Assessment Report

on

Rainfall Prediction Model:

“Build a model to predict whether it will rain tomorrow using classification algorithms and weather data.”

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY

DEGREE

SESSION 2024-25

in

ARTIFICIAL INTELLIGENCE

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May, 2025

RAINFALL PREDICTION MODEL USING RANDOM FOREST CLASSIFICATION

1. Introduction

Weather forecasting plays a crucial role in agriculture, disaster prevention, and urban planning. Predicting whether it will rain tomorrow helps in scheduling daily tasks and preventing weather-related disruptions. This project uses machine learning classification algorithms to predict the likelihood of rainfall using historical weather data from the Australian Bureau of Meteorology.

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2. Methodology

The project consists of three main parts:

1. **Data Preprocessing:**
    - Dropped features with excessive missing values (e.g., Evaporation, Sunshine).
    - Handled missing values in numeric columns using mean imputation.
    - Encoded categorical columns using LabelEncoder.
2. **Model Building:**
    - Split the dataset into training (80%) and testing (20%) sets.
    - Trained a RandomForestClassifier model.
3. **Evaluation:**
    - Calculated accuracy, precision, recall, and F1-score.
    - Plotted confusion matrix and feature importance graph.

3. Code

```
from google.colab import files

uploaded = files.upload()

import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import LabelEncoder

from sklearn.impute import SimpleImputer

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

import joblib

# Load dataset

df = pd.read_csv('weatherAUS.csv')

# Drop columns with many missing values

df = df.drop(columns=['Evaporation', 'Sunshine', 'Cloud9am', 'Cloud3pm'])

# Drop rows with missing target

df = df.dropna(subset=['RainTomorrow'])


# Fill numeric missing values with mean

numeric_cols = df.select_dtypes(include=['float64']).columns

imputer = SimpleImputer(strategy='mean')

df[numeric_cols] = imputer.fit_transform(df[numeric_cols])

# Encode all object-type columns using LabelEncoder

categorical_cols = df.select_dtypes(include=['object']).columns

label_encoders = {}
```

```
for col in categorical_cols:
    le = LabelEncoder()
    df[col] = le.fit_transform(df[col].astype(str))
    label_encoders[col] = le

# Separate features and target
X = df.drop(columns=['RainTomorrow'])
y = df['RainTomorrow']
# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Train the model
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)
# Make predictions
y_pred = rf_model.predict(X_test)
# Evaluate
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Classification Report:\n", classification_report(y_test, y_pred))
# Generate the confusion matrix
cm = confusion_matrix(y_test, y_pred)
# Plot it using seaborn heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['No', 'Yes'],
yticklabels=['No', 'Yes'])
plt.xlabel('Predicted')
```

```
plt.ylabel('Actual')
plt.title('Confusion Matrix for RainTomorrow Prediction')
plt.tight_layout()
plt.show()
# Feature Importance Graph
importances = rf.feature_importances_
features = X.columns
indices = importances.argsort()[::-1]

plt.figure(figsize=(10, 6))
sns.barplot(x=importances[indices], y=features[indices])
plt.title('Feature Importances from Random Forest')
plt.xlabel('Importance')
plt.ylabel('Features')
plt.tight_layout()
plt.show()
```

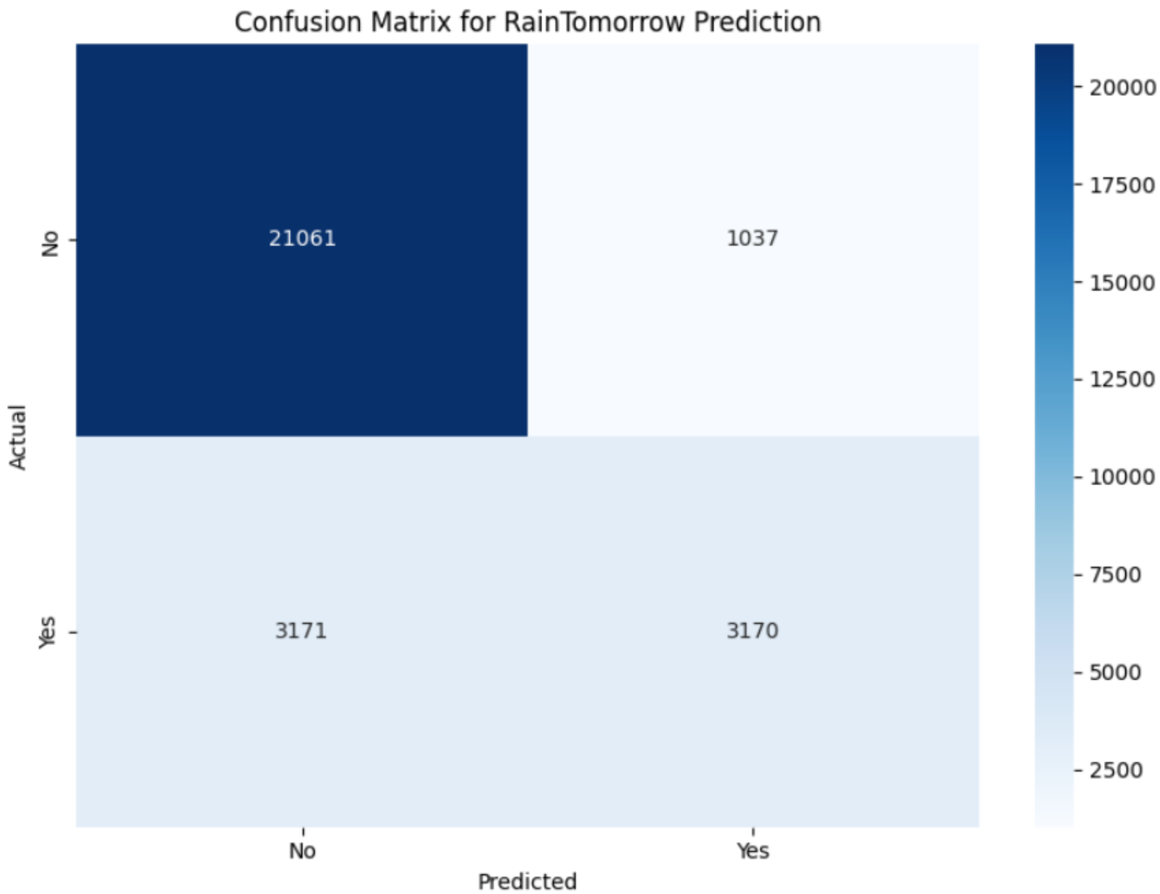
4. Output

4.1 Classification Results:

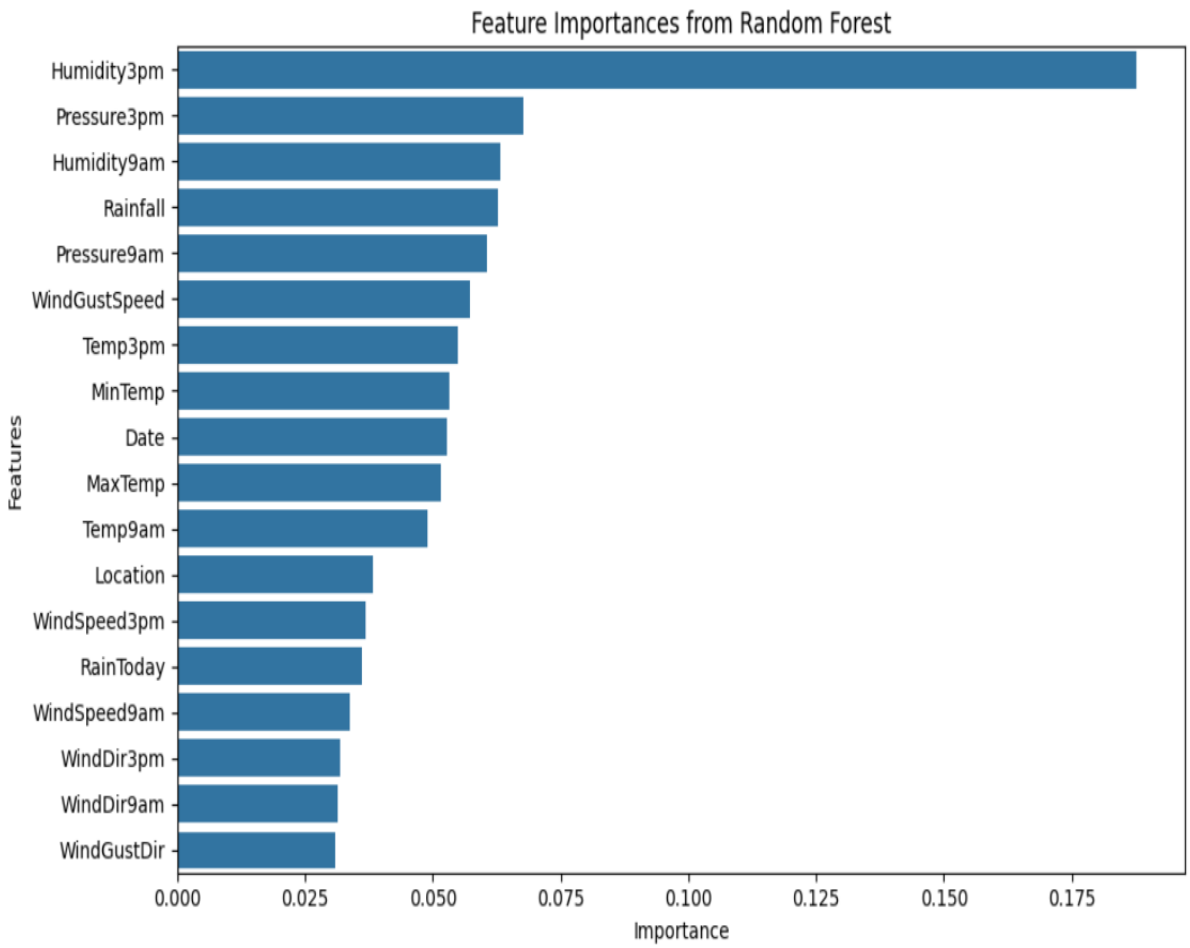
- **Accuracy: ~85%**

```
Accuracy: 0.8520341784169626
Classification Report:
              precision    recall  f1-score   support

           0       0.87      0.95      0.91     22098
           1       0.75      0.50      0.60      6341

    accuracy                           0.85     28439
   macro avg       0.81      0.73      0.76     28439
weighted avg       0.84      0.85      0.84     28439
```

- **Confusion Matrix: (visual shown in graph)**



- **Feature Importance Graph: (displays most impactful weather features)**



5. References

- Dataset: Kaggle - Australian Weather Data
- Seaborn, Matplotlib, Scikit-learn documentation
- Project developed by Uday Gangwar, KIET Group of Institutions