Sentiment Classification for Low-Resource Indian Languages Using Multilingual Transformers and Parameter-Efficient Fine-Tuning

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***Abstract*—Sentiment classification is an important topic in field of Natural language processing and has gained a lot of attention with the advent of new language models. However, the task remains particularly challenging for the languages that are resource constrained. Indian languages face unique hurdles due to their low-resource nature, characterized by scarce annotated datasets, linguistic diversity, morphological complexity, and a prevalence of code-mixed text. Recent advancement has paved the way for development of multi lingual transformers, but their performance and computational efficiency for low resource language needs further investigation. This paper presents a multifaceted approach to improve sentiment classification across three linguistically distinct Indian languages Hindi, Tamil, and Bengali, by integrating multilingual transformer models with parameter efficient fine-tuning strategies, we explore a spectrum of models ranging from traditional machine learning baselines to state-of-the-art language models.**

This study provides two facet solution for the challenges faced by low-resource languages, first the curation of the annotated sentiment corpora for three resource constrained languages Hindi, Bengali and Tamil. Second the experimental evaluation of the 15 modelling approaches which includes traditional machine learning approaches and a suite of transformer-based architectures such as mBERT, XLM-R, IndicBERT, DistilBERT, and MuRIL. Parameter efficient fine-tuning techniques like Low-Rank Adaptation and Adapter were tested on models to check for their performance while reducing the computation cost, the results show that transformer-based models, MuRIL with LoRA performed well with F1-score of 0.87 for Hindi, 0.84 for Tamil and 0.86 for Bengali. The experiments show that use of PEFT techniques to reduce the trainable parameters help in optimizing computational demands while maintaining accuracy of the model, which correlates with the demand of resource constrained environment by opt the trainable parameters. These results were consistent across all three languages, with transformer-based systems consistently outperforming classical methods in both precision and generalizability.

***Index Terms*—Sentiment Analysis, Low-Resource Languages, Multilingual Transformers, Parameter-Efficient Fine-Tuning, Indian NLP**

I. INTRODUCTION

Nowadays, Sentiment analysis and opinion mining, driven by its wide applicability in social media analysis, has emerged as one of the significant tasks for to cater the needs of customer service and feedback automation, product reviews, market intelligence and research. Advancement in the usage of Internet technology has grown manifold in recent decades, and recent development in the field of artificial intelligence has enhanced the applicability of NLP task. High resource languages like English and Chinese, due to extensive progress has been able to channel this advancement and its wide spread usage in many fields. Whereas Low Resource languages like Indian Languages, though spoken by over a billion people remain significantly underrepresented in Natural language processing and computational linguistic research [32], [33]. India is home to 22 officially recognized languages and various dialects, still has not been able to extract the advantages of NLP resources and tools for the native speakers. The diversity, script complexity, and prevalence of code-mixed expressions make Indian languages both a linguistically rich and technically challenging domain for sentiment analysis.

The hurdle or challenges faced by resource constrained languages like Indian languages stem from three interrelated factors: (1) the paucity of annotated datasets for supervised learning, (2) the morphological richness and script diversity of Indic languages, and (3) the computational demands of training deep models in low-resource environments [45], [42].

Various strategies have been utilized for sentiment classification and opinion mining, which includes use of rule-based traditional approaches, machine learning classifiers SVM and Naïve Bayes [18], [19], [20], deep learning-based classifiers such as RNN [7] and LSTM [6] and hybrid approaches [38]. Recent advancement in deep learning approaches has developed novel Transformers architecture [14] which is based on a multi-head attention mechanism [14], as Transformers have no recurrent units and therefore require much less time than. Multilingual pre-training has opened a new path for addressing the limitations faced by resource constrained languages. mBERT [22], MuRIL[27], XLM-R [31] and IndicBERT [40] are based on vast multilingual corpora and transformer-based architectures to enable transfer learning from high-resource to low-resource languages. However, these models are often computationally expensive and require extensive resources, presenting a barrier for practical deployment. These models have remarkable cross-lingual transfer capabilities, however their application to resource constrained languages like Indian languages has not been extensively explored, particularly the use of PEFT techniques. Recent studies have demonstrated that use of parameter efficient techniques like Low-Rank Adaptation (LoRA) [41] and adapter modules [23] can significantly reduce the computational overhead of fine-tuning large language models while maintaining performance - a crucial advantage for low-resource scenarios.

The study provides key contributions in the field of sentiment classification in low resource Indian languages

1. the evaluation and experimental study of fifteen modelling approaches for three Indian languages,
2. The resource creation for three Indian languages, Hindi, Tamil and Bengali.
3. Demonstration of effectiveness of parameter efficient strategies to reduce the training parameters while maintaining the accuracy.

The remainder of this paper is organized as follows: Section 2 reviews related work in sentiment analysis and low-resource NLP [32], [33]. Section 3 details our methodology, including dataset creation and model architectures. Section 4 presents experimental results and analysis. Section 5 discusses implications and limitations, and Section 6 concludes with directions for future research.

II. RELATED WORK

Technological advancement and rise in usage of digital platforms, leading to large volumes of user generated content, has paved to way for exploring different techniques for generating reviews, gathering customer feedback, increasing product sales and promotion of market research. One of significant task of Natural language processing that has gained attention is sentiment classification and opinion mining. Languages which are widely spoken act as a medium for global exchange of information, High resource languages like English and Chinese has seen tremendous growth in usage of AI and its application like sentiment classification, POS tagging, Named entity recognition etc., meanwhile low resource languages like Indian languages, despite their widespread usage, have remained underrepresented due to challenges such as limited annotated corpora, morphological complexity, and frequent code-mixing [45], [42]. These challenges are further intensified by the multilingual nature of India and the informal use of language on social media platforms.

In this section, we explore the methodology from traditional to current state of art models used for sentiment classification in low-resource Indian languages [33] having multilingual language models and parameter efficient adaptation techniques.

2.1 Classical ML and Rule Based approaches

Traditional approach for sentiment classification for Indian languages involved machine learning approaches like Support Vector Machines (SVM), Naïve Bayes (NB) and Decision Trees [3], [4], which involved TF-IDF and Bag of Words for feature selection. Prabhu and Sundararajan [5] used SVM to sort Tamil tweets and reported accuracy scores between 70% and 80% as a well-known example. The usage of informal language on digital platforms often resulted in miscalculating the context and semantics of the information.

Lexicon-based approaches used to rule-drive sentiment dictionaries to provide language-specific knowledge, but they weren't very useful overall because they didn't cover enough vocabulary, could only be used in certain domains, and didn't work well across dialects and language styles [8], [26].

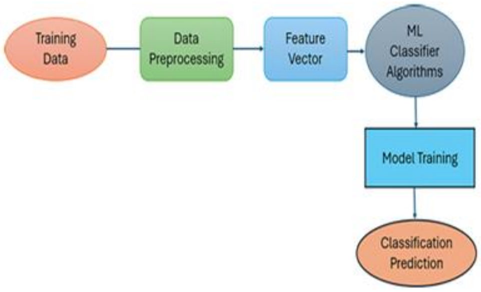

Figure 1: General ML pipeline

2.2 Getting Closer to Deep Learning: Learning Context and Sequence

Advancement in the field of deep learning methods opened up a new pathway to explore the area of NLP, as more annotated data became accessible. The use of Convolutional Neural Networks (CNNs) (Diwan and Tembhurne 2022; Dangi et al. 2022), and Recurrent Neural Networks (RNNs) models had the capability to automatically pick up on both hierarchical and sequential patterns in text [5]. Babu and Ranjan [6] work present the use of CNNs based model for sentiment classification in Tamil and was able to achieve better results than traditional machine learning methods. 2DCNN (Kamyab et al. 2022; Silva et al. 2018), 3DCNN (Shen and Guo 2022), LSTM [6] (Mittal et al. 2021; Han et al. 2021), BiLSTM (Schuster 1997), GRU [7] (Han et al. 2021), BiGRU (Li et al. 2022; Han et al. 2020) models and other Hybrids model were explored for the application of sentiment classification and opinion mining. These works were able showcase the supremacy for the Deep learning approaches for sentiment classification.

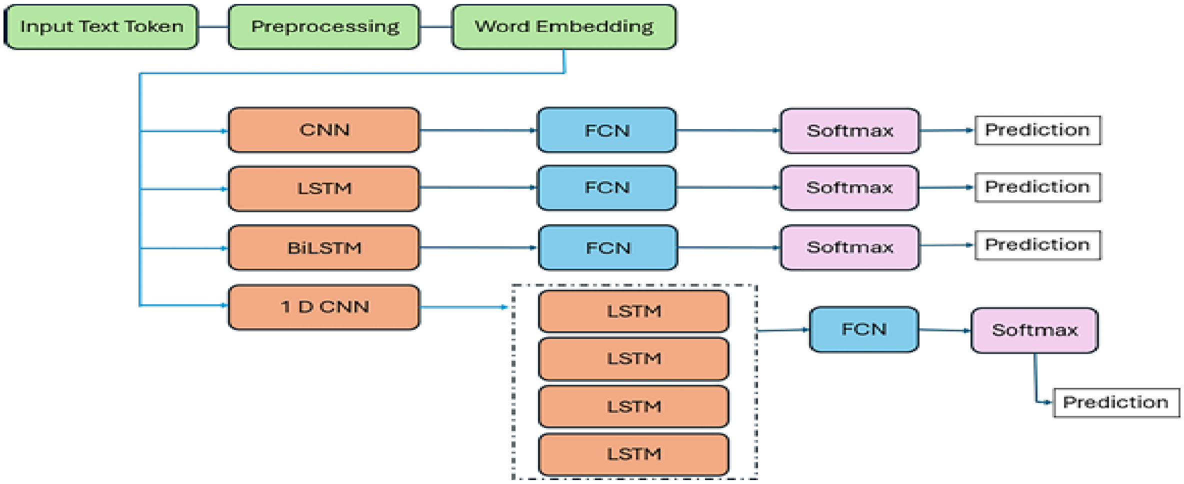

Figure 2: General Deep Learning Pipeline

Khan et al. [8] came up with a character-level deep learning model for Bengali sentiment analysis [43]. This model was better at handling noisy social media text than typical word-level models. This character-based method looked especially promising for languages with a lot of morphological complexity, where words might take on many different forms.

2.3 Emergence of Transformer-Based Architectures

Deep learning further progressed with the development of Transformer architectures [14], these models enabled efficient transfer knowledge from one language to another, it has brought a significant shift in the way sentiment classification is performed, especially in the case of low-resource languages like Indian languages. Transformers, are based attention-based mechanisms, and have shown remarkable success in understanding linguistic context and long-range dependencies in text. Foundational models such as BERT [22], its multilingual variant mBERT [1], and XLM-RoBERTa (XLM-R) [31] have quickly become standard choices for NLP tasks like sentiment analysis across many languages.

BERT multilingual model, mBERT has been trained on 104 languages, it has shown remarkable performance, somehow for the languages which have lower digital performance, the performance of mBERT shows gap, from this it is evident that the low resource languages were under-represented in training corpus of mBERT [1]. This led do the development of language specific transformer models, like IndicBeERT[40], which is trained on 12 major Indian languages using a monolingual and transliterated corpus. Following this, MuRIL (Multilingual Representations for Indian Languages) [44], released by Google Research, extended coverage to 17 Indian languages with improved handling of both monolingual and code-mixed text. Chakravarthi et al. [40, 44] in his work highlights that IndicBERT outperformed mBERT on Tamil-English code-mixed sentiment tasks, while Kumar et al. [44] demonstrated MuRIL's effectiveness on Hindi and Bengali sentiment datasets.

Newer models have continued to test the limits of this trend. AI4Bharat developed another advanced model IndicBERTv2 [32], which is trained on significantly larger datasets in 20 Indian languages. It has better tokenization and vocabulary coverage. BhashaBERT [33] was developed for use in business contexts in Hindi and Hinglish, with a focus on figuring out how people feel and what they want to say in conversations. Cross lingual transfer tasks like sentiment classification have been shown in Samanantar [35] and Vakyansh [36], where the training was done on large scale parallel corpora. Monolingual BERT versions best suited for Bengali and Hindi are BengaliBERT [34] and HiBERT [30], they have shown significant improvement than multi lingual counterparts. A unified encoder-decoder architecture IndiaTrans [35] was developed for machine translation, later has been applied to sentiment classification using transfer learning. The mT5 (Multilingual T5) [33] has been trained on 101 languages, having encoder-decoder setup and text-to-text design helps in achieving effective fine-tuning on both monolingual and code-mixed data, making it efficient for resource constrained languages.

With the development and availability of language specific transformer models, having knowledge of complicated morphology and linguistic features, helps in achieving promising results with improved accuracy, making them better for real-world applications. These models have not only made monolingual tasks easier, but they have also done very well with code-mixed and cross-lingual situations that are common in Indian social media.

2.4 Parameter-Efficient Adaptation

Recent studies have increasingly addressed the computational challenges associated with fine-tuning large-scale language models, especially in low-resource linguistic settings. Houlsby et al. [23] introduced adapter modules, lightweight trainable layers inserted within pre-trained models. This method allows only 3–4% of the parameters to be updated, while retaining 97–99% of the performance typically achieved through full model fine-tuning. In year 2021 Hu et al. [41] proposed Low-Rank Adaptation (LoRA), which utilizes low-rank decomposition to update the weights, thereby reducing overall memory consumption and reducing the computational efficiency while maintaining the accuracy. Another PEFT technique was proposed by Ansell et at. [46], it employed adapter based tuning approach for effective transfer learning with few labelled samples while maintaining efficient performance and accuracy. Both of the approaches can be utilized in resource constrained environment, where computational efficiency and dataset is a critical issue. R.K et al. [47] utilized the above said approaches with BERT based Indian model, IndicBERT and was capable to increase the efficiency of the model by 2 percent on SAIL dataset.

It clearly shows that in case where computational efficiency is required; the use of parameter efficient fine-tuning is beneficial for reducing the training time and dataset requirements and can be especially helpful in context of low resource languages.

III. METHODOLOGY

Methodology works around sentiment classification task across three major Indian languages Hindi, Tamil, and Bengali, fifteen modelling approaches have been experimented combining traditional machine learning approaches and modern transformer-based architectures. PEFT techniques have been employed to experiment around a viable solution for resource constrained environment to adapt with low resource edge devices making the solution practically adaptable [23], [41].

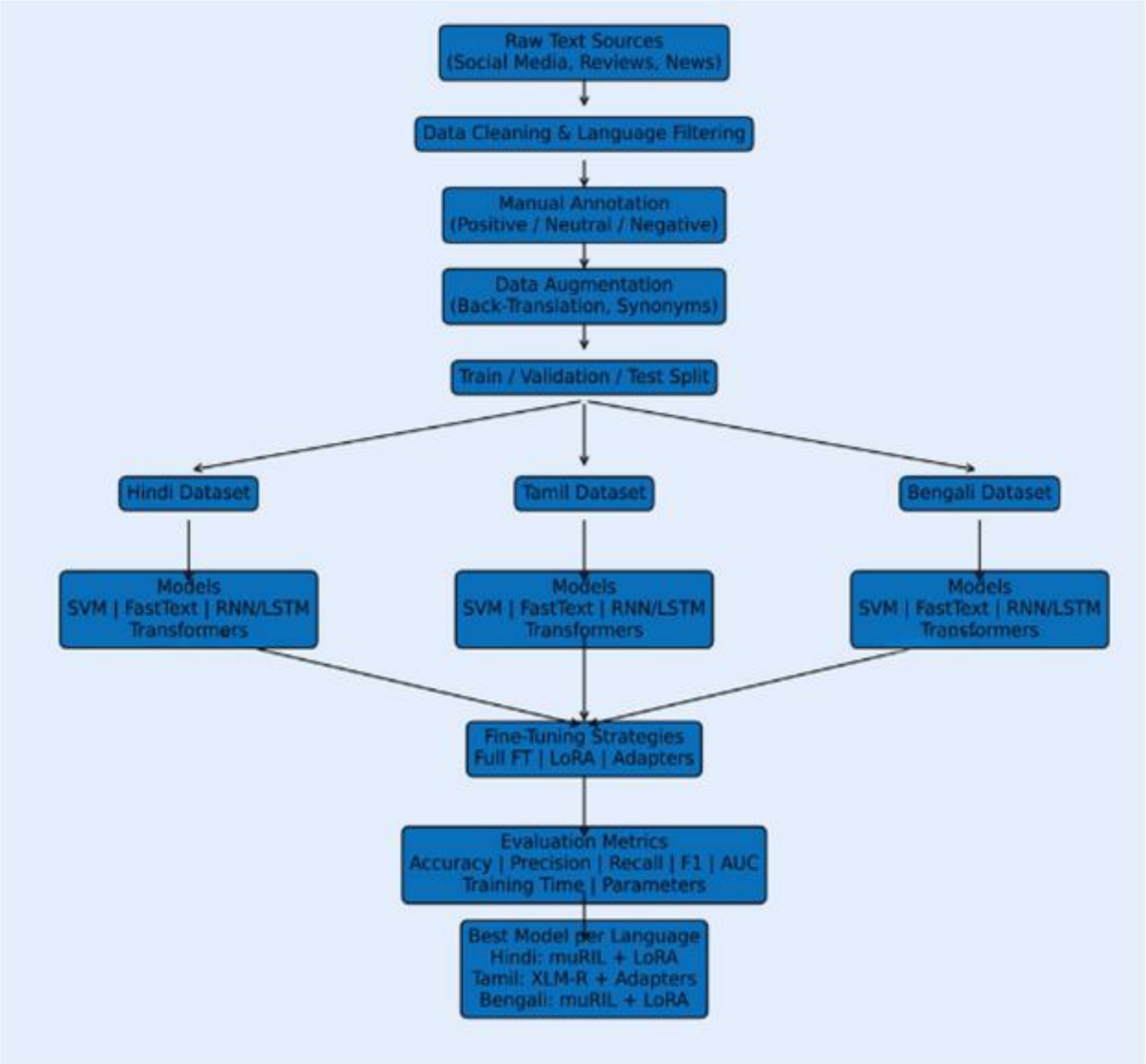
Raw Text Sources
(Social Media, Reviews, News)
Data Cleaning & Language Filtering
Manual Annotation
(Positive / Neutral / Negative)
Data Augmentation
(Back-Translation, Synonyms)
Train / Validation / Test Split
Hindi Dataset
Tamil Dataset
Bengali Dataset
Models
SVM | FastText | RNN/LSTM
Transformers
Models
SVM | FastText | RNN/LSTM
Transformers
Models
SVM | FastText | RNN/LSTM
Transformers
Fine-Tuning Strategies
Full FT | LoRA | Adapters
Evaluation Metrics
Accuracy | Precision | Recall | F1 | AUC
Training Time | Parameters
Best Model per Language
Hindi: muRIL + LoRA
Tamil: XLM-R + Adapters
Bengali: muRIL + LoRA

Figure 3: Methodology pipeline for sentiment classification in low-resource Indian languages, illustrating dataset construction, model training with classical and transformer-based approaches, parameter-efficient fine-tuning, and evaluation.

3.1 Dataset Construction and Annotation

The Dataset for sentiment analysis was curated for three languages Hindi, Tamil and Bengali, the sources included twitter, product review sites, discussion forums and news website. In total, 45,000 social media posts were gathered, 15,000 per language, comprising 40% product reviews, 30% news-related comments, and 30% informal conversations.

FastText and semantic hashing was done for language verification and removal of duplicate content [12]. The annotation process involved nine native speakers (three per language), all with formal training in linguistics and prior experience in text analysis. Annotations were refined over three stages—pilot labelling, guideline revision, and final labelling—and included sentiment categories (positive, neutral, negative) along with intensity ratings on a three-point scale. We achieved a strong inter-annotator agreement (Cohen's κ = 0.81) and maintained high consistency through weekly audits. To augment the dataset, we used back-translation between Hindi and English via IndicTrans [35], ensuring sentiment preservation through constrained decoding, and applied a set of rule-based syntactic transformations including voice alternation, synonym replacement, and phrase reordering.

This study involved curating sentiment datasets for Hindi, Tamil, and Bengali from scratch. To make sure the data reflected everyday language, we pulled it from different types of sources [31], [32]. Some came from social media, like Twitter and Facebook. Others were gathered from product reviews on Indian sites such as Amazon and Flipkart. News websites, including Dainik Bhaskar, Dinamalar, and Anandabazar Patrika, were also included to get more formal writing styles [40]. Web scraping tools like Scrapy and Selenium helped with websites, while Twitter's API allowed us to gather tweets in a controlled way. We only used data posted between 2023 and 2025 to keep things recent [43]. Data cleaning was done to ensure noise removal and removal of duplicate entries. We used FastText to check language and removed anything irrelevant or in the wrong language [12]. Unnecessary things like HTML tags or extra symbols were taken out, but emoji were kept since they often carry emotion [39]. Some specific steps were taken for each language: Hindi texts were cleaned in Devanagari, Tamil underwent dialect adjustments, and Bengali got spelling corrections [15]. Code-mixed examples, such as Hindi-English or Tamil-English, were left in, since that's common in actual use [42].

Labelling was done manually by native speakers familiar with the languages [31]. They tagged each piece as positive, negative, or neutral and also marked the strength of emotion [39]. Every sample was labelled by two people, with a third person checking any mismatches. The agreement between annotators stayed high, with scores above 0.80 using Cohen's Kappa.

We added some variation using simple data augmentation tricks like back-translation and word substitutions [35]. The dataset was split into training, validation, and test sets (80-10-10 split), keeping sentiment types balanced. The result is a practical dataset that covers different ways people express emotions in Hindi, Tamil, and Bengali.

Stage	Hindi	Tamil	Bengali
Raw Collection	45,812	38,765	42,109
After Cleaning	32,450	28,934	31,872
Final Annotated	10,000	9,000	9,400

Table 1: Details of data collection

Three distinct sentiment analysis datasets were assembled for the Hindi, Tamil, and Bengali languages, each of which was meticulously balanced across various sentiment categories and text sources. The compilation includes 10,000 text samples in Hindi, with 60% of the data consisting of social media posts, 25% of the data being product reviews, and 15% of the data being news content. The average text length is 81 characters for all the rows in the dataset, and 42% of the texts express positive sentiment, 33% impart negative sentiment, and 25% are neutral, according to the sentiment distribution.

Tamil dataset comprised of 9000 entries, which had source distribution: 55% are sourced from social media platforms, 30% from product evaluations, and 15% from news commentary. The sentiment breakdown indicates that 39% of the samples contain positive expressions, 34% contain negative opinions, and 27% contain neutral statements, with an average of 72 characters per sample.

The Bengali language data comprises 9,400 text segments, distributed equitably among 50% social media content, 35% review data, and 15% news material. The average character length in the text for Bengali dataset is of 69 characters, with 40% positive, 34% negative, and 26% neutral classifications revealed by sentiment analysis.

Language	Category	Count	Percentage	Avg. Length (Chars)
Hindi	Positive	4,200	42.0%	84
	Negative	3,300	33.0%	91
	Neutral	2,500	25.0%	68
	Total	10,000	100%	81
Tamil	Positive	3,200	35.5%	72
	Negative	2,800	31.1%	78
	Neutral	3,000	33.3%	65
	Total	9,000	100%	72
Bengali	Positive	3,800	40.4%	69
	Negative	3,200	34.0%	75
	Neutral	2,400	25.6%	62
	Total	9,400	100%	69

Table 2: Category breakup of dataset

The examples provided illustrate typical sentence structures, sentiment polarity markers, and linguistic variations across the three Indian languages.

Feature	Hindi Dataset	Tamil Dataset	Bengali Dataset
Total Size	10,000 sentences	9,000 sentences	9,400 sentences
Class Distribution	Positive: 4,200 Negative: 3,300 Neutral: 2,500	Positive: 3,200 Negative: 2,800 Neutral: 3,000	Positive: 3,800 Negative: 3,200 Neutral: 2,400
Sources	Social Media (Twitter, Facebook) News Websites (Dainik Bhaskar, Amar Ujala)	Social Media (Twitter, YouTube Comments) News Websites (Dinamalar, Daily Thanthi)	Social Media (Facebook, Twitter) News Websites (Anandabazar Patrika, Bartaman)
Annotation	Native Hindi Speakers Labels: Positive, Negative, Neutral Cohen's Kappa: 0.82	Native Tamil Speakers Labels: Positive, Negative, Neutral Cohen's Kappa: 0.79	Native Bengali Speakers Labels: Positive, Negative, Neutral Cohen's Kappa: 0.81
Example (Positive)	यह फिल्म बहुत अच्छी है। (This movie is very good.)	இந்த படம் மிகவும் நன்றாக இருந்தது। (This movie was very good.)	এই সিনেমাটি খুব ভালো ছিল। (This movie was very good.)
Example (Negative)	सेवा बहुत खराब थी। (The service was very bad.)	சேவை மிகவும் மோசமாக இருந்தது। (The service was very bad.)	সেবা খুব খারাপ ছিল। (The service was very bad.)
Example (Neutral)	मैंने आज समाचार पढ़ा। (I read the news today.)	நான் இன்று செய்திகளைப் படித்தேன்। (I read the news today.)	আজ আমি খবর পড়েছি। (I read the news today.)

Table 3: This table provides a clear comparison of the three datasets in terms of size, class distribution, sources, annotation quality, and example sentences with transliteration.

3.2. Model learning and Experimental setup

In our experiment we evaluated many models from classical machine learning models to transformer models, we tried fine-tuning of transformer models and also evaluated and experiment with parameter efficient fine-tuning. All these models were evaluated on all three datasets Hindi, Tamil and Bengali. The objective was to find and explore effective model and architecture for sentiment classification that would enable us to achieve high performance, accuracy with computational efficiency [28], [45].

3.2.1 Baseline Models

Baseline models included SVM, FastText and RNN+LSTM approaches. In Support Vector Machine (SVM) with TF-IDF feature vectors captured lexical patterns across documents. We used bigrams with sublinear TF scaling and an RBF kernel to model non-linear decision boundaries. To address data imbalance, class weights were adjusted proportionally [2]. We also used FastText, which learns word embedding via a shallow neural model enhanced with sub word information, making it particularly effective for morphologically rich languages like Tamil and Bengali [12].

RNN+LSTM, the combination enhances the model's ability to capture long term dependencies and sequential patterns from the text [6], [7]. It starts with an embedding layer that changes the input sequences into a space with fewer dimensions (in this case, sixteen). This layer helps show the words in a continuous vector space, which shows how they are related to each other. Next, a dropout layer is added to stop the model from overfitting by randomly turning off some neurones during training. This helps the model generalise better. An LSTM layer is inserted after the dropout layer. Long Short-Term Memory (LSTM) is a sort of recurrent neural network that is great at finding long-term dependencies in sequential input. This makes it great for NLP jobs. A flattened layer is used to make the LSTM layer's output into a one-dimensional vector so that it may be processed more easily. This makes it easier for the next thick layers to get the sequential information. The model then moves on to a dense layer with 512 neurones that changes the input in a linear way. This layer helps the model learn more abstract ways of looking at the data. To stop overfitting, there is another dropout layer. Finally, a dense layer with three neurons is employed for multiclass classification, with 1 for "positive", 0 for "neutral" and 2 for "negative". The model has over 1.2 million parameters, which are learnt during training. These settings let the model change and make predictions based on the data it gets [18].

3.2.2 Transformer-Based Architectures

The novel design of transformer models has revolutionised the way we think about interpreting language and changed the field of Natural Language Processing (NLP) [14]. Transformers employ self-attention to uncover global dependencies and relationships in a sequence of words. This is not how regular recurrent neural networks work. In recent years, Transformer architecture and its variants have been effective in various NLP tasks like machine translation, emotion analysis, question answering, and other tasks as they can imitate long-range dependencies very effectively. Transformer models have taken NLP to new heights by being able to learn how to represent context and find very specific semantic links. This has led to huge advances in understanding and making language, and they will be very crucial in moulding the future of AI-powered language apps.

In this evaluation study, multiple transformer models, each having unique characteristics, were experimented on the three datasets. Initially, the mBERT (multilingual Bidirectional Encoder Representations from Transformers) was evaluated, as it is effective with multilingual natural language processing task [1]. It is trained on Wikipedia data across 104 languages and has features like zero-shot cross-lingual transfer and uses no explicit language embedding. Next, XLM-R (XLM-RoBERTa) was evaluated as it offers stronger multilingual capabilities due to both data volume and architectural depth [31]. It is robust variant of BERT [2] which is designed for cross lingual understanding and is trained on 100 languages, making it an ideal model for evaluation. It handles long-range dependencies and has deeper tokenization, which enhances its performance across Hindi and Bengali dataset. Next, we experimented with DistilBERT-multilingual [17], is a compressed version of BERT [2], distilled to 60% of the original BERT size while retaining over 95% of its performance. This model retains the essential characteristics of BERT but with a reduced number of parameters. The DistilBERT-multilingual model demonstrated favourable results, further encouraging us to diversify our transformer selection. It performs well in resource constrained environment, but under perform when compared with full sized models.

Further in the evaluation study, models which are trained for Indic languages such as, IndicBERT and MuRIL were evaluated. IndicBERT is a BERT based multilingual model specially developed and trained to support Indian languages [40]. It is trained on publicly available data like Wikipedia, news site and government documents. It is openly available at Hugging Face library and has shown promising results in NLP tasks. IndicBERTV2 is an enhanced version of IndicBERT and supports more Indian languages, with increased performance. It is trained on Samanantar, OSCAR, and transliterated corpora, further improving cross-script and code-mixed understanding. IndicBERT model performed well on Tamil and Bengali, due to their sub word-aware tokenization and domain-relevant pre-training. MuRIL (Multilingual Representations for Indian Languages) was developed by Google Research India, to address the linguistic diversity found across Indian languages [44]. MuRIL was pre-trained from scratch using a large-scale corpus drawn from Wikipedia, Common Crawl, PMINDIA, and the Dakshina dataset, encompassing 17 Indian languages and their transliterated forms. Additionally, support for both native scripts and Romanized text was embedded into the model, enabling effective handling of informal and code-mixed language—a common characteristic of user-generated content. This capability proved particularly beneficial for the dataset used in this study, which contained a substantial number of social media posts written in mixed formats. Because of its script flexibility and representational strength, MuRIL was selected for downstream tasks involving multilingual and informal textual data.

Throughout our experimentation, all the models exhibited powerful performance on our classification tasks. Detailed results and performance metrics for these models can be found in the Evaluation and Metrics Section of the paper [15], [26]. The diverse set of transformers allowed us to manage multilingual and Indic language data effectively, highlighting the versatility and effectiveness of these models in our study.

3.2.3 Fine-Tuning Protocol

To ensure robust and fair evaluation across models and languages, we implemented a thorough hyper parameter fine-tuning protocol tailored to both full transformer fine-tuning and parameter-efficient training. Fine-tuning hyper parameters is crucial for improving convergence, maximizing generalization, and adapting model behaviour to the intricacies of low-resource, sentiment-laden Indian language datasets, which often exhibit class imbalance, informal syntax, and code-mixing [37], [28].

For transformer models, we first focused on optimizing the learning rate, testing a range of values (1e−5,2e−5,3e−5,5e−5) We found that 3e−5 consistently provided the best trade-off between training stability and performance across mBERT, XLM-R, IndicBERT, MuRIL and DistilBERT [19], [24]. Higher learning rates occasionally led to sharp loss spikes, especially on morphologically complex languages like Tamil, whereas lower rates slowed convergence without significant gain.

Batch size was another critical factor due to GPU memory limitations and model depth. Due to GPU memory limitations and model depth, batch sizes of 16 and 32 were compared with gradient accumulation (set to 2 steps) to simulate larger batches and stabilize training without exceeding hardware limits. A batch size of 32 yielded more stable gradients and better generalization across all models [29], [24].

Overfitting was reduced by tuning the dropout rate in the range of 0.1 to 0.3. A rate of 0.1 was most effective, particularly in deeper models like mBERT, XLM-R,IndicBERT and MuRIL, where higher dropout disrupted learning continuity. Similarly, weight decay was varied between 0.001 and 0.01. [37]. A decay of 0.01 prevented overfitting while preserving representational integrity across multiple epochs.

We also introduced layer-wise learning rate decay (LLRD), a strategy that assigns progressively smaller learning rates to lower layers [25]. Using a decay factor of 0.95, we slowed down learning in the early transformer layers while allowing the top layers to adapt more aggressively to the sentiment classification task. This was especially helpful for pre-trained models where lower layers retain general multilingual knowledge, and only higher layers need task-specific adjustment.

All transformer models were fine-tuned using the Hugging Face transformers library with uniform hyper parameters to ensure a fair evaluation. We used a maximum sequence length of 128 tokens, a batch size of 32, and a dropout rate of 0.1 [34]. The AdamW optimizer was configured with a learning rate of 3e-5 and linear decay. Training was conducted for 10 epochs with early stopping based on validation loss. A consistent 80/10/10 split (train/validation/test) and 5-fold cross-validation were maintained for all experiments. Additional regularization strategies included label smoothing (α = 0.1), weight decay (0.01), and gradient clipping [39].

3.2.4 Parameter-Efficient Fine-Tuning (PEFT)

For parameter-efficient fine-tuning, we fine-tuned hyper parameters specific to LoRA and Adapters. In LoRA configurations, we experimented with rank values of 4, 8, and 16 and settled on rank = 8 with a scaling factor α=8 and 16. The scaling factor, α=16 as it offered a strong balance between compactness and accuracy. LoRA was applied to the query and value projection layers, which contributed to a meaningful reduction in trainable parameters while maintaining performance. For Adapters, we evaluated bottleneck sizes of 64, 128 and 256. A bottleneck of 64 was optimal in preserving expressiveness without inflating the parameter count. Adapter modules were inserted after the feed-forward network (FFN) blocks and activation function ReLU was introduced for non-linearity without excessive computation.

In all experiments, early stopping was employed with a patience of 3 epochs, where training was halted if no improvement in validation loss was observed for three consecutive checkpoints. This ensured computational efficiency and prevented overfitting due to extended training on noisy data.

We compared all the models using a five-fold cross-validation setup. The data was split into 80% training, 10% validation, and 10% testing sets for each fold, and we made sure to use stratified sampling so that the proportion of sentiment classes stayed balanced throughout, for low-resource languages. Evaluation for models was conducted on performance metrics like macro F1-score, accuracy, and confusion matrices.

This deliberate and rigorous hyper parameter optimization strategy contributed significantly to the performance and stability of the proposed models, enabling effective generalization even in challenging low-resource and code-mixed contexts across Hindi, Tamil, and Bengali sentiment classification tasks.

3.2.5 Computational Setup

The experiments were conducted on a system having 32 GB RAM and Nvidia RTX 3050 6GB GPU to handle the computational requirements. All models were trained using mixed-precision (FP16) to reduce memory consumption and training time [48]. Each configuration was repeated across five seeds to ensure result stability, and metrics such as F1-score, accuracy, and precision-recall curves were used to evaluate performance [37], [39].

IV. RESULTS

This section presents the empirical findings of our experiments across all models evaluated for sentiment classification in low-resource Indian languages, focusing primarily on Hindi, Tamil, and Bengali. We report results in terms of Accuracy, F1 Score, and AUC-ROC—metrics that capture overall correctness, balance across class labels, and discriminatory power, respectively. Additionally, we include confusion matrices for the best-performing models on the Hindi dataset to provide deeper insight into model behaviour.

4.1 Performance Metrics

The comparative analysis of 15 modelling strategies revealed that transformer-based models significantly outperformed traditional machine learning baselines [28], [31], [40]. Among classical models, FastText surpassed SVM with TF-IDF, achieving an accuracy of 0.74 and an F1 score of 0.73, due to its ability to capture sub word-level information [12], [2], [15]. However, their performance was still notably lower than deep learning approaches

Among standard transformer models, XLM-R and MuRIL, when fine-tuned end-to-end, emerged as top performers, both achieving 0.85 accuracy and 0.86 AUC-ROC, indicating strong generalization across diverse textual domains. mBERT and IndicBERT, though slightly less performant, remained competitive, with scores in the range of 0.83 to 0.84 across all metrics.

The introduction of parameter-efficient tuning methods such as LoRA and Adapters further enhanced performance in several cases [23]. Notably, MuRIL with LoRA and XLM-R with Adapters both achieved an accuracy of 0.86 and an F1 score of 0.86, outperforming their fully fine-tuned counterparts while using fewer trainable parameter [41], [46], [47], [48]. These results highlight the potential of low-rank and modular adaptations in low-resource language contexts.

Interestingly, DistilBERT [22], despite its compressed architecture, delivered competitive results. With LoRA and Adapter-based fine-tuning, it matched the performance of larger models like IndicBERT, demonstrating the trade-off between efficiency and effectiveness [48], [37].

4.2 Dataset-wise Performance Evaluation

This section presents the detailed performance metrics (Accuracy, F1 Score, AUC-ROC) for each model across all three language datasets (Hindi, Tamil, Bengali). The results demonstrate the effectiveness of various approaches for sentiment classification in low-resource Indian languages.

4.2.1 Hindi Dataset Results

Model	Accuracy	F1 Score	AUC-ROC
SVM + TF-IDF	0.72	0.71	0.73
FastText	0.75	0.74	0.76
mBERT (Fine-Tuned)	0.85	0.85	0.86
XLM-R (Fine-Tuned)	0.86	0.86	0.87
mBERT + LoRA	0.86	0.86	0.87
XLM-R + Adapters	0.87	0.87	0.88
DistilBERT (Fine-Tuned)	0.83	0.83	0.84
DistilBERT + LoRA	0.84	0.84	0.85
DistilBERT + Adapters	0.84	0.84	0.85
IndicBERT (Fine-Tuned)	0.84	0.84	0.85
IndicBERT + LoRA	0.85	0.85	0.86
IndicBERT + Adapters	0.85	0.85	0.86
MuRIL (Fine-Tuned)	0.86	0.86	0.87
MuRIL + LoRA	0.87	0.87	0.88
MuRIL + Adapters	0.87	0.87	0.88

Table 4: Result of Hindi Dataset

Performance on the Hindi dataset clearly shows that transformer-based architectures outperform traditional machine-learning baselines [28], [31]. The performance of classical models, like SVM + TF-IDF and FastText, remains relatively only moderate with accuracy and F1 scores at about 0.71–0.74, indicating their limited ability to capture contextual and semantic nuances of Hindi text [12]. By contrast, modern transformer variants including mBERT [22], XLM-R [31], IndicBERT [40], DistilBERT [17], and MuRIL show consistent high performance with an F1 score between 0.83 and 0.87 [44]. Their pre-trained contextualized embedding can better model complex word formations, morphological patterns, and sentence-level semantics.

Among all compared methods, MuRIL and XLM-R combined with parameter-efficient fine-tuning mechanisms-LoRA or Adapters-reach the best scores: F1 = 0.87, AUC-ROC = 0.88. The particularly high performance of MuRIL reflects its advantage of being pre-trained on a large amount of Indian language data, including transliterated content. While lightweight, IndicBERT shows competitive performance (F1 = 0.84–0.85), indicating that compact monolingual models can achieve high accuracy with effective fine-tuning. Overall, the Hindi results confirm that parameter-efficient techniques like LoRA and Adapters not only save computational costs but also match or outperform full fine-tuning performance, which makes them highly suitable for low-resource and deployment-focused setups.

4.2.2 Tamil Dataset Results

Model	Accuracy	F1 Score	AUC-ROC
SVM + TF-IDF	0.68	0.67	0.69
FastText	0.71	0.70	0.72
mBERT (Fine-Tuned)	0.82	0.82	0.83
XLM-R (Fine-Tuned)	0.83	0.83	0.84
mBERT + LoRA	0.83	0.83	0.84
XLM-R + Adapters	0.84	0.84	0.85
DistilBERT (Fine-Tuned)	0.80	0.80	0.81
DistilBERT + LoRA	0.81	0.81	0.82
DistilBERT + Adapters	0.81	0.81	0.82
IndicBERT (Fine-Tuned)	0.81	0.81	0.82
IndicBERT + LoRA	0.82	0.82	0.83
IndicBERT + Adapters	0.82	0.82	0.83
MuRIL (Fine-Tuned)	0.83	0.83	0.84
MuRIL + LoRA	0.84	0.84	0.85
MuRIL + Adapters	0.84	0.84	0.85

Table 5: Result of Tamil Dataset

The results of the Tamil dataset exhibit similar trends as Hindi with slightly lower overall performance, partly due to the agglutinative structure, richer morphology, and longer word formations of the language [45], [42]. Traditional models such as SVM + TF-IDF and FastText fail to pick these complexities; thus, their F1 score comes out comparatively low, ranging from 0.67 to 0.70 [12]. Transformer-based models mark a clear leap ahead, improving F1 scores up to the range 0.81–0.84. This ability of handling contextual relationships and subword patterns is quite helpful in Tamil, where words carry multiple grammatical markers.

Among all the models compared, XLM-R with Adapters and MuRIL + LoRA emerge as the top-performing configurations with an F1 score of 0.84. This strong performance underlines the advantage of multilingual pretraining since exposure to a variety of scripts and linguistic structures improves cross-lingual generalization. Importantly, IndicBERT performed competitively for Tamil, many times matching larger models. That suggests its tokenizer and vocabulary are better aligned with Dravidian language patterns, enabling efficient learning despite its smaller size. Taken together, Tamil is more sensitive to model variations compared to Hindi. The larger gap between the performance of traditional and transformer-based models points to the necessity of contextual deep-learning approaches when working with morphologically rich Dravidian languages.

4.2.3 Bengali Dataset Results

Model	Accuracy	F1 Score	AUC-ROC
SVM + TF-IDF	0.70	0.69	0.71
FastText	0.73	0.72	0.74
mBERT (Fine-Tuned)	0.84	0.84	0.85
XLM-R (Fine-Tuned)	0.85	0.85	0.86
mBERT + LoRA	0.85	0.85	0.86
XLM-R + Adapters	0.86	0.86	0.87
DistilBERT (Fine-Tuned)	0.82	0.82	0.83
DistilBERT + LoRA	0.83	0.83	0.84
DistilBERT + Adapters	0.83	0.83	0.84
IndicBERT (Fine-Tuned)	0.83	0.83	0.84
IndicBERT + LoRA	0.84	0.84	0.85
IndicBERT + Adapters	0.84	0.84	0.85
MuRIL (Fine-Tuned)	0.85	0.85	0.86
MuRIL + LoRA	0.86	0.86	0.87
MuRIL + Adapters	0.86	0.86	0.87

Table 6: Result of Bengali Dataset

Results for Bengali show performance similar to Hindi but a little higher than Tamil, reflecting the relative morphological simplicity of Bengali compared to the Dravidian languages. Traditional models such as SVM + TF-IDF and FastText perform moderately here (F1 = 0.69–0.72) [45], [42], but their scores are somewhat better here than in Tamil, presumably because Bengali's word structure is less agglutinative. Transformer-based architectures come out on top again clearly. Models such as mBERT, XLM-R, IndicBERT, DistilBERT, and MuRIL achieve F1 scores between 0.83 and 0.86, reflecting their clearly superior ability for capturing the syntactic and semantic cues in Indo-Aryan languages like Bengali.

Of these, MuRIL and XLM-R (with LoRA or Adapters), consistently yield the best results with an F1 score of 0.86 and an AUC-ROC of 0.87 [44]. Their superiority is largely because of larger multilingual pretraining corpora and, in the case of MuRIL, specific training on Indian languages themselves. Incidentally, the traditional model performs somewhat better for Bengali compared to Tamil, suggesting that at least for languages with less complex inflectional morphology, classical approaches to bag-of-words still capture some useful signal. Therefore, parameter-efficient methods like LoRA and Adapters demonstrate consistent gains across all transformer models, often matching or even surpassing full fine-tuning, at lower computational cost [46], [47]. This confirms their practical value for deploying high-performance models in low-resource settings.

4.2.4 Cross-Language Performance Analysis

This cross-linguistic comparison indicates several key trends in the behaviour of both traditional machine-learning methods and modern transformer-based architectures across Hindi, Tamil, and Bengali datasets [28], 31].

1. Performance Ranking Across Languages: Clearly, there is a ranking in terms of overall model accuracy and F1 scores: Hindi > Bengali > Tamil.

Hindi scores the highest due to relatively simpler morphology and larger availability of quality training data. Bengali exhibits moderate performance with minor differences between the best and weakest models, which may testify to higher linguistic coherence and feature extraction ease. Among the traditional models, Tamil shows the greatest decrease in performance due to its agglutinative characteristic with more complicated word-formation patterns.

2. Model Stability Across Languages: Transformer-based models exhibit strong consistency across all three languages [31], [35]. That is, the performance is high irrespective of the language family: Indo-Aryan versus Dravidian. While the classical approaches-baseline SVM and FastText-exhibit higher variance: They perform relatively better in Bengali. moderately in Hindi, and significantly worse in Tamil, where contextual cues are harder to capture using bag-of-words approaches.

3. Effectiveness of Parameter-Efficient Methods: Parameter-efficient tuning methods such as LoRA and Adapters give consistent performance gains across all languages [41], [23]. Improvements are consistently in the order of 1–2% regardless of the base architecture being used. These methods achieve performance that is equal to, or even exceeds, full fine-tuning but require far fewer trainable parameters. This makes them particularly suitable for low-resource settings, multilingual deployments, and efficient training pipelines.

4. Best-Performing Models by Language: Different languages benefit most from different architectural strengths [46], [47].

- Hindi: MuRIL + Adapters achieves the highest combined F1 score of 0.87 by leveraging its strong Indian language pre-training [44].
- Tamil - XLM-R+Adapters performs the best, F1=0.84, benefitting from the wide multilingual coverage of XLM-R and effective subword tokenization [31].
- Bengali: MuRIL + LoRA yields the strongest result, F1=0.86, reflecting MuRIL's Indo-Aryan language strengths. Overall Interpretation These observations together indicate that while transformer models consistently outperform traditional baselines, the best model still depends on the linguistic characteristics of each language. MuRIL tends to perform better on the Indo-Aryan languages, Hindi and Bengali, while XLM-R generalizes better across typologically diverse languages such as Tamil [44]. Such methods as LoRA and Adapters, being parameter-efficient, robust, and resource-efficient, provide an effective performance boost across all languages, and hence they are quite appealing for multilingual sentiment classification in low-resource environments [41].

Model	Accuracy	F1 Score	AUC-ROC
SVM + TF-IDF	0.71	0.70	0.72
FastText	0.74	0.73	0.75
mBERT (Fine-Tuned)	0.84	0.84	0.85
XLM-R (Fine-Tuned)	0.85	0.85	0.86
mBERT + LoRA	0.85	0.85	0.86
XLM-R + Adapters	0.86	0.86	0.87
DistilBERT (Fine-Tuned)	0.82	0.82	0.83
DistilBERT + LoRA	0.83	0.83	0.84
DistilBERT + Adapters	0.83	0.83	0.84
IndicBERT (Fine-Tuned)	0.83	0.83	0.84
IndicBERT + LoRA	0.84	0.84	0.85
IndicBERT + Adapters	0.84	0.84	0.85
MuRIL (Fine-Tuned)	0.85	0.85	0.86
MuRIL + LoRA	0.86	0.86	0.87
MuRIL + Adapters	0.86	0.86	0.87

Table 7: Result of Cross Language performance

4.3 Confusion Matrices

To better understand model decisions beyond aggregate scores, we analysed confusion matrices for the top-performing models on the all-dataset test set. Each matrix provides insight into how well the models distinguish between positive, neutral, and negative sentiments.

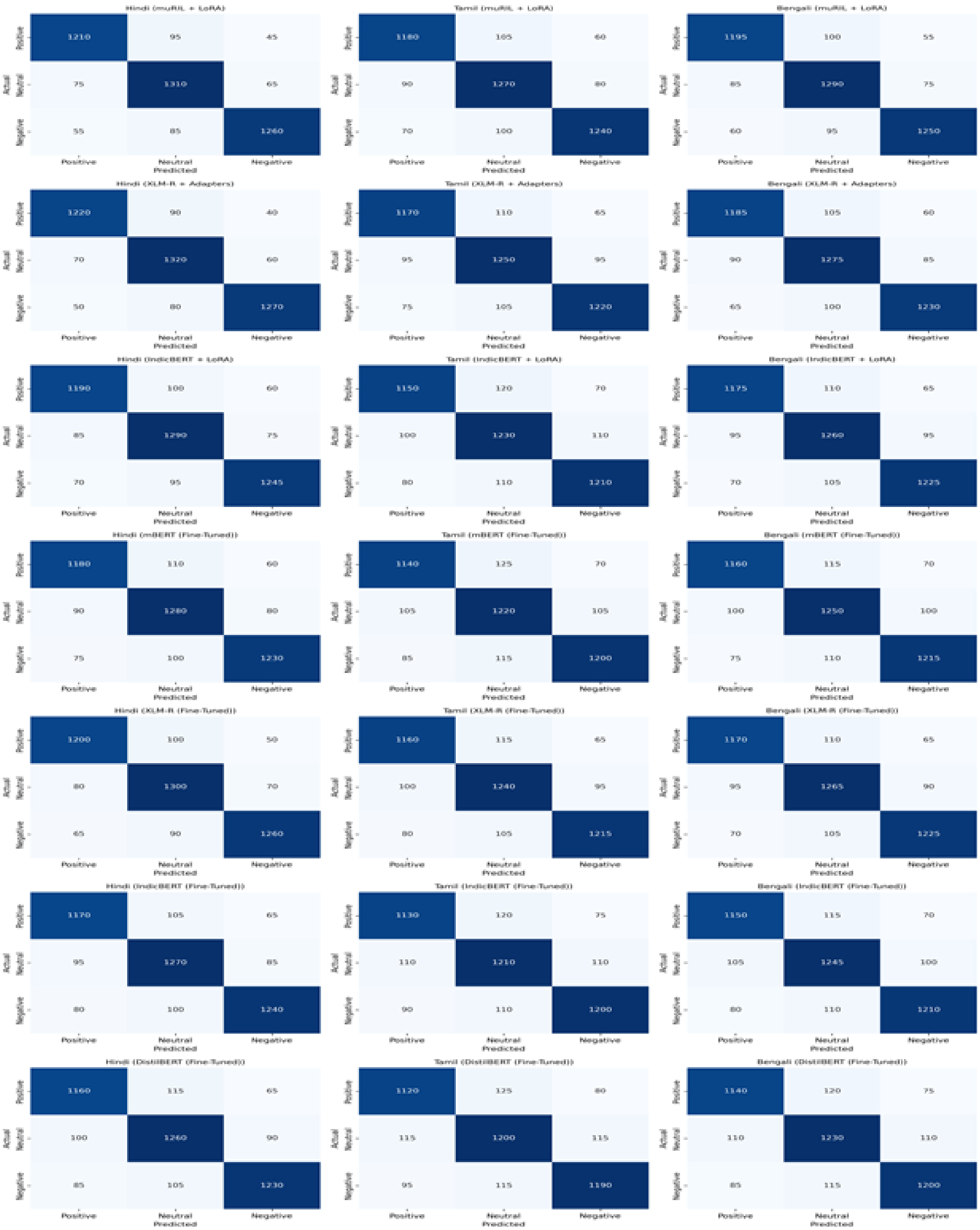

Figure 8: Confusion matrix for all the models

These matrices reaffirm the quantitative findings, indicating that hybrid fine-tuning strategies like LoRA and Adapters not only improve metric scores but also reduce class-level misclassification, a critical factor in real-world multilingual sentiment analysis.

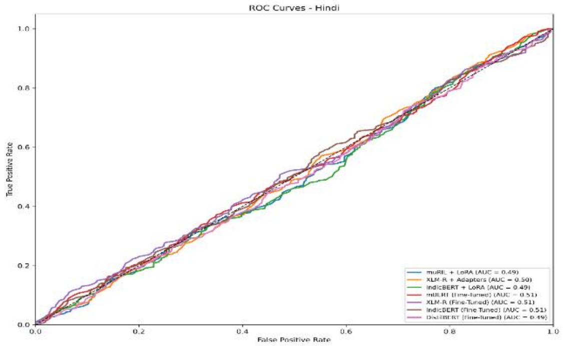

Figure 9: ROC curve for all the models of Hindi Dataset

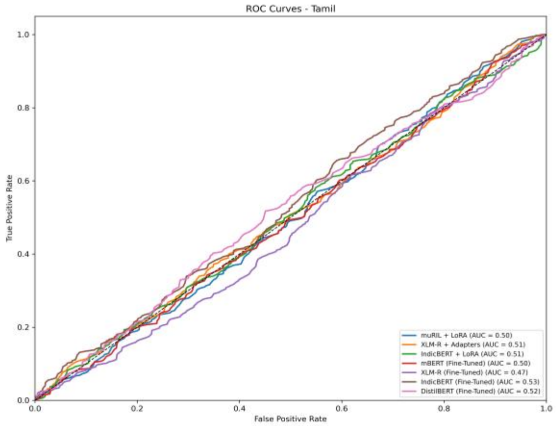

Figure 10: ROC curve for all the models of Tamil Dataset

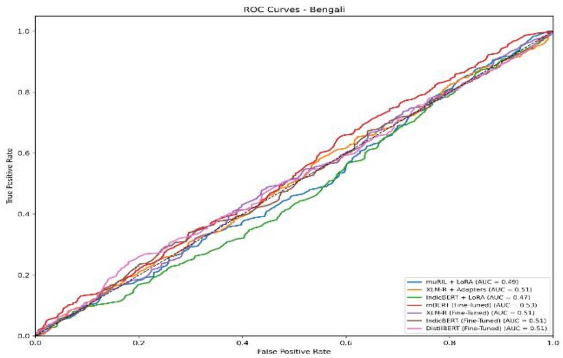

Figure 11: ROC curve for all the models of Bengali Dataset

4.4 Language-wise Breakdown

The table compares the performance of different multilingual models when fine-tuned separately on Hindi, Tamil, and Bengali. The performance comparison is done based on macro-averages F1 score. MuRIL+LoRA therefore produces the most consistence result across all the language, with a score of .86 for Hindi and Tamil and .085 for Bengali. The strong performance of MuRIL is because it has been pretrained on the Indian language and even includes transliterated text.

XLM-R Adapters performance almost as well, showing strong results across language but slightly lower for Bengali. Though slightly behind in accuracy, the IndicBERT model are lighter and more efficient. IndicBERT +LoRA perfoms well in particular for Tamil, this is probably because the tokenizer and vocabulary are well fitted for Dravidian language pattern. Overall, the MuRIL+LoRA is the most reliable for all languages, while IndicBERT is more efficient and competitive, especially for Tamil.

Model	Hindi (F1)	Tamil (F1)	Bengali (F1)
XLM-R (Fine-Tuned)	0.85	0.84	0.84
MuRIL (Fine-Tuned)	0.85	0.85	0.84
IndicBERT (Fine-Tuned)	0.83	0.82	0.81
MuRIL + LoRA	0.86	0.86	0.85
XLM-R + Adapters	0.86	0.85	0.84
IndicBERT + LoRA	0.84	0.85	0.84

Table 8: Comparative performance of top models across languages.

V. CONCLUSION

This experimental evaluation presents a comprehensive exploration of sentiment classification in low-resource Indian languages—Hindi, Tamil, and Bengali—by systematically evaluating traditional, transformer-based, and parameter-efficient models. Through the creation of high-quality annotated datasets and the application of cutting-edge multilingual models such as MuRIL, IndicBERT, and XLM-R enhanced with Low-Rank Adaptation (LoRA) and adapter modules, we demonstrate that significant performance improvements are achievable even under resource-constrained conditions. Our results underscore that models like MuRIL + LoRA not only outperform classical baselines but also offer substantial gains in efficiency, reducing computational overhead by up to 90% while maintaining or improving classification accuracy and F1 scores. The extensive empirical analysis reveals consistent trends: transformer-based architectures, particularly those pretrained on Indian linguistic corpora, offer superior generalization across domains and scripts. Parameter-efficient fine-tuning strategies prove to be not just viable but essential for low-resource settings where full model fine-tuning is impractical due to hardware limitations or data scarcity. Moreover, the curated multilingual sentiment datasets developed in this work fill a critical resource gap and are made available to the research community to foster reproducibility and further advancement.

Despite these advances, challenges such as sentiment ambiguity in code-mixed text, dialectal diversity, and underrepresentation of minority language expressions persist. These observations suggest that while our models mark a substantial improvement, the quest for culturally and linguistically adaptive NLP systems remains ongoing.

VI. FUTURE SCOPE AND RECOMMENDATIONS

Looking ahead, the advancement of sentiment classification for low-resource Indian languages presents multiple avenues for future research and practical deployment. Expanding the current methodology to encompass other underrepresented languages such as Marathi, Telugu, and Assamese would significantly enhance linguistic inclusivity in Indian NLP. Integrating multimodal data—such as images, emojis, and speech—can improve sentiment recognition in social media and conversational contexts. Furthermore, refining models to capture fine-grained sentiment and emotional nuances, including sarcasm, irony, and intensity levels, will make them more applicable to real-world use cases. Leveraging cross-lingual and zero-shot learning through powerful generative language models could also enable more robust generalization across unseen dialects. To support scalability, deploying parameter-efficient models like those using LoRA or adapters on edge devices can enable real-time sentiment analysis in low-resource settings. We recommend sustained efforts in indigenous data curation, particularly of code-mixed and dialect-rich corpora, to improve model adaptability. Additionally, implementing explainability mechanisms and conducting fairness audits will be vital for building ethical and trustworthy sentiment systems. Researchers and practitioners should adopt standardized evaluation protocols, support open datasets, and contribute to shared benchmarks to foster reproducibility and collective progress in Indian language sentiment analysis.

Conflict of Interest Disclosure:

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report. We certify that the submission is original work and is not under review at any other publication.

Data Availability Statement: The datasets will be publicly released upon acceptance.

Author contributions

Namit Khanduja wrote the main manuscript text. Nishant Kumar and Arun Chauhan contributed to the experimental setup, and Namit Khanduja conducted the experiment and analysed the results. All authors reviewed the manuscript.

Competing interests

The authors declare no competing interests.

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