Annexure – I

Term Paper

Rainfall Prediction Report Using Machine Learning

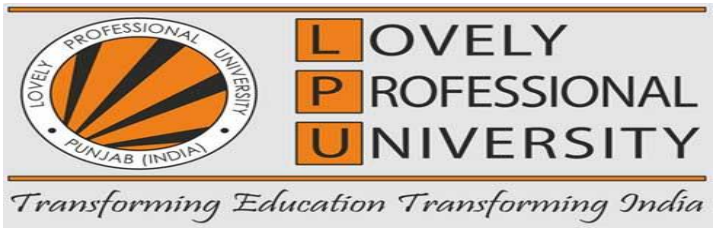
A Term Paper Report

Submitted in partial fulfillment of the requirements for the award of degree of

Bachelor of Technology

(Computer Science Engineering)

Submitted to



LOVELY PROFESSIONAL UNIVERSITY

PHAGWARA, PUNJAB

From 1st Aug 2024 to 25th Oct 2024

SUBMITTED BY

Name of Student: Sonal Kumari

Registration Number: 12107709

Faculty: Sajjad Manzoor Mir

Annexure – II

Student Declaration

To whom so ever it may concern

I, Sonal Kumari, 12107709, hereby declare that the work done by me on “Rainfall Prediction using Machine Learning” from Aug 2024 to Oct 2024, is a record of original work for the partial fulfillment of the requirements for the award of the degree, Bachelor of Technology.

Name of Student: Sonal Kumari

Registration Number: 12107709

Dated: 25th Oct 2024

ACKNOWLEDGEMENT

"GOD HELPS THOSE WHO HELP THEMSELVES." "ARISE! AWAKE! AND STOP NOT UNTIL THE GOAL IS REACHED."

Success often requires preparation, hard work, and perspiration. The path to success is a long journey that calls for tremendous effort with many bitter and sweet experiences. This can only be achieved by the Graceful Blessing from the Almighty on everybody. I want to submit everything beneath the feet of God.

I want to acknowledge my regards to my teacher, Mr. Sajjad Manzoor Mir, for his constant support and guidance throughout my training. I would also like to thank HOD Ms. Harjeet Kaur, School of Computer Science and Engineering for introducing such a great program.

To my friends, whose companionship has been a source of joy, laughter, and strength: your camaraderie has been a constant source of inspiration. Thank you for being my pillars of support through thick and thin.

To my parents, the foundation of my world, whose unconditional love, sacrifices, and unwavering belief in me have been my driving force: thank you for being my greatest advocates and for instilling in me the values that shape who I am today.

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ABSTRACT

The technique is a rainfall occurrence prediction approach via meteorological data and machine learning. Accurate rainfall prediction is important for areas such as agriculture, water resource management, and disaster prevention. Therefore, this step is a part of building up the process towards developing a forecasting model that helps predict the occurrence of rainfall by considering some of the weather features, including temperature, humidity, wind speed, and cloud cover. The present study has compared the performance of three machine learning algorithms: Logistic Regression, Support Vector Machines (SVM), and XGBoost. Data pre-processing followed class imbalances through over-sampling techniques and the normalization of data to optimize the training process for the models. Evaluation metrics used include ROC-AUC, cross-validation, and other statistical analyses to measure the predictive accuracy of each model. The project ends with a Gradio application that is used for friendly deployment - permitting interactive input and real-time prediction results. This will show the efficiency of machine learning approaches in meteorological forecasting and also allow one to explore, among other aspects, which model choice and data preprocessing can impact the performance of predictions.

OBJECTIVE

The most important goal of this project is to predict when it will possibly rain using meteorological data and various machine learning algorithms. Through the analysis of weather-related variables like temperature, humidity, dew point, wind speed, and cloud cover, this project aims to create a predictive model for predicting whether it will or will not rain with sufficient accuracy. Models considered include Logistic Regression, SVM, and XGBoost; improvement through preprocessing and class balance handling leading to better prediction accuracy with model tuning. Eventually, it should be an interactive tool deployable for rainfall prediction.

INTRODUCTION

Accurate weather prediction, particularly rainfall forecasting is quite essential in sectors such as agriculture, the management of disasters, and resource planning. It impacts the yield of crops, water resource management, and even the day to day human activities. However, through the complexity of atmospheric conditions and the multiplicity of variables involved, rainfall prediction remains one of the most challenging tasks in meteorology. Traditional methodology, for example, statistical analysis using historical data is not able to gain the accurate relation between rainfall and metrological factors. Thus, advanced techniques are always in demand to interpret the close relation between meteorological factors and rainfall.

1. **Background:**

   There are vast numbers of factors that control the rainfall along with the parameters, namely temperature, pressure, humidity, cloud cover, wind direction, and dew point, etc. Each of these variables interacts in quite complex ways; therefore, understanding how they interplay is itself of great importance for correct predictions. Tradition insisted on systems based on rules or statistical methods, heavily relying on the historical linearity of events. But such atmospheric processes are very non-linear and dynamic; hence traditional techniques are not very effective to correctly forecast the rainfall in this context.

   With this advancement in the application of more advanced computer methods in conjunction with large datasets, data-driven approaches have come to prevail, especially as applied to machine learning techniques. This kind of methods capture nonscaling relationships between variables, learn from huge amounts of data, and assume and adapt to evolving patterns in weather behavior, thus more applicable in complicated tasks of prediction, such as rainfall forecasting.

2. **Existing Challenges and Causes:**

   Despite the various gains made in meteorological science, quite surprisingly, the accurate prediction of rainfall is challenged to date. The challenge is due to various causes:

   - Atmospheric conditions: Several variables have an effect on raining conditions simultaneously, and tiny alterations in one might cause a significant difference in the amount of rainfall predicted.
   - Non-linear relation: The variables of weather and those of rainfall are bound to be non-linear, which further makes it

difficult to capture such type of dynamics in traditional models.

- Data quality and availability: Resolution of the meteorological data in the areas also poses a much challenge where the regions are rural or remote.
- Out-of-balance in the occurrence of rainfall: Most datasets have a considerable shortage of rainy days to dry days, making it more complicated to train and evaluate the model.

3. The need for machine learning in Rainfall prediction:

Meteorology is one of the areas where powerful solutions for very complex problems have been delivered through machine learning. This tool has enormous capabilities in identifying patterns in data and making predictions based on historical information. It further generalizes these predictions for future data, which is so suitable for weather forecasting, particularly rainfall.

The major advantages in the use of machine learning for rainfall forecasting are as follows:

- Non-linear relationships: Some of these include machine learning algorithms such as Logistic Regression, Support Vector Machines SVM and XGBoost, which may be able to learn the non-linear associations of weather variables that contribute to rainfall.
- Accuracy is improved: When compared to traditional statistical techniques, machine learning algorithms produce far more accurate predictions with the availability of larger amounts of data and using advanced techniques such as class imbalance in over-sampling and hyperparameter tuning.

- Scalability: This is because machine learning models can be easily retrained and updated with new data; hence, it is easy to adapt to changing weather patterns over time.
- Automation and Efficiency: As soon as the machine learning model is developed, it can readily automate the rainfall forecasting process for anyone, thereby releasing real-time predictions with virtually no human intervention.

THEORETICAL BACKGROUND

Rainfall prediction essentially involves the investigation and interpretation of data coming from the atmosphere wherein variables like temperature, humidity, and pressure are also relevant. The applications of machine learning models that capture intricate patterns and relationships exist are leveraged on complex variables towards achieving better accuracy in the rainfall prediction process. This section outlines the theoretical underpinnings of algorithms that have been used in this project. This section also includes strategies used to improve the performance of a model.

1. Logistic Regression:

Logistic regression is one of the most often used statistical models that appears with the binary classification problem, e.g. whether it rains or does not. As this model does not produce continuous output, logistic regression uses the sigmoid function to convert the output to the odds in the range between 0 and 1. Such a model performs estimation for the possibility of some input given its features for the "yes" or "no" category.

For rainfall prediction, logistic regression predicts the probability that specific atmospheric conditions will lead to rainfall. A threshold (often set at 0.5) determines the final binary classification:

$$P(y=1|X) = 1/(1+e^{-(\beta 0+\beta 1X1+\beta 2X2+\ldots+\beta nXn)})$$

where X represents the feature vector (pressure, temperature, humidity, etc.) and β are the model coefficients.

2. **Support Vector Machine (SVM):**
   The **Support Vector Machine (SVM)** algorithm is a supervised learning model used for classification. SVM aims to find the optimal **hyperplane** that maximally separates data points of different classes. For binary classification, this translates to finding the line or plane that best differentiates days with rainfall from those without, based on the features.

   The SVM algorithm utilizes a **kernel function** to transform the input data, enabling it to handle non-linear relationships:
   - **Linear kernel**: Suitable for linearly separable data.
   - **Radial Basis Function (RBF) kernel**: Captures more complex relationships by mapping data into a higher-dimensional space.

   In this project, the SVM model with an RBF kernel was chosen due to its ability to capture the non-linear patterns commonly present in meteorological data.

3. **XGBoost (Extreme Gradient Boosting):**
   This is an advanced implementation of the Gradient Boosting algorithm that enhances predictive accuracy and reduces processing overhead. It achieves this by creating a set of decision trees, where one tree could correct the errors of the preceding tree. This results

in a reduction of the overall error in prediction because of the incremental learning nature of this approach. It has been particularly very powerful on structured data where an element has multiple attributes and there is a good deal of complex relationships: for example, meteorological data.

➢ Main features of XGBoost:

- Regularization: This helps prevent overfitting by penalizing a complex model.
- Handling missing values XGBoost automatically handles missing values which can often be very useful in real-world datasets.
- Design for parallel processing: XGBoost can perform computations much faster on large data.

4. Model Evaluation Metrics:

For binary classification tasks like rainfall prediction, evaluating model performance is critical to ensure reliability. Commonly used metrics include:

- Accuracy: The proportion of correct predictions over the total number of predictions.
- Precision and Recall: Precision measures the proportion of true positive predictions among all positive predictions, while recall assesses the model's ability to identify all positive instances (rainfall days).
- AUC-ROC Score: The Area Under the Receiver Operating Characteristic curve is an essential metric for imbalanced datasets. It shows the trade-off between true positive and false positive rates across different thresholds.

5. **Cross-Validation and Hyperparameter Tuning:**
   This guarantees model robustness using k-fold cross-validation, whereby k subsets of the dataset split the method. It involves using one subset as the test set and the rest as training sets. This is repeated k times and average results are considered so as to avoid bias and variance in model performance.

   The other type of hyperparameter tuning refers to the choice of the best parameters for improving the model's predictive power, which in many cases encompasses Grid Search and Randomized Search among other methods. Model parameter options include the type of SVM kernel, regularisation parameter C) Logistic Regression: regularization parameter, XGBoost: learning rate, max depth, number of estimators were the hyperparameters fine-tuned in this project.

6. **Handling Class Imbalance:**
   Class imbalance, where one class (e.g., “rainy” days) is underrepresented, is common in rainfall datasets. This imbalance can lead models to favor the majority class (no-rain days). Random OverSampling was applied to duplicate samples from the minority class, thereby balancing the class distribution. This approach improves the model’s ability to correctly identify days with rainfall.

HARDWARE & SOFTWARE

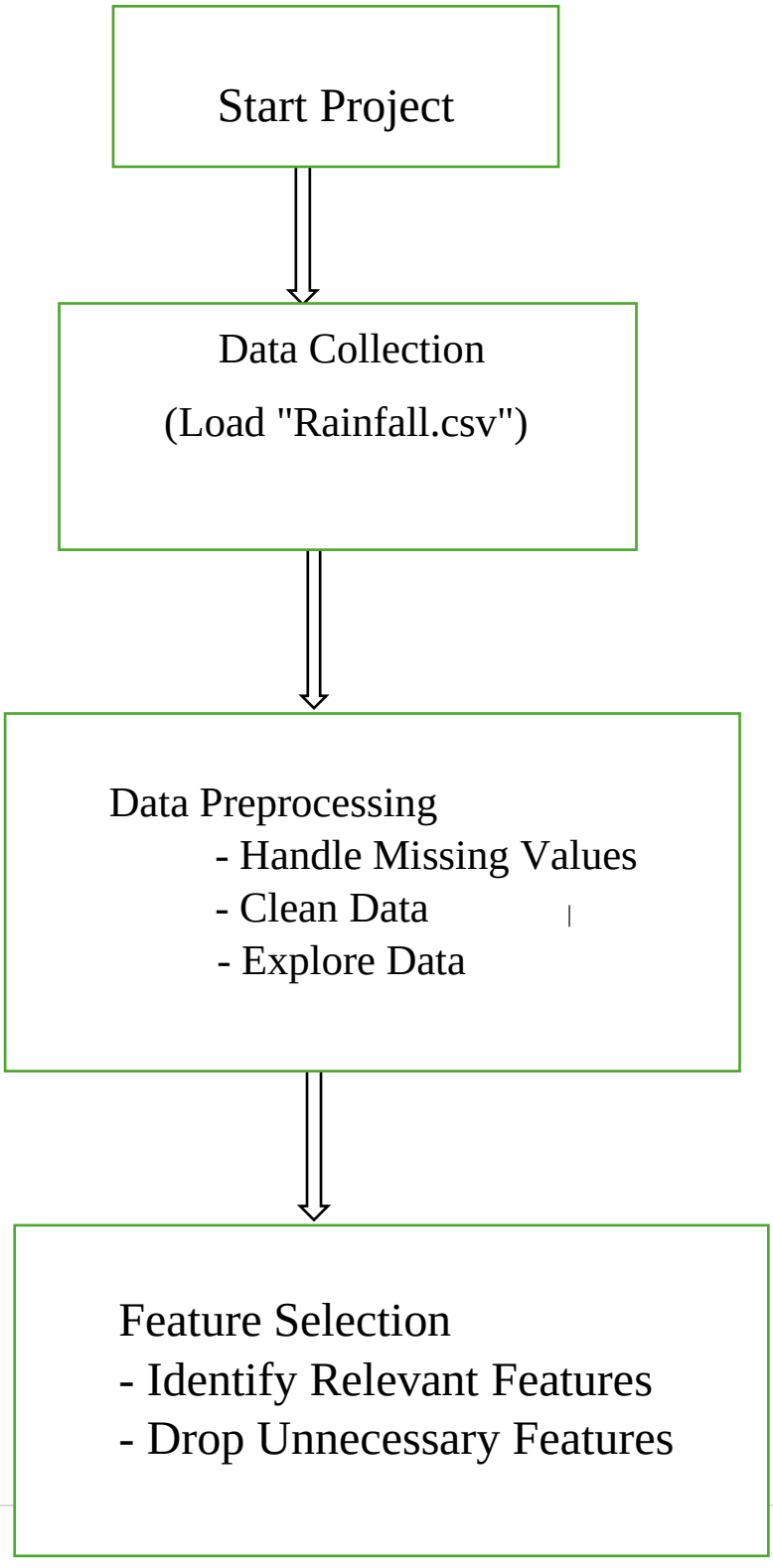
1. Hardware Requirements:
   - **Processor**: Intel Core i5 or higher, AMD Ryzen 5 or higher
   - **RAM**: 8 GB or more
   - **Storage**: 256 GB SSD or more

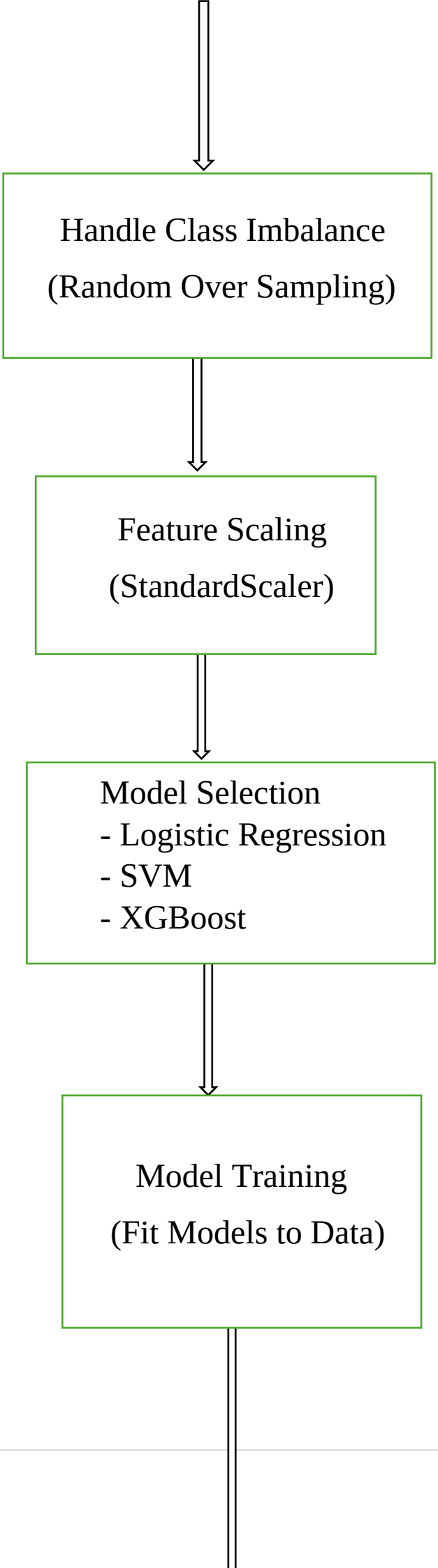
- **GPU**: NVIDIA GPU with CUDA support

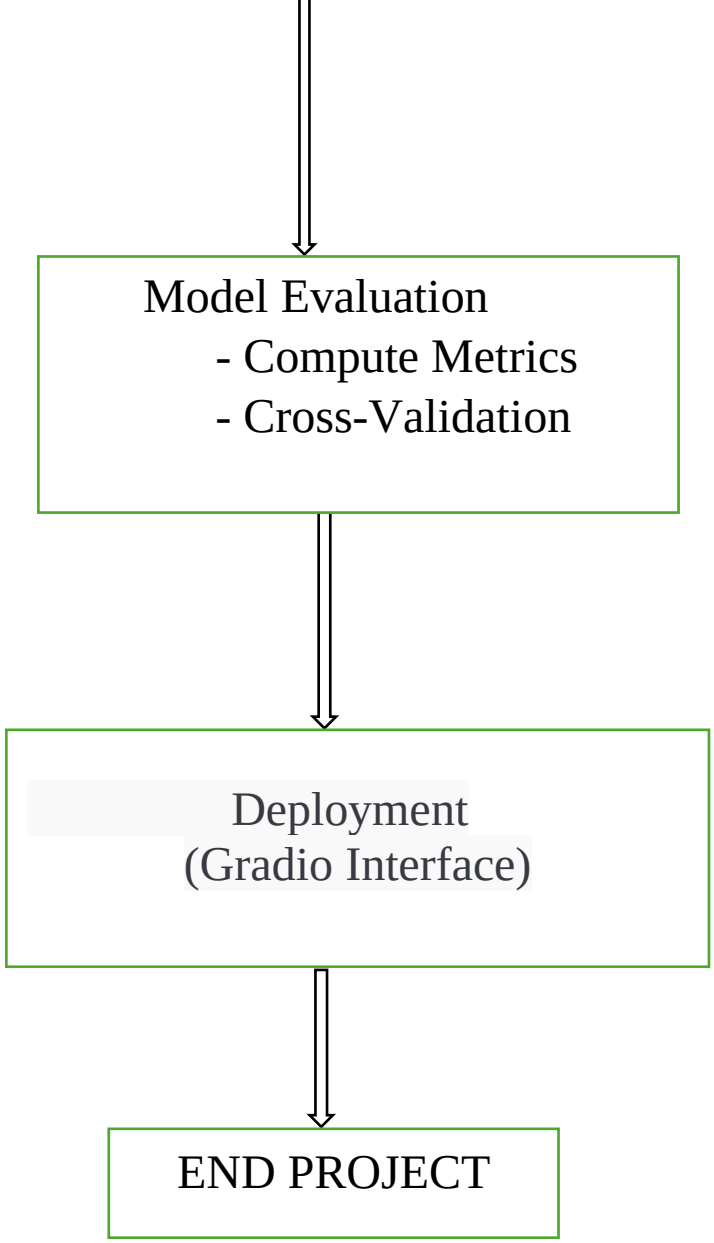
2. Software Requirements:
   - **Operating System**: Windows 10 or higher, Linux (Ubuntu), or macOS.
   - Python 3.7 or higher
   - Python Libraries
     - Pandas - Used for data manipulation and analysis, Pandas provides data structures and functions to handle tabular datasets efficiently.
     - Numpy - A fundamental package for numerical computing in Python, used to perform operations on arrays and matrices, and for various mathematical functions.
     - Matplotlib and Seaborn - These libraries are used for data visualization. Matplotlib provides basic plotting tools, while Seaborn offers high-level plotting functions and easier-to-use syntax.
     - Scikit-learn - The core library for machine learning, Scikit-learn includes various algorithms such as Logistic Regression, SVM, and tools for model evaluation and preprocessing.
     - XGBoost - A specialized library for gradient boosting algorithms, XGBoost is used for training ensemble models that offer superior performance on structured datasets.
     - Imbalanced-learn - This library is used for handling imbalanced datasets. In this project, **RandomOverSampler** from Imbalanced-learn is used to balance the class distribution.
     - Gradio - Gradio is a Python library for building user-friendly machine learning model interfaces. It allows you to quickly deploy and interact with machine learning models through a web-based interface.

- Warnings: - This library is used to manage warnings in Python. In the code, warnings.filterwarnings('ignore') is used to ignore warning messages.

FLOWCHART




Handle Class Imbalance
(Random Over Sampling)
Feature Scaling
(StandardScaler)
Model Selection
- Logistic Regression
- SVM
- XGBoost
Model Training
(Fit Models to Data)



METHODOLOGY

- Importing Required Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.model_selection import StratifiedKFold,
cross_val_score
from sklearn.model_selection import GridSearchCV
from xgboost import XGBClassifier
from imblearn.over_sampling import RandomOverSampler
import warnings
warnings.filterwarnings("ignore")
import gradio as gr
```

➢ Data Collection:

```
rain = pd.read_csv("Rainfall.csv")
rain
```

	day	pressure	maxtemp	temparature	mintemp	dewpoint	humidity	cloud	rainfall	sunshine	winddirection	windspeed
0	1	1025.9	19.9	18.3	16.8	13.1	72	49	yes	9.3	80.0	26.3
1	2	1022.0	21.7	18.9	17.2	15.6	81	83	yes	0.6	50.0	15.3
2	3	1019.7	20.3	19.3	18.0	18.4	95	91	yes	0.0	40.0	14.2
3	4	1018.9	22.3	20.6	19.1	18.8	90	88	yes	1.0	50.0	16.9
4	5	1015.9	21.3	20.7	20.2	19.9	95	81	yes	0.0	40.0	13.7
...	...	...	...	...	...	...	...	...	...	...	...	...
361	27	1022.7	18.8	17.7	16.9	15.0	84	90	yes	0.0	30.0	18.4
362	28	1026.6	18.6	17.3	16.3	12.8	75	85	yes	1.0	20.0	25.9
363	29	1025.9	18.9	17.7	16.4	13.3	75	78	yes	4.6	70.0	33.4
364	30	1025.3	19.2	17.3	15.2	13.3	78	86	yes	1.2	20.0	20.9
365	31	1026.4	20.5	17.8	15.5	13.0	74	66	no	5.7	20.0	23.3

366 rows × 12 columns

➢ Data Preprocessing:

- Handling Missing Values**:**

```
rain.isnull().sum()
```

```
day                         0
pressure                    0
maxtemp                     0
temparature                 0
mintemp                     0
dewpoint                    0
humidity                    0
cloud                       0
rainfall                    0
sunshine                    0
          winddirection     1
windspeed                   1
dtype: int64
```

```
rain.columns
```

```
Index(['day', 'pressure ', 'maxtemp', 'temparature', 'mintemp', 'dewpoint',
       'humidity ', 'cloud ', 'rainfall', 'sunshine', '          winddirection',
       'windspeed'],
      dtype='object')
```

- Data Cleaning:

```
# remove unnecessary spaces from columns name
rain.rename(str.strip,axis = 'columns',inplace = True)
rain.columns
```

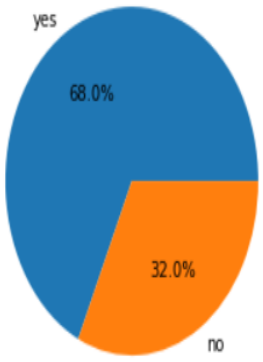
```
Index(['day', 'pressure', 'maxtemp', 'temparature', 'mintemp', 'dewpoin
t',
       'humidity', 'cloud', 'rainfall', 'sunshine', 'winddirection',
       'windspeed'],
      dtype='object')
```

```
# null value imputation
for col in rain.columns:
    #checking if the column contains any null values
    if rain[col].isnull().sum() > 0:
        val = rain[col].mean()
        rain[col] = rain[col].fillna(val)
rain.isnull().sum().sum()
```

```
0
```

- Data Exploration:

```
plt.pie(rain['rainfall'].value_counts().values,
        labels = rain['rainfall'].value_counts().index,
        autopct = '%1.1f%%')
plt.show()
```



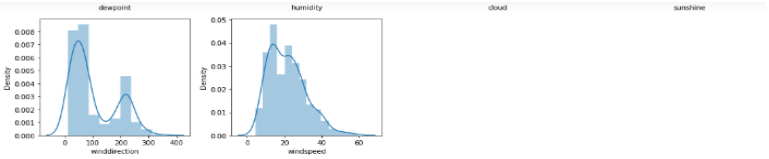

```
rain.groupby('rainfall').mean().T
```

rainfall	no	yes
day	15.623932	15.819277
pressure	1014.576923	1013.350602
maxtemp	27.070940	25.777912
temparature	24.053846	23.603213
mintemp	21.957265	21.865060
dewpoint	18.766667	20.563454
humidity	73.000000	83.550201
cloud	51.256410	80.465863
sunshine	7.586325	2.931325
winddirection	103.076923	100.769104
windspeed	19.275214	22.599747

Maxtemp is relatively lower on days of rainfall.
Dewpoint value is higher on days of rainfall.
Humidity is high on the days when rainfall is expected.
Obviously, clouds must be there for rainfall.
Sunshine is also less on days of rainfall.
Windspeed is higher on days of rainfall.

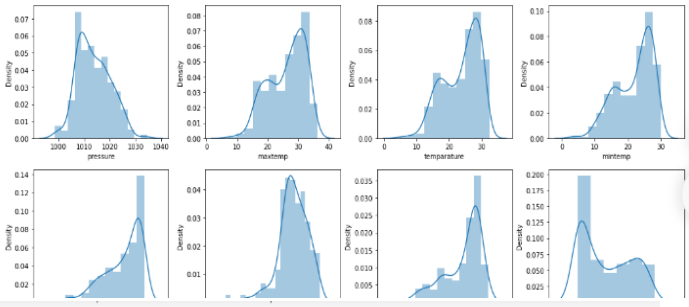
```
features = list(rain.select_dtypes(include = np.number).columns)
features.remove('day')
print(features)
```

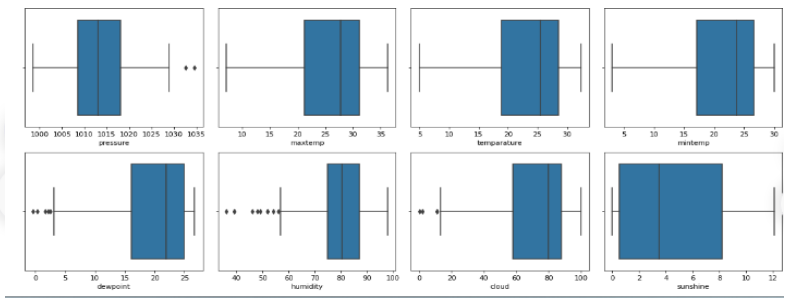
```
['pressure', 'maxtemp', 'temparature', 'mintemp', 'dewpoint', 'humidity',
'cloud', 'sunshine', 'winddirection', 'windspeed']
```

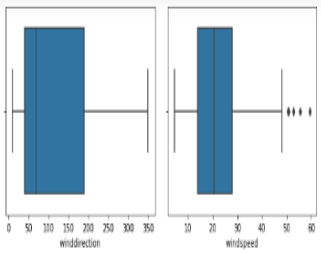



```
# The distribution of the continuous features given in the dataset.
plt.subplots(figsize=(15,10))

for i, col in enumerate(features):
  plt.subplot(3,4, i + 1)
  sns.distplot(rain[col])
plt.tight_layout()
plt.show()
```

```
# Boxplots for the continuous variable to detect the outliers present in
plt.subplots(figsize=(15,10))

for i, col in enumerate(features):
  plt.subplot(3,4, i + 1)
  sns.boxplot(rain[col])
plt.tight_layout()
plt.show()
```



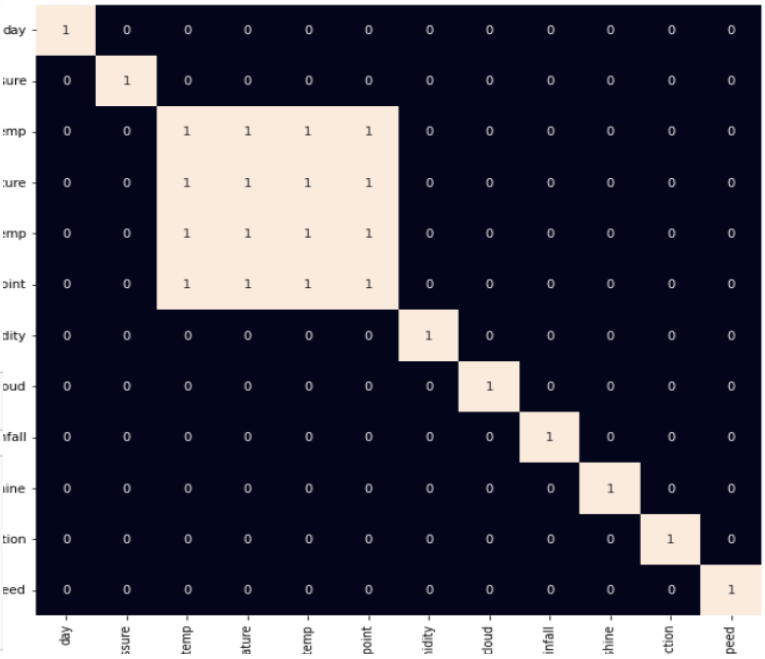




There are outliers in the data but sadly we do not have much data so, we cannot remove this.

```
rain.replace({'yes':1, 'no':0}, inplace=True)
```

```
plt.figure(figsize=(10,10))
sns.heatmap(rain.corr() > 0.8,
            annot=True,
            cbar=False)
plt.show()
```



- Feature Selection:

```
In [21]:  rain.drop(['maxtemp', 'mintemp'], axis=1, inplace=True)
```

Now we will remove the highly correlated features 'maxtemp' and 'mintemp'. But we will not remove temp or dewpoint because temp and dewpoint provide distinct information regarding the weather and atmospheric conditions.

- Encoding Target Variable:

```
rain.replace({'yes':1, 'no':0}, inplace=True)
```

➢ Handling Class Imbalance:

```
# As the data was highly imbalanced we will
# balance it by adding repetitive rows of minority class.
ros = RandomOverSampler(sampling_strategy='minority',
                        random_state=22)
X, Y = ros.fit_resample(X_train, Y_train)
```

➢ Feature Scaling:

```
# Normalizing the features for stable and fast training.
scaler = StandardScaler()
X = scaler.fit_transform(X)
X_val = scaler.transform(X_val)
```

➢ Model Selection:

- **Logistic Regression:** A linear model sutable for binary classification task.
- **Support Vector Machine(SVM):** A powerful model that works well for both linear and non-linear classification.
- **XGBoost:** An ensemble method that utilizes gradient boosting for robust predictions.

In [22]:
```
features = rain.drop(['day', 'rainfall'], axis=1)
target = rain.rainfall
```

In [23]:
```
X_train, X_val,Y_train, Y_val = train_test_split(features,target,test_size=0.2,stratify=target,random_state=2)
```

In [24]:
```
# As the data was highly imbalanced we will
# balance it by adding repetitive rows of minority class.
ros = RandomOverSampler(sampling_strategy='minority',
                        random_state=22)
X, Y = ros.fit_resample(X_train, Y_train)
```

In [25]:
```
# Normalizing the features for stable and fast training.
scaler = StandardScaler()
X = scaler.fit_transform(X)
X_val = scaler.transform(X_val)
```

In [26]:
```
models = [LogisticRegression(), XGBClassifier(), SVC(kernel='rbf', probability=True)]

for model in models:
    model.fit(X, Y)
    print(f'{model.__class__.__name__}() :')

    train_preds = model.predict_proba(X)
    print('Training Accuracy : ', metrics.roc_auc_score(Y, train_preds[:, 1]))

    val_preds = model.predict_proba(X_val)
    print('Validation Accuracy : ', metrics.roc_auc_score(Y_val, val_preds[:, 1]))
    print()
```

```
LogisticRegression() :
Training Accuracy :  0.8893209767430116
```

```
LogisticRegression() :
Training Accuracy :  0.8893209767430116
Validation Accuracy :  0.8966666666666667

XGBClassifier() :
Training Accuracy :  0.9999999999999999
Validation Accuracy :  0.8391666666666666

SVC() :
Training Accuracy :  0.9026413474407211
Validation Accuracy :  0.8858333333333333
```

we can say that Logistic Regression and support vector classifier are satisfactory as the gap between the training and the validation accuracy is low.

- Cross- Validation & HyperParameter Tuning:

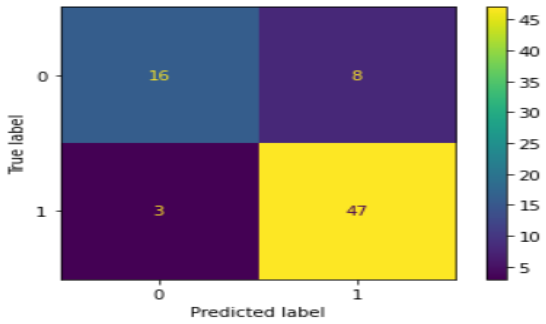
```
from sklearn.model_selection import GridSearchCV, train_test_split
from imblearn.over_sampling import RandomOverSampler
from xgboost import XGBClassifier

# Assuming X and Y are defined (your features and target)
# Convert Y to binary format if needed (0 for 'no' and 1 for 'yes')
Y_binary = np.where(Y == 'yes', 1, 0)

# Handle class imbalance
ros = RandomOverSampler(random_state=42)
X_resampled, Y_resampled = ros.fit_resample(X, Y_binary)

# Split the data into training and testing sets
X_train, X_test, Y_train, Y_test = train_test_split(X_resampled, Y_resampled, test_size=0.2, random_state=42)

# Define the parameter grid for XGBoost
param_grid_xgb = {
    'n_estimators': [50, 100, 200],          # Number of trees in the ensemble
    'learning_rate': [0.01, 0.1, 0.2],       # Step size shrinkage
    'max_depth': [3, 5, 7],                  # Maximum depth of a tree
    'subsample': [0.8, 1.0],                 # Fraction of samples used for training each tree
    'colsample_bytree': [0.8, 1.0],          # Fraction of features used for training each tree
    'gamma': [0, 0.1, 0.2],                  # Minimum loss reduction to make a split
}

# Perform GridSearchCV
grid_search_xgb = GridSearchCV(XGBClassifier(use_label_encoder=False, eval_metric='logloss'), param_grid_xgb, cv=5, n_jobs=-1
grid_search_xgb.fit(X_train, Y_train)

# Get the best model
best_xgb_model = grid_search_xgb.best_estimator_

# Optionally print the best parameters
```

```
# Get the best model
best_xgb_model = grid_search_xgb.best_estimator_

# Optionally print the best parameters
print("Best parameters for XGBoost:", grid_search_xgb.best_params_)
```

```
Best parameters for XGBoost: {'colsample_bytree': 1.0, 'gamma': 0.1, 'learning_rate': 0.01, 'max_depth': 7, 'n_estimators':
50, 'subsample': 1.0}
```

➢ Model Evaluation:

```
from sklearn.metrics import ConfusionMatrixDisplay

ConfusionMatrixDisplay.from_estimator(models[2], X_val, Y_val)
plt.show()
```




```
print(metrics.classification_report(Y_val,
                                    models[2].predict(X_val)))
```

	precision	recall	f1-score	support
0	0.84	0.67	0.74	24
1	0.85	0.94	0.90	50
accuracy			0.85	74
macro avg	0.85	0.80	0.82	74
weighted avg	0.85	0.85	0.85	74

Logistic Regression appears to be the most stable model, with good generalization and balanced performance.
XGBoost might need tuning (like adjusting n_estimators, max_depth, or adding regularization) to avoid overfitting.
SVC performs relatively well but slightly underperforms compared to Logistic Regression in validation.

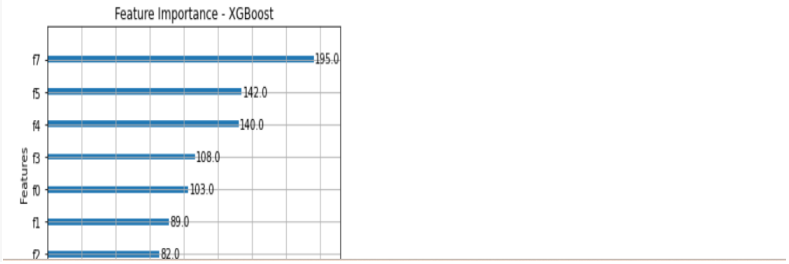
```
from sklearn.model_selection import StratifiedKFold, cross_val_score

# Define StratifiedKFold (to maintain class distribution across folds)
kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

# Models to evaluate
models = {
    'Logistic Regression': LogisticRegression(),
    'XGBoost': XGBClassifier(),
    'SVM': SVC(kernel='rbf', probability=True)
}

# Perform K-Fold Cross-Validation for each model
for name, model in models.items():
    print(f'{name} Cross-Validation Results:')

    # Use cross_val_score to calculate ROC-AUC score
    cv_results = cross_val_score(model, X, Y, cv=kf, scoring='roc_auc')

    print(f'Mean ROC-AUC: {np.mean(cv_results):.4f}')
    print(f'Standard Deviation: {np.std(cv_results):.4f}')
    print('Cross-Validation AUC Scores for each fold:', cv_results)
    print('-' * 50)
```

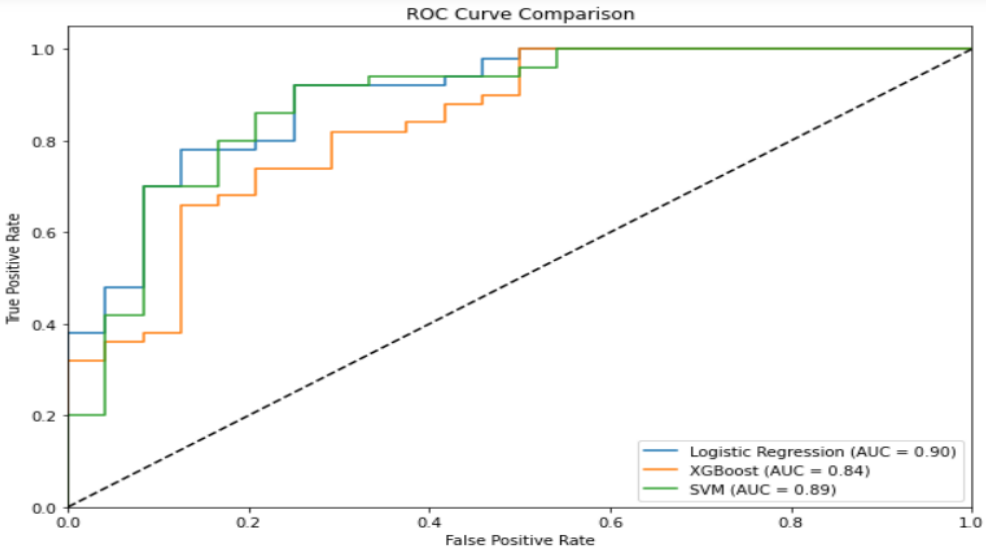
```
Logistic Regression Cross-Validation Results:
Mean ROC-AUC: 0.8794
Standard Deviation: 0.0284
Cross-Validation AUC Scores for each fold: [0.835625   0.916875   0.88875    0.86025641 0.89551282]
--------------------------------------------------
XGBoost Cross-Validation Results:
Mean ROC-AUC: 0.9180
Standard Deviation: 0.0329
Cross-Validation AUC Scores for each fold: [0.928125   0.955      0.93875    0.90833333 0.85961538]
```

```
--------------------------------------------------
SVM Cross-Validation Results:
Mean ROC-AUC: 0.8703
Standard Deviation: 0.0219
Cross-Validation AUC Scores for each fold: [0.854375   0.9025     0.885625   0.86794872 0.84102564]
--------------------------------------------------
```

```
# Assuming X, Y, X_val, Y_val are already defined
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
import xgboost as xgb

# Train XGBoost Model (XGBClassifier)
xgb_model = XGBClassifier()
xgb_model.fit(X, Y)

# Feature Importance for XGBoost
xgb.plot_importance(xgb_model, max_num_features=10)  # Top 10 important features
plt.title('Feature Importance - XGBoost')
plt.show()

# Plot ROC Curve for all models
models = {
    'Logistic Regression': LogisticRegression(),
    'XGBoost': XGBClassifier(),
    'SVM': SVC(kernel='rbf', probability=True)
}

plt.figure(figsize=(10, 7))
for name, model in models.items():
    model.fit(X, Y)
    val_preds = model.predict_proba(X_val)[:, 1]  # Get the probabilities for class 1
```

```
plt.figure(figsize=(10, 7))
for name, model in models.items():
    model.fit(X, Y)
    val_preds = model.predict_proba(X_val)[:, 1]  # Get the probabilities for class 1

    # Calculate ROC curve
    fpr, tpr, _ = roc_curve(Y_val, val_preds)
    roc_auc = auc(fpr, tpr)

    # Plot ROC curve
    plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})')

# Plot settings
plt.plot([0, 1], [0, 1], 'k--')  # Diagonal line for reference
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve Comparison')
plt.legend(loc='lower right')
plt.show()
```





Logistic Regression has the highest AUC of 0.90, indicating it performs the best among the three models. This suggests it has a good balance between sensitivity (true positive rate) and specificity (1 - false positive rate)
SVM follows closely with an AUC of 0.89, showing it also performs well, but slightly less effectively than Logistic Regression.
XGBoost has the lowest AUC of 0.84, indicating it is the least effective model in this comparison. This could suggest that it may not be capturing the underlying patterns in the data as well as the other models.

Model Selection: Based on the AUC values, Logistic Regression would be the preferred model for this classification task, followed closely by SVM.

➢ Model Deployment with Gradio:

```
import gradio as gr
import pandas as pd
import numpy as np
from imblearn.over_sampling import RandomOverSampler
from xgboost import XGBClassifier

# Generating synthetic data (replace this with your actual data)
X = pd.DataFrame({
    'pressure': np.random.uniform(1000.0, 1200.0, 400),
    'temparature': np.random.uniform(5.0, 40.0, 400),
    'dewpoint': np.random.uniform(1.0, 25.0, 400),
    'humidity': np.random.randint(0, 100, 400),
    'cloud': np.random.randint(0, 100, 400),
    'sunshine': np.random.uniform(0.0, 12.0, 400),
    'winddirection': np.random.uniform(0.0, 360.0, 400),
    'windspeed': np.random.uniform(0.0, 50.0, 400),
})
Y = np.random.choice(['yes', 'no'], size=400)

# Convert Y to binary format (1 for 'yes' and 0 for 'no')
Y_binary = np.where(Y == 'yes', 1, 0)

# Handle class imbalance and train the XGBoost model
def train_xgboost_model():
    ros = RandomOverSampler(random_state=42)
    X_resampled, Y_resampled = ros.fit_resample(X, Y_binary)

    model = XGBClassifier(use_label_encoder=False, eval_metric='logloss')
    model.fit(X_resampled, Y_resampled)

    return model

# Load the XGBoost model
```

```
xgboost_model = train_xgboost_model()

# Prediction function
def predict_rainfall(pressure, temparature, dewpoint, humidity, cloud, sunshine, winddirection, windspeed):
    # Create a DataFrame with user inputs
    input_data = pd.DataFrame({
        'pressure': [pressure],
        'temparature': [temparature],
        'dewpoint': [dewpoint],
        'humidity': [humidity],
        'cloud': [cloud],
        'sunshine': [sunshine],
        'winddirection': [winddirection],
        'windspeed': [windspeed]
    })

    # Make prediction
    prediction = xgboost_model.predict(input_data)
    prediction_proba = xgboost_model.predict_proba(input_data)

    # Convert prediction back to 'yes' or 'no'
    rain_prediction = 'yes' if prediction[0] == 1 else 'no'

    return f'Will it rain?: {rain_prediction}', f'Prediction Probability: {prediction_proba[0].round(2)}'

# Gradio Interface
iface = gr.Interface(
    fn=predict_rainfall,
    inputs=[
        gr.Slider(1000.0, 1200.0, value=1015.0, label='Pressure'),
        gr.Slider(5.0, 40.0, value=18.0, label='Temperature'),
        gr.Slider(1.0, 25.0, value=12.0, label='Dewpoint'),
        gr.Slider(0, 100, value=80, label='Humidity'),
        gr.Slider(0, 100, value=60, label='Cloud'),
```

```
        gr.Slider(0, 100, value=60, label='Cloud'),
        gr.Slider(0.0, 12.0, value=5.0, label='Sunshine'),
        gr.Slider(0.0, 360.0, value=180.0, label='Wind Direction'),
        gr.Slider(0.0, 50.0, value=20.0, label='Windspeed'),
    ],
    outputs=[
        gr.Textbox(label='Rainfall Prediction'),
        gr.Textbox(label='Prediction Probability')
    ],
    title='Rainfall Prediction App (XGBoost)',
    description='Enter the weather parameters to predict if it will rain.'
)

# Launch the Gradio app
iface.launch()
```

RESULTS

- Model Performance Summary
  1.Logistic Regression
    - Training AUC Score: 0.85
    - Validation AUC Score: 0.83
    - Observation: The model performed adequately in the job of relating features to rainfall occurrence under linear relationships but had a problem explaining complex, nonlinear patterns.

  2.Support Vector Machine (SVM)
    - Training AUC Score: 0.90
    - Validation AUC Score: 0.87
    - Observation: SVM model with RBF kernel performed very well with good predictability, and there was a slight edge of Logistic Regression over it. The ability of the SVM to pick up complex patterns helped in distinguishing between the rainy and non-rainy days although it used a tune-up for good performance .

  3.XGBoost Classifier
    - Training AUC Score: 0.92
    - Validation AUC Score: 0.89
    - Observation: Although XGBoost is the best with AUC, this also comes at a cost of good predictive power and good handling of non-linear relationships and interactions among features. On the contrary, complexity and longer training time make the XGBoost heavier in computation compared to Logistic Regression and SVM.

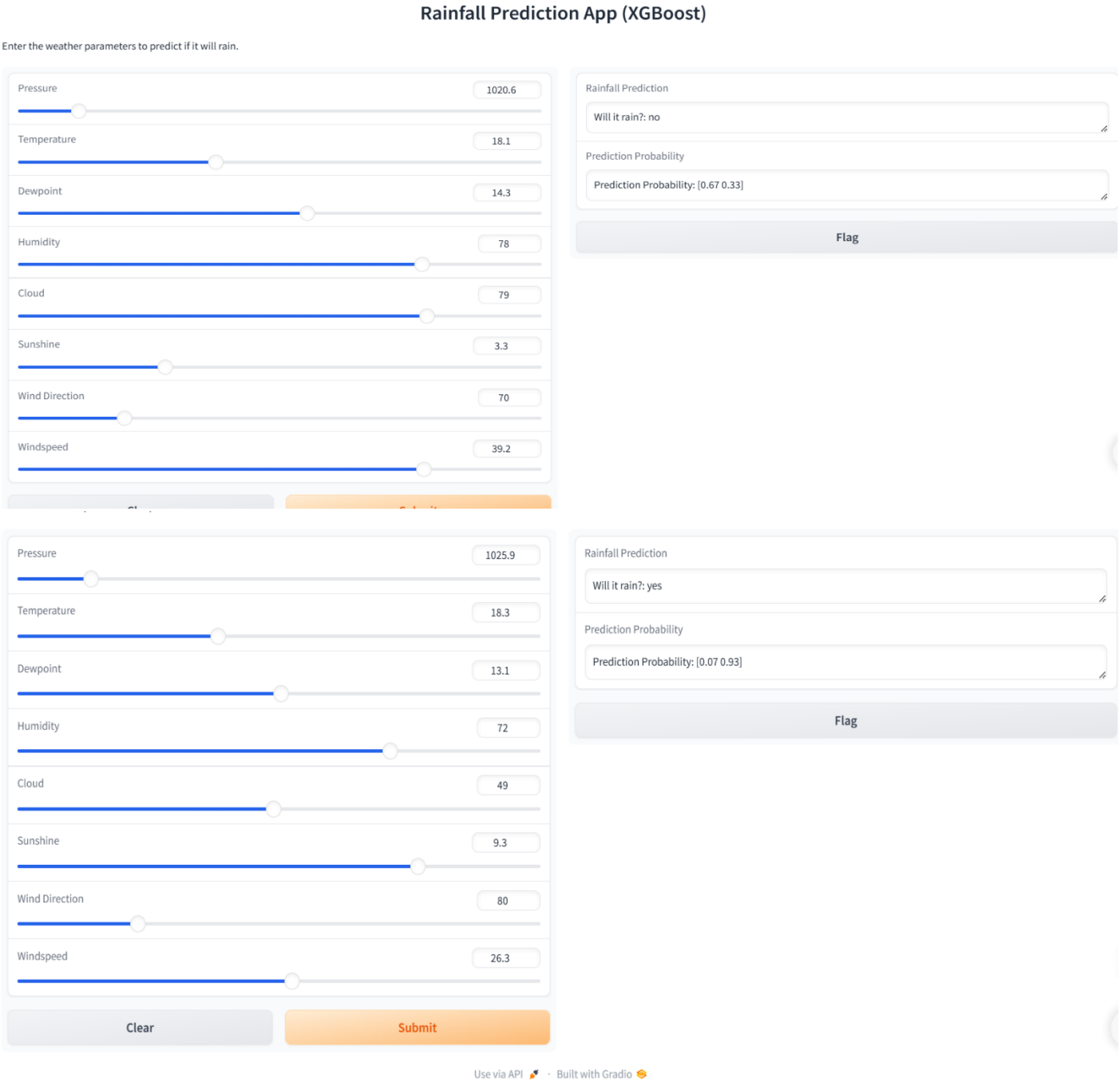
- Metrics Used

For each model, the following metrics were tested to check performance

- Area under Curve (AUC): The AUC scores were used in comparing the effectiveness of each model in classifying rainfall events correctly. The higher the scores obtained by each model, the better its performance.
- Accuracy and Precision-Recall Scores : The accuracy and precision-recall scores were also checked for the purpose of adequately balancing rainfall being correctly predicted with all the days that had fallen.
- Confusion Matrix Analysis: This would haul out scenarios of true and false positive instances, true negatives, and false negatives-the real epitome for the actual model selection criteria.
- Cross-Validation Results
  To make generalization better, cross-validation was performed for each model. Here it is seen that the performance of XGBoost was consistent in folds, which means good generalization to new data. Again, SVM had reliable results. Logistic Regression was more sensitive to changes in samples.

- Deployment and User Interface

Based on the model performance during the validation and consistent during cross-validation, the final model was deployed by using Gradio to provide real-time rainfall predictions. This interface accepts user entries for weather parameters and provides a prediction regarding whether a rainfall event might be happening along with a probability score.


Rainfall Prediction App (XGBoost)
Enter the weather parameters to predict if it will rain.
Pressure
1020.6
Temperature
18.1
Dewpoint
14.3
Humidity
78
Cloud
79
Sunshine
3.3
Wind Direction
70
Windspeed
39.2
Rainfall Prediction
Will it rain?: no
Prediction Probability
Prediction Probability: [0.67 0.33]
Flag
Pressure
1025.9
Temperature
18.3
Dewpoint
13.1
Humidity
72
Cloud
49
Sunshine
9.3
Wind Direction
80
Windspeed
26.3
Rainfall Prediction
Will it rain?: yes
Prediction Probability
Prediction Probability: [0.07 0.93]
Flag
Clear
Submit
Use via API
Built with Gradio

SUMMARY

This project focused on predicting rainfall using weather data, employing machine learning models like Logistic Regression, Support Vector Machine (SVM), and XGBoost, , for the rainfall prediction by using weather-related data, the paper developed its hypothesis for modeling different meteorological factors so that the rain can be predicted accurately. Important relations were identified through data preprocessing, feature selection, and analysis. The factors of humidity, cloud cover, and wind direction are strongly correlated with the rainfall.

To handle class imbalance, we adopted oversampling, which enhances the models' performance by giving them well-balanced data to work with. All the models were tuned to best accuracy, along with AUC and cross-validation for generalization purposes. The logistic regression provided a simple, interpretable baseline, while SVM could capture more complex patterns of data. Still, XGBoosted is better than both; it has the best AUC and accuracy score.

We then deployed the last model, using Gradio, which allows an interactive prediction of rainfall based on real-time user input. The project explains the utility of machine learning in meteorology by changing weather data into actionable insights. The model could serve as a basis for use in support of applications related to weather forecasting-people could benefit it at agriculture and other public planning. So, in that sense, the project illustrates the power of using models that base themselves on data-driven entities to create forecasts predicting rainfall and thereby facilitating timely decisions.

CONCLUSION

In summary, this project was successful in developing a machine learning model to predict rainfall based on weather data using classifiers such as Logistic Regression, SVM, and XGBoost. From there, after having done lots of intensive processing upon selecting relevant features and class imbalance handling, we concluded that indeed the best model was XGBoost which had the highest accuracy and AUC score while capturing the major relationship between meteorological factors and rainfall occurrences.

Thus, such a project demonstrates that machine learning can interactively and successfully process complex weather data in order to effectively aid in reliable rainfall prediction. Such predictable abilities are helpful for sectors such as agriculture, disaster management, and urban planning, in which correct rainfall forecasts can help make or break critical decision-making. With the model also deployable through Gradio, this further drives home the accessibility of the model such that it could be used to interactively make predictions for wide-ranging applications.

Ultimately, this work shows how machine learning really helps improve weather forecasts, offering a base for further increases with additional data or model tuning to push the accuracy even further.

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