IDENTIFY THE BEST MODEL FOR CLASS IMBALANCE DATA IN MULTICLASS PROBLEM

PHASE II REPORT

Submitted by

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Certified that this project report "**IDENTIFY THE BEST MODEL FOR CLASS IMBALANCE DATA IN MULTICLASS PROBLEM**" is the bonafide work of "**E.KEERTHANA",** who carried out the project work under my supervision. Certified Further that to the best of my knowledge the work reported here in does not form part of any other thesis or dissertation on the basic of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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Submitted for the university Project Viva-voce Phase-II Examination held on _____________ at Priyadarshini Engineering College,Vaniyambadi-635 751.

INTERNAL EXAMINER **EXTERNAL EXAMINER**

ABSTRACT

In Robust model for Imbalanced class of data, a research on an Infinite possibility of imbalanced class of data and we would like to investigate what are the best models through all possible imbalanced situation of a data set. Usually we do Up-Sampling Or Down-Sampling of the imbalanced data and make it balanced before applying machine learning models. In both the cases, We lose information about that data set. In this project, we would like to investigate what are the best models through all possible imbalanced situation of a data set. There is no particular definition for imbalanced class of data. In general, data that is not balanced is called imbalanced. Generating Data Points in Square Pattern Keeping a boundary classifying the data points as belongs to multiple class and name them as class_1, class_2 and class_3. Adding some jitter points to every data points to make every data points fall under different class and make them misclassify in itself. Make the balance dataset to imbalance by making one class with the proportion of samples like 1%,2%,3%.......10% keeping other classes same. Referring to the above that at least one of the class having significantly less number of training examples or the examples in the training data belonging to one class heavily outnumber the examples in the other class. Currently, most of the Machine learning algorithms assume the training data to be balanced like SVM, Logistic-Regression, Naïve-Bayes etc., Last few decades ,some effective methods have been proposed to attack this problem like up-sampling, down-sampling, Smote etc…

சுருக்கம்

சமநிலையற்ற தரவின் தரவிற்கான வலுவான மாதிரியில், சமநிலையற்ற தரவின் எல்லையற்ற சாத்தியக்கூறு குறித்த ஆராய்ச்சி மற்றும் தரவுத் தொகுப்பின் சாத்தியமான அனைத்து சமநிலையற்ற சூழ்நிலையிலும் சிறந்த மாதிரிகள் எவை என்பதை நாங்கள் ஆராய விரும்புகிறோம். வழக்கமாக நாம் சமநிலையற்ற தரவின் அப்-சாம்பிளிங் அல்லது டவுன்-சாம்பிளிங் செய்கிறோம் மற்றும் இயந்திர கற்றல் மாதிரிகளைப் பயன்படுத்துவதற்கு முன்பு அதை சீரானதாக ஆக்குகிறோம். இரண்டு நிகழ்வுகளிலும், அந்த தரவு தொகுப்பு பற்றிய தகவல்களை இழக்கிறோம். இந்த திட்டத்தில், என்னவென்று விசாரிக்க விரும்புகிறோம். தரவு தொகுப்பின் அனைத்து சமநிலையற்ற சூழ்நிலையிலும் சிறந்த மாதிரிகள். தரவின் சமநிலையற்ற வகுப்புக்கு குறிப்பிட்ட வரையறை இல்லை. பொதுவாக, சமநிலையற்ற தரவு சமநிலையற்றது என்று அழைக்கப்படுகிறது. சதுர வடிவத்தில் தரவு புள்ளிகளை உருவாக்குதல் தரவு புள்ளிகளை பல வகுப்புகளுக்கு சொந்தமானது என வகைப்படுத்தி அவற்றை வகுப்பு_1, வகுப்பு_2 மற்றும் வகுப்பு_3 என பெயரிடுங்கள். ஒவ்வொரு தரவு புள்ளிகளிலும் சில நடுக்கம் புள்ளிகளைச் சேர்ப்பது, ஒவ்வொரு

தரவு புள்ளிகளும் வெவ்வேறு வகுப்பின் கீழ் வருவதற்கும் அவற்றை தானாகவே வகைப்படுத்துவதற்கும் செய்கிறது. 1%, 2%, 3% .... 10% போன்ற மாதிரிகளின் விகிதத்துடன் ஒரு வகுப்பை உருவாக்குவதன் மூலம் இருப்பு தரவுத்தொகுப்பை ஏற்றத்தாழ்வுக்கு ஆக்குங்கள். மேற்கூறியவற்றைக் குறிப்பிடுவது, வகுப்பில் குறைந்தபட்சம் ஒருவரையாவது குறைந்த எண்ணிக்கையிலான பயிற்சி எடுத்துக்காட்டுகள் அல்லது ஒரு வகுப்பைச் சேர்ந்த பயிற்சி தரவுகளில் உள்ள எடுத்துக்காட்டுகள் மற்ற வகுப்பில் உள்ள எடுத்துக்காட்டுகளை விட அதிகமாக உள்ளன. தற்போது, பெரும்பாலான இயந்திர கற்றல் வழிமுறைகள் பயிற்சி தரவை எஸ்.வி.எம், லாஜிஸ்டிக்-ரிக்ரஷன், நேவ்-பேஸ் போன்றவை, சில தசாப்தங்களாக, அப்-சாம்பிளிங், டவுன்-சாம்பிளிங், ஸ்மோட் போன்ற இந்த சிக்கலைத் தாக்க சில பயனுள்ள முறைகள் முன்மொழியப்பட்டுள்ளன…

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E.KEERTHANA

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LIST OF ABBREVATION

Conda	Anaconda prompt
Csv	Comma-separated values
ML	Machine Learning
AI	Artificial Intelligence
DS	Data Science
GUI	Graphical User Interface
CLI	Command line Interface

CHAPTER 1
INTRODUCTION

1.1 OVERVIEW

Imbalanced data typically refers to a problem with classification problems where the classes are not represented equally. Most classification data set do not have exactly equal Number of instance in each class, but a small difference often does not matter. There are problems where a class imbalance is not just common it is expected. The accuracy paradox is the name for the exact situation in the introduction to this post. In this case where your accuracy is only reflecting the underlying the class distribution. A large dataset might expose a different and perhaps more balanced perspective on the classes. Accuracy is not the metric to use when working with an imbalanced dataset. We have seen that it misleading. There is a metrics that have been designed to tell you a more truthful story when working with imbalanced class. You can change the dataset that you use to build you can predictive model to have more balanced data. They have their own algorithm measure and terminology.

1.2 SCOPE OF THE PROJECT

Generating Data points on our own and make the balance dataset in to imbalance data in different proportions and check the classification report on all possible situation of the data and suggesting which are the models are giving best results. Do a research on an Infinite possibility of imbalanced class of data and we would like to investigate what are the best models through all possible imbalanced situation of a data set. Most of the Machine learning algorithms assume the training data to be balanced like SVM, Logistic-Regression, Naïve-Bayes etc., the classifier and the decision rule have to be set with respect to a well-chosen goal that can be, for example, minimizing a cost.

1.3 DATA SCIENCE

Data Science is the concept to unify scientific methods process algorithm and system to extract knowledge and insight from structured and unstructured data. Data science is the same concepts as data mining and big data. Use the most powerful hardware and effective algorithm to solve problems. Data science is a concepts to unify statistics, data analysis, Machine learning and their related methods in order to understand and analyze actual phenomena with data in order to became a buzz word . It is a now often used interchangeable with earlier concepts like business analytics, business intelligence, Predictive modeling and statistics. Even when the data science approaches and solution are now simply rebranded as data analysis to be more attractive which can cause them to curriculum contents.

1.4 ANACONDA

A downloadable, free, open source, high-performance and optimized Python and R distribution. Anaconda includes conda, conda-build, Python, and 100+ automatically installed, open source scientific packages and their dependencies that have been tested to work well together, including SciPy, NumPy and many others. Use the conda install command to easily install 1,000+ popular open source packages for data science including advanced and scientific analytics–from the Anaconda repository. Use the conda command to install thousands more open source packages. Because Anaconda is a Python distribution, it can make installing Python quick and easy even for new users. Available for Windows, macOS and Linux, all versions of Anaconda are supported by the community. See also Miniconda and Conda. Conda keeps track of the dependencies between packages and platforms. The conda package format is identical across platforms and operating systems. Only files, including symbolic links, are part of a conda package. Directories are not included. Directories are created and removed as needed, but you cannot create an empty directory from the tar archive directly.

Anaconda Cloud

A web-based repository hosting service in the cloud. Packages created locally can be published to the cloud to be shared with others. Free accounts on Cloud can publish packages to be shared publicly. Paid subscriptions to Cloud can designate packages as private to be shared with authorized users. Anaconda Cloud is a public version of Anaconda Repository.

Anaconda Navigator

A desktop graphical user interface (GUI) included in all versions of Anaconda that allows you to easily manage conda packages, environments, channels and notebooks without a command line interface (CLI). **Channels** The locations of the repositories where conda looks for packages. Channels may point to a Cloud repository or a private location on a remote or local repository that you or your organization created. The conda channel command has a default set of channels to search, beginning with https://repo.continuum.io/pkgs/, which you may override, for example, to maintain a private or internal channel. These default channels are referred to in conda commands and in the .condarc file by the channel name "defaults."

Conda

The package and environment manager program bundled with Anaconda that installs and updates conda packages and their dependencies. Conda also lets you easily switch between conda environments on your local computer.

Conda environment

A folder or directory that contains a specific collection of conda packages and their dependencies, so they can be maintained and run separately without interference from each other. For example, you may use a conda environment for only Python 2 and Python 2 packages, maintain another conda environment with only Python 3 and Python 3 packages, and maintain another for R language packages. Environments can be created from:

• The Navigator GUI

• The command line

• An environment specification file with the name your-environment-name.yml.

Conda package

A compressed file that contains everything that a software program needs in order to be installed and run, so that you do not have to manually find and install each dependency separately. A conda package includes system-level libraries, Python or R language modules, executable programs and other components. You manage conda packages with conda.

Conda repository

A cloud-based repository that contains 720+ open source certified packages that are easily installed locally with the conda install command. Anyone can access the repository from:

• The Navigator GUI

• A terminal or Anaconda Prompt using conda commands

Meta package

A meta package is a very simple package that has at least a name and a version. It need not have any dependencies or build steps. Meta packages may list dependencies to several core, low-level libraries and may contain links to software files that are automatically downloaded when executed.

Miniconda

A free minimal installer for conda. Miniconda is a small, bootstrap version of Anaconda that includes only conda, Python, the packages they depend on and a small number of other useful packages, including pip, zlib and a few others. Use the conda install command to install 720+ additional conda packages from the Anaconda repository. Because Mini conda is a Python distribution, and it can make installing Python quick and easy even for new users.

Noarch package

A conda package that contains nothing specific to any system architecture, so it may be installed from any system. When conda searches for packages on any system in a channel, conda checks both the system-specific subdirectory, such as linux-64, and the noarch directory. Noarch is a contraction of "no architecture".

Package manager

A collection of software tools that automates the process of installing, updating, configuring and removing computer programs for a computer’s operating system. Also known as a package management system. Conda is a package manager.

Packages

Software files and information about the software, such as its name, the specific version and a description, bundled into a file that can be installed and managed by a package manager.

Repository

Any storage location from which software assets may be retrieved and installed on a local computer. See also Anaconda Cloud and Conda repository.

Silent mode installation

When installing Miniconda or Anaconda in silent mode, screen prompts are not shown on screen and default settings are automatically accepted.

Anaconda package is a compressed Tarbell file (.tar.bz2) or .conda file that contains:

- system-level libraries
- Python or other modules
- executable programs and other components
- metadata under the info/ directory
- a collection of files that are installed directly into an install prefix

Anaconda file format

The .conda file format was introduced in conda 4.7 as a more compact, and thus faster, alternative to a tarball. The .conda file format consists of an outer, uncompressed ZIP-format container, with two inner compressed .tar files. For the .conda format's initial internal compression format support, we chose Zstandard (zstd). The actual compression format used does not matter, as long as the format is supported by libarchive. The compression format may change in the future as more advanced compression algorithms are developed and no change to the .conda format is necessary.

Only an updated libarchive would be required to add a new compression format to .conda files. These compressed files can be significantly smaller than their bzip2 equivalents. In addition, they decompress much more quickly. .conda is the preferred file format to use where available, although we continue to provide .tar.bz.

Virtual environments

A virtual environment is a tool that helps to keep dependencies required by different projects separate by creating isolated spaces for them that contain per-project dependencies for them. Users can create virtual environments using one of several tools such as Pipenv or Poetry, or a conda virtual environment. Pipenv and Poetry are based around Python's built-in venv library, whereas conda has its own notion of virtual environments that is lower-level (Python itself is a dependency provided in conda environments).

CHAPTER 2
LITERATURE REVIEW

TITLE 1: Variance Ranking Attributes Selection Techniques for Binary Classification problem in Imbalance Data[1]

YEAR: 2019

AUTHOR: SOLOMON H. EBENUWA, MHD SAEED SHARIF, MAMOUN ALAZAB

CONCEPT: In typical predictive modeling, the inability to effectively address a class imbalance in a real-life dataset is an important shortcoming of the existing machine learning algorithms. This paper presents a new attribute selection technique called variance ranking for handling imbalance class problems in a dataset.

TITLE 2: Kernel Modified optimal margin Distribution machine for imbalanced data classification.[4]

YEAR: 2019

AUTHOR: xiaogang zhang , Dingxiang wang.

CONCEPT: A kernel modified ODM to eliminate the side effect of Imbalanced data. a novel conformal function is designed to scale the kernel matrix of ODM. This can increases the seperability of the training data in the feature space.

TITLE 3: Novel approach to predict Hospital readmission using feature selection from unstructured data with the class imbalance data. [8]

YEAR: 2019

AUTHOR: Arun sundararaman, Ramprasad Thati

CONCEPT: In this paper, Predictive models uses the feature along with the relevant structured data. Five iteration of prediction are performed to tune and improve the models results of which are presented and analyzed. Future directions in implementing the hospitals clinic aimed at leveraging structured and unstructured discharge summary notes.

TITLE 4: Integrating of feature vector selection and support vector machine for classification of imbalanced data[5]

YEAR: 2019

AUTHOR: jieliu,Enrico zio.

CONCEPT: In this paper classification of imbalance data is considered. A featured vector selection method with respect to maximal separable is proposed. The decision threshold is optimized considering a specific accuracy time. Comparison with various kernel methods show the effectiveness.

TITLE 5: Improving the classification performance on imbalanced data sets via new hybrid parameterization model[11].

YEAR: 2018

AUTHOR: masurah Mohamed, ondrej krejcar

CONCEPT: The hybrid model is an integration of three main Phases which are soft set, rough set. Imbalanced data set where used to evaluate the capability of the hybrid model in handling problematic data.

CHAPTER 3

SYSTEM DESIGN AND IMPLEMENTATION

3.1 EXISTING SYSTEM

- Usually we do Up-Sampling Or Down-Sampling of the imbalanced data
- Making it balanced before applying machine learning models.
- In both the cases, We lose information about that data set.

Existing Technique

- Up-sampling and down sampling

Disadvantage

- Less effective.
- Prediction of target data is low due to low samples.
- Lose of information about the data set.

3.2 PROPOSED SYSTEM

- Investigate the best models through all possible imbalanced situation of a data set.
- Adding Noise to the dataset.
- Making the balanced data to imbalanced data using their proportion of the sample like 1%,2%,…10% using other data classes evaluate the chart for each classes.
- Built the Model.
- Find the robust model for data imbalance.

Proposed Technique

Creating the data set, Making the balanced data using their proportion of the sample Building the model and find the robust model for data imbalance.

Advantage

- More effective
- No loss of data /sampleS
- Robust model for imbalanced data

3.3 SYSTEM REQUIREMENTS

3.3.1 Software Requirement

The software requirements document is the specification of the system. It should include both a definition and a specification of requirements. The software requirements provide a basis for creating the software requirements specification.

FRONT END	:	Jupiter Notebook, PYTHON Programming.
BACK END	:	Database (excel format)
OPERATING SYSTEM	:	Windows 7

3.3.2 Hardware Requirement

The hardware requirements may serve as the basis for a contract for the implementation of the system and should therefore be a complete and consistent specification of the whole system. They are used by software engineers as the starting point for the system design. It shows what the system does and not how it should be implemented.

PROCESSOR	:	PENTIUM IV 2.6 GHz
RAM	:	2GB DD RAM
MONITOR	:	15" COLOR
HARD DISK	:	40 GB

3.4 HARDWARE DESCRIPTION

Dual Core Processor

This Dual core Processor is a CPU with two processor or execution cores in the same integrated circuit. Each individual Processor has it won cache and controller which enables it to function as effective as a single processor. However these two processor are linked together, they can perform operation up to twice as fast as a single processor can.

RAM

RAM is a random access memory, a type of computer memory that can be accessed randomly; that is, any byte of memory can be accessed without touching the preceding bytes. This RAM is found in servers, PCs, tablets, Smart phones and other devices.

Types of RAM

There are two types of ram

- DRAM(Dynamic Random Access Memory)
- SRAM(Static Random Access Memory)

Hard Disk

When we want to save data or install programs on our computer, the information is typically written to your hard disk. This Hard disk us a spindle if magnetic disks called platters. That record and store information, Hard disk is a magnetic material coated disk, Hard drive is a device it is storing data into a Hard disk. Here this drive means a moving actuator arm with magnetic heads arranged on it read and write data to the hard disk surface.

3.5 SOFTWARE DESCRIPTION

Jupiter Notebook

The Jupiter Notebook is an interactive computing environment that enables users to author notebook documents that include: - Live code - Interactive widgets - Plots - Narrative text - Equations - Images – Video These documents provide a complete and self-contained record of a computation that can be converted to various formats and shared with others using email, Drop box, version control systems (like git / GitHub) or nbviewer.jupyter.org.

Components

The Jupiter Notebook combines three components:

• The notebook web application: An interactive web application for writing and running code interactively and authoring notebook documents.

• Kernels: Separate processes started by the notebook web application that runs users' code in a given language and returns output back to the notebook web application.

The kernel also handles things like computations for interactive widgets, tab completion and introspection.

• Notebook documents: Self-contained documents that contain a representation of all content visible in the notebook web application, including inputs and outputs of the computations, narrative text, equations, images, and rich media representations of objects. Each notebook document has its own kernel.

Python Programming

The programming language you will learn is Python. Python is an example of a high-level language; other high-level languages you might have heard of are C, C++, Perl, and Java There are also low-level languages, sometimes referred to as "machine languages" or "assembly languages." Loosely speaking, computers can only run programs written in low level languages. So programs written in a high-level language have to be processed before they can run. This extra processing takes some time, which is a small disadvantage of high-level languages. The advantages are enormous. First, it is much easier to program in a high-level language. Programs written in a high-level language take less time to write, they are shorter and easier to read, and they are more likely to be correct. Second, high-level languages are portable, meaning that they can run on different kinds of computers with few or no modifications. Low-level programs can run on only one kind of computer and have to be rewritten to run on another.

Syntax Error

Python can only execute a program if the syntax is correct; otherwise, the interpreter displays an error message. **Syntax** refers to the structure of a program and the rules about that structure. For example, parentheses have to come in matching pairs, so (1 + 2) is legal, but 8) is a **syntax error**. In English, readers can tolerate most syntax errors, which is why we can read the poetry of e. e. Cummings without spewing error messages. Python is not so forgiving. If there is a single syntax error anywhere in your program, Python will display an error message and quit, and you will not be able to run your program. During the first few weeks of your programming career, you will probably spend a lot of time tracking down syntax errors. As you gain experience, you will make fewer errors and find them faster.

Runtime Error

The second type of error is a runtime error, so called because the error does not appear until after the program has started running. These errors are also called **exceptions** because they usually indicate that something exceptional (and bad) has happened. Runtime errors are rare in the simple programs you will see in the first few chapters, so it might be a while before you encounter one.

Semantic Error

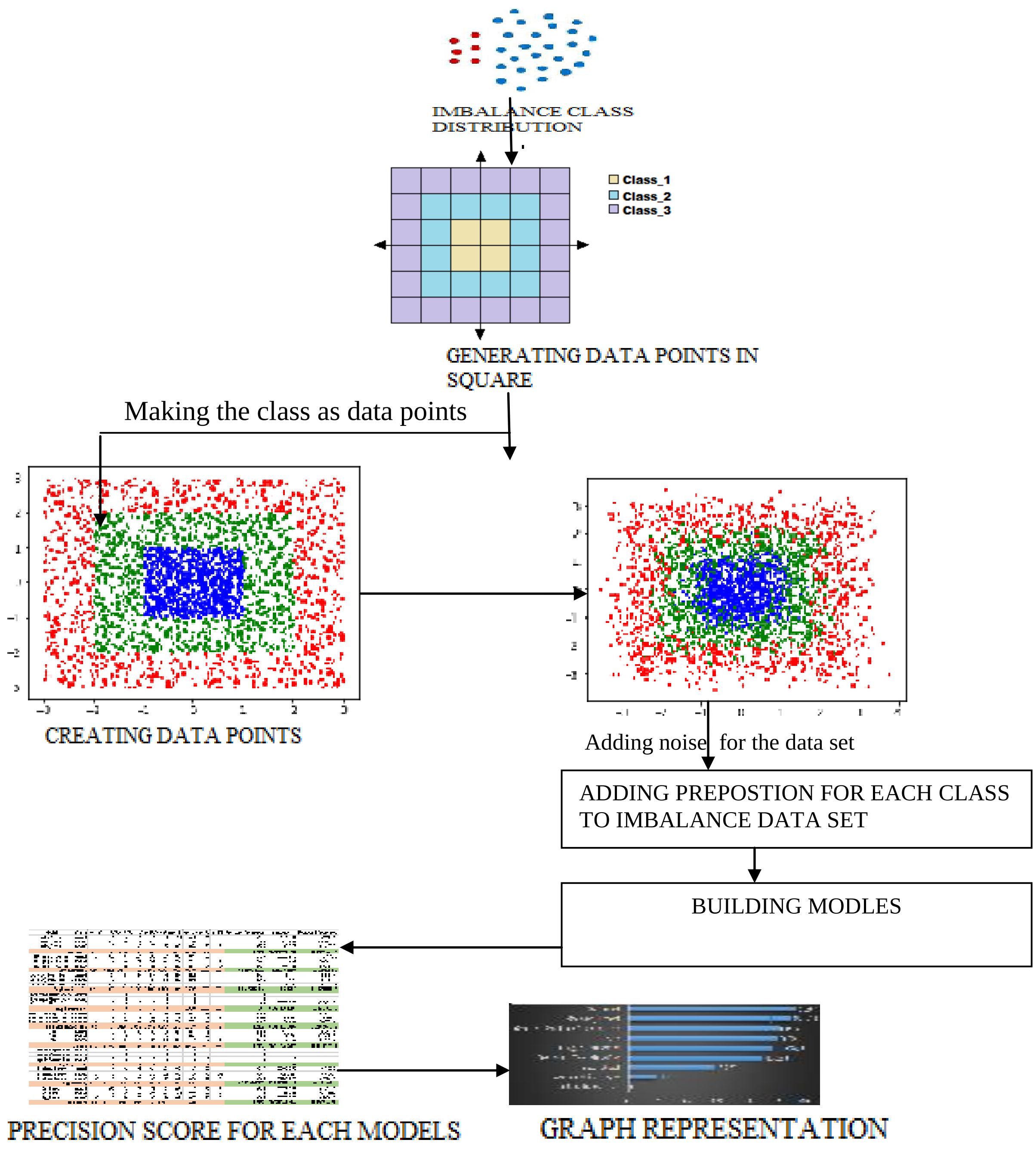
The third type of error is the semantic error. If there is a semantic error in your program, it will run successfully in the sense that the computer will not generate any error messages, but it will not do the right thing. It will do something else. Specifically, it will do what you told it to do. The problem is that the program you wrote is not the program you wanted to write. The meaning of the program (its semantics) is wrong. Identifying semantic errors can be tricky because it requires you to work backward by looking at the output of the program and trying to figure out what it is doing.

Experimental Debugging

One of the most important skills you will acquire is debugging. Although it can be frustrating, debugging is one of the most intellectually rich, challenging, and interesting parts of programming. In some ways, debugging is like detective work. You are confronted with clues, and you have to infer the processes and events that led to the results you see. Debugging is also like an experimental science. Once you have an idea about what is going wrong, you modify your program and try again. If your hypothesis was correct, then you can predict the result of the modification, and you take a step closer to a working program. If your hypothesis was wrong, you have to come up with a new one. As Sherlock Holmes pointed out, “When you have eliminated the impossible, whatever remains, however improbable, must be the truth.” (A. Conan Doyle, The Sign of Four) For some people, programming and debugging are the same thing. That is, programming is the process of gradually debugging a program until it does what you want. The idea is that you should start with a program that does something and make small modifications, debugging them as you go, so that you always have a working program. For example, Linux is an operating system that contains thousands of lines of code, but it started out as a simple program Linus Torvalds used to explore the Intel 80386 chip. According to Larry Greenfield, “One of Linus’s earlier projects was a program that would switch between printing AAAA and BBBB. This later evolved to Linux.

3.6 DESIGN DIAGRAMS

3.6.1 SYTEM ARCHITECTURE


IMBALANCE CLASS DISTRIBUTION
Class_1
Class_2
Class_3
GENERATING DATA POINTS IN SQUARE
Making the class as data points
CREATING DATA POINTS
Adding noise for the data set
ADDING PREPOSTION FOR EACH CLASS TO IMBALANCE DATA SET
BUILDING MODLES
PRECISION SCORE FOR EACH MODELS
GRAPH REPRESENTATION

Explanation

In Robust model for Imbalanced class of data, a research on an Infinite possibility of imbalanced class of data and we would like to investigate what are the best models through all possible imbalanced situation of a data set Generating Data Points in Square Pattern Keeping a boundary classifying the data points as belongs to multiple class and name them as class_1, class_2 and class_3. Adding some jitter points to every data points to make every data points fall under different class and make them misclassify in itself. Make the balance dataset to imbalance by making one class with the proportion of samples like 1%,2%,3%.......10% keeping other classes same. Referring to the above that at least one of the classes having significantly less number of training examples or the examples in the training data belonging to one class heavily out number the examples in the other class. Currently, most of the Machine learning algorithms assume the training data to be balanced like SVM, Logistic-Regression, Naïve-Bayes etc.,BLast few decades, some effective methods have been proposed to attack this problem like up-sampling, down-sampling, Smote etc…

3.7 MODULES

- Generating data points and getting data set in square format
- Creating data points and adding noise to the data set
- Adding preposition for each data set to imbalance the Dataset
- Built the models
    - Logistic Regression
    - Gaussian Naive Bayes
    - Decision_Tree_Classifier
    - Random_Forest
    - Knn
    - Ada_Boost
    - Gradient Boosting Classification
    - Bagging Classifier
    - Xg – Boost
- Graph

3.7.1 GENERATING DATA POINTS AND GETTING DATA SET IN SQUARE FORMAT

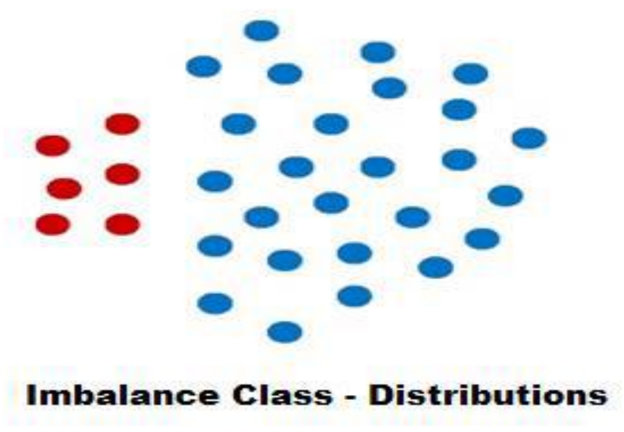


Fig. No. 3.7.1 Imbalance Sample

There is no particular definition for imbalanced class of data. In general, data that is not balanced is called imbalanced. Referring to the above that at least one of the class format having significantly less number of training examples or the examples in the training data belonging to one class heavily outnumber the examples in the other class. Currently, most of the Machine learning algorithms assume the training data to be balanced like SVM, Logistic-Regression, Naïve-Bayes etc., Last few decades, some effective methods have been proposed to attack this problem like up-sampling, down-sampling, Smote etc…

Getting Dataset

Generating Data Points in Square Pattern Keeping a boundary classifying the data points as belongs to multiple class and name them as class_1, class_2 and class_3.

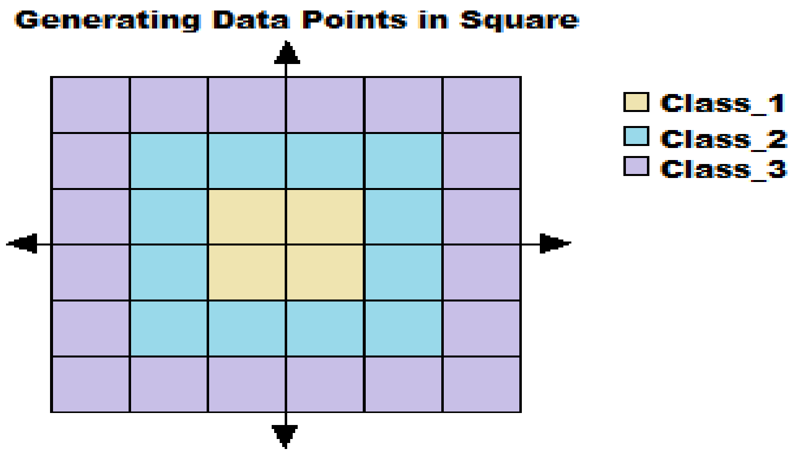
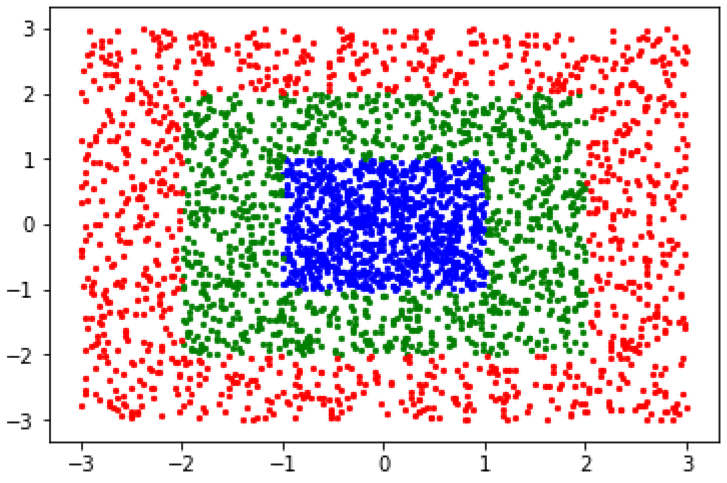


Fig. No. 3.7.1 Generating Datapoint Square

The data-points created here with the help of a graph generating a random data points quadrant wise and once every data points generated we are concatenating every data points and making a target column and assigning those data points to one class. Similarly, for other two classes we follow the same steps to generate data points and assign them to their respective class. Now Concatenate All the three classes and make it a Data frame.

3.7.2 CREATING DATA POINTS AND ADDING NOISE TO THE DATA SET



For our Analysis we want our data set to be misclassified so adding impurity will make the data points in the dataset fall under different class and making it misclassified though it will be a good representation for our analysis in the future.

ADDING NOISE

For doing Classification Experiments in Machine Learning Algorithms using our created dataset which is clearly classified we are adding some jitter points to every data points to make every data points fall under different class and make them misclassify in itself. Following Code will explain how we are adding the noise to the data.

Code For Adding Noise :

x_noise = [ ] ------------Make a list for X column

y_noise = [ ] ------------similarly for Y column

for index,row in data.iterrows(): -------using loop for each & every points

mu,sigma = row['X'],0.3 ------Generating data point in interval of value and 0.3

noise_x = np.random.normal(mu,sigma)-----Random Data point between two values

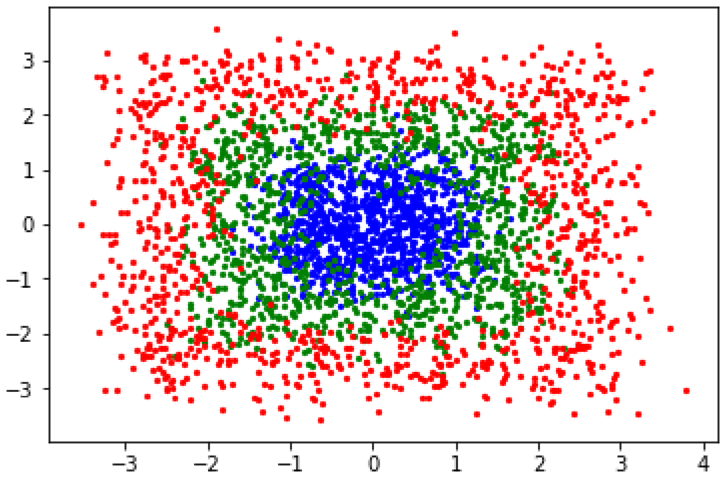
x_noise.append(noise_x) ------Append those values in the list

for index,row in data.iterrows(): -----Similarly for Y column

mu,sigma = row['Y'],0.3

```
noise_y = np.random.normal(mu,sigma)
y_noise.append(noise_y)
x_noise = pd.DataFrame(x_noise x_noise.rename(columns = {0:'X',},inplace = True)
y_noise = pd.DataFrame(y_noise)
y_noise.rename(columns = {0:'Y',},inplace = True)
```

Now convert that appended List of X and Y values in to a Data Frame and make a dataset with a noise and assign the targets respect to them. After adding Noise to the data



Is the Dataset Imbalanced?...............No

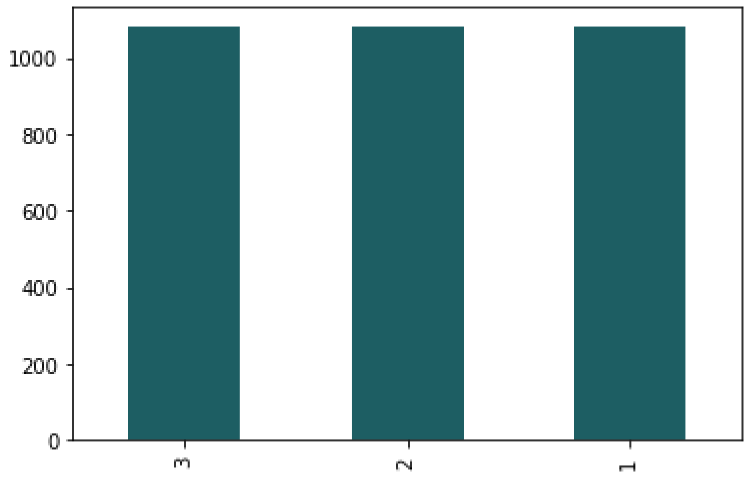


Fig. No 3.7.2 Class Balanced Graph

Every Class got Balanced though our analysis is for Imbalanced data we make this dataset an imbalance for our further process.

3.7.3 ADDING PREPOSITION FOR EACH DATA SET TO IMBALANCE THE DATA SET

Now let’s make the balance dataset to imbalance by making one class with the proportion of samples like 1%,2%,3%.......10% keeping other classes same.

1%? Means how many samples should we take to make that class as minority?

$$Samples\ to\ take\ for\ making\ one\ class\ as\ minority = \frac{data\ points\ in\ the\ other\ classes * percentage}{1 - percentage}$$

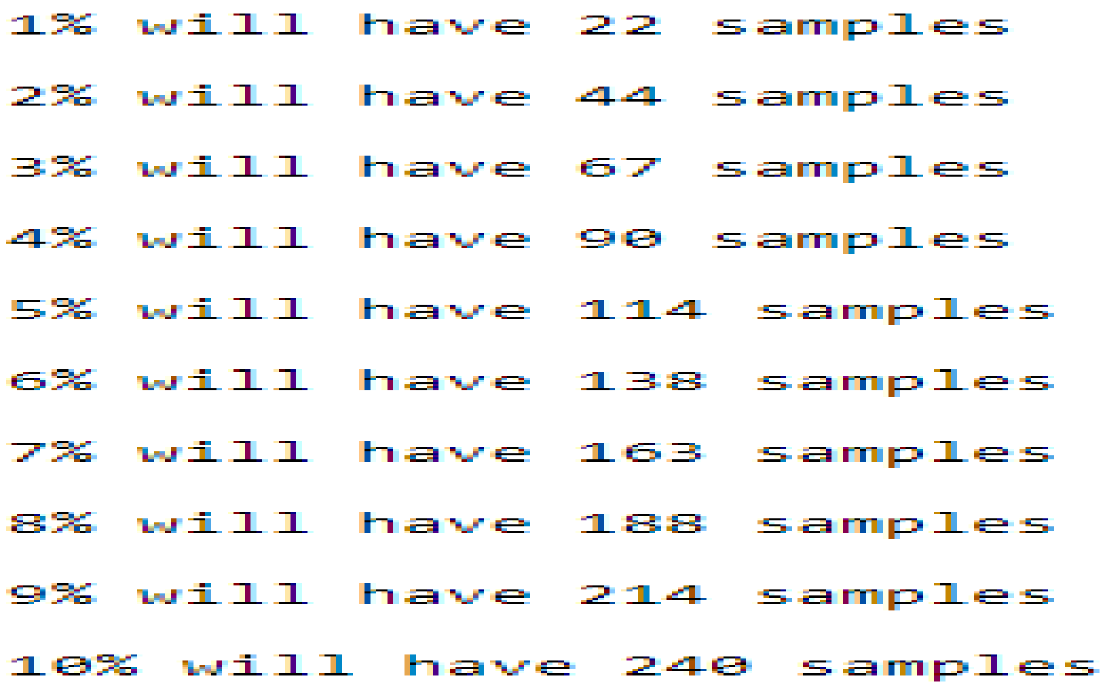
Example:

If the three classes have shape (1080,3) (1080,3) (1080,3) $if\ its$ 1%,y=1100=0.01

$Similarly\ for\ every\ percentages$

$samples$=(1080+1080)∗0.01 1−0.01=21.81 = 22

Total 22 samples for making that class as minority, similarly for other percentages we calculated as shown.



```
1% will have 22 samples
2% will have 44 samples
3% will have 67 samples
4% will have 90 samples
5% will have 114 samples
6% will have 138 samples
7% will have 163 samples
8% will have 188 samples
9% will have 214 samples
10% will have 240 samples
```

After Creating the Dataset Class_1 as minority and created 10 datasets as per percentage proportions. The Count of the records in each class is shown in the figure.

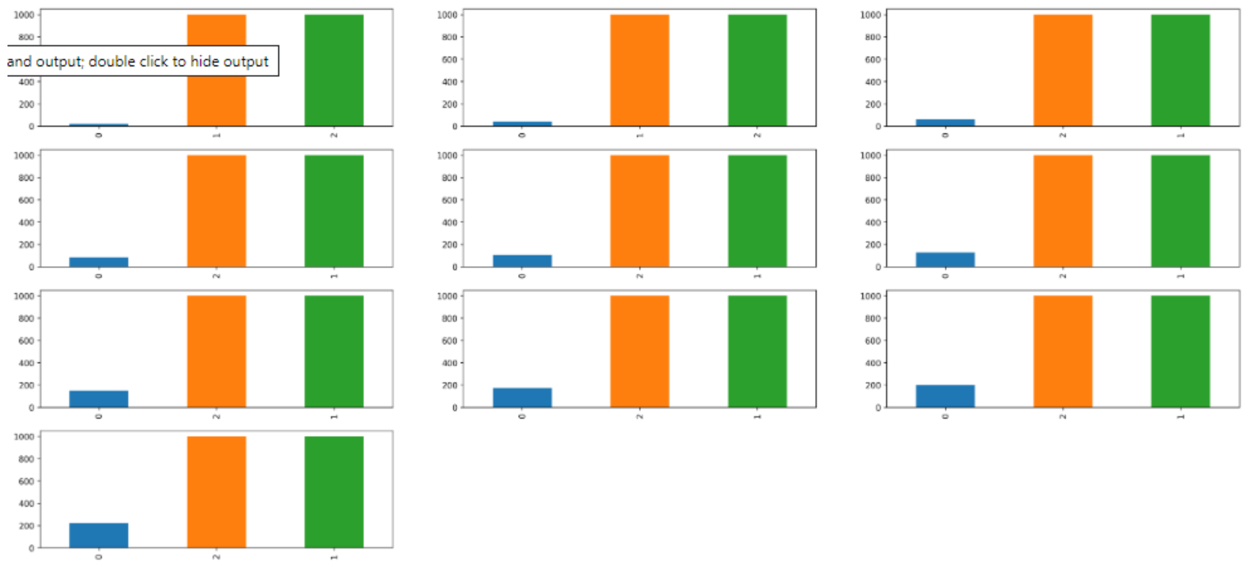


Fig. No 3.7.3 Sample of Minority Classes

Similarly, for other 2 classes create a data set. With the 30 data sets created try to implement every Machine Learning Algorithms and collect the Classification report on only Minority class and see which algorithms performing well on the given sample of minority class.

3.7.4 MODELS BUILT

3.7.4.1 LOGISTIC REGRESSION

Logistic Regression is a Machine Learning classification algorithm that is used to predict the probability of a categorical dependent variable. In logistic regression, the dependent variable is a binary variable that contains data coded as 1 (yes, success, etc.) or 0 (no, failure, etc.). In other words, the logistic regression model predicts P(Y=1) as a function of X. Logistic Regression is one of the most popular ways to fit models for categorical data, especially for binary response data in Data Modeling. It is the most important (and probably most used) member of a class of models called generalized linear models. Unlike linear regression, logistic regression can directly predict probabilities (values that are restricted to the (0,1) interval); furthermore, those probabilities are well-calibrated when compared to the probabilities predicted by some other classifiers, such as Naive Bayes. Logistic regression preserves the marginal probabilities of the training data. The coefficients of the model also provide some hint of the relative importance of each input variable. Logistic Regression is used when the dependent variable (target) is categorical.

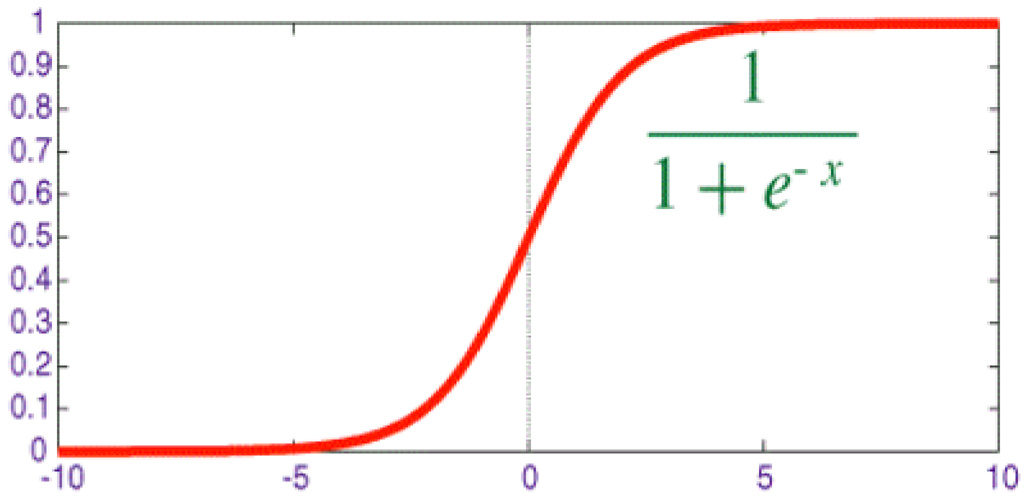


Fig.No 3.7.4 Logistic Regression

For example, To predict whether an email is a spam (1) or (0) Whether the tumour is malignant (1) or not (0) Logistic Regression Assumptions: 1. Binary logistic regression requires the dependent variable to be binary. 2. For a binary regression, the factor level 1 of the dependent variable should represent the desired outcome. 3. Only meaningful variables should be included. 4. The independent variables should be independent of each other.i.e., the model should have little or no multi-collinearity.

5. The independent variables are linearly related to the log odds. 6. Logistic regression requires quite large sample sizes. Even though logistic (logit) regression is frequently used for binary variables (2 classes), it can be used for categorical dependent variables with more than 2 classes. In this case, it's called Multinomial Logistic Regression.

Types of Logistic Regression:

1. Binary Logistic Regression: The categorical response has only two 2 possible outcomes. E.g.: Spam or Not

2 Multinomial Logistic Regression: Three or more categories without ordering.

E.g.: Predicting which food is preferred more (Veg, Non-Veg, Vegan)

3. Ordinal Logistic Regression: Three or more categories with ordering.

E.g.: Movie rating from 1 to 5.

Sigmoid or Logistic Function:

The Sigmoid Function curve looks like a S-shape. The main reason why we use sigmoid function is because it exists between (0 to 1). The function is differentiable. That means, we can find the slope of the sigmoid curve at any two points.

$$E(Y|X=x)=f(x)=P(Y=1|X=x) = \frac{1}{1+e^{-x}} = \frac{e^{x}}{1+e^{x}}$$

3.7.4.2 NAVIE-BAYES

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature. For example, a fruit may be considered to be an apple if it is red, round, and about 3 inches in diameter. Even if these features depend on each other or upon the existence of the other features, all of these properties independently contribute to the probability that this fruit is an apple and that is why it is known as 'Naive'. Naive Bayes model is easy to build and particularly useful for very large data sets. Along with simplicity, Naive Bayes is known to outperform even highly sophisticated classification methods. Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c). Look at the equation below:

classification methods. Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c). Look at the equation below:

$$\mathrm{P(c|x)} = \frac{\mathrm{P(x|c)} * \mathrm{P(c)}}{\mathrm{P(x)}}$$

$$P(c|X) = P(x_1|c) * P(x_2|c) * \ldots\ldots.* P(x_n|c) * P(c)$$

Above,

P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes) P(c) is the prior probability of class.

P(x|c) is the likelihood which is the probability of predictor given class.

P(x) is the prior probability of the predictor.

3.7.4.3 DECISION TREE CLASSIFIERS

A decision tree is a type of supervised learning algorithm (having a predefined target variable) that is mostly used in classification problems. It works for both categorical and continuous input and output variables. In this technique, we split the population or sample into two or more homogeneous sets (or sub-populations) based on most significant splitter/differentiator in input variables.

Let’s look at the basic terminology used with Decision trees:

1. Root Node: It represents the entire population or sample and this further gets divided into two or more homogeneous sets.
2. Splitting: It is a process of dividing a node into two or more sub-nodes.
3. Decision Node: When a sub-node splits into further sub-nodes, then it is called a decision node.
4. Leaf/ Terminal Node: Nodes do not split is called Leaf or Terminal node.
5. Pruning: When we remove sub-nodes of a decision node, this process is called pruning. You can say the opposite process of splitting.
6. Branch / Sub-Tree: A subsection of the entire tree is called branch or sub-tree.

7. Parent and Child Node: A node, which is divided into sub-nodes is called a parent node of sub-nodes whereas sub-nodes are the children of the parent node.

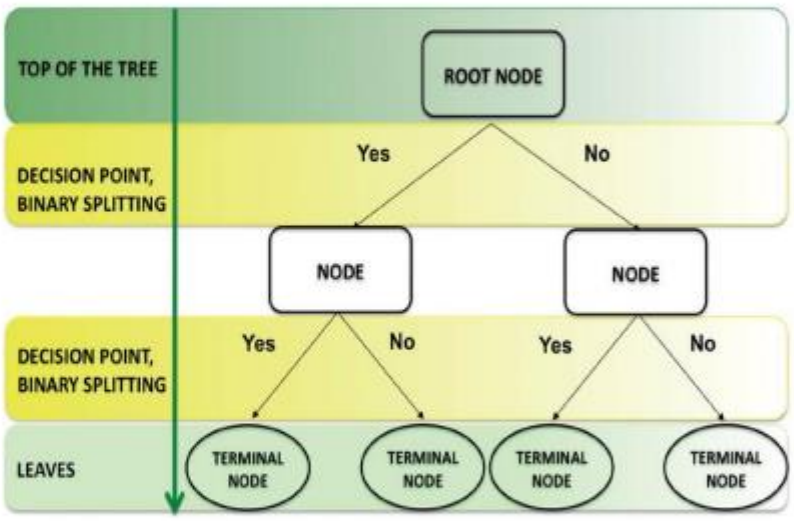


Fig.No 3.7.5 Decision tree classifiers

Advantages:

1. Simple to understand and to interpret. Trees can be visualized.
2. Requires little data preparation. Other techniques often require data normalization, dummy variables need to be created and blank values to be removed.
3. Able to handle both numerical and categorical data. Other techniques are usually specialized in analyzing datasets that have only one type of variable.
4. They work well for both regression and classification tasks.
5. They require relatively less effort for training the algorithm.
6. They can be used to classify non-linearly separable data.
7. They're very fast and efficient compared to KNN and other classification algorithms.
8. Uses a white box model. If a given situation is observable in a model, the explanation for the condition is easily explained by Boolean logic. By contrast, in a black box model (e.g., in an artificial neural network), results may be more difficult to interpret.

Dis-Advantages:

1. Decision-tree learners can create over-complex trees that do not generalize the data well. This is called over fitting. Mechanisms such as pruning - setting the minimum

number of samples required at a leaf node or setting the maximum depth of the tree are necessary to avoid this problem.

2. Decision trees can be unstable because small variations in the data might result in a completely different tree being generated. This problem is mitigated by using decision trees within an ensemble.

3. The problem of learning an optimal decision tree is known to be NP-complete under several aspects of optimality and even for simple concepts. Consequently, practical decision-tree learning algorithms are based on heuristic algorithms such as the greedy algorithm where locally optimal decisions are made at each node. Such algorithms cannot guarantee to return the globally optimal decision tree. This can be mitigated by training multiple trees in an ensemble learner, where the features and samples are randomly sampled with replacement.

4. Decision tree learners create biased trees if some classes dominate. It is therefore recommended to balance the dataset prior to fitting with the decision tree.

3.7.4.4 RANDOM FOREST CLASSIFIERS

Random forest classifier creates a set of decision trees from randomly selected subset of training set. It then aggregates the votes from different decision trees to decide the final class of the test object. Suppose training set is given as: [X1, X2, X3, X4] with corresponding labels as [L1, L2, L3, L4], random forest may create three decision trees taking input of subset
for example,

[X1, X2, X3]

[X1, X2, X4]

[X2, X3, X4]

So finally, it predicts based on the majority of votes from each of the decision trees made.

Why use Random Forest Machine Learning Algorithm?

1. It maintains accuracy when there is missing data and is also resistant to outliers.ie we could have run this model on our original data without removing customers with NA values.

2. Capable of handling numerical, binary and categorical features, without scaling, transformation or modification. Our data has variables which have largely different values

3. Implicit feature selection as it gives estimates on what variables are important in the classification. We have few features and the models select what it presumes well.

Pros and cons:

1. Both training and prediction are very fast, because of the simplicity of the underlying decision trees. In addition, both tasks can be straightforwardly parallelized, because the individual trees are entirely independent entities.

2. The multiple trees allow for a probabilistic classification: a majority vote among estimators gives an estimate of the probability.

3. The nonparametric model is extremely flexible, and can thus perform well on tasks that are under-fit by other estimators.

A primary disadvantage of random forests is that the results are not easily interpretable: that is, if you would like to draw conclusions about the meaning of the classification model, random forests may not be the best choice.

3.7.4.5 K-NEAREST NEIGHBOUR:

The algorithm uses 'feature similarity' to predict the values of any new data points. This means that the new point is assigned a value based on how closely it resembles the points in the training set.

The first step is to calculate the distance between the new point and each training point. There are various methods for calculating this distance, of which the most commonly known methods are – Euclidean, Manhattan (for continuous) and Hamming distance (for categorical).

1. **Euclidean Distance:** Euclidean distance is calculated as the square root of the sum of the squared differences between a new point (x) and an existing point (y).

$$Euclidean = \sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

2. **Manhattan Distance:** This is the distance between real vectors using the sum of their absolute difference.

$$Manhattan = \sum_{i=1}^{k} |x_i - y_i|$$

3. **Hamming Distance:** It is used for categorical variables. If the predicted value (x) and the real value (y) are the same, the distance D will be equal to 0 Otherwise D=1.

$$D_H = \sum_{i=1}^{k} |x_i - y_i|$$
$$x = y \rightarrow D = 0$$
$$x \neq y \rightarrow D = 1$$

Once the distance of a new observation from the points in our training set has been measured, the next step is to pick the closest points. The number of points to be considered is defined by the value of k.

3.7.4.6 XG-BOOST

Xg-Boost (extreme Gradient Boosting) is an advanced implementation of the gradient boosting algorithm. Xg-Boost has proved to be a highly effective ML algorithm, extensively used in machine learning competitions and Hackathon.

Xg-Boost has high predictive power and is almost 10 times faster than the other gradient boosting techniques. It also includes a variety of regularization which reduces over fitting and improves overall performance. Hence it is also known as regularized boosting technique.

Let us see how Xg-Boost is comparatively better than other techniques:

1. Regularization: Standard GBM implementation has no regularization like Xg-Boost. Thus Xg-Boost also helps to reduce over fitting.

2. Parallel Processing: Xg-Boost implements parallel processing and is faster than GBM. Xg-Boost also supports implementation on Hadoop.

3. High Flexibility: Xg-Boost allows users to define custom optimization objectives and evaluation criteria adding a whole new dimension to the model.

4. Handling Missing Values: Xg-Boost has an in-built routine to handle missing values.

5. Tree Pruning: Xg-Boost makes splits up to the max_depth specified and then starts pruning the tree backward and removes splits beyond which there is no positive gain.

6. Built-in Cross-Validation: Xg-Boost allows a user to run cross-validation at each iteration of the boosting process and thus it is easy to get the exact optimum number of boosting iterations in a single run.

3.7.4.7 ADA-BOOST:

Adaptive boosting or AdaBoost is one of the simplest boosting algorithms. Usually, decision trees are used for modeling. Multiple sequential models are created, each correcting the errors from the last model.

AdaBoost assigns weights to the observations which are incorrectly predicted and the subsequent model works to predict these values correctly.

Below are the steps for performing the AdaBoost algorithm:

1. Initially, all observations in the dataset are given equal weights.
2. A model is built on a subset of data.
3. Using this model, predictions are made on the whole dataset.
4. Errors are calculated by comparing the predictions and actual values.
5. While creating the next model, higher weights are given to the data points which were predicted incorrectly.
6. Weights can be determined using the error value. For instance, higher the error more is the weight assigned to the observation.
7. This process is repeated until the error function does not change, or the maximum limit of the number of estimators is reached.

3.7.4.8 GRADIENT BOOSTING ALGORITHM

Gradient boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees. It builds the model in a stage-wise fashion as other boosting methods do, and it generalizes them by allowing optimization of an arbitrary differentiable loss function.

The idea of gradient boosting originated in the observation by Leo Breiman that boosting can be interpreted as an optimization algorithm on a suitable cost function. Explicit regression gradient boosting algorithms were subsequently developed by Jerome H. Friedman, simultaneously with the more general functional gradient boosting perspective of Llew Mason, Jonathan Baxter, Peter Bartlett, and Marcus Frean.

Then latter two papers introduced the view of boosting algorithms as iterative functional gradient descent algorithms. That is, algorithms that optimize a cost function over function space by iteratively choosing a function (weak hypothesis) that points in the negative gradient direction.

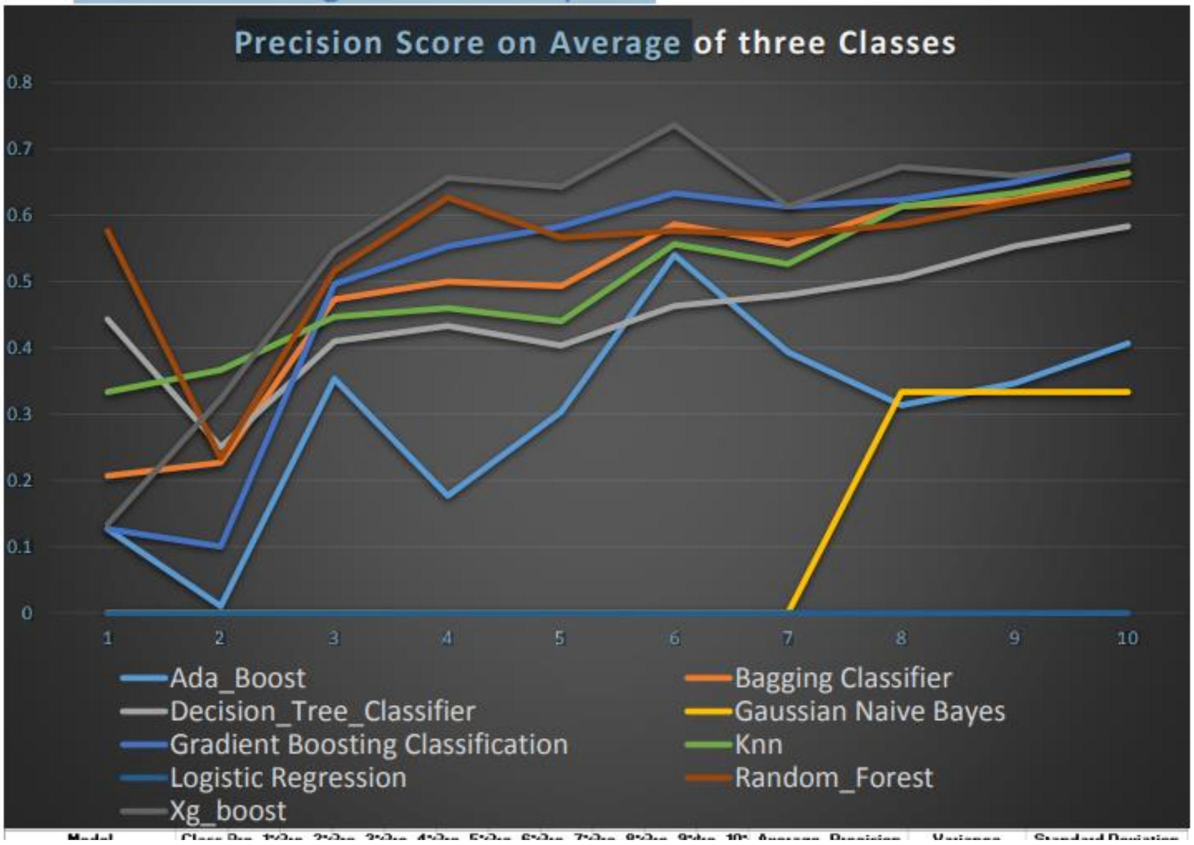
This functional gradient view of boosting has led to the development of boosting algorithms in many areas of machine learning and statistics beyond regression and classification.

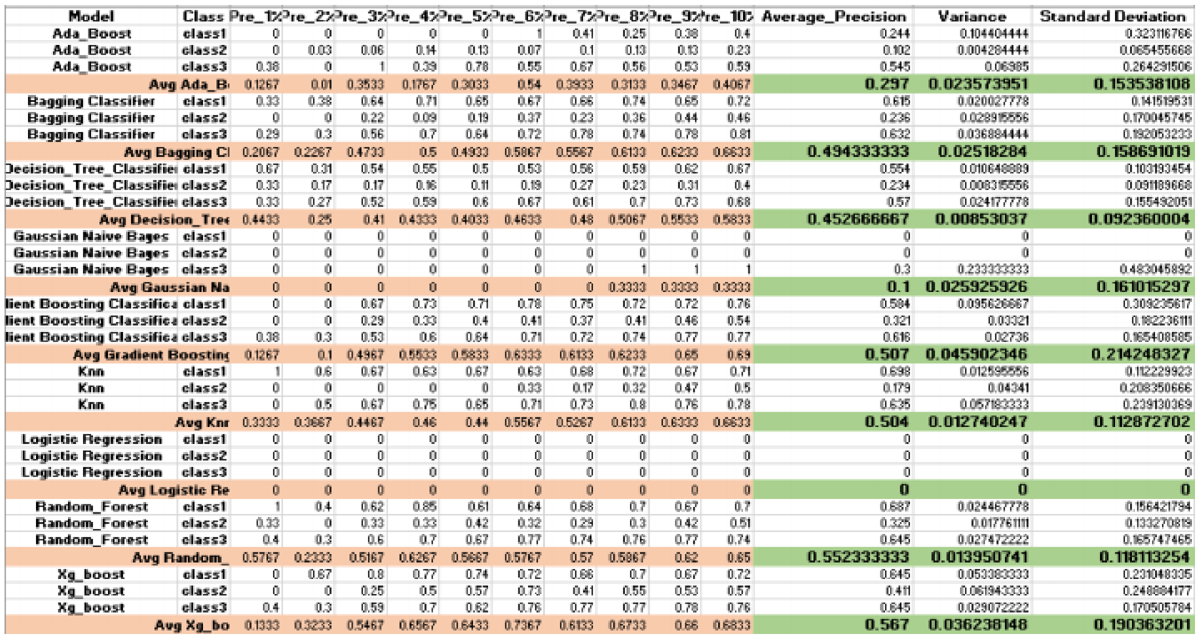
3.7.4.9 BAGGING CLASSIFIER

Bagging (Bootstrap Aggregating) is a widely used an ensemble learning algorithm in machine learning. The algorithm builds multiple models from randomly taken subsets of train dataset and aggregates learners to build overall stronger learner. In this post, we’ll learn how to classify data with Bagging Classifier class of a sklearn library in Python.

4. 1GRAPH

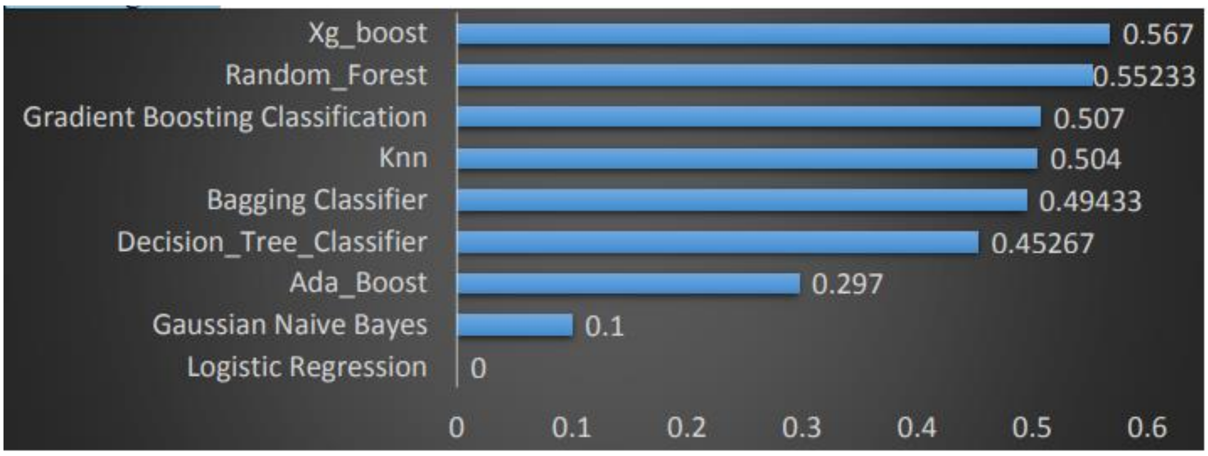
4.1.1 Model Building and their reports



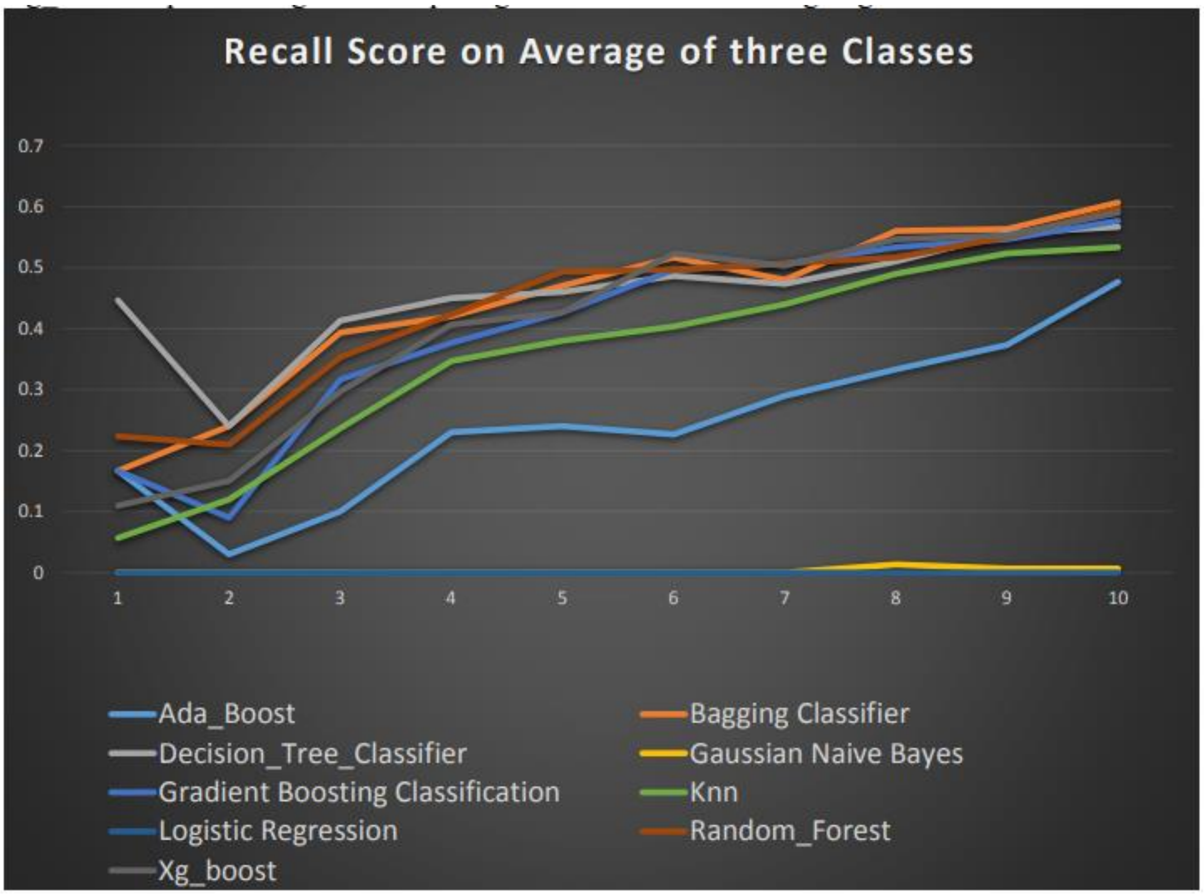


Model	Class	Pre_1%	Pre_2%	Pre_3%	Pre_4%	Pre_5%	Pre_6%	Pre_7%	Pre_8%	Pre_9%	Pre_10%	Average_Precision	Variance	Standard Deviation
Ada_Boost	class1	0	0	0	0	0	1	0.41	0.25	0.38	0.4	0.244	0.104404444	0.323116766
Ada_Boost	class2	0	0.03	0.06	0.14	0.13	0.07	0.1	0.13	0.13	0.23	0.102	0.004284444	0.065455668
Ada_Boost	class3	0.38	0	1	0.39	0.78	0.55	0.67	0.56	0.53	0.59	0.545	0.06985	0.264291506
Avg Ada_B		0.1267	0.01	0.3533	0.1767	0.3033	0.54	0.3933	0.3133	0.3467	0.4067	0.297	0.023573951	0.153538108
Bagging Classifier	class1	0.33	0.38	0.64	0.71	0.65	0.67	0.66	0.74	0.65	0.72	0.615	0.020027778	0.141519531
Bagging Classifier	class2	0	0	0.22	0.09	0.19	0.37	0.23	0.36	0.44	0.46	0.236	0.028915556	0.170045745
Bagging Classifier	class3	0.29	0.3	0.56	0.7	0.64	0.72	0.78	0.74	0.78	0.81	0.632	0.036884444	0.192053233
Avg Bagging Cl		0.2067	0.2267	0.4733	0.5	0.4933	0.5867	0.5567	0.6133	0.6233	0.6633	0.494333333	0.02518284	0.158691019
Decision_Tree_Classifie	class1	0.67	0.31	0.54	0.55	0.5	0.53	0.56	0.59	0.62	0.67	0.554	0.010648889	0.103193454
Decision_Tree_Classifie	class2	0.33	0.17	0.17	0.16	0.11	0.19	0.27	0.23	0.31	0.4	0.234	0.008315556	0.091189668
Decision_Tree_Classifie	class3	0.33	0.27	0.52	0.59	0.6	0.67	0.61	0.7	0.73	0.68	0.57	0.024177778	0.155492051
Avg Decision_Tre		0.4433	0.25	0.41	0.4333	0.4033	0.4633	0.48	0.5067	0.5533	0.5833	0.452666667	0.00853037	0.092360004
Gaussian Naive Bayes	class1	0	0	0	0	0	0	0	0	0	0	0	0	0
Gaussian Naive Bayes	class2	0	0	0	0	0	0	0	0	0	0	0	0	0
Gaussian Naive Bayes	class3	0	0	0	0	0	0	0	1	1	1	0.3	0.233333333	0.483045892
Avg Gaussian Na		0	0	0	0	0	0	0	0.3333	0.3333	0.3333	0.1	0.025925926	0.161015297
lient Boosting Classifica	class1	0	0	0.67	0.73	0.71	0.78	0.75	0.72	0.72	0.76	0.584	0.095626667	0.309235617
lient Boosting Classifica	class2	0	0	0.29	0.33	0.4	0.41	0.37	0.41	0.46	0.54	0.321	0.03321	0.182236111
lient Boosting Classifica	class3	0.38	0.3	0.53	0.6	0.64	0.71	0.72	0.74	0.77	0.77	0.616	0.02736	0.165408585
Avg Gradient Boosting		0.1267	0.1	0.4967	0.5533	0.5833	0.6333	0.6133	0.6233	0.65	0.69	0.507	0.045902346	0.214248327
Knn	class1	1	0.6	0.67	0.63	0.67	0.63	0.68	0.72	0.67	0.71	0.698	0.012595556	0.112229923
Knn	class2	0	0	0	0	0	0.33	0.17	0.32	0.47	0.5	0.179	0.04341	0.208350666
Knn	class3	0	0.5	0.67	0.75	0.65	0.71	0.73	0.8	0.76	0.78	0.635	0.057183333	0.239130369
Avg Knr		0.3333	0.3667	0.4467	0.46	0.44	0.5567	0.5267	0.6133	0.6333	0.6633	0.504	0.012740247	0.112872702
Logistic Regression	class1	0	0	0	0	0	0	0	0	0	0	0	0	0
Logistic Regression	class2	0	0	0	0	0	0	0	0	0	0	0	0	0
Logistic Regression	class3	0	0	0	0	0	0	0	0	0	0	0	0	0
Avg Logistic Re		0	0	0	0	0	0	0	0	0	0	0	0	0
Random_Forest	class1	1	0.4	0.62	0.85	0.61	0.64	0.68	0.7	0.67	0.7	0.687	0.024467778	0.156421794
Random_Forest	class2	0.33	0	0.33	0.33	0.42	0.32	0.29	0.3	0.42	0.51	0.325	0.017761111	0.133270819
Random_Forest	class3	0.4	0.3	0.6	0.7	0.67	0.77	0.74	0.76	0.77	0.74	0.645	0.027472222	0.165747465
Avg Random_		0.5767	0.2333	0.5167	0.6267	0.5667	0.5767	0.57	0.5867	0.62	0.65	0.552333333	0.013950741	0.118113254
Xg_boost	class1	0	0.67	0.8	0.77	0.74	0.72	0.66	0.7	0.67	0.72	0.645	0.053383333	0.231048335
Xg_boost	class2	0	0	0.25	0.5	0.57	0.73	0.41	0.55	0.53	0.57	0.411	0.061943333	0.248884177
Xg_boost	class3	0.4	0.3	0.59	0.7	0.62	0.76	0.77	0.77	0.78	0.76	0.645	0.029072222	0.170505784
Avg Xg_bo		0.1333	0.3233	0.5467	0.6567	0.6433	0.7367	0.6133	0.6733	0.66	0.6833	0.567	0.036238148	0.190363201

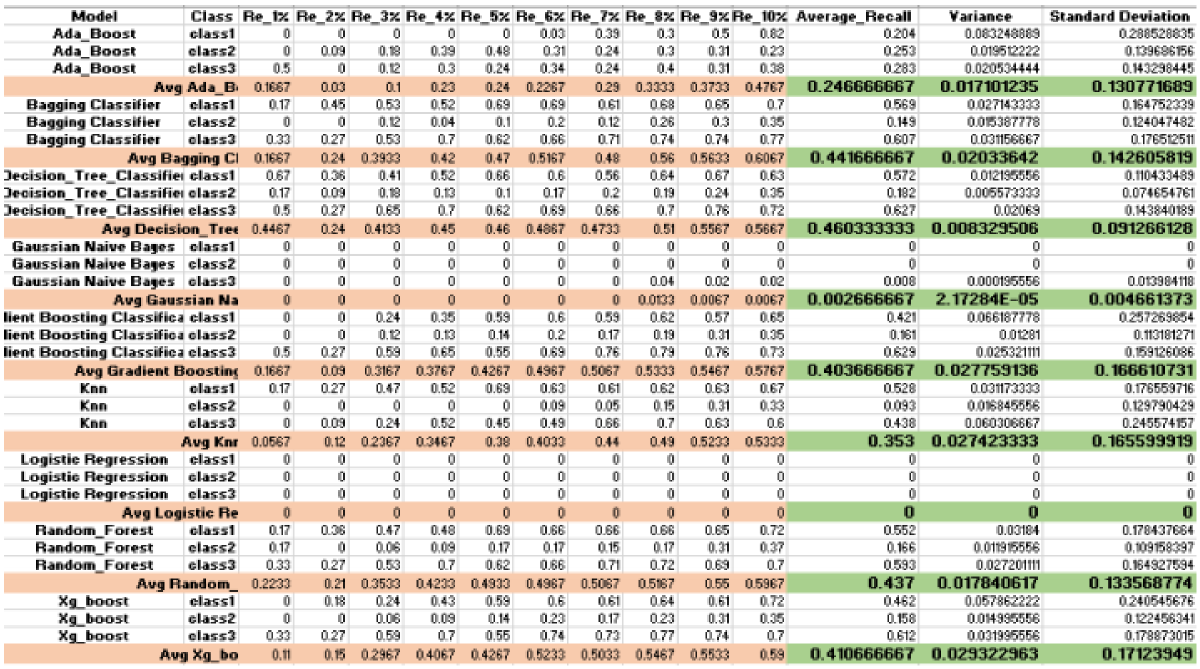
From the above it is seen that Naïve Bayes Algorithm and Logistic Regression is not performing well.



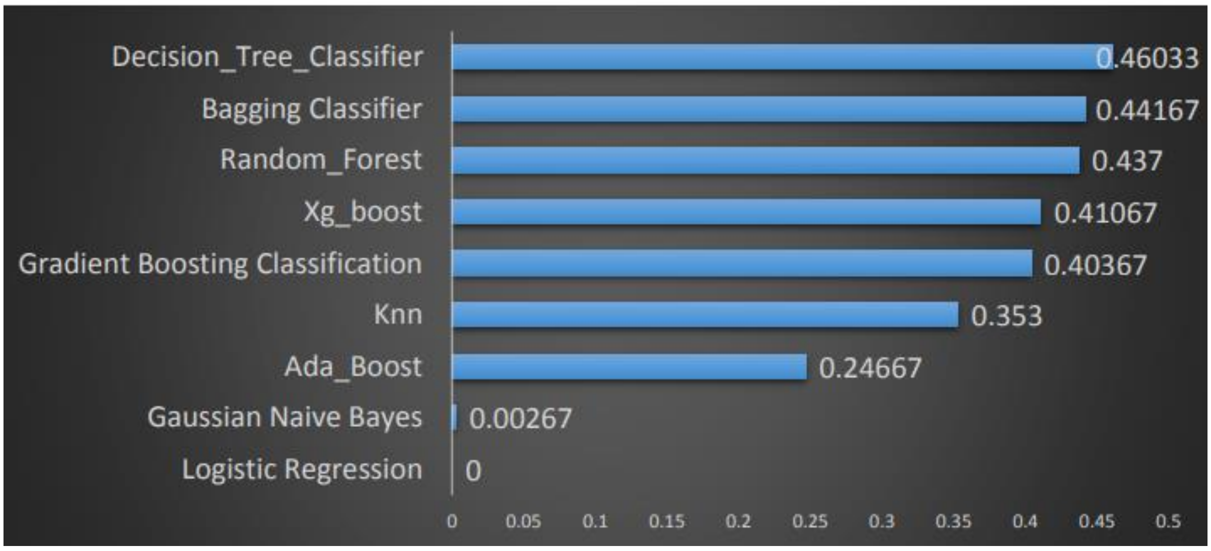
Overall when considering Precision score for imbalance data from our analysis Xg_Boost is performing well comparing other Machine Learning Algorithms.



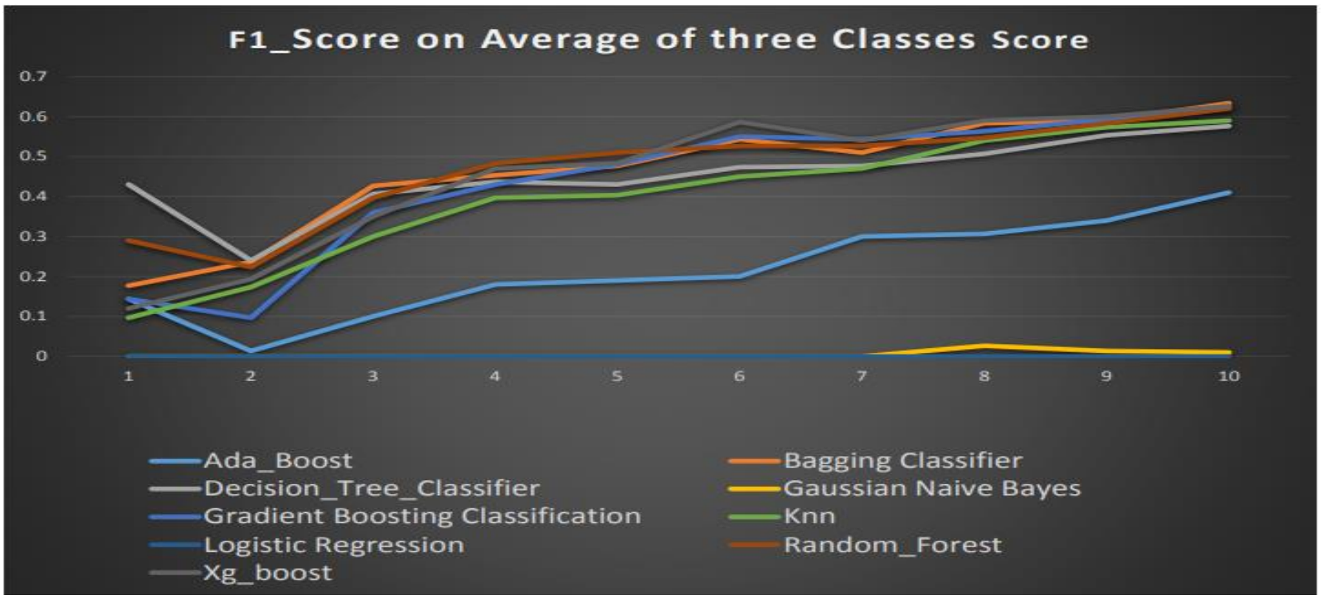
From the above it is seen that Naïve Bayes and Logistic Regression is not Performing well.



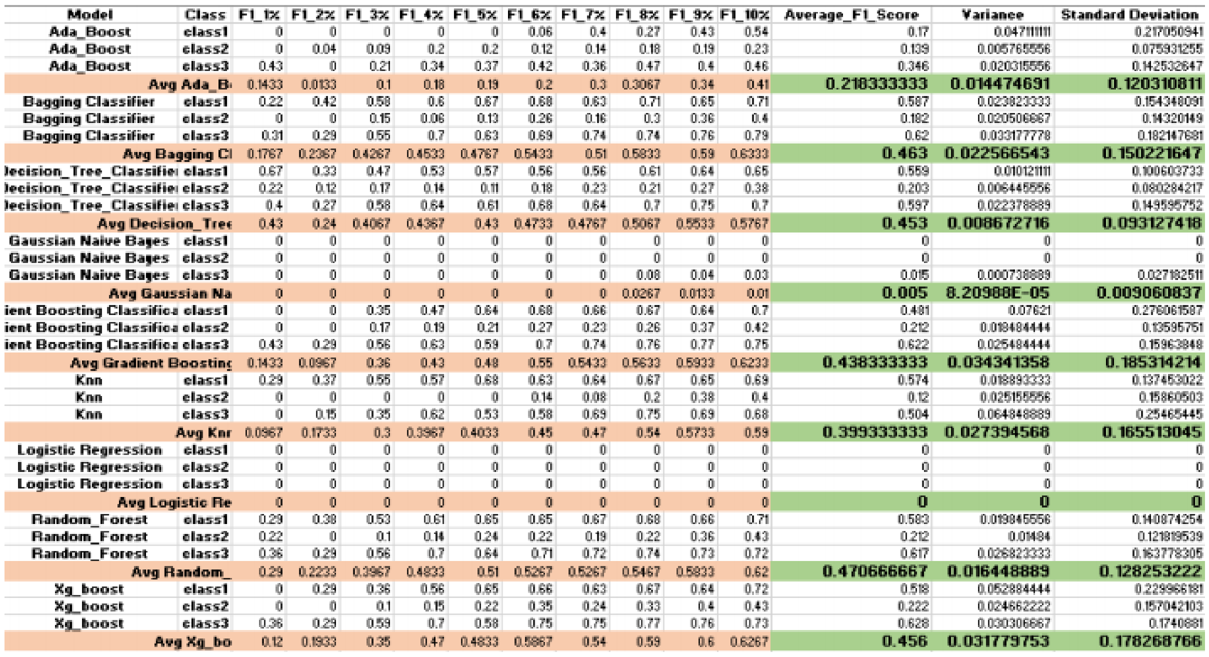
Model	Class	Re_1%	Re_2%	Re_3%	Re_4%	Re_5%	Re_6%	Re_7%	Re_8%	Re_9%	Re_10%	Average_Recall	Variance	Standard Deviation
Ada_Boost	class1	0	0	0	0	0	0.03	0.39	0.3	0.5	0.82	0.204	0.083248889	0.288528835
Ada_Boost	class2	0	0.09	0.18	0.39	0.48	0.31	0.24	0.3	0.31	0.23	0.253	0.019512222	0.139686156
Ada_Boost	class3	0.5	0	0.12	0.3	0.24	0.34	0.24	0.4	0.31	0.38	0.283	0.020534444	0.143298445
Avg Ada_B		0.1667	0.03	0.1	0.23	0.24	0.2267	0.29	0.3333	0.3733	0.4767	0.246666667	0.017101235	0.130771689
Bagging Classifier	class1	0.17	0.45	0.53	0.52	0.69	0.69	0.61	0.68	0.65	0.7	0.569	0.027143333	0.164752339
Bagging Classifier	class2	0	0	0.12	0.04	0.1	0.2	0.12	0.26	0.3	0.35	0.149	0.015387778	0.124047482
Bagging Classifier	class3	0.33	0.27	0.53	0.7	0.62	0.66	0.71	0.74	0.74	0.77	0.607	0.031156667	0.176512511
Avg Bagging Cl		0.1667	0.24	0.3933	0.42	0.47	0.5167	0.48	0.56	0.5633	0.6067	0.441666667	0.02033642	0.142605819
Decision_Tree_Classifie	class1	0.67	0.36	0.41	0.52	0.66	0.6	0.56	0.64	0.67	0.63	0.572	0.012195556	0.110433489
Decision_Tree_Classifie	class2	0.17	0.09	0.18	0.13	0.1	0.17	0.2	0.19	0.24	0.35	0.182	0.005573333	0.074654761
Decision_Tree_Classifie	class3	0.5	0.27	0.65	0.7	0.62	0.69	0.66	0.7	0.76	0.72	0.627	0.02069	0.143840189
Avg Decision_Tree		0.4467	0.24	0.4133	0.45	0.46	0.4867	0.4733	0.51	0.5567	0.5667	0.460333333	0.008329506	0.091266128
Gaussian Naive Bayes	class1	0	0	0	0	0	0	0	0	0	0	0	0	0
Gaussian Naive Bayes	class2	0	0	0	0	0	0	0	0	0	0	0	0	0
Gaussian Naive Bayes	class3	0	0	0	0	0	0	0	0.04	0.02	0.02	0.008	0.000195556	0.013984118
Avg Gaussian Na		0	0	0	0	0	0	0	0.0133	0.0067	0.0067	0.002666667	2.17284E-05	0.004661373
lient Boosting Classifica	class1	0	0	0.24	0.35	0.59	0.6	0.59	0.62	0.57	0.65	0.421	0.066187778	0.257269854
lient Boosting Classifica	class2	0	0	0.12	0.13	0.14	0.2	0.17	0.19	0.31	0.35	0.161	0.01281	0.113181271
lient Boosting Classifica	class3	0.5	0.27	0.59	0.65	0.55	0.69	0.76	0.79	0.76	0.73	0.629	0.025321111	0.159126086
Avg Gradient Boosting		0.1667	0.09	0.3167	0.3767	0.4267	0.4967	0.5067	0.5333	0.5467	0.5767	0.403666667	0.027759136	0.166610731
Knn	class1	0.17	0.27	0.47	0.52	0.69	0.63	0.61	0.62	0.63	0.67	0.528	0.031173333	0.176559716
Knn	class2	0	0	0	0	0	0.09	0.05	0.15	0.31	0.33	0.093	0.016845556	0.129790429
Knn	class3	0	0.09	0.24	0.52	0.45	0.49	0.66	0.7	0.63	0.6	0.438	0.060306667	0.245574157
Avg Knr		0.0567	0.12	0.2367	0.3467	0.38	0.4033	0.44	0.49	0.5233	0.5333	0.353	0.027423333	0.165599919
Logistic Regression	class1	0	0	0	0	0	0	0	0	0	0	0	0	0
Logistic Regression	class2	0	0	0	0	0	0	0	0	0	0	0	0	0
Logistic Regression	class3	0	0	0	0	0	0	0	0	0	0	0	0	0
Avg Logistic Re		0	0	0	0	0	0	0	0	0	0	0	0	0
Random_Forest	class1	0.17	0.36	0.47	0.48	0.69	0.66	0.66	0.66	0.65	0.72	0.552	0.03184	0.178437684
Random_Forest	class2	0.17	0	0.06	0.09	0.17	0.17	0.15	0.17	0.31	0.37	0.166	0.011915556	0.109158397
Random_Forest	class3	0.33	0.27	0.53	0.7	0.62	0.66	0.71	0.72	0.69	0.7	0.593	0.027201111	0.164927594
Avg Random_		0.2233	0.21	0.3533	0.4233	0.4933	0.4967	0.5067	0.5167	0.55	0.5967	0.437	0.017840617	0.133568774
Xg_boost	class1	0	0.18	0.24	0.43	0.59	0.6	0.61	0.64	0.61	0.72	0.462	0.057862222	0.240545676
Xg_boost	class2	0	0	0.06	0.09	0.14	0.23	0.17	0.23	0.31	0.35	0.158	0.014995556	0.122456341
Xg_boost	class3	0.33	0.27	0.59	0.7	0.55	0.74	0.73	0.77	0.74	0.7	0.612	0.031995556	0.178873015
Avg Xg_bo		0.11	0.15	0.2967	0.4067	0.4267	0.5233	0.5033	0.5467	0.5533	0.59	0.410666667	0.029322963	0.17123949



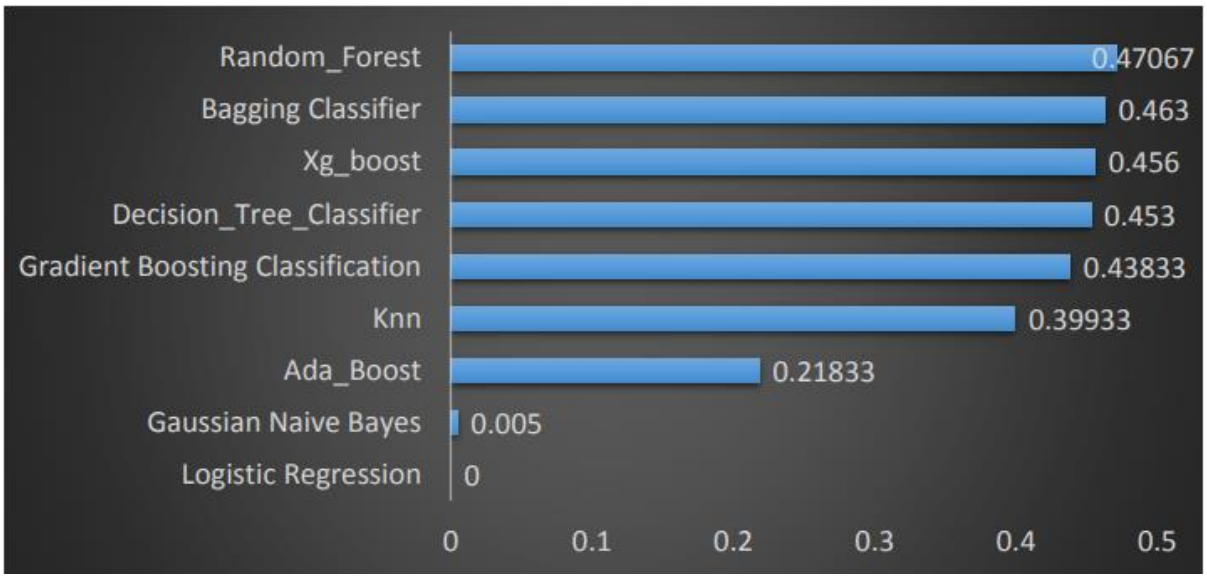
Overall when we considering Recall Score for Imbalance Data It is clearly Seen that from our analysis Decision Tree Algorithm is Performing Well Comparing Other Algorithms.



From the above it is seen that Naïve Bayes and Logistic Regression is not Performing well.



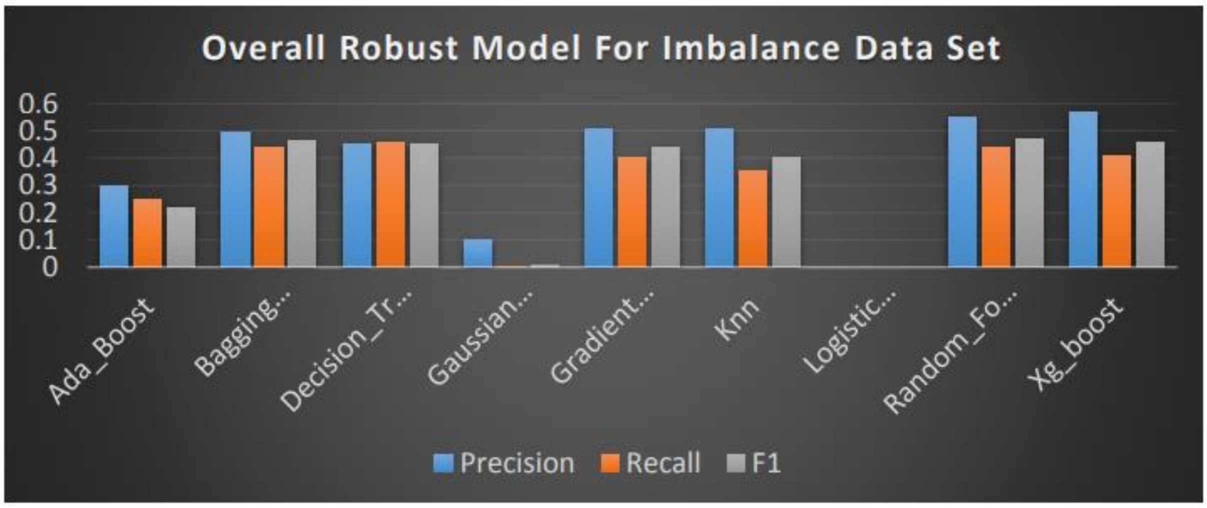
Model	Class	F1_1%	F1_2%	F1_3%	F1_4%	F1_5%	F1_6%	F1_7%	F1_8%	F1_9%	F1_10%	Average_F1_Score	Variance	Standard Deviation
Ada_Boost	class1	0	0	0	0	0	0.06	0.4	0.27	0.43	0.54	0.17	0.04711111	0.217050941
Ada_Boost	class2	0	0.04	0.09	0.2	0.2	0.12	0.14	0.18	0.19	0.23	0.139	0.005765556	0.075931255
Ada_Boost	class3	0.43	0	0.21	0.34	0.37	0.42	0.36	0.47	0.4	0.46	0.346	0.020315556	0.142532647
Avg Ada_B		0.1433	0.0133	0.1	0.18	0.19	0.2	0.3	0.3067	0.34	0.41	0.218333333	0.014474691	0.120310811
Bagging Classifier	class1	0.22	0.42	0.58	0.6	0.67	0.68	0.63	0.71	0.65	0.71	0.587	0.023823333	0.154348091
Bagging Classifier	class2	0	0	0.15	0.06	0.13	0.26	0.16	0.3	0.36	0.4	0.182	0.020506667	0.14320149
Bagging Classifier	class3	0.31	0.29	0.55	0.7	0.63	0.69	0.74	0.74	0.76	0.79	0.62	0.033177778	0.182147681
Avg Bagging Cl		0.1767	0.2367	0.4267	0.4533	0.4767	0.5433	0.51	0.5833	0.59	0.6333	0.463	0.022566543	0.150221647
ecision_Tree_Classifie	class1	0.67	0.33	0.47	0.53	0.57	0.56	0.56	0.61	0.64	0.65	0.559	0.01012111	0.100603733
ecision_Tree_Classifie	class2	0.22	0.12	0.17	0.14	0.11	0.18	0.23	0.21	0.27	0.38	0.203	0.006445556	0.080284217
ecision_Tree_Classifie	class3	0.4	0.27	0.58	0.64	0.61	0.68	0.64	0.7	0.75	0.7	0.597	0.022378889	0.149595752
Avg Decision_Tree		0.43	0.24	0.4067	0.4367	0.43	0.4733	0.4767	0.5067	0.5533	0.5767	0.453	0.008672716	0.093127418
Gaussian Naive Bayes	class1	0	0	0	0	0	0	0	0	0	0	0	0	0
Gaussian Naive Bayes	class2	0	0	0	0	0	0	0	0	0	0	0	0	0
Gaussian Naive Bayes	class3	0	0	0	0	0	0	0	0.08	0.04	0.03	0.015	0.000738889	0.027182511
Avg Gaussian Na		0	0	0	0	0	0	0	0.0267	0.0133	0.01	0.005	8.20988E-05	0.009060837
ient Boosting Classifica	class1	0	0	0.35	0.47	0.64	0.68	0.66	0.67	0.64	0.7	0.481	0.07621	0.276061587
ient Boosting Classifica	class2	0	0	0.17	0.19	0.21	0.27	0.23	0.26	0.37	0.42	0.212	0.018484444	0.13595751
ient Boosting Classifica	class3	0.43	0.29	0.56	0.63	0.59	0.7	0.74	0.76	0.77	0.75	0.622	0.025484444	0.15963848
Avg Gradient Boosting		0.1433	0.0967	0.36	0.43	0.48	0.55	0.5433	0.5633	0.5933	0.6233	0.438333333	0.034341358	0.185314214
Knn	class1	0.29	0.37	0.55	0.57	0.68	0.63	0.64	0.67	0.65	0.69	0.574	0.018893333	0.137453022
Knn	class2	0	0	0	0	0	0.14	0.08	0.2	0.38	0.4	0.12	0.025155556	0.15860503
Knn	class3	0	0.15	0.35	0.62	0.53	0.58	0.69	0.75	0.69	0.68	0.504	0.064848889	0.25465445
Avg Knn		0.0967	0.1733	0.3	0.3967	0.4033	0.45	0.47	0.54	0.5733	0.59	0.399333333	0.027394568	0.165513045
Logistic Regression	class1	0	0	0	0	0	0	0	0	0	0	0	0	0
Logistic Regression	class2	0	0	0	0	0	0	0	0	0	0	0	0	0
Logistic Regression	class3	0	0	0	0	0	0	0	0	0	0	0	0	0
Avg Logistic Re		0	0	0	0	0	0	0	0	0	0	0	0	0
Random_Forest	class1	0.29	0.38	0.53	0.61	0.65	0.65	0.67	0.68	0.66	0.71	0.583	0.019845556	0.140874254
Random_Forest	class2	0.22	0	0.1	0.14	0.24	0.22	0.19	0.22	0.36	0.43	0.212	0.01484	0.121819539
Random_Forest	class3	0.36	0.29	0.56	0.7	0.64	0.71	0.72	0.74	0.73	0.72	0.617	0.026823333	0.163778305
Avg Random_		0.29	0.2233	0.3967	0.4833	0.51	0.5267	0.5267	0.5467	0.5833	0.62	0.470666667	0.016448889	0.128253222
Xg_boost	class1	0	0.29	0.36	0.56	0.65	0.66	0.63	0.67	0.64	0.72	0.518	0.052884444	0.229966181
Xg_boost	class2	0	0	0.1	0.15	0.22	0.35	0.24	0.33	0.4	0.43	0.222	0.024662222	0.157042103
Xg_boost	class3	0.36	0.29	0.59	0.7	0.58	0.75	0.75	0.77	0.76	0.73	0.628	0.030306667	0.1740881
Avg Xg_bo		0.12	0.1933	0.35	0.47	0.4833	0.5867	0.54	0.59	0.6	0.6267	0.456	0.031779753	0.178268766



Overall when we considering F1- Score for Imbalance Data It is clearly Seen that from our analysis Random-Forest Algorithm is Performing Well Comparing Other Algorithms.

4.1.2 Robust Model for Imbalance Data

From the above reports now will see from Overall Reports Which model is performing well in either of the proportions.



Based on the results shown above when each class is proportioned the following is observed: Gradient Boosting, Xg-Boost, Random Forest, Knn, Bagging Classifier and Decision Tree are performing better across the imbalanced classes.

Logistic Regression, Gaussian Naive Bayes, Ada_Boost, Knn, Gradient Boosting Classification, Decision_Tree_Classifier, Xg_boost, Bagging Classifier Random_Forest.

Overall Robust Model For Imbalance Data Set Precision Recall F1 Boosting Models are more consistent across the imbalanced classes. Logistic Regression, NB are inconsistent with imbalanced data. For high Precision and Recall, Random Forest and Boosting models are the best.

CHAPTER 4

CONCLUSION & FUTURE ENHANCEMENT

CONCLUSION

Whenever using a machine learning algorithm, evaluation metrics for the model have to be chosen cautiously: we must use the metrics that give us the best overview of how well our model is doing with regards to our goals. When dealing with an imbalanced dataset, if classes are not well separable with the given variables and if our goal is to get the best possible accuracy, the best classifier can be a “naive” one that always answers the majority class.

FUTURE ENHANCEMENT

Reworking the problem itself is often the best way to tackle an imbalanced classes problem: the classifier and the decision rule have to be set with respect to a well-chosen goal that can be, for example, minimizing a cost.

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