SARCASTIC NEWS HEADLINE DETECTION

GROUP BY 6:

SHIKHA SHARMA

TANMAY KSHIRSAGAR

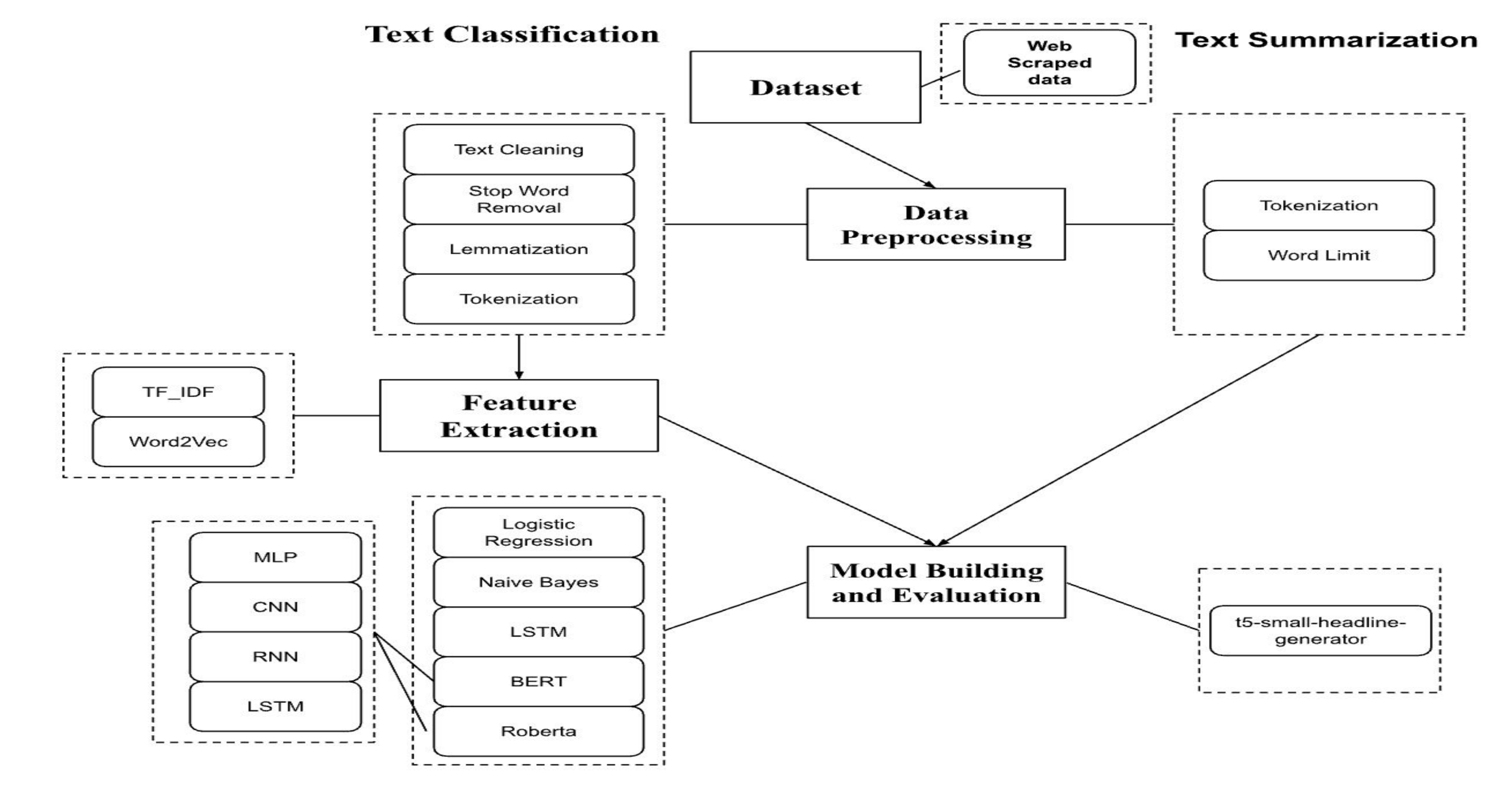
PURVI JAIN

OBJECTIVE

- Develop a nuanced NLP model capable of accurately classifying news headlines as sarcastic or non-sarcastic.
- Utilize a mix of classical ML algorithms (Random Forest, MLP, LR) and advanced neural networks (LSTM, BERT, Roberta) for effective sarcasm detection.
- Implement transformer-based models, specifically the T5-small-headline-generator, to create summaries that can potentially mimic sarcasm in news headlines.
- Focus on model explain ability to ensure transparency in how the models discern and generate sarcastic content.

DATA SOURCE

- Dataset Selection: 'News Headlines Dataset For Sarcasm Detection' from Kaggle.
- Volume & Sources:
  - Contains 55,328 headlines with articles.
  - Compiled from two distinct websites to reduce noise and ambiguity.
- Composition & Reliability:
  - Sarcastic headlines from TheOnion's satirical news sections.
  - Non-sarcastic headlines from HuffPost for serious news content.
- Dataset Attributes:
  - is_sarcastic: Binary indicator (1 for sarcastic, 0 for non-sarcastic).
  - headline: Text of the news headline.
  - article_link: URL to the original news article.
- Web Scraping for sarcastic news.


Text Classification
Text Summarization
Dataset
Web Scraped data
Text Cleaning
Stop Word Removal
Lemmatization
Tokenization
Data Preprocessing
Tokenization
Word Limit
TF_IDF
Word2Vec
Feature Extraction
MLP
CNN
RNN
LSTM
Logistic Regression
Naive Bayes
LSTM
BERT
Roberta
Model Building and Evaluation
t5-small-headline-generator

PREPROCESSING

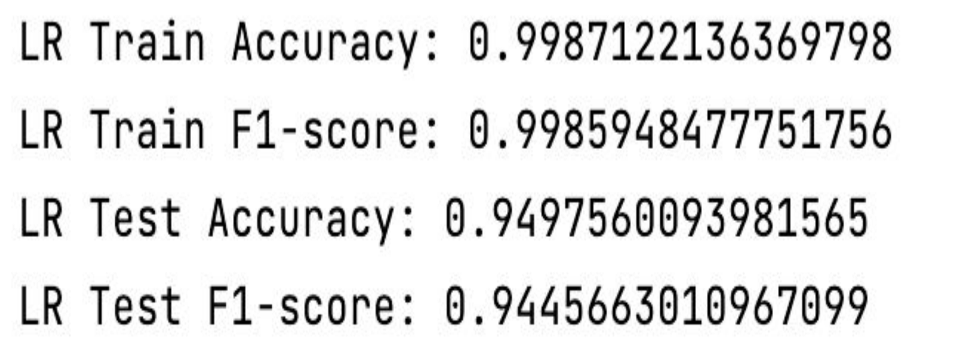
- Data Cleaning: Applied regular expressions to eliminate numbers, punctuations, and extraneous characters; transformed text to lowercase for uniformity.

- Stop Words Removal: Utilized NLTK package to filter out stop words, streamlining the dataset for more efficient processing.

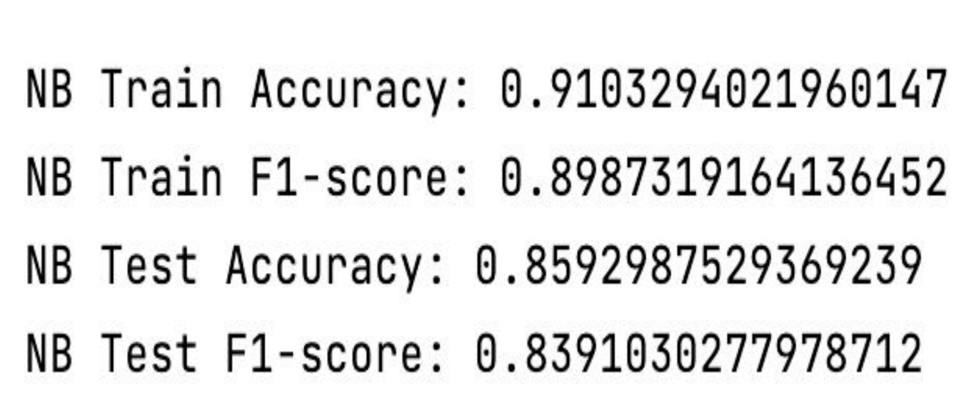
- Text Normalization: Conducted lemmatization to consolidate word variants to their dictionary form, enhancing the consistency of the dataset.

CLASSIFICATION
Classical Models

- Used unprocessed data for baseline model performance.
- Segregated data into training and testing sets without preprocessing.
- Transformed text into feature vectors using TF IDF.
- Evaluated Logistic Regression and Naive Bayes with scikit-learn.



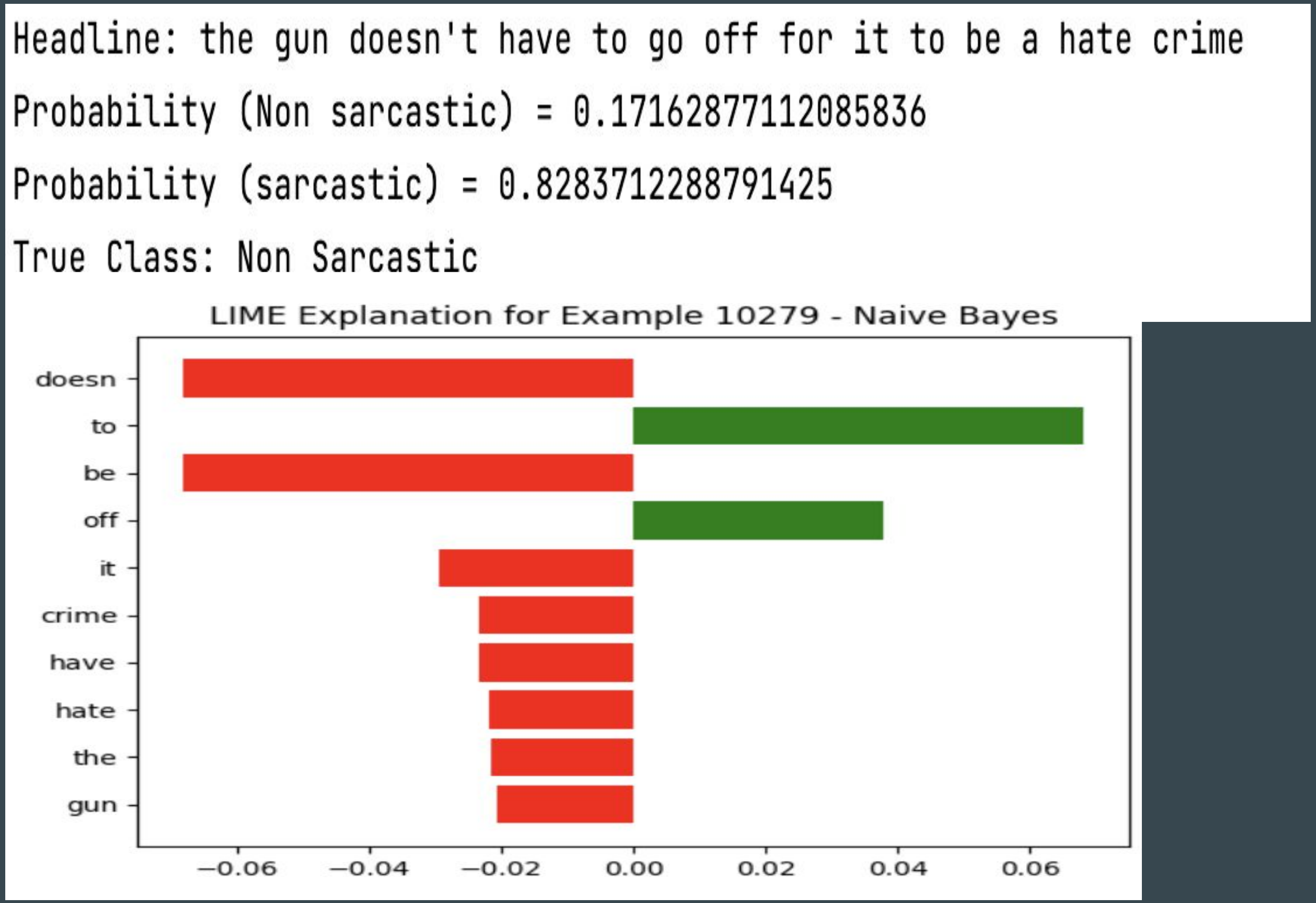
```
LR Train Accuracy: 0.9987122136369798
LR Train F1-score: 0.9985948477751756
LR Test Accuracy: 0.9497560093981565
LR Test F1-score: 0.9445663010967099
```



```
NB Train Accuracy: 0.9103294021960147
NB Train F1-score: 0.8987319164136452
NB Test Accuracy: 0.8592987529369239
NB Test F1-score: 0.8391030277978712
```

Model Explainability : LIME

- Uses LIME to shed light on the predictions made by complex models.
- Words 'doesn't', 'it', 'crime', 'have', 'hate', 'gun' negatively influence the prediction.
- Words 'be' and 'off' positively affect the model's outcome.
- Bar length indicates the magnitude of each word's impact on the classification.
- LIME clarifies model reasoning, revealing keywords that lead to the Naive Bayes decision.

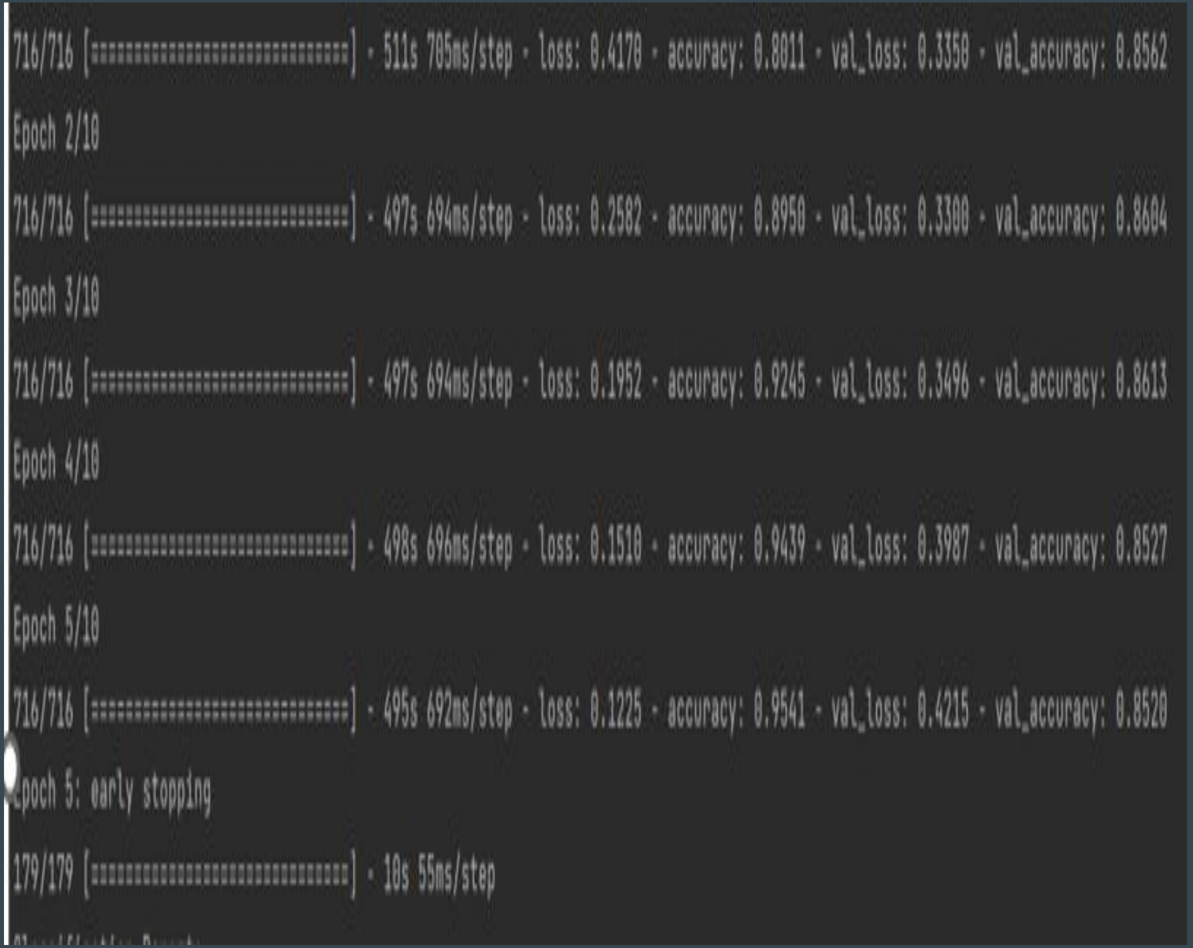


```
Headline: the gun doesn't have to go off for it to be a hate crime

Probability (Non sarcastic) = 0.17162877112085836

Probability (sarcastic) = 0.8283712288791425

True Class: Non Sarcastic
```

LIME Explanation for Example 10279 - Naive Bayes

CLASSIFICATION LSTM

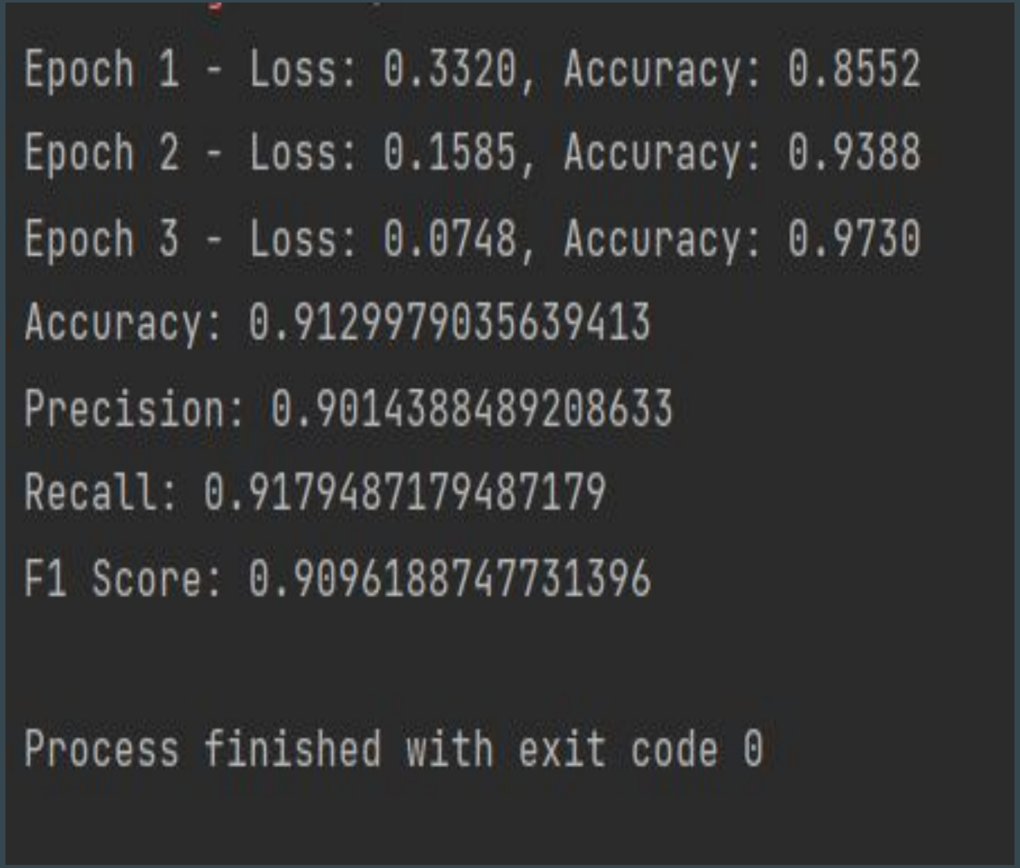
- Training accuracy progressed from 80.11% to 95.41% across five epochs.
- Validation accuracy peaked at 86.13%, reflecting high model performance.
- The model demonstrated a consistent decrease in loss, showing effective learning.
- Early stopping after the 5th epoch suggests the model's robustness in generalization without overfitting.



```
716/716 [==============================] - 511s 705ms/step - loss: 0.4170 - accuracy: 0.8011 - val_loss: 0.3358 - val_accuracy: 0.8562
Epoch 2/10
716/716 [==============================] - 497s 694ms/step - loss: 0.2582 - accuracy: 0.8950 - val_loss: 0.3300 - val_accuracy: 0.8604
Epoch 3/10
716/716 [==============================] - 497s 694ms/step - loss: 0.1952 - accuracy: 0.9245 - val_loss: 0.3496 - val_accuracy: 0.8613
Epoch 4/10
716/716 [==============================] - 498s 696ms/step - loss: 0.1510 - accuracy: 0.9439 - val_loss: 0.3987 - val_accuracy: 0.8527
Epoch 5/10
716/716 [==============================] - 495s 692ms/step - loss: 0.1225 - accuracy: 0.9541 - val_loss: 0.4215 - val_accuracy: 0.8520
Epoch 5: early stopping
179/179 [==============================] - 10s 55ms/step
```

CLASSIFICATION BERT

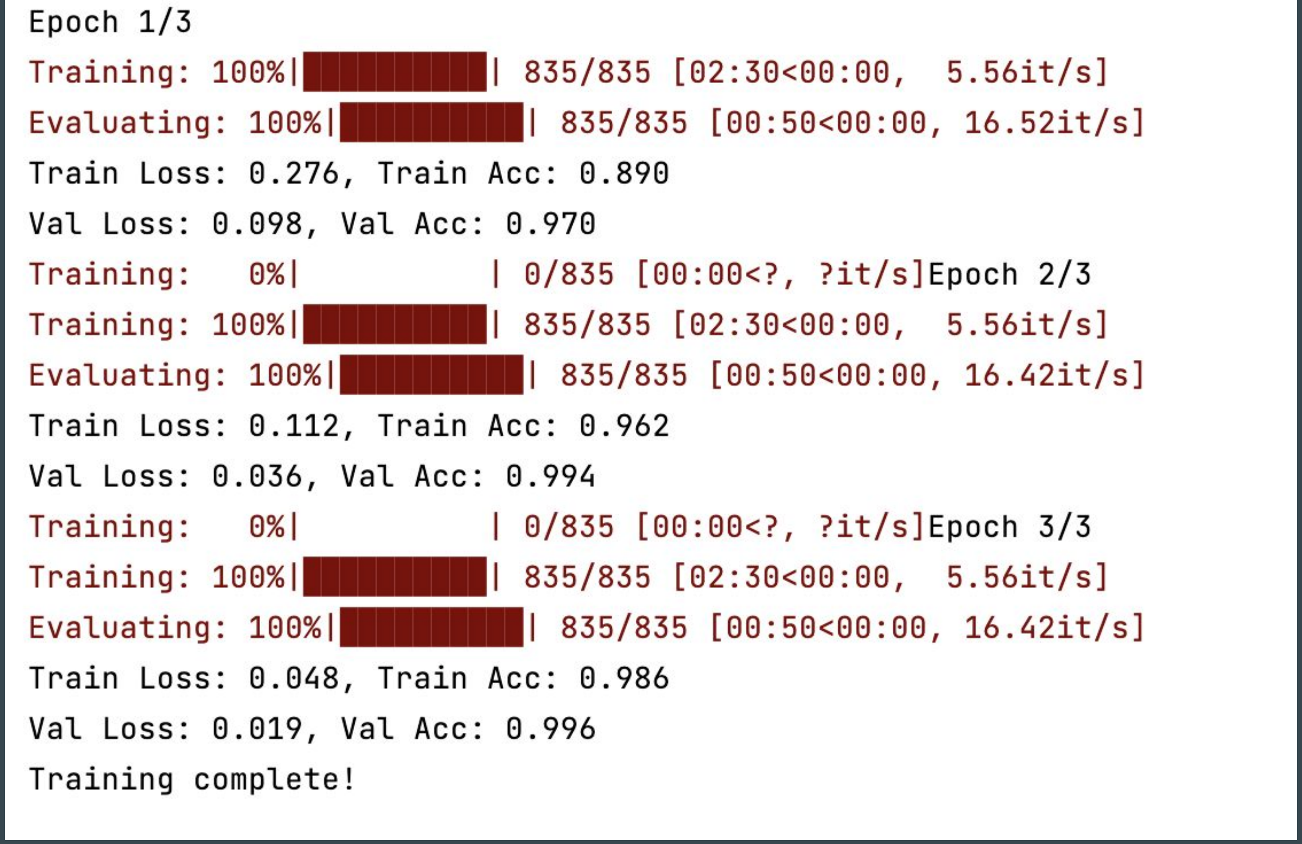
- Training showcased consistent improvement, with constant decrease in training loss.
- The model achieved an impressive accuracy of 97.30% on training and 91.47% on validation data.



```
Epoch 1 - Loss: 0.3320, Accuracy: 0.8552
Epoch 2 - Loss: 0.1585, Accuracy: 0.9388
Epoch 3 - Loss: 0.0748, Accuracy: 0.9730
Accuracy: 0.9129979035639413
Precision: 0.9014388489208633
Recall: 0.9179487179487179
F1 Score: 0.9096188747731396


Process finished with exit code 0
```

CLASSIFICATION
Transformers - BERT + MLP

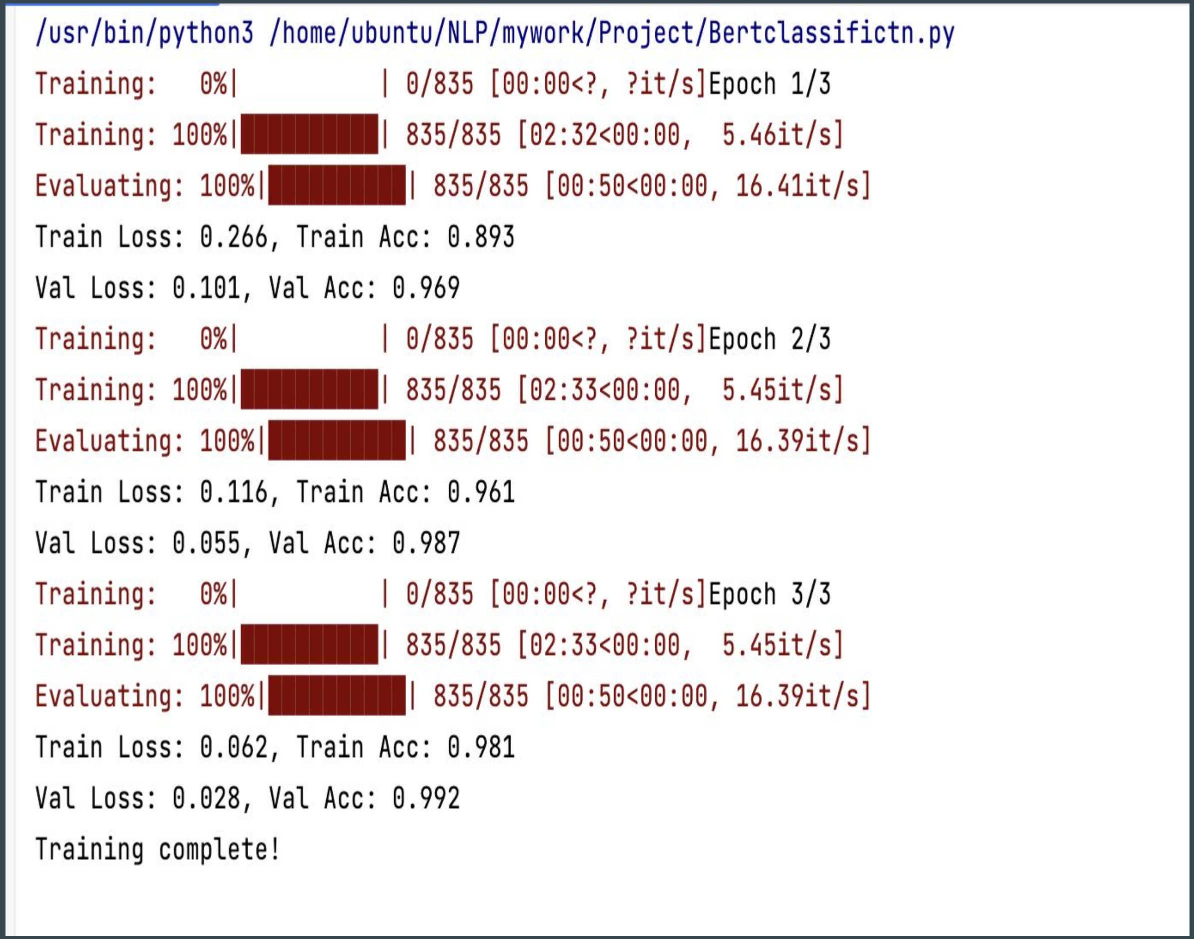
- ➢ BERT+MLP reached 99.6% validation accuracy.
- ➢ Consistent gains over three epochs.
- ➢ Well-tuned model with reduced losses.



```
Epoch 1/3
Training: 100%|██████████| 835/835 [02:30<00:00,  5.56it/s]
Evaluating: 100%|██████████| 835/835 [00:50<00:00, 16.52it/s]
Train Loss: 0.276, Train Acc: 0.890
Val Loss: 0.098, Val Acc: 0.970
Training:   0%|          | 0/835 [00:00<?, ?it/s]Epoch 2/3
Training: 100%|██████████| 835/835 [02:30<00:00,  5.56it/s]
Evaluating: 100%|██████████| 835/835 [00:50<00:00, 16.42it/s]
Train Loss: 0.112, Train Acc: 0.962
Val Loss: 0.036, Val Acc: 0.994
Training:   0%|          | 0/835 [00:00<?, ?it/s]Epoch 3/3
Training: 100%|██████████| 835/835 [02:30<00:00,  5.56it/s]
Evaluating: 100%|██████████| 835/835 [00:50<00:00, 16.42it/s]
Train Loss: 0.048, Train Acc: 0.986
Val Loss: 0.019, Val Acc: 0.996
Training complete!
```

CLASSIFICATION
Transformers - BERT + LSTM

- Training accuracy improved from 89.3% to 98.1% over three epochs.
- Validation accuracy increased from 96.9% to 99.2%.
- Both training and validation losses significantly decreased, indicating effective learning.



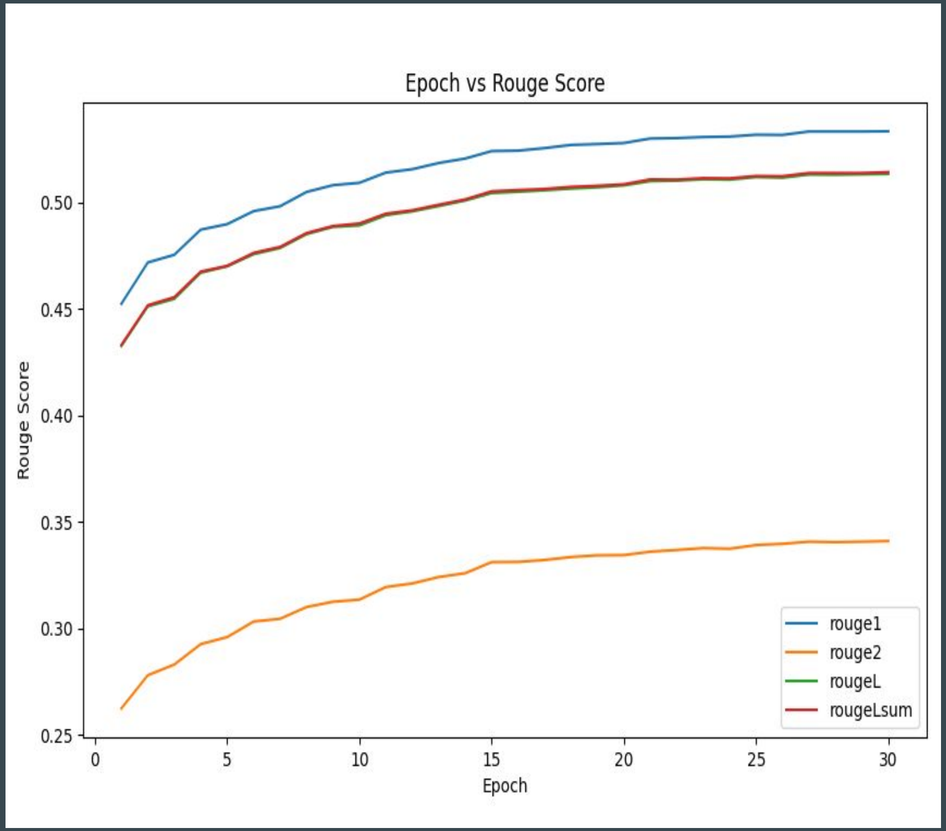
```
/usr/bin/python3 /home/ubuntu/NLP/mywork/Project/Bertclassifictn.py
Training:   0%|          | 0/835 [00:00<?, ?it/s]Epoch 1/3
Training: 100%|██████████| 835/835 [02:32<00:00,  5.46it/s]
Evaluating: 100%|██████████| 835/835 [00:50<00:00, 16.41it/s]
Train Loss: 0.266, Train Acc: 0.893
Val Loss: 0.101, Val Acc: 0.969
Training:   0%|          | 0/835 [00:00<?, ?it/s]Epoch 2/3
Training: 100%|██████████| 835/835 [02:33<00:00,  5.45it/s]
Evaluating: 100%|██████████| 835/835 [00:50<00:00, 16.39it/s]
Train Loss: 0.116, Train Acc: 0.961
Val Loss: 0.055, Val Acc: 0.987
Training:   0%|          | 0/835 [00:00<?, ?it/s]Epoch 3/3
Training: 100%|██████████| 835/835 [02:33<00:00,  5.45it/s]
Evaluating: 100%|██████████| 835/835 [00:50<00:00, 16.39it/s]
Train Loss: 0.062, Train Acc: 0.981
Val Loss: 0.028, Val Acc: 0.992
Training complete!
```

CLASSIFICATION

Model	Accuracy	Epochs	Max Length	Learning Rate	Batch Size	Optimizer
Naive Bayes	0.86					
Logistic Regression	0.94					
LSTM	0.95	4	120			Adam
CNN	0.98	4	120			Adam
BERT	0.97	3	120	2e-5	32	AdamW
BERT + LSTM	0.98	3	128	2e-6	32	AdamW
BERT + CNN	0.82	5	128	2e-5	32	AdamW
BERT+MLP	0.98	3	128	5e-5	32	AdamW
RoBERTa	0.76	10	256	1e-5	32	Adam

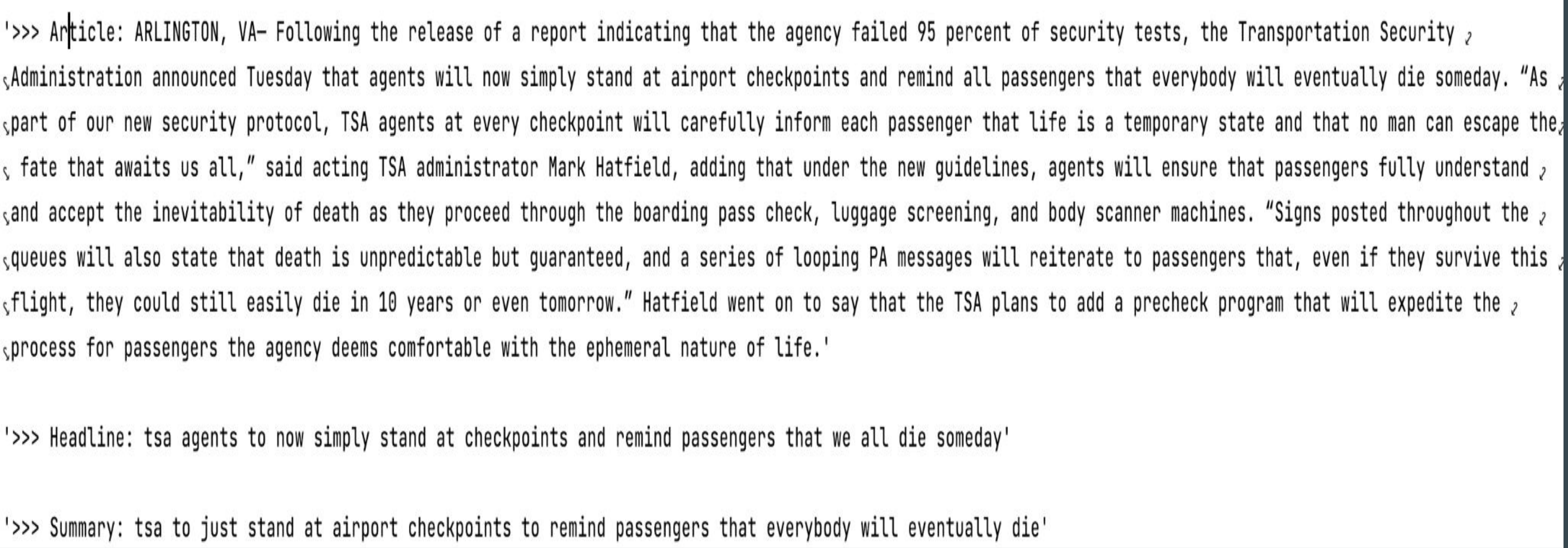
SUMMARIZATION

- Model: t5-small-headline-generator (Text-to-Text Transfer Transformer)
- Evaluation Metric: ROUGE scores provide insights into the quality of the generated summaries concerning the ground truth.

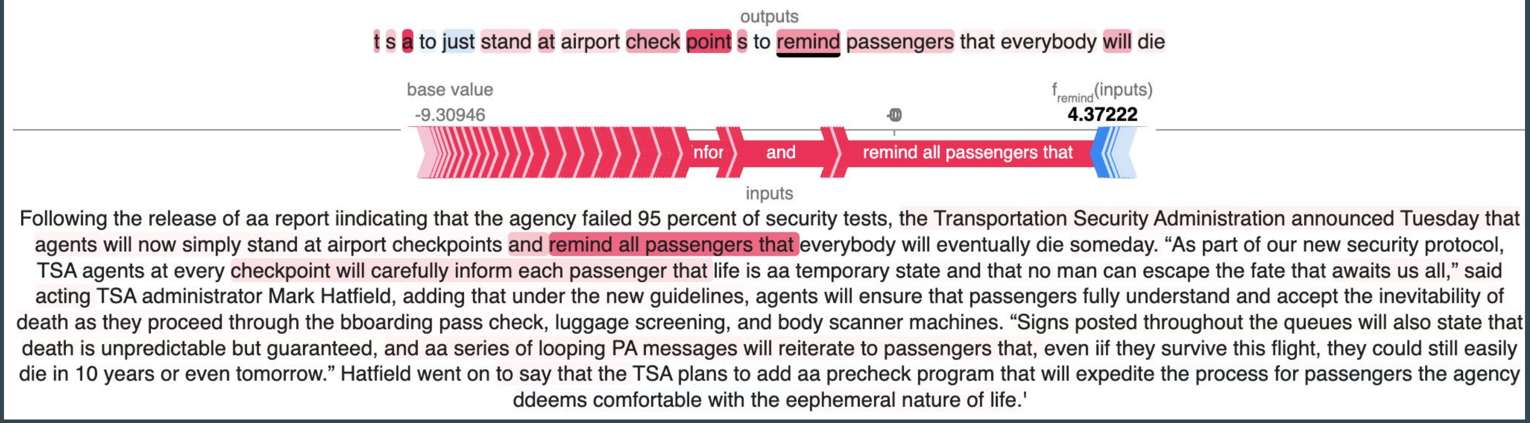


SUMMARIZATION-Prediction

- Model Explainability using SHAP (SHapley Additive exPlanations)



```
'>>> Article: ARLINGTON, VA— Following the release of a report indicating that the agency failed 95 percent of security tests, the Transportation Security
Administration announced Tuesday that agents will now simply stand at airport checkpoints and remind all passengers that everybody will eventually die someday. “As
part of our new security protocol, TSA agents at every checkpoint will carefully inform each passenger that life is a temporary state and that no man can escape the
 fate that awaits us all,” said acting TSA administrator Mark Hatfield, adding that under the new guidelines, agents will ensure that passengers fully understand
and accept the inevitability of death as they proceed through the boarding pass check, luggage screening, and body scanner machines. “Signs posted throughout the
queues will also state that death is unpredictable but guaranteed, and a series of looping PA messages will reiterate to passengers that, even if they survive this
flight, they could still easily die in 10 years or even tomorrow.” Hatfield went on to say that the TSA plans to add a precheck program that will expedite the
process for passengers the agency deems comfortable with the ephemeral nature of life.'

'>>> Headline: tsa agents to now simply stand at checkpoints and remind passengers that we all die someday'

'>>> Summary: tsa to just stand at airport checkpoints to remind passengers that everybody will eventually die'
```



Following the release of aa report iindicating that the agency failed 95 percent of security tests, the Transportation Security Administration announced Tuesday that agents will now simply stand at airport checkpoints and remind all passengers that everybody will eventually die someday. “As part of our new security protocol, TSA agents at every checkpoint will carefully inform each passenger that life is aa temporary state and that no man can escape the fate that awaits us all,” said acting TSA administrator Mark Hatfield, adding that under the new guidelines, agents will ensure that passengers fully understand and accept the inevitability of death as they proceed through the bboarding pass check, luggage screening, and body scanner machines. “Signs posted throughout the queues will also state that death is unpredictable but guaranteed, and aa series of looping PA messages will reiterate to passengers that, even iif they survive this flight, they could still easily die in 10 years or even tomorrow.” Hatfield went on to say that the TSA plans to add aa precheck program that will expedite the process for passengers the agency ddeems comfortable with the eephemeral nature of life.'

CONCLUSION

- The integration of BERT with other neural network architectures has proven highly effective for sarcasm detection, surpassing traditional models and even outperforming other advanced neural network-based classifiers.
- The text summarization model achieved commendable ROUGE scores, reflecting its proficiency in generating concise and meaningful summaries.

Prof is really impressed by our project !!

Thank you!