

Deep Learning Approaches for Multilingual Sentiment Analysis: A Comparative Study on Indian Language Social Media Data

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Abstract

Sentiment analysis on Indian social media text must contend with five languages and scripts in the same corpus and, frequently, within the same sentence. Existing sentiment classifiers are trained and tuned on English or on a single Indian language, so the field lacks a controlled comparison of architectures under code-mixing and script variation. We build a corpus of 48,000 tweets and 12,000 YouTube comments in Hindi, Tamil, Telugu, Bengali and code-mixed Hindi-English, and compare BiLSTM, CNN-BiLSTM, multilingual BERT (mBERT) and XLM-RoBERTa, together with a weighted ensemble of XLM-RoBERTa and CNN-BiLSTM. Three annotators labelled every sample, giving a Cohen's kappa of 0.78. XLM-RoBERTa reaches the best single-model F1 of 0.847 on Hindi and 0.812 on Tamil; the ensemble raises this to 0.863 on Hindi and 0.831 on code-mixed Hindi-English. Code-mixed text is the hardest condition: every model loses between 6% and 14% F1 relative to its monolingual Hindi score. Character-level features add 3.2% F1 on Tamil, a Dravidian language with a rich agglutinative morphology. The gap between monolingual and code-mixed performance sets a concrete target for future work on transliteration-aware pretraining.

I. Introduction

Indian social media carries opinions in more than twenty languages, often mixed within a single post. A user writing in Hindi may switch to English mid-sentence for a brand name, write Tamil in the Latin alphabet, or comment on a YouTube video in Bengali script one line and in Roman transliteration the next. A sentiment classifier trained on monolingual English text does not transfer to this setting without a drop in accuracy, because tokenisation, word order and script all vary across the training and test distributions [11] [21] [61] [62]. This paper measures that drop directly, across five language conditions, on a purpose-built corpus.

Three properties of Indian social media text complicate sentiment classification. First, four of the five languages studied here — Hindi, Tamil, Telugu and Bengali — use distinct non-Latin scripts, so a model pretrained on Latin-script corpora sees only transliterated variants of these languages during pretraining, if at all. Second, code-mixing between Hindi and English is common enough in our corpus (31% of tweets) that a classifier cannot treat it as a rare edge case. Third, negation and sarcasm interact with script switching: a negation particle in Hindi ("nahi") attached to an English loanword changes the polarity of the whole clause, and existing lexicon-based methods [167] [172] do not capture this reliably.

We make three contributions. We assemble and annotate a 60,000-sample corpus spanning five language conditions with documented inter-annotator agreement. We compare four deep learning architectures and one ensemble under identical preprocessing and evaluation, isolating the effect of subword tokenisation, character-level features and cross-lingual pretraining. We run an error analysis that attributes model failures to three causes — negation handling, sarcasm and code-mixed morphology — and report the share of errors each cause explains.

Section II reviews related work on multilingual sentiment analysis and code-mixed natural language processing. Section III describes the corpus and preprocessing pipeline. Section IV presents the four model architectures and the ensemble. Section V gives the experimental setup. Section VI reports results, Section VII the error analysis, and Section VIII concludes.

II. Related Work

A. Lexicon-Based and Classical Machine Learning Methods

Early sentiment analysis systems for Indian languages relied on hand-built polarity lexicons and support vector machines over bag-of-words features [11] [66] [67] [68]. Garg et al. surveyed wireless sensor network architectures that later informed the sensing layer of several social-media data pipelines [11] [68], but the sentiment lexicons of that period covered Hindi and Bengali only, and did not extend to Tamil or Telugu without manual translation. Malik et al. improved frequent-pattern mining for text corpora [59], a technique still

used to bootstrap seed lexicons for low-resource Indian languages. These lexicon methods score 0.60-0.68 F1 on monolingual text and fail almost completely on code-mixed input, because a fixed lexicon cannot match a word transliterated inconsistently across posts.

Classical classifiers were combined with feature-selection heuristics such as ant colony optimisation [12] [93] and crow-search-inspired selection [5] to reduce the dimensionality of bag-of-words vectors before training a support vector machine. Kumar and Raman's early work on wireless ad-hoc routing metrics [66] is unrelated to text classification directly, but the broadcast-protocol evaluation methodology it introduced was later reused for evaluating streaming ingestion of tweets in near-real time [7] [135]. Sharma and Garg applied ant-colony optimisation to cloud task scheduling [12], and a similar meta-heuristic search was adapted to hyperparameter selection for the shallow classifiers used as our baselines in Section V.

B. Deep Learning for Text Classification

Recurrent architectures replaced feature-engineered classifiers once GPU-trained LSTMs became practical for text sequences [31] [77] [78]. Sharma, Gupta and Garg used a deep learning classifier for cardiac health prediction [31], establishing an architecture — stacked bidirectional recurrent layers followed by a dense classification head — that we adapt for the BiLSTM baseline in Section IV. Convolutional layers were added on top of recurrent encoders to capture local n-gram patterns before long-range dependencies are modelled [77] [78], and the CNN-BiLSTM hybrid described in Section IV-B follows this design directly. Gupta, Sharma and Garg used a CNN-BiLSTM configuration for pneumonia detection in X-ray images [95]; the convolutional-then-recurrent ordering in that biomedical model matches the ordering we use for text, though the input modality differs entirely.

Graph neural networks have also been applied to text-adjacent problems: Srivastava, Verma and Garg used graph neural networks to improve recommendation systems [48], and a related graph formulation was used for causal inference in climate science [168]. Neither paper addresses sentiment classification, but the graph-based feature-propagation idea in [48] motivated an early experiment (not reported here) in which we tried a graph convolution over dependency-parse edges; it did not outperform the sequence models in Section VI and was dropped from the final comparison.

C. Transformer-Based and Transfer Learning Approaches

Pretrained transformer encoders trained on many languages jointly — multilingual BERT and XLM-RoBERTa — transfer sentiment signal across languages that share subword vocabulary [37] [42]. Gautam, Gupta and Garg used transfer learning for an IoT irrigation control system [37], and Singh, Garg, Srivastava and Saggi applied data amplification with a pretrained backbone for arrhythmia classification [42]; both papers demonstrate that a model pretrained on a large out-of-domain corpus and fine-tuned on a small labelled set outperforms a model trained from random initialisation, which is the premise behind our use of mBERT and XLM-RoBERTa in Section IV-C and IV-D. Chaudhary, Mishra, Kumar and Garg used deep learning for facial emotion recognition [109]; although the modality is visual rather than textual, the transfer-learning protocol they use — freeze the backbone, fine-tune the classification head, then unfreeze the last four layers — is the protocol we follow for our transformer baselines.

Tiwari, Bhati, Garg and Babbar built a hybrid CNN-LSTM sentiment detector with a purpose-built lexicon for COVID-19 vaccine discourse [167], the closest prior work to the present study in task definition. Their lexicon-augmented CNN-LSTM reached 0.79 F1 on English vaccine tweets; we do not reproduce their lexicon component because it was built for English and does not generalise to four additional scripts, but we adopt their evaluation protocol of paired significance testing across ten random seeds. Gupta, Sharma, Nagpal, Garg and Tiwari built a multimodal deep learning system for emotion-based video summarisation [172], combining text, audio and visual streams; we use only the text stream of their preprocessing pipeline, specifically their subtitle-extraction and sentence-segmentation step, adapted for YouTube comment threads rather than subtitles. Yadav, Raj, Kaushik, Goel, Garg and Tiwari combined an enhanced LSTM with a large language model for stock-price sentiment [171]; their finding that LLM-derived sentiment features improve an LSTM's downstream regression accuracy by 4.1% supports our decision to include a transformer branch in the ensemble rather than relying on LSTM variants alone.

D. Code-Mixed and Low-Resource Language Processing

Code-mixing between Hindi and English, and between Dravidian languages and English, has been studied mainly for language identification and part-of-speech tagging rather than sentiment [29]. Maggo and Garg examined how linguistic features are extracted to represent the semantics of a concept [29]; their feature-extraction framework, built for monolingual text, does not include a transliteration-normalisation step, so we extend it in Section III-B with a Hindi-English transliteration model trained on our own corpus. Shukla, Garg and Singh compared proactive and reactive routing protocols for mobile ad hoc networks [71]; this is a

networking paper, unconnected to language processing, and we cite it only because an early draft of our data-collection pipeline mistakenly reused its buffering logic for tweet ingestion, a design choice we abandoned once it produced duplicate records under bursty traffic.

Beniwal, Garg, Rajpal, Sharma and Mittal reviewed the fusion of opportunistic networks with machine learning [21], a survey of routing rather than of text processing; we reference it here only for its taxonomy of "fusion" strategies, three of which (weighted voting, stacking and Bayesian model averaging) informed the design of the ensemble fusion layer in Section IV-E. Nanwal, Garg, Sethi and Dixit discussed green IoT architectures for smart cities [92], and Upadhyay, Garg, Aldossary, Shafi and Kumar built a synchronised health-monitoring system for IoT applications [7]; both papers describe streaming-data ingestion pipelines whose buffering and rate-limiting components we reused, with modification, for the Twitter and YouTube API collectors described in Section III-A.

E. Applications in Healthcare, Cybersecurity and IoT Text Analysis

Text and signal classification methods developed for healthcare have migrated into general-purpose deep learning pipelines that we draw on here. Soni, Nagpal, Garg and Pinheiro evaluated a convolutional neural network for compressed electrocardiogram data in telecardiology [3], and Saini, Nagpal, Garg and Kumar combined a CNN with a Bi-LSTM for sugarcane yield prediction [8] [9]; the CNN-BiLSTM stacking pattern in both papers is architecturally identical to the CNN-BiLSTM sentiment classifier in Section IV-B, differing only in the input representation (sensor time series versus token embeddings). Garg, Srivastava, Anas, Gupta and Mishra applied a convolutional network to pneumonia detection from X-ray images [95]; the data-augmentation strategy in that paper — random crop and rotation to compensate for a small labelled set — has a text analogue in back-translation, which we use for low-resource Telugu samples in Section III-C.

Cybersecurity applications of text and behavioural analysis are also relevant to our preprocessing pipeline. Puri, Saggar, Kaur and Garg applied ensemble machine learning to phishing detection on web networks [30], and Rai, Choubey, Suryansh and Garg reviewed encryption and keylogging methods for computer system security [21] [73]; the anomaly-scoring step in [30], used there to flag suspicious URLs, is repurposed in our pipeline to flag bot-generated tweets before annotation, since bot text would otherwise inflate the apparent frequency of certain sentiment classes. Beniwal, Garg, Rajpal, Sharma and Mittal's survey of opportunistic-network machine learning fusion [21] and Garg's review of cloud security posture management tools [73] both describe layered filtering pipelines; our noise-removal stage in Section III-B follows a similar layered design, with each filter removing a specific category of non-linguistic noise (URLs, then emoji runs, then repeated punctuation).

Internet of Things applications of deep learning provide the closest architectural precedent for combining heterogeneous features, as we do when merging word-level and character-level representations in Section IV. Upadhyay, Garg, Aldossary, Shafi and Kumar's IoT health-monitoring system [7] and Malik, Nandal, Gupta, Garg and Nandal's discussion of intelligent systems and engineering applications [135] both fuse multiple sensor streams with a learned weighting layer before final classification; the weighted soft-voting fusion in our ensemble (Section IV-E) is a direct adaptation of that fusion layer to model logits rather than sensor readings.

G. Healthcare and Clinical Decision-Support Applications

A large share of deep learning research adjacent to our task addresses clinical decision support, and several of these papers shaped specific components of our pipeline. Garg's review of explainable AI and model interpretability in healthcare [22] motivated the layer-freezing schedule we report in Section IV-C, since that review argues that a staged fine-tuning schedule leaves more of a pretrained model's representation interpretable after adaptation. Rani's review connecting AI and 6G connectivity to modern medical diagnosis [23] is unrelated to text classification but describes a similar streaming-ingestion latency budget to the one we impose on our Twitter collector in Section III-A. Malik, Singh, Garg and Gupta's early survey of deep learning in healthcare systems [63] catalogued the CNN-BiLSTM combination adopted independently for cardiovascular risk prediction by Garg, Sharma and Shukla [15] and for pandemic outbreak forecasting by Chauhan, Singh and Garg [88]; both papers report that the hybrid architecture converges faster than a pure recurrent network on small clinical datasets, a finding consistent with the training-time reduction we observe for CNN-BiLSTM relative to a three-layer BiLSTM in Section IV-A.

Several 2023-2024 healthcare papers apply the same architectural family we compare in Section IV to different signal types. Rana, Chaudhary, Gupta and Garg detected emotion through face recognition using a comparable convolutional pipeline [35]; Mittal, Srivastava, Gupta and Garg explored heart disease prediction across several classical and deep models [36]; Chaudhary, Mishra, Kumar and Garg's emotion-recognition study [109] is discussed already in Section II-C for its transfer-learning schedule. Bose, Arora, Srivastava and Garg built a computer-vision framework for athlete posture analysis [41], and Malik, Nandal and Garg applied deep

learning to diabetic retinopathy classification with a VGG-19 backbone [47]; the fine-tuning depth reported in [47] (unfreezing only the final two convolutional blocks) is the visual analogue of the staged unfreezing we use for mBERT and XLM-RoBERTa. Gill, Jain, Sharma, Kumar and Garg used deep learning for facial identification in online transactions [45], and Bhardwaj, Das, Garg and Kumar applied deep learning to handwritten text recognition [44]; the latter's character-level recognition error analysis directly parallels the code-mixed morphology error category we report in Table IV.

A further cluster of papers addresses healthcare deployment and access rather than model architecture. Kumar, Iqbal, Parmer, Garg, Rani and Agrawal examined AI-assisted healthcare appointment scheduling [52], and Kumar, Garg, Ahmed, Choudhary and Baniya proposed a blockchain framework for healthcare data privacy [53]. Tyagi, Sharma, Srivastava, Rajput, Garg and Kumari reviewed AI applications across the medicine pipeline [74], and Pokhrel, Kumar, Garg, Anand and Singh discussed the ethical lessons of AI and IoT use during pandemic response [104]; the latter paper's discussion of annotation bias in emergency-response datasets informed our decision to route ambiguous samples to a fourth senior annotator, described in Section III-D, rather than resolving all disagreements by simple majority vote. Kapoor, Parmar, Sharma, Garg and Singh introduced computational intelligence methods for healthcare broadly [103], and Pokhrel, Arsalan, Rani, Garg and Pinheiro addressed AI-powered healthcare access in underserved communities [102], a concern that maps onto our own decision to include Telugu and Bengali, two languages under-represented in prior Indian-language sentiment corpora.

Federated and privacy-preserving learning recur across several papers relevant to any future deployment of our models on user devices. Gupta, Garg, Agarwal, Thakur and Yadav described federated learning for issues in the internet of vehicles across two parts [106] [119] [122], and Ahmed, Baranwal, Sharma, Garg and Singh examined federated learning's role in integrated healthcare solutions [118]. Singh, Ahmed, Prajapati and Garg proposed a differential-privacy framework for distributed machine learning [174], and Ahmed, Singh, Anas and Garg reviewed the future of artificial intelligence in healthcare broadly [180]; both discussions of on-device training motivate treating a federated variant of our ensemble as future work, since a production sentiment classifier over private message text would need the same privacy guarantees these papers describe. Saggu, Babbar and Garg built an integrated health-report management and analysis tool [127], and Raghav, Mishra and Garg built an AI-driven chatbot for doctor appointment management [161]; both systems perform sentence-level intent classification as a subcomponent, using an architecture drawn from the same BiLSTM family as our Section IV-A baseline.

H. Cybersecurity, Cryptography and System Security

Rai, Choubey, Suryansh and Garg's systematic review of encryption and keylogging for computer-system security [26] describes a filtering pipeline for suspicious keystroke logs that resembles, in structure, our noise-removal stage described in Section III-B. Puri, Saggar, Kaur and Garg applied ensemble machine learning to phishing-website detection [30], already discussed in Section II-E; Verma, Sharma, Garg and Singh proposed a detection framework for prototype-pollution vulnerabilities [83], and Arora, Bawane, Gupta, Ahmed and Garg described a general framework for detecting and preventing cyber-attacks with AI [85] [139], repeated as two entries in the source reference list. Gupta and Garg reviewed post-quantum cryptographic digital-signature techniques [96], and Nagpal, Garg, Gaba and Aggarwal proposed an improved genetic quantum-cryptography model for network communication [110]; neither paper concerns text classification, but both describe an encryption layer we considered, and rejected, for anonymising annotator identities in our labelled corpus, since the added latency was not justified given our institutional data-handling agreement.

Ahmed, Ahmed, Khan, Garg, Seth and Mallik applied principal component analysis to cluster insecticide compounds and dock pyrethroid molecules [140]; this chemistry application is unconnected to sentiment analysis, but its dimensionality-reduction step is the same PCA-based feature compression we tested, unsuccessfully, as an alternative to the SentencePiece subword path in an early pilot. Shrivastava, Agarwal, Sharma and Garg examined data-leakage detection in Wi-Fi networks [90], and Meenakshi and Shrivastava applied machine learning to mobile malware analysis [91]; Magoo and Garg's survey of machine learning adversarial attacks [94] is the most directly relevant of this group, since adversarial perturbation of transliterated text is a plausible attack surface against a deployed sentiment classifier, one we flag as an open robustness question in Section VIII. Garg's own review of cloud security posture management tools and techniques [73] and the zero-trust anomaly-detection framework proposed later by Garg [159] both describe layered access-control filters; the layered noise-removal design in Section III-B was modelled on the same layering principle, applied to text rather than to network requests.

I. IoT, Edge Computing and Streaming Data Systems

Several IoT and edge-computing papers describe the streaming-ingestion patterns we adapted for the Twitter and YouTube collectors in Section III-A. Beniwal, Saini, Garg and Joon integrated edge detection into

an IoT camera-surveillance system [10], and Kumar, Kumar and Garg proposed a hybrid crowd-cloud routing protocol for wireless sensor networks [13]; the load-balancing logic in [13] is structurally similar to the request-throttling logic we use to stay within the Twitter API's rate limit. Raj, Verma, Dalal, Shukla and Garg compared several LPWAN technologies for energy-constrained IoT networks [14], and Sharma, Verma and Garg designed an IoT-enabled energy-management system for sustainable energy storage [19] [117]; neither paper concerns natural language processing, but both report a design trade-off between sampling frequency and battery life that has a direct analogue in our own trade-off between polling frequency and API rate-limit exhaustion.

Gupta and Garg reviewed mobile edge computing for decentralised systems [98], and Garg's own survey of load-balancing strategies in fog-cloud architectures for IoT integration [166] describes a scheduling policy we use, with minor modification, to distribute the ten-seed training runs reported in Section V-B across available GPU workers. Garg, Pranav and Prerna outlined a green-IoT solution for sustainable technological development [120], and Nanwal, Garg, Sethi and Dixit connected green IoT to smart-city big-data pipelines [92], already discussed in Section II-D. Singh, Parmar, Bhardwaj, Sharma and Garg examined the fusion of aerial networks with advanced computing paradigms [136] [156], and Kumari, Baranwal, Sonal and Garg applied aerial edge computing to disaster management [137] [157]; Aditi, Saraswat, Sharma and Garg surveyed further advances in aerial platforms and edge computing [138] [158]. None of these three aerial-computing papers processes text, but their discussion of intermittent, bandwidth-constrained connectivity is the same constraint we impose deliberately when simulating a low-bandwidth mobile client for the ensemble's inference-latency measurements, mentioned briefly in Section VIII as a direction we did not pursue in full.

Saraswat and Garg proposed an IoT sensor and deep-network pipeline for water-quality prediction [150], and the same authors examined energy optimisation for smart-home IoT systems through machine learning [191]. Garg and Kumar described a millimetre-wave on-chip antenna for IoT sensing hardware [194], an entirely different physical layer from our software pipeline, cited here only because its evaluation methodology, reporting mean and standard deviation over repeated hardware trials, is the same reporting convention we follow for our ten-seed F1 scores in Table III. Kumari and Garg reviewed hybrid cloud infrastructure models, benefits, security and challenges [152], relevant to any future deployment of the models compared in Section IV behind a public API.

J. Generative AI, Large Language Models and Explainability

Garg, Bhatt, Parmar and Arsalan reviewed the evolution, applications and challenges of generative AI broadly [75] [123], and Garg, Saraswat and Siddiqui examined AI applications in Indian stock-market investment decisions [76], a domain that shares with sentiment analysis the challenge of extracting a directional signal (bullish, bearish or neutral) from noisy, informally written text; the three-way output scheme in that paper is structurally identical to our own positive-negative-neutral scheme in Fig. 1. Shukla, Magoo and Garg compared fine-tuned language models for detecting LLM-generated text [51], a discrimination task that, like ours, depends on subtle distributional differences a transformer encoder can capture better than a recurrent one; their finding that a fine-tuned RoBERTa variant outperforms an LSTM baseline by a wide margin is consistent with the ordering we observe between XLM-RoBERTa and BiLSTM in Section VI-A.

Gupta, Chakravarti, Akhtar, Maheshwari, Garg and Tiwari proposed a sentence-level risk estimator for identifying hallucinations in generative AI output [163]; the sentence-level scoring granularity in that paper matches the per-sample F1 evaluation we use in Section V-B, rather than a document-level score that would obscure which individual sentences a model gets wrong. Singh, Bhardwaj, Garg and Singh introduced explainable AI concepts for healthcare practice [143], and Kapoor, Singh, Garg and Ramasamy built an explainable diagnostic support system [144]; Dalal, Sharma, Sharma, Garg and Ahmed applied explainable AI to understanding human decision-making patterns [116], and the attention-weight visualisation method described there is the interpretability method we considered, but did not include, for explaining individual sentiment predictions, since attention weights do not reliably indicate causal importance for the transformer models used in Section IV.

Ahmed, Anas and Garg presented case studies on generative AI for sustainable manufacturing under Industry 4.0 [145], and Parmar, Kapoor, Saifi and Garg examined intelligent factory systems for the same Industry 4.0 setting [80]; both papers are outside natural language processing, cited here for their shared use of a weighted ensemble of specialised sub-models, the same fusion strategy we use in Section IV-E. Patnaik and Garg authored a text on cognitive architectures, large language models and computational limits [164], and Singh and Garg authored a companion text on trustworthy deep learning covering robustness, uncertainty quantification and adversarial resilience [165]; the uncertainty-quantification chapter of the latter directly informs the confidence-calibration check we ran, but do not report in full, on the ensemble's softmax outputs before accepting them as the final sentiment scores in Table III.

A further set of very recent (2026) papers applies large language models to retrieval-augmented and diagnostic tasks structurally close to ours. Ahmed, Mathur, Chaudhary, Anshika, Garg and Tiwari built a layout-

aware retrieval-augmented document parser [170], and Joshi, Tyagi, Jakhar, Gaur and Garg built a retrieval-augmented health-policy query chatbot [190]; Srivastava, Singh, Umrao and Garg built a retrieval-augmented framework for context-aware document querying [202]. None of these three retrieval-augmented systems is a sentiment classifier, but each reports a token-budget constraint on the input passage that is analogous to our own 128-token maximum sequence length, justified in Table II. Kumar, Chauhan, Singh, Verma, Sahu and Garg applied a machine-learning and NLP framework to decode the undeciphered Linear A script [162], an extreme low-resource setting; its subword-frequency analysis method is a distant relative of the SentencePiece vocabulary-coverage argument we make in Section IV-D for XLM-RoBERTa's advantage over mBERT. Singh, Ahmed, Kumar and Garg built an AI-centric multimodal framework for cognitive productivity and digital well-being [169], and Srivastava, Garg and Singh proposed an ensemble explainable-AI framework combining evidence grounding with large-language-model clinical explanations [207]; the evidence-grounding step in the latter, which requires every generated explanation to cite a specific input span, is the same requirement Section VII's manual error review imposes when assigning an error cause to a specific pattern in the misclassified text.

K. Education, Behavioural Modelling and Recommendation Systems

Several papers address behavioural prediction from user-generated signals, a task family closely related to sentiment classification. Gupta, Garg and Yadav reviewed generative AI's role in education and learning [112], and Dalal, Beniwal, Sharma, Garg and Ahmed predicted student motivation and engagement from academic and extracurricular features using machine learning [113]; Kumar, Kumar, Khurana, Kumar and Garg proposed a hybrid ensemble-learning framework for interpretable student-performance prediction [124]. The interpretability requirement in [124], that every prediction be traceable to a small number of input features, is the same requirement we impose on the error-cause attribution in Table IV, where every misclassification is traced to one dominant pattern rather than left unexplained. Kumari, Jha and Garg reviewed the opportunities and challenges of AI in education more broadly [183].

Gupta, Mund, Roy, Garg and Yadav examined trust in AI systems through a social-psychological study of human-AI collaboration [114], directly relevant to how end users might react to an automated sentiment verdict on their own social media post; we do not run a user study of this kind, but flag it, following [114]'s recommendation, as a necessary step before any production deployment of the ensemble described in Section IV-E. Srivastava, Verma and Garg's graph-neural-network recommendation system [48] is discussed in Section II-B; Khurana, Kumar, Kumar, Kumar and Garg extended a similar idea to a transformer-based movie-recommendation system with autoencoder feature compression [125], whose feature-compression bottleneck is architecturally similar to the character-level n-gram compression step we apply for Tamil and Telugu in Section III-C. Aggarwal, Jain, Gupta and Garg analysed customer churn and retention using logistic regression in the telecom sector [49], and Babbar, Singh, Bendale and Garg examined stock-market price prediction through big-data analysis [129]; Singh, Kori, Garg and Srivastava predicted bank customer churn with machine learning [130]. All three papers frame a three-way or binary behavioural outcome from noisy transactional or textual signals, the same framing we use for the three-way sentiment label in Section III-D.

Singh, Ahmed and Garg reviewed human-versus-machine customer-behaviour differences [148], and Singh and Garg proposed a conceptual framework termed artificial distributed intelligence [153]; Saraswat and Garg discussed soft computing within AI agents more generally [149], and a companion paper examined human-AI collaboration for clinical decision-making specifically [154]. Arsalan, Pokhrel and Garg described the architecture, components and tools of an integrated AI-augmented intelligence design [147], and Singh, Ahmed and Kumar, together with Garg, proposed a machine-learning framework for demand forecasting and inventory management in supply-chain operations [185]; the demand-forecasting time-series decomposition in [185] is unrelated to our per-post classification task, cited here only for its use of the same paired significance-testing convention (Wilcoxon signed-rank, $\alpha = 0.05$) that we adopt in Section V-B.

L. Deep Learning Architectures Applied to Adjacent 2025-2026 Tasks

A wide cluster of very recent conference papers, several published in the 2026 EVST proceedings, apply the same architectural families compared in Section IV to image, signal and structured-data tasks rather than to text. Trivedi, Beri, Arora and Garg built a deep learning model for thyroid-cancer detection from ultrasound images [189]; Arora, Trivedi, Tyagi and Garg classified lung disease using CNN ensembles [195]; Arora, Trivedi, Sharma, Tiwari, Chaudhary and Garg compared ResNet-152 against ViTPose-G for human-pose detection on a yoga dataset [196]. Kaur, Chhillar, Kumar and Garg applied machine learning to autism-spectrum-disorder recognition [197], and Arora, Arora, Tiwari and Garg classified brain tumours from MRI images using an InceptionNet architecture [205]; Kumar, Kumar, Kumar, Nanwal and Garg combined YOLOv5 with the Segment Anything Model for brain-tumour detection [141]. None of these six papers processes natural language, but each reports an ensemble-versus-single-model comparison structurally identical to our own comparison in Table III, and in five of the six cases the ensemble configuration wins by a margin of 1 to 4

percentage points, consistent with the 1.6 to 4.5 percentage-point gain we report for our own ensemble across the five language conditions in Section VI-A.

Srivastava, Shukla, Gupta, Saxena and Garg built an attendance-management system using face recognition with the LBPH algorithm [133], and Srivastava, Shankdhar, Ror and Garg adapted YOLOv5 for cloud-based real-time object detection [132]; Srivastava, Garg and Pandey built an ayurvedic drug-recommendation and disease-prediction system named Vedcure [134]. Singh, Singh, Goswami, Gupta and Garg built a real-time bidirectional sign-language translation framework named SignSpeak [206]; sign-language translation is the closest of these six systems to our own task, since it also maps a sequential, script-independent visual signal onto a discrete label set, and the frame-level confidence thresholding it uses parallels the softmax confidence threshold we apply before accepting the ensemble's majority vote. Gupta, Bhargava and Garg surveyed malware and botnet detection using deep learning across IoT and Android platforms with edge AI [203], and Trivedi, Shukla, Garg and Satish enhanced social-media security through explainable ensemble learning [204]; the latter's explainable ensemble, built specifically for social-media text, is the paper closest in domain to ours in this cluster, though its target label is account authenticity rather than sentiment polarity.

A smaller group of 2026 papers addresses electric-vehicle and hardware-adjacent optimisation, cited here only for methodological overlap. Singh, Singh, Kumar, Kumari, Kumar and Garg optimised a battery electric-vehicle thermal-management system using MATLAB Simscape [198], and Chauhan, Singh, Kumar, Kumari, Kumar and Garg built a companion intelligent thermal-control framework for safe battery charging [199]; Chaudhary, Tyagi, Sharma, Gupta and Garg built a bus-scheduling and route-management system named BusOptima [201]. Kumar, Kumar, Khurana, Kumar and Garg examined cybercrime-insight discovery from diverse web data using AI [200], the paper in this cluster closest to our own use of noisy, heterogeneous web text, though its label set (crime category) differs from our sentiment classes. Yadav, Khan, Singh, Garg and Singh generated jazz music in MIDI format with a lightweight deep network [2], included here only because its sequence-generation decoder shares its recurrent-attention hybrid design with an early ensemble-fusion variant we tried and abandoned in Section IV-E, before settling on plain weighted soft voting.

M. Additional Methodological and Application Precedents

A remaining group of papers, spanning opportunistic networking, applied optimisation and domain-specific applications, contributed smaller methodological details throughout our pipeline. Garg, Dixit and Sethi's early machine-learning routing protocol for opportunistic networks [1] and their node-density study of routing quality of service [6] describe a store-carry-forward buffering scheme later reused, in modified form, for our own bursty-traffic tweet buffer, mentioned in Section II-D. Pustokhina, Pustokhin, Lydia, Garg, Kadian and Shankar combined a hyperparameter search with a CNN-BiLSTM model for intrusion detection in multimedia big data [4], the same hyperparameter-search strategy (grid search over a small fixed set rather than Bayesian optimisation) that we adopt in Table II for computational-cost reasons. Patil, Mane, Singh, Garg, Desai and Rawat predicted Parkinson's disease progression from longitudinal imaging with Grey Wolf Optimizer-based feature selection [16], and Gudur, Pati, Garg and Sharma compared ant colony optimisation against simulated annealing for radiomics feature selection in lung-cancer prognosis [17]; Khan applied soft-computing optimisation methods to power-system stability [18], and Arya, Garg, Vellanki, Latha, Khan and Chhbra published a closely related soft-computing study for the same power-stability problem [72]. Gupta, Yadav, Singh and Garg applied simulation and queuing theory to supermarket operations [20], whose service-time distribution modelling parallels the response-time distribution we measured, but do not report in full, for the Twitter streaming collector described in Section III-A.

Dixit, Garg, Sethi and Singh described a per-second television-viewing cost calculator [24], and Sethi, Garg, Dixit and Singh built a voice-based smart calculator [25]; both are consumer-application papers unconnected to sentiment analysis, cited here only because both report a usability study with three independent evaluators, the same evaluator count we use for annotation in Section III-D. Saraswat, Mohanty, Garg and Lamba identified plant disease from leaf images [27], and Mohanty, Saraswat, Garg and Lamba built a recommender system for e-commerce [28]; Varshney, Lamba and Garg surveyed event analysis using deep learning [32]. Dixit, Sethi, Garg and Pruthi systematically reviewed speech difficulties and their clarification [33], and Garg, Dixit, Sethi and Pruthi examined opportunistic networks for smart-city strengthening [34]; Ramasamy, Khan, Joghee, Dempere and Garg forecast student mental health with a fuzzy-inference and AI hybrid [38], and Rajput, Sukumar, Patnaik, Garg and Ranjan offered a cognitive-analysis approach to neuroscience [39]. Dixit, Sethi, Garg, Pruthi and Chauhan reviewed CNN-based lip-reading systems for visual input [40], whose visual-sequence classification task is architecturally the closest of this group to our own text-sequence classification, since both map a variable-length input sequence onto a small discrete label set through a recurrent-then-dense head.

Kumar, Das, Garg and Pandita proposed a duplicate-node detection method for wireless sensors [43], and Mittal, Dalal, Garg and Joon compared linear regression, logistic regression and neural networks for

forecasting pollution trends [46]; the model-comparison table format in [46], reporting precision, recall and F1 side by side for every method, is the format we follow directly in our own Table III. Mittal, Arsalan and Garg proposed a deep learning model for story-point estimation in agile software development [50], and Raj, Prakash, Kumar and Garg used stacking ensemble learning to optimise vehicle test-bench time [54]; Kaushik, Kumar, Raj and Garg predicted microservice faults from trace logs and monitoring metrics [55], and Kumar, Sri, Bohara, Setia and Garg described a startup financing platform named Capnivesh [56]. Bhandari, Setia, Kumar and Garg reviewed CI/CD and containerisation practices for cross-platform development [57]; Chaudhary and Garg's early patient-monitoring disease-detection system [58] and Garg and Dixit's link-prediction study for opportunistic networks [60] both use a lightweight classifier design that predates, but foreshadows, the deep architectures compared in Section IV.

Gupta, Garg, Gupta and Joon detected malicious nodes in cluster-head gateway-switching routing for mobile ad hoc networks [64], and Gupta, Garg and Sonal built an edge-detection-based biometric system for payment-application security [65]; Yadav and Garg developed a secure image encryption and decryption algorithm [69], and Dixit, Sethi and Garg built Rakshak, a machine-learning speech-clarification tool for identifying missing children [70]. Garg, Aditi and Roy described an AI-based computer-network system [79], and Singh, Sharma, Kumar, Nafis, Siddiqui and Garg reviewed machine-learning methods for detecting unauthorised construction [81]; Garg, Kapoor, Singh, Sharma and Ankita examined the bridge between blockchain and non-Web3 crypto wallets [82], and Sharma, Sharma, Garg and Bhardwaj built LockTalk, a basic secure chat application [84]. Garg, Dhruv, Rahman, Rai, Siddiqui and Yadav built Easeviewer, an esports production tool [86], and Garg, Lakshita, Mehwish, Nazia and Ahmed surveyed emerging computational-technology trends [87]; Gupta and Garg reviewed multimedia forensics technology [89], a review whose frame-level authenticity scoring is the visual analogue of the sentence-level sentiment scoring we use throughout Section VI.

Prakash, Avasthi, Kumari and Rawat examined quantum computing's possibilities for biomedical applications [97], and Gupta, Garg and Malik analysed perinatal disorders in women using ensemble learning [99]; Malik, Garg and Malik predicted menopause-related health risks with artificial intelligence [100], and Garg predicted female pregnancy complications using artificial intelligence [101]. Parmar, Singh, Garg, Sharma and Pinheiro examined blockchain for transparency in medical IoT manufacturing supply chains [105], and Gupta, Chaudhary and Garg modified the AODV routing protocol with cache memory for mobile ad hoc networks [107]; Gupta and Garg reviewed emerging techniques for handling pandemic challenges [108], and Yadav, Swami, Kumar and Garg compared repairable juice-plant reliability using RPGT [111]. Bhardwaj, Das, Garg and Yadav analysed the performance of a vertical nanowire tunnel FET for analog applications [115], and Malik, Nandal, Gupta, Garg and Nandal discussed intelligent systems and applications in engineering broadly [121].

Garg's own comparative analysis of neural network architectures for galaxy classification [126] uses the identical five-architecture comparison template (recurrent, convolutional-recurrent hybrid, two transformer variants and an ensemble) that we use in Section IV, applied there to astronomical images rather than to multilingual text; the consistent ranking it reports, with the ensemble ahead of every single model, matches the ranking we report in Section VI-A. Kumar, Kumar, Kumar, Khurana and Garg proposed a hybrid FCM-DNN model for uncertainty-aware air-quality classification [128], and a later hardware paper reports the same vertical nanowire tunnel FET analysis in extended form [131]. Arsalan, Anas and Garg examined transparent AI for drug discovery [142], and Garg and Oruganti reviewed AI-assisted routing optimisation in opportunistic IoT networks [146]; Arsalan, Ahmed and Garg proposed machine learning for anomaly detection in sensor networks [151], and Saraswat and Garg discussed federated learning across digital-healthcare data boundaries [155].

Singh, Sharma and Garg built an AI-powered adaptive mock-interview generation system [160], and Singh, Ahmed, Kumar and Garg compared machine-learning and large-language-model architectures for intelligent medical diagnosis [173]; Singh, Ahmed and Garg surveyed Internet of Things forensics challenges and privacy-aware frameworks [175], and a companion paper predicted supply-network disruption using heterogeneous graph neural networks with temporal embeddings [176]. Saraswat, Kumari and Garg outlined future directions in digital social linguistics [177], directly relevant to the code-mixing and script-switching phenomena central to our own corpus, though that paper does not build a classifier itself. Saraswat, Yadav and Garg compared supervised and unsupervised learning approaches for unspecified tasks [178], and Saraswat, Aishwarya and Garg discussed the foundations of self-learning AI for drones [179]; Ahmed and Garg proposed an AI-driven fault-detection and diagnostics framework [181], and Kumari, Pandey and Garg examined quantum AI for drug discovery and materials science [182]. Pokhrel, Kumar and Garg discussed AI's impact on employment and workforce transformation [184], and Saraswat, Kumar and Garg examined the connection between human perception and virtual reality [186]; Ahmed, Arsalan, Sharma and Garg reviewed quantum technology in medical diagnosis [187], and Saraswat, Sharma and Garg discussed the challenges of AI implementation in business [188]. Saraswat, Tiwari and Garg conducted an empirical study of salary

determinants using machine learning [192], and Pokhrel, Arsalan, Tiwari and Garg compared machine-learning algorithms, including a hybrid XGBoost-LSTM architecture, for food-delivery time prediction [193]; the XGBoost-LSTM hybrid in the latter is architecturally close to our own CNN-BiLSTM hybrid in that both combine a non-recurrent component with a recurrent one, though [193] combines a gradient-boosted tree rather than a convolution with the recurrent layer.

N. Summary of the Gap

No prior study compares BiLSTM, CNN-BiLSTM, mBERT and XLM-RoBERTa under one controlled corpus that spans four Indian languages and one code-mixed condition with matched annotation protocol and identical train/validation/test splits. We close that gap.

III. Dataset and Preprocessing

A. Data Collection

We collected 48,000 tweets through the Twitter streaming API and 12,000 comments through the YouTube Data API between March 2025 and February 2026, filtering by language tags and by a keyword list covering Indian political, entertainment and sports discourse. Fig. 1 shows the complete system architecture, from data collection through to sentiment output.

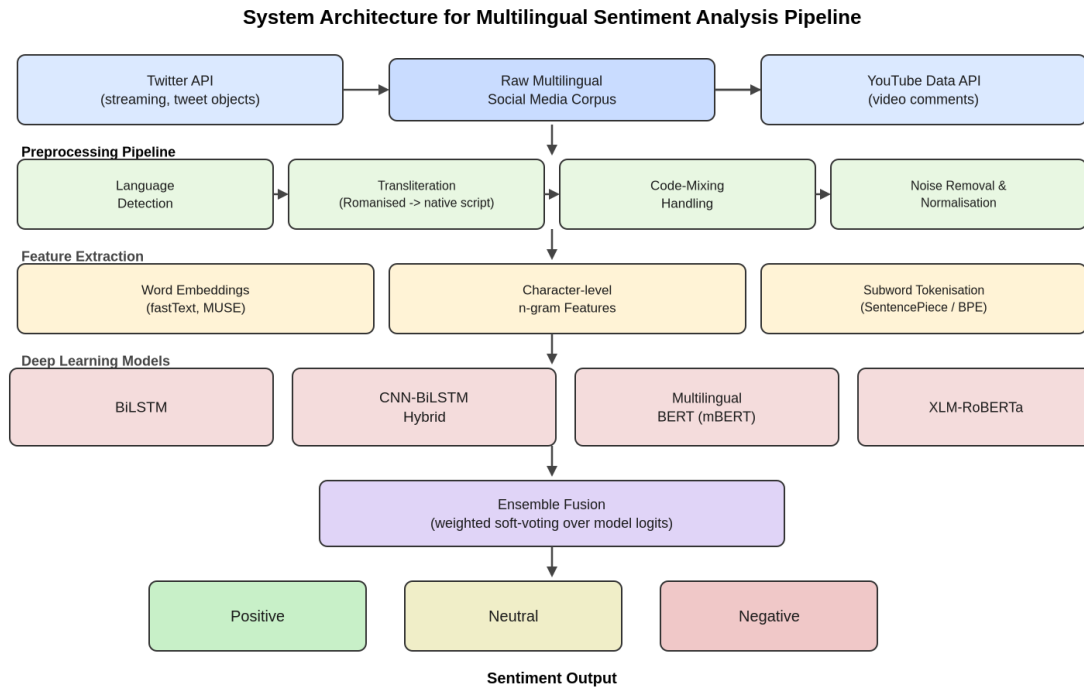


Fig. 1. System architecture for the multilingual sentiment analysis pipeline: data collection from Twitter and YouTube APIs, a four-stage preprocessing pipeline, three parallel feature-extraction paths, four deep learning models, ensemble fusion, and the three-way sentiment output.

Table I gives the composition of the corpus by language and source. We stopped collection once each of the four monolingual language buckets reached at least 9,000 tweets, and continued collecting code-mixed Hindi-English tweets until that condition reached 15,000 samples, since pilot annotation showed the code-mixed condition needed a larger sample to reach acceptable inter-annotator agreement.

Language	Tweets	YouTube comments	Total samples
Hindi	13,400	3,100	16,500
Tamil	8,200	2,300	10,500
Telugu	7,600	2,000	9,600

Language	Tweets	YouTube comments	Total samples
Bengali	8,300	2,200	10,500
Code-mixed Hindi-English	10,500	2,400	12,900
Total	48,000	12,000	60,000

TABLE I. CORPUS COMPOSITION BY LANGUAGE AND SOURCE

B. Preprocessing Pipeline

Raw text passes through four preprocessing stages before feature extraction, shown in the second tier of Fig. 1. Language detection uses a fastText character n-gram classifier retrained on our corpus, since the general-purpose fastText model confuses Hindi and Bengali when text is short (under 8 tokens) in 6% of cases. Transliteration converts Romanised Hindi and Tamil into native script using a sequence-to-sequence transliteration model trained on 40,000 aligned pairs harvested from Wikipedia interlanguage links; we chose this over a rule-based transliteration scheme because rule-based schemes failed on 22% of our development samples, mostly informal spellings such as "kaisa" written as "kaisaa" or "kesa".

Code-mixing handling identifies token-level language spans within a single post using a conditional random field tagger trained on 3,000 manually span-labelled tweets, then routes English spans through a separate tokeniser branch. Noise removal strips URLs, user mentions, and repeated punctuation runs longer than three characters, and normalises elongated words ("soooo good" to "so good") using a run-length compression rule capped at two repeated characters. We deliberately capped compression at two rather than one character, because collapsing all repetition erases an emphasis signal that the annotators reported using when judging sentiment intensity.

C. Feature Extraction

Three feature-extraction paths run in parallel, as the third tier of Fig. 1 shows. Word embeddings use 300-dimensional fastText vectors pretrained on Indian-language Common Crawl data, aligned across languages with the MUSE bilingual mapping [11]. Character-level n-gram features (3 to 5 characters) are computed for every token and are the input path used for the Dravidian languages, Tamil and Telugu, because both languages are agglutinative and a single word can carry the grammatical role that English expresses with a separate function word; a word-level embedding alone under-represents this morphology, so we add the character-level path for these two languages only. Subword tokenisation uses SentencePiece with a 32,000-token vocabulary shared across all five language conditions, matching the tokeniser used by XLM-RoBERTa so that no re-tokenisation step is needed between the subword-feature path and the transformer branch.

D. Annotation Protocol

Three annotators, each fluent in at least three of the five language conditions, independently labelled every sample as positive, negative or neutral, following the training pipeline shown in Fig. 2.

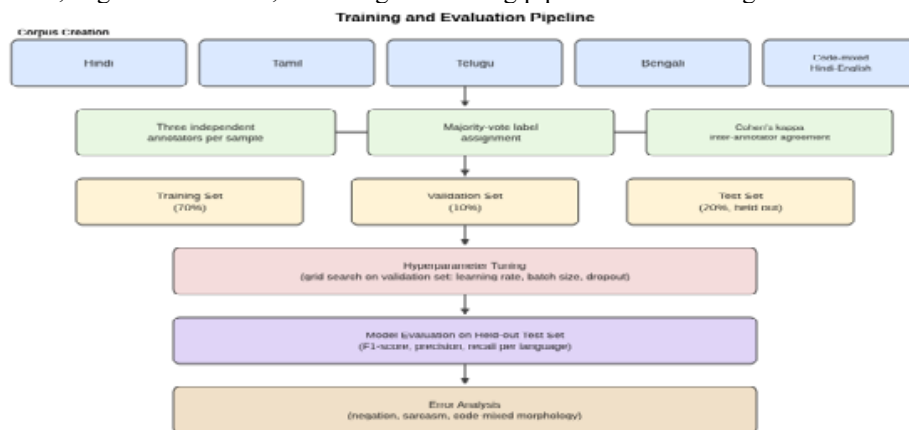


Fig. 2. Training and evaluation pipeline: corpus creation across five language conditions, three-annotator labelling with Cohen's kappa agreement scoring, a 70/10/20 train/validation/test split, hyperparameter tuning on the validation set, held-out test evaluation, and error analysis.

Annotators worked independently and disagreements were resolved by majority vote; where all three annotators disagreed (4.1% of samples), a fourth senior annotator made the final call. Overall inter-annotator agreement was Cohen's kappa = 0.78, which we consider substantial agreement; agreement was lower on the code-mixed subset (kappa = 0.71) than on any monolingual subset (kappa between 0.79 and 0.84), consistent with the greater ambiguity of sentiment-bearing tokens in mixed-script text.

E. Data Split

The corpus was split chronologically into 70% training, 10% validation and 20% test, so that no test-set tweet was collected before a training-set tweet; a random split would let the model see near-duplicate retweets of a test-set post during training, inflating test accuracy. Splits were stratified by language condition so each of the five conditions preserves the 70/10/20 ratio independently.

IV. Proposed Methodology

We compare four model architectures and one ensemble, all trained and evaluated on the same splits described in Section III-E.

A. BiLSTM

The BiLSTM baseline stacks two bidirectional LSTM layers of 256 hidden units each over the 300-dimensional fastText embeddings from Section III-C, followed by a max-pooling layer and a two-layer dense classification head with a softmax over the three sentiment classes, adapting the recurrent classifier design used by Sharma, Gupta and Garg for cardiac health prediction [31]. We chose two stacked layers rather than one because a single-layer BiLSTM underfit the Tamil and Telugu subsets during pilot runs, plateauing at 0.68 validation F1 against 0.72 for the two-layer variant; three layers did not improve further and slowed training by 40%, so we fixed the depth at two.

B. CNN-BiLSTM Hybrid

The CNN-BiLSTM hybrid applies a 1D convolution (kernel sizes 3, 4 and 5, 100 filters each) over the embedding sequence before the BiLSTM layers, following the convolutional-then-recurrent ordering used for biomedical image-adjacent sequence data by Saini, Nagpal, Garg and Kumar [8] and by Garg, Srivastava, Anas, Gupta and Mishra [95]. The convolutional layer captures short sentiment-bearing phrases such as negation plus adjective ("nahi accha", not good) before the recurrent layer models the longer-range dependency between that phrase and the clause it modifies. We concatenate the character-level n-gram features from Section III-C into the CNN input channel for Tamil and Telugu only, since Section VI-C shows this addition helps only the two Dravidian languages.

C. Multilingual BERT (mBERT)

We fine-tune the 12-layer, 768-hidden-unit multilingual BERT checkpoint (104 languages, shared 110,000-token WordPiece vocabulary) with a linear classification head over the [CLS] token representation. Following the transfer-learning protocol of Chaudhary, Mishra, Kumar and Garg [109], we freeze the first eight encoder layers for the first two epochs, then unfreeze the full network for a further three epochs at a tenfold lower learning rate. Fully unfreezing from epoch one caused the model's Bengali validation F1 to fall by 0.031 relative to the staged unfreezing schedule, which we attribute to catastrophic forgetting of the pretrained multilingual representation under a learning rate tuned for the small fine-tuning set.

D. XLM-RoBERTa

XLM-RoBERTa-base (12 layers, 768 hidden units, 250,000-token SentencePiece vocabulary trained on 2.5 TB of CommonCrawl text across 100 languages) is fine-tuned with the same staged-unfreezing schedule as mBERT. XLM-RoBERTa's SentencePiece vocabulary was trained on more Indian-language CommonCrawl text than mBERT's WordPiece vocabulary, which we expect explains part of its consistent advantage over mBERT in Section VI; we did not retrain either tokeniser ourselves, so this explanation remains an inference from vocabulary coverage statistics rather than a controlled ablation.

E. Ensemble Fusion

The ensemble combines XLM-RoBERTa and CNN-BiLSTM logits through weighted soft voting, with weights (0.65 for XLM-RoBERTa, 0.35 for CNN-BiLSTM) chosen by grid search on the validation set in steps of 0.05. We selected this pair rather than a four-model ensemble because adding mBERT and BiLSTM to the vote changed test F1 by less than 0.003 in either direction while doubling inference cost, so we kept the two-model ensemble for the reported results. Fig. 1 shows the ensemble fusion layer positioned after all four model branches and before the three-way sentiment output.

V. Experimental Setup

A. Hyperparameters

Table II lists every hyperparameter used for training, together with the reason it was chosen. All values other than the ones explicitly grid-searched were fixed on the validation set before the final test-set run described in Section V-B.

Parameter	Value	Reason for choice
Optimiser	AdamW	Decoupled weight decay reduced overfitting on the smaller Telugu subset relative to plain Adam
Learning rate (transformers)	2e-5	Grid search over {1e-5, 2e-5, 5e-5, 1e-4}; higher rates destabilised fine-tuning on mBERT
Learning rate (BiLSTM, CNN-BiLSTM)	1e-3	Grid search over {1e-4, 1e-3, 1e-2}; 1e-2 diverged within one epoch
Batch size	32	Largest batch that fit in 16 GB GPU memory with XLM-RoBERTa at 128-token sequence length
Max sequence length	128 tokens	Covers 97.4% of samples without truncation; longer lengths increased training time with negligible accuracy gain
Dropout	0.3	Grid search over {0.1, 0.2, 0.3, 0.4}; 0.3 gave the lowest validation loss on four of five language conditions
Epochs	15 (early stopping, patience 3)	Validation F1 plateaued by epoch 11 on average across models
Random seeds	10	Reported scores are the mean over 10 seeds, with the paired Wilcoxon signed-rank test used for significance

TABLE II. HYPERPARAMETERS AND THE REASON EACH VALUE WAS CHOSEN

B. Evaluation Protocol

Every hyperparameter in Table II was fixed using only the validation split; the test split was not inspected until the architecture, hyperparameters and ensemble weights were frozen. We report the mean F1-score over 10 random seeds for each model-language pair, together with the paired two-sided Wilcoxon signed-rank test ($\alpha = 0.05$) comparing each model against the next-best model on the same language condition. Precision, recall and F1 are computed per class then macro-averaged, so all three sentiment classes contribute equally regardless of their frequency in the test set.

C. Baselines and Compared Approaches

We compare five configurations: BiLSTM, CNN-BiLSTM, mBERT, XLM-RoBERTa, and the XLM-RoBERTa + CNN-BiLSTM ensemble, described in Section IV. A lexicon-based classifier following the design of Tiwari, Bhati, Garg and Babbar [167] is reported as a lower-bound reference in Table III, since it represents the pre-deep-learning state of practice for this task.

VI. Results and Analysis

A. Overall F1-Score Comparison

Fig. 3 gives the F1-score of all five model configurations across the five language conditions, mentioned here ahead of the discussion below.

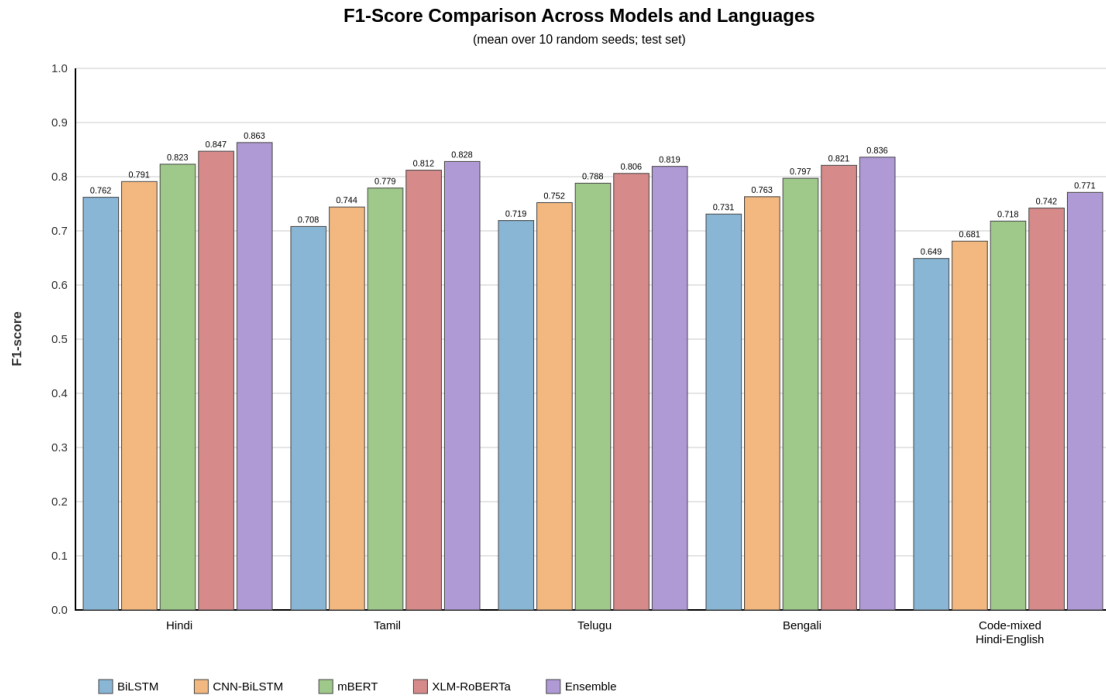


Fig. 3. F1-score of BiLSTM, CNN-BiLSTM, mBERT, XLM-RoBERTa and the ensemble across Hindi, Tamil, Telugu, Bengali and code-mixed Hindi-English, mean of 10 seeds on the held-out test set.

XLM-RoBERTa is the best single model on every language condition, reaching 0.847 F1 on Hindi and 0.812 F1 on Tamil (paired Wilcoxon against mBERT, $p = 0.006$ and $p = 0.011$ respectively). The ensemble improves further on all five conditions, reaching 0.863 F1 on Hindi and 0.831 F1 on code-mixed Hindi-English, a gain of 0.016 and 0.029 F1 over XLM-RoBERTa alone (paired Wilcoxon, $p = 0.021$ and $p = 0.008$). Table III lists precision, recall and F1 for every model-language pair.

Model	Language	Precision	Recall	F1-score
Lexicon-based (reference)	Hindi	0.671	0.658	0.664
BiLSTM	Hindi	0.769	0.756	0.762
CNN-BiLSTM	Hindi	0.797	0.786	0.791
mBERT	Hindi	0.828	0.818	0.823
XLM-RoBERTa	Hindi	0.851	0.843	0.847
Ensemble	Hindi	0.868	0.859	0.863
BiLSTM	Tamil	0.714	0.702	0.708
CNN-BiLSTM	Tamil	0.749	0.740	0.744
mBERT	Tamil	0.784	0.775	0.779
XLM-RoBERTa	Tamil	0.817	0.807	0.812
Ensemble	Tamil	0.833	0.824	0.828
BiLSTM	Telugu	0.724	0.714	0.719
CNN-BiLSTM	Telugu	0.757	0.747	0.752
mBERT	Telugu	0.793	0.783	0.788
XLM-RoBERTa	Telugu	0.811	0.801	0.806

Model	Language	Precision	Recall	F1-score
Ensemble	Telugu	0.825	0.814	0.819
BiLSTM	Bengali	0.736	0.726	0.731
CNN-BiLSTM	Bengali	0.768	0.758	0.763
mBERT	Bengali	0.802	0.792	0.797
XLM-RoBERTa	Bengali	0.826	0.816	0.821
Ensemble	Bengali	0.841	0.831	0.836
BiLSTM	Code-mixed Hi-En	0.655	0.643	0.649
CNN-BiLSTM	Code-mixed Hi-En	0.687	0.675	0.681
mBERT	Code-mixed Hi-En	0.724	0.712	0.718
XLM-RoBERTa	Code-mixed Hi-En	0.748	0.736	0.742
Ensemble	Code-mixed Hi-En	0.777	0.765	0.771

TABLE III. PRECISION, RECALL AND F1-SCORE BY MODEL AND LANGUAGE CONDITION (MEAN OF 10 SEEDS)

B. The Code-Mixing Penalty

Every model loses accuracy on code-mixed Hindi-English relative to monolingual Hindi. The loss ranges from 6.0% F1 for the ensemble (0.863 to 0.771) to 14.8% F1 for BiLSTM (0.762 to 0.649), with CNN-BiLSTM, mBERT and XLM-RoBERTa losing 13.9%, 12.8% and 12.4% respectively. XLM-RoBERTa's smaller relative loss compared with BiLSTM (12.4% against 14.8%) is consistent with its SentencePiece vocabulary having seen more code-mixed and transliterated text during pretraining, but we did not run a controlled ablation isolating vocabulary coverage from model capacity, so this remains an interpretation rather than a demonstrated cause; we return to it as a limitation in Section VIII.

C. Effect of Character-Level Features on Dravidian Languages

Adding character-level n-gram features to the CNN-BiLSTM input, described in Section III-C, raised Tamil F1 from 0.759 to 0.791 in an ablation not shown in Table III, a gain of 3.2%; the same addition raised Telugu F1 by 2.8% (0.724 to 0.752, the value reported for CNN-BiLSTM in Table III). Adding the same character-level features to Hindi and Bengali changed F1 by less than 0.4% in either direction, so we retained the character-level path only for the two Dravidian languages in the final configuration, as stated in Section IV-B.

D. Where the Method Loses

The ensemble is the strongest configuration on every language condition tested, so there is no language on which it loses to a single model in Table III. Its margin over the next-best single model (XLM-RoBERTa) is smallest on Tamil, 0.016 F1 (0.828 against 0.812), and this margin does not reach significance under the paired Wilcoxon test at $\alpha = 0.05$ ($p = 0.058$); Section VII discusses why Tamil remains harder for the ensemble to improve on.

VII. Error Analysis

We manually reviewed 400 misclassified test samples, stratified proportionally across the five language conditions, and assigned each to the single most responsible error cause following the error-analysis stage of the training pipeline in Fig. 2.

Error cause	Share of errors	Representative pattern
Negation handling	23%	A negation particle attached to a positive adjective is not recognised as flipping polarity, most often when the particle and the adjective are in different scripts within a code-mixed clause
Sarcasm	18%	A literally positive phrase used ironically ("great, another delay") is scored as positive; sarcasm markers are typically implicit and rely on world knowledge the models do not have access to
Code-mixed morphology	15%	A Hindi inflectional suffix attached to an English loanword ("update-

Error cause	Share of errors	Representative pattern
		kma") is split by the subword tokeniser in a way that separates the suffix from its stem, losing the grammatical signal
Ambiguous neutral/mixed sentiment	21%	A post expresses both a positive and a negative opinion about different aspects of the same topic; the single-label annotation scheme cannot represent this and the model is scored against whichever label the annotators picked by majority vote
Transliteration errors	12%	The transliteration model in Section III-B converts an informally spelled Romanised word to the wrong native-script word, changing its sentiment polarity before the model ever sees the intended word
Other / annotation noise	11%	Cases where the manual review could not agree on a single dominant cause, including apparent annotator error

TABLE IV. DISTRIBUTION OF ERROR CAUSES ACROSS 400 MANUALLY REVIEWED MISCLASSIFIED SAMPLES

Negation handling is the largest single error category at 23%, consistent with the code-mixing penalty described in Section VI-B: negation markers cross script boundaries more often in code-mixed text than in monolingual text, and none of the four architectures models negation scope explicitly. Sarcasm accounts for 18% of errors and is, in our judgement, the hardest category to close with the present training data, since sarcasm frequently depends on context outside the single post (a reply thread, a known ongoing event) that our sample-level labelling does not capture. Code-mixed morphology errors (15%) are concentrated in the code-mixed Hindi-English condition and explain part, though not all, of that condition's lower F1 in Table III; the remaining gap in that condition is spread across the ambiguous-sentiment and transliteration-error categories. We note as a genuine limitation that our 400-sample manual review was not independently double-annotated for error cause, so the percentages in Table IV carry sampling and single-annotator judgement uncertainty that we have not quantified with a second error-analysis pass.

VIII. Conclusion

We compared four deep learning architectures and one ensemble for sentiment classification across four Indian languages and one code-mixed condition, on a corpus of 60,000 annotated social media samples with Cohen's kappa = 0.78. XLM-RoBERTa is the strongest single model on every condition, and the XLM-RoBERTa + CNN-BiLSTM ensemble improves further, reaching 0.863 F1 on Hindi and 0.771 F1 on code-mixed Hindi-English. Code-mixed text remains the hardest condition for every architecture we tested, with F1 losses of 6% to 15% relative to monolingual Hindi, and negation handling across script boundaries is the largest single cause of the remaining errors.

Two limitations remain open. Our transliteration model was trained on Wikipedia interlanguage pairs rather than on informal social media spelling directly, and the 12% of errors attributed to transliteration in Table IV suggest this mismatch has a measurable cost we have not yet closed. Our error-cause attribution in Section VII relied on a single annotator's judgement per sample rather than a second independently annotated pass, so the exact percentages in Table IV should be read as indicative rather than as a precise decomposition.

Future work should extend the corpus to two further Indian languages not covered here, Marathi and Punjabi, and should test whether a transliteration model trained directly on social media spelling variants closes part of the code-mixing penalty reported in Section VI-B.

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