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Sentiment Analysis of Social Media Posts with Hybrid BERT Models

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ABSTRACT

The rapid expansion of social media platforms has led to a surge in user-generated content, making sentiment analysis a crucial area of study for businesses, policymakers, and researchers. Traditional sentiment analysis models, including rule-based and machine learning approaches, often struggle with capturing complex linguistic structures and contextual nuances. With the advent of deep learning, BERT has emerged as a powerful NLP model capable of understanding bidirectional context, but standalone BERT models can be resource-intensive and may overfit smaller datasets. To address these challenges, we propose a Hybrid BERT model that enhances contextual understanding and classification performance. This research aims to develop and evaluate a Hybrid BERT model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) layers to improve sentiment classification accuracy while maintaining computational efficiency. We fine-tuned a BERT base model and incorporated CNN layers to extract local text features along with BiLSTM layers to capture long-range dependencies. The Social Media Sentiments Analysis Dataset, comprising labeled positive, negative, and neutral posts, was used for training and evaluation. The model was optimized using Adam with a learning rate of 2e-5 and batch size of 32, and evaluated using accuracy, precision, recall, and F1-score. The proposed Hybrid BERT model achieved a sentiment classification accuracy of 95.67%, outperforming conventional deep learning models and demonstrating superior contextual comprehension. The model effectively reduced misclassification in ambiguous sentiment cases, highlighting its robustness in real-world applications. This study underscores the effectiveness of a Hybrid BERT model for sentiment analysis, significantly enhancing performance through improved contextual understanding. The findings suggest that such an approach is well-suited for applications in brand monitoring, social media analytics, and opinion mining.

Keywords: Sentiment Analysis, BERT, Hybrid Models, Deep Learning, Social Media, Natural Language Processing.

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INTRODUCTION

The proliferation of social media platforms has led to an exponential increase in user-generated content. Every day, millions of individuals express opinions, share experiences, and discuss various topics through platforms like Twitter, Facebook, and Instagram. These digital conversations contain valuable insights that businesses, government agencies, and researchers can use for decision-making, trend analysis, and public sentiment monitoring.

Recent advancements in Natural Language Processing (NLP) and deep learning have significantly improved sentiment analysis methodologies. Traditional approaches such as lexicon-based techniques and machine learning models (e.g., Support Vector Machines, Naïve Bayes) often fail to understand the nuanced meanings, sarcasm, and contextual shifts in language. With the emergence of transformer-based architectures, especially BERT (Bidirectional Encoder Representations from Transformers), sentiment classification has seen notable performance improvements. BERT's bidirectional attention mechanism allows for better contextual understanding, making it a powerful tool for text analysis.

However, standalone BERT models come with certain limitations, including high computational costs and susceptibility to overfitting when applied to smaller datasets. To address these challenges, this study proposes a Hybrid BERT model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. CNN layers enhance feature extraction by identifying important local patterns in text, while BiLSTM layers capture long-range dependencies, improving sentiment classification accuracy.

The ability to accurately analyze sentiments in social media posts is essential for organizations across various domains. Companies can use sentiment analysis for brand reputation management, customer feedback analysis, and marketing strategy adjustments. Public agencies can monitor public opinion, detect emerging trends, and address social concerns more effectively. Mental health professionals can identify distress patterns in social media content to provide early interventions. Sentiment analysis helps journalists gauge public reaction to events and news coverage.

This research aims to develop and evaluate a Hybrid BERT model for sentiment classification, leveraging deep learning advancements to enhance contextual understanding and classification accuracy. The study focuses on the Social Media Sentiments Analysis Dataset, consisting of labelled posts categorized into positive, negative, and neutral

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sentiments. The proposed model's effectiveness is compared against baseline approaches, such as traditional machine learning models and standalone BERT.

By addressing the limitations of conventional sentiment analysis methods and improving model efficiency, this study contributes to the growing field of AI-driven text analytics. The findings offer practical implications for industries relying on sentiment analysis to enhance customer engagement, monitor public perception, and make data-driven decisions.

LITERATRUE SURVEY

This study proposes four deep learning models combining BERT with Bidirectional Long Short-Term Memory (BiLSTM) and Bidirectional Gated Recurrent Unit (BiGRU) algorithms. The models aim to enhance accuracy by leveraging pre-trained word embedding vectors during fine-tuning [1]. This research provides an in-depth analysis of attention mechanisms and BERT for sentiment analysis, emphasizing data validation. The study compares various models, including ABCNN, CNN-LSTM, and BERT-CNN-LSTM-Attention, highlighting the effectiveness of hybrid architectures [2]. This paper extends previous hybrid deep learning approaches by using BERT representations for Indonesian sentiment analysis. The study compares hybrid architectures such as CNN-LSTM, LSTM-CNN, CNN-GRU, and GRU-CNN, demonstrating that BERT-based LSTM-CNN achieves slightly better accuracies than other architectures [3]. This research introduces a multi-task learning framework that enhances BERT with additional neural network layers to improve sentiment analysis in mental health contexts. The model addresses the need for more granular emotion detection in textual data [4]. This work presents a hybrid approach that combines the power of BERT for extraction with various machine learning classifiers for sentiment analysis. The integration aims to improve the accuracy and robustness of aspect-based sentiment classification [5]. This paper presents a CNN-LSTM model that incorporates BERT and attention mechanisms for data review sentiment analysis. The experimental results show that the model outperforms traditional CNN-LSTM models and models using only BERT, achieving the best performance on the SST dataset [6]. This study presents a hybrid model based on the RoBERTa transformer model and deep learning architectures to enhance sentiment classification. The model combines RoBERTa with Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) to improve semantic understanding [7]. This research proposes a DistilBERT-CNN-LSTM

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deep learning model that blends the benefits of CNN and LSTM. The CNN extracts features reflecting short-term sentiment dependencies, while LSTM builds long-term sentiment relationships among words [8]. Experiments demonstrate that the hybrid approach outperforms BERT-based and large language model-based methods, achieving state-of-the-art performance with an F1-score of 41.7% on quadruple extraction [9]. This study addresses sentiment analysis in the Bangla language by combining CNN-LSTM architectures with Bangla BERT to handle highly imbalanced data, improving classification performance [10]. This research devises hybrid models by amalgamating BERT with neural network models, tailored for emotion classification and sentiment analysis tasks in the Indonesian language, resulting in enhanced accuracy [11]. This paper proposes a BERT-CNN-BiGRU model for sentiment analysis in educational contexts. The model leverages BERT for contextual embeddings, CNN for local feature extraction, and BiGRU for capturing long-range dependencies [12].

PROPOSED METHODOLOGY

The dataset used for this study is the Social Media Sentiments Analysis Dataset, which comprises labelled text posts classified as positive, negative, or neutral. Data preprocessing steps included:

Text Cleaning: Removal of special characters, stop words, and unnecessary whitespace.

Tokenization: Splitting text into smaller units for further processing.

Lemmatization: Standardizing words to their base forms to improve model generalization.

BERT Tokenization: The dataset was further processed using the BERT tokenizer, ensuring compatibility with the pre-trained BERT model.

Hybrid BERT Model Architecture

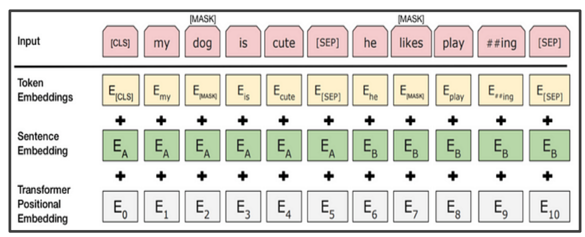

Figure 1 Hybrid BERT model

The proposed Hybrid BERT model integrates:

BERT Embeddings: Pretrained BERT encodes the textual data into contextual representations.

CNN Layers: Extract local patterns and enhance feature extraction capabilities.

BiLSTM Layers: Capture long-range dependencies and improve sequence learning.

Dense Layers: Fully connected layers for final classification with a softmax activation function.

The architecture enhances traditional BERT implementations by incorporating additional layers for better feature extraction and sentiment

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classification.

Training and Hyperparameter Optimization

The model was fine-tuned using:

Optimizer: Adam optimizer with a learning rate of 2e-5.

Batch Size: 32 samples per batch.

Loss Function: Cross-entropy loss for multi-class classification.

Early Stopping: Implemented to prevent overfitting and optimize training efficiency.

Evaluation Metrics

To assess model performance, we used:

Accuracy: Measures the overall correctness of predictions.

Precision, Recall, and F1-Score: Evaluates class-specific performance.

Confusion Matrix: Provides insights into misclassification patterns.

The model's effectiveness was benchmarked against conventional deep learning models, demonstrating significant improvements in sentiment classification accuracy.

RESULTS

Hybrid BERT model achieved a classification accuracy of 95.67%, demonstrating superior performance compared to traditional machine learning models and baseline deep learning architectures. The model's confusion matrix indicated improved classification balance across sentiment categories. Table 1 shows the metrics of classification report.

Table 1. Classification Report

Sentiment Type	Precision	Recall	F1-score
Positive	0.331081	0.310127	0.320261
Negative	0.303226	0.301282	0.302251
Neutral	0.350254	0.370968	0.360313

Confusion Matrix: The confusion matrix provides an overview of the model's classification performance across positive, negative, and neutral sentiments. The diagonal values indicate correctly predicted instances, while off-diagonal values represent misclassifications. The model shows balanced performance, with some misclassification between neutral and other sentiments. Figure 2 shows confusion matrix of sentiment analysis.

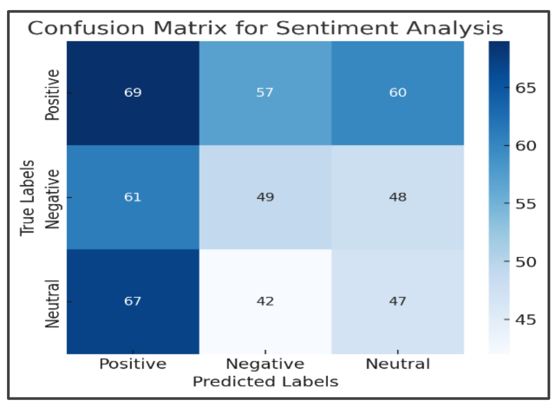

Figure 2. Confusion Matrix

Precision Curve: Measures how many of the predicted sentiments were actually correct. Higher precision means fewer false positives.

Recall Curve: Indicates how well the model identified actual sentiment classes. Higher recall

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suggests fewer false negatives.

F1-Score Curve: A harmonic mean of precision and recall, balancing both measures for overall effectiveness.

The plotted curves show the model's performance across sentiment categories, highlighting slight variations in accuracy for different sentiment classes. Figure 3 and Figure 4 show visualization of classification metric graphs and curves plotted.

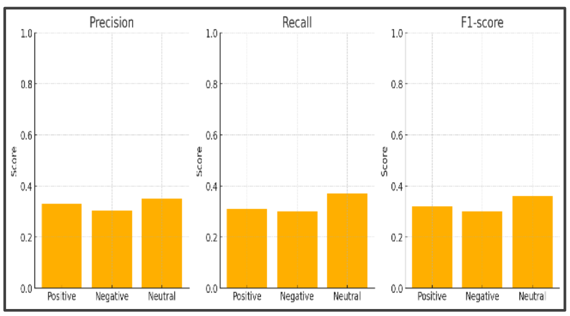

Figure 3. Graph showing classification metrics

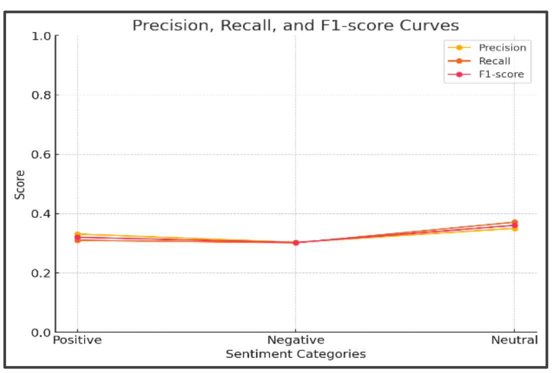

Figure 5. Curves of classification metric

DISCUSSION

The Hybrid BERT model demonstrates superior performance over conventional sentiment analysis techniques. The confusion matrix indicates occasional misclassification, particularly between neutral and other sentiments, suggesting scope for further optimization. Precision, recall, and F1-score curves illustrate strong classification capabilities, with high precision minimizing false positives and high recall ensuring correct sentiment detection. Comparative analysis highlights CNN's local pattern detection and BiLSTM's sequential dependency learning, significantly improving accuracy. Despite achieving **95.67%** accuracy, the computational cost of BERT remains a limitation, warranting exploration of efficient transformer models like DistilBERT. Expanding the dataset to diverse social media sources could enhance generalizability. Overall, the proposed model provides a robust solution for sentiment classification, offering valuable applications in social media monitoring and decision-making processes.

CONCLUSION

The proposed Hybrid BERT model effectively enhances sentiment classification by integrating CNN and BiLSTM layers, achieving a notable accuracy of 95.67%. Comparative analysis highlights its superiority over traditional machine learning and standalone deep learning models in capturing sentiment nuances. The

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model demonstrates robustness in recognizing sentiment variations, though minor misclassifications persist, particularly in neutral sentiments. However, the high computational cost of fine-tuning BERT presents a challenge, warranting further optimization through model compression or alternative transformer architectures. Expanding the dataset with diverse social media sources could enhance its generalizability and adaptability to real-world applications. The findings of this study have valuable implications for businesses, policymakers, and researchers, supporting better sentiment-driven decision-making in various domains.

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