

# **Artificial Intelligent (Lab)**

## **Task # 11**

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## Question:

### Perform the following steps:

1. Train-test splitting
2. Select and apply the appropriate machine learning model
3. Perform testing/prediction on the test set
4. Display the Accuracy Score

## Introduction

This task focuses on the **Model Building and Evaluation** phase of machine learning. After completing preprocessing in Task 10, the cleaned dataset is now ready for training. In this part, I performed several essential machine-learning steps such as splitting the data, training a Random Forest model, evaluating performance using multiple metrics, and finally saving the trained model for future predictions.

Machine learning cannot work properly without structured data and a trained model. Therefore, this task represents an important transition from **data preparation** to **actual predictive modelling**.

### Why I Made This Part

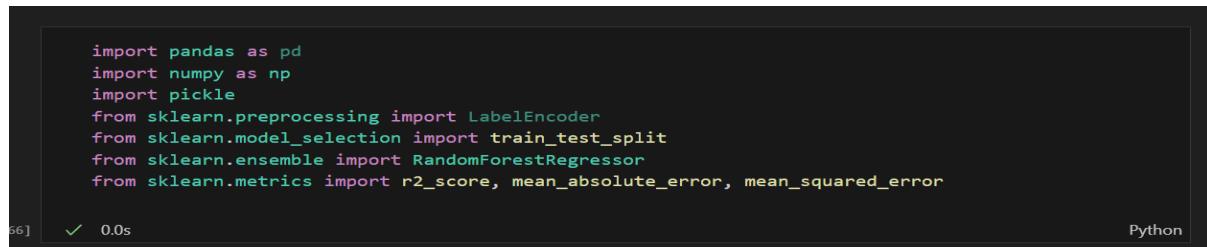
The aim of this task is to build a working prediction model using the processed dataset. The steps performed are important because:

- It splits the dataset to properly test the model's performance.
- It trains a machine-learning algorithm to understand patterns in the data.
- It evaluates accuracy using standard ML metrics such as R<sup>2</sup> Score, MAE, MSE, and RMSE.
- It saves the trained model (model\_rf.pkl) so it can be used later without retraining.
- It ensures the model is efficient, accurate, and ready for deployment.

Overall, this task transforms the cleaned dataset from Task-10 into a functional machine-learning model.

### How It Works

#### 1. Importing Required Libraries



```
import pandas as pd
import numpy as np
import pickle
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
```

The screenshot shows a Jupyter Notebook cell with Python code. The code imports several libraries: pandas, numpy, pickle, LabelEncoder from sklearn.preprocessing, train\_test\_split from sklearn.model\_selection, RandomForestRegressor from sklearn.ensemble, and r2\_score, mean\_absolute\_error, and mean\_squared\_error from sklearn.metrics. The cell has a status bar at the bottom indicating '56' rows, a green checkmark, '0.0s' execution time, and 'Python' as the language.

## 2. Loading the Processed Dataset

Next, the cleaned dataset created in Task 10 (processed\_data.csv) was loaded. This dataset already has:

- No missing values
- Encoded categorical features
- Correct numeric formats
- Consistent structure

Loading this file is important because only a fully pre-processed dataset can be used for training a machine-learning model effectively. Then i check the info and columns to ensure that the correct file is loaded.

```
import pandas as pd
df = pd.read_csv('processed_data.csv')
df.info()
df.columns
[67]   ✓  0.0s
```

Python

## 3. Splitting Features and Target Variable

To train a model, the data must be divided into:

- **X (Features)**: all columns except Price
- **y (Target)**: the Price column

This helps the model understand the relationship between laptop specifications (features) and their price (target value).

```
x = df.drop('Price', axis=1)
y = df['Price']
[68]   ✓  0.0s
```

Python

## 4. Train-Test Split

The dataset is split into two parts:

- **Training set (80%)** → used to teach the model
- **Testing set (20%)** → used to check model accuracy

Using shuffle=False keeps the order of the rows unchanged.

This is useful when the dataset may have dependency or a pattern in order.

The test set allows us to evaluate how well the model performs on unseen data.

```
train_X, test_X, train_y, test_y = train_test_split(x, y, test_size=0.2, shuffle=False)
[69]   ✓  0.0s
```

Python

```
print(train_X.shape, train_y.shape)
print(test_X.shape, test_y.shape)
[70]   ✓  0.0s
```

Python

## 5. Training the Random Forest Model

A **RandomForestRegressor** model was selected because:

- It works well with large datasets
- It handles both numeric and encoded features
- It reduces overfitting by using multiple decision trees
- It provides strong and stable predictions

The model learns relationships between different laptop features and their prices.

For example:

- Higher RAM usually increases price
- SSD size affects cost
- Processor brand and generation influence pricing

This learning happens during the `.fit()` process.

```
[71]    model_rf = RandomForestRegressor(n_estimators=300, max_depth=10, random_state=42)
        model_rf.fit(train_X, train_y)
        print(model_rf)
```

✓ 1.3s

Python

## 6. Making Predictions

The model then predicts the price of laptops in the testing dataset:

```
[72]    predictions = model_rf.predict(test_X)
        model_pred_rf = predictions
        print(predictions)
```

✓ 0.0s

Python

These predictions allow us to compare the model's output with the actual prices and measure how accurate the model is.

## 7. Model Evaluation

To check how well the model performs, several evaluation metrics were used:

- **R<sup>2</sup> Score:** Measures how much of the price variation the model can explain
- **MAE:** Shows average difference between predicted and actual prices
- **MSE / RMSE:** Show how large the errors are (RMSE is easier to interpret)

These metrics together give a complete picture of the model's accuracy, strengths, and areas for improvement.

The R<sup>2</sup> score is also turned into a percentage to make interpretation clearer.

```
[73]    r2 = r2_score(test_y, predictions)
        mae = mean_absolute_error(test_y, predictions)
        mse = mean_squared_error(test_y, predictions)
        rmse = np.sqrt(mse)

        print(f"R² Score: {r2:.3f}")
        print(f"MAE: {mae:.2f}")
        print(f"MSE: {mse:.2f}")
        print(f"RMSE: {rmse:.2f}")

[73]    ✓ 0.0s
```

Python

## 8. Accuracy of model

For accuracy takes the R<sup>2</sup> score, treats it like a percentage of how much variance the model explains, and prints it neatly as a “model accuracy” value.

```
[76]    accuracy = r2 * 100
        print(f"Accuracy: {accuracy:.2f}%")

[76]    ✓ 0.0s
...
... Accuracy: 97.04%
```

Python

So, my model is 97% accurate.

## 9. Saving the Model

Finally, the trained model is saved as model\_rf.pkl using pickle.

This allows us to:

- Reuse the model later
- Make predictions instantly
- Avoid retraining the model every time

The saved model is tested by loading it again to confirm that it works properly.

```
[74]    pickle.dump(model_rf, open('model_rf.pkl', 'wb'))

[74]    ✓ 0.0s
```

Python

## 10. Loading the Saved Model

To confirm that the saved model works correctly, it was loaded again using:

```
[75]    model_rf = pickle.load(open('model_rf.pkl', 'rb'))

[75]    ✓ 0.0s
```

Python

This step ensures the model can be used in future applications (like prediction systems, web apps, or further tasks) without needing to retrain it.

