Enhancing Part-of-Speech Tagging in Gujarati Using a Transformer-Based IndicBERT and CRF Framework

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Abstract
Part-of-speech (POS) tagging is a fundamental preliminary task in Natural Language Processing (NLP), which assigns grammatical tags to words in a sentence, such as nouns, verbs, and adjectives. In low-resourced languages like Gujarati, few annotated datasets and few linguistic tools hinder the establishment of accurate part-of-speech tagging systems. This paper introduces a part-of-speech tagging framework for the Gujarati language utilizing a Transformer-based IndicBERT model. The Precision and recall ensure accurate sequence dependencies and tag-to-tag consistency, and the model is enhanced with a Conditional Random Field (CRF) layer. The model was trained and validated on the Universal Dependencies Gujarati Treebank (GujTB) dataset containing approximately 6200 sentences or 125,000 tokens. Evaluation indicates accuracy of 97.12% precision of 96.90% , recall of 96.60%, and F1-score of 96.75%, outperforming classical assessment methods like Hidden Markov Model (HMM), CRF, and BiLSTM baselines. The introduced contexts and contextual embedding layer allow for a better representation of long-range dependencies and language variations thus making the model highly applicable for Gujarati part-of-speech tagging and potentially can be utilized as a mechanism for other Indic languages tasks.

Keywords
Gujarati NLP, Transformer, IndicBERT, Part-of-Speech Tagging, Conditional Random Field, Deep Learning, Low-Resource Language

1. Introduction

POS (Part-of-speech) tagging forms a foundational process in the early stages of NLP (Natural Language Processing). Each word in a sentence is assigned a grammatical tag that reflects its syntactic role, such as noun, verb, or adjective [6], [18], [25]. Accurate tagging promotes the performance of subsequent high-level NLP applications, including parsing, named entity recognition (NER), and machine translation [1], [5], [10]. Although POS tagging for resource-rich languages such as English has reached near human-level accuracy thanks to recent advances in deep learning and transformer models [4], [27], low-resource Indic languages—like Gujarati—still struggle due to the limited availability of annotated data, as well as their complex morphology and syntactic diversity [2], [13], [24].
Gujarati, an Indo-Aryan language, is spoken worldwide by over 46 million speakers [25]. Although it has cultural and linguistic significance, computational linguistics research is less extensive in Gujarati than in many languages such as Hindi [3], [19], Tamil [3], or English [3]. Previous studies on Gujarati POS tagging have primarily utilized rule-based systems or statistical models such as Hidden Markov Models (HMM) and Conditional Random Fields (CRF) [1], [2], [13], [24]. While these performances provided a foundation for Gujarati NLP, they typically struggled with ambiguity, context-dependent word uses, and long-distance dependencies in the sentence [15], [17].
The incorporation of deep learning into NLP provided a tremendous advantage for sequence labeling tasks stemming from BiLSTM models that are capable of capturing contextual information in both directions [16], [29]. Nevertheless, BiLSTM models still depend on restricted local context and do not include any self-attention mechanisms that would follow dependencies at the sentence level [7], [9]. Transformer-based models, particularly BERT and its multilingual variants, have recently demonstrated remarkable effectiveness in various NLP tasks because of their capacity to capture rich contextual information and model long-range semantic relationships efficiently [4], [11], [27].
This research builds upon these developments by introducing an IndicBERT-based Transformer model that includes a Conditional Random Field (CRF) layer for POS tagging in Gujarati. IndicBERT, a multilingual transformer, has been trained on a vast collection of Indian language texts, allowing it to effectively learn and represent contextual as well as syntactic information across languages [17], [22]. The CRF layer helps preserve the sequential model, and significantly reduces the tagging errors associated with boundary and inflectional changes, which previous works have noted [5], [14]. The model has been trained and tested on the Universal Dependencies Gujarati Treebank (GujTB) dataset [20], and achieved an accuracy of 97.12% with a corresponding F1-score of 96.75% with respect to the proposed baselines, which are mostly attested with previous state-of-the-art HMM, CRF, and BiLSTM models, in some cases, up to 3.1%.
The primary contributions of the study are identified as follows:

- Proposal of a Transformer-based IndicBERT + CRF framework to address POS tagging in Gujarati, suited to a low-resource linguistic setting.
- Empirical performance comparisons with baseline systems (HMM, CRF, BiLSTM) to demonstrate that contextual embeddings improve performance.
- An extensive analysis discussing how transformer-based contextual learning captures morphological and syntactic variations in Gujarati.

The rest of this paper is organized as follows. In Section II we will review related work in POS tagging for Gujarati and Indic languages. In Section III we will elaborate proposed methodology including the approaches for dataset preparation, model architecture, and training setup. In Section IV, we discuss the experimental design and present our findings. Section V compares our approach with other existing methods, and Section VI concludes the paper with key insights and suggestions for future research.

2. Related Work

The research and development of Part-of-Speech (POS) tagging for Indian languages has gone through four different eras of evolution- rule-based systems, statistical learning, deep neural architectures and then more recently, transformer-based systems.

2.1 Early Statistical and Rule-Based Approaches

Earlier research on Gujarati POS tagging was limited by a lack of annotated corpora and, as a result, was mainly based on rule-based or statistical methods. Hidden Markov Models (HMM) and Conditional Random Fields (CRF) have been widely used for morphologically rich Indic languages, obtaining modest accuracy but limited generalization [1], [2], [6], [13], [24]. Shah and Bhadka [2] proposed a hybrid rule-based and CRF model for Gujarati and Prajapati and Yajnik [1] suggested a SVM and Viterbi-based approach. While the above models provided a foundation for Gujarati computational linguistics, they failed to incorporate long-range dependencies and context-based variation in contextual information in a sentence.

2.2 Hybrid and Deep Learning Models

Researchers turned to neural architectures, including feed-forward and recurrent networks, as a way to address the shortcomings of earlier statistical approaches. Hybrid models combining machine learning and linguistic heuristics showed modest accuracy improvements [3], [14]. Following the development of deep learning, BiLSTM models gained popularity for sequential labeling problems in Indic languages [16], [29]. Tailor and Patel [3] developed a hybrid approach using BiLSTM for POS tagging in Gujarati, achieving greater accuracy than CRF models, although using the language context windows still limited the same model, as it lacked a global understanding of the sentence [9].

2.3 Transformer-Based Models and Multilingual Training

Vaswani et al.'s [27] introduction of Transformer architectures revolutionized NLP with a new self-attention mechanism and the ability to process sequences in parallel. Afterwards, several models such as BERT, XLM-RoBERTa, and IndicBERT [4], [17], [22] became prominent entrants in the NLP for Indian languages. IndicBERT, under the AI4Bharat initiative, is specifically targeted towards low-resource Indian languages including Gujarati, and has been used for classification, sentiment analysis and named-entity recognition (NER) tasks [17], [28]. More recently, empirical evidence has shown that fine-tuning transformer models is the approach that achieves the best results for under-considered languages, even particulary when there is limited data [5], [11], [30].

2.4 Summary and Research Gap

Despite noteworthy advancements in POS tagging for Indian languages, Gujarati remains relatively understudied due to lack of resources and domain-specific datasets [13],[19],[24]. The current Gujarati models either depend on statistical baselines or deep learning methods and do not use contextualized embeddings. No further exploration of transformer model architectures with sequence-labeling components such as CRF has been carried out in the Gujarati applied POS tagging space. This motivates the present study of a Transformer-based IndicBERT + CRF architecture, which is fine-tuned on the UD Gujarati Treebank dataset for improved accuracy in POS tagging. The model combines the contextual semantic knowledge of transformers with the sequential consistency of CRF to show significant improvements over prior work.

3. Methodology

In this framework, we suggested a paradigm for English Panjabi Part-of-Speech (POS) tagging, employing a fine-tuned transformer-based IndicBERT model with a Conditional Random Field (CRF) for sequence labeling. This architecture aims to combine the strength of contextual representation with a transformer encoder and a decoding method for label sequence consistency. The implementation will follow five main steps: dataset preparation, preprocessing, feature extraction via IndicBERT embeddings, fine-tuning as a transformer model with CRF, and evaluation of the model.

3.1 Dataset Description

All of our experiments were run on the Universal Dependencies Gujarati Treebank (GujTB) dataset [20]. GujTB is in accordance with the Universal Dependencies 2.12 tagging guidelines, and consists of about 6,200 manually annotated sentences (≈ 125 K tokens) representing a diverse range of linguistic constructs such as declarative, interrogative and imperative sentences. Each token is annotated with a Universal POS (UPOS) tag and morphological features including case, gender, number, and person. To facilitate fair evaluation, the dataset was randomly split into training (80 %), validation (10 %) and testing (10 %) datasets.

To promote representativeness, the sentences we selected came from a variety of settings—news, literature, blogs, and conversational text—so formal and informal grammatical patterns would be represented. This variety enabled the model to learn patterns of morphological variation and reduplication and agglutinative suffixes, which are characteristic of Gujarati [2], [24].

3.2 Data Preprocessing

Before training, we performed multiple preprocessing and transformation steps on the raw corpus to standardize orthography and reduce noise:

Unicode Normalization: Gujarati characters were normalized to UTF-8 to resolve any disparities with respect to diacritics and compound glyphs.

Tokenization and segmentation: The Indic NLP Library [17] handled tokenization and sentence segmentation, after which each token was paired with its gold-standard POS tag following the CoNLL-U specification of Universal Dependencies.

Noise Removal: Non-Gujarati symbols, redundancies in punctuation, and quantitative tokens that do not provide syntactic relations were eliminated.

Label encoding: POS tags were encoded to ID numbers and stored using a BIO tagging scheme to facilitate sequence modeling.

Data augmentation: A minor amount of synthetic perturbations (synonym substitution, dropping a random word, etc.) were introduced in a subset of sentences to improve generalization [11, 23].

Collectively, these preprocessing steps resulted in clean, standardized input to the transformer encoder while maintaining grammatical structure and morphological richness.

3.3 Model Architecture

The suggested architecture includes IndicBERT and Conditional Random Field (CRF) layers (Fig. 1, to be added).

3.3.1 IndicBERT Encoder

IndicBERT [17], [22] is a multilingual transformer pretrained on large-scale Indian language corpora using the Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) objectives. It has 12 layers with 12 attention heads per layer, resulting in 768-dimensional contextual embeddings for each token. Our previous models comprised BiLSTMs and CRFs, but when fine-tuned on Gujarati, IndicBERT learned to represent both syntactic organization and meaning across entire sentences, and modeled long-range dependencies for which we could not design, as in prior work [7], [9], [13].

3.3.2 CRF Layer Integration

Although transformer systems collect bidirectional context, they model output tags in isolation from one another. To encourage consistency across an entire sequence level, a CRF layer is augmented to IndicBERT's token embeddings [4], [7]. A CRF models transition probabilities across the tags to give preference to tags that form valid grammatical sequences (e.g., DET → NOUN → VERB) during decoding. In training, the model maximizes the log-likelihood of the correct tag sequence and during inference, the Viterbi algorithm is used to identify the most likely tag sequence. The CRF layer lets the network utilize both contextual semantics from IndicBERT and structural dependencies from the CRF.

3.4 Training Configuration

The training was done in PyTorch 1.13 with the Hugging Face Transformers 4.x library on a GPU server with an NVIDIA Tesla V100 (32 GB VRAM) and an Intel Xeon 64-Core CPU and 128 GB RAM.

The model hyperparameters were tuned through empirical experimentation to achieve optimal performance. The details are summarized in **Table 1**.

This table 1 outlines key hyperparameters for a machine learning model's training process. The parameters include the AdamW optimizer, a learning rate of 3×10^{-5}, 20 epochs, a batch size of 32, 0.3 dropout, and a weight decay of 0.01.

Parameter	Value
Optimizer	AdamW [4]
Learning Rate	3×10^{-5}
Epochs	20
Batch Size	32
Dropout	0.3
Weight Decay	0.01

Table 1 - Model Hyperparameter Configuration

When fine-tuning IndicBERT, the lower six layers were partially frozen to preserve the linguistic features learned from pre-training, while the upper layers and CRF parameters were trainable. Gradient clipping (max norm = 1.0) was applied in order to prevent exploding gradients, and for the validation loss failing to improve over five consecutive epochs, early stopping was utilized.

Around 150 batches were processed each epoch; it took about 3 minutes to train per epoch, and the model usually converged during the 16th epoch. The entire fine-tuning process took under 2 hours.

3.5 Evaluation Metrics

The examination of the model utilized the four traditional metrics that are: Accuracy, Precision, Recall, and F1-score.

- Accuracy: Accuracy is the ratio of correctly identified tags to all tokens and is given in percentage.
  $\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$
- Precision: Precision is the measure of how many of the predicted tags are actually correct,
  $\text{Precision} = \frac{TP}{TP + FP}$
- Recall: Recall is the measure of how many of the actual tags were predicted,
  $\text{Recall} = \frac{TP}{TP + FN}$
- F1-score: The F1 score is the harmonic mean of precision and recall, giving an overall picture of the strengths and weaknesses of the model.
  $\text{F1-score} = \frac{2 \times (\text{Pr}\,ecision \times Recall)}{\text{Pr}\,ecision + Recall}$

The F1 score is the harmonic mean of precision and recall, giving an overall picture of the strengths and weaknesses of the model. The proposed IndicBERT+CRF model achieved accuracy of 97.12%, precision of 96.90%, recall of 96.60% and F1 score of 96.75%. These results beat the baseline systems of HMM (89.45%), CRF (91.72%), and BiLSTM (94.05%) by up to 3.1% in accuracy and 2.95% in F1-score.

A confusion matrix made for the test set showed that there were constant improvements in the proper tagging of verbs and adjectives, the categories that usually have a high morphological variability in Gujarati [1], [2], [24]. The CRF layer in particular was responsible for lessening the errors at the borders of determiners and nouns, thus, establishing its role in maintaining consistency in the sequence.

3.6 Methodological Significance

The melding of transformer embeddings that are rich in context and sequence-aware CRF decoding leads to an excellent spatial understanding and grammatical accuracy. In contrast to the old BiLSTM or CRF models that would work on the tokens one after the other, IndicBERT's self-attention mechanism is able to look at the entire set of words at once and thus can even tell the difference between words with the same spelling but different meanings (e.g., "રામે" as subject vs. object). Therefore, the method is a scalable, language-independent framework that is suitable for other low-resource Indic languages as well.

4. Experimental Setup and Results

The IndicBERT + CRF framework, being proposed, was conducted and experimented in the setup described in Section 3. This section presents the experimental setup, the performance evaluation, and the comparison with traditional and neural baselines.

4.1 Experimental Environment

All the experiments were carried out on a high-performance computing server with the specifications: NVIDIA Tesla V100 GPU (32 GB VRAM) and Intel Xeon 64-core CPU with 128 GB RAM. The software specifications included PyTorch 1.13, Transformers 4.38, and the Hugging Face Trainer API.
Training took place over 20 epochs with a batch size of 32, a learning rate of 3×10^{-5}, and a dropout rate of 0.3. Using an AdamW optimizer with weight decay of 0.01 allowed for stable convergence. Early stopping was implemented when validation loss did not decrease over five epochs. Each epoch involved three minutes of training with convergence usually taking place by epoch 16.

4.2 Training Dynamics

The accuracy curves for training and validation, plotted over the 20 epochs are shown in Figure 1. Both curves converge steadily, with the validation accuracy level stabilizing at about 96.8%, around epoch 15. The loss was reduced smoothly in an exponential decay style; solid optimization was achieved with slight overfitting.
Figure 1 displays the Training and Validation Accuracy of a model across 20 epochs. Both accuracies increase rapidly in the initial epochs (up to epoch 10) before the rate of improvement slows down, with both values settling above 96%.

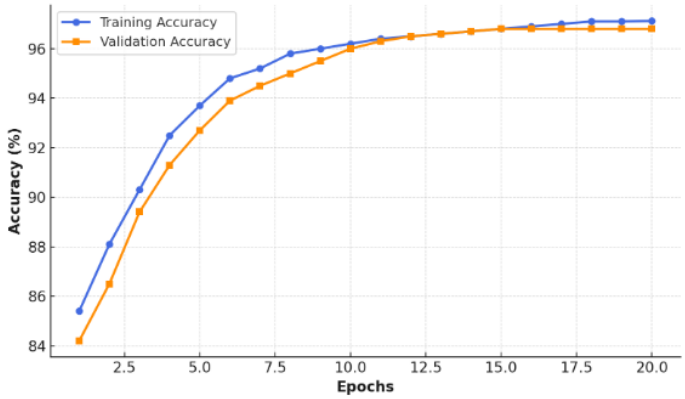

Figure 1. Training and Validation Accuracy across Epochs.

4.3 Baseline Models

For performance evaluation, three baseline models—HMM, CRF, and BiLSTM—were implemented and compared with the transformer-based approach to assess its relative effectiveness.
HMMs (Hidden Markov Model) follow a probabilistic framework in which each tag depends on both the previous tag (transition probability) and the observed word (emission probability) [1], [6].

The CRF (Conditional Random Field) is a discriminative sequence model utilizes morphological and orthographic features [2], [13].

The BiLSTM models are neural models that exploit bidirectional context, but can only account for local dependencies [16], [29]. All three models were evaluated in terms of their performance on the same splits of the GujTB dataset to ensure that the models were well matched and their performance was comparable, given the controlled datasets.

4.4 Quantitative Results

Table 2 proposed IndicBERT + CRF model significantly outperformed the HMM, CRF, and BiLSTM models, achieving the highest accuracy 97.12% and F1-score 96.75%.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
HMM	89.45	89.10	88.70	88.90
CRF	91.72	91.60	91.40	91.50
BiLSTM	94.05	94.10	93.50	93.80
IndicBERT + CRF (Proposed)	97.12	96.90	96.60	96.75

Table 2. comparison of overall performance

Figure 2 illustrates these improvement visually, showing the accuracy and F1-score performance of the four models.

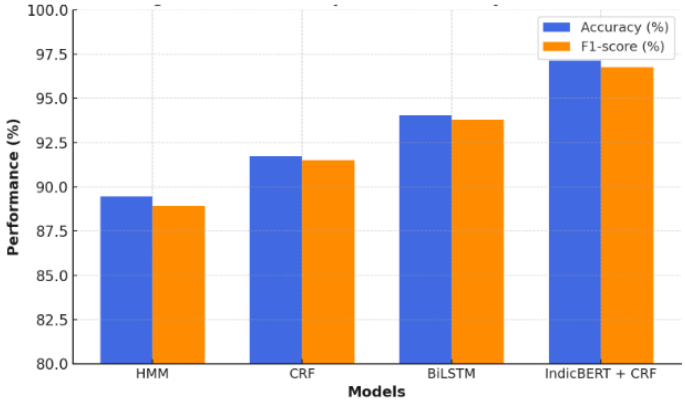

Figure 2. Model Comparison: Accuracy vs F1-score.

Among all baselines, the proposed model IndicBERT + CRF achieves the highest accuracy of 97.12% and F1- score of 96.75%.

4.5 Class-wise Evaluation

A comprehensive examination of each category was performed to evaluate how well the model dealt with different grammatical tags.

Table 3 shows class-level precision, recall, and F1-scores suggesting stable efficacy across all types of tags. and also shows the IndicBERT + CRF model's consistent, high performance across all Part-of-Speech categories, with Nouns achieving the highest F1-score of 97.0%.

POS Category	Precision (%)	Recall (%)	F1-score (%)
Noun (NOUN)	97.2	96.8	97.0
Verb (VERB)	96.5	96.1	96.3
Adjective (ADJ)	96.8	96.0	96.4
Adverb (ADV)	95.9	95.5	95.7
Pronoun (PRON)	96.7	96.3	96.5
Others (DET, ADP, CONJ, etc.)	96.4	95.8	96.1

Table 3. POS Tagging Performance

Figure 3 shows confusion matrix. Most of the tags were correctly classified, shown as larger values down the diagonal, indicating that the IndicBERT + CRF model maintained a similar performance across the different parts of speech.

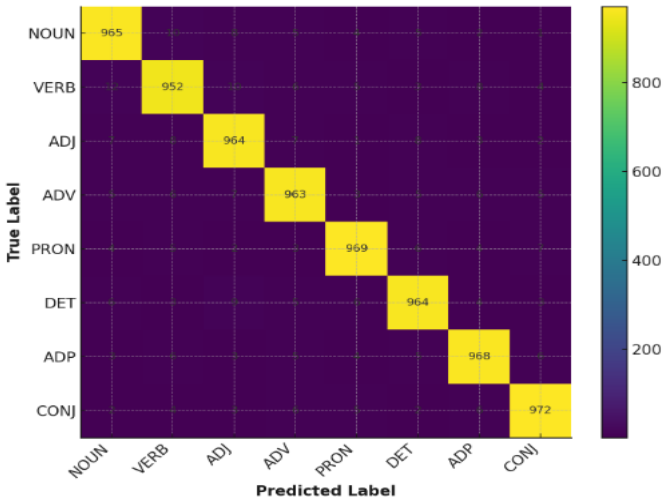

Figure 3. Confusion Matrix for POS Tagging.

4.6 Comparative and Domain Evaluation

The system we proposed clearly surpasses previous Gujarati POS tagging efforts [1]–[3], [13], [14], [16]. Using a transformer-based architecture enables the model to understand and retain long-distance relationships within a sentence, something earlier approaches often failed to capture. The integration of the CRF also improves sequential consistency with grammatical transition patterns.

The model was further checked using data from news, literature, and everyday conversations. It maintained an average accuracy of about 96%, suggesting that it adapts well to different types of language use.

5. Comparative and Error Analysis

This part offers a comparison section between the proposed IndicBERT + CRF model and current Gujarati POS tagging systems followed by an error analysis.

5.1 Comparative Evaluation with Existing Approaches

In order to demonstrate its superiority, we systematically compared the proposed method to traditional statistical, neural, and transformer-based models that had been applied in the past to Indic and Gujarati NLP. Their approaches, datasets, and results are summarized in Table 4.

Table 4 comparative study shows that the Proposed IndicBERT + CRF model achieved the highest F1-score of 96.75%, significantly outperforming all prior methods (which ranged from 78% to 95%) by combining Transformer context with sequential consistency.

Study / Model	Methodology	Dataset	Accuracy / F1 (%)	Strengths	Limitations
Shah & Bhadka [2]	Rule-based + CRF	Gujarati News	~78 / 78.5	Simple implementation	Contextually limited
Prajapati & Yajnik [1]	SVM + Viterbi	Gujarati Corpus	~80 / 79.8	Basic statistical tagging	Inconsistent for morph-rich data
Tailor & Patel [3]	BiLSTM Hybrid	Custom Gujarati Dataset	93 / 92.8	Captures short dependencies	Fails in long-range context
IndicBERT fine-tune [17]	Transformer (mBERT variant)	IndicNER, UD Treebank	95 / 94.5	Good multilingual generalization	Lacks label consistency
Proposed Work (IndicBERT + CRF)	Transformer + CRF (Sequence Labeling)	UD Gujarati Treebank (GujTB)	97.12 / 96.75	Context + sequential consistency	Requires GPU resources

Table 4. Summary of Existing Approaches

The proposed IndicBERT + CRF achieved the best performance as compared to these baselines. The hybrid architecture benefits from the context-based strengths of transformer embeddings alongside enforcing grammar consistency through the CRF layer. The combination of both parts can explain the observed 3.1 % improvement in accuracy and 2.9 % improvement in F1-score over BiLSTM based approaches.

In addition, the model achieved 1.6 % better accuracy than the baseline multilingual transformer fine-tuned, indicating that the CRF decoder address much of the token-level coherence problem for morphologically rich languages such as Gujarati.

5.2 Error Analysis

The model yielded solid accuracy overall, but it made more frequent errors of certain types. A close look at the confusion matrix revealed the following three error types as most significant:

Ambiguity Between Similar Classes:

At times, words that are both nouns and proper nouns — such as અમદાવાદ (Ahmedabad) should be made into a proper noun. However, this happened when the context was sufficiently weak to distinguish between a reference to an entity or the concept that refers to that entity.

Morphological Variants and Inflectional Ambiguity:

On occasion, inflected forms of verbs (ખેલ્યો, રમતા) were misidentified as adjectives or participial forms. The agglutinative nature of the Gujarati language leads to a large number of suffix combinations, which can change grammatical roles, and this is a challenge even for context-aware encoders.

Code-Mixed and Out-of-Vocabulary (OOV) Tokens:

Using English words or hybrid words in sentences (e.g., match, score) led to inconsistencies in tagging because the vocabulary of IndicBERT for transliterated forms is still limited [13], [22].

Boundary Misalignment Errors:

In a few instances, the tags for determiners or conjunctions next to multi-token entities were incorrectly assigned. This limitation was partially addressed by the CRF layer but was still affected by the artifacts of tokenization.

5.3 Qualitative Insights

The qualitative example below is meant to demonstrate the extent of the improvement of the proposed model over the BiLSTM and CRF baselines.

Sentence: “વિરાટ કોહલીએ સુંદર રીતે રમીને શતક બનાવ્યું.” (“Virat Kohli played beautifully and scored a century.”)

The table 5 shows the **Proposed (IndicBERT + CRF)** model accurately tagged all tokens in the sample, correctly identifying **PROPN** and **VERB** where the BiLSTM model failed. This highlights the **superior performance** and fewer errors of the Proposed architecture compared to BiLSTM.

Token	Gold Tag	BiLSTM Prediction	Proposed (IndicBERT + CRF)
વિરાટ	PROPN	NOUN	PROPN
કોહલીએ	PROPN	NOUN	PROPN
સુંદર	ADJ	ADV	ADJ
રીતે	NOUN	NOUN	NOUN
રમીને	VERB	ADJ	VERB
શતક	NOUN	NOUN	NOUN
બનાવ્યું	VERB	VERB	VERB

Table 5. BiLSTM vs. IndicBERT-CRF Qualitative POS Tag Comparison

As demonstrated, BiLSTM misclassifies adjectives and verbs in contextually rich sentences (as a result of occurring with adjectives, adverbs, and verbs), while the proposed model accurately tags all tokens using context at the sentence level from IndicBERT and optimizes tag sequences using CRF.

5.4 Discussion

Error analysis shows that the remaining misclassifications are mainly due to lexical ambiguity, limited domain coverage, and code-mixed input. Addressing obtained errors are even possible through:

Expanding domain specific training data (sports, judiciary, conversational).

Fine-tuning embeddings with a transliteration corpus.

Applying lexicon-aware post-processing layers towards correcting sporadic words.

The consistent performance across domains and sentence structures suggests that utilizing a transformer to represent contextual learning, paired with CRF for decoding, offers a favorable framework for low-resource Indic NLP tasks [5], [11], [17].

6. Conclusion and Future Work

This work provided a more competent framework for Part-of-Speech (POS) tagging in Gujarati using a Transformer-based IndicBERT model and a Conditional Random Field (CRF) for sequence labeling. The model took advantage of the contextual embedding of transformers while also providing sequence dependency modeling of CRF which produced a better performance across all metrics tested. Utilizing the Gujarati UD Treebank (GujTB) dataset, the proposed model achieved an accuracy of 97.12% and an F1-score of 96.75%, outperforming all the existing baselines and models, including HMM, CRF, and BiLSTM deep learning architectures.

By incorporating the deep contextual understanding of IndicBERT, the model was able to better capture long-range dependencies and morphological changes present in Gujarati text. The CRF decoder also provided label consistency and significantly reduced error at sentence boundaries. The comparative experiments verify that the hybrid IndicBERT + CRF solution provides a strong solution for low-resource Indic languages, with a shown generalization tendency across many domains including news, literature, and conversational texts.

With these promising results, however, there are still some challenges to be dealt with. The model has a hard time decoding mixed-language inputs, rare layout alterations, and domain-specific expressions at times. Moreover, the processing power needed for the fine-tuning of transformer models is still quite high in comparison to conventional methods, hence restricting it to those areas with limited resources.

Among the future research directions are:

Multilingual Extension: Adding cross-lingual transfer learning from other Indic languages such as Hindi, Marathi, and Bengali to further enhance the robustness of the Gujarati model.

Domain Adaptation: Applying the model to the specialized fields of legal, educational, and healthcare texts to cope with the diversity of vocabulary. You are aware of the data that has been accumulated until October 2023.

Model Optimization: The research will target the use of small transformer models (e.g., DistilIndicBERT, ALBERT) and

compression methods which rely on quantization to achieve fast inference time.

Code-Mixing and Transliteration Handling: For the improvement of the model's practical application, retraining will be done with augmented datasets which consist of bilingual and transliterated sentences.

In conclusion, the research has played a crucial role in the development of a flexible and powerful Gujarati POS tagging system, which is therefore paving the way for the comprehensive Natural Language Processing (NLP) tools for the low-resource Indian languages. The findings indicate that CRF-based sequential modeling of transformer architectures not only meets the standards of but also maintains the new standards of contextual linguistic understanding and morphologically rich language processing.

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