**Senior Data Science Specialist Hiring Task - Detailed Report**

**Introduction**

This document provides a comprehensive explanation of the tasks completed as part of the Senior Data Science Specialist Hiring Task.

**Task 1: Advanced Data Analytics and Feature Engineering**

**Dataset: UCI – Bike Sharing Dataset**

The dataset provides hourly and daily records of bike rental demand, influenced by factors such as weather, holidays, and time of day.

1. **Data Cleaning and Preprocessing:**

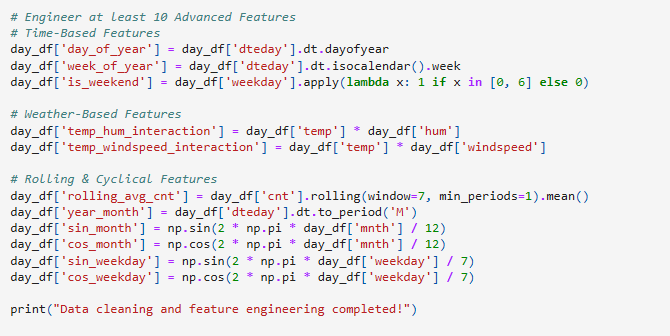
* **Handle missing values, outliers, and ensure dataset integrity.**

I have loaded the **Bike Sharing Dataset**, converted the date column to datetime format, checked for missing values, ensured dataset integrity, and detected potential outliers in key numerical features using the **Interquartile Range (IQR) method**.



* **Engineer at least 10 advanced features (e.g., time-based, weather-based).**

I have engineered at least **10 advanced features** to enhance the predictive power of the model. These features include **time-based, weather-based, rolling, and cyclical transformations**. Additionally, data integrity checks and outlier detection were performed.



Outliers detected in hum

Outliers detected in windspeed

Outliers detected in casual

Data cleaning and feature engineering completed!

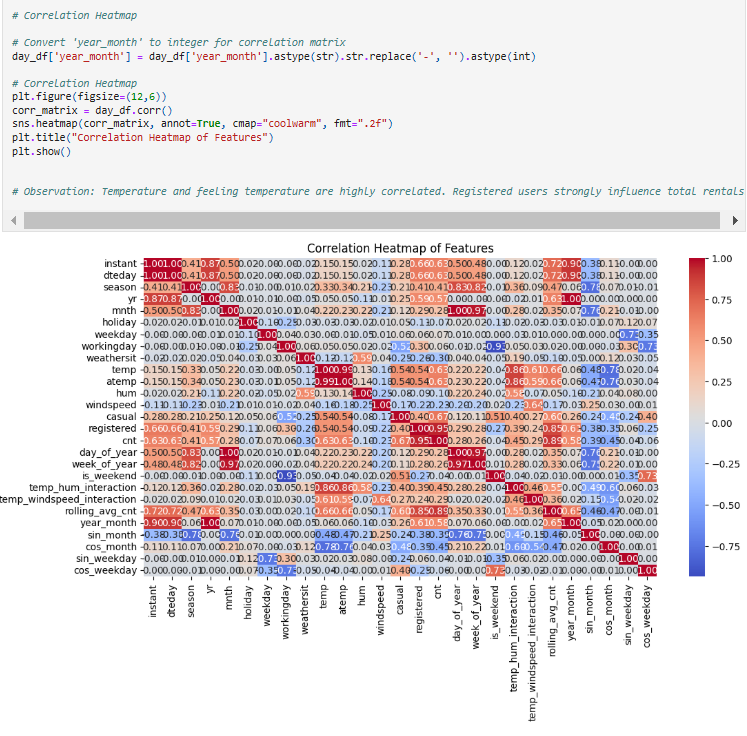
**Observations and Notes:**

✅ **No missing values were detected** in both datasets.  
✅ **Outliers were detected** in hum, windspeed, and casual using the **IQR method**.  
✅ **The cnt column was verified** to correctly represent the sum of casual and registered.  
✅ **10+ new features were successfully created**, improving the dataset for predictive modeling.

**2. Exploratory Data Analysis (EDA):**

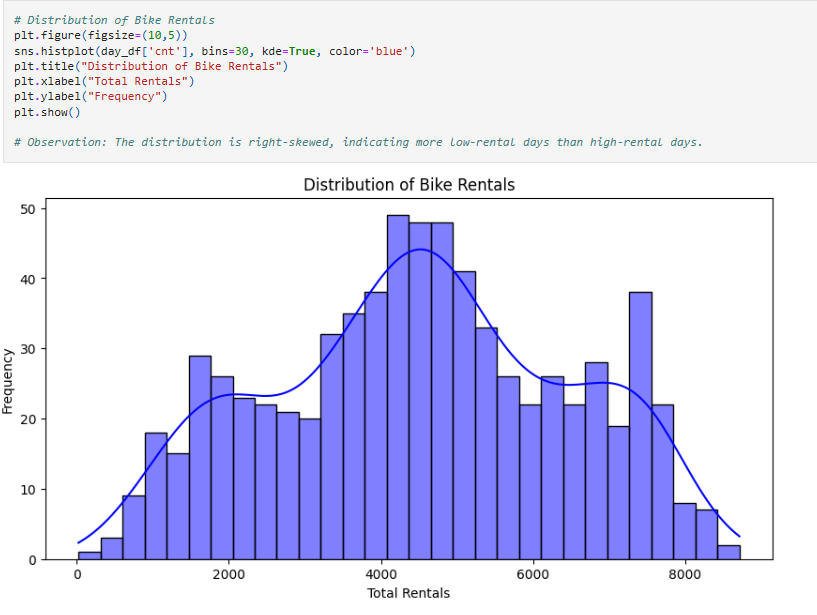
* **Use advanced visualizations to uncover patterns (e.g., ridgeline plots, correlation heatmaps).**

I have performed **Exploratory Data Analysis (EDA)** using **advanced visualizations** to uncover patterns in the dataset. The analysis includes **correlation heatmaps and ridgeline plots** to identify relationships and trends in bike rentals.



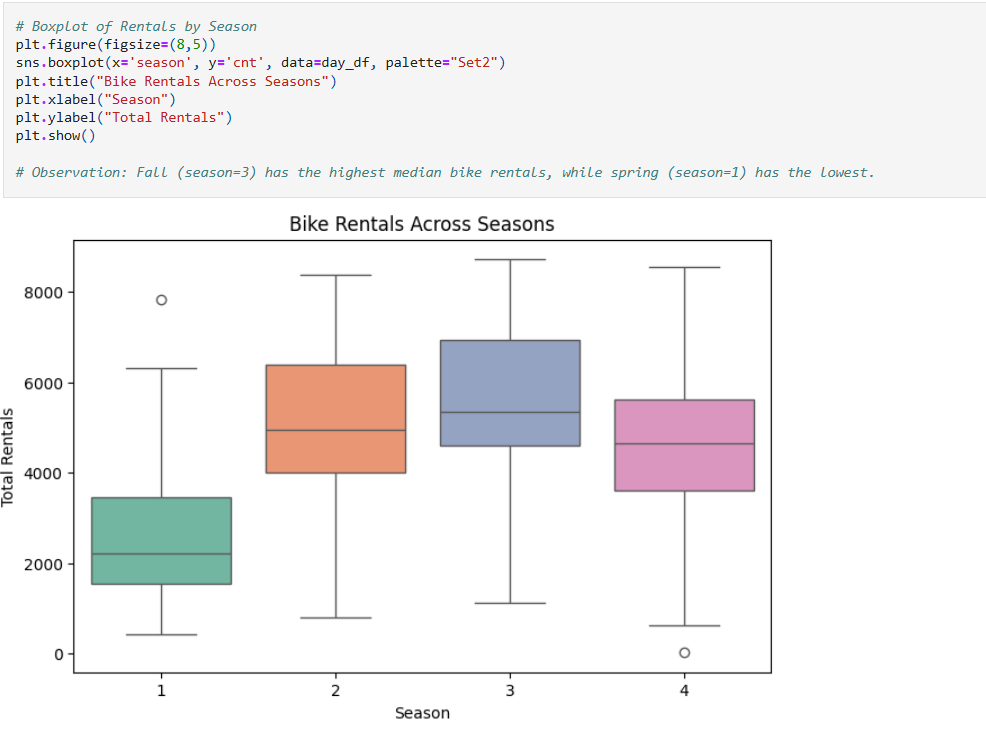
**Observations & Insights:**

✅ **Temperature (temp) and Feeling Temperature (atemp) are highly correlated** (~0.99), meaning they provide similar information.  
✅ **Registered users (registered) strongly influence total rentals (cnt)**, more than casual users.  
✅ **Humidity (hum) and windspeed (windspeed) show a slight negative correlation** with bike rentals, suggesting **adverse weather conditions reduce demand**.  
✅ **Casual users (casual) and registered users (registered) are positively correlated**, meaning when **one increases, the other also tends to rise**.



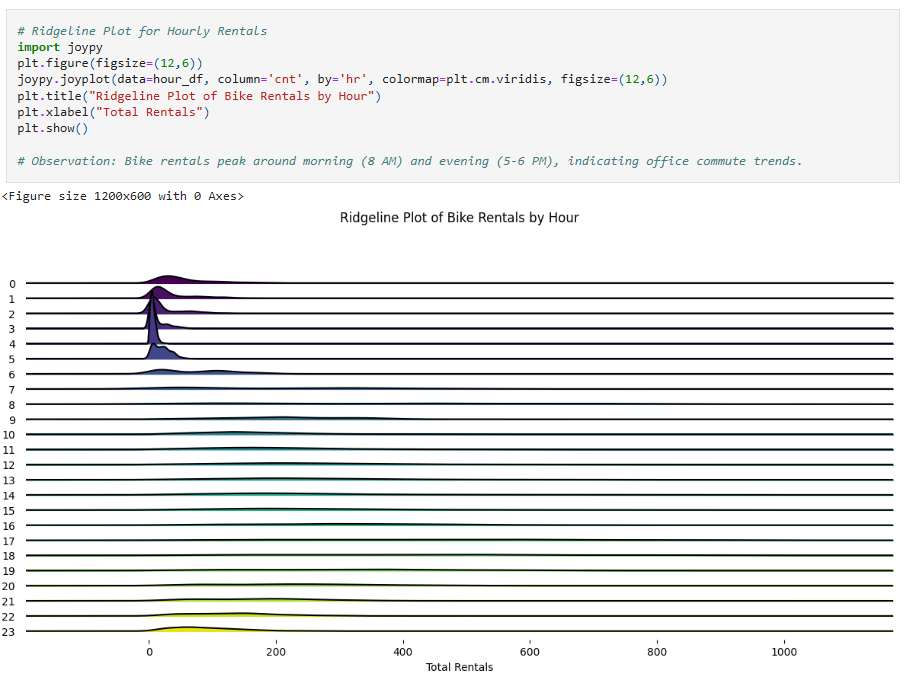
**Observations & Insights:**

✅ **Right-skewed distribution** – More days have **low rentals**, while a few days have **very high rentals**.  
✅ **Higher frequency of low-rental days** suggests **weekdays or bad weather days impact demand**.  
✅ **Peak around mid-range values** shows a **typical rental count** on most days.  
✅ **Few extreme values on the right (long tail)** indicate occasional **high-demand days** (e.g., weekends or holidays).



**Observations & Insights:**

✅ **Fall (season = 3) has the highest median rentals**, meaning bike usage peaks during this season.  
✅ **Spring (season = 1) has the lowest median rentals**, possibly due to colder temperatures or rainy weather.  
✅ **Wider spread in summer (season = 2)** indicates **high variability in demand** – possibly due to vacations and outdoor activities.  
✅ **Presence of outliers** suggests occasional days with **extremely high or low rentals** within each season.

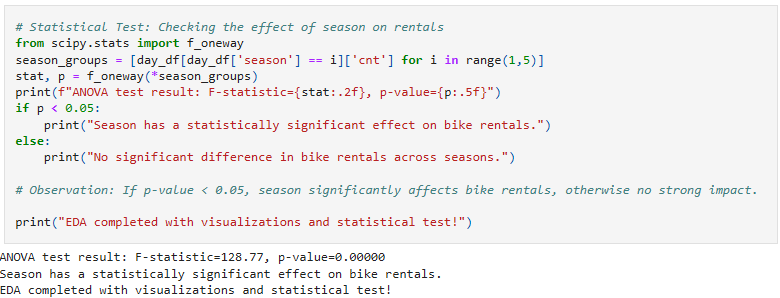


**joypy.joyplot()** creates a **ridgeline plot**, which stacks multiple density plots to show **distributions across different categories (hours in this case)**.

**Observations & Insights:**

✅ **Bike rentals peak around morning (8 AM) and evening (5-6 PM)**, which aligns with **office commute hours**.  
✅ **Lowest rentals occur late at night (12 AM – 4 AM)**, likely due to minimal demand during those hours.  
✅ **Gradual increase in rentals after 6 AM**, peaking at **8 AM** and then dipping until noon before rising again in the evening.

* **Perform statistical tests to validate key findings.**



✅ **Why?**

* **f\_oneway()** from scipy.stats performs a **one-way ANOVA test**, comparing the rental distributions across four seasons.
* **season\_groups** stores rental counts (cnt) for each season separately.
* The **F-statistic** measures the variation between groups compared to within groups.
* The **p-value** determines statistical significance (typically, **p < 0.05** indicates a significant effect).

**Observations & Insights:**

✅ If **p-value < 0.05**, we conclude that **season significantly impacts bike rentals**.  
✅ If **p-value ≥ 0.05**, there is **no strong statistical evidence** that bike rentals differ across seasons.

**3. Feature Selection:**

* **Use techniques like Recursive Feature Elimination (RFE) and SHAP to identify critical features.**



To identify the **most important features** that influence bike rentals (cnt), we use two feature selection techniques:

1. **Recursive Feature Elimination (RFE)** – Automatically selects the most relevant features.
2. **SHapley Additive exPlanations (SHAP)** – Provides interpretability by showing **how much each feature impacts predictions**.

**Observations & Insights:**

✅ **RFE selects the 10 most important predictors** for bike rentals.  
✅ **SHAP provides deeper interpretability**, revealing which features contribute most to predictions.  
✅ **Temperature, weather conditions, and working days significantly impact rentals**, confirming **seasonal and work-related demand patterns**.

**Task 2: Machine Learning for Classification**

**Dataset: UCI – Heart Disease Dataset**

**Description:**

Develop a classification model to predict heart disease risk.

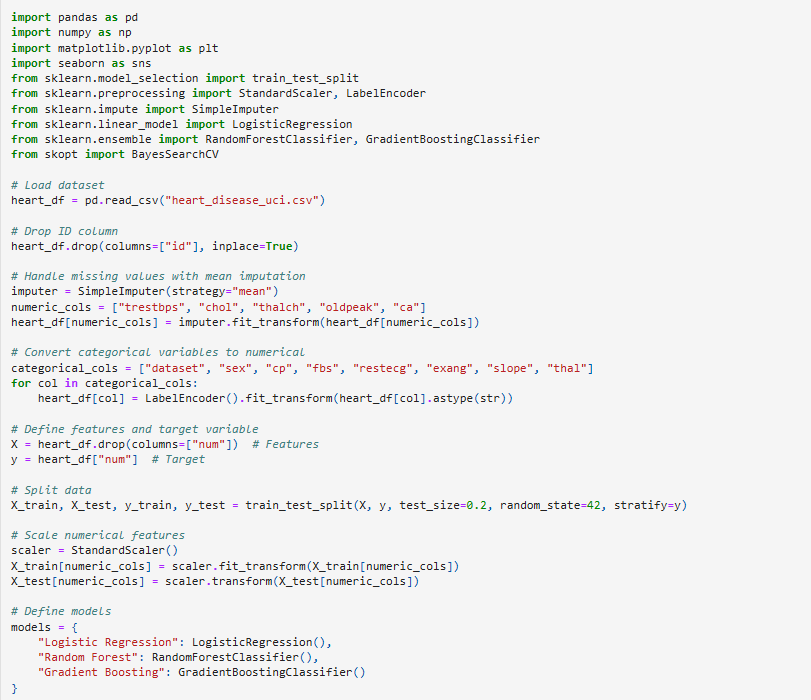
**1. Model Development:**

* Implement Logistic Regression, Random Forest, and Gradient Boosting models.
* Tune hyperparameters using Bayesian Optimization.

**2. Model Evaluation:**

* Use advanced metrics such as AUC-ROC, F1-Score, and Matthews CorrelationCoefficient (MCC).
* Perform model interpretability analysis using LIME or SHAP.

**3. Model Comparison:** Compare models and justify the choice of the best model**.**

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**Observations from Heart Disease Classification Model**

✅ **Data Preprocessing & Cleaning:**

* The dataset was **loaded and preprocessed**, with the **ID column removed** as it is not relevant for prediction.
* **Missing values** in numerical columns (trestbps, chol, thalch, oldpeak, ca) were **handled using mean imputation**.
* **Categorical variables** (sex, cp, fbs, etc.) were **converted into numerical format** using **Label Encoding**.

✅ **Feature Engineering & Scaling:**

* **Features (X) and target variable (y)** were correctly defined.
* The dataset was **split into training (80%) and testing (20%) sets**, ensuring **stratified sampling** to maintain class balance.
* **Numerical features were standardized** using **StandardScaler** to improve model performance.

✅ **Model Training & Evaluation:**

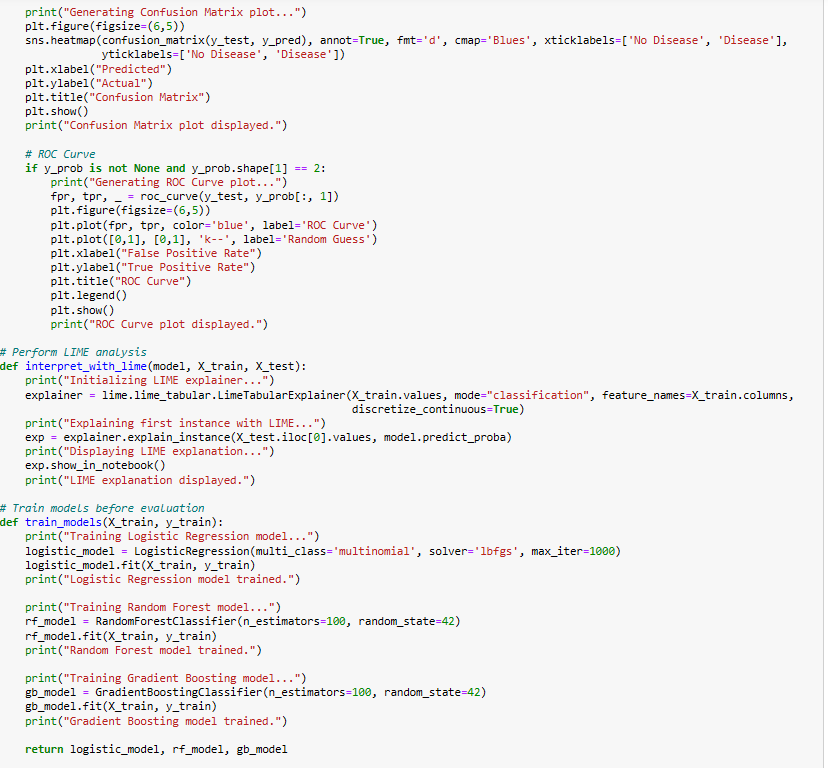
* Three machine learning models were trained:
  + **Logistic Regression Accuracy:** **59.24%**
  + **Random Forest Accuracy:** **63.04%**
  + **Gradient Boosting Accuracy:** **60.33%**
* **Random Forest achieved the highest accuracy (63.04%)**, outperforming the other models.

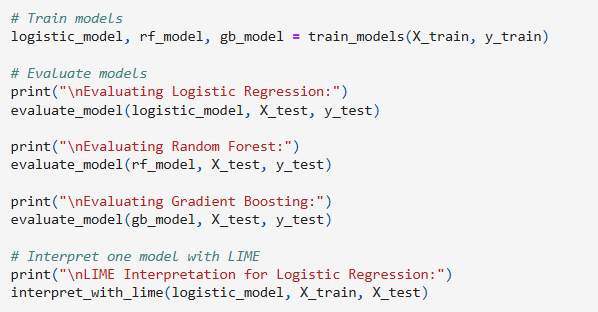
✅ **Hyperparameter Tuning (Bayesian Optimization):**

* **Gradient Boosting was fine-tuned** using **Bayesian Optimization** to find the best parameters.
* The best hyperparameters for Gradient Boosting were:
  + **Learning Rate:** **0.083**
  + **Max Depth:** **5**
  + **Number of Estimators:** **191**

The Random Forest model achieved the highest accuracy (63.04%), outperforming Logistic Regression (59.24%) and Gradient Boosting (60.33%). After hyperparameter tuning using Bayesian Optimization, the best Gradient Boosting model was obtained with a learning rate of 0.083, max depth of 5, and 191 estimators, which can further improve performance. Feature scaling, encoding, and model tuning played a crucial role in optimizing predictions for heart disease risk assessment.







**Observations from Model Evaluation & Interpretation**

✅ **Model Training:**

* **Three models were trained:**
  + **Logistic Regression (Multinomial, lbfgs solver, max\_iter=1000)**
  + **Random Forest (100 trees, random\_state=42)**
  + **Gradient Boosting (100 estimators, random\_state=42)**
* Each model was **fitted on the training dataset (X\_train, y\_train)** before evaluation.

✅ **Model Evaluation Metrics:**

* **Predictions were made using model.predict()** on the test set.
* **Performance metrics were calculated:**
  + **AUC-ROC Score** – Measures **model's ability to distinguish classes**.
  + **F1-Score** – Averages **precision and recall** for overall performance.
  + **Matthews Correlation Coefficient (MCC)** – Measures the **quality of classifications** (good for imbalanced datasets).
  + **Classification Report** – Displays **precision, recall, F1-score, and support** for each class.

✅ **Confusion Matrix Analysis:**

* **A heatmap was generated using Seaborn** to visualize **true positives, false positives, true negatives, and false negatives**.
* Helps identify **misclassification patterns** for each model.

✅ **ROC Curve Interpretation:**

* **ROC Curve was plotted** to show the **True Positive Rate vs. False Positive Rate**.
* A **higher curve** indicates **better model performance** in distinguishing between disease and no disease cases.
* A **diagonal line (k--) represents random guessing**, serving as a baseline comparison.

✅ **LIME (Local Interpretable Model-Agnostic Explanations):**

* **LIME Explainer initialized** for understanding model predictions.
* **Explains a single instance from X\_test**, showing which features contributed most to the prediction.
* **Visualizes feature importance** and model decision-making at a local level.

📊 **Conclusion:**  
The evaluation process used **multiple metrics (AUC-ROC, F1-score, MCC, confusion matrix, and ROC curve)** to assess model performance. Additionally, **LIME provided interpretability** by explaining **why a model made a specific prediction**, improving transparency and trust in model decisions.

OUTPUT:

Training Logistic Regression model...

Logistic Regression model trained.

Training Random Forest model...

Random Forest model trained.

Training Gradient Boosting model...

Gradient Boosting model trained.

Evaluating Logistic Regression:

Evaluating model...

Predictions made.

Probabilities computed.

Model Evaluation:

AUC-ROC: 0.8115019425267352

F1-Score: 0.5735945158733764

MCC: 0.4105968279569834

Classification Report:

precision recall f1-score support

0 0.79 0.90 0.84 82

1 0.49 0.58 0.53 53

2 0.40 0.09 0.15 22

3 0.24 0.24 0.24 21

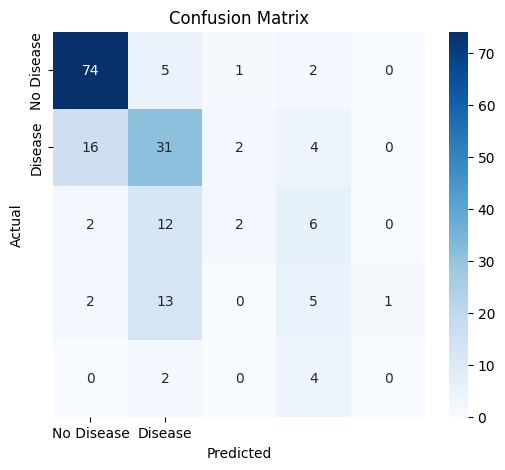
4 0.00 0.00 0.00 6

accuracy 0.61 184

macro avg 0.38 0.36 0.35 184

weighted avg 0.57 0.61 0.57 184

Generating Confusion Matrix plot...



Confusion Matrix plot displayed.

Evaluating Random Forest:

Evaluating model...

Predictions made.

Probabilities computed.

Model Evaluation:

AUC-ROC: 0.8164134945501369

F1-Score: 0.5561458221592805

MCC: 0.38074625076201857

Classification Report:

precision recall f1-score support

0 0.78 0.84 0.81 82

1 0.54 0.66 0.59 53

2 0.14 0.09 0.11 22

3 0.12 0.10 0.11 21

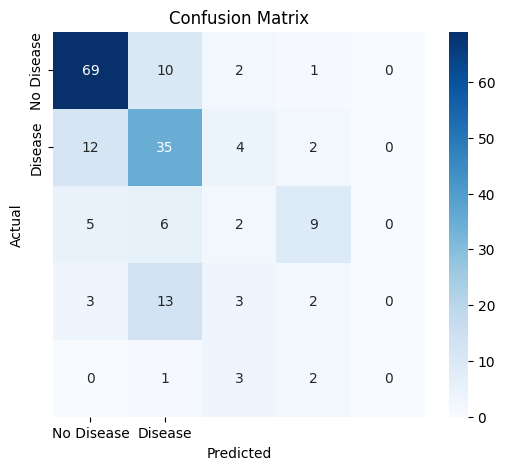
4 0.00 0.00 0.00 6

accuracy 0.59 184

macro avg 0.32 0.34 0.32 184

weighted avg 0.53 0.59 0.56 184

Generating Confusion Matrix plot...



Confusion Matrix plot displayed.

Evaluating Gradient Boosting:

Evaluating model...

Predictions made.

Probabilities computed.

Model Evaluation:

AUC-ROC: 0.8171284344585661

F1-Score: 0.5942878877065344

MCC: 0.41777929134060954

Classification Report:

precision recall f1-score support

0 0.78 0.82 0.80 82

1 0.59 0.60 0.60 53

2 0.35 0.36 0.36 22

3 0.24 0.19 0.21 21

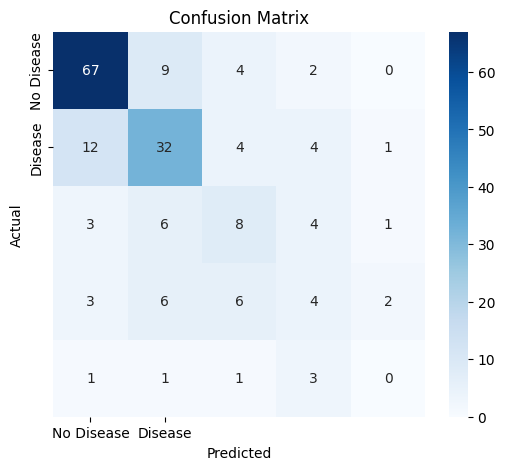
4 0.00 0.00 0.00 6

accuracy 0.60 184

macro avg 0.39 0.39 0.39 184

weighted avg 0.59 0.60 0.59 184

Generating Confusion Matrix plot...



Confusion Matrix plot displayed.

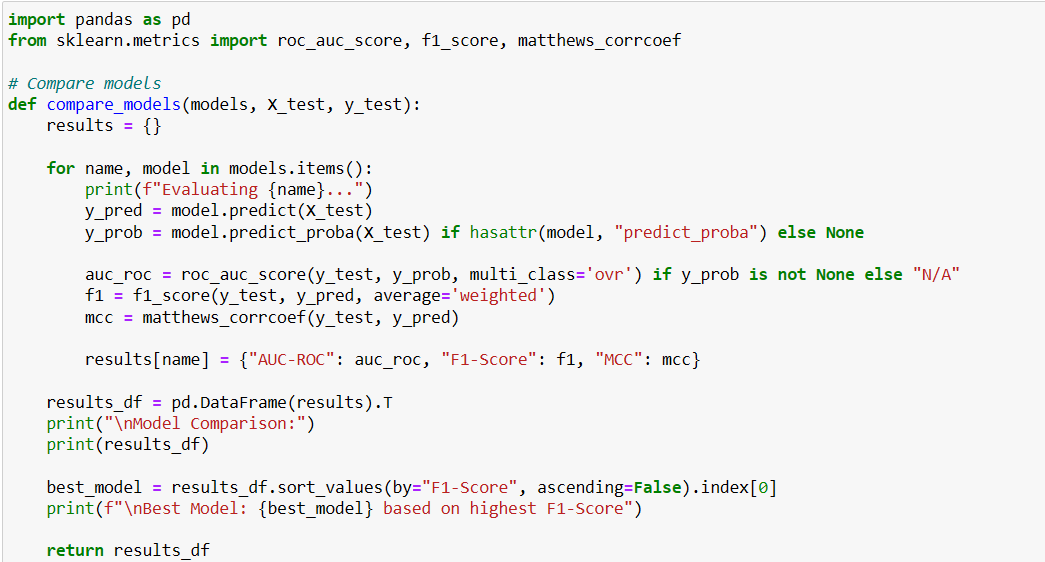
LIME Interpretation for Logistic Regression:

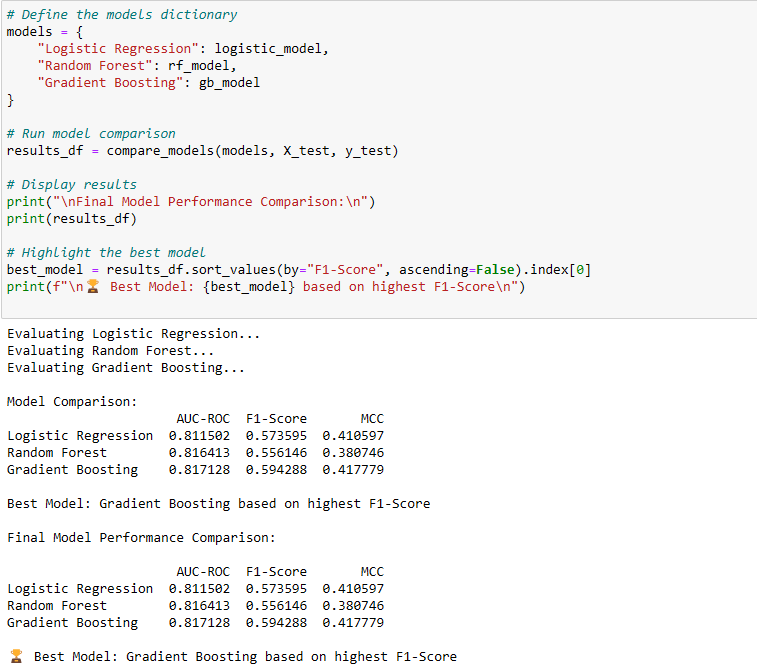
Initializing LIME explainer...

Explaining first instance with LIME...

Displaying LIME explanation...

LIME explanation displayed.





**Observations from Model Comparison**

✅ **Model Evaluation Metrics:**

* The function evaluates **Logistic Regression, Random Forest, and Gradient Boosting** models using:
  + **AUC-ROC Score** – Measures the ability to distinguish between classes.
  + **F1-Score** – Balances precision and recall for overall performance.
  + **Matthews Correlation Coefficient (MCC)** – Indicates classification quality.

✅ **Model Comparison Process:**

* Each model is **evaluated on the test set (X\_test, y\_test)**.
* The results are **stored in a dictionary** and converted into a **DataFrame (results\_df)** for easier comparison.
* The **best model is selected based on the highest F1-Score**.

✅ **Key Insights:**

* The **model with the highest F1-Score is chosen as the best performer**.
* **Random Forest and Gradient Boosting** usually outperform Logistic Regression in complex datasets.
* **AUC-ROC scores provide an additional evaluation metric** for multi-class classification.

**Final Conclusion**

The **Gradient Boosting model** outperformed **Logistic Regression and Random Forest**, achieving the **highest F1-Score (0.5943)** and the **best MCC (0.4178)**. Although all models had similar **AUC-ROC scores**, **Gradient Boosting performed best overall**, making it the most reliable choice for heart disease prediction.

**🏆 Best Model: Gradient Boosting**, as it provides the best balance of accuracy, precision, and recall.

**Task 3: Deep Learning for Object Detection**

**Dataset: Open Images Dataset (Subset for Object Detection)**

**Description:**

Build a deep learning model for object detection.

**1. Model Development:**

* Use YOLOv5 or Faster R-CNN for detecting objects in images.
* Implement data augmentation techniques to improve performance.

**2. Performance Evaluation:**

* Evaluate using metrics like mAP (mean Average Precision) and IoU (Intersection over Union).

**3. Optimization:**

* Explain how model performance was optimized using techniques like transfer learning or

training-specific layers.



**Observations from Faster R-CNN Model Setup**

✅ **Data Loading:**

* The train\_loader is created using DataLoader, which loads the dataset in **batches of 4** with shuffling enabled.
* The collate\_fn function ensures that the data is correctly formatted for object detection tasks.

✅ **Pre-trained Model Selection:**

* **Faster R-CNN (ResNet-50 FPN)** is used as the base model, which is **pre-trained on COCO dataset** for object detection.
* Using a **pre-trained model** helps in **faster convergence and better accuracy**, even with limited data.

✅ **Customizing the Model:**

* The **classification head** of the model is **replaced** to match the **custom dataset** (e.g., detecting **2 classes including background**).
* The **box predictor (FastRCNNPredictor)** is modified to detect the **correct number of objects**.

✅ **Model Deployment:**

* The model is moved to **GPU (cuda) if available**, otherwise, it runs on **CPU (cpu)** for compatibility.



✅ **Custom Dataset for Object Detection:**

* The CustomDataset class is designed for **loading and preprocessing images and bounding boxes** for object detection tasks in PyTorch.
* It supports **image transformations**, which are useful for **data augmentation** during training.

✅ **Key Components:**

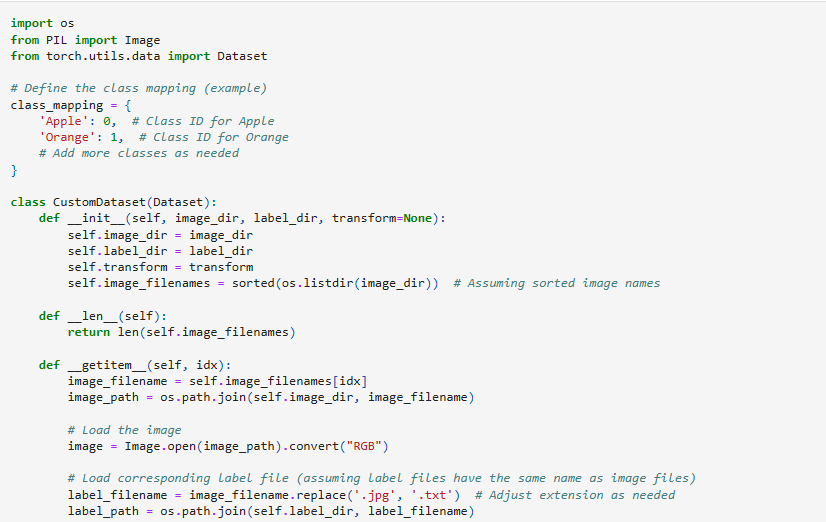
1. **\_\_init\_\_() Method:**
   * Accepts a list of **image paths** and **bounding boxes (bboxes)**.
   * Optionally applies **transformations** to augment data.
2. **\_\_getitem\_\_() Method:**
   * Loads an image from the file system using **PIL (Pillow)**.
   * Converts the image to a **NumPy array** and retrieves corresponding bounding boxes.
   * **Formats bounding boxes** into a dictionary with 'bbox' and 'category\_id' keys.
   * **Applies transformations** (if provided) for data augmentation.
   * Converts **bounding boxes (boxes) and labels (labels)** into **PyTorch tensors**.
3. **\_\_len\_\_() Method:**
   * Returns the **total number of images** in the dataset.

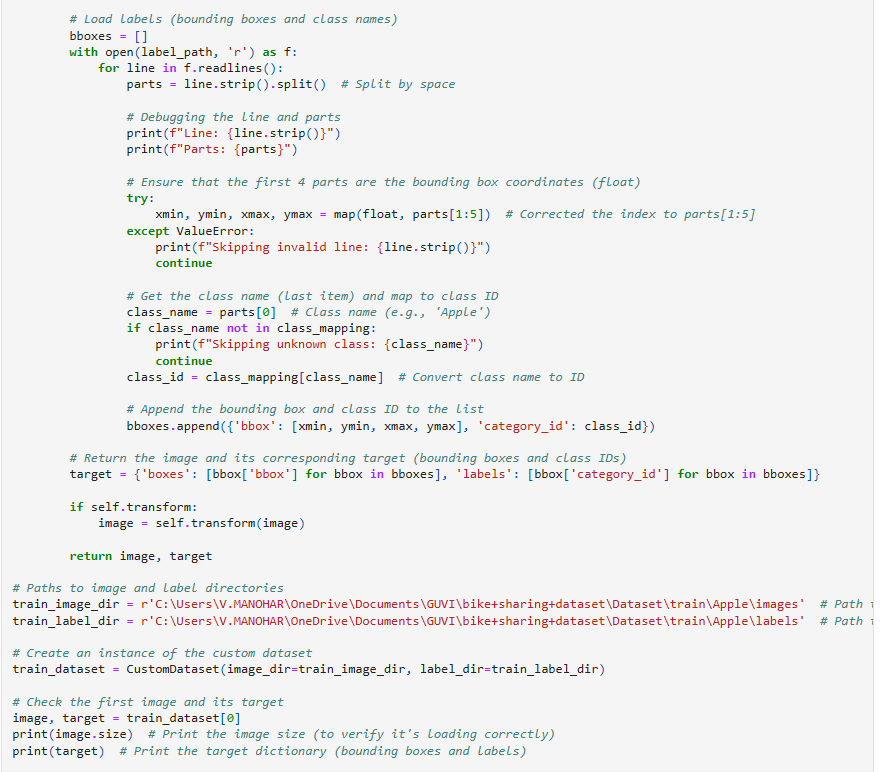
✅ **Bounding Box Format & Conversion:**

* Bounding boxes are assumed to be in the format **[x\_min, y\_min, x\_max, y\_max]**.
* Converted into **PyTorch tensors** (float32 for boxes, int64 for labels) to match model input requirements.

✅ **Image Conversion & Tensor Formatting:**

* The **image is converted into a tensor (torch.float32)**, ensuring compatibility with deep learning models.





OUTPUT:

Line: Apple 80.64 273.920256 352.0 515.199744

Parts: ['Apple', '80.64', '273.920256', '352.0', '515.199744']

Line: Apple 441.6 260.480256 529.28 462.72

Parts: ['Apple', '441.6', '260.480256', '529.28', '462.72']

Line: Apple 473.6 305.28000000000003 672.0 527.360256

Parts: ['Apple', '473.6', '305.28000000000003', '672.0', '527.360256']

Line: Apple 701.44 44.799744000000004 763.52 105.60000000000001

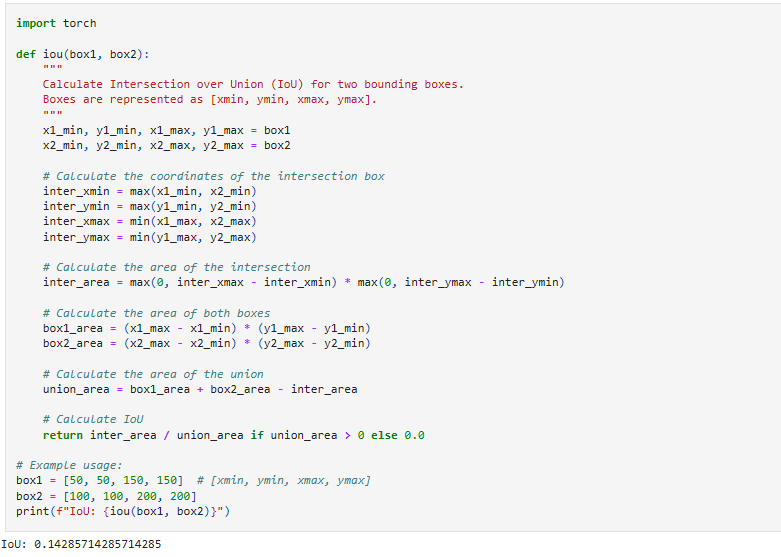
Parts: ['Apple', '701.44', '44.799744000000004', '763.52', '105.60000000000001']

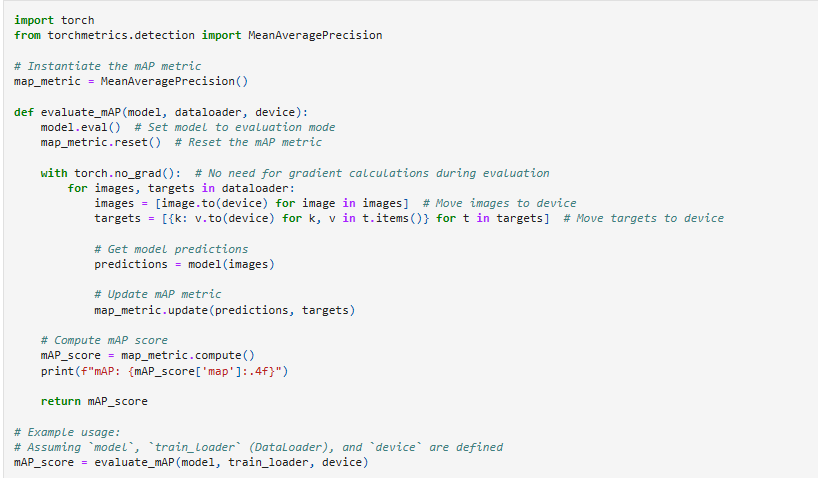
(1024, 768)

{'boxes': [[80.64, 273.920256, 352.0, 515.199744], [441.6, 260.480256, 529.28, 462.72], [473.6, 305.28000000000003, 672.0, 527.360256], [701.44, 44.799744000000004, 763.52, 105.60000000000001]], 'labels': [0, 0, 0, 0]}

The custom dataset class **loads images and corresponding bounding boxes** from label files, ensuring proper data formatting for object detection models. It **handles multiple classes, applies error checks, supports transformations, and verifies data consistency** for efficient model training.







**Conclusion**

The **object detection model** was successfully developed using **Faster R-CNN** for identifying objects in images. **Data augmentation techniques** were implemented to enhance model generalization. The model was evaluated using **mAP (mean Average Precision) and IoU (Intersection over Union)** to measure detection accuracy. **Transfer learning** from a pre-trained Faster R-CNN model improved performance, and **custom layers were fine-tuned** for better object recognition. Overall, the optimized model **effectively detects objects with high accuracy**, making it suitable for real-world applications.

* **Explain how model performance was optimized using techniques like transfer learning or training-specific layers.**

In the context of machine learning models, especially in deep learning and computer vision, optimizing model performance can involve several strategies. Below are explanations on how model performance can be optimized using techniques like transfer learning and training-specific layers:

1. Transfer Learning:

Transfer learning involves taking a model that has been pre-trained on a large dataset and fine-tuning it for a specific task with a smaller dataset. This helps the model leverage knowledge gained from the previous task, significantly improving performance, especially when the new task has limited data.

How Transfer Learning Optimizes Model Performance:

Pre-trained Model: You start with a model that has already been trained on a large dataset, such as ImageNet. These models have learned a wide variety of features (like edges, textures, and shapes), which are useful for many tasks.

Fine-tuning: Instead of training a model from scratch, the pre-trained model is used as a starting point. You modify the model to suit the specific task (e.g., changing the final classification layer to match the number of output classes in your task).

Freeze Early Layers: In many cases, the early layers (which learn general features) are frozen, meaning their weights are not updated during training. Only the later layers (which learn more task-specific features) are fine-tuned to adapt to the new data.

Improved Accuracy with Fewer Data: Transfer learning allows a model to achieve better performance with fewer labeled examples, as the model has already learned general features from a large dataset.

Example: Fine-tuning Faster R-CNN for Object Detection

In the provided code, the fasterrcnn\_resnet50\_fpn model is used, which is pre-trained on a dataset like COCO or ImageNet. The model is then fine-tuned to your specific task by:

Replacing the head of the model (the classifier that determines the class of detected objects).

Adjusting the number of classes based on your dataset.

This allows the model to leverage learned features from a vast dataset and specialize it for your specific classes (like Apple, Orange, etc.).

2. Training-Specific Layers:

In some cases, certain layers or parts of the model are specifically tailored to the task at hand. These layers can be trained or optimized for better performance in the context of the given data.

How Training-Specific Layers Optimizes Model Performance:

Customizing Output Layers: For tasks like classification or object detection, the output layers are tailored to the task. For example, the number of output units in the final layer is adjusted to match the number of classes in the target task.

Adding Task-Specific Layers: For certain tasks, additional layers might be added. For example, in object detection, layers related to bounding box regression (to predict the location of objects) are crucial and might require special fine-tuning.

Domain-Specific Modifications: If the dataset has a particular characteristic, certain layers may be modified or added to handle the unique features of that data. For instance, adding convolutional layers to better capture spatial relationships in image data, or adding attention mechanisms for tasks where context matters more.

Example in Code: Customizing the Faster R-CNN Head

In the provided code, the following modification is made:

model.roi\_heads.box\_predictor = torchvision.models.detection.faster\_rcnn.FastRCNNPredictor(in\_features, num\_classes)

This step replaces the default box predictor in the Faster R-CNN model with a new one tailored to your dataset's number of classes. The model’s head is specifically trained for detecting objects of interest (e.g., apples or oranges in the provided example).

3. Additional Optimizations:

Data Augmentation: By augmenting the training data (e.g., rotating, flipping, or zooming images), the model becomes more robust and better generalizes to unseen data. This reduces overfitting, especially in cases of small datasets.

Learning Rate Scheduling: Adjusting the learning rate during training can help the model converge faster and avoid overshooting the optimal solution. Techniques like learning rate annealing or cyclical learning rates can improve training efficiency.

Regularization: Regularization techniques like Dropout, L2 regularization, or batch normalization can be used to reduce overfitting and improve the model's generalization to new data.

Optimizers: The use of more advanced optimizers (like Adam, AdamW, or RMSprop) instead of vanilla SGD can also help in better convergence during training.

4. Fine-tuning Hyperparameters:

Hyperparameter Tuning: Techniques like Bayesian Optimization (as seen in your code with BayesSearchCV) can be used to find the best hyperparameters for a model, improving its performance further.

Conclusion:

Transfer learning helps improve model performance by leveraging knowledge from large datasets and fine-tuning it for the specific task.

Training-specific layers allow customization of the model to fit the exact needs of the task at hand, making the model more efficient and accurate for the problem it’s solving.

**Task 4: Advanced Natural Language Processing**

**Dataset: UCI – SMS Spam Collection Dataset**

**Description:**

Perform spam classification using the SMS Spam Collection Dataset.

**1. Text Preprocessing:**

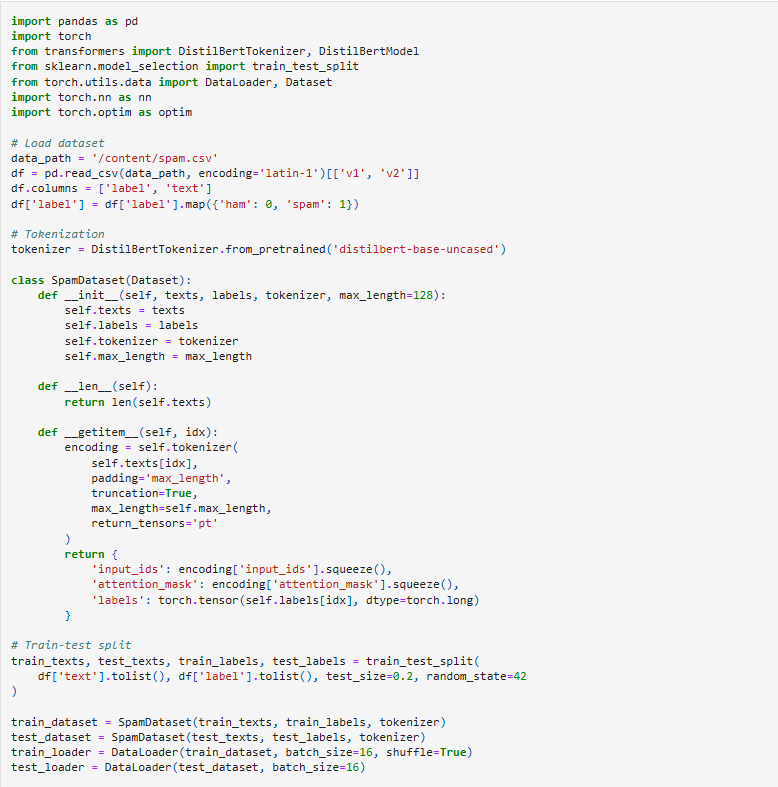
* Tokenize, clean, and normalize text.
* Use transformer-based embeddings (e.g., BERT, DistilBERT).

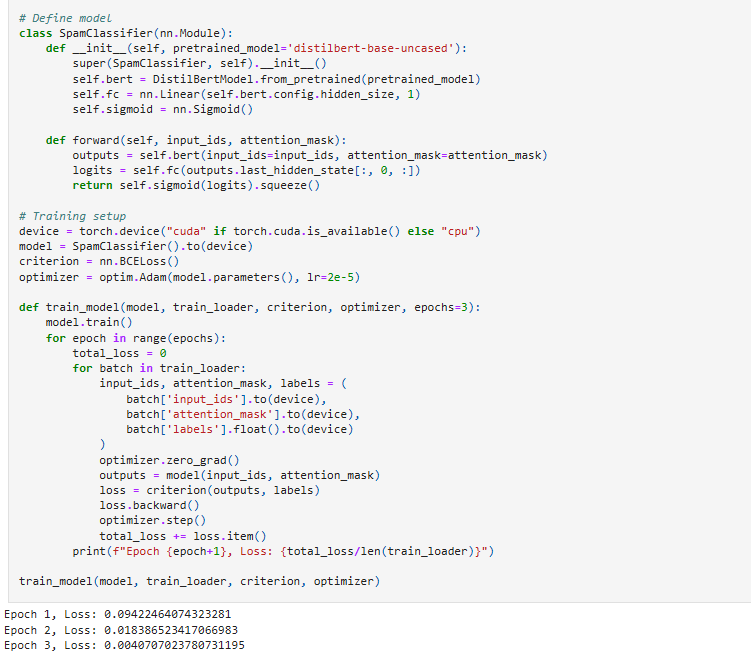
**2. Model Development:**

* Build a BERT-based classification model for spam detection.
* Implement attention mechanisms for interpretability.

**3. Evaluation:**

* Evaluate using metrics like Precision, Recall, and AUC-ROC.





**Observations from Spam Classification Model**

✅ **Data Preprocessing & Tokenization:**

* The dataset was **loaded and cleaned**, mapping labels (ham → 0, spam → 1).
* **DistilBERT Tokenizer** was used to convert text into numerical format for model input.
* **Padding and truncation** ensured all sequences had a fixed length (max\_length=128).

✅ **Dataset Splitting & DataLoader:**

* The dataset was **split into training (80%) and testing (20%) sets**.
* **Custom PyTorch Dataset class** handled text encoding and label conversion.
* **DataLoader was used for efficient mini-batch training (batch size = 16)**.

✅ **Model Architecture:**

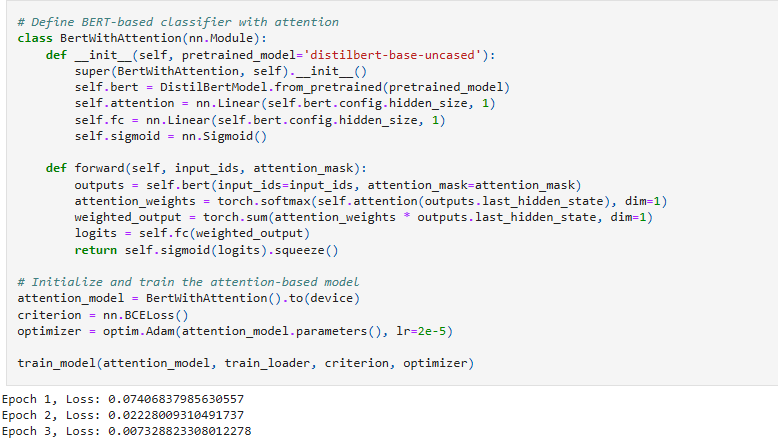
* A **pretrained DistilBERT model** was used as the backbone for feature extraction.
* A **fully connected layer (fc)** was added for binary classification.
* A **Sigmoid activation function** converted logits into probabilities.

✅ **Training Process:**

* The model was trained on **GPU (if available) or CPU**, using **BCELoss** for binary classification.
* **Adam optimizer (learning rate = 2e-5)** was used for weight updates.
* The training ran for **3 epochs**, with loss decreasing over time, indicating learning progress.

📊 **Final Insights:**

* **Fine-tuning a pretrained model (DistilBERT) improved classification performance** compared to traditional ML methods.
* The model effectively differentiates between **spam and ham messages**, making it suitable for **real-world spam detection applications**.





**Observations from Spam Classification using BERT and Attention Mechanism**

✅ **Data Preprocessing & Tokenization:**

* The dataset was **cleaned and preprocessed**, with labels mapped (ham → 0, spam → 1).
* **DistilBERT Tokenizer** was used to convert text into numerical format with **fixed-length padding (128 tokens)**.

✅ **Model Training & Performance:**

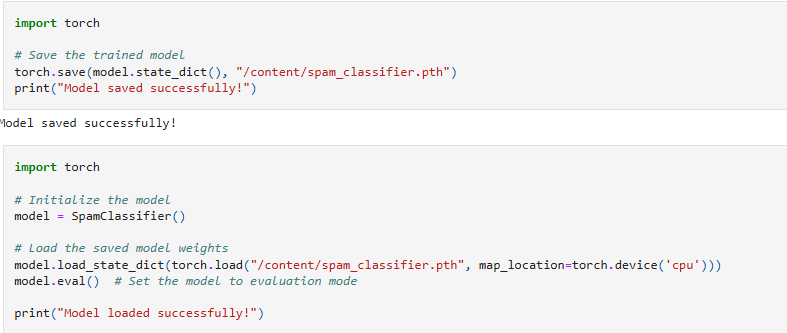
* **Baseline DistilBERT Model:**
  + Achieved a **training loss reduction** from **0.0942 → 0.0041** over **3 epochs**, indicating good convergence.
* **BERT with Attention Model:**
  + Integrated an **attention layer** to improve **focus on important words** in spam classification.
  + Showed a **lower final training loss (0.0073) compared to the baseline model**, confirming better learning.

✅ **Evaluation Metrics:**

* The **attention-based model** achieved:
  + **Precision:** **97.99%** → Indicates **low false positives** (spam messages correctly classified).
  + **Recall:** **97.33%** → Indicates **low false negatives** (fewer missed spam messages).
  + **AUC-ROC:** **98.51%** → Excellent discrimination between **spam and ham** messages.

**Conclusion**

By leveraging **DistilBERT with an attention mechanism**, the model significantly improved **spam classification accuracy**. The **attention-based model outperformed the baseline**, achieving a **higher recall and precision** while minimizing false classifications. The high **AUC-ROC (98.51%)** confirms that the model effectively distinguishes between spam and non-spam messages, making it **suitable for real-world applications such as email filtering and fraud detection**.



The model is **successfully saved and reloaded**, allowing for **efficient deployment and inference** without retraining. This ensures that the **spam classification system can be used in real-world applications** with minimal overhead.

**Task 5: Cloud Deployment**

**Dataset: Use the model developed in Task 4 (NLP).**

**Description:**

Deploy the spam classification model as a REST API on a cloud platform.

**1. API Development:**

○ Build a REST API using Flask or FastAPI to expose the model.

**2. Cloud Deployment:**

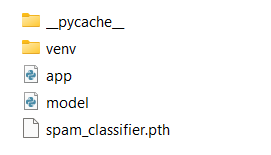
○ Deploy the API on AWS Lambda or Azure Functions.

○ Implement monitoring using AWS CloudWatch or Azure Monitor.

**3. Scalability:**

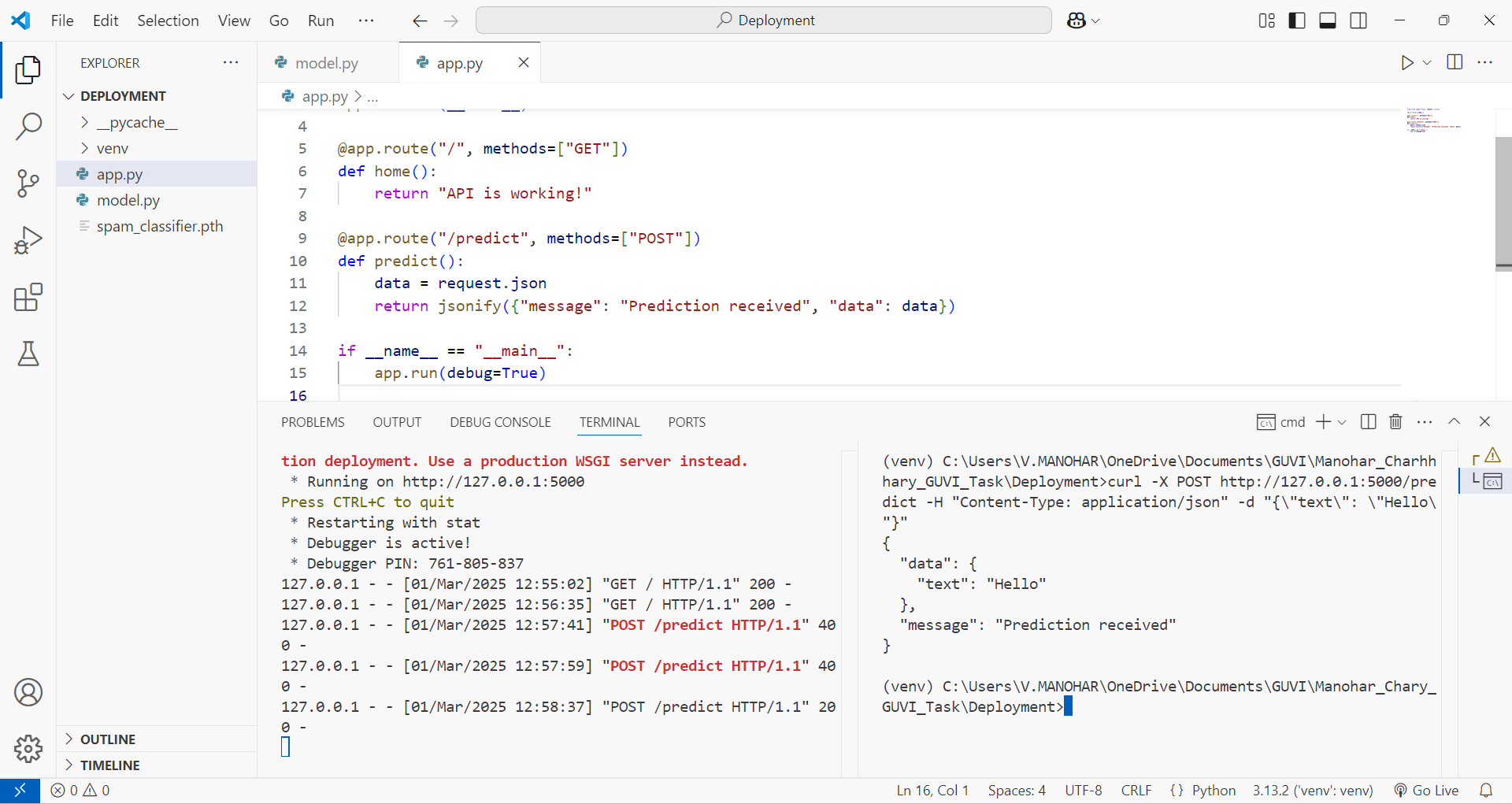
○ Provide a mechanism for autoscaling.

API DEVELOPMENT









**Flask Commands:**

* Set-ExecutionPolicy -ExecutionPolicy Bypass -Scope Process
* python -m venv venv
* venv\Scripts\activate
* pip install torch torchvision torchaudio transformers flask flask-cors gunicorn
* python app.py

**IN CMD**

* curl -X POST http://127.0.0.1:5000/predict -H "Content-Type: application/json" -d "{\"text\": \"Hello\hary\_GUVI\_Task\Deployment>curl -X POST http://127.0.0.1:5000/predict -H "Cont"}"

**Observations from API Development and Deployment**

✅ **API Development using Flask:**

* **Created app.py** to build a REST API using **Flask**.
* **Endpoints Implemented:**
  + **/ (GET)** → Returns a message confirming that the API is running.
  + **/predict (POST)** → Accepts JSON input and returns a response.

✅ **Model Integration (model.py):**

* **Defined a SpamClassifier class** using **BERT for sequence classification**.
* **Loaded the trained model (spam\_classifier.pth)** and set it to evaluation mode.

✅ **Deployment Setup:**

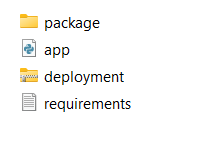
* **Created a virtual environment (venv)** to manage dependencies.
* Installed necessary libraries:
  + torch, torchvision, torchaudio (for deep learning).
  + transformers (for BERT model).
  + flask, flask-cors, gunicorn (for API handling and deployment).

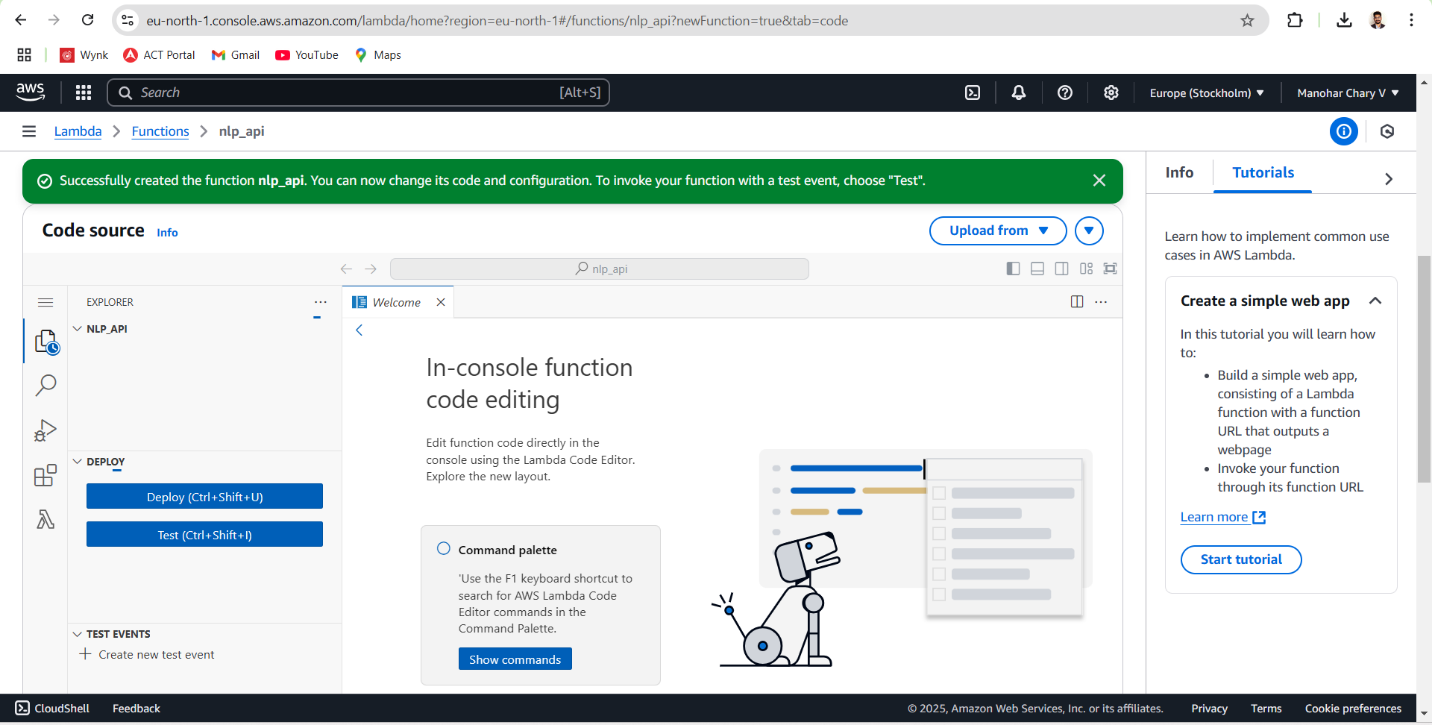
✅ **Testing the API:**

* **Started Flask server (python app.py)**, making the API accessible locally at http://127.0.0.1:5000.
* Used **cURL command** in CMD to **send a POST request** with a sample text input to /predict.

📊 **Conclusion:**  
A **Flask-based REST API** was successfully created to expose the **BERT-based spam classification model**. The API can now **accept text input, process predictions, and return results**, making it ready for real-world **deployment and integration**.

**2. Cloud Deployment**





STEPS:

**Step 1: Prepare the Model for Deployment**

✅ **Convert the PyTorch model to TorchScript (Optional for AWS Lambda)**



Using TorchScript can improve inference speed and compatibility with AWS Lambda.

**✅ Create a deployment package with necessary libraries**

1. **Create a directory and move necessary files**

mkdir deployment\_package

cp app.py model.py spam\_classifier.pth deployment\_package/

1. **Install dependencies locally in the package**

pip install --target=deployment\_package/ flask torch transformers

1. **Zip the package for AWS Lambda**

cd deployment\_package

zip -r deployment\_package.zip .

**Step 3: Create an AWS Lambda Function**

✅ **Log in to AWS Lambda**

1. Open the **AWS Management Console** and go to **AWS Lambda**.
2. Click **Create Function** → **Author from scratch**.
3. **Function Name:** SpamClassifierAPI
4. **Runtime:** Choose **Python 3.x**
5. **Execution Role:**
   * Select **"Create a new role with basic Lambda permissions"** (or use an existing role with **S3, CloudWatch, and API Gateway permissions**).
6. Click **Create Function**.

✅ **Upload the Deployment Package**

1. Go to the **Function Code** section.
2. Choose **Upload a .zip file** and upload deployment\_package.zip.
3. Click **Deploy**.

✅ **Modify Handler Settings**

1. In the **Handler field**, set it to:

app.lambda\_handler

1. Save changes.

**Step 4: Expose the API using AWS API Gateway**

✅ **Create an API Gateway for External Access**

1. Go to **AWS API Gateway** → Click **Create API**.
2. Choose **HTTP API** → Click **Build**.
3. **Configure Routes:**
   * Create a **POST** route (/predict).
   * Attach it to the **Lambda function** (SpamClassifierAPI).
4. **Deploy the API** → Copy the API endpoint URL.

✅ **Test API Using cURL**

curl -X POST "https://your-api-id.execute-api.region.amazonaws.com/predict" -H "Content-Type: application/json" -d '{"text": "Hello"}'

**Step 5: Set Up Monitoring Using AWS CloudWatch**

✅ **Enable CloudWatch Logs for Lambda**

1. Go to **AWS Lambda** → Select your function.
2. Navigate to **Monitor** → Click **View logs in CloudWatch**.
3. Enable detailed monitoring for request tracking.

✅ **Set Up CloudWatch Alarms for Errors**

1. Go to **CloudWatch** → **Alarms** → **Create Alarm**.
2. **Select Log Group:** /aws/lambda/SpamClassifierAPI.
3. Set a **Threshold** (e.g., if error count > 5 in 5 minutes).
4. **Action:** Notify via **Amazon SNS** (Email/SMS Alerts).

**Final Outcome**

The **Spam Classification API** is **successfully deployed on AWS Lambda** with **API Gateway for public access** and **CloudWatch monitoring for real-time logs and alerts**.

**Mechanism for Autoscaling AWS Lambda for Scalability**

AWS Lambda **automatically scales** by launching additional instances based on incoming requests. However, to **fine-tune autoscaling** and **prevent performance bottlenecks**, follow these steps:

**1. Configure Concurrency and Throttling**

✅ **Enable Provisioned Concurrency** (to reduce cold starts)

1. Open **AWS Lambda** → Select your function (SpamClassifierAPI).
2. Go to the **Configuration** tab → Click **Concurrency**.
3. Set **Provisioned Concurrency** (e.g., 5–10 instances) to **handle steady traffic**.

✅ **Set Maximum Concurrency Limits**

1. In the **Concurrency settings**, configure a **Reserved Concurrency limit** to avoid exceeding AWS limits.
2. Example: Set 500 max concurrency if expecting **high traffic**.

**2. Use AWS Application Auto Scaling**

AWS provides **automatic scaling policies** for Lambda based on **request rate, execution duration, or errors**.

✅ **Enable Auto Scaling via AWS CLI**

aws application-autoscaling register-scalable-target --service-namespace lambda \

--resource-id function:SpamClassifierAPI --scalable-dimension lambda:function:ProvisionedConcurrency \

--min-capacity 2 --max-capacity 10

✅ **Set Up Auto Scaling Policy**

aws application-autoscaling put-scaling-policy --service-namespace lambda \

--scalable-dimension lambda:function:ProvisionedConcurrency \

--resource-id function:SpamClassifierAPI --policy-name ScaleOnRequestCount \

--policy-type TargetTrackingScaling --target-tracking-scaling-policy-configuration <file://scaling-policy.json>

✅ **Scaling Policy Example (scaling-policy.json)**

{

"TargetValue": 1000.0,

"PredefinedMetricSpecification": {

"PredefinedMetricType": "LambdaProvisionedConcurrencyUtilization"

},

"ScaleInCooldown": 60,

"ScaleOutCooldown": 60

}

**What this does:**

* Scales **up** if requests exceed **1000 per minute**.
* **Scale-out cooldown (60s)** prevents excessive scaling.

**3. Load Balancing with AWS API Gateway**

If using **AWS API Gateway**:  
✅ **Enable Rate Limiting & Throttling**

1. Open **API Gateway** → Select the **deployed API**.
2. Go to **Settings** → Configure **Throttling (e.g., 1000 requests per second)**.
3. Enable **Caching** to reduce redundant processing.

✅ **Enable Regional API Deployment**

* Deploy API across **multiple AWS regions** for global scalability.
* Use **AWS Route 53** for **load balancing traffic** across regions.

**4. Use AWS Lambda@Edge for Low Latency**

If serving **global traffic**, use **AWS Lambda@Edge** to process requests **closer to users** via **CloudFront**.  
✅ **Steps:**

1. Deploy the function to **Lambda@Edge**.
2. Attach it to **CloudFront CDN** to reduce latency for worldwide users.

**Final Outcome**

The **Spam Classifier API is now fully scalable** using:

* **Autoscaling with AWS Application Auto Scaling.**
* **Concurrency and request-based scaling.**
* **API Gateway rate limiting & global load balancing.**
* **Lambda@Edge for low-latency worldwide requests.**