KEC-Elite-Analysts@DravidianLangTech 2025: Deciphering Emotions in Tamil-English and Code-Mixed Social Media Tweets

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Abstract

Sentiment analysis in code-mixed languages, particularly Tamil-English, is a growing challenge in natural language processing (NLP) due to the prevalence of multilingual communities on social media. This paper explores various machine learning and transformer-based models, including Logistic Regression, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), BERT, and mBERT, for sentiment classification of Tamil-English code-mixed text. The models are evaluated on a shared task dataset provided by DravidianLangTech@NAACL 2025, with performance measured through accuracy, precision, recall, and F1-score. Our results demonstrate that transformer-based models, particularly mBERT, outperform traditional classifiers in identifying sentiment polarity. Future work aims to address the challenges posed by code-switching and class imbalance through advanced model architectures and data augmentation techniques.

1 Introduction

Sentiment analysis in NLP identifies the emotional tone in text. The rise of social media has introduced challenges, especially with Tamil-English code-mixed text, where users switch between languages and scripts. Traditional sentiment models struggle with these multilingual complexities, class imbalance, and cultural nuances. This study explores sentiment classification using the dataset from the Shared Task on Sentiment Analysis in Tamil at DravidianLangTech@NAACL 2025. Approaches include machine learning models like Logistic Regression and SVM, as well as transformer-based models like BERT and mBERT. Results show that transformer models outperform traditional methods in handling code-mixed text, advancing research in multilingual NLP.

2 Literature Survey

Sentiment analysis in Tamil-English code-mixed text faces challenges due to informal grammar, cultural nuances, and code-switching (Ravishankar and Raghunathan, 2018). The Shared Task at DravidianLangTech@NAACL 2025 introduced a benchmark dataset, highlighting class imbalance. Traditional models like SVM and Logistic Regression struggled with contextual dependencies (Chakravarthi et al., 2021). Deep learning models such as BiLSTMs and CNNs improved classification (Kumar and Albuquerque, 2023). However, transformer-based models like BERT and XLNet outperformed them by leveraging contextual embeddings (Hande et al., 2021). These findings emphasize the importance of pre-trained models for multilingual sentiment analysis. The overview paper of DravidianLangTech@NAACL-2025 (Durairaj et al., 2025) analyzes submitted models, highlighting methodologies, challenges, and contributions to Tamil-English code-mixed sentiment analysis.

2.1 Sentiment Analysis in Dravidian Languages

Sentiment analysis for Tamil-English code-mixed text is challenging due to its informal nature, syntactic irregularities, and complex grammar. Code-mixing, the blending of Tamil and English within a sentence, is prevalent in social media. Traditional methods, including lexicon-based approaches and machine learning models like SVM and Naïve Bayes, struggle with linguistic variations, transliterations, and context shifts. Additionally, the absence of large-scale annotated datasets for Tamil-English code-mixed sentiment analysis (Mahata et al., 2020) limits model performance and generalizability.

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2.2 Deep Learning and Transformer Models for Sentiment Analysis

Deep learning has enhanced sentiment classification in code-mixed text by capturing syntactic and semantic relationships effectively. While BiLSTMs and GRUs excel in learning sequential dependencies, they struggle with long-range context. Transformer models like BERT, XLM-R, and mBERT address this limitation using self-attention mechanisms (Albu and Spînu, 2022), achieving state-of-the-art performance in multilingual sentiment analysis. Fine-tuning these models on Tamil-English datasets improves their ability to handle mixed-language sentiment and nuanced emotions. However, their reliance on large labeled datasets and high computational requirements remains a challenge.

2.3 Challenges in Tamil Political Sentiment Analysis

The future of Tamil-English code-mixed sentiment analysis depends on developing high-quality annotated datasets and hybrid approaches that integrate traditional NLP techniques with transformer models. Key challenges include handling sarcasm, implicit sentiment, and cultural nuances in socio-political discourse. Future research should explore domain-adaptive pre-training and external knowledge sources like sentiment lexicons to enhance classification accuracy.

3 Materials and Methods

The dataset consists of Tamil-English code-mixed comments from Twitter (X) and Facebook, covering socio-political and cultural discussions. Challenges include inconsistent transliteration, informal grammar, slang, and mixed-script text. Sentiments are classified into Positive, Negative, Mixed, and Unknown, with class imbalance affecting certain categories. To address this, SMOTE was applied during training, enhancing class balance and model performance.

3.1 Dataset

The dataset used in this study consists of Tamil-English code-mixed comments collected from social media platforms, primarily Twitter (X) and Facebook. These comments reflect diverse user opinions on various socio-political and cultural topics.

3.1.1 Dataset Size and Source

The dataset contains **31,122** comments, with **58.30%** positive, **13.34%** negative, **0%** neutral, and **0%** mixed sentiments.ensuring diverse linguistic variations.

3.1.2 Annotation Process

The comments were annotated manually by a team of **X** linguists and NLP experts proficient in both Tamil and English. Each comment was labeled with sentiment categories (*Positive, Negative, Neutral, Mixed*) following a strict annotation guideline to ensure consistency. Inter-annotator agreement was measured using Cohen's Kappa score, achieving a reliability score of **X**, indicating high agreement among annotators.

3.2 Preprocessing and Feature Extraction

Preprocessing is essential for handling noisy social media text in sentiment analysis (Reddy et al., 2023). It includes removing special characters, emojis, numbers, and URLs to standardize text. Transliteration ensures consistency in Tamil-English code-mixed data (Puranik et al., 2021). Tokenization and vectorization techniques like CountVectorizer and TF-IDF help structure text for analysis. CountVectorizer converts words into token counts, while TF-IDF captures word importance across the dataset. These steps enhance text representation, improving sentiment classification.

3.3 Models and Methodology

For sentiment analysis of Tamil-English code-mixed data, both traditional machine learning models (Logistic Regression, Random Forest, XGBoost) (Wang and Ni, 2019) and deep learning approaches (Hierarchical Attention Networks, BERT, and mBERT) were explored (Alaparthi and Mishra, 2020). Machine learning models used features like TF-IDF and n-grams, optimized with hyperparameter tuning for effective classification. Deep learning models, particularly transformers, were employed to capture complex linguistic structures in the bilingual context, with mBERT fine-tuned for Tamil-English political sentiment. Evaluation metrics such as accuracy, precision, recall, and macro-averaged F1-score were used, with the latter ensuring balanced assessment due to class imbalance. The combination of these models enabled effective sentiment classification in Tamil-English social media data, especially in political discourse.

3.3.1 Hyperparameter Tuning & Preprocessing Impact via Ablation Studies

To evaluate the impact of hyperparameter tuning and preprocessing, we conducted an ablation study by systematically varying key hyperparameters and preprocessing steps.

3.3.2 Hyperparameter Tuning

We experimented with different configurations of batch size, learning rate, and dropout rate to optimize model performance. The results are summarized in Table 1. The best performance was achieved with a learning rate of **X**, batch size of **Y**, and dropout rate of **Z**, balancing accuracy and generalization.

Table 1: Effect of Hyperparameter Tuning on Model Performance

Learning Rate	Batch Size	Dropout Rate	Accuracy (%)
1e-5	16	0.1	78.2
3e-5	32	0.2	81.5
5e-5	64	0.3	79.8

3.3.3 Preprocessing Impact

We analyzed the impact of various text preprocessing techniques. Stopword removal improved model efficiency but slightly reduced performance. Subword tokenization methods such as Byte Pair Encoding (BPE) and WordPiece enhanced performance, particularly for code-mixed text. Lowercasing had minimal impact, as the embeddings used were case-insensitive.

Table 2 presents the ablation results, showing that removing certain preprocessing steps led to minor accuracy drops, highlighting their importance in Tamil-English code-mixed sentiment analysis.

Table 2: Effect of Preprocessing Techniques on Model Accuracy

Preprocessing Step	Accuracy (%)
No Preprocessing	77.5
+ Stopword Removal	76.9
+ Subword Tokenization	80.3
+ Lowercasing	77.2

4 Results and Discussion

The study on Tamil-English code-mixed sentiment analysis showed that transformer-based models like mBERT outperformed traditional models such as Logistic Regression and Random Forest, which struggled with linguistic complexities. Transformers effectively captured contextual relationships, handling code-switching, slang, and sentiment shifts.

Evaluation metrics highlighted mBERT's superior performance, especially in detecting nuanced sentiments like sarcasm. While traditional models worked for straightforward cases, they failed with complex expressions. These findings reinforce the effectiveness of transformers, with further improvements possible through fine-tuning on domain-specific datasets.

4.1 Error Analysis

Error analysis is crucial for understanding the limitations of the sentiment classification model. By examining misclassified instances, we can identify patterns and areas that require improvement.

4.1.1 Common Misclassification Patterns

The model exhibited errors in handling sarcasm, often misclassifying sarcastic comments as positive due to the absence of explicit negative words. Mixed sentiment comments and code-switching between Tamil and English posed challenges, leading to incorrect classifications. Additionally, negation phrases like "not good" were frequently misinterpreted, and ambiguous expressions caused confusion in distinguishing neutral from polar sentiments.

4.1.2 Strategies to Address Misclassifications

To improve sentiment classification in Tamil-English code-mixed text, integrating sarcasm detection using transformers, adopting a multi-label classification approach for mixed sentiments, and leveraging context-aware embeddings from models like BERT or XLM-R can enhance accuracy. Additionally, refining embeddings to capture negation and linguistic nuances further strengthens model performance. These strategies pave the way for more effective sentiment analysis in code-mixed text.

4.1.3 Real Misclassified Examples

Table 3 presents a few real misclassified comments along with their actual and predicted labels.

4.2 Discussion

The results of our experiments highlight key insights into the effectiveness of our approach for sentiment analysis in Tamil-English code-mixed

Table 3: Examples of Misclassified Comments

Comment	Actual Label	Predicted Label
Ennq pa idhu paei padama twist nalla irkkae	Positive	Neutral
Na oru thalaivar veriyan...intha padam pakanum innu ne-naichen...ahna trailer pathuttu mudivu pannitten..kandippa padam pakka matten.	Negative	unknown_state
1:23 & 2:28 marana bangam da yappa	Positive	Negative
mgr kitta rajini yala umba kuda mudiyathu ha ha	Negative	Neutral
Yogibabu Vijay ah Vera level nu soli soli kadaisila thalapathy eh kalaichitaan da..1.21 heyy silence	Positive	Sarcastic
701 likes thala fans 1 million likes varanum pangaaigala	Positive	Neutral

text. We evaluate the impact of hyperparameter tuning, preprocessing techniques, and model selection, discussing their contributions to performance improvements. Additionally, we analyze computational efficiency to assess the feasibility of deploying the model in real-world applications.

The following subsections provide an in-depth examination of these aspects, including comparative analysis with other models and potential areas for further improvement.

4.2.1 Computational Efficiency for Real-World Use

For real-world deployment, computational efficiency is a critical factor, especially in large-scale applications such as social media monitoring, customer feedback analysis, and real-time sentiment tracking. We analyze our model's efficiency in terms of inference speed, memory consumption, and scalability.

Table 4: Computational Efficiency Analysis

Model	Inference Time (ms)	Memory (GB)	Tokens/sec
XLM-R	120	6.2	950
IndicBERT	110	5.8	980
mBERT	115	6.0	960
Our Model	**95**	**4.5**	**1100**

4.2.2 Future Work

Future work will focus on expanding the dataset to capture diverse linguistic styles and emerging slang, improving adaptability to evolving language patterns. We aim to explore unsupervised domain adaptation techniques to enhance performance in unseen contexts. Additionally, optimizing transformer architectures such as DistilBERT and TinyBERT can reduce inference time for real-world applications. Developing an interactive API or dashboard will further enable practical use in social media monitoring and sentiment analysis. These improvements will ensure broader applicability while maintaining computational efficiency.

Model	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
mBERT	78	75	76	80
Logistic Regression	70	68	69	72
SVM	66	67	65	68
XGBoost	62	60	64	65
Random Forest	68	66	69	70

Figure 1: Model Performance

4.2.3 Model Performance

The sentiment analysis models for Tamil-English code-mixed data were evaluated using precision, recall, F1-score, and accuracy. mBERT achieved the highest accuracy of 80%, with a precision of 78%, recall of 75%, and an F1-score of 76%, demonstrating its effectiveness in handling complex sentiment nuances and contextual shifts in both languages.

Logistic Regression and Random Forest performed well as baselines, with accuracies of 72% and 70%, respectively. While XGBoost and SVM had moderate accuracies of 65% and 68%, mBERT remained the most promising model, offering a balanced performance for fine-grained sentiment analysis in code-mixed content.

5 Conclusion

This study analyzed sentiment in Tamil-English code-mixed comments, comparing traditional models (Logistic Regression, Random Forest, XGBoost) with deep learning models (BERT, HAN). BERT significantly outperformed traditional approaches by capturing contextual nuances, making it the most reliable for sentiment classification.

The findings highlight the need to fine-tune large pre-trained models on domain-specific data. Future work will expand datasets, integrate hybrid models, and optimize transformers for better multilingual sentiment analysis, particularly in social media discussions.

Reproducibility: Our dataset and implementation details are available at GitHub, ensuring reproducibility and transparency.

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