

# WEB IMPLEMENTATION FOR BANK TO PREDICT ELIGIBLE CUSTOMER USING MACHINE LEARNING AND AWS



Submitted by

**Asfand Ali** (2068882)

**Mahesh Yadav Udutha** (2056251)

**Professor**

Massimo Mecella

Submitted in the partial fulfilled of the requirement for the Laboratory of Advance  
Programming in Computer Science and Engineering

Facoltà di ingegneria dell'informazione, informatica e statistica Engineering in  
Computer Science Sapienza, Rome, Italy

SAPIENZA UNIVERSITY OF ROME ITALY

Academic Year 2022/2023

# ABSTRACT

Getting loans from financial organizations has become very common in today's society. For a wide range of reasons, many individuals apply for loans every day. However, not all candidates are trustworthy, and not everyone will be accepted. There are instances where borrowers fail to repay the majority of their loans to the bank, which causes enormous financial losses. Choosing to approve a loan carries a significant amount of danger. Therefore, the goal of this project is to use machine learning techniques on the loaded data set from kaggle to extract key information, and then forecast whether or not a customer will be able to repay the loan. Therefore, the objective is to determine whether you can predict the customer defaulting or not. Among the most prominent research areas in the banking and insurance industries, loan prediction for eligible customers is one of the most important in the modern environment identifying and analyzing the patterns of the dataset plays a vital role in this era. The loan prediction involves the application of various machine learning algorithms. This project will be developed using machine learning algorithms such as logistic regression, K Nearest Neighbor, Decision tree. Python programming language in Visual Studio code will be used for the implementation using GitHub and then finally deployment will be done on AWS Cloud. The proposed system expects to deliver high accuracy results and moderate loss for training and validate data.

# TABLE OF CONTENTS

<b>Abstract</b>	<b>i</b>
<b>List of Figures</b>	<b>iii</b>
<b>1 INTRODUCTION</b>	<b>1</b>
1.1 Background . . . . .	1
1.2 Problem Statement . . . . .	2
1.3 Motivation . . . . .	3
<b>2 LITERATURE REVIEW</b>	<b>4</b>
2.1 Review of the Loan Prediction . . . . .	4
2.2 Machine Learning . . . . .	5
2.3 Machine Learning process . . . . .	6
2.4 Existing System . . . . .	6
<b>3 DATA SET</b>	<b>7</b>
<b>4 METHODOLOGY</b>	<b>9</b>
4.1 Data Cleaning and Processing . . . . .	9
4.2 Feature Extraction . . . . .	9
4.3 Data Splitting . . . . .	9
4.4 Data Collection . . . . .	9
4.5 Train model on training data set . . . . .	10
4.6 Correlating attributes . . . . .	11
4.7 Selecting the Models . . . . .	12
4.7.1 Logistic Regression . . . . .	12
4.7.2 Decision Tree classifier . . . . .	12
<b>5 SUMMARY</b>	<b>13</b>
5.1 Results . . . . .	13
5.2 Conclusion . . . . .	17
5.3 Learning Experience . . . . .	17
5.4 Future Enhancement . . . . .	17
<b>References</b>	<b>18</b>

## LIST OF FIGURES

1.1	UML class diagram of Loan Prediction . . . . .	2
1.2	Different types of loan offered by Bank . . . . .	3
2.1	Machine Learning Process . . . . .	6
3.1	Train Data . . . . .	7
3.2	Test Data . . . . .	8
3.3	Workflow of the work . . . . .	8
4.1	Table Variable vs Description . . . . .	10
4.2	Chronology of Data . . . . .	11
4.3	Decision Tree Model . . . . .	12
5.1	Final Layout . . . . .	13
5.2	AWS Output . . . . .	14
5.3	Prediction Page Area Rural . . . . .	14
5.4	Prediction Page Area Urban . . . . .	15
5.5	Cmd output eligible . . . . .	15
5.6	Console Output Eligible . . . . .	16
5.7	A case of Loan Approval . . . . .	16
5.8	A case of Loan Rejection . . . . .	17

# CHAPTER 1

## INTRODUCTION

### 1.1 BACKGROUND

People want to apply for loans via the internet as data volumes grow due to digitization in the banking sector. Artificial intelligence (AI), as a common method of information scrutiny, is gaining popularity. Individuals from multiple sectors are using AI calculations to solve problems based on their industry knowledge. Banks are having a difficult time getting loans approved. Every day, there are numerous applications that bank employees must manage, and the possibility of errors is high. Most banks profit from loans but choosing deserving customers from a large number of applications is risky. Just a single blunder can result in a massive loss for a bank. Almost every bank's main business is loan distribution. This project aims to provide a loan to a deserving applicant from among all applicants. An efficient and non-biased system that saves the bank time checks every applicant on a priority basis. All other customer formalities are completed on time by bank officials, which benefits the customers. The best part is that it is beneficial to both banks and applicants[7]. Customers apply for loans first, followed by the company/bank verifies their eligibility for the loan. The company/bank then wishes to automate the loan eligibility process (in real time) based on the information provided by the customer while filling out the application form. Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History, and other details are included. This project used previous customer data from various banks to whom loans were approved based on a set of rules. As a result, the machine learning model is applied to that method to obtain approximate values. This project's primary goal is to forecast loan safety. KNN, logistic regression, and decision tree algorithms are used to predict loan safety. Data is expanding day by day scheduled to digitization People like to apply for loans in the banking sector through the internet. For intelligence research, we are getting more attention more and more. Using individuals from different companies AI Computation handles dependent problems their production information. Banks face serious problems Loan approval issues. there are many everyday

Applications that are difficult for banks to administer employees, and the chances of some errors are also higher. Most banks profit from loans, but the choice is risky Attracting customers from the number of applications. One mistake can cost a bank a huge loss. Credit distribution is First's core business for all banks. This project aims to provide consumption A worthy applicant among all applicants. Efficient An unbiased system that cuts bank time Priority will be given to each applicant. Bank We handle all other customer guideline This has a positive effect on the customer. the best Part is that it is efficient for both banks and applicants. This system enables launching specific apps that.

deserve to be given special approval. Prediction characteristics include things like: Gender, Married, Dependents, Education, Self-Employed, Applicant Income, Co-Applicant Income, Loan Amount, Loan Term, Credit History, Property Area, and Loan Status

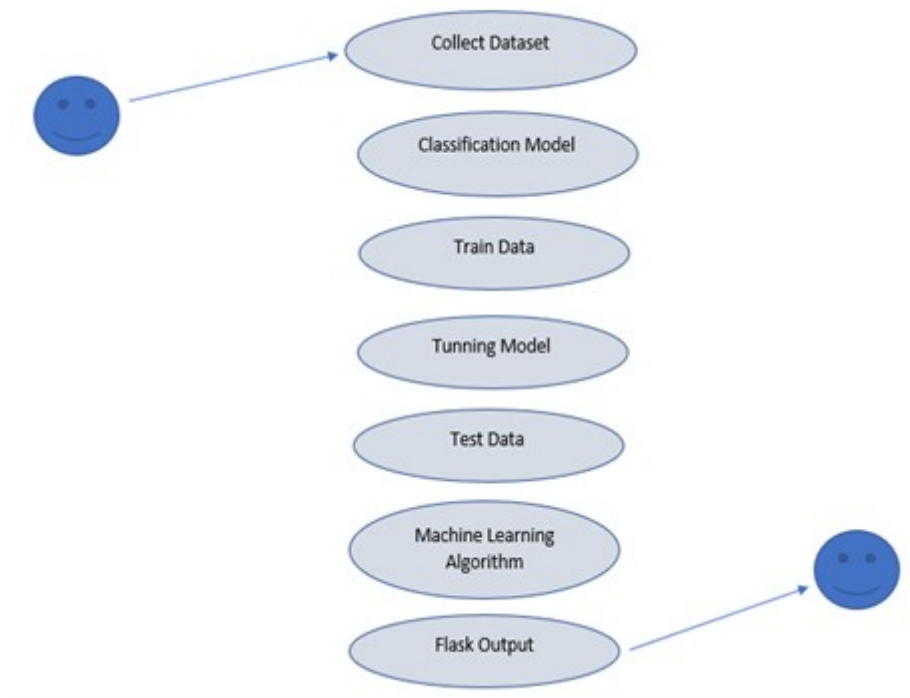


Figure 1.1: UML class diagram of Loan Prediction

## 1.2 PROBLEM STATEMENT

In the area of banking and finance, this project seeks to offer a solution for automating a crucial process. Numerous different kinds of personal and business loans are offered by banks and housing finance companies all over the globe. When a company applies for a loan, these firms verify the company's eligibility. Our project will automate this process by using machine learning to analyze the online form that customers must fill out in order to determine whether or not they are qualified for a loan. Details

on this form include the applicant's sex, marital status, qualifications, dependents' information, yearly income, loan amount, credit history, and other information. Many banks are associated with different kinds of loans like house loan, educational loan, personal loan, vehicle loan, etc.

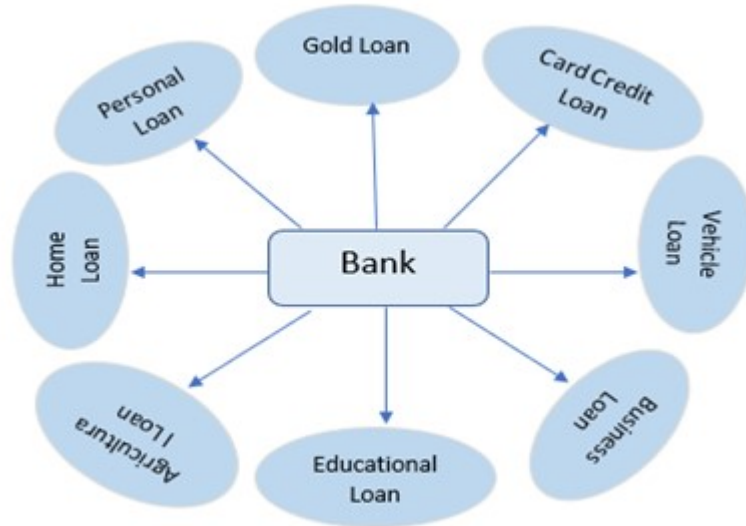


Figure 1.2: Different types of loan offered by Bank

has having different areas rural/urban and firstly a customer tries to get the loan from bank and banks check the validates for eligibility for the loan and of approve like marital status, gender, education, income, amount, credit history, and many different peoples are given the form to fill the applicant details. Therefor taking the input applicants details to verify whether applicant is eligible to apply loan or not. After build up ML model web applicant is developed for user interface that allows to user can directly check she/he is eligibility to get loan or not by entering given details.

### 1.3 MOTIVATION

Now a days loan prediction is very common real life problems that every bank faces leading operation customer can save many hours when loan approval process is automated when bank has robust model to predict which loan customer's loan it should be approve or reject in order to reduce loan defaulter.

## CHAPTER 2

### LITERATURE REVIEW

#### 2.1 REVIEW OF THE LOAN PREDICTION

classification model is used to predict outcomes Yes or No. We have use supervised machine learning to design the pattern of dataset which will help the algorithm to predict anyother new dataset. we have used test data set, which is used to evaluate the performance of built algorithms. Classification algorithms create predictors while learning. The training dataset is used to teach the classifier and the class designations that go with them (variables). The classifier is used for categorization in classifying. Here Classification algorithms' accuracy is estimated using test data. The components of classification can be transferred to the new datasets tuples if the accuracy is deemed adequate, which will be determined by the the degree of confidence or tolerance. The classifier-training method utilizes these pre-classified examples to identify all of the variables (parameters) required for correct judgment or analysis. The algorithm then encodes these factors (variables) into a data structure. Neural networks, which have been successfully applied in a variety of areas such as banking institutions, database mining, and computer security, can also be used to solve the default prediction problem. Recently, many machine learning ‘ standard-oriented approaches to debt default prediction have been developed[?] A significant portion of these approaches are based on Logistics Regression, classification, or a combination of these and other ensemble methods. Preliminary literature review reveals that previous studies focused on the loan default of online lending clubs and online lending institutions for credit risk assessment by using historical data of customers and FICO score to measure the risk associated with the borrowers, implying that the data collected online was insufficient and difficult to clean. Loan default trends have been long studied from a socio-economic viewpoint. Most research papers believe in empirical modelling of these complex systems in order to be able to predict the loan default rate for a specific individual. The use of machine learning for such jobs is a trend which we are perceiving now Previously lenders and financial institutions employed highly professional people to evaluate a borrower's worthiness before approving



or rejecting a loan application. However, recently these institutions have started employing various models for loan evaluation in order to decide whether to reject or approve a loan to a borrower based on their credit score and ability to repay a given loan. They chose models based on machine learning models and artificial neural networks for accurately predicting credit defaulters among borrowers. Many peer-to-peer lending platforms encourage borrowers to form online groups in order to reduce information asymmetry. The practical results of the research show that the closer the location of the borrowers in the group, the lower the likelihood of default. In addition, if they have a definite connection in real life, joining the group will significantly reduce the borrower default probability. According to the borrower's social media disclosure, borrowers with many friends are more likely to obtain loans, and the default probability is very low. Because of the vast amount of data that the banking industry works with, data analysis and transformation into useful knowledge has become a job that is beyond human capability. Data mining techniques can be adopted in answering business problems by finding patterns, associations and correlations which are masked in the business information stored in the databases. By employing data mining techniques to investigate the patterns and trends associated with them, bank executives can predict, with high accuracy, how customers will respond to adjustments in interest rates, which customers are likely to receive new product offers, which customers will be at a higher risk for defaulting on a loan, Lenders in the lending industry and financial institutions typically assess loaners' repayment ability as well as the risks of lending money to borrowers from customer. Based on the repayment ability and risks associated, the lenders, especially the banks, can balance the interest rates of the loans which are issued to the client or borrowers.

## **2.2 MACHINE LEARNING**

Machine learning is a type of algorithm that allows software applications to become more precisely unpredictable without being explicitly programmed. A subset of AI supports the notion that a system can learn from data, recognize patterns, and make decisions to achieve optimal solutions with minimal human intervention. There are two types of ML algorithms, supervised machine learning algorithms and unsupervised machine learning algorithms.

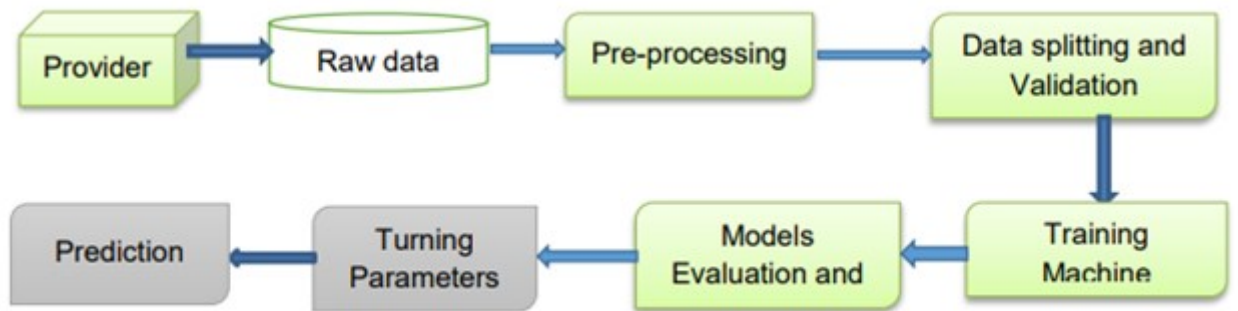


Figure 2.1: Machine Learning Process

## 2.3 MACHINE LEARNING PROCESS

## 2.4 EXISTING SYSTEM

Existing systems uses traditional methods of Planning and strategic management for predicting the loan to the customer which delays the process as well as the outcome is not efficient. To overcome this solution in this project we have used Machine Learning algorithms which gain amazing results by using different machine learning models.

## CHAPTER 3

### DATA SET

The dataset for our implementation has been downloaded from the website name as Kaggle which has good collection public data. And dataset consists important features like loan\_ID, gender, marital status, dependents, level of education, self-employment, applicant and applicant incomes, loan amount, loan amount and term, and credit history.

The titles of the columns with the int64 data type are Property Area. Each row contains values with Loan\_ID being unique, Gender having either a masculine or female value, The dependents values are 'standard+', the credit history value is 0 or 1, the married and self-employed values are either yes or no values, the education input is either graduate or not graduate, and the remaining values are all of the numerical type[3]. The dataset consists of an acceptable loan application. The dataset consists 614 records with 13 attributes. It has labelled data for customer loan eligibility may become comes outcomes Yes/No. so Yes means customer are able to get loan and No means customer are not eligible to get loan.

Loan ID	Customer	Current Lz	Term	Credit	Score	Annual	In	Years	In	o	Home	Ow	Purpose	Monthly	C	Years	of	C	Months	si	Number	of	Current	O	Maximum	Bankrupts	Tax	Liens
7738779f-cded0b3c3	611314	Short	Terr	747	2074016	10+	years	Home	Mlo	Debt	Cons	42000.83	21.8	NA	9	0	621908	1058970	0	0								
6dcd0947-1630ee63	266662	Short	Terr	734	1919190	10+	years	Home	Mlo	Debt	Cons	36624.4	19.4	NA	11	0	679573	904442	0	0								
77744011-2a90938b	153494	Short	Terr	709	871112	2	years	Rent	Debt	Cons	8391.73	12.5	10	10	0	38532	388036	0	0									
83721f9b-112136654	176242	Short	Terr	727	790083	10+	years	Rent	Debt	Cons	18771.87	16.5	27	16	1	154940	510122	1	0									
08f5789f-c39888105	321992	Short	Terr	744	1781348	10+	years	Home	Mlo	Debt	Cons	39478.77	26	44	14	0	359795	468072	0	0								
a4957289-68780414	202928	Short	Terr	741	760380	1	year	Rent	Debt	Cons	6526.69	13.8	NA	6	0	258847	478872	0	0									
43467932-481134e8	621786	Long	Terr	733	1783606	10+	years	Home	Mlo	Debt	Cons	30563.98	15.3	NA	42	0	281299	1449162	0	0								
930c7e1b-10941861	266794	Long	Terr		<1	year		Own	Hom	Debt	Cons	12336.89	5.8	NA	9	0	293206	342232	0	0								
0c271346-8a1ade5a	201466	Short	Terr	736	1068617	5	years	Rent	Debt	Cons	18795.21	20.5	NA	2	0	0	0	0	0									
008f3a5e-4030a028	266288	Long	Terr	683	2015118	2	years	Rent	Debt	Cons	12443.1	24.4	56	8	2	31445	251130	2	0									
3102e499-8116023d	121110	Short	Terr		<1	year		Rent	Debt	Cons	10748.44	19.2	52	4	0	102087	198130	0	0									
663ad9a3-8ec9f388	258104	Short	Terr	723	1284514	7	years	Rent	Debt	Cons	6368.99	14.6	64	12	0	128402	266904	0	0									
1a177f73-d69b330	161722	Short	Terr	680	504374	7	years	Rent	other		6094.61	9.5	NA	13	0	167903	388828	0	0									
79e99297-3b4ae7fe	753016	Long	Terr		5	years		Home	Mlo	Debt	Cons	9627.49	21.7	21	9	0	384532	657646	0	0								
c3e31913-1622ad056	444664	Short	Terr		5	years		Rent	Debt	Cons	22817.86	17.9	8	25	0	318953	971872	0	0									
a913063f-49f38e0c	172282	Short	Terr	696	669580	3	years	Home	Mlo	Debt	Cons	17966.78	18.2	NA	16	0	431490	999362	0	0								
e328613a-8c48e3f3	279440	Short	Terr	729	1236976	6	years	Rent	Debt	Cons	25647.08	35.8	NA	13	0	151088	264242	0	0									
add946a5-1618a025	218834	Short	Terr	742	1077262	3	years	Own	Hom	Home	Inc	19390.64	24.5	29	37	0	212800	502876	0	0								

Figure 3.1: Train Data

Basically, Data test has many attributes such as salary, marital status loan without the loan approval status so if we want to deploy the test data we have build the trained data.

Loan ID	Customer ID	Current Loan Term	Credit Score	Annual Income	Years in Current Home	Business Purpose	Monthly Debt Ratio	Months in U.S.	Months in Current U.S.	Months in Bankruptcy	Days Late
1000000001	1000000001	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000002	1000000002	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000003	1000000003	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000004	1000000004	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000005	1000000005	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000006	1000000006	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000007	1000000007	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000008	1000000008	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000009	1000000009	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000010	1000000010	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000011	1000000011	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000012	1000000012	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000013	1000000013	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000014	1000000014	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000015	1000000015	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000016	1000000016	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000017	1000000017	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000018	1000000018	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000019	1000000019	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000020	1000000020	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000021	1000000021	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000022	1000000022	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000023	1000000023	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000024	1000000024	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000025	1000000025	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000026	1000000026	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000027	1000000027	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000028	1000000028	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000029	1000000029	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000030	1000000030	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000031	1000000031	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000032	1000000032	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000033	1000000033	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000034	1000000034	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000035	1000000035	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000036	1000000036	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000037	1000000037	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000038	1000000038	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000039	1000000039	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000040	1000000040	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000041	1000000041	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000042	1000000042	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000043	1000000043	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000044	1000000044	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000045	1000000045	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000046	1000000046	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000047	1000000047	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000048	1000000048	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000049	1000000049	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000050	1000000050	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000051	1000000051	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000052	1000000052	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000053	1000000053	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000054	1000000054	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000055	1000000055	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000056	1000000056	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000057	1000000057	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000058	1000000058	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000059	1000000059	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000060	1000000060	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000061	1000000061	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000062	1000000062	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000063	1000000063	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000064	1000000064	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000065	1000000065	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000066	1000000066	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000067	1000000067	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000068	1000000068	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000069	1000000069	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000070	1000000070	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000071	1000000071	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000072	1000000072	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000073	1000000073	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000074	1000000074	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000075	1000000075	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000076	1000000076	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000077	1000000077	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000078	1000000078	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000079	1000000079	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000080	1000000080	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000081	1000000081	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000082	1000000082	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000083	1000000083	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000084	1000000084	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000085	1000000085	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000086	1000000086	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000087	1000000087	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000088	1000000088	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000089	1000000089	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000090	1000000090	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000091	1000000091	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000092	1000000092	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000093	1000000093	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000094	1000000094	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000095	1000000095	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000096	1000000096	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000097	1000000097	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000098	1000000098	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000099	1000000099	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0
1000000100	1000000100	12 months	720	100000	10 years	Home Mortgage	0.25	12	12	0	0

Figure 3.2: Test Data

The data gathering, preprocessing, selection of key features, training of the model, and testing of the model's performance are the main stages in this work. The information for this effort is gathered from a public repository using data from kaggle' customers. the 13 attributes of the gathered dataset. Output label, which indicates the state of the customer loan, is one of those attributes. One indicates that the applicant's credit has been approved, and zero indicates that it has not. Figure 2 depicts the project's process. Data collection is the first step, followed by data preprocessing, feature selection, data splitting into train and test parts, model training, performance assessment of the model, and comparison of the results[1]. Step 1 is data collection, step 2 is data preprocessing, step 3 is feature selection, step 4 is data splitting into train and test parts, step 5 is model training and step 6 is model performance evaluation and finally work concluded with comparison of decision tree, support vector machine, k nearest neighbor, and decision tree techniques accuracy in predicting customer loan eligibility Accuracy is one of the performance evaluation metrics for machine learning model. It gives the value which is the ration of number of correct predictions with total number of predictions[2].

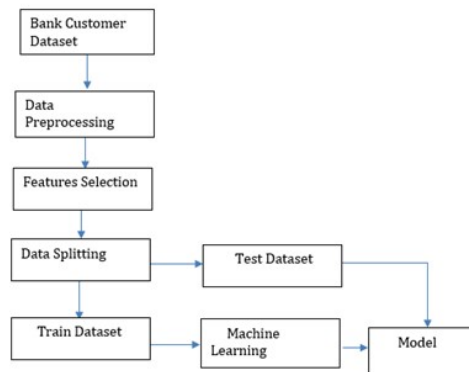


Figure 3.3: Workflow of the work

## **CHAPTER 4**

### **METHODOLOGY**

#### **4.1 DATA CLEANING AND PROCESSING**

Missing values in the dependent's column are filled with the column's average value, those in the applicant income attribute are filled with the column's lowest value, those in the loan \_amount \_term field are filled with the field's maximum term period, and those in the credit\_history field are filled with 0. Data processing raises the level of data quality generally.

#### **4.2 FEATURE EXTRACTION**

The feature selection approach is used to choose more the right characteristics to determine a customer's credit eligibility. Application of the feature selection technique and analysis of variance on dataset to enhance the classifier's efficiency.

#### **4.3 DATA SPLITTING**

The foundation of a machine learning algorithm is data. In this study, the data is split in half, 80:20, for training and evaluating the model. The model was trained using the train dataset, and the model was validated using the test dataset portion.

#### **4.4 DATA COLLECTION**

The training set and testing set are created from the dataset that was gathered for forecasting loan failure. On the training set, the decision tree-created data model is applied, and test set forecasting is carried out based on the test pick fineness. Bank Loan eligibility prediction is conducted using attributes describes eligibility the attributes is associated with information of person's age, gender, educational background,

properties, credit card information etc. and class attribute is bank loan eligibility prediction. where there are following attributes.

Variable	Description
Loan id	Unique loan id
Gender	Male/Female
Married	Yes/No
Dependent	Number of Dependent
Education	Graduate/ Undergraduate
Self employed	Yes/ No
Applicant income	Applicant Income
Loan Amount	Amount loan in Hundred/ Thousands
Loan Amount Term	Term of loan in Months
Credit History	Credits history meets guidelines
Property Area	Urban/Rural
Loan Status	Loan Approved Yes/No

Figure 4.1: Table Variable vs Description

## 4.5 TRAIN MODEL ON TRAINING DATA SET

The model is then trained using the two datasets - training and assessment. Our train collection is divided into two parts: tract train and testimony. The model is then trained on this portion to make the testimony part easier[4]. As we have the true sooth sayings for the testimony portion (which we do not have for the test dataset), we can verify our sooth sayings in this manner. So entries of new application will able to act test data which are filled at the time of submitting the application while performing the test model will determine whether loan will be approved or not on the basis of the various training dataset.

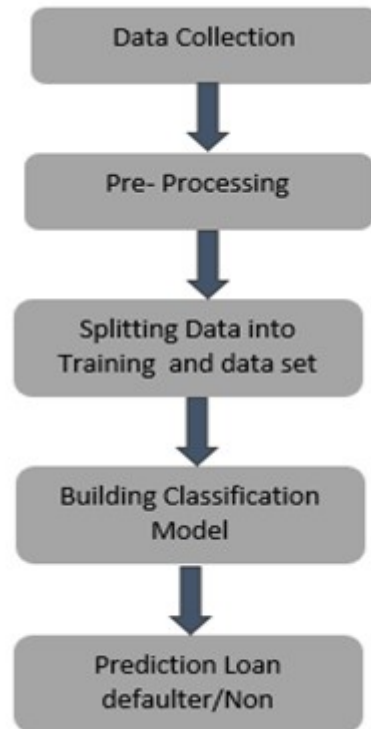


Figure 4.2: Chronology of Data

## 4.6 CORRELATING ATTRIBUTES

Based on the correlation between attributes, it was discovered that they were more likely to repay their debts[5]. Individual and essential attributes include property area, education, loan measure, and originally credit History, which is regarded as important. In the Python platform, the characteristics are associated using scatter-plot and Boxplot. The approach is used:

The proposed model is used to determine the output, i.e., predicting whether the loan will be authorized in the end.

In the following section, we get the results after finally entering the data of customers into web page built on flask server..

### **Proposed Model**

We have developed the software application for approval/not approval of loan and we have also used machine learning to have symmetric model from existing dataset and it has been used for test the dataset consists two data train and dataset so model has been used testing dataset for result and Decision Tree uses and builds model for existing training the dataset.

## 4.7 SELECTING THE MODELS

### 4.7.1 Logistic Regression

A classified dependent variable's outcome is predicted using logistic regression. As a result, the conclusion must be categorical or distinct. It can be Yes or No, true or False, and so on, but instead of providing the precise values as 0 and 1, it provides the probabilistic values that fall between 0 and 1.

### 4.7.2 Decision Tree classifier

It is a technique for obtaining all possible solutions to an issue based on constraints[6]. Because the model's depiction resembles a tree, it is known as a decision tree. Figure 3 depicts the design of a decision tree model. It is a tree-structured classifier in which internal nodes reflect dataset characteristics, branches represent judgment criteria, and each leaf node symbolizes the result. it uses for asking the loan approved or not.

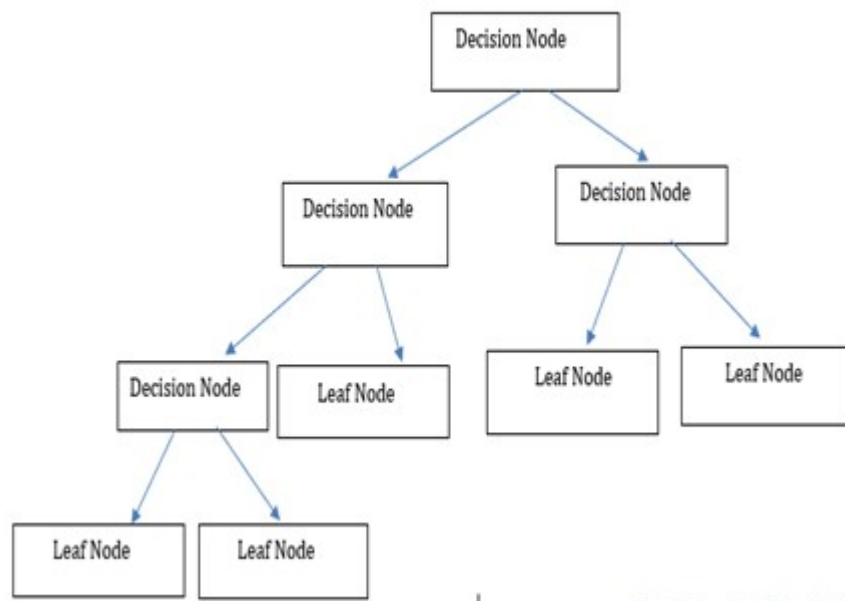


Figure 4.3: Decision Tree Model

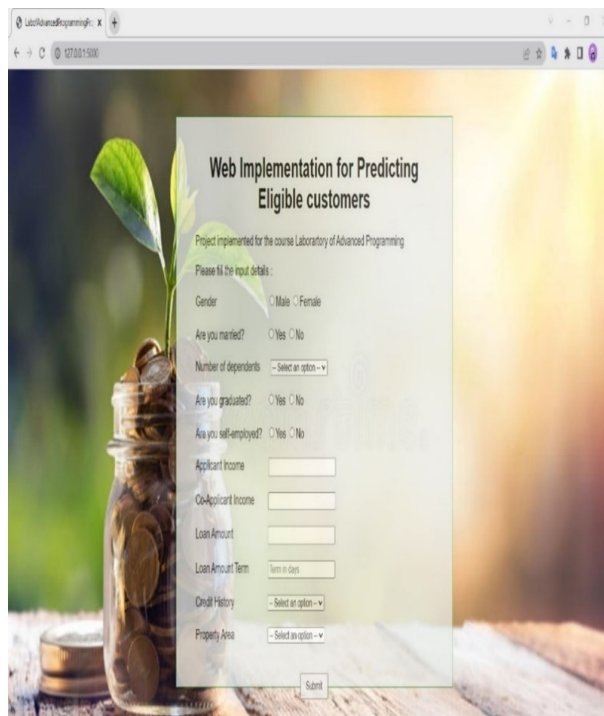


## CHAPTER 5

### SUMMARY

#### 5.1 RESULTS

In this section we can see the attributes are displayed in a form manner and this is need to be filled and according to the given values either loan will be approved or rejected. In this section, We have used machine learning algorithms on a loan dataset and predicted the result. using HTML, CSS with python jupyter notebook at the flask server. It shows the loan prediction system of the applicants based on the value entered by the bank employee.



The screenshot shows a web browser window displaying a form titled "Web Implementation for Predicting Eligible customers". The form is overlaid on a background image of a glass jar filled with coins and a small green plant growing from it. The form contains the following fields and options:

- Gender: ☐ Male ☐ Female
- Are you married?: ☐ Yes ☐ No
- Number of dependents: --Select an option--
- Are you graduated?: ☐ Yes ☐ No
- Are you self-employed?: ☐ Yes ☐ No
- Applicant Income:
- Co-Applicant Income:
- Loan Amount:
- Loan Amount Term:
- Credit History: --Select an option--
- Property Area: --Select an option--
- Submit:

Figure 5.1: Final Layout

The attributes is select gender either male or female second attributes is marital status married or single after dependent attributes it means applicant is dependent some attributes are education of customer employment status applicant income loan amount term credit history residential area of applicant and show the status of loan.

Figure 5.2: AWS Output

The screenshot shows a web browser window with the address bar displaying 'http://localhost:8080/EligibleCustomer'. The page content features a light green background with a subtle pattern of small white dots. On the left side, there is a decorative image of a green plant in a glass jar filled with coins. The main content area is a white rectangular box with a title 'Web Implementation for Predicting Eligible customers' and a subtitle 'Project implementation for the course Laboratory of Advanced Programming'. Below the subtitle, there is a form with the following fields and labels:

- Gender: ☐ Male ☐ Female
- Are you married? ☐ Yes ☐ No
- Number of dependents:
- Are you employed? ☐ Yes ☐ No
- Are you self-employed? ☐ Yes ☐ No
- Number Income:
- Child-Dependent Income:
- Loan Interest:
- Loan Amount Term:
- Child-Dependent Income:
- Payment Plan:
- Submit

Figure 5.3: Prediction Page Area Rural

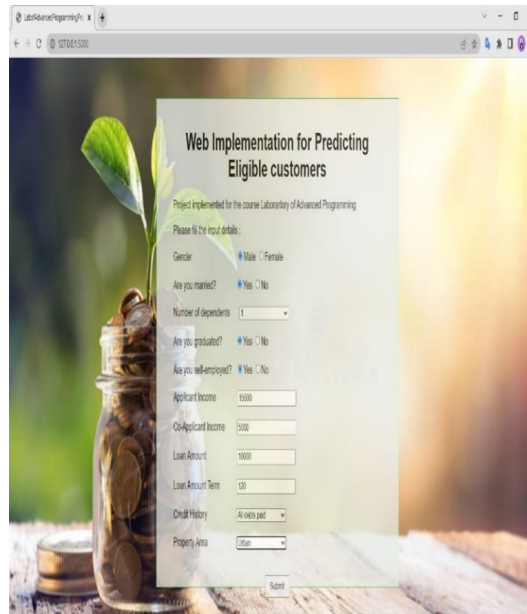


Figure 5.4: Prediction Page Area Urban

After filling in the mentioned details, we can click the submit button and there is used for proposed. Model which will give us predict. output it has been observed two cases loan approval and Loan. rejection based on different. attributes. The dataset has been used in this work hence attributes contribute to be better. to be an accurate real time prediction.

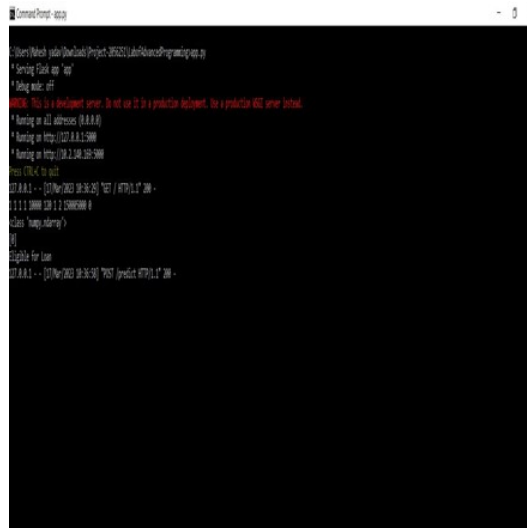


Figure 5.5: Cmd output eligible



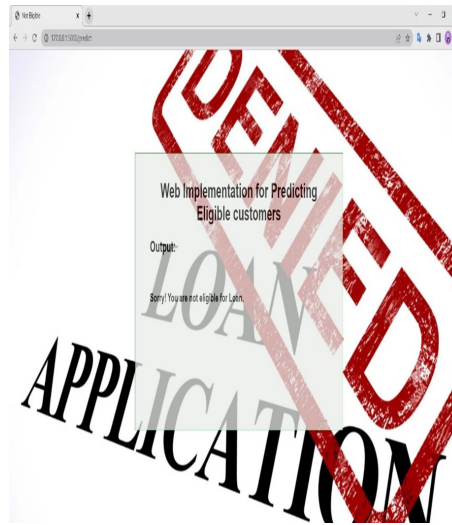


Figure 5.8: A case of Loan Rejection

So the result has been obtained according out train and test the data which our data has been measured as per requirement.

## 5.2 CONCLUSION

At the start, we have cleaned the dataset. Then exploratory data analysis and feature engineering was performed. Then different model were created which predicted whether the applicant would repay the loan or not.

## 5.3 LEARNING EXPERIENCE

The project development provided us with a sense of new technologies that we were not familiar with at the beginning of this project. we have learned to work with Jupyter notebooks, Scrum project management, Functional point Analysis, COCOMO-2, Github and usage of different Python libraries for Machine Learning while deployment on AWS EC2. Plus, we understood the concepts of Machine Learning by building models.

## 5.4 FUTURE ENHANCEMENT

Using different machine learning techniques can be implemented and to get good results so machine learning model is valuable for customer loan eligibility prediction and all existing model doesn't give 100 percent accuracy so it means there is need to design the innovative model for customer loan eligibility prediction .In the future a deep model is about propose for customer loan eligibility for future work.

## REFERENCES

- [1] Kumar Arun, Garg Ishan, and Kaur Sanmeet. Loan approval prediction based on machine learning approach. *IOSR J. Comput. Eng*, 18(3):18–21, 2016.
- [2] Anshika Gupta, Vinay Pant, Sudhanshu Kumar, and Pravesh Kumar Bansal. Bank loan prediction system using machine learning. In *2020 9th International Conference System Modeling and Advancement in Research Trends (SMART)*, pages 423–426. IEEE, 2020.
- [3] Ch Naveen Kumar, D Keerthana, M Kavitha, and M Kalyani. Customer loan eligibility prediction using machine learning algorithms in banking sector. In *2022 7th International Conference on Communication and Electronics Systems (ICCES)*, pages 1007–1012. IEEE, 2022.
- [4] Mohammad Ahmad Sheikh, Amit Kumar Goel, and Tapas Kumar. An approach for prediction of loan approval using machine learning algorithm. In *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, pages 490–494. IEEE, 2020.
- [5] Mohammad Ahmad Sheikh, Amit Kumar Goel, and Tapas Kumar. An approach for prediction of loan approval using machine learning algorithm. In *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, pages 490–494. IEEE, 2020.
- [6] Vishal Singh, Ayushman Yadav, Rajat Awasthi, and Guide N Partheeban. Prediction of modernized loan approval system based on machine learning approach. In *2021 International Conference on Intelligent Technologies (CONIT)*, pages 1–4. IEEE, 2021.
- [7] CN Sujatha, Abhishek Gudipalli, Bh Pushyami, N Karthik, and BN Sanjana. Loan prediction using machine learning and its deployment on web application. In *2021 Innovations in Power and Advanced Computing Technologies (i-PACT)*, pages 1–7. IEEE, 2021.