REPORT

Credora Internship **– Data Science**

WEEK 3 -Task 03

[Decision Tree Classifier for Customer Purchase Prediction]

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1. *Objective*

The goal of this task is to build a **Decision Tree Classifier** that predicts whether a customer will purchase a product/service based on demographic and behavioral data. This task emphasizes data preprocessing, visualization, model training, and evaluation using classification techniques.

2. *Dataset Overview*

The dataset comes from the UCI Bank Marketing Repository and contains information about bank marketing campaigns targeting customers for term deposits.

- **Target Variable**: y (yes = client subscribed; no = client did not subscribe)
- **Total Records**: 45,211
- **Key Features**:
  - Demographics: age, job, marital, education
  - Financial: balance, loan, housing
  - Contact: contact, day, month, duration
  - Campaign Behavior: campaign, pdays, previous, poutcome

3. *Data Cleaning & Preprocessing*

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No missing values were found in the dataset.

□
All categorical columns were **Label Encoded** using LabelEncoder from sklearn.

□
Target variable y was converted to binary: **'yes'** → **1**, **'no'** → **0**

□
The dataset was split into **training (80%)** and **testing (20%)** sets.

4. Model Building & Evaluation

4.1 Models Used

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Decision Tree Classifier (baseline)

□
Random Forest Classifier (comparison)

□
Support Vector Machine (SVM) (benchmark)

4.2 Evaluation Metrics

Model =
Accuracy

Decision Tree =
84%

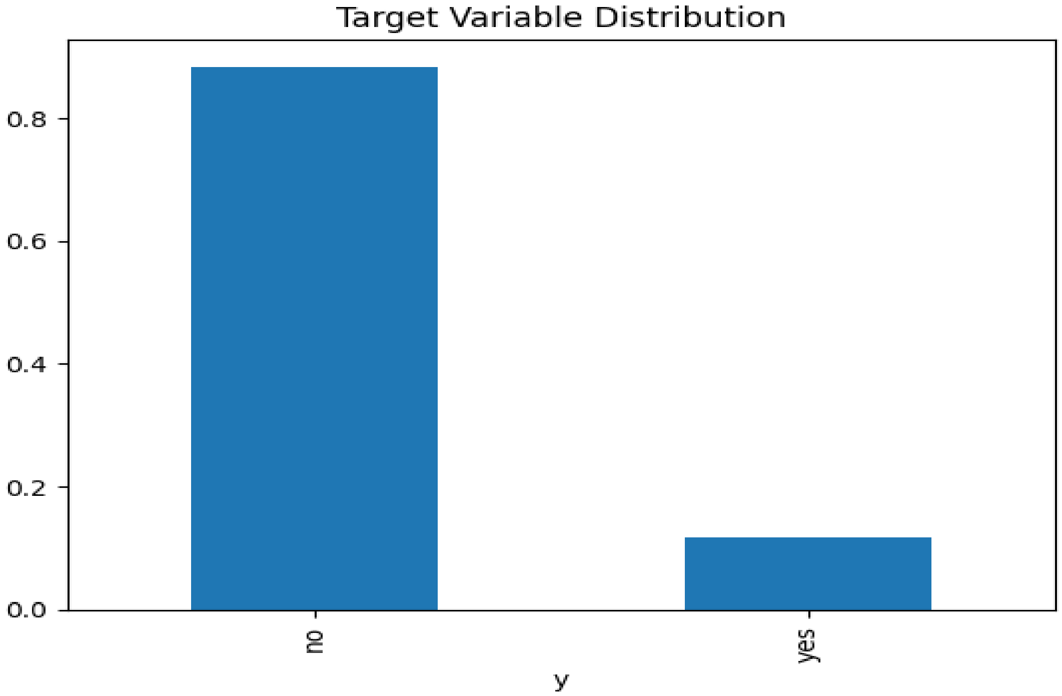
Random Forest =
87%

- Evaluation was done using **accuracy**, **confusion matrix**, and **classification report**
- **Research** was applied to Decision Tree to tune max_depth, min_samples_split
- **5-fold cross-validation** validated model reliability

5. *Key Insights & Visualizations*

5.1 Target Distribution

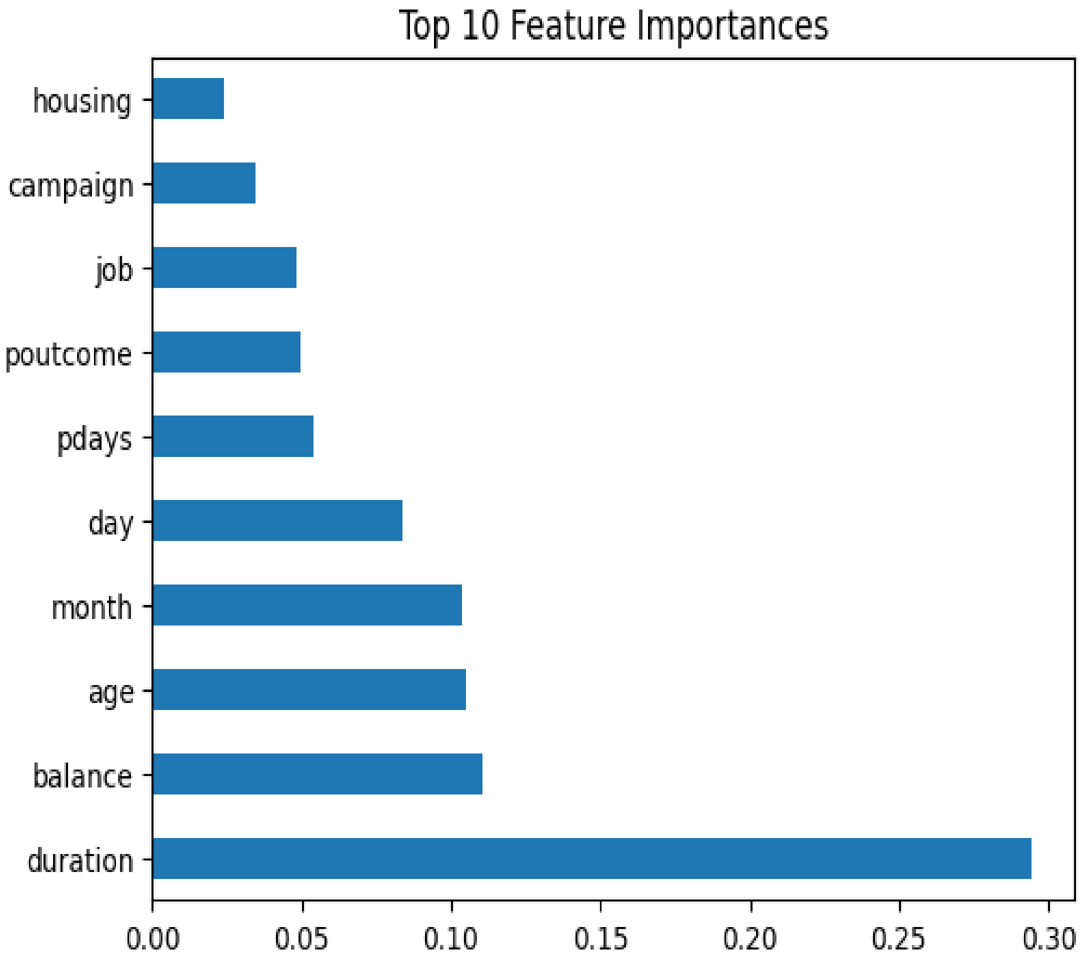
- Majority of the customers did **not** subscribe to the product (~88%)



5.2 Important Features

□

duration, month, poutcome, contact, and previous were highly influential



5.3 Tree Visualizations

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Full decision tree was plotted using plot_tree()

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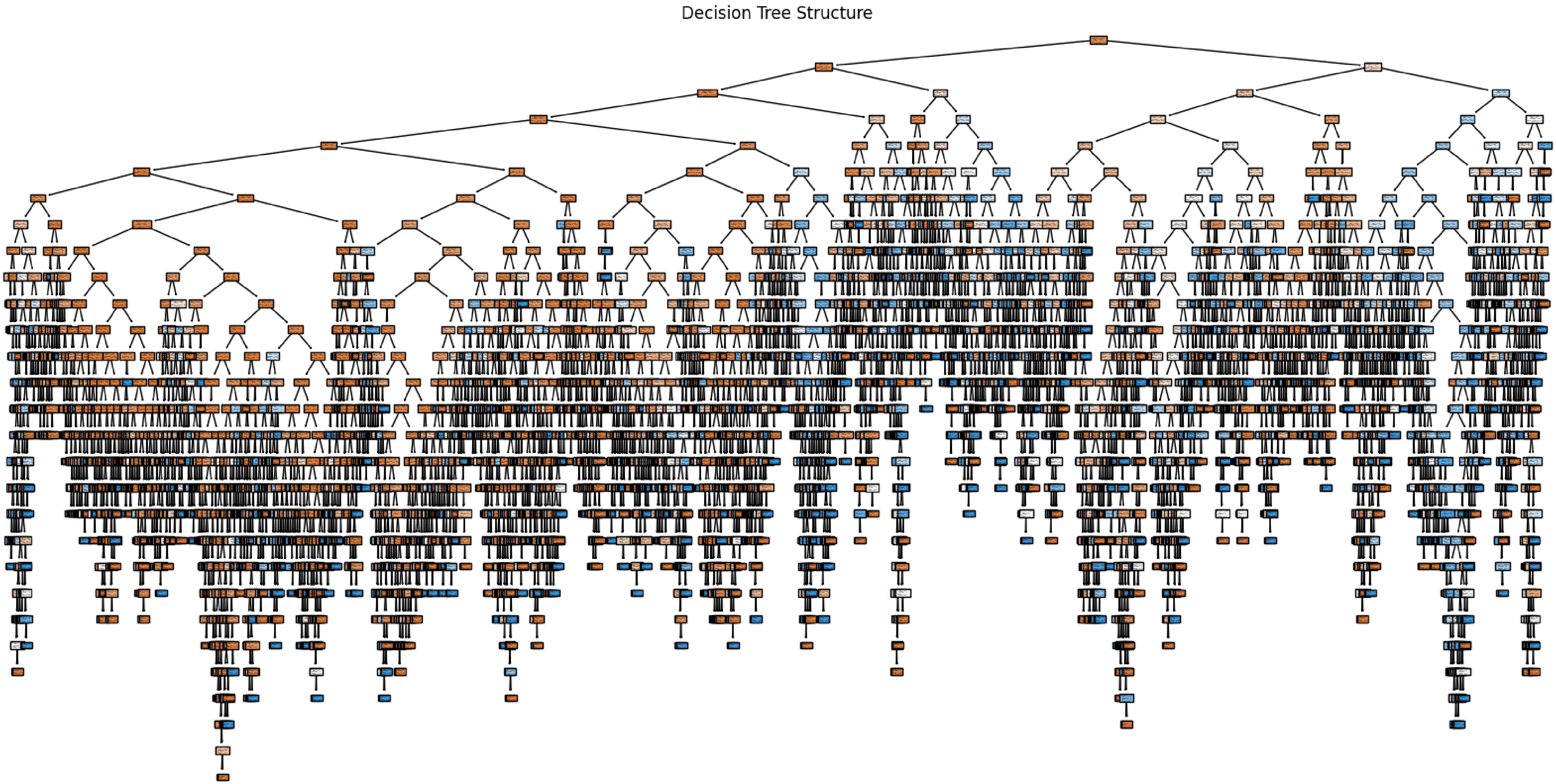
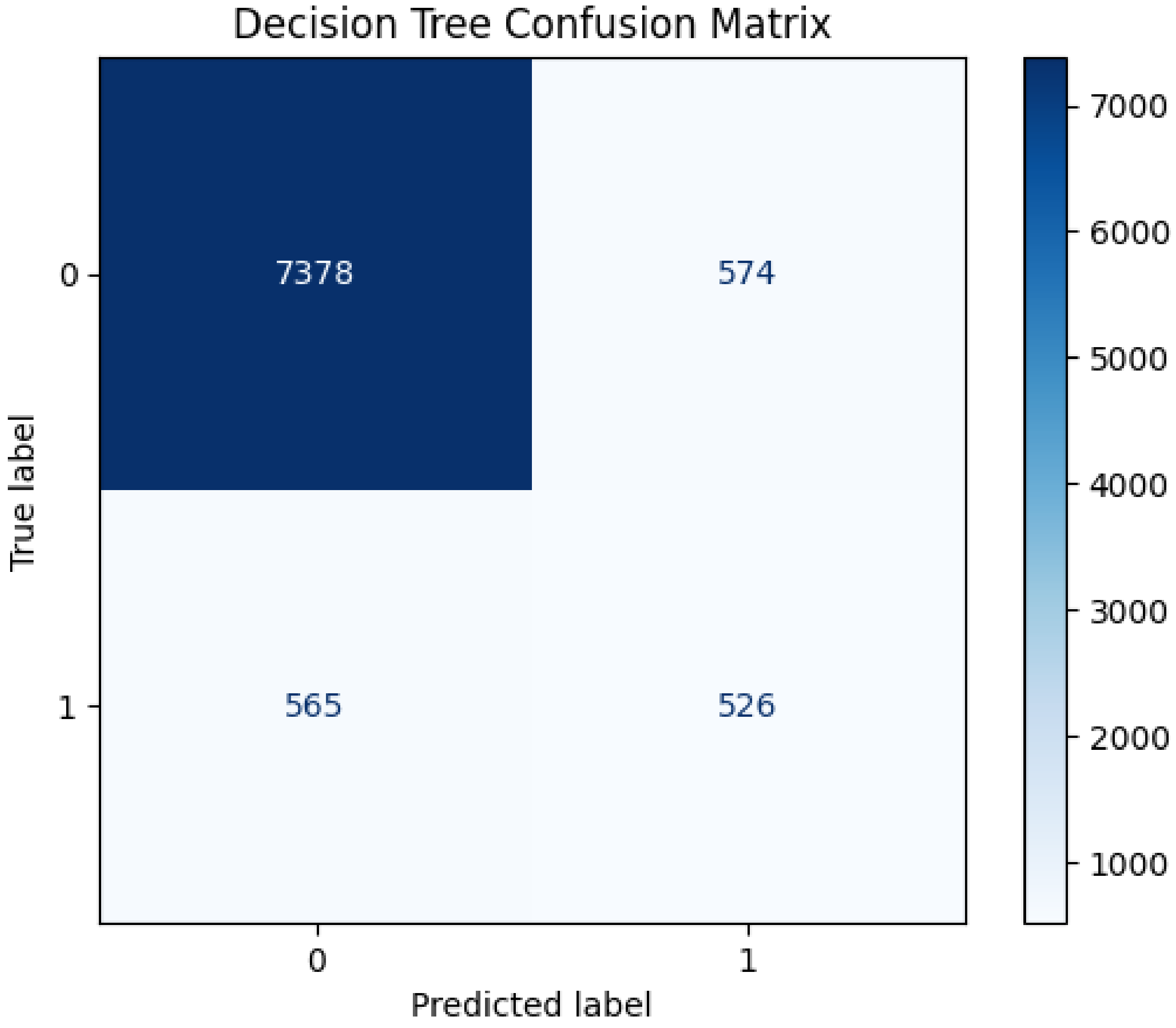
Feature importance was visualized using a horizontal bar chart


Decision Tree Structure

5.4 Confusion Matrix

□

Clearly displayed classification performance with minimal false positives



6. Challenges Faced & Solutions

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High Cardinality in Categorical Columns

→ Many features like job, education, month, and poutcome had many unique string values.
Solution: Used **Label Encoding** to convert them into numeric form while preserving label meaning.

□

Imbalanced Dataset

→ Majority class (no) dominated the dataset, which could

mislead accuracy metrics.
Solution: Evaluated model using **confusion matrix** and **classification report** (precision, recall, F1-score) to get a clearer picture.

□

Overfitting in Decision Tree

→ The initial Decision Tree model overfit the training data performed poorly on unseen data

Solution: Applied **hyperparameter tuning** using GridSearchCV to find the best max_depth and min_samples_

□

Difficulty Interpreting Model Results

→ Tree logic was complex when visualized at full scale.
Solution: Visualized top 10 **feature importances** and used a **pruned decision tree** for easier interpretation.

8. Links

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🗁 GitHub Repohttps://github.com/chessmanandsmiley/credora-internship-task-3.git

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🔗 Google Colab Notebook:
[https://colab.research.google.com/drive/16ybGbq60ppdpyet3xIN0p70w18LIAch0?usp=sharing]

🌐 Dataset: UCI Bank Marketing Repository

9. Contact

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