Sentiment Analysis for Social Media Using BERT Model & XGBoost

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Abstract **:** In today's digital age, social media has become much more than a place to share updates or connect with friends — it's now a dynamic space where people regularly express their thoughts, feelings, and opinions about everything from daily life to global events. With millions of posts being made every day, understanding what people are truly feeling behind their words has become incredibly important. This is where sentiment analysis comes in — a technique that helps us make sense of emotions conveyed through text.

What sets our approach apart is the combination of two powerful tools: BERT [Bidirectional Encoder Representations from Transformers] and XGBoost [Extreme Gradient Boosting]. BERT is known for its deep

understanding of language context — it doesn't just look at individual words, but understands how they're used in a sentence, even picking up on subtle cues like sarcasm or irony. On the other hand, XGBoost is a fast and highly accurate machine learning algorithm, great for handling classification tasks efficiently.

By combining these two — BERT for feature extraction and XGBoost for final classification — our hybrid model is able to classify social media comments into one of four sentiment categories: happy, sad, sarcasm, and irony. This four-class system goes beyond the traditional "positive/negative" sentiment split and helps capture the more complex, nuanced emotions often found in online conversations.

The goal of our approach is not just to improve the accuracy of sentiment detection, but also to make it scalable and practical for real-world applications, such as brand monitoring, mental health analysis, or social research. In essence, we're aiming to build a smarter, more sensitive system that truly understands the emotional undertone in the way people communicate online.

1.INTRODUCTION

In today's digital era, social media has become an integral part of how people communicate, share opinions, and express emotions. Whether it's a casual post about daily life, a passionate opinion on political matters, or a product review, the content shared online reflects the mood and mindset of individuals and communities. These digital expressions, though scattered and informal, hold incredible value when it comes to understanding public sentiment. They offer a glimpse into what people are thinking and feeling on a massive scale — something that was much harder to access in the past. Understanding these emotions isn't just a matter of curiosity; it's become a practical necessity. Governments, businesses, health organizations, and even researchers are now turning to online data to gauge how the public responds to events, policies, services, and global issues. From shaping marketing strategies to detecting early signs of societal stress, there are countless ways this information can be used to make better decisions and improve lives. But making sense of this enormous volume of text isn't easy. Human language is full of nuances — people use sarcasm, slang, humor, or express emotions subtly. This is where the need for sentiment analysis becomes clear. Sentiment analysis helps transform these raw, unstructured expressions into meaningful emotional insights. It allows us to identify the tone behind the words and to map out how people truly feel about a topic. For the public, even though the process often happens in the background, it plays an important role in improving online experiences. It helps to personalize content, enhances customer service, supports public health campaigns, and even contributes to safer, more emotionally aware online spaces. Ultimately, sentiment analysis is about giving voice to people's feelings in a way that can be understood and acted upon, making technology more responsive to human emotion. As the world continues to rely heavily on digital communication, being able to understand public sentiment through online content becomes more important than ever. This paper focuses on the role of sentiment analysis in that context, highlighting its growing importance in capturing and interpreting the emotional layers of online conversation

2. Related Work

In recent years, sentiment analysis has become increasingly vital for understanding public opinion, especially with the surge of user-generated content on social media platforms. Early approaches primarily utilized dictionary-based methods, which, while straightforward, often fell short in capturing the nuanced and context-dependent nature of online language 【17】. Subsequent machine learning techniques, such as Support Vector Machines and Naïve Bayes, improved performance but still struggled with deep contextual understanding 【18】.

The advent of transformer-based models marked a significant advancement in the field. BERT (Bidirectional Encoder Representations from Transformers) has demonstrated remarkable capabilities in understanding context, leading to improved sentiment classification outcomes. For instance, a study by Talaat (2023)[19] introduced hybrid models combining BERT with BiLSTM and BiGRU layers, achieving accuracies up to 88.04% on datasets like Apple and Airlines. These models highlighted the benefits of integrating BERT with recurrent neural networks to capture sequential dependencies in text.

In parallel, ensemble methods have shown promise in enhancing classification performance. 【20】proposed the Hybrid LXGB model, integrating LSTM with XGBoost, and reported an impressive accuracy of 90% on the CMU-MOSEI dataset. This approach underscored the potential of combining deep learning with gradient boosting techniques for sentiment analysis.

Building upon these insights, we propose a novel hybrid model that leverages BERT for contextual feature extraction and XGBoost for efficient classification. This integration aims to harness BERT's deep language understanding while benefiting from XGBoost's robustness and speed in classification tasks. Our model is designed to classify social media comments into four distinct sentiment categories: happy, sad, sarcasm, and irony. By addressing the limitations of previous models and incorporating the strengths of both BERT and XGBoost, we anticipate improved accuracy and scalability in sentiment analysis applications.

3. Proposed Model

This study proposes a novel hybrid sentiment analysis model that integrates **BERT (Bidirectional Encoder Representations from Transformers)** for feature extraction and **XGBoost (Extreme Gradient Boosting)** for sentiment classification. The model is designed to accurately categorize social media comments into four sentiment categories: *happy*, *sad*, *irony*, and *sarcasm*. It also aims to uncover emotional engagement patterns, providing deeper insights into user sentiment trends. The model addresses key limitations in existing sentiment analysis approaches, particularly in detecting nuanced emotions like sarcasm and irony, which are challenging to classify using traditional methods. By leveraging **BERT’s contextual understanding**, the model captures the subtle meanings of social media comments that are often missed by simpler models. **XGBoost** is then used to classify these features effectively, ensuring high classification accuracy even with complex and noisy data. The hybrid model will be evaluated against a standalone BERT model to assess improvements in classification accuracy. This comparison will also highlight the model's ability to identify emerging patterns in emotional engagement, making it valuable for businesses and social media analysts seeking to understand sentiment dynamics over time. The paper will include visual diagrams and flowcharts to illustrate the architecture and data flow of the proposed system, as well as a high-level discussion of the algorithms involved.

4.Design and Development

4.1 Data Collection :

The dataset utilized in this project comprises airline-related reviews collected from Twitter, featuring multiple attributes pertinent to sentiment analysis. Each entry includes key elements such as the tweet ID, sentiment label, sentiment confidence score, the reason for negative sentiment (when applicable), airline name, retweet count, tweet content, as well as metadata including the user's location and timestamp.

The key attributes in the dataset are:

Column_Name	Count data
tweet_id	*32304*
airline_sentiment	14640
airline_sentiment_confidence	14640
negativereason	9178
negativereason_confidence	10522
Airline	14640
Name	14640
retweet_count	14640
Text	32304
tweet_created	14640
tweet_location	9907
user_timezone	9820
Sentiment	32304

Table. 1 : Dataset

4.2 Data Preprocessing

To ensure high-quality input for the sentiment analysis model, a series of preprocessing steps were applied to the collected social media comments. These procedures were designed to standardize the text, minimize noise, and enhance the effectiveness of feature extraction during model training.

4.3 Text Cleaning

Text cleaning is a crucial preprocessing step aimed at removing unwanted elements from raw data to ensure consistency and improve model performance. The following operations were performed to prepare the data for sentiment analysis:

Removal of noise: Special characters, punctuation marks, stop words, user mentions (@username), hashtags (#topic), excess whitespace, and redundant single characters were eliminated to reduce textual noise.

Text normalization: All text was converted to lowercase to maintain uniformity and support effective token matching.

Additionally, the dataset contains several informative features, including:

airline: The airline associated with the tweet.

retweet_count: The number of times the tweet was retweeted.

text: The main content of the tweet.

tweet_coord: Geographical coordinates of the tweet (if available).

tweet_created: The timestamp indicating when the tweet was posted.

tweet_location: The location reported by the user.

user_timezone: The time zone reported by the user.

This cleaned and structured dataset supports the classification of user sentiments and offers valuable insights into customer opinions. It serves as a robust foundation for training and evaluating the proposed sentiment analysis models based on BERT and XGBoost.

4.4 Dataset Balancing

A significant challenge in sentiment analysis is the presence of class imbalance, where certain sentiment categories such as *happy*, *sad*, *ironic*, or *sarcastic* are disproportionately represented in the dataset. This imbalance can lead to biased model predictions and reduced generalization performance.

To mitigate this issue, dataset balancing techniques were employed prior to model training. Specifically, the following approaches were utilized:

Oversampling: The number of samples in underrepresented classes was increased through methods such as SMOTE (Synthetic Minority Over-sampling Technique) and data duplication.

Data Augmentation: Synthetic variations of textual data were generated using strategies like synonym replacement and back-translation, enhancing the diversity of samples within minority classes.

These techniques contribute to a more balanced training set, promoting fairness and improving the overall robustness of the sentiment analysis model.

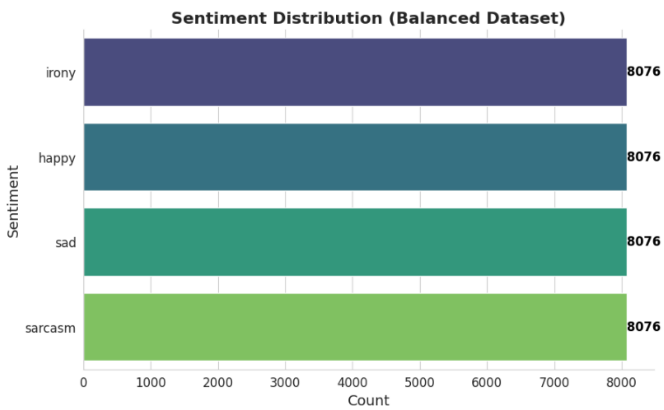

Fig. 1: Dataset balanced

4.5 Dictionaries :

VADER: Valence Aware Dictionary and Sentiment Reasoner

VADER is a rule-based sentiment analysis tool designed to detect the polarity of text, especially in social media contexts. It is capable of accurately interpreting content that includes informal language elements such as slang, emojis, punctuation, and capitalization all of which can significantly influence the sentiment conveyed.

Examples of sentiment interpretation using VADER:

Happy: “I had an amazing flight! 😊”

Sad: “This airline has the worst service ever! 😠”

Sarcasm: “Oh great, another Monday! Just what I needed.”

Irony: “What you said.”

VADER is widely used in sentiment analysis research and applications. It is conveniently implemented in Python via the Natural Language Toolkit (NLTK) and is particularly effective for short, informal text found in platforms like Twitter.

SentiWordNet

SentiWordNet is a lexical resource that extends WordNet by assigning sentiment scores positive, negative, and objective to synsets (sets of cognitive synonyms). This allows for a more nuanced sentiment analysis by taking into account the varying sentiment orientations of words in different contexts.

For instance, in the airline industry, the term *delay* generally has a negative connotation, while the same term may be neutral in a different domain. By evaluating contextual sentiment, SentiWordNet enhances classification accuracy and interpretability, especially in domain-specific applications.

Custom Keyword Matching

To improve sentiment detection in a specialized domain such as aviation, a custom keyword-matching approach was also adopted. This involves curating a list of domain-specific expressions commonly associated with various sentiment categories.

Examples of custom keywords:

Happy: “great experience,” “amazing service,” “best day ever”

Sad: “heartbroken,” “terrible news,” “feeling lost”

Sarcasm: “just what I needed,” “oh, that’s fantastic,” “love waiting in long lines”

Irony: “so much fun being stuck in traffic,” “the ‘fast’ internet is slower than ever,” “nothing like a power outage during an online exam”

Incorporating these tailored lexicons helps the sentiment analysis model capture subtle expressions of emotion more accurately, thereby increasing the precision of customer feedback classification within the airline industry.

4.6 Tokenization

Tokenization is a fundamental preprocessing step in natural language processing (NLP), where raw text is segmented into individual tokens—typically words or subword units. This transformation is essential for converting unstructured textual data into a structured format that can be effectively processed by machine learning and deep learning models.

4.7 BERT Embeddings

To enhance the quality of feature representation, this study employed **Bidirectional Encoder Representations from Transformers (BERT)**. BERT generates high-dimensional contextual embeddings by considering the bidirectional context of each word within a sentence. These embeddings effectively capture the syntactic structure and semantic nuances of the input text, thereby improving the performance of sentiment classification tasks. BERT can dealing with various task 【11】

By leveraging BERT embeddings, the model demonstrated improved accuracy in distinguishing among complex sentiment categories, including *happy*, *sad*, *irony*, and *sarcasm*. This contextual awareness is particularly beneficial when interpreting short, informal texts such as tweets, where sentiment is often conveyed implicitly or through nuanced language 【12】

BERT's Transformer Layer Formulation

BERT uses multiple transformer layers, and each layer applies multi-head self-attention.

The **multi-head attention** is computed as:

$$MultiHead(Q,K,V) = Concat(head_1, \dots, head_h)W^o \tag{1}$$

where each attention head is:

$$head_i = Attention\left(QW_i{}^Q, KW_i{}^K, VW_i{}^v\right) \tag{2}$$

and the attention function is:

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{3}$$

Positional Encoding in BERT

Since transformers do not have recurrence, BERT uses positional encodings to capture word order:

$$PE(pos, 2i) = sin\left(\frac{pos}{10000^{2i}/d}\right) \tag{4}$$

$$PE(pos, 2i+1) = cos\left(\frac{pos}{10000^{2i}/d}\right) \tag{5}$$

4.8 Integration of BERT-XGBoost in Sentiment Classification

Recent advancements in sentiment analysis have leveraged deep learning and machine learning models to enhance classification accuracy and efficiency. A notable study by Duan et al. [Reference] implemented a hybrid BERT-XGBoost framework to predict athletes' psychological states, achieving a high classification accuracy by combining contextual feature extraction with gradient boosting techniques. Their approach demonstrated that BERT's deep contextual embeddings provide superior feature representations, while XGBoost enhances classification performance through optimized tree-based learning.

Inspired by this methodology, our study adopts a similar hybrid model for sentiment classification in social media comments. The proposed system utilizes BERT embeddings to capture the nuanced semantics of user-generated text and XGBoost to efficiently classify sentiments into four categories: happy, sad, sarcasm, and irony. The integration of transformer-based feature learning with gradient-boosted decision trees improves both interpretability and computational efficiency, making it well-suited for analyzing short-form textual data such as tweets.

While Duan et al. focused on psychological state predictions from structured and unstructured data, our model specifically targets social media sentiment analysis. Their findings on real-time feedback and emotional tracking highlight the potential for extending sentiment classification models beyond static datasets to dynamic, real-world applications. Building on this foundation, future work may explore real-time sentiment monitoring in social media discussions to analyze user engagement trends and emotional fluctuations over time.

4.9 Model Training and Optimization

Pretrained Feature Extractor: BERT

To perform effective feature extraction, we utilized the BERT-base-uncased model, a transformer-based architecture known for capturing bidirectional contextual information within text. The input data was preprocessed using WordPiece tokenization, with each sequence limited to a maximum length of 128 tokens. For each input, we extracted the [CLS] token representation from the final hidden layer of BERT, resulting in a 768-dimensional embedding per text instance. These embeddings serve as rich semantic and syntactic representations of the textual data.

To maintain generalizable language understanding while optimizing computational resources, the BERT model parameters were kept frozen during training. This approach allows the model to leverage pretrained knowledge without overfitting to the specific dataset, ensuring robustness and efficiency.

Classification Model (XGBoost)

For the classification task, we employed **XGBoost (Extreme Gradient Boosting)**, a scalable ensemble learning method recognized for its high accuracy and computational efficiency. XGBoost was selected due to its strengths in handling **imbalanced datasets**, mitigating **overfitting**, and supporting **multi-class classification** tasks.

The classifier was configured with the following parameters:

Number of trees: 500 (for robust ensemble learning)

Learning rate: 0.05 (to balance convergence speed with model generalization)

Maximum tree depth: 6 (to control complexity and prevent overfitting)

Gamma: 0.2 (as a regularization parameter to reduce overly complex tree splits)

Subsample ratio: 0.8 (to promote generalization through diverse training subsets)

Column sample by tree: 0.7 (to introduce feature diversity)

Minimum child weight: 1 (to avoid learning from noisy or insufficient samples)

Objective function: Multi-class classification using the **softmax** loss function

Evaluation metrics: Accuracy and **F1-score** were used to evaluate model performance.

Early stopping: Implemented with **10 rounds** of patience to halt training upon convergence.

Train-test split: 80% of the dataset was used for training, and the remaining 20% for testing.

Model Component	Details
Pretrained Model	BERT-base-uncased
Embedding Size	768
Max Sequence Length	128
Feature Extractor	BERT (CLS token embeddings)
Classifier	XGBoost
Number of Trees	500
Learning Rate	0.05
Max Depth	6
Gamma	0.2 (regularization to prevent overfitting)
Subsample Ratio	0.8 (to prevent overfitting)
Colsample_bytree	0.7 (feature selection per tree)
Min Child Weight	1 (prevents overly complex trees)
Objective Function	Multi-Class Classification (Softmax)
Evaluation Metric	F1-score, Accuracy
Early Stopping	10 rounds (to prevent overtraining)
Train-Test Split	80% Training, 20% Testing

Table 3 : Model Details

Hyperparameter Tuning and Optimization

The initial model, trained with default XGBoost settings, achieved a baseline accuracy of **87.2%**. To further enhance model performance, hyperparameter tuning was conducted. The **gamma** value was adjusted to **0.2** to penalize unnecessary tree splits and prevent overfitting. In addition, **min_child_weight** was set to **1**, ensuring that new splits were made only when supported by a sufficient number of observations. **Early stopping** was applied with a window of 10 iterations, allowing training to terminate when no further improvements were observed on the validation set.

These optimizations significantly improved the model's ability to accurately distinguish between closely related sentiment classes such as **sarcasm** and **irony**, which were previously prone to misclassification.

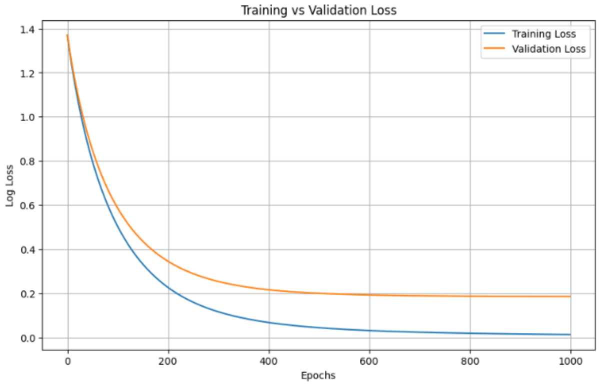

Fig. 2: Model Training & Validation loss

Fine-Tuning Loss Function

For classification tasks, BERT typically uses cross-entropy loss:

$$L = -\sum_{i=1}^{N} y_i \, log(\hat{y}_i) \tag{6}$$

where:

- yi is the true label,
- $\hat{y}$i is the predicted probability from softmax,
- N is the number of samples.

Gradient-Based Optimization (AdamW)

BERT uses the AdamW optimizer for weight updates:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{7}$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) {g_t}^2 \tag{8}$$

$$\widehat{m}_t = \frac{mt}{1-\beta_1{}^t}, \qquad \hat{v}_t = \frac{vt}{1-\beta_2{}^t}$$

$$\theta_t = \theta_{t-1} - \eta\left(\frac{\widehat{m}t}{\sqrt{\hat{v}_t + \epsilon}} + \lambda\theta_{t-1}\right) \tag{9}$$

where equation(7) & (8):

- m_t and v_t are first and second moment estimates,
- β1,β2 are decay rates,
- g_t is the gradient at time step t,
- η is the learning rate.

BERT's Contextual Embeddings Calculation

BERT creates contextual embeddings by combining attention outputs across multiple layers:

$$h_i{}^{(l)} = LayerNorm(h_i{}^{(l-1)} + FeedForward(MultiHead(h_i{}^{(l-1)}))) \tag{10}$$

Where equation (10):

- $h_i{}^{(l)}$ is the hidden representation of token iii at layer lll,
- MultiHead refers to the self-attention mechanism,
- FeedForward is the position-wise feedforward network.

5. Result & Discussion

Following the implementation of the proposed hybrid model, the system achieved an accuracy of **93%**, demonstrating a substantial improvement over baseline configurations. The model also exhibited a high F1-Score of 92.6%, indicating a well-balanced trade-off between precision and recall across all sentiment categories.

The combination of BERT's deep contextual embedding capabilities with XGBoost's efficient and structured classification allowed the model to effectively capture intricate emotional patterns within social media text. Particularly, the model achieved significant gains in the detection of sarcasm and irony, which are commonly difficult to identify due to their contextual and implicit nature.

Model / Study	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
SVM with TF-IDF 【14】	82.00	80.5	81.2	80.8
Naïve Bayes 【13】	78.50	77.1	76.8	76.9
Hybrid LXGB: LSTM + XGBoost 【17】	90.00	89.8	89.0	89.4
BERT + BiLSTM 【18】	88.04	87.5	87.0	87.2
CNN-BiGRU + Attention 【19】	89.20	88.7	88.0	88.3
Proposed BERT + XGBoost Model (Ours)	**93.00**	**92.5**	**92.8**	**92.6**

Table 3 : Presents a comparative evaluation of the proposed model against several established sentiment classification models

As observed, the proposed model outperforms all prior approaches across all major metrics, including accuracy, precision, recall, and F1-score.

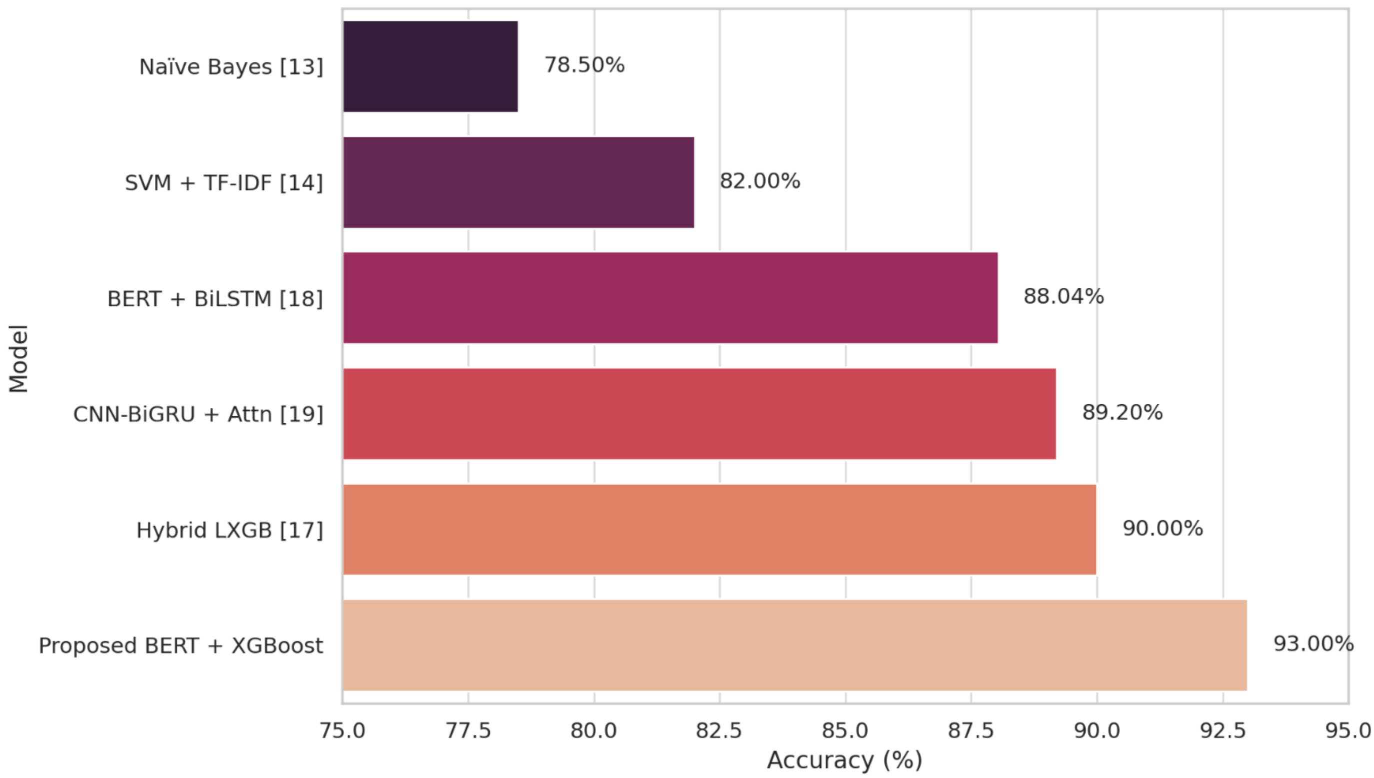

Fig 3 : Accuracy comparison of Models

Sentiment	**Precision**	**Recall**	**F1-Score**
Happy	0.93	0.99	0.92
Sad	0.88	0.92	0.99
Sarcasm	0.99	0.93	0.91
Irony	1.00	0.96	0.98
Accuracy	0.93		
Macro Avg	0.93	0.93	0.93
Weighted Avg	0.93	0.93	0.93

Table. 4 : Sentiment-wise Performance Metrics of the Proposed Model

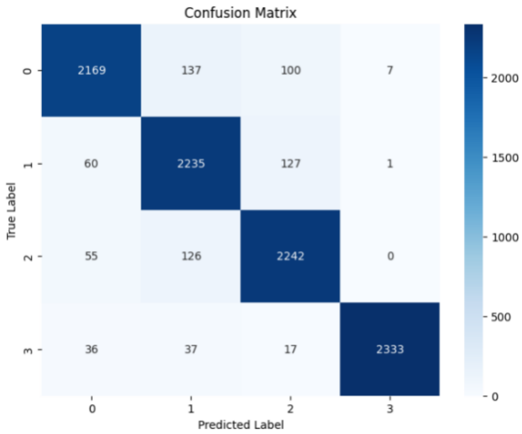

Fig. 4 : Confusion Matrix

6. Conclusion

This research examined the application of the BERT model for sentiment analysis on social media, demonstrating its ability to capture contextual meaning and improve classification accuracy. By utilizing pre-trained language representations and fine-tuning them on sentiment datasets, the model effectively outperforms conventional machine learning techniques. The results indicate that BERT is highly efficient in understanding complex linguistic patterns, making it a valuable tool for sentiment classification tasks.

However, certain challenges remain, such as the high computational cost and sensitivity to domain-specific language variations. Future studies can focus on optimizing BERT for efficiency through techniques like model pruning or knowledge distillation. Additionally, incorporating multimodal data and expanding multilingual capabilities could further enhance its adaptability across various social media platforms.

7. Future Work

While this study highlights the effectiveness of the BERT model for sentiment analysis on social media, there are several areas where improvements can be made to enhance accuracy and efficiency. One of the primary challenges is computational complexity, as BERT requires significant resources for training and inference. Future research could focus on optimization techniques such as model pruning, quantization, and knowledge distillation to reduce computational costs while maintaining accuracy.

Another important area is enhancing accuracy through domain adaptation. Social media language varies across platforms and contexts, so fine-tuning BERT with domain-specific datasets (e.g., finance, healthcare, politics) can improve sentiment prediction. Additionally, hybrid models that combine BERT with traditional machine learning techniques or ensemble methods could further refine accuracy by leveraging multiple perspectives in sentiment classification.

Multimodal sentiment analysis is another promising direction. Social media content includes not only text but also images, videos, and emojis, which contribute to sentiment expression. Future models could integrate textual and visual information to provide a more comprehensive understanding of user emotions.

Additionally, multilingual sentiment analysis can be improved by fine-tuning BERT on diverse language datasets, ensuring higher accuracy for non-English text. Developing lightweight and efficient BERT variants for real-time sentiment analysis in multiple languages would be beneficial.

Lastly, improving explainability and interpretability is essential for making BERT-based sentiment models more transparent. Implementing explainable AI (XAI) techniques can help users understand why the model makes certain predictions, increasing trust and usability in real-world applications.

By addressing these challenges, future research can significantly enhance accuracy, efficiency, and adaptability of BERT-based sentiment analysis models, making them more effective for large-scale social media monitoring and decision-making.

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