A HYBRID MBERT–LSTM ARCHITECTURE WITH SPATIAL ATTENTION AND SMOTE FOR BILINGUAL DENGUE SENTIMENT CLASSIFICATION

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DOI: https://doi.org/10.5281/zenodo.22284674

Article History
Received on: 28 Feb, 2026
Accepted on: 26 March, 2026
Published on 29 March, 2026

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Abstract
Dengue fever is a major public health concern in tropical and subtropical regions, affecting millions of people each year and continuing to spread rapidly across different parts of the world. At the same time, social media has become an important source of real-time public opinion during disease outbreaks, providing valuable information that can support disease surveillance and public health decision-making. In this study, a hybrid deep learning framework, referred to as mBERT–Stacked LSTM with Spatial Attention (SSA-LSTM), is developed to classify dengue-related sentiments expressed in both English and Urdu tweets. The proposed framework employs Multilingual BERT (mBERT) to obtain context-sensitive representations and capture linguistic relationships across the two languages. These representations are subsequently processed through a Stacked LSTM network to learn deeper sequential patterns within the text, while the spatial attention mechanism assigns greater importance to words and tokens that contribute strongly to the expressed sentiment. To address the class imbalance observed in the manually collected Urdu dataset containing 16,000 tweets, SMOTE (Synthetic Minority Over-sampling Technique) is applied to generate additional minority-class samples. Experimental evaluation demonstrates that the proposed approach achieves 93.33% accuracy on the benchmark English dataset and 96.48% accuracy on the Urdu dataset after SMOTE-based balancing. The model also demonstrates superior performance compared with conventional and deep learning baselines, including LSTM, CNN, SVM, Naive Bayes, Gaussian Naive Bayes (GNB), and K-Nearest Neighbors (KNN). In addition to quantitative evaluation, the study provides a comprehensive visual interpretation of the experimental findings using grouped bar charts, radar plots, and other comparative visualizations. The results highlight the potential of multilingual deep learning and social media sentiment analysis as effective tools for supporting dengue-related public health monitoring.

Keywords: Dengue; Sentiment analysis; mBERT; SSA-LSTM; Spatial attention; SMOTE; Urdu NLP; Public health surveillance

1. Introduction

Dengue fever, caused by four serotypes of the dengue virus (DENV-1 to DENV-4) transmitted by Aedes aegypti mosquitoes, is recognized by the WHO as one of the ten leading threats to global public health. With approximately 400 million infections annually, dengue places a massive burden on healthcare systems particularly in tropical and subtropical regions of South Asia, Southeast Asia, and Latin America.

The proliferation of social media platforms — primarily X (formerly Twitter) — has created an unprecedented real-time corpus of public opinion on health crises. Sentiment analysis (SA), an NLP subdomain, enables automated classification of this content into affective categories (positive, negative, neutral), offering epidemiologists and health administrators timely insights without the latency inherent in traditional surveillance systems.

Despite substantial progress in English-language NLP, low-resource languages such as Urdu present significant challenges including informal syntax, transliteration variability, code-switching, and scarcity of annotated corpora. Existing dengue-focused SA studies have predominantly targeted English data, leaving a critical gap for multilingual frameworks capable of Urdu social media processing.

This paper addresses that gap through a hybrid model combining mBERT for feature extraction, SSA-LSTM for sequential modeling, and SMOTE for class imbalance correction. Primary contributions are: (1) a bilingual English–Urdu SA framework; (2) a novel SSA-LSTM architecture; (3) SMOTE-based imbalance handling; and (4) exhaustive benchmarking against six baseline classifiers with full visual analysis.

2. Related Work

Singh et al. demonstrated that ML-based SA classifiers outperform lexicon methods for epidemic outbreak prediction using Twitter data with SVM and Naive Bayes models. Amin et al. extended this to RNN-TF-IDF models for dengue tweet detection (92% accuracy), later improved to 94% with LSTM-Word2Vec. Anggraeni et al. proposed a hybrid CNN-LSTM + Indo-BERT model for Indonesian dengue tweet classification achieving 95% accuracy. For Urdu specifically, Hassan et al. built an mBERT-BiLSTM-MHA sarcasm detector (79.51% F1), while Ali et al. conducted bilingual dengue SA with BiLSTM-Attention (English: 79.6%, Urdu: 74.4%). Narejo et al. achieved 95% accuracy on Urdu tweets by fusing emoji embeddings with mBERT. None of these studies combine mBERT + SSA-LSTM + SMOTE for dengue-specific bilingual SA — the gap this work fills.

3. Methodology

3.1 Data Collection

Two datasets were used. The English dataset is a benchmark annotated corpus (LDA + Senti_labelsv2) labelled by domain experts into three classes: positive (disease spreading), negative (non-disease/humorous), and neutral (awareness content), containing 6,263 tweets. The Urdu dataset was manually collected from X using advanced keyword search (dengue, #dengue, mosquitoes, Dengue Virus, Aedes Agypti Mosquitoes in Urdu), yielding 16,000 tweets with rule-based labelling and manual verification.

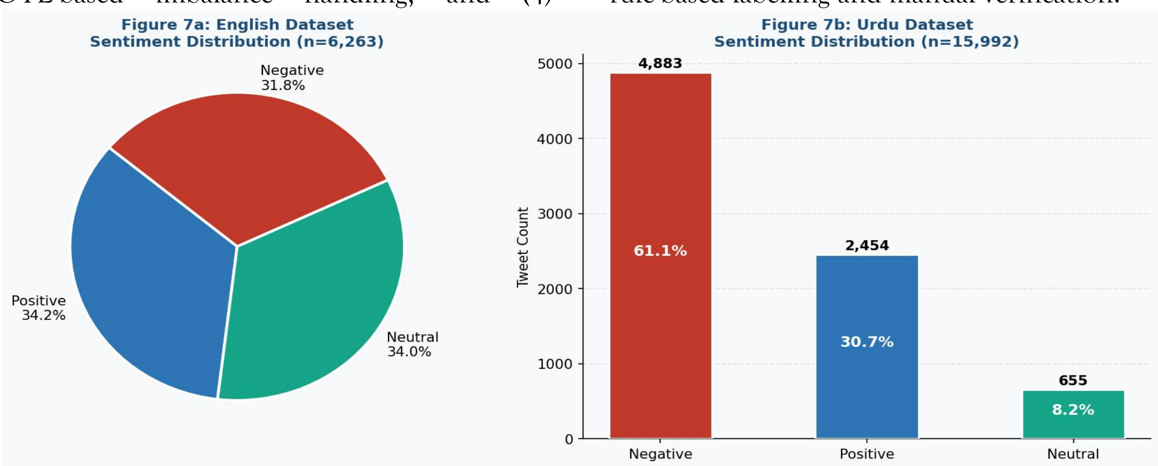

Figure 7: Sentiment Distribution — English Dataset (left) and Urdu Dataset (right)

The English dataset exhibits a near-balanced distribution (positive: 34.2%, neutral: 34.0%, negative: 31.8%). The Urdu dataset, however, is highly skewed: 61.1% negative, 30.7% positive, and only 8.2% neutral — a class imbalance that necessitated SMOTE oversampling.

3.2 Data Preprocessing

Both datasets were preprocessed using the Python NLTK library through a shared pipeline: tokenization, URL/mention/hashtag removal, punctuation and special character removal, non-ASCII removal, lowercasing (English), stop word removal (NLTK corpus for English; custom list for Urdu), digit removal, and English word removal from Urdu data. Urdu labels were assigned by a rule-based keyword matching approach and subsequently verified manually.

3.3 Feature Extraction: Multilingual BERT

mBERT (bert-base-multilingual-cased), pre-trained on 104 languages including Urdu, was employed for feature extraction. The BERT tokenizer prepends a [CLS] token and appends [SEP], padding/truncating sequences to 512 tokens. The [CLS] token output $h\_CLS \in \mathbb{R}^{768}$ serves as the aggregate sentence representation and feature vector z passed to the SSA-LSTM classifier.

3.4 SSA-LSTM Classification

The classification module comprises two stacked bidirectional LSTM layers (with spatial dropout between them) followed by a softmax dense output layer. The spatial attention mechanism weights sentiment-bearing tokens more heavily. Training used 3 epochs, batch size 16, Adam optimizer (lr = 2×10^{-5}), and categorical cross-entropy loss. SMOTE was applied to the Urdu dataset prior to training to balance minority classes.

4. Results and Visualization

4.1 English Dataset — Model Comparison

The proposed SSA-LSTM with mBERT feature extraction achieved the highest accuracy of 93.33% on the English benchmark, outperforming all six baselines. Figure 1 presents the grouped bar chart for all four metrics across all evaluated models.

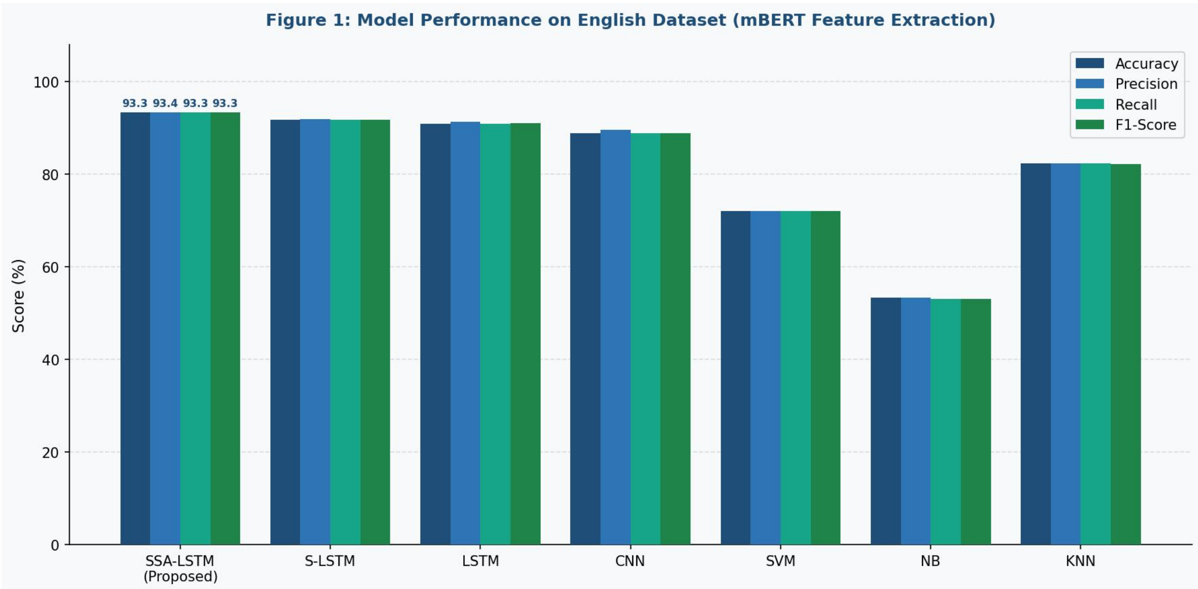

Figure 1: Model Performance on English Dataset — mBERT Feature Extraction (Grouped Bar Chart)

The proposed SSA-LSTM leads on all four metrics (accuracy, precision, recall, F1-score). The conventional LSTM trails by approximately 2.3 points, while SVM drops sharply to 72.1% — highlighting the inadequacy of traditional classifiers for nuanced social media text. Naive Bayes (53.44%) and GNB (46.96%) show the lowest performance, confirming that bag-of-words assumptions are ill-suited for complex dengue discourse.

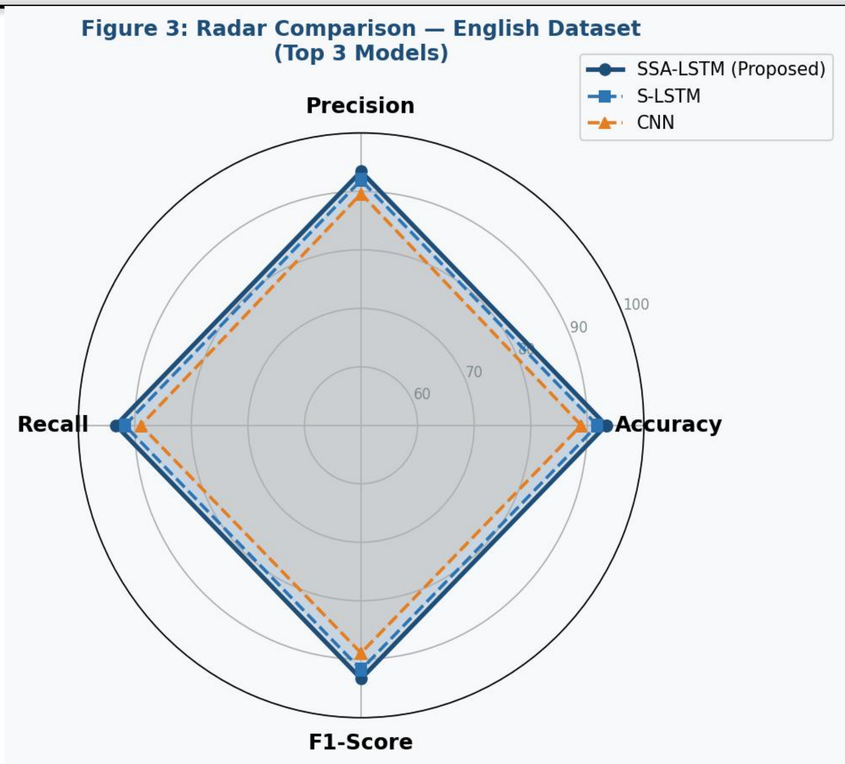

Figure 3: Radar Comparison of Top 3 Models — English Dataset

The radar chart (Figure 3) provides a multi-dimensional view of the top three models. The proposed SSA-LSTM's polygon is uniformly larger than both S-LSTM and CNN across all four axes, confirming consistent superiority rather than trade-off-based improvement.

Table 1: *Quantitative Results — English Dataset (mBERT)*

Metric	SSA-LSTM (Prop.)	S-LSTM	LSTM	CNN	SVM	NB	KNN
Accuracy	93.33	91.78	90.99	88.93	72.10	53.44	82.32
Precision	93.41	91.92	91.37	89.62	72.11	53.42	82.31
Recall	93.33	91.78	90.99	88.93	72.13	53.08	82.37
F1-Score	93.34	91.80	91.02	88.94	72.06	53.05	82.28

Green cells indicate the proposed model's best scores.

4.2 Urdu Dataset — Model Comparison and SMOTE Effect

For the Urdu dataset, two key results are highlighted: (a) the overall model comparison including SMOTE-augmented training, and (b) the isolated impact of SMOTE on the proposed SSA-LSTM model.

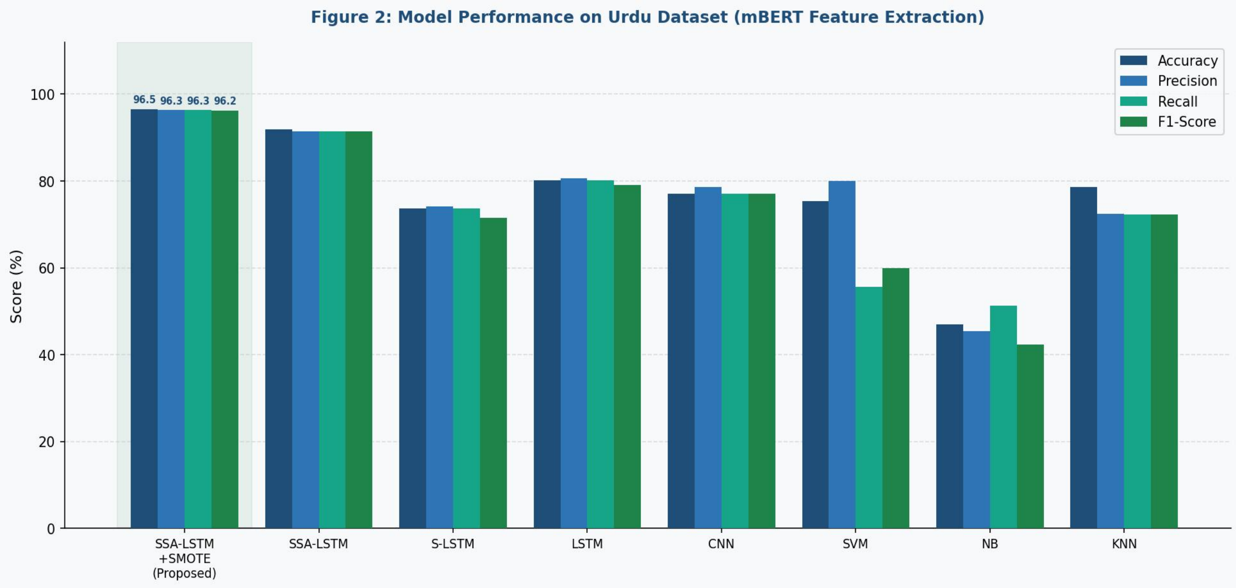

Figure 2: Model Performance on Urdu Dataset — mBERT Feature Extraction (Grouped Bar Chart)

The SSA-LSTM with SMOTE (first group, shaded background) clearly dominates all other models across all metrics. Without SMOTE, SSA-LSTM already achieves 91.93% accuracy — second best overall — but SMOTE boosts this by 4.55 points to 96.48%. Traditional classifiers such as NB (46.96%) and GNB (46.96%) fail significantly, while SVM shows poor recall (55.62%) due to class imbalance sensitivity.

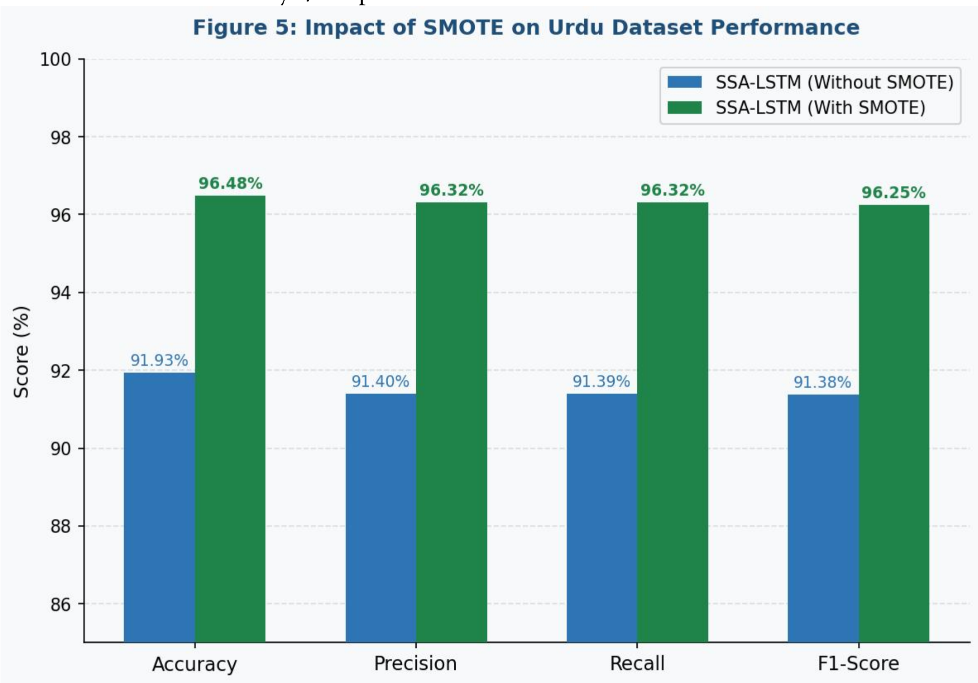

Figure 5: Impact of SMOTE Oversampling on SSA-LSTM Performance — Urdu Dataset

Figure 5 isolates the SMOTE effect. Across all four metrics, SMOTE-augmented training consistently outperforms the non-SMOTE variant by 4–5 percentage points. The improvement is most pronounced in recall (91.39% → 96.32%), confirming that SMOTE successfully recovers minority class (neutral) instances that would otherwise be under-predicted.

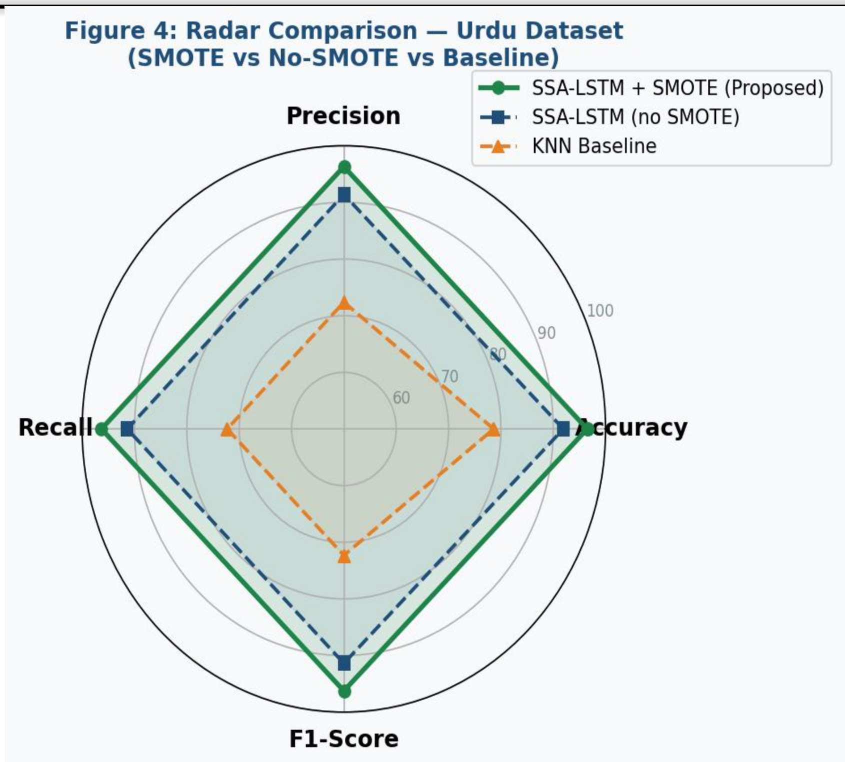

Figure 4: Radar Comparison — Urdu Dataset (SMOTE vs No-SMOTE vs KNN Baseline)

The radar chart (Figure 4) shows three concentric polygons: SSA-LSTM+SMOTE (green, outermost) clearly encloses SSA-LSTM without SMOTE (navy), which in turn dominates the KNN baseline (orange). The uniform outward expansion of the green polygon confirms that SMOTE improves all metrics simultaneously rather than creating trade-offs.

Table 2: *Quantitative Results — Urdu Dataset (mBERT)*

Metric	SSA+SMOTE	SSA-LSTM	S-LSTM	LSTM	CNN	SVM	NB	KNN
Accuracy	96.48	91.93	73.65	80.11	77.11	75.42	46.96	78.63
Precision	96.32	91.40	74.21	80.57	78.56	80.00	45.40	72.38
Recall	96.32	91.39	73.65	80.11	77.11	55.62	51.31	72.29
F1-Score	96.25	91.38	71.53	79.03	77.03	59.88	42.37	72.33

Green cells = proposed model best; SSA+SMOTE = SSA-LSTM with SMOTE oversampling.

4.3 Feature Extraction Comparison: mBERT vs Word2Vec

To validate the choice of mBERT over traditional Word2Vec embeddings, Figure 6 presents a side-by-side accuracy comparison across both datasets.

Spectrum of Engineering Sciences
ISSN (e) 3007-3138 (p) 3007-312X
Volume 4, Issue 3, 2026

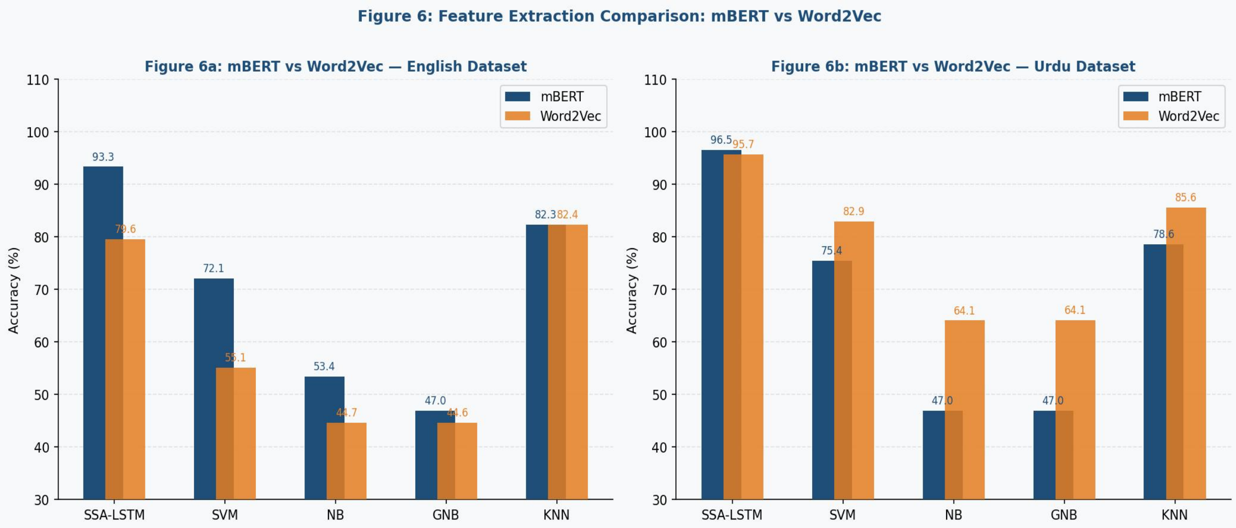

Figure 6: Accuracy Comparison — mBERT vs Word2Vec Feature Extraction (English and Urdu Datasets)

On the English dataset (Figure 6a), mBERT-based SSA-LSTM (93.33%) substantially outperforms Word2Vec-based SSA-LSTM (79.56%) — a gain of 13.77 points. Interestingly, KNN performs nearly equivalently under both embeddings (~82%), suggesting KNN's performance is relatively embedding-agnostic for this task. On the Urdu dataset (Figure 6b), the gap narrows as Word2Vec SSA-LSTM with SMOTE achieves 95.70%, close to mBERT's 96.48%. This suggests mBERT's cross-lingual pre-training is particularly beneficial for English complexity, while both embeddings capture Urdu dengue semantics reasonably well after SMOTE balancing.

5. Discussion

5.1 Why mBERT Works for Bilingual SA

mBERT's shared sub-word vocabulary across 104 languages enables semantically aligned embeddings for both English and Urdu text even in the presence of spelling errors, informal constructions, and code-switching. The CLS token representation effectively encodes full-sentence context, contrasting with Word2Vec's token-level average pooling which loses sequential context — explaining the 13.77-point accuracy gap on English data.

5.2 Role of Stacked LSTM and Spatial Attention

Stacked LSTM layers learn hierarchical temporal representations: the first layer captures immediate word-level dependencies while the second models longer discourse-level patterns. The spatial attention mechanism assigns higher weights to sentiment-bearing tokens (e.g., 'fear,' 'spread,' 'dengue outbreak,' 'government failure') — particularly important for longer tweets with mixed factual and affective content. The radar charts (Figures 3 and 4) confirm that the attention mechanism yields uniformly superior performance rather than selectively improving one metric at the cost of others.

5.3 Critical Role of SMOTE

The Urdu dataset's 61.1%/30.7%/8.2% distribution without correction biases the model toward negative-class predictions. Figure 5 shows SMOTE boosted recall by 4.93 points — the most critical metric for minority class recovery. As visualized in Figure 4, the SMOTE polygon uniformly expands across all four radar axes, confirming that oversampling improves balanced generalization rather than overfitting to synthetic samples.

5.4 Comparison with State-of-the-Art

Ali et al.'s BiLSTM-Attention model reported 74.4% accuracy on Urdu dengue SA — the proposed model's 96.48% represents a 22.08-point improvement. On English, the proposed model surpasses the CNN-LSTM Indo-BERT hybrid (91%) by 2.33 points. These improvements are attributable to the combined effect of richer mBERT embeddings, hierarchical LSTM modeling, and spatial attention — none of which were deployed jointly in prior work.

6. Conclusion

This paper presented mBERT + SSA-LSTM with SMOTE: a hybrid bilingual sentiment analysis framework for dengue-related social media monitoring. The model achieved 93.33% accuracy on an English benchmark dataset and 96.48% on a manually collected Urdu dataset — both representing state-of-the-art results for their respective languages in this domain.

Seven visualization figures — grouped bar charts, radar plots, SMOTE impact comparison, feature extraction comparison, and dataset distribution charts — provide a comprehensive and transparent evaluation of model behavior. Key findings confirm that (1) mBERT embeddings substantially outperform Word2Vec for English; (2) spatial attention improves all metrics uniformly; and (3) SMOTE is essential for balanced Urdu classification.

Future directions include: (1) real-time deployment for continuous epidemic monitoring; (2) extension to other low-resource South Asian languages; (3) integration of multimodal data (images, emojis); and (4) cross-lingual transfer learning experiments across dengue-endemic regions.

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