V Semester

MINOR PROJECT REPORT
ON

"PATH LOSS PREDICTION USING MACHINE LEARNING"

BY

HARSH SINGH	17101021
CHARCHIT DHAWAN	17100013
SHIVAM GUPTA	17101043

UNDER THE GUIDANCE OF
PROF. AMRITA MISHRA

Dr. SPM INTERNATIONAL INSTITUTE OF INFORMATION TECHNOLOGY NAYA RAIPUR
ATAL NAGAR - 493661, INDIA

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Declaration

We declare that this written submission represents our ideas in our own words and where other's ideas or words have been included, we have adequately cited and referenced the original sources. we also declare that we have adhered to all principles of academic honesty and integrity and have not mis-represented or fabricated or falsified any idea/data/fact/source in the submission.Also, understanding the violation of the above will be cause for disciplinary action by the Institute and can also evoke pe-nal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

Dated: Dec 11, 2019

Harsh Singh
Charchit Dhawan
Shivam Gupta

Certificate

This is to certify that the project titled “Path Loss Prediction Using Machine Learning” by “Harsh Singh, Charchit Dhawan and Shivam Gupta” has been carried out under my supervision and that this work has not been submitted elsewhere for a evaluation.

Dated: Dec 11, 2019

Dr. Amrita Mishra
Assistant Professor
Department of ECE
Dr. SPM IIIT Naya Raipur-493661

Acknowledgments

At the outset, we would like to express my whole hearted and deep sense of gratitude to my guide Prof. Amrita Mishra for her guidance, help and encouragement throughout our research work. we greatly admire his attitude towards project, creative thinking, hard work and dedication in work. we are highly grateful to her for patiently checking all the work we have done. This thesis would not have been possible without her bounteous efforts. More than guide, she is our mentor for shaping our personal and professional life, without whom we would not learn and explore. we owe our profound gratitude to Dr. Amrita Mishra for her supports in all respects.

ABSTRACT

Path loss prediction is of great significance for the performance optimization of wireless networks. With the development and deployment of the fifth-generation (5G) mobile communication systems, new path loss prediction methods with high accuracy and low complexity should be proposed. In this paper, the principle and procedure of machine-learning-based path loss prediction are presented. Measured data are used to evaluate the performance of different models such as artificial neu-ral network, support vector regression, and random forest. It is shown that these machine-learning-based models outperform the log-distance model. In view of the fact that the volume of measured data sometimes cannot meet the requirements of machine learning algorithms, we propose two mechanisms to expand the training dataset.

The path-loss prediction results obtained by using the ANN models are evaluated against different versions of the semi-terrain based propagation model and the Oku-mura–Hata model. The statistical analysis shows that a non-complex ANN model performs very well compared with traditional propagation models with regard to prediction accuracy, complexity, and prediction time. The average ANN prediction results were 1) maximum error: 22 dB; 2) mean error: 0 dB; and 3) standard devia-tion: 7 dB.

Recently, unmanned aerial vehicle (UAV) plays an important role in many appli-cations because of its high fexibility and low cost. To realize reliable UAV commu-nications, a fundamental work is to investigate the propagation characteristics of the channels. In this paper, we propose path loss models for the UAV air-to-air (AA) scenario based on machine learning. A ray-tracing sofware is employed to generate samples for multiple routes in a typical urban environment, and diferent altitudes of Tx and Rx UAVs are taken into consideration. Two machine-learning algorithms, Random Forest and KNN, are exploited to build prediction models on the basis of the training data.

Keywords: : 5G communication systems; data expansion; machine learning, Artificial neural network (ANN).

Contents

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Chapter 1

Introduction

Path loss is used to describe the attenuation of an electromagnetic wave as it propagates through space. An accurate, simple, and general model for the path loss is essential for link budget, coverage prediction, system performance optimization, and selection of base station (BS) locations. Consequently, researchers and engineers have made great efforts to find out reasonable models for[2] the path loss prediction in different scenarios and at different frequencies. Many measurement campaigns have been conducted worldwide to collect data, which have been used to build, ad-just, and evaluate these models. The upcoming fifth-generation (5G) networks are designed to support increased throughput, wide coverage, improved connection den-sity, reduced radio latency, and enhanced spectral efficiency. Supporting Internet of Things (IoT) applications will involve vast coverage areas and various terrains.

a) The basic principle and procedure of the path loss prediction based on machine learning are presented. Some crucial issues such as data collection, data prepro-cessing, algorithm selection, model hyper-parameter settings, and performance evaluation, are discussed.

b) In order to obtain enough data for machine-learning-based models, two mecha-nisms are proposed to enlarge the training dataset by taking full advantage of the existing data and the classical models. Data transferring is considered in both the scenario dimension and the frequency dimension.

c) Different machine learning algorithms are employed to validate the proposed methods based on the measured data. Both outdoor and indoor scenarios are taken into account and measured data are used to verify the feasibility of the machine-learning-based predictors.

d) Here the hierarchy of work is:

    Empirical Model

    Deterministic Model

    Machine Learning Approaches

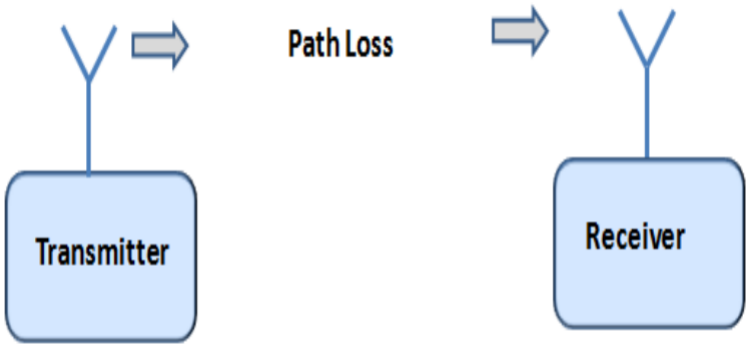
Chapter 2

Literature Survey

2.1 Path Loss

2.1.1 What is Path Loss ?

In wireless communication the path loss defined as electromagnetic reduction of power density in EM-Waves as it propagates through space, in other words the attenuation between the sender and receiver ends of communication is to be known by path loss.referring [3][7].



$$P_L = \frac{P_t}{P_r} > 1$$

Figure 2.1: Formulation

Where P_t : transmissionpower; P_r : received power

2.1.2 Description of Propagation Environment

Built-in signal propagation models can be used to simulate multi-path propagation in rural, sub-urban and urban areas.

Propagation Model: Satellites above the Open Sky limit are not affected by mult-ipath propagation. [12]Satellites in the Mult-ipath Zone (elevation angle between Obstruction Limit and Open Sky Limit) are considered LOS signals, but affected by multipath propagation. The ITU model for LOS situation is used for these satellites.
For satellites in the Obstruction Zone (elevation angle below Obstruction Limit), the direct signal path may be obstructed, e.g., by a building. This is modelled by giving a probability for an NLOS situation. With the given probability, the simulator classifies satellites as NLOS and takes the ITU model for the NLOS situation into use. The NLOS situation changes only when a satellite leaves the Obstruction Zone.

Note that: In addition to the two elevation limits mentioned above, the Elevation mask setting applies to the simulation as normally.The Propagation[1] environment is defined by the environment type (open/rural/sub-urban/ urban) and three parameters.

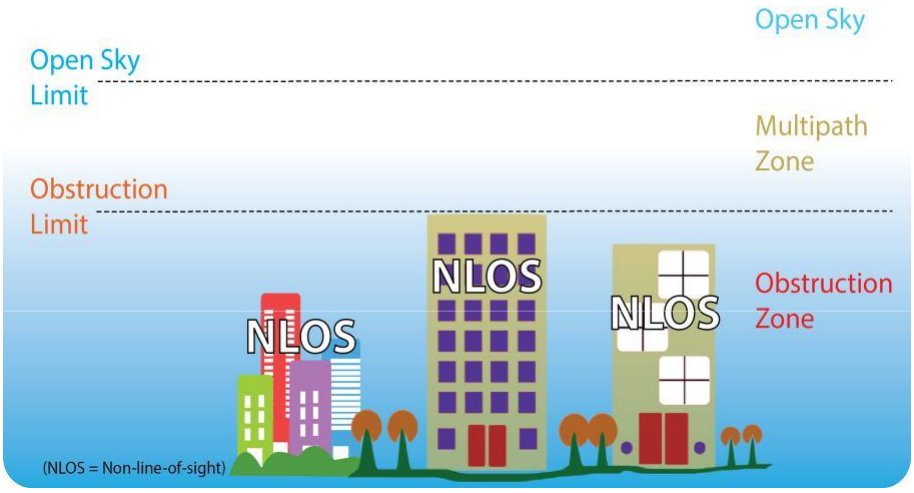


Figure 2.2: ITU multi-path propagation model

2.2 Traditional Approaches

2.2.1 Empirical Method

This path-loss model determines the predicted path-losses to the distance covered by the signal with a Gaussian random variable due to the shadow fading and to make this work linear regression is used.

Different types of Empirical models

Log-Distance Model

Okumura-Hata Model

Log-Distance Model: Log distance path loss model is an extension to the Friis free space model. It is used to predict the propagation loss for a wide range of environments, whereas, the Friis free space model is restricted to unobstructed clear path between the transmitter and the receiver. The model encompasses random shadowing effects due to signal blockage by hills, trees, buildings etc. It is also referred as log normal shadowing model.[8]

$[P_L(d)]dB = [P_L(d_0)]dB + 10n\log_{10}(d=d_0) + X$

The path-loss exponent (PLE) — values given in Table below are for reference only. They may or may not fit the actual environment we are trying to model. Usually,[3] PLE is considered to be known apriori, but mostly that is not the case. Care must be taken to estimate the PLE for the given environment before design and modeling. PLE is estimated by equating the observed (empirical) values over several time instants, to the established theoretical values.

Figure 2.3: figure

Usually to model real environments the shadowing effects cannot be neglected. If the shadowing effect is neglected, the Path Loss is simply a straight line (see the plot below). To add shadowing effect a zeromean Gaussian random variable with standard deviation – is added to the equation. The actual path loss may still vary due to other factors. Thus the path loss exponent (modeling the slope) and the standard deviation of the random variable should be known precisely for a better modeling

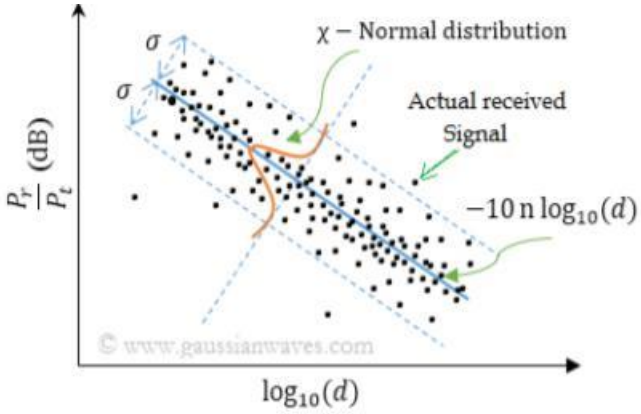


Figure 2.4: The Path Loss Exponent (PLE)

Okumura-Hata-Model: This model is widely used models for signal func-tioning prediction in urban areas. It is an empirical model with a frequency range of 150 MHz to 1920 MHz distances within 1 to 100 Km. It can be extrapolated up to 3 GHz.

Path Loss = FPL + A(f,d) - G(ht e) G(hre) G(Area)

where;
FPL = FreeSpacePathLoss = 20log4 PI d f =c
c = Speedo f Light
d = distance
f = Frequency

Free Space Loss:

Assumption

Transmitter and receiver are in free

space No obstructing objects in between

The earth is at an infinite distance!

In irregular terrain, one frequently encounters non-line-of-sight paths caused[2] by terrain obstacles. Okumura's model includes a correction factor called the

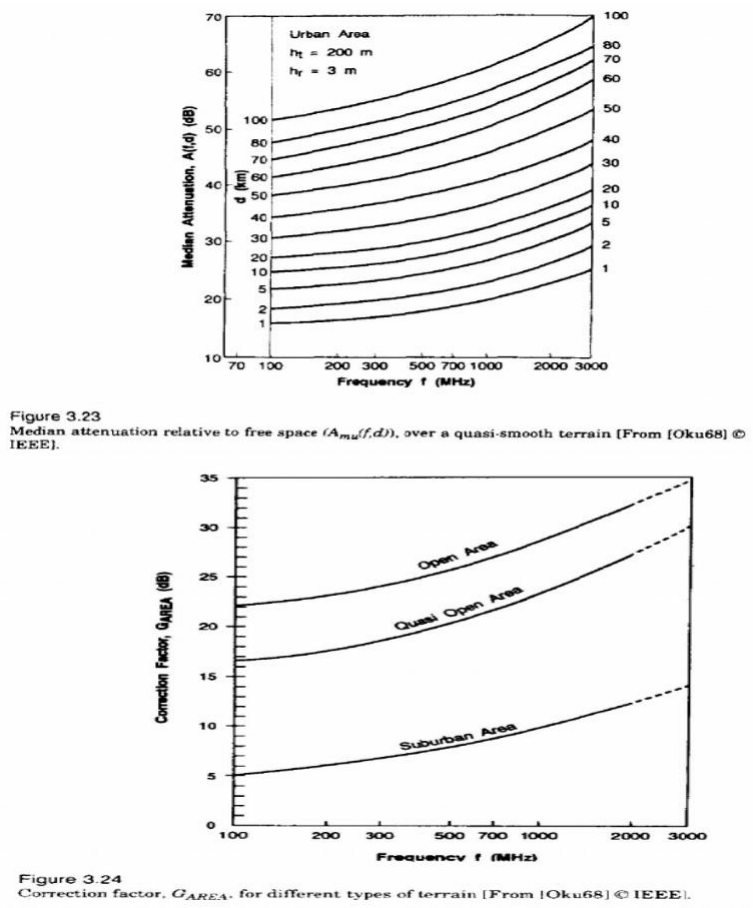


Figure 3.23
Median attenuation relative to free space ($A_{mu}(f,d)$), over a quasi-smooth terrain [From [Oku68] © IEEE].

Figure 3.24
Correction factor, G_{AREA}, for different types of terrain [From [Oku68] © IEEE].

Figure 2.5: Okumura Visualization

”Isolated Ridge” factor to account for obstacles. However, the applicability of this correction is only to obstacles conforming to that description; i.e. an iso-lated ridge. More complex terrain cannot be modeled by the Isolated Ridge cor-rection factor. A number of more general models exist for calculating diffrac-tion loss. However, none of these can be applied directly to Okumura’s basic mean attenuation.

Hata-Model: It is an empirical formulation of the path loss data provided by Okumura, is valid from 150 Mhz to 1500 MHz for urban area.

Path Loss in Urban areas is given by:

Path Loss = 69.55 + 26.16*log(f) - 13.82*log($h_{t\ e}$) a(h_{re})+(44:9 6:55 log($h_{t\ e}$) log(d)

W here :

f = Frequency(inMHz) f rom150MHzto1500MHz

Operating frequency, Base Station Antenna height.This model is suited for both point-to-point and broadcast transmissions.]It is also known as the Okumura-Hata model for being a advanced version of the Okumura Model,

is the most widely used model in radio frequency propagation for predicting the[11] behavior of cellular transmissions in city outskirts and other rural ar-eas. This model incorporates the graphical information from Okumura model and develops it further to better suit the need . Hata Model predicts the total path loss along a link of terrestrial microwave or other type of cellular commu-nications.

Operating frequency, Base Station Antenna height.This model is suited for both point-to-point and broadcast transmissions.

2.2.2 Deterministic Method

Crucially propagation models are for the prediction of radio channels. The deterministic model usually ray-optical method, also known as ray tracing propagation, This model can be classified, namely, as time dispersive or non-time dispersive: time dispersive is modeled to predict the path loss from channel measurement results. The deterministic approach is accurate as the previous approaches are assumptions. Efficiency Increases.

Ray-Tracing Model: Algorithms for the ray-tracing method are classified into two general types: the imaging method and ray-launching method. The imaging method derives a propagation path by using geometric optics from a combination of the transmission position, receiving position, and reflecting sur-faces. On the other hand, the ray-launching method derives the propagation path using rays discretely launched at given regular intervals and searching for the rays that arrive at the received position.

Estimating the propagation characteristics using the ray-tracing method requires three parameters: the propagation distance,[7] incident angle to the re-flecting surface, and complex permittivity of the reflecting surface. The propa-gation distance and the incident angle to the reflecting surface are derived from ray-tracing estimation results. The complex permittivity of the reflecting sur-face is a predetermined static parameter.

Special problem in applying ray tracing to MIMO systems:
MIMO technology, which uses multiple antennas at the transmitter and at the receiver to improve the transmission rate, has recently been widely stud-ied. IEEE 802.11n which are recently standardized wireless schemes, both use MIMO technology. MIMO propagation channel evaluations that use the ray-tracing method have been reported. However, whether a reflection point exists on a wall must be judged a total of m n A^Btimes:

2.3 Machine Learning Approach

2.3.1 What is Machine learning ?

Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.

[14]After knowing the output (path loss observation) and the correspond-ing input features such as antenna-separation distance and frequency, we can employ machine learning methods to find a good estimation function for the path loss prediction. This function is to map input features to output path loss value.

I) DATA COLLECTION AND FEATURE EXTRACTION:

The collected data refer to samples obtained from measurement, and each sam-ple should include the path loss value and the corresponding input features. The input features can be divided into two categories, system-dependent pa-rameters and environment-dependent parameters. System-dependent param-eters are those independent of the propagation environment, such as carrier frequency, heights and positions of the transmitter and receiver, and so on. According to the above parameters, more system-dependent features can be acquired, such as the antenna-separation distance and the angle between the line-of-sight path and the horizontal plane.

The performance of the path loss model is closely related to the number of training samples. After obtaining enough data, these samples should be divided into the training dataset and the test dataset. The former is used to build the prediction model, whereas the latter is used to verify and further improve the model performance.

II) FEATURE SELECTION AND SCALING:

According to the relationship between feature selection process and model de-sign, there are usually three alternative feature selection approaches, including

filter, wrapper and embedded. The filter approach is independent of the pro-posed model when evaluating feature importance. The wrapper approach takes the prediction performance into account when calculating the feature scores. The embedded approach combines feature selection and the accuracy of the prediction into its procedure. For different algorithms, the stopping conditions are related to the selection of the search algorithm, the feature evaluation crite-ria, and the specific application requirements.

Some machine-learning-based algorithms, such as regression techniques, neive based, random forest, ANN and KNN, are sensitive to the scale of the in-put space. Thus, normalization process should be finished before the training begins. That is, all input features and path loss values should be changed in the range from 1 to 1 or from 0 to 1. The normalization method chosen in this paper is the same as that in [7]. It can be expressed as

$$x_N = (2(x \quad x_{min})/x_{max} \; x_{min}) \quad 1$$

III) HYPERPARAMETER SETTING AND MODEL TRAINING:

Hyper parameters are those parameters for which values are set before the learning process begins. Typical hyper parameters include the number of hid-den layers and neurons in ANN, A set of optimal hyperparameters should be carefully chosen in order to optimize the performance and effectiveness of the path loss prediction.

the possible values of the parameters. Model parameters are those pa-rameters learned from training samples. It is worth mentioning that different learning methods have different model parameters. During the model train-ing process, model parameters such as weights and biases are automatically learned.

IV) MODEL EVALUATION AND PATH LOSS PREDICTION:

path loss models is measured by samples in the test dataset, which do not appear in the model training process. The evaluation metrics include predic-tion accuracy, generalization property, and complexity. In terms of evaluating the accuracy, performance indicators like maximum prediction error (MaxPE), mean absolute error (MAE), error standard deviation (ESD), correlation factor (CF), root mean square error (RMSE), and mean absolute error (MAE), mean squared error are commonly used.

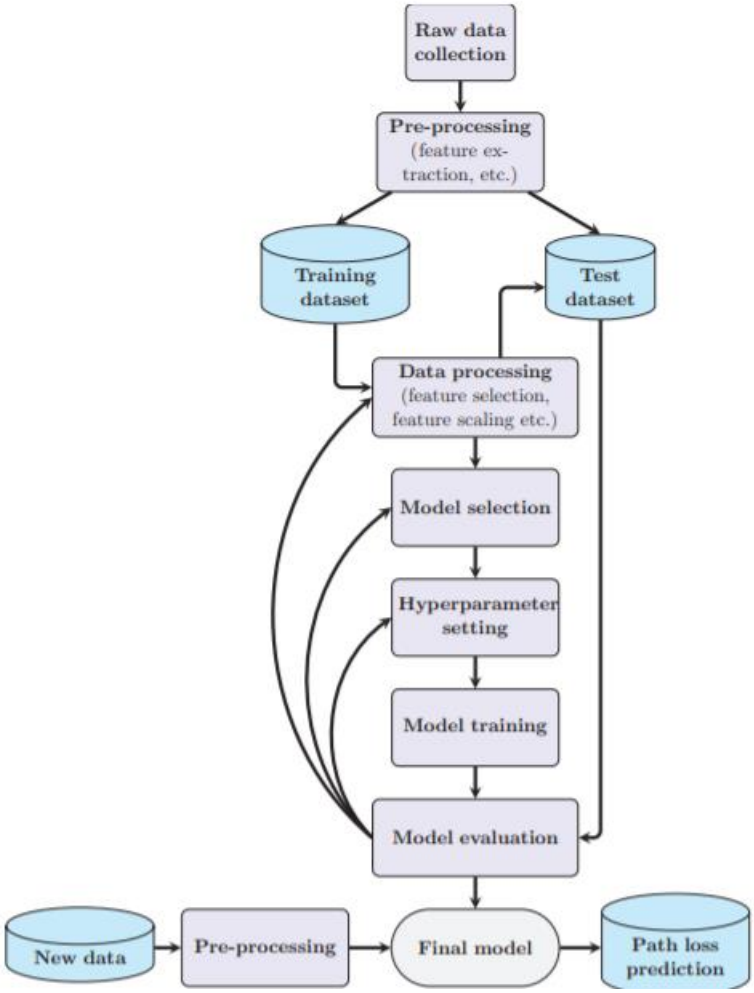


Figure 2.6: Machine Learning Based approach.

The model may have better generalization performance with more data collected from diverse scenarios, such as different terrains, frequencies, and vegetative cover conditions.

2.3.2 Machine Learning Based Prediction

There are basically six algorithm that have been implemented in model:

1. Linear Regression
2. Logistic Regression
3. KNN
4. Naive Bayes
5. Random Forest
6. Artificial Neural Network(ANN)

I) LINEAR REGRESSION

Linear Regression is a supervised learning algorithm. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting. Different regression models differ based on – the kind of relationship between dependent and independent variables, they are considering and the number of independent variables being used[12].

$$[\ y = B_0 + B_1{:}X]$$

It is common to talk about the complexity of a regression model like linear regression. This refers to the number of coefficients used in the model.In higher dimensions when we have more than one input (x), the line is called a plane or a hyper-plane. The representation therefore is the form of the equation and the specific values used for the coefficients (e.g. B0 and B1 in the above example).

It is common to talk about the complexity of a regression model like linear regression. This refers to the number of coefficients used in the model.

How Linear Regression is learning the model:

Learning a linear regression model means estimating the values of the coeffi-cients used in the representation with the data that are available.

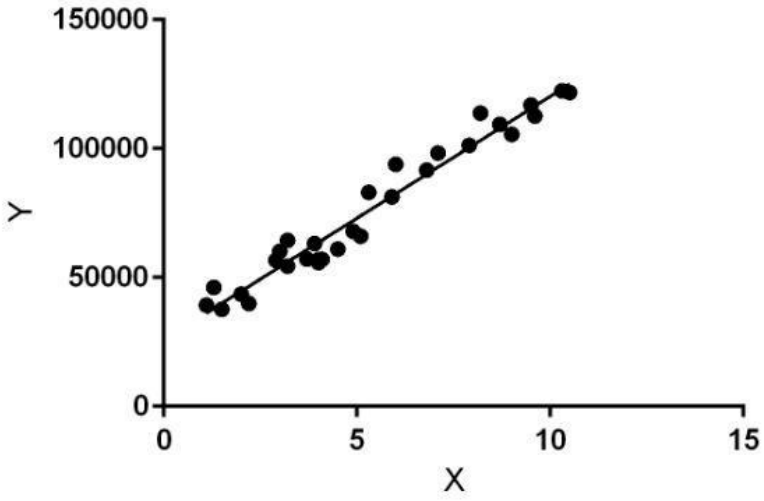


Figure 2.7: Linear Regression

II) LOGISTIC REGRESSION

Logistic regression is a classification algorithm used to assign observations to a discrete set of classes. Unlike linear regression which outputs continuous number values, logistic regression transforms its output using the logistic sigmoid function to return a probability value which can then be mapped to two or more discrete classes.

Basically logistic regression is used as binary classification. Multiclass classification with logistic regression can be done either through the [11]one-vs-rest scheme in which for each class a binary classification problem of data belonging or not to that class is done, or changing the loss function to cross- entropy loss.

It is expressed as:

$$[\ y = B_0 + B_1{:}X_1 + ::: + B_n{:}X_n]$$

The logistic function is a Sigmoid function, which takes any real value between zero and one. It is defined as:

$$\sigma(t) = \frac{e^t}{e^t + 1} = \frac{1}{1 + e^{-t}}$$

What is Decision Boundary?

Decision boundary helps to differentiate probabilities into positive class and negative class.

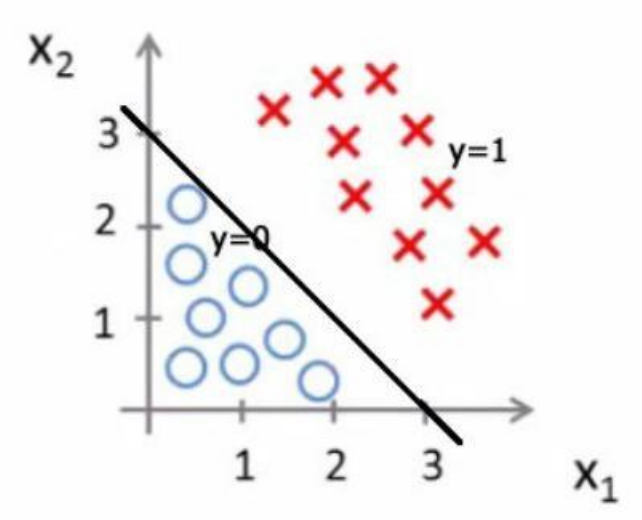


Figure 2.8: Linear Decision Boundary

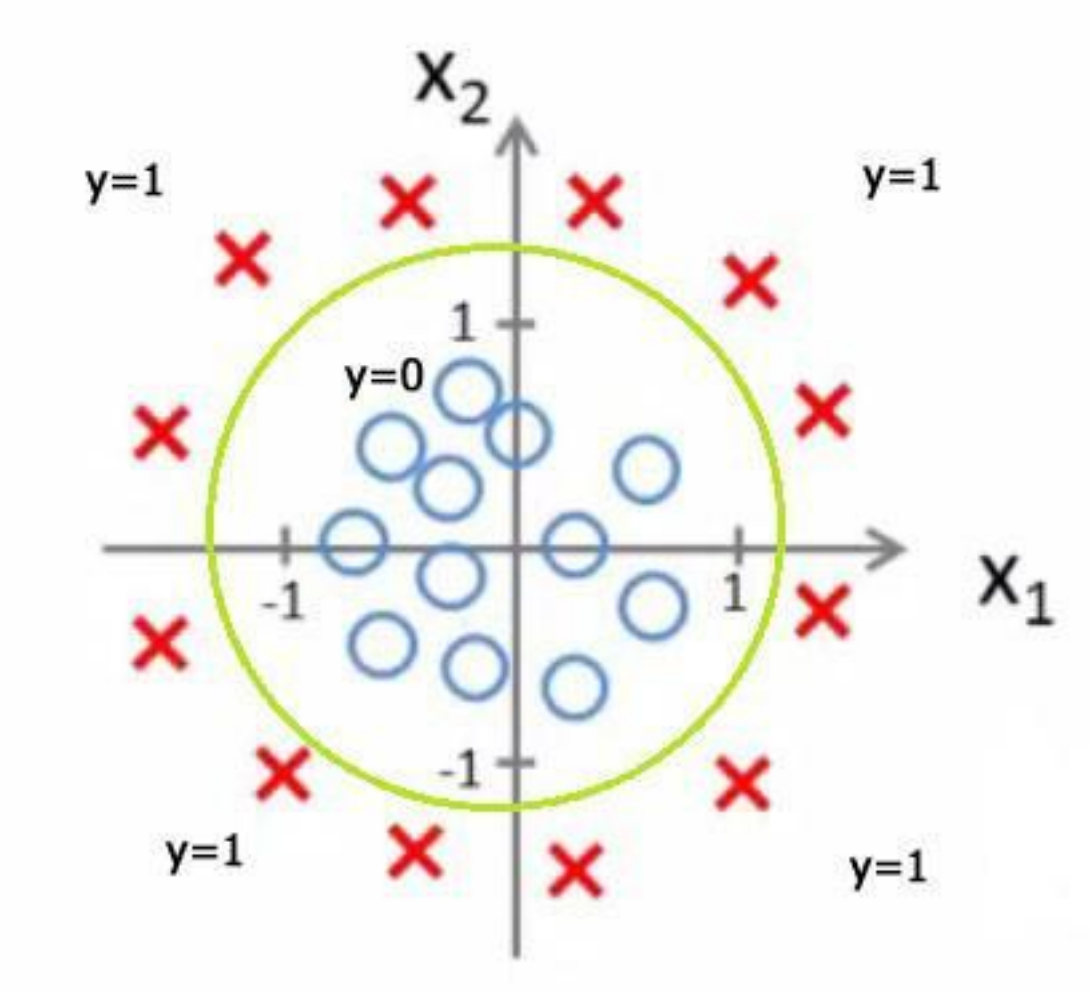


Figure 2.9: Non-Linear Decision Boundary

III) K-NEAREST NEIGHBOUR(KNN)

A supervised machine learning algorithm (as opposed to an unsupervised [5]ma-chine learning algorithm) is one that relies on labeled input data to learn a function that produces an appropriate output when given new unlabeled data.

The KNN algorithm assumes that similar things exist in close proximity. In other words, similar things are near to each other.

KNN can be used for both classification and regression predictive problems. However, it is more widely used in classification problems in the industry.

To evaluate any technique we generally look at 3 important aspects:
1. Ease to interpret output
2. Calculation time
3. Predictive Power

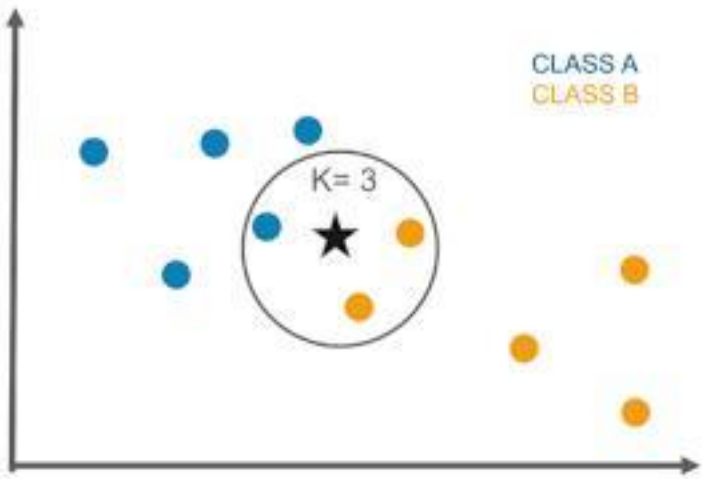


Figure 2.10: KNN Model

HOW DO WE CHOOSE THE FACTOR K?

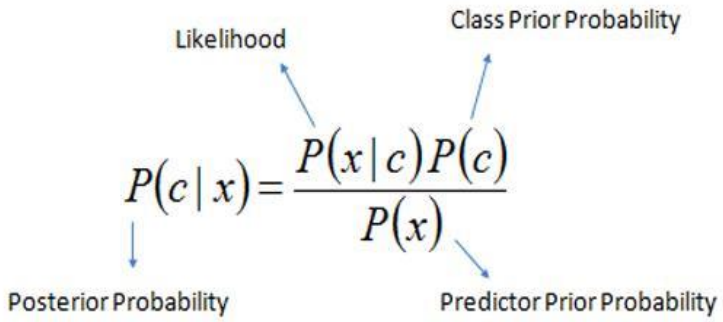
what exactly does K influence in the algorithm. If we see the last example, given that all the 10 training observation remain constant, with a given K value we can make boundaries of each class. These boundaries will segregate RC from GS. The same way, let's try to see the effect of value "K" on the class boundaries. Following are the different boundaries separating the two classes with different values of K.

IV) NAIVE BAYES CLASSIFICATION

Naive Bayes classifiers are a collection of classification algorithms based on Bayes' Theorem. It is not a single algorithm but a family of algorithms where all of them share a common principle, i.e. every pair of features being classified is independent of each other.

The fundamental Naive Bayes assumption is that each feature makes an:
1. independent and 2. equal
contribution to the outcome.

Bayes' Theorem finds the probability of an event occurring given the probability of another event that has already occurred. Bayes' theorem is stated mathematically as the following equation:



$$P(c \mid \mathrm{X}) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

V) RANDOM FOREST CLASSIFICATION

The Random Forest Algorithm is composed of different decision trees, each with the same nodes, but using different data that leads to different leaves. It merges the decisions of multiple decision trees in order to find an answer, which represents the average of all these decision trees.

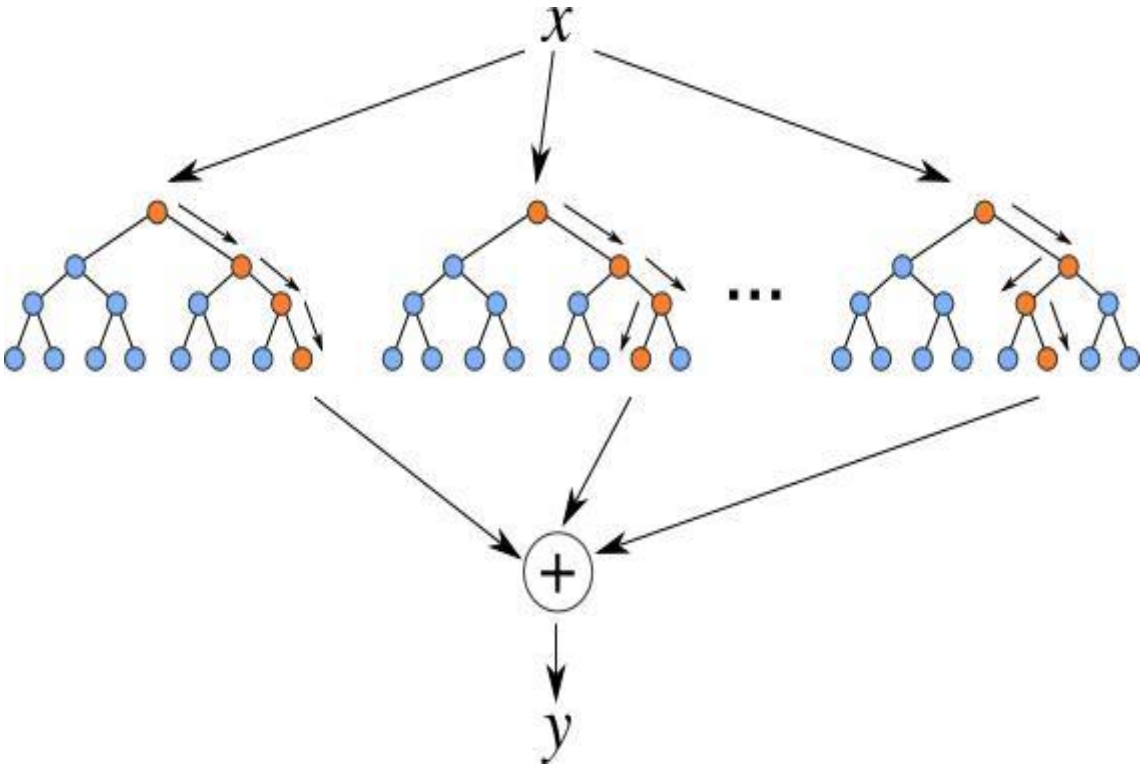


Figure 2.11: Random Forest Model

In the above example, we have three individual decision trees which together make up a Random Forest. Random Forest is considered ensemble learning, meaning it helps to create more accurate results by using multiple models to come to its conclusion. The algorithm uses the leaves, or final decisions, of each node to come to a conclusion of its own. This increases the accuracy of the model since it's looking at the results of many different decision trees and finding an average.

THE MATHEMATICS BEHIND RANDOM FOREST:

Regression Problems: [12] When using the Random Forest Algorithm to solve regression problems, you are using the mean squared error (MSE) to how your data branches from each node.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (fi - yi)^2$$

Where N is the number of data points,
fi is the value returned by the model and
yi is the actual value for data point i.

VI) ARTIFICIAL NEURAL NETWORK(ANN)

Artificial Neural network is typically organized in layers. Layers are being made up of many interconnected ‘nodes’ which contain an ‘activation function’. A neural network may contain the following 3 layers:

A. INPUT LAYER

The purpose of the input layer is to receive as input the values of the explanatory attributes for each observation. Usually, the number of input nodes in an input layer is equal to the number of explanatory variables. ‘input layer’ presents the patterns to the network, which communicates to one or more ‘hidden layers’.

The nodes of the input layer are passive, meaning they do not change the data. They receive a single value on their input and duplicate the value to their many outputs. From the input layer, it duplicates each value and sent to all the hidden nodes.

B. HIDDEN LAYER

The Hidden layers apply given transformations to the input values inside the network. In this, incoming arcs that go from other hidden nodes or from input nodes connected to each node. It connects with outgoing arcs to output nodes or to other hidden nodes. In hidden layer, the actual processing is done via a system of weighted ‘connections’. There may be one or more hidden layers. The values entering a hidden node multiplied by weights, a set of predetermined numbers stored in the program. The weighted inputs are then added to produce a single number.

C. OUTPUT LAYER

The hidden layers then link to an ‘output layer‘. Output layer receives connections from hidden layers or from input layer. It returns an output value that corresponds to the prediction of the response variable. In classification problems, there is usually only one output node. The active nodes of the output layer combine and change the data to produce the output values.

The ability of the neural network to provide useful data manipulation lies in the proper selection of the weights. This is different from conventional information processing.

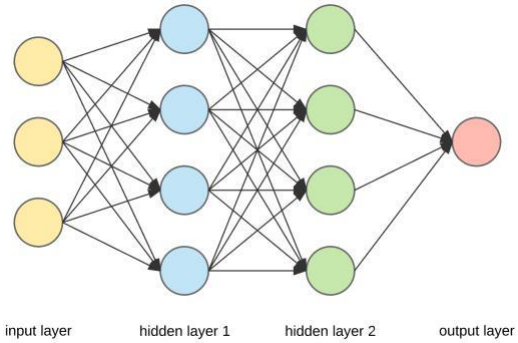


Figure 2.12: Artificial Neural Network(ANN)

Chapter 3

RESULTS

3.1 Results Based on various algorithm

3.1.1 Logistic Regression Classification

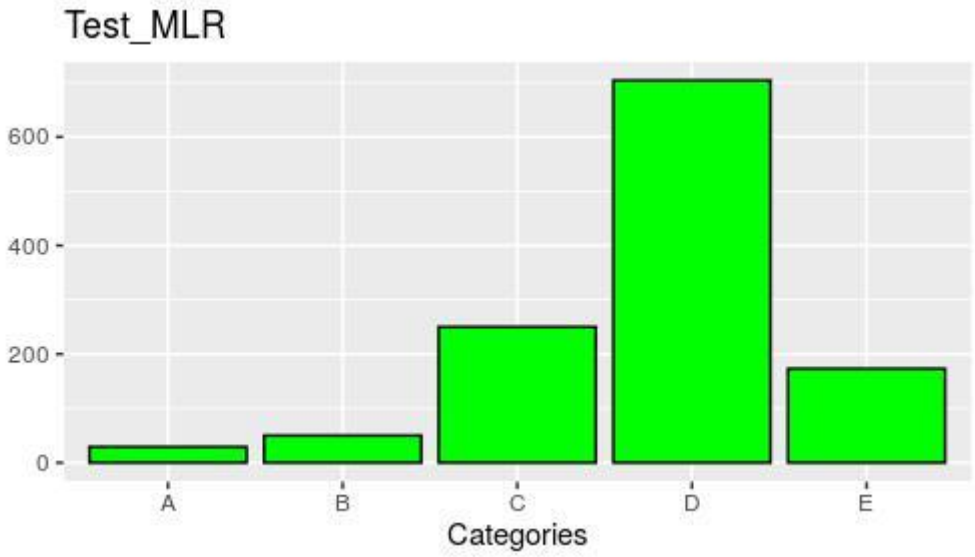


Figure 3.1: Test-MLR

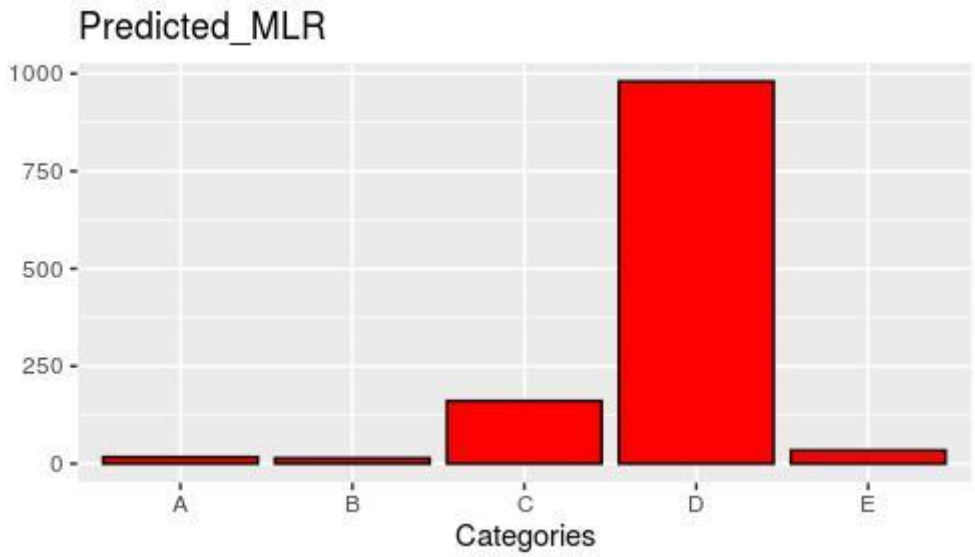


Figure 3.2: Predicted-MLR

TRAINING SCORE: 63% TESTING SCORE: 58%

3.1.2 KNN Classification

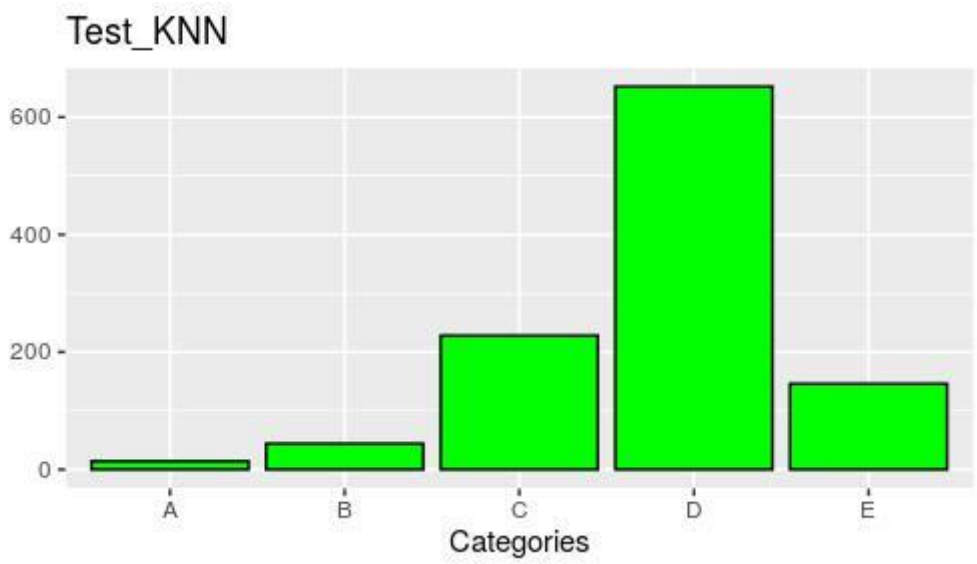


Figure 3.3: Test-KNN

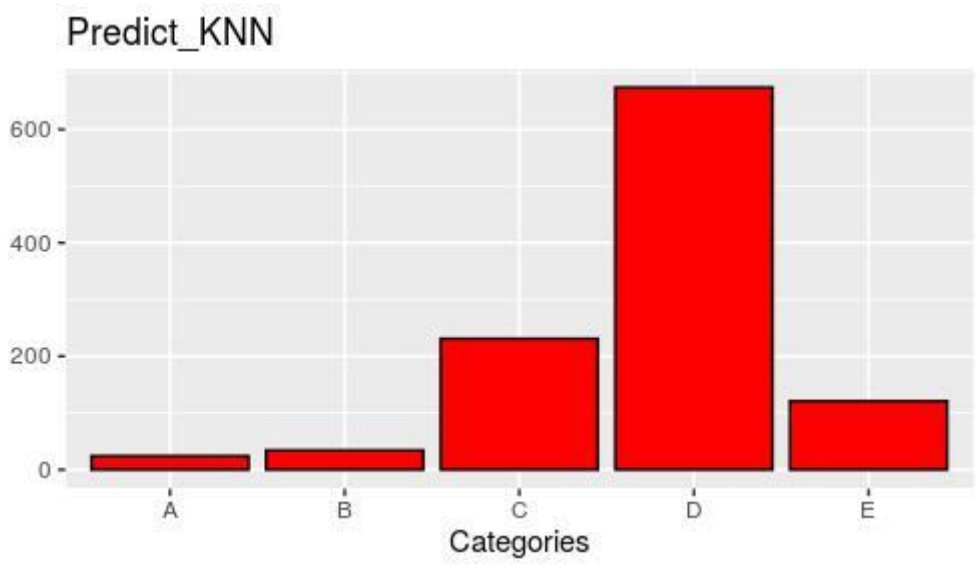


Figure 3.4: Predicted-KNN
TRAINING SCORE:87% TESTING SCORE: 74%

3.1.3 Naive Bayes Classification

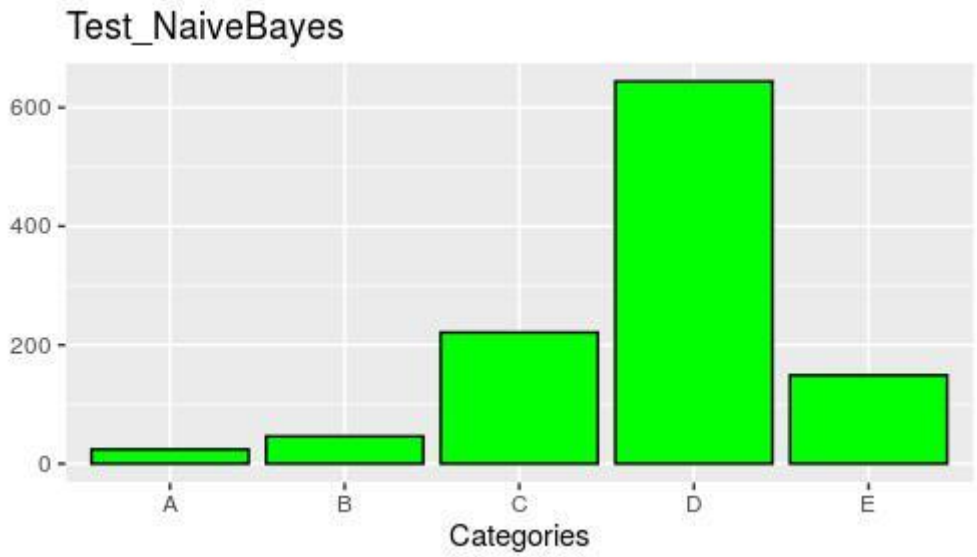


Figure 3.5: Test-Naive Bayes

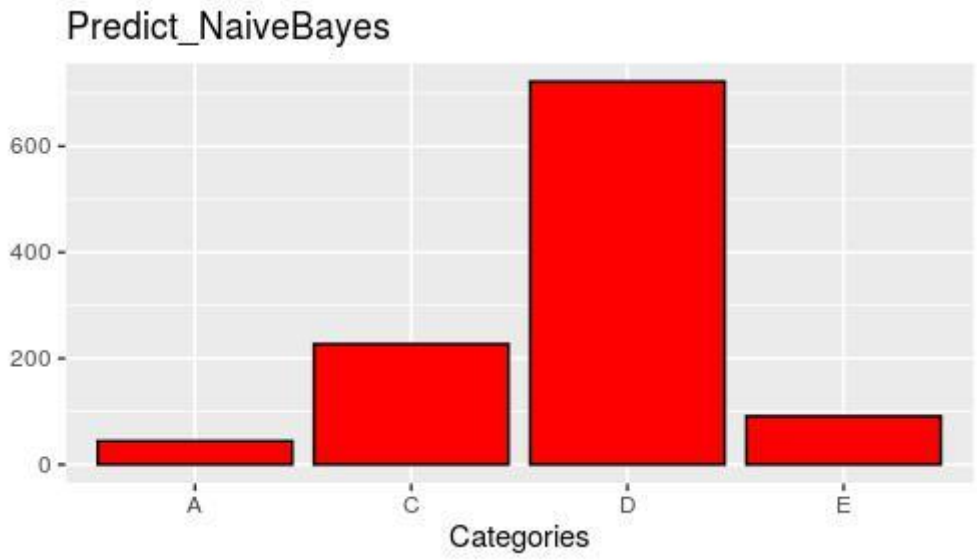


Figure 3.6: Predicted-Naive Bayes
TRAINING SCORE: 67% TESTING SCORE: 58%

3.1.4 Random Forest Classification

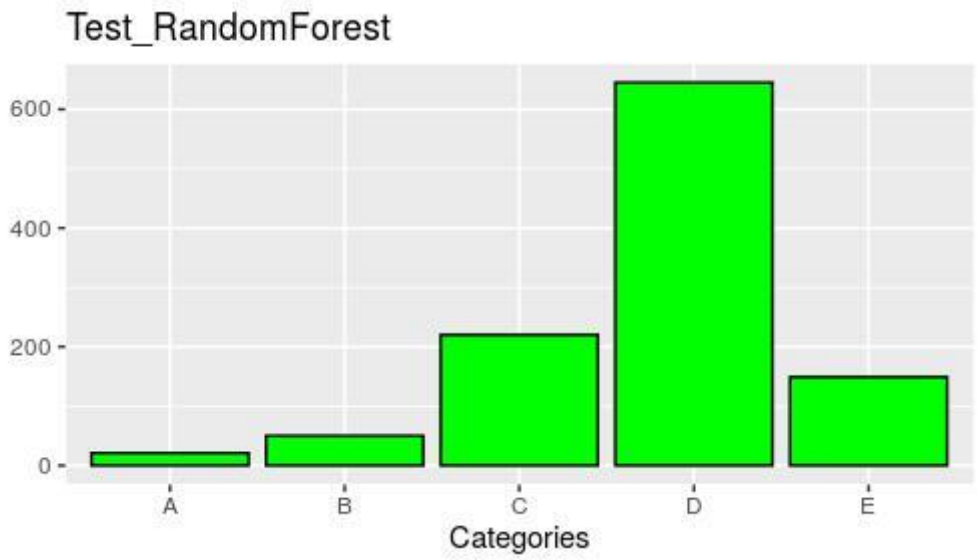


Figure 3.7: Test-Random Forest

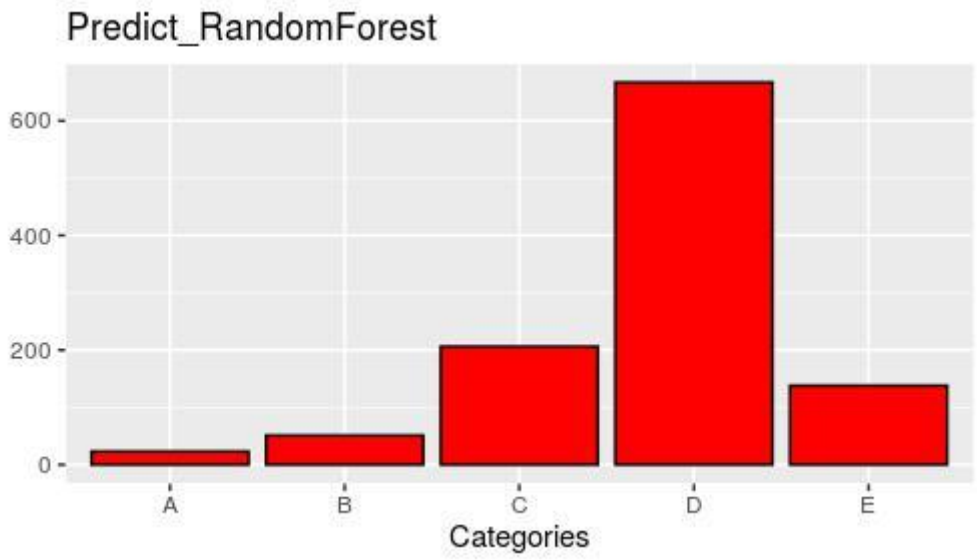


Figure 3.8: Predicted-random forest
TRAINING SCORE: 93% TESTING SCORE: 84%

3.1.5 Artificial Neural Network(ANN)

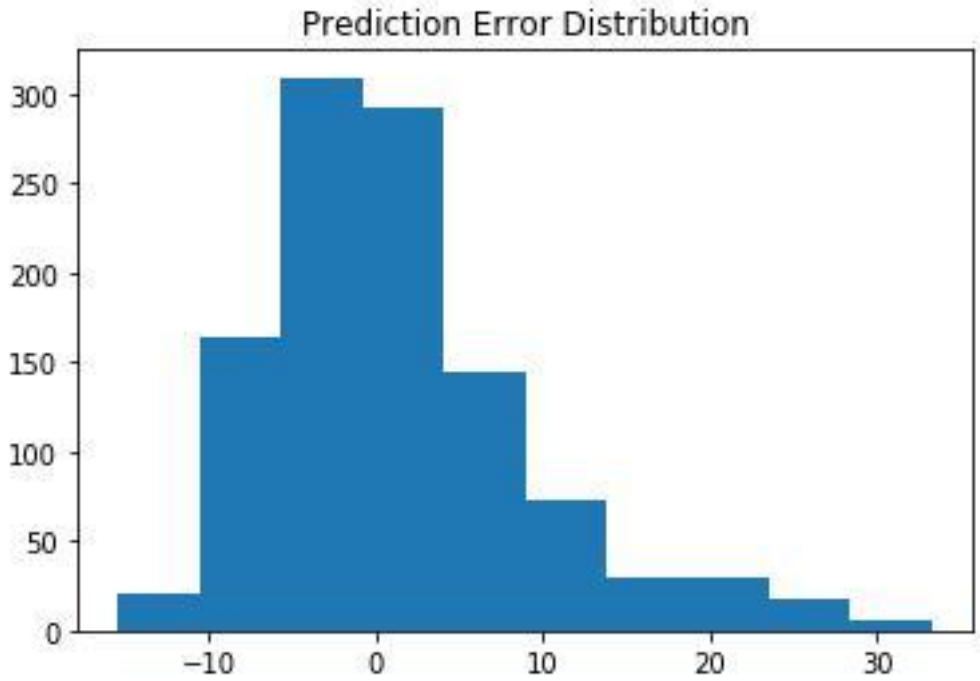


Figure 3.9: ANN-Mean Squared error
ACCURACY SCORE: MORE THAN 90%

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