CS 513 - B KNOWLEDGE DISCOVERY AND DATA MINING

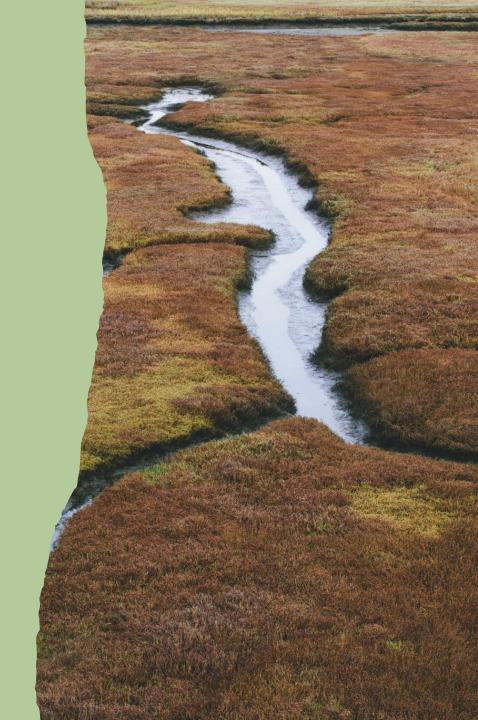
NEXT-DAY RAIN PREDICTION IN AUSTRALIA USING SEVERAL CLASSIFICATION MODELS





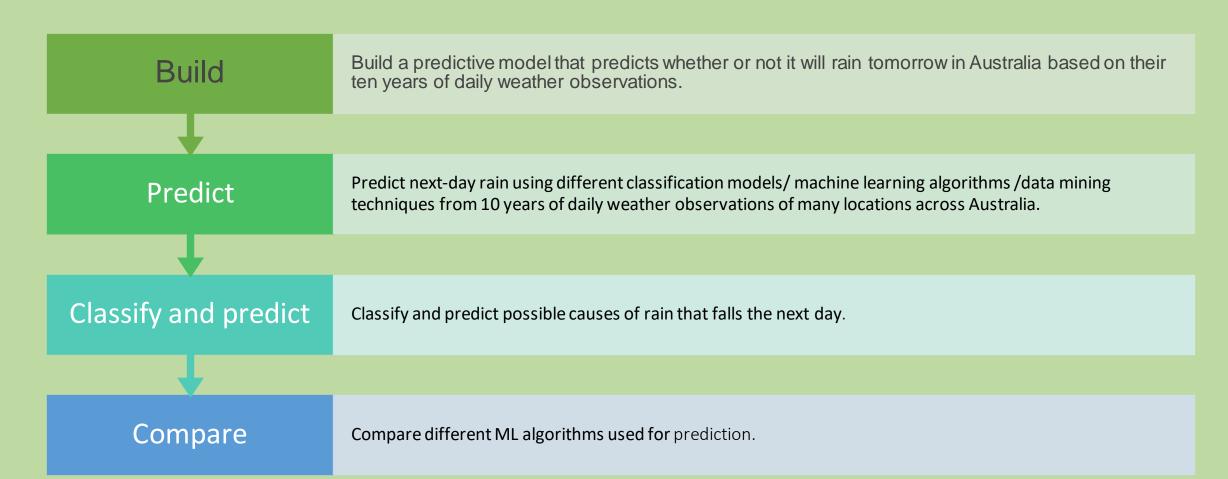
INTRODUCTION AND PROBLEM OVERVIEW

- Rain plays a vital role in our lives. Clouds are responsible for bringing rain to humans. In order to forecast when it will rain, the weather department tries to do some forecasting.
- Agriculture is a major industry in Australia, and rainfall plays a crucial role in determining crop yields. Accurate rainfall predictions can help farmers plan their planting and harvesting activities, and make decisions regarding irrigation and fertilization.
- Australia is the driest inhabited continent on earth; 70% of it is either arid or semi arid land, and water is a scarce resource. Predicting rainfall is essential for effective water management, including planning for water storage, allocation, and distribution.
- Heavy rainfall can cause flooding in many parts of Australia. Accurate predictions of rainfall can help emergency services and authorities prepare for and respond to potential floods.





OBJECTIVE AND GOAL



ABOUT THE DATASET

• This dataset contains about 10 years of daily weather observations from many locations across Australia.

| Dataset statistics | | Variable types | |
|-------------------------------|----------|----------------|----|
| Number of variables | 23 | Categorical | 5 |
| Number of observations | 145460 | Numeric | 16 |
| Missing cells | 343248 | Boolean | 2 |
| Missing cells (%) | 10.3% | | |
| Duplicate rows | 0 | | |
| Duplicate rows (%) | 0.0% | | |
| Total size in memory | 25.5 MiB | | |
| Average record size in memory | 184.0 B | | |
| | | | |

Data Source References:

https://www.kaggle.com/datasets/jsphyg/weather-dataset-rattle-package

DATA FIELDS

| Column Name | Types | Description |
|---------------|-------------|---|
| Date | Categorical | The date of observation |
| Location | Categorical | The common name of the location of the weather station |
| MinTemp | Numeric | The minimum temperature in degrees celsius |
| MaxTemp | Numeric | The maximum temperature in degrees celsius |
| Rainfall | Numeric | The amount of rainfall recorded for the day in mm |
| Evaporation | Numeric | The so-called Class A pan evaporation (mm) in the 24 hours to 9am |
| Sunshine | Numeric | The number of hours of bright sunshine in the day |
| WindGusDir | Categorical | The direction of the strongest wind gust in the 24 hours to midnight |
| WindGustSpeed | Categorical | The speed (km/h) of the strongest wind gust in the 24 hours to midnight |
| WindDir9am | Categorical | Direction of the wind at 9am |
| WindDir3pm | Categorical | Direction of the wind at 3pm |
| WindSpeed9am | Numeric | Wind speed (km/hr) averaged over 10 minutes prior to 9am |

| Column Name | Type | Description |
|---------------------|--------------------|--|
| WindSpeed3pm | Numeric | Wind speed (km/hr) averaged over 10 minutes prior to 3pm |
| Humidity9am | Numeric | Humidity (percent) at 9am |
| Humidity3pm | Numeric | Humidity (percent) at 3pm |
| Pressure9am | Numeric | Atmospheric pressure (hpa) reduced to mean sea level at 9am |
| Cloud9am | Numeric | Fraction of sky obscured by cloud at 9am. This is measured in "oktas", which are a unit of eigths. It records how many |
| Cloud3pm | Numeric | Fraction of sky obscured by cloud (in "oktas": eighths) at 3pm. See Cload9am for a description of the values |
| Temp9am | Numeric | Temperature (degrees C) at 9am |
| Temp3pm | Numeric | Temperature (degrees C) at 3pm |
| RainToday | Boolean | Boolean: 1 if precipitation (mm) in the 24 hours to 9am exceeds 1mm, otherwise O |
| RainTomorrow | Boolean | The amount of next day rain in mm. Used to create response variable RainTomorrow. A kind of measure of the "risk". |
| RainTomorrow: It is | the taraet variabl | e to predict next-day rain |

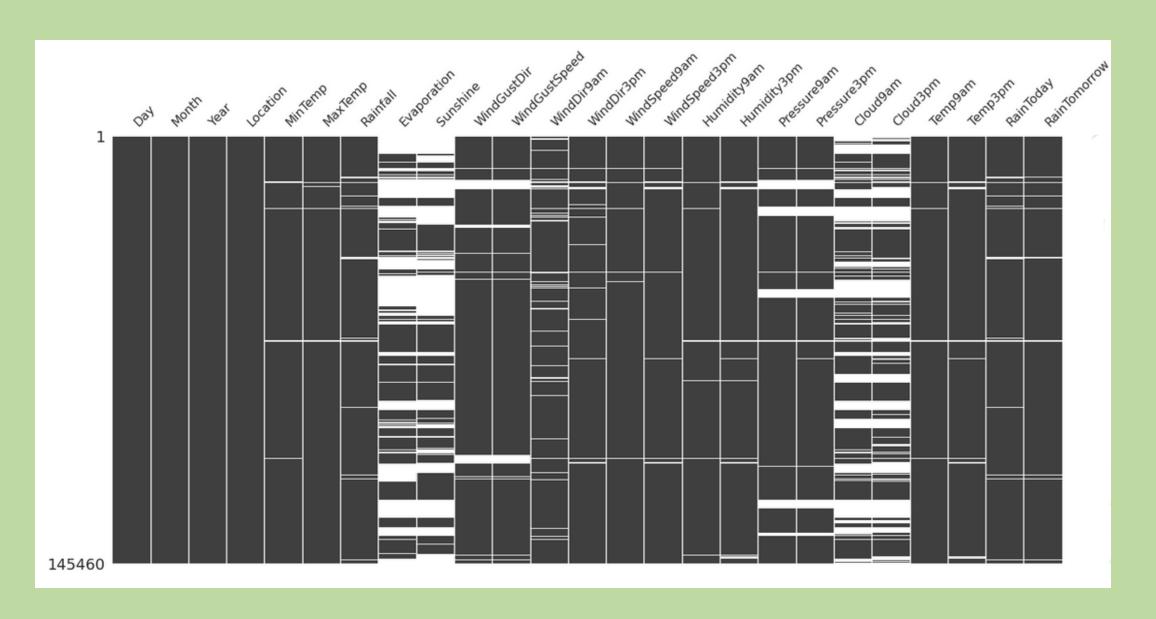
RainTomorrow: It is the target variable to predict next-day rain

ORIGINAL DATASET

| | Date | Location | MinTemp | MaxTemp | Rainfall | Evaporation | Sunshine | WindGustDir | WindGustSpeed | WindDir9am | WindDir3pm | WindSpeed9am |
|---|------------|----------|---------|---------|----------|-------------|----------|-------------|---------------|------------|------------|--------------|
| 0 | 2008-12-01 | Albury | 13.4 | 22.9 | 0.6 | NaN | NaN | W | 44.0 | W | WNW | 20.0 |
| 1 | 2008-12-02 | Albury | 7.4 | 25.1 | 0.0 | NaN | NaN | WNW | 44.0 | NNW | WSW | 4.0 |
| 2 | 2008-12-03 | Albury | 12.9 | 25.7 | 0.0 | NaN | NaN | WSW | 46.0 | W | WSW | 19.0 |
| 3 | 2008-12-04 | Albury | 9.2 | 28.0 | 0.0 | NaN | NaN | NE | 24.0 | SE | E | 11.0 |
| 4 | 2008-12-05 | Albury | 17.5 | 32.3 | 1.0 | NaN | NaN | W | 41.0 | ENE | NW | 7.0 |
| 5 | 2008-12-06 | Albury | 14.6 | 29.7 | 0.2 | NaN | NaN | WNW | 56.0 | W | W | 19.0 |
| 6 | 2008-12-07 | Albury | 14.3 | 25.0 | 0.0 | NaN | NaN | W | 50.0 | SW | W | 20.0 |
| 7 | 2008-12-08 | Albury | 7.7 | 26.7 | 0.0 | NaN | NaN | W | 35.0 | SSE | W | 6.0 |
| 8 | 2008-12-09 | Albury | 9.7 | 31.9 | 0.0 | NaN | NaN | NNW | 80.0 | SE | NW | 7.0 |
| 9 | 2008-12-10 | Albury | 13.1 | 30.1 | 1.4 | NaN | NaN | W | 28.0 | S | SSE | 15.0 |

| WindSpeed3pm | Humidity9am | Humidity3pm | Pressure9am | Pressure3pm | Cloud9am | Cloud3pm | Temp9am | Temp3pm | RainToday | RainTomorrow |
|--------------|-------------|-------------|-------------|-------------|----------|----------|---------|---------|-----------|--------------|
| 24.0 | 71.0 | 22.0 | 1007.7 | 1007.1 | 8.0 | NaN | 16.9 | 21.8 | No | No |
| 22.0 | 44.0 | 25.0 | 1010.6 | 1007.8 | NaN | NaN | 17.2 | 24.3 | No | No |
| 26.0 | 38.0 | 30.0 | 1007.6 | 1008.7 | NaN | 2.0 | 21.0 | 23.2 | No | No |
| 9.0 | 45.0 | 16.0 | 1017.6 | 1012.8 | NaN | NaN | 18.1 | 26.5 | No | No |
| 20.0 | 82.0 | 33.0 | 1010.8 | 1006.0 | 7.0 | 8.0 | 17.8 | 29.7 | No | No |
| 24.0 | 55.0 | 23.0 | 1009.2 | 1005.4 | NaN | NaN | 20.6 | 28.9 | No | No |
| 24.0 | 49.0 | 19.0 | 1009.6 | 1008.2 | 1.0 | NaN | 18.1 | 24.6 | No | No |
| 17.0 | 48.0 | 19.0 | 1013.4 | 1010.1 | NaN | NaN | 16.3 | 25.5 | No | No |
| 28.0 | 42.0 | 9.0 | 1008.9 | 1003.6 | NaN | NaN | 18.3 | 30.2 | No | Yes |
| 11.0 | 58.0 | 27.0 | 1007.0 | 1005.7 | NaN | NaN | 20.1 | 28.2 | Yes | No |

MISSING VALUES

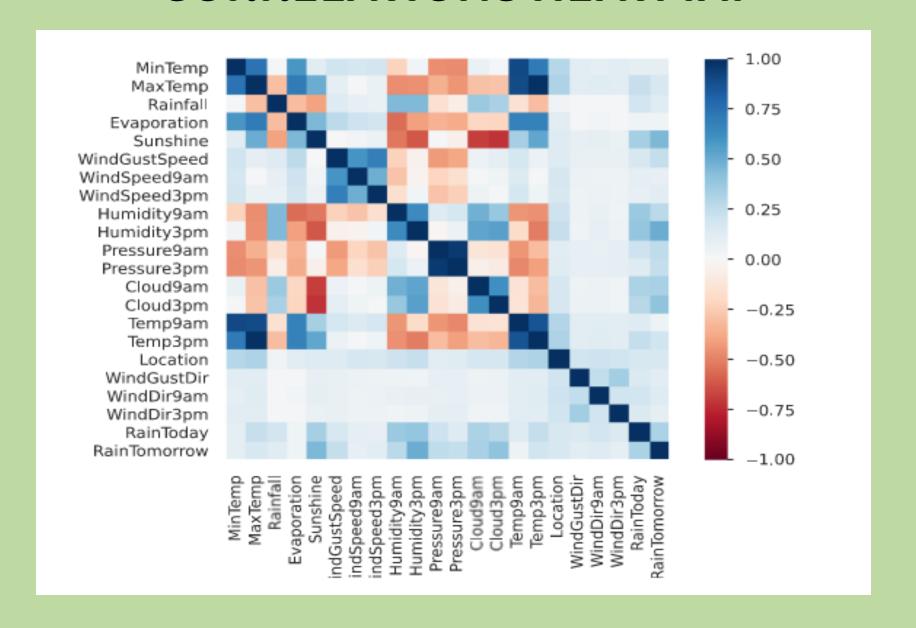


SKEWNESS

| Day | 0.009040 |
|---------------|-----------|
| Day | |
| Month | 0.030343 |
| Year | -0.049357 |
| MinTemp | 0.022230 |
| MaxTemp | 0.224055 |
| Rainfall | 9.940909 |
| Evaporation | 5.177252 |
| Sunshine | -1.070901 |
| WindGustSpeed | 0.923588 |
| WindSpeed9am | 0.786472 |
| WindSpeed3pm | 0.632461 |
| Humidity9am | -0.491644 |
| Humidity3pm | 0.032054 |
| Pressure9am | -0.098584 |
| Pressure3pm | -0.045578 |
| Cloud9am | -0.560375 |
| Cloud3pm | -0.568990 |
| Temp9am | 0.090721 |
| Temp3pm | 0.247228 |

- Rainfall and Evaporation are highly positively skewed
- Sunshine is highly negatively skewed

CORRELATIONS HEATMAP



PREPROCESSING

- The feature MaxTemp has been removed from the training and testing datasets due to its high correlation with Temp3pm, Temp9am, and MinTemp.
- New features for Year, Month, and Day have been included by extracting their values from the original Date column. As a result, the Date feature has been removed from both the training and testing datasets.
- Reciprocal transformation was performed on Rainfall and square root transformation was performed on Evaporation because they were highly positively skewed. Additionally, the square of Sunshine was taken because it was highly negatively skewed.
- The values of No and Yes in the RainToday and RainTomorrow columns were substituted with O and 1 respectively.

PREPROCESSING

- The missing values in categorical features
 (WindGustDir, WindDir9am, WindDir3pm, RainToday and RainTomorrow)
 were filled by replacing them with the mode value of the corresponding
 feature.
- The missing values in numerical features were filled by replacing them with the median value of the corresponding feature
- Target encoding was utilized for the purpose of converting categorical variables of categorical features into numerical variables.
- MinMaxScaler was used to normalize features in the dataset.
- To address the bais in the training dataset, we utilized the SMOTETomek technique.

MODEL BUILDING

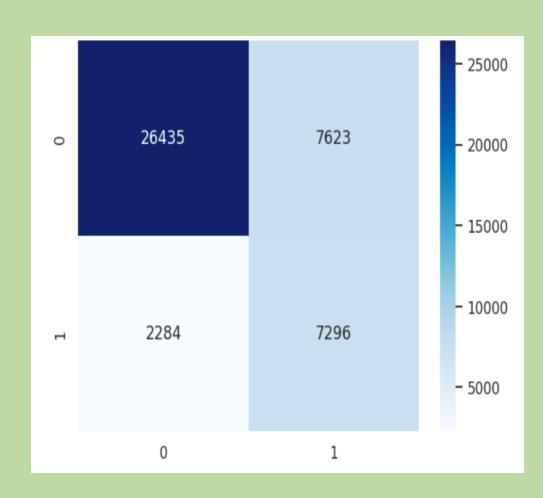
- The features ['Day', 'Month', 'Year', 'Location', 'MinTemp', 'Rainfall', 'Evaporation', 'Sunshine', 'WindGustDir', 'WindGustSpeed', 'WindDir9am', 'WindDir3pm', 'WindSpeed9am', 'WindSpeed3pm', 'Humidity9am', 'Humidity3pm', 'Pressure9am', 'Pressure3pm', 'Cloud9am', 'Cloud3pm', 'Temp9am', 'Temp3pm', 'RainToday'] were used for training the model.
- ['RainTomorrow'] is the feature that we aim to predict.
- The normalized and imputed data was divided into training and testing datasets in an 80:20 ratio.
- To validate the model against the validation dataset, we employed k-fold cross validation.

CLASSIFICATION ALGORITHMS/MODELS

- LOGISTIC REGRESSION
- NAIVE BAYES
- DECISION TREE
- RANDOM FOREST
- KNEIGHBORS
- EXTREME GRADIENT BOOST
- SUPPORT VECTOR CLASSIFIER

LOGISTIC REGRESSION

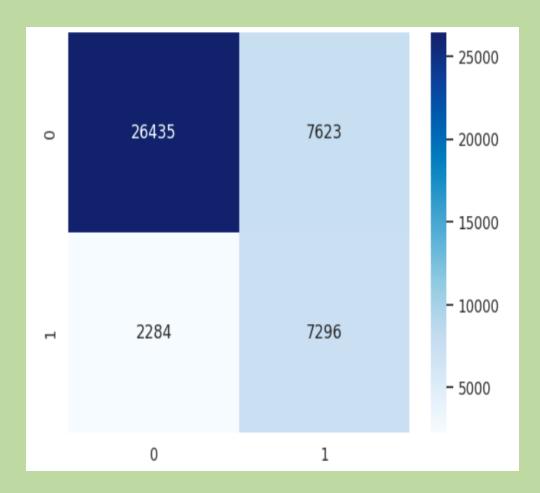
| | Accuracy of Logistic Regression: 77.29730968422017 | | | | | | | | |
|----|--|--------------|--------------|------------|-------------------------|------------|--|--|--|
| | | precision | recall | f1-score | support | | | | |
| | 0 1 | 0.92 0.49 | 0.78 0.76 | | 34058 9580 | | | | |
| | accuracy macro avg weighted avg | 0.70 0.83 | | | 43638 43638 43638 | | | | |
| [] | scorel=cross print(f"Afte | _ | _ | - | | .mean()}") | | | |
| | After k-fold | cross valida | ation scor | e is 0.839 | 19987004291 | 177 | | | |



Confusion Matrix

NAIVE BAYES

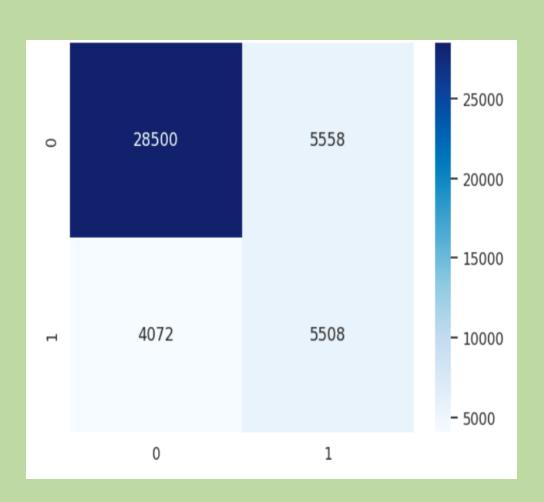
| Accuracy of | Naive Bayes m | odel: 73. | 87368807003 | 3071 | |
|---------------------------------------|----------------------------------|--------------|----------------------|---------------|-----------|
| | precision | recall | f1-score | support | |
| | 0.92 0.45 | | | 34058 9580 | |
| accuracy macro ave weighted ave | g 0.68 | 0.75 0.74 | 0.74 0.69 0.76 | 43638 | |
| | s_val_score(nb er k-fold cros | _ | _ | | mean()}") |
| After k-fol | d cross valida | tion scor | e is 0.7823 | 345416512868 | 37 |



Confusion Matrix

DECISION TREE

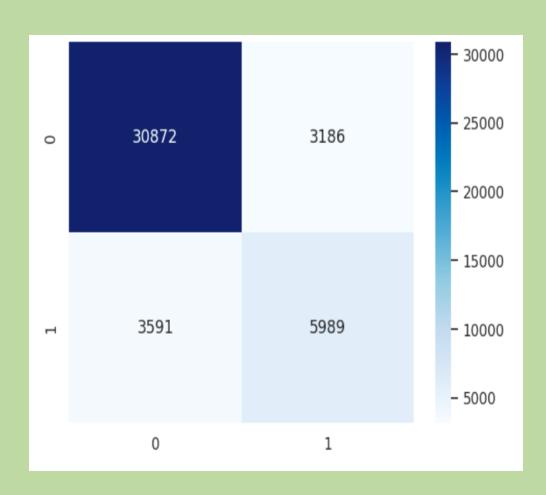
| Accuracy of De | Accuracy of DecisionTreeClassifier: 77.93207754709198 | | | | | | | |
|---------------------------------------|---|--------------|-------------|---------------|-----------|--|--|--|
| | precision | recall | f1-score | support | | | | |
| 0 1 | 0.87 0.50 | 0.84 0.57 | | 34058 9580 | | | | |
| accuracy macro avg weighted avg | 0.69 0.79 | 0.71 0.78 | | | | | | |
| [] score6=cross_v print(f"After | | _ | | | mean()}") | | | |
| After k-fold c | ross valida | tion scor | e is 0.7829 | 8712424892 | 86 | | | |



Confusion Matrix

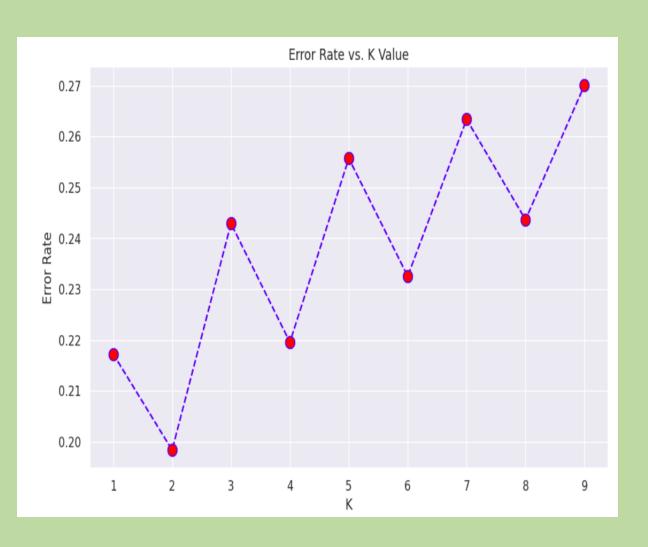
RANDOM FOREST

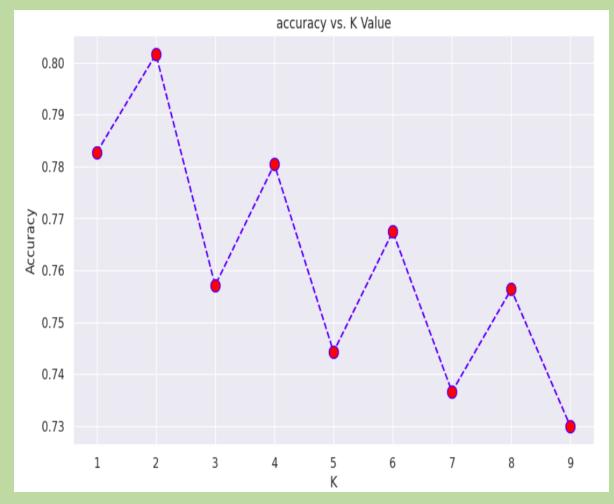
| | Accuracy | of Rando | m Forest: | 84.4699 | 5737659839 | | |
|-----|----------------------------|----------|--------------|--------------|----------------------------|---------------|------------|
| | | pre | cision | recall | f1-score | support | |
| | | 0 1 | 0.90 0.65 | 0.91 0.63 | 0.90 0.64 | 34058 9580 | |
| | accur macro weighted | avg | 0.77 0.84 | 0.77 0.84 | 0.84 0.77 0.84 | | |
| [] | | | | _ | y_valid,cv= ion score i | | .mean()}") |
| | After k-f | old cros | s validat | ion scor | e is 0.8513 | 34504844819 | 936 |



Confusion Matrix

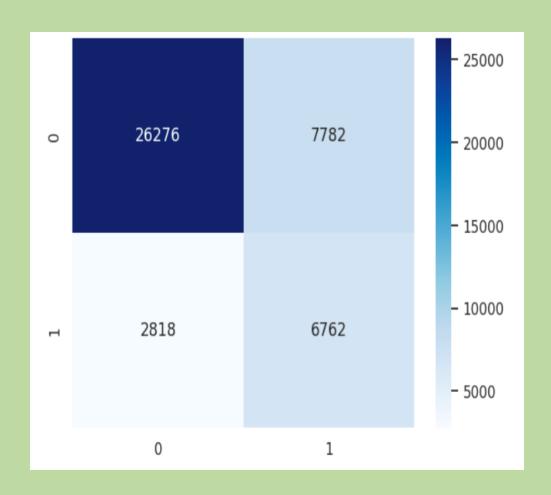
KNEIGHBORS





KNEIGHBORS

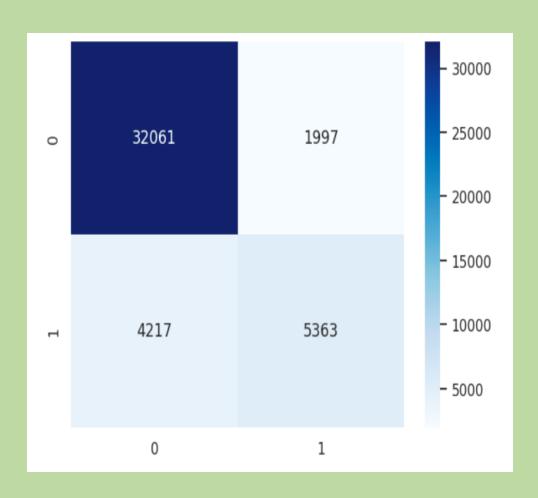
| Accuracy of | Accuracy of K-NeighborsClassifier: 75.70924423667445 | | | | | | | | |
|---------------------------------------|--|--------------|----------------------|-------------------------|-----------|--|--|--|--|
| | precision | recall | f1-score | support | | | | | |
| 0 1 | | 0.77 0.71 | 0.83 0.56 | 34058 9580 | | | | | |
| accuracy macro avg weighted avg | 0.68 | 0.74 0.76 | 0.76 0.70 0.77 | 43638 43638 43638 | | | | | |
| | s_val_score(kn er k-fold cros | _ | | * | mean()}") | | | | |
| After k-fold | cross valida | tion scor | e is 0.7968 | 30528475327 | 8 | | | | |



Confusion Matrix

EXTREME GRADIENT BOOST

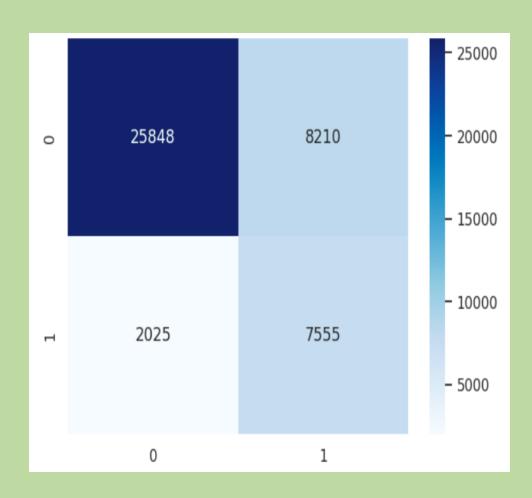
| | Accuracy of E | Accuracy of Extreme Gradient Boost: 85.76011732893349 | | | | | | | | |
|----|---------------------------------------|---|--------------|-------------|---------------|---------------------------|--|--|--|--|
| | | precision | recall | f1-score | support | | | | | |
| | 0 1 | 0.88 0.73 | 0.94 0.56 | | 34058 9580 | | | | | |
| | accuracy macro avg weighted avg | 0.81 0.85 | 0.75 0.86 | | | | | | | |
| [] | score4=cross_ print(f"After | _ | _ | _ | | .mean()} <mark>"</mark>) | | | | |
| | After k-fold | cross valida | tion scor | e is 0.8520 | 57423566181 | .16 | | | | |



Confusion Matrix

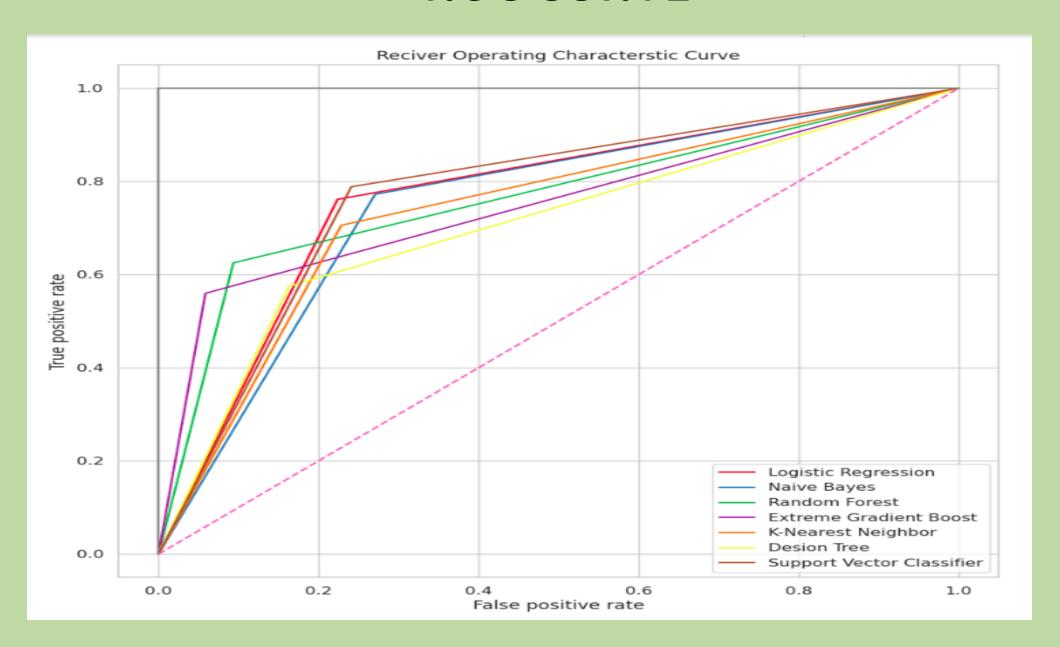
SUPPORT VECTOR CLASSIFIER

| Accuracy of Support Vector Classifier: 76.5456712039965 | | | | | |
|---|--------------|--------------|--------------|---------------|--|
| р | recision | recall | f1-score | support | |
| 0 1 | 0.93 0.48 | 0.76 0.79 | 0.83 0.60 | 34058 9580 | |
| accuracy macro avg weighted avg | 0.70 0.83 | 0.77 0.77 | | | |
| <pre>[] score7=cross_val_score(svc,X_valid,y_valid,cv=10) print(f"After k-fold cross validation score is {score7.mean()}")</pre> | | | | | |
| After k-fold cross validation score is 0.8399560885397224 | | | | | |

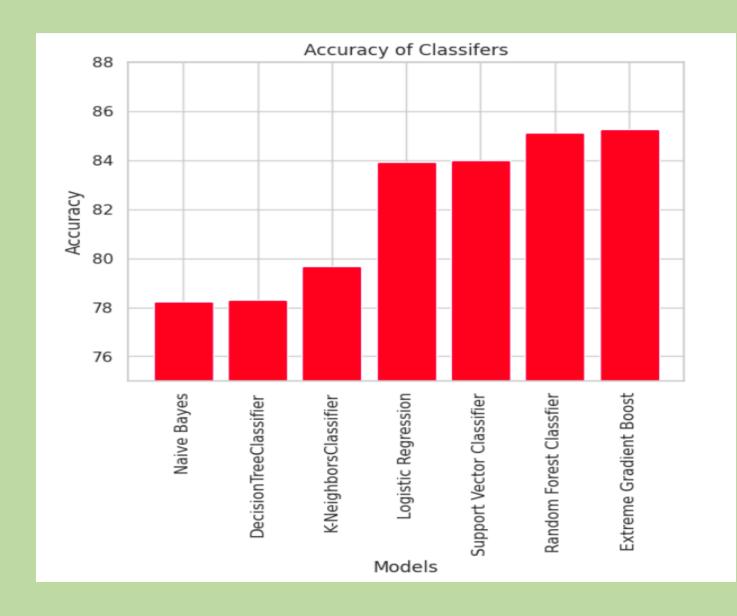


Confusion Matrix

ROC CURVE



ACCURACY COMPARISON

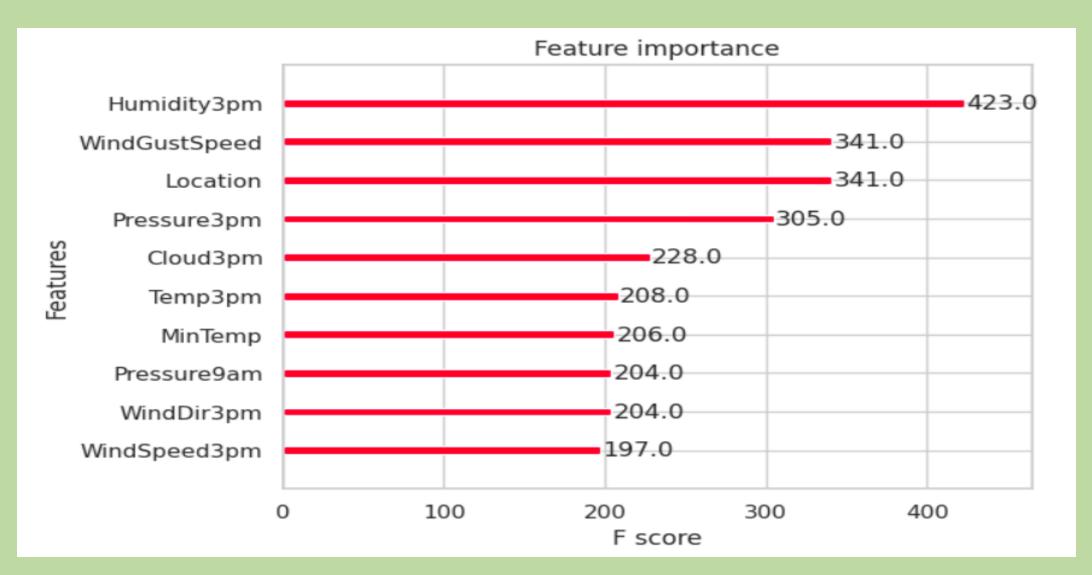


As we can see,

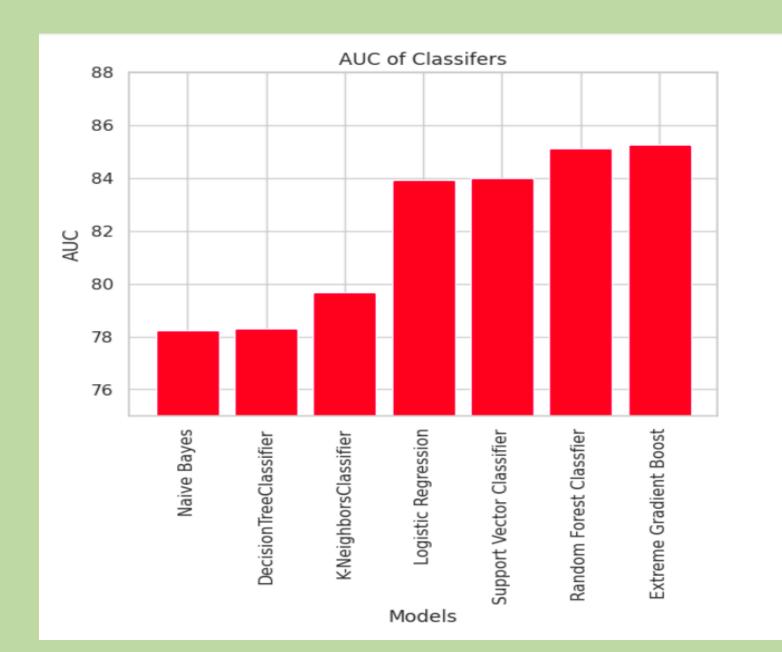
Extreme Gradient Boost

algorithm has highest
accuracy for this dataset.

IMPORTANT FEATURES OF EXTREME GRADIENT BOOST CLASSIFIER



AUC COMPARISON



As we can see,

Extreme Gradient Boost

algorithm has most AUC

for this dataset.

