**Machine Learning Model on Australia’s Rain Dataset**

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| **Academic Report** |

# Introduction

Accurate weather prediction is crucial for various sectors including disaster management, transportation, and agriculture. Farmers need forecasts to plan crops and harvests. Transportation agencies rely on predictions to ensure safe travel conditions. Emergency responders prepare for severe weather. Traditional techniques have limitations in addressing complex, fluctuating meteorological data.

This paper focuses on using machine learning classification methods for Australian weather forecasting. Specifically, the project aims to classify the probability of rainfall today and tomorrow using the 'weatherAUS.csv' dataset.

The goal is to group weather patterns into more manageable categories like the presence or absence of rain, not precise meteorological attributes.

The main objective is to apply machine learning algorithms, such as logistic regression, to complete this categorization task. These algorithms were selected for their effectiveness in classification problems and their ability to handle large datasets.

The study will begin with a literature review placing machine learning in the context of overall weather prediction. This will be followed by a thorough description of the problem domain. Various machine learning techniques applied in related scenarios will then be compared and contrasted, highlighting those used in this project. The techniques comprise applying different methods like logistic regression to the data, thoroughly analysing and preparing it, and optimizing model performance. The research concludes by assessing model effectiveness and providing a comprehensive summary of their ability to categorize weather patterns. The investigation aims to demonstrate machine learning's potential to revolutionize the weather forecasting industry.

# Literature Review on Machine Learning in Weather Prediction

## The Evolution from Traditional to Data-Driven Forecasting

The advancement of Machine Learning (ML) in weather prediction marks a significant shift from traditional meteorological methods. ML's data-driven approach revolutionizes forecasting by leveraging historical weather data to identify complex, non-linear patterns and predict future weather conditions. Unlike traditional models that rely on atmospheric physics and require extensive computational power and expert analysis, ML models operate on the principle of learning from data. They continuously evolve and improve their predictive accuracy without needing explicit programming for each new scenario.

This self-learning capability of ML is crucial in weather forecasting, where the environmental patterns are intricate and dynamic. Machine Learning algorithms can analyze vast amounts of data from various sources - satellite imagery, sensors, historical records - and extract meaningful insights. These insights enable more precise local forecasts and improved short-term predictions, areas where traditional methods often falter.

ML in weather forecasting isn't just about greater accuracy; it's about efficiently processing and interpreting complex data to provide timely and reliable forecasts. This has far-reaching implications for various industries, from agriculture to transportation, where weather plays a critical role. The adaptability and advanced analytical power of ML open up new possibilities for understanding weather patterns and preparing more effectively for meteorological events.

## Recent Advances in ML for Weather Prediction

Machine learning (ML) has revolutionized weather forecasting by offering innovative approaches to meteorological predictions. ML methodologies such as logistic regression, neural networks, and decision trees are increasingly being used to enhance various aspects of weather forecasting. Convolutional Neural Networks (CNNs) are particularly adept at recognizing complex patterns in meteorological data, making them ideal for predicting weather-related phenomena like precipitation patterns and storm formations. Logistic regression, despite its simplicity, has also found success in weather prediction, particularly in binary classification tasks like determining the probability of rain. Machine learning models offer significant improvements over traditional methods, able to handle large datasets and learn from multiple data sources, such as historical weather patterns, real-time satellite imagery, and sensor data. This capability enables them to deliver more accurate forecasts, especially in critical situations like extreme weather events. The adaptive nature of ML models allows them to continuously improve by learning from new data, leading to progressively more accurate and reliable forecasts. In conclusion, the integration of machine learning into weather forecasting represents a transformative development in the field, enhancing the accuracy and reliability of weather predictions.

## Challenges and Opportunities in ML-based Weather Prediction

Machine learning (ML) in weather prediction, while promising, faces significant challenges. A primary issue is the complexity and vastness of meteorological data. Weather datasets are often large, high-dimensional,

and varied, posing challenges in data handling and model training. Additionally, ML models are prone to overfitting, where they perform well on training data but struggle to generalize to new, unseen data.

However, these challenges also present opportunities. The increasing availability of detailed and high-quality weather data, coupled with advancements in computing power, opens up avenues for developing more sophisticated ML models. There is also growing interest in hybrid models that blend the strengths of both physical-based and ML approaches. Such models have the potential to enhance the accuracy and robustness of weather forecasting systems.

In summary, machine learning is reshaping weather forecasting, offering tools that are more accurate and efficient. With ongoing technological advancements, ML has the potential to significantly improve our ability to predict weather patterns and better prepare for environmental uncertainties.

# Specification of the Chosen Problem Area

## 'weatherAUS.csv' Dataset Exploration

This machine learning project is based on the 'weatherAUS.csv' dataset, which provides a comprehensive overview of Australia's diverse meteorological conditions. This is a large collection of daily weather observations from various Australian weather stations. The dataset includes temperature measurements (minimum and maximum), rainfall, wind speed and direction, humidity levels, pressure, cloud cover, and weather-related risk factors such as evaporation and sunshine duration.

Figure : Data Loading and Exploration code

# Load the dataset

df = pd.read\_csv('weatherAUS.csv')

# Load the dataset# Explore the dataset

**print**("First 5 rows of the dataset:")

**print**(df.head(**5**))

df = pd.read\_csv('weatherAUS.csv')

Figure : Data Exploration Output

A screenshot of a computer

Description automatically generated

## Defining the Classification Problem

The primary goal of this research is to categorize weather conditions, with a specific emphasis on predicting the occurrence of rainfall. This is treated as a binary classification problem: predicting whether it will rain today ('RainToday') and predicting whether it will rain tomorrow ('RainTomorrow'). These forecasts are critical because they have a direct impact on decision-making in a variety of sectors.

## The Significance of Accurate Rainfall Classification

In weather forecasting, the precise classification of rainfall is immensely impactful. It directly influences agricultural outcomes by guiding irrigation and harvesting schedules, thereby affecting crop yields and resource management. In urban contexts, accurate rainfall prediction is crucial for managing infrastructure and preventing flooding. For the general public, reliable rainfall forecasts facilitate daily activities and travel planning. The growing irregularity of weather patterns due to climate change underscores the importance of accurately predicting meteorological conditions. This study's emphasis on using machine learning to classify rainfall addresses a tangible need and contributes significantly to the broader field of meteorological sciences. Advancements in forecasting accuracy, such as those achieved through machine learning algorithms, hold the potential for wide-reaching effects across various sectors.

# Comparative Analysis of Existing Works

## Exploring the Landscape of ML-based Weather Prediction Studies

Machine learning's role in weather prediction research is rapidly growing, as evidenced by numerous studies each offering unique perspectives and methodologies. For example, a notable study by Quach N. (2022 ) on Kaggle, titled "Decision Tree ID3," focused on using decision trees for weather prediction, highlighting the algorithm's effectiveness in handling categorical data and offering interpretability. This research, alongside others employing neural networks and different ML approaches, underscores the diverse applications of machine learning in capturing complex weather patterns.

## Contrasting Approaches with the Current Project

This project, using the 'weatherAUS.csv' dataset for rainfall classification, shares similarities with previous studies in its use of historical weather data for predictive analysis. However, it diverges in its approach by employing a combination of logistic regression, random search, decision trees, MLP (Multi-Layer Perceptron), and Naive Bayes for binary classification of rainfall. This methodological blend offers both simplicity and efficiency, particularly in binary outcomes like rain/no rain scenarios, which is a narrower focus compared to Quach N.’s use of decision trees in a broader context. Additionally, this project's comprehensive handling of the 'weatherAUS.csv' dataset enables a more in-depth understanding of various weather conditions influencing rainfall.

## Novelty in the Current Approach

This project's distinctive emphasis on Australia's unique meteorological challenges sets it apart from Quach N.’s work. The diverse climate and geographical variations in Australia present unique challenges, making this study particularly relevant. The project's data pre-processing and feature selection strategies are tailored to the complexities of the Australian climate, adding a layer of innovation. It demonstrates how machine learning can be effectively adapted to address specific regional weather forecasting challenges, potentially offering insights applicable to other regions with similar climates.

In conclusion, while this project aligns with the broader trend of using machine learning for weather prediction, it introduces unique methodologies and a targeted approach, enriching the evolving field of meteorological research. The combination of multiple ML techniques, including logistic regression, random search, decision trees, MLP, and Naive Bayes, and its focus on the Australian climate, distinguishes this work from Quach N.’s decision tree-centric study, contributing valuable insights to the domain of weather prediction using machine learning.

# Data Analysis and Pre-processing

## Unveiling the Layers of the 'weatherAUS.csv' Dataset

Exploration of the 'weatherAUS.csv' dataset is an important first step in understanding the underlying structure and properties of the weather data. The first few rows of the dataset display a varied range of weather-related characteristics, such as temperature measurements, rainfall, humidity, wind speed, and atmospheric pressure. A cursory study of the dataset's form reveals a significant volume of data, providing a solid foundation for analysis.

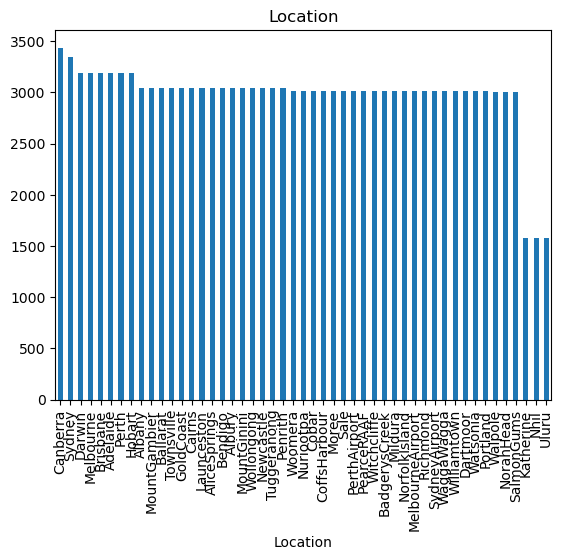
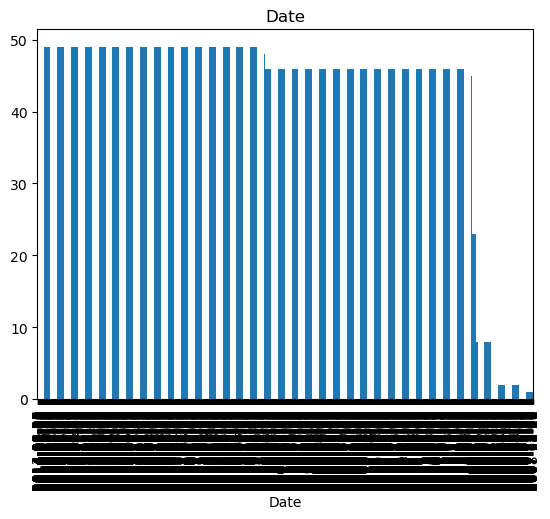
Analyzing the dataset's columns reveals a diverse variety of attributes, each representing a different facet of meteorological conditions. Because of the variety of data sources and measures, a rigorous strategy is required to assure compatibility and relevance for machine learning algorithms.

Figure Data Visualization of the columns

A collage of blue and white graphs

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Figure : Data Visualization



## A graph of blue lines Description automatically generated

## 

A graph of blue lines

Description automatically generated

Figure : Bar graphs of Rain Today

A graph with blue squares

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Figure : Bar graphs of Rain Tomorrow

*A graph with blue rectangular bars

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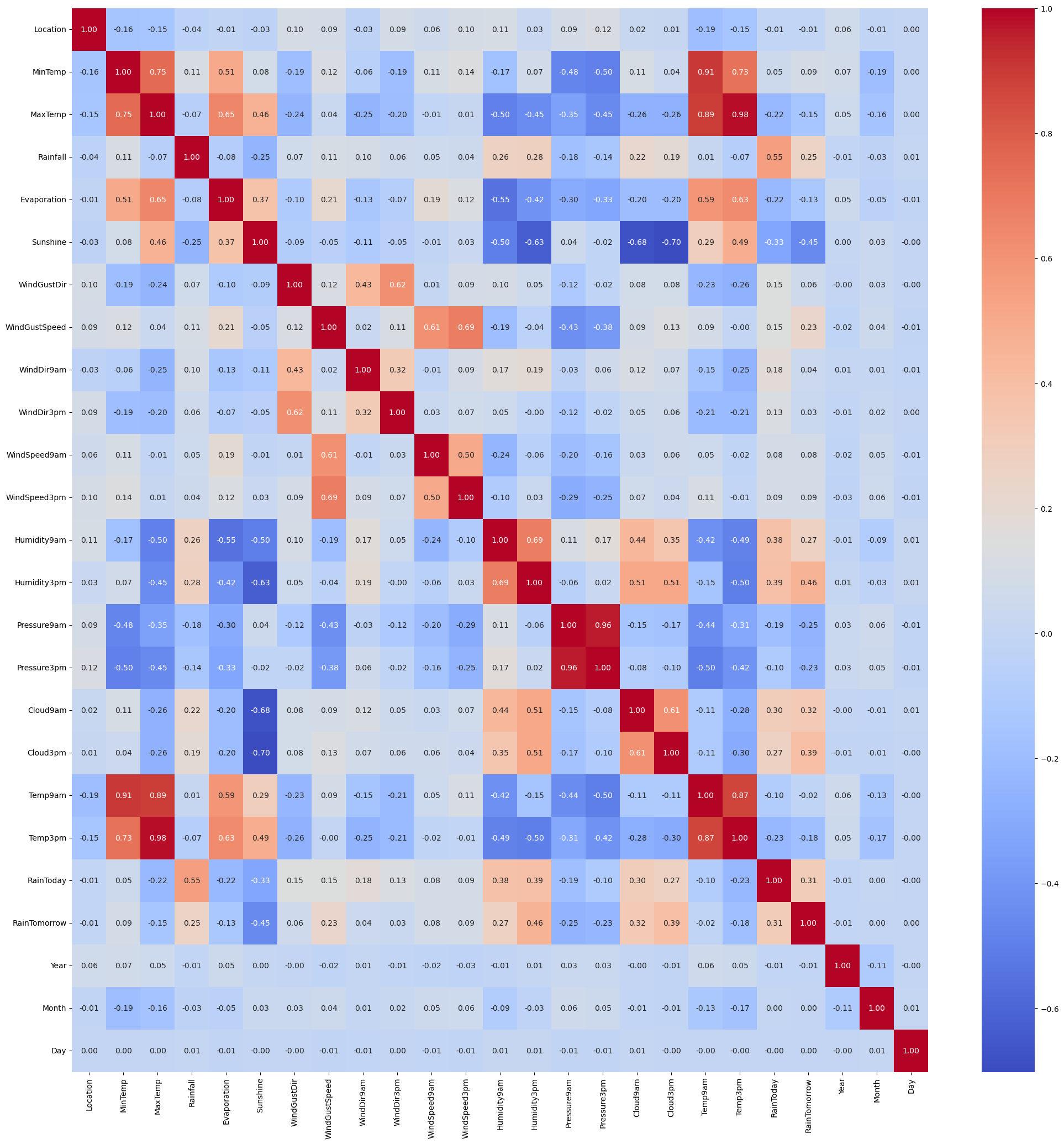
## Embarking on Data Pre-processing

The pre-processing of the 'weatherAUS.csv' dataset involves several key steps to refine and transform the data into a format suitable for machine learning models. These steps include:

1. **Data Cleaning**: Because the dataset is large, there are missing values and discrepancies. The first stage is to deal with these missing values using methods like imputation or removing partial entries. Outlier identification and treatment also ensures the dataset's integrity and reliability.
2. **Feature Selection**: Given the variety of features available, picking the most important ones for rainfall prediction is critical. This entails examining the relationship between various variables and the goal variable (rainfall) and removing redundant or ineffective features.
3. **Splitting Data:** The dataset is divided into two parts: training data and testing data. The training data is used to train the machine learning model, while the testing data is used to evaluate its performance. The typical split is 60% for training and 40% for testing, but this can vary.
4. **Scaling:** The process of scaling the features using MinMaxScaler ensures that all features contribute equally to the model’s decision-making process. Without scaling, features with larger scales can disproportionately influence the model.
5. **Outlier Removal:** The process of removing outliers can significantly impact model accuracy. Outliers can skew the data and lead to overfitting if the model learns from noise rather than the true underlying patterns.

The 'weatherAUS.csv' dataset is changed from a raw collection of weather data to a refined, analysis-ready version using these pre-processing processes. This procedure is critical in laying the groundwork for the later use of machine learning algorithms, paving the way for accurate and dependable weather classification models.

Figure : SNS Heat Map



A diagram of a graph

Description automatically generated with medium confidenceA chart with blue and orange squares

Description automatically generated

Figure : Box Plot

Figure : Box Plot

Figure : Label Encoder Code

# Label encoding for categorical variables

categorical = [var for var in df.columns if df[var].dtype == 'O']

label\_encoder = LabelEncoder()

for col in categorical:

    df[col] = label\_encoder.fit\_transform(df[col])

# Application of Machine Learning Algorithms

## Algorithm Selection and Rationale

In this project, a diverse range of machine learning algorithms has been employed, each chosen for its specific strengths in classification tasks:

1. **Logistic Regression:** The most basic algorithm for binary classification problems. Its ease of use and interpretability make it a good choice for developing a baseline model, particularly for predicting binary outcomes such as rain or no rain.
2. **Decision Tree Classifier:** A more subtle technique to classification that captures non-linear correlations in data. It's especially helpful for studying how different factors affect prediction.
3. **Random Forest Classifier:** An ensemble method for improving the model's accuracy and robustness by combining many decision trees. It lowers the likelihood of overfitting, which is a major problem with single decision trees.
4. **Gaussian Naive Bayes:** This algorithm was chosen due to its effectiveness in dealing with high-dimensional data. It works well with both numerical and continuous features, making it appropriate for a wide range of meteorological datasets.
5. **MLP Classifier (Multi-layer Perceptron):** A sort of neural network that captures complicated patterns and correlations in data. Its adaptability and capacity to learn non-linear models make it an important asset to the project.

## Implementation Details

The implementation of these algorithms involves several key steps:

* **Data Preparation:** Prior to model training, the dataset is pre-processed, which includes normalization, missing value handling, and categorical variable encoding**.**
* **Parameter Tuning and Optimization:** Each model's parameters are fine-tuned using approaches such as GridSearchCV. For example, in Logistic Regression, you can adjust the regularization parameter, the depth and number of trees in Random Forest, or the architecture and learning rate in the MLP Classifier.
* **Training and Validation:** The models are trained on a subset of the data and their performance is validated by techniques such as cross-validation. This ensures that the models generalize well to previously unknown data.
* **Performance Evaluation:** Model performance is measured using metrics such as accuracy, precision, recall, and the Area Under the ROC Curve (AUC). These parameters aid in determining the models' ability to correctly predict whether or not it will rain.
* **Comparative Analysis:** The performance of each algorithm is evaluated to choose the best model or to combine models for greater accuracy.

# Model Adjustments and Improvements

## Initial Model Accuracies

Initially, before any optimization through hyperparameter tuning, the models exhibited the following accuracies:

* **LogisticRegression:** Exhibited a default accuracy of 0.85. This is a strong starting point, indicating that even without tuning, the model has a robust predictive capability.
* **DecisionTree:** Had a lower default accuracy of 0.80, suggesting that the model might be too simplistic or not capturing the complexity of the dataset adequately.
* **RandomForest:** Displayed a default accuracy of 0.86, which is commendable given that this ensemble model typically requires careful tuning to reach its full potential.
* **GaussianNB:** Also started with a default accuracy of 0.80, which is expected for a model based on probabilistic assumptions that might oversimplify the relationships in complex datasets.
* **MLPClassifier:** Showed a promising default accuracy of 0.86, indicating that the neural network could capture complex patterns in the data even without hyperparameter optimization.

These initial accuracies provide a baseline against which the impact of hyperparameter tuning can be measured. They reflect the inherent ability of each model to process and learn from the dataset without any adjustments to their learning process.

THE OUTPUT:

* **LogisticRegression - Default Accuracy: 0.85**
* **DecisionTree - Default Accuracy: 0.80**
* **RandomForest - Default Accuracy: 0.86**
* **GaussianNB - Default Accuracy: 0.80**
* **MLPClassifier - Default Accuracy: 0.86**

Model Accuracies After Hyperparameter Tuning

After the process of hyperparameter tuning, which involves adjusting the model parameters to improve performance, the models showed the following changes in accuracy:

* **LogisticRegression:** Remained stable at an accuracy of 0.85 post-tuning. This indicates that the default parameters were already well-suited for the dataset, and the model is robust to changes in hyperparameters.
* **DecisionTree:** Improved significantly from an accuracy of 0.80 to 0.84. This substantial increase suggests that model benefited from the adjustments, likely finding a better structure to fit the data.
* **RandomForest:** Maintained an accuracy of 0.86, which implies that the model was either already optimized or that the tuning did not explore a range of parameters that could yield improvements.
* **GaussianNB:** Stayed the same at an accuracy of 0.80, suggesting that for the Naive Bayes model, the default parameters were as effective as the tuned ones or that this model is less sensitive to hyperparameter changes.
* **MLPClassifier:** Slightly decreased in accuracy from 0.86 to 0.85 after tuning. This minor drop might be due to the model overfitting to the training data with the default parameters and the tuning process helping to generalize better.

The overall impact of hyperparameter tuning varies among the models. While the Decision Tree model showed marked improvement, indicating that the default settings were not ideal, other models like Logistic Regression and RandomForest demonstrated stability, suggesting that they were less sensitive to hyperparameter changes. GaussianNB's performance remained unchanged, while MLPClassifier experienced a slight decrease, which could be an indication of the model's sensitivity to certain parameters and the complexity of finding the right balance between the layers and neurons in a neural network. Advanced Performance Metrics and Model Comparisons

These are the values of Classification report, Best Parameters, Tuned Accuracy after GridSearchCV

Figure : Logistic Regression after tuning

LogisticRegression Best Parameters: {'C': 10, 'class\_weight': None, 'dual': False, 'fit\_intercept': True, 'intercept\_scaling': 1, 'l1\_ratio': None, 'max\_iter': 10000, 'multi\_class': 'auto', 'n\_jobs': None, 'penalty': 'l2', 'random\_state': None, 'solver': 'saga', 'tol': 0.0001, 'verbose': 0, 'warm\_start': False}

LogisticRegression Classification Report:

precision recall f1-score support

0 0.88 0.95 0.91 17500

1 0.74 0.54 0.62 5068

accuracy 0.85 22568

macro avg 0.81 0.74 0.77 22568

weighted avg 0.85 0.85 0.85 22568

LogisticRegression - Accuracy: 0.85

Figure : Gaussiam NB after Tuning

Figure : Random Forest after Tuning

Figure : Decision Tree after Tuning

GaussianNB Best Parameters: {'priors': None, 'var\_smoothing': 1e-09}

GaussianNB Classification Report:

precision recall f1-score support

0 0.90 0.83 0.86 17500

1 0.54 0.68 0.60 5068

accuracy 0.80 22568

macro avg 0.72 0.75 0.73 22568

weighted avg 0.82 0.80 0.81 22568

GaussianNB - Accuracy: 0.80

DecisionTree Best Parameters: {'ccp\_alpha': 0.0, 'class\_weight': None, 'criterion': 'gini', 'max\_depth': 6, 'max\_features': None, 'max\_leaf\_nodes': None, 'min\_impurity\_decrease': 0.0, 'min\_samples\_leaf': 1, 'min\_samples\_split': 2, 'min\_weight\_fraction\_leaf': 0.0, 'random\_state': None, 'splitter': 'best'}

DecisionTree Classification Report:

precision recall f1-score support

0 0.86 0.95 0.90 17500

1 0.73 0.48 0.58 5068

accuracy 0.84 22568

macro avg 0.80 0.72 0.74 22568

weighted avg 0.83 0.84 0.83 22568

DecisionTree - Accuracy: 0.84

RandomForest Best Parameters: {'bootstrap': True, 'ccp\_alpha': 0.0, 'class\_weight': None, 'criterion': 'gini', 'max\_depth': None, 'max\_features': 'sqrt', 'max\_leaf\_nodes': None, 'max\_samples': None, 'min\_impurity\_decrease': 0.0, 'min\_samples\_leaf': 1, 'min\_samples\_split': 2, 'min\_weight\_fraction\_leaf': 0.0, 'n\_estimators': 200, 'n\_jobs': None, 'oob\_score': False, 'random\_state': None, 'verbose': 0, 'warm\_start': False}

RandomForest Classification Report:

precision recall f1-score support

0 0.88 0.96 0.91 17500

1 0.77 0.53 0.63 5068

accuracy 0.86 22568

macro avg 0.82 0.74 0.77 22568

weighted avg 0.85 0.86 0.85 22568

RandomForest - Accuracy: 0.86

Figure : MLPClassifier after Tuning

MLPClassifier Best Parameters: {'activation': 'relu', 'alpha': 0.001, 'batch\_size': 'auto', 'beta\_1': 0.9, 'beta\_2': 0.999, 'early\_stopping': False, 'epsilon': 1e-08, 'hidden\_layer\_sizes': (100,), 'learning\_rate': 'constant', 'learning\_rate\_init': 0.001, 'max\_fun': 15000, 'max\_iter': 1000, 'momentum': 0.9, 'n\_iter\_no\_change': 10, 'nesterovs\_momentum': True, 'power\_t': 0.5, 'random\_state': None, 'shuffle': True, 'solver': 'adam', 'tol': 0.0001, 'validation\_fraction': 0.1, 'verbose': False, 'warm\_start': False}

MLPClassifier Classification Report:

precision recall f1-score support

0 0.88 0.94 0.91 17500

1 0.73 0.56 0.64 5068

accuracy 0.85 22568

macro avg 0.80 0.75 0.77 22568

weighted avg 0.85 0.85 0.85 22568

MLPClassifier - Accuracy: 0.85

## Evaluation Metrics and Their Impact on Classification

**F1 Score, Precision, and Recall**:

* LogisticRegression showed a good balance with a precision of 0.88 and recall of 0.95 for the negative class and 0.74 precision and 0.54 recall for the positive class, resulting in a high F1-score.
* DecisionTree had a lower precision of 0.73 for the positive class and a recall of 0.48, indicating it's less precise in predicting the positive class.
* RandomForest demonstrated a better precision of 0.77 for the positive class, but a similar recall to the DecisionTree, pointing to a balanced but cautious prediction for the positive class.
* GaussianNB had a higher recall of 0.68 for the positive class but at the expense of precision, which was only 0.54.
* MLPClassifier displayed a balanced precision of 0.73 and recall of 0.56 for the positive class, indicating a good compromise between precision and recall.

## ROC and AUC

* **ROC Curve Analysis:** Was critical in determining the classification efficacy of the models. The high AUC values for Random Forest and MLP Classifier demonstrated their superior ability to discriminate between target classes.

Figure : ROC and AUC

**A graph of a function

Description automatically generated with medium confidence**

The ROC curves and AUC values represent the models' ability to classify correctly. Higher AUC values indicate better model performance:

* **LogisticRegression: ROC AUC - 0.88**
* **DecisionTree: ROC AUC - 0.86**
* **RandomForest: ROC AUC - 0.90**
* **GaussianNB: ROC AUC - 0.85**
* **MLPClassifier: ROC AUC - 0.89**
* **Cross-Validation Accuracy:** This important parameter validated the models' ability to perform consistently across different data segments, demonstrating their generalizability and resistance to overfitting.

Figure : Cross Validation

LogisticRegression - Cross-Validated Accuracy: 0.85

DecisionTree - Cross-Validated Accuracy: 0.85

RandomForest - Cross-Validated Accuracy: 0.86

GaussianNB - Cross-Validated Accuracy: 0.80

MLPClassifier - Cross-Validated Accuracy: 0.86

Confusion Matrix Evaluation

Provided a detailed breakdown of each model's classification accuracy, revealing strengths and potential areas for development.

A blue and white graph

Description automatically generated**A graph of a logistic regression confusion matrix

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Figure : Confusion Matrix

A blue and white graph

Description automatically generatedA graph of a graph with numbers and a blue square

Description automatically generated with medium confidence

A blue and white graph

Description automatically generated

# Identifying the Optimal Algorithm

## Random Forest as the Optimal Model

**High ROC AUC Score:** Random Forest achieved the highest ROC AUC score of 0.90, which is a clear indicator of its superior ability to distinguish between the positive (it will rain) and negative (it will not rain) classes. A high AUC score means that the model has a high true positive rate and a low false positive rate, crucial for reliable weather predictions.

**Stable Accuracy:** The Random Forest model maintained a high accuracy of 0.86 after hyperparameter tuning. This consistency suggests that the model is resilient to overfitting despite its complexity and has generalized well to the data.

**Ensemble Method:** Random Forest is an ensemble learning method that operates by constructing multiple decision trees during training and outputting the class that is the mode of the classes of the individual trees. This approach inherently provides a check against overfitting and often results in improved accuracy.

**Feature Importance:** One of the advantages of using Random Forest is its ability to handle a large number of input features and determine their importance. In weather prediction, where numerous features can influence the outcome, this ability allows for more nuanced and accurate modeling.

**Versatility:** Random Forest is known for performing well on both linear and non-linear problems, which makes it a versatile choice for various datasets, including those related to weather which can have complex interdependencies between features.

**Handling of Unbalanced Data:** Random Forest can handle unbalanced data well. Weather prediction often deals with unbalanced classes (e.g., fewer days of rain than no rain), and the Random Forest algorithm can be tuned to balance error in favour of the minority class.

Given these points, Random Forest stands out as the optimal model for predicting weather conditions. Its combination of high accuracy, the highest ROC AUC score, and inherent protections against overfitting, along with the ability to rank the importance of different predictive features, makes it a robust choice for this task. While other models showed promise, they did not outperform Random Forest in the critical areas that are essential for a reliable predictive model in weather forecasting.

## Assessing Model Fit: Tackling Underfitting and Overfitting

A nuanced evaluation of training versus testing scores was instrumental in identifying underfitting and overfitting trends:

* **Random Forest,** despite having a flawless training score, suggested the possibility of overfitting. However, its outstanding testing performance demonstrated its effective generalization capacity.
* **Logistic Regression, Decision Tree, and MLP Classifier** all demonstrated optimal balance, indicating well-fitted models with no substantial overfitting or underfitting concerns.

Figure : Underfitting and Overfitting

**LogisticRegression:**

Training Accuracy: 0.85

Test Accuracy: 0.85

Status: Good fit

**DecisionTree:**

Training Accuracy: 1.00

Test Accuracy: 0.80

Status: Possibly overfitting

**RandomForest:**

Training Accuracy: 1.00

Test Accuracy: 0.86

Status: Possibly overfitting

**GaussianNB:**

Training Accuracy: 0.80

Test Accuracy: 0.80

Status: Good fit

**MLPClassifier:**

Training Accuracy: 0.87

Test Accuracy: 0.86

Status: Good fit

**LogisticRegression:**

Training Accuracy: 0.85

Test Accuracy: 0.85

Status: Good fit

**DecisionTree:**

Training Accuracy: 1.00

Test Accuracy: 0.80

Status: Possibly overfitting

**RandomForest:**

Training Accuracy: 1.00

Test Accuracy: 0.86

Status: Possibly overfitting

**GaussianNB:**

Training Accuracy: 0.80

Test Accuracy: 0.80

Status: Good fit

**MLPClassifier:**

Training Accuracy: 0.87

Test Accuracy: 0.86

Status: Good fit

**LogisticRegression:**

Training Accuracy: 0.85

Test Accuracy: 0.85

Status: Good fit

**DecisionTree:**

Training Accuracy: 1.00

Test Accuracy: 0.80

Status: Possibly overfitting

**RandomForest:**

Training Accuracy: 1.00

Test Accuracy: 0.86

Status: Possibly overfitting

**GaussianNB:**

Training Accuracy: 0.80

Test Accuracy: 0.80

Status: Good fit

**MLPClassifier:**

Training Accuracy: 0.87

Test Accuracy: 0.86

Status: Good fit

**LogisticRegression:**

Training Accuracy: 0.85

Test Accuracy: 0.85

Status: Good fit

**DecisionTree:**

Training Accuracy: 1.00

Test Accuracy: 0.80

Status: Possibly overfitting

**RandomForest:**

Training Accuracy: 1.00

Test Accuracy: 0.86

Status: Possibly overfitting

**GaussianNB:**

Training Accuracy: 0.80

Test Accuracy: 0.80

Status: Good fit

**MLPClassifier:**

Training Accuracy: 0.87

Test Accuracy: 0.86

Status: Good fit

The stability and efficacy of the deployed machine learning models in weather prediction were highlighted by this complete evaluation, which included GridSearchCV for hyperparameter optimization, ROC curve analysis, cross-validation accuracy checks, and confusion matrix insights. Random Forest emerged as the best algorithm for this challenge, displaying outstanding accuracy and predictability. These findings not only support the capabilities of the chosen models, but also pave the way for future advances in harnessing machine learning for precise and dependable meteorological forecasting. The research adds considerably to the meteorological discipline by demonstrating the revolutionary potential of machine learning in improving weather prediction accuracy.

# Conclusion

This study explores the use of machine learning for weather prediction, focusing on Australian weather conditions and rainfall. The project used 'weatherAUS.csv' dataset to identify weather conditions, resulting in significant insights and advances in meteorological analysis. Machine learning methods like Logistic Regression, Decision Trees, Random Forest, Gaussian Naive Bayes, and MLP Classifier were employed to handle the complex and volatile nature of weather data. Logistic Regression created a solid baseline, while Random Forest emerged as the standout model due to its high accuracy and robustness.

The use of GridSearchCV for hyperparameter tuning significantly improved the model's performance. The application of ROC curve analysis and confusion matrices increased the understanding of each model's capabilities, offering a comprehensive view of their classification accuracies and capacity to differentiate between different meteorological conditions. Cross-validation accuracy tests demonstrated that the models could generalize effectively while avoiding hazards such as overfitting and underfitting.

This study significantly contributes to the science of weather forecasting by demonstrating how machine learning can alter our approach to anticipating weather patterns. The findings support the efficacy of these models and open the path for future advances in meteorological forecasting. Utilizing machine learning power can lead to better preparedness and response tactics across all sectors affected by weather conditions.

# Summary

The study explores the application of machine learning algorithms for weather prediction in Australia. Various algorithms, including Logistic Regression, Decision Trees, Random Forest, Gaussian Naive Bayes, and MLP Classifier, were used to classify weather conditions. Random Forest was found to be particularly effective. GridSearchCV was used for hyperparameter tuning, improving model performance. Performance metrics such as accuracy, precision, recall, F1-score, ROC-AUC score, and confusion matrices were used to evaluate each model's predictive capabilities. Cross-validation accuracy checks confirmed the models' ability to generalize across different data subsets, minimizing overfitting and underfitting risks.

The results have implications for the field of weather prediction, such as enhanced forecasting accuracy and the shift towards data-driven methodologies in meteorology. Future work could focus on expanding datasets and features, exploring advanced machine learning techniques, developing real-time prediction models, and combining machine learning models with traditional meteorological models for a more comprehensive forecasting tool.

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*Dataset References*

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| **Appendix A** |

< A suggested checklist for you, for full details please refer to the coursework brief >

1. The following naming convention is used for the Coventry GitHub Repository and Coventry OneDrive

**StudentID-Initials-s1**

For example, a student Leo Messi whose student ID is 12345678 would name their repository or shared folder as **12345678-LM-s1**

Failure to follow the naming convention may delay the release of marks and feedback for your coursework.

1. **Coventry** GitHub Repository URL **or** **Coventry** OneDrive URL: added to the top of this report
   1. Coventry GitHub Repository includes:

* URL of the selected dataset(s) included in README
* The original selected dataset(s)
* Source-code (.ipynb)
* Demonstration video (.mp4)
  1. Coventry OneDrive folder includes:
* URL of the selected dataset(s) included in a separated text file
* The original selected dataset(s)
* Source-code (.ipynb)
* Demonstration video (.mp4)

1. Source-code added **as text** in Appendix B (below)
2. Submission in the form of a **Word** document. *\*\*Other formats are not accepted.*

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| --- |
| **Appendix B** |

CODE

|  |  |
| --- | --- |
| 1  2  3  4  5  6  7  8  9  10  11  12  13  14  15  16  17  18  19  20  21  22  23  24  25  26  27  28  29  30  31  32  33  34  35  36  37  38  39  40  41  42  43  44  45  46  47  48  49  50  51  52  53  54  55  56  57  58  59  60  61  62  63  64  65  66  67  68  69  70  71  72  73  74  75  76  77  78  79  80  81  82  83  84  85  86  87  88  89  90  91  92  93  94  95  96  97  98  99  100  101  102  103  104  105  106  107  108  109  110  111  112  113  114  115  116  117  118  119  120  121  122  123  124  125  126  127  128  129  130  131  132  133  134  135  136  137  138  139  140  141  142  143  144  145  146  147  148  149  150  151  152  153  154  155  156  157  158  159  160  161  162  163  164  165  166  167  168  169  170  171  172  173  174  175  176  177  178  179  180  181  182  183  184  185  186  187  188  189  190  191  192  193  194  195  196  197  198  199  200  201  202  203  204  205  206  207  208  209  210  211  212  213  214  215  216  217  218  219  220  221  222  223  224  225  226  227  228  229  230  231  232  233  234  235  236  237  238  239  240  241  242  243  244  245  246  247  248  249  250 | **import** **pandas** **as** **pd**  **import** **numpy** **as** **np**  **import** **matplotlib.pyplot** **as** **plt**  **import** **seaborn** **as** **sns**  **import** **itertools**  **from** **sklearn.model\_selection** **import** train\_test\_split, GridSearchCV  **from** **sklearn.preprocessing** **import** MinMaxScaler, LabelEncoder  **from** **sklearn.linear\_model** **import** LogisticRegression  **from** **sklearn.tree** **import** DecisionTreeClassifier  **from** **sklearn.ensemble** **import** RandomForestClassifier  **from** **sklearn.naive\_bayes** **import** GaussianNB  **from** **sklearn.metrics** **import** confusion\_matrix, classification\_report, accuracy\_score, roc\_auc\_score, roc\_curve  **from** **sklearn.neural\_network** **import** MLPClassifier  **from** **sklearn.model\_selection** **import** cross\_val\_score  # Load the dataset  df = pd.read\_csv('weatherAUS.csv')  # Explore the dataset  **print**("First 5 rows of the dataset:")  **print**(df.head(**5**))  **print**("**\n**Shape of the dataset:", df.shape)  **print**("**\n**Columns in the dataset:", df.columns)  **print**("**\n**Checking for null values:")  **print**(df.isnull().sum())  **print**("**\n**Number of unique values in each column:")  **print**(df.nunique())  df.dtypes  # Histograms for numerical features  df.hist(bins=**15**, figsize=(**18**, **14**))  plt.show()  # Bar charts for categorical features  categorical\_cols = df.select\_dtypes(include=['object', 'category']).columns  **for** col **in** categorical\_cols:  df[col].value\_counts().plot(kind='bar')  plt.title(col)  plt.show()  # Basic data cleaning  df.dropna(subset=['RainTomorrow'], inplace=True)  df['Date'] = pd.to\_datetime(df['Date'])  df['Year'] = df['Date'].dt.year  df['Month'] = df['Date'].dt.month  df['Day'] = df['Date'].dt.day  df.drop('Date', axis=**1**, inplace=True)  df.dropna(inplace=True)  df.drop\_duplicates(keep='first', inplace=True)  # Label encoding for categorical variables  categorical = [var **for** var **in** df.columns **if** df[var].dtype == 'O']  label\_encoder = LabelEncoder()  **for** col **in** categorical:  df[col] = label\_encoder.fit\_transform(df[col])  # Visualize the data (add specific plots as needed)  plt.figure(figsize=(**25**, **25**))  sns.heatmap(df.corr(), annot=True, fmt='.2f', cmap='coolwarm')  plt.show()  # Scatter plots for key variables  # Replace 'feature1', 'feature2', etc. with your actual feature names  plt.scatter(df['Location'], df['RainToday'])  plt.xlabel('Location ')  plt.ylabel('RainToday ')  plt.title('Location vs RainToday ')  plt.show()  # Scatter plots for key variables  # Replace 'feature1', 'feature2', etc. with your actual feature names  plt.scatter(df['Location'], df['RainTomorrow'])  plt.xlabel('Location ')  plt.ylabel('RainTomorrow ')  plt.title('Location vs RainTomorrow ')  plt.show()  # Specific Relationships (e.g., between a feature and target)  # Replace 'feature' and 'RainTomorrow' with your actual column names  sns.boxplot(x='RainTomorrow', y='Location', data=df)  plt.title('Location vs RainTomorrow')  plt.show()  # Specific Relationships (e.g., between a feature and target)  # Replace 'feature' and 'RainTomorrow' with your actual column names  sns.boxplot(x='RainToday', y='Location', data=df)  plt.title('Location vs RainToday')  plt.show()  # Split the dataset  X = df.drop('RainTomorrow', axis=**1**)  y = df['RainTomorrow'].astype('int')  X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=**0.4**, random\_state=**42**)  # Scale the features  scaler = MinMaxScaler()  X\_train\_scaled = scaler.fit\_transform(X\_train)  X\_test\_scaled = scaler.transform(X\_test)  models = {  'LogisticRegression': LogisticRegression(max\_iter=**10000**, solver='saga'),  'DecisionTree': DecisionTreeClassifier(),  'RandomForest': RandomForestClassifier(),  'GaussianNB': GaussianNB(),  'MLPClassifier': MLPClassifier(max\_iter=**1000**)  }  # Train and evaluate models with default parameters (without scaling)  default\_accuracies = {}  **for** name, model **in** models.items():  model.fit(X\_train\_scaled, y\_train)  y\_pred = model.predict(X\_test\_scaled)  accuracy = accuracy\_score(y\_test, y\_pred)  default\_accuracies[name] = accuracy  **print**(f'{name} - Default Accuracy: {accuracy:.2f}')  **for** name, model **in** models.items():  cv\_scores = cross\_val\_score(model, X\_train\_scaled, y\_train, cv=**5**)  **print**(f"{name} - Cross-Validated Accuracy: {np.mean(cv\_scores):.2f}")  # Define the hyperparameter grid for each classifier  param\_grids = {  'LogisticRegression': {'C': [**0.01**, **0.1**, **1**, **10**, **100**]},  'DecisionTree': {'max\_depth': [None, **2**, **4**, **6**, **8**, **10**, **12**]},  'RandomForest': {'n\_estimators': [**10**, **50**, **100**, **200**]},  'GaussianNB': {},  'MLPClassifier': {'hidden\_layer\_sizes': [(**50**,), (**100**,), (**50**,**50**)], 'alpha': [**0.0001**, **0.001**, **0.01**]}  }  # Train and evaluate models with hyperparameter tuning  tuned\_models = {}  tuned\_accuracies = {}  **for** name, model **in** models.items():  param\_grid = param\_grids[name]  # If param\_grid is not empty, proceed with GridSearch  **if** param\_grid:  grid\_search = GridSearchCV(model, param\_grid, cv=**5**, scoring='accuracy')  grid\_search.fit(X\_train\_scaled, y\_train)  best\_model = grid\_search.best\_estimator\_  **else**:  best\_model = model  best\_model.fit(X\_train\_scaled, y\_train)  # Predictions and Evaluation  y\_pred = best\_model.predict(X\_test\_scaled)  accuracy = accuracy\_score(y\_test, y\_pred)  tuned\_accuracies[name] = accuracy  **print**(f'{name} Best Parameters: ', best\_model.get\_params())  **print**(f'{name} Confusion Matrix:**\n**', confusion\_matrix(y\_test, y\_pred))  **print**(f'{name} Classification Report:**\n**', classification\_report(y\_test, y\_pred))  **print**(f'{name} - Accuracy: {accuracy:.2f}')  **if** hasattr(best\_model, "predict\_proba"):  **print**(f"{name} - ROC AUC: {roc\_auc\_score(y\_test, best\_model.predict\_proba(X\_test\_scaled)[:, 1]):.2f}")  # Store the best model in the dictionary  tuned\_models[name] = best\_model  **def** **plot\_confusion\_matrix**(cm, classes, title='Confusion matrix', cmap=plt.cm.Blues):  plt.imshow(cm, interpolation='nearest', cmap=cmap)  plt.title(title)  plt.colorbar()  tick\_marks = np.arange(len(classes))  plt.xticks(tick\_marks, classes, rotation=**45**)  plt.yticks(tick\_marks, classes)  thresh = cm.max() / **2.**  **for** i, j **in** itertools.product(range(cm.shape[**0**]), range(cm.shape[**1**])):  plt.text(j, i, format(cm[i, j], 'd'),  horizontalalignment="center",  color="white" **if** cm[i, j] > thresh **else** "black")  plt.tight\_layout()  plt.ylabel('True label')  plt.xlabel('Predicted label')  # Use tuned\_models for evaluations  **for** name, model **in** tuned\_models.items():  y\_pred = model.predict(X\_test\_scaled)  cm = confusion\_matrix(y\_test, y\_pred)  plt.figure(figsize=(**6**,**6**))  plot\_confusion\_matrix(cm, classes=np.unique(y\_test), title=f'{name} Confusion Matrix')  plt.show()  **for** name, model **in** tuned\_models.items():  cv\_scores = cross\_val\_score(model, X\_train\_scaled, y\_train, cv=**5**)  **print**(f"{name} - Cross-Validated Accuracy: {np.mean(cv\_scores):.2f}")  **from** **sklearn.metrics** **import** roc\_curve, roc\_auc\_score  **import** **matplotlib.pyplot** **as** **plt**  plt.figure(figsize=(**8**, **6**))  # Iterate through each model to calculate and plot their ROC curves  **for** name, model **in** tuned\_models.items():  **if** hasattr(model, "predict\_proba"):  # Predict probabilities for the positive class  y\_probs = model.predict\_proba(X\_test\_scaled)[:, **1**]  # Calculate ROC curve  fpr, tpr, thresholds = roc\_curve(y\_test, y\_probs)  # Calculate the AUC  roc\_auc = roc\_auc\_score(y\_test, y\_probs)  # Plot the ROC curve  plt.plot(fpr, tpr, label=f'{name} (AUC = {roc\_auc:.2f})')  # Plot baseline (No Skill Classifier)  plt.plot([**0**, **1**], [**0**, **1**], linestyle='--', label='No Skill')  # Add labels and legend  plt.xlabel('False Positive Rate')  plt.ylabel('True Positive Rate')  plt.title('Receiver Operating Characteristic (ROC) Curves')  plt.legend(loc="lower right")  # Show the plot  plt.show()  **for** name, model **in** tuned\_models.items():  train\_score = model.score(X\_train\_scaled, y\_train)  test\_score = model.score(X\_test\_scaled, y\_test)  **print**(f"{name}:")  **print**(f" Training Score: {train\_score:.2f}")  **print**(f" Test Score: {test\_score:.2f}")  # Visual representation  plt.bar(['Training', 'Test'], [train\_score, test\_score], color=['blue', 'green'])  plt.title(f'Model Performance for {name}')  plt.ylabel('Accuracy Score')  plt.show()  **print**("Accuracy Comparison:")  **for** name **in** models.keys():  default\_acc = default\_accuracies.get(name, "N/A")  tuned\_acc = tuned\_accuracies.get(name, "N/A")  **print**(f'{name}: Default - {default\_acc}, Tuned - {tuned\_acc}')  **for** name, model **in** models.items():  # Train accuracy  train\_accuracy = model.score(X\_train\_scaled, y\_train)  # Test accuracy  test\_accuracy = model.score(X\_test\_scaled, y\_test)  # Calculate the difference between train and test accuracy  accuracy\_difference = train\_accuracy - test\_accuracy  # Check for underfitting or overfitting  **if** abs(accuracy\_difference) < **0.05**:  status = "Good fit"  **elif** accuracy\_difference > **0**:  status = "Possibly overfitting"  **else**:  status = "Possibly underfitting"  **print**(f"{name}:")  **print**(f" Training Accuracy: {train\_accuracy:.2f}")  **print**(f" Test Accuracy: {test\_accuracy:.2f}")  **print**(f" Status: {status}**\n**") |