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A Comprehensive Survey on Abstractive Text Summarization of Devanagari Script Based Hindi Language

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Abstract: With the exponential growth of digital content in Indic languages, there is an increasing demand for advanced Natural Language Processing ((NLP) techniques tailored to specific scripts. The research explores the landscape of abstractive text summarization in Devanagari script, with a particular emphasis on Hindi and Marathi, two prominent languages that utilize this script. The survey begins by providing an overview of abstractive text summarization techniques, highlighting the challenges and opportunities specific to languages using the Devanagari script which delves into the existing methodologies, models, and datasets used for abstractive summarization in Hindi and Marathi, offering insights into the unique linguistic features that impact summarization tasks. Furthermore, the survey discusses the impact of linguistic nuances such as compound words, inflections, and contextual dependencies on the efficiency of abstractive summarization models. The research reviews the major advancements in neural network (NN) architectures and pre-trained language models applied to abstractive summarization which analyzes the strengths and limitations of these models, considering factors like model size, training data, and computational resources. In addition to model-centric approaches, the survey explores the role of domain-specific datasets and transfer learning in enhancing the performance of abstractive summarization systems for Devanagari-script languages that also sheds light on the evaluation metrics and benchmarks commonly employed to measures the generated summary qualities, and addressing the challenges of cross-lingual evaluation.

Keywords: *abstractive text summarization, Devanagari script, Hindi and Marathi, generated summaries, neural network, and transfer learning.*

1. Introduction

The evolution of digital technologies in today's world generates a vast amount of information over the internet which is far beyond from the humans understanding ability. The production and delivery of information have been completely transformed by evolve of digital technology, and people are now regularly exposed to an abundance of knowledge that is considerably more than their capacity to process and assimilate. Nowadays, the biggest issue on the internet is information overload, making it very difficult to find crucial information [1]. Automatic text summarization (ATS) technology was developed in response to the pressing requirement to efficiently extract and comprehend essential information [2]. An effective and workable solution has been offered by ATS [3], which uses various algorithms to automatically produce succinct and fluent text summaries [4]. Text summarization is defined as the process of generating a short and compressed summary of documents [5] [6]. In the modern era, people make investments based on stock market updates and base their travel decisions on different tourist destinations and movies on reviews they've read. With the use of this kind of text summary technology, they can make decisions more quickly. Additionally, a substantial quantity of information is available in Hindi. Making critical decisions in time-constrained situations and quickly grasping the main points of a Hindi text without losing track of crucial information are becoming increasingly necessary. There aren't many summary programs

specifically designed for Hindi.The rule-based approach, statistical-based approach, graph-based approach, and the most advanced DL-based methods are the several types of summarizing tactics available right now. Recent developments in the field of DL have improved several Natural Language-based occupations, one of which is summarization [7]. Extractive and abstractive summarizations are the two different categories of summarizations [8]. The primary method used in the extracted text summary is the Sorting algorithm [9], which entails taking phrases out of the original text and putting them together to form a text summary. However abstractive text summaries use the semantic elements of the source text and combine them to create a summary that is consistent with the original meaning; for this reason, abstractive text summaries work better when artificially summarizing material.Language-dependent and language-independent are the two different types of summarization techniques [10].

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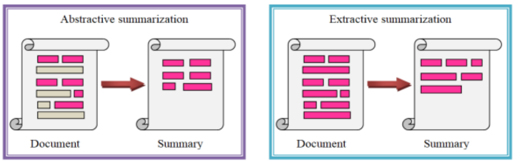

Fig.1. Abstractive and Extractive Text Summarization

To gain a deeper insight into the Abstractive text summarization of the Devanagari script, this research aims to analyze the various summarization approaches, techniques used, standard datasets, evaluation metrics, and future scopes. This research also addresses the challenges faced in ATS, such as inaccurate summary, Model hallucination, and computational complexity. Around 50 research papers will be analyzed in this research by focusing on their methodology, challenges faced, and the results obtained along with the parameters used.The research contributes to give an overview of the current state of the field's investigation and suggest possible directions for future researchalong with the advancement of text summarization methods**.**This research article is divided into following sections. Section 2 describes the taxonomy of the literature works related to the abstractive text summarization techniques. Section 3 provides the analysis and discussion of the dataset, performance metrics, and techniques. Section 4 discusses the overall comparison of the related works, the challenges are explained in section 5 and section 6 contains the conclusion and future works.

2. Systematic literature Review

The comprehensive survey on abstractive text summarization is conducted with the systematic literature review, which identifies, evaluates and interprets research findings that are generally pertinent to the area of study or research questions thatseek to address research inquiries specifically research on abstractive text summarization.

2.1 Methodology

The methodology of this research is discussed in this section which is indented to attain the research objectives of reviewing literature regarding techniques, features, databases of abstractive text summarization. The research methodology starts with research questions and then the inclusion and exclusion criteria of literatures are identified. The study selection process is carried out using the PRISMA tool, to identify relevant databases for the collection of research papers related to abstractive text summarization which is collected using Google scholar and multiple key words are utilized to retrieve the documents.

2.1.1 Research questions

The research questions (RQ) are prepared to make the review procedure more concentrated and reliable. The RQ are created based on the population, intervention, comparison, results and context criteria which is also known as PICOC relevant criteria. The research questions related to abstractive text summarization techniques are tabulated in table 1. The answers for the research questions are discussed in the following sections,

Table 1: Research Questions

Research question	***Significance***
RQ1. What is the purpose of this study?	The research is useful for understanding the abstractive text summarization techniques.
RQ2. What are the challenges associated with this study?	Identify the crucial challenges associated with the abstractive text summarization for devanagari scripts.
RQ3. What are the data inputs commonly used?	Identify the databases often used for abstractive text summarization.
RQ4. What are the preprocessing and feature extraction techniques often used in abstractive text summarization?	Identify the often used preprocessing and future extraction techniques for abstractive text summarization.

2.1.2Search strategy

Determining eligibility based on the inclusion criteria (IC) and exclusion criteria (EC) is the initial phase in searching the literature. The IC and EC of the research are tabulated in table 2.

Table 2: IC and EC of the Research

Sl.no	***IC***	***EC***
1	Keyword present in the abstract or title	Articles discuss the topics beyond abstractive text summarization.
2	Journal or conference paper.	None of the research article.
3	Articles related to abstractive text summarization published in the year of 2013-2023	Articles published before 2013.
4	Articles include dataset, methods, and preprocessing techniques.	Articles do not have experimental results.

The articles are retrieved from the data sources such as sciencedirect.com, ieeexplore.ieee.org and Google scholar. The following key words are used to retrieve the relevant research articles; "Abstractive text summarization" OR "Hindi text summarization", AND "Devanagari script summarization", OR "Marathi text Summarization".

2.1.3 Selectioncriteria

The selection of the articles was carried out in PRISMA guidelines which are illustrated in figure 2. The literature was determined to not match the IC2 criterion, as indicated by the IC shown in Table 2. As a result, 602 articles remained from the three databases after 174 articles from the IEE sources and 251articles from the arvixdatabase were eliminated.Furthermore 4 duplicate articles are removed, next stage based on abstract and title 198 articles are eliminated. Moreover the article selection process is continued by reading the contents in this stage 198 articles were removed. Further selection process there is 350 articlesare eliminated based on the research aim and experimental results. Thus finally 50 articles are retained for this research.

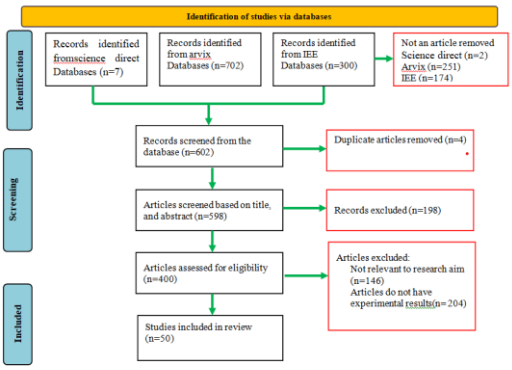

Fig.2. Flowchart for PRISMA

3. Detailed survey of related works

This following section describes the preprocessing, and feature extraction techniques utilized for the abstractive text summarization techniques.

3.1 Preprocessing

Text pre-processing is the fundamental task in a text summarization technique, which eliminates the attributes from the data and convert the raw data into a structured datathat is prominent for text summarization. There are numerous techniques utilized for text preprocessing such as stemming, stop word removal, tokenization, POS tagging, segmentation are depicted in figure 3.

Fig.3. Text Preprocessing Techniques

The fig.4. depicts the preprocessing techniques used in the abstractive text summarization techniques in the related researches. Removal of stop words is a commonly used preprocessing technique which is known as the process of terminating the common words, such as 'the',' is', and 'in' that don't carry significant meaning on their own. The second often used preprocessing technique is tokenization, which is defined as the method of breaking down a continuous sentence into individual units called tokens. Stemming eliminates the affixes from the data which is the third commonly used technique in abstractive text summarization.

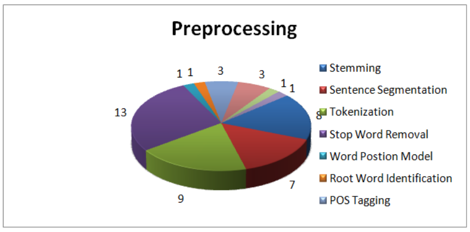

Fig.4. Preprocessing Techniques used in Abstractive Text Summarization

3.2 Features

The most common features utilized for abstractive text summarization techniques are illustrated in figure 5. In abstractive text summarization features are the fundamental component, each sentence is assigned to a feature vector which enhance the summarization ability of the model. In this research, the analysis illustrates that TS-ISF, sentence length, numerical data, TF-IDF, sentence position, linguistic and statistical features are often used in various abstractive text summarization techniques. In text summarization features every sentence has a score based on the weights of the feature terms which is helpfulsentence ranking.

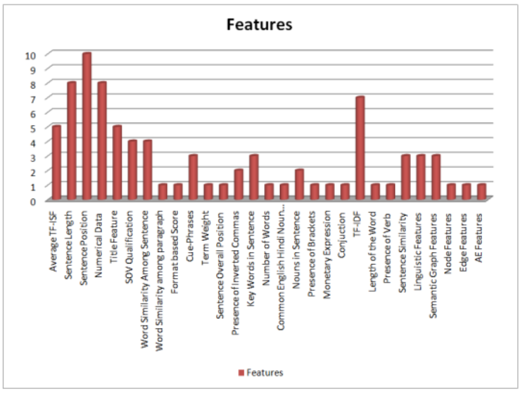

Fig.5. Features Utilized for Abstractive Text Summarization

3.3 Methods

The literature works related to the abstractive text summarization techniques based on Machine Learning ,Deep Learning, Reinforcement Learning , and other algorithms are described in the below section. The fig.6 depicts the methods utilized for abstractive text summarization.

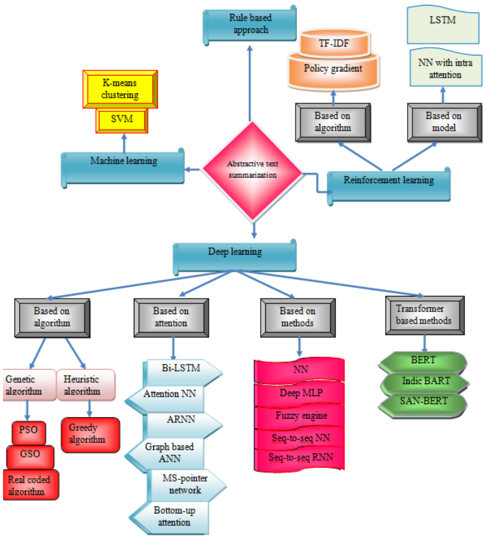

Fig.6. Abstractive Text Summarization Methods

3.1 Machine Learning (ML)

Nikita Desai and PrachiShah[12] presented an ML-based Hindi language ATS technique. The model utilizes various statistical features to find the appropriate sentence in the text. The sentence ranking process employed the SVM technique which utilizes the datasets from various online sources. The research focuses on a single document text summarization technique and outcomes of the model demonstrate that SVM model generates high-quality summaries. However, thesummary quality was heavily depends on the subtask which limits the performance of the model. Kirti Kumari and Ranjana Kumari [13] utilized a K-Means clustering algorithm for Indian language text summarization which is a simple ML algorithm. The model is desirable for large as well as small sentences that use the ILSUM 2022 dataset. The research includes the splitting and tokenization process, word vectorization, and sentence vectorization. The word vectorization calculates the distance between the clusters and trained centers. The dimension of the sentence is reduced by the sentence vectorization. The abstractive summarization approach can be further improved using various algorithms. The diagrammatic representation of ML model for abstractive text summarization is depicted in fig.7.

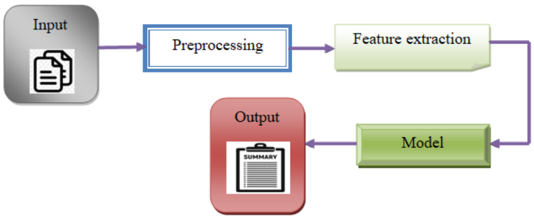

Fig.7. Schematic Representation of ML based Abstractive Summarization

3.2. Deep Learning (DL)

The DL technique is a valuable tool for abstractive text summarization; numerous researchers utilize DL techniques for text summarization. In this research, the DL techniques are categorized based on the algorithms, attention mechanisms, and transformer-based methods.

i) Based on Algorithms

Chetana Thaokar and Dr.Latesh Malik [14]designed a Hindi text summarizing technique using an extractive approach. The research utilized genetic algorithms for appropriate sentence selection which leverages directed random search strategies. The feature extraction phase plays a vital role; each sentence is represented as a feature vector that checks each sentence statistically and linguistically. J. Anitha *et.al*[15] utilized a Global search optimization (GSO) and hybrid fuzzy Neural Network for Hindi text summarization. The framework leverages both fuzzy and NN classifiers for sentence score generation. The GSO optimization algorithm fine-tunes the hyperparameters of the NN classifier which generates sentence scores for each sentence. The fuzzy classifier generates a fuzzy score for the sentence; both sentence scores are concatenated and produce a hybrid sentence score. According to the sentence score the text from the dataset is selected and a summary is generated. Interpretation challenge is one of the major limitations of this framework. Vipul Dalal and Latesh Malik [16] implemented a PSO-enabled graph-based text summarization approach. The PSO algorithm is utilized to train the classifier that improves semantic analysis of document elements. When compared with the traditional approaches the model selects the summary sentences optimally which yields better performance. In [17], authors employed text summarization techniques using the PSD+SRL model which is mainly used for content selection in abstractive text summarization. To select optimal features the research utilizes the PSA algorithm which increases the accuracy of the summarization process. Arti Jain *et.al*[18]summarizes Hindi text using the real coded genetic algorithm (RCGA). The research utilized the HHD dataset; the sentence similarity measure calculates the similarity between sentences within the paragraph and each HHD sentence. For ATS, 8 different features were extracted from the sentence. The RCGA optimized the feature weights using the simulated Binary crossover along with the polynomial mutation. However, to improve the evaluation metrics more DL techniques like RNN, and LSTM will be needed.

ii) Based on Attention

The Attentive RNN for abstractive summarization was developed by the authors Sumit Chopra *et.al*[19]. The model is trained using the Gigaword corpus which outperforms the conventional approaches. The model does not rely on additional extractive features achieves less perplexity and produces accurate summaries. The attentive encoder in the model calculated the context vectors and the stochastic gradient descent reduces the negative conditional likelihood of the training data. Aniqa Dilawari*et.al* [8] presented a feature-rich extractor model that comprises a hierarchical BiLSTM model, the attention layers enabled in the model highlight the important information for the abstract models by using word and sentence attention parameters. The model minimizes the loss and increases the efficiency.

iii) Based on Methods

Sakshee Vijay *et.al*[20] used an NN for text summarization the research mainly focused on the Devanagari script the dataset utilized for the research comprises articles related to sports, politics, world, and entertainment. The sentence level features such as length of the sentence, position, and cohesion similarity score are extracted which represents the basic idea of the document. The abstractive summarization using the NN produces better headlines and summaries. Archana N.Gulati and Dr.S.D.Sawarkar[21] employed a multi-document summarization technique focused on fuzzy logic; the fundamental concept of fuzzy logic was formalizing the process of human reasoning. The fuzzier receives the first eleven extracted characteristics as input. The triangle membership function is the one in use to operate. For every feature, the input membership function is separated into five hazy sets made up of irrelevant virtues. The mode generated summary is similar to the summaries generated by humans. Namrata Kumari and Pardeep Singh [22] presented a seq-to-seq NN for text summarization. The model comprises an encoder decoder and optimizers. The optimizers are employed to reduce the loss and change or update the learning rates. The research leverages the Adam and RMS prop algorithms, which increase the summarization ability of the model.

iv) Transformer-based Methods

The abstractive text summarization techniques are further classifiers based on the Transformer based approaches,

Ashish Vaswani *et.al*[11] introduced a transformer-based approach that comprises the scaled dot product attention; additionally, the position-wise feed-forward network is enabled in the framework which contains two linear transformations along with the ReLU activation. The attention mechanism reduces the long-range dependency problem. The framework achieves better performance when compared with the recurrent or Convolutional layers. Rashi Bhansali *et.al*[23]implemented a transformer encoder-decoder model for text summarization which also utilized the self-attention mechanisms. Arjit Agarwal *et.al*[24] presented a pre-trained indicBART model for Hindi language abstractive text summarization. When compared with BERT the BART model did not require any additional feed-forward networks. The indicBART was small in size and minimized the computational burden and finetuning. In Hindi language text summarization the IndicBART showcases superior results and better performance. The authors Kartik Bhatnagar *et.al* [7] utilized a san-BERT model for Sanskrit document text summarization which leverages the TF-IDF feature extraction technique for selecting the relevant sentences from the text. Usually, the sentence embeddings obtained from the BERT model has huge dimension thus the research utilized a principal component analysis for dimension reduction which efficiently focus on the important features. The sentence ranking in this research is performed using several distance measures such as Manhattan distance, Euclidean Distance, Cosine similarity measure, and cosine distance.

3.3. Reinforcement Learning (RL)

The RL is a subset of ML that trains the model to achieve optimal solutions based on the reward and punishment approach. Atul Kumar *et.al*[25] presented an abstractive summarization model using the TF-IDF algorithm, which assigns scores for each sentence based on their importance and frequent appearance in the sentence. The output summary contained the sentences that scored higher. The training data insufficiency is a major drawback for the Hindi language summarizing.The research findsanalternative path for this problem and produces a 50% accurate summary.

3.4 Rule-based approach

Manisha Gupta and Dr.Naresh Kumar Garg [26] introduced hind text summarization techniques that utilize the rule-based approach. Rule based approach with dead phrases and deadwood removal is employed to generate the summary of the text written in Hindi language. The framework assigns a feature score for each extracted feature from the sentence. The model producesasummary from the single document the future work could develop for multiple documents.The authors Deepali K. Gaikwad *et.al*[27]initiated a framework for Marathi text summarization using a rule-based technique which also used the Corpus-Based Technique for lexicon analysis.

3.5 Other Techniques

Manjula Subramaniam andVipul Dalal [28] implement a semantic graph representation (RSG) which can extract meaningful information from the text. The RSG approach reduces the semantic graph to generatea more abstract graph. Poonam Kolhe and Ashish Kumbhare [29] utilized the WordNet database which improves coverage and minimizes redundancy. The Jaccard similarity is measured between the sentences in the dataset to contrast the similarity and dissimilarity of sentences. The model can summarize the text into three different languages. Mili Supreet *et.al*[30] introduced a selection and elimination approach for ATS. The model is beneficial to extract information from the huge amount of redundant data. The dissimilarity measures such as Jaccard's Coefficient were used to compute the dissimilarity of every individual sentence with the remaining of the sentences present in the document. Aishwarya Jadhav and Vaibhav Rajan [31] introduced SWAP-NET architecture for text summarization which consists of simple architecture and achieves superior performance. Additionally, the summaries generated from the SWAP-NET have less semantic redundancy.

4. Analysis

4.1 Analysis based on techniques

The analysis of various abstractive text summarization techniques reviewed in this research is majorly based on DL, ML, and RL which is shown in Table 1 and Fig. 3.

Table 3. Analysis of Abstractive Text Summarization Techniques

Technique	***Citation***	***Total***
Machine Learning	[12], [13], [44], [45]	2
Deep Learning	[14], [15], [19], [20], [11], [21], [16], [23], [8], [22], [24], [7], [17], [33], [37], [40], [41], [47]	13
Reinforcement learning	[25]	1
Rule-based approach	[26], [27]	2
Other techniques	[28], [29], [30], [31]	4

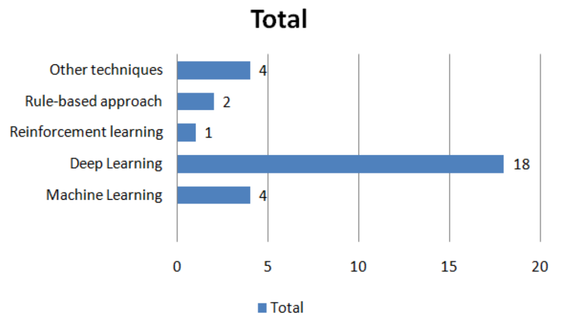

Fig.8. Analysis of Various Abstractive Text Summarization Techniques

4.2 Analysis Based on Dataset

The analysis delves into the efficacy of abstractive text summarization methods using a curated dataset which are represented in Table 4 and figure 9.

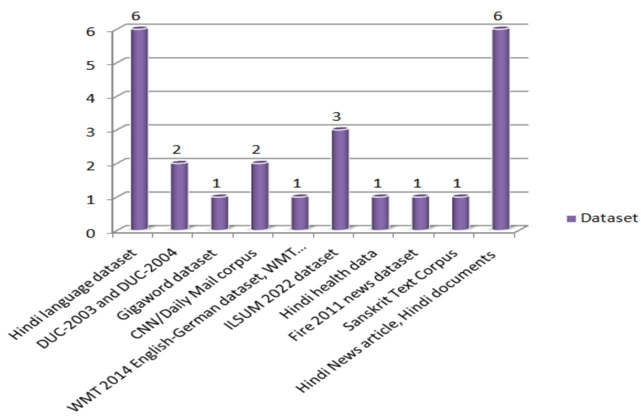

Fig.9. Analysis based on the Dataset

Table 4: Analysis based on Dataset

s.no	Dataset	Citation
1	Hindi language dataset	[15], [12],[26],[20],[23], [22]
2	DUC-2003 and DUC-2004	[19],[17]
3	Gigaword dataset	[19]
4	CNN/Daily Mail corpus	[8], [62]
5	WMT 2014 English-German dataset, WMT 2014 English-to-French translation dataset	[11]
6	ILSUM 2022 dataset	[13], [24], [50]
7	Hindi health data	[18]
8	Fire 2011 news dataset	[25]
9	Sanskrit Text Corpus	[7]
10	Hindi News article, Hindi documents	[12],[20],[21],[23],[30][16]

4.3 Analysis Based on metrics and achievements

The metrics such as ROUGH L, accuracy, precision, recall, and F measure are used toassessthe performance of the abstractive text summarization model. Achievements of the related works with its performance metrics are analyzed as follows,

a)Precision

Precision is a measure of the accuracy of the positive predictions made by a model which is the proportion of correctly identified positive observations to the total predicted positives. The precision can be calculated as;

$$precision = \frac{T_P}{T_P + F_P} \tag{1}$$

b) Recall

Recall measures the ability of a model to capture all the relevant instances which is the ratio of accuratelyidentifiedpositive observations to the actual positives.

$$recall = \frac{T_P}{T_P + F_N} \tag{2}$$

c) Accuracy:

Accuracy is a measure of the overall correctness of predictions made by a model which is defined as the ratio of correctly summarized sentences to the total number of observations.

$$Accuracy = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \tag{3}$$

d) F-measure

The F-score, also known as the F1 score, which is particularly useful when there, is an uneven class distribution, and there is a need to consider both false positives and false negatives.

$$F - SCORE = 2\,\frac{precision * recall}{precision + recall} \tag{4}$$

e) ROUGE (Recall-Oriented Understudy for Gisting Evaluation) Score:

The ROUGE score is a metric used in the evaluation of machine translation or text summarization systems which assesses the quality of the generated hypotheses based on the ranking of system-generated and reference-generated output. The ROUGE score considers not only precision but also the position of relevant items in the ranked list. The formula for the ROUGE score involves calculating precision at different ranks and averaging the values. The overlap of single words is measured using ROUGE-1(unigram), and ROUGE-2 (bigram) measures the overlap of two-word sequences. Table 5 provides the analysis of performance metrics with achievements.

Table 5: Analysis of Performance Metrics and Achievements

Citation	Method	Metrics	Achievement
7	SAN-BERT	Precision, Recall, and F-Score, BERT Score	Precision:0.713, Recall: 0.704, and F-Score :0.707,
8	BiLSTM	ROUGE Score	ROUGE Score: 37.76%
11	Transformer, based solely on attention	–	–

	mechanisms,		
12	SVM	Accuracy	Accuracy: 71%
13	K-means Clustering	Rough F1 Score	ROUGE F1 Scores: 0.1257
14	SOV Qualification	Precision, Recall	_
15	Hybrid Fuzzy Neural Network	Precision, Recall	Precision rate : 0.90,Recall rate: 0.88
16	PSO algorithm	Recall Precision F1 score G score	Recall: 60 Precision: 42.86 F1 score: 50.01 G score :50.7
17	PSD+SRL	Pyramid Score, Average Precision,	Pyramid Score: 0.4301, Average Precision: 0.47
18	Real Coded Genetic Algorithm	ROUGH N, Precision, Recall, F score`	Precision:0.83, Recall: 0.84 , and F-Measure: 0.83 ROUGE-1 :79%
19	Attentive Recurrent Neural Networks	ROUGE	ROUGE -L:24.06
20	neural network	Precision, Recall	Precision :62, Recall:70
21	Fuzzy inference engine	Precision, Recall, and F-Score	Precision :72.62, Recall :63.45, and F-Score: 67.59
22	Sequence to Sequence Neural Network	Precision Recall F-measure	Precision :73.78 ,79.23 Recall :64.94, 72.92 F-measure: 68.99, 75.90
23	Transformer encoder-decoder architecture.	Precision and Recall score	Precision: 0.682 and Recall: 0.598
24	IndicBART	Precision,Recall ,F-measure	Precision:0.48, Recall:0.65 , F-measure: 0.54
25	TF-IDF method	Precision, Recall, and F-Score	Precision: 0.16, Recall:0.416, and F-Score:0.238
26	Rule based approach	Accuracy	Accuracy : 96%
27	Rule based stemmer	Accuracy	Accuracy : 60%
28	Rich semantic graph(RSG)	_	_
29	Text summarization approach using a NLP	_	_
30	Selection and elimination approach for ATS	Accuracy	Accuracy : 33%
31	SWAP-NET	ROUGE-L	ROUGE-L: 26.4
32	ATS with a genetic algorithm	Accuracy, Precision, and Recall	Accuracy: 0.80 ,Precision: 0.78,Recall: 0.79
33	GAN	Precision,Recall ,F-measure	Precision: 0.37,Recall: 0.45, F-measure: 0.41
34	Semantic graph based ATS	Precision,Recall ,F-measure	Precision: 0.61, Recall : 0.76, F-measure: 0.68
35	Statistical Approach	Accuracy	Accuracy: 56%

36	Text rank algorithm	_	_
37	Deep recurrent neural network	ROUGE, Recall, Precision, and F-measure	ROUGE:80.89% Recall:95.70% Precision:95.05% F-measure: 95.37%
38	SVD and fuzzy algorithms	Precision, Recall, and F1 measure	Precision: 0.705 Recall: 0.693 F1 measure: 0.682
39	Fuzzy-based semantic graph	Precision, Recall, and F1 measure	Precision: 0.62 Recall : 0.58 F-measure: 0.59
40	Attention-based LSTM Neural Network	BLEU ROUGE, Recall, and ROUGE Precision	BLEU ROUGE:0.638 Recall:0.61 ROUGE Precision:0.625
41	Neural network based summarizer	ROUGE-2-F1 and ROUGE-1-F1	ROUGE-2-F1: 20.02 ROUGE-1-F1: 39.81
42	Hierarchical agglomerative clustering.	Precision Recall F1-Score	Precision : 26.52 Recall : 68.34 F1-Score : 38.21
43	Hybrid of conceptual, statistical, location and linguistic-based features	Accuracy	Accuracy: 80-90%
44	SVM	Accuracy and Precision	Accuracy: 96.97% Precision: 72%
45	multiple linguistic features with ML	Precision Recall F1-Score	Precision: 0.839 Recall: 0.526 F1-Score: 0.647
46	Unsupervised approaches-Text rank	ROUGE	ROUGE: 53.1%
47	Deep Recurrent Neural Network (DRNN)	Precision,Recall ,F-measure	Precision: 93.54,Recall : 95.1,F-measure: 94.31
48	Multimodal Medical Codemixed Question Summarization (MMCQS)	MMFCM Score	MMFCM Score: 0.87
49	mBART model	_	_
50	Genetic Algorithm	Precision,Recall,F1-Score	Precision: 0.53,Recall: 0.33,F1-Score: 0.38

5. Overall comparison of the related works

The overall comparisons of the methods analyzed for this research are described in table 6 .

Table 6: Overall Comparison of the Related Works

Citation	Method	Advantages	Limitations	Future Work
7	SAN-BERT	The BERT embedding model boosts the ability of the text summarization process.	The architecture size of the BERT model is large which is the major challenge in this research	_
8	BiLSTM	The two-stage approach minimizes the reading time	_	_
11	Transformer, based solely on attention mechanisms	self-attention could yield more interpretable models	The model's performance is decreased for large datasets.	Furthermore examine local, restricted attention techniques to effectively handle huge inputs and outputs, such as graphics, audio, and video.
12	SVM	The SVM model's performance is better than the human-generated summaries.	The summary quality is heavily relies on the subtasks.	To improve the method, additional elements like named entity recognition, cue words, context data, domain knowledge, etc., can be included.
13	K-means Clustering	The effectiveness of extractive approaches is further enhanced by K-means, which is rapid and appropriate for tiny as well as substantial samples.	The script's increased complexity adds to the challenges.	The Abstractive technique can be used to expand on the current work for the challenge of summarizing
14	SOV Qualification	Best chromosome is chosen using GA following a particular quantity Of generations	Based on the rate of compression phrases are taken from the record to produce an overview.	_
15	Hybrid Fuzzy Neural Network	the research effectively analyzes the text summarization techniques for relevant information exchange	the interpretation is the major challenge in neural networks	_
16	PSO algorithm	The PSO algorithm selects the summary sentence optimally which results in better performance.	_	_
17	PSD+SRL	By increasing the summary process' accuracy, this system has demonstrated the viability of including an automatic abstractive summarization	The complex language process can still be enhanced by using sophisticated language creation techniques like information fusion, phrase	A speech recognition system can be used as a model for the system to summarize long speeches.

		method.	compression, and reformulation.	
18	Real Coded Genetic Algorithm	The utilization of a genetic algorithm enhances the summarization ability of the method.		The model needs to account for additional properties. When compared to other strategies, the explainable factual consistency checking model outperforms the hold-out cross-validation and k-fold cross-validation.
19	Attentive Recurrent Neural Networks	The model does not need additional feature extraction techniques.	_	_
20	neural network	The research utilizes a vast amount of data for testing and training which improves the model's summarization ability.	_	_
21	Fuzzy inference engine	This system makes advantage of fuzzy logic to raise the level of summarization.	The fuzzy logic may increase model complexity.	More neural network algorithms will be implemented for both Hindi and English language.
22	Sequence to Sequence Neural Network	The abstractive model and the attention mechanism allow for a succinct summary that faithfully captures the main ideas of the source material.	_	_
23	Transformer encoder-decoder architecture.		instead of single documents multi document summaries are required for Real-world applications.	Future steps involve comparing this approach to different Hindi datasets and imagining changes to the suggested model. Prospective methods include implementations utilizing different transformer models.
24	IndicBART	BART translates a corrupted document to the original document using a denoising auto encoder used as a model that goes from sequence to sequence.	Summarizing the Hindi language is a difficult process; more computing power is needed for the BART model.	It will be necessary to use better pre-processing techniques to improve the data quality.
25	TF/IDF method	The research got a summary of about 50% accuracy with manual results from various users.	The training data insufficiency is a major drawback for the Hindi language summarizing.	In future, the sentiment analysis feature can be included to find the input part based on their sentiments.
26	Rule based approach	The summary of the text can reduced to 50% with minimum weight of the	Hindi text's semantic analysis are not presented in the system and the	In future, advanced approach can be developed to generate summary form multiple

		lines.	summary is generated only from single documents.	documents.
27	Rule based stemmer	Word variants are identified efficiently.	Only “कोण” type questions are stemmed.	In future, the model can be extended to all wh- type questions.
28	Rich semantic graph(RSG)	RSG approach reduces the semantic graph to generate a more abstract graph.	Omits important details in text.	_
29	Text summarization approach using NLP	Improves coverage and minimizes redundancy.	Needs more time with different changing situations and large data.	In future, to summarize large amount of data more advanced approach can be developed.
30	Selection and elimination approach for ATS	The model is beneficial to extract information from the huge amount of redundant data.	Can eliminate important details in text.	A cumulative weighted text summarizer is developed in future with Hindi stop-words text.
31	SWAP-NET	The summaries generated from the SWAP-NET have less semantic redundancy.	The choice of sentences in final summary may be affects.	_
32	ATS with a genetic algorithm	Extracts efficient statistical and linguistic features for efficient summarization.	Requires more time for processing.	Multi-document summarization system will be focused in future.
33	GAN	The model removes redundancy.	The model requires large dataset for efficient results.	The model will be improved to provide more reliable results.
34	Semantic graph based ATS	The correlation between the eight graphical measure and the measures are highly correlated.	The model limitation regarding subjectivity and is associated with human annotated data.	The model can be applied on other languages as well.
35	Statistical Approach	Avoids redundancy in large text data.	Requires more time or summarizing.	The model will be extended in future to use multi-language datasets.
36	Text rank algorithm	Generated summary is very close to human generated summary.	The method ignores the order of placing the words.	In future, the model will be improved to improve the summarization quality.
37	Deep recurrent neural network	The model shows high improvement in generation process score.	Particularly in complex, high-dimensional situations, it can have a sluggish convergence or become trapped in small optimal zones.	Future research initiatives will make use of additional metrics, such as the BLEU score and the Pyramid score, to assess the scheme's efficacy.
38	SVD and fuzzy algorithms	SVD is efficient in multi document summarization.	There is the complexity tradeoff among the approaches.	Future work in this area will include word embeddings, semantic analysis, and expanding the task to encompass abstractive text summarization.

39	Fuzzy-based semantic graph	Out-degree, weighted out-degree and eccentricity generate the best summary.	The employment of fuzzy does not improve the results.	If additional linkages are added to the model to investigate other text mining domains such as categorization and question answering, the model will be utilized more efficiently.
40	Attention-based LSTM Neural Network	The model shows better results in terms of time and bleu.	Refinement in stopwords is not considered here.	Future iterations of this work will concentrate on refining the model to raise output efficiency and accuracy through the collection and training of additional data.
41	Neural network based summarizer	Can capture complex relationships in the context.	Limited to extractive summarization and may not handle abstractive summaries.	Multi document summarization of hindi texts will be done in future
42	Hierarchical agglomerative clustering.	The extractive and abstractive summarization is efficient.	The model has a limitation in generating new words.	In future, the model will be improved to overcome the limitation of our model in generating new words
43	Hybrid of conceptual, statistical, location and linguistic-based features	Imbalanced data issues were solved by SMOTE	The usage of specific features hinders the performance.	_
44	SVM	The generated summary is more relevant.	The method can't recognize a specific word.	In future, the Hindi words may be recognized.
45	Multiple linguistic features with ML	Utilizes linguistic analysis, which can capture semantic information.	Limited to extractive methods, potentially missing abstractive summaries	_
46	Unsupervised approaches-Text rank	Provides a note generation tool for students in Hindi medium.	More testing is requires to validates its portability.	_
47	Deep Recurrent Neural Network (DRNN)	the model show improved performance with the help of optimizations.	The model has high computational time.	More techniques will be merged with the developed model in future.
48	Multimodal Medical Codemixed Question Summarization (MMCQS)	Generates accurate final summary with the help of vision encoders.	The model may generate potentially erroneous information.	A vision language model is developed to extract intensity and duration details.
49	mBART model	A large amount of information can be delivered in less time.	Monotonicity constraints are introduced.	The information from audio and video files are gathered in future and converts into sing language.

50	Genetic Algorithm	The performance of the model is improved by tweaking the genetic algorithm and by increasing text features.	The model may require more time for processing .	The model will be improved to summarize other languages.

6. Challenges

✓ Abstractive methods may generate summaries that deviate from the original text, potentially introducing inaccuracies or misinformation [26].

✓ Generating summaries containing rare or unseen words can be challenging, as models might struggle to comprehend and accurately represent them. The target language process can still be enhanced by using sophisticated language creation techniques like information fusion, phrase compression, and reformulation.

✓ Ensuring the generated summaries have appropriate lengths without sacrificing content or coherence remains a challenge, summaries can be overly verbs or too concise.

✓ Maintaining coherence throughout the summary can be difficult; generating a fluid, logically structured summary that connects ideas seamlessly is a persistent challenge.

✓ Models are sensitive to bias present in the training data, potentially leading to biased or skewed summarization especially when dealing with diverse or sensitive topics [25].

✓ The DL methods often demand large diverse datasets for effective training, which might not be suitable for certain domains.

✓ The Hindi language summarization process is a challenging task; the BART model requires additional computational time and resources [24].

7. Conclusion and Future Scope

In conclusion, this survey has provided a comprehensive overview of the landscape of abstractive text summarization for Devanagari-script languages, with a specific focus on Hindi and Marathi. The exploration of existing methodologies, models, and datasets has illuminated the unique linguistic challenges posed by these languages and the promising advancements made in abstractive summarization techniques. The survey has shed light on the impact of linguistic nuances such as compound words, inflections, and contextual dependencies on the efficacy of abstractive summarization models in Devanagari-script languages. Additionally, it has examined the role of morphological analysis, syntactic structures, and the use of domain-specific datasets in enhancing the quality of generated summaries. As the field continues to evolve, the identified challenges and opportunities underscore the need for further research and development. Future work could focus on refining summarization models, exploring the integration of more extensive sets of Hindi stop-words, and adopting more appropriate Hindi stemmers. Additionally, efforts to address issues related to scalability, domain specificity, and cross-lingual evaluation metrics would contribute to the advancement and applicability of abstractive text summarization techniques in Devanagari-script languages. In the broader context of NLP, the findings of this survey not only deepen our understanding of abstractive summarization challenges in Hindi and Marathi but also pave the way for the continued innovation and optimization of technologies crucial for effective information extraction and distribution in these languages. As research in this domain progresses, the potential for facilitating improved access to information and knowledge dissemination in Devanagari-script languages becomes increasingly promising.

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