A Hybrid LSTM-CNN Approach Using Multilingual BERT for Sentiment Analysis of GERD Tweets

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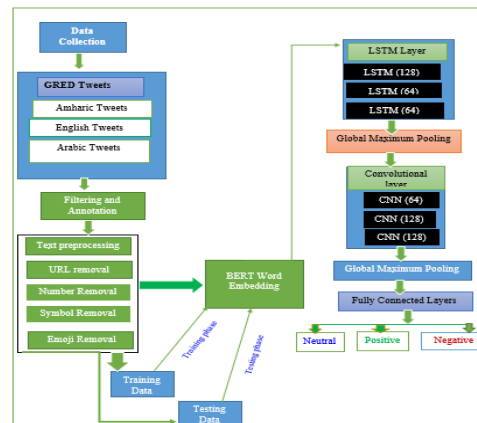## ARTICLE INFORMATION

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ABSTRACT

Analyzing public sentiment through platforms like Twitter is a common approach for understanding opinions on political matters. This study introduces a deep learning sentiment analysis model that integrates Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) to assess attitudes toward the Grand Ethiopian Renaissance Dam (GERD). LSTM is utilized to capture long-range dependencies in text, while CNN identifies significant local patterns. An initial dataset of 30,000 unlabeled tweets was collected in 2024 G.C., out of which 17,064 were labeled as positive, negative, or neutral. The labeled tweets were divided into 13,112 for training and the remaining for testing. The hybrid LSTM-CNN model demonstrated superior performance compared to the standalone models, delivering more accurate and balanced sentiment classification. A major feature of this study is the analysis of tweets written in Amharic, Arabic, and English. The model was trained over 35 epochs with a batch size of 46 and a learning rate of 0.001. Using multilingual BERT (mBERT) embeddings notably enhanced the model's performance, with training and testing accuracies reaching 95.3% and 92%, respectively. The hybrid model also achieved a precision, recall, and F1-score of 90%. In a focused analysis of Arabic tweets, 3,710 were negative, 9,793 positive, and 4,814 neutral. These results emphasize the influence of linguistic diversity and class distribution on classification performance. While mBERT showed strong results, addressing class imbalance and expanding language-specific features remains crucial for further improvements.

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1. INTRODUCTION

The Grand Ethiopian Renaissance Dam (GERD), officially named "ታላቁ የኢትዮጵያ ሕዳሴ ግድብ" in Amharic, represents a transformative hydroelectric project on Ethiopia's Blue Nile River. This study employs an innovative LSTM-CNN neural network architecture to perform sentiment classification of multilingual social media content (English, Amharic, and Arabic) concerning this controversial infrastructure development. Initiated in 2011 near Ethiopia's Sudanese border in Benishangul-Gumuz Region, GERD's 6.45GW capacity will position it as Africa's most powerful hydroelectric facility and among the world's top ten [1]-[2]. The project addresses Ethiopia's domestic energy demands while enabling regional power exports, though downstream nations Egypt and Sudan have raised concerns about hydrological impacts.The Blue Nile Basin, encompassing Lake Tana's Gilgel Abay tributary, exhibits particular climate vulnerability with projected shifts in rainfall and temperature regimes [3]-[5]. Our research applies NLP-based sentiment analysis to Twitter data, enabling systematic tracking of public opinion across linguistic groups. This computational approach automatically categorizes tweets as positive, negative or neutral through machine learning algorithms.

As the Nile Basin's nine hydrological zones [6]-[10] represent critical water management units, social media analytics provide real-time insights into transnational perspectives on GERD. The instantaneous nature of Twitter communications allows for monitoring evolving public sentiment, helping identify emerging concerns and misinformation patterns regarding the dam's socioeconomic consequences [7].This methodology combines:CNN networks for localized feature extraction from tweet text, LSTM layers to model sequential dependencies in multilingual content, Sentiment classification across three languages and Geopolitical context analysis of GERD-related discourse The hybrid architecture demonstrates particular effectiveness in handling Amharic's morphological complexity and Arabic's dialectal variations while maintaining strong performance on English tweets.

2. RELATED WORK

Pioneered sentiment analysis by focusing on sentiment polarity classification using Naive Bayes and Support Vector Machines (SVM). They worked with a dataset of 2000 movie reviews, classified into positive and negative categories. Their work explored the use of negation, word locations, and part-of-speech (POS) information but found that such strategies often reduced sentiment polarity accuracy. Their dataset, consisting of 1000 positive and 1000 negative reviews, became a standard for training and evaluating sentiment analysis models. Chetan Kaushik and Atul Mishra [11]-[17] advanced the field by employing a lexicon-based technique, using a domain-specific dictionary of sentiment-bearing words to classify tweets as positive, negative, or neutral. Their approach, implemented on Hadoop, achieved an impressive speed, analyzing 674,412 tweets in just 14.8 seconds, with an accuracy of 73.5%. However, the method was implemented on a single node, and its performance could be improved in a multi-node configuration. Proposed a combined approach for Arabic sentiment analysis, using a lexicon-based method, a maximum entropy model, and k-nearest neighbors (KNN) to classify documents. This multi-method approach achieved an accuracy of 80.29% after refining the results from earlier stages. Lei Zhang *et al* [18]. introduced a hybrid lexicon and learning-based method for Twitter sentiment analysis, using a lexicon-based approach to identify opinionated tweets and a classifier to assign sentiment polarities. Their unsupervised method showed significant improvements in recall and F-score compared to state-of-the-art techniques. Sentiment analysis techniques are broadly divided into machine learning-based and lexicon-based approaches. The machine learning method uses labeled datasets for supervised learning, while unsupervised methods are helpful when labeled data is scarce. The lexicon-based method relies on predefined sentiment lexicons to categorize text according to sentiment and includes both corpus-based and dictionary-based approaches. Deep learning techniques, such as CNNs and LSTM networks, have been successfully applied to sentiment analysis tasks in recent years [19]–[22]. These models often use word embeddings to represent text as sequences of vectors that can be processed by neural networks. CNNs, in particular, have shown effectiveness in feature extraction from text data due to their convolutional layers, which detect complex patterns. Unlike traditional neural networks, CNNs address the issue of vanishing gradients by using sparse connections and smaller filters. The architecture of CNNs includes layers for convolution, pooling, and full connectivity, with each layer modifying the input data in a way that enhances feature detection, making it ideal for NLP tasks like sentiment analysis [23]-[26]. Recent advances in sentiment analysis emphasize hybrid models that combine deep learning with transformer-based techniques. The proposed RoBERTa-BiLSTM, which captures both contextual and sequential information for improved classification [27]-[28]. Additionally developed an aspect-based framework for precise product recommendations, reflecting a trend toward context-aware, hybrid models [29]-[32].

3. METHODS

Sentiment analysis, a technique within natural language processing (NLP), is used to identify whether a piece of text expresses a positive, negative, or neutral opinion. It is commonly employed to assess public

attitudes toward topics, products, and societal issues. This study examines public sentiment surrounding the Grand Ethiopian Renaissance Dam (GERD) by analyzing Twitter data through a structured process can be seen in Figure 1. The workflow starts with collecting tweets via the Tweepy library, focusing on posts in English, Amharic, and Arabic. Human annotators then categorize the tweets based on sentiment polarity: positive, negative, or neutral. The collected tweets undergo preprocessing, including tokenization, removal of stop words, and elimination of irrelevant elements such as URLs, numbers, hashtags, special characters, and emojis. Tweets in non-English languages are translated into English to standardize the dataset. Once cleaned, the dataset is divided into training and testing subsets. For sentiment prediction, the study uses the BERT model to create context-aware word embeddings. These embeddings are passed into a Long Short-Term Memory (LSTM) layer to capture the sequence of words and their relationships. A maximum pooling layer condenses the LSTM output into a fixed-size vector, which is then processed by a convolutional layer to detect local features in the text. A secondary pooling layer refines this output for final feature extraction. The resulting features are fed into a fully connected layer with a softmax function to classify the sentiment of each tweet.

The data collection (Figure 2) process involved gathering tweets from Twitter using specific keywords and hashtags related to the GERD. The selected keywords included #GERD, #Grand Ethiopian Renaissance Dam, #Renaissance Dam, #Ethiopian Dam, #السدالاستطلاعي, and #السدالاثيوبى. The Tweepy library, a Python tool for accessing the Twitter API, was used to collect around 26,000 tweets during the second filling of the GERD, capturing multilingual content. This approach aimed to analyze public sentiment or opinions regarding the dam during this period. The collected data was stored in JSON format for further analysis.

The dataset collected from Twitter on the GERD was filtered to include only English, Arabic, and Amharic tweets. Filtering was performed using Python, selecting tweets based on language codes ("en," "ar," "am"). After filtering, five annotators classified tweets into positive, negative, or neutral sentiments. Disagreements were resolved using majority voting. Preprocessing removed URLs, emojis, and special characters to improve model performance. Word embedding was applied using the multilingual BERT (mBERT) model to convert text into numerical vectors. The dataset was split into training (80 %) and testing (20 %) sets for deep learning model development. The LSTM-CNN hybrid model was chosen for sentiment classification, leveraging LSTM for sequential dependencies and CNN for feature extraction. Training included validation to prevent overfitting, using dropout and parameter tuning. Finally, model performance was evaluated on unseen data to ensure its effectiveness in classifying GERD-related sentiments.
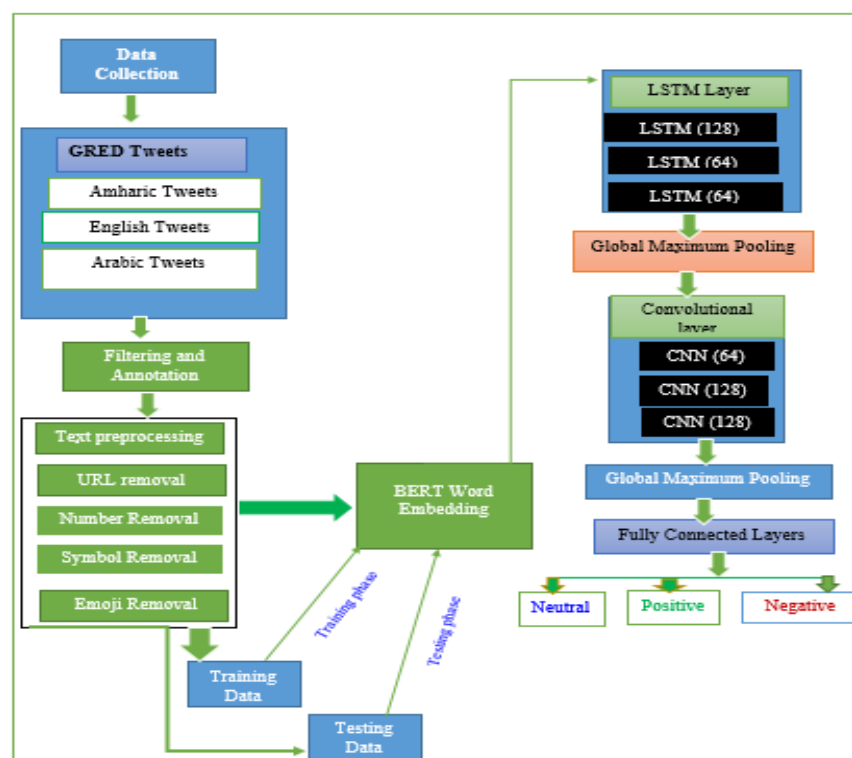

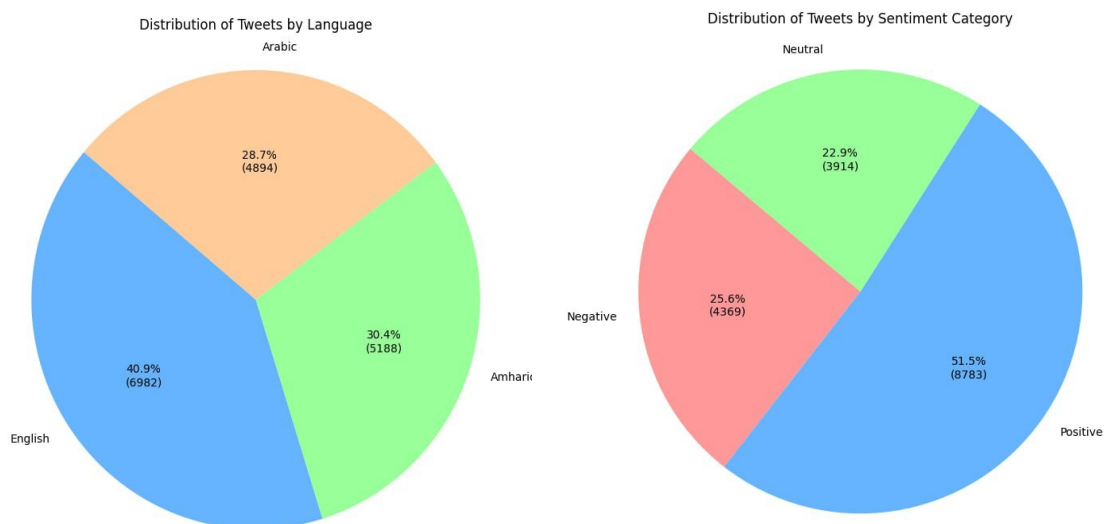**Figure 1.** Proposed System Architecture

Figure 2. Collected data

4. RESULT AND DISCUSSION

The dataset collected from Twitter on the GERD was filtered to include only English, Arabic, and Amharic tweets. Filtering was performed using Python, selecting tweets based on language codes ("en," "ar," "am"). After filtering, five annotators classified tweets into positive, negative, or neutral sentiments. Disagreements were resolved using majority voting. Preprocessing removed URLs, emojis, and special characters to improve model performance. Word embedding was applied using the multilingual BERT (mBERT) model to convert text into numerical vectors. The dataset was split into training (80%) and testing (20%) sets for deep learning model development. The LSTM-CNN hybrid model was chosen for sentiment classification, leveraging LSTM for sequential dependencies and CNN for feature extraction. Training included validation to prevent overfitting, using dropout and parameter tuning. Finally, model performance was evaluated on unseen data to ensure its effectiveness in classifying GERD-related sentiments.

4.1. Dataset Description

Sentiment analysis relies on user comments, opinions, and feelings regarding a specific topic. This article aims to analyze the sentiment of people, particularly those from downstream countries, regarding GERD and its construction. The dataset was collected from Twitter using the Twitter API, with over 30,000 tweets gathered based on relevant keywords and hashtags. The research team used the Tweepy library, a Python-based API, to scrape tweets. After collection, the dataset was filtered to include tweets in English, Arabic, and Amharic. Ultimately, 17,064 tweets were selected for annotation. Each tweet was manually labeled as positive, negative, or neutral. This dataset was then used to develop a multilingual sentiment analysis model.

4.2. Experimental Result

The dataset underwent preprocessing to eliminate irrelevant elements before being divided into training and testing sets, with 80 % allocated for training and 20 % for testing. The models were assessed using standard performance metrics such as accuracy, precision, recall, and loss. To analyze sentiment related to the Grand Ethiopian Renaissance Dam (GERD), three deep learning models were developed: a Convolutional Neural Network (CNN), a Long Short-Term Memory (LSTM) network, and a combined LSTM-CNN model. Training was conducted using a batch size of 46 and a learning rate of 0.001. As the task involves multi-class classification, categorical cross-entropy was used as the loss function, and the Adam optimizer was chosen for model optimization. The CNN architecture included an input layer followed by a BERT-based embedding layer. It then passed through three convolutional layers with 64, 128, and 256 filters, each using a kernel size of three. A pooling layer and dropout layer were added to reduce overfitting, and a final dense layer with a SoftMax activation function was used to output sentiment categories. This model achieved a training accuracy of 91.25% and a validation accuracy of 88.63%. The LSTM model utilized a two-layer architecture, drawing input from multilingual BERT (mBERT) embeddings. The first LSTM layer contained 128 units and generated a sequence of hidden states, while the second layer had 64 units. A dropout rate of 0.5 was applied. Trained on 11,252 tweets, the model achieved a training accuracy of 89.81% and a validation accuracy of 86.05%.

4.3. Model Evaluation Results

The model is evaluated on a test set comprising 2,814 tweets. The confusion matrices for LSTM-CNN models are shown Figure 3. For Arabic tweets, the LSTM-CNN model predicted 2,817 tweets as Negative, 633 as Positive, and 444 as Neutral. The evaluation metrics showed an accuracy of 75.5%, a precision of 79.6%, a recall of 75.4%, and anF1-score of 80.9% can be seen in Figure 4.
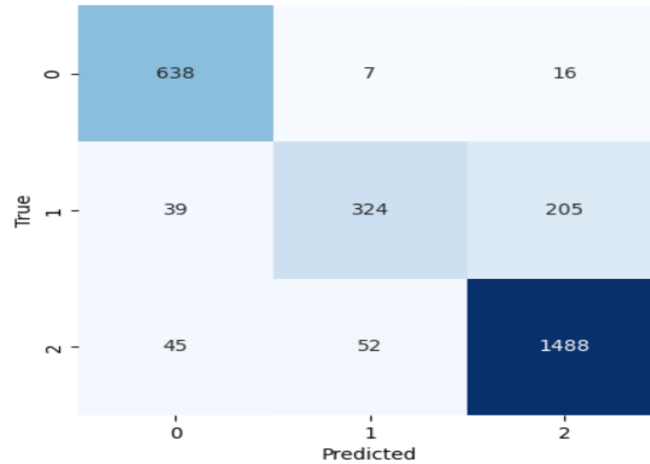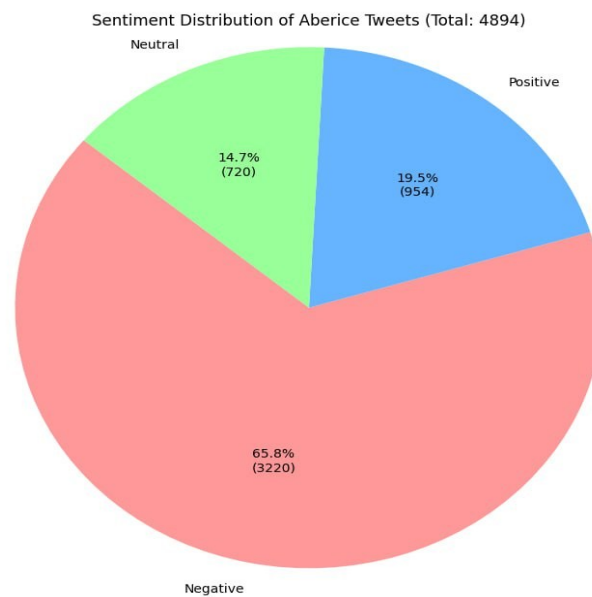

Figure 3. Confusion Matrix for LSTM-CNN

Figure 4. Evaluation of Arabic Tweets

4.4. Model Comparison

A comparison of training accuracy, test accuracy, precision, recall, and F1-score for the three models is provided Table 1 and Figure 5.

Table 1. Model Performance Comparison

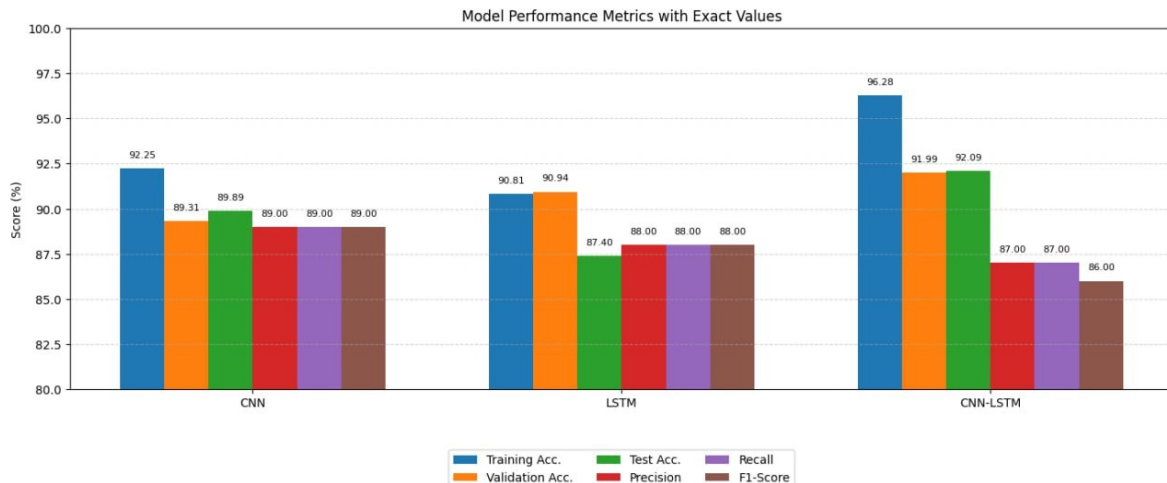| Model	Training Accuracy	Validation Accuracy	Test Accuracy	Precision	Recall	F1-Score
CNN	92.25	89.31	89.89	89	89	89
LSTM	90.81	90.94	87.40	88	88	88
CNN-LSTM	96.28	91.99	92.09	87	87	86

Figure 5. Model Performance Comparison

5. DISCUSSION

A dataset comprising 30,000 unlabeled tweets was gathered in 2024 G.C., from which 17,064 were categorized into positive, negative, or neutral sentiments. This study explores and compares three multilingual sentiment analysis models, CNN, LSTM, and a hybrid LSTM-CNN, applied to these labeled tweets in Amharic, Arabic, and English. The data was divided into 13,651 tweets for training and the remainder 3,413 for testing. The CNN model achieved 91.25% training accuracy and 89% testing accuracy. The LSTM model performed closely with training and testing accuracies of 89.81% and 88%, respectively. The hybrid LSTM-CNN model demonstrated the best performance, achieving 94.28% training accuracy and 91% testing accuracy. Despite its superior accuracy, the hybrid model exhibited slightly lower precision, recall, and F1-score compared to the individual CNN and LSTM models. Notably, it improved testing accuracy by 5.76% over the standalone models, thanks to its ability to combine local and sequential feature extraction. The study also highlights the effectiveness of multilingual BERT (mBERT) embeddings in handling sentiment analysis across languages. For instance, analysis of 4,894 Arabic tweets revealed 72% were negative, 16% positive, and 11% neutral, with an overall classification accuracy of 77.5%. In contrast, among 5,982 English tweets, 49.5% were positive, 41.3% neutral, and 9.2% negative. These findings suggest a predominantly negative sentiment in Arabic tweets about GERD, while English tweets were more balanced. Although the hybrid model proved effective, further research with larger and more diverse datasets is necessary to enhance accuracy and generalizability.

6. CONCLUSION

This study presents and evaluates three multilingual sentiment analysis models for assessing public opinion on the Grand Ethiopian Renaissance Dam (GERD), using a dataset of 17,064 tweets written in Amharic, Arabic, and English. From the total, 11,252 tweets were used for training, with the remainder reserved for testing. The Convolutional Neural Network (CNN) model achieved 91.25% training accuracy and 89% testing accuracy. The Long Short-Term Memory (LSTM) model followed closely with 89.81% training accuracy and 88% on the test set. The hybrid LSTM-CNN model, combining the strengths of both approaches, attained the highest training accuracy of 94.28% and a testing accuracy of 91%, though its precision, recall, and F1-score were slightly lower. The combined CNN-LSTM architecture enhanced testing accuracy by 4.76% compared to the standalone models due to improved feature extraction capabilities. Additionally, the study demonstrates the effectiveness of multilingual BERT (mBERT) embeddings for sentiment classification across languages. Analysis of 3,894 Arabic tweets showed that 72% were negative, 16% positive, and 11% neutral, with an overall accuracy of 77.5%. For 5,982 English tweets, 49.5% were positive, 41.3% neutral, and 9.2% negative. These results indicate that Arabic tweets tend to reflect more negative sentiment about GERD, whereas English tweets show a more balanced or positive tone. While the CNN-LSTM model shows promise, further research with larger and more diverse datasets is recommended to enhance performance and generalizability.

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