



Sentiment Analysis - Report and Demonstration

Student Name: Mohammad Lakhi

Student ID: 2512430

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University of Wales Trinity Saint David

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Abstract

This study uses a CNN-LSTM hybrid architecture to classify sentiment in the IMDB 50K dataset, aiming to strike a balance between high-level accuracy and computational efficiency. Using an 80/20 train-test split, a 10,000 word vocabulary, and 250 word sequence padding, the model combines 1D-Convolutional layers for local feature extraction with a Bidirectional LSTM for sequential narrative flow. The results showed a peak validation accuracy of 89.08%, which exceeded the Logistic Regression baseline of 84.33%. While training logs showed rapid overfitting by epoch three, with a training accuracy of 96.32%, using Early Stopping successfully restored the optimal weights from the first epoch at 0.2768 loss. This study concludes that the CNN-LSTM hybrid has a higher performance-to-cost ratio, making it a more scalable alternative to larger Transformer models for sentiment analysis tasks.

TABLE OF CONTENTS

1	Introduction and Problem Statement	1
1.1	Context and Industry Relevance	1
1.2	Evolution of Sentiment Analysis	1
1.3	Problem Statement	1
1.4	Objectives	2
2	Related Work	3
2.1	Traditional Machine Learning methods	3
2.2	Shift to Deep Learning methods	3
2.3	Impact of Trasformer Models	3
2.4	Performance and Explainability	4
2.5	Lexicon based Approaches	4
2.6	Advanced Transformer Variants	4
3	Methodology	5
3.1	Data Collection and Pre-processing	5
3.2	Feature Representation	5
3.3	Hybrid Architecture(CNN+LSTM)	5
3.4	Training and Optimization	6
3.5	Baseline Model for Comparison	6
3.6	Evaluation Framework	6
4	Results	7
4.1	Quantitative Findings	7
4.2	Model Performance Comparison	7
4.3	Training Dynamics and Learning Curves	7

5	Discussion	9
6	Conclusion and Recommendation	11
	REFERENCES	12

Chapter 1

Introduction and Problem Statement

1.1 Context and Industry Relevance

The massive amount of user-generated content created each day estimated at 2.5 quintillion bytes, has completely changed how we analyse public opinion. For the film industry, the ability to automatically sort through the 50,000 reviews in the IMDB dataset is a "critical" tool for forecasting box-office success and informing marketing strategies. While humans can easily read a review and know if it is "positive" or "negative" doing this with AI is difficult because human language is messy, full of sarcasm, and very context-dependent [4, 6].

1.2 Evolution of Sentiment Analysis

Historically, research started with traditional methods such as Logistic Regression or Support Vector Machines (SVM) combined with TF-IDF to convert text to numbers. These models are useful baseline procedures because they are quick and simple to understand, but they have a major flaw: they treat words as separate tokens and do not account for how word order influences meaning. According to the papers I reviewed, traditional models typically reach a performance ceiling, with Logistic Regression reaching approximately 84.33% accuracy [6, 11].

1.3 Problem Statement

The main problem in this assignment is to identify the "sweet spot" between computational efficiency and predictive performance. While heavy Transformer models such as

BERT are extremely accurate up to 94.68%, they require a lot of computing power and a long training time. Conversely, simple models lack context. This study investigates whether a hybrid CNN-LSTM architecture can achieve near-state-of-the-art accuracy while remaining scalable and computationally inexpensive [9, 10].

1.4 Objectives

To solve this issue, my report focuses on the following.

- The IMDB 50K dataset is being preprocessed using a robust pipeline of tokenization, HTML stripping, and noise reduction.
- Creating a traditional baseline like TF-IDF + Logistic Regression, to test how it handles noisy reviews.
- Using a Hybrid Architecture, specifically a CNN-LSTM model, to capture both local sentiment and long-term sequential context.
- Optimizing training with modern techniques such as Spatial Dropout and Early Stopping to avoid overfitting while maintaining high validation accuracy.
- Comparative analysis of the models using F1-scores, training time, and computational resource requirements to provide practical deployment advice.

Chapter 2

Related Work

2.1 Traditional Machine Learning methods

When it comes to sentiment analysis, the majority of the early work was based on what we now refer to as traditional machine learning techniques. These models, such as Logistic Regression and Support Vector Machines (SVM), typically use TF-IDF to convert text into numbers. While these methods are quick and simple to set up, they treat words as independent units and don't understand how the order of words affects the meaning of the sentence. Several studies found that Logistic Regression was the strongest traditional model, with an accuracy of approximately 84.33% on the IMDB dataset [6, 7, 11].

2.2 Shift to Deep Learning methods

To address the context issue, researchers began exploring deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. CNNs excel at identifying specific patterns or features in text, whereas LSTMs are designed to remember word sequences, which is critical for understanding lengthy reviews. Some papers attempted to combine them into a CNN-LSTM hybrid, which pushed the performance a little higher, reaching an F1-score of around 89.11% [3, 12].

2.3 Impact of Transformer Models

The most significant change in the literature occurred with the introduction of Transformer models, specifically BERT. Unlike older models, which read text from left to right or right to left, BERT reads everything at once, allowing it to better understand the vibe of a sentence. Most papers I reviewed showed that even a basic BERT model easily beats the old ones, with accuracy scores ranging from 91.35% and 92.40% [1, 3].

2.4 Performance and Explainability

Some researchers have gone even further, combining BERT with other techniques like n grams to capture even more linguistic detail, resulting in a peak accuracy of 94.68%. However, a common theme in the most recent papers is that these models are black boxes, which means we don't really understand why they make their decisions. This has led to a new focus on Explainable AI (XAI) tools like LIME, which help show which specific words triggered the model's decision [2, 10].

2.5 Lexicon based Approaches

Earlier research frequently relied on lexicon-based methods, which used predefined dictionaries of "positive" and "negative" words to calculate sentiment scores. Although these methods are useful for quick analysis, they struggle with informal language and slang commonly found in datasets like Twitter, making them less robust than modern machine learning classifiers [8].

2.6 Advanced Transformer Variants

As the field advanced beyond the original BERT architecture, researchers began to investigate optimized versions such as RoBERTa (Robustly Optimized BERT Pretraining Approach). Training on larger datasets and removing the next sentence prediction task resulted in slight but consistent improvements in handling the linguistic nuances of movie reviews and social media posts [5].

Chapter 3

Methodology

3.1 Data Collection and Pre-processing

The implementation makes use of the IMDB 50K dataset, which is divided into 25,000 samples for training and 25,000 for testing. To ensure that the model focuses on semantic content rather than noise, an accurate pre-processing pipeline is used, which includes the removal of HTML tags, punctuation stripping, and converting all text to lowercase. To ensure uniform input dimensions for neural network layers, the text is tokenized using a frequency-based vocabulary and padded to a fixed sequence length of 250 words [3, 12].

3.2 Feature Representation

Unlike traditional models that use sparse TF-IDF vectors, this hybrid approach uses dense word embeddings to represent reviews in a continuous vector space. By using pre-trained embeddings or learning them during the training process, the model can capture the closeness of word meanings. The dense representation is necessary for the convolutional layer to extract meaningful patterns from the text without incurring high computational costs associated with large transformer weights [4, 6].

3.3 Hybrid Architecture(CNN+LSTM)

The methodology is based on a structured architecture that begins with a 1D Convolutional layer and then uses Global Max Pooling to identify key sentiment focused phrases. These extracted features are then passed to a Long Short-Term Memory (LSTM) layer, which processes the features sequentially in order to understand the review’s overall narrative flow. This combination enables the model to handle local sentiment cues while maintaining a memory of the entire text, resulting in significantly

better performance than individual CNN or LSTM models [3, 4].

3.4 Training and Optimization

To optimize the hybrid model, I created a training loop with the Adam optimizer and a binary cross-entropy loss function. Dropout layers are added between the LSTM and the final Dense layer to keep the model from overfitting to specific IMDB reviewer styles. This "hit-and-trial" setup, combined with early stopping, ensures the model achieves an F1-score of around 89% while remaining fast enough to train on a standard laptop GPU [1, 12].

3.5 Baseline Model for Comparison

To assess the effectiveness of the hybrid CNN-LSTM approach, a baseline Logistic Regression model was implemented. This model uses TF-IDF (Term Frequency-Inverse Document Frequency) vectorization to convert text into sparse numerical features. Comparing the hybrid neural network to the traditional machine learning baseline provides a clear measurement of the performance gain provided by deep learning architectures [6, 7].

3.6 Evaluation Framework

The model's performance is evaluated using a comprehensive set of metrics, including accuracy, precision, recall, and the F1-score. Because the IMDB dataset is balanced, Accuracy is a reliable overall performance indicator. However, the F1-score is prioritized to ensure that the model identifies both positive and negative sentiments without bias. Confusion matrices and learning curves (loss/accuracy) are used to visualize the training process and detect potential overfitting [?, 12].

Chapter 4

Results

4.1 Quantitative Findings

- **Baseline Model:** Logistic Regression achieved an accuracy of 84.33%.
- **Hybrid Model:** The CNN-LSTM model achieved a validation accuracy of 89.08%.
- **Performance Gain:** The hybrid approach shows an improvement of 5% over the baseline model
- **F1-Score:** A final score of 0.89 indicates a strong balance of positive and negative sentiment detection.

4.2 Model Performance Comparison

Metric	Logistic Regression (Baseline)	CNN-LSTM (Hybrid)
Accuracy	84.33%	89.08%
Loss (Best)	N/A	0.2768
Training Time	< 1 minute	~ 21 minutes
Hardware Requirement	Low (CPU)	Moderate (GPU recommended)

Table 4.1: Model Comparison

4.3 Training Dynamics and Learning Curves

- **Rapid Convergence:** The model achieved its highest validation accuracy during the first epoch.
- **Overfitting Observation:** By Epoch 3, training accuracy had reached 96.32%, while validation loss had risen from 0.2768 to 0.3802.

- Early Stopping: The callback successfully terminated training at Epoch 3 and restored the top-performing weights from Epoch 1.

Chapter 5

Discussion

The hybrid CNN-LSTM model achieved 89.08% peak validation accuracy, which is significantly higher than the traditional Logistic Regression model's baseline of 84.33%. This performance improvement demonstrates the theoretical advantage of deep learning architectures in capturing complex semantic relationships that frequency-based methods, such as those described by Manning et al. [6], frequently overlook. By achieving this level of accuracy, the model aligns with the benchmarks established in Maas et al. [1] original study of the IMDB dataset, which found that while linear classifiers are robust, they lack the ability to interpret sequential nuances required for high-fidelity sentiment analysis.

The training logs show that the model reached its optimal state in the first epoch, with a validation loss of 0.2768. The subsequent divergence observed in the third epoch, in which training accuracy increased to 96.32% while validation accuracy remained constant, is a clear demonstration of overfitting, a common challenge in high-capacity neural networks. According to Chollet et al. [12], regularization is required for the memorization of training data noise rather than general sentiment patterns. The Early Stopping mechanism successfully restored the weights from the first epoch, ensuring that the model preserved the maximum generalization capability required for processing unseen reviews.

The architecture's effectiveness is based on the specific roles of its constituent layers. The 1D-Convolutional layer, which followed Kim et al. [4] principles, functioned as a local feature extractor to identify key sentiment-carrying phrases. These features were then processed by the Bidirectional LSTM, which, as pioneered by Hochreiter and Schmidhuber et al. [3], successfully managed long-term dependencies to understand the overall narrative flow. This particular hybrid configuration has been identified in

recent literature as an optimal balance between CNNs’ local focus and LSTMs’ global context, providing a performance-to-cost ratio superior to individual models [8].

Finally, the model’s computational efficiency remains critical for practical deployment. The hybrid design provides a sustainable alternative to large-scale Transformer models, taking approximately seven minutes per training epoch. While those models may achieve slightly higher accuracy, the CNN-LSTM architecture is a scalable solution for environments with limited hardware resources that still achieves a 5% accuracy increase over traditional machine learning baselines. This balance points out the importance of matching architectural complexity to both the dataset’s specific requirements and the available computational budget.

Chapter 6

Conclusion and Recommendation

The study successfully created a robust sentiment analysis pipeline that uses a hybrid CNN-LSTM architecture to classify movie reviews with high accuracy. The primary goal of outperforming traditional machine learning benchmarks was met, as the model achieved a peak validation accuracy of 89.08%, significantly exceeding the Logistic Regression model's baseline of 84.33%. By combining convolutional layers for local feature extraction and bidirectional LSTM layers for sequential context, the system outperformed traditional frequency-based approaches in interpreting complex semantic structures.

The implementation demonstrated that a deep learning approach can be computationally efficient, with training sessions lasting about seven minutes per epoch on standard hardware. A key finding of the study was the rapid onset of overfitting, which was detected by the divergence of training and validation loss after the initial epoch. The implementation of an Early Stopping mechanism was critical in maintaining the model's integrity, as it allowed for the restoration of the optimal weights from the first epoch, when the validation loss was at its lowest of 0.2768.

While the hybrid model strikes a good balance between performance and speed, future improvements should look into the use of pre-trained word embeddings to broaden the model's semantic understanding beyond the initial vocabulary. Furthermore, the use of Explainable AI tools would increase transparency by identifying the specific linguistic features that influence classification decisions. Finally, this project validates the CNN-LSTM hybrid as a scalable and effective solution for high-fidelity sentiment analysis in environments where computational resources must be managed strategically.

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