# BUILDING A MODEL FOR LOAN
# APPROVAL USING STACKING
# MODEL

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering

By

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# DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

# SCHOOL OF COMPUTING

# SATHYABAMA
## INSTITUTE OF SCIENCE AND TECHNOLOGY
## (DEEMED TO BE UNIVERSITY)
**Accredited with Grade "A" by NAAC | 12B Status by UGC | Approved by AICTE**
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## APRIL 2023

# DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

## BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Annam Poornachand (Reg.No - 39110065) and Gundala Asish Preetham (Reg.No - 39110097)** who carried out the Project Phase-2 entitled **"BUILDING A MODEL FOR LOANAPPROVAL USING STACKING MODEL"** under my supervision from January 2023 to April 2023.

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# DECLARATION

I, **Annam Poornachand (Reg.No - 39110065), hereby** declare that the Project Phase-2 Report entitled "**A STACKED MODEL FOR APPROVING BANK LOANS"** done by me under the guidance of **Dr. S. Bangaru Kamatchi, M.E., Ph.D.** is submitted in partial fulfillment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

**DATE:**

**PLACE: Chennai**                              **SIGNATURE OF THE CANDIDATE**

# ACKNOWLEDGEMENT

I am pleased to acknowledge my sincere thanks to **Board of Management** of **SATHYABAMA** for their kind encouragement in doing this project and for completing it successfully. I am grateful to them.

I convey my thanks to **Dr. T. Sasikala M.E., Ph. D**, **Dean**, School of Computing, **Dr. L. Lakshmanan M.E., Ph.D.,** Head of the Department of Computer Science and Engineering for providing me necessary support and details at the right time during the progressive reviews.

I would like to express my sincere and deep sense of gratitude to my Project Guide **Dr. S. Bangaru Kamatchi M.E., Ph. D,** for her valuable guidance, suggestions and constant encouragement paved way for the successful completion of my phase-2 project work.

I wish to express my thanks to all Teaching and Non-teaching staff members of the **Department of Computer Science and Engineering** who were helpful in many ways for the completion of the project.

# ABSTRACT

Machine learning is playing a prominent role in current era. In this modernized world almost all the applications are manipulated and controlled by machine learning algorithms. By the use of historical data there are possibilities to predict the future. Even though a number of researchers are working on various machine learning, the performance and exactness of the algorithms still remains as a challenge. This work focuses on the performance analysis of various classification algorithms like Logistic Regression, Gaussian Naïve Bayes, Decision Tree Classifier and Random Forest Classifier in terms of confusion matrix, accuracy, precision, recall, f-measure etc., and performance enhancement of those algorithms using stacking to predict the bank loan approval status so we can overcome the need to depend on a single machine learning model instead we can combine multiple models so to obtain a stacked model which provides better predictions as compared to each individual model.

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# LIST OF ABBREVIATIONS

| S.NO | ABBREVIATION | DEFINITION |
|------|------|------|
| 1 | ASM | ATTRIBUTE SELECTION MEASURE |
| 2 | FN | FALSE NEGATIVE |
| 3 | FP | FALSE POSITIVE |
| 4 | ML | MACHINE LEARNING |
| 5 | RL | REINFORCEMENT LEARING |
| 6 | TN | TRUE NEGATIVES |
| 7 | TR | TRUE POSITIVE |

# CHAPTER 1

# INTRODUCTION

Machine Learning is utilized to show machines how to handle the information all the more efficiently. Once in a while in the wake of review the information, we can't decipher the example or concentrate data from the information. All things considered, we apply machine learning. With the plenitude of data set accessible,the interest for machine learning is in rise. Numerous businesses from drug to military apply machine figuring out how to extricate applicable data. The present overwhelming worldview for ML is to run a ML calculation on an offered dataset to produce a model. The model is then connected, all things considered, and theassignments are executed. This is valid for both supervised and unsupervised learning.

Major Machine Learning Types:

1. Supervised Learning

2. Unsupervised Learning

3. Reinforcement Learning

## 1.1 Supervised Learning:

In training data set contains the features with target values. This is likewise called gaining from the models. This is generally composed as a lot of information ($x_i$, $t_i$), where the sources of info are $x_i$, the objectives are $t_i$ , ordered by running from 1 to some maximum limit N.

### 1.1.1 Regression

Regression is a supervised learning approach considered when our target value($t_i$) is a continuous value. It is a straight wat to deal with demonstrating the connection between a scalar reaction (or dependent variable) and at least one illustrate factors
(or independent).

### 1.1.2 Classification

Regression is a supervised learning approach considered when our target value($t_i$) is a categorical value.

## 1.2 Unsupervised Learning:

Unsupervised learning is a lot harder on the grounds that here the model needs to figure out how to perform indicated assignments without revealing to it how toperform because the dataset will only have input features without any target values. Clustering is one of the approaches to deal with unsupervised learning.

## 1.3. Reinforcement Learning (RL):

This learning lies between supervised and unsupervised learning. The calculation finds told when the solution is wrong, yet does not get advised how to right it. Itneeds to investigate and experiment with various potential outcomes until find the solution right. RL sometime called learning with a commentator as a result of this screen scores the appropriate response, however does not recommend upgrades.

# CHAPTER 2

# LITERATURE SURVEY

This chapter contains a list of literature review of previous research where it is considered vital in development of this project. [1] With the plenitude of data set accessible, the interest for machine learning is in rise. Numerous businesses from drug to military apply machine figuring out how to extricate applicable data. Naive Bayes', which can be amazingly quick in respect to other order calculations. [5] It takes a shot at Bayes hypothesis of likelihood to foresee the class of unknown dataset. Regarding Logistic Regression Tabachnick and Fidell (2013) recommend that as long relationship coefficients among autonomous factors are under .90 the suspicion is met. At the Focal point of the logistic regression examination is undertaking evaluating the log chances of an occasion. In case of random forest, If one tree is extraordinary, various trees (a forest) should be better, given that there is adequate combination between them. [4] The most fascinating thing about the random forest is the habits in which that it makes randomness from a standard dataset. In the essence, stacking makes prediction by using a meta-model trained from a pool of base models — a pool of base models are first trained using training data and asked to give their prediction; a different meta model is then trained to use outputs from base models to give the final prediction. As machine learning is a research intensive field   constant performance  and behavioral analysis and striving to improve existing algorithms using innovative techniques or developing new algorithms or approaches are mandatory.

# CHAPTER 3

# PROBLEM STATEMENT

In any machine learning based solution the basic approach involves taking the most suitable machine learning algorithm and obtaining a model through training on the well pre-processed dataset and then testing that model withthe test data to analyze it's performance. Sometimes this model maybe underfitted or overfitted which requires complex tuning process which may or may not improve model's performance. Hence using more than one algorithm and preparing multiple models and then combining them using stacking approach in such a way that will improve prediction capabilities of a stacked model as compared to individual model is definitely a better choice. The main objective of the proposed system is to **analyze and enhance the performance of various machine learning classification algorithms through extensive stacking**. To Achieve such an objective problem statement satisfying being a classification problem is considered.

Problem Statement: Whether a person will be approved for personal bank loan?

Target value: Yes (or) 1 if a person is approved to be granted by a personal loan.

No (or) 0 if a person is not approved to be granted by a personal loan.

The above target values specifies that the problem statement is a binary classification problem, as there are only two possible categories or target labels.

# CHAPTER 4

# ALGORITHMS AND METHODOLOGY

## 4.1 Classification Algorithms

1.1 Logistic Regression

1.2 Decision Tree Classifier

1.3 Gaussian Naïve Bayes Classifier

1.4 Random Forest Classifier

## 4.1.1 Logistic Regression

Logistic regression is one of the most popular Machine Learning algorithms, which comes under the Supervised Learning technique. It is used for predicting the categorical dependent variable using a given set of independent variables.

Logistic regression predicts the output of a categorical dependent variable. Therefore, the outcome must be a categorical or discrete value. It can be either Yes or No, 0 or 1, true or False, etc. but instead of giving the exact value as 0 and 1, **it gives the probabilistic values which lie between 0 and 1**.

### Logistic Function (Sigmoid Function):

- The sigmoid function is a mathematical function used to map the predicted values to probabilities.
- It maps any real value into another value within a range of 0 and 1.
- The value of the logistic regression must be between 0 and 1, which cannot go beyond this limit, so it forms a curve like the "S" form. The S-form curve is called the Sigmoid function or the logistic function.

- In logistic regression, we use the concept of the threshold value,  which defines the probability of either 0 or 1. Such as values above the threshold value tends to 1, and a value below the threshold values tends to 0.
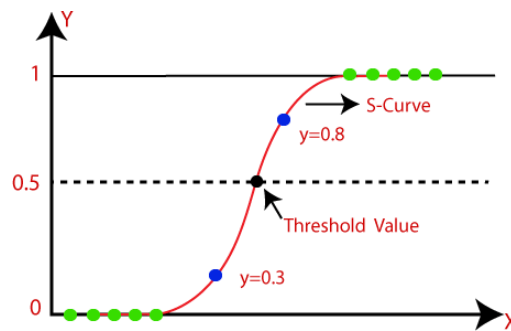


Figure 4.1 Sigmoid Function

**Logistic Regression Equations**

$P (Y = 0 / X) = 1 / 1 + e^z$  [max for class 0]          **[Equation 3.1]**

$P (Y = 1/ X) = e^z/ 1 + e^z$ [max for class 1]          **[Equation 3.2]**

where $z = w_o x_o + w_1 x_1 + w_2 x_2 + \ldots\ldots + w_n x_n$ [network sum] [Equation 3.3]

Y: target label [yes/no (or) 1/0]

X:  sample

P(Y = 0 / X): probability that a sample X will belong to class 0

P(Y = 1 / X): probability that a sample X will belong to class 1


**4.1.2 Decision Tree Classifier**

- It is a Supervised Machine Learning where the data is continuously split according  to a certain parameter.
- In a decision tree, for predicting the class of the given dataset, the algorithm starts from  the  root node  of  the  tree. This  algorithm  compares the values of root attribute  with  the   record (real dataset)  attribute  and, based  on  the comparison, follows  the  branch  and  jumps  to  the  next node.
- For the next node, the algorithm  again  compares  the  attribute  value  with the other sub-nodes and move further. It continues the process until it

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reaches the leaf node of the tree. The complete process can be better understood using  the below algorithm:

**Step-1:** Begin the tree  with  the  root  node,  says   S, which contains the complete dataset.

**Step-2:** Find the best attribute in the dataset using Attribute Selection Measure(ASM).

**Step-3:** Divide the S into  subsets  that  contains  possible  values  for  the best attributes.

**Step-4:** Generate  the  decision  tree  node, which  contains  the  best attribute.

**Step-5:** Recursively make new decision trees using the subsets  of  the dataset created in step -3. Continue this process until a stage is reached where you cannot  further  classify  the nodes  and  called  the  final  node  asa leaf node.

- A Decision Tree consists of :

    i) Nodes : Test for the value of a certain attribute.

    ii)  Edges/ Branch : Correspond to the outcome of a test and connect to

      the next  node or leaf.

    iii) Leaf nodes : Terminal nodes that predict the outcome (represent class
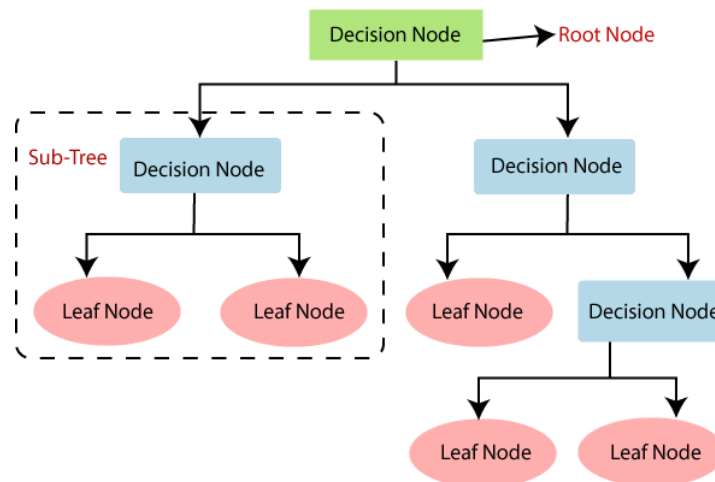
      labels or  class distribution).

Figure 4.2 Decision Tree

**ASM (Attribute Selection Measures)**

While implementing a Decision tree, the main issue arises that how to select the best attribute for the root node and for sub-nodes. So, to solve such problems there is a technique which is called as **Attribute selection measure or ASM.**

**i) Information Gain**

Information gain is the measurement of changes In entropy after the segmentation of a dataset based on an attribute. It calculates how much information a feature provides us about a class. According to the valueof information gain, we split the node and build the decision tree.A decision tree algorithm always tries to maximize the value of information gain, and a node/attribute having the highest information gain is split first. It can be calculated using the below formula:

IG = Entropy(S)- [(Weighted Avg) *Entropy (each feature)    [Equation 3.4]

**Entropy:** Entropy is a metric to measure the impurity in a given attribute. It specifies randomness in data. Entropy can be calculated as:

$$\text{Entropy(s)} = -P(yes)\log_2 P(yes) - P(no)\log_2 P(no) \qquad \text{[Equation 3.5]}$$

### 4.1.3 Gaussian Naïve Bayes Classifier

Naïve Bayes classifier is constructed from Bayes Theorem with a assumption. Naïve Bayes Classifier is a multi-class classifier.

According to the Bayes Theorem:

$$P(Y/X) = P(X/Y)\,P(Y)\,/\,P(X) \qquad \text{[Equatio3.6]}$$

Where

P(Y/X)= probability of Y occurring given evidence X has already occurred[posterior]

P(X/Y)= probability of X occurring given evidence Y has already occurred[likelihood]

P(X)= probability of X occurring [class prior probability]

P(Y)= probability of Y occurring [predictor prior probability]

Why Naïve?

In addition to the Naïve Bayes theorem we make a assumption that every feature/attribute is independent of other features and every feature/attribute contributes towards predicting target class. This is called as Conditional Independence.

Hence we have:

$$P(Y/X) = P(x_1/Y)* P(x_2/Y)* P(x_3/Y)*\ldots\ldots P(x_n/Y)*P(Y) \qquad \text{[Equation 3.7]}$$

We consider Gaussian Naïve Bayes when our input features are of continuous values instead of categorical.

To determine $P(X_i/Y_i)$ we us e probability density function[conditionalprobability]:

$$P(x_i \mid y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$$

[Equation 3.8]

Where $\mu = \sum X/N$ [mean]

[Equation 3.9]

$\sigma_s = \sqrt{(\sum(X-\mu)^2 /N-1)}$ [Standard Deviation of samples]

[Equation 3.10]

N= number of samples

## 4.1.4 Random Forest Classifier

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regressionproblems in ML. It is based on the concept of **ensemble learning,** which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

As the name suggests, "Random Forest is a classifier that contains a numberof decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset." Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

The greater number of trees In the forest leads to higher accuracy and prevents the problem of overfitting.
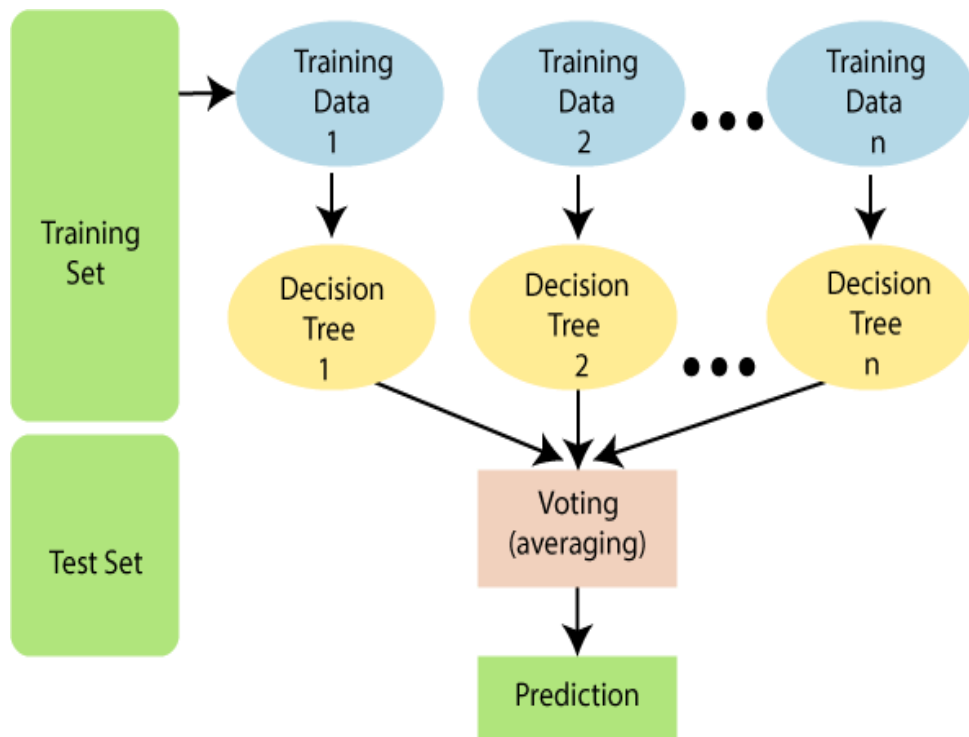
Figure 4.3 Random Forest Classifier

# CHAPTER 5

# STACKING

Stacking is an ensemble machine learning algorithm. It uses a meta-learning algorithm to learn how best combine the predictions from two or more base machine learning algorithms. The benefit of stacking is that it harnesses the capabilities of a range of well performing models on a classification or regression task and make predictions that have better performance than any single model in the ensemble.

Hence by using stacking we will be able to create a new classifier that hopefully will give better accuracy compared to all other base models.



Figure 5.1 Stacking Architecture

## 5.1 UNDERSTANDING STACKING

In the essence, stacking makes prediction by using a meta-model trained from a pool of base models — a pool of base models a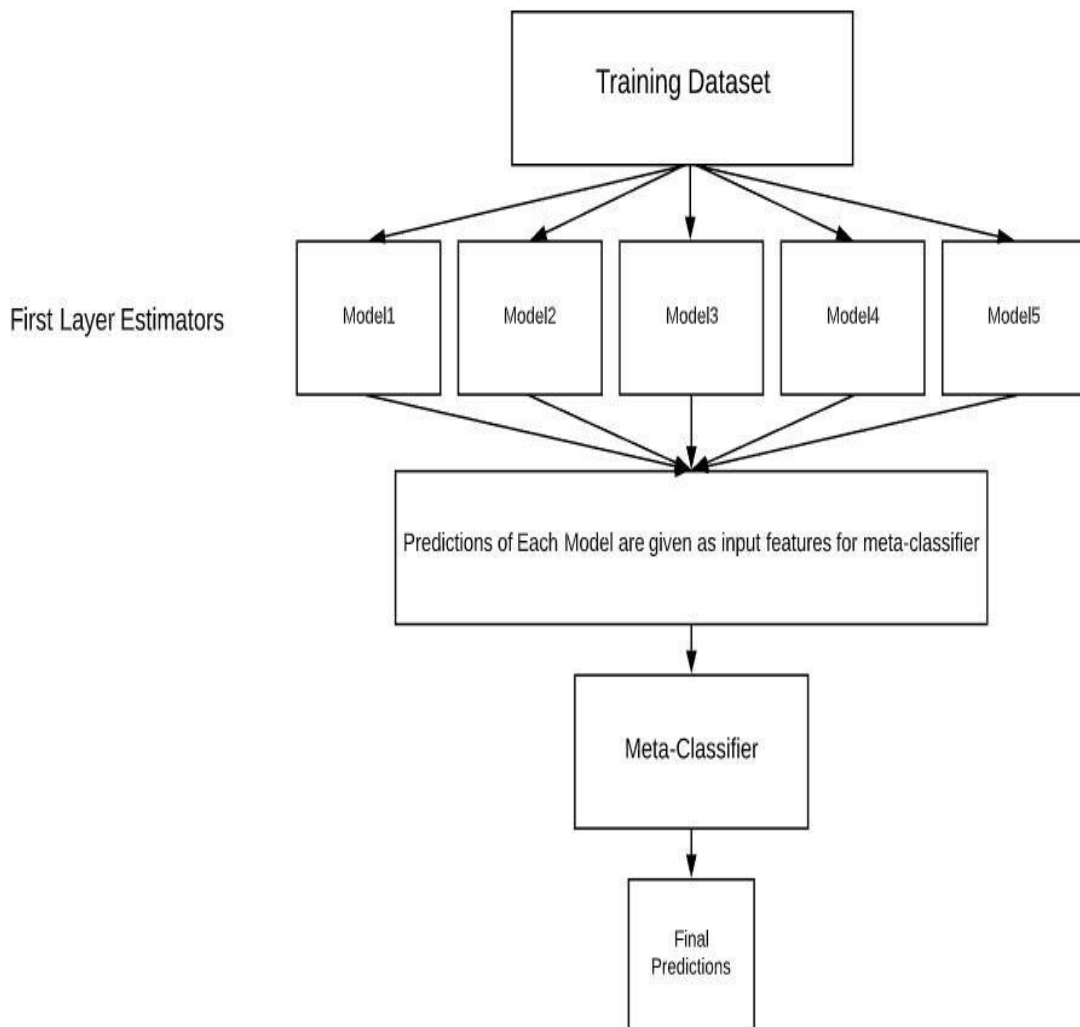re first trained using training data and asked to give their prediction; a different meta model is then trained to use outputs from base models to give the final prediction. The process is actually simple. To train a base model,
K-fold cross validation technique is used.

We can understand the stacking in **7** steps:

**Step 1:** You have Train Data and Test Data as shown in Fig 3.5. Assume we are using 4-fold cross validation to train base models, the train_data is then divided into 4 parts.

train_data

| | x_0 | x_1 | x_2 | x_3 | y |
|---|---|---|---|---|---|
| fold_1 | 0.94 | 0.27 | 0.80 | 0.34 | 1 |
| | 0.02 | 0.22 | 0.17 | 0.84 | 0 |
| fold_2 | 0.83 | 0.11 | 0.23 | 0.42 | 1 |
| | 0.74 | 0.26 | 0.03 | 0.41 | 0 |
| fold_3 | 0.08 | 0.29 | 0.76 | 0.37 | 0 |
| | 0.71 | 0.76 | 0.43 | 0.95 | 1 |
| fold_4 | 0.08 | 0.71 | 0.97 | 0.04 | 0 |
| | 0.84 | 0.97 | 0.89 | 0.05 | 1 |

test_data

| x_0 | x_1 | x_2 | x_3 | y |
|---|---|---|---|---|
| 0.74 | 0.17 | 0.820 | 0.31 | 1 |
| 0.04 | 0.27 | 0.13 | 0.80 | 0 |
| 0.87 | 0.10 | 0.24 | 0.39 | 1 |

Figure 5.2 Train Data and Test Data

**Step 2:** Using the 4-part train_data, the 1st base model (assuming it's a decision tree) is fitted on 3 parts and predictions are made for the 4th part. This is done for each part of the training data. At the end, all instance from training data will have a prediction. This creates a new feature fortrain_data, call it pred_m1 (predictions model 1) as shown in fig 3.6.
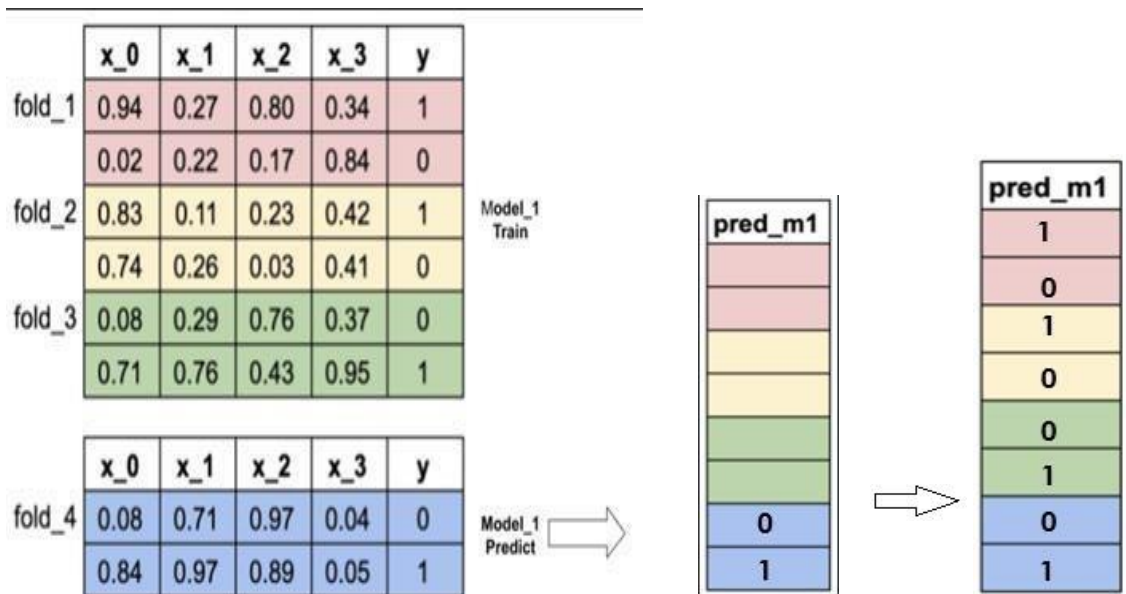
Figure 5.3 Prediction from model_1

**Step 3:** Step 2 is repeated for the 2nd model (e.g., GNB) and the 3$^{rd}$ model (e.g., Random Forest). These will give two more predictions, pred_m2 and pred_m3.



Figure 5.4 Prediction from model 1,2 and 3.

**Step 4:** Combine the above 3 prediction along with the actual target column 'y' from the train_data to obtain a dataset with predicted outcomes as input features (from each model) and actual outcome from 'y'.

| new_features | new_features | new_features | |
|:---:|:---:|:---:|:---:|
| **Pred_m1** | **Pred_m2** | **Pred_m3** | **y** |
| 1 | 1 | 1 | 1 |
| 0 | 0 | 1 | 0 |
| 1 | 1 | 1 | 1 |
| 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 |
| 1 | 1 | 1 | 1 |
| 0 | 1 | 0 | 0 |
| 1 | 1 | 1 | 1 |

Figure 5.5 Train_Data for Meta-Model

**Step 5:** Select you desired meta model for ex: Logistic Regression, and train this model on the dataset created in step 4.

**Step 6:** The meta model(Logistic Regression) is now ready to predict if given atest sample but if we observe we can't directly provide our real input features to the meta model as it's trained on 3 features which are actually prediction from different models. So, first we need to freshly initialize our base models(GNB, Decision Tree, Random Forest) and train them on whole train_data without any k-folding.

**Step 7:** Predict the test data by using each base model and combine the predictions as a single data frame. Give this data frame as a input to our meta- model for prediction which finally will give our desired prediction.

# CHAPTER 6

## Performance Measures

Analysis o performance of models is very important to ensure the correctness ofmodel. Accuracy may provide good overview of how our model has performed but it isn't enough to analyze where our model is lagging, so we can puteffort to overcome those problems. Hence with using quality and different measures we can analyze our model much better.

**Confusion Matrix**

A confusion matrix is a table that is often used to describe the performance of a classification model (or "classifier") on a set of test data for which the true values are known.



Figure 6.1 Confusion Matrix

In a confusion matrix the Actual values are represented along the rows whereas the Predicted Values are represented along the columns.

-  **True Positive (TR) :** these are the no of sample which are predicted as positive and they are positive in real.

- **True Negatives (TN):** these are the no of sample which are predicted as negative and they are negative in real.
- **False Positive (FP):** these are the no of sample which are predicted as positive and they are negative in real.
- **False Negative (FN):** these are the no of sample which are predicted as negative and they are positive in real.

From the confusion matrix we obtain different performance measure to sufficiently analyze our model.

$$\text{Accuracy} = TP+TN+FP+FN \qquad \text{[Equation 3.11]}$$

$$\text{Sensitivity or Recall or True Positive Rate} = \frac{TP}{TP+FN} \qquad \text{[Equation 3.12]}$$

$$\text{Specificity or True Negative Error} = TN \qquad \text{[Equation 3.13]}$$

$$\text{Precision} = TP \qquad \text{[Equation 3.14]}$$

$$\text{F measure} = 2 * \frac{Precision * Recall}{Precision + Recall} \qquad \text{[Equation 3.15]}$$

$$\text{Classification Error} = \frac{Error}{Total} = \frac{FP}{TP+TN+FP+FN} \qquad \text{[Equation 3.16]}$$

- Hence for the successful implementation of the proposed system three objectives must be reached as listed below and explained above :

1. **Extensive Data Preprocessing Techniques.**

2. **Stacking for Model Enhancement.**

3. **Quality Performance Measures for proper model analysis.**

- At the we are optimistic that our new model (stacking) would provide better performance in most of the aspects (performance measures) compared to all individual base models.

# CHAPTER 7

## Design
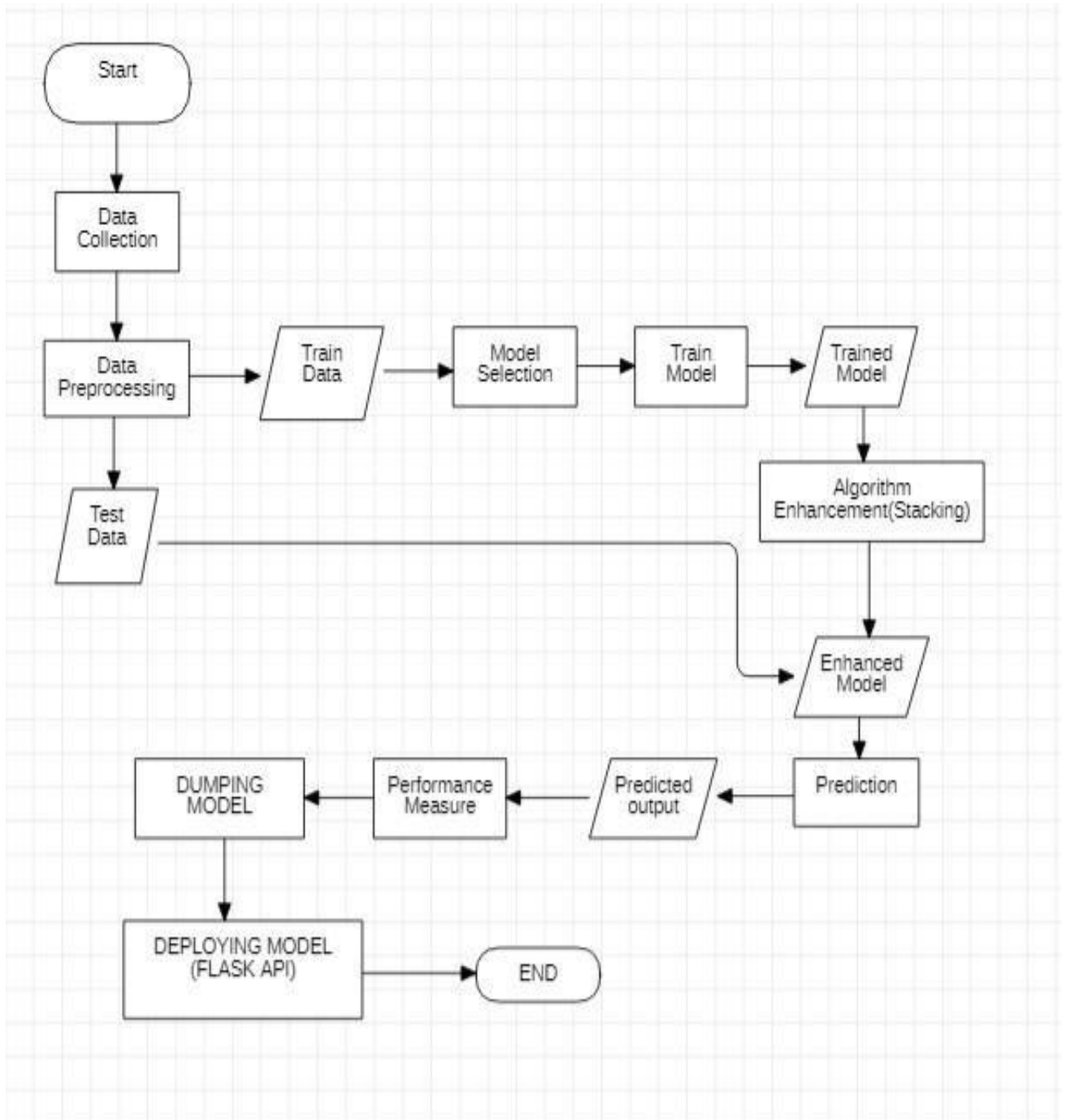


Figure 7.1 Flowchart of Design
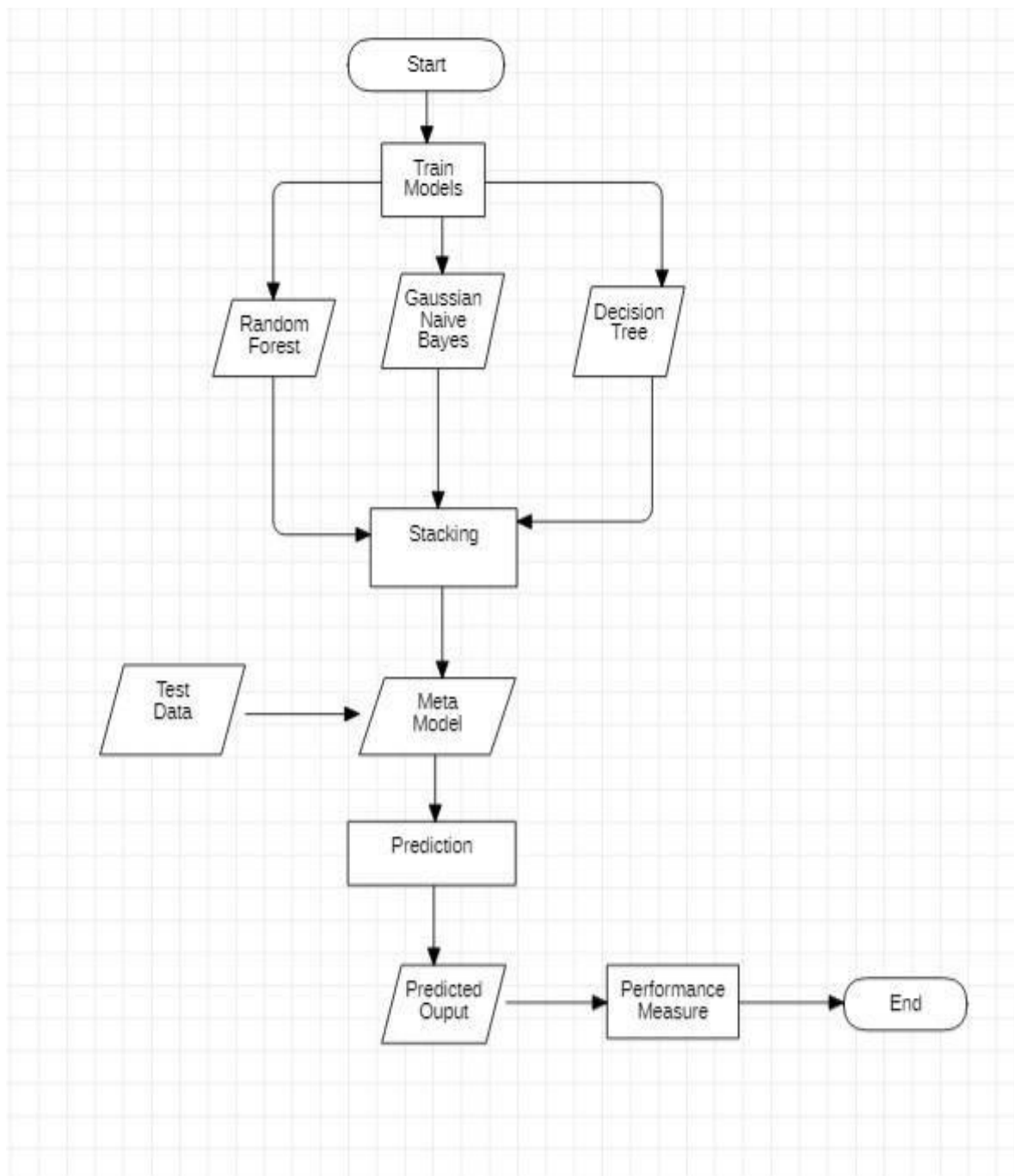
Figure 7.2 Flowchart of Stacking

# CHAPTER 8

# HARDWARE AND SOFTWARE REQUIREMENTS

## 8.1 Software  Requirements

- In this project we have use Jupyter Notebook which is integrated in Anaconda Navigator Version 4.11.0.

- We have used Spyder IDE integrated in Anaconda Navigator to deploy Machine

  Learning models through Flask API.

- We also used a Web Browser to access Localhost port.

- We require basic machine learning classification algorithms (Random Forest Classifier, Gaussian Naïve Bayes Classifier, Decision Tree Classifier and Logistic Regression) and packages like (Pandas, NumPy, Matplotlib and Seaborn).

## 8.2 Hardware Requirements

- Operating System with Windows 7 or above.

- RAM of 2 GB (Minimum)

- Hard Disk: 1 GB

- Processor: i3 or Above

## 8.3 Dataset

- https://www.kaggle.com/itsmesunil/bank-loan-modelling

# CHAPTER 9

# CODE IMPLEMENTATION

In this project, you will learn how to combine various machine learning classification algorithms using stacking approach, so to obtain a better model that can predict better as compared to individual models.

As we require to adopt a problem statement to implement a classification algorithm we have taken "Bank Loan Approval" problem which a binaryclassification problem, where a person will be either be approved for a personal loan or not.

Initially we take our desired classification algorithms whom we want to combine which are called as our "Base Models". In this project we have taken Random Forest Classifier, Decision Tree Classifier, Gaussian Naïve BayesClassifier and Gradient Boosting Classifier as our base models. We perform stacking approach explained in detail in section 6 on this 4 base models and hence obtain a train dataset for our meta model which is in our case is Logistic Regression.

After we obtain a train dataset for our meta model we train our meta-model( Logistic Regression) on that dataset. Now our meta model is trained and ready for prediction.

But we can't give our initial dataset directly as test data to meta-model because metamodel is trained on four features that are the predictions from four base models, not on features of our actual dataset. So, firstly we need to freshly create our base model instances after training meta-model. Then, we have to train these four new instances of base models with train data. Now our base models are trained and ready for prediction.

To predict a sample first give it to base models as test sample. We get four predictions from our four base models. Combine these 4 prediction into a single data frame and then give this new sample as test data to our meta- model to obtain final prediction.

To implement the project we will follow a general machine learning workflow.

### 9.1 Data Preprocessing

### 1. Import required packages.

```
import pandas as pd

import numpy as np

import seaborn as sns
```

### 2. Load the Dataset

```
df = pd.read_csv('Bank_Data.csv')
```

### 3. Print the Dataframe

```
df.head()
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History | Property_Area | Loan_Status |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | LP001002 | Male | No | 0 | Graduate | No | 5849 | 0.0 | NaN | 360.0 | 1.0 | Urban | Y |
| 1 | LP001003 | Male | Yes | 1 | Graduate | No | 4583 | 1508.0 | 128.0 | 360.0 | 1.0 | Rural | N |
| 2 | LP001005 | Male | Yes | 0 | Graduate | Yes | 3000 | 0.0 | 66.0 | 360.0 | 1.0 | Urban | Y |
| 3 | LP001006 | Male | Yes | 0 | Not Graduate | No | 2583 | 2358.0 | 120.0 | 360.0 | 1.0 | Urban | Y |
| 4 | LP001008 | Male | No | 0 | Graduate | No | 6000 | 0.0 | 141.0 | 360.0 | 1.0 | Urban | Y |

### 4. Check the Datatypes of all features

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

### 5. Data Cleaning

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Finding out null values in each column and dropping those records as the count is less to affect the quality of dataset.

```
df.isnull().sum()
```

```
Loan_ID            0
Gender            13
Married            3
Dependents        15
Education          0
Self_Employed     32
ApplicantIncome    0
CoapplicantIncome  0
LoanAmount        22
Loan_Amount_Term  14
Credit_History    50
Property_Area      0
Loan_Status        0
dtype: int64
```

```
df=df.dropna()
df.isnull().sum()
```

```
Loan_ID            0
Gender             0
Married            0
Dependents         0
Education          0
Self_Employed      0
ApplicantIncome    0
CoapplicantIncome  0
LoanAmount         0
Loan_Amount_Term   0
Credit_History     0
Property_Area      0
Loan_Status        0
dtype: int64
```

## 9.2. Data Visualization

By performing visualization, we can get the intuition about how each feature is contributing

```
sns.countplot(x='Education',hue='Loan_Status',data=df)

sns.countplot(x='Loan_Amount_Term',hue='Loan_Status',data=df)

sns.countplot(x='Married',hue='Loan_Status',data=df)

sns.countplot(x='Gender',hue='Loan_Status',data=df)

sns.countplot(x='Dependents',hue='Loan_Status',data=df)

sns.countplot(x='Self_Employed',hue='Loan_Status',data=df)

sns.countplot(x='Credit_History',hue='Loan_Status',data=df)

sns.countplot(x='Property_Area',hue='Loan_Status',data=df)

sns.displot(df['ApplicantIncome']) sns.displot(df['CoapplicantIncome'])
```
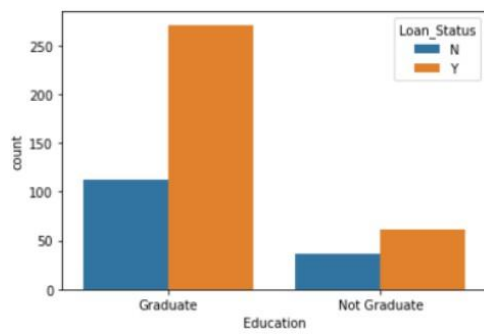
Education vs Loan Status
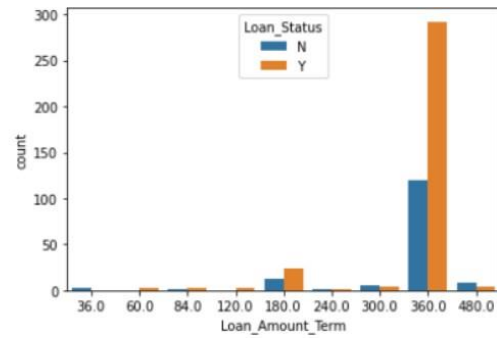


Loan_Term vs Loan Status
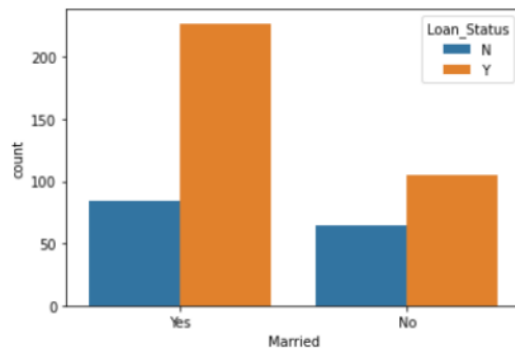


Married vs Loan Status
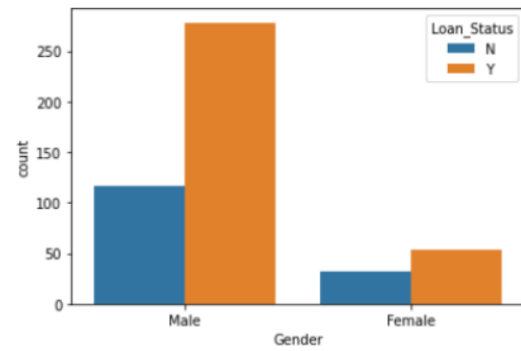


Gender vs Loan Status
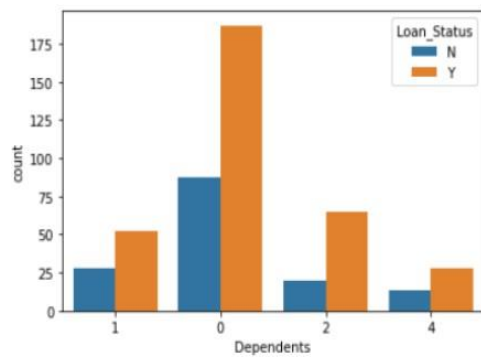


Dependents vs Loan Status
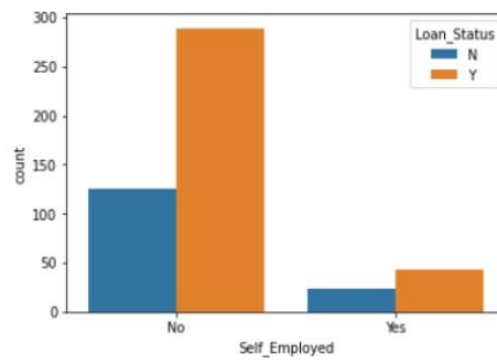


Self Employed vs Loan Status
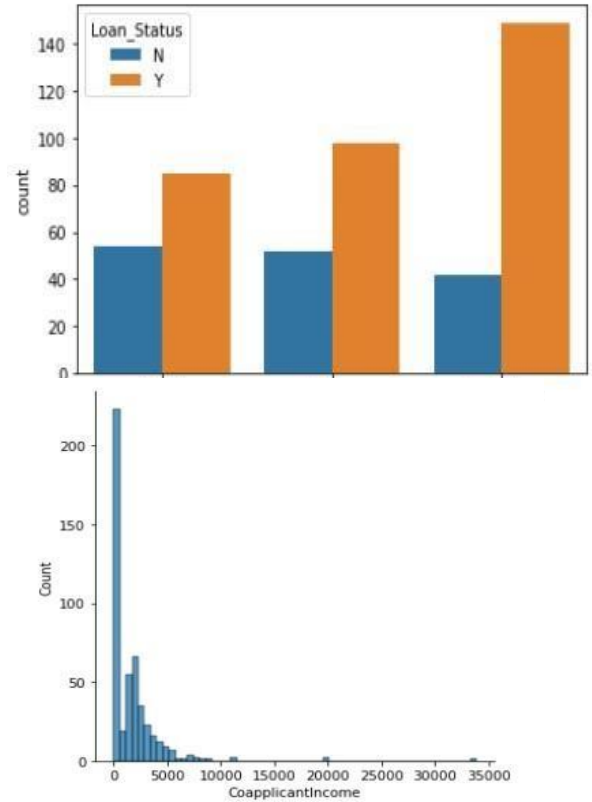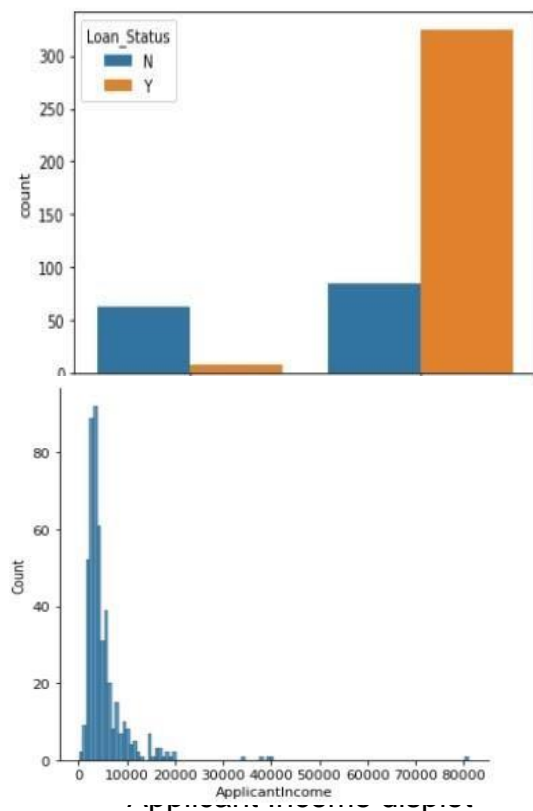
From this visualization we get to know that all features play a prominent rolein deciding the target label, so we don't need to drop any of the features except Loan_ID as it doesn't contribute.

### 9.3 Label Encoding

To make the work easy for the ML algorithms we will encode the values of feature labels that are categorical but in string format into numeric category. For ex: male as 0 and female as 1.

```
from sklearn.preprocessing import LabelEncoder
cols=['Gender','Married','Dependents','Education','Self_Employed',
      'Property_Area','Loan_Status']
le=LabelEncoder() for col in cols:
df[col]=le.fit_transform(df[col])
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History |
|---|---------|--------|---------|------------|-----------|---------------|-----------------|-------------------|------------|------------------|----------------|
| 1 | LP001003 | 1 | 1 | 1 | 0 | 0 | 4583 | 1508.0 | 128.0 | 360.0 | 1.0 |
| 2 | LP001005 | 1 | 1 | 0 | 0 | 1 | 3000 | 0.0 | 66.0 | 360.0 | 1.0 |
| 3 | LP001006 | 1 | 1 | 0 | 1 | 0 | 2583 | 2358.0 | 120.0 | 360.0 | 1.0 |
| 4 | LP001008 | 1 | 0 | 0 | 0 | 0 | 6000 | 0.0 | 141.0 | 360.0 | 1.0 |
| 5 | LP001011 | 1 | 1 | 2 | 0 | 1 | 5417 | 4196.0 | 267.0 | 360.0 | 1.0 |

| Property_Area | Loan_Status |
|---------------|-------------|
| 0 | 0 |
| 2 | 1 |
| 2 | 1 |
| 2 | 1 |
| 2 | 1 |

## 9.4 Observing performance of Base Models

1. **Splitting the data into features and target label.**

```
X=df.drop(columns=['Loan_ID','Loan_Status'],axis=1)
Y=df[['Loan_Status']]
```

2. **Splitting the data into train-data and test-data.**

```
from sklearn.model_selection import train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X,y,test_size=0.2,stratify=y ,random_state=42)
```

3. **Observe the performance of each base model before stacking.**

**i) Random Forest Classifier** – Clearly overfitted as train accuracy is 100% and their is big difference between train and test accuracy.

```
from sklearn.ensemble
import RandomForestClassifier
model=RandomForestClassifier()
model.fit(X_train,Y_train)
yt_pred=model.predict(X_train)
accuracy_score(yt_pred,Y_train)//train
accuracy 1.0
y_pred=model.predict(X_test)
accuracy_score(y_pred,Y_test)//test accuracy
0.8125
```

**ii) Decision Tree Classifier** - Clearly overfitted as train accuracy is 100% and their is big difference between train and test accuracy.

```
from sklearn.tree
import DecisionTreeClassifier
model2=DecisionTreeClassifier()
model2.fit(X_train,Y_train)
yt_pred=model2.predict(X_train)
accuracy_score(yt_pred,Y_train)//train
accurcay 1.0
y_pred=model2.predict(X_test)
accuracy_score(y_pred,Y_test)//test accuracy
0.739583333333333
```

**iii) Gaussian Naïve Bayes Classifier -** Clearly not overfitted as train accuracy is 76% and test accuracy is 80% and there is no big difference between train and test accuracy but test accuracy is not that satisfactory.

```
from  sklearn.naive_bayes
import GaussianNB
model3=GaussianNB()
model3.fit(X_train,Y_train)
yt_pred=model3.predict(X_train)
accuracy_score(yt_pred,Y_train) //train accuracy
0.796875
y_pred3=model3.predict(X_test)
accuracy_score(y_pred3,Y_test) //test accuracy
0.8020833333333334
```

**iv) Gradient Boosting Classifier** - Clearly not overfitted as train accuracy is 90% and test accuracy is 84% and their is no big difference between train and test accuracy and test accuracy is satisfactory.

```
from sklearn.ensemble

import GradientBoostingClassifier

model4=GradientBoostingClassifier()

model4.fit(X_train,Y_train)

yt_pred=model4.predict(X_train)

accuracy_score(yt_pred,Y_train)//train a

0.90625

y_pred4=model4.predict(X_test) accuracy_score(y_pred4, Y_test)

0.8333333333333334
```

## 9.5. Perform Stacking.

## i) Freshly Initialize Base Models.

```
model=RandomForestClassifier(n_estimators=5)
model2=DecisionTreeClassifier()
model3=GaussianNB()
model4=GradientBoostingClassifier()
```

## ii) Split the data into Train data and Test data

```
 X_train,X_test,Y_train,Y_test=train_test_split(X,y,test_size=0.25,      stratify=y,
random_state=42)
```

## iii)   Perform K-Folding

```
from sklearn.model_selection import StratifiedKFold

def Stacking(model,train,y,n_fold):

folds=StratifiedKFold(n_splits=n_fold)

train_pred=np.empty((0,1),int)

for train_indices,val_indices in folds.split(train,y.values):
x_train,x_val=train.iloc[train_indices],train.iloc[val_indices]
```

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```
print(x_train,x_val)#x_val=x_test

y_train,y_val=y.iloc[train_indices],y.iloc[val_indices]

print(y_train,y_val)#y_val=y_test

model.fit(x_train,y_train)
```

```
train_pred=np.append(train_pred,model.predict(x_val))

print(train_pred)

return train_pred train_pred_1=Stacking(model=model,n_fold=5,train=X_train,y=Y_train)
train_pred_2=Stacking(model=model2,n_fold=5,train=X_train,y=Y_train)
train_pred_3=Stacking(model=model3,n_fold=5, train=X_train,y=Y_train)
train_pred_4=Stacking(model=model4,n_fold=5, train=X_train,y=Y_train)
```

**iv) Combine the Predictions of 4 Base Models to get the train data for meta model.**

```
train_pred_1=pd.DataFrame(train_pred_1)
train_pred_2=pd.DataFrame(train_pred_2)
train_pred_3=pd.DataFrame(train_pred_3)
train_pred_4=pd.DataFrame(train_pred_4)
train_data_meta =
pd.concat([train_pred_1,train_pred_2,train_pred_3,train_pred_4], axis=1)
print(train_data-meta)
```

|     | 0 | 0 | 0 | 0 |
|-----|---|---|---|---|
| 0   | 0 | 0 | 0 | 0 |
| 1   | 1 | 1 | 0 | 1 |
| 2   | 0 | 0 | 0 | 0 |
| 3   | 0 | 0 | 0 | 0 |
| 4   | 1 | 1 | 1 | 1 |
| ... | ... | ... | ... | ... |
| 355 | 0 | 0 | 1 | 1 |
| 356 | 1 | 1 | 1 | 0 |
| 357 | 1 | 1 | 1 | 1 |
| 358 | 1 | 0 | 1 | 1 |
| 359 | 1 | 1 | 1 | 1 |

**v) Train the meta-model [Logistic Regression] with train_data_meta.**

```
from sklearn.linear_model import LogisticRegression

meta_model = LogisticRegression()

meta_model.fit(train_data_meta,Y_train)
```

**vi) Freshly train your base models on train_data as we used same names for models in checking performance before stacking and in K-Folding.**

```
model= RandomForestClassifier()

model2= DecisionTreeClassifier()

model3= GaussianNB()

model4= GradientBoostingClassifier()
```

```
model.fit(X_train,Y_train)
model2.fit(X_train,Y_train)
model3.fit(X_train,Y_train)
model4.fit(X_train,Y_train)
```

**vii) Predict the Test_data with trained based model and combine them to prepare the test_data for our meta model.**

```
y1_pred= model.predict(X_test) y2_pred=
model2.predict(X_test) y3_pred=
model3.predict(X_test)      y4_pred=
model4.predict(X_test) y1_pred=
pd.DataFrame(y1_pred) y2_pred=
pd.DataFrame(y2_pred) y3_pred=
pd.DataFrame(y3_pred) y4_pred=
pd.DataFrame(y4_pred)
test_res = pd.concat([y1_pred, y2_pred, y3_pred,y4_pred], axis=1)
print(test_res)
```

|     | 0 | 0 | 0 | 0 |
|-----|---|---|---|---|
| 0   | 0 | 0 | 0 | 0 |
| 1   | 0 | 0 | 0 | 1 |
| 2   | 1 | 1 | 1 | 1 |
| 3   | 1 | 0 | 1 | 1 |
| 4   | 1 | 1 | 1 | 1 |
| ... | ... | ... | ... | ... |
| 115 | 1 | 1 | 1 | 1 |
| 116 | 1 | 1 | 1 | 1 |
| 117 | 1 | 1 | 1 | 1 |
| 118 | 1 | 0 | 1 | 1 |
| 119 | 1 | 1 | 1 | 1 |

**viii) Test the meta-model (LR) with the test_res to get final predictions.**

```
meta_model.score(test_res,Y_test)
```
```
0.8416666666666667
```

Now that we have trained and tested our base models as well as meta model a.k.a Stacked Model we can observe that Stacked model gave the better accuracy as compared to each base model.

## 9.6 Dump the base models and meta-model.

```
import pickle
pickle.dump(meta_model,open('StackModel.pkl','wb'))
pickle.dump(model,open('model.pkl','wb'))
pickle.dump(model2,open('model2.pkl','wb'))
pickle.dump(model3,open('model3.pkl','wb'))
pickle.dump(model4,open('model4.pkl','wb'))
```

## 9.7 Deploy the models using Flask-API.

**i)** Open Spyder IDE and create a project say 'BankLoan'.

**ii)** Copy the dumped models from previous directory to this BankLoanFolder.

**iii)** Create two sub-folders inside BankLoan names 'templates' and 'static'.

**iv)** The 'static' folder will contain the 'index.html' file, and 'template' will contain 'CSS' file for 'index.html'.

**v)** Create a python file named 'app.py' inside the BankLoan Folder.

**app.py**

```python
from flask import Flask, request, render_template
import pickle

app = Flask(__name__)

pickle_in=open('StackModel.pkl','rb')
p_model=open('model.pkl','rb')
p_model2=open('model2.pkl','rb')
p_model3=open('model3.pkl','rb')
p_model4=open('model4.pkl','rb')
stack_model=pickle.load(pickle_in)
model=pickle.load(p_model) model2=pickle.load(p_model2)
model3=pickle.load(p_model3)
model4=pickle.load(p_model4)

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

@app.route('/predict',methods=['POST']) def
predict():
    '''
    For rendering results on HTML GUI
    '''
    features = [ x for x in request.form.values()]
    Gender=features[5]
    Married=features[6]
    Dependents=features[7]
    Education=features[8]
    SelfEmployed=features[9]
    PropertyArea=features[10]
    CreditHistory=features[4]
    ApplicantIncome=float(features[0])/10.0
    CoapplicantIncome=float(features[1])/10.0
```

```python
    LoanAmount=float(features[3])/1000.0
    Loan_Amount_Term=int(features[2])*30


p1=int(model.predict([[Gender,Married,Dependents,Education,SelfEmployed,ApplicantIncome,CoapplicantIncome,LoanAmount,Loan_Amount_Term,CreditHistory,PropertyA rea]]))

p2=int(model2.predict([[Gender,Married,Dependents,Education,SelfEmployed,ApplicantIncome,CoapplicantIncome,LoanAmount,Loan_Amount_Term,CreditHistory,Property Area]]))

p3=int(model3.predict([[Gender,Married,Dependents,Education,SelfEmployed,ApplicantIncome,CoapplicantIncome,LoanAmount,Loan_Amount_Term,CreditHistory,PropertyArea]]))


p4=int(model4.predict([[Gender,Married,Dependents,Education,SelfEmployed,ApplicantIncoyArea]]))me,CoapplicantIncome,LoanAmount,Loan_Amount_Term,CreditHistory,Propert

prediction=stack_model.predict([[p1,p2,p3,p4]])



prediction_text=prediction,ai=features[0],ci=features[1],la=features[3],lt=featureturn render_template('index.html',
res[2],ch=int(features[4]),gd=int(features[5]),mr=int(features[6]),dp=int(features[7]),ed=int(features[8]),se=int(features[9]),pa=int(features[10]))

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

## Index.html

```html
<!DOCTYPE html>
<html >
<head>
<link rel="preconnect" href="https://fonts.googleapis.com">
<link rel="preconnect" href="https://fonts.gstatic.com" crossorigin>
<link
href="https://fonts.googleapis.com/css2?family=Khand:wght@600&family=Monda&di
splay=swap" rel="stylesheet">
<link rel="preconnect" href="https://fonts.googleapis.com">
<link rel="preconnect" href="https://fonts.gstatic.com" crossorigin>
<link
href="https://fonts.googleapis.com/css2?family=Khand:wght@600&display=swap"
rel="stylesheet">
 <link href='https://fonts.googleapis.com/css?family=Pacifico' rel='stylesheet'
type='text/css'>
<link href='https://fonts.googleapis.com/css?family=Arimo' rel='stylesheet'
type='text/css'>
<link href='https://fonts.googleapis.com/css?family=Hind:300' rel='stylesheet'
type='text/css'>
<link href='https://fonts.googleapis.com/css?family=Open+Sans+Condensed:300'
rel='stylesheet' type='text/css'>
 <link rel="stylesheet" href="{{ url_for('static', filename='styles.css') }}">
 <title>Bank Loan Approval</title>
</head>
<body>
<div class="login">
<h1>   Predict Loan Approval</h1><br/><br/>

 <div class="sam">
 <form action="{{ url_for('predict')}}" method="post" class="fom">
 <table >
 <tr>
 <td></td>
 </tr>
```

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```html
<tr>
<td></td>
</tr>
<tr>
<td><label>Applicant_Income</label></td>
<td class="colon"><label>:</label>  </td>
<td><input id="ai" type="text" value="{{ai}}" name="Applicant_Income"
required="required" /></td>
</tr>
<tr>
<td><label>CoApplicant_Income</label></td>
<td class="colon"><label>:</label></td>
<td><input id="ci" type="text" value="{{ci}}" name="CoApplicant_Income"
required="required" /></td>
</tr>
<tr>
<td><label>Loan_Amount_Term</label></td>
<td class="colon"><label>:</label></td>
<td><input id="Term" type="text" value="{{lt}}" name="Term"
required="required" /></td>
</tr>
<tr>
<td><label>Loan_Amount</label></td>
<td class="colon"><label>:</label></td>
<td><input id="la" type="text" value="{{la}}" name="Loan_Amount"
required="required" /></td>
</tr>
<tr>
<td><label>Credit_History</label></td>
<td class="colon"><label>:</label></td>
<td><select id="Credit" name="Credit" required="required" >
{% if ch == 1 %}
<option value="1" selected >Have Credit History</option>
<option value="0">Doesn't have Credit History</option>
{% else %}
<option value="1">Have Credit History</option>
```

```html
<option value="0" selected>Doesn't have Credit History</option>
{% endif %}


</select>
</td>
</tr>
<tr>
<td><label>Gender</label></td>
<td class="colon"><label>:</label></td>
<td><select id="Gender" name="Gender" required="required" >
{% if gd == 1 %}
<option value="1" selected>Male</option>
<option value="0">Female</option>
{% else %}
<option value="1">Male</option>
<option value="0" selected>Female</option>
{% endif %}
</select></td>
</tr>
<tr>
<td><label>Marital Status</label></td>
<td class="colon"><label>:</label></td>
<td><select id="Marital" name="Marital" required="required" >
{% if mr == 1 %}
<option value="1" selected>Married</option>
<option value="0">Not Married</option>
{% else %}
<option value="1">Married</option>
<option value="0" selected>Not Married</option>
{% endif %}
</select></td>
</tr>
<tr>
<td><label>Dependents</label></td>
<td class="colon"><label>:</label></td>
<td><select id="Dept" name="Dept" required="required" >
{% if dp == 0 %}
<option value="0" selected>0</option>
<option value="1">1</option>
<option value="2">2</option>
<option value="4">3+</option>
{% elif dp == 1 %}
<option value="0" >0</option>
<option value="1" selected>1</option>
<option value="2">2</option>
```

```
<option value="4">3+</option>
{% elif dp == 2 %}
<option value="0" >0</option>
<option value="1">1</option>
<option value="2" selected>2</option>
<option value="4">3+</option>
{% else %}
</select></td>
</tr>
<tr>
<td><label>Education</label></td>
<td class="colon"><label>:</label></td>
<td><select id="Edu" name="Edu" required="required" >
{% if ed == 0 %}
<option value="0" selected>Graduate</option>
<option value="1">Under Graduate</option>
{% else %}
<option value="0">Graduate</option>
<option value="1" selected>Under Graduate</option>
{% endif %}
</select></td>
</tr>
<tr>
<td><label>Employment</label></td>
<td class="colon"><label>:</label></td>
<td><select id="Emp" name="Emp" required="required" >
{% if se == 1 %}
<option value="1" selected>Self Employed</option>
<option value="0">Not Self Employment</option>
{% else %}
<option value="1">Self Employed</option>
<option value="0" selected>Not Self Employment</option>
{% endif %}
</select></td>
</tr>
<tr>
<td> <label>Property_Area</label></td>
<td class="colon"><label>:</label></td>
<td><select id="PA" name="PA" required="required" >
{% if pa == 0 %}
<option value="0" selected>Rural</option>
<option value="2">Urban</option>
<option value="1">Semi-Urban</option>
{% elif pa == 2 %}
<option value="0">Rural</option>
<option value="2" selected>Urban</option>
<option value="1">Semi-Urban</option>
```

```
{% else %}
<option value="0">Rural</option>
<option value="2">Urban</option>
<option value="1" selected>Semi-Urban</option>
{% endif %}
```

```
</select></td>
 </tr>
 <tr>
 <td><button type="submit" class="btn btn-primary btn-block btn  large"
>Predict</button></td>
 <td class="colon"><label></label></td>
 <td><button onclick="Reset()" class="btn btn-primary btn-block
btn  large">Reset</button></td>
 </tr>
 <tr>
{% if prediction_text == 1 %}
<td style="text-align:center" colspan="3"><p class="tr">You are eligible for
Loan</p>
</td>
{% endif %}
{% if prediction_text == 0 %}
<td style="text-align:center" colspan="3"><p class="fr">You are not eligible
for Loan</p>
</td>
{% endif %}
 </tr>
 </table>
 </form>
 </div> <br/><br/>
 </div> <br/><br/>
 </body>
</html>
```

**styles.css**

```
html { width: 100%; height:100%; }
label{
font-family:Monda;
}
body {
width: 100%;
height:100%;
```

```css
font-family: 'Open Sans', sans-serif;
background-attachment:fixed;
background: linear-gradient(to bottom, #cc0066 0%, #0000cc 100%);
background-repeat:no-repeat;
background-size:cover;
background-attachment:fixed;
color: #fff;
font-size: 15px;
text-align:center;
letter-spacing:1.2px;
}
fom{
 padding-top:10px;
 padding-bottom:15px;
}
.sam{
background:rgba(0,0,0,0.3);
width:540px;
border-radius:15px;
}
td {
 text-align: left;
 padding-left:40px;
}
.login {
position: relative;
top: 30%;
left: 45%;
margin: -150px 0 0 -150px;
width:460px;
height:500px;
padding-top:20px;
}
.tr{
 color:rgb(78,212,78);
 font-size: 1.5em;
 font-weight: bold;
}
.fr{
 color:rgb(247,67,76);
 font-size: 1.5em;
 font-weight: bold;
}
```

```
.login h1 { color: #fff; text-shadow: 0 0 10px rgba(0,0,0,0.3); letter-spacing:1px;
text-align:center;display:inline;font-family:Khand;font-size:42px; }
input {
width: 200px;
margin-bottom: 10px;
background: rgba(0,0,0,0.3);
border: none;
outline: none;
padding: 10px;
font-size: 13px;
color: #fff;
text-shadow: 1px 1px 1px rgba(0,0,0,0.3);
border: 1px solid rgba(0,0,0,0.3);

border-radius: 4px;

box-shadow: inset 0 -5px 45px rgba(100,100,100,0.2), 0 1px 1px

rgba(255,255,255,0.2);

-webkit-transition: box-shadow .5s ease;

-moz-transition: box-shadow .5s ease;

-o-transition: box-shadow .5s ease;

-ms-transition: box-shadow .5s ease;

transition: box-shadow .5s ease;

}select{

width: 100%;

margin-bottom: 10px;

background: rgba(0,0,0,0.3);

border: none;

outline: none;

padding: 10px;

font-size: 13px;

color: #fff;

text-shadow: 1px 1px 1px rgba(0,0,0,0.3);

border: 1px solid rgba(0,0,0,0.3);

border-radius: 4px;

box-shadow: inset 0 -5px 45px rgba(100,100,100,0.2), 0 1px 1px

rgba(255,255,255,0.2);

-webkit-transition: box-shadow .5s ease;
```

```
-moz-transition: box-shadow .5s ease;

-o-transition: box-shadow .5s ease;

-ms-transition: box-shadow .5s ease;

transition: box-shadow .5s ease;

}

input:focus { box-shadow: inset 0 -5px 45px rgba(100,100,100,0.4), 0 1px 1px
rgba(255,255,255,0.2); }

select:focus{ box-shadow: inset 0 -5px 45px rgba(100,100,100,0.4), 0 1px 1px
rgba(255,255,255,0.2);}
```

**vi)** After writing the code we need to execute the project by opening the anaconda

prompt and enter command "python app.py". The web application canbe accessed

at port http://127.0.0.1:5000/ by entering port address in an standard browser.

## 9.8 Output



Fig 9.1 Interface for Prediction



Fig 9.2 Prediction for Eligible Borrower

Fig 9.3 Prediction for Ineligible Borrower

# CONCLUSION

In this project we have tried to combine the knowledge of multiple machine learning model through stacking, where we obtained a meta model that can perform predictions on the predictions of base models. So, we have removed the requirement of using a single machine learning algorithms that gives best accuracy which may in turn be overfitted or underfitted as we have seen with our base models.

Hence adding a extra layer that can give us prediction using the knowledge of the meta-model that is gained from base models, we can do predictions with a model that are not underfitted or overfitted. As a part of future work more techniques like stacking that can combine the knowledge of various machine learning models at more deep and core logical levels will lead to a very efficient and robust machine learning models.

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