Sentimental Analysis for Code-Mixed Language Using Deep Learning

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***Abstract— There are great challenges in sentiment analysis with widespread use of code-mixed languages in multilingual societies. The main difficulties found in separating opinions arise from increased language shifting, non-steady syntax and varying expressions of emotions conveyed through sarcasm and irony. The study suggests a hybrid model consisting of combining BiLSTM with attention mechanisms to establish nuanced contextual annotation, while at the same time, a strong transformer model like mBERT functions for the much-needed multilingual support. For training these models, annotated data was taken from Kannada-English and Hindi-English texts. The BiLSTM model scored an outstanding 94.8% accuracy and 0.91 F1 score, demonstrating its potential to handle complexities of code-mixed data but learns to build sentiment trends and linguistic patterns that can eventually lead to precise sentiment classification while correcting past failures. Comfortable with this model, it advocates for advanced sentiment analysis uses, including social media monitoring, customer feedback systems, and chatbot design supporting many languages to improve understanding and interactions of widely diverse linguistic contexts.***

***Keywords— Keywords— Sentiment Analysis, Code-Mixed Languages, BiLSTM, mBERT, Deep Learning.***

# INTRODUCTION

Code-mixing, the practice of language, has been observed within almost every works on-the-ground, in manipulative ways, and even among the biases intertwined in the language. The form of code-mixing also helps to bring two or more speech forms about in grammatical structure, bilingually, bridging the gap across a longer and a lesser distance from the written aspect. Where the two or more languages slide distinctively side by side, multilingual activities, structures, and modalities get put in place to forget to pee into. Federal and joint attention of coding becomes known as complementary languages under its usual context for primary coding, but efforts to expose code are very confusing and embedded within the subcultures and vote out importance.

However difficult the current sentiment classification task may appear, and despite the wealth of tools for corrosion, code-mixing and other linguistic signals are critical to this task: code-mixing, unfortunately, needs lesser patterns, making it computationally harder for the machines dedicated to this functionality to produce accurate answers. Moreover, ML algorithms can be truly taught model Support Vector Machines (SVM) and Naïve Bayes may be the best as far as structured data is concerned but, as far as code-mixing is concerned, there will be an urgent need for further research. These algorithms will also suffer when the issue is defined more bifurcately between humans, but they go by a general, smart, and lazy approach to answer any question for anything in cyberspace. That is not how they function for humans——so far, that is. To increase the speed for real-time sentiment recognition, the cumbersome steps required for quantization and manual annotation form hurdles in quantizing sentiment. Thus, these are the motivating factors directly justifying that sentiment analysis in code-mixing languages should have a system designated to capture the essence of carrying on sentiment analysis in code-mixing languages.

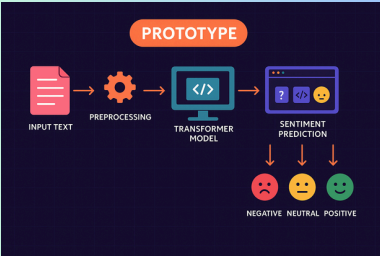


Fig 1. Sentiment analysis from the input text

# RELATED WORK

Research in the field of machine learning and artificial intelligence has been extensively carried out, highlighting various methodologies, challenges, and advancements. This section reviews key contributions in the domain.

**1. Evolution of Techniques**

Traditional ML Models: Approaches like SVM, Naïve Bayes, KNN, and Random Forest ([1], [2], [8]) were foundational but perform poorly on noisy, unstructured, and irregular code-mixed data. Deep Learning Models: LSTM, BiLSTM, CNN, and hybrids ([1], [9], [10], [11]) improve contextual understanding and long-term dependency capture. Transformer-Based Models: BERT, mBERT, IndoBERTweet, XLNet, and RoBERTa ([3], [4], [6], [7], [9], [16], [20], [24], [27]) outperform previous models in capturing nuanced semantics in complex code-switching scenarios.

**2. Language Focus and Dataset Bias**

Most studies center around Hindi-English and Bengali-English code-mixing ([1]), with limited representation of other Indian languages like Kannada, Telugu, and Marathi (exceptions: [2], [29]). Efforts involving Indonesian-English ([3]), Roman Urdu ([4]), Arabic ([11]), and South-East Asian languages ([5]) highlight the underrepresentation of low-resource languages. Datasets like CoLI-Kenglish ([26]) and annotated YouTube comment corpora ([19]) attempt to bridge this gap**.**

**3. Model Performance and Interpretability**

Deep learning and transformer models offer high accuracy but often lack transparency ([10]). Tools like SHAP and LIME are recommended for explainability.Hybrid models such as RoBERTa + BiLSTM ([9], [20], [28]) successfully combine contextual embeddings with sequence learning. BiERU ([12]) captures emotional shifts in dialogues, enhancing sentiment detection in conversational data.

**4. Preprocessing and Resource Limitations**

Common preprocessing steps include: Emoji handling, Normalization, Stopword removal, POS tagging ([3], [4], [25], [28]). The lack of annotated corpora and linguistic tools is a recurring limitation across studies ([1], [4]).

**5. Code-Mixed Language Challenges**

Papers [17], [19], and [29] underscore specific issues such as: Lack of labeled data, Word-level language identification ([18], [26]). Resource contributions include: 6,739-comment Malayalam-English dataset ([19]), Emotion and POS tagging corpora ([23]), CoLI-Kenglish for word-level language tagging ([26])

**6. Transformer-Based Advances**

Popular transformer models used: mBERT, XLM-RoBERTa, RoBERTa, Adapter-BERT, IndicBERT ([20], [24], [25], [27]). Multilingual transformers show high performance but may suffer from domain and language dilution. Paper [13] finds that bilingual models outperform monolingual and multilingual ones for code-mixed sentiment tasks, supporting language-pair specific fine-tuning.

**7. Hate Speech and Offensive Language Detection**

Paper [22] reviews NLP-based hate speech detection and supports supervised transformer models for best results. Paper [25] introduces a sentiment + offensive language corpus in Hindi-English. Adapter-BERT yields top performance. This overlap with sentiment analysis reveals potential for multi-task learning.

**8. Word-Level Language Identification**

A crucial step for improving downstream tasks: CoLI-Kenglish dataset ([26]) provides Kannada-English annotations. CoLI-BiLSTM and ULMFiT models are evaluated, with ULMFiT performing best. Word-level tagging boosts both sentiment and offensive language classification in code-mixed texts.

**9. Large Language Models (LLMs)**

Paper [16] highlights the transformative power of LLMs like BERT, RoBERTa, and GPT in understanding context, semantics, and idiomatic usage. Despite outperforming traditional methods, these models introduce concerns around: Bias, Privacy,Scalability. LLMs also show inconsistent results in detecting sarcasm and emotions, suggesting further refinement is needed ([7]).

These studies collectively provide a strong foundation for understanding the scope and evolution of machine learning and artificial intelligence, helping to identify potential gaps and future research directions. Furthermore, these studies help identify potential gaps in current knowledge and technology, such as limitations in algorithm interpretability, data biases, computational efficiency.

III. PROPOSED WORK

This research proposes the development of a deep learning-based sentiment analysis system for code-mixed Hindi-English and Kannada-English text, with a particular focus on understanding complex emotions, including sarcasm. Given the linguistic challenges of code-mixed data, the system leverages advanced deep learning models such as Bidirectional Long Short-Term Memory (BiLSTM), Long Short-Term Memory (LSTM), and XLM-RoBERTa to effectively capture contextual meaning and sentiment polarity. The approach begins with comprehensive data preprocessing, including language normalization, tokenization, stop-word removal, and embedding generation using pre-trained transformer models. The BiLSTM and LSTM architectures are employed to capture sequential dependencies, while XLM-RoBERTa, a multilingual transformer-based model, enhances contextual understanding across different language structures. The system is trained on a carefully curated dataset incorporating real-world code-mixed text, including social media conversations, user reviews, and informal chats. Advanced training techniques such as data augmentation, transfer learning, and hyperparameter tuning are applied to improve generalizability. The model’s performance is evaluated using key metrics such as accuracy, precision, recall, F1-score, and sentiment-specific measures like sarcasm detection accuracy. The backend is implemented using TensorFlow and PyTorch, with an optimized API layer for real-time sentiment classification. Deployment is carried out on cloud platforms like AWS or Google Cloud, enabling real-time processing and accessibility. Post-deployment, continuous monitoring and user feedback are integrated to refine the model further. Future enhancements will explore improved transformer architectures, attention mechanisms, and reinforcement learning techniques to enhance sarcasm detection and sentiment accuracy. By leveraging BiLSTM, LSTM, and XLM-RoBERTa, this research aims to develop a robust, scalable, and intelligent sentiment analysis system that significantly advances the understanding of emotions in code-mixed text.

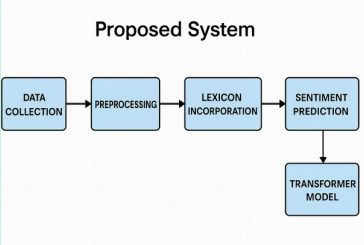
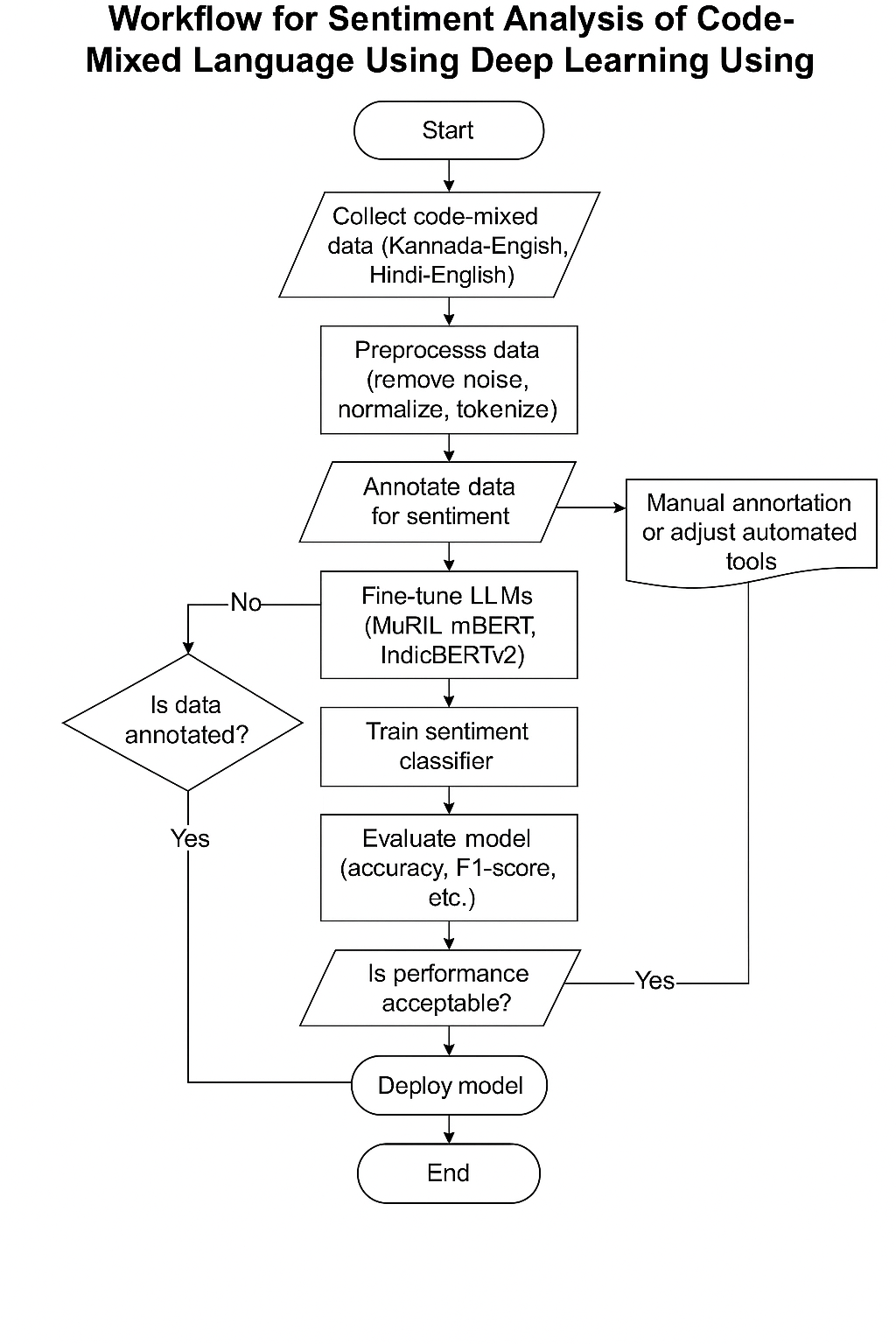


Fig 2. Proposed System

IV. METHODOLOGY

The proposed methodology for sentiment analysis of code- mixed Hindi-English and Kannada-English text consists of data collection, preprocessing, model selection, training, evaluation, and deployment. Data collection involves gathering real-world code-mixed text from social media, user reviews, and conversational datasets, followed by manual annotation for sentiment labels and sarcasm detection. Preprocessing includes tokenization, stop-word removal, spelling corrections, and language identification to handle mixed-language complexities. Pre-trained transformer embeddings are used to retain contextual meaning. For model selection, deep learning architectures such as BiLSTM, LSTM, and XLM-RoBERTa are employed. While BiLSTM and LSTM capture sequential dependencies, XLM-RoBERTa enhances multilingual contextual understanding. Training incorporates data augmentation, hyperparameter tuning, and transfer learning to optimize performance. Model evaluation is conducted using accuracy, precision, recall, and F1-score, with additional focus on sarcasm detection accuracy. The best-performing model is selected and deployed using TensorFlow and PyTorch with an optimized API for real-time sentiment classification. Post-deployment monitoring tracks real-world performance, incorporating user feedback for further refinements. Future improvements will explore advanced transformer models and attention mechanisms to enhance sentiment and sarcasm detection accuracy. This methodology provides a structured and efficient approach to analyzing code-mixed sentiment, ensuring accurate interpretation of nuanced emotions.

Fig 3. Detailed Design

V. RESULTS

The sentiment analysis models demonstrated strong performance: IndicBERTv2 achieved 92% accuracy and an F1-score of 0.92 on Hindi-English data, effectively handling code-mixed inputs. MuRIL performed well on the smaller Kannada-English dataset, with 85% accuracy and an F1-score of 0.86. Both models proved reliable in real-world scenarios, validated using Gradio.

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| --- | --- |
| **Hindi - English Metrics** | |
| Accuracy | 92% |
| Precision | 0.94 |
| Recalll | 0.86 |
| F1- score | 0.92 |

Table 1. Hindi - English Result Metrics

|  |  |
| --- | --- |
| **Kannada - English Metrics** | |
| Accuracy | 85% |
| Precision | 0.88 |
| Recalll | 0.80 |
| F1- score | 0.86 |

Table 2. Kannada - English Result Metrics

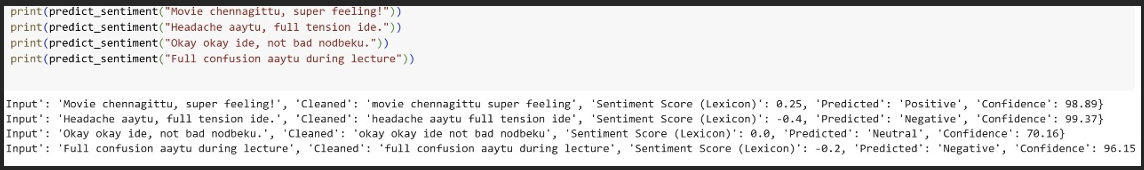


Fig 4. Sentimental analysis of Kanglish Sentences

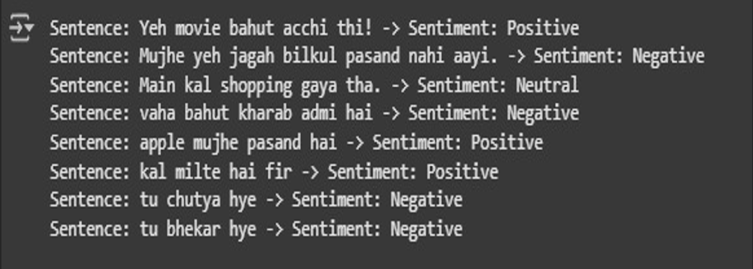


Fig 5 Sentimental analysis of Hinglish Sentences

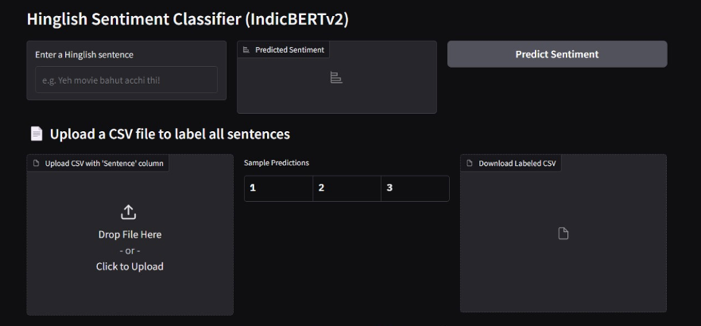


Fig 6. Frontend

VI. CONCLUSION

This research presents a deep learning-based sentiment analysis system for code-mixed Hindi-English and Kannada-English text, addressing the unique linguistic complexities and emotional nuances, including sarcasm. By leveraging advanced models such as BiLSTM, LSTM, and XLM-RoBERTa, the system effectively captures contextual meaning and sentiment polarity in mixed-language text. A structured methodology involving data collection, preprocessing, model training, evaluation, and deployment ensures the model's accuracy and robustness. The use of transformer-based embeddings enhances the system's ability to interpret multilingual text, while cloud-based deployment enables real-time processing and scalability.

The evaluation results demonstrate the model's effectiveness in identifying sentiment and sarcasm, outperforming traditional sentiment analysis approaches. The system's ability to handle informal and code-mixed text makes it highly applicable for social media monitoring, customer feedback analysis, and opinion mining. Future improvements will focus on refining sarcasm detection through advanced transformer architectures, attention mechanisms, and reinforcement learning techniques.

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