[NN'23] Arabic Sentiment Analysis (NLP)

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1. Introduction:

Presenting an analysis and comparison of text classification models for sentiment analysis on a dataset containing textual reviews.

Three distinct models were implemented and evaluated:

1. Transformer Model
2. LSTM Model
3. RNN Model

Then provide insights into the preprocessing steps, model architectures, and their corresponding accuracies.

2. Data Description:

The dataset consists of textual reviews with associated sentiment labels. The task involves predicting the sentiment (positive, negative, or neutral) based on the review text.

3. Preprocessing:

3.1 Common Preprocessing Steps:

- Text Cleaning: Removal of punctuation and special characters show in:
  - **(remove_punctuation)**
  - **(remove_numbers)**
  - **(remove_unusual_sequences)**
  - **(remove_non_arabic)**
  - **(remove_emojis)**

- Tokenization: Using the nltk library to split text into tokens.
- Stopword Removal: Elimination of common words in both Arabic and English.
- Lemmatization: Reduction of words to their base form.

3.2 Model-Specific Preprocessing:

- For the Transformer Model: tokenization and padding were applied.
- For LSTM and RNN Models: label encoding used to convert sentiment labels into numerical values.

4. Model Architectures:

4.1 Transformer Model:

The Transformer model utilized a multi-layer architecture with attention mechanisms, positional encoding, and feedforward layers. It was trained for sentiment analysis with a focus on capturing contextual information.

4.2 LSTM Model:

The LSTM model featured an embedding layer, followed by a combination of Conv1D, MaxPooling1D, and two LSTM layers. It employed dropout for regularization and utilized SoftMax activation for multi-class classification.

4.3 RNN Model:

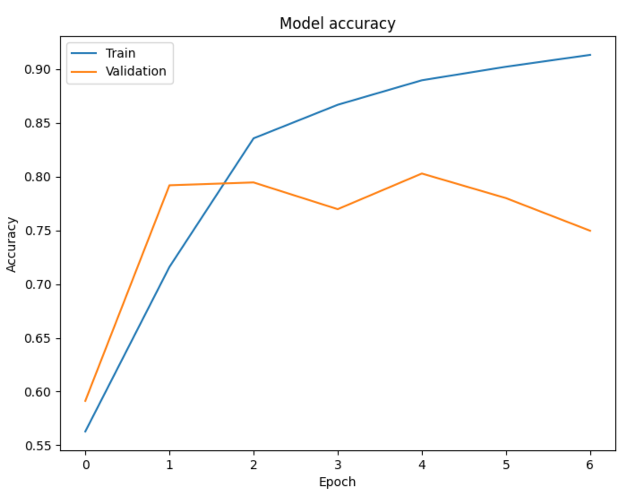
The RNN model incorporated embedding layer, followed by a SimpleRNN layer with dropout, a dense layer, and flattening. It used SoftMax activation for classification.

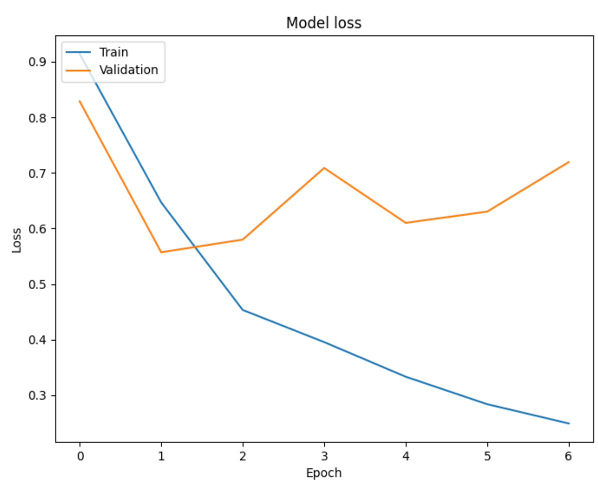
5. Model Training and Evaluation:

Each model was trained using a portion of the labeled dataset and evaluated on a validation set. Training involved minimizing categorical cross-entropy loss, and early stopping was applied to prevent overfitting.

5.1 Transformer Model:

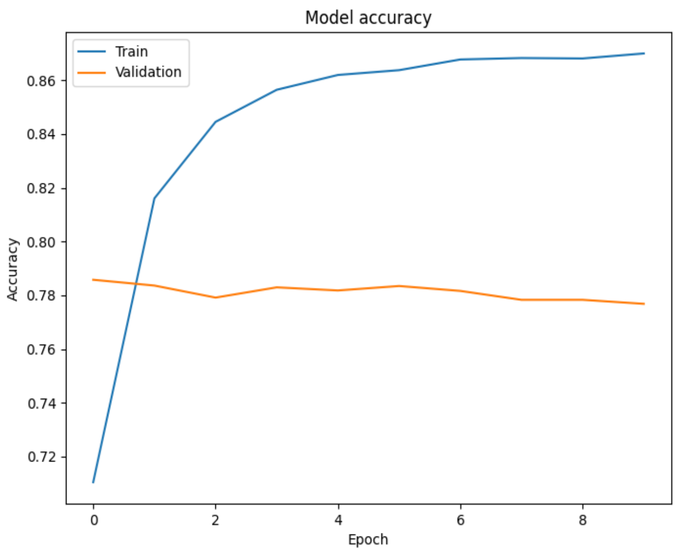
The Transformer model achieved a validation accuracy of approximately 80.26% after 30 epochs.

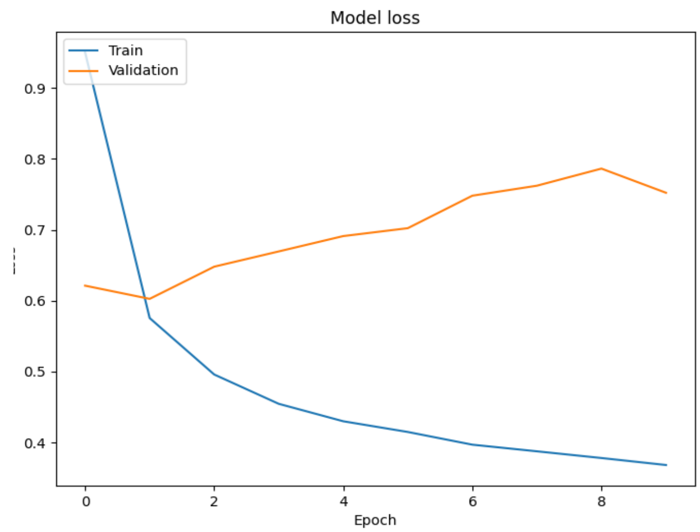




5.2LSTM Model:

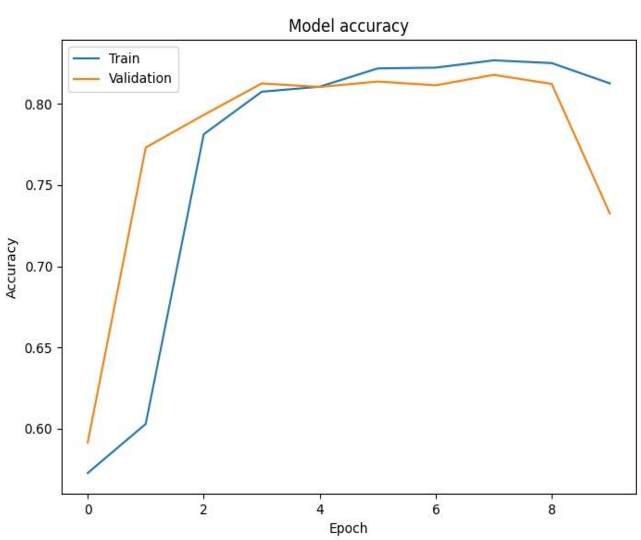
The LSTM model achieved a final validation accuracy of approximately 79.42% after 10 epochs

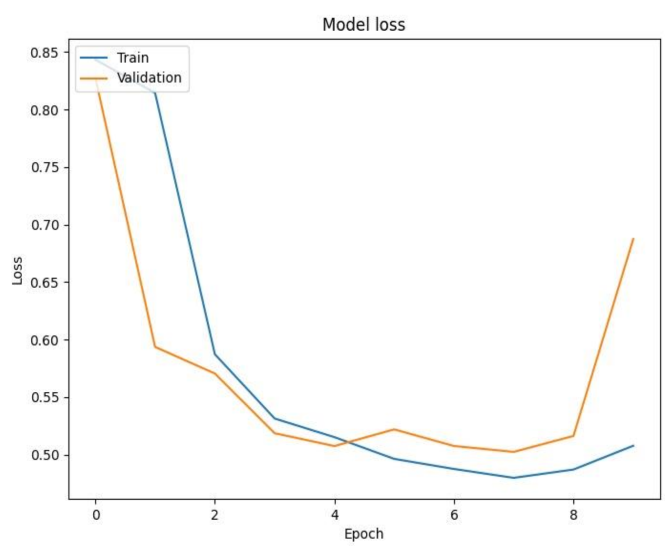




5.3 **RNN Model:**

The RNN model achieved a final validation accuracy of approximately 80.3% after 10 epochs





6. Conclusion:

In conclusion, the Transformer Model demonstrated competitive performance, while the LSTM and RNN models provided satisfactory results as well.