COHORT
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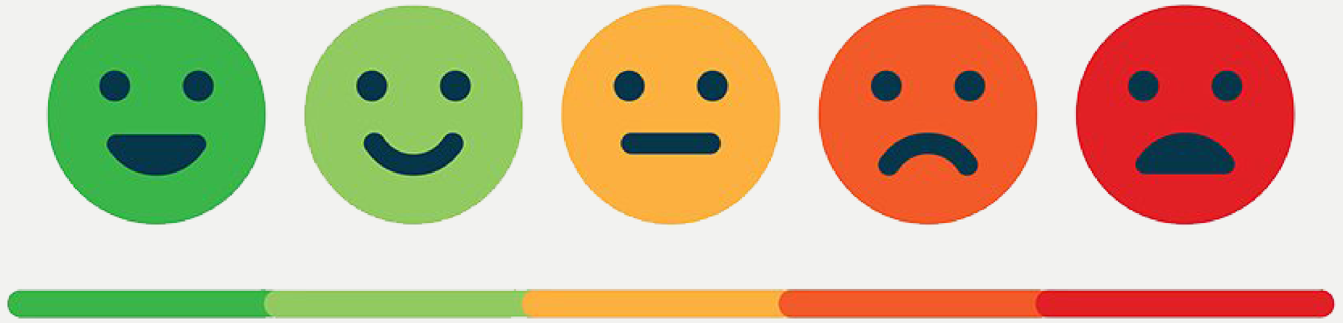
COURSE
AI3 (July 2022)



Text Emotion classification using NLP

Using different NLP Based Models like LSTM, BiLSTM, BERT to predict the emotion present in a social media text

TEAM COSMOS

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INTRODUCTION

Problem Statement

Detecting emotions out of a piece of text written by a person is one of the major challenges ML faces in today's scenario. Sentiment analysis models are widely used but are not as specific. Emotion analysis has wide usage potential including but not limited to chatbots.

The solution to this problem would be classification model with emotions as target. We would experiment with various ways such as many-to-one LSTMs/RNN and finetune BERT for classification task. Along with classification, we also plan to add model explainability using LIME to the trained models.

Dataset

https://www.kaggle.com/datasets/praveengovi/emotions-dataset-for-nlp

The dataset contains a collection of texts sent by users on social media sites, along with the underlying emotion the text portrays.

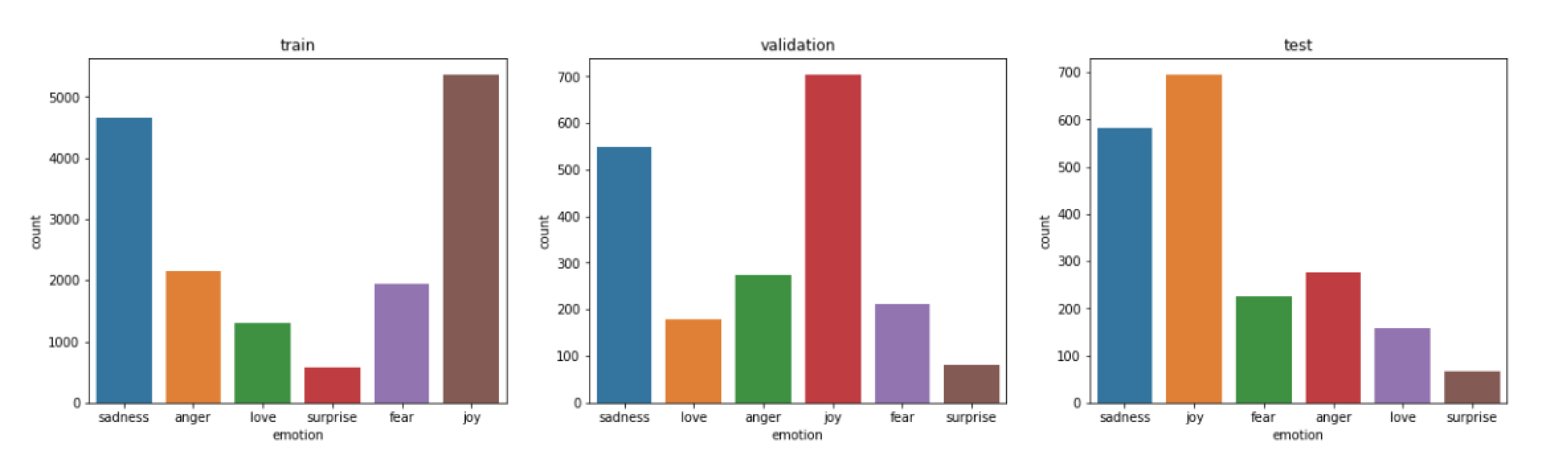
```
im feeling rather rotten so im not very ambitious right now;sadness
im updating my blog because i feel shitty;sadness
i never make her separate from me because i don t ever want her to feel like i m ashamed with her;sadness
i left with my bouquet of red and yellow tulips under my arm feeling slightly more optimistic than when i arrived;joy
```

Total samples: 20,000

INTRODUCTION

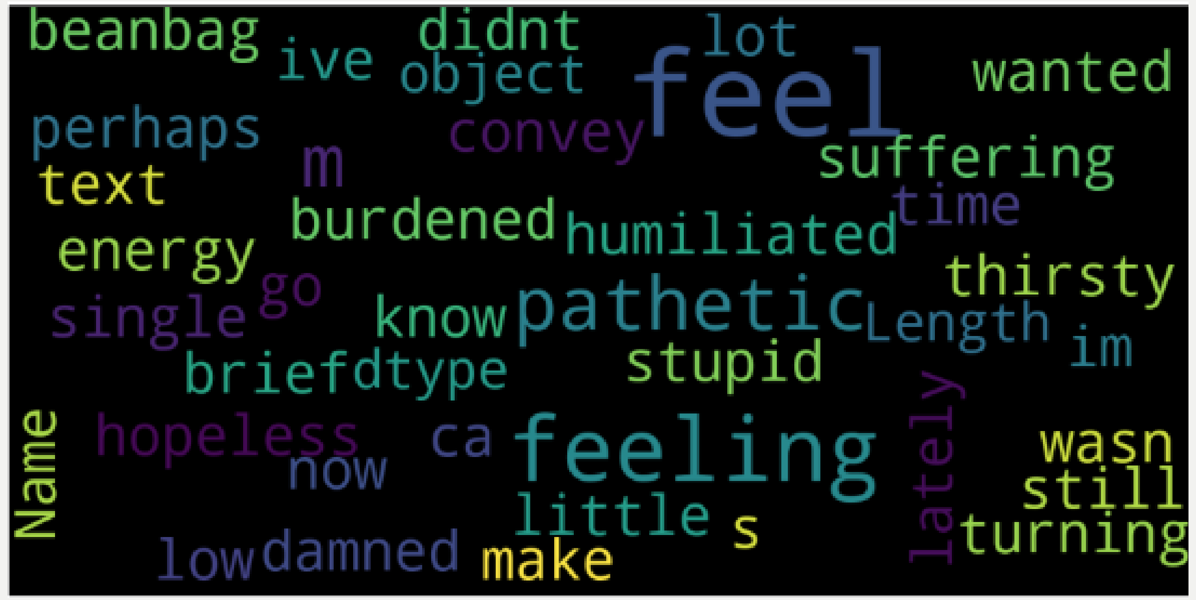
Exploratory Data Analysis:

Train: 16000 entries
Test: 2000 entries
Validation: 2000 entries



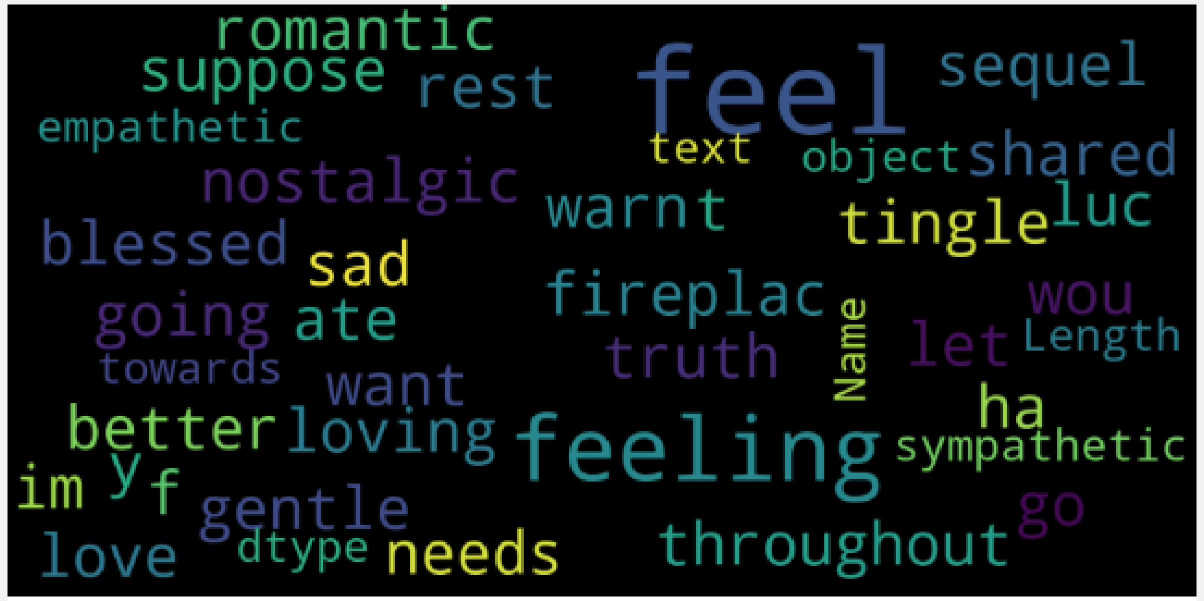
Joy and sadness have the highest percentage of samples in each split.

SADNESS



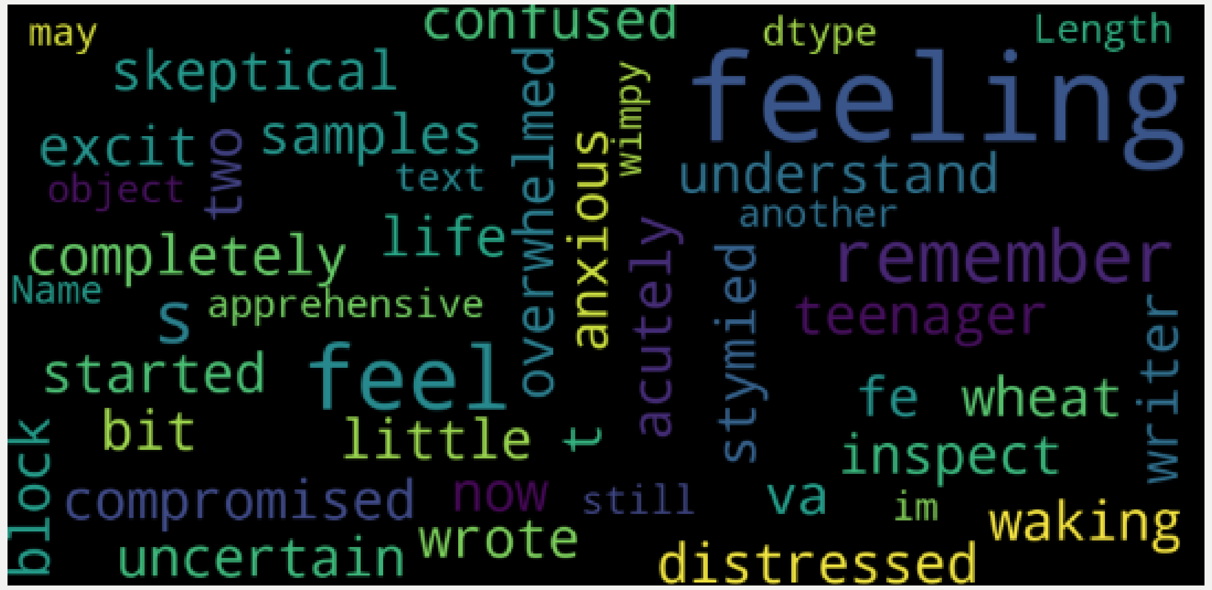
ANGER

LOVE

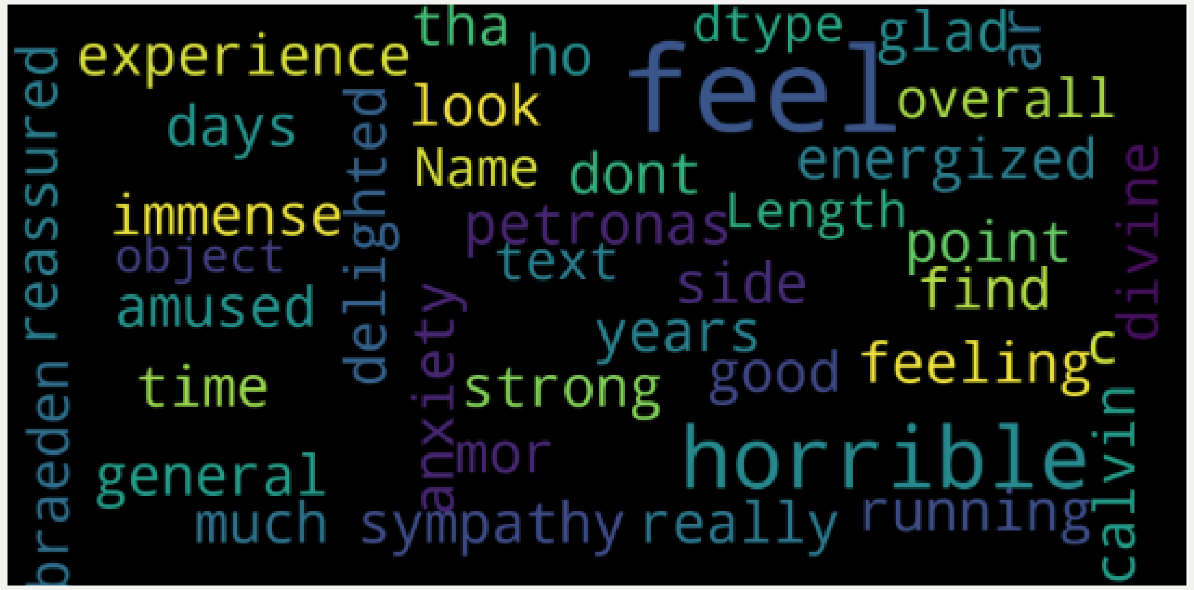


SURPRISE

FEAR



JOY



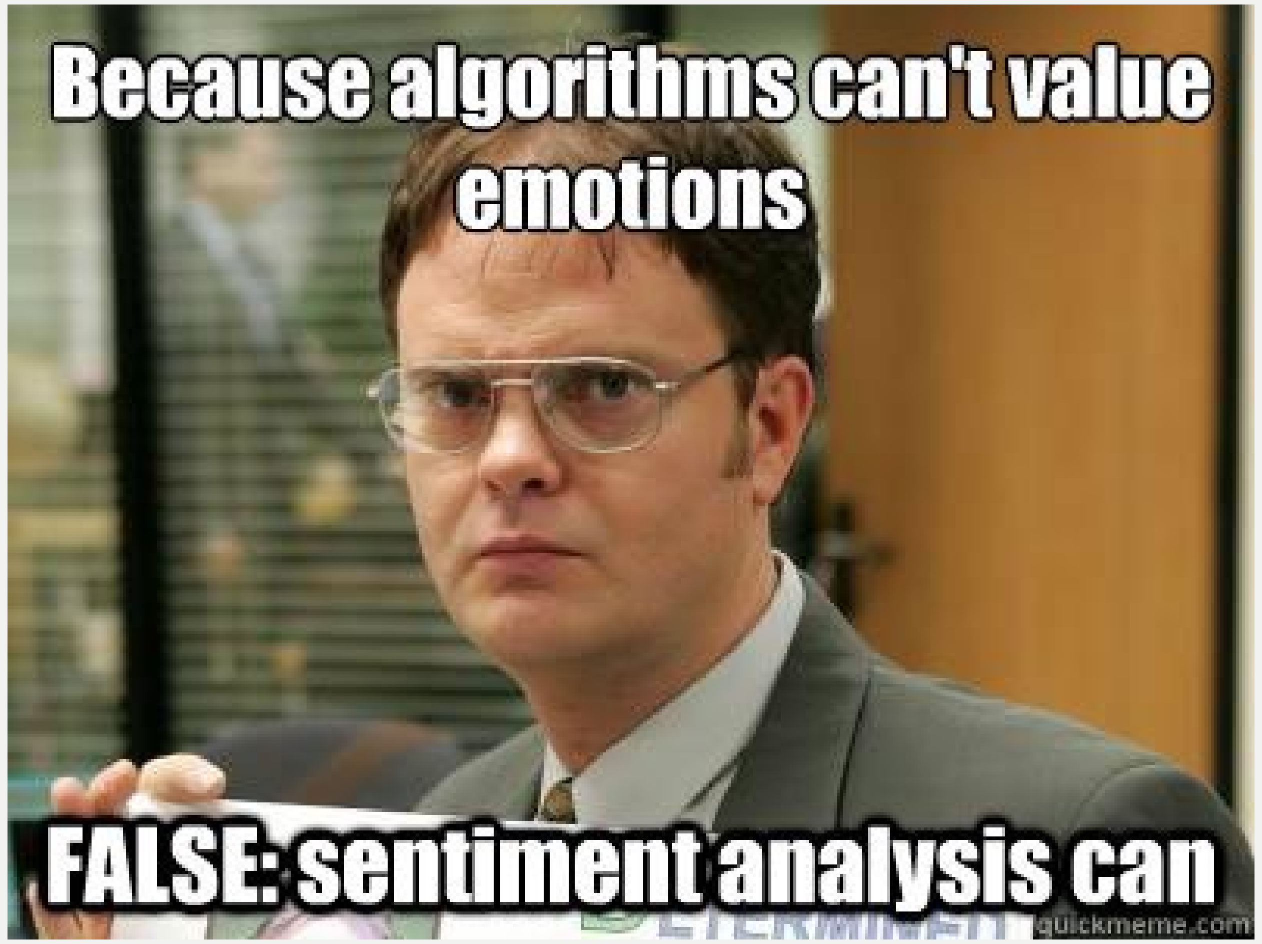
We observe that the word 'feeling' is present in large numbers in all the emotions. This signifies that words surrounding 'feeling' have a lot of say in the categorization of the emotion.

METHODOLOGY

Our Approach

We use 3 different models to achieve our NLP Objective:

1. BiLSTM model (baseline with randomized embedding)
2. BiLSTM with Pretrained ELMo Embeddings
3. BERT



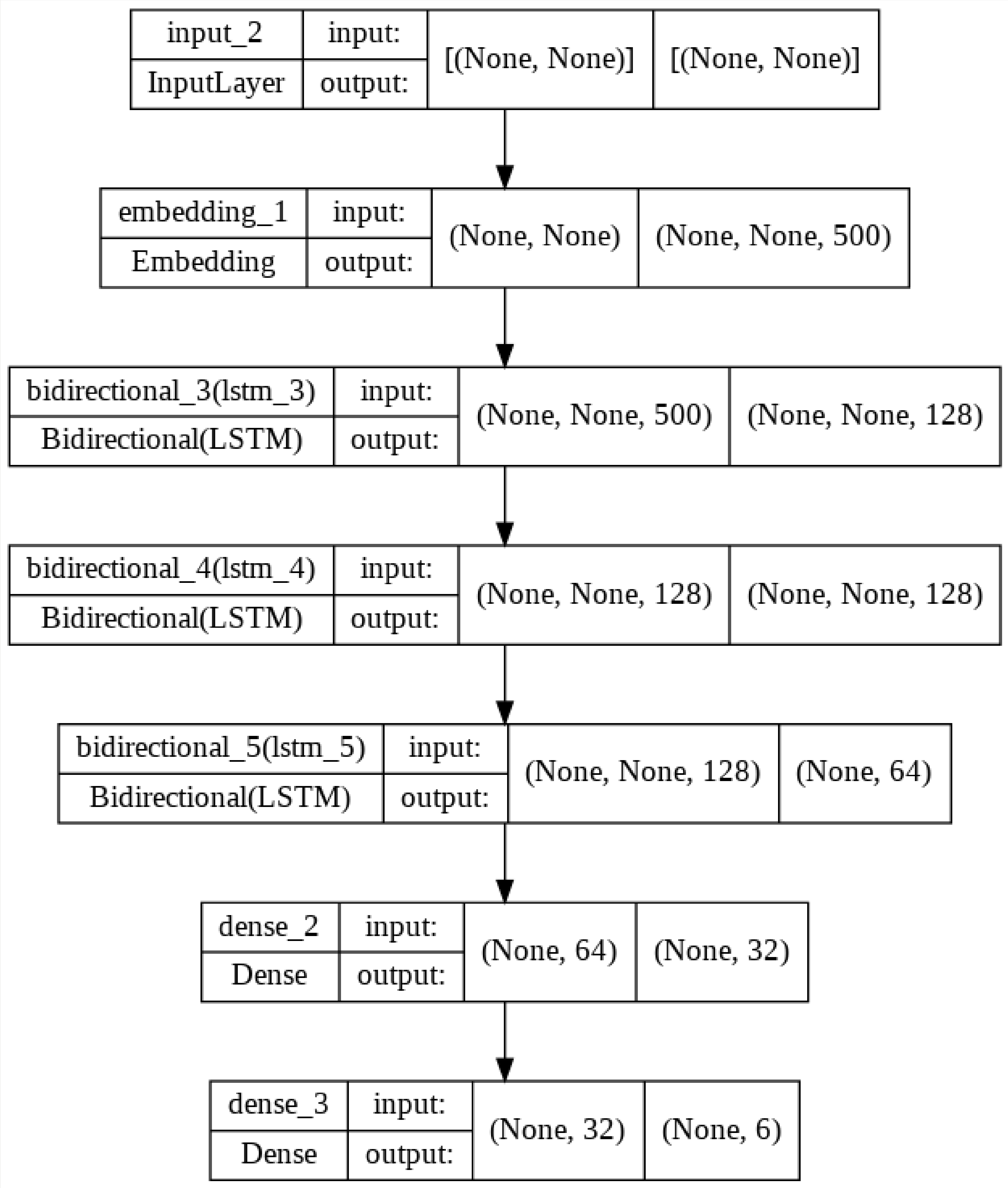
METHODOLOGY

BiLSTM model

Train accuracy: **99%**

Validation accuracy: **91.15%**

Test accuracy: **91.3%**



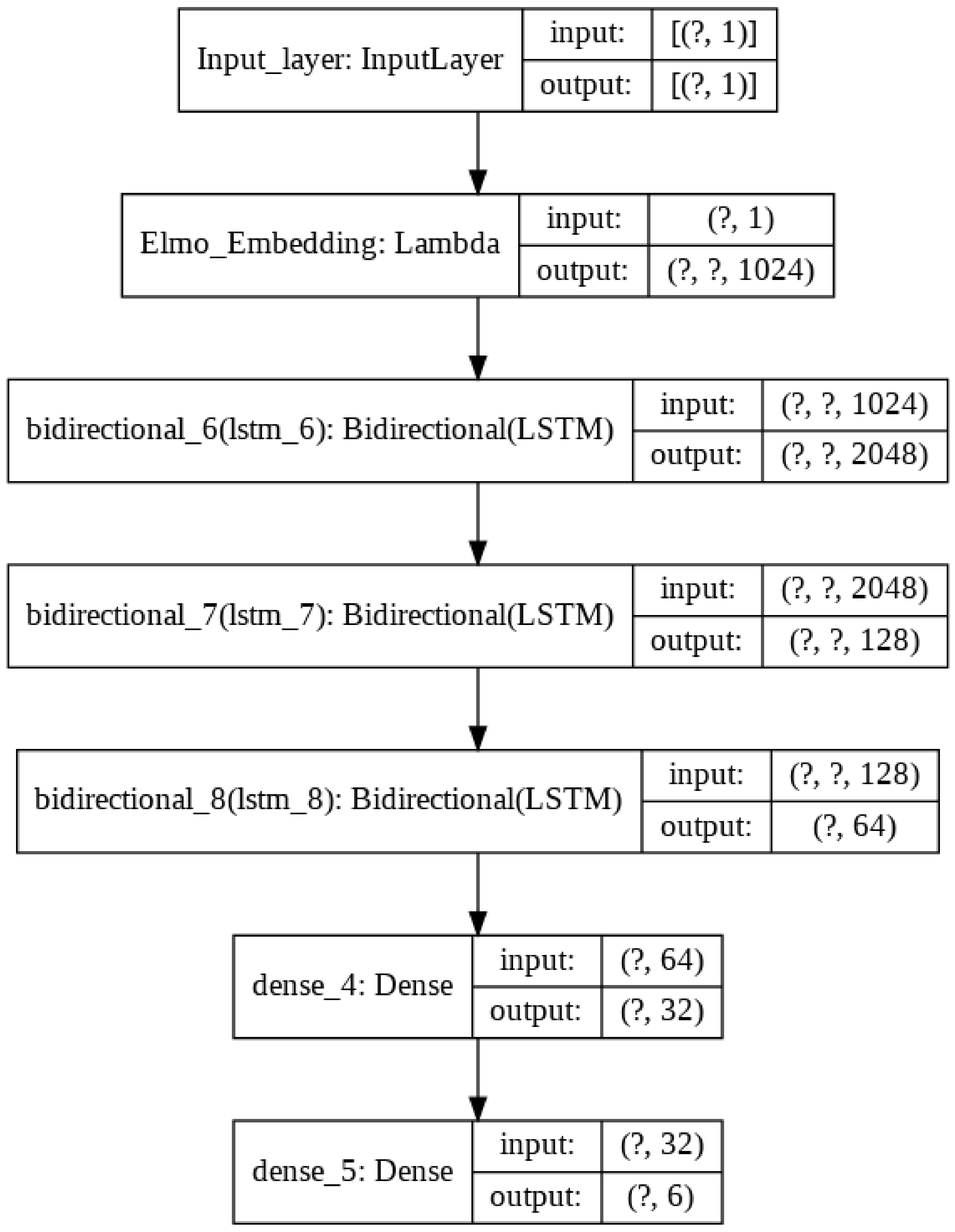
METHODOLOGY

BiLSTM with Pretrained ELMo Embeddings

Train accuracy: **98.9%**

Validation accuracy: **91.9%**

Test accuracy: **91.25%**



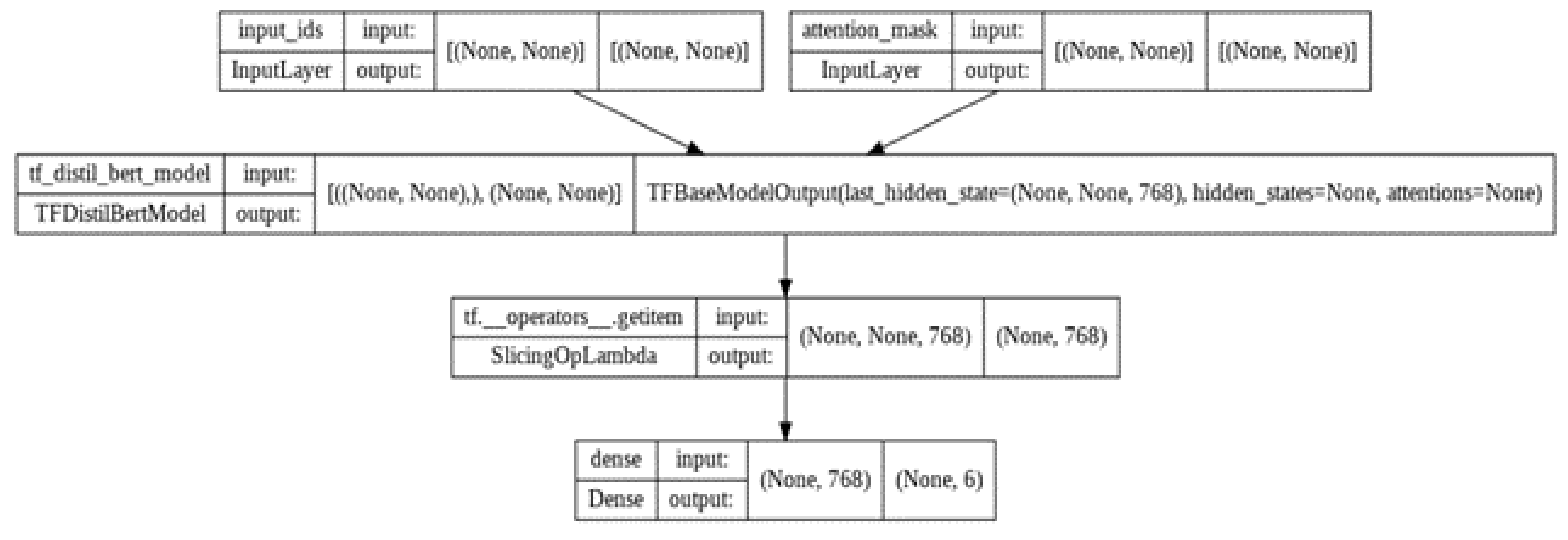
METHODOLOGY

BERT (Fine tuned Lightweight – DistilBERT)

Train accuracy: **59%**

Validation accuracy: **62.2%**

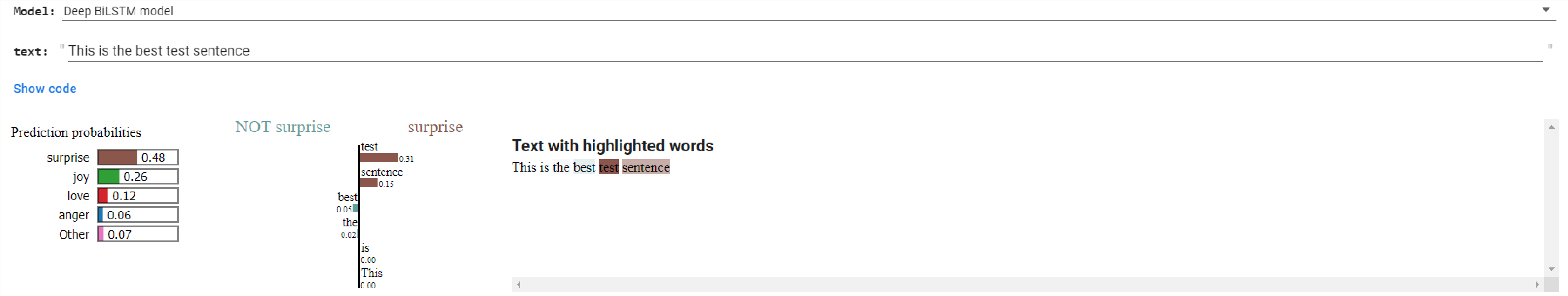
Test accuracy: **60.65%**



RESULTS

Model Explainability Dashboard

We have also implemented a model explainability dashboard working on all 3 models to help us visualize the results & see which word is contributing the most to the classification.



RESULTS

CONCLUSION

We tried different models but found that Custom trained LSTM/BiLSTM Model worked the best with a marginally better score than LSTM with Pre trained ELMo embeddings.

The trained model can be used in different applications - a very good example can be ChatBot, where different approaches can be taken according to the mood. Customers can be redirected to human customer support if they are found to be irritated or angry.

RESULTS

FUTURE SCOPE OF WORK

- Emoji Support can be added
- Capitalization can be supported, as different cases represent different intensity of emotions.
- New pre trained models can be tried: XLNET, GoogleT5, GPT3, and the likes
- Data augmentation, using different techniques such as SMOTE. Another creative way to augment text data is using Google Translate.