CS203 Lab 7

Team Number: 33

Team Members

Member 1

- Name: Vivek Raj
- Roll No: 23110362
- Github: VivekRaj2708

Member 2

- Name: Sharvari Mirge
- Roll No: 23110298
- Github: msharvari31

Repository Details

- Repository Link: https://github.com/VivekRaj2708/LAB7_CS203

Dataset

Download

We download 3 different datasets for training our MLP Model. These datasets names are given below

1. Train.TSV (Dataset - 1)
2. Test.TSV (Dataset - 1)
3. IMDB.CSV (Dataset - 2)

```
curl https://raw.githubusercontent.com/clairett/pytorch-sentiment-classification/master/data/SST2/train.tsv -o train.tsv
curl https://raw.githubusercontent.com/clairett/pytorch-sentiment-classification/master/data/SST2/test.tsv -o test.tsv
curl https://raw.githubusercontent.com/Ankit152/IMDB-sentiment-analysis/master/IMDB-Dataset.csv -o IMDB.csv
```

Imports

We importedthe folowing modules

1. `pandas`: For Reading CSV Files and X, y splitting using `iloc`
2. `train_test_split`: From `sklearn` to split the dataset into training and validation datasets
3. `matplotlib`: To visualise the current dataset sizes

```
from sklearn.model_selection import train_test_split
import pandas as pd
import matplotlib.pyplot as plt
```

Reading and Splitting

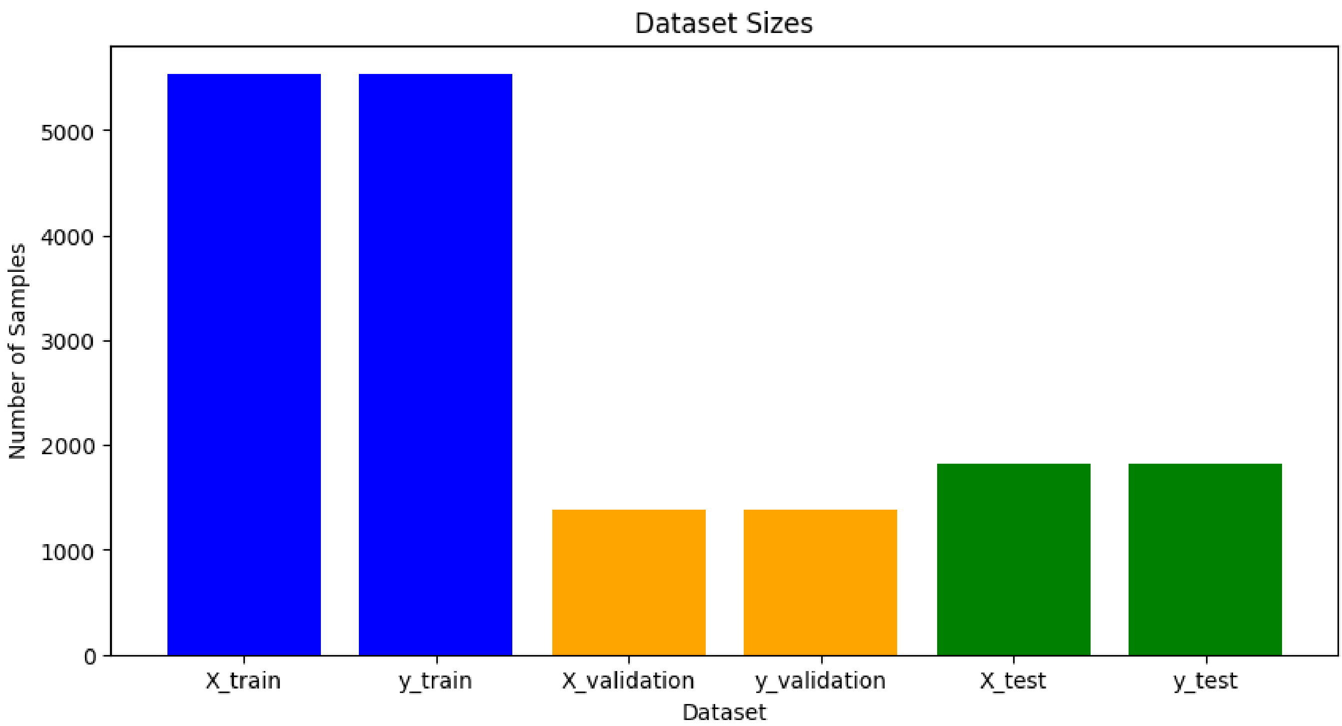
As mentioned above we will read the tsv files using the pandas module and spilt into X_train and X_validation

```
data = pd.read_csv('train.tsv', sep='\t')
test_data = pd.read_csv('test.tsv', sep='\t')

X = data.iloc[:, 0]
y = data.iloc[:, 1]
X_test = test_data.iloc[:, 0]
y_test = test_data.iloc[:, 1]

X_train, X_validation, y_train, y_validation = train_test_split(X, y,
test_size=0.2, random_state=20)
```

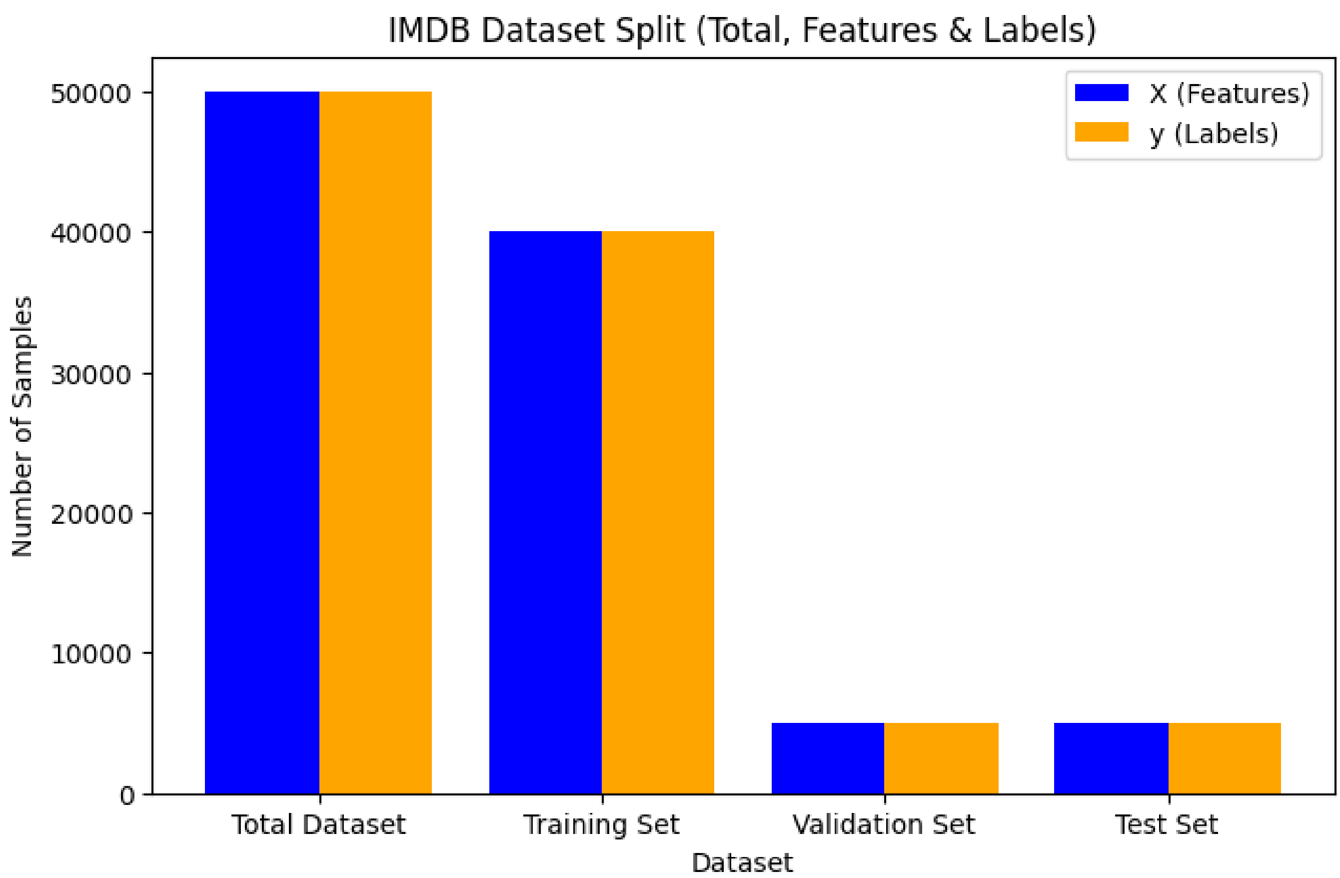
Dataset Sizes

The dataset sizes given to us are shown in the following bar graph:

Dataset 1



Dataset 2



Imports

Module Name	Import	Reason for Import
`torch`	`nn`	Provides neural network layers and loss functions
`torch`	`optim`	Contains optimizers for training models (e.g., Adam)
`torch`	`utils.data`	Handles dataset loading and batching
`torch.utils`	`tensorboard`	Logs training metrics for TensorBoard visualization
`torchsummary`	`summary`	Displays model architecture summary
`transformers`	`DistilBertTokenizer`, `DistilBertModel`, `AutoTokenizer`, `AutoModel`	Loads pre-trained transformer models and tokenizers
`sklearn`	`metrics`	Computes evaluation metrics (accuracy, precision, recall)
`sklearn.feature_extraction`	`text`	Converts text data into numerical features (e.g., CountVectorizer)
`tensorflow`	`tensorflow`	Used for deep learning tasks
`gzip`	`gzip`	Compresses and decompresses model checkpoints
`pickle`	`pickle`	Serializes and deserializes Python objects (e.g., model state dicts)
`numpy`	`numpy`	Performs numerical operations
`pandas`	`pandas`	Handles data manipulation and analysis
`matplotlib`	`pyplot`	Plots data visualizations
`seaborn`	`sns`	Creates statistical data visualizations
`tqdm`	`notebook`	Displays progress bars in Jupyter Notebook

Checkpointing

`save_checkpoint`

This function **saves the model's weights** in a compressed `.gz` format to reduce storage space.

```python
import torch
import gzip
import pickle

def save_checkpoint(model, path="checkpoint.pt.gz"):
    checkpoint = {
        "model_state_dict": model.state_dict()
    }
    with gzip.open(path, 'wb') as f:
        pickle.dump(checkpoint, f)

    print(f"Model weights saved successfully to {path}")
```

`load_checkpoint`

This function **loads the model's weights** from a compressed `.gz` file.

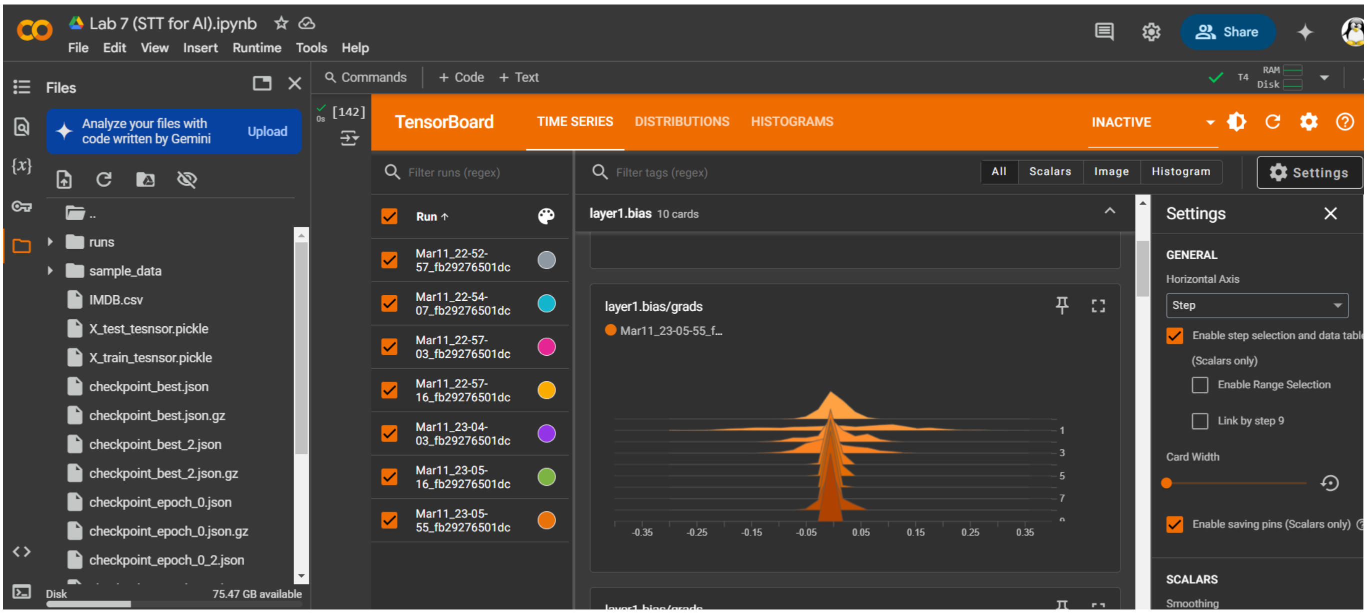
```python
import torch
import gzip
import pickle

def load_checkpoint(model, path="checkpoint.pt.gz"):
    with gzip.open(path, 'rb') as f:
        checkpoint = pickle.load(f)
    model.load_state_dict(checkpoint["model_state_dict"])
    print(f"Model weights loaded successfully from {path}")
```

TensorBoard

TensorBoard is a powerful tool for visualizing and tracking deep learning experiments. It provides interactive dashboards to analyze different aspects of model training.

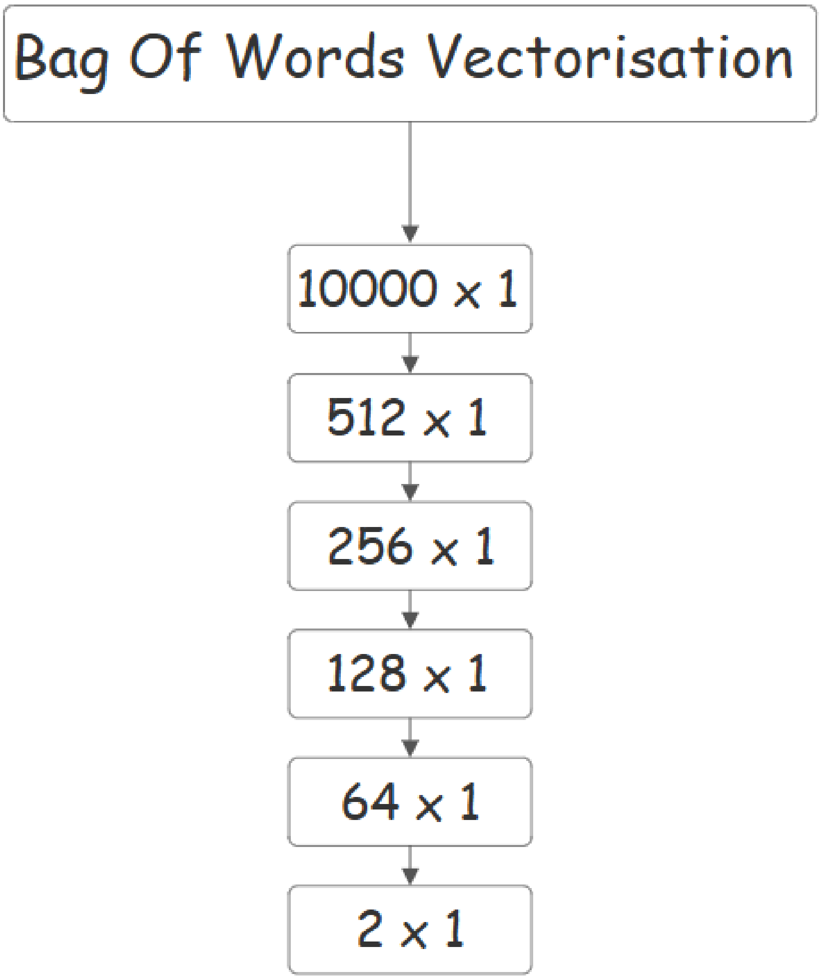
1. **Track Training Progress**
   - Plots loss, accuracy, and other metrics over time.
   - Helps in diagnosing overfitting or underfitting.
2. **Monitor Weights and Gradients**
   - Displays histograms of parameter distributions.
   - Helps in detecting vanishing or exploding gradients.
3. **Compare Multiple Experiments**
   - Enables hyperparameter tuning by visualizing different runs.
   - Helps in selecting the best-performing model.

Current Run:



MLP (Case - 1)

ML Architecture



Model

```python
class MLP(nn.Module):
    def __init__(self) -> None:
        super(MLP, self).__init__()
        self.layer1 = nn.Linear(10000, 512)
        self.layer2 = nn.Linear(512, 256)
        self.layer3 = nn.Linear(256, 128)
        self.layer4 = nn.Linear(128, 64)
        self.layer5 = nn.Linear(64, 2)

        self.activation = nn.ReLU()
        self.dropout = nn.Dropout(p=0.3)

    def forward(self, x):
        x = self.dropout(self.activation(self.layer1(x)))
        x = self.dropout(self.activation(self.layer2(x)))
        x = self.dropout(self.activation(self.layer3(x)))
        x = self.dropout(self.activation(self.layer4(x)))
        x = self.layer5(x)

        return x
```

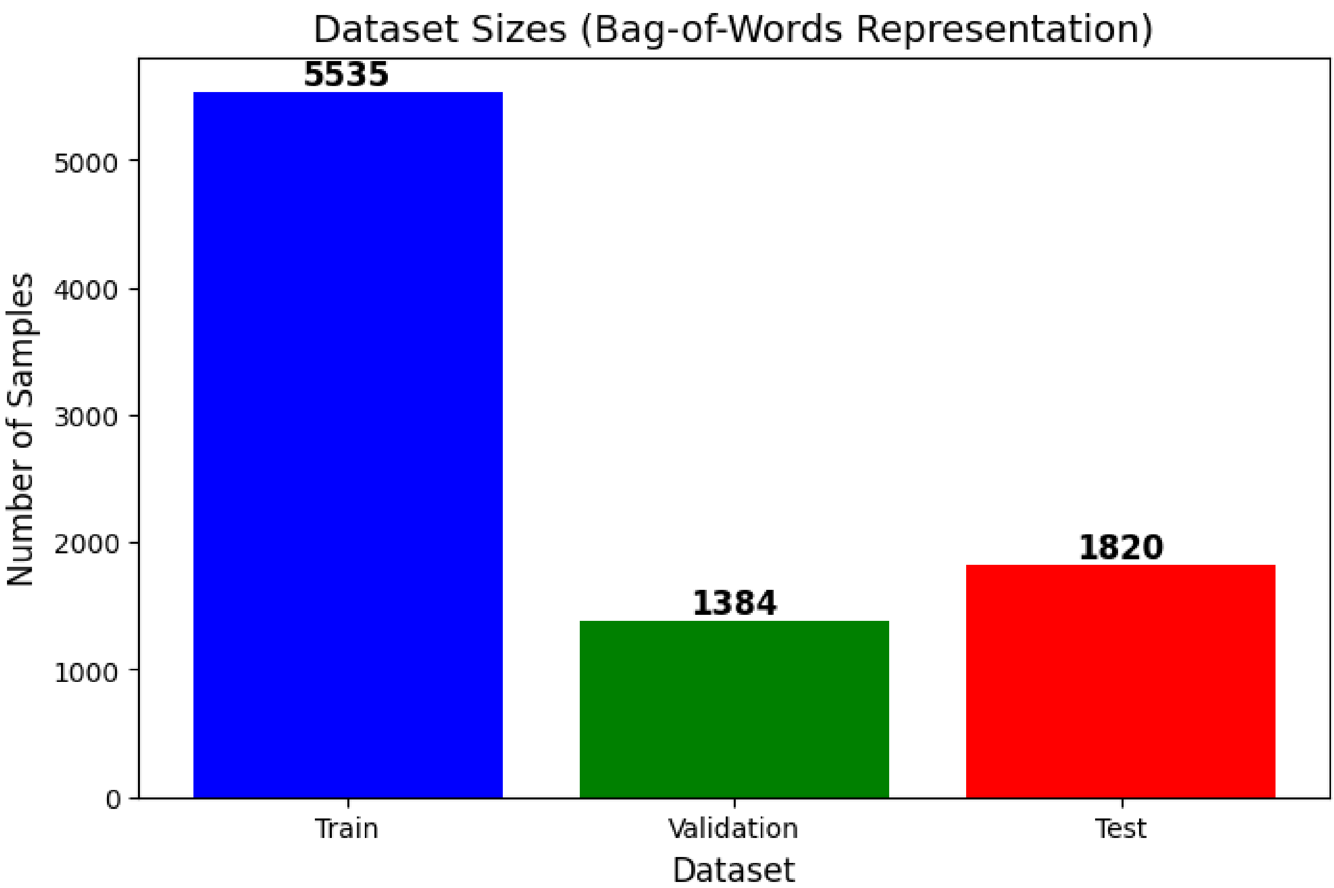
Model Outputs

```
MLP(
  (layer1): Linear(in_features=10000, out_features=512, bias=True)
  (layer2): Linear(in_features=512, out_features=256, bias=True)
  (layer3): Linear(in_features=256, out_features=128, bias=True)
  (layer4): Linear(in_features=128, out_features=64, bias=True)
  (layer5): Linear(in_features=64, out_features=2, bias=True)
  (activation): ReLU()
  (dropout): Dropout(p=0.3, inplace=False)
)
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1               [-1, 1, 512]       5,120,512
              ReLU-2               [-1, 1, 512]               0
           Dropout-3               [-1, 1, 512]               0
            Linear-4               [-1, 1, 256]         131,328
              ReLU-5               [-1, 1, 256]               0
           Dropout-6               [-1, 1, 256]               0
            Linear-7               [-1, 1, 128]          32,896
              ReLU-8               [-1, 1, 128]               0
           Dropout-9               [-1, 1, 128]               0
           Linear-10                [-1, 1, 64]           8,256
             ReLU-11                [-1, 1, 64]               0
          Dropout-12                [-1, 1, 64]               0
           Linear-13                 [-1, 1, 2]             130
================================================================
Total params: 5,293,122
Trainable params: 5,293,122
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.04
Forward/backward pass size (MB): 0.02
Params size (MB): 20.19
Estimated Total Size (MB): 20.25
```

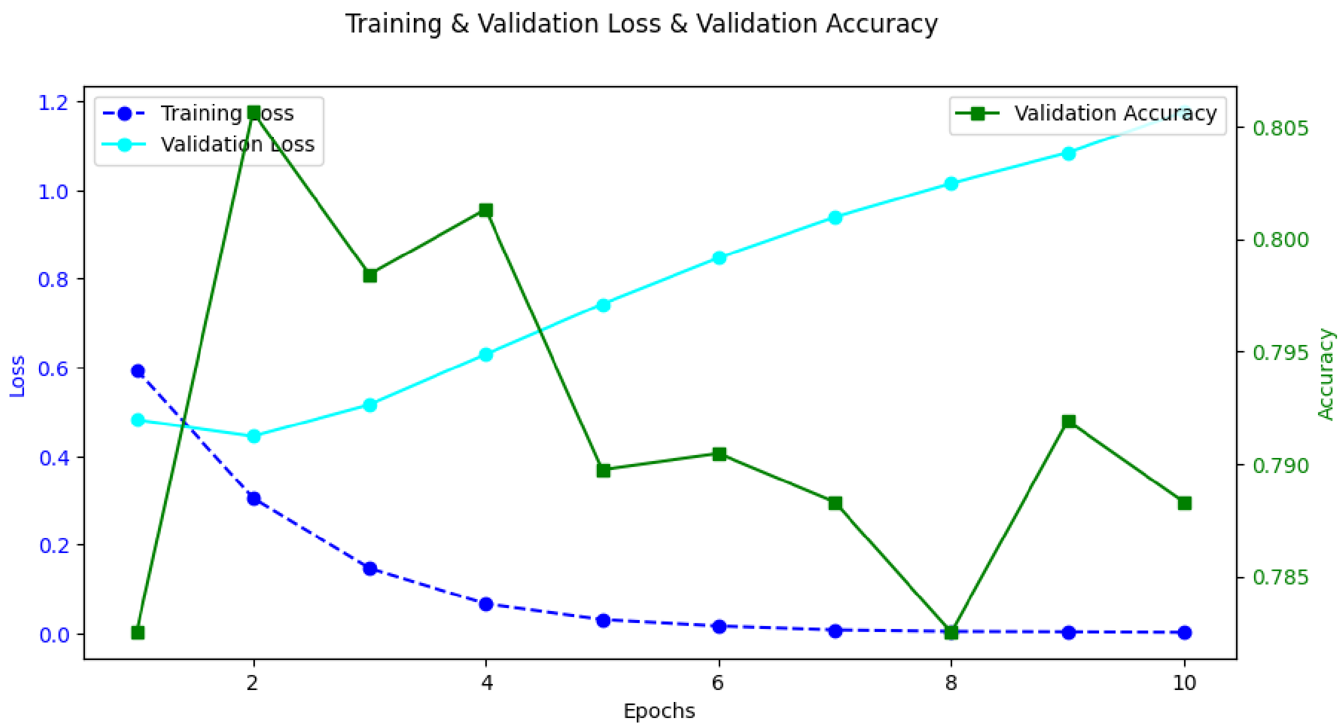
Bag of Words Vectorisation (Count Vector)

We need to convert textual data into numerical representations using the Bag-of-Words (BoW) model with `CountVectorizer` from `sklearn.feature_extraction.text` to train our MLP

```
vectorizer = CountVectorizer(max_features=10000)
X_train_bow = vectorizer.fit_transform(X_train)
X_validation_bow = vectorizer.transform(X_validation)
X_test_bow = vectorizer.transform(X_test)
```



Training Curve



Observation

1. Training Loss (Blue, Dashed Line)
    - Starts relatively high and gradually decreases, which is expected as the model learns from the data.
    - A steady decline suggests that the model is effectively minimizing the error on the training data.
2. Validation Loss (Cyan, Solid Line)
    - Unlike training loss, validation loss starts lower but increases over time.
    - This could indicate overfitting, where the model is performing well on training data but not generalizing well to unseen validation data.
3. Validation Accuracy (Green, Solid Line)
    - Initially increases sharply, peaking around Epoch 2.
    - However, it fluctuates after that, indicating that the model might not be consistently improving on validation data.
    - The final accuracy value suggests a decent performance

MLP (Case 2)

LLama3-Embedder

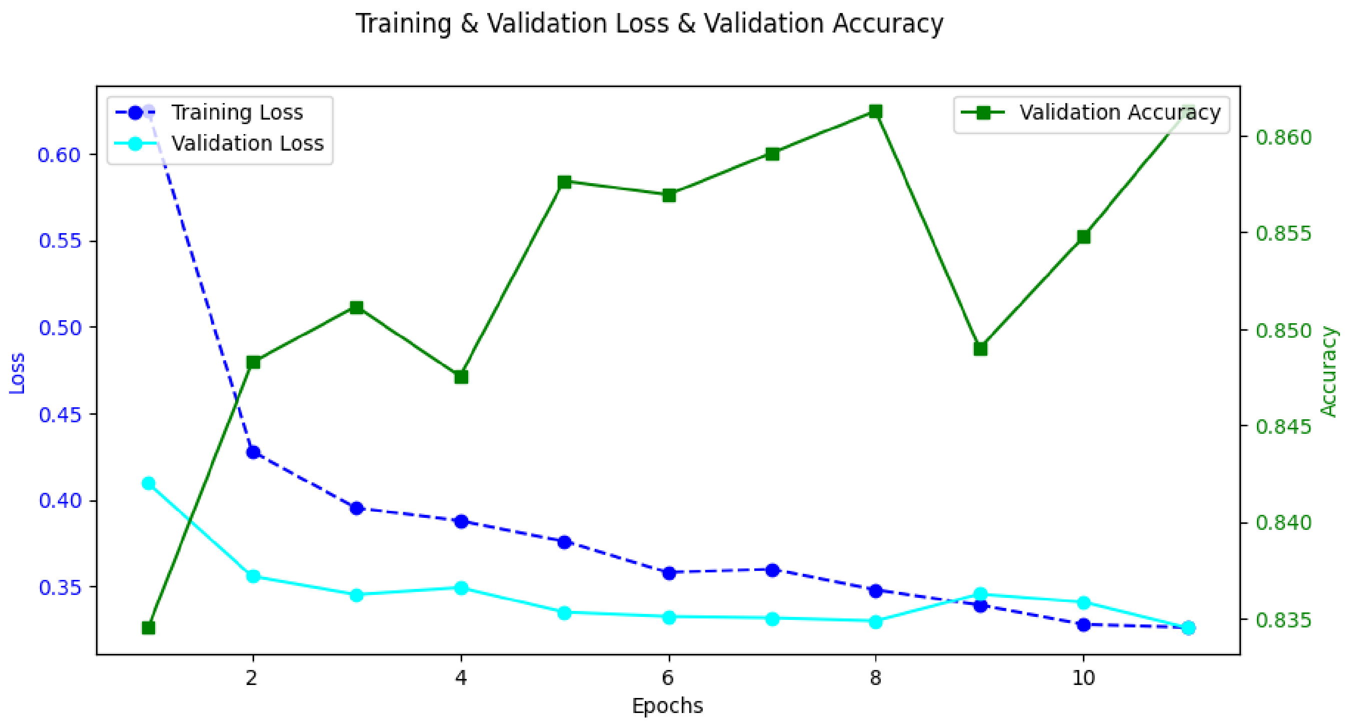
The Embedder class is designed to generate text embeddings using the **Llama 3.1-8B model from Meta**. It tokenizes input text, passes it through the model, and extracts meaningful vector representations.

```
class Embedder:
    def __init__(self):
        self.tokenizer = AutoTokenizer.from_pretrained("meta-llama/Llama-3.1-8B")
        self.model = AutoModel.from_pretrained("meta-llama/Llama-3.1-
8B").to(device)
        self.embedding_size = self.model.config.hidden_size
        self.tokenizer.pad_token = self.tokenizer.eos_token
        self.model_loaded = True

    def get_embeddings(self, text):
        inputs = self.tokenizer(text, return_tensors="pt", padding=True,
truncation=True, max_length=32).to(device)
        with torch.no_grad():
            outputs = self.model(**inputs)
        return outputs.last_hidden_state.mean(dim=1)
```

Model

```
class MLP2(nn.Module):
    def __init__(self, input_layer=4096) -> None:
        super(MLP2, self).__init__()
        self.layer1 = nn.Linear(input_layer, 512)
        self.layer2 = nn.Linear(512, 256)
        self.layer3 = nn.Linear(256, 128)
        self.layer4 = nn.Linear(128, 64)
        self.layer5 = nn.Linear(64, 2)

        self.activation = nn.ReLU()
        self.dropout = nn.Dropout(p=0.3)

    def forward(self, x):
        x = self.dropout(self.activation(self.layer1(x)))
        x = self.dropout(self.activation(self.layer2(x)))
        x = self.dropout(self.activation(self.layer3(x)))
        x = self.dropout(self.activation(self.layer4(x)))
        x = self.layer5(x)

        return x
```

Training Curve

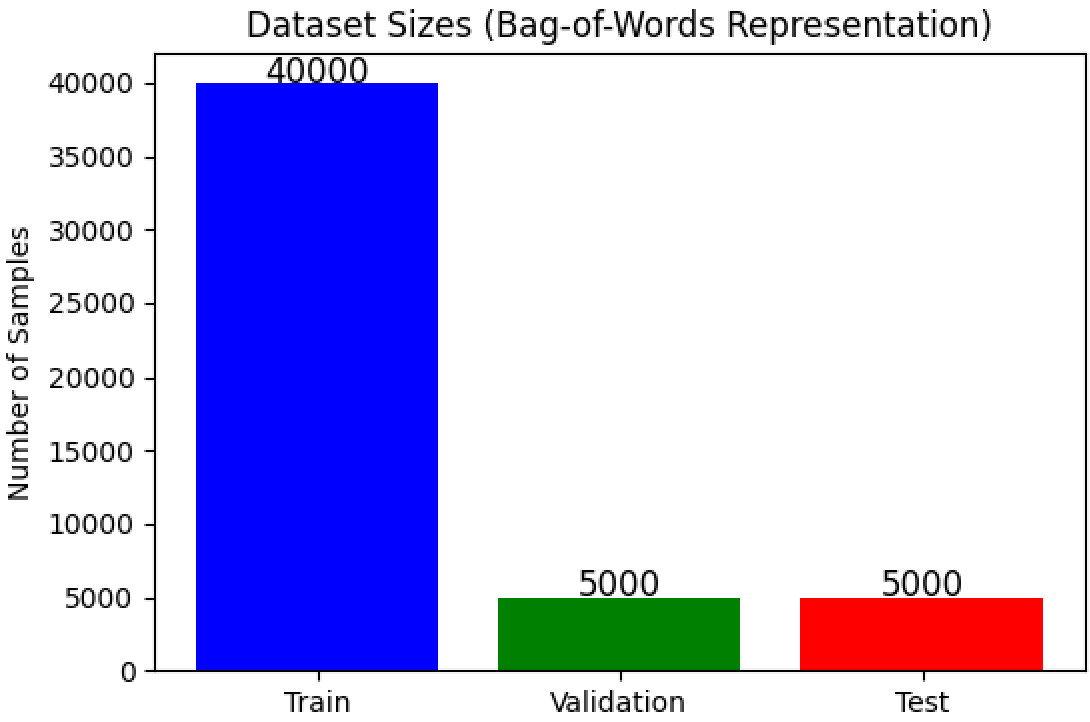


Observation

1. Training Loss (Blue, Dashed Line, Circular Markers)
    - Decreases over time, indicating the model is learning from the training data.
2. Validation Loss (Cyan, Solid Line, Circular Markers)
    - Initially decreases but stabilizes, suggesting the model generalizes well.
3. Validation Accuracy (Green, Solid Line, Square Markers)
    - Increases with epochs, meaning the model's performance on unseen data is improving.

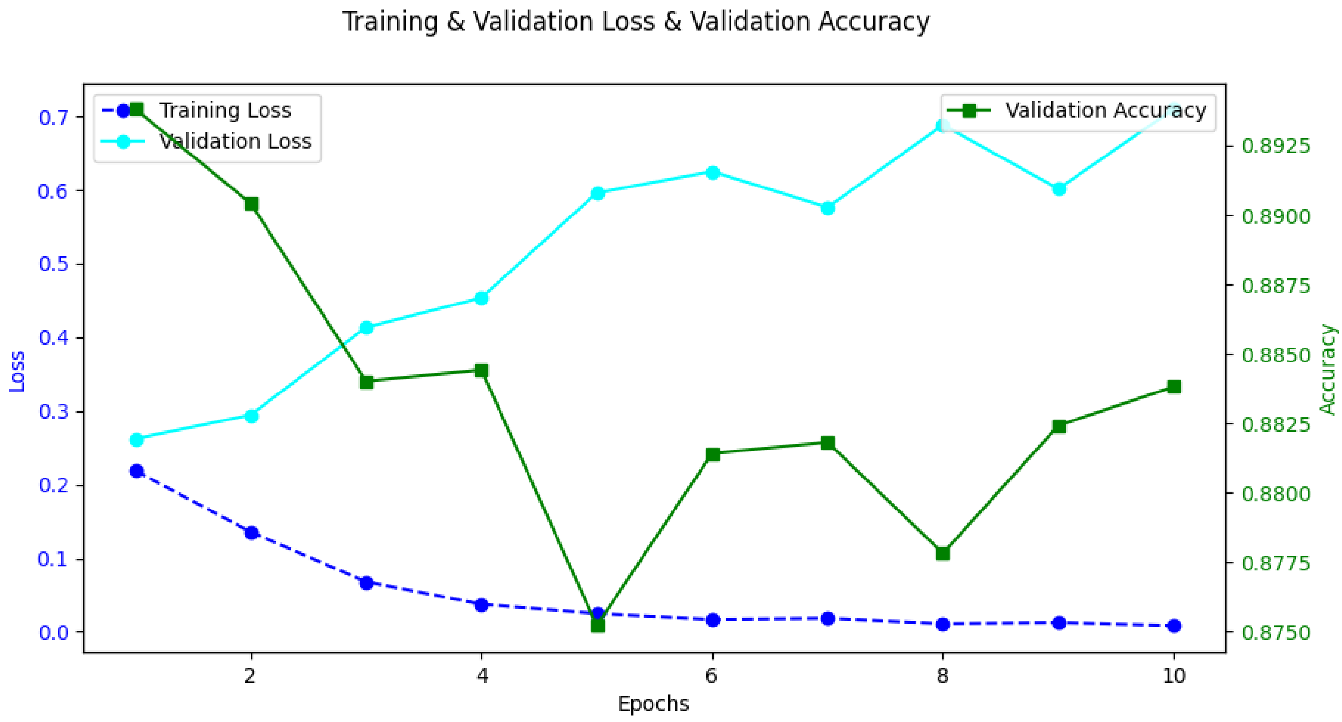
IMDB (Case - 1)

Bag of Words



1. Train Dataset (Blue Bar)
    - Contains 40,000 samples, which is significantly larger than the other two datasets.
    - This is because training a model typically requires the largest dataset to learn effectively.
2. Validation Dataset (Green Bar)
    - Contains 5,000 samples, used to fine-tune hyperparameters and monitor overfitting.
3. Test Dataset (Red Bar)
    - Also contains 5,000 samples, used to evaluate the final model performance.

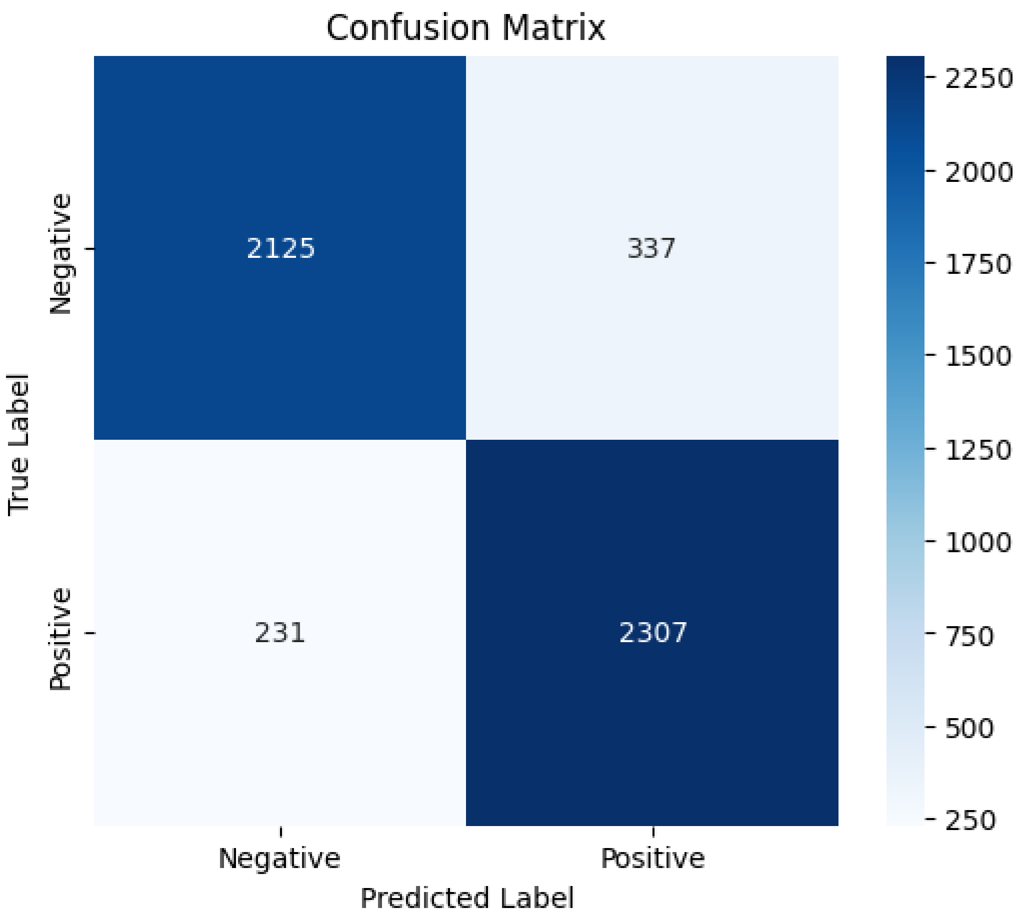
Training Curve



Observation

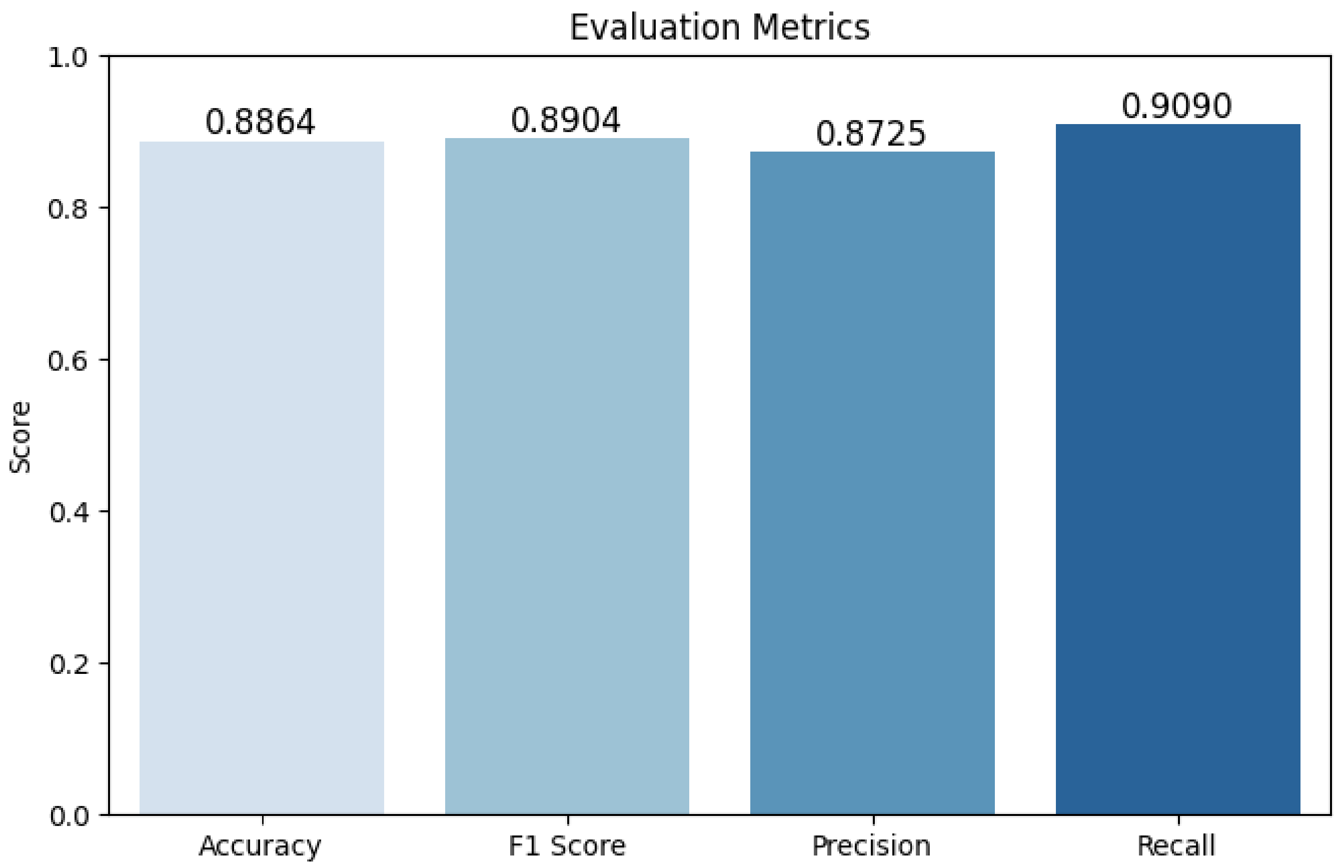
1. Training Loss (Blue, Dashed Line)
    - Starts relatively high and gradually decreases, which is expected as the model learns from the data.
    - A steady decline suggests that the model is effectively minimizing the error on the training data.
2. Validation Loss (Cyan, Solid Line)
    - Unlike training loss, validation loss starts lower but increases over time.
    - This could indicate overfitting, where the model is performing well on training data but not generalizing well to unseen validation data.
3. Validation Accuracy (Green, Solid Line)
    - Increases overall, indicating that the model is improving its performance on unseen data.
    - Some fluctuations suggest the model is adjusting its parameters dynamically.

Confusion Matrix



1. High true positives and true negatives indicate good overall performance.
2. 337 false positives may indicate a need to fine-tune decision thresholds.
3. 231 false negatives suggest recall improvement strategies, such as data balancing or adjusting loss

Evaluation Matrix



This bar chart represents the key evaluation metrics for the model's performance:

1. Accuracy (0.8864)

- The proportion of correctly classified instances out of all predictions.
- **88.64%** accuracy suggests strong overall performance.

2. F1 Score (0.8904)

- The harmonic mean of **precision** and **recall**.
- A high F1 score (~89%) indicates a balanced model with strong performance in both identifying positives and minimizing false positives/negatives.

3. Precision (0.8725)

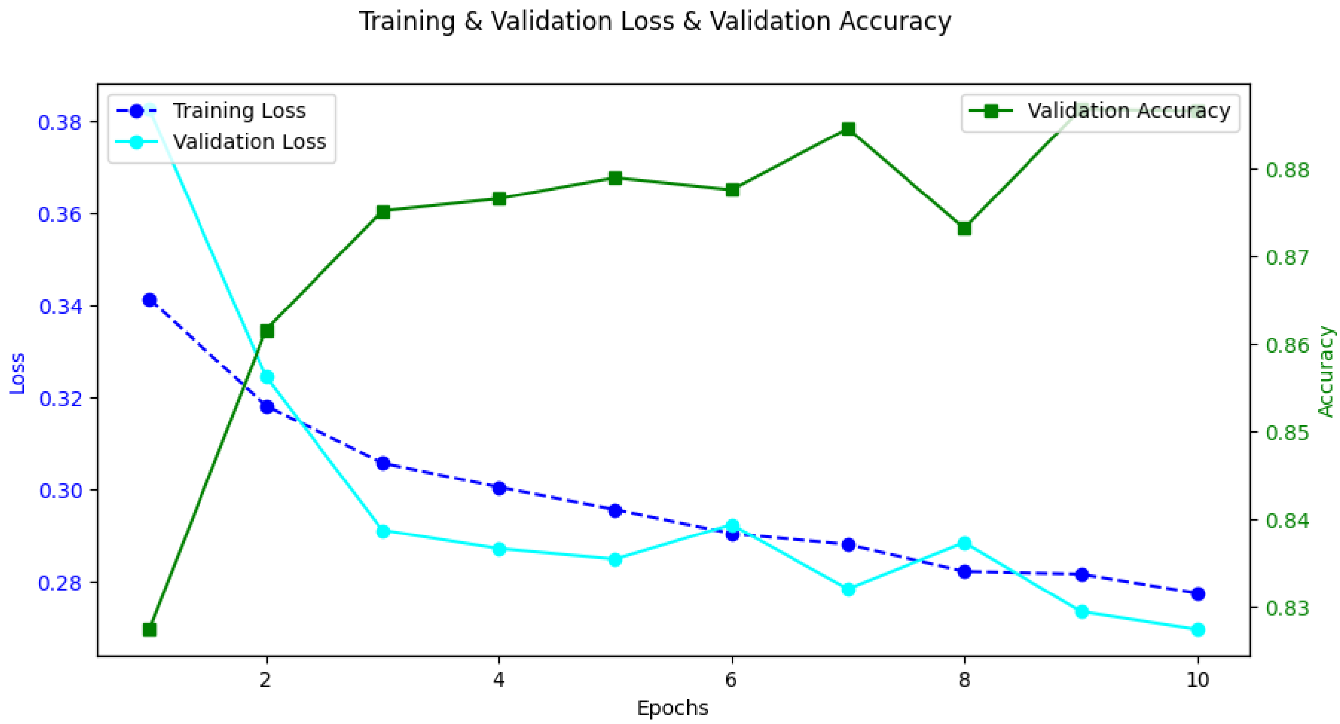
- The proportion of true positive predictions out of all positive predictions made.
- **87.25%** precision suggests that most of the predicted positives are indeed correct.

4. Recall (0.9090)

- The proportion of actual positive instances correctly identified.
- **90.90%** recall suggests the model effectively captures most positive cases.

IMDB (Case - 2)

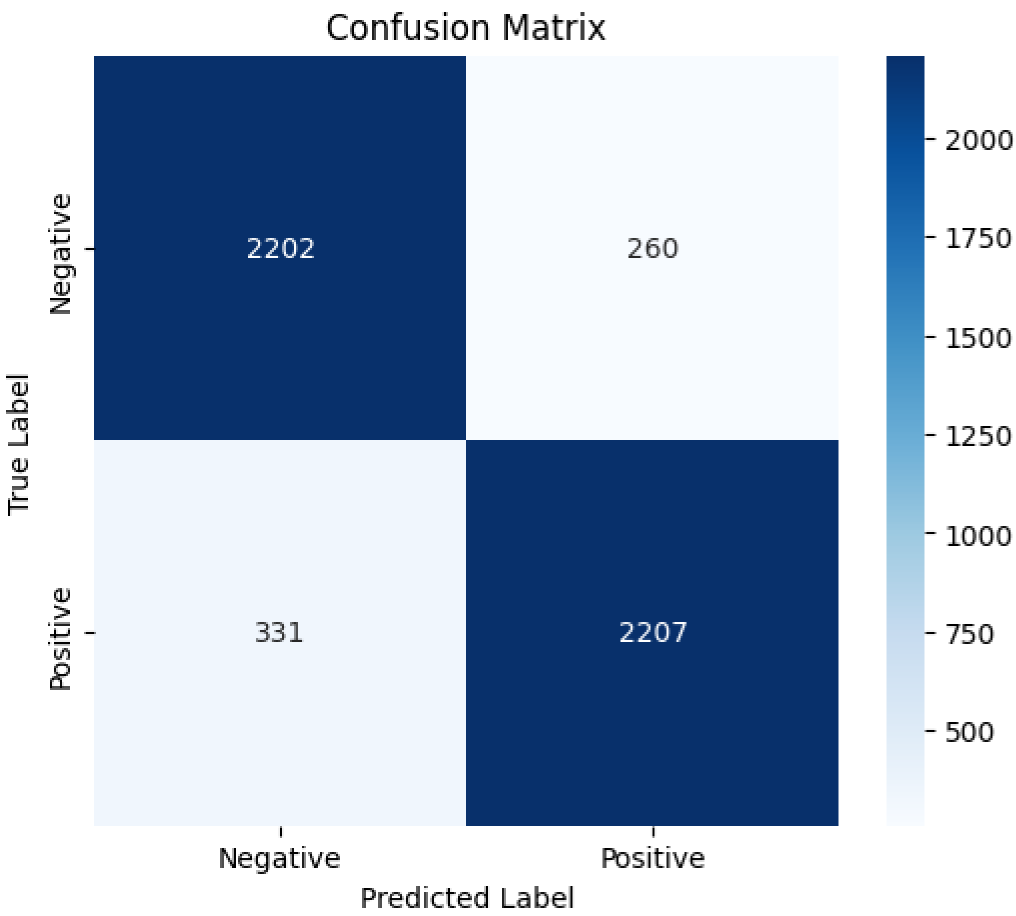
Training Curve



Observation

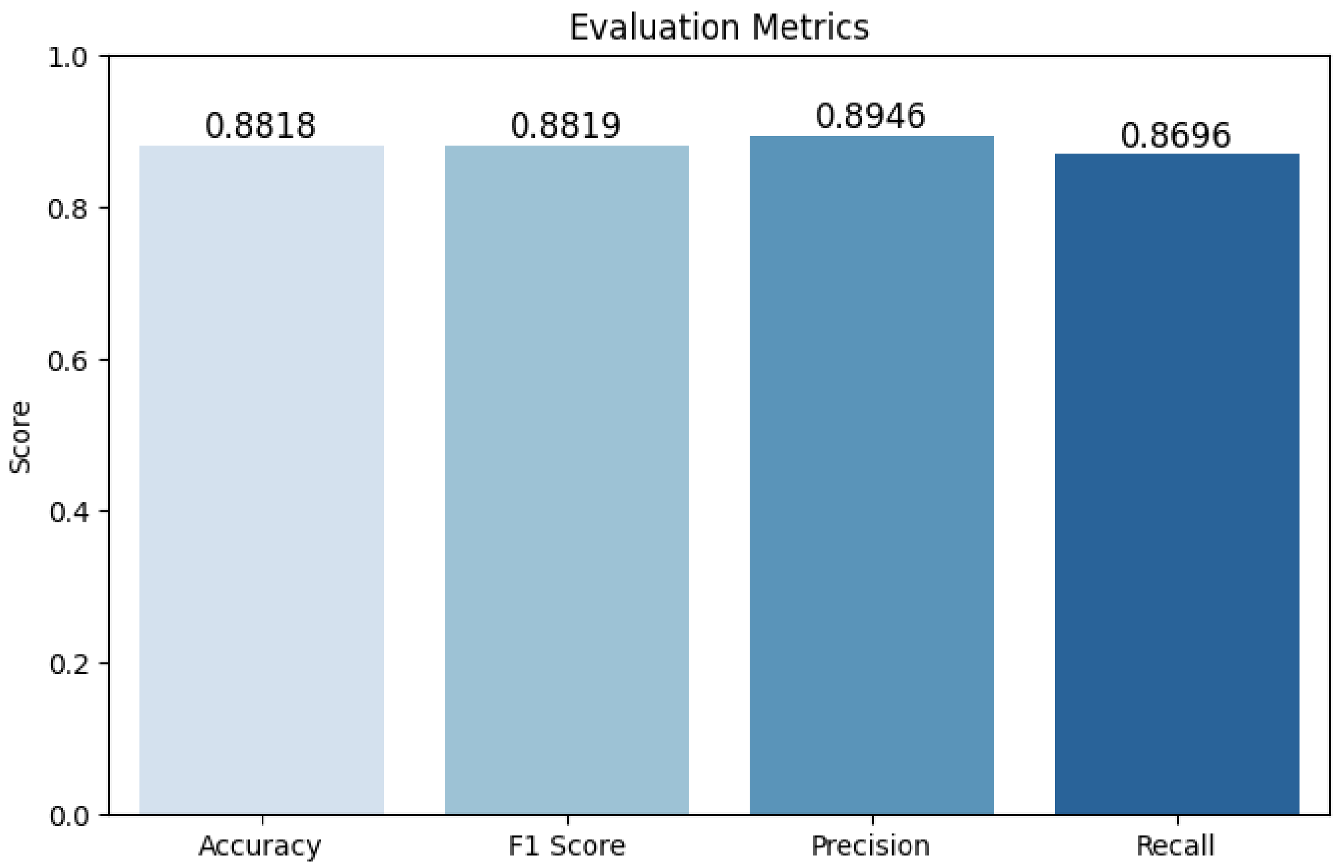
1. **Training Loss (blue dashed line)**
    - Starts high but decreases steadily, indicating that the model is learning effectively.
2. **Validation Loss (cyan solid line)**
    - Initially high but drops significantly, then stabilizes.
    - A small increase after epoch 6 suggests possible **overfitting**.
3. **Validation Accuracy (green line, right axis)**
    - Increases initially and stabilizes around **88%**.
    - A slight dip around epoch 7, followed by an increase, shows minor fluctuations.

Confusion Matrix



1. **High True Positives & True Negatives**
    - The model correctly classifies most negative and positive samples.
2. **Misclassification Cases (FP & FN)**
    - **False Positives (260 cases):** Some negative samples were misclassified as positive.
    - **False Negatives (331 cases):** Some positive samples were misclassified as negative.
3. **Potential Improvements**
    - Adjusting decision thresholds to reduce false negatives.
    - Implementing better feature engineering or handling class imbalance.

Evaluation Matrics



Metrics Breakdown

- **Accuracy: 0.8818** → The proportion of correctly classified samples.
- **F1 Score: 0.8819** → The harmonic mean of precision and recall.
- **Precision: 0.8946** → The proportion of correctly predicted positive cases.
- **Recall: 0.8696** → The proportion of actual positive cases correctly identified.

Observation

1. **Balanced Performance**
    - Accuracy and F1 score are close, indicating a well-performing model.
    - Precision is slightly higher than recall, suggesting fewer false positives.
2. **Potential Trade-offs**
    - If false negatives are costly, increasing recall might be beneficial.
    - If false positives are critical, precision should be prioritized.

Comaprison BoW vs Embedding System

1. Evaluation Metrics

Metric	BoW	Embed
Accuracy	0.8864	0.8818
F1 Score	0.8904	0.8819
Precision	0.8725	0.8946
Recall	0.9090	0.8696

---

2. Performance Analysis

1. **Accuracy**
    - BoW (0.8864) is slightly higher than Embed (0.8818), meaning BoW has slightly better overall correctness.
2. **F1 Score**
    - BoW (0.8904) is slightly higher than Embed (0.8819), indicating better balance between precision and recall.
3. **Precision**
    - Embed (0.8946) outperforms BoW (0.8725), meaning it makes fewer false positive errors.
4. **Recall**
    - BoW (0.9090) is higher than Embed (0.8696), meaning BoW identifies more positive instances correctly.

---

3. Conclusion

- **BoW performs better in recall**, meaning it captures more positive cases correctly but at the cost of slightly lower precision.
- **Embed has higher precision**, meaning it makes fewer false positives but at the cost of lower recall.
- **Overall, BoW slightly outperforms Embed in accuracy and F1-score**, but the choice depends on whether **recall (BoW)** or **precision (Embed)** is more important for the specific task.