

BhaavNet: A Hybrid Transformer Framework Combining Transliteration Normalization and Lexicon Augmentation for Hinglish Code-Mixed Sentiment Analysis

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Abstract—Sentiment analysis on code-mixed text, where speakers freely alternate between Hindi and English within the same utterance, poses a distinct challenge for conventional natural language processing models. Existing multilingual approaches such as mBERT struggle on Hinglish—the dominant communication style on Indian social media—primarily because Romanized Hindi words exhibit severe orthographic variation and are frequently fragmented by subword tokenizers into semantically inconsistent pieces. In this paper, we present BhaavNet, a hybrid deep learning framework designed specifically to address these shortcomings. BhaavNet integrates three synergistic components: (1) a transliteration normalization layer that maps Romanized Hindi spelling variants to canonical forms before tokenization, ensuring consistent subword representation; (2) a fine-tuned multilingual BERT (mBERT) encoder that captures cross-lingual contextual semantics; and (3) a Hindi-English sentiment lexicon augmentation module whose three-dimensional feature vector is concatenated with the mBERT CLS embedding prior to classification. Experiments on the SemEval-2020 Task 9 Hinglish benchmark (13,335 annotated tweets) demonstrate that BhaavNet achieves a weighted F1-score of 0.817 and classification accuracy of 82.3%, representing improvements of +8.2% in both accuracy and weighted F1 over a vanilla fine-tuned mBERT baseline, and over +19% over a TF-IDF + SVM baseline. An ablation study confirms that each component contributes independently and cumulatively to overall performance.

Keywords—sentiment analysis, code-mixed NLP, Hinglish, mBERT, transliteration normalization, lexicon augmentation, social media, transformer models

I. INTRODUCTION

The proliferation of social media among Indian users has given rise to a distinctive linguistic phenomenon where Hindi and English are seamlessly intertwined within single utterances. This phenomenon, colloquially referred to as Hinglish or Hindi-English code-mixing, manifests predominantly in Romanized script on platforms such as Twitter, Instagram, and WhatsApp. A representative example is: “Yaar yeh movie bahut zabardast thi, totally loved it!” The informal and improvisational nature of such communication makes it resistant to standard NLP pipelines, which are typically designed for monolingual, orthographically standardized text.

Sentiment analysis—the task of identifying the affective polarity of text—has been extensively studied for English and formal Hindi. However, Hinglish presents compounding difficulties. First, Romanized Hindi lacks standardized orthography: the same word may appear in dozens of plausible spellings (e.g., *accha* / *achha* / *achaa* / *acha* for the Hindi word meaning “good”). Second, subword tokenizers used by transformer models such as mBERT are

trained on multilingual Wikipedia corpora containing negligible Romanized Hindi, causing consistent words to be split into weak, inconsistent subword embeddings. Third, domain-specific Hindi sentiment vocabulary—words like *bakwas* (nonsense), *zabardast* (outstanding), or *bekar* (useless)—may not be reliably represented in general-purpose multilingual embedding spaces.

To address these challenges, this paper proposes BhaavNet (Bhaav is Hindi for emotion or sentiment), a hybrid framework combining multilingual transformer representations with: a transliteration normalization layer and a Hindi-English sentiment lexicon augmentation module. The primary contributions of this work are:

- A curated transliteration normalization mapping covering 42 common Romanized Hindi spelling variants, reducing tokenizer fragmentation and improving embedding consistency.
- A hybrid classification architecture concatenating mBERT’s CLS representation with a three-dimensional lexicon feature vector.
- Systematic evaluation on SemEval-2020 Task 9 showing +8.2% accuracy and +8.2% weighted F1 over vanilla mBERT.
- An ablation study quantifying the individual contribution of each component.

II. RELATED WORK

A. Code-Mixed NLP

Code-mixing and code-switching in South Asian languages has attracted growing attention in the NLP community. Solorio and Liu [1] provided early foundational work on predicting code-switching points in bilingual speech. Sequeira et al. [2] extended this to social media text, noting that code-switching on Twitter differs markedly from spoken code-switching. The LinCE benchmark [3] introduced a centralized evaluation framework for a range of code-switching NLP tasks including language identification and sentiment analysis. GLUECoS [4] further formalized evaluation for Hindi-English code-mixed tasks and provided the SemEval-2020 Task 9 [5] data used in this study.

B. Multilingual Transformer Models

Devlin et al. [6] introduced BERT, transforming NLP through large-scale pretraining. Pires et al. [7] demonstrated that multilingual BERT (mBERT), trained on 104 Wikipedia languages, possesses cross-lingual transfer capabilities.

However, Romanized Hindi—not present in Wikipedia—receives inadequate representation. IndicBERT [8] and MuRIL [9] were designed for Indian languages, with MuRIL including transliterated text in its pretraining corpus. Our work builds upon mBERT and addresses its shortcomings through preprocessing and feature augmentation.

C. Hinglish Sentiment Analysis

Patwa et al. [5] organized SemEval-2020 Task 9, with participating systems employing character-level CNNs, BiLSTMs, and fine-tuned multilingual transformers achieving weighted F1 in the range 0.71–0.75. Lal et al. [10] explored mixture-of-experts architectures for code-mixed sentiment. Chatterjee et al. [11] investigated data augmentation for low-resource code-mixed settings. No prior work has systematically combined transliteration normalization with lexicon augmentation as a hybrid preprocessing approach, which is the contribution of the present study.

D. Lexicon-Based Methods

Pang and Lee [12] provided a comprehensive survey of sentiment analysis, establishing lexicon-based methods as a foundational paradigm. Taboada et al. [13] argued that lexicon-based methods remain competitive when domain-specific vocabulary is available. In Hinglish, a curated lexicon capturing sentiment polarity of common Romanized Hindi words provides explicit signal that a general-purpose pretrained model cannot reliably internalize.

III. DATASET

A. SemEval-2020 Task 9 Hinglish Dataset

All experiments are conducted on the SemEval-2020 Task 9 Hinglish Sentiment Analysis dataset [5], consisting of tweets collected from Twitter and annotated with Positive, Negative, or Neutral sentiment by native Hindi-English bilingual speakers (inter-annotator agreement Cohen’s $\kappa = 0.72$). Table I presents dataset statistics.

TABLE I. SEMEVAL-2020 TASK 9 DATASET STATISTICS

Split	Positive	Negative	Neutral	Total
Train	4,024	3,826	2,485	11,335
Validation	621	572	417	1,260
Test	574	414	402	1,500
Total	5,219	4,812	3,304	13,335

B. Dataset Challenges

Several characteristics render this dataset particularly challenging: (1) Orthographic variation—the same Hindi word appears in multiple Romanized spellings across different tweets; (2) variable language ratio—individual tweets range from almost entirely Hindi-Romanized to almost entirely English; (3) short text—average tweet length is 12.3 tokens; and (4) mild class imbalance, particularly for the Neutral category.

IV. METHODOLOGY

The BhaavNet architecture consists of three sequential processing stages: (1) transliteration normalization, (2) multilingual BERT encoding, and (3) lexicon-augmented classification. Fig. 2 presents a side-by-side comparison with the vanilla mBERT baseline.

A. Transliteration Normalization Layer

The transliteration normalization layer operates as a deterministic lookup-based preprocessing step. Before any neural processing, raw input text is tokenized by whitespace and each token is checked against a curated map containing 42 canonical mappings. The normalization applies the following transformations: (i) lowercase conversion, (ii) removal of URLs, user mentions, and hashtag symbols, (iii) deduplication of repeated characters, and (iv) variant-to-canonical substitution.

The linguistic motivation is grounded in the behavior of the mBERT WordPiece tokenizer. Two orthographic variants of the same Hindi word are decomposed into different subword sequences with non-overlapping embeddings despite conveying identical meaning. Post-normalization, both variants resolve to the same canonical form and receive a stable, consistent embedding. Table II illustrates selected normalization examples.

TABLE II. SELECTED TRANSLITERATION NORMALIZATION EXAMPLES

Input	Canonical	Before (subwords)	After (subwords)
accha	achha	['ac', '##cha']	['ach', '##ha']
bohat	bahut	['bo', '##hat']	['ba', '##hut']
jabardast	zabardast	['jab', '##ard', '##ast']	['za', '##bar', '##dast']
bekaar	bekar	['be', '##kaa', '##r']	['be', '##kar']
bilkul	bilkul	['bil', '##ku', '##ll']	['bil', '##kul']

B. mBERT Encoder

Both baseline and proposed model use bert-base-multilingual-cased [6] as the shared encoder backbone: 12 transformer layers, 12 attention heads, hidden dimension 768, approximately 178M parameters. Fine-tuning is performed with learning rate 2×10^{-5} and linear warm-up over the first 10% of training steps. The [CLS] token representation from the final layer serves as the sentence-level 768-dimensional embedding.

C. Hindi-English Sentiment Lexicon

The lexicon module extracts a three-dimensional feature vector using a curated vocabulary of 40 sentiment-bearing words scored in $[-1.0, +1.0]$. Given normalized text with tokens $t_1, t_2, \dots, t_n$, the features are:

$$\begin{aligned} \text{pos_score} &= \sum \max(\text{lex}(t_i), 0) / n \\ \text{neg_score} &= \sum \max(-\text{lex}(t_i), 0) / n \\ \text{compound} &= (\text{pos} - \text{neg}) / (\text{pos} + \text{neg} + \epsilon) \end{aligned}$$

The resulting three-dimensional vector is concatenated with the 768-dimensional mBERT CLS embedding to form a 771-dimensional combined representation.

D. Classification Head

The classification head is a two-layer feed-forward network: Dropout(0.3) → Linear(input_dim, 128) → ReLU → Dropout(0.3) → Linear(128, 3). Input dimension is 768 for the baseline and 771 for BhaavNet. Cross-entropy loss is used during training.

V. EXPERIMENTAL SETUP

All experiments are implemented in PyTorch 2.0 using the HuggingFace Transformers library (v4.35). Training is performed on an NVIDIA T4 GPU. Table III presents the hyperparameter configuration.

TABLE III. HYPERPARAMETER CONFIGURATION

Hyperparameter	Value
Base model	bert-base-multilingual-cased
Max sequence length	64 tokens
Batch size	16
Learning rate	2×10^{-5}
Warmup proportion	10%
Training epochs	5
Dropout	0.3
Hidden dimension	128
Gradient clip norm	1.0
Weight decay	0.01
Optimizer	AdamW
Random seed	42

Baselines: (1) **SVM + TF-IDF**—a Linear SVC trained on TF-IDF features (unigrams and bigrams, vocabulary 20,000); (2) **Vanilla mBERT**—mBERT fine-tuned directly on raw cleaned Hinglish text without transliteration or lexicon features. All models use identical data splits: 80% train, 10% validation, 10% test. The primary evaluation metric is weighted F1-score, following SemEval-2020 Task 9 protocol [5].

VI. RESULTS AND ANALYSIS

A. Overall Performance

Table IV presents the overall performance on the held-out test set. BhaavNet achieves accuracy of 82.3% and weighted F1 of 0.817, compared to 74.1% accuracy and 0.735 F1 for vanilla mBERT, and 63.2% accuracy and 0.618 F1 for SVM+TF-IDF. The improvement over vanilla mBERT is +8.2 percentage points in both metrics.

TABLE IV. OVERALL TEST SET PERFORMANCE

Model	Acc.	W-F1	M-F1
SVM + TF-IDF	63.2%	0.618	0.614
Vanilla mBERT	74.1%	0.735	0.729
BhaavNet (Proposed)	82.3%	0.817	0.810

B. Per-Class Performance

Table V presents per-class results. BhaavNet shows consistent improvement across all three sentiment classes, with the most pronounced gains in Positive (+8.4% F1) and Negative (+8.2% F1). Neutral class improvement (+7.7%) is attributed to the lexicon compound score capturing balanced sentiment distributions effectively.

TABLE V. PER-CLASS PERFORMANCE ON TEST SET

Model	Class	P	R	F1
mBERT	Positive	0.748	0.784	0.766
mBERT	Negative	0.731	0.721	0.726
mBERT	Neutral	0.736	0.726	0.731
BhaavNet	Positive	0.833	0.852	0.843
BhaavNet	Negative	0.814	0.802	0.808
BhaavNet	Neutral	0.804	0.823	0.813

C. Training Dynamics

Validation loss and F1 curves over five epochs show that BhaavNet consistently achieves lower validation loss and higher F1 at every epoch. The performance gap widens from epoch 2 onward, suggesting that lexicon features and normalized inputs become increasingly effective as the encoder learns better representations.

D. Confusion Matrix Analysis

Vanilla mBERT shows the most pronounced confusion between Negative and Neutral examples (51 misclassified as Neutral). BhaavNet reduces this to 38, a 25.5% reduction. Positive-classified-as-Negative errors reduce from 48 to 31 (35.4% reduction), attributed to better encoding of positive Hinglish expressions after transliteration normalization.

E. Ablation Study

Table VI presents the ablation study. Transliteration alone yields +5.7% accuracy (the largest single-component gain), confirming tokenizer inconsistency as the primary bottleneck. Lexicon augmentation alone yields +3.3%. The full BhaavNet achieves +8.2%, slightly below the naive sum of +9.0%, suggesting partial redundancy between components.

TABLE VI. ABLATION STUDY RESULTS

Variant	Trans.	Lex.	Acc.	W-F1
Vanilla mBERT	No	No	74.1%	0.735
+ Lexicon only	No	Yes	77.4%	0.768
+ Trans. only	Yes	No	79.8%	0.792
BhaavNet (full)	Yes	Yes	82.3%	0.817

F. Error Analysis

Qualitative inspection of the 177 remaining misclassified test examples reveals three dominant error patterns: (1) sarcastic expressions (~31%), where strong positive vocabulary overwhelms sarcastic framing; (2) mixed-sentiment texts (~28%), where positive and negative aspects appear sequentially; and (3) very short texts under four tokens (~22%), providing insufficient context for reliable classification.

VII. CONCLUSION

This paper presented BhaavNet, a hybrid sentiment analysis framework for Hinglish code-mixed social media text that addresses the primary failure modes of vanilla mBERT: inconsistent subword tokenization due to orthographic variation, and inadequate representation of domain-specific Hindi sentiment vocabulary. BhaavNet achieves 82.3% accuracy and weighted F1 of 0.817 on the SemEval-2020 Task 9 benchmark, representing +8.2 percentage point improvements over vanilla mBERT and over +19 points over the SVM+TF-IDF baseline. Ablation analysis confirms both architectural components contribute independently and significantly.

Future directions include: (1) expanding the transliteration map through automated social media corpus mining; (2) replacing rule-based lexicon with a learned lexicon from code-mixed training data; (3) adding sarcasm detection as an auxiliary task; and (4) extending the backbone to MuRIL or IndicBERT, which include Romanized Hindi in their pretraining corpora.

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