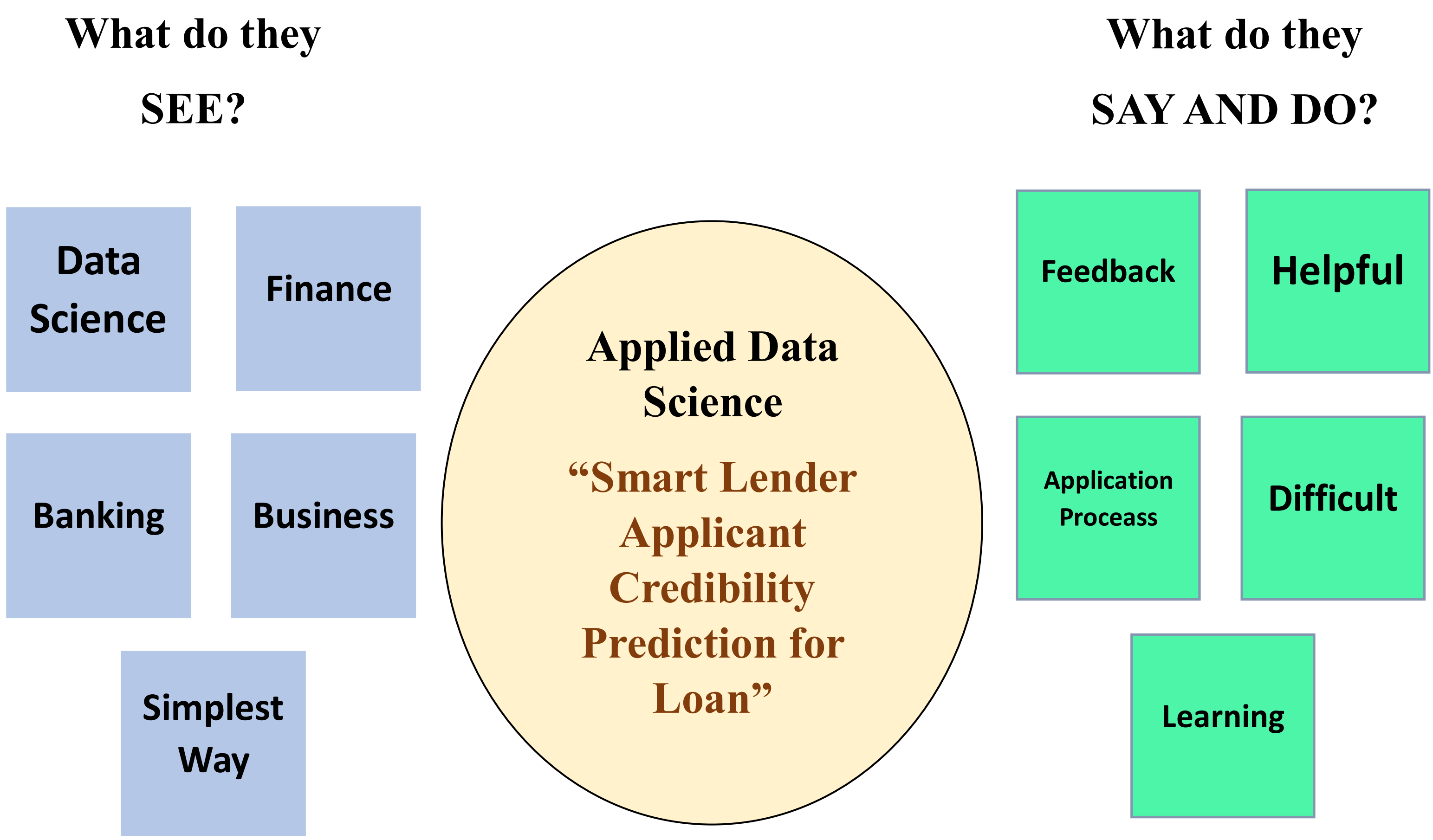
c) Problem Statement Definition

Dream Housing Finance company deals in all home loans. They have a presence across all urban, semi-urban and rural areas. Customers first apply for a home loan after that company validates the customer's eligibility for a loan. The company wants to automate the loan eligibility process (real-time) based on customer detail provided while filling out the online application form. These details are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History, and others. To automate this process, they have given a problem to identify the customer segments, that are eligible for loan amounts so that they can specifically target these customers.

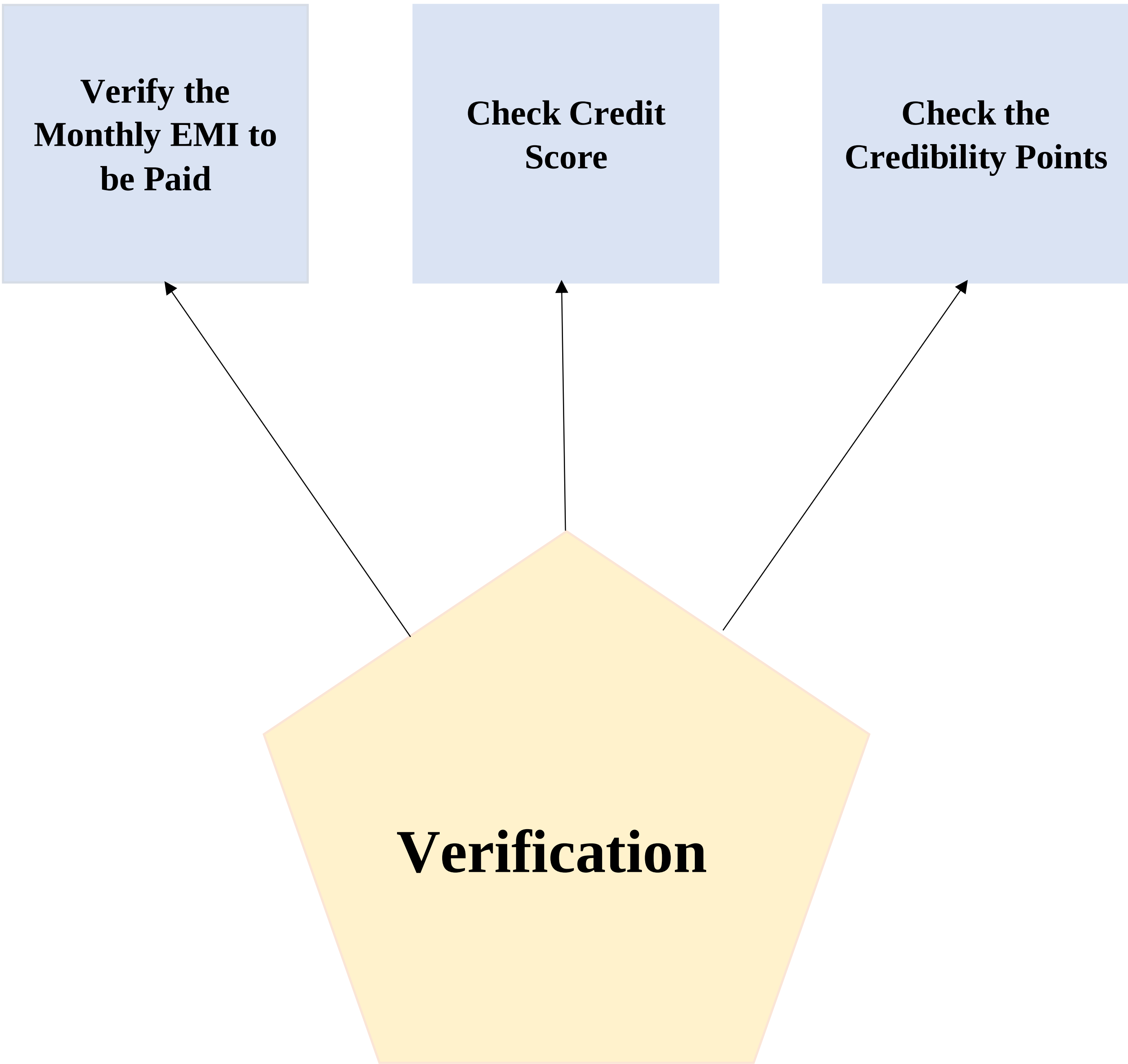
3. IDEATION & PROPOSED SOLUTION

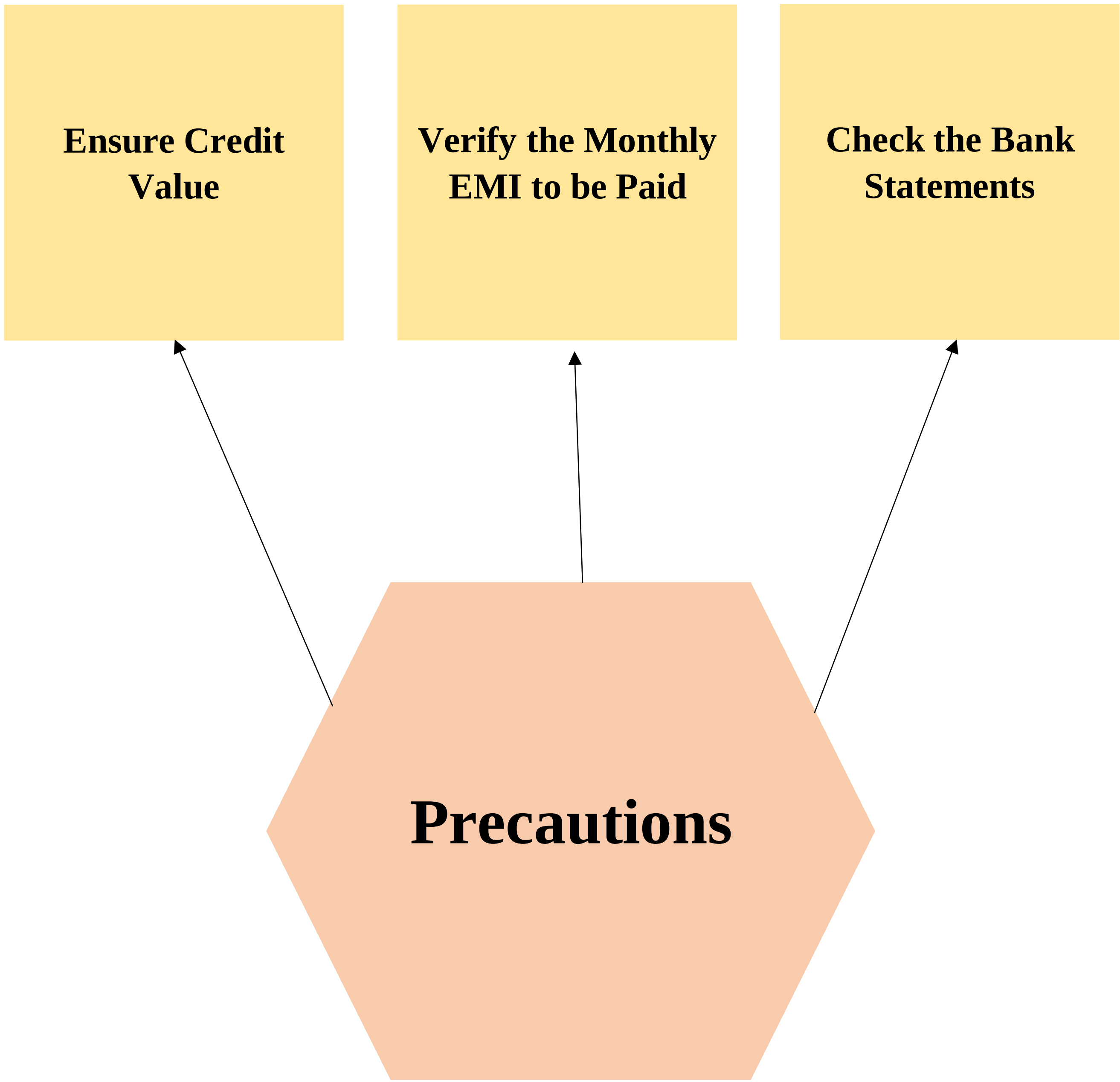
a) Empathy Map Canvas




What do they SEE?
Data Science
Finance
Banking
Business
Simplest Way
Applied Data Science
“Smart Lender Applicant Credibility Prediction for Loan”
What do they SAY AND DO?
Feedback
Helpful
Application Proceass
Difficult
Learning

b) Ideation & Brainstorming





Ensure Credit Value
Verify the Monthly EMI to be Paid
Check the Bank Statements
Precautions

Brainstorming:

JEYANANDHI J

Get the Monthly Income

Check the Bank Statements

User Must Verify the Bank

Compare with Other Banks

Verify the Income Certificate

Check Credit Score

Verify the Monthly EMI to be Paid

Try to avoid Penalties

Make Appropriate Loan Suggestions

Check the Mortage Value

Consider Your needs and choose your Loan Amount

Check the Credibility Points

SIVARANJANI K		BRINDHA S	
Average Interest Bearing Liabilities	Check the Loan Range	Check user bank credit history	Create eligible credit scores
Avoid falling for gimmicky offers and plans	Improving Client Experience	Add as many banks as possible	Provide Customer Care support to improve user experience
Acceptable EMI	Cross-Selling Complexities	Provide every banks loan Process Information	Add Banks Interest Comparison Features

SIVANI K

Simplicity of Application Process	Verify the Time taken for Loan Disposal
Have the documents on stand by	Foreclosure Possibilities
Ensure Credit Value	Project Loan growth Curve

c) Proposed Solution

1.	Problem Statement (Problem to be solved)	Howard is a businessman. He wants to build his own house. He doesn't have enough savings to build a house so he needs a personal loan from the bank. He wants to know whether his credit is enough to get his loan approved.
2.	Idea / Solution Description	Users can get knowledge about the loan process from the app and also apply for loans from the App itself.
3.	Novelty / Uniqueness	An automated customer support system will help the user and guide them through the loan approval process.
4.	Social Impact / Customer Satisfaction	Customers can use the Loan amount to improve their business which in turn impacts the economy of the country.
5.	Business Model (Revenue Model)	Can monetize features like viewing multiple banks or applying for multiple banks or we can also have subscriptions once we hit a certain user rate.
6.	Scalability of the Solution	his will provide access to people across the country to approach the banks, and also helps users in remote locations to access the bank's loan approval process.

d) Problem Solution fit

What is the Issue?	**People who need loan.**
What is the issue?	**People want to check whether they are eligible for loan.**
When does the issue occurs?	**When a person needs extra money to achieve their goal.**
Where is the issue occurring?	**Lack of knowledge about loan and credits.**
Why is it important that we fix the problem?	**By solving this issue, we can make the process for getting the loan easy.**

4. REQUIREMENT ANALYSIS

a) Functional requirement

FR No.	Functional Requirement (Epic)	Sub Requirement (Story / Sub-Task)
FR-1	User Registration	Registration through Bank Website Registration through Gmail Registration through mobile Application
FR-2	User Confirmation	Confirmation via Email Confirmation via OTP
FR-2	Loan type	Personal Loan Education Loan
FR-4	User Details	Name, Address, Income, Occupation.
FR-5	Assets Proof	Name, Address, Income, Occupation.
FR-6	Verification	Verification of user Details which are provided above.

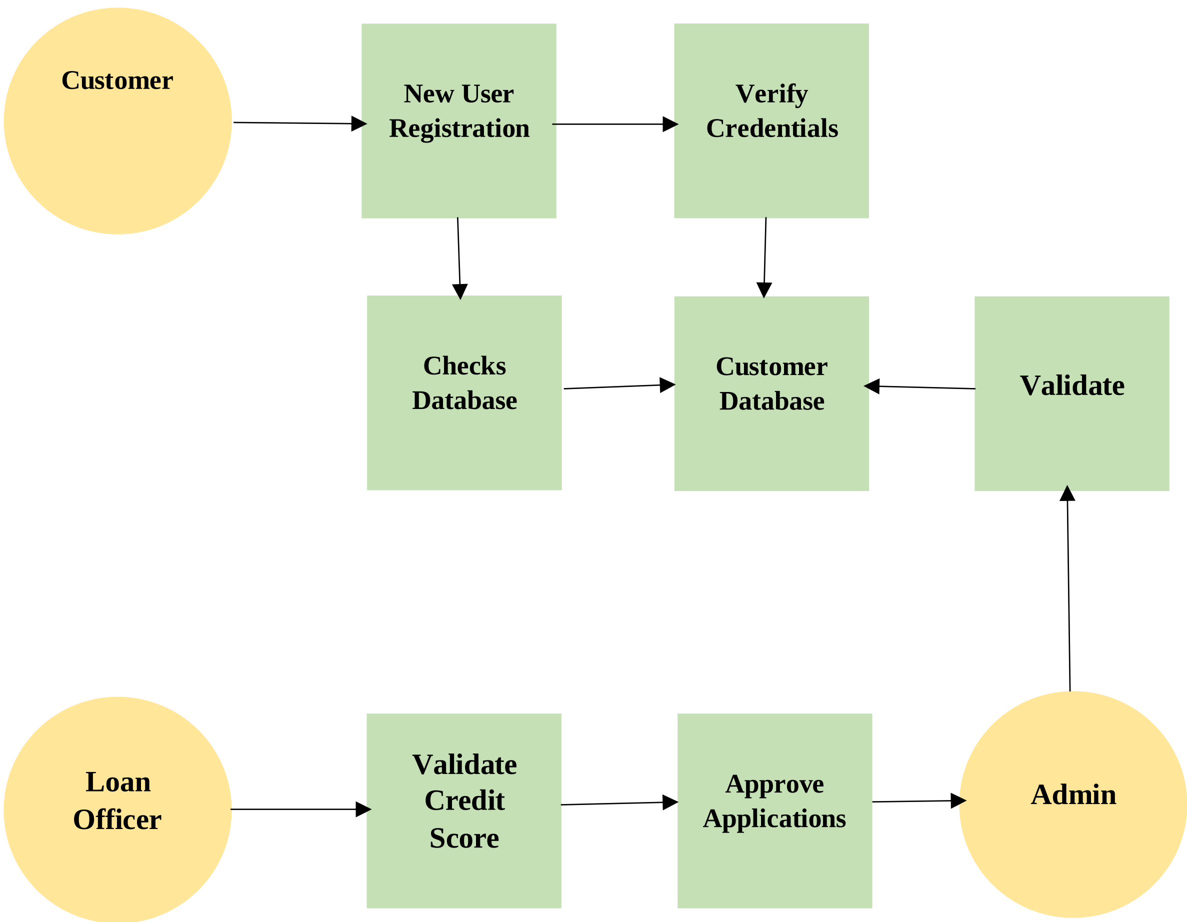
b) Non-functional Requirements:

FR No.	Non-Functional Requirement	Description
NFR-1	Usability	Easy to access
NFR-2	Security	User proofs
NFR-3	Reliability	Based on the customer Income
NFR-4	Performance	Previous History User Bank Account
NFR-5	Availability	Based on the Customer Address
NFR-6	Scalability	Based on the Customer Assets Proofs

5. PROJECT DESIGN

a) Data Flow Diagrams

- A Data Flow Diagram (DFD) is a traditional visual representation of the information flows within a system.
- A neat and clear DFD can depict the right amount of the system requirement graphically.
- It shows how data enters and leaves the system, what changes the information, and where data is stored.



b) Solution & Technical Architecture

Solution architecture is a complex process – with many sub-processes – that bridges the gap between business problems and technology solutions. Its goals are to:

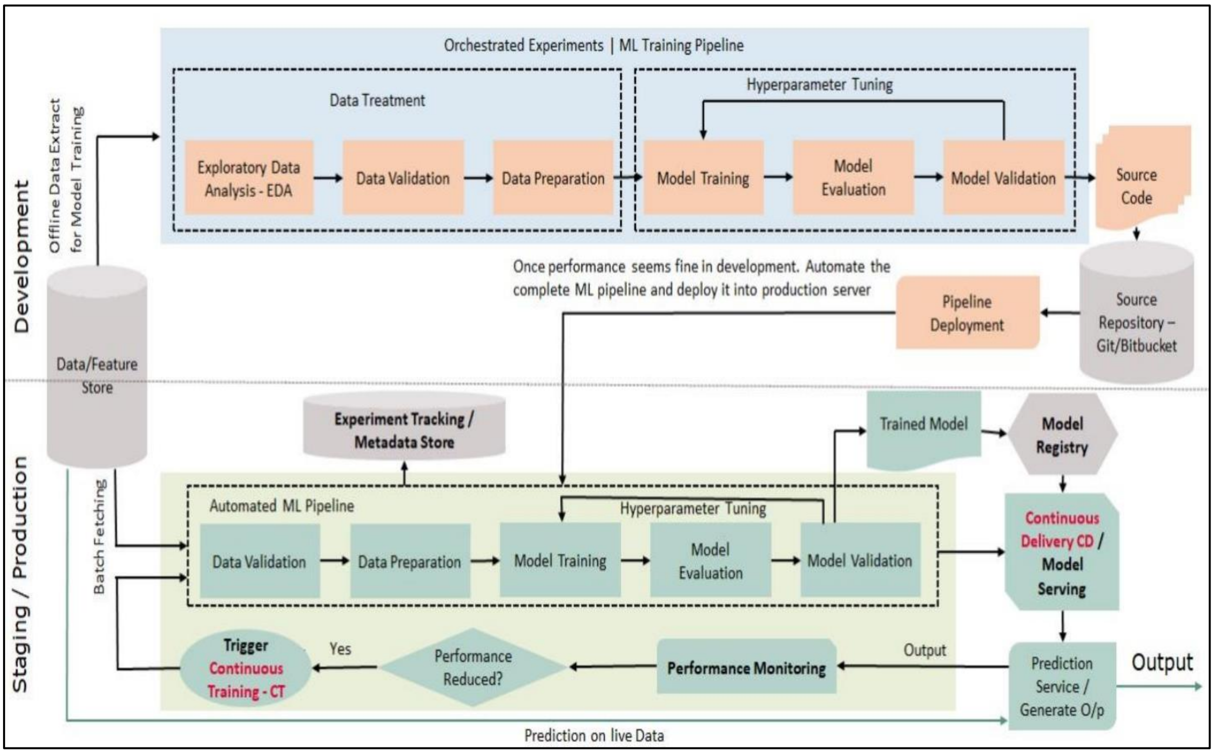
• Find the best tech solution to solve existing business problems.

• Describe the structure, characteristics, behavior, and other aspects of the software to project stakeholders.

• Define features, development phases, and solution requirements.

• Provide specifications according to which the solution is defined, managed, and delivered.

Architecture:



c) User Stories

User Type	Functional Requirements(Epic)	User Story Number	User Story / Task	Acceptance Criteria	Priority	Release
Customer (Mobile User)	Registration	USN – 1	I may sign up for the application as a user by providing my email address, a password and a password confirmation.	I can my Dashboard or Account.	High	Sprint – 1
		USN – 2	When I Register for the application as a user, I will get a Confirmation Email.	I can receive confirmation email & click confirm.	High	Sprint – 1
		USN – 3	I may sign up for the application as a user through Facebook.	I can register & access the dashboard with Facebook Login.	Low	Sprint – 1
		USN – 4	I may Sign up for the application as a user using Gmail.	I can receive confirmation email & click confirm.	Medium	Sprint – 1
	Login	USN - 5	I may access the application as a user by providing my email address	Able to Login	High	Sprint – 1

			and password.			
	Dashboard	USN – 6	I should be able to utilize anything I am permitted to use on the dashboard as a user.	Access the dashboard.	Medium.	Sprint - 1
Customer (Web User)	Registration	USN – 7	I may sign up for the programme as a user by providing my email address, a password and a password confirmation.	I can access my account or dashboard.	High	Sprint – 1
		USN – 8	When I register for the application as a user, I will get a Confirmation Email.	I can receive confirmation email & click confirm	High	Sprint – 1
		USN – 9	I can register for the application through Facebook.	I can register & access the dashboard with Facebook Login	Low	Sprint – 1
		USN – 10	I can register for the application through Gmail.	I can receive confirmation email & click confirm.	Medium	Sprint – 1

	Login	USN – 11	I can log into the application by entering email & password	Able to login	High	Sprint – 1
	Dashboard	USN – 12	I should be able to access the dashboard with everything I am allowed to use.	Access the dashboard.	Medium	Sprint – 1
Loan Approval Officer	Register	USN – 13	I should be able to reister myself as one using unique email and password.	I can access my account.	Medium	Sprint – 2
	Login	USN – 14	I should be able to login myself as one using unique email and password.	Access Loan approval dashboard	Medium	Sprint – 2
	Automated Analysis of Credit History	USN - 15	I can access the dashboard where I feed application for loan prediction.	I can access the dashboard for loan application prediction.	High	Sprint – 3
		USN – 16	I can get a decision followed by some details fo the decision when I feed	Get a decision for loan prediction with details regarding the deision.	High	Sprint – 3

			an application for loan prediction.			
Admin	Register	USN – 17	I should be able to register myself as one using unique email and password.	I can access my account.	Medium	Sprint – 4
	Login	USN – 18	I Should be able to login myself as one using a unique email and password.	Able to login	Medium	Sprint – 4
	Dashboard	USN – 19	I should be abole to access the dashboard with everything I am allowed to Use.	Access the Dashboard.	Medium	Sprint - 4

6. PROJECT PLANNING & SCHEDULING

a) Sprint Planning & Estimation

Sprint	Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1	Registration	USN – 1	As a user, I can register for the application by entering my email, password, and confirming my password.	2	High	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1		USN – 2	As a user, I will receive confirmation email once I have registered for the application .	1	High	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1		USN – 3	As a user, I can register for the application through Facebook .	2	Low	Jeyanandhini, Sivaranjani, Brindha, Sivani

Sprint-1		USN – 4	As a user, I can register for the application through Gmail .	2	Medium	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1	Login	USN - 5	As a user, I can log into the application by entering email & password.	1	High	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1	Dashboard	USN – 6	As a user, I should be able to access the dashboard with everything I am allowed to use.	2	Medium.	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1	Registration	USN – 7	As a user, I can register for the application by entering my email, password, and confirming my password.	3	High	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1		USN – 8	As a user, I will receive confirmation email once I have registered for the app.	3	High	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1		USN – 9	As a user, I will receiv econfirmation email once I have	1	Low	Jeyanandhini, Sivaranjani, Brindha, Sivani

			registered for the app.			
Sprint-1		USN – 10	As a user, I can register for the application through Gmail.	2	Medium	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1	Login	USN – 11	As a user, I can log into the application by entering email & password.	3	High	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-1	Dashboard	USN – 12	As a user, I should be able to access the dashboard with everything I am allowed to use.	2	Medium	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-2	Register	USN – 13	As a loan approval officer, I should be able to register myself as one using a unique email and password.	5	Medium	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-2	Login	USN – 14	As a loan approval officer I should be able to login myself as one	5	Medium	Jeyanandhini, Sivaranjani, Brindha, Sivani

			using a unique email and password.			
Sprint-3	Automated Analysis of Credit History	USN - 15	As a loan approval officer, I can access the dashboard where I feed applications for loan prediction.	10	High	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-3		USN – 16	As a loan approval officer, I can get a decision followed by some details for the decision when I feed an application for loan prediction.	15	High	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-4	Register	USN – 17	As an admin, I should be able to register myself as one using a unique email and password.	2	Medium	Jeyanandhini, Sivaranjani, Brindha, Sivani
Sprint-4	Login	USN – 18	As an admin, I should be able to register myself as one using a unique email and password.	2	Medium	Jeyanandhini, Sivaranjani, Brindha, Sivani

Sprint-4	Dashboard	USN – 19	As an admin, I should be able to access the dashboard with everything I am allowed to use.	2	Medium	Jeyanandhini, Sivaranjani, Brindha, Sivani

b. Sprint Delivery Schedule

Sprint	Total Story Points	Duration	Sprint Start Date	Sprint End Date (Planned)	Story Points Completed (as on Planned End Date)	Sprint Release Date (Actual)
Sprint-1	20	6 Days	24 Oct 2022	29 Oct 2022	20	29 Oct 2022
Sprint-2	20	6 Days	31 Oct 2022	05 Nov 2022	10	05 Nov 2022
Sprint-3	20	6 Days	07 Oct 2022	12 Nov 2022	25	12 Nov 2022
Sprint-4	20	6 Days	14 Nov 2022	19 Nov 2022	6	19 Nov 2022

c) Reports from JIRA

Velocity:

Imagine we have a 10-day sprint duration, and the velocity of the team is 20 (points per sprint). Let’s calculate the team’s average velocity (AV) per iteration unit (story points per day).

$$\boldsymbol{AV = \frac{\text{Sprint Duration}}{Velocity} = \frac{20}{10} = 2}$$

Burndown Chart:

A burn down chart is a graphical representation of work left to do versus time. It is often used in agile software development methodologies such as Scrum. However, burn down charts can be applied to any project containing measurable progress over time.

Our Project Velocity :

Sprint – 1 = 11 / 6 = 1.833

Sprint – 2 = 18 / 6 = 3

Sprint – 3 = 16 / 6 = 2.67

Sprint – 4 = 16 / 6 = 2.67

Total Velocity = 61 / 24 = 2.54

Burndown Chart :

A Burndown chart is a graphical representation of work left to do versus time. It is often used in agile software development methodologies such as Scrum. However, Burndown charts can be applied to any project containing measurable progress over time.

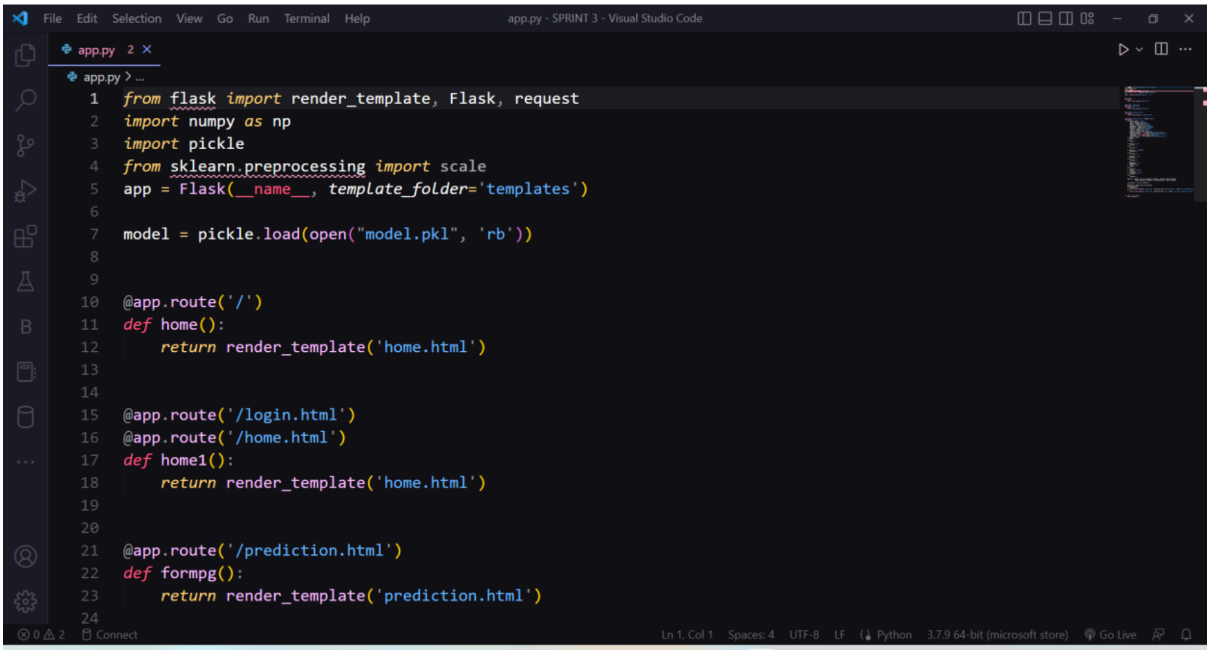
Burndown Chart:

7. CODING & SOLUTIONING

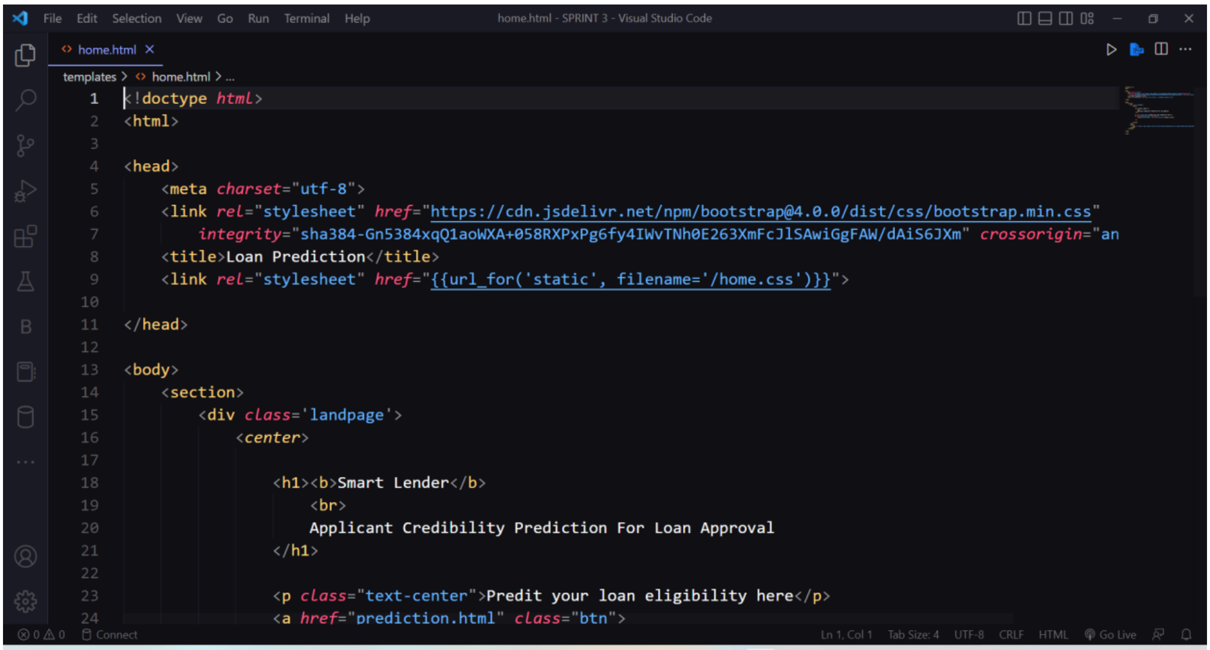
(Explain the features added in the project along with code)

a) Feature 1

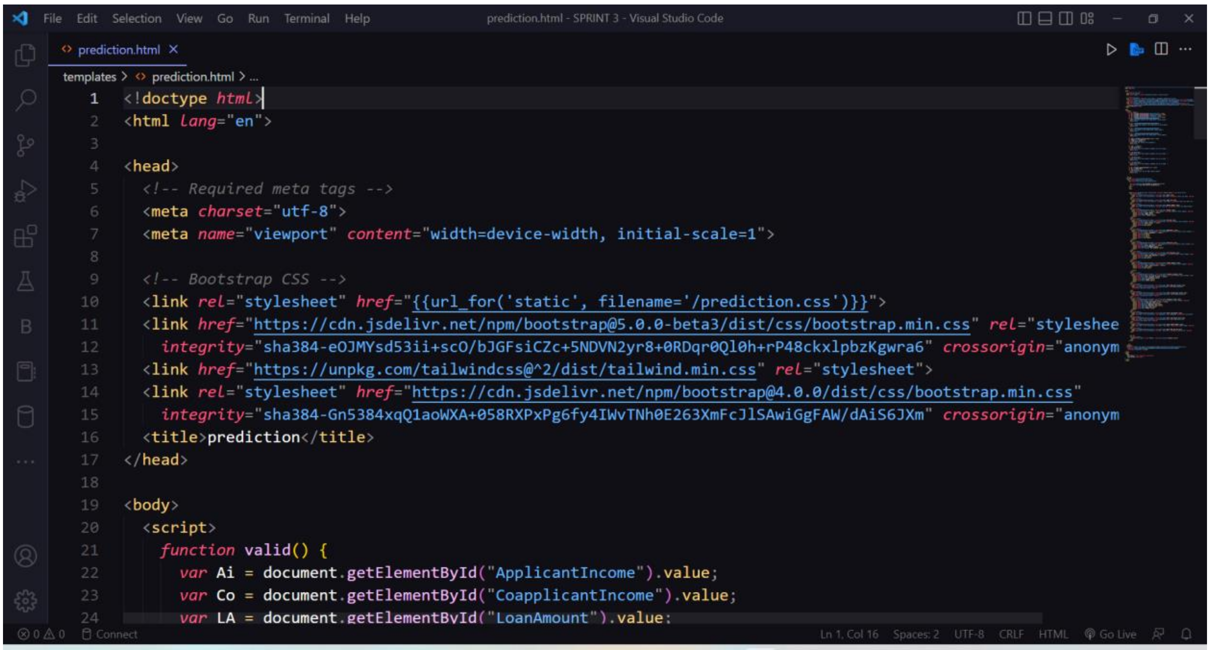
(FORM FILLING BT APPLICANT TO CHECK HIS CREDIT ELIGIBILITY)

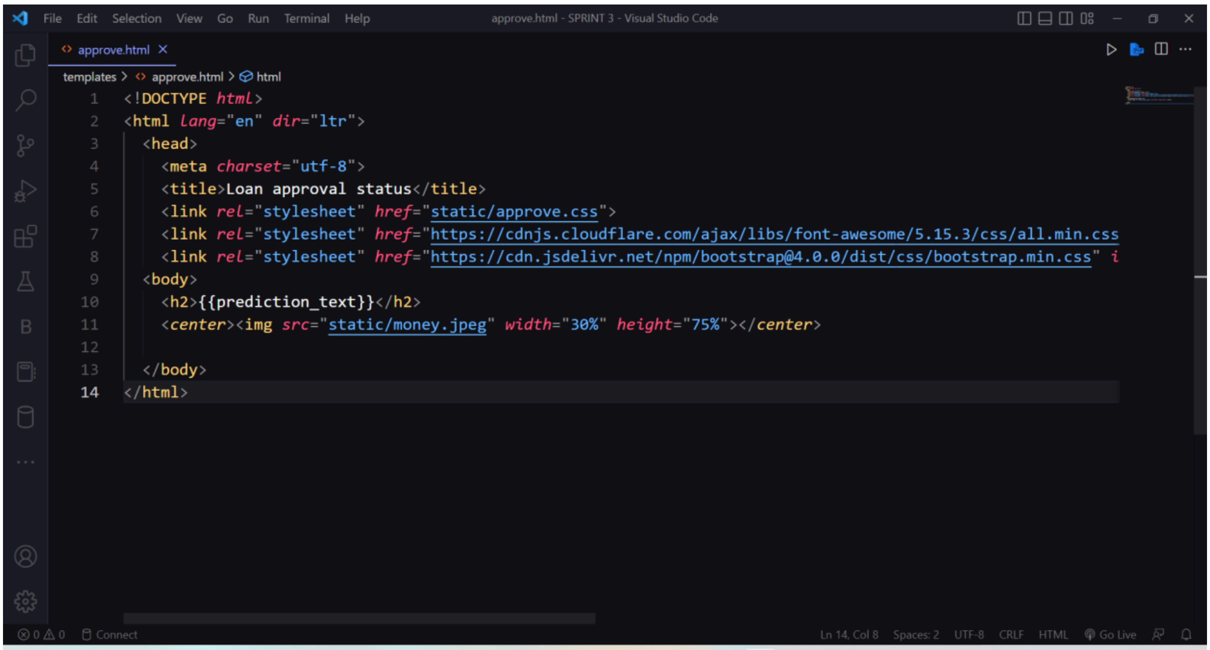


```python
from flask import render_template, Flask, request
import numpy as np
import pickle
from sklearn.preprocessing import scale
app = Flask(__name__, template_folder='templates')

model = pickle.load(open("model.pkl", 'rb'))


@app.route('/')
def home():
    return render_template('home.html')


@app.route('/login.html')
@app.route('/home.html')
def home1():
    return render_template('home.html')


@app.route('/prediction.html')
def formpg():
    return render_template('prediction.html')

```


File Edit Selection View Go Run Terminal Help
home.html - SPRINT 3 - Visual Studio Code
home.html
templates > home.html > ...
<!doctype html>
<html>
<head>
<meta charset="utf-8">
<link rel="stylesheet" href="https://cdn.jsdelivr.net/npm/bootstrap@4.0.0/dist/css/bootstrap.min.css"
integrity="sha384-Gn5384xqQ1aoWXA+058RXPxPg6fy4IWvTNh0E263XmFcJlSAwiGgFAW/dAiS6JXm" crossorigin="an
<title>Loan Prediction</title>
<link rel="stylesheet" href="{{url_for('static', filename='/home.css')}}">
</head>
<body>
<section>
<div class='landpage'>
<center>
<h1>Smart Lender

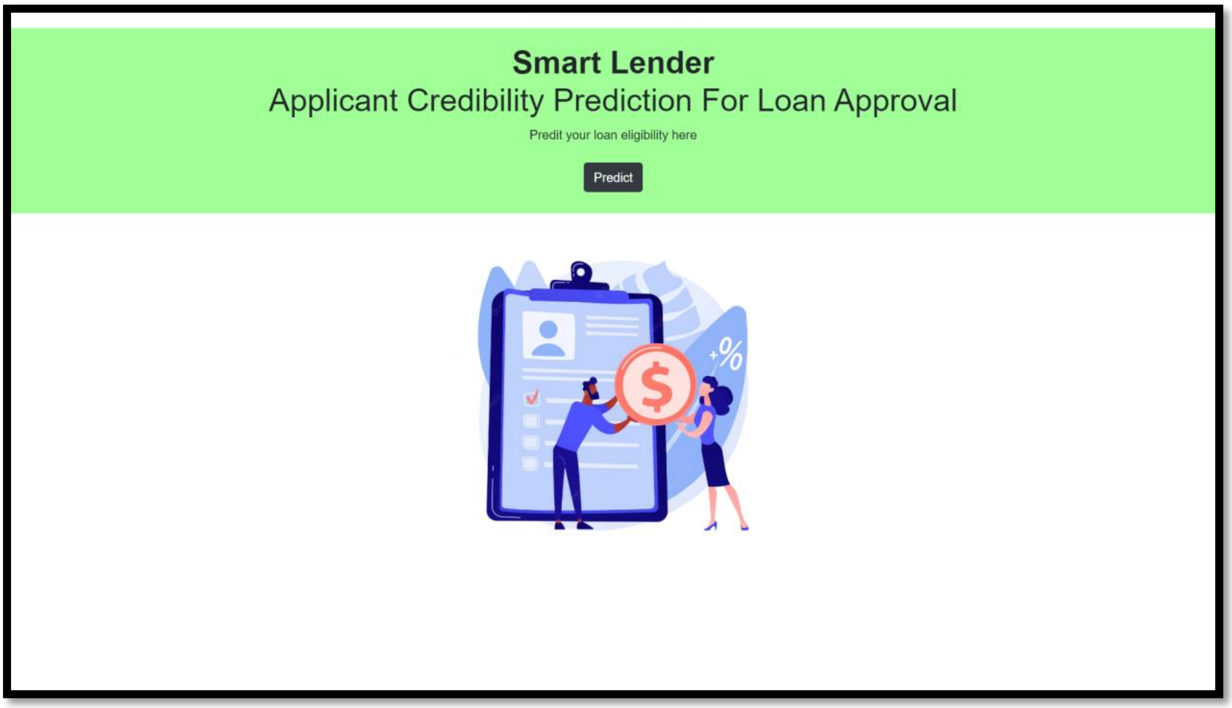
Applicant Credibility Prediction For Loan Approval
</h1>
<p class="text-center">Predit your loan eligibility here</p>
<a href="prediction.html" class="btn">
Ln 1, Col 1 Tab Size: 4 UTF-8 CRLF HTML Go Live

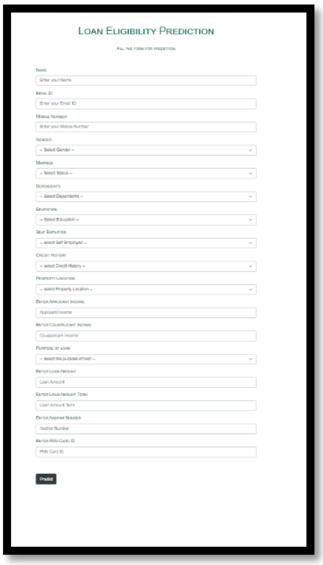

File Edit Selection View Go Run Terminal Help
prediction.html - SPRINT 3 - Visual Studio Code
prediction.html
templates > prediction.html > ...
<!doctype html>
<html lang="en">
<head>
<!-- Required meta tags -->
<meta charset="utf-8">
<meta name="viewport" content="width=device-width, initial-scale=1">
<!-- Bootstrap CSS -->
<link rel="stylesheet" href="{{url_for('static', filename='/prediction.css')}}">
<link href="https://cdn.jsdelivr.net/npm/bootstrap@5.0.0-beta3/dist/css/bootstrap.min.css" rel="styleshee
integrity="sha384-eOJMYsd53ii+scO/bJGFsiCZc+5NDVN2yr8+0RDqr0Ql0h+rP48ckxlpbzKgwra6" crossorigin="anonym
<link href="https://unpkg.com/tailwindcss@^2/dist/tailwind.min.css" rel="stylesheet">
<link rel="stylesheet" href="https://cdn.jsdelivr.net/npm/bootstrap@4.0.0/dist/css/bootstrap.min.css"
integrity="sha384-Gn5384xqQ1aoWXA+058RXPxPg6fy4IWvTNh0E263XmFcJlSAwiGgFAW/dAiS6JXm" crossorigin="anonym
<title>prediction</title>
</head>
<body>
<script>
function valid() {
var Ai = document.getElementById("ApplicantIncome").value;
var Co = document.getElementById("CoapplicantIncome").value;
var LA = document.getElementById("LoanAmount").value;
Ln 1, Col 16 Spaces: 2 UTF-8 CRLF HTML Go Live

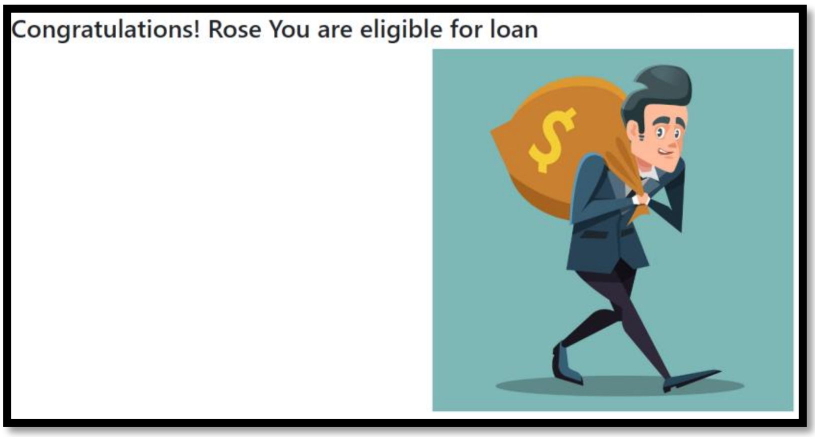


b) Feature 2

(THE MACHINE LEARNING MODEL PREDICTS THE APPLICANT'S ELIGIBILITY)







8. TESTING

a) Test Cases

Loan_ID	Gender	Married	Dependents	Education	Self-employed	Applicant Income	Co-applicant Income	Loan Amount	Loan Amount Term	Credit History	Property Area	Loan Status
LP001002	Male	No	0	Graduate	No	5849	0		360	1	Urban	Y
LP001003	Male	Yes	1	Graduate	No	4583	1508	128	360	1	Rural	N
LP001005	Male	Yes	0	Graduate	Yes	3000	0	66	360	1	Urban	Y
LP001006	Male	Yes	0	Not Graduate	No	2583	2358	120	360	1	Urban	Y
LP001008	Male	No	0	Graduate	No	6000	0	141	360	1	Urban	Y
LP001011	Male	Yes	2	Graduate	Yes	5417	4196	267	360	1	Urban	Y
LP001013	Male	Yes	0	Not Graduate	No	2333	1516	95	360	1	Urban	Y
LP001014	Male	Yes	3	Graduate	No	3036	2504	158	360	0	Semiurban	N
LP001018	Male	Yes	2	Graduate	No	4006	1526	168	360	1	Urban	Y
LP001020	Male	Yes	1	Graduate	No	12841	10968	349	360	1	Semiurban	N

b) USER ACCEPTANCE TESTING

1. Purpose of Document

The purpose of this document is to briefly explain the test coverage and open issues of the Smart Lender - Applicant Credibility Prediction for Loan Approval project at the time of the release to User Acceptance Testing (UAT).

2. Defect Analysis

This report shows the number of resolved or closed bugs at each severity level, and how they were resolved

Resolution	Severity 1	Severity 2	Severity 3	Severity 4	Subtotal
By Design	10	4	2	3	20
Duplicate	1	0	3	0	4
External	2	3	0	1	6
Fixed	11	2	4	20	37
Not Reproduced	0	0	1	0	1
Skipped	0	0	1	1	2
Won't Fix	0	5	2	1	8
Totals	24	14	13	26	77

3. Test Case Analysis

This report shows the number of test cases that have passed, failed, and untested

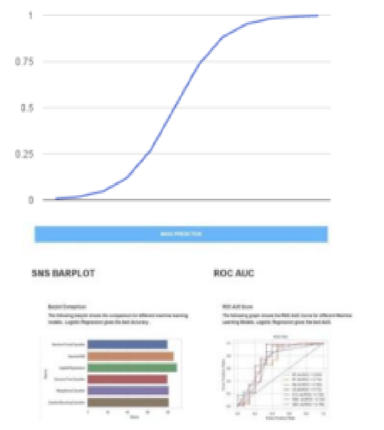
Section	Total Cases	Not Tested	Fail	Pass
Print Engine	7	0	0	7
Client Application	51	0	0	51
Security	2	0	0	2
Outsource Shipping	3	0	0	3
Exception Reporting	9	0	0	9
Final Report Output	4	0	0	4
Version Control	2	0	0	2

9. RESULTS

a) Performance Metrics

Model Performance Testing:

Project team shall fill the following information in model performance testing template.

S.No	Parameter	Values	Screenshot
1.	Metrics	**Regression Model:** MAE - , MSE - , RMSE - , R2 score -**Classification Model:** Confusion Matrix - , Accuray Score- & Classification Report -	
2.	Tune the Model	Hyperparameter Tuning - Validation Method -	

- ✓ For the purpose of predicting the loan approval status of the applied customer, we have chosen the machine learning approach to study the bank dataset.
- ✓ We have applied various machine learning algorithms to decide which one will be the best for applying on the dataset to get the result with the highest accuracy.
- ✓ Following this approach, we found that apart from the logistic regression, the rest of the algorithms performed satisfactory in terms of giving out the accuracy.
- ✓ The accuracy range of the rest of the algorithms were from 75% to 85%. Whereas the logistic regression gave us the best possible accuracy (88.70%) after the comparative study of all the algorithms.
- ✓ We also determined the most important features that influence the loan approval status.
- ✓ These most important features are then used on some selected algorithms and their performance accuracy is compared with the instance of using all the features.
- ✓ This model can help the banks in figuring out which factors are important for the loan approval procedure.
- ✓ The comparative study makes us clear about which algorithm will be the best and ignores the rest, based on their accuracy.

10. ADVANTAGES AND DISADVANTAGES

ADVANTAGES

The benefits of loan tech servicing software for lenders include:

● **Eliminating human error**

It's no secret, that calculations are something that algorithms handle better than we, humans. In a lending system, there are just too many variables, which is why it is errorprone. The best loan servicing software, however, is created to completely rule out any errors, which is, undoubtedly, beneficial from every standpoint.

● **Preventing delays in payment**

Not being able to collect a debt is something that most lenders are especially wary of. However, if they leverage a traditional loan management approach, they may not see it coming. Loan servicing systems, on the other hand, integrate analytic modules capable of detecting even the most subtle fluctuations in clients' credibility and preventing payment delays in a timely manner.

● **Saving time**

Loan management requires a great level of meticulousness and attention to detail. As a rule, a full-fledged team is required to deal with every aspect of a loan process. Needless to say, loan management carried out manually and based on paperwork takes up a lot of time. A digital lending system, on the other hand, automates the routines and enables your team to dedicate time to other important tasks. Read also: Use Trunk Based Development for Product Agility Learn how to deliver a product in real-time easy and fast

● **Automated reporting** Automated report generation is another invaluable feature offered by a digital loan servicing platform. Accounting, tax reports, and invoices are often requested by regulatory bodies, borrowers and investors. These high urgency reports should be provided on demand, and contain information, which is 100% accurate. Loan tracking software enables lenders to quickly generate reports of different types and submit them urgently, in the required formats.

● **Increased revenue**

This stems from all of the above: an automated loan processing system enables lenders to process more applications, assign and manage more loans, and see them all the way through closing all while detecting scams and preventing delays. The staff is free to oversee the process and focus on client relationships and look for new business opportunities. This enables financial companies to gain a distinct competitive edge and increase revenue.

DISADVANTAGES

1. Accessibility

An organization looking to build loan software may not have enough on-premise infrastructure capacities to ensure its non disruptive operation, updates, and support. Scaling during peak workloads and handling an increase in the number of users and subscriptions may also be quite challenging. Using cloud infrastructure is best to ensure optimal scalability and availability.

2. Servicing different loan types

The more types of loans your money lending software is capable of servicing, the better. Lending applications that have a wide range of use cases, will surely attract more users than apps targeting only one specific loan type. A loan Tech software to create loan app estimation, for example, may have a broad range of applications from student loan tech calculations to estimating business loans and mortgages.

1. Centralized data storage

Every stage of the lending process involves working with customer data. The best loan servicing software stores this data in centralized storage accessible during every loan processing stage. A legacy loan management system, on the other hand, uses a siloed approach to data storage, which makes loan processing more laborious and lengthier.

2. **Integrated credit assessment capabilities**

   Modern loan servicing software for private lenders should be able to instantly connect with credit bureaus and any other bodies responsible for credibility assessment. Such platforms should receive regular credit data updates and leverage big data analytics to assess the trustworthiness of applicants. The client's social media activity, for example, can be a valid source of alternative assessment of credibility.

3. **Automation of routine processes**

   Using robotic process automation to streamline simple rule-based processes is another must-have feature of a loan management platform. Automation accelerates loan origination and processing and accounts for increasing client satisfaction. On top of that, it helps to avoid human error.

4. **In-built analytic modules**

   Leveraging artificial intelligence (AI) and big data is another hallmark of excellent loan servicing software for lenders. Not only does it help to generate reports but also enables companies to evaluate market trends, detect patterns in customer behavior and come up with new products and offerings.

5. **Third-party integration**

   Another feature that most organizations find especially attractive in a loan processing system, is its capability to integrate with other enterprise software. ERP and CRM solutions are capable of enriching the lending system with data and insights. Systems integrating lending modules with software for remote sales personnel are also enjoying high popularity among lenders.

6. **Security**

   Finance company software works with classified and highly sensitive data, and for both lenders and customers, security is a matter of paramount importance. An excellent lending system should possess advanced security capabilities, and ensure the highest level of customer, data, and network protection.

11. CONCLUSION

In the debate over which supervised learning model to use for credit risk assessment, we have come to the conclusion that support vector machines can outperform other treebased models or regression models if the setup of the experiment is similar to that of ours. Furthermore, in the debate over which dimensionality reduction technique to use, our model has shown us that recursive feature elimination with cross-validation can outperform models based on principal component analysis. For future improvements we would like to use more current data and from different sources for illustrating a better understanding of the trends present in this field. Datasets similar to the above-mentioned experiments from previous works will be used to test this model for better comparison. It has been mentioned that in order to reduce computational cost and complexity we have omitted the idea of using neural networks. But as we are looking forward to work with even larger amount of data, we would like to make a comparative analysis using neural networks as well. It is a known fact that neural networks tend to perform better with large datasets and we would like to test this hypothesis in our future works. Again, as we are also discussing the contributions of feature selection/extraction techniques, we would like to implement other dimensionality reduction techniques such as genetic algorithm, univariate feature selection methods, tree-based feature selections etc. to gauge their performances and further improve the efficiency of the credit lending sector. Therefore, this paper can be concluded with the statement that this model illustrates an interesting approach in identifying loan defaulters in this ever-changing economy. Using the dataset from Lending Club our model has brought about remarkable results which in turn can play a major role in assessing the credit risk of borrowers, assist credit lending institutions and enable financial institutions to keep operating in a transparent and profitable way.

12. FUTURE SCOPE

In this section, based on various performance metrics, a comparative analysis will be made of all the generated models. A precise classifier is the backbone of any machine learning model. Four supervised algorithms: Support vector machine (SVM), Logistic Regression (LR), Extreme Gradient Boosting (XGB) and Random Forest (RF) have been selected for the analysis. The hyperparameters of these algorithms will be tuned using GridSearchCV to select the best set of values for each model. The results will be discussed in two categories and will be illustrated in both a graphical and tabular manner. Firstly the models will be evaluated on a holdout test set using a train test split. Then another comparative analysis will be made of the same models but using a 5 fold crossvalidation and GridSearchCV. Z-score has been chosen over normalization (min-max scaling) for scaling the features. Classifiers such as support vector machine, logistic regression or neural network prefer standardization over normalization. Additionally, this paper proposes to use such feature extraction methodologies where maximizing the variance is highly preferred. This can be achieved using standardization. Furthermore GridSearchCV has been used to optimize the hyperparameters of each classifier. Studies done in perfectly show the effectiveness of GridSearchCV in maximizing the performance of classifiers.

13. APPENDIX

SOURCE CODE

app.py (PYTHON FILE)

```python
from flask import render_template, Flask, request
import numpy as np
import pickle
from sklearn.preprocessing import scale
app = Flask(__name__, template_folder='templates')

model = pickle.load(open("model.pkl", 'rb'))


@app.route('/')
def home():
    return render_template('home.html')


@app.route('/login.html')
@app.route('/home.html')
def home1():
    return render_template('home.html')


@app.route('/prediction.html')
def formpg():
    return render_template('prediction.html')


@app.route('/prediction.html', methods=['POST'])
def predict():
    if request.method == 'POST':
```

```
        name = request.form['Name']
        gender = request.form['gender']
        married = request.form['married']
        dependents = request.form['dependents']
        education = request.form['education']
        employed = request.form['employed']
        credit = request.form['credit']
        proparea = request.form['proparea']
        ApplicantIncome =
float(request.form['ApplicantIncome'])
        CoapplicantIncome =
float(request.form['CoapplicantIncome'])
        LoanAmount = float(request.form['LoanAmount'])
        Loan_Amount_Term =
float(request.form['Loan_Amount_Term'])
    if gender == 'Male':
        gender = 1
    else:
        gender = 0

    if married == 'Yes':
        married = 1
    else:
        married = 0

    if education == 'Graduate':
        education = 0
    else:
        education = 1

    if employed == 'Yes':
        employed = 1
    else:
        employed = 0

    if dependents == '3+':
        dependents = 3
    if credit == 'Yes':
```

```python
        credit = 1
    else:
        credit = 0
    if proparea == 'Urban':
        proparea = 2
    elif proparea == 'Rural':
        proparea = 0
    else:
        proparea = 1

    features = [gender, married, dependents, education,
employed, ApplicantIncome,
                CoapplicantIncome, LoanAmount,
Loan_Amount_Term, credit, proparea]

    con_features = [np.array(features)]

    prediction = model.predict(con_features)
    print(prediction)
    if prediction == 1:
        return render_template('approve.html',
prediction_text='Congratulations! '+name+' You are eligible
for loan')
    else:
        return render_template('reject.html',
prediction_text='Sorry '+name+' You are not eligible for
loan')


if __name__ == "__main__":
    app.run(debug=True)
```

HOME

home.html

```html
<!Doctype html>
<html>

<head>
    <meta charset="utf-8">
    <link rel="stylesheet"
href="https://cdn.jsdelivr.net/npm/bootstrap@4.0.0/dist/css/
bootstrap.min.css"
        integrity="sha384-
Gn5384xqQ1aoWXA+058RXPxPg6fy4IWvTNh0E263XmFcJlSAwiGgFAW/dAiS
6JXm" crossorigin="anonymous">
    <title>Loan Prediction</title>
    <link rel="stylesheet" href="{{url_for('static',
filename='/home.css')}}">

</head>

<body>
    <section>
        <div class='landpage'>
            <center>

                <h1><b>Smart Lender</b>
                    <br>
                    Applicant Credibility Prediction For
Loan Approval
                </h1>

                <p class="text-center">Predit your loan
eligibility here</p>
                <a href="prediction.html" class="btn">
                    <button type="button" class="btn btn-
dark">Predict</button>

                </a>

            </center>
        </div>
```

```
        <center>
            <img src="https://img.freepik.com/free-
vector/money-lending-abstract-concept_335657-
3053.jpg?w=2000">
        </center>
    </section>

</body>

</html>
```

PREDICT

prediction.html

```
<!Doctype html>
<html lang="en">

<head>
  <!-- Required meta tags -->
  <meta charset="utf-8">
  <meta name="viewport" content="width=device-width,
initial-scale=1">

  <!-- Bootstrap CSS -->
  <link rel="stylesheet" href="{{url_for('static',
filename='/prediction.css')}}">
  <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.0.0-
beta3/dist/css/bootstrap.min.css" rel="stylesheet"
    integrity="sha384-
eOJMYsd53ii+scO/bJGFsiCZc+5NDVN2yr8+0RDqr0Ql0h+rP48ckxlpbzKg
wra6" crossorigin="anonymous">
  <link
href="https://unpkg.com/tailwindcss@^2/dist/tailwind.min.css
" rel="stylesheet">
```

```
  <link rel="stylesheet"
href="https://cdn.jsdelivr.net/npm/bootstrap@4.0.0/dist/css/
bootstrap.min.css"
    integrity="sha384-
Gn5384xqQ1aoWXA+058RXPxPg6fy4IWvTNh0E263XmFcJlSAwiGgFAW/dAiS
6JXm" crossorigin="anonymous">
  <title>prediction</title>
</head>

<body>
  <script>
    function valid() {
      var Ai =
document.getElementById("ApplicantIncome").value;
      var Co =
document.getElementById("CoapplicantIncome").value;
      var LA = document.getElementById("LoanAmount").value;
      var LT =
document.getElementById("Loan_Amount_Term").value;
      if (Ai > 100000000000000000000000000000000000000) {
        alert("Applicant income is too large enter a valid
number")
        return false;
      }
      if (Co > 100000000000000000000000000000000000000) {
        alert("Coapplicant income is too large enter a valid
number")
        return false;
      }
      if (LA > 100000000000000000000000000000000000000) {
        alert("Loan Amount is too large enter a valid
number")
        return false;
      }
      if (LT > 100000000000000000000000000000000000000) {
        alert("loan amount term is too large enter a valid
number")
        return false;
```

```
      }
      var name = document.getElementById("Name").value;
      var letters = /^[a-zA-Z]*$/;
      if (!name.match(letters)) {
        alert("Name must contain only alphabets")
        return false;
      }
      var num = /^[0-9]+$/;
      if (!Ai.match(num)) {
        alert("Enter only valid numbers alphabets are not
allowed  ")
        return false;
      }
      if (!Co.match(num)) {
        alert("Enter only valid numbers alphabets are not
allowed  ")
        return false;
      }
      if (!LA.match(num)) {
        alert("Enter only valid numbers alphabets are not
allowed  ")
        return false;
      }
      if (!LT.match(num)) {
        alert("Enter only valid numbers alphabets are not
allowed  ")
        return false;
      }
      var mo = document.getElementById("mon").value;
      var mn = /^[0-9]{10}$/;
      if (!mo.match(mn)) {
        alert("Please enter only 10 digit mobile number")
        return false;
      }

    }
  </script>
  <section class="text-green-800 body-font">
```

```html
    <div class="container px-1 py-12 mx-auto">
      <div class="flex flex-col text-center mb-10">

        <h1 class="Heading">Loan Eligibility 
Prediction</h1><br>
        <p class="fill">Fill the form for prediction</p>
      </div>
      <div>
      </div>


      <form action='/prediction.html' method="post" 
onsubmit="return valid()" class="px-24 mx-12">
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Name</label>
          <input type="text" class="form-control" id="Name" 
name="Name" placeholder="Enter your Name" required>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Email ID</label>
          <input type="email" class="form-control" 
id="email" name="email" placeholder="Enter your Email ID" 
required>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Mobile Number</label>
          <input type="text" class="form-control" id="mon" 
name="mon" placeholder="Enter your Mobile Number" required>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Gender</label>
          <select class="form-select" id="gender" 
name="gender" aria-label="Default select example" required>
            <option selected>-- Select Gender --</option>
            <option value="Male">Male</option>
```

```
            <option value="Female">Female</option>
          </select>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Married</label>
          <select class="form-select" id="married"
name="married" aria-label="Default select example" required>
            <option selected>-- Select Status --</option>
            <option value="Yes">Yes</option>
            <option value="No">No</option>
          </select>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Dependents</label>
          <select class="form-select" id="dependents"
name="dependents" aria-label="Default select example"
required>
            <option selected>-- Select Dependents --
</option>
            <option value="0">0</option>
            <option value="1">1</option>
            <option value="2">2</option>
            <option value="3+">3+</option>
          </select>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Education</label>
          <select class="form-select" id="education"
name="education" aria-label="Default select example"
required>
            <option selected>-- Select Education --</option>
            <option value="Graduate">Graduate</option>
            <option value="Not Graduate">Not
Graduate</option>
          </select>
```

```
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Self Employed</label>
          <select class="form-select" id="employed"
name="employed" aria-label="Default select example"
required>
            <option selected>-- select Self Employed --
</option>
            <option value="Yes">Yes</option>
            <option value="No">No</option>
          </select>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Credit History</label>
          <select class="form-select" id="credit"
name="credit" aria-label="Default select example" required>
            <option selected>-- select Credit History --
</option>
            <option value="Yes">Yes</option>
            <option value="No">No</option>

          </select>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Property Location</label>
          <select class="form-select" id="proparea"
name="proparea" aria-label="Default select example"
required>
            <option selected>-- select Property Location --
</option>
            <option value="Semiurban">Semiurban</option>
            <option value="Urban">Urban</option>
            <option value="Rural">Rural</option>
          </select>
        </div>
```

```
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Enter Applicant Income</label>
          <input type="text" class="form-control"
id="ApplicantIncome" name="ApplicantIncome"
            placeholder="Applicant Income" required>

        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Enter Co-applicant Income</label>
          <input type="text" class="form-control"
id="CoapplicantIncome" name="CoapplicantIncome"
            placeholder="Co-applicant Income" required>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Purpose of loan</label>
          <select class="form-select" id="pur" name="pur"
aria-label="Default select example" required>
            <option selected>-- select the purpose of loan -
-</option>
            <option value="person">Personal Loan</option>
            <option value="Bussiness">Business Loan</option>
            <option value="Education">Education
Loan</option>
            <option value="Home">Home Loan</option>
            <option value="Other">Other</option>
          </select>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Enter Loan Amount</label>
          <input type="text" class="form-control"
id="LoanAmount" name="LoanAmount" placeholder="Loan Amount"
required>
        </div>
        <div class="mb-3">
```

```
          <label for="exampleFormControlInput1" class="form-
label">Enter Loan Amount Term</label>
          <input type="text" class="form-control"
id="Loan_Amount_Term" name="Loan_Amount_Term"
            placeholder="Loan Amount Term" required>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Enter Aadhar Number</label>
          <input type="text" class="form-control" id="Adhar"
name="Adhar" placeholder="Aadhar Number" required>
        </div>
        <div class="mb-3">
          <label for="exampleFormControlInput1" class="form-
label">Enter PAN Card ID</label>
          <input type="text" class="form-control" id="PAN "
name="PAN " placeholder="PAN Card ID" required>
        </div>


        <br><br>
        <div class="mb-3">
          <button type="submit" value="PREDICT" class="btn
btn-dark">Predict</button>
        </div>
      </form>


    </div>
  </section>
  <script src="https://cdn.jsdelivr.net/npm/bootstrap@5.0.0-
beta3/dist/js/bootstrap.bundle.min.js"
    integrity="sha384-
JEW9xMcG8R+pH31jmWH6WWP0WintQrMb4s7ZOdauHnUtxwoG2vI5DkLtS3qm
9Ekf"
    crossorigin="anonymous"></script>

</body>
<style>
```

```
  body{
    font-family: Arial, Helvetica, sans-serif;
    font-variant: small-caps;
}
</style>
</html>
```

SUBMIT

approve.html

```
<!DOCTYPE html>
<html lang="en" dir="ltr">
  <head>
    <meta charset="utf-8">
    <title>Loan approval status</title>
    <link rel="stylesheet" href="static/approve.css">
    <link rel="stylesheet"
href="https://cdnjs.cloudflare.com/ajax/libs/font-
awesome/5.15.3/css/all.min.css"/>
    <link rel="stylesheet"
href="https://cdn.jsdelivr.net/npm/bootstrap@4.0.0/dist/css/
bootstrap.min.css" integrity="sha384-
Gn5384xqQ1aoWXA+058RXPxPg6fy4IWvTNh0E263XmFcJlSAwiGgFAW/dAiS
6JXm" crossorigin="anonymous">  </head>
  <body>
    <h2>{{prediction_text}}</h2>
    <center><img src="static/money.jpeg" width="30%"
height="75%"></center>

  </body>
</html>
```

reject.html

```
<!DOCTYPE html>
<html lang="en" dir="ltr">
  <head>
    <meta charset="utf-8">
    <title>Loan approval status</title>
    <link rel="stylesheet" href="static/reject.css">
    <link rel="stylesheet"
href="https://cdnjs.cloudflare.com/ajax/libs/font-awesome/5.15.3/css/all.min.css"/>
    <link rel="stylesheet"
href="https://cdn.jsdelivr.net/npm/bootstrap@4.0.0/dist/css/bootstrap.min.css" integrity="sha384-Gn5384xqQ1aoWXA+058RXPxPg6fy4IWvTNh0E263XmFcJlSAwiGgFAW/dAiS6JXm" crossorigin="anonymous">  </head>
  <body>

    <h2>{{prediction_text}}</h2>
    <center><img src="static/rejected.jpeg" width="30%"
height="75%"></center>


  </body>
</html>
```

GITHUB LINK :-

https://github.com/IBM-EPBL/IBM-Project-17376-1659637497

PROJECT DEMO LINK :-

https://drive.google.com/file/d/12Urm7aJmXM4w-yz5JDtUa0eqY2CkRFvt/view?usp=sharing