


MACHINE LEARNING LAB REPORT

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Abstract — Comparative Analysis of Machine Learning Models for Rainfall Prediction

Predicting rainfall accurately is essential for planning in sectors like agriculture, transportation, and disaster management. Traditional forecasting methods may not fully leverage historical data patterns. The challenge is to build a reliable classification model that predicts whether it will rain tomorrow, using weather data and machine learning techniques. This project addresses this problem by applying multiple supervised learning algorithms within the KNIME platform.

I. INTRODUCTION

This project aims to build and evaluate five machine learning classification models using KNIME on a weather dataset stored locally.

The models include:

Logistic Regression

Decision Tree

Random Forest

Gradient Boosting

Support Vector Classifier (SVC)

Evaluation is based on:

Accuracy

Precision

Recall

F1 Score

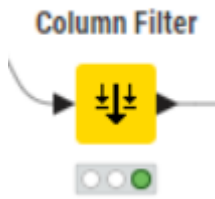
II. DATASET DESCRIPTION

The dataset used in this study is a weather-related dataset located locally on the system. The target variable is `raintomorrow`, indicating whether it will rain the next day.

1) *Data Preprocessing:*

Column Removal:

Removing unnecessary columns: `['date', 'location', 'evaporation', 'sunshine']` using the **Column Filter** node.



Missing Value Handling: Using the **Missing Value** node.



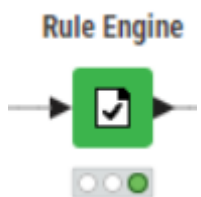
One-hot encoding:

Applied to categorical columns: ['raintoday', 'windgustdir', 'winddir9am', 'winddir3pm'] using **One to Many** node.



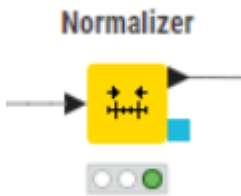
Label Encoding:

Label encode the 'raintomorrow' column (target variable) using a **Rule Engine** node.



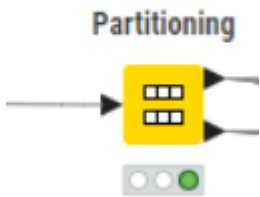
Normalization:

Applied to continuous features using the **Normalizer** node.



2) *Train-Test Split:*

Split the dataset using the **Partitioning** node with:



Training size: 80%

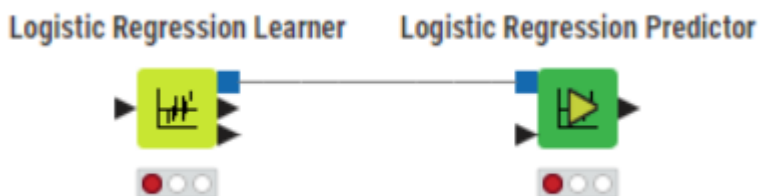
Testing size : 20%

Random seed: 10

3) *Model Configuration and Training:*

Each of the five models trained with specific hyperparameters:

Logistic Regression :



penalty='l2'

C=0.8

random_state=4

Decision Tree :

Decision Tree Learner



Decision Tree Predictor



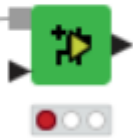
```
criterion='entropy'  
min_samples_split=4  
random_state=32
```

Random Forest :

Random Forest Learner



Random Forest Predictor



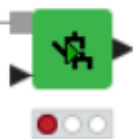
```
n_estimators=128  
criterion='entropy'  
min_samples_split=8
```

Gradient Boosted classifier :

Gradient Boosted Trees Learner

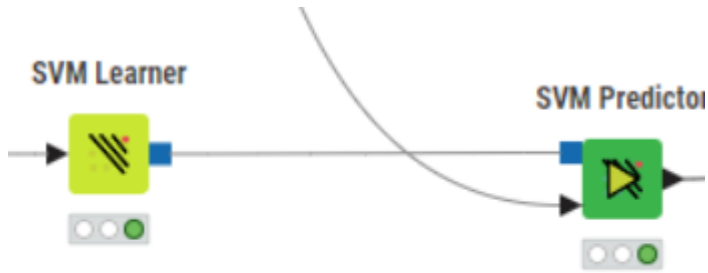


Gradient Boosted Trees Predictor



```
loss='exponential'  
learning_rate=0.3  
n_estimators=64  
criteria='friedman_mse'
```

SVC :



kernel='sigmoid'

gamma='auto'

random_state=64

These settings were manually configured in the corresponding learner nodes.

4) *Model Training and Prediction:*

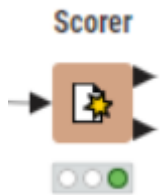
Each model follows this flow:

Learner node: Trained with x_{train} and y_{train} .

Predictor node: Used to predict y_{pred} from x_{test} .

Scorer node: Used to compute evaluation metrics.

scorer node :



5) *Evaluation Metrics:*

Each model's performance was evaluated using:

Confusion Matrix

Accuracy

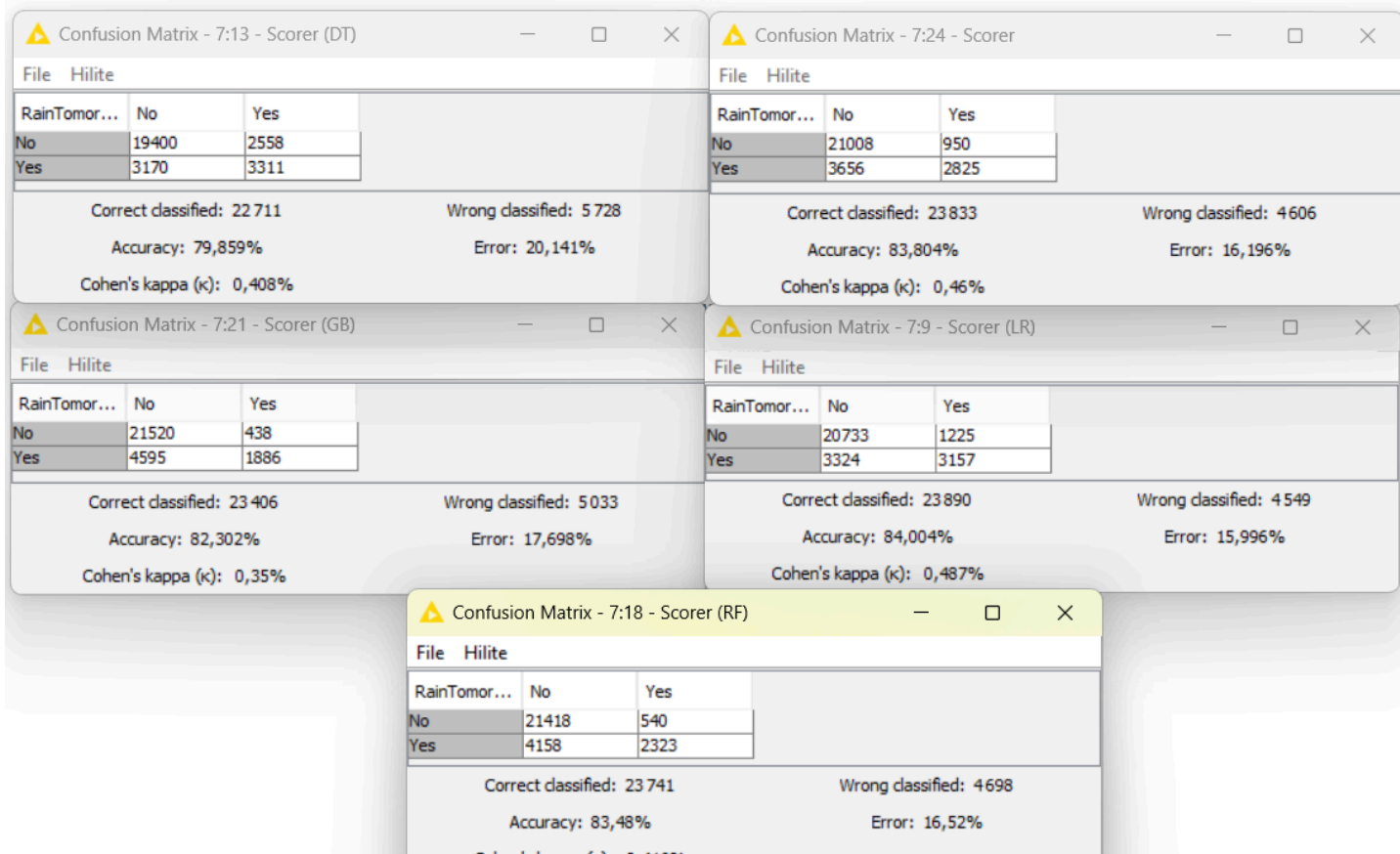
Precision

Recall

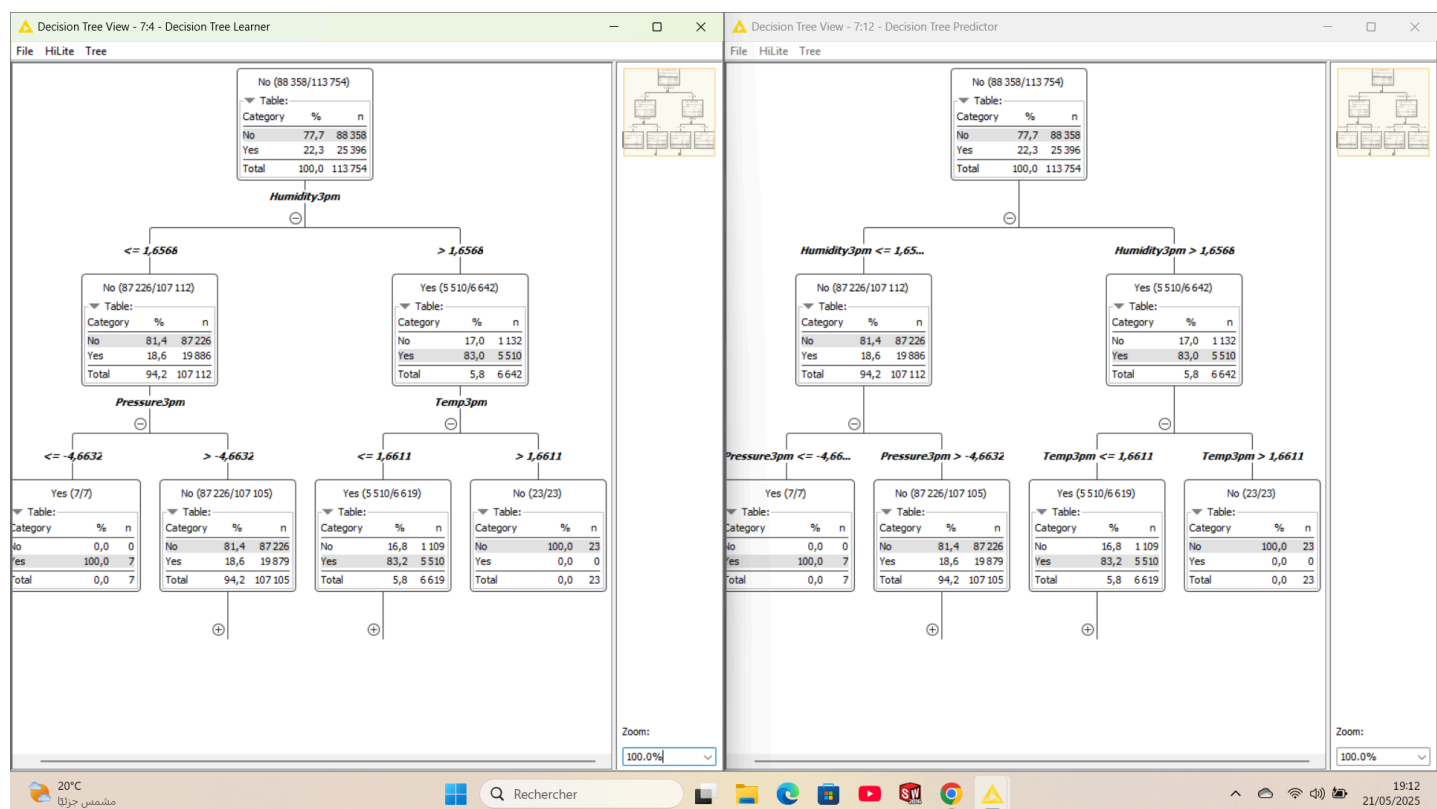
F1 Score

6) *Confusion Matrix:*

Each model's confusion matrix was analyzed to assess classification performance visually.

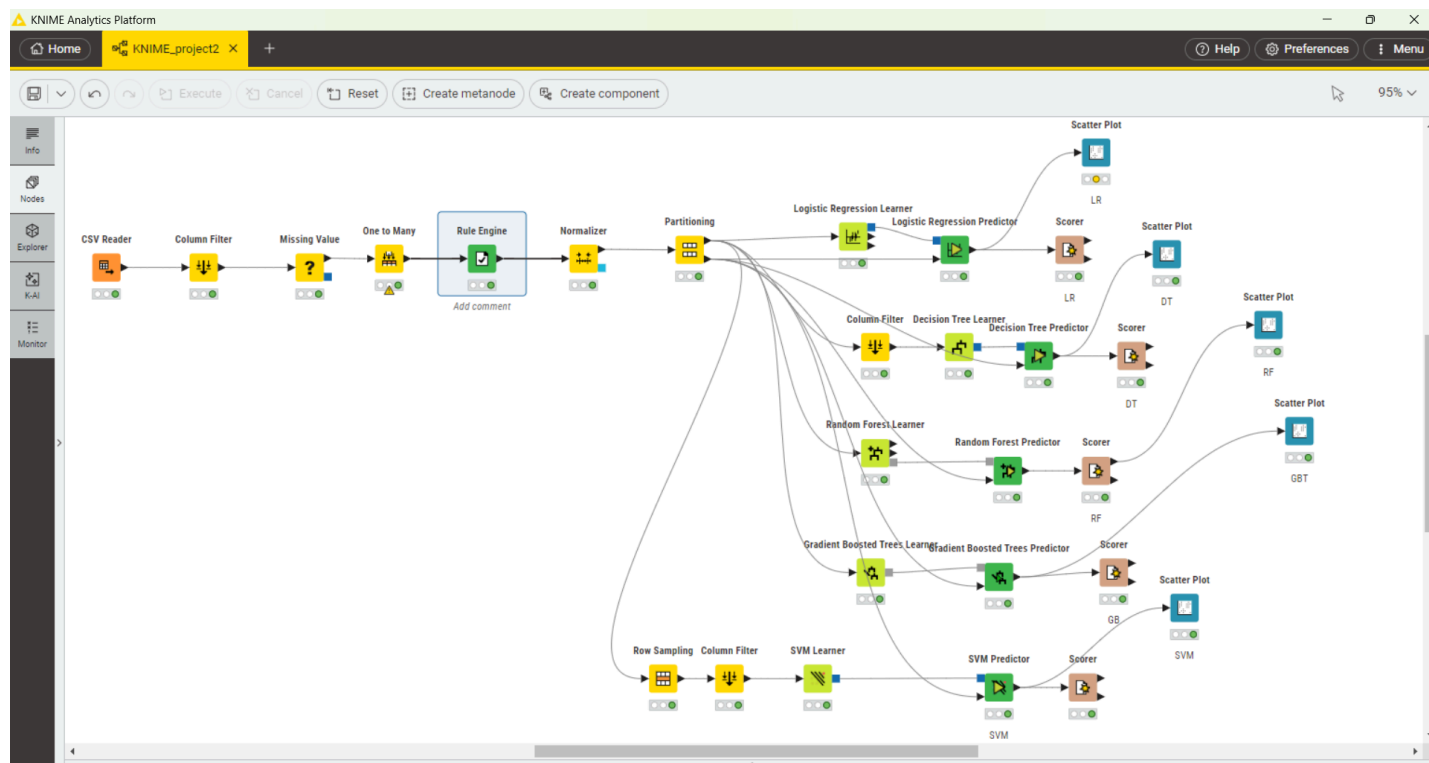


Decision Tree Learner and Predictor Results



7) KNIME Workflow Overview:

The complete KNIME workflow, illustrated below, outlines all steps followed in the project — from data preprocessing to model training, prediction, evaluation, and visualization.



III. OBSERVATIONS

Best Performing Model: Logistic Regression achieved the highest accuracy (83.804%) and highest Cohen’s Kappa score (0.46), indicating it was the most effective at predicting rainfall tomorrow.

Precision-Recall Tradeoff:

Gradient Boosting had the fewest false positives (438) but also the fewest true positives (1,886), suggesting it’s very conservative about predicting rain.

Logistic Regression had more balanced results with 2,825 true positives while maintaining reasonable false positives (950).

IV. CONCLUSION

This KNIME workflow demonstrates how to apply multiple classification algorithms to a preprocessed dataset, evaluate performance using standard metrics, and visualize predictions.