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POS Tagging: A Review of Recent Techniques

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Abstract

Part-of-Speech (POS) tagging is a fundamental task in Natural Language Pro-cessing (NLP) that involves assigning grammatical categories such as noun, verb, adjective, and adverb to words in a text. Accurate POS tagging serves as a critical preprocessing step for higher-level NLP applications, including syntactic parsing, machine translation, information retrieval, and sentiment analysis. Over the past decades, a wide range of POS tagging techniques has been proposed, by different research scholars from rule-based systems to da-ta-driven and neural approaches. This review provides a systematic examination of recent techniques, highlighting their core methodologies, strengths, limitations, and applicability to different languages.

Introduction

Natural Language Processing (NLP) is a crucial field of artificial intelligence that enables computers to analyze, understand, and interpret human language. The primary objective of NLP is to create systems that can efficiently process and produce natural language. NLP systems generally consist of three stages: Pre-processing, Main-processing, and post-processing. Part of Speech (POS) tagging is one of the crucial task under the pre-processing phase. Success of further sub-sequent core processing largely depends on correct POS tagging. POS tagging deals with assigning correct part of speech tag to the words of input sentence. POS tagging enables a variety of downstream applications such as named entity recognition, machine translation, parsing, and sentiment analysis. POS tagging methods have changed over the last 20 years, moving from rule-based systems to machine learning and, more recently, neural and transformer-based architectures. A systematic overview of the main POS tagging techniques is provided in this paper, which highlights important techniques, datasets, tagsets, advantages, and limitations.

POS Tagging Techniques

POS tagging has evolved from simple rule-driven methods to highly sophisticated deep learning and transformer-based approaches. Each generation of techniques has contributed uniquely to improved linguistic representation, scalability, and performance across languages, including low-resource Indian languages such as Marathi, Gujarati, and Hindi. The following subsections presents a comprehensive explanation of all major POS tagging techniques.

1. Rule-Based POS Tagging

Rule-based POS tagging is one of the earliest approaches [2], grounded in linguis-tic knowledge and handcrafted grammar rules. These systems rely on predefined lexical dictionaries and contextual rules specifying which tags can occur in a given syntactic environment. Typically, morphological cues such as suffixes, prefixes, word endings, and agreement patterns are used to infer POS categories. The major advantage of rule-based methods is their interpretability and high pre-cision for syntactically regular languages. However, rule construction is extreme-ly time-consuming, domain-dependent, and lacks scalability. Their inability to generalize to unseen words or ambiguous constructions limits their applicability to modern, large-scale NLP tasks.

2. Statistical POS Tagging

Statistical taggers model POS tagging as a probabilistic sequence labelling task. These methods rely on training data with annotated tags.

- **Hidden Markov Models (HMM):** HMM-based taggers compute the most likely sequence of tags by combining transition probabilities (likelihood of tag sequences) and emission probabilities (likelihood of a word given a tag). The Viterbi algorithm is typically used to find the optimal tag path. HMMs are easy to train and computationally efficient; how-ever, they assume independence between words and rely heavily on surface probabilities, limiting performance for languages with rich morphology.
- **Maximum Entropy Models (MEMM):** ME taggers use a feature-based probabilistic framework that integrates various linguistic cues lexical, orthographic, and contextual without assuming condition-al independence. As a result, they offer higher flexibility than HMMs. Although ME models provide improved accuracy, feature engineering requires expertise and significant effort.
- **Conditional Random Fields (CRF):** CRFs represent a discriminative sequence modelling method that jointly considers dependencies between adjacent tags. CRFs allow for rich feature incorporation, capturing contextual patterns more precisely than generative models like HMMs. Due to their effectiveness and relatively lower computational cost, CRFs became the dominant approach prior to deep learning. Their main limitation lies in reliance on manual feature extraction.

3. Machine Learning and Deep Learning Techniques

Neural approaches eliminated the need for hand-crafted features by learning representations automatically. Section 3 presents the detailed literature survey of this approach.

- **Feed-Forward Neural Networks (FFNNs):** Early neural taggers used word embeddings combined with feed-forward layers. These models improved performance but were limited in capturing long-term dependencies due to their fixed context window.
- **Recurrent Neural Networks (RNNs):** RNNs introduced sequential modelling capability, making them suitable for POS tagging. However, simple RNNs suffer from vanishing gradients, limiting their performance for long sequences.
- **Long Short-Term Memory Networks (LSTMs):** LSTMs addressed vanishing gradient issues and became standard for POS tagging. Bidirectional LSTMs (Bi-LSTMs) capture both past and future contextual information, resulting in substantial accuracy improvements, especially for morphologically rich languages.

4. Transformer-Based POS Tagging

Transformer models revolutionized POS tagging due to their self-attention mech-anism and ability to model global dependency structures without recurrence.

- **BERT-Based Taggers:** BERT and its multilingual variants learn contextual word representations from massive amounts of unlabeled text. Fine-tuning BERT for POS tagging yields state-of-the-art performance across languages, including low-resource ones, because:
    - Self-attention captures both short-range and long-range dependencies.
    - Sub word-level tokenization handles morphology effectively.
    - Transfer learning enables robust performance with limited training data.

  Section 4 presents the detailed literature survey of this approach.
- **Language-Specific models:** Models such as IndicBERT, MuRIL, and XLM-R deliver improved POS tagging for Indian languages. They capture morphological and syntactic patterns that traditional models cannot handle efficiently.

5. Hybrid Approaches

Hybrid taggers combine rule-based, statistical, and neural methods to handle edge cases more effectively. For example:

- A rule-based layer may handle special tokens, numerals, or punctuation.
- A neural network may tag the remaining words.

- A CRF layer may refine tag sequences.

Hybrid systems are particularly suitable for low-resource Indian languages, where linguistic rules supplement limited data availability.

6. Summary of POS tagging techniques

Table 1 presents a comprehensive summary of diverse POS tagging techniques along with their key models, advantages, and constraints.

Table 1. Summary of POS Tagging Techniques

Technique	Key Models / Examples	Strengths	Limitations	Suitable For
Rule-Based Tagging	Brill Tagger, ENGTWOL	High interpretability; linguistically accurate rules	Requires manual rules; poor scalability; weak with unseen words	Resource-rich languages with strong linguistic resources
Statistical Tagging (HMM, CRF)	HMM Tagger, CRF Tagger	Handles ambiguity; stable performance; well-studied	Requires feature engineering; limited context modeling	Medium-resource languages; classical NLP pipelines
Machine Learning Approaches	MaxEnt, SVM Tagger	Flexible features; decent accuracy	Heavy feature creation; weak long-range dependency handling	Languages with moderate annotated data
Deep Learning (BiLSTM, BiLSTM-CRF)	BiLSTM, GRU, BiLSTM-CRF	Learns features automatically; strong sequential modeling; SOTA before transformers	Requires large data; slower training; struggles in low-resource settings	Most languages; morphologically rich languages
Transformer Based Models	BERT, RoBERTa, XLM-R, IndicBERT, mBERT	Context-aware; highest accuracy; minimal feature engineering; effective for low-resource languages	Requires GPU; large memory usage; may overfit small datasets	All languages, especially low-resource and multilingual corpora

Review of Related Work

Literature survey has been carried out in order to investigate the efforts done in the research subject. For performing survey of POS Tagging systems various re-quired parameters have been studied like: Basic concepts of POS tagging, Size of datasets and various approaches for POS Tagging Systems. Literature survey has been carried out at two levels i.e. Literature survey for Foreign Languages, Literature survey for Indian Languages.

1. Literature Survey for Foreign Languages

English is the most extensively used language for POS tagging in the world. Table I describes summary of research work for English and some other foreign languages.

Table 2. Survey of Research Work for Foreign Languages

Language (Year)	Method	Dataset	Accuracy
Pashto (2024) [1]	RNN and BLSTM Networks	2,81,205 words	98.82%
English (2021) [2]	combines deep learning and rule-based methods	GMB dataset 62,010 sentences (1,354,149 tokens)	per-token: 98.6% and for sentence76.04%.
English (2017) [3]	Neural Network	Penn Treebank WSJ corpus	97.58%
English (2017) [4]	combination of bidirectional LSTM, CNN and CRF	Penn Treebank WSJ corpus	97.55%
English (2011) [5]	3 Gram MEMM, 5wShapesDS	Wall Street Journal corpus	97.28% token accuracy
Hungarian (2006) [6]	MEMM	Not Specified	98.17%
Mandarin (2005) [7]	Mandarin MEMM	Chinese Treebank 5.0	80%
English (2003) [8]	Dependency Network	Penn Treebank WSJ corpus	. 97.24%
English (1996) [9]	MEMM	Penn Treebank WSJ corpus	96.6%
English (1994) [10]	HMM	BNC(100 million words)	96%
English (1992) [11]	Rule based	Brown Corpus	95%

Shaheen ullah, et. al. [1] developed deep learning-based model utilizing Recursive Neural Networks (RNN) and Bidirectional Long Short Term Memory Networks (BLSTM) that tags a tag set of 2,81,205 words with 17 distinct POS tags. 98.82% accuracy was attained by the suggested method utilizing the word embedding technique and BLSTM model. This is the first study to attain excellent accuracy in Pashto using a deep learning approach with a sizable dataset. Future research will concentrate on developing a parser for the Pashto language using deep learning.

Hongwei Li et al. [2] suggests a unique method for POS tagging that incorporates a deep learning model based on Transformer and rule-based data preparation. The technique allows the model to forecast the POS tags of the re-maining tokens by reducing the number of possible POS tags for the majority of tokens to one. The model takes use of bidirectional settings by using masking and self-attention. The success of the suggested approach is confirmed by experiments conducted on the Groningen Meaning Bank (GMB) dataset, which yielded a whole-sentence accurate rate of 76.04% and a per-token tag accuracy of 98.6%. In order to increase the accuracy of POS tagging, future research will try to expand the methodology to other languages and enhance the rule-based data pre-processing and deep learning model.

Michihiro Yasunaga et al. [3] In order to reduce over-fitting in low-resource languages, increase tagging accuracy for uncommon or unheard words, and en-hance overall tagging accuracy, this work develops and examines a neural POS tagging model that incorporates adversarial training (AT). The model helps with dependency parsing, learns cleaner word and internal representations, and reach-es state-of-the-art performance on almost all languages in UD v1.2. The findings encourage the continued use of AT for tasks involving natural language, such as machine translation and named entity recognition. The study offers a solid foundation for using AT in tasks using natural language.

. Xuezhe Ma and Eduard Hovy [4] described a neural network architecture for automatically using word- and character-level representations for sequence tagging is presented. The system can be used for a variety of sequence labelling jobs because it is end-to-end and doesn't require feature engineering or data pre-processing. On two language sequence labelling tasks, the system demonstrated state-of-the-art performance, achieving 91.21% F1 for named enti-ty recognition and 97.55% accuracy for part-of-speech tagging. Future research might examine multi-task learning strategies and use the model to analyze data from other fields, such as social media.

Christopher D. Manning [5] The text explores the potential to improve part-of-speech tagging performance from 97.3% token accuracy to near 100% accuracy. It suggests that improvements to the Stanford POS Tagger could be beneficial. However, the author suggests that further progress lies in improving the taxonom-ic basis of linguistic resources used for tagger training, specifically descriptive linguistics. They also highlight the limitations of this process, as certain words may not be adequately captured by categorizing them.

Halácsy, et. al. [6] Using an open-source morphological analyzer, the study as-sesses maximum POS disambiguation systems in Hungarian natural language processing tasks. The optimal suggested architecture, the initial implementation of the maximum entropy framework, performs better than cutting-edge tagging techniques and robustly manages out-of-vocabulary objects. This makes it possible to analyze big web-based corpora effectively. The study shows that combining stochastic elements with a symbolic morphological analyzer can result in a 98.17% performance level that is on par with English taggers. Plans for the future call for a system of permissive licensing.

Huihsin Tseng et.al.[7] The study explores part-of-speech tagging in Mandarin Chinese, finding unknown words more challenging than in English. Researchers propose new morphological features for POS tagging, improving performance from 61% to 80%. The study suggests cross-linguistic similarities between Chinese and German, despite genetic differences.

Toutanova, K., et al. [8] this research presents Dependency network representation, broad lexical features, efficient priors, and fine-grained modelling of un-known word properties are used to create a new part-of-speech tagger. In comparison to earlier single automatically learned tagging results, the tagger reduces errors by 4.4% and achieves 97.24% accuracy on the Penn Treebank WSJ. With an accuracy of 97.16% across the same WSJ data, the tagger performs better than the most well-known combination tagger, Brill and Wu (1998). The ramifications of this study extend to sequence model NLP problems over sparse multinomial distributions.

Adwait Ratnaparkhi [9] The paper presents a statistical model that accurately predicts Part-Of-Speech tags (POS) from corpus tagged using Part-Of-Speech tags, discussing corpus consistency difficulties and suggesting a training technique, and employing specialized features for challenging tagging decisions. The Maximum Entropy model is a flexible linguistic modelling technique, with a state-of-the-art POS tagger achieving 96.6% accuracy on an unseen test set. How-ever, specialized features do not outperform the baseline model, and a single annotator-trained model performs.5% higher, providing more consistent input for tagged text applications.

Geoffrey Leech, et.al.[10] The CLAWS4 general-purpose grammatical tagger, which is used to tag the 100 million-word British National Corpus which contains about 70 million words is described in this publication. In order to increase quality and consistency, the tagger strives for general-purpose adaptability, measures accuracy consistently, and does so in a linguistically informed manner. Ten mil-lion words of spoken language and a vast array of written texts, including un-published sources, make up the approximately 100 million words of English writ-ten texts and spoken transcriptions that make up the BNC. Although it can accept other forms, the tagger must accept and output text in the corpus-oriented TEL confonnant markup definition known as CDIF. Though there is still need for improvement, CLAWS4 contains aspects of flexibility and linguistic analysis advances over 14 years.

Eric Brill [11] presents a simple rule-based part of speech tagger that can automatically learn its rules and tags with accuracy on par with stochastic taggers is shown in this study. Compared to stochastic taggers, the rule-based tagger has a number of advantages, such as less stored information, a smaller set of meaningful rules, more portability between tag sets, corpus genres, and languages, and simplicity of identifying and implementing changes. The study shows that there are other practical methods for part-of-speech tagging besides the stochastic method. The rule-based tagger is highly portable, requiring only the proper noun discovery procedure. It also eliminates the need for large tables of statistics, capturing contextual information in fewer than 80 rules, making it more perspicuous and easier to understand. In order to create better and more expressive rule templates, this study suggests researchers to investigate rule-based tagging.

2. Literature Survey for Indian Languages

This section presents the literature survey on Indian languages with key aspects. Indian languages are mainly phonetic and do not employ capitalization like Eng-lish, it is difficult to detect POS in raw data in these languages. It is difficult to find resources like dictionaries, morphological analyzers, and stemmers. There are many different writing styles. Table 2. describes the summary of survey of POS tagging systems for Indian languages.

Table 3. Survey Of Research Work For Indian Languages

Language (Year)	Method	Dataset	Accuracy
Marathi (2025) [12]	RNN, LSTM, GRU, and BiLSTM	48,420 annotated words.	97.86%
Gujrati (2024) [13]	RNN, LSTM, BiLSTM, and GRU	29,000 sentences	98%
Tamil (2024) [14]	BLSTM	51 607 sentences (421 050 words.)	95.03%
Hindi (2023) [15]	VITERBI and K-Nearest Neighbour,	universal dependencies corpus Hindi setion	95%
Assame (2023) [16]	Rulebase, neural network(BiLSTM-CRF)	corpus with 404k tokens	F1 score of 0.925
Odia (2023) [17]	CRF, convolutional neural network (CNN).	publicly accessible corpus ILCI phase-II project	CRF- 92.08, CNN-94.48
Malayalam (2020) [18]	Neural network	287,588 total tagged words, 237,000 words for training, remaining for testing	F1 measure 0.9832
Maithili (2020) [19]	CRF, Neural network	52,190-word	CRF, 82.67%, Neural network 85.88%

Deore P. R et.al.[12] presents a deep learning–based framework for Parts-of-Speech (POS) tagging in the Marathi language, a low-resource and morphologically rich language. Traditional rule-based and statistical approaches have shown limited performance due to inflectional complexity and the lack of annotated corpora. To address these challenges, the study constructs a manually annotated dataset of 48,420 Marathi tokens using the IIT-Hyderabad tagset and evaluates four recurrent neural architectures RNN, LSTM, GRU, and BiLSTM. The dataset is divided using an 80:20 train–test split, with further separation of training and validation subsets. Experiments were conducted by varying hidden states (4, 16, 32, 64) and epochs (30, 50, 100) to identify optimal configurations for each model. The findings reveal that all deep learning models deliver strong performance, with BiLSTM achieving the highest accuracy (97.86%) and F1-score (97.78%), outperforming RNN, LSTM, and GRU architectures. The results confirm that bidi-rectional contextual processing significantly enhances POS tagging accuracy for Marathi. This work contributes a new annotated corpus, a comparative evaluation of deep learning models, and establishes a strong baseline for POS tagging in low-resource Indic languages.

Mehta [13] developed a BIS-tagged Gujarati POS corpus consisting of 29,000 sentences and conducted a comprehensive evaluation of various tagging models. Traditional approaches, such as CRF implemented through NLTK's TnT tagger, achieved moderate performance. In contrast, deep learning architectures including RNN, LSTM, BiLSTM, and GRU delivered significantly higher accuracy, reaching approximately 98%. Multilingual BERT, however, performed notably lower (around 88%), primarily due to the absence of POS-tagged data in its pre-training and the limited size of the Gujarati dataset for effective fine-tuning. The findings indicate that sequence-based neural models are better suited for handling Gujarati's rich morphology compared to large multilingual transformer models. Overall, the study establishes a strong benchmark for Gujarati POS tag-ging and demonstrates that task-specific deep learning approaches outperform generalized pre-trained language models in low-resource environments.

Hemakasiny Visuwalingam, et.al.[14] This research uses Bi-directional Long Short Term Memory (BLSTM) to propose a deep learning-based POS tagger for Tamil. For 63.21% of unknown words in test sentences, the model, which com-bines word-level, character-level, and pre-trained word embeddings, achieves an accuracy of 95.03%. As the number of unfamiliar terms rises, the accuracy falls. With an accuracy of 95.03%, the suggested model improves 63.21% of unknown terms by 2.57%. Future research will concentrate on creating a POS tagger utilizing other deep-learning techniques and testing the model on different corpora.

Devashish Dutta et al. [15] Based on K-Nearest Neighbour and VITERBI, this research suggests an intelligent POS tagger for Hindi. The morphological characteristics of Hindi grammar and the presence of a word or lexeme in a sentence serve as the foundation for the POS tagging technique. Due to its free word order structure, Hindi may not be compatible with current English POS tagging approaches. Since specific tags are less common in the Hindi word corpora that are currently accessible, a larger corpus with a wider variety of sentence patterns is needed. However, when there are unknown words, the majority of taggers do not produce accurate findings. The suggested tagger is thought to be an improvement to VITERBI for more accurate results when unknown words are present, and it can handle non-consecutive unknown words.

Dhrubajyoti Pathak, et al. [16] An ensemble system for part-of-speech (POS) tagging in Assamese, an Indian scheduled language with a rich morphology and limited resources, is presented in this paper. The ensemble system makes use of the advantages of different kinds of POS taggers while including a language's linguistic traits. The F1 scores of the top two POS tagging models are 0.746 and 0.745, respectively. With an F1 score of 0.85, the researchers created a rule-based POS tagger that took into account a number of linguistic morphological phenomena. After integrating the ensemble approach with the top two DL-based taggers, the F1 score improved to 0.925. The fact that the new ensemble POS taggers outperformed the baseline taggers in terms of performance indicates that the taggers' integration combined the best features of each tagger to create the new tagger. A larger dataset is produced by the ensemble tagger, which aids in the training of an improved DL-based model

Tusarkanta Dalai, et al. [17] This study develops an Odia part-of-speech tagger using a conditional random field (CRF) and deep learning techniques (CNN and Bidirectional Long Short-Term Memory). The study made use of a publically available corpus that was annotated with the Bureau of Indian Standards (BIS) tagset as part of the Indian Languages Corpora Initiative (ILCI) phase-II project. The CNN network, Bi-LSTM network, CRF layer, character sequence information, and pre-trained word vector are all components of the deep learning-based model. With CNN-extracted character sequence features and pre-trained word embedding, the Bi-LSTM model achieved 94.48 percent accuracy. When compared to previous research on the Odia language, the suggested methods yield more accurate results. Applying the model to data from different domains, creating more labelled datasets from all domains, and using deep learning to solve other natural language processing issues are some potential avenues for future research.

K. K Akhil, et al. [18] This study suggests a deep learning-based method for Malayalam parts-of-speech labeling. The technique makes use of four deep learning architectures: Bi-directional Long Short Term Memory (BLSTM), Long Short Term Memory (LSTM), Gated Recurrent Unit (GRU), and Recurrent Neural Network (RNN). Tests on actual datasets demonstrate that the suggested approach performs better in terms of accuracy and precision than some current approaches. The authors hope to expand this work to include named entity recognition in Indic languages, especially Malayalam, and other natural language processing applications. Additionally, they intend to produce additional tagged datasets for additional study in the field of Malayalam computing.

Ankur Priyadarshi, et al. [19] Part of speech (POS) tagging in Maithili, an Indi-an language, has not been investigated. With about 50 million native speakers, Maithili is one of the official languages, despite efforts to create POS taggers in other languages. Given that the language is utilized in government and educational settings in some states, the creation of Maithili natural language processing (NLP) techniques and resources is essential. By manually annotating a POS-tagged corpus, creating a POS tagset, and manually annotating a 52,190-word Maithili corpus, the researchers created a Maithili POS tagger. Using a variety of feature sets, the system's accuracy rose to 82.67%; when big raw corpora incorporating Wikipedia dumps and other Maithili web resources were used, the accuracy rose to 85.88%.

Conclusion

Form the study of survey we conclude that POS tagging relies on linguistic rules, statistical dependencies, or learned representations that define syntactic and se-mantic roles of words. Traditional approaches like rule-based systems depend on handcrafted lexicons and grammar rules. Statistical models such as HMM and CRF introduced probabilistic learning for disambiguation. Deep learning eliminated the need for manual feature engineering, enabling the automatic extraction of contextual patterns. Recently, trans-former-based models such as BERT have further improved contextual representation, particularly for languages with rich morphology. Also we observed that Various POS tagging techniques are used like rule based, statistical, machine learning, deep learning models but transformer-based BERT model has not been used for Marathi language yet. So, there is a scope to develop POS tagger for Ma-rathi using BERT model because Marathi is a morphologically rich, free word order, and highly inflectional in nature. BERT has ability to capture left and right context simultaneously so gives accurate meaning of each word.

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