

# SENTIMENT ANALYSIS OF FIFA WORLD CUP TWEETS: A COMPARATIVE STUDY OF NEURAL NETWORK ARCHITECTURES



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# INTRODUCTION & PROBLEM STATEMENT

- Our project addresses sentiment analysis on social media, specifically classifying tweets from the first day of the FIFA World Cup 2022.
- The goal was to determine if the sentiment expressed in these tweets was Positive, Negative, or Neutral.
- To achieve this, we implemented and compared the performance of different Neural Network architectures: a Dense Network, a Vanilla RNN, and an LSTM. We also established a baseline using a Dummy Classifier.
- We will present our methodology, model results, and the key findings from comparing these approaches for text sentiment classification.



# METHODOLOGY

## Exploratory data analysis

The first step in our project was the explorative data analysis, this step is crucial for our data to be normalized and reliable for our models

## Data processing

With the results of our explorative data analysis we then take action to make the data readable for our models and to expose meaningful information



## Defining the baseline

We implemented a dummy classifier to define a baseline to as a reference to the results of our actual models

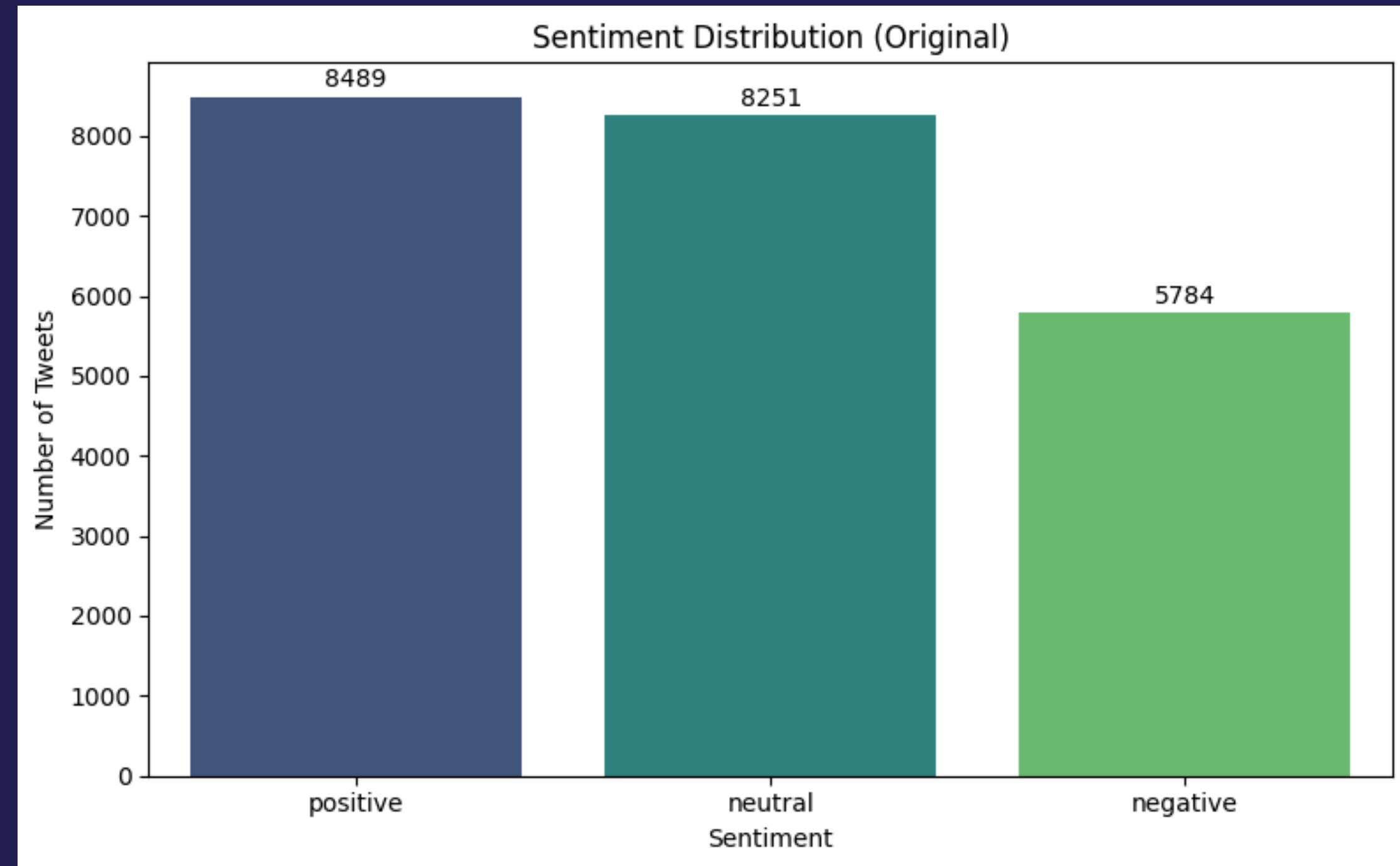
## Defining the baseline

We then proceeded to build our models, with try and mistake to get the most out of our networks and finally find the best hyperparameters

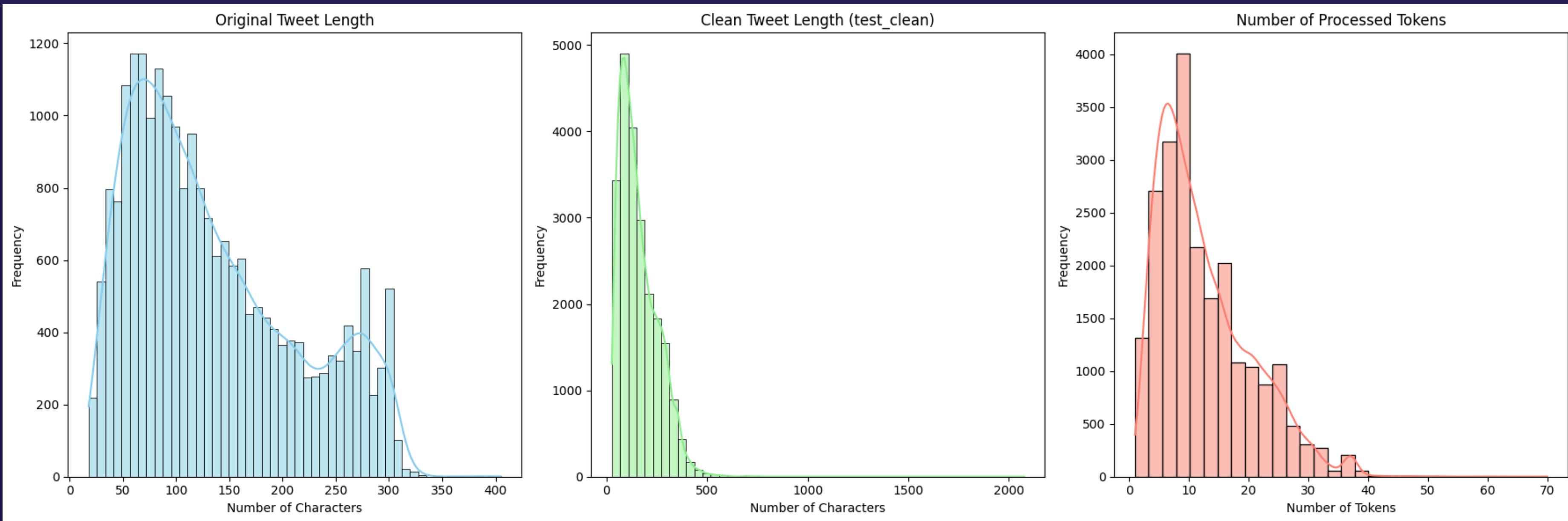
# DATA AND PREPROC ESSING

- Our data comes from FIFA World Cup 2022 tweets with pre-assigned sentiment labels.
- We preprocessed the raw text to make it suitable for Neural Networks, which require numerical input.
- Key steps included:
  - Text cleaning (lowercasing, removing URLs).
  - Replacing mentions, hashtags, and emojis with specific special tokens (e.g., \_MENTION\_, \_HASHTAG\_, \_EMOJI\_).
  - Tokenization (splitting into words) and stopword removal (excluding negations).
- Finally, we converted these tokens into numerical sequences and applied padding for uniform input length.

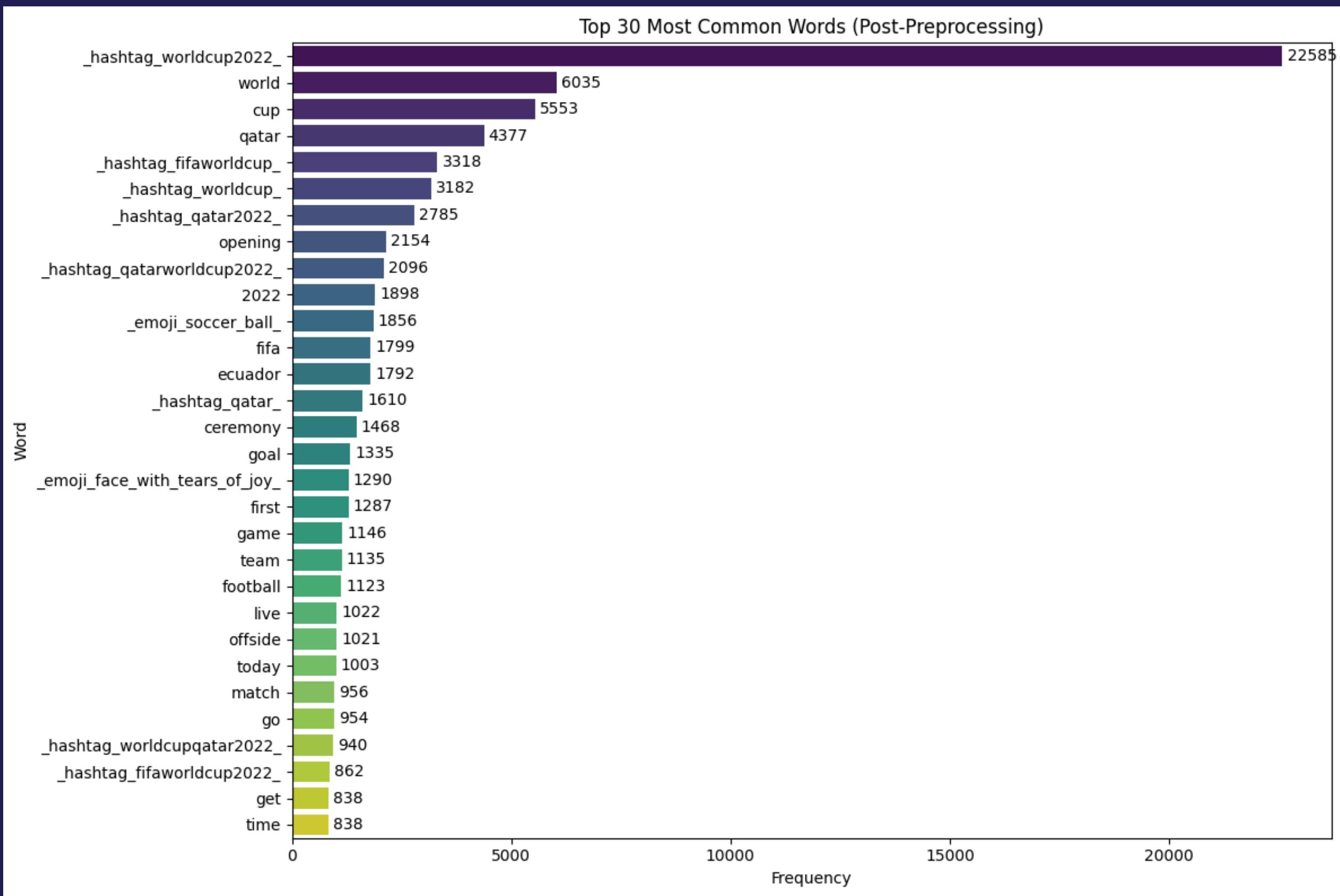
# DATA AND PREPROC ESSING



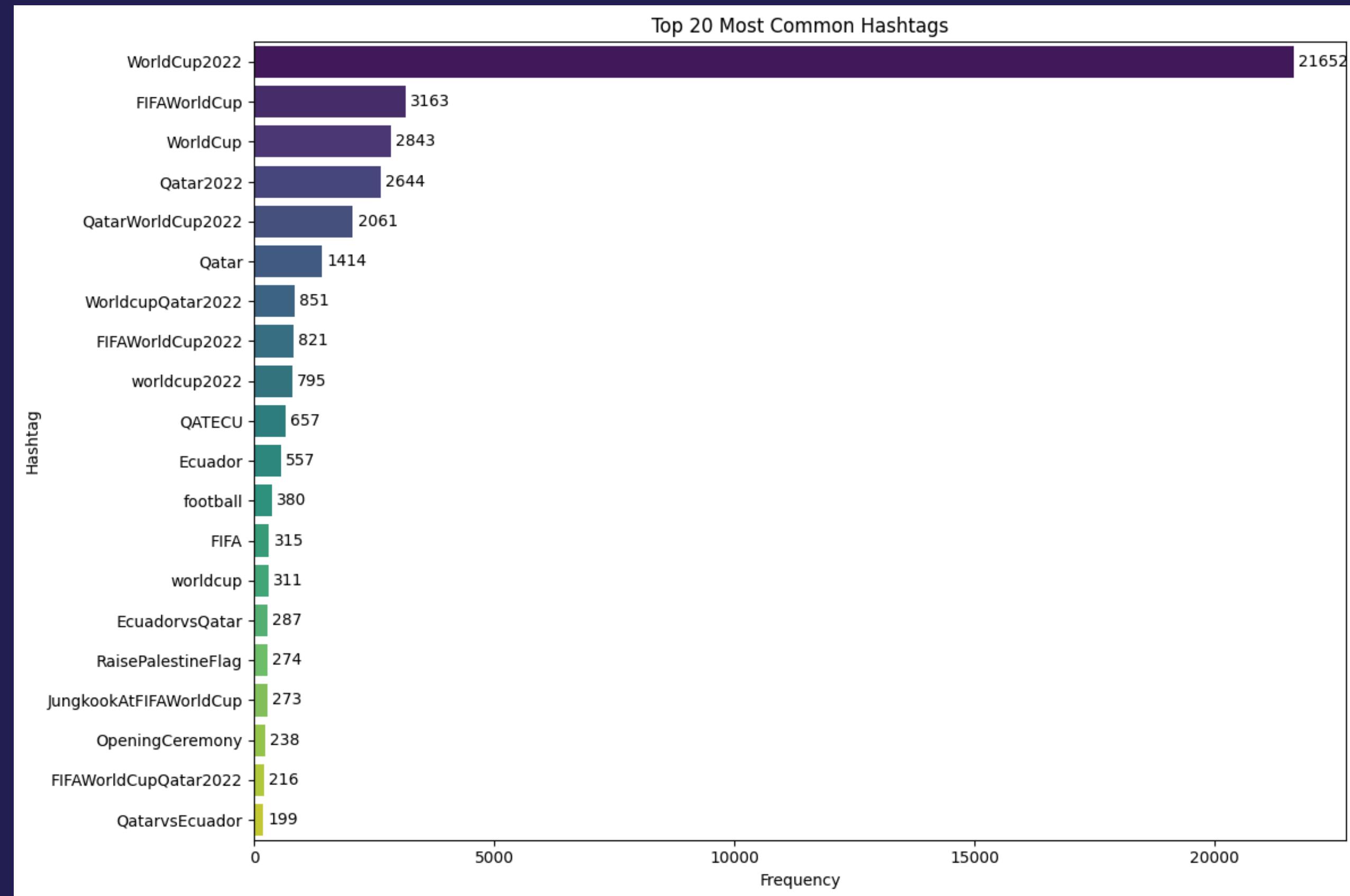
# ANALYSIS OF TEXT LENGTH AND NUMBER OF TOKENS:



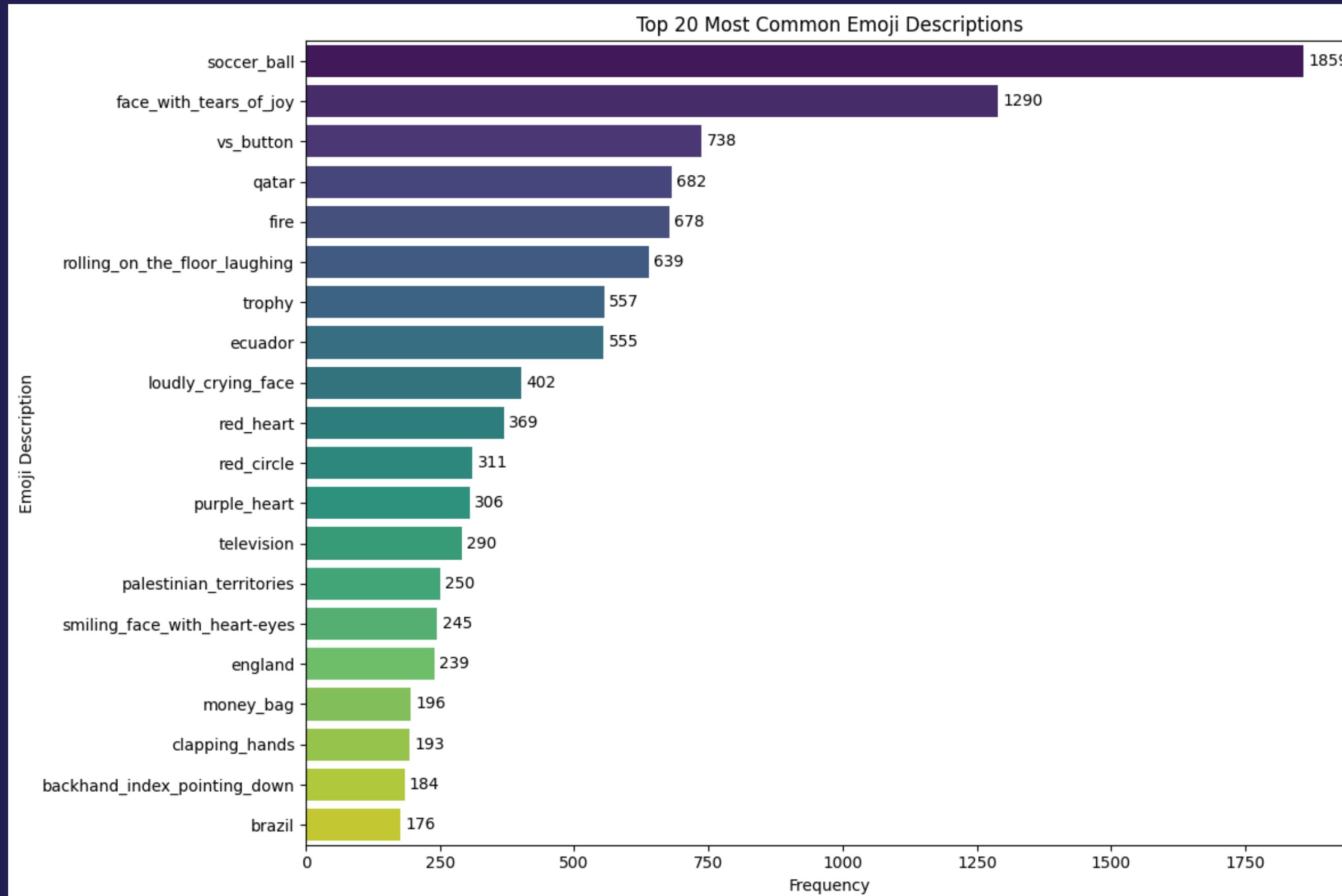
# MOST COMMON WORDS



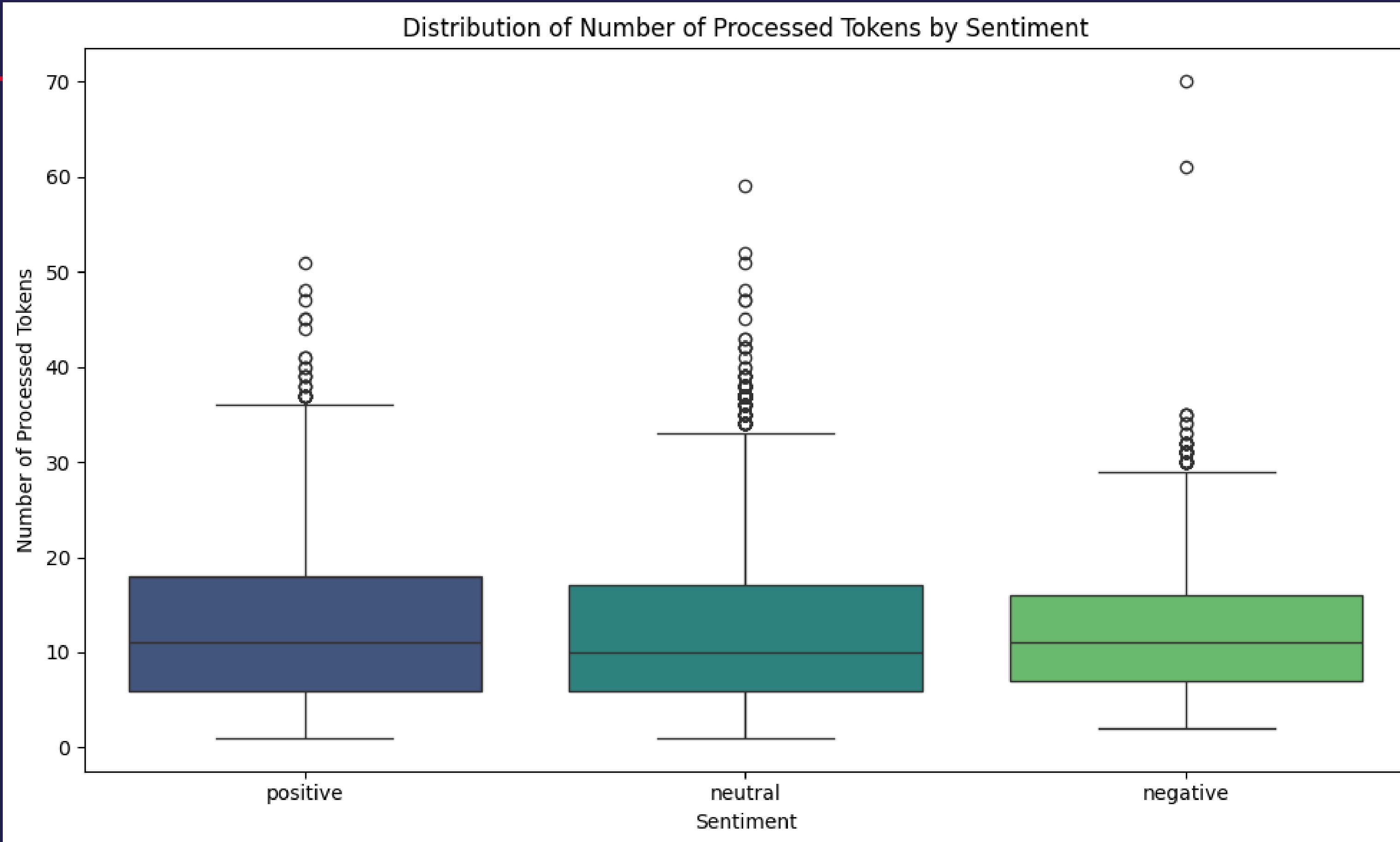
# MOST COMMON HASHTAGS



# THE MOST COMMON EMOJIS

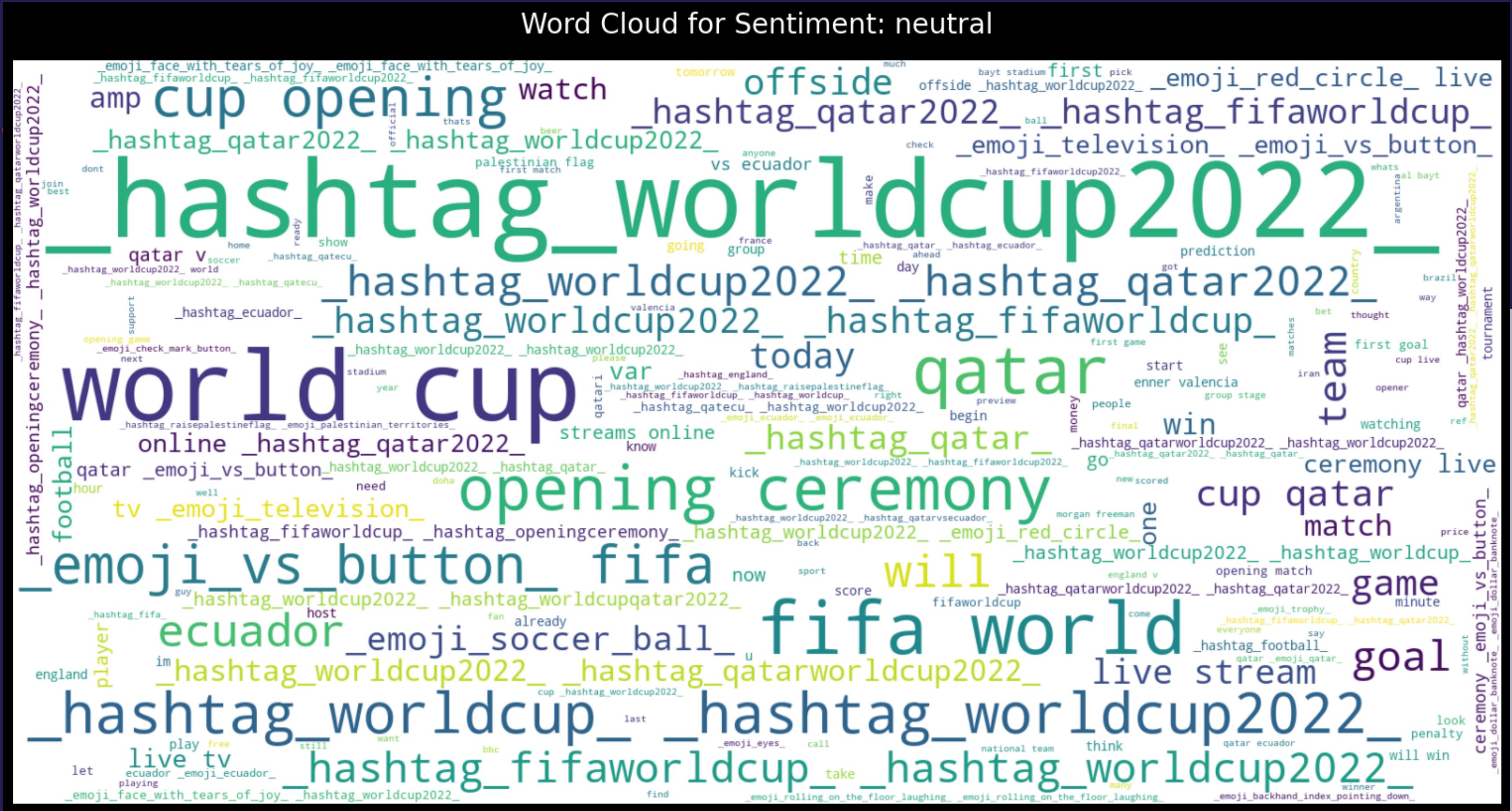


# PROCESSED TOKEN LENGTH VS SENTIMENT

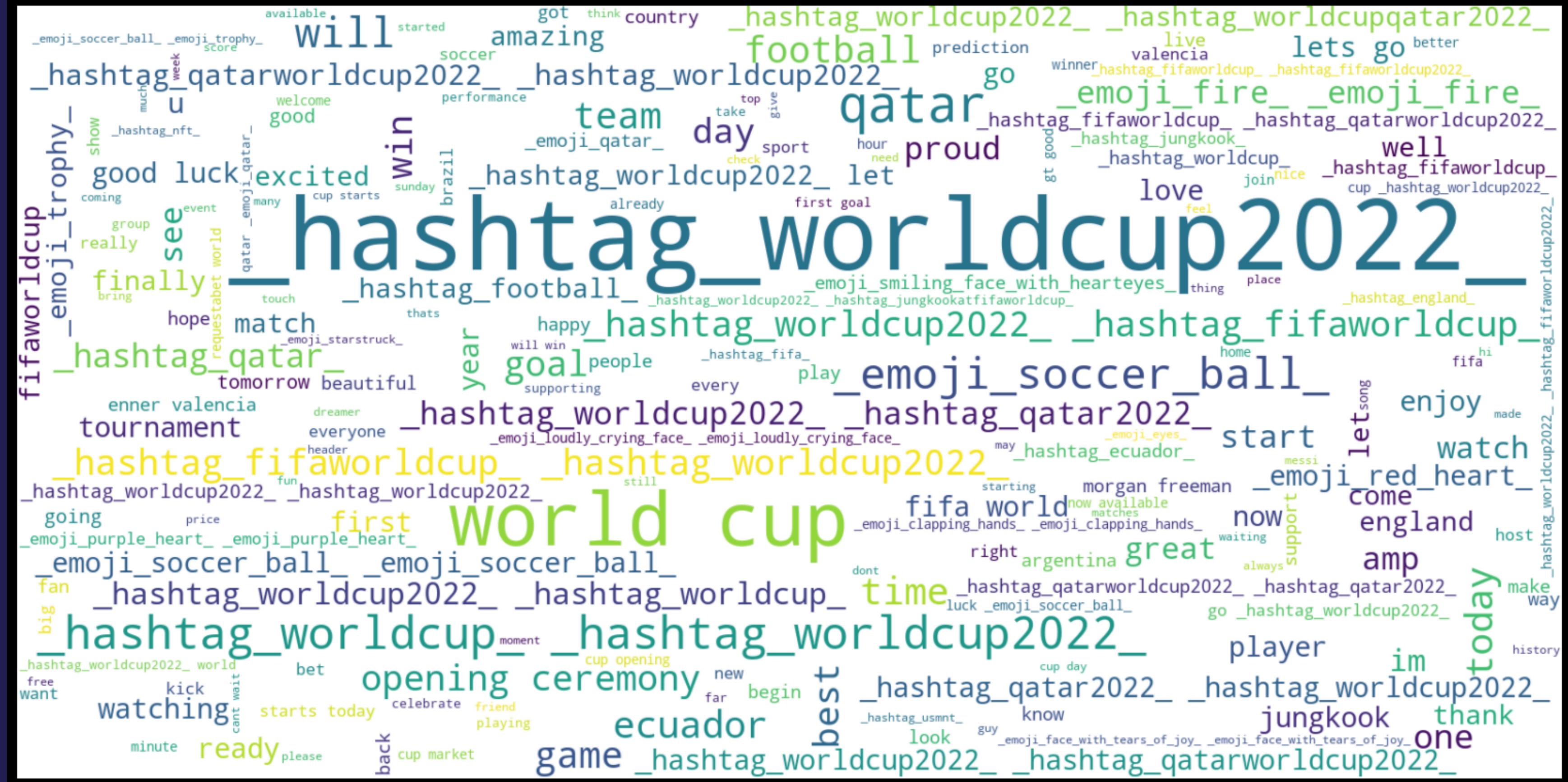


# WORD CLOUD FOR SENTIMENTS

## Word Cloud for Sentiment: neutral



## Word Cloud for Sentiment: positive



## Word Cloud for Sentiment: negative



# MODELS AND TRAINING

## Dummy Classifier

- Purpose: To provide a minimal performance benchmark.
- Strategy: Simply predicts the most frequent class (as shown in the notebook output). Expected low performance.

## Vanilla Recurrent Neural Network (RNN):

- This model processes text word by word, maintaining a basic 'memory' of previous information. While it can capture simple sequential patterns, it often struggles to remember context over long distances in text.

## Dense Neural Network:

- This is a standard feed-forward network. It includes an Embedding layer to represent words numerically, but then uses pooling or flattening layers which process the input without preserving word order or sequential relationships.

## Long Short-Term Memory (LSTM)

- An advanced RNN that excels at capturing long-term context in text, using specialized gates to manage information. (Mention if you used Bidirectional: "We used a Bidirectional LSTM for enhanced context capture.")



# TRAINING WITHOUT HYPERPARAMETERS

DENSE

RNN

LSTM

```
--- Evaluación del Modelo: Modelo de Sentimiento ---
141/141 ━━━━━━ 0s 3ms/step
precision    recall   f1-score   support
negative (0)  0.63    0.88    0.74    1157
neutral (1)   0.72    0.64    0.68    1650
positive (2)  0.85    0.70    0.77    1698
accuracy      0.73    0.73    0.73    4505
macro avg     0.73    0.74    0.73    4505
weighted avg  0.74    0.73    0.73    4505

Accuracy: 0.7263
Precision: 0.7431
Recall: 0.7263
F1-Score: 0.7261
Cohen's Kappa: 0.5913
```

```
141/141 ━━━━━━ 6s 42ms/step
Classification Report:
precision    recall   f1-score   support
negative     0.65    0.78    0.71    1157
...
accuracy      0.70    0.70    0.70    4505
weighted avg  0.70    0.70    0.70    4505
```

DUMMY

```
Accuracy: 0.35753908219868885
Precision: 0.11917969406622962
Recall: 0.3333333333333333
F1-score: 0.1755819712729074
```

Classification Report:

	precision	recall	f1-score	support
negative	0.00	0.00	0.00	600
neutral	0.00	0.00	0.00	674
positive	0.36	1.00	0.53	709
accuracy			0.36	1983
macro avg	0.12	0.33	0.18	1983
weighted avg	0.13	0.36	0.19	1983

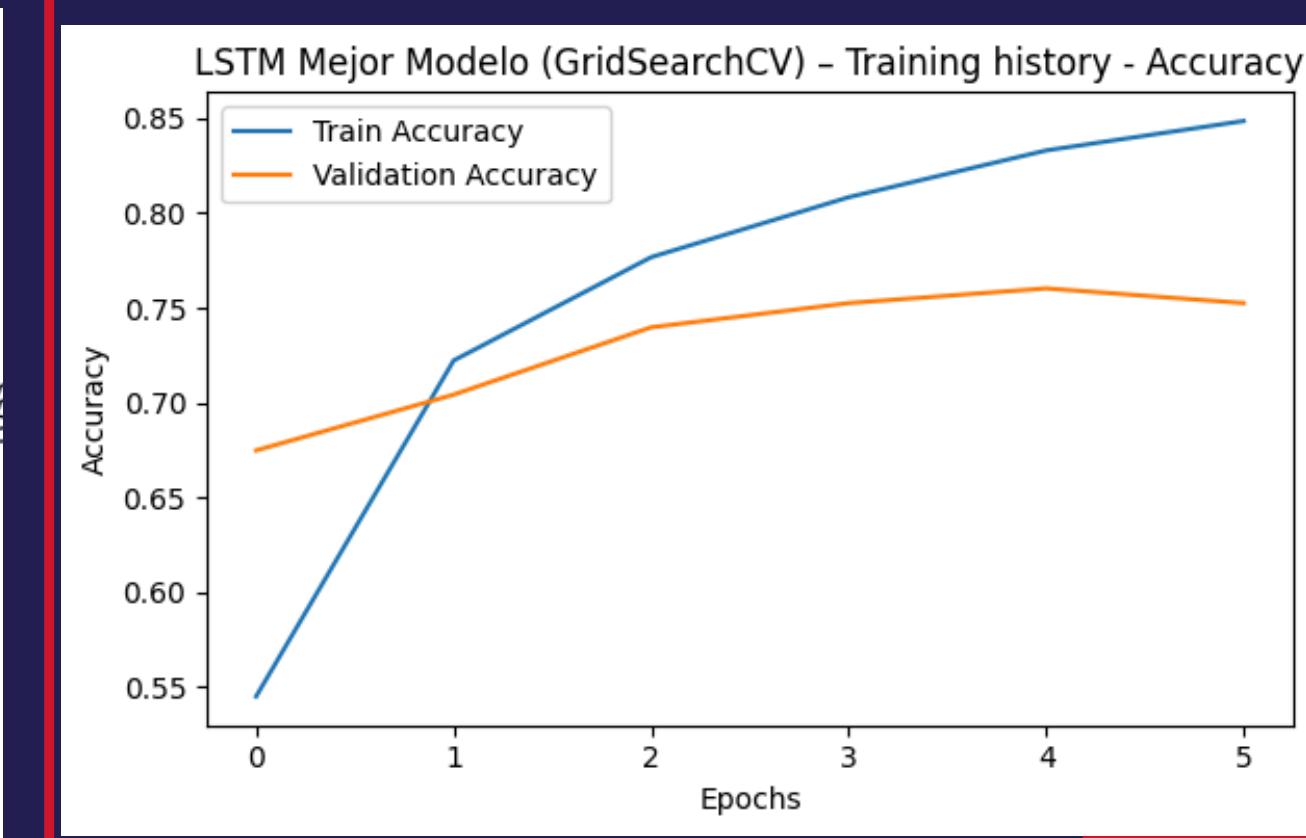
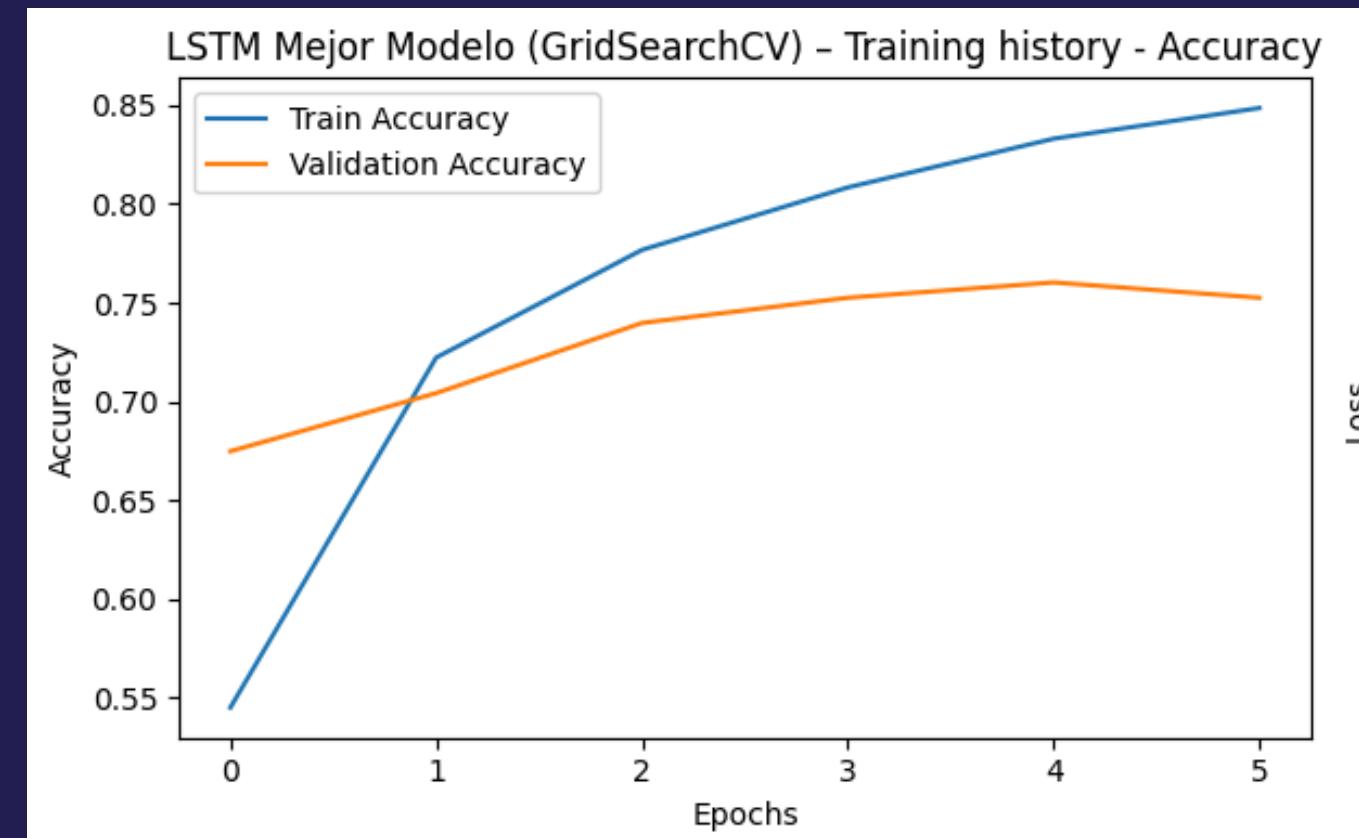
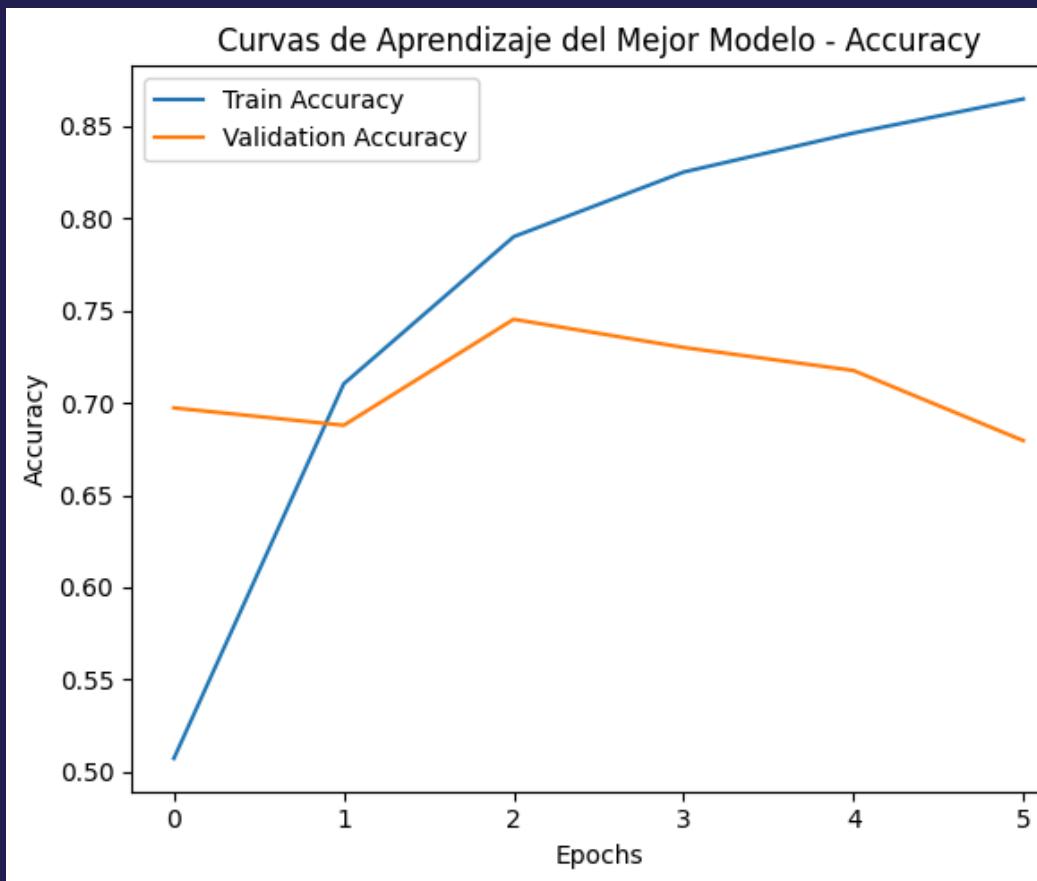
	precision	recall	f1-score	support
negative	0.72	0.74	0.73	1157
neutral	0.70	0.69	0.69	1650
positive	0.79	0.79	0.79	1698
accuracy			0.74	4505
macro avg	0.74	0.74	0.74	4505
weighted avg	0.74	0.74	0.74	4505

# HYPERPARAMETER TUNING

## DENSE

## RNN

## LSTM

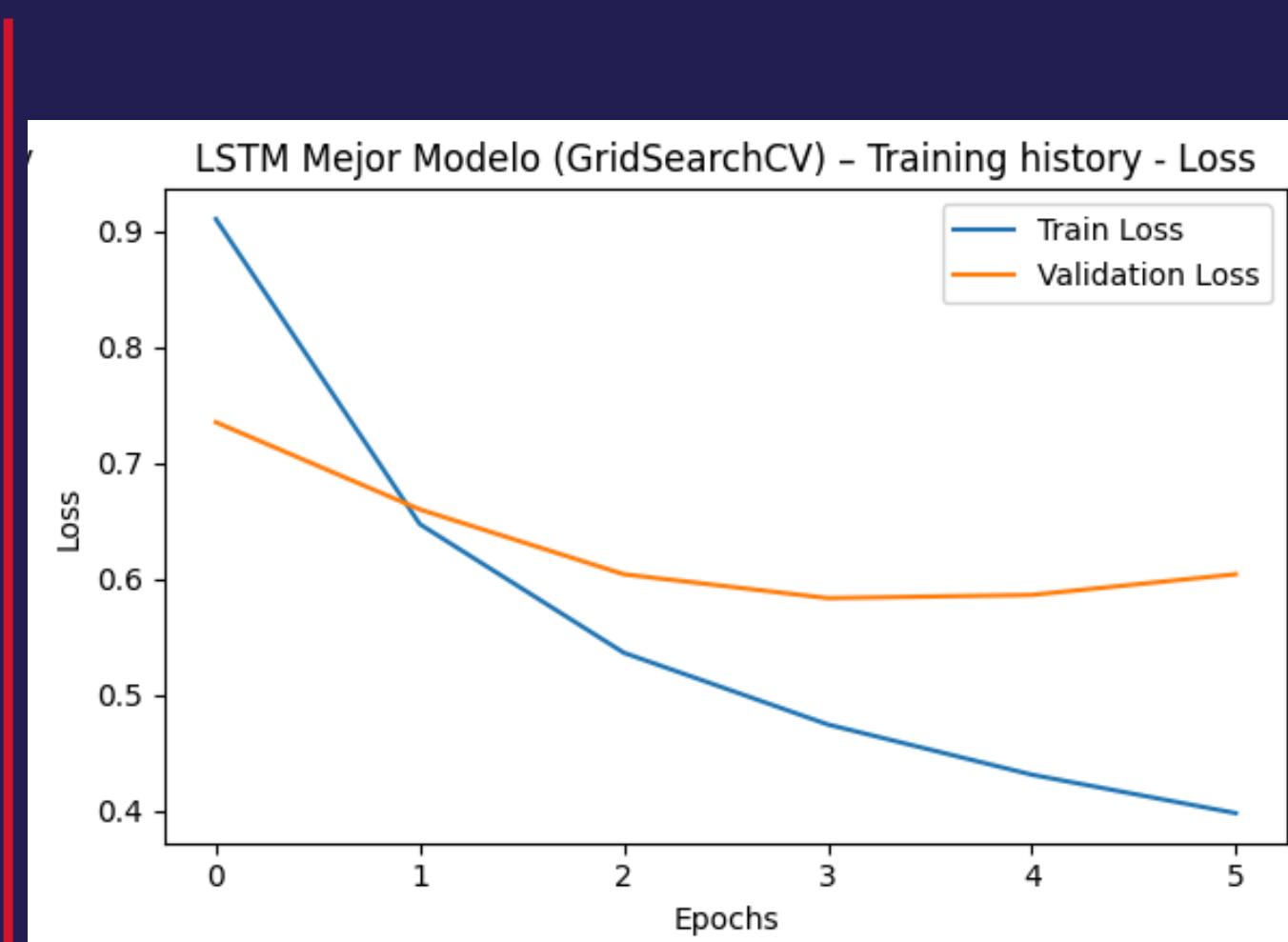
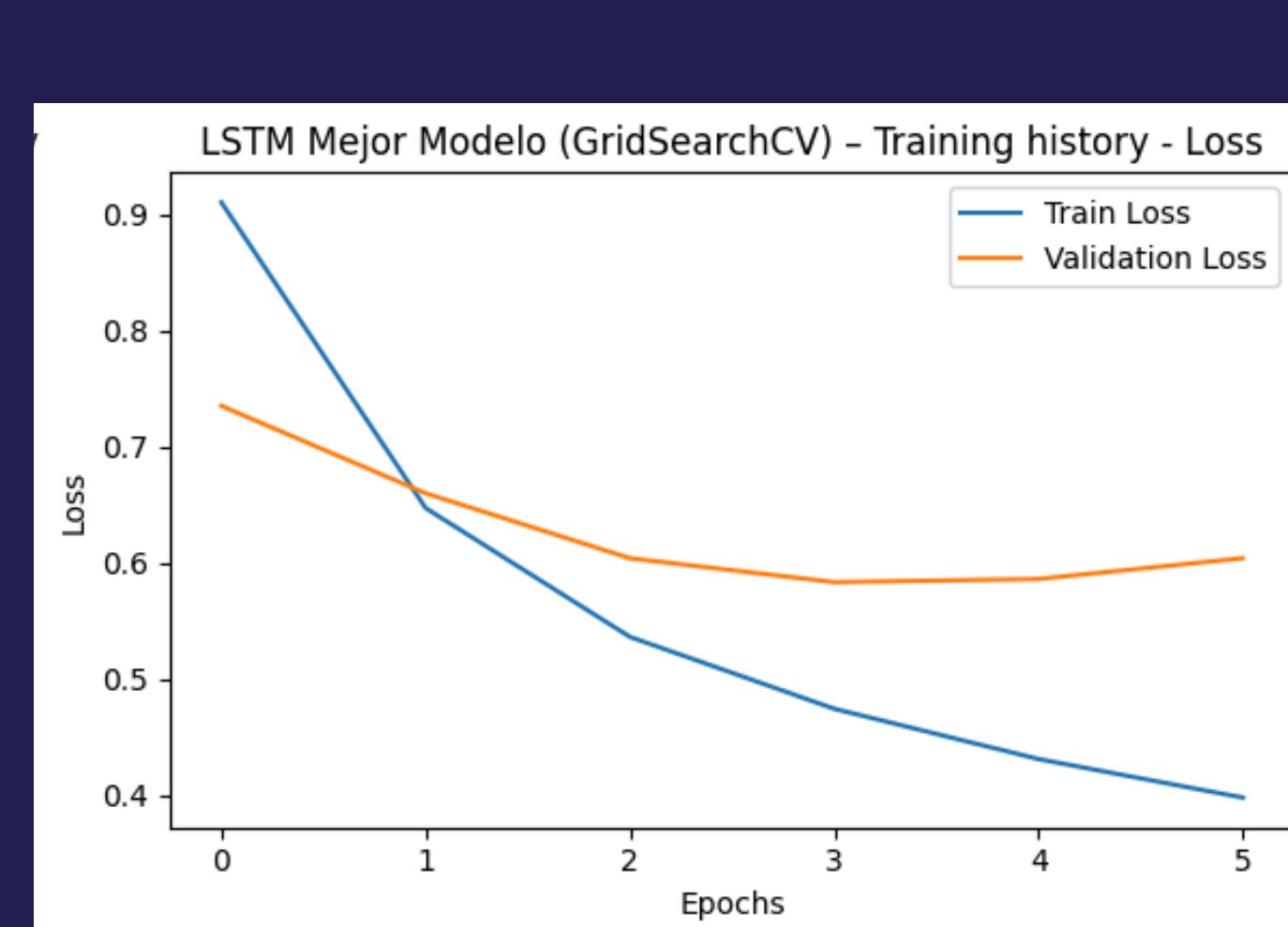
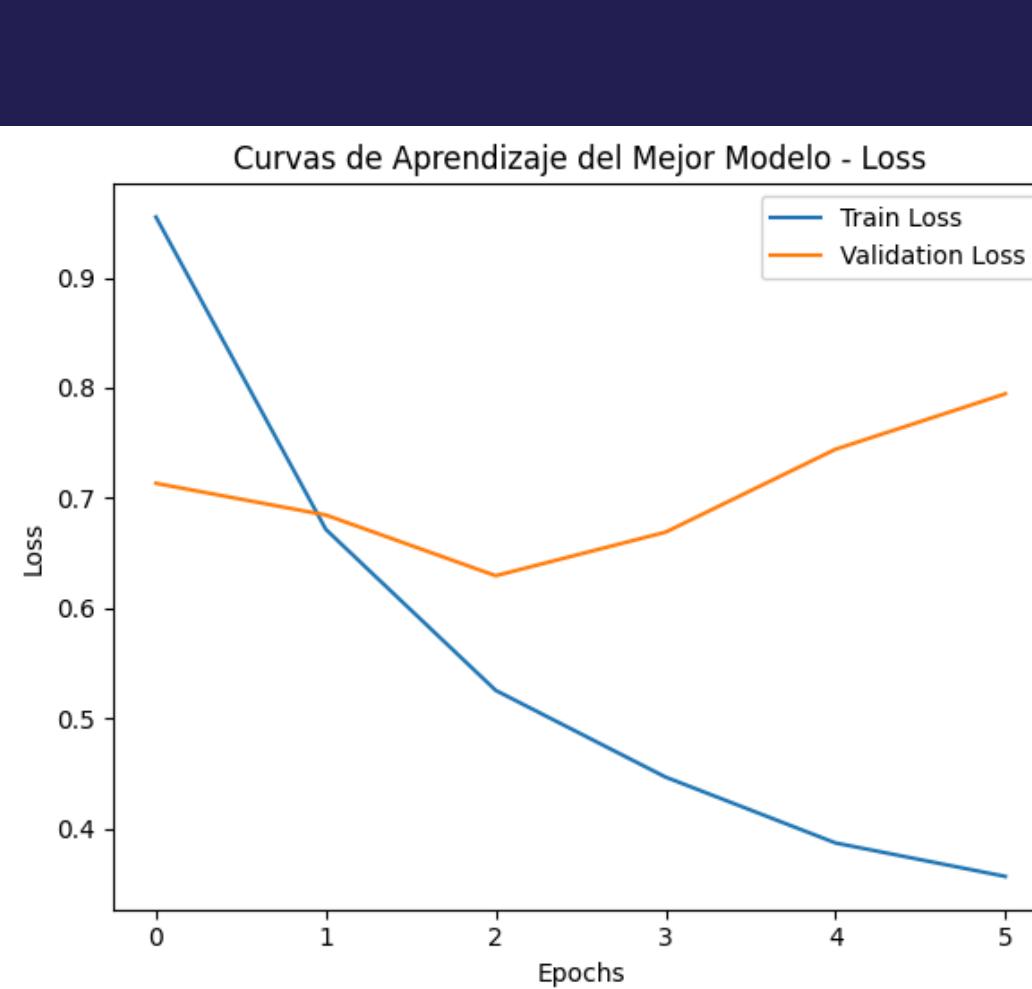


# HYPERPARAMETER TUNING

DENSE

RNN

LSTM

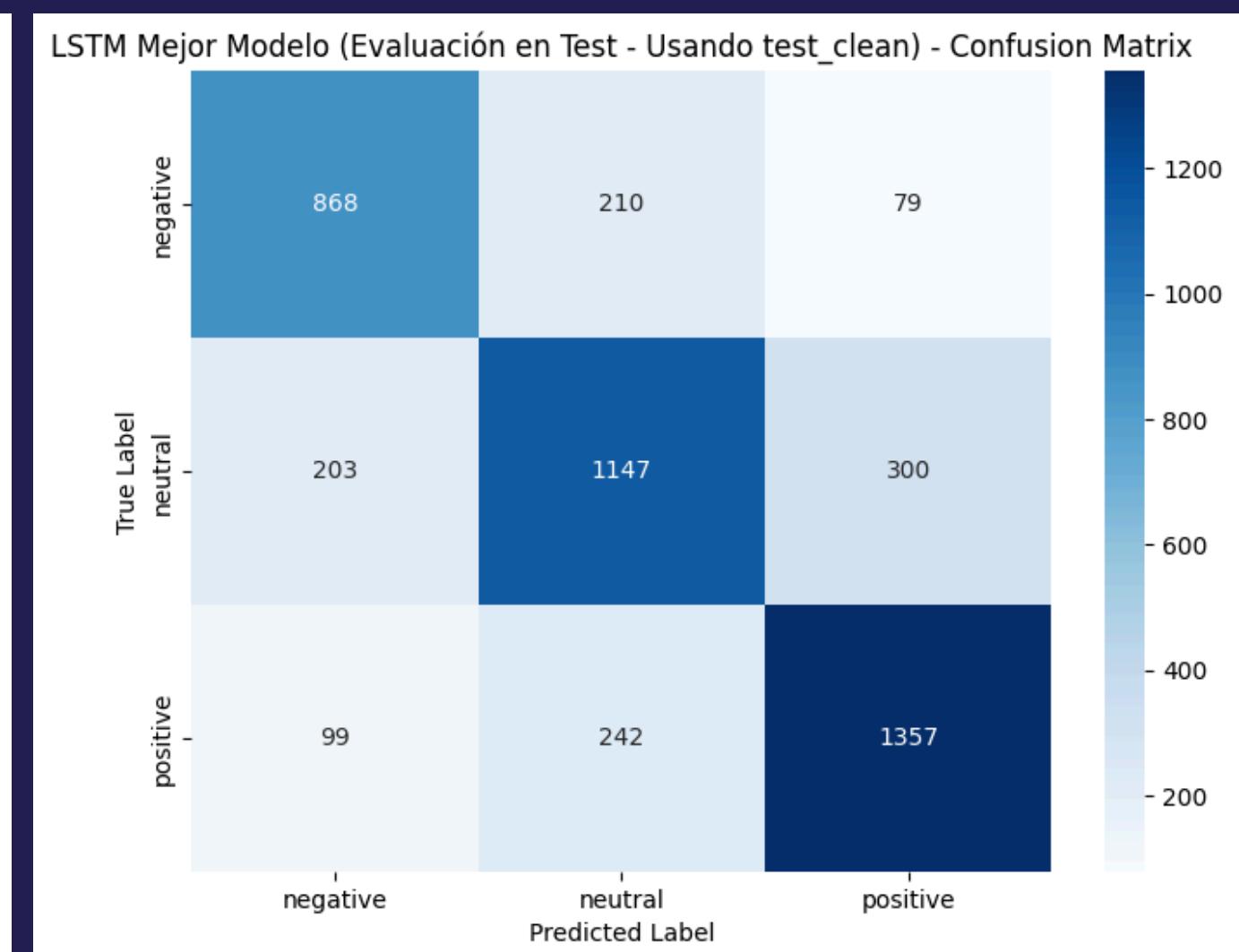
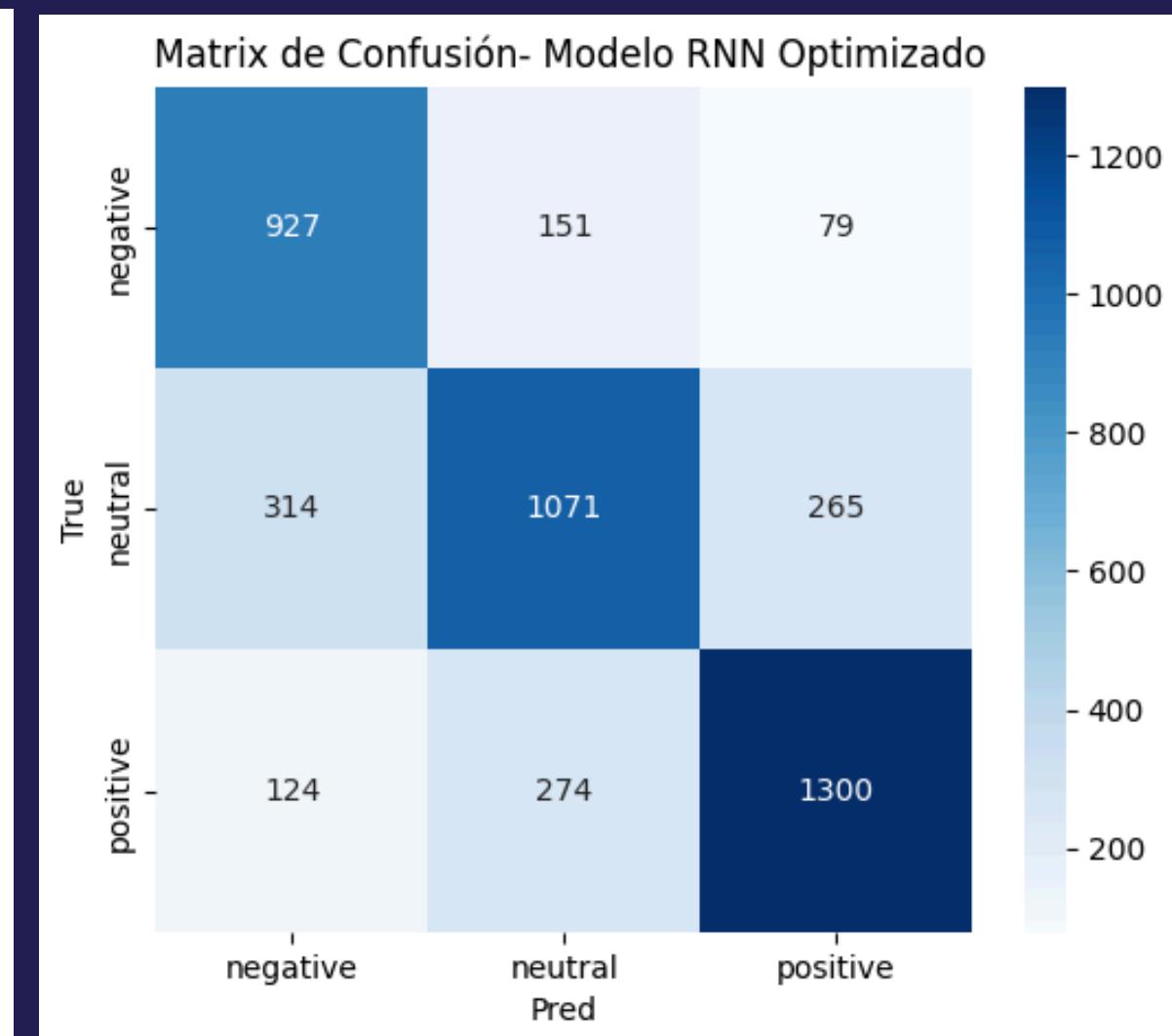
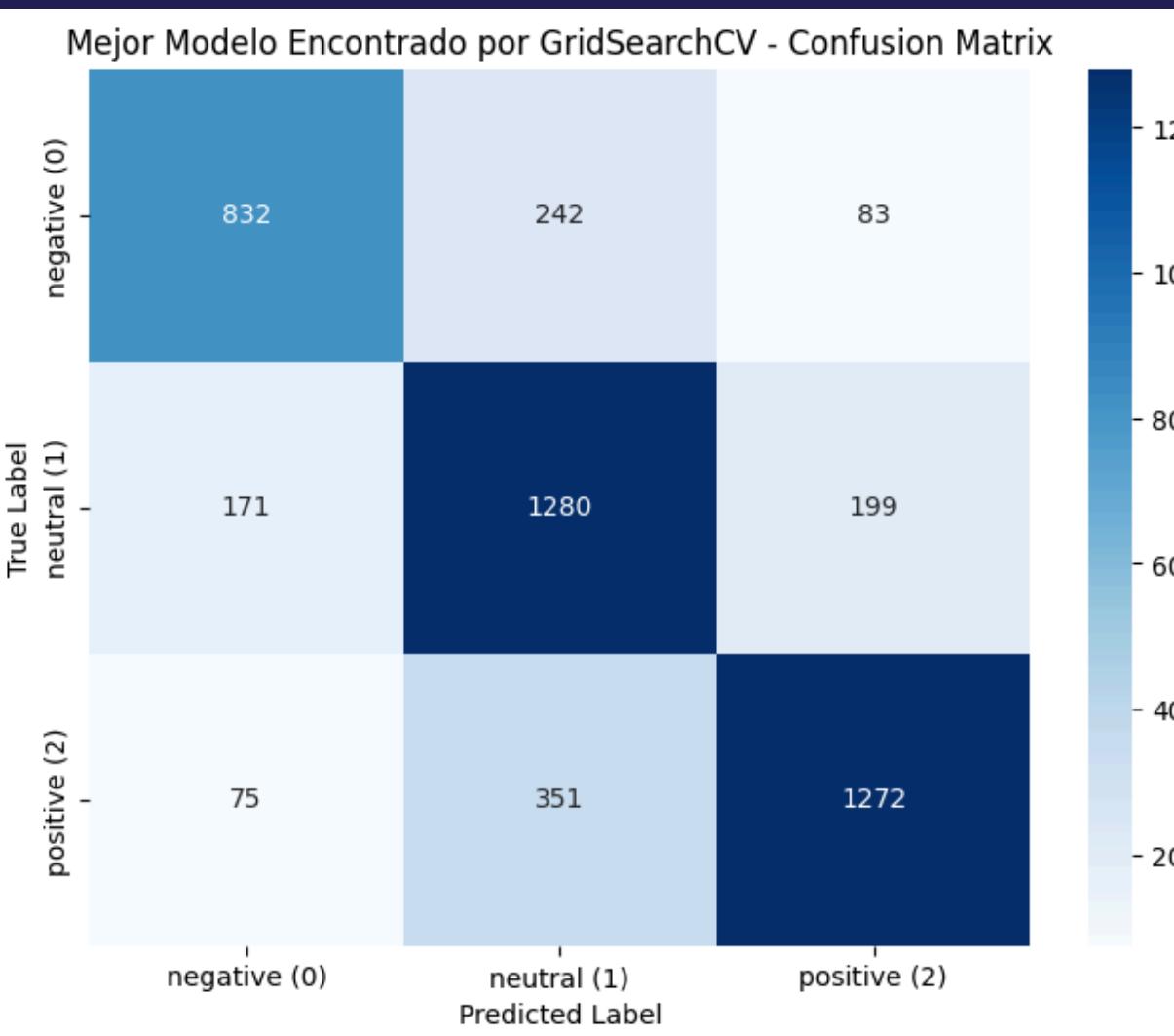


# HYPERPARAMETER TUNING

## DENSE

## RNN

## LSTM



# HYPERPARAMETER TUNING

## DENSE

Precisión (Accuracy): 0.7412  
Precisión (Precision - Weighted): 0.7570  
Exhaustividad (Recall - Weighted): 0.7512  
Puntuación F1 (F1-score - Weighted): 0.7522  
Kappa de Cohen: 0.6208

### Reporte Detallado de Clasificación:

	precision	recall	f1-score	support
negative (0)	0.77	0.72	0.74	1157
neutral (1)	0.68	0.78	0.73	1650
positive (2)	0.82	0.75	0.78	1698
accuracy				
macro avg	0.75	0.75	0.75	4505
weighted avg	0.76	0.75	0.75	4505

## RNN

Accuracy: 0.7258    Precision: 0.72  
Recall: 0.71    F1-score: 0.715    Kappa: 0.68

precision	recall	f1-score	support
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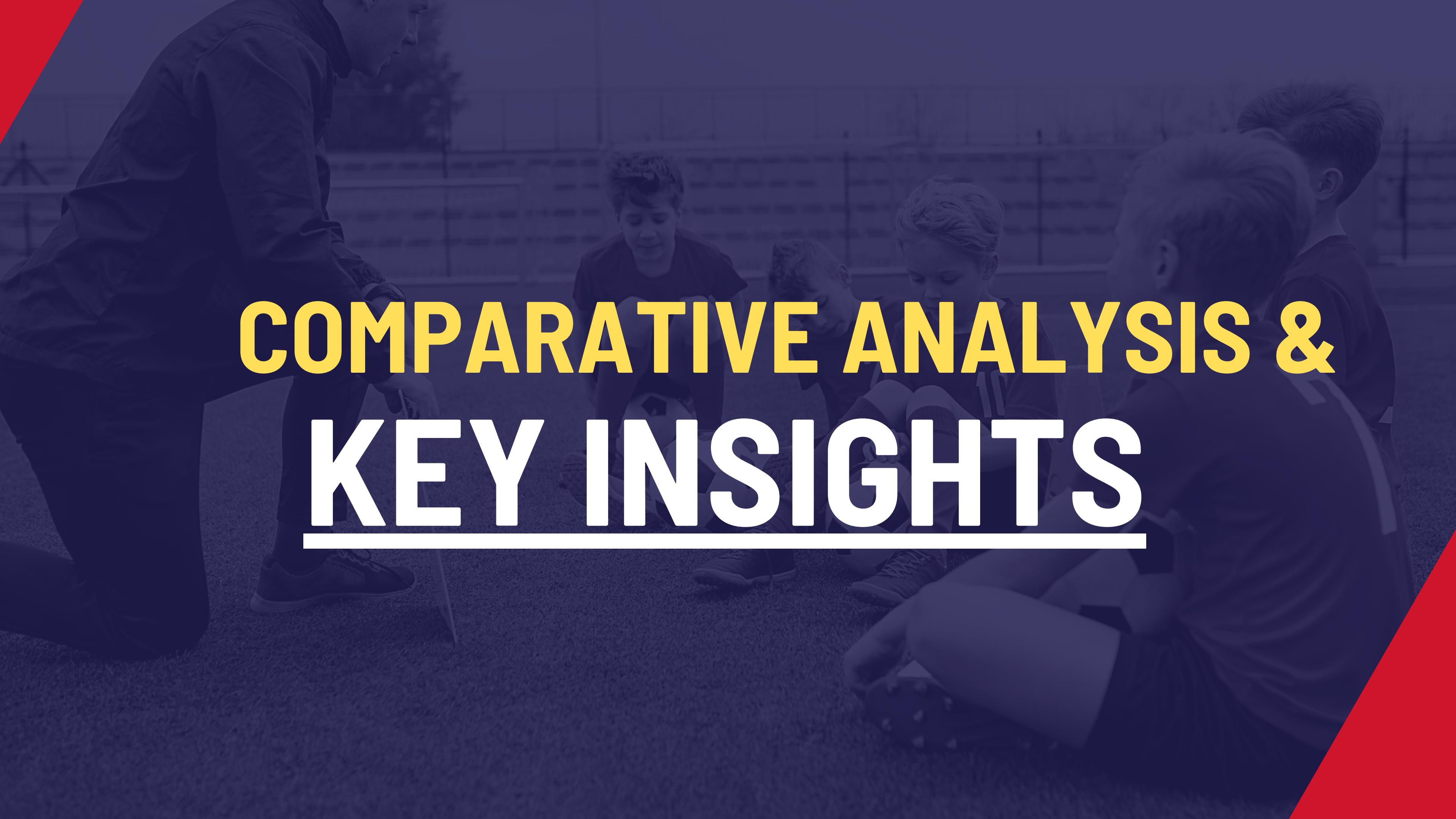
negative	0.67	0.80	0.72	1157
neutral	0.72	0.65	0.68	1650
positive	0.79	0.77	0.78	1698
accuracy			0.72	4505
macro avg	0.72	0.73	0.72	4505
weighted avg	0.72	0.72	0.72	4505

## LSTM

Precisión (Accuracy): 0.7485  
Precisión (Precision - Weighted): 0.7479  
Exhaustividad (Recall - Weighted): 0.7485  
Puntuación F1 (F1-score - Weighted): 0.7481  
Kappa de Cohen: 0.6178

	precision	recall	f1-score	support
negative	0.74	0.75	0.75	1157
neutral	0.72	0.70	0.71	1650
positive	0.78	0.80	0.79	1698
accuracy				
macro avg	0.75	0.75	0.75	4505
weighted avg	0.75	0.75	0.75	4505



A black and white photograph showing a group of young boys playing soccer on a grassy field. In the foreground, a boy in a dark jersey is looking down at the ground. Behind him, several other boys are visible, some sitting on the grass and others standing. A soccer ball is on the ground between them. The background shows a chain-link fence and some trees.

# **COMPARATIVE ANALYSIS & KEY INSIGHTS**

# HYPERPARAMETER TUNING

## DENSE

- The Dense NN's performance improvement over the Dummy is expected, as it learns patterns, but its inability to capture word order limits its effectiveness for text.

## RNN

- The sequential models (RNN and LSTM) significantly outperformed the Dense NN, demonstrating the critical importance of considering the context and sequence of words in text data.

## LSTM

- The LSTM generally performed better than the Vanilla RNN, which aligns with its design to handle longer-range dependencies more effectively.

## RNN

The Dummy Classifier's low score confirms that sentiment analysis is a non-trivial task requiring learning.



A black and white photograph of a youth soccer team. A coach in a dark polo shirt and shorts stands on the left, gesturing with his hands. Several young players in dark jerseys and shorts are scattered across the grassy field; one player in the center is looking down at a soccer ball. The background shows a chain-link fence and trees.

# CONCLUSION & QUESTIONS

## Conclusion

- Our project successfully implemented and compared different Neural Network architectures for classifying the sentiment of FIFA World Cup tweets.
- The results clearly demonstrate that models designed to process sequential data, like the Vanilla RNN and especially the LSTM, significantly outperform the baseline (Dummy) and a non-sequential Dense network.



# Questions ?

- The LSTM model achieved the best performance across key metrics, highlighting its effectiveness in capturing the contextual nuances within tweet text.



Soccer Club

**THANK  
YOU**

