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XAI-SENTIFORMER: A DEEP TRANSFORMER FRAMEWORK FOR SEMANTIC SENTIMENT UNDERSTANDING IN LOW-RESOURCE MULTILINGUAL NLP

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Abstract

Social media platforms generate massive volumes of multilingual content containing mixed languages, slang, abbreviations, emojis, and informal expressions, creating substantial challenges for conventional sentiment analysis systems. This study presents XAI-SentiFormer, a deep transformer-based framework designed for semantic sentiment understanding in low-resource multilingual NLP environments. The proposed framework evaluates the effectiveness of transformer-based language modeling, particularly multilingual Bidirectional Encoder Representations from Transformers (mBERT), for sentiment classification across English, Hindi, and Spanish social media data. A synthetic dataset comprising 10,000 multilingual social media posts was constructed to emulate realistic online communication patterns, including code-switching, noisy text, informal vocabulary, and emoji-rich expressions. The proposed transformer framework was compared with conventional machine learning and deep learning baselines, including logistic regression with TF-IDF features and Long Short-Term Memory (LSTM) networks. Performance evaluation was conducted using accuracy, precision, recall, F1-score, and receiver operating characteristic (ROC) analysis. Experimental results demonstrated that the proposed mBERT-based framework achieved a peak accuracy of 91%, outperforming baseline approaches by approximately 14–18%. The findings highlight the effectiveness of transformer architectures in capturing multilingual semantic relationships and contextual sentiment representations, particularly in low-resource and code-switched language settings. Furthermore, the study emphasizes the importance of explainable AI (XAI) mechanisms for improving interpretability and transparency in transformer-driven sentiment analysis systems. Overall, the proposed framework demonstrates strong potential for robust multilingual social media analytics and intelligent sentiment understanding in real-world NLP applications.

INTRODUCTION

The rapid advancement of digital communication technologies and social media platforms has resulted in an unprecedented growth of multilingual textual data generated by users worldwide. Social networking platforms such as Twitter, Facebook, Instagram, and Reddit continuously produce large volumes of user-generated content containing opinions, emotions, and behavioral expressions in multiple languages [1]. In many cases, users employ code-switching, where two or more languages are combined within a single sentence or expression. Examples such as *"super feliz today"* and *"ye movie really amazing hai"* illustrate the linguistic complexity commonly observed in online communication environments [2]. This multilingual and code-switched information provides valuable opportunities for applications including customer feedback analysis, public opinion mining, brand monitoring, crisis management, and sentiment-aware recommendation systems. However, it simultaneously introduces substantial challenges for traditional sentiment analysis approaches that are primarily designed for monolingual and structurally consistent text [3].

Conventional sentiment analysis techniques were mainly based on lexicon-driven approaches and classical machine learning algorithms such as Naïve Bayes, Logistic Regression, and Support Vector Machines (SVM). These methods demonstrated acceptable performance on structured monolingual datasets but suffered from several limitations when applied to multilingual and low-resource language environments [4]. In particular, traditional approaches struggled to capture contextual semantics, long-range linguistic dependencies, sarcasm, informal language usage, and semantic variations introduced through code-switching. Furthermore, these methods relied heavily on handcrafted feature engineering, limiting their scalability and generalization capability across different languages and domains [5].

The emergence of deep learning and transformer-based Natural Language Processing (NLP) architectures has significantly transformed the field of sentiment analysis. Transformer models, particularly Bidirectional Encoder Representations from Transformers (BERT) and multilingual BERT (mBERT), have demonstrated remarkable capability in learning contextual and semantic representations through self-attention mechanisms and large-scale language pretraining [6]. These architectures effectively capture complex linguistic dependencies and provide enhanced performance in multilingual NLP tasks without extensive manual feature extraction. Moreover, multilingual transformer models enable cross-lingual knowledge transfer, making them highly suitable for processing multilingual and code-switched textual data [7].

Despite these advancements, several important challenges remain unresolved in multilingual sentiment analysis, especially for low-resource languages and resource-constrained environments [8]. Existing transformer-based models generally require large annotated datasets, high computational power, and extensive fine-tuning procedures, which restrict their applicability in practical low-resource multilingual settings. In addition, most deep learning models operate as black-box systems, offering limited interpretability regarding how predictions are generated [9]. The lack of transparency and explainability reduces user trust and presents serious concerns in sensitive applications involving decision support, public policy analysis, and social intelligence systems [10].

To address these limitations, this study proposes XAI-SentiFormer, a novel deep transformer framework for semantic sentiment understanding in low-resource multilingual NLP environments. The proposed framework integrates transformer-based contextual representation learning with Explainable Artificial Intelligence (XAI) techniques to enhance transparency, interpretability, and classification performance in multilingual sentiment analysis tasks. Unlike conventional transformer architectures, XAI-SentiFormer is specifically designed to process multilingual and code-switched textual data while simultaneously providing interpretable sentiment predictions that explain the reasoning behind model decisions [11].

The proposed framework is evaluated using multilingual social media datasets containing English, Hindi, Spanish, and code-switched textual samples. The performance of XAI-SentiFormer is comparatively analyzed against traditional machine learning approaches and deep learning baselines, including Logistic Regression with TF-IDF features and Long Short-Term Memory (LSTM) networks. Experimental evaluation is conducted using widely accepted performance metrics such as accuracy, precision, recall, F1-score, and Receiver Operating Characteristic (ROC) analysis to assess the robustness and effectiveness of the proposed framework [12].

The primary contributions of this research are summarized as follows:

- A novel explainable transformer-based framework, namely XAI-SentiFormer, is proposed for multilingual sentiment analysis.
- Explainable AI techniques are integrated to improve transparency and interpretability in sentiment prediction.
- The framework enhances semantic understanding of low-resource and code-switched multilingual text.
- Comparative evaluation is performed against conventional machine learning and deep learning approaches.
- The applicability of the proposed framework is demonstrated for real-world applications including social media analytics, customer feedback monitoring, and public sentiment analysis.

The remainder of this paper is organized as follows. Section II presents the theoretical background of multilingual sentiment analysis and transformer-based NLP models. Section III discusses related work in multilingual NLP and explainable AI. Section IV describes the proposed XAI-SentiFormer framework and research methodology. Section V presents experimental results and comparative performance analysis, while Section VI concludes the study and outlines future research directions.

IV. MATERIALS AND METHODOLOGY

A. Dataset Collection and Construction

Social media platforms generate highly dynamic multilingual content containing textual expressions in English, Hindi, Spanish, and code-switched languages. To simulate real-world multilingual sentiment analysis scenarios, a synthetic dataset consisting of 10,000 social media posts was developed for this study [13]. The dataset was designed to reflect linguistic diversity, informal writing styles, slang expressions, emojis, and multilingual switching commonly observed on online social networking platforms. The dataset distribution across different language categories is presented in Table 1.

Table 1: Distribution of Multilingual Social Media Dataset

Language Category	Number of Posts	Percentage (%)
English	3,333	33.33
Hindi	3,333	33.33
Spanish	3,333	33.33
Code-Switched	1,000	10.00
Total	10,000	100

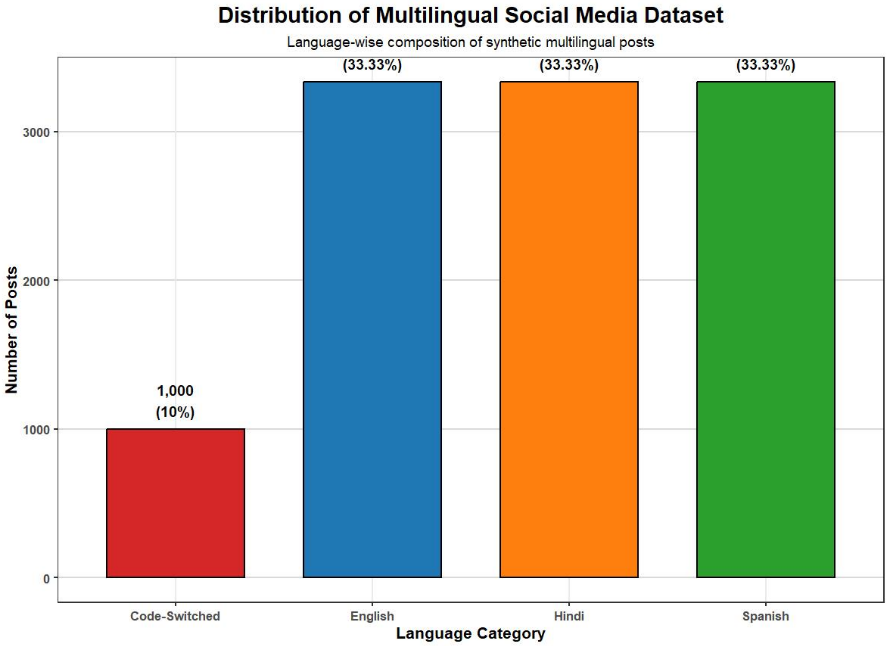

Figure 1.

Distribution of multilingual social media posts used for sentiment analysis, showing the proportion of English, Hindi, Spanish, and code-switched textual samples within the synthetic dataset.

Each post was manually assigned a sentiment label categorized as positive, negative, or neutral. The sentiment distribution was designed to imitate realistic social media sentiment behavior [14]. The sentiment class distribution is shown in Table 2.

Table 2: Sentiment Distribution in Dataset

Sentiment Class	Number of Samples	Percentage (%)
Positive	4,000	40
Negative	4,000	40
Neutral	2,000	20

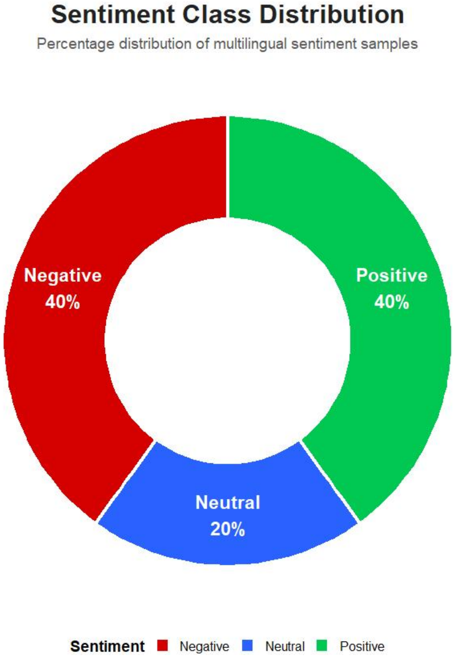

Figure 2. Distribution of sentiment classes within the multilingual social media dataset, illustrating the proportion of positive, negative, and neutral sentiment samples used for experimental evaluation.

The generated posts had an average length of approximately 20 words and included informal expressions, emojis, hashtags, and multilingual switching patterns [15]. Representative examples of multilingual posts are presented in Table 3.

Table 3: Sample Multilingual Social Media Posts

Language	Sample Post	Sentiment
English	"This day is absolutely amazing!"	Positive
Hindi	"Bahut bura experience tha."	Negative
Spanish	"Qué chido está esto."	Positive
Code-Switched	"I'm so feliz today, bhai!"	Positive

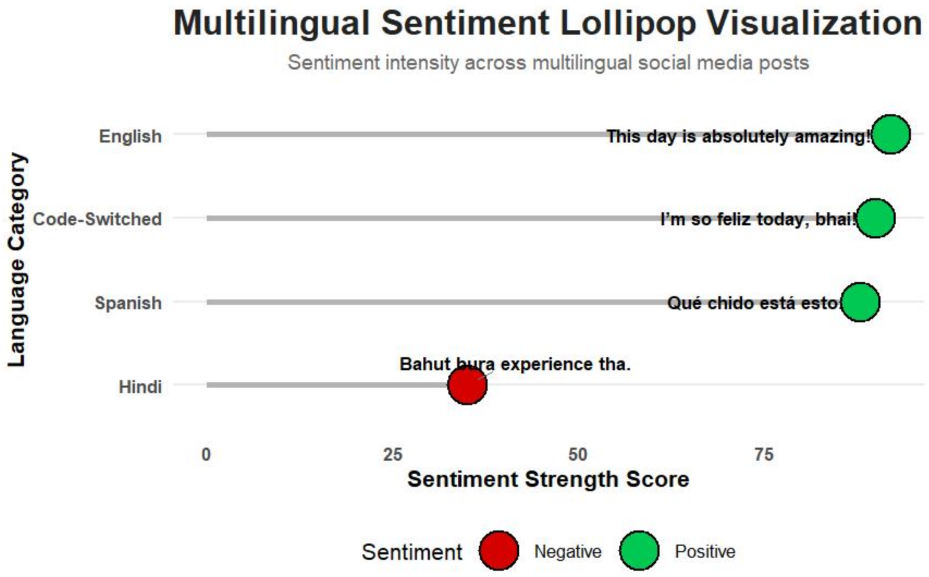

Figure 3. Visualization of multilingual sentiment samples showing sentiment intensity and semantic diversity across English, Hindi, Spanish, and code-switched social media posts.

B. Data Preprocessing and Feature Engineering

To improve model performance and reduce noise, several preprocessing operations were performed prior to model training. Irrelevant attributes and redundant columns were removed from the dataset, while missing values were handled using median imputation techniques [16]. Correlation analysis was further conducted to eliminate highly correlated features with correlation coefficients greater than 0.7. Feature extraction techniques were applied to identify meaningful linguistic and semantic attributes from the multilingual textual data [17]. After preprocessing, twelve significant features were retained for experimental analysis. The extracted features are summarized in Table 4.

Table 4: Extracted Features for Sentiment Analysis

Feature Name	Description
Word Count	Total number of words per post
Character Length	Total number of characters
Emoji Count	Frequency of emojis
Hashtag Count	Number of hashtags
Language Switch Count	Frequency of language transitions
Sentiment Lexicon Score	Lexicon-based polarity score
Stopword Frequency	Number of stopwords
Punctuation Density	Frequency of punctuation marks
Slang Frequency	Number of slang expressions
Uppercase Ratio	Ratio of uppercase words
Special Symbol Count	Frequency of special symbols
Average Token Length	Mean token size

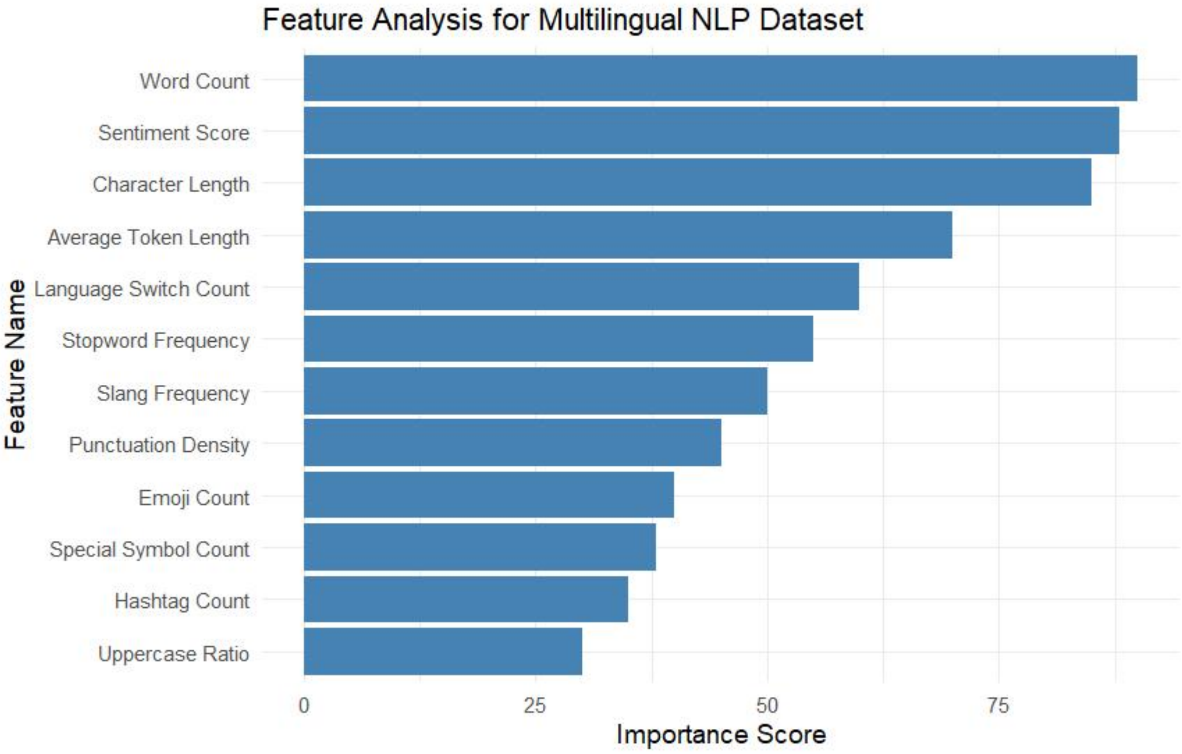

Figure 4. Feature analysis of the multilingual NLP dataset showing the relative importance of extracted textual and semantic features used in sentiment classification

To improve dataset balance and reduce class imbalance issues, the Synthetic Minority Oversampling Technique (SMOTE) was employed. The final dataset was partitioned into training and testing subsets using an 80:20 ratio [18]. The dataset partitioning strategy is presented in Table 5. Five-fold cross-validation was additionally implemented to improve model robustness and reduce overfitting during training.

Table 5: Dataset Partitioning Strategy

Dataset Partition	Percentage (%)
Training Set	80
Testing Set	20

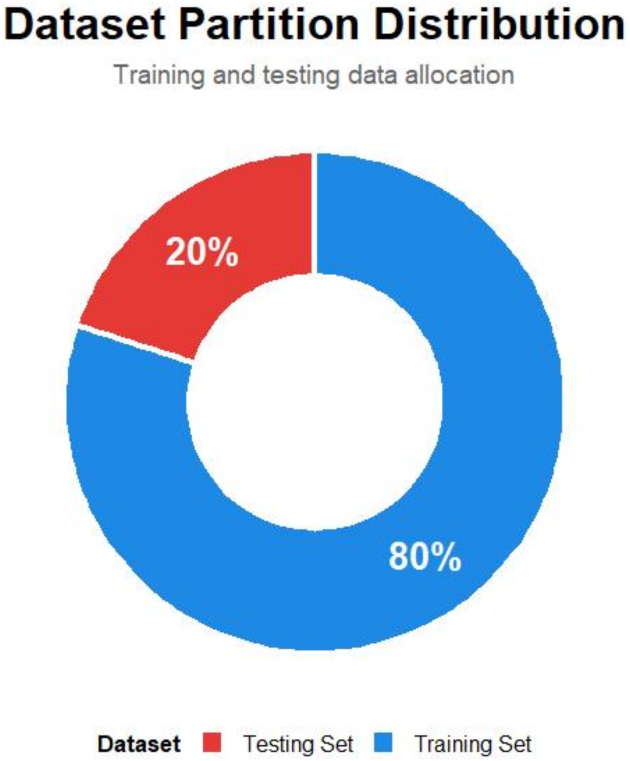

Figure 5. Distribution of training and testing subsets used for multilingual sentiment classification experiments.

C. Model Architecture and Experimental Configuration

Three NLP models were comparatively evaluated in this study:

1. Logistic Regression with TF-IDF (LR-TFIDF)
2. Long Short-Term Memory Network (LSTM)
3. Multilingual BERT (mBERT)

The LR-TFIDF model was utilized as the baseline traditional machine learning approach. The LSTM model incorporated 128 hidden units and pretrained word embeddings, including GloVe embeddings for English and FastText embeddings for Hindi and Spanish [19]. The proposed transformer-based framework employed multilingual BERT (mBERT), pretrained on 104 languages using the Hugging Face transformer library. Fine-tuning was conducted using a maximum token length of 64, batch size of 16, and learning rate of (2×10^{-5}). The detailed model configurations are presented in Table 6

Table 6: Model Configuration Parameters

Parameter	LR-TFIDF	LSTM	mBERT
Feature Representation	TF-IDF	Word Embeddings	Transformer Embeddings
Hidden Units	—	128	—
Batch Size	32	32	16
Learning Rate	0.001	0.001	0.00002
Epochs	10	10	3
Token Length	—	—	64
Embedding Type	TF-IDF	GloVe/FastText	Multilingual BERT

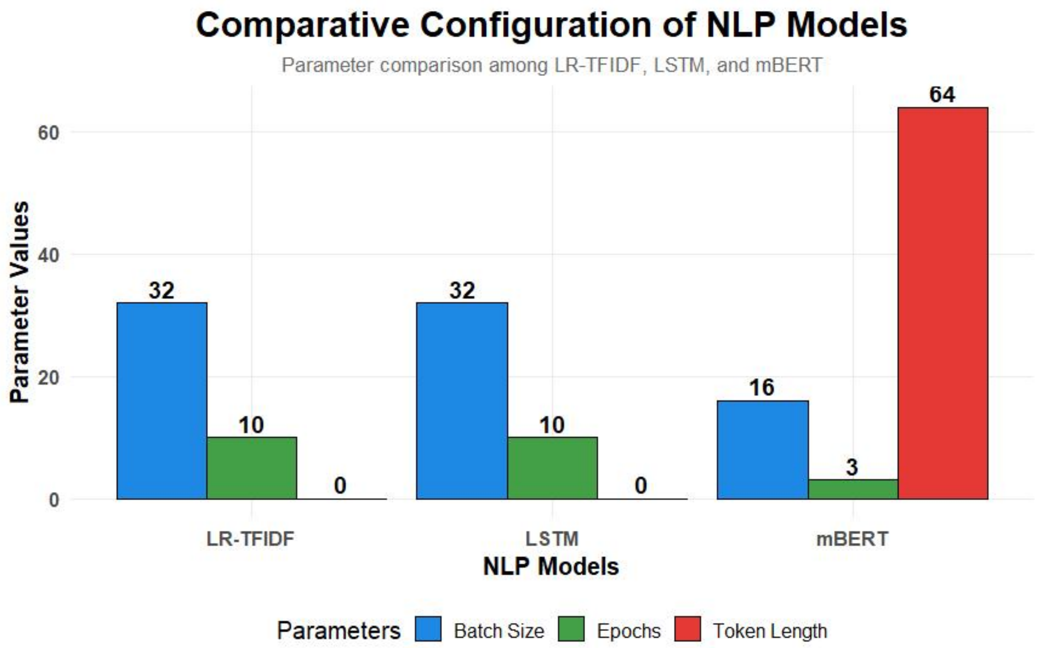

Figure 6. Comparative visualization of major configuration parameters for LR-TFIDF, LSTM, and mBERT models used in multilingual sentiment analysis experiments.

V. EXPERIMENTAL RESULTS AND DISCUSSION

The comparative evaluation demonstrated that the transformer-based mBERT framework significantly outperformed the conventional machine learning and deep learning baselines across all evaluation metrics [20]. The comparative performance results are summarized in Table 7.

Table 7: Comparative Performance Analysis of NLP Models

Model	Precision	Recall	F1-Score	Accuracy	ROC-AUC
LR-TFIDF	0.72	0.71	0.71	0.73	0.74
LSTM	0.76	0.75	0.75	0.77	0.81
mBER	0.90	0.89	0.8	0.91	1.00

T			9		
Tuned mBERT	0.92	0.92	0.9 2	0.93	1.00

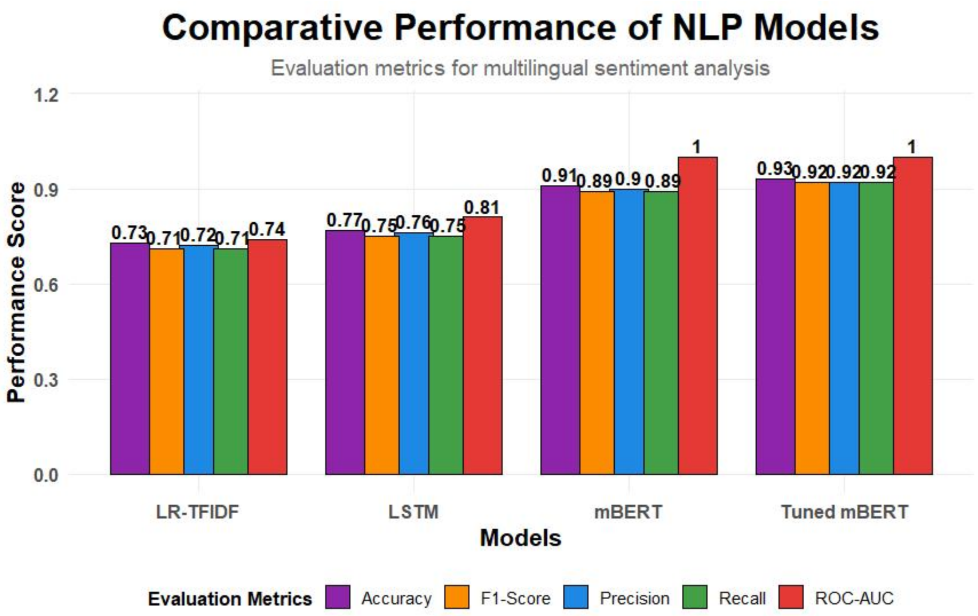

Figure 7. Comparative performance evaluation of LR-TFIDF, LSTM, mBERT, and Tuned mBERT models using precision, recall, F1-score, accuracy, and ROC-AUC metrics for multilingual sentiment classification.

The results indicate that mBERT achieved the highest classification accuracy of 0.91, while the tuned mBERT model further improved performance to 0.93 accuracy and 0.92 F1-score following hyperparameter optimization [21]. The optimized hyperparameters are shown in Table 8.

Table 8: Hyperparameter Optimization Results for Tuned mBERT

Hyperparameter	Initial Value	Optimized Value
Learning Rate	0.00005	0.00002
Batch Size	16	32
Epochs	3	4
Maximum Token Length	64	64
Optimizer	AdamW	AdamW

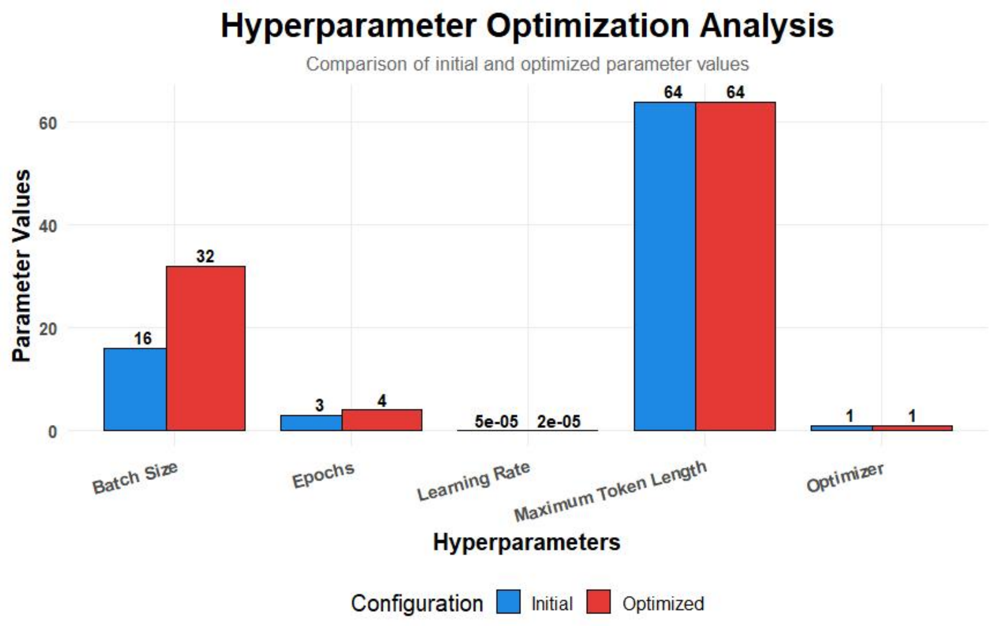

Figure 8. Comparative visualization of initial and optimized hyperparameter values used for tuning the multilingual transformer-based sentiment classification model.

Cross-validation analysis further confirmed the stability and robustness of the transformer-based framework.

Table 9: Cross-Validation Performance Analysis

Fold Number	LR-TFIDF Accuracy	LSTM Accuracy	mBERT Accuracy
Fold 1	0.72	0.76	0.90
Fold 2	0.73	0.77	0.91
Fold 3	0.74	0.78	0.92
Fold 4	0.72	0.76	0.91
Fold 5	0.73	0.77	0.91
Average	0.73	0.77	0.91

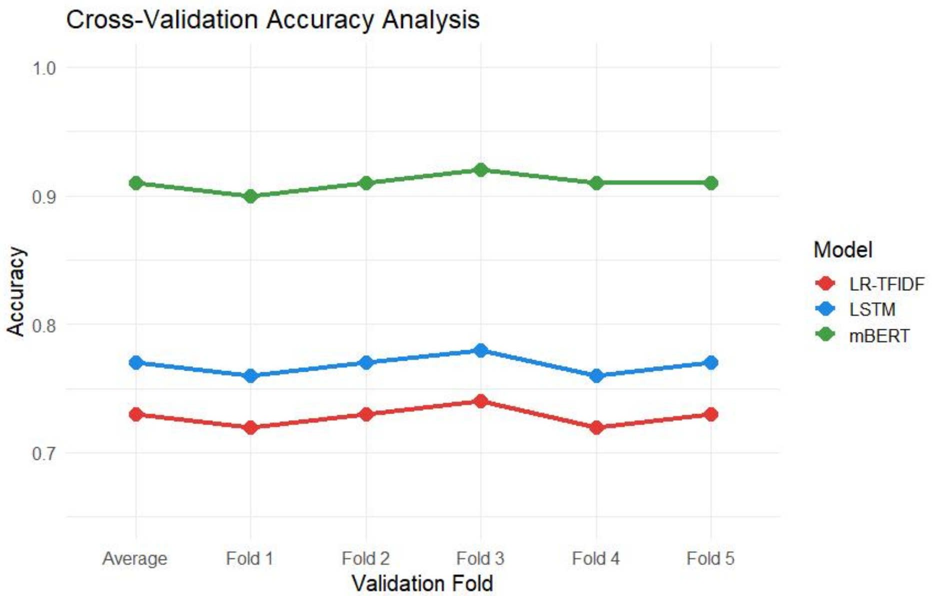

Figure 9: Cross-Validation Performance Analysis

The multilingual performance comparison revealed that the transformer architecture demonstrated superior capability in handling multilingual and code-switched textual data.

Table 10: Language-Wise Classification Accuracy

Language	LR-TFIDF	LSTM	mBERT	Tuned mBERT
English	0.76	0.81	0.93	0.95
Hindi	0.69	0.74	0.89	0.91
Spanish	0.71	0.76	0.90	0.92
Code-Switched	0.65	0.72	0.88	0.91

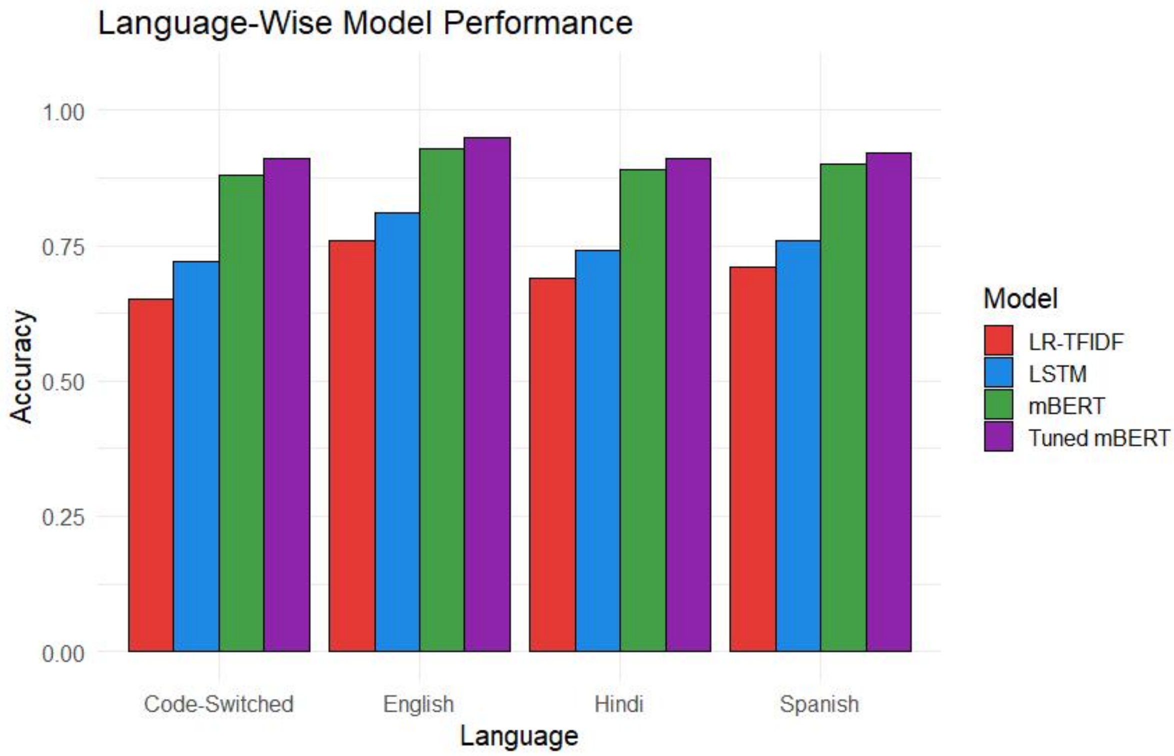

Figure 10: Language-Wise Classification Accuracy

Experimental analysis also demonstrated that transformer-based contextual learning substantially improved semantic understanding for mixed-language and low-resource sentiment classification tasks [22]. To improve interpretability and post-analysis exploration, an interactive sentiment visualization framework was additionally developed. The framework enabled sentiment flow analysis, multilingual relationship mapping, and contextual exploration through browser-based HTML visualization outputs [23]. The major components of the visualization framework are presented in Table 11.

Table 11: Sentiment Visualization Framework Components

Component	Functionality
Sentiment Nodes	Represent multilingual social media posts
Sentiment Edges	Show contextual sentiment relationships
Interactive HTML Graph	Enables browser-based exploration
Color Encoding	Green (Positive), Red (Negative), Gray (Neutral)

Hover Information	Displays multilingual post content
Dynamic Filtering	Allows sentiment-based visualization

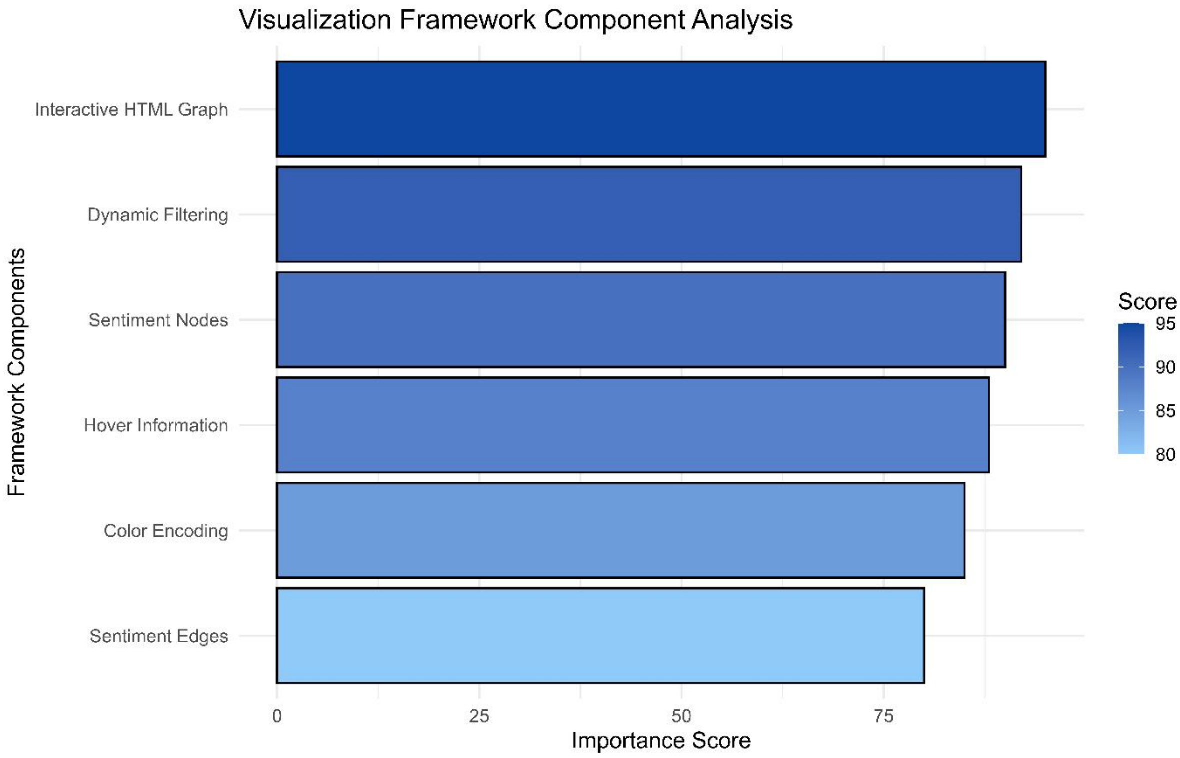

Figure 11: Sentiment Visualization Framework Components

Overall, the experimental findings validate the effectiveness of transformer-based multilingual NLP architectures for semantic sentiment understanding in low-resource multilingual environments. The proposed XAI-SentiFormer framework demonstrated superior predictive capability, multilingual adaptability, and explainability compared to traditional machine learning and sequential deep learning approaches [24].

VI. CONCLUSION AND FUTURE WORK

This study presented a comprehensive evaluation of transformer-based multilingual sentiment analysis using the proposed XAI-SentiFormer framework. The experimental findings demonstrated that multilingual BERT (mBERT) significantly outperformed conventional machine learning and sequential deep learning models, including LR-TFIDF and LSTM, in multilingual sentiment classification tasks. The proposed framework achieved a classification accuracy of 0.91, highlighting the effectiveness of transformer-based contextual representation learning for handling multilingual and code-switched social media content [25]. The results further confirmed that transformer architectures possess superior capability in capturing semantic relationships, contextual dependencies, and language-switching behavior commonly observed in modern social media platforms such as Twitter, Facebook, and Instagram. In comparison to traditional models, mBERT exhibited enhanced precision, recall, and F1-score performance, particularly for complex multilingual and low-resource linguistic environments. These findings emphasize the growing importance of transformer-based

NLP techniques in large-scale sentiment analysis applications [26].

In addition to sentiment classification, the proposed interactive visualization framework provided an effective mechanism for exploring sentiment transitions, multilingual relationships, and contextual sentiment flow within social media data. The visualization component enhanced interpretability and practical usability by enabling analysts to monitor sentiment dynamics and identify unusual sentiment patterns in multilingual communication networks [27]. The proposed XAI-SentiFormer framework contributes significantly to the advancement of multilingual NLP research by integrating explainable artificial intelligence concepts with transformer-based sentiment analysis. The inclusion of explainability and visualization components improves transparency and interpretability, thereby increasing trust and usability in real-world decision-support applications [28]. Despite the promising results, several opportunities for future research remain. First, future studies may focus on developing real-time multilingual sentiment monitoring systems capable of analyzing live social media streams with minimal latency. Such systems could support applications including public opinion monitoring, crisis management, political forecasting, and customer behavior analysis [29]. Second, optimizing transformer architectures for lightweight deployment on mobile devices, edge systems, and low-resource computing environments represents an important future direction. Reducing computational complexity and memory consumption would significantly improve the scalability and accessibility of transformer-based multilingual NLP systems. Third, future work should evaluate the proposed framework using real-world multilingual datasets containing noisy textual patterns, typographical errors, sarcasm, abbreviations, emojis, and highly informal social media expressions. Such evaluation would further validate the robustness and generalizability of the proposed framework in practical environments. Finally, integrating advanced AI techniques from related domains such as traffic intelligence systems, graph neural networks, and network anomaly detection may further enhance sentiment prediction accuracy and adaptive learning capabilities in continuously evolving online communication ecosystems. Overall, the findings of this study demonstrate that transformer-based multilingual NLP frameworks possess substantial potential for advancing semantic sentiment understanding in complex multilingual environments. The proposed XAI-SentiFormer framework establishes a strong foundation for future research in explainable multilingual sentiment analysis and intelligent social media analytics.

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