Sentiment Analysis with Deep Learning

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1. Preprocessing Decisions

Contraction Expansion: Replaced contractions (e.g., "don't" → "do not") for consistent text representation.

Email, URL, and HTML Tag Removal: Removed irrelevant elements using regex to retain only meaningful content.

Special Characters, Numbers, and Accented Characters: Eliminated non-alphabetic characters and converted accented ones to their non-accented forms for compatibility with GloVe embeddings.

Text Normalization: Converted text to lowercase, removed extra whitespaces, and corrected spelling errors for uniform tokenization.

2. Model Architecture

Embedding Layer: Used pre-trained 100-dimensional GloVe embeddings; words not in the GloVe vocabulary were assigned zero vectors.

Bidirectional LSTM Layers: Captured context in both directions for improved understanding of sentiment nuances.

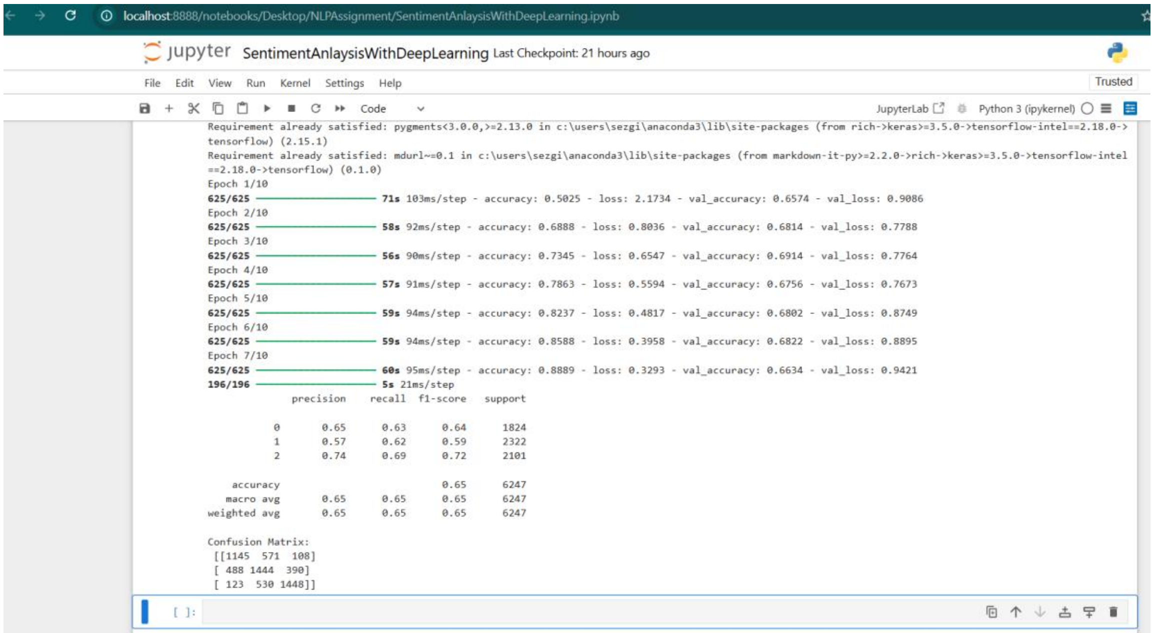
Dropout Layers: Reduced overfitting by randomly deactivating neurons during training.

Dense Layers: Performed feature extraction and dimensionality reduction before the final classification.

Output Layer: Utilized softmax activation for three-class sentiment classification (negative, neutral, positive).

3. Analysis of Results

Training and Validation: Trained the model for 10 epochs with early stopping (patience=3) to prevent overfitting.

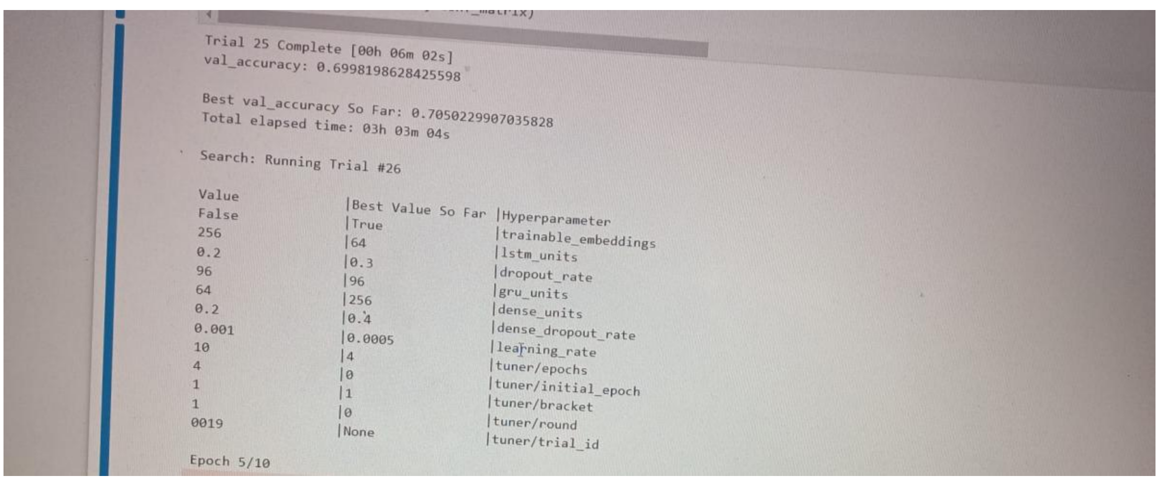


Challenges and Improvements:

Initial simple architecture resulted in low accuracy (~41%).

Introducing bidirectional LSTMs and improved preprocessing significantly enhanced performance.

Used Keras Tuner to optimize hyperparameters within three hours. Find best parameters in below.



Observations:

The model struggled with ambiguous or context-dependent texts. Future improvements could include attention mechanisms or fine-tuning transformer models like BERT.