

Classification of Wildfire Spread Severity using Machine Learning Algorithm

MSc Research Project

Data Analytics

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Classification of Wildfire Spread Severity using Machine Learning Algorithm

Amit Sahoo

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MSc Research Project in Data Analytics

17th August 2020

**Abstract**

Wildfire is one of the natural disasters, that can burn millions of acres of land at a very fast speed, almost burning everything that comes in the way. However, only a few of the wildfire occurs on their own, while majority are human caused. In this research, the size of the fire spread has been predicted, with respect to the weather details of the last five days of the outbreak. This research will help the Fire Fighting Department and the local governing body to predict the fire spread in advance and make decisions accordingly. Alaska location has been chosen specifically, for this research as there is a huge difference in temperature in summer and winter. Data has been collected from various sources and have been merged. At every stage of pre-processing, a Logistic Regression has been used as a baseline model. The technique that produces the highest accuracy has been carried forward to the next stage. Several Machine Learning algorithms have been performed, and it is observed that Artificial Neural Network, outperforms the other tree-based algorithms, ensembled algorithms and LSTM with an accuracy of 68%.

# Introduction

Various countries have been battling with forest fires for a long time now. Such unfortunate incidents take place due to natural reasons like volcanic eruptions and lightning but mostly happens because of human activities like unextinguished cigarette butts, fire camping, and garbage deposit burning. Such incidents have become quite frequent over the last few years. As a result, a lot of flora and fauna species are getting disappeared, natural habitat and food chains are getting imbalanced. It also emits a lot of carbon emission to the environment, which leads to a green-house effect and climate change, soil erosion. Therefore, it will be useful if the wildfire spread can be predicted at its initial stage and classified as per the National Wildfire Coordinating Group’s fire classification chart[[1]](#footnote-1).

## Motivation and Project Background

A lot of studies have been carried out on this global problem, especially in the last few decades. Several ways to prevent such wildfires and minimize the loss due to high voltage overhead electric powerlines in the Mediterranean forest have been proposed(Martinez-Canales, 1997). Numerous studies have also been done on fire detection. A few of the previous studies on fire detection at the early stages is done with the help of a real-time TV camera(Cappellini, Mattii, and Mecocci, 1989). These camera helps to detect smoke during the day and flames during night. One more significant study on the detection of fire incidents in the boreal forest of Alaska was done by Bourgeau et al. (Bourgeau-Chavez, Kasischke, and French, 1993) using ERS-1 C-VV SAR imagery. It also determined the fire appearance based on elapsed time, geomorphology of the area under fire, and metrological parameters. Multi-dimensional satellite images are used for detecting forest fire in the eastern region of Russia (Kawano, Kudoh, and Makino, 1999).

Various studies have also been conducted on modeling and forecasting of the fire. The likelihood of severe fires is determined from fire indices(Minardi, Marchisio and Treder, 1999), which are extracted through ground and remote satellite observation. These indices are collected for a period of seven years and are interpolated across various grids of The United States to determine the density of the fire occurrence. A detailed study on the type of land and the extent of the forest fire has been done on the 1997 Indonesian fire dataset(Lee et al., 1999). Information about the land cover was derived by comparing the land cover maps with SPOT satellite images. After superimposing the burn scar on a digitized land cover, it was evident that fire occurs mostly in easily accessible areas such as agricultural lands and plantation areas. Surveys were conducted to better understand the effect of fire and the characteristics of the fire signatures with the help of three remote sensing systems, operating in two different spectrums (French, Kasischke, and Bourgeau-Chavez, 1994).

Geographical information system(GIS) is integrated with the Evidential Belief Function(EBF) to determine the probability of wildfire(Nami et al., 2018). Factors like topology, soil type, meteorological factors were taken as input features. Based on the derived probability, areas were classified into moderate, high, and very high zones. Forest department in few countries uses National Forest Fire Danger Rating System(NFFDRS) for predicting the severity of the fire. Among all, the Canadian NFFRDS(CFFRDS) has been widely accepted across the globe in terms of reliability and consistency.

For the last few years, there has been a lot of studies conducted in this field using Machine Learning(ML) and Deep Learning(DL). ML algorithms such as Logistic regression has been used to find the probability of lightning causing a sustainable ignition as well as the probability of the ignition being detected by the firefighting department(Wotton and Martell, 2005). Predictors such as historical lightning strikes, weather, and the number of fire occurrences have been used. Since most of the fires are caused by humans, a logistic generalized additive model(Vilar et al., 2010) is designed to find out the probability of ignition at a 1km2 grid. Meteorological factors and socio-economic factors are used as independent variables. Deep learning has proved to be better in terms of accuracy when dealing with a huge amount of data for training and validation. Traditional ML cannot process datasets with huge size and numerous features. Research by Safi and Bouroumi (Safi, Bouroumi and Bouroumi, 2011) was one of the oldest studies where the Neural Network approach is applied in predicting the size of the forest fire. The values of the hyperparameters were determined heuristically. Deep neural network models such as Long short-term memory(LSTM) has been used to predict the size of the fire at the beginning of its occurrence(Liang, Zhang, and Wang, 2019). This model has been implemented on a time series data, which was able to predict the occurrence trends with an accuracy of 90.9%. In this research, we have taken a step further in classifying the wildfire spread by using meteorological parameters such as temperature, relative humidity, wind speed, precipitation, visibility, due point, sea level pressure of the past four days. ML models are built on these input features, considering them as independent attributes. A DL model has also been built which considers the sequence of weather parameters for the past five days to classify the severity of the fire spread. Finally, a comparison has been done, if a sequence of weather parameters over the past five days can better classify a fire spread with respect to the same parameters considered independently.

Accurately predicting the size of the forest fire at an early stage will help the firefighting team to strategize fire extinguishing operations, positioning the crew member and equipment in the best possible position. This can reduce the spread of the fire and help in saving the life of the local people, and the firefighters deployed on the site.

This research will also help the local governing body to formulate rescue or evacuation operations for the people under the possible threat of fire. This will assist in granting permission to carry out the local business at the fire vicinity, restrict the tourist from entering the fire zone, and speculating the possible amount of carbon emission into the environment.

## Research Question

Prediction of forest fire is helpful for the local governing bodies and the fire-fighting department, so that adequate resources can be arranged before it gets too difficult to handle such untoward incidents.

RQ - *“How well machine learning can predict the size of a forest fire, based on weather details such as temperature, sea level pressure, dew point, precipitation, visibility, wind speed , preparedness level of the firefighting department and the number of fire incident taken place”.*

Sub RQ –‘‘*How well a sequence of weather parameters for the past four days can better classify a fire spread severity as compared to the same features considered independently?* ”

## Research Objective

Obj1: Critical review of the literature on prediction of wildfire (2005-2020)

Obj2: Extracting the weather details of the day of the fire outbreak and four days before that date.

Obj3: Merging the Fire dataset and the weather dataset and conducting initial pre-processing.

Obj4: Implementation of Feature selection methods to determine the relevant predictors.

Obj5: Implementation of Dimension Reduction to reduce the number of dimensions.

Obj6: Implementation of SMOTE oversampling to handle the imbalanced data.

Obj7: Implement and evaluate results of Logistic Regression with independent features.

Obj8: Implement and evaluate results of Decision Tree with independent features.

Obj9: Implement and evaluate results of Bagging(Ensemble Technique) with independent features.

Obj10: Implement and evaluate results of K-Nearest Neighbour with independent features.

Obj11: Implement and evaluate results of Random Forest with independent features.

Obj12: Implement and evaluate the results of Extra Trees Classifier with independent features.

Obj13: Implement and evaluate results of Boosting(Ensemble Technique) with independent features.

Obj14: Implement and evaluate results of Neural Network with independent features.

Obj15: Implement and evaluate results of Recurrent Neural Network with a sequence of features.

Obj16: Comparison of developed methods.

Section 2 provides a literature review on this field of study using fire indices and ML with different algorithms. Based on the findings from the previous section, Section-3 provides an overview of the methodology that has been used for this research. Data acquisition for this research, along with the pre-processing, data modelling done in section 4. In section 5, various algorithm that has been implemented and their corresponding evaluation has been explained. Section-6 explains the comparison of all the models used in the previous section based on a few evaluation parameters. Section 6 concludes this paper with the scope of future works.

# Literature Review on Forest Fire Spread Prediction and Identified Gaps

In this section, we investigate a few of the already used models or techniques for predicting the size of a forest fire from its initial outbreak. This section is further divided into subsections i.e. (i) Correlation between weather and wildfire occurrence (ii) Predicting the size of a forest fire from fire indices (iii) Use of machine learning in predicting the forest fire size (iv) Use of neural network in predicting the size of the forest fire (iv) Use of Sequence for classification through DL.

## Correlation between weather and wildfires occurrence.

A lot of research has been done to prove that wildfires and climate are highly correlated. A long-term association was proved between fire and weather (Koutsias et al., 2013) by analysing the data which spans over period of more than a century(1984-2010). The analysis revealed that statistically significant growth in fire occurrences have occurred after 1970. The number of fire occurrences is highly correlated with maximum air temperature and negatively correlated with precipitation. Thus, it establishes the fact that weather has a profound effect on the fire spread by directly controlling fuel moisture.

## Predicting the size of a forest fire from fire indices.

The Canadian Fire Weather Index (FWI) is one the most popular and widely used tool to predict the severity of a fire hazard. It is one of the subsystems of Canadian Forest Fire danger(CFFDRS). FWI provides information on fire weather information, fuel moisture codes, and fire behavior indexes(Vetrita et al., 2012). An adaption of FWI is proposed by considering Mediterranean vegetation and climate(Chelli et al., 2015). The indexes are measured by fitting the collected data on fuel moisture content and the other values, as per the expected inputs for Canadian FWI. The results obtained can describe the fuel moisture dynamics despite small sample areas and time constraints for data collection. Another such index used for fire danger estimation is the McArthur Forest Fire Danger Index(FFDI). This Index cannot be used in few regions due to the unavailability of instruments and human resources. This index is modified by introducing a Normalized Multi-brand Drought Index(NMDI) and achieved an overall accuracy of 82% (Suresh Babu et al., 2017). Various fire danger rating system is being used in different part of the world, FFDI(McArthur et al. 1967)is used in Australia, Forest Fire Behaviour Table(FFBT) in western Australia (Beggs, 1976), FWI in Canada(Wagner, 1987), National Fire Danger Rating System(NFDRS) in USA(Bradshaw et al., 1984) and Nesterov Fire Danger Index System in Russia(V. G Nesterov, 1949). Most of these fire danger rating systems only use four weather parameters such as temperature, relative humidity, precipitation, and wind speed. However other factors such as topography, visibility and fuel properties, preparedness level of the fire-fighting department is assumed to be constant. Few of the other fire rating system uses ground data on a regular basis, which is not feasible all the time. Using machine learning techniques to tackle such problems can be a better solution.

## Use of machine learning in predicting the forest fire size

Various machine learning algorithms such as Logistic regression, Support Vector Machine(SVM), Decision Tree, Random forest to classify a fire or a no-fire have been proposed(Molovtsev and Sineva, 2019) using a one of the most popular data source present in UCI repository (Forest Fires Data Set,) i.e. data from The National park of Monteshino located in the northern part of Portugal. All these models for binary classification were evaluated with the help of a confusion matrix. Random forest algorithm proved to be superior among all the other models with respect to Recall, Precision, F1-Score, Accuracy. On the same dataset, the prediction on the fire size is also done(Cortez and Morais, 2007) using various data mining techniques such as Multiple Regression, Decision Tree, Random Forest, Neural Network and SVM on four different features i.e. spatial, temporal, FWI components, weather attributes. Low-cost real-time data is used instead of the satellite and scanner approaches. SVM proved to be the best among all other data mining techniques in terms of MAD, RMSE, and REC curve. However, the model has a very low predictive accuracy for large fires(> 1 hectare). Linear regression proved to be the most efficient machine learning technique in predicting the size of the forest fire with taking the area burnt as a dependent variable and the meteorological factors as a predictor (Afifuddin et al., 2019). Predictors such as high temperature and low humidity are found to be statistically significant in finding the exact amount of area burnt. However global average temperature increases every year because of interaction effects with other climatic components(Zhang, 2018). Pattern analysis has also been performed in the same research. However, the fire size usually depends on not only the current day but also on the previous days. Therefore, considering the previous weather details may produce more accurate results.

## Use of Neural Network in predicting the forest fire size

With the advancement of Neural Network over the last decade, the application is seen even in the field of natural disasters. Detection of forest fire has been done by Novac(Novac et al., 2020) through an RGB-D enabled quadcopter which moves in a snake-like pattern and sweeps the targeted area. Once it senses the fire, it extracts the blob, and the same is then fed to a Deep Convolution Neural Network(DCNN). However, with this technique, only detection for fire can be done, but enough data cannot be extracted for the prediction of the fire size. Feedforward Neural network technique had been applied in predicting the size of a forest fire in Monteshino Natural Park, Portugal(Safi and Bouroumi, 2013). Hyperparameter such as the number of neurons in a layer and the number of hidden layers is determined heuristically. After a lot of hyperparameter fine-tuning, the architecture was finalized with one hidden layer, 36 neurons, and 10,000 iterations. Since optimizing such hyperparameters can take a lot of effort and calculation, a different approach was applied by Anshori (Anshori et al., 2019) called Extreme learning machine(ELM) which removed the way of learning from a slow gradient-based algorithm as well as the repetitive task of hyperparameter tuning. This technique uses a single hidden layer and is more stable in terms of accuracy and relatively faster in computation as compared to neural networks with backpropagation. ELM training includes several steps like initializing weights and bias, determining the output from the hidden layer, applying the required activation function, calculating the Moore-Penrose Pseudo Inverse Matrix, deriving the output weights, and then the predicted results.

Study by Liang (Liang, Zhang, and Wang, 2019) is done on the dataset collected from Canada National Fire Database(CNFDB) containing the wildfire and meteorological data for Alberta, Canada. Multi-collinearity and feature normalization are performed on the data and then fed to various deep learning models such as Backpropagation Neural Network(BPNN), Recurrent Neural Network(RNN), and Long-Short Term Memory(LSTM) for predicting the fire size. LSTM showed the best accuracy rate of 90.9%. In this research, a similar approach has been implemented with creating a sequence of weather details for the previous four days of the fire incidents. The algorithm classifies the fire spread based on this sequence of weather data.

## Use of Recurrent Neural Network for Sequence Classification

Sequence classification comes into picture when a sequence of input over fixed space or time is predicting the category of the sequence. This kind of application is commonly seen in classifying the sequence of DNA into a particular category(Rizzo *et al.*, 2016) and text classification, where the algorithm reads a sequence of inputs and predicts the class it falls under. Similarly, in this research, the algorithm reads a sequence of weather data for the past 5days and predicts the size of the forest fire it falls into. Since the algorithm needs to memorize the past patters, LSTM has been used in this research.

# Research Methodology

## Introduction

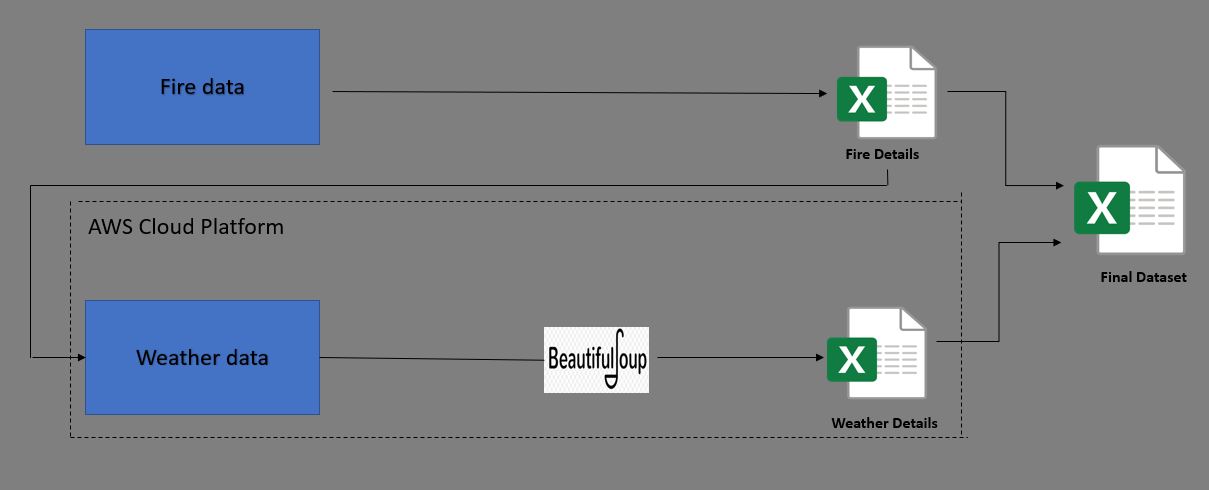
A data mining research is usually carried out in either KDD(Knowledge Discovery in Databases), SEMMA(Sample, Explore, Modify, Model, Access) or CRISP-DM(Cross-Industry Standard Process for Data Mining) methodology. KDD method has been used in this research it as it extracts what is deemed knowledge using a selected dataset with pre-processing, transformation, data mining, and evaluation because SEEMA doesn’t focus much on data specific task and is applied to general data science task and CRISP-DM focuses on understanding the objective from a business perspective and then converts this knowledge into data mining problem designs a preliminary plan to achieve those objectives(Azevedo and Santos, 2008).

## Modified KDD and Data Mining Methodologies

This modified KDD methodology for predicting the size of the forest fire consists of following stages (i) Data selection for forest fire in CSV format from Alaska Interagency Coordination Center (AICC) (ii) Data selection for historic weather details for the day in which the fire incident takes place and the previous 4 days from The Old Farmer’s Almanac[[2]](#footnote-2) in form of CSV (iii) Pre-processing, EDA and normalizing the input vectors and selecting the most important features (iv) Reducing the dimension of the input features (v) Applying oversampling through SMOTE to make the data balanced (iv) Models such as KNN, ANN, RNN, Decision Tree, SVM, Random Forest, Ensembled Methods are trained on the training data (v) Models were evaluated based on few parameters.

## Data Preparation Process Flow

The data preparation process(depicted in Fig1) consists of the following steps: (i) Downloading the fire data from AICC which contains the number of fire occurred, the total area impacted preparedness level and the date in which the fire incident was reported in form of a CSV (ii) This fire reported date is used to get the weather details from The Old Farmer’s Almanac website for that particular date as well as the previous four days (iii)The data is extracted(as a CSV file) with python libraries such as Beautifulsoup (iv) Python libraries for extraction of data is done in separate instances created in AWS cloud platform because it is a very time-consuming process and had to be executed in parallel systems. (v) The extracted weather data is finally merged with the fire data to obtain the final dataset for this research(vi) Fire spread area is divided into 3 bins named as ‘Small’, ’Large’, ‘Severe’ which is a combination of Class A-C, D-E, F-G respectively(considering the unavailability of large volume of data).



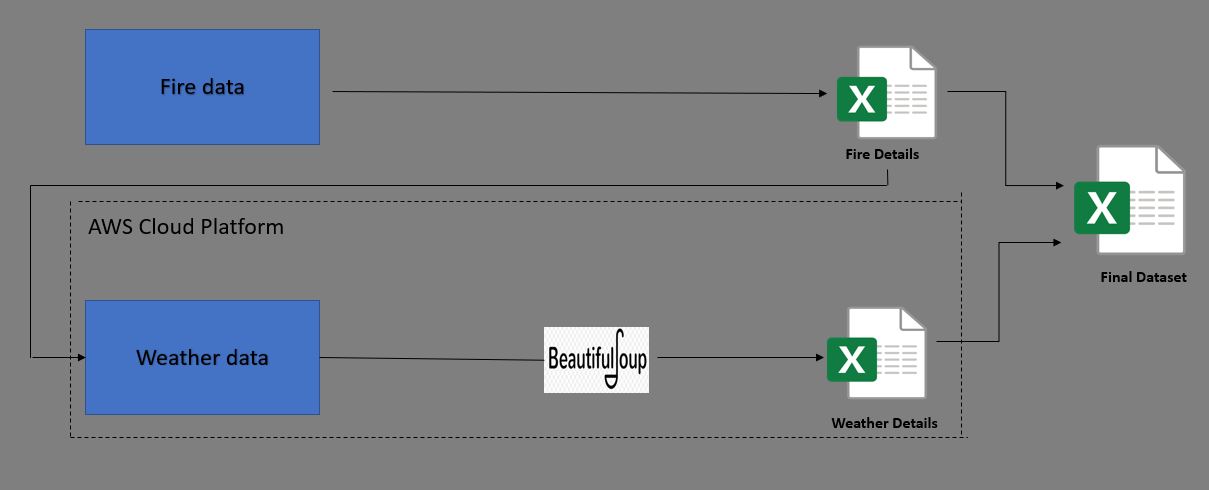


Fig 1- Data Creation Process flow

## Project Design Process Flow

The project design phase(depicted in Fig 2) consists of three layers (i) Presentation layer (ii) Business layer (iii) Database layer. In presentation layer various visualization are done using Tableau, Python, R. In business layer, explanatory analysis, feature engineering, feature selection and feature reduction and model implementation has been implemented using various predefined packages and few custom functions in Python and R. Data resides in the form a CSV in the data layer.

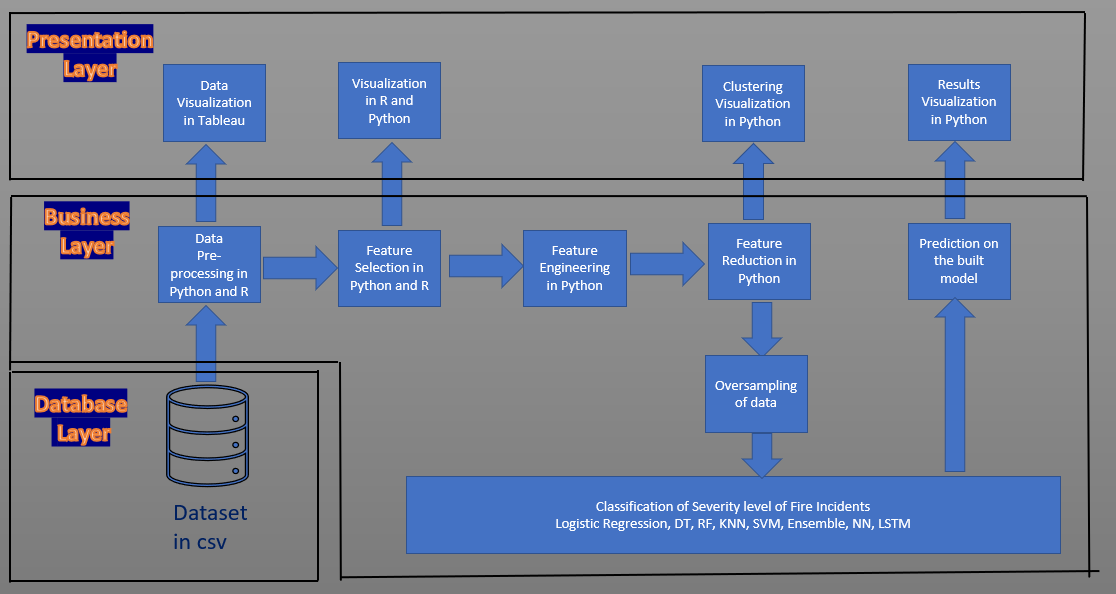


Figure 2: Project Design process flow

## Conclusion

Traditional KDD methodology has been modified as per the problem statement and requirement. Data has been collected from multiple sources and merged to build the final dataset. Explanatory analysis has been performed in the final dataset to provide few insights about the data. Data Acquisition, business understanding, merging of the datasets, and initial pre-processing been done in the next section.

# Data Pre-Processing

## Introduction

This section provides a detailed description on the process of creating the dataset from scratch, for this research, its initial pre-processing, methods for selecting the important features, checking the distribution of the variables used, transforming the data as required, reducing it into minimal components and visualizing the data in reduced dimensions to check if there are any clusters formed.

## Business Understanding

The first intuitive factor behind a forest fire is Temperature. But the temperature of the day of the incident does not give sufficient information, however, a sequence of the temperature before the day of the fire gives more intuition. Similarly, other factors such as precipitation, wind speed, dew point, visibility can combine to give a better understanding of the severity of the fire. Therefore, all these parameters were collected for the day of the fire incident(Day-0) and the previous four days(Day-1.Day-2, Day-3, Day-4) and used as independent variables to predict the size of fire spread.

## Data Acquisition

Fire Incidents have been collected from Alaska Interagency Coordination Centre – Alaska Daily Stats Report[[1]](#_ftn1), which contains the details of fire incident from 1993 to 2019 with the date of the incident, the total number of fires(cumulative over a year), total acres of area burnt(cumulative over a year), preparedness level of the Fire Department on the scale of 1-5, where 5 is the best preparedness level and 1 is the worst preparedness level, total number of fire incidents occurred due to human activities and lightening and their corresponding acres of area burnt. Analysis of classification of fire based on its reason(human activities or lightening) has been kept out of the scope for this research, thus related columns are dropped. Columns that are considered relevant for this research are as follows:- ‘ID’, ’FireSeason’, ’Month’, ’Day’, ’SitReportDate’, ’TotalFires’,' TotalAcres’, ‘PrepLevel’.

Historical weather data has been collected from ‘THE OLD FARMER’S ALMANAC’ website[[2]](#_ftn2) which contains historical weather data for the USA and Canada. The inputs that need to be provided for extracting the weather details are – (i) Area name (ii)date in the form of YYYY-MON-DD. The same details are also present in the URL of the resultant page. Akiachak area has been chosen for this research, and dates are selected from the fire incident data. URLs were created for scrapping the data for the fire incident day, as well as 4days before it. With the help of predefined packages in Python, an automated system was designed so that system will browse all the given URLs and extract the meteorological details such as minimum temperature in Fahrenheit(F), mean temperature(F), maximum(F), mean sea level pressure in Inches of Mercury(IN), Mean due point(F), Total precipitation in inches(IN), visibility in Miles(MI), Mean wind speed in miles per hour(MPH), maximum sustained wind speed(MPH), maximum wind gust(MPH). All these details were extracted for the reported day for fire incident(Day0) and four days before the same day (Day-1, Day-2, Day-3, Day-4). The total number of features and observation extracted is shown in Fig3.

[[1]](#_ftnref1) <https://fire.ak.blm.gov/predsvcs/intel.php>

[[2]](#_ftnref2) <https://www.almanac.com/weather/history>

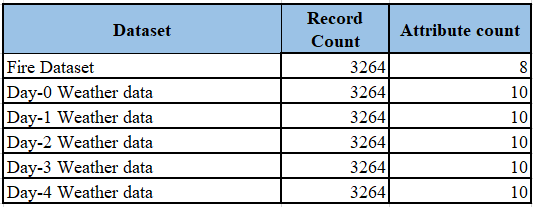


Fig3- Dataset Description

## Data Merging

Once the dataset is extracted for all five days, the next step is to merge them all based on the date. The same has been depicted in Fig 4. In this case, the number of fire incidents and the total acres burnt is cumulative over a year. Thus, for simplicity, the cumulative numbers were converted into individual numbers. Further few duplicate records were removed from the dataset. Therefore, the number of records in the dataset got reduced from 3264 to 3249.

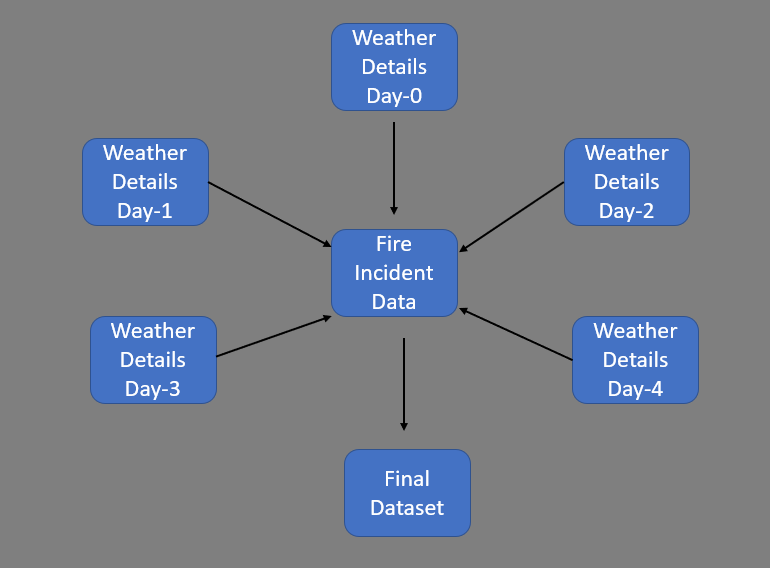


Fig4 - Merging of dataset

## Handling of Missing values

Missing values is the first obstacle that needs to be dealt with,before building any model in machine learning. Missing values in this dataset were checked to find out the percentage of data missing for every column(whichever has atleast one missing value). Figure5 depicts the same information in form a of bar chart.

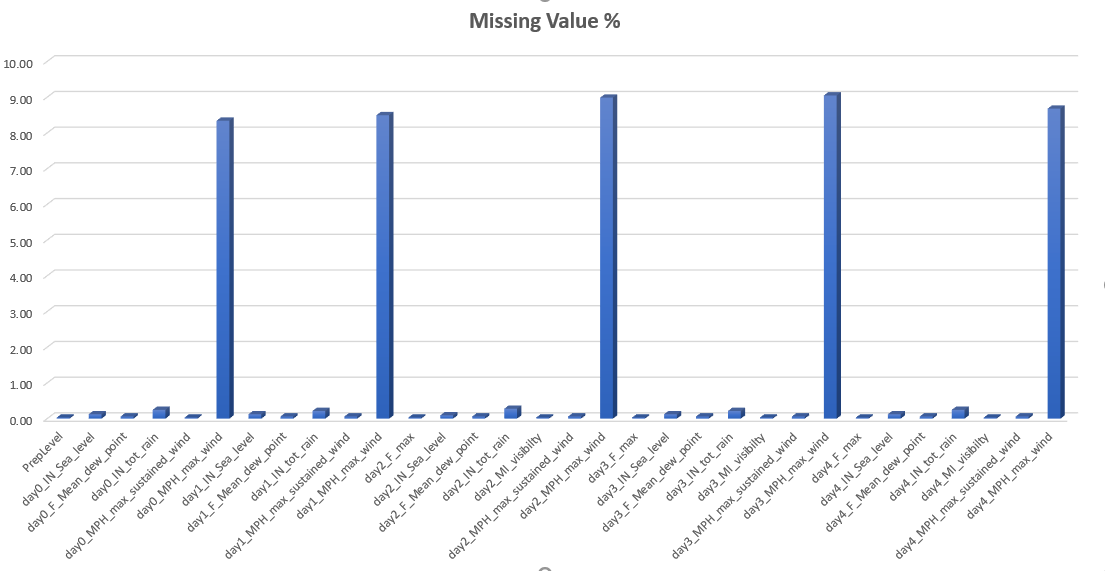


Fig5-Precentage of missing values

Upon checking the distribution of the various attributes, it was observed that Maximum wind gust for all 5days(Day0, Day-1, Day-2, Day-3,day-4) has outlier(999MPH) which constitute 33% of the data. Figure6 depicts the distribution of Maximum wind gust for all 5days. All these outliers were replaced by Null which is further imputed(with the help of few missing learning techniques) in the next stage. There is no influential outlier in the remaining data. The same has been checked through the box plot for all the features.

Package knowns as MICE(Multivariate Imputation via Chained Equation) in R as been used to impute the missing values as it creates multiple imputations as compared to the single imputation by mean. It imputes the missing value in a column based on other observed values and an imputation model(default is Predictive Mean Matching for numerical variables and Multinomial Logistic regression). This package generates three different datasets which are only different in missing values. The dataset whose column mean is closest to the corresponding original observed column has been accepted to be the final dataset. Fig7 represents the missing values in a column in red while the observed values in blue. The first block(row-1,column-1) represents the original dataset, while the other blocks represent the imputed values in different datasets generated through MICE.

Fig6- Distribution of max wind

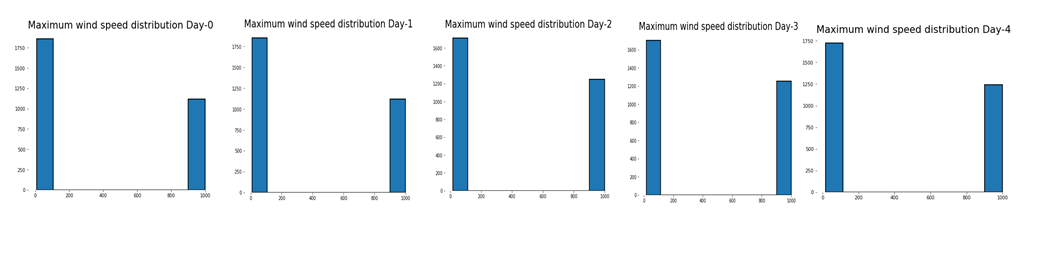
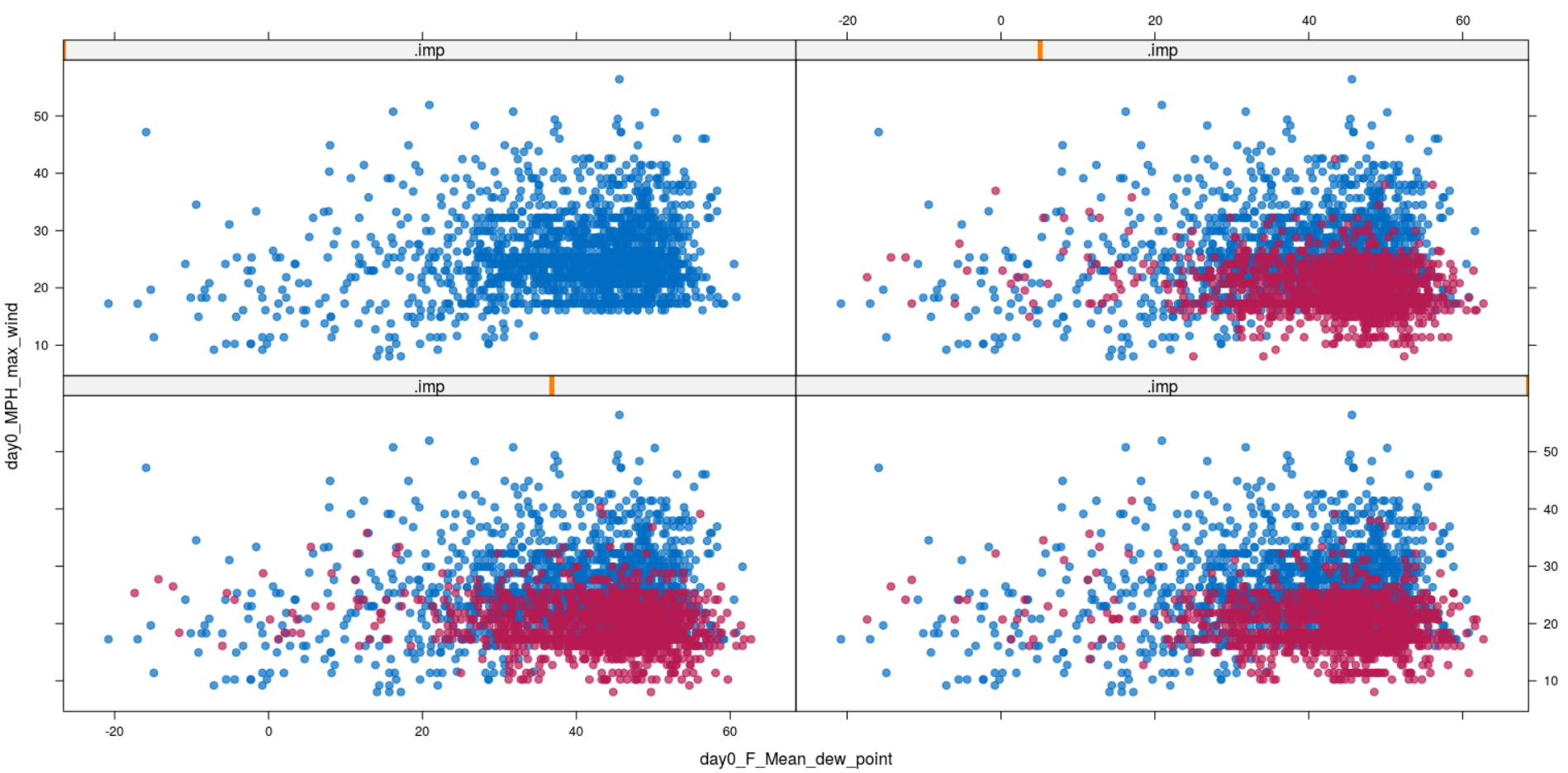


Fig7- Missing value imputation



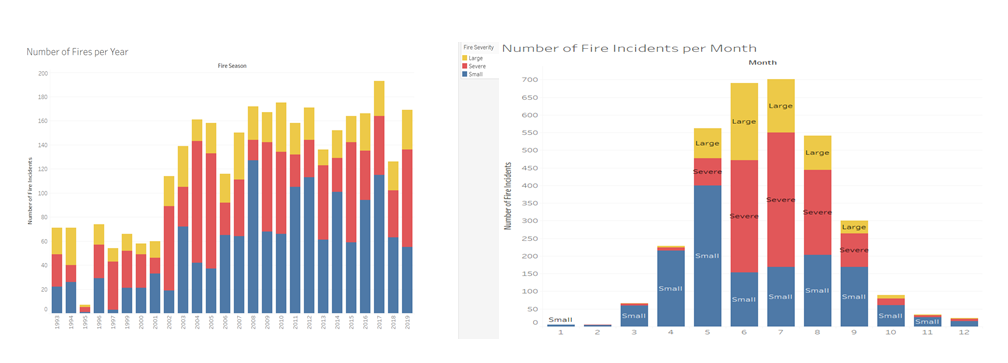
## Explanatory Data Analysis

Explanatory Data Analysis(EDA) is one of the crucial steps in machine learning, which helps to visualize, summarize, and interpret information present in the tabular data. In this research, the Tableau tool has been used for EDA. Univariate analysis is done on the number of fires each year. It is evident from Fig 8 that the number of fire incidents is on an increasing trend since 2001. Most of the severe fires(spread > 5000acres) were observed after 2002. Since 1993, the maximum number of incidents took place in 2017 and the lowest number of incidents has taken place in 1995. A maximum number of severe fires took place in 2004. With respect to the months, most of the incidents have taken place in June and July(as shown in Fig8) and approximately 50% of the incidents were reported as ‘Severe’. The least number of cases has been reported in February. Around 75% of the fires reported in May are of low severity. On checking the distribution of the Fire severity labels, it can be seen that approx. 46% of the data belongs to ‘Small Fires’ class whereas 36% fall under the ’Severe Fire’ category and a mere 18% falls under the ‘Large fires’ category(shown in Fig9). This shows that data is imbalanced, and therefore multiple evaluation parameters need to be considered to evaluate the performance of any algorithm.

## Feature Engineering

The final dataset contains both numerical and categorical values and each requires a different kind of treatment before applying machine learning models to train. Below are the few feature engineering techniques applied to this dataset.

Fig8- Number of fires in Years and Months



(a)Number of fires per year (b) Number of fires per month

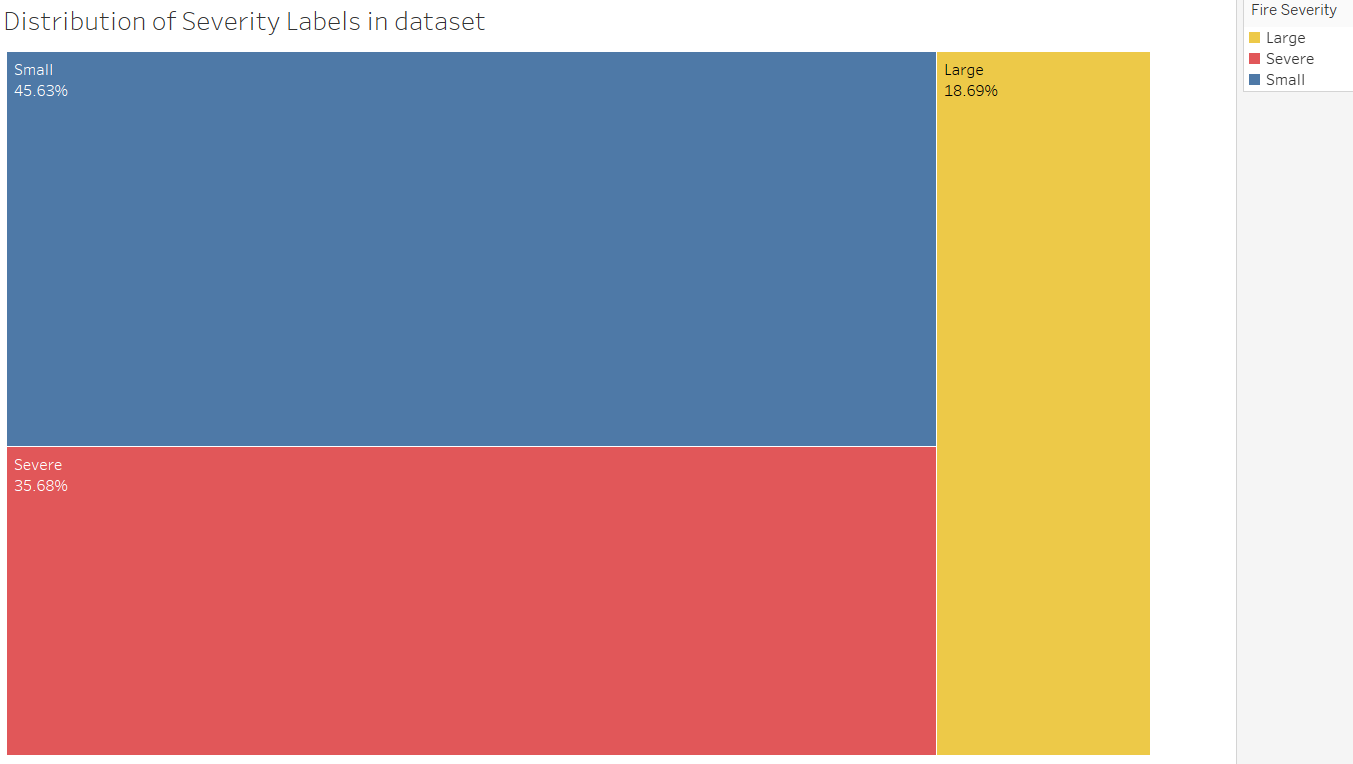


Fig9- Distribution of severity class

### One-Hot Encoding

Categorical values present in the dataset are Month, Year while Preparedness level for firefighters is ordinal data. One hot encoding has been applied to all the nominal and ordinal data, to transform each category to a different feature resulting in a binary transformation of 0 and 1. For example, the month column has different values (Jan – Dec), which are transformed into different columns with the name ‘month\_Jan’ and so on. After one-hot encoding, the shape of the data increased from (3248,55) to (3248,95).

### Feature Scaling

Numerical values in the dataset are on different scales such as temperature feature is in Fahrenheit while visibility is in miles, precipitation is in inch, and wind speed is in miles per hour. All these measuring units are different, and so as the values. Machine learning algorithms only see numbers, where more significant numbers play a decisive role during training. Even Gradient-Descent in Neural Network converges faster in scaled data. Therefore, it is necessary to bring all the values into a common scale of 0-1. Normalization has not been performed for tree-based models such as XGBoost and Random Forest.

### Feature Transformation

Data such as precipitation are highly skewed, with a maximum amount of rainfall only in few months and approximately zero in the remaining months. In such scenarios data has been transformed to a logarithmic scale to achieve a normal distribution.

## Feature Selection

Feature selection plays an important role in machine learning as it selects only key features to train the model. It is not advisable to use all the available features to build an algorithm. Multiple features often contain noise, which reduces the model’s accuracy and complicates the computation. Thus, Feature selection eliminates data redundancy, avoid multi-collinearity, thus improving the model’s accuracy and reduces complexity.

### Pearson's Correlation Coefficient

Pearson’s Correlation Coefficient has been used to determine if there is any correlation between the weather data for the past five days and the fire incident data. Correlated columns are removed, resulting in a dataset of shape (3248,58) from (3248,95). A Multiple Logistic regression model has been implemented with uncorrelated data and evaluation parameters were checked(refer to Fig13) as a baseline for feature selection algorithms. The correlation matrix is shown in Fig10.

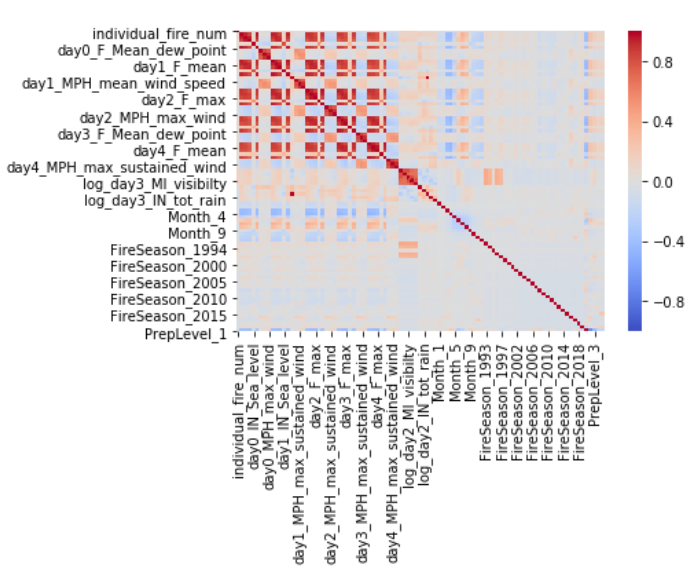


Fig10- Correlation Matrix

### Boruta Selection Algorithm

This feature selection algorithm works as a wrapper algorithm on random Forest. It retains all the features which are relevant to the output variable. This algorithm fits a Random Forest model on the dataset and recursively gets rid of the features that did not perform well in each iteration. Finally, the errors in the random forest model minimize which keeps only the minimal optimal subset of features. This algorithm has been applied in this dataset which retained 61 important features. The same is depicted in Fig11, were green features are relevant ones, while features in red can be removed. The shape of the dataset got changed form (3248,95) to (3248,61). Multinomial logistic regression was built on the selected data and accuracy of the model is compared with the baseline feature selection model(refer to Fig13).

### Recursive Feature Elimination

Recursive Feature Elimination(RFE) is one of the traditional Feature selections used in ML. This method has been used in the same dataset with Random Forest as the underlying algorithm. RFE fits the model and removes the weakest feature(or features) until a specified number of features are retained. This algorithm retained only 8 important features(shown in Fig12) on which a multinomial logistic regression was build and evaluated in terms of accuracy(refer to Fig13).

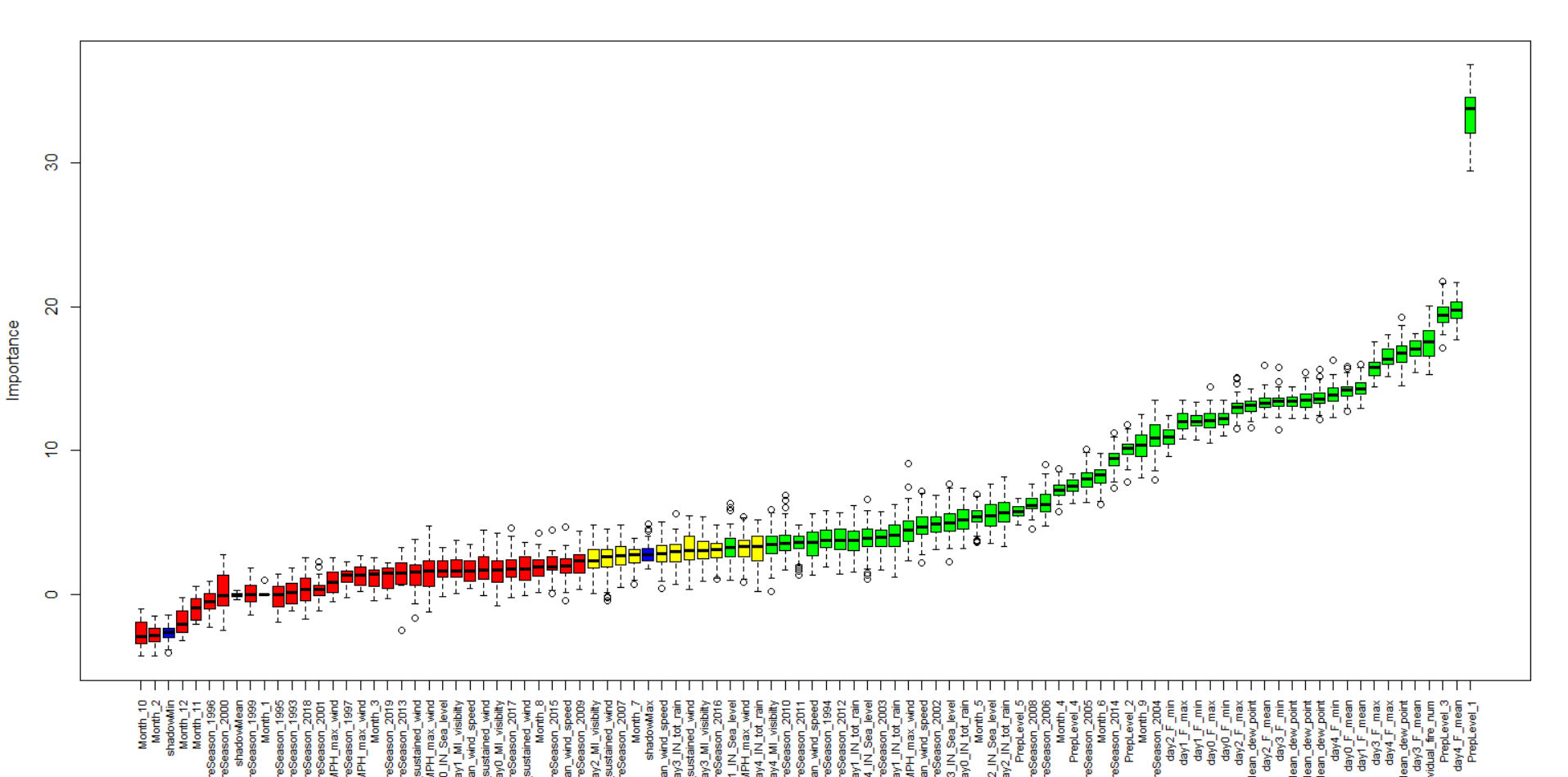


Fig11- Feature Selection by Boruta Algorithm

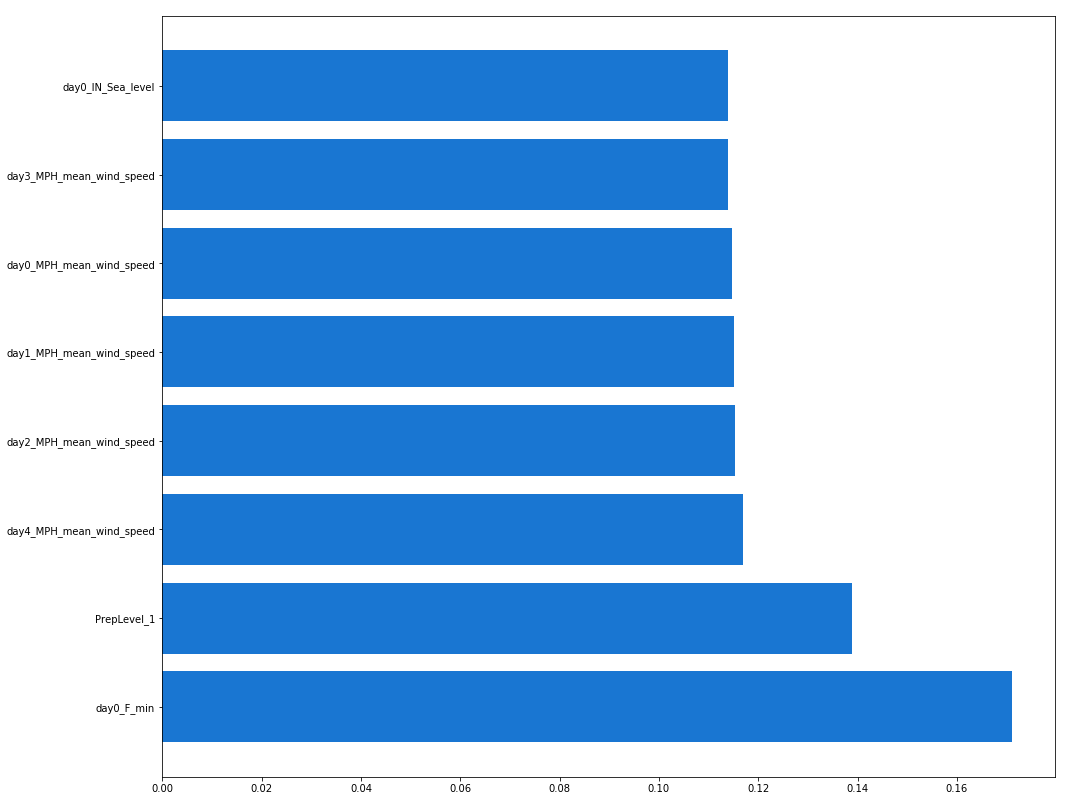


Fig12- Feature Selection by Recursive Feature Elimination

### Random Forest Feature Selection

Random Forest is one of the embedded methods used for Feature Selection which is a combination of filter and wrapper methods(Kursa and Rudnicki, 2011). These kinds of feature selection are highly accurate, generalize better, and interpretable. This algorithm creates multiple decision trees with a random set of observations and features. The impurity is measured in the Gini Index or Information Gain. While training a tree, the feature that decreases the impurity more, is more important and is averaged out across all tress to determine the importance of the variable. This algorithm chose only 48 features to be important in this dataset. Several caveats concern the use of a random forest selection algorithm. These include concerns such as the assignment of equal importance to correlated features and assigning preferences to high cardinality features. Another tree-based feature selection algorithm called as LGBMClassifier(from the Python package - lightgbm ) derived 49 important features. Multinomial logistic regression is built on the selected features and the accuracy of the model is observed and compared with the baseline feature selection model(shown in Fig13).

### Conclusion

All the above Feature Selection has been applied on the dataset and a multinomial Logistic Regression is built on the important features derived by each of the above discussed algorithms. Refer to the Fig13, which shows the comparison among all the used algorithms. It is evident that Boruta Feature Selection works the best among them. Hence the features that are considered important by the Boruta algorithms are finalized to build the model.

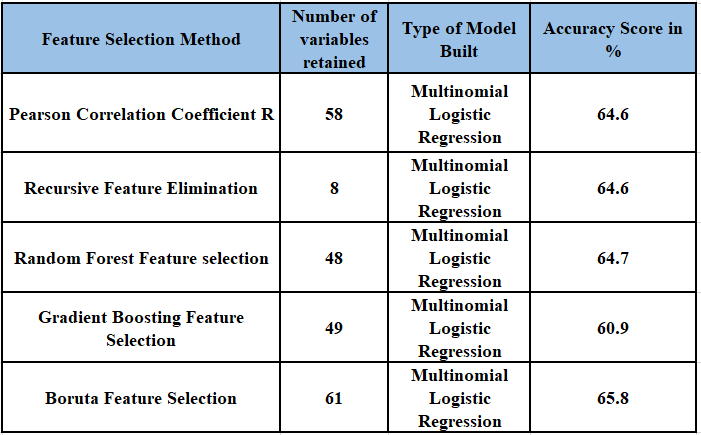


Fig13- Comparison of different Feature Selection methods

## Dimension Reduction

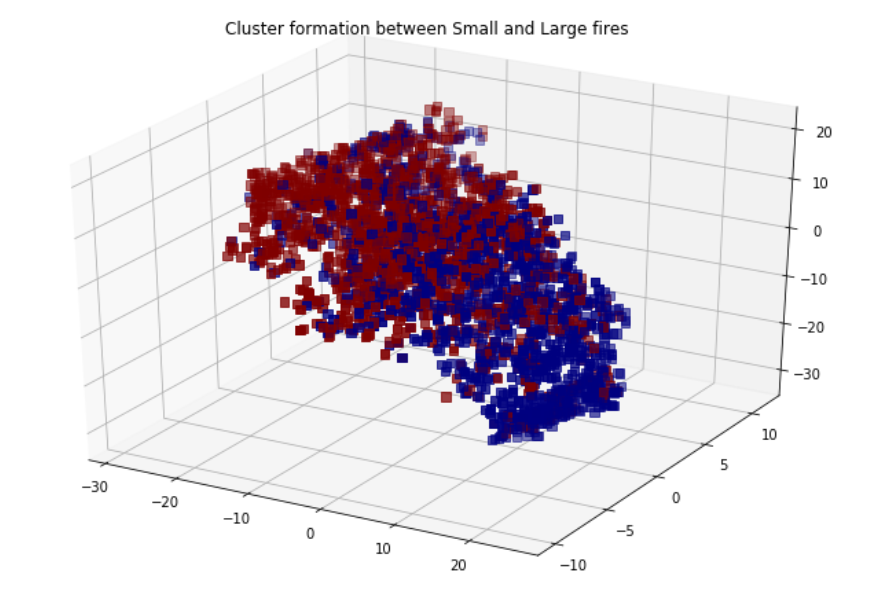
Dimension Reduction is a process of reducing the number of features in the dataset. The dataset after the initial pre-processing and feature selection has 61 features. More the number of features, more is the number of samples required, which would not only make the model complex but also increases the probability of overfitting and removes the redundant features and noise.

### Principal Component Analysis

Principal Component Analysis(PCA) is one of the fundamental and traditional methods to derive a new set of components from the existing features, called ‘Principal Components’. These principal components explain most of the variance in the dataset. The first Component explains most of the variance, followed by the second component and so on. The components are orthogonal to each other meaning, there is no correlation among the extracted features. PCA has been implemented on this dataset which shows that there is one major component which is explaining 80% of the variance in the dataset. The same has been demonstrated in the elbow plot in Fig14. In the graph, the blue line represents the component-wise explained variance while the orange line represents the cumulative explained variance. The problem with PCA is that the extracted features are the linear combination of the original features which are not interpretable. Therefore, there is a need for few advanced dimension reduction techniques.

### T-distributed Stochastic Neighbour Embeddings

T-distributed Stochastic Neighbour Embeddings(t-SNE) is one of the modern techniques for dimension reduction, which was brought to implantation is 2008. Unlike PCA, it is a non-linear method that preserves the local(cluster) structure which helps to give a better visualization of the clusters. In this research, the dataset of 61features is reduced to 3dimension, and clusters are created with the severity of the fire as labels. Two separate clusters for fire severity are being created with blue as ‘small scale’ fires and marron color indicates ‘large and severe’ fire incidents(shown in Fig 15).



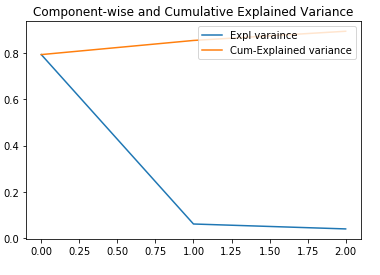


Fig14- Elbow plot for PCA Fig15- Clusters in t-SNE

### Conclusion

Similar clusters are created using other non-linear dimension reduction algorithms, such as Isomap, Umap to check if any distinguished clusters are visible in reduced dimensions. A Simple multinomial logistic regression is built on the reduced dimension, derived from all the techniques applied and accuracy scores were compared. It was noticed that accuracy for t-SNE is highest as compared to other dimension reduction techniques(shown in Fig16). Thus, the features extracted from t-SNE has been used to train a model.

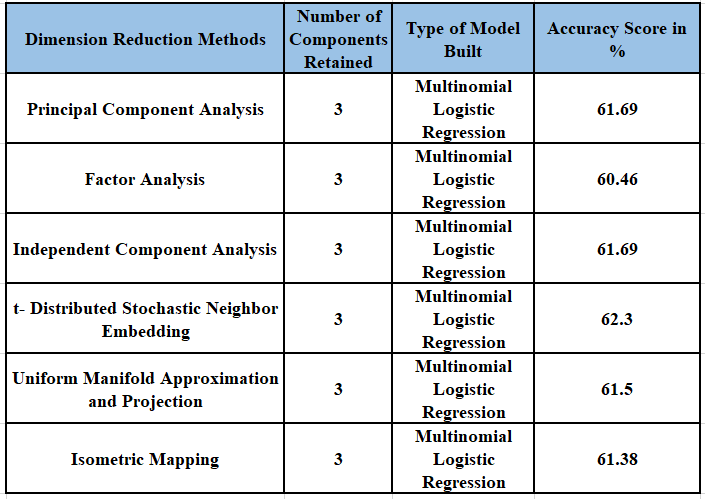


Fig16- Comparison of Dimension Reduction Techniques

# Implementation

The implementation is divided into three important phases, namely: sampling of data, cross-validation and hyperparameter tuning based on grid search optimization algorithm. Implementation has been carried out in two processes. In the first process, all the input weather features for different days are considered independent of each other and predict the severity of the fire spread. Derived features(after Dimension Reduction mentioned in 4.9.3) have been used to train the traditional machine learning methods for classification. In the second process, Neural Network has been implemented on all the available features of the dataset and an LSTM model on a sequence of input weather features for each day has been built to predict the severity of the fire spread. In other words, LSTM model retains the information of the previous day to predict the fire severity. Grid-search algorithm has been implemented on all ML algorithms to obtain the best possible hyperparameters for tuning. Pythons package- sklearn has been used to instantiate various ML models and their evaluation matrices.

## Data Preparation

The final Dataset has 3248 observations and 3 derived components from t-SNE. The data is then split into 80% training and 20% validation data. To reduce overfitting and achieve effective sampling of data K-fold Cross Validation has been used with the value of K varying from 3-20. Multinomial Logistic regression has been used to train the model with different values of K and accuracy is measured for each value of K. It was observed that Logistic regression algorithm performs best with K value as 3, all other models were built with same K value.

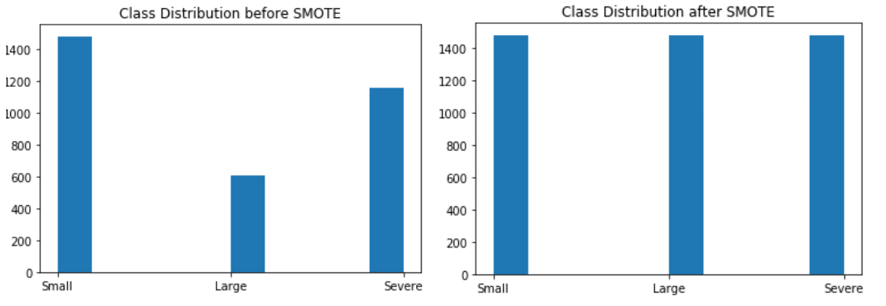
## Evaluation Parameters

In the case of imbalanced data, accuracy metrics cannot be used to judge a classifier algorithm as it assumes that False Positives and False Negatives have a similar cost. For this research, Confusion Matrix has been used to derive a few other parameters to evaluate all the machine learning algorithms such as Precision, Recall, F1-Score. Precision is the number of True positives against the sum of True Positives and False Positives. It is also called as classifier’s exactness. A low precision value will indicate many False Positives cases. On the other hand, Recall is the number of True Positives divided by the number of True Positives and False Negatives. It is also called the classifier’s completeness, where low recall value indicates, high False Negatives.The [F1-Score](http://en.wikipedia.org/wiki/F1_score) is the 2\*((Precision\*Recall)/(Precision+Recall)). It conveys the balance between Precision and Recall.

## SMOTE (Synthetic Minority Oversampling Technique) – Oversampling

From Fig 17(a), it is evident that the dataset is not balanced with respect to the dependent variable, in other words, all the classes are not represented equally. Therefore, machine learning algorithms tend to ignore the minority class. SMOTE is one of the most common oversampling methods to solve this class imbalance problem. It oversamples the minority class by taking a minority sample and introducing synthetic examples along the line segment joining any of the K minority class nearest neighbours. Python package ‘imblearn’ has been used for this kind of oversampling.

In this case, the number of small fires is more than large and severe fires. A simple multinomial logistic regression model was built to check the Precision, Recall, and F1-Score. Since the distribution of the data is more inclined to small and severe fires, the algorithm learns to classify these fires correctly, however, due to the presence of very few large fires, it fails to classify the large fires correctly. The same can be seen with the help of evaluation parameters(shown in Fig18). However, after applying SMOTE the distribution of all the classes becomes identical (shown in Fig17) and the evaluation parameters for the minority class have also improved(shown in Fig18).

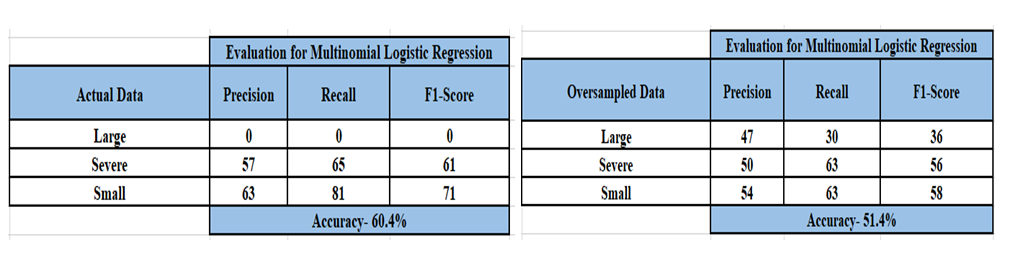


1. (b)

Fig17- Distribution of severity class before and after SMOTE

Fig17. Distribution of severity class before(a) and after SMOTE(b)

Fig18- Evaluation parameters before and after SMOTE



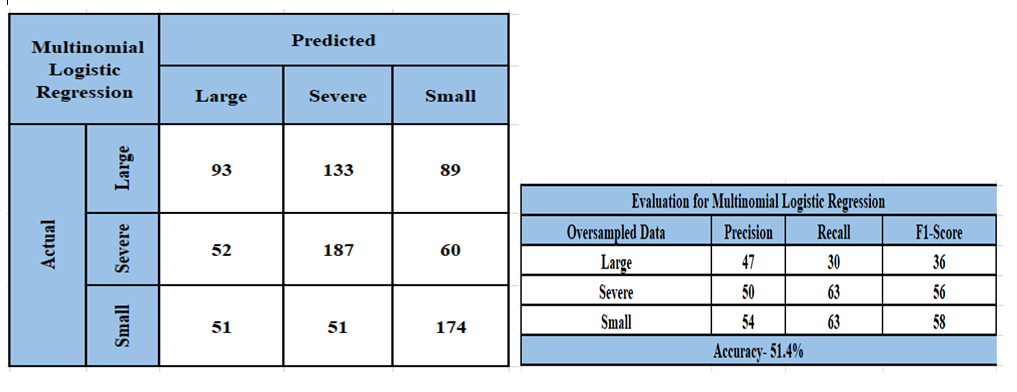
## Logistic Regression

This is one of the fundamental machine learning models to explain the relationship between nominal(two or more levels) dependent variable and multiple independent variables. In this algorithm, the log of odds of the outcome is regressed with the linear combination of the predictor variables. The outcome of this algorithm is a density function of cumulative probabilities ranging from 0-1. In this case, the dependent variable has 3 levels, therefore the model estimates 2(3-1) logit equations. Various hyperparameters are of the model are tuned with the help of grid-search to find the most accurate predictions(penalty as L2, C value as 0.1, solver as newton-cg).

**Evaluation**

One the model is trained with the training data, validation data is used to make prediction through the model and this predicted output is then compared with the original data to check Precision, Recall and F1-score(shown in Fig19) for each of the class and the overall accuracy of the algorithm. Confusion-matrix built on validation data can be seen in Fig19. The Accuracy of the model is found to be 51.4%.

Fig 19- Confusion matrix and Evaluation for Logistic regression



## Decision Tree Classifier

As the name suggests, Decision Tree(DT) algorithm follows a tree-like structure where features are represented an internal node, branch as decision rule and leaf node as outcomes. Recursive partitioning happens based on attribute values. Because of its tree-like structure, it is easy to understand and interpret. Since it is a non-parametric method, it does not depend on the probability distribution assumption. Grid-search technique has been leveraged to find the best hyperparameters for the model. Models shows maximum accuracy with maximum\_number of leaf node as 99, minimum sample split as 13.

**Evaluation**

Confusion matrix has been generated to validate the model prediction using the validation data and compare it with the ground truth data. The same is shown in Fig20. Another Evaluation parameter such as Precision, Recall, F1-Score for all the classes has been mentioned in the Fig20. The model has an overall accuracy of 56.4%.

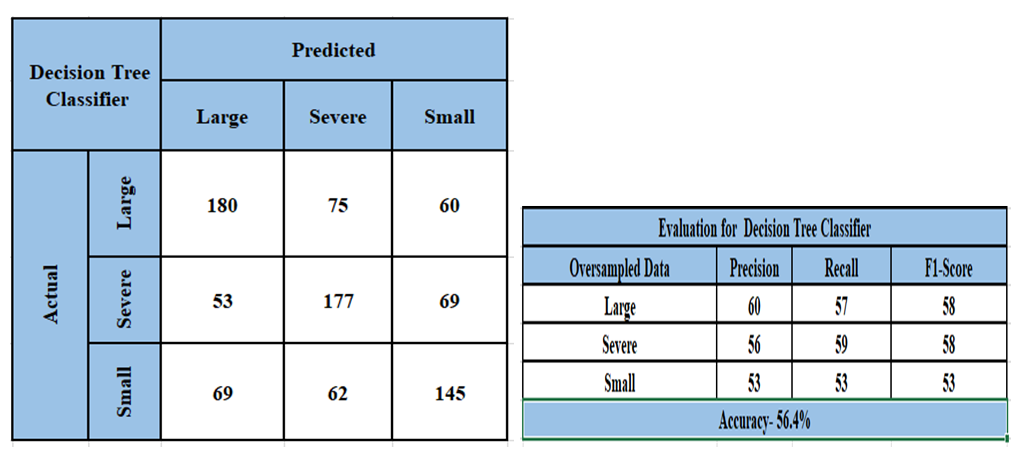


Fig 20- Confusion matrix and Evaluation for Decision Tree classifier

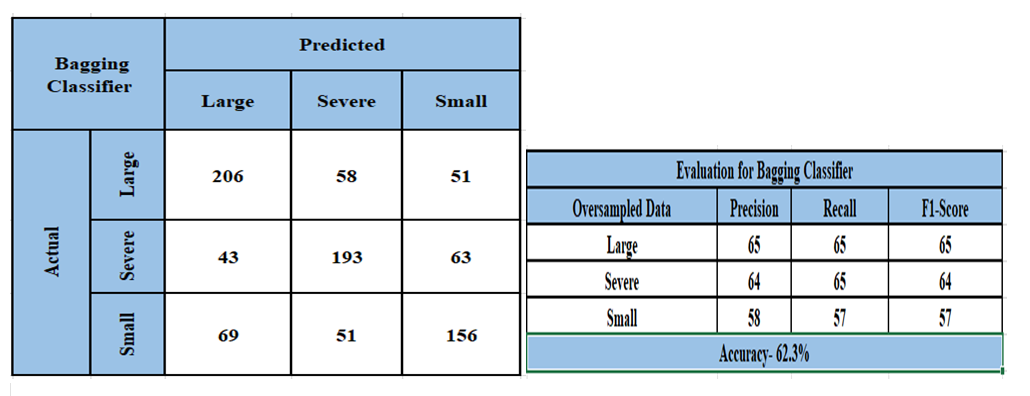
## Bagging Classifier

This is one of the ensemble techniques that fit random subsets of the original dataset to base classifiers and then average out(or maximum vote criteria) their predictions to result in the final prediction. Thus, it combines several weak learners to form a single strong learner thus reducing variance and bring stability. Decision tree has been chosen to be the base learners in this research.

**Evaluation**

Confusion-matrix to validate the model has been shown in Fig21. The model works better in terms of Accuracy, Precision, Recall and F1-score in comparison with the previous model. The same is evident from Fig21.

Fig 21- Confusion matrix and Evaluation for Bagging classifier



## K-Nearest Neighbour Classifier

K-nearest Neighbour(KNN) is non-parametric method where an object is classified by the number of votes from its neighbours witch the object classified to the most among its K nearest neighbour, where K is a positive integer number. Normalized data has been used for training as it improves the accuracy. Model is run on various values of K and it was observed that model runs with optimum performance with K values as 5, and distance metric as Euclidean.

**Evaluation**

Corresponding Confusion-Matrix and evaluation parameters can be seen in Fig 22.The Accuracy is found to be around 61%.

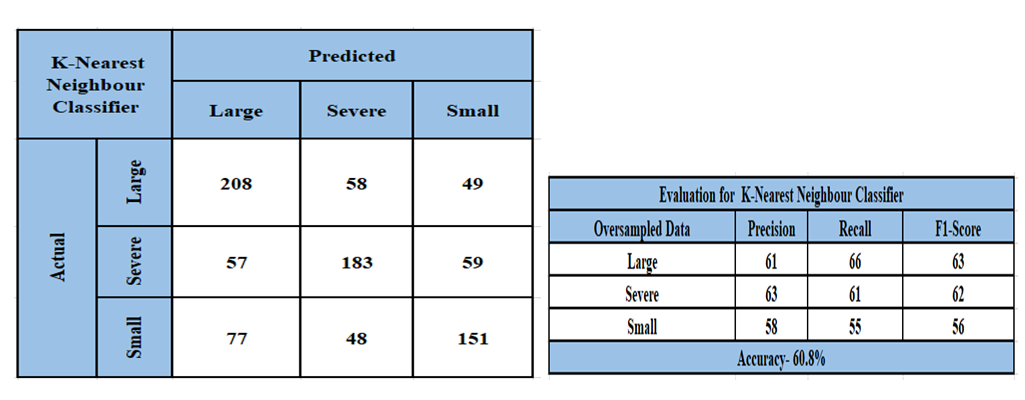


Fig 21- Confusion matrix and Evaluation for KNN

## Random Forest Classifier

Random Forest(RF) basically consists of a large number of individual decision trees that operate together. Each tree determines a class prediction and the class with maximum votes becomes the model prediction. Randomized search with cross-validation enabled, has been used to find the best hyperparameters for tuning the model. Model runs with maximum accuracy on n\_estimator as 733,min\_sample\_split as 2, min\_sample\_leafs=1,max\_dept- 100, max\_features as 'auto’ and bootstrap as True).

**Evaluation**

Confusion matrix has been used to compare the predicted output and observed validation data, which can be seen in Fig 28. Evaluation parameters such as Precision, Recall,F1-Score of all the output class and model accuracy(64.2%) can seen in Fig23.

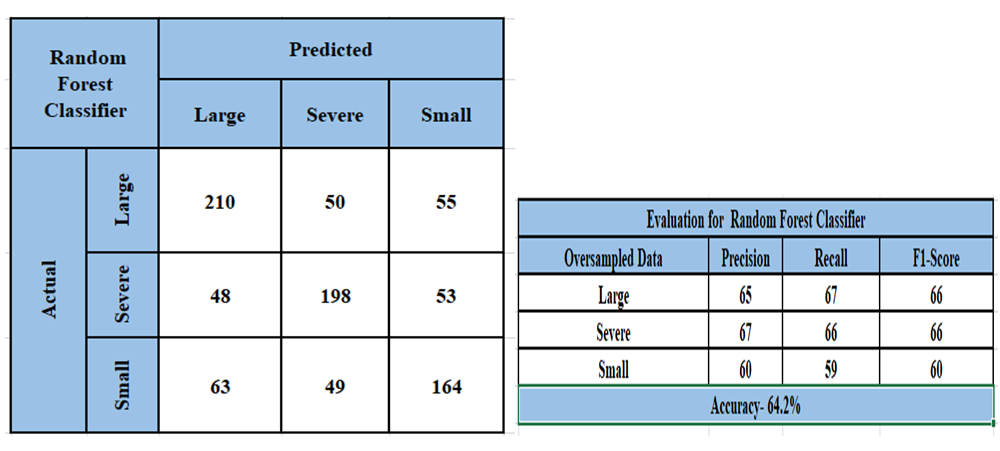


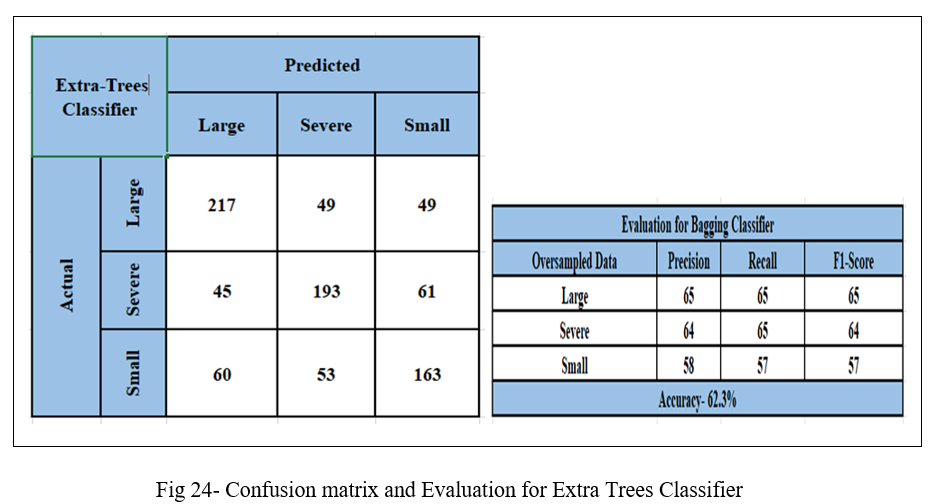
Fig 23- Confusion matrix and Evaluation for Random Forest

## Extra Trees Classifier

This algorithm is very similar to RF apart from the fact that in this case trees are randomized to introduce more variation. In this algorithm features and splits are selected at random. Therefore, it is also called a ‘Extremely Randomized Tree’. Since the splits are in random, it is computationally less expensive than Random Forest.

**Evaluation:**

Confusion matrix and other evaluation parameters have been shown in Fig24. The accuracy of this model is comparatively better than the other models.

****

## Support Vector Machine

Support Vector Machine(SVM) is one of the supervised models, which can perform linear classification as well non0linear classification with the help of a kernel trick(mapping the input features into a high dimensional feature space). It uses a subset of observations in the decision function, which makes this algorithm memory efficient. Gridsearch has been used to find the optimal parameters such as C=1, gamma=1 and kernel as ‘rbf’.

**Evaluation:**

Correlation matrix and evaluation parameters has used to evaluate the model(shown in Fig 25). Accuracy of the model is mere 53%.

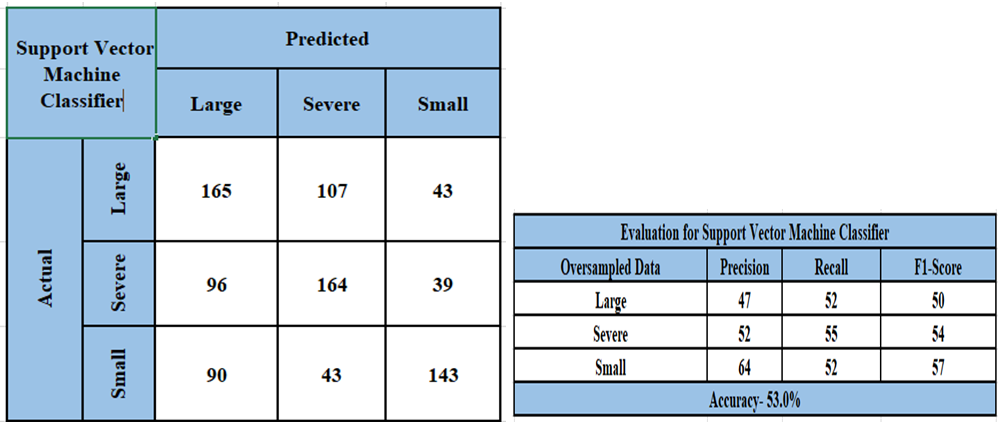


Fig 25- Confusion matrix and Evaluation for SVM

## Gradient Boosting Classifier

Boosting is an ensemble sequential technique that combines various weak learners and results an improved prediction accuracy. At any instant, the model outcomes are weighed based on the previous instant. The outcomes that are predicted correctly at the previous instance are given lower weights and the misclassification are given the higher weights. Hyperparameters used to fine-tune the model are n\_estimators=20, learning\_rate=0.5, max\_features=2, max\_depth=2.

**Evaluation**: Confusion matrix and evaluation parameters of the algorithm is shown in figure 26.

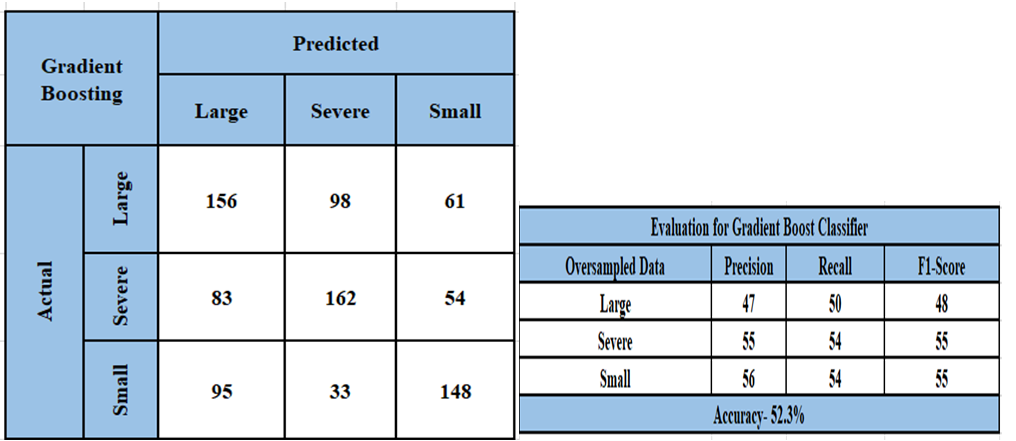


Fig 26- Confusion matrix and Evaluation for GBM

## Extreme Gradient Boosting

Extreme Gradient Boosting(XGBoost) is an advanced version of The Gradient Boosting Algorithm, which increases the speed and accuracy of the model drastically. This has a built capability to handle even the missing data and implements cross-validation at each iteration. It implements parallel processing and gives the flexibility to define custom optimization objectives and evaluation criteria. This algorithm implements gradient-boosted trees and the model learns from the residuals of the previous predictor variables.

**Evaluation**:

Confusion matrix and evaluation parameters for this model is depicted in Fig27. Both the boosting technique(5.11 and 5.12) did not perform better than the bagging technique(5.6) in terms of accuracy.

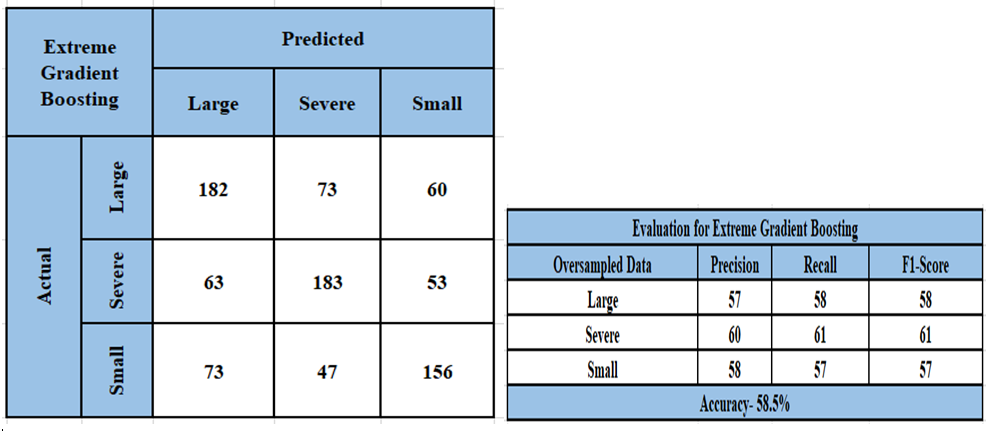


Fig 27- Confusion matrix and Evaluation for XGBoost

## Artificial Neural Network

Artificial Neural Network(ANN) works like a human brain. It consists of a single input layer, single/multiple hidden layers, and an output layer. The number of neurons in the input layer is the same as the number of input features(68 in this case), while the number of neurons in the hidden layers is determined heuristically. In this study, keras library in Python has been used to implement ANN with the number of layers and the number of neurons in each layer is defined with the help of a Dense constructor. Error minimization has been done using ‘adam’ optimizer, loss function as ‘Categorical CrossEntropy’ with accuracy as the evaluation metrics. The model summary can be seen in the Fig28.

**Evaluation:**

From Fig 29(a), it is observed that the loss function of the training data approaches towards zero while the loss function of the validation of data decreases rapidly till 45 epochs, but later tends to gradually increase. Fig29(b) shows the accuracy graph of training and validation data. Model's accuracy reaches the highest value of 67% after 45 epochs. The confusion matrix and other evaluation parameters have been mentioned in Fig 40,41.

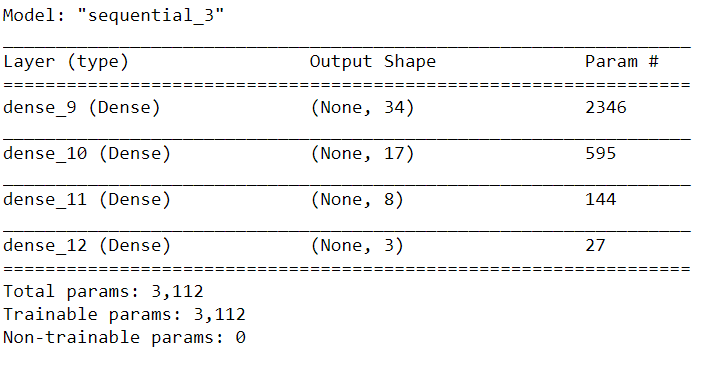
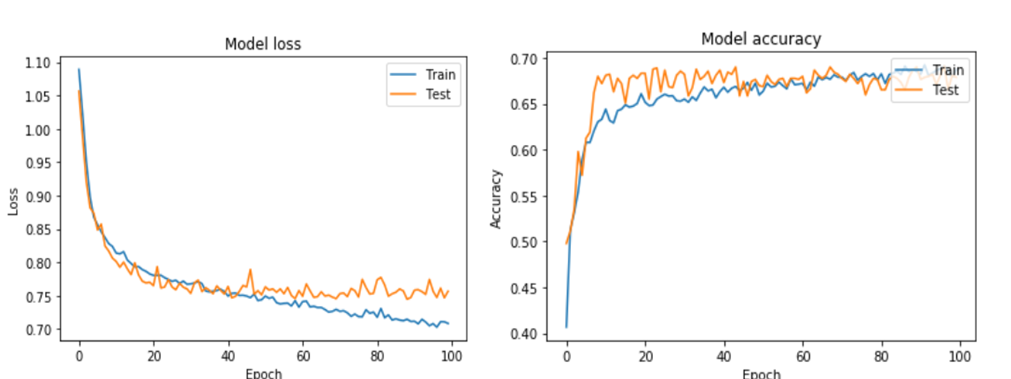


Fig28- Model summary of ANN



1. (b)

Fig29- Loss and accuracy of train and test data

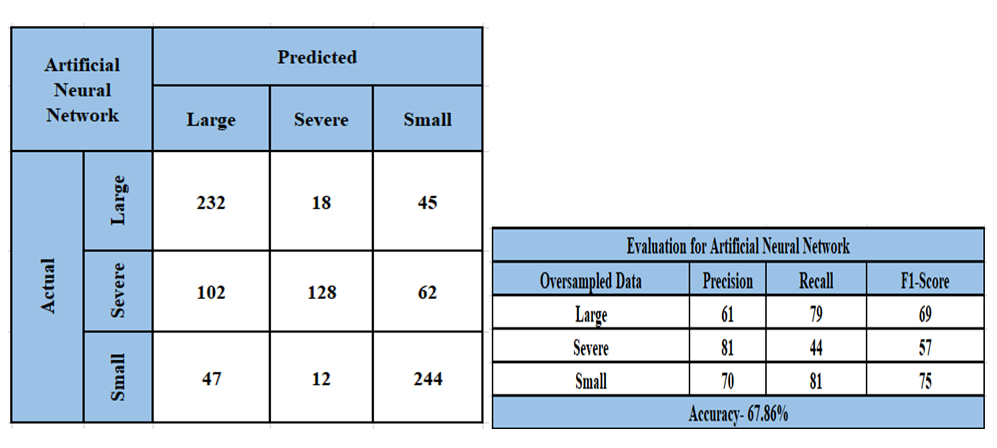


Fig 30- Confusion matrix and Evaluation of ANN

## Long-Short Term Memory

Long-Shot Term Memory(LSTM) is a special kind of RNN that are naturally suited to sequential data using some hidden units where the output depends on the previous computations. In this case, the weather details of each day(total 5 days) create a sequence to classify the severity of the fire. Therefore, the maximum number of time steps in this research is five. In each time steps, 12 features were given as input sequentially. A 3-Dimensional array (-1,5,12) has been created to feed the same into an LSTM.

**Evaluation:**

The model summary has been shown in Fig31. Like ANN, Keras has been implemented, with a LSTM layer and two dense layers with 4 and 3neurons. The model is compiled with ‘adam’ optimizer and accuracy as the evaluation metrics and the number of epochs as 1000. The loss function(shown in 32(a)) and the accuracy curve(shown in 32(b)) remains constant after 400epochs. The Confusion Matrix and evaluation parameter have been shown in Fig33.

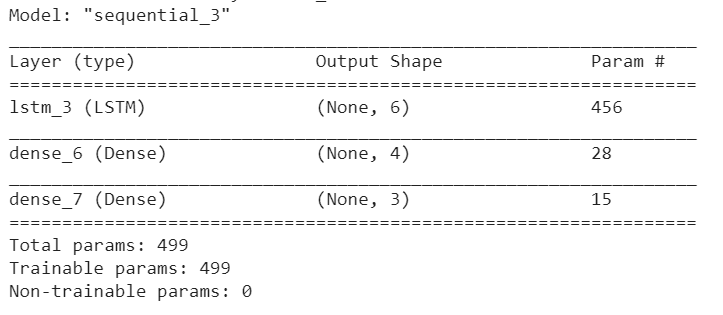
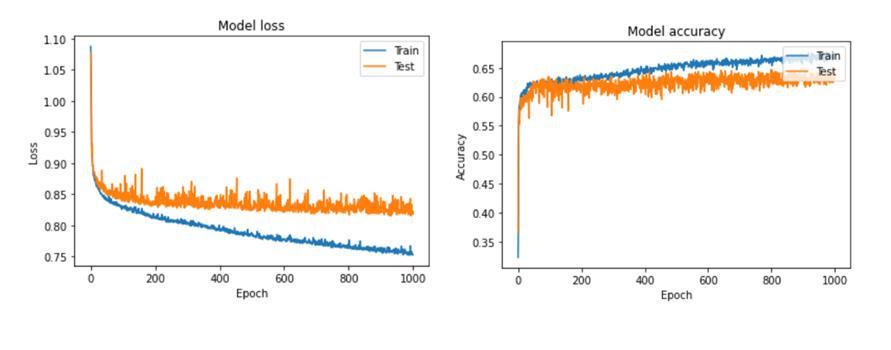


Fig31- Summary of LSTM Layers



1. (b)

Fig32- Loss and accuracy curve for LSTM

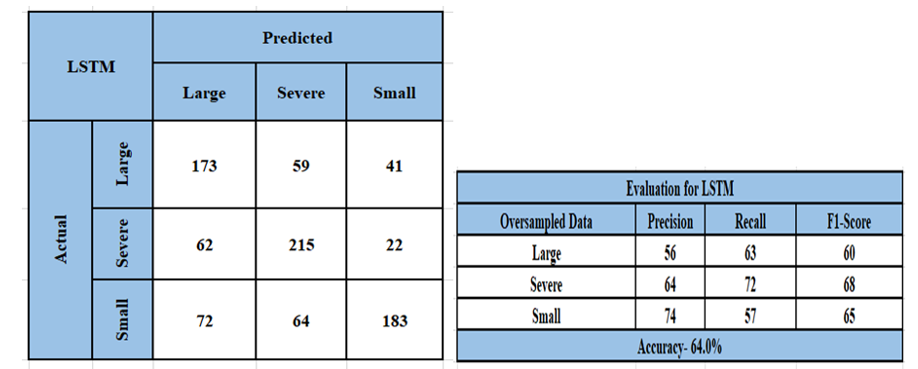


Fig 33- Confusion matrix and Evaluation of LSTM

Fig33. Confusion matrix and Evaluation of LSTM

# Evaluation Comparison

Since the dataset is made balanced with the help of SMOTE-oversampling, accuracy can be used for model evaluation. Comparing all the developed models, in the previous section in terms of accuracy, it is observed that ANN with only 4layers and 100epochs works best in comparison to all other developed models. Even the sequence of inputs over the last 5days of fire incident did not produce better results than ANN. The same can be shown in the form of a graph in Fig34. The precision value of severe fires is 81%, which means, out of fires classified as ‘severe’, 81% of them were actually ‘severe’. Similarly, the precision of small fires is 70%, which means out of the fires classified as ‘small’, 70% of them are actually ‘small’. Likewise, precision of ‘large’ fires is 61%, which means out of the fires classified as ‘Large’, 61% of them are actually large. On the other hand, recall value of ‘Large’ fires is 79, which means out of the fires that are actually large, 79% of them are classified as ‘Large’. Similarly, recall of ‘small’ and ‘severe’ fires is 44 and 81% which means, out of fires that are actually small and severe, 44 and 81% of them are classified as small and severe respectively. F1 score is a harmonic mean of precision and recall, which means it treats both precision and recall equally important. F1 score of Large, Severe, and Small fires are 69, 57, 75% respectively.

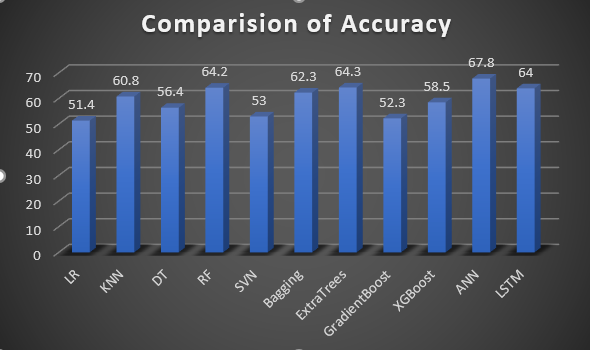


Fig34- Comparison of developed models

# Discussion

Collecting weather data through web-scrap can become a tedious task because few of the weather parameters were missing in the website and had to be handled correctly. Web scraping around 3500 records took around 6-7hrs of execution time. And the same cycle was repeated five times to collect data for five days. Enough sleep time was introduced, to avoid multiple hits within a small interval of time. Python files were executed in a virtual system made in the AWS cloud platform.

Once the data is collected, all the datasets were merged with the date as the key(similar to lookup is xls ). Popular packages in R and Python are explored to leverage the best use of them for implementation. For example, package in R such as mice for missing value imputation, Boruta for feature selection has been used, while for model implementation sklearn package in python has been used. For, visualization, python packages such as Plotly and Seaborn have been used, while EDA is performed on Tableau. For Neural Network and DL, Google Colab has been used to leverage the power of GPUs.

Various techniques for missing value imputation were tried, such as mean imputation, median imputation, and mice imputation. The later one has been implemented as it provides more meaningful information. During feature selection, a lot of advanced techniques were applied and tested on a multinomial logistic regression, to pick the best selection algorithm. A similar approach has been performed during feature reduction. SMOTE- oversampling helped not only to increase the number of observations but also to balance the data. Therefore, accuracy has been the primary focus while evaluating any model. Various tree-based and non-tree-based algorithms have been applied. It was ensured that data points are scaled between 0-1 before applying any non-tree-based algorithm. Out of all the applied algorithm, ANN proved to be best on accuracy. It also outperformed the sequential classification models like LSTM(shown in Fig34).

# Conclusion

The study started with understanding the relationship of fire with respect to local weather. But the hypothesis that was kept for this research was that the weather does not depend entirely on the day on which the fire takes place, instead it depends on the weather details of the previous few days. But the number of previous days that needs to be considered was unclear. Therefore, it was assumed that the weather details of the past five days, might help to predict the size of a forest fire. By considering the weather details of the past five days, and an accuracy of 67% has been achieved through ANN. Even fire classification on a sequence(with memory enabled) of weather inputs could not classify the fire spread better than ANN. The assumption for this research is that the weather of Alaska is the same all over the counties. It also assumed that if the fire incident has happened in a specific month, the past four days also falls in the same month. The preparedness levels of the firefighters also assumed to be the same on the day of the outbreak of fire and its previous four days.

As a part of future work, a sequence of weather details of the last 10-15days can be fed into a Recurring Neural Network and check if it performs better as compared to the last 4days data. In addition to the implementation of this research, a bi-directional LSTM or a GRU can be used to check if it outperforms the basic ANN. Other factors such as local population, topology, road connectivity, availability of water sources, type of soil, type of vegetation can be considered as input features.

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1. https://www.nwcg.gov/term/glossary/size-class-of-fire#:~:text=Class%20D%20%2D%20100%20acres%20or,G%20%2D%205%2C000%20acres%20or%20more. [↑](#footnote-ref-1)
2. <https://www.almanac.com/weather/history/AK> [↑](#footnote-ref-2)