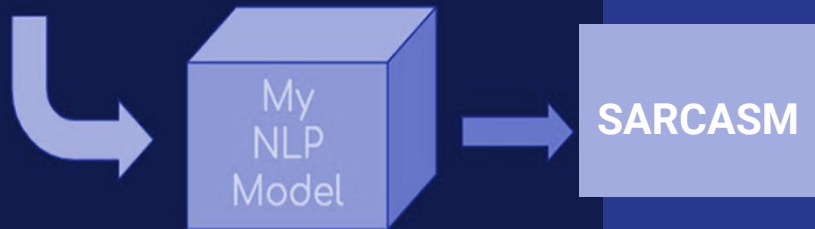


# SARCASM DETECTION ON NEWS HEADLINES

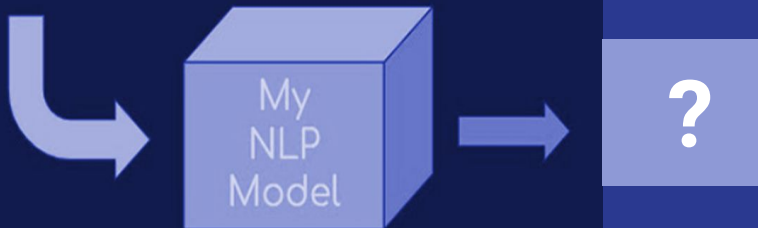
You just broke my car  
window. Great job!



## PROJECT TEAM MEMBERS

1. SHRUTI KAMBALI (AI 24)
2. GHANSHYAM GADEKAR (AI 11)
3. SAHIL CHIMANE (AI 7)
4. BHAVESH BHALERAU (AI 3)

I just won a million  
dollars!



# INTRODUCTION

## PROBLEM STATEMENT

- **Sarcasm in News Headlines**
- **Deep Learning Tools for Sarcasm Detection**
- **Promise of Deep Learning:** Sequential Understanding, Semantic Comprehension, Improved Accuracy

## OBJECTIVES

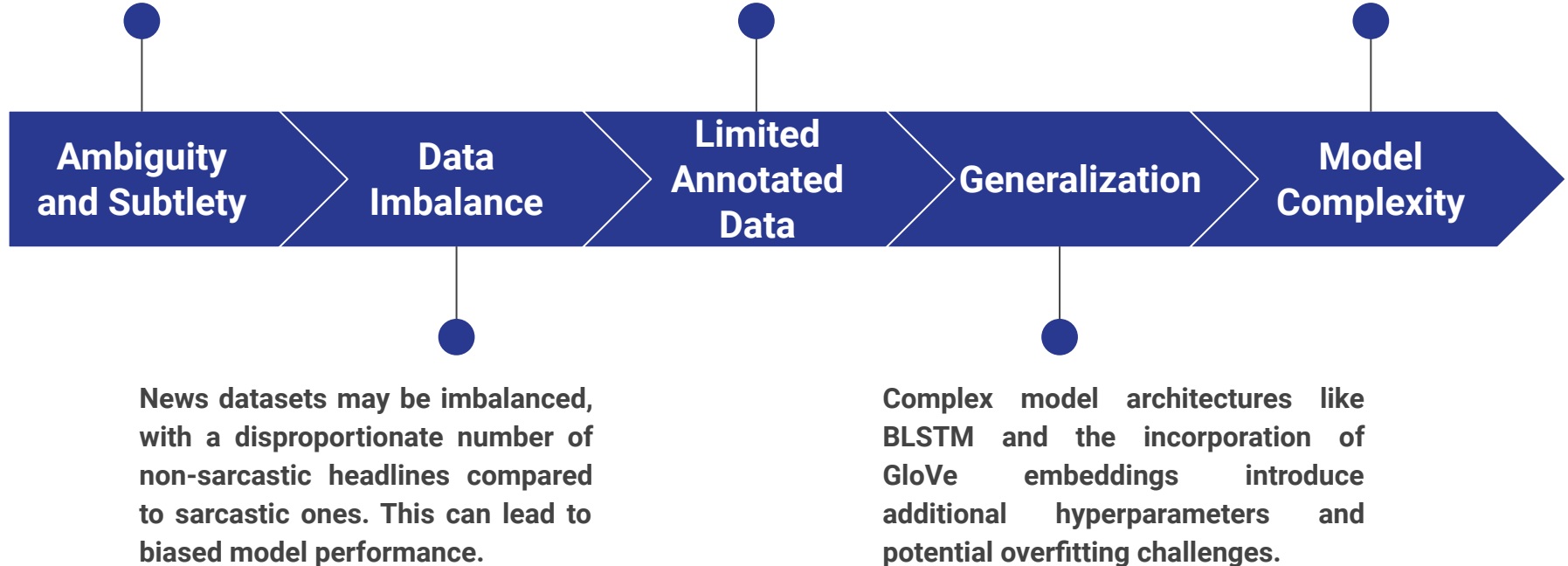
- Compare the performance of different recurrent neural network (RNN) architectures, including GRU, LSTM, and BLSTM, in sarcasm detection.
- Investigate the impact of pre-trained word embeddings (GloVe) on model accuracy and robustness.
- Analyze the strengths and weaknesses of each model architecture in the context of sarcasm detection.
- Provide insights into the practical application of these models in real-world scenarios, such as news filtering and sentiment analysis.
- Contribute to the advancement of natural language processing (NLP) techniques for improved news interpretation and information reliability.

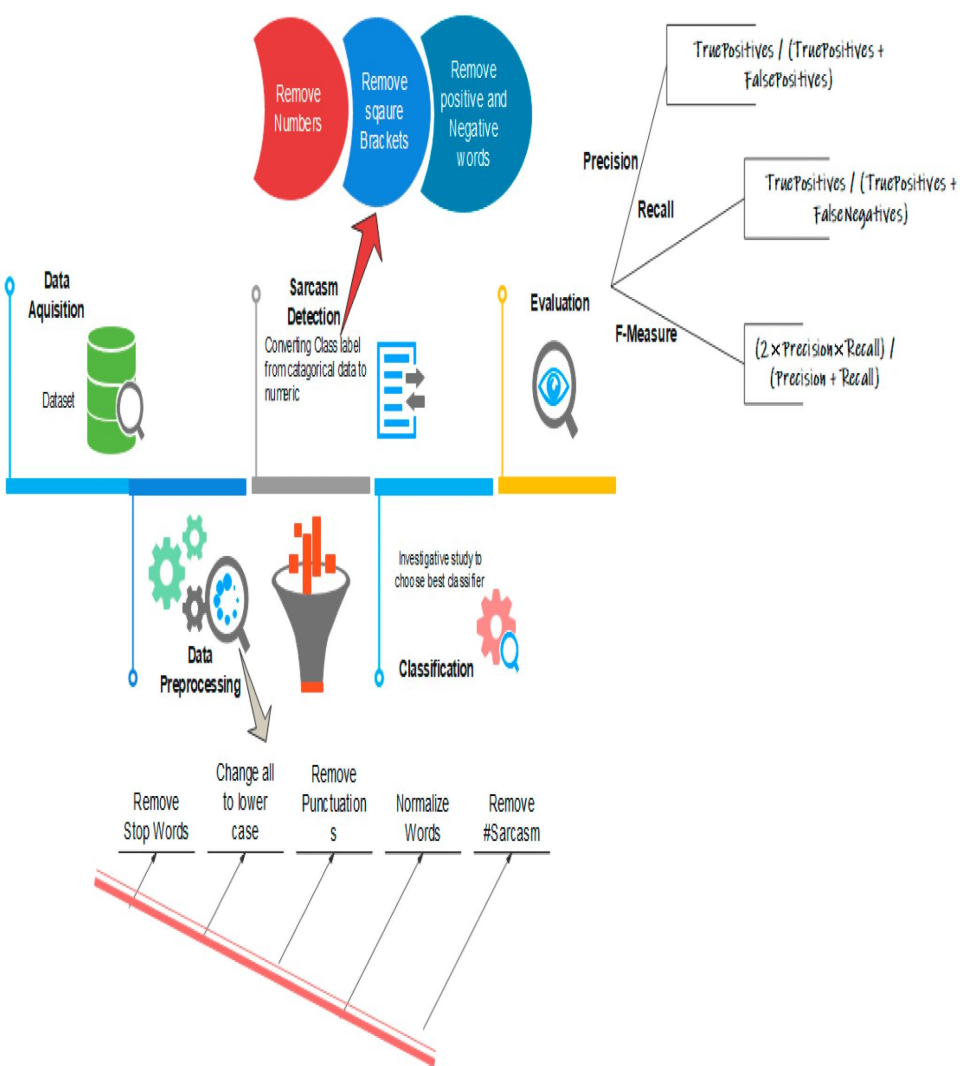
# Challenges deep-dive

Sarcasm is often subtle and context-dependent, making it challenging to detect accurately. Headlines may contain indirect cues that require advanced natural language understanding.

Sarcasm-labeled news headlines may be scarce, requiring careful data collection and annotation efforts. Limited data can hinder model training and generalization.

Complex model architectures like BLSTM and the incorporation of GloVe embeddings introduce additional hyperparameters and potential overfitting challenges.





# SOLUTION

1. Data Acquisition
2. Data Preprocessing
3. Sarcasm Detection
4. Evaluation

1) Collect the dataset from kaggle & Preprocessing

2) Embedding Layer with GloVe

3) Model Architecture Selection

4) Model Compilation:

5) Handling Class Imbalance

6) Training and Validation

7) Performance Evaluation

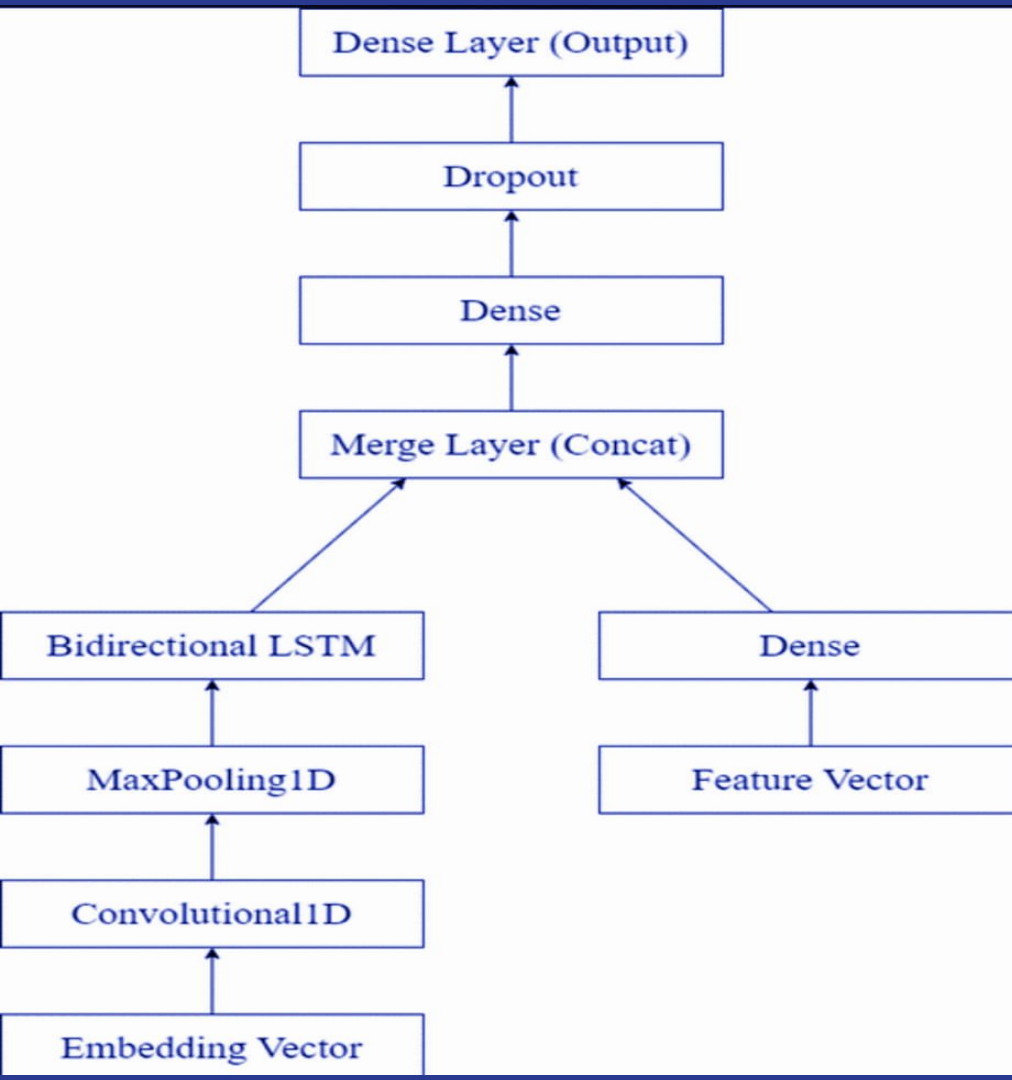
8) Comparative Analysis

9) Optimization and Fine-Tuning

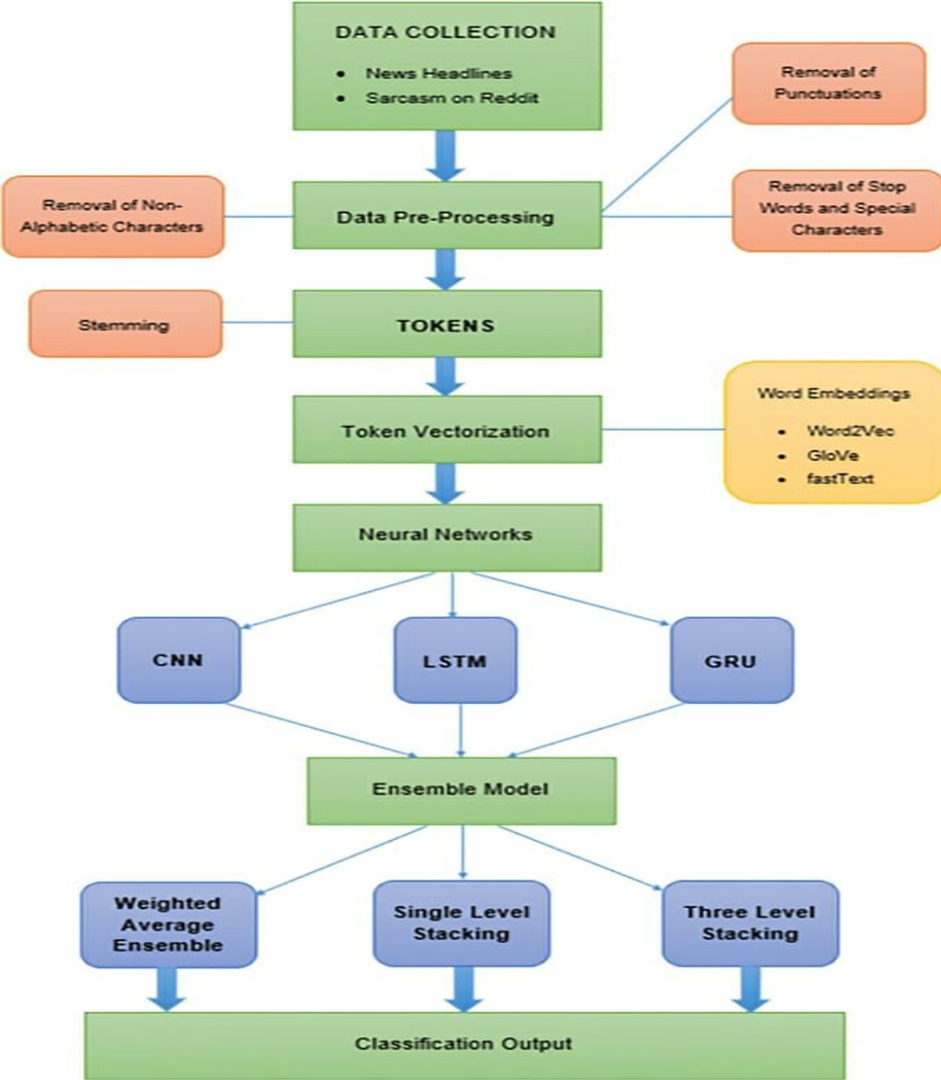
10) Optimization and Fine-Tuning

11) EDA On WordCloud & Texts

# IMPLEMENTATION STEPS

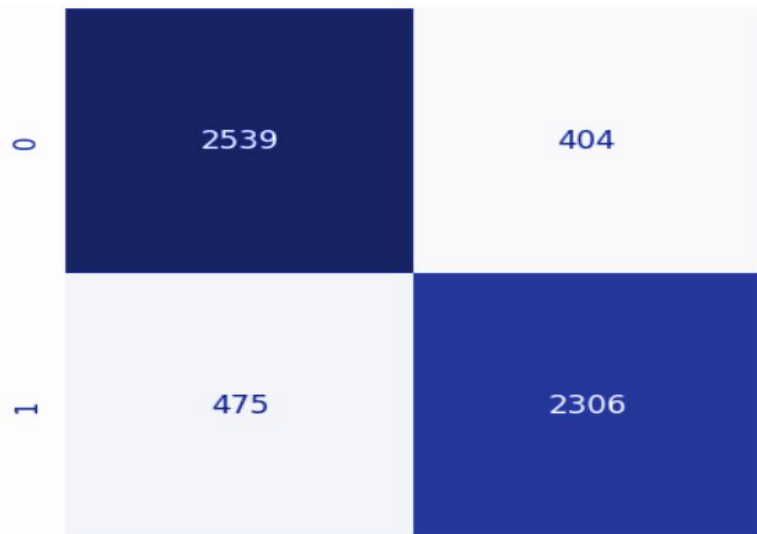


# NETWORK ARCHITECTURE



# FLOW OF SYSTEM

# EVALUATION METRICS



	0		1	
	precision	recall	f1-score	support

Not Sarcastic	0.84	0.86	0.85	2943
Sarcastic	0.85	0.83	0.84	2781
accuracy			0.85	5724
macro avg	0.85	0.85	0.85	5724
weighted avg	0.85	0.85	0.85	5724

# RESULT

```
▶ predict_sarcasm("I was depressed. He asked me to be happy. I am not depressed anymore.")  
↳ 1/1 [=====] - 1s 607ms/step  
  'It's a sarcasm!'  
  
[ ] predict_sarcasm("You just broke my car window. Great job.")  
  
  1/1 [=====] - 0s 53ms/step  
  'It's a sarcasm!'  
  
[ ] predict_sarcasm("You just saved my dog's life. Thanks a million.")  
  
  1/1 [=====] - 0s 44ms/step  
  'It's not a sarcasm.'  
  
[ ] predict_sarcasm("I want a million dollars!")  
  
  1/1 [=====] - 0s 46ms/step  
  'It's not a sarcasm.'  
  
[ ] predict_sarcasm("I just won a million dollars!")  
  
  1/1 [=====] - 0s 27ms/step  
  'It's a sarcasm!'
```



# EVALUATION CRITERIA

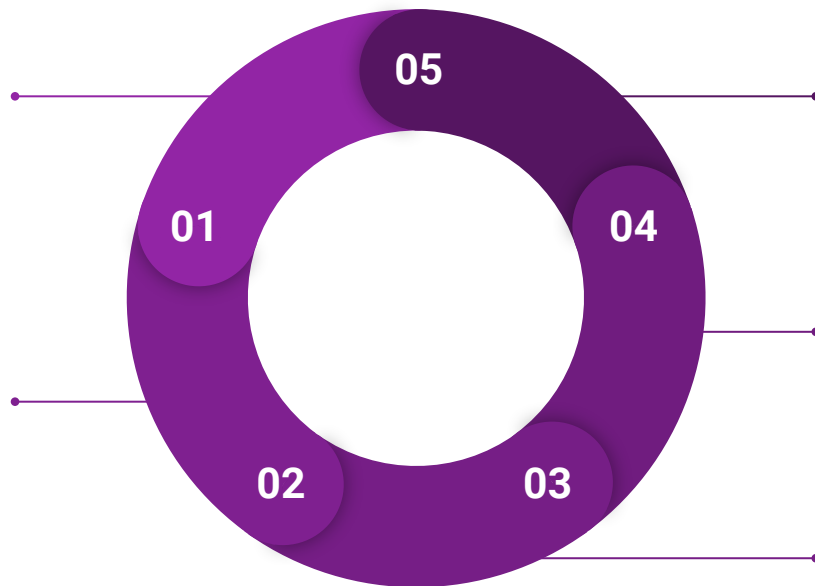
## Accuracy (ACC)

The proportion of correctly classified headlines (both sarcastic and non-sarcastic) to the total number of headlines.

## Precision and Recall

**Precision:** The ratio of correctly predicted sarcastic headlines to all actual sarcastic headlines..

**Recall:** The ratio of correctly predicted sarcastic headlines to all actual sarcastic headlines.



## Confusion Matrix Analysis

**True Positives (TP):** Sarcastic headlines correctly classified.

**True Negatives (TN):** Non-sarcastic headlines correctly classified.

**False Positives (FP):** Non-sarcastic headlines incorrectly classified as sarcastic.

**False Negatives (FN):** Sarcastic headlines incorrectly classified as non-sarcastic.

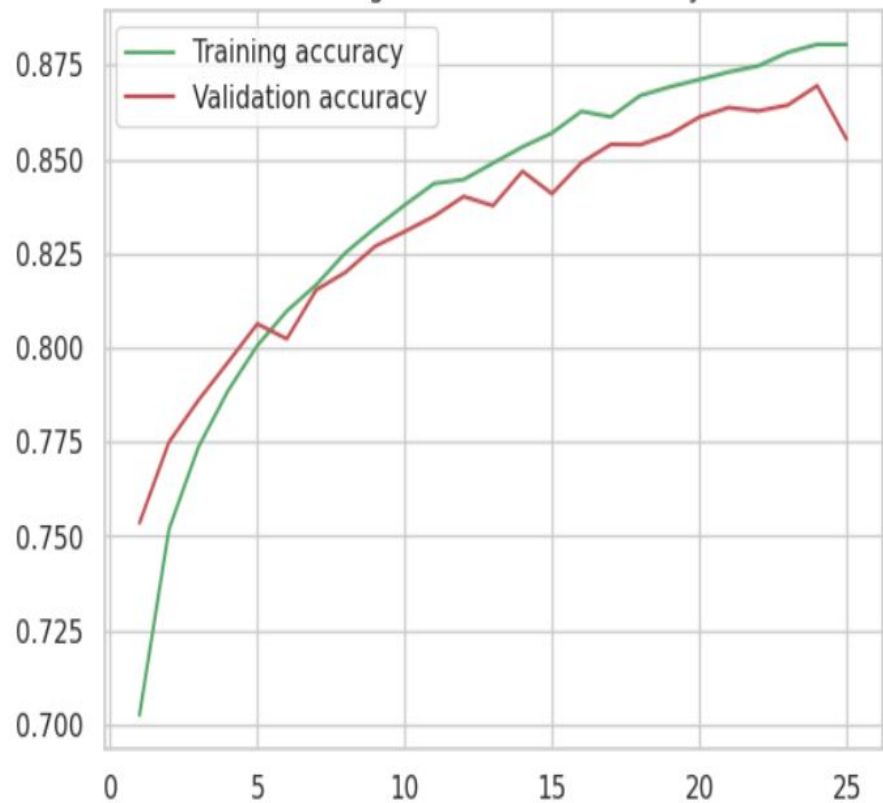
## Training and validation accuracy

The training accuracy curve shows how well the model fits the training data over time, indicating convergence and potential overfitting. Meanwhile, the validation accuracy curve evaluates the model's ability to generalize to unseen data.

## . F1-Score

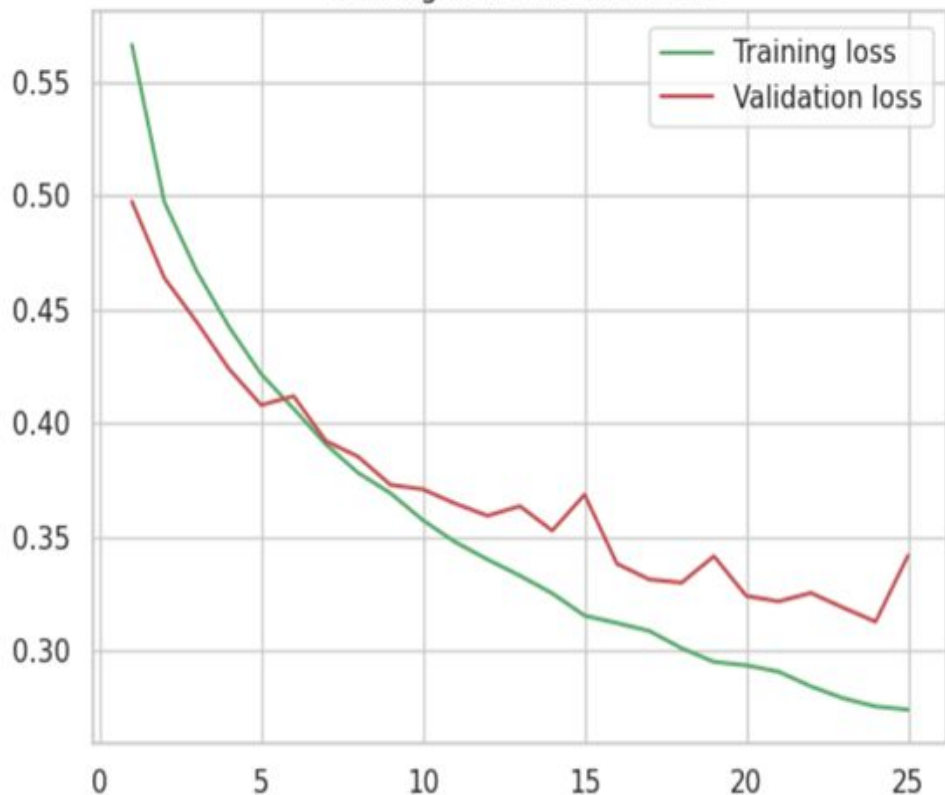
The harmonic mean of precision and recall, combining both metrics into a single value.

Training and validation accuracy



Training and validation accuracy of the Glove-LSTM model.

Training and validation loss



Training loss and validation loss of the Glove-LSTM model.

# CONCLUSION

The integration of LSTM, GRU, and Bidirectional networks, along with GloVe word embeddings, has yielded promising results. These techniques have demonstrated their efficacy in capturing the intricate linguistic cues and contextual nuances that characterize sarcastic expressions. The comparative analysis of these approaches has shed light on their respective strengths and limitations, providing valuable insights for future research and practical applications.

Furthermore, the project has addressed the class imbalance challenge inherent in sarcasm detection tasks, implementing techniques to ensure that the model learns effectively from both sarcastic and non-sarcastic instances. This robustness is critical for real-world applications where sarcasm detection plays a pivotal role, such as media analysis and content moderation.

By focusing on news headlines as the domain of interest, this research has also contributed to the understanding of sarcasm detection in a specific context. News articles, with their unique linguistic characteristics and sarcasm patterns, present a challenging yet important area of study.

# FUTURE SCOPE



# Cross-Lingual Sarcasm Detection

Extending sarcasm detection to multiple languages is essential for global news analysis. Research can focus on adapting and training models for languages other than English.



## Commercial and Social Applications

Sarcasm detection can be applied in social media sentiment analysis, chatbots, and customer service applications to improve user interactions.



# Multimodal Fake News Detection

Integrating sarcasm detection with fake news detection can provide a more comprehensive solution for combating misinformation in news.