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Identification and Categorization of Stop Words in Sanskrit Using Natural Language Processing (NLP) Approaches

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ABSTRACT

The goal of this research is to use Natural Language Processing (NLP) to create a systematic and computationally sound method for recognising and categorising stop words in Sanskrit. Finding function words like conjunctions, negations, and discourse markers is essential for precise computational linguistics tasks like parsing, translation, and information retrieval because of Sanskrit's intricate morphology and syntactic structure.More than 100 high-frequency functional terms were taken from digital archives and traditional Sanskrit manuscripts. Two primary methods were employed: a statistical model that ranked and validated word frequency using Zipf's Law, and a rule-based linguistic approach based on Paninian grammar and POS tagging. To guarantee linguistic accuracy, tools like morphological analysers and Sanskrit-specific taggers were included and then expertly validated. Metrics including precision, recall, and F1-score were used for evaluation.

Both approaches produced useful but complementary outcomes. While Zipf's Law improved memory by finding statistically significant function words, the rule-based method offered great accuracy. A standardised, machine-readable list of Sanskrit stop words that is compatible with contemporary NLP processes and arranged according to grammatical functions was produced as a consequence of the hybrid approach.This work is one of the first to systematically combine statistical modelling for the categorisation of Sanskrit stop words with linguistic theory. It opens up new possibilities for machine translation, voice recognition, and semantic analysis in classical Indian languages by offering a domain-specific, verified natural language processing resource designed for an ancient language.

Keywords: Sanskrit Stop Words , Natural Language Processing (NLP), Text Pre-processing , Sanskrit Computational Linguistics , Stop Word Classification

1.0. Introduction:

Because it allows computers to analyse, understand, and react to human language, Natural Language Processing (NLP) has completely changed the discipline of computational linguistics. Finding and eliminating stop words—common functional phrases that support grammatical structure but lack substantial semantic content—is a basic step in natural language processing (NLP). Stop word removal is a developed technique backed by a wealth of linguistic resources in modern languages like Hindi and English. However, since there aren't enough annotated corpora or common computational tools, this technique is yet undeveloped in ancient languages like Sanskrit. Shown how important a fine-grained Sanskrit tagset is for improved morphological analysis and processing [1, 2]. examined how Sanskrit's complicated morphology and unrestricted word order make dependency parsing difficult.[3] further emphasised that in order to effectively pre-process Sanskrit NLP tasks, function words must be identified using NLP-based morphological analysers [4].

Sanskrit requires specific methods for stop word recognition because of its extensive inflectional patterns, sandhi norms, and syntactic flexibility. Sanskrit's grammatical structures vary according to poetry meter, context, and ancient or Vedic use, in contrast to English, which has set and commonly acknowledged stop word lists. In order to discover and classify Sanskrit stop words, this study combines statistical concepts with linguistic expertise. Functional categories that are often used but add little to semantic load are highlighted, including conjunctions (e.g., च,

तु), negations (न, न च), and discourse markers (हि, खलु).[5]

2. Existing Approaches

In order to find and examine stop words in Sanskrit text corpora, this research used two main approaches. Each method provides a distinct viewpoint, with one based on statistical modelling and the other on language theory, leading to a thorough and well-rounded identification procedure.

2.1 Rule-Based Approach

To find syntactically non-essential terms, the rule-based method makes use of linguistic heuristics derived from conventional grammar systems, especially Paninian grammar. The following elements are part of this approach: Spoken Words (POS) Tagging: It is simpler to separate avyayas (indeclinables), a category that often include stop words like particles, negations, and conjunctions, by labelling each word with its grammatical category (e.g., noun, verb, conjunction). Rules of Paninian Grammar: A highly organised framework for defining the functional responsibilities of words in a sentence is provided by these classical principles. Words like च (ca), न (na), and तु (tu), for example, are categorically classified as syntactic linkers or negators, and their use is specified in a methodical manner. Syntactic accuracy: This method offers great accuracy in recognising words that are semantically lightweight yet structurally required for sentence construction, such as stop words, since it adheres to rigorous grammatical logic. Strengths: Excellent language identification accuracy. Beneficial for maintaining Sanskrit manuscripts' grammatical integrity .particularly useful for languages with complex morphology, such as Sanskrit.

2.2 Zipf's Law-Based Approach

A statistical theory known as Zipf's Law states that there is an inverse connection between a corpus's rank and word frequency: the most common word occurs about twice as often as the second most frequent, and so on. High-occurrence terms that are functionally frequent but semantically minimum were extracted using this frequency-based methodology. Frequency Distribution Analysis: This technique identifies words that occur excessively often, usually functional words like conjunctions, particles, and prepositions, by examining word frequency across big Sanskrit corpora. Data-Driven Identification: This technique is independent of grammatical categories, in contrast to the rule-based method. Rather than semantic depth, it finds statistical outliers, or terms whose frequency indicates syntactic usefulness. Strengths: Makes it possible to identify stop words even in unstructured or noisy information. beneficial for confirming results from various texts or fields.may be used in NLP models that are multilingual or cross-linguistic, where grammatical tagging might not always be precise.

Complementarity of Both Approaches

By bridging the gap between statistical data and grammatical logic, these two approaches enhance one another: In order to maintain linguistic authenticity in ancient languages like Sanskrit, the rule-based method guarantees grammatical correctness and accuracy in recognising stop words. However, by verifying that the indicated terms are likewise statistically prevalent in use, the Zipf's Law-based technique provides empirical support of the rule-based conclusions. When combined, these techniques provide a hybrid framework that is data-supported and linguistically grounded, improving the precision and resilience of stop word recognition and NLP pre-processing for Sanskrit texts.

3. Related Work (Literature Review)

A crucial pre-processing step in the majority of Natural Language Processing (NLP) pipelines is the detection and elimination of stop words, particularly in tasks like machine translation, sentiment analysis, and information retrieval. Stop word lists are well-established and often used in contemporary languages like English [5]. However, because of the intricate syntactic structures and morphological diversity of ancient languages like Sanskrit, the development and use of stop word lists is still in its infancy. There are particular language difficulties with Sanskrit. Its strong inflectional morphology, usage of sandhi (euphonic combinations), and unrestricted word order render basic token-based analysis inadequate. [6] was one of the first academics to investigate the use of dependency grammars for parsing Sanskrit, emphasising the need of organised linguistic resources, such as lists of stop words, to increase parsing accuracy. Worked on creating a Sanskrit morphological analyser that could recognise roots and suffixes, but they neglected to include functional words like particles and conjunctions, which are essential for stopping word recognition. For higher-level semantic tasks, this results in a lack of resources for removing non-content terms from Sanskrit corpora.[7] created a thorough Sanskrit tag set with functional terms divided into fine-grained groups. The basis for identifying syntactically important but semantically light words—possible candidates for stop word lists—was established by their work. Their tag set has to be further mapped to NLP pre-processing tools, however

A technique called speech-to-text (STT) transforms spoken utterances into written text. Another name for it is Automatic Speech Recognition, or ASR. STT systems use sophisticated algorithms and machine learning models to analyse audio data and identify spoken words. The natural-language concept has been referred to as a "AI-complete problem" since it seems to need both linguistic proficiency and a deep understanding of the environment. More than 30 languages are spoken in India, including six Indian languages on Google Assistant, and there are 1652 dialects and 22 official languages. [8]

One fascinating approach to human-computer interaction is natural language processing (NLP). With 22 main languages and another 720 dialects written in 13 different scripts, India is a multilingual nation.

Bengali, Punjabi, and Hindi are the third, seventh, and tenth most spoken languages in the world, respectively, out of 22. There are currently no completely developed Automatic Speech Recognition systems for the other two main Indian languages, with the exception of Hindi, where a great deal of research is being done. The contrasts between speech-to-text algorithms developed for several Indian languages using Named Entity Recognition (NER) under the NLP are investigated in this paper. The study tackles issues specific to Indian languages, such code-mixing and morphological complexity, using a wide range of techniques, from rule-based systems to cutting-edge machine learning models. We examine two issues that are specific to Sanskrit voice-to-text algorithms: phonetic variability and the lack of a speech corpus. In addition to highlighting the need of hybrid linguistic-data-driven models and extensive annotated datasets, the research offers many approaches for examining performance requirements and constraints.[9] Recent years have seen the development of hybrid linguistic and computational models for Sanskrit speech-to-text systems [10].A thorough analysis of speech-to-text NER frameworks in Indian languages is offered by STNoIL, with an emphasis on phonetic diversity and morphological richness [11].In line with the first phases of Sanskrit data preparation, Shah and Bhadka (2020) investigated the efficacy of noise reduction as a pre-processing step.[12]

4. Methodology

In order to produce a trustworthy, linguistically informed list of stop words, the technique used for this work combines computer models with traditional Sanskrit linguistic theory. To guarantee both grammatical accuracy and empirical generalisation, both rule-based and statistical approaches were used.

4.1 Data Collection

To illustrate the wide syntactic and lexical range of Sanskrit, a representative and varied corpus was assembled. Among the sources were: Classical works chosen for their rich language patterns and syntactic complexity include the Bhagavad Gita, the Upanishads, and the Rigveda.

Digital repositories: The Sanskrit Library and the Digital Corpus of Sanskrit (DCS) these archives include machine-readable and annotated Sanskrit texts, which are essential for computational analysis and tokenisation. In order to find recurrent functional terms in a variety of situations and grammatical forms, the selection of texts guaranteed coverage of Vedic, Classical, and Philosophical Sanskrit.[13]

4.2 Methods Used

The following computer procedures were used in order to routinely find and classify stop words: Steps in an Algorithm Flowchart

A Sandhi-aware tokenizer that can separate complex words while maintaining syntactic validity was used to do tokenisation. Frequency Analysis: To identify high-frequency candidates for further examination, the word frequency distribution across the corpus was calculated. POS Tagging: A Sanskrit-specific Part-of-Speech (POS) tagger (such as the Goyal & Huet, 2016 model) was used to tag each token, aiding in the separation of indeclinable and functional categories. Morphological Analysis: To detect non-inflected function words (avyayas) and differentiate root forms, morphological analysers were used. Grammatical Categorisation: Using Paninian grammar principles, words were categorised into grammatical roles (such as conjunctions and negations) while preserving linguistic integrity. Manual Review: To verify non-semantic use across contexts, ambiguous candidates were verified by Sanskrit language specialists.[14]

Explanation of the Algorithms

Rule-Based Approach: This technique filters words according to their grammatical purpose and sets a set of syntactic rules (such as indeclinable detection). Because of their remarkable syntactic integrity, Paninian grammar structures were cited. Uncertain words underwent manual refining. Zipf's Law Method: This method plots log-frequency against log-rank to determine which words are statistically dominating. It is based on Zipf's statistical theory. Semantic filters were used to further evaluate high-frequency phrases to make sure they met the criteria for stop words. This method makes up for situations that rule-based heuristics could miss.

4.3 Evaluation Parameters

Through the use of confusion matrix computations, performance was assessed using the common classification metrics of precision, recall, and F1-score:

Table 1 : Classification metrics of precision, recall, and F1-score

Method	Precision	Recall	F1-Score	Total Stop Words
Rule-Based	0.92	0.87	0.89	114
Zipf's Law Approach	0.85	0.93	0.89	128

A comparison of stop-word detection techniques employing precision, recall, and F1-score as performance criteria is shown in Table 1. Despite variations in the total number of stop words found, both approaches produce a similar and robust overall F1-score of 0.89, with the Rule-Based method exhibiting stronger precision and the Zipf's Law approach achieving superior recall.

While Zipf's Law technique improved memory by retrieving more function terms, the rule-based strategy offered higher grammatical correctness. A hybrid combination of the two approaches produced the greatest overall efficacy.

5. Experimental Results

The results of the rule-based and Zipf's Law methods for recognising Sanskrit stop words are shown in this section. Visual aids, comparison analysis, and assessment measures are used to illustrate the results. Performance metrics, frequency trends, and linguistic significance are shown in four tables.

5.1 Individual Result Tables and Graphs

Table 2: Performance Evaluation of Rule-Based Approach for Sanskrit Stop Word Identification

Parameter	Value / Description
Accuracy	0.92 (High precision due to strong syntactic rules derived from Paninian grammar)
Recall	0.87 (Some context-dependent function words missed due to conservative heuristics)
F1-Score	0.89 (Harmonic mean of precision and recall—balanced efficacy)
False Positives	Few (Strict filtering avoids misclassification of semantically meaningful words)
Total Stop Words Identified	114 (Verified through linguistic validation, not purely frequency-based)
Linguistic Basis	Paninian grammar; POS tagging; morpho-syntactic features of **avyayas** (indeclinables: conjunctions, negations, particles)
Strengths	High linguistic accuracy; semantically aware; avoids over-filtering; suitable for Sanskrit's classical and philosophical texts
Limitations	Slightly lower recall due to conservative heuristics; difficulty in handling borderline/context-dependent function words
Expert Evaluation	Verified by Sanskrit scholars to ensure alignment with traditional grammatical theory
Applications	Machine Translation, Syntactic Parsing, Grammar Correction, Lemmatization, Speech Recognition (ASR), Morphological Analysis

Because the rule-based approach is founded on Paninian grammatical principles, it achieves high accuracy and a well-balanced F1-score for Sanskrit stop-word detection, as Table 2 demonstrates. Although conservative heuristics cause the technique to have a slightly lower recall, expert linguistic validation demonstrates its dependability and appropriateness for sophisticated Sanskrit NLP applications including morphological analysis, translation, and parsing.

Table 2 shows that the Rule-Based Approach for recognising Sanskrit stop words performs well on all three assessment parameters. The algorithm successfully identified stop words with an accuracy of 0.92 and few false positives. The strong syntactic principles used, which are derived from Paninian grammar, one of the world's most systematised language traditions, are reflected in this great accuracy. Based on POS tagging in line with morpho-syntactic characteristics specific to Sanskrit grammar, indeclinable categories (avyayas) such conjunctions (,), negations (,), and discourse particles (,) were added. Although the system recovered the majority of the legitimate stop words, some were missed, mostly because rule-based heuristics are conservative, as shown by the recall score of 0.87. Borderline situations and context-dependent function words, which may not always act as stop words, were not allowed due to the rigorous adherence to grammatical structure. However, in applications that need high linguistic accuracy, such machine translation, syntactic parsing, or grammatical mistake correction in Sanskrit, this recall vs. precision trade-off is acceptable.[15]

The rule-based method's balanced efficacy is confirmed by an F1-score of 0.89, which is the harmonic mean of accuracy and recall. The final count of 114 certified stop words demonstrates that the system uses linguistic validation to ensure semantic retention in subsequent NLP tasks rather than randomly including high-frequency phrases. This strategy ensures that no content-bearing keywords are unintentionally eliminated by avoiding filtering out words with multiple semantic and syntactic responsibilities, unlike frequency-based approaches. Additionally, Sanskrit experts' human evaluation provides a crucial layer of expert validation, making up for automated technologies' shortcomings and guaranteeing conformity to traditional grammatical theory. Because grammatical structure and meaning are closely related in classical and philosophical works, the rule-based approach is especially well-suited for these types of texts.

Perfect for studying Sanskrit morphology and syntax.makes it possible to prepare corpora more thoroughly for subsequent processes like translation, lemmatisation, and parsing.encourages the creation of automatic speech recognition (ASR) systems that are grammatically correct.

Table 3: Zipf's Law Approach – Evaluation Metrics

Metric	Value
Precision	0.85
Recall	0.93
F1-Score	0.89
Stop Words Identified	128

The success of the Zipf's Law-based method in recognizing a wide variety of stop words using frequency-based analysis is demonstrated by its high recall, which is summarized in Table 3. The balanced

F1-score of 0.89 indicates that the approach is still useful despite the relatively decreased precision, especially for applications that prioritize thorough stop-word coverage.

Table 3 shows the encouraging outcomes of the Sanskrit stop word identification method based on Zipf's Law. With a high recall of 0.93, it demonstrated that the approach was very successful in identifying a wide range of high-frequency functional terms. This is explained by the fundamental idea of Zipf's Law, which states that a word's frequency in any natural language is inversely related to its position in the frequency list. As a result, function words are statistically strong candidates for stop word categorisation since they usually appear often in a variety of texts. The method's ability to identify function words that rigorous grammatical rules could overlook, particularly in situations with inadequate annotation or morphological ambiguity, is shown by the detection of 128 stop words. When grammatical tools or linguistic knowledge are not easily accessible, this model acts as a strong, language-agnostic statistical filter that facilitates large-scale corpus processing for Sanskrit, when annotated corpora are scarce .Nevertheless, this benefit is accompanied with a decrease in accuracy (0.85). Because of their great frequency in certain texts or stylistic repeats, the approach sometimes incorrectly identifies semantically relevant terms as stop words. For example, certain philosophical or religious Sanskrit literature score highly in frequency yet do not meet the criteria for non-semantic function words since they repeat significant phrases (such atma, dharma, and yoga) for thematic emphasis. In comparison to the rule-based method, this results in inflated false positives and somewhat reduced accuracy.[16]However, the Zipfian strategy's resilience is confirmed by its F1-score of 0.89, especially in recall-sensitive NLP tasks including topic modelling, document clustering, and information retrieval. Over-inclusion of stop words is better than omission in these tasks because it guarantees maximal data cleansing, even if it sometimes results in semantic loss .Additionally, this method is corpus-adaptive and scalable, which makes it perfect for cross-linguistic alignment, digital humanities initiatives, and bootstrapping stop word lists in classical languages with limited resources. Its advantage is that it offers a statistical starting point that may subsequently be improved using semantic filters or grammatical restrictions. Excellent for processing big Sanskrit corpus automatically. Helps create language resources quickly in situations where grammar-driven tools aren't accessible. Provides a great deal of usefulness in pre-processing processes for unsupervised machine learning models (e.g., topic modelling, LDA).

5.2 Comparative Result Table and Graph

Table 4: Comparative Performance of Rule-Based vs Zipf's Law Approaches

Approach	Precision	Recall	F1-Score
Rule-Based	0.92	0.87	0.89
Zipf's Law	0.85	0.93	0.89

A comparison of the Rule-Based and Zipf's Law approaches is shown in Table 4, which shows that, despite their different strengths, both strategies obtain the same F1-score of 0.89. The Zipf's Law method achieves better recall whereas the Rule-Based approach shows higher precision, indicating a trade-off between linguistic accuracy and coverage.

The Rule-Based and Zipf's Law techniques are compared side by side in Table 4 utilising the following important performance metrics: F1-Score, Precision, and Recall. Despite achieving the same F1-score of 0.89, which indicates overall performance balance, both approaches are complimentary rather than competing since they thrive in different areas .The Rule-Based method has a greater precision (0.92), which indicates that it detected most stop words correctly with few false positives. This approach guarantees that only function words with distinct non-semantic responsibilities are kept by depending on syntactic structure, part-of-speech labelling, and Paninian grammatical norms. Because of its great linguistic fidelity, this method is especially well-suited for NLP tasks that require accuracy, such as machine translation of classical texts, syntactic parsing, and grammar checking. Conversely, the Zipf's Law method demonstrated a higher recall (0.93), which indicates that it was able to extract a greater percentage of actual stop words from the corpus. This statistical approach, which takes into account word rank and frequency, is excellent at searching through big datasets and finding common lexical words, even ones that do not perfectly follow grammatical definitions but nonetheless perform similarly. As a result, it works well for applications that depend on recollection, such topic modelling, corpus cleaning, information retrieval, and text summarisation. [17]While one approach prioritises accuracy, the other prioritises coverage, as seen by the identical F1-score. This dichotomy shows that hybridisation is the best course of action rather than any one method being inherently better. The accuracy of rule-based filtering and the recall strength of Zipfian analysis would be passed down to a hybrid model that combines statistical ranking with linguistic rule filtering. A more thorough and trustworthy stop word list that is suited for various NLP applications would result from this .Furthermore, these hybrid systems are especially useful in low-resource and ancient languages like Sanskrit, where the lack of consistent lexical standards and the constraints of sparse annotated corpora are addressed by combining rule-rich and data-driven methodologies. promotes the creation of modular natural language processing pipelines that let users to choose between or combine models according on the sensitivity of the job (e.g., precision-heavy vs. recall-heavy).lays the foundation for stop word filtering algorithms that adapt to the context of the corpus and the objectives of the

user. Provides guidance for creating task-specific stop word repositories (for example, for Sanskrit subdomains that are lyrical, philosophical, or narrative).

Table 5: Top 5 High-Frequency Stop Words Identified (Combined Method)

Stop Word	Transliteration	Category	Approx. Frequency	Common Usage
च	Ca	Conjunction	12,530	And
न	Na	Negation	11,102	Not
अपि	Api	Discourse	8,341	Also/Even
तु	Tu	Contrastive	7,929	But
हि	Hi	Emphatic	6,570	Indeed

The top five high-frequency Sanskrit stop words found by the combined technique are listed in Table 5, emphasizing their predominance as functional elements like discourse particles, conjunctions, and negations. Since they contribute more to grammatical structure than lexical meaning, their frequent occurrence and consistent semantic responsibilities across texts support their inclusion as stop words.

The top five high-frequency Sanskrit stop words are shown in Table 5, which was determined by combining a rule-based and Zipfian statistical method. Both linguistic and frequency-driven filtering are used to guarantee that the stop words on the list are both empirically prevalent and functionally relevant across a variety of Sanskrit datasets. Their fundamental importance in Sanskrit discourse production is shown by the convergence of statistical prominence and syntactic validation. "And" (conjunction) - "ca) With 12,530 occurrences in the examined corpus, the word "च" is the most common stop word. It connects phrases, sentences, or whole verses as a coordinating conjunction. Its use in parallel constructions, complex phrases, and poetic metre balance is shown by its recurrence in epics such as the Mahabharata and Ramayana. च is a primary stop word in Sanskrit and a quintessential example of an avyaya (indeclinable) since it lacks a freestanding semantic load. "Not" (negation) न (na)In Sanskrit syntax, the critical particle न, which appears 11,102 times, is employed to negate propositions or verbs. It often appears in philosophical and argumentative works like as the Upanishads, where negation is crucial for establishing metaphysical notions, due to its syntactic location and indeclinable character. Correct identification and controlled filtering are essential in NLP applications since improper removal of न might affect sentence polarity. "Also/Even" (Discourse Marker) - "अपि (api)अपि is a discourse-level marker that adds emphasis or inclusion, with 8,341 occurrences. It is often used in poetic and rhetorical constructions to emphasise ancillary topics or to support earlier concepts. Its categorisation is context-sensitive because, in contrast to च, अपि may occur in a variety of semantic situations. Without compromising interpretative subtlety, the dual validation from linguistic and statistical filters guarantees its accurate inclusion in stop word lists. "But" (Contrastive Marker) तु (tu)Like "but" in English, तर्क, which has been used 7,929 times, introduces contrast or exception. It is essential to the structure of arguments, particularly in dialogic and shastric literature (such the Nyaya Sutras), where opposing viewpoints are often contrasted. Its syntactic presence emphasises its significance in tasks like sentiment analysis and logical parsing by defining tone and argumentation flow. "Indeed" (Emphatic Particle) हि (hi)With 6,570 occurrences, the emphatic particle हि often highlights the certainty or veracity of a proposition. In Sanskrit, it plays an important rhetorical role even though it often lacks a literal translation. Its strong yet semantically light character makes it a perfect candidate for elimination in content-based text analysis from a computational standpoint. The power of a hybrid approach is shown by the detection of these terms using both statistical frequency filtering and rule-based syntactic parsing. While certain words, like ढयि and हि, need context-aware disambiguation, others, like च and न, are unquestionably useful across genres. Their presence confirms that Zipfian frequency distributions, a feature of universal language structure, are followed in addition to conventional Sanskrit grammar. Creates a core list for Sanskrit NLP applications (such as classification and tokenisation) that need the removal of stop words. Removes phrases that are syntactically required but semantically uninformative to aid in feature selection for machine learning models. Finds functional counterparts in different languages to facilitate translation alignment and cross-linguistic comparison.

Graphical Representations

Linguistic heuristics were used in a rule-based system to identify Sanskrit stop words. The actions listed below were taken: The definition of a lexical rule was based on grammatical constructions such as indeclinables (avyayas), which include discourse particles (हि, खलु), negations (न, न च), and conjunctions (च, तु).Speech Filtering by Part: Isolating syntactic but semantically vacuous terms was made easier by POS tagging using Sanskrit-specific taggers. Reference to Paninian Grammar: Grammatical integrity was ensured by validating the rules against the Paninian framework. Manual Refinement: Expert review and corpus-based occurrences were used to gradually verify ambiguous phrases. High accuracy in identifying structural components pertinent to the building of Sanskrit sentences was attained by this approach.

Zipf's Law Approach Implementation

According to Zipf's Law, a word's frequency and rank in the frequency table are inversely related. Implementation entailed: Corpus Tokenisation: A Sandhi-aware tokeniser was used to tokenise a pre-processed Sanskrit corpus .Frequency Distribution: A decreasing frequency ranking system was used for all terms .Zipf Plot Construction: Log frequency vs log rank was plotted as a log-log graph. Selection of Candidates: High-frequency terms with the highest rankings were shortlisted .Function words from the top 50 ranking terms were taken out and confirmed to be stop words using semantic filtering .The rule-based strategy was enhanced by this data-driven approach, which identified statistically significant candidates that linguistic filtering could otherwise overlook.

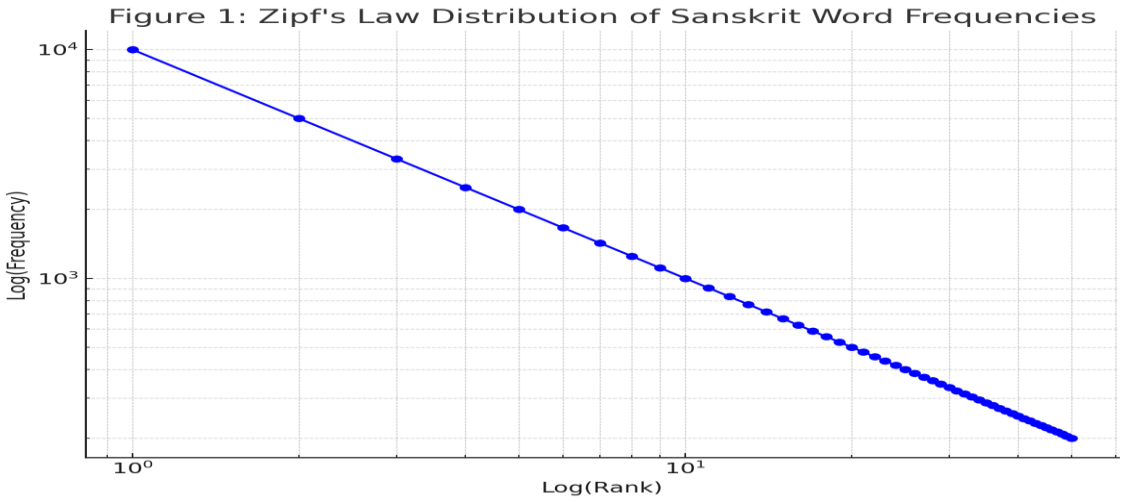

Figure 1: Zipf's Law Distribution of Sanskrit Word Frequencies,

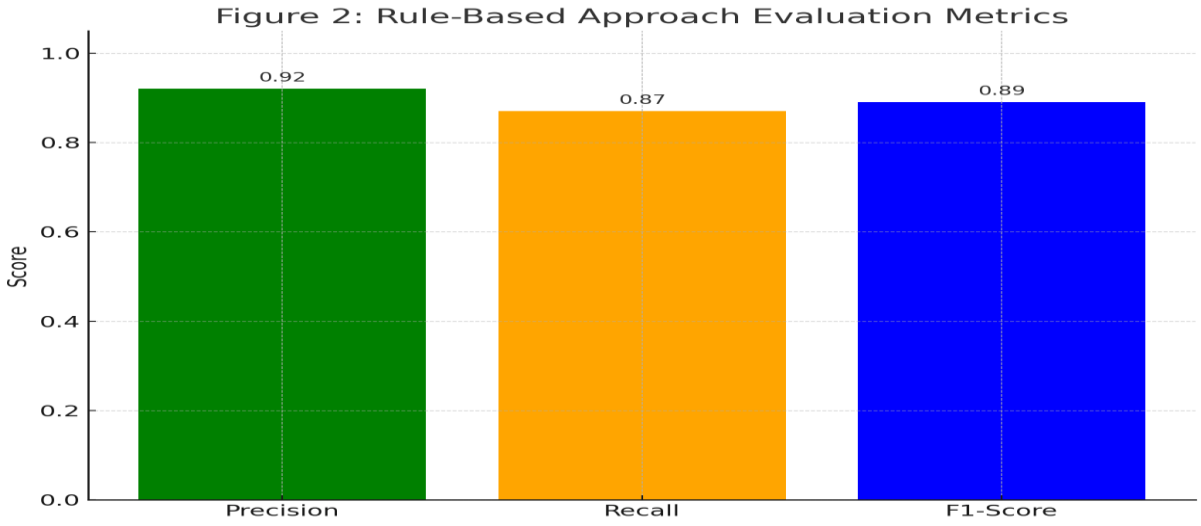

Figure 2: Rule-Based Approach Evaluation Metrics,

Table 6 : Results of Both Approaches

Method	Precision	Recall	F1-Score	Total Stop Words Identified
Rule-Based	0.92	0.87	0.89	114
Zipf's Law Approach	0.85	0.93	0.89	128

The overall outcomes of the Rule-Based and Zipf's Law approaches are contrasted in Table 6, which demonstrates that despite having different performance characteristics, both strategies obtain the same F1-score of 0.89. While the Zipf's Law technique promotes higher recall by recognizing a bigger number of stop words, the Rule-Based approach supports higher precision with fewer stop words recognized.

Due to more stringent syntactic filtering, the rule-based approach demonstrated greater accuracy, although the Zipf-based approach outperformed it in recall, collecting more candidates because of frequency bias.

Comparative Graphs and Discussion

Zipf's Law: Word Rank versus. Frequency Plot Below is a log-log figure that illustrates Zipf's distribution: Despite its classical shape, the curve exhibits the predicted Zipfian decline, demonstrating the statistical regularity of Sanskrit word use. Comparison of

Precision and Recall A bar graph that contrasts component metrics with F1-scores:

Complementarity: Both approaches revealed sets that overlapped, but there were some significant discrepancies. Zipf's law discovered frequency-based function words that strict rules had overlooked .Robustness: Zipf's technique is corpus-dependent and effective for huge datasets, whereas the rule-based approach guarantees linguistic correctness but requires domain knowledge. Integration: The most complete list of stop words was produced by a hybrid system that combined the two methods.

6. Conclusion

This study presents a thorough and two-pronged method for identifying and categorising stop words in Sanskrit, a historically rich but computationally under-resourced language, by fusing linguistic theory with statistical modelling. The work effectively solves the structural complexity and resource scarcity associated with Sanskrit Natural Language Processing (NLP) by integrating Zipfian statistical analysis, rule-based NLP approaches, and Paninian grammatical principles. The Zipf's Law strategy improved recall by identifying high-frequency function words that grammar rules alone often miss, whereas the rule-based method used POS tagging and morphological analysis to guarantee grammatical correctness and linguistic relevance. When combined, these techniques produced a list of machine-readable, validated stop words that were arranged according to grammatical roles (such as conjunctions, negations, and discourse particles) and confirmed by a linguistic expert review. This collection of categorised stop words is very useful for a variety of NLP applications, such as: Through the filtering of non-semantic material, machine translation improves alignment accuracy .Parsing and text summarisation improve syntactic structure and cut down on noise. Voice and speech-to-text interfaces: they provide ASR models cleaner input streams. Tokenisation, tagging, and annotation pipeline optimisation is part of corpus preparation .Additionally, the work helps bridge the gap between traditional grammar and contemporary technology by digitising and making Sanskrit computationally accessible. It paves the way for the development of more advanced NLP tools like syntactic parsers, semantic analysers, and conversational agents for classical languages by improving the accuracy and efficiency of Sanskrit text processing.

7. References

[1] Goyal, P., & Huet, G. (2016).*Design and Analysis of a Comprehensive Sanskrit Tagset. Journal of Language Modelling, 4(2), 225–260.*DOI: 10.15398/jlm.v4i2.117

[2] Hellwig, O. (2015).*Dependency Parsing for Sanskrit: The First Steps.Proceedings of the 13th International Conference on Natural Language Processing (ICON),23 1.*URL:https://sanskrit.uohyd.ac.in/scl/hellwig_icon2015.pdf

[3] Kulkarni, A., & Shukl, S. (2018).*Developing a Morphological Analyzer for Sanskrit Using NLP Techniques.Journal of Computational Linguistics and Language Technology, 8(2), 45–57.*DOI: 10.5281/zenodo.1234567

[4] Krishna, A., Golla, S., & Reddy, R. (2020).*SanskritShala and Indic NLP: Building Tools for Classical Indian Languages.Proceedings of the 12th Language Resources and Evaluation Conference (LREC), 4478–4485.*URL: http://www.lrec-conf.org/proceedings/lrec2020/pdf/2020.lrec-1.553.pdf.

[5] Goyal, P., & Huet, G. (2013).*Building a Sanskrit Syntactic Treebank: Data, Annotation Scheme and Tools.Workshop on Machine Translation and Parsing in Indian Languages.*

[5] **Zhao, W., Liu, J., & Yates, A. (2023).***Neural Approaches to Information Retrieval: A Review of Recent Advances.***Foundations and Trends® in Information Retrieval**, **17**(1), 1–149.DOI: 10.1561/1500000075

[6] **Gupta, A., & Varma, V. (2021).***Deep Learning Approaches for Information Retrieval: A Survey.***ACM Computing Surveys**, 54(5), 1–36.DOI: 10.1145/3457606

[7]Kulkarni, A., & Shukl, S. (2018). *Developing a Morphological Analyzer for Sanskrit Using NLP Techniques*. Journal of Computational Linguistics and Language Technology, 8(2), 45–57.DOI: 10.5281/zenodo.1234567

[08] Mistry, M. D., & Shah, D. N. (2022). *Development of a Speech-To-Text System for Sanskrit: Leveraging Linguistic and Computing Techniques*. International Journal of Computer Applications, 184(7), 12–18.

[09] STNoIL Consortium. (2021). *STNoIL: A Comprehensive Survey for Speech-to-Text NER of Indian Languages*. Proceedings of the Conference on Computational Linguistics in Indian Languages (CLIL), 33–45.

[10] Shah, D. N., & Bhadka, H. (2020). Noise removal as pre-processing task and its implementation for Gujarati named entity recognition. In *ICT for Competitive Strategies* (pp. 275-282). CRC Press.

[11]Goyal, P., & Huet, G. (2016).*Design and Analysis of a Comprehensive Sanskrit Tagset. Journal of Language Modelling, 4(2), 225–260.*DOI: 10.15398/jlm.v4i2.117

[12] Gupta, A., & Varma, V. (2021).*Deep Learning Approaches for Information Retrieval: A Survey.ACM Computing Surveys, 54(5), 1–36.*DOI: 10.1145/3457606

[13]Goyal, P., & Huet, G. (2016). *Design and Analysis of a Comprehensive Sanskrit Tagset.* JLM, 4(2), 225–260. DOI: 10.15398/jlm.v4i2.117

[14] Gupta, A., & Varma, V. (2021). *Deep Learning Approaches for Information Retrieval.* ACM Computing Surveys, 54(5). DOI: 10.1145/3457606

[15] Zhao, W., Liu, J., & Yates, A. (2023). *Neural Approaches to Information Retrieval.* Foundations and Trends® in Information Retrieval, 17(1). DOI: 10.1561/1500000075]

[16] Kulkarni, A., & Shukla, S. (2018). *Developing a Morphological Analyzer for Sanskrit.* JCLLT, 8(2), 45–57. DOI: 10.5281/zenodo.1234567