A Classification Based approach for predicting Smartphone Price Categories

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Outline

Introduction

Background

- The smartphone industry experiences continuous technological innovations, with manufacturers introducing advanced features.
- Multiple global players, such as Apple, Samsung, and Xiaomi, vie for market share, leading to frequent product launches and **pricing battles**.
- Consumers demand **value for money**, with preferences shifting toward devices offering high performance at competitive prices.

Motivation

We hope our model will help:

- Simplify pricing strategies for **manufacturers**
- Increase pricing transparency for **consumers**

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Objectives and Scope

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What This Project Does Cover

- We will train multiple classification models to **predict the price range** of smartphones.
- We will analyze the **feature importance** to determine the most influential factors behind smartphone pricing.
- We will **compare the performance** of various machine learning algorithms.

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What This Project Does Not Cover

- Does not predict **the exact price of smartphones**, only the price category.
- Does not include **real-time** data updates or predictions.
- Does not cover hardware or software **implementation details** of the smartphone features.
- Does not account for **market trends** or **external factors** influencing smartphone prices.
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Dataset Description

Source

Link - https://www.kaggle.com/datasets/iabhishekofficial/smartphone-price-classification

The dataset is publicly available and contains **2000 smartphone entries** with **19 feature variables** and **1 target variable** representing `price_range`.

Features

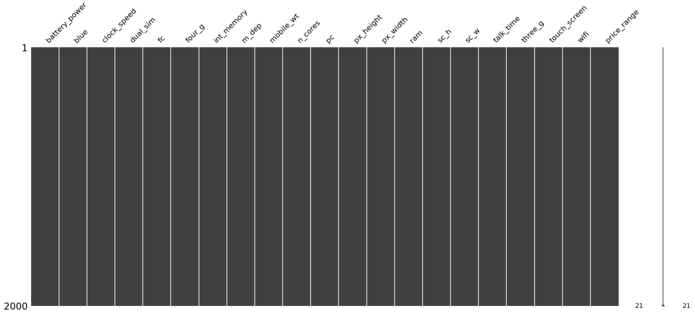
Feature Name	Description	Type
battery_power	battery capacity in mAh	Numerical
clock_speed	speed at which processor executes instructions	Numerical
fc	front Camera Megapixels	Numerical
pc	primary Camera Megapixels	Numerical
int_memory	internal Memory capacity	Numerical
m_dep	smartphone Depth in cm	Numerical
mobile_wt	weight of the smartphone	Numerical
n_cores	number of cores in processor	Numerical
px_height	pixel Resolution Height	Numerical
px_width	pixel Resolution Width	Numerical
ram	RAM in MB	Numerical
sc_h	screen Height in cm	Numerical
sc_w	screen Width in cm	Numerical
talk_time	longest time that a single battery charge will last over a call	Numerical
blue	has bluetooth or not	Categorical
dual_sim	has dual sim support or not	Categorical
four_g	has 4G or not	Categorical
three_g	has 3G or not	Categorical
wifi	has wifi or not	Categorical
touch_screen	has touch screen or not	Categorical

Target Variable

- The target variable `price_range` is **categorical** with **4 classes**.
    - 0 - Low Cost - **Budget** Smartphones
    - 1 - Medium Cost - **Mid-Range** Smartphones
    - 2 - High Cost - **High-End** Smartphones
    - 3 - Very High Cost - **Flagship** Smartphones

Data Preprocessing

Data Cleaning - Handling Missing Values I



Significance: Machine learning models often require complete data to function correctly. Missing values can lead to errors.

Observation: There are no missing values in the dataset.

Data Cleaning - Handling Duplicate Values

```
df.duplicated().sum()
```

```
np.int64(0)
```

Significance: Duplicate entries can distort the true representation of the data, leading to **bias**.

Observation: There are no duplicate values in the dataset.

Data Cleaning - Handling Invalid Values I

```python
negative_counts = df.apply(lambda x: (x < 0).sum())
print(negative_counts)
```

```
battery_power    0
blue             0
clock_speed      0
dual_sim         0
fc               0
four_g           0
int_memory       0
m_dep            0
mobile_wt        0
n_cores          0
pc               0
px_height        0
px_width         0
ram              0
sc_h             0
sc_w             0
talk_time        0
three_g          0
touch_screen     0
wifi             0
price_range      0
dtype: int64
```

Significance: None of the features can have negative values.

Observation: There are no negative values in the dataset.

Data Cleaning - Handling Invalid Values II

```
zero_counts = df.apply(lambda x: (x == 0).sum())
print(zero_counts)
```

```
battery_power       0
blue             1010
clock_speed         0
dual_sim          981
fc                474
four_g            957
int_memory          0
m_dep               0
mobile_wt           0
n_cores             0
pc                101
px_height           2
px_width            0
ram                 0
sc_h                0
sc_w              180
talk_time           0
three_g           477
touch_screen      994
wifi              986
price_range       500
dtype: int64
```

Significance: Most of the numerical features can not be zero except `fc` and `pc`. These two being zero means the phone does not have a front or primary camera.

Observation: `px_height` and `sc_w` are have 2 and 180 zero values respectively.

Action: We replaced these zero values with the mean of the respective features.

Data Cleaning - Handling Invalid Values III

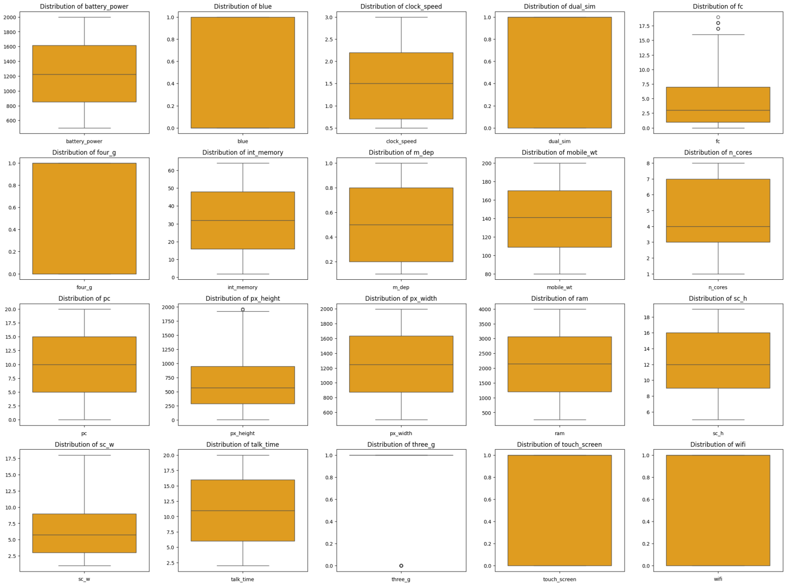
```
to_replace_with_mean = ['sc_w', 'px_height']

for feature in to_replace_with_mean:
  df[feature] = df[feature].replace(0, df[feature].mean())
```

Data Cleaning - Outlier Handling I

Significance:

- Outliers can distort the true representation of data.
- Machine learning models can be sensitive to outliers.

Data Cleaning - Outlier Handling II



Data Cleaning - Outlier Handling (cont.)

Observation: The box plots revealed outliers in two features, `fc` and `px_height`.

Action: To identify these outliers, we will use the IQR (Interquartile Range) method and remove extreme values.

$$\mathrm{IQR} = Q3 - Q1$$

Once the IQR is calculated, outliers are identified using the following bounds:

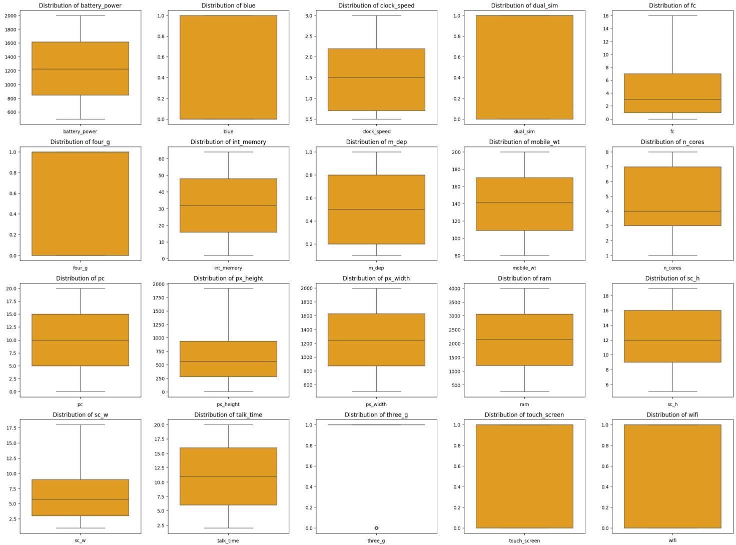
$$\text{Lower Bound} = Q1 - 1.5 \times \mathrm{IQR} \qquad \text{Upper Bound} = Q3 + 1.5 \times \mathrm{IQR}$$

Any data point that falls below the lower bound or above the upper bound is considered an outlier.

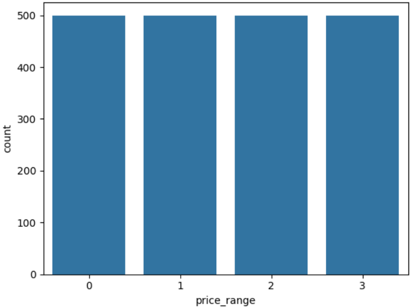
Data Cleaning - Outlier Handling (cont.)

```
def remove_outliers_iqr(data, column):
  Q1 = data[column].quantile(0.25)
  Q3 = data[column].quantile(0.75)
  IQR = Q3 - Q1

  lower_bound = Q1 - 1.5 * IQR
  upper_bound = Q3 + 1.5 * IQR

  filtered_data = data[(data[column] >= lower_bound) &
                       (data[column] <= upper_bound)]
  return filtered_data

df = remove_outliers_iqr(df, 'fc')
df = remove_outliers_iqr(df, 'px_height')
```

Data Cleaning - Outlier Handling (cont.)



Data Cleaning - Checking for Class Imbalance

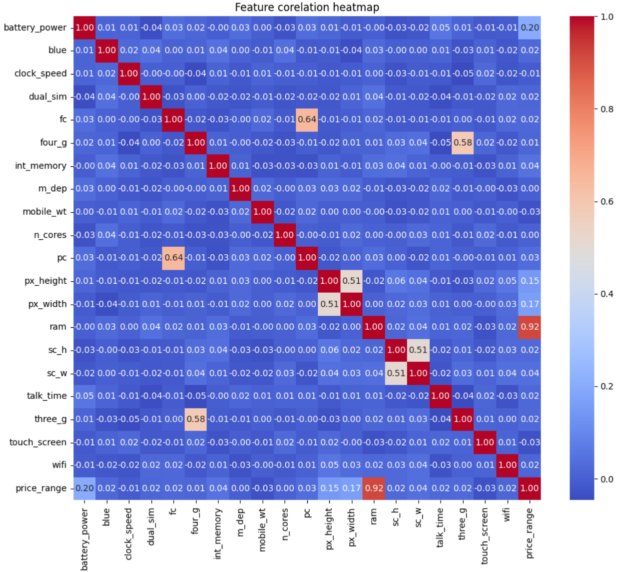


Significance: Imbalanced dataset makes the model biased towards the majority class.

Observation: There are no class imbalance in the dataset.

Data Cleaning - Correlation Analysis I

Significance:
Correlation analysis helps identify relationships between features. It can help in feature engineering.



Data Cleaning - Correlation Analysis II

Observation:

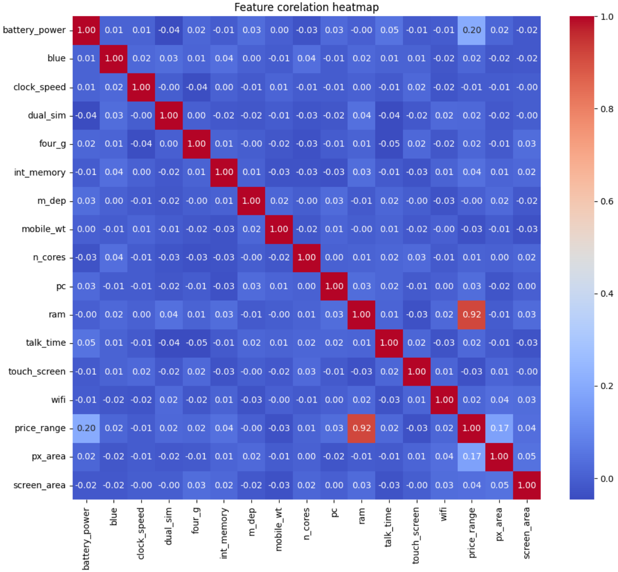
1. **ram and price_range :** Higher RAM capacity leads to higher price range.
2. **three_g and four_g :** A high correlation here suggests that devices with 4G almost always support 3G, making one of these features redundant.
3. **fc and pc :** These features are correlated, as better primary cameras often accompany better front cameras.
4. **px_height and px_width :** These are components of screen resolution and are naturally correlated.
5. **sc_h and sc_w :** These are also naturally correlated.

Data Cleaning - Correlation Analysis III

Action:

1. **three_g and four_g :** `three_g` was removed from the dataset.
2. **fc and pc :** `fc` was removed from the dataset.
3. **px_height and px_width :** They were combined to form a new feature `px_area = px_height * px_width`.
4. **sc_h and sc_w :** They were combined to form a new feature `screen_area = sc_h * sc_w`.

Data Cleaning - Correlation Analysis IV



Correlation Matrix after feature engineering

Feature Selection I

Significance: By selecting the most relevant features, the model can focus on the **most important** information. Moreover, including irrelevant or redundant features can cause the model to **overfit** the training data. Also, fewer features mean **less data to process**.

Action: In our project, we used the ANOVA F-test (Analysis of Variance) method to evaluate each feature's relationship with the target variable, price_range, and select features that are statistically significant. The threshold for selection is a p-value of less than 0.1 i.e. a 90% confidence level.

Feature Selection II

```
y = df.pop('price_range')
X = df
feature_selector = SelectKBest(f_classif, k='all')
X_selected = feature_selector.fit_transform(X, y)
p_values = feature_selector.pvalues_
f_scores = feature_selector.scores_

selected_features = X.columns[p_values < 0.1]
```

Outcome: The selected features are:
'battery_power', 'int_memory', 'mobile_wt', 'n_cores', 'ram', 'px_area', 'screen_area'

Train-Test Split

Significance: Splitting the dataset into training and testing sets allows us to evaluate model performance and ensure that the model generalizes well to unseen data.

Action: We used `train_test_split` from `sklearn.model_selection` to split the dataset into 80% training and 20% testing sets.

Outcome: The train-test split resulted in 1584 samples with 7 features for training and 396 samples with 7 features for testing, with corresponding target arrays of 1584 and 396 elements, respectively.

Scaling

Significance: Scaling ensures that all feature values are normalized, which improves the performance and convergence of many machine learning algorithms.

Action: We used the `StandardScaler` from `sklearn.preprocessing` to scale the feature values.

Outcome: The dataset was successfully scaled, resulting in normalized feature values that contribute equally to the model training process.

Methodology and Analysis

Tools and Libraries

1. Python
2. Jupyter Notebook
3. Data Handling Libraries:
    1. Pandas
    2. Numpy
4. **Visualization Libraries:**
    1. Matplotlib
    2. Seaborn
5. **Machine Learning Libraries:**
    1. Scikit-learn
    2. XGBoost
6. **Other Libraries:**
    1. TQDM
    2. Time

Models Development

We trained 6 models based on following algorithms:

1. Logistic Regression
2. K-Nearest Neighbors
3. Decision Tree
4. Random Forest
5. Support Vector Machine
6. XGBoost

Initial Training I

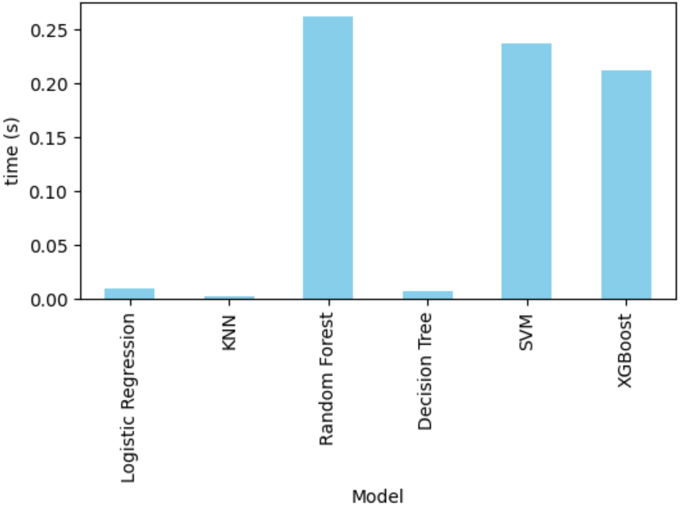
```python
models = {
    'Logistic Regression': LogisticRegression(max_iter=1000),
    'KNN': KNeighborsClassifier(),
    'Random Forest': RandomForestClassifier(),
    'Decision Tree': DecisionTreeClassifier(),
    'SVM': SVC(probability=True),
    'XGBoost': XGBClassifier(eval_metric='mlogloss'),
}
```

Initial Training II

Model	Accuracy Train	Accuracy Test	Precision Train	Precision Test	Recall Train	Recall Test	F1-Score Train	F1-Score Test
Logistic Regression	0.9463	0.9444	0.9465	0.9445	0.9463	0.9444	0.9464	0.9443
KNN	0.8580	0.7222	0.8608	0.7401	0.8580	0.7222	0.8588	0.7279
Random Forest	1.0000	0.8889	1.0000	0.8886	1.0000	0.8889	1.0000	0.8885
Decision Tree	1.0000	0.8712	1.0000	0.8722	1.0000	0.8712	1.0000	0.8715
SVM	0.9545	0.9066	0.9549	0.9084	0.9545	0.9066	0.9546	0.9070
XGBoost	1.0000	0.9167	1.0000	0.9168	1.0000	0.9167	1.0000	0.9164

Table: Initial Model Performance Metrics

Initial Training III



Hyperparameter Tuning I

Hyperparameter Tuning is done to optimize the models for better generalization and prediction accuracy. We used `GridSearchCV` to get the best parameters for each model.

Hyperparameter Tuning II

```python
param_grids = {
  'Logistic Regression': {
    'C': [0.01, 0.1, 1, 10],
    'solver': ['liblinear', 'saga'],
    'penalty': ['l1', 'l2'],
    'max_iter': [500, 1000]
  },
  'KNN': {
    'n_neighbors': [3, 5, 7],
    'weights': ['uniform', 'distance'],
    'p': [1, 2]
  },
  'Random Forest': {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5]
  },
  'Decision Tree': {
    'max_depth': [None, 10, 20],
    'criterion': ['gini', 'entropy']
  },
  'SVM': {
    'C': [0.1, 1, 10],
    'kernel': ['linear', 'rbf'],
    'gamma': ['scale']
  },
  'XGBoost': {
    'learning_rate': [0.05, 0.1],
    'n_estimators': [100, 200],
    'max_depth': [3, 6]
  },
}
```

Hyperparameter Tuning III

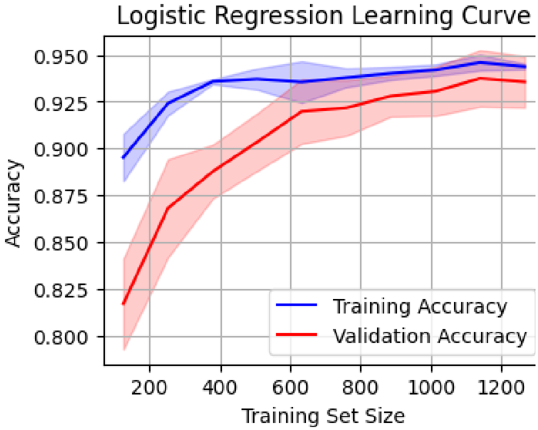
```
for model_name, model in models.items():
  pipeline = Pipeline([
      ('scaler', StandardScaler()),
      ('classifier', model)
  ])
  param_grid = {
      f'classifier__{key}': value for key, value in param_grids[model_name].items()
  }
  grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='accuracy',
                             verbose=1, error_score='raise')
  grid_search.fit(X_train, y_train)

  best_params = grid_search.best_params_
  best_score = grid_search.best_score_
  best_pipeline = grid_search.best_estimator_
  best_model = best_pipeline.named_steps['classifier']

  y_train_pred = best_pipeline.predict(X_train)
  y_test_pred = best_pipeline.predict(X_test)
```

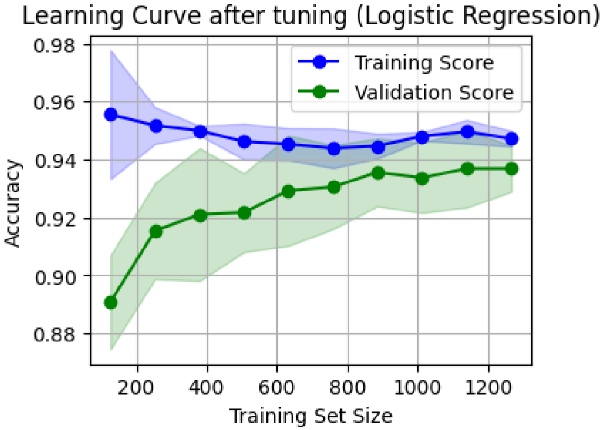
Hyperparameter Tuning IV

Model	Accuracy Train	Accuracy Test	Precision Train	Precision Test	Recall Train	Recall Test	F1-Score Train	F1-Score Test
Logistic Regression	0.9457	0.9495	0.9458	0.9492	0.9457	0.9495	0.9457	0.9493
KNN	0.8592	0.7626	0.8615	0.7790	0.8592	0.7626	0.8596	0.7670
Random Forest	1.0000	0.8889	1.0000	0.8906	1.0000	0.8889	1.0000	0.8889
Decision Tree	0.9968	0.8712	0.9968	0.8718	0.9968	0.8712	0.9968	0.8710
SVM	0.9476	0.9520	0.9477	0.9518	0.9476	0.9520	0.9476	0.9518
XGBoost	0.9962	0.9192	0.9962	0.9196	0.9962	0.9192	0.9962	0.9190

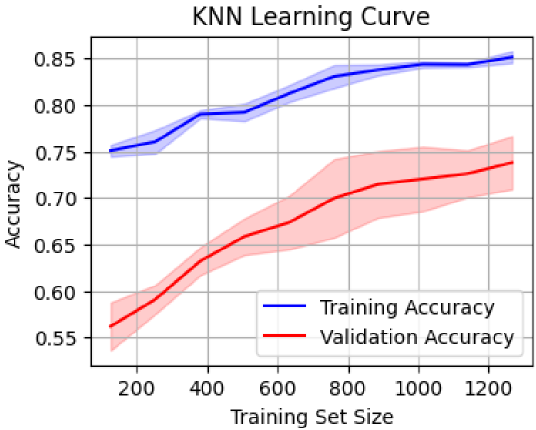
Table: Model Performance Metrics after Hyperparameter Tuning

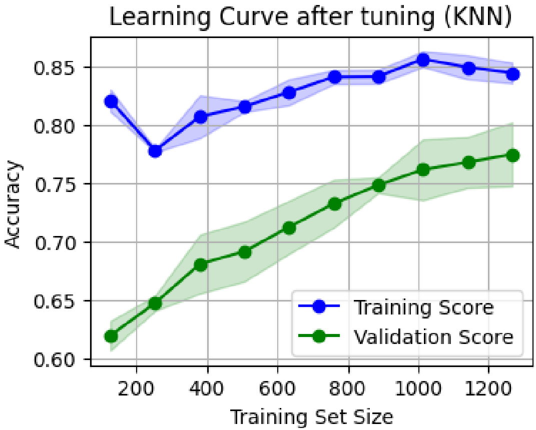
Analysis I


Logistic Regression Learning Curve
0.950
0.925
0.900
0.875
0.850
0.825
0.800
Accuracy
Training Accuracy
Validation Accuracy
200
400
600
800
1000
1200
Training Set Size

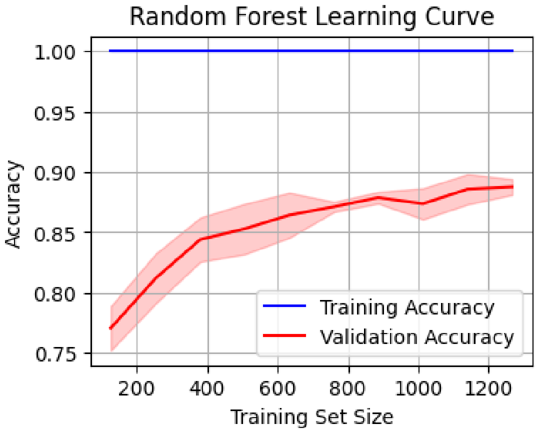

Learning Curve after tuning (Logistic Regression)
0.98
0.96
0.94
0.92
0.90
0.88
Accuracy
Training Score
Validation Score
200
400
600
800
1000
1200
Training Set Size

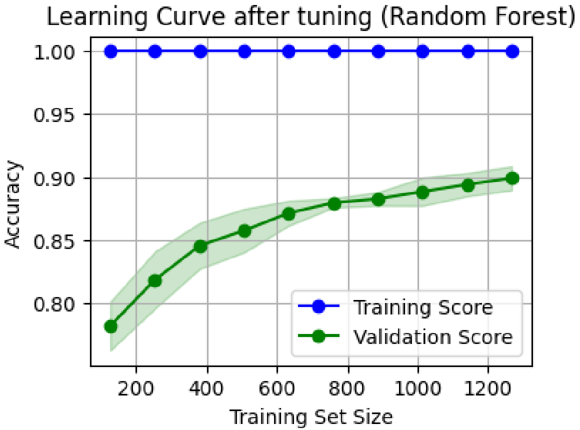
Analysis II


KNN Learning Curve
Accuracy
Training Set Size
0.85
0.80
0.75
0.70
0.65
0.60
0.55
200
400
600
800
1000
1200
Training Accuracy
Validation Accuracy

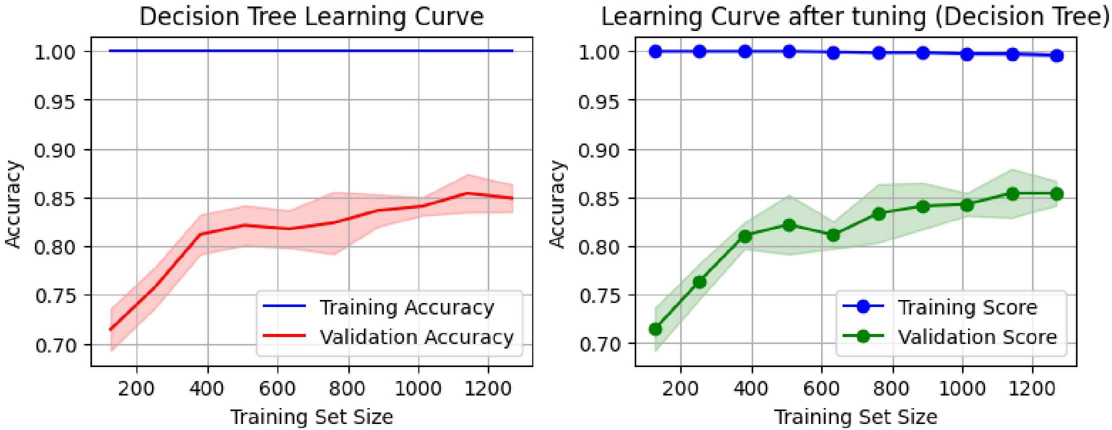

Learning Curve after tuning (KNN)
Accuracy
Training Set Size
0.85
0.80
0.75
0.70
0.65
0.60
200
400
600
800
1000
1200
Training Score
Validation Score

Analysis III

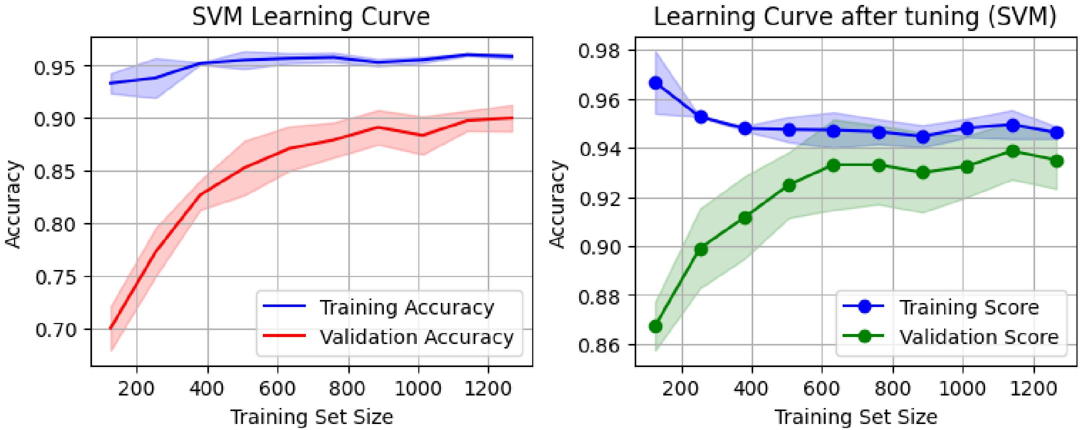




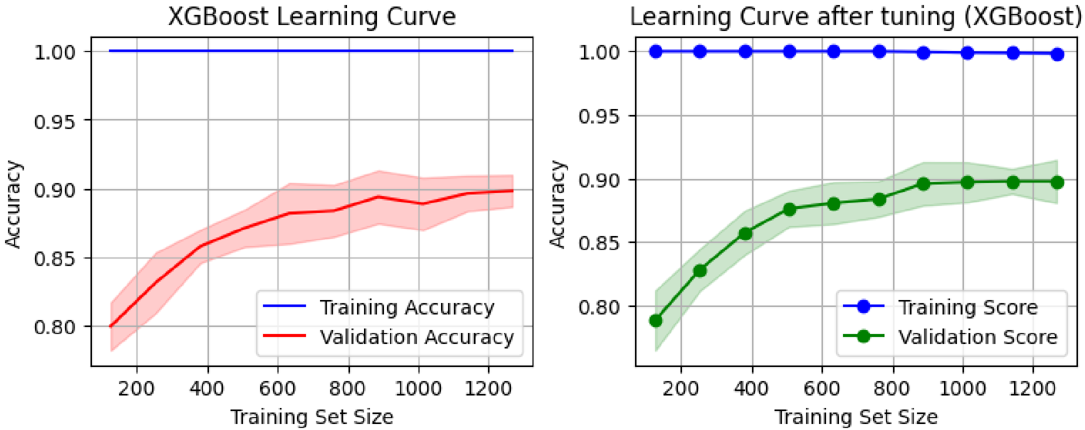
Analysis IV


Decision Tree Learning Curve
Accuracy
1.00
0.95
0.90
0.85
0.80
0.75
0.70
200
400
600
800
1000
1200
Training Set Size
Training Accuracy
Validation Accuracy
Learning Curve after tuning (Decision Tree)
Accuracy
1.00
0.95
0.90
0.85
0.80
0.75
0.70
200
400
600
800
1000
1200
Training Set Size
Training Score
Validation Score

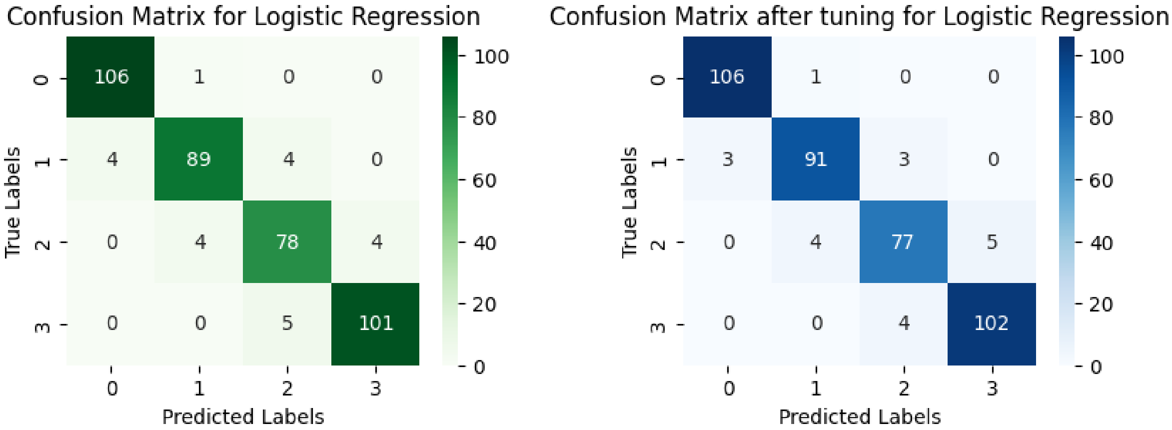
Analysis V


SVM Learning Curve
Accuracy
0.95
0.90
0.85
0.80
0.75
0.70
200
400
600
800
1000
1200
Training Set Size
Training Accuracy
Validation Accuracy
Learning Curve after tuning (SVM)
0.98
0.96
0.94
0.92
0.90
0.88
0.86
Training Score
Validation Score

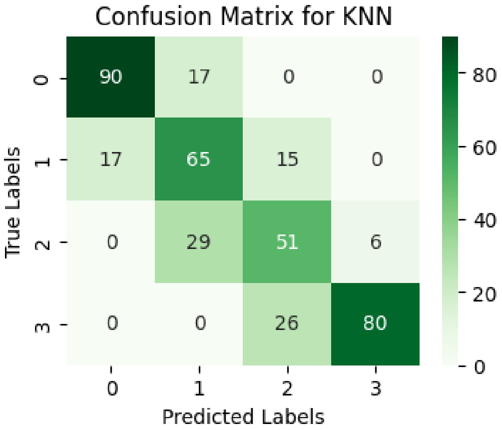
Analysis VI

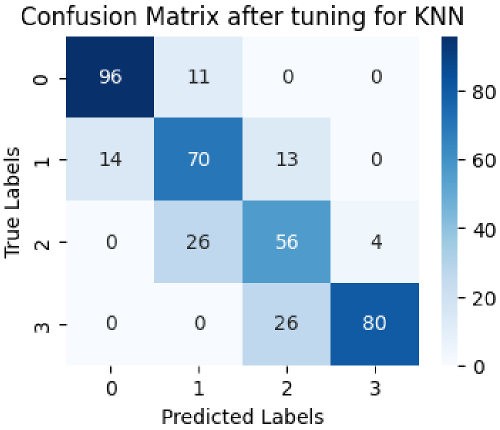

XGBoost Learning Curve
Accuracy
1.00
0.95
0.90
0.85
0.80
200
400
600
800
1000
1200
Training Set Size
Training Accuracy
Validation Accuracy
Learning Curve after tuning (XGBoost)
Accuracy
Training Score
Validation Score
Training Set Size

Analysis VII

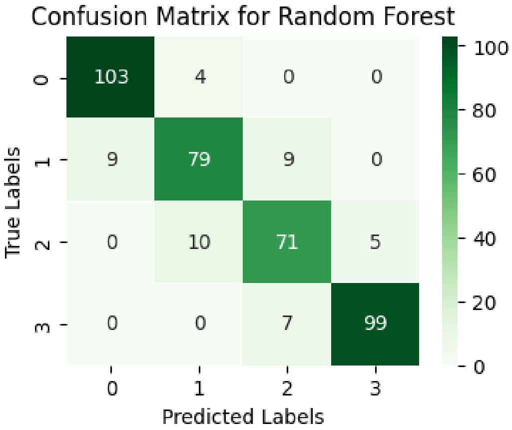


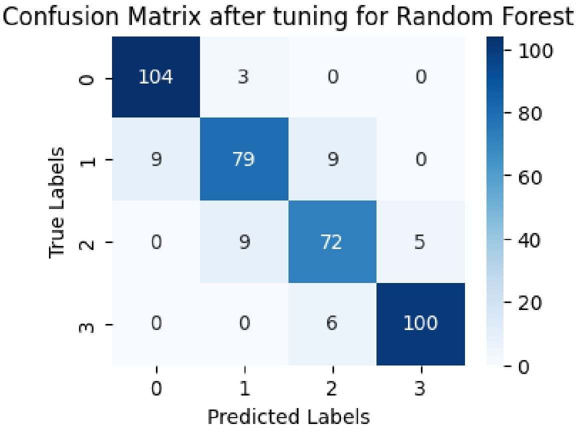
Analysis VIII



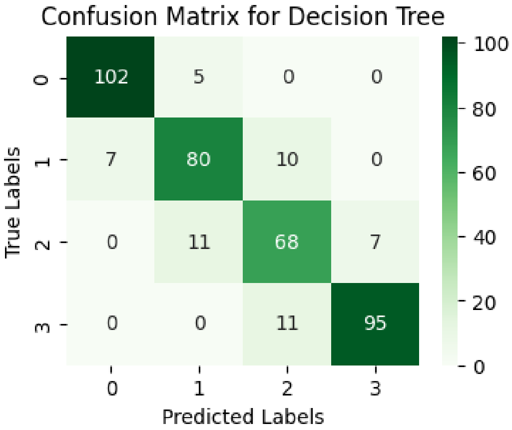


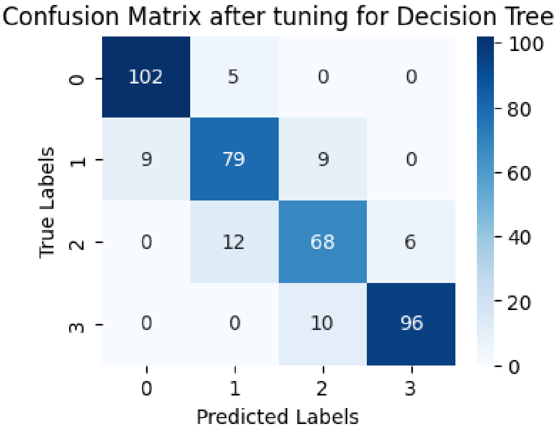
Analysis IX


Confusion Matrix for Random Forest
True Labels
Predicted Labels
103 4 0 0
9 79 9 0
0 10 71 5
0 0 7 99
0 1 2 3
0 20 40 60 80 100

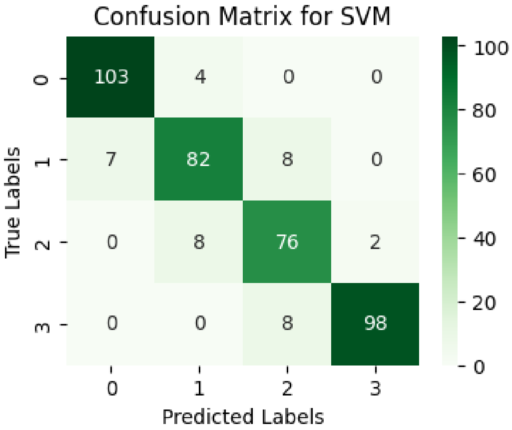

Confusion Matrix after tuning for Random Forest
True Labels
Predicted Labels
104 3 0 0
9 79 9 0
0 9 72 5
0 0 6 100
0 1 2 3
0 20 40 60 80 100

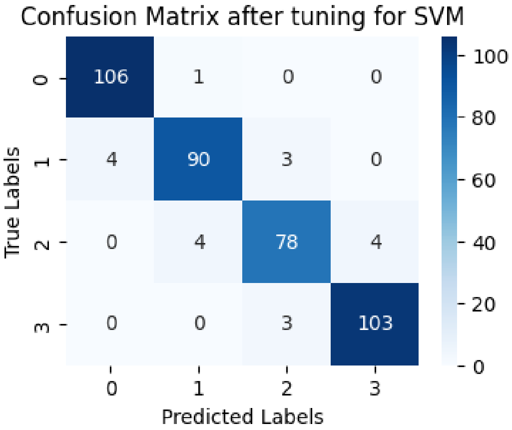
Analysis X


Confusion Matrix for Decision Tree
True Labels
Predicted Labels
0
1
2
3
102
5
0
0
7
80
10
0
0
11
68
7
0
0
11
95
100
80
60
40
20
0

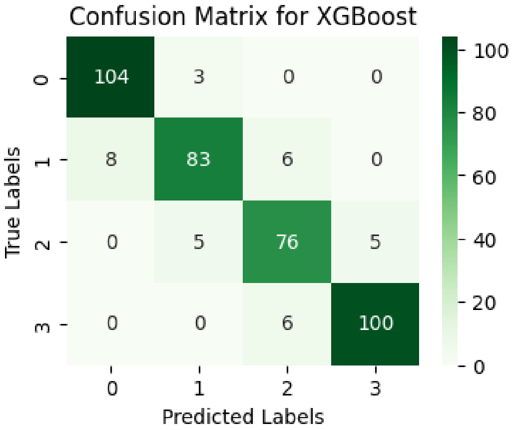

Confusion Matrix after tuning for Decision Tree
True Labels
Predicted Labels
0
1
2
3
102
5
0
0
9
79
9
0
0
12
68
6
0
0
10
96
100
80
60
40
20
0

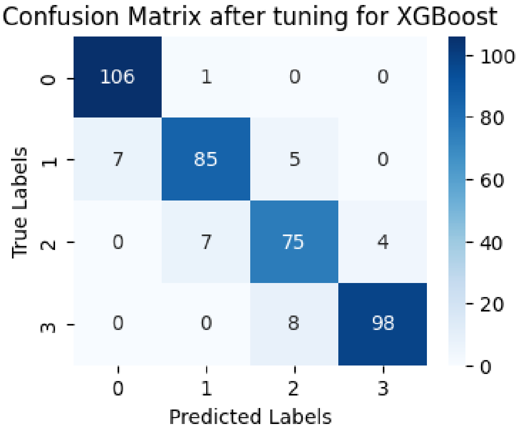
Analysis XI


Confusion Matrix for SVM
True Labels
Predicted Labels
0 1 2 3
103 4 0 0
7 82 8 0
0 8 76 2
0 0 8 98
100 80 60 40 20 0

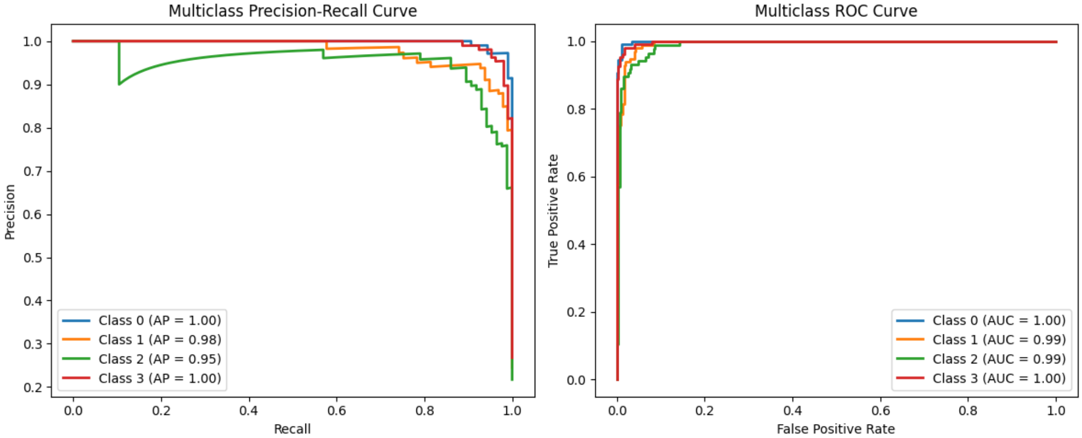

Confusion Matrix after tuning for SVM
True Labels
Predicted Labels
0 1 2 3
106 1 0 0
4 90 3 0
0 4 78 4
0 0 3 103
100 80 60 40 20 0

Analysis XII

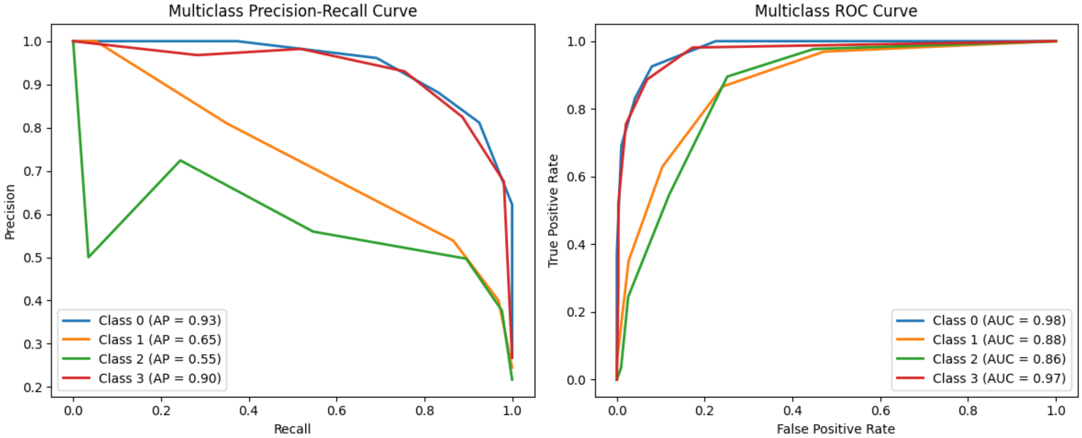




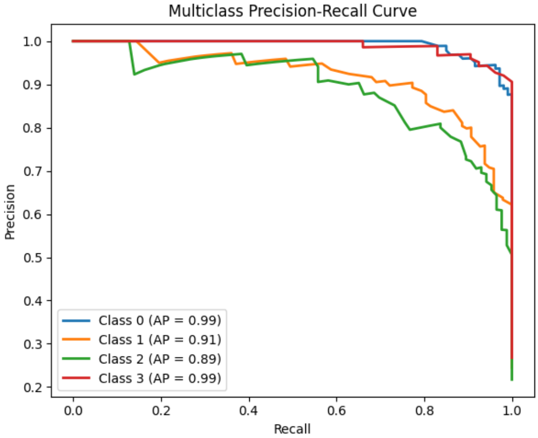
Analysis XIII



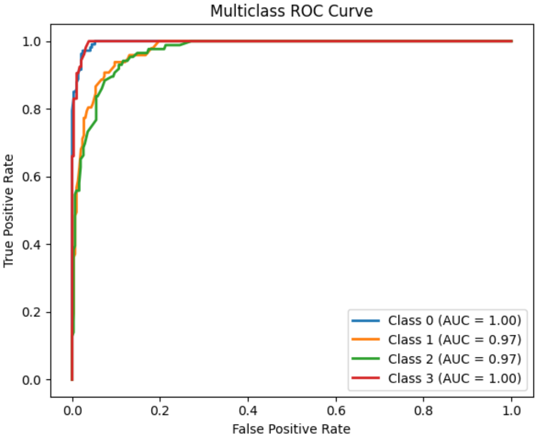
Analysis XIV



Analysis XV

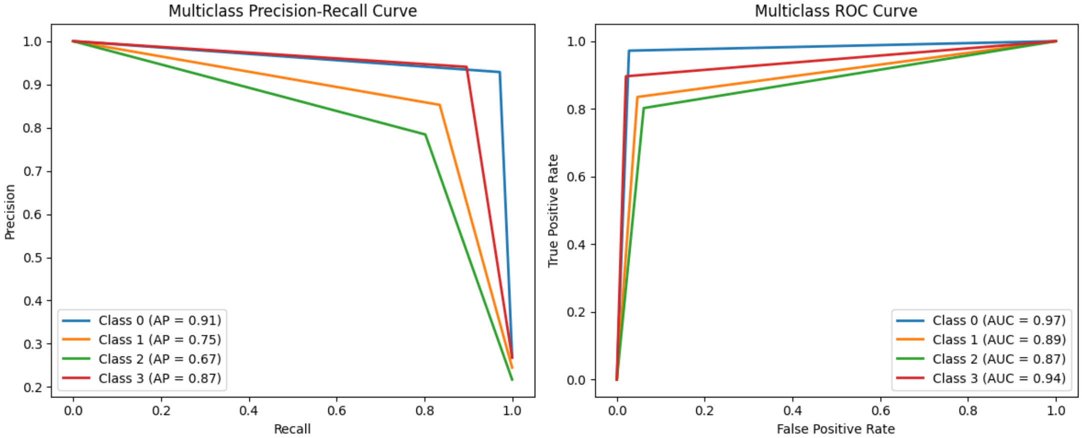


Multiclass Precision-Recall Curve
Precision
Recall
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.0
0.2
0.4
0.6
0.8
1.0
Class 0 (AP = 0.99)
Class 1 (AP = 0.91)
Class 2 (AP = 0.89)
Class 3 (AP = 0.99)

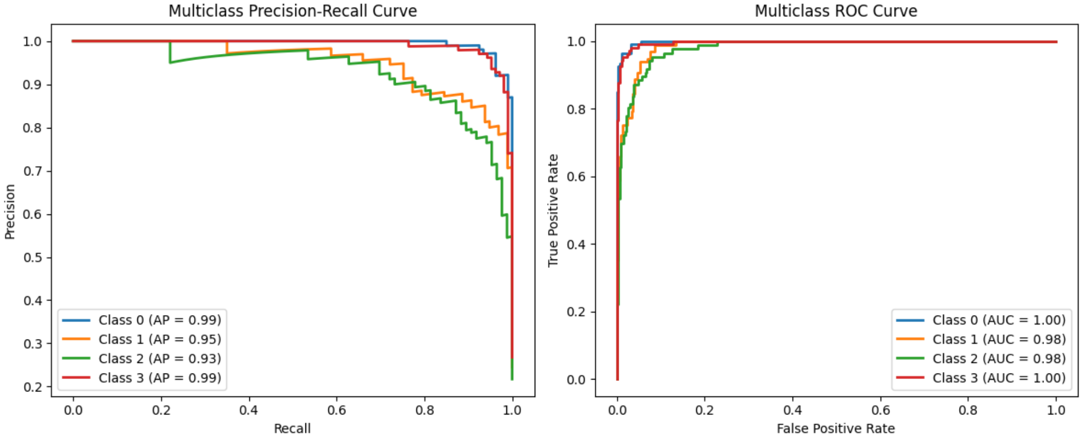


Multiclass ROC Curve
True Positive Rate
False Positive Rate
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
Class 0 (AUC = 1.00)
Class 1 (AUC = 0.97)
Class 2 (AUC = 0.97)
Class 3 (AUC = 1.00)

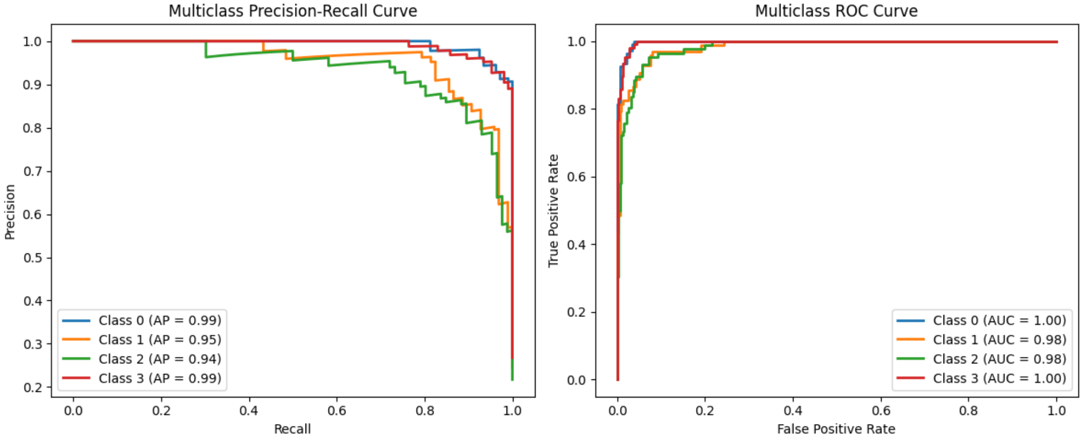
Analysis XVI



Analysis XVII



Analysis XVIII



Challenges and Learnings

Challanges and Learnings I

Challenges

- **Feature Engineering:** Feature engineering was challenging as we had to combine features to create new ones. This required understanding of both the dataset and domain knowledge.
- **Hyperparameter Tuning:** Tuning hyperparameters for each model was time-consuming and required a lot of time as well as computational resources.

Challanges and Learnings II

Learnings

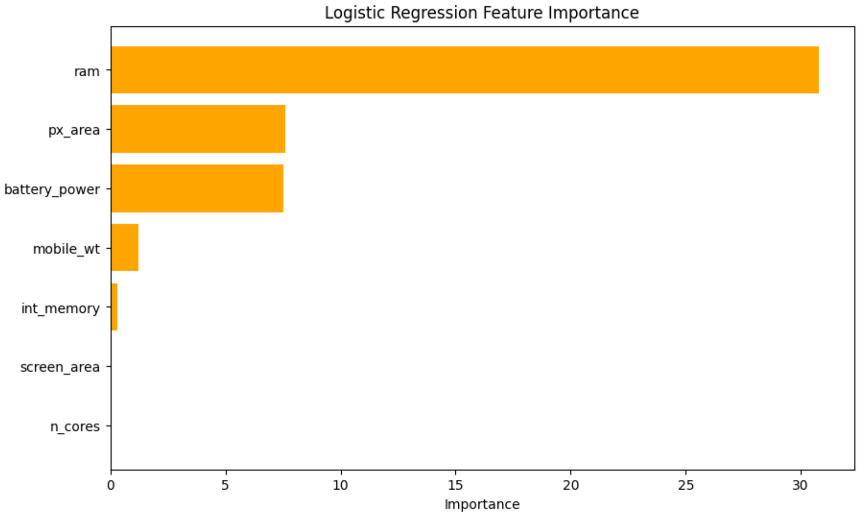
- **Data Preprocessing:** The importance of thorough data cleaning, normalization, and scaling to improve model performance.
- **Model Evaluation:** The value of using multiple evaluation metrics (accuracy, precision, recall, F1-score) to get a comprehensive understanding of model performance.
- **Feature Engineering:** How creating new features and selecting the most relevant ones can significantly impact model accuracy.
- **Hyperparameter Tuning:** The impact of hyperparameter tuning on model performance and the importance of using techniques like GridSearchCV.
- **Model Comparison:** The benefits of comparing multiple machine learning algorithms to identify the best-performing model for a given task.

Conclusion

Best Model

- **Best Model:** Logistic Regression
- **Second Best:** SVM

Most Important Features



Future Work

- **Recommendation System:** This model can be improved upon to develop a recommendation system that takes inputs about features like RAM, megapixels, screen size, etc., and provides a possible price (budget) and even suggests smartphone models based on real-time data.
- **Deployment:** Deploying the model as a web application or API to provide real-time predictions and insights for users and businesses.

References

Géron, Aurélien. *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*. 3rd ed., O'Reilly Media, 2023.

Asim, Muhammad, and Zafar Khan. "Mobile Price Class Prediction Using Machine Learning Techniques." *International Journal of Computer Applications*, March 2018. DOI: `10.5120/ijca2018916555`.

Thank You!