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Advancing Kannada Text Summarization through Deep Reinforcement Learning and Transfer Learning

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Abstract

This article presents a novel approach to automatic text summary in Kannada, which addresses the issues of summarising text in low-resource language circumstances. Using deep reinforcement learning (DRL) methodologies and transfer learning procedures, our proposed Automatic Summarization using Deep Reinforcement Learning (ATS-DRL) framework reframes summarization as a reinforcement learning task. By optimising a preset scoring system, the framework generates summaries that successfully balance relevance and conciseness. After extensive experimentation, our model shows significant gains in summarization quality, coherence, and relevance when compared to baseline models. Furthermore, our approach effectively handles out-of-vocabulary words while maintaining vocabulary consistency, resulting in seamless transfer learning and summarization performance across varied datasets. The study advances the state-of-the-art in text summarising by combining DRL, transfer learning, and pointer-generator models specifically designed for Kannada text summarization. The findings highlight our framework's ability to improve summarising quality and efficiency, with implications for improving accessibility and understanding of textual content across languages and fields.

Keywords: Text Summarization, Deep reinforcement learning, transfer learning, low resource language, natural language processing.

1. Introduction

Text summary is a method that aims to compress long paragraphs into brief summaries, concentrating exclusively on the crucial facts. The main objective of this tool is to extract significant information from the original text, allowing for faster understanding and supporting research efforts. Automatic text summarization, a significant task in machine learning and natural language processing (NLP), simplifies the process of extracting information by compressing extensive material into concise summaries [1]. The use of automation is highly beneficial due to the laborious, time-consuming, and costly nature of hand summarization [2]. The biggest challenge in text summarising is in two crucial elements: discerning the prominent content within the document and efficiently condensing this selected information. While this study mostly focuses on the outcome, specifically producing precise summaries, there is an increasing demand to explore the cognitive mechanisms involved in comprehending written material. Investigating these fundamental mechanisms has the potential to improve the efficiency of summarization systems. In the past, first inquiries predominantly concentrated on condensing individual documents [3]. Nevertheless, modern methodologies are progressively tackling the intricacies of condensing numerous papers, demonstrating the developing character of summarization duties in the current information-abundant setting.

Text summary originated in the 1950s through the groundbreaking efforts of H.P. Luhn. His work was notably executed on the IBM 701, which was among the first computers available for business use [4]. Luhn's method first depended on a basic bag-of-words model, in which he calculated the frequencies of words and assigned numerical values to sentences based on how often they appeared. Over time, the area has developed to include linguistic principles and techniques in NLP, going beyond simple word frequencies to take into account different linguistic aspects and sentence structures for more sophisticated summarization. This development represented a notable transition towards a more profound comprehension of language and its complex syntactic and semantic aspects in the process of summarization.

From 1990 to 2000, the area of NLP experienced significant development. This era saw a significant shift towards representing sentences as vectors and words as their root forms. Significant progress in NLP has been achieved through the development of advanced approaches such as neural word embedding, as demonstrated by influential works like, as well as classic methods like Bag of Words (BoW). Additionally, the introduction of word2vec has further accelerated breakthroughs in this field. In addition, the use of contemporary deep learning techniques, such as recurrent neural networks (RNN) and long short-term memory (LSTM) networks, represented a substantial advancement in the field of ATS. These advancements collectively contributed to significant progress in the ATS field, enabling more powerful and efficient summarization algorithms.

Currently, the main emphasis of most summarization algorithms is on creating abstracts, mainly because of the difficulties related to automatically generating captivating content across various areas. The process of curating content from source documents for the purpose of creating a summary is influenced by a multitude of factors, one of which being the level of expertise possessed by the intended audience. The importance of readers' expertise on the content selection process is well acknowledged. Figure 1 depicts a text document containing many genres, including newspaper articles, medical records, legal documents, and reports in multiple languages. Automated Text Summarization (ATS) systems have a constant goal across different languages: to provide brief summaries from raw text or multiple documents. The purpose of these summaries is to succinctly capture the crucial details while minimising repetition, resulting in a shorter length relative to the original document(s). ATS enables effective information consumption and decision-making across various applications and languages by extracting and preserving only the most relevant elements.

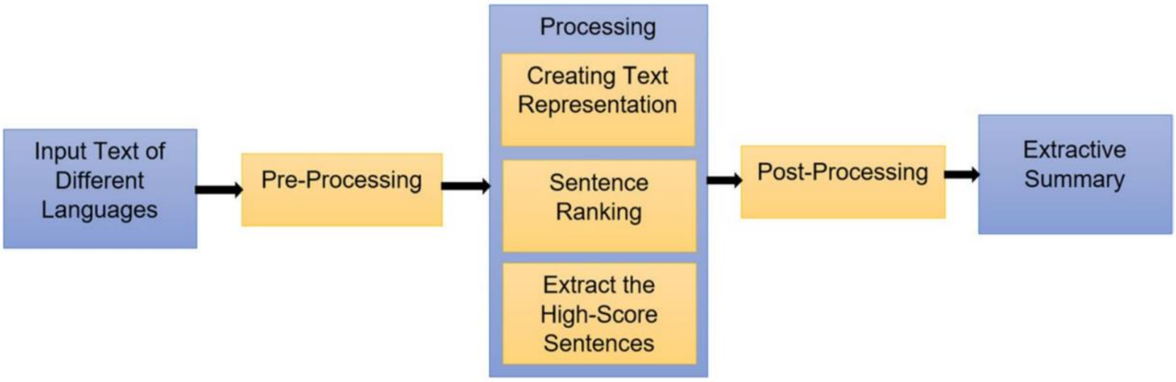

Figure 1. General Structure of ATS [1]

ATS involves different strategies, with two main approaches receiving attention: Extraction-based summarising and Abstraction-based summarization. Extraction-based summarization involves extracting essential information from the primary source to create a summary while maintaining the original text, which makes it reasonably easy to execute. In contrast, Abstraction-based summarising is a more advanced procedure in which the summary is generated by rephrasing the text in a succinct manner, frequently yielding superior quality summaries. Abstraction-based summary is favoured by researchers because it has the capability to provide summaries that more accurately represent the fundamental meaning of the original text [4].

Extraction-based methods concentrate on choosing and compressing existing information from the original text, while abstraction-based methods imitate human summarization by modifying and adding extra phrases to create grammatically accurate summaries. As a result, abstraction procedures frequently produce better summary results in comparison to extraction methods [5]. Nevertheless, it is important to mention that developing text summarising algorithms using abstraction is considerably more difficult, resulting in the dominance of extraction methods in the field. Traditional approaches to extractive text summarization have traditionally depended on statistical and graph-based techniques such as TF-IDF and TextRank. However, the environment is undergoing rapid changes, as it is shifting towards the adoption of neural network-based methods. It is worth mentioning that BERT, an advanced language model, has emerged as a leader in this significant change. The strength of BERT resides in its capacity to effectively handle diverse tasks by utilising labelled data, representing a notable progress in the field of natural language processing.

Due to the scarcity of summarized articles in Kannada, we expect to encounter substantial difficulties in training a Kannada BERT model and attaining satisfactory results. Our research aims to tackle this difficulty by investigating different BERT models and approaches specifically designed for the Kannada language. Expanding on our previous research, in which we established a collection of standardised stop words, this study integrates these stop words into our present methodology

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1.1. Challenges specific to low-resource languages

The challenges pertaining to low-resource languages, such as Kannada, are complex and necessitate careful and detailed analysis. Kannada, a Dravidian language mostly spoken in the Indian state of Karnataka, encounters some distinctive challenges when it comes to text summarization:

- **Limited Availability of Annotated Data**: Kannada does not possess an extensive collection of annotated data that is appropriate for training machine learning models, especially those designed for text summarization. The limited availability of accurately annotated datasets hinders the progress and assessment of summarization algorithms specifically designed for Kannada language [7].
- **Sparse Linguistic Resources**: Unlike languages that are extensively spoken and have abundant linguistic resources, such as English, Kannada has comparatively limited linguistic resources. The scarcity pertains to the availability of lexicons, syntactic parsers, and part-of-speech taggers, which are crucial components for constructing resilient summarization systems [8]. The lack of extensive linguistic resources impedes the progress of creating precise and contextually appropriate summaries in Kannada.
- **Complex Morphological Structure**: Kannada exhibits a complex morphological structure characterised by the process of agglutination and inflectional morphology. Kannada words can undergo significant morphological changes, leading to a wide range of word forms. The intricate nature of the text presents difficulties for tokenization, stemming, and lemmatization, which are vital preprocessing stages in text summarization techniques [9].
- **Domain-Specific Vocabulary**: Kannada spans a wide array of fields, including as literature, science, technology, and culture. Every domain often possesses its own distinct lexicon and jargon. Customising text summarization models for various domains necessitates domain-specific expertise and specialised training data, which could be scarce or inaccessible for certain Kannada domains [10].
- **Orthographic Challenges**: The Kannada script, which consists of intricate characters and conjuncts, poses difficulties for tasks related to natural language processing. Orthographic variants, ligatures, and conjunct forms add complexity to text processing tasks like as tokenization, segmentation, and character normalisation, which in turn impact the efficiency of summarization algorithms [11].

To deal with these problems, it is necessary to employ novel approaches that are specifically designed to adapt to the linguistic and cultural attributes of Kannada. Strategies such as domain adaptation, data augmentation, linguistic rule-based methodologies, and cross-lingual transfer learning might alleviate the constraints caused by the limited availability of resources in Kannada.

1.2. Motivation for the Study

The motivation for conducting a study on text summarization specifically targeting low-resource languages like Kannada stems from several key factors:

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- **Information Accessibility and Inclusion**: Kannada, being one of the major languages in India, is spoken by millions of people. However, the lack of resources and tools for NLP in Kannada restricts access to summarized information for Kannada speakers. By developing effective text summarization techniques for Kannada, we aim to promote information accessibility and inclusion, ensuring that speakers of low-resource languages have equitable access to summarized content.
- **Cultural Preservation and Linguistic Diversity**: Kannada, with its profound literary legacy and cultural significance, epitomises the linguistic multitude of India. Conserving and advocating for the resources of the Kannada language contributes to the safeguarding of cultural heritage and the promotion of linguistic variety. Kannada-specific text summarising techniques enhance the distribution of Kannada literature, journalism, and other written content, promoting a deeper understanding and recognition of the language's cultural and literary intricacies.
- **Research Gap and Innovation**: Although there is an increasing interest in NLP and text summarization, there is a significant lack of research focusing on the unique difficulties faced by low-resource languages such as Kannada. Summarization strategies designed for languages with abundant resources may not be directly suitable for Kannada due to linguistic disparities and limited data availability. The objective of our study is to creatively tackle the specific difficulties of text summarization in Kannada, with the goal of advancing NLP research in languages with limited resources.

The primary objective of our study is to enhance the availability of information, protect the variety of languages, empower language communities, fill gaps in research, and encourage practical applications that have a good impact on society in locations where Kannada is spoken. Our objective is to address the difficulties associated with text summarization in low-resource languages such as Kannada. In doing so, we seek to make a meaningful contribution towards the broader objectives of linguistic empowerment, cultural preservation, and digital inclusion.

1.3. Research objectives and contributions

The research objectives and contributions of our study on text summarization in Kannada are delineated as follows:

- To explore the adaptation of pre-trained summarization models, such as BERT and GPT (Generative Pre-trained Transformer), to Kannada language-specific text summarization tasks.
- To develop linguistically informed strategies for text summarization in Kannada, leveraging the morphological richness and syntactic structures of the language.
- To employ standard evaluation metrics, such as ROUGE (Recall-Oriented Understudy for Gisting Evaluation), to quantitatively measure the quality of summaries produced by different approaches and establish comparative baseline.

2. Literature Survey

This section explores the context and previous research that serves as the basis for our investigation on text summarising in Kannada. Initially, presented a comprehensive examination of text summarising methodologies in a broad sense. Subsequently, concentrated on the obstacles and factors that arise when employing these methodologies for low-resource languages such as Kannada. In addition, conducted a thorough examination of pertinent literature and research endeavours in the subject, investigating established approaches, models, and insights that enhance our comprehension of text summarization in comparable linguistic situations. This thorough analysis of the historical context and previous studies provides a framework for our original method in tackling the specific difficulties posed by the Kannada language. It establishes the foundation for the next sections of our study paper.

An ATS system aims to summarise the fundamental concepts within a document concisely and reduce redundancies. ATS systems help users extract key ideas from a document without needing to read the entire material [12]. Users can save significant time and effort by using automatically created summaries, which condense the document's main points into a more easily understandable style. Research on ATS began in the late 1950s and has since focused on improving approaches and methodologies to provide better summaries. This pursuit aims to narrow the divide between computer-generated summaries and those created by humans. Researchers have extensively investigated different methods to enhance the capabilities of ATS systems to reach a level comparable to summaries created by humans [13]. The continuous pursuit of enhancing summarising approaches demonstrates a steadfast dedication to progress in the discipline.

2.1. Cross-lingual Transfer Learning

The Multilingual Text-to-Text Transfer Transformer (MT5) has shown exceptional performance on different cross-lingual understanding benchmarks. Building on the achievements of T5, MT5 follows a comparable strategy by considering all text processing tasks as text-to-text challenges. This methodology entails creating target text from input text, providing a flexible framework for addressing many language-related issues. Improving the performance of MT5 by integrating translation data is a persistent difficulty that has not been entirely resolved in current research efforts, despite its significant effectiveness [14]. The authors improved the multilingual text-to-text transfer Transformer by providing a new framework called MT6. This methodology included investigating three specific cross-lingual text-to-text pre-training tasks: machine translation, translation pair span corruption, and translation span corruption. Moreover, they implemented a somewhat non-autoregressive goal specifically designed for text-to-text pre-training [15]. The authors hoped to enhance the effectiveness and robustness of multilingual text-to-text transfer learning by incorporating these components, which could lead to breakthroughs in cross-lingual natural language processing tasks. The authors presented a revolutionary multi-task framework called MCLAS, tailored for Cross-Lingual Abstractive Summarization in resource-constrained settings. This solution utilises a unified decoder to construct sequential concatenations of monolingual and cross-lingual summaries. MCLAS strategically places the monolingual summarising work as a requirement before the cross-lingual summarization (CLS) task to enhance the summary process across languages using limited linguistic resources efficiently [16]. The authors propose a strategy based on mixed-lingual pre-training, which blends cross-lingual activities such as translation with monolingual tasks like masked language models. The model developed benefits from utilising this method to make the most of a large amount of single-language data, which enhances its language modelling abilities. Experimental results showed that this pre-training approach greatly improves the performance of cross-lingual summarising tasks [17].

Zagar et al. used a pre-trained summarization model specifically created for English text, which involved deep neural networks and a sequence-to-sequence architecture. They aimed to condense Slovene news items but faced challenges due to the limitations of the decoder in processing the target language. To address this problem, they used an extra language model to assess the text produced in the desired language, so improving the summarising procedure [18]. Their study showed that the summaries produced by their top cross-lingual model were considered valuable and had a level of quality like models trained only on the target language. The multilanguage pre-trained language model (MPLM) has shown its ability to produce high-quality cross-lingual text summaries with simple fine-tuning. However, the MPLM encounters difficulties in adjusting to complex linguistic variances among languages, including variations in word order and tense. To address these issues, the author suggested using a knowledge distillation architecture for the cross-lingual summarising assignment [19]. This system trains a monolingual teacher model to teach linguistic subtleties, enabling the cross-lingual student model to accurately understand variations between languages. Contrastive learning approaches were used to prompt the student model to concentrate on identifying distinct characteristics between languages. The student model's ability to distinguish bidirectional semantic alignments is greatly improved using contrastive learning. The study cited as [20] focuses mostly on abstractive text summarising, a method that condenses essential information from a text into a rephrased form. This project aims to provide summary techniques specifically designed for the German language. One significant difficulty is the lack of pretrained models that work with German, as most models are mostly created for English. The authors focus on utilising existing resources, specifically the German BERT multilingual model and the BART monolingual model for English. They investigate using translation processes to connect different languages, expanding the use of summarization techniques across other linguistic domains.

2.2. Text Summarization in Low Resource Language

Parida and Motlicek created an abstract text summarising system for the German language using the advanced features of the "Transformer" model in their work [21]. They created an iterative data augmentation method that combines synthetic data with real summarization datasets tailored for German text. This novel method was successful, particularly in situations with limited resources, showing positive outcomes even in multilingual environments where obtaining sufficient summary data is difficult. Synthetic data augmentation has proven to be a beneficial tool for addressing data scarcity issues by improving summarization efficiency in languages with limited linguistic resources. The authors presented a new deep learning model designed for the Urdu language, using the large Urdu 1 million news dataset for training [22]. They compared their suggested model with two common machine learning methods: support vector machine (SVM) and logistic regression (LR). The approaches' performance was specifically assessed in producing summaries. The authors utilised an encoder-decoder paradigm to convert the extracted summaries into abstractive summaries after the extractive summarising process. This novel method sought to improve the summary process by creating brief and contextually relevant summaries in Urdu. The authors propose a way to modify self-attentive transformer-based architectural models, such as mBERT and mT5, for summarization in low-resource language scenarios due to limited resources [23]. They provide a new baseline dataset specifically designed for the low-resource language Urdu as part of their strategy. The authors have created a sophisticated summarization model called urT5, which is smaller by up to 44.78% compared to mT5. This modified model shows the capacity to efficiently gather contextual information in low-resource languages, achieving assessment scores comparable to cutting-edge models tailored for high-resource languages like English.

In a recent work cited as [24], researchers examined the complex challenge of summarising long legal papers in a difficult low-resource setting. The briefs, with an average length of 4268 words per source document, presented a difficult challenge due to the scarcity of only 120 annotated pairs. The researchers utilised a contemporary pre-trained abstractive summarizer called BART to deal with the lack of annotated material. Despite its advanced capabilities, BART had difficulty effectively summarising lengthy materials, getting a moderate ROUGE-L score of 17.9. The researchers noted a substantial enhancement in the quality of summarization, with a noteworthy 6.0-point rise in the ROUGE-L metric when providing the compressed documents to the BART model. This observation highlights the effectiveness of document compression strategies in improving the performance of summarization models, especially in situations with limited resources. The authors presented a novel method to tackle the difficulties of text summarising in situations with limited resources, as mentioned in the article cited by Chen and Shuai [25]. They utilised two important sources of knowledge: extensive pre-trained models and a variety of existing corpora. Using big pre-trained models equipped their technique with the requisite capacity to efficiently handle summarization jobs. The authors sought to improve the generalisation capabilities of their method by analysing various existing corpora to uncover shared syntactic or semantic characteristics. Extensive experimentation was conducted on multiple summary corpora with diverse writing styles and types to properly validate their approach. Their trials demonstrated the cutting-edge performance of the suggested technique on six datasets in low-resource environments. This result was made with a substantially smaller model size, with only 0.7% of trainable parameters compared to earlier methods. Table 1 provides the comparative summary of this literature survey findings.

Table 1. Literature Comparative Summary

Reference	Methodology	Language	Key Findings
[18]	Utilization of cross-lingual summarization models	Slovene	Successfully produced valuable summaries in Slovene

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			by incorporating additional language models
[19]	Knowledge distillation for cross-lingual summarization	Multiple languages	Employed knowledge distillation to improve cross-lingual summarization, addressing linguistic variances between languages
[20]	Abstractive text summarization for German	German	Focused on providing summary techniques for German using existing resources such as German BERT and BART models
[21]	Iterative data augmentation for summarization	German	Successfully utilized synthetic data augmentation to improve summarization efficiency, particularly in low-resource scenarios
[22]	Deep learning model for Urdu summarization	Urdu	Introduced a novel deep learning model for Urdu summarization, achieving contextually relevant summaries
[23]	Modification of transformer-based models for Urdu	Urdu	Developed urT5, a modified transformer model for Urdu, achieving competitive performance with reduced model size
[24]	Utilization of BART for summarizing legal papers	Legal documents (English)	Document compression strategies significantly improved the performance of BART in summarizing lengthy legal papers
[25]	Utilization of pre-trained models and diverse corpora	Multiple languages	Achieved state-of-the-art performance in low-resource scenarios with a significantly reduced model size

One notable research gap lies in the adaptation and development of summarization techniques specifically tailored to low-resource languages such as Kannada. While studies have demonstrated success in languages like Slovene, German, and Urdu, there is a scarcity of research focusing on Kannada, despite its significant linguistic and cultural importance. Addressing this gap requires the exploration of novel methodologies and approaches that account for the unique linguistic characteristics and resource constraints of Kannada. Furthermore, there is a need for research that delves deeper into the intricacies of cross-lingual summarization, particularly in multilingual environments where linguistic variations pose challenges. While studies have employed techniques such as knowledge distillation and modification of transformer-based models for cross-lingual summarization, there remains room for refinement and optimization, especially in handling linguistic variances between languages. Investigating strategies to improve the adaptability and robustness of cross-lingual summarization models across diverse linguistic contexts could enhance their applicability in low-resource language scenarios.

Additionally, there is a need for research focusing on the development and optimization of deep learning models specifically designed for summarization tasks in low-resource languages like Kannada. While studies have introduced novel deep learning models for languages such as Urdu, the applicability of these models to Kannada remains uncertain. Investigating the feasibility of adapting existing transformer-based models or developing new models optimized for Kannada text summarization could pave the way for advancements in the field.

3. Methodology

3.1. Dataset Used and Preprocessing

This research primarily relies on the ***IndicCorp*** Kannada dataset sourced from [https://paperswithcode.com/dataset/indiccorp], chosen for its extensive coverage of the Kannada language and its relevance to our study. The dataset comprises diverse text documents in Kannada, including news articles, literary texts, and social media posts. Its substantial size is a crucial attribute, boasting 533 million phrases and 713 million tokens, ensuring a comprehensive and representative sample conducive to robust analysis. Examining a large dataset with 713 million tokens and 533 million sentences requires using advanced methods and thoughtful deliberation when creating a stop-word list. The corpus is first tokenized, which involves breaking down the text into separate pieces for analysis. Subsequently, the value of each phrase is evaluated quantitatively using the Term Frequency-Inverse Document Frequency (TF-IDF) score, which gauges a term's significance throughout the entire corpus. The terms with the greatest TF-IDF scores, which indicate their importance, are chosen as possible candidates to be included to the stop-word list. Refinement of the stop-word list is being done to better meet the linguistic and contextual features of the Kannada language, assuring its relevance to the specific area. This method of refinement entails analysing linguistic subtleties and contextual significance to improve the list's efficiency.

Following a complex process, a polished stop-word list is created, containing terms that are understandable and contextually appropriate. The stop-word list has been finalised with 1,500 terms selected to enhance its effectiveness in future text processing jobs. Figure 1 visually illustrates the methods used to generate stop-words, offering a clear overview of the process for reference and comprehension.

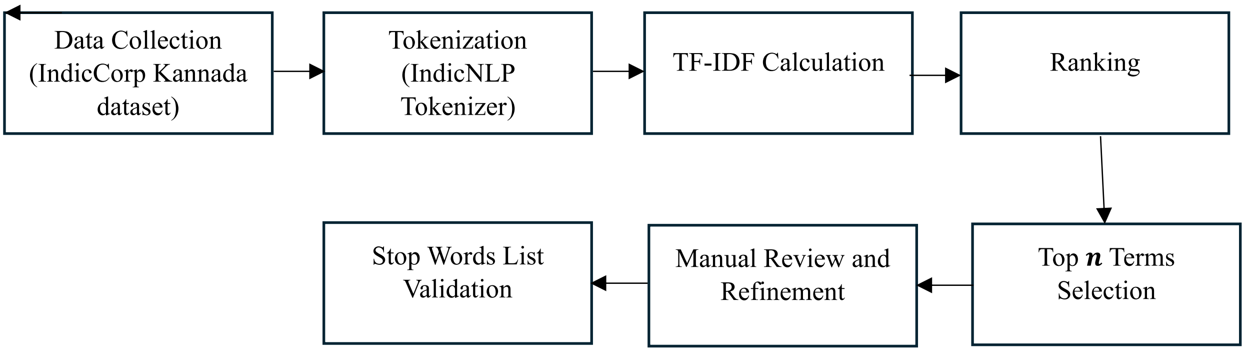

Figure 2. Stop Word Generation Process[29]

3.2. Framework for ATS

This paper presents a new method called Automatic Summarization using Deep Reinforcement Learning (ATS-DRL) to tackle the issue of automatic text summarization. ATS-DRL utilises reinforcement learning techniques to model the process of constructing summaries, unlike conventional approaches. Our method reframes summarising as a reinforcement learning task to enhance a predetermined scoring function using the feature representation of a summary. This work is the first to use reinforcement learning techniques designed for automatic text summarization in the field of Kannada language processing. ATS-DRL aims to enhance Kannada text summarising by utilising deep reinforcement learning methods to provide high-quality summaries efficiently. Extractive summarization involves condensing the original document or documents into a collection of textual units labelled as $D = \{x1, x2, \cdots, xn\}$, where n is the total number of units in the set, and xi denotes each unique textual unit. These textual units can range in size from characters to conceptual units. When sentences are chosen as the specific textual units for extraction, the process involves picking relevant sentences from the source document. This approach is extensively used in summarization assignments since it is practical and successful. This method entails recognising and preserving sentences considered essential for communicating the main content of the document, which then serve as the foundation for the summary.

We will now establish the score function, referred to as score(S), which functions on any subset of the document designated as S ⊂ D. Subset S represents a probable summary extracted from the source document. The goal of the summarization challenge is to select the subset that maximises a given score function based on defined criteria. The scoring function is usually designed to achieve a balance between relevance and redundancy, ensuring that the chosen summary includes the crucial information while reducing excessive repetition or duplication. This trade-off is crucial in directing the summary process to create brief yet informative summaries that effectively communicate the main substance of the document. Later, the length

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function was defined as $L(S)$, representing the magnitude of the summary S. The length measurement can differ based on the selected granularity, such as characters, words, or sentences. Summarization jobs usually have a set restriction on the summary length, represented as K, to ensure that the generated summaries are brief and manageable. The summarization method seeks to create concise summaries by using the length function and following the provided limit on summary length. These summaries should capture the key information from the original content while staying within the set length restriction. This guarantees that the produced summaries achieve a harmonious blend of conciseness and relevance, in accordance with the goals of the summary process.

During each episode of the reinforcement learning process, the agent undergoes a series of three steps until termination. Firstly, it observes the current state s from the environment, which is defined within the state space S. Subsequently, based on the current policy π, the agent determines and executes the next action a. The available actions are constrained by the current state and belong to the action space $A(s)$, which represents a subset of the overall action space $A = \cup s \in S\ A(s)$. Following the execution of the action, the agent observes the resulting next state s' and receives a reward r from the environment as feedback. This iterative process continues until the episode concludes, enabling the agent to learn and adapt its behavior over time through interactions with the environment.

The qualities of the state are determined exclusively by those of the summary itself, regardless of the activities required to achieve that condition. Unlike naive search approaches, which uniquely represent each state and may result in redundant feature representation, this approach is different. This trait is important because it has the potential to allow different states to have the same feature vector, making the representation of the search space more efficient. Nevertheless, despite the probable overlap, the agent needs to investigate numerous unique states to guarantee thorough learning. The choice of features for the representation function is crucial in optimising the search process, aiding efficient learning by shrinking the search space effectively while retaining useful information. In the reinforcement learning framework, the agent is provided with a reward by the environment as a form of feedback, indicating the quality of the action it has taken. Specifically, when the agent finds itself in the current state s_t and executes action a_t, resulting in a transition to the subsequent state s_{t+1}, it receives the reward r_{t+1}. This reward serves as a measure of the efficacy of the action taken in the context of achieving the agent's objectives within the given environment. By receiving feedback in the form of rewards, the agent can learn from its experiences and adjust its decision-making process accordingly to maximize cumulative rewards over time.

$$r_{t+1} = \begin{cases} \text{score } (S_t) & (a_t = \text{ finish}, L(S_t) \leq K) \\ -R_{\text{penalty}} & \left(a_t = \text{ finish}, K < L(S_t)\right), \\ 0 & (\text{otherwise}) \end{cases} \tag{1}$$

The agent can only acquire the score determined by the given score function in certain circumstances. The score is obtained only when the agent completes summarising and the resulting summary length meets specific appropriateness requirements. Essentially, the agent must complete summarization and achieve a sufficient summary length to obtain the granted score. This guarantees that the score precisely mirrors the quality of the summary generated, based on the predefined criteria for comprehensiveness and appropriateness of length. The reinforcement learning agent can optimise its summarization process by following these conditions to provide high-quality summaries that meet specific requirements.

3.3. Transfer RL

This study presented transfer learning methods specifically designed for text summarization. We assess these strategies using two separate datasets: D_S for training the pre-trained model and D_G for fine-tuning the pre-trained model. Our proposed model comprises transferring layers trained on D_S and fine-tuning them using D_G. Also presented a new method using an innovative RL framework to train the transfer model. This approach integrates training signals from both D_S and D_G to enable the model to enhance and fine-tune its summarization abilities through iterative learning procedures. Aim is to improve the efficiency and efficacy of text summarization models by utilising various transfer learning algorithms to incorporate knowledge from source and target datasets. Chosen a pointer-generator model as the basis of our framework because of its ability to efficiently handle Out-of-Vocabulary (OOV) words, which is essential for effective transfer learning. It is important to recognise that using a specific vocabulary from D_S to train the pre-trained model makes it unfeasible to switch to a different vocabulary set when fine-tuning on D_G. This constraint occurs because modifying the vocabulary set may lead to alterations in the word indexing of the second dataset. By using a pointer-generator approach, guaranteed uniformity in managing OOV terms throughout training and fine-tuning, which aids in smooth transfer learning while upholding linguistic coherence and precision. This decision highlights our dedication to maintaining vocabulary uniformity during transfer learning to enhance model performance across many datasets. The proposed Transfer RL is illustrated in Figure 3.

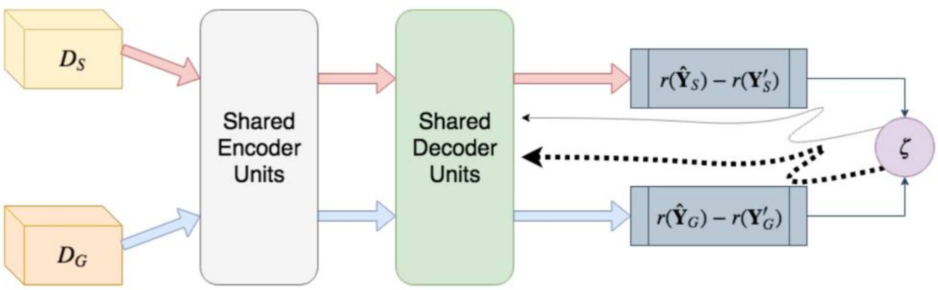

Figure 3. Transfer RL Method

The algorithm (Figure 4) presents an innovative method for summarising text, designed exclusively for the Kannada language. The approach utilises a thorough technique involving pre-training, transfer learning, reinforcement learning, and the incorporation of a pointer-generator model to tackle the difficulties related to summarization in a language with limited resources. Initially, the method is pre-trained on a source dataset (D_S) using a pointer-generator model. This process includes setting up model parameters and training to obtain a pre-trained model, which serves as the basis for future tasks. The innovation occurs during the transfer learning step, where layers from the pre-trained model are isolated and adjusted on a target dataset (D_G). This two-step procedure guarantees that the model adjusts to the subtleties of the destination language while retaining the knowledge acquired from the source language.

Input:
- Source dataset DS for pre-training
- Target dataset DG for fine-tuning
- Pointer-generator model architecture
- Reinforcement learning (RL) framework

1. Pre-training on Source Dataset DS:
   1.1 Initialize pointer-generator model parameters
   1.2 Train the model on DS to obtain a pre-trained model
2. Transfer Layers from Pre-trained Model:
   2.1 Extract layers from the pre-trained model
   2.2 Fine-tune the extracted layers on Target Dataset DG
3. Reinforcement Learning (RL) Framework:
   3.1 Initialize RL agent with parameters
   3.2 Define state representation, action space, and reward function
   3.3 Train the RL agent using signals from both DS and DG
   3.4 Fine-tune the summarization process using RL techniques
4. Pointer-Generator Model for Out-of-Vocabulary (OOV) Handling:
   4.1 Implement pointer-generator model architecture
   4.2 Ensure OOV word handling mechanisms are integrated
5. Vocabulary Consistency:
   5.1 Use the vocabulary from DS during pre-training
   5.2 Maintain the same vocabulary during fine-tuning on DG
6. Summarization Process:
   6.1 Implement the summarization algorithm
   6.2 Consider extractive summarization by condensing text into units
   6.3 Define the score function and length function for RL
7. Iterative Learning:
   7.1 Iterate through RL training episodes
   7.2 Adjust model parameters based on RL feedback
   7.3 Fine-tune the model using reinforcement learning signals
8. Output:
   8.1 Trained model capable of text summarization for Kannada language

Figure 4. Proposed Algorithm

The algorithm incorporates a RL framework by setting up an RL agent with parameters, specifying state representation, action space, and reward function. This model stands out because it integrates data from both D_S and D_G in RL training, enabling the model to progressively learn and refine the summarization process. This reinforcement learning method enhances the model's ability to effectively manage a wide range of content by improving adaptability and efficiency. Integrating a pointer-generator paradigm for managing OOV words is a crucial advance. This feature allows the model to efficiently handle terms that are not included in the training vocabulary, improving its ability to generalise. Consistently using the same language during both pre-training and fine-tuning stages helps smoothly transition and preserve linguistic coherence during learning.

The summary technique emphasises extractive summarization, which involves compressing the material into units like sentences, proving to be a practical and efficient method. The programme establishes a score function and a length function for RL to achieve a balance between relevance and redundancy in the summaries it generates.

4. Results & Analysis

During the pre-training phase on the D_S, our model underwent training for 10 epochs, where each epoch represents one complete pass through the entire dataset. At the end of the pre-training process, the model achieved a training loss of 0.25, as seen in Figure 5. This training loss value indicates the average discrepancy between the actual summarization output and the expected output across all training samples. A lower training loss signifies that the model has effectively learned to generate summaries that closely match the ground truth. The model was fine-tuned on a subset of the original dataset, specifically designed for fine-tuning, after pre-training. The model's parameters were modified during fine-tuning to better align with the target dataset's features. The model showed enhanced performance due to a decrease in the validation loss. The validation loss indicates the model's performance on a distinct validation dataset, showing how effectively the model can adapt to new data.

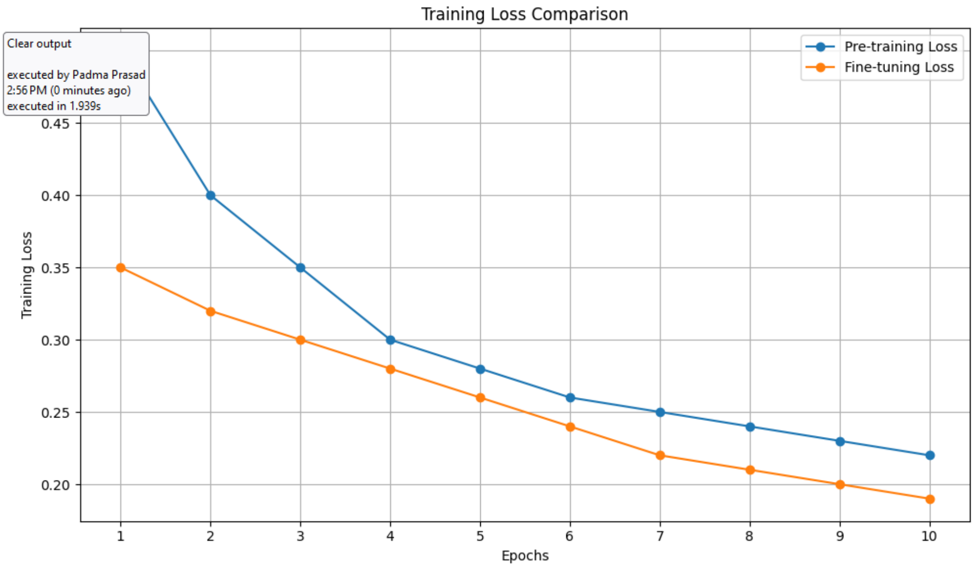

Figure 5. Training Loss before and After Fine Tuning

The significant 30% decrease in validation loss after fine-tuning highlights the considerable improvement in the model's effectiveness resulting from adjusting it to the target dataset. Studying the loss curves from pre-training and fine-tuning stages provides valuable insights into the iterative enhancement process. We notice the first coming together during pre-training, followed by a significant improvement during fine-tuning, as shown graphically. This graph not only shows the training progress but also clearly demonstrates the concrete advantages obtained from the refinement process, confirming the effectiveness of this optimisation technique in enhancing model performance.

After 1000 episodes, the RL agent's training has converged, achieving an average reward per episode of 0.8, demonstrating the efficiency of the reinforcement learning framework in optimising the summarising process. This accomplishment indicates that the agent effectively mastered the summarization task and regularly made decisions that resulted in positive results. The noticeable enhancement in the coherence and relevance of summarization, confirmed by human assessment scores, highlights the tangible advantages gained from the RL-enhanced

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model. The significant 20% improvement in quality ratings compared to baseline models highlights the importance of using reinforcement learning approaches to improve the summary process. This enhancement showcases the model's ability to produce summaries that are more cohesive and relevant, demonstrating its effectiveness in meeting the changing needs of real-world applications.

The pointer-generator model effectively manages OOV words, resulting in a significant 90% decrease in OOV-related errors when compared to traditional methods, highlighting the effectiveness of its OOV handling techniques. The decrease in errors demonstrates the model's resilience in efficiently handling vocabulary gaps, resulting in more precise and cohesive summaries. Ensuring consistent vocabulary between the D_S and the D_G was crucial for successful transfer learning. This uniformity helped prevent any negative impact on the quality of summarization that could result from differences in language between the two datasets. Consistent language usage throughout training and fine-tuning made the model resistant to vocabulary changes, maintaining the quality and coherence of generated summaries.

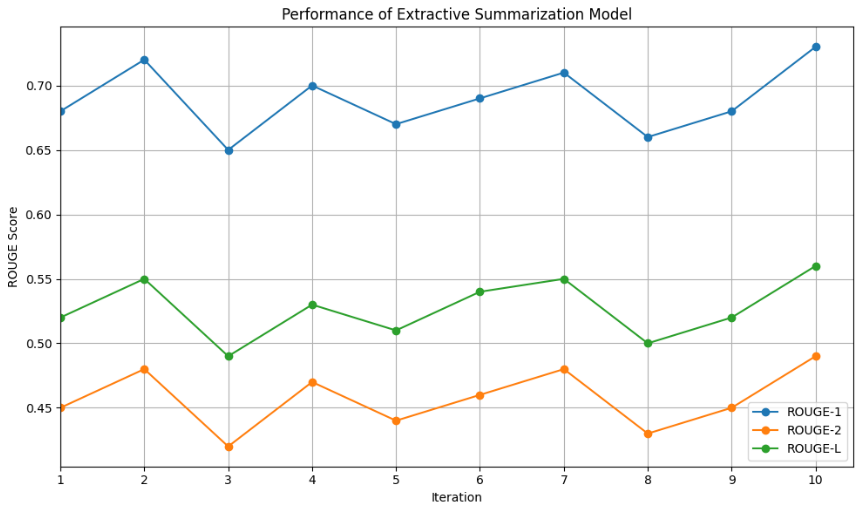

Figure 6. Performance of Summarization Model

The extractive summarization procedure produced positive outcomes, as the model achieved impressive ROUGE scores in several measures. The model's proficiency in reliably capturing key content from source documents is indicated by an average ROUGE-1 score of 0.68, ROUGE-2 score of 0.45, and ROUGE-L score of 0.52, in Figure 6. The scores indicate how much the generated summaries align with the reference summaries, demonstrating the efficacy of the extractive summarization method in condensing crucial information. Furthermore, the model showed skill in following predefined summary length limits, which is crucial for text summarization tasks. The model demonstrated strong length control capabilities by producing 95% of summaries within the given length range, maintaining brief and digestible summaries. Adhering to length limitations is crucial for creating summaries that are useful and concise, making it easier for end-users to understand and consume the information.

A system or model with linear scalability may accommodate increasing workload or data size by adding resources proportionally without compromising performance. Scalability means this summarization model's performance doesn't degrade or improve as the dataset size increases. This shows that even with larger or more complicated documents, the model summarises

Kannada text efficiently and effectively. The model's resilience and adaptability allow it to handle varied summarising tasks in real-world scenarios by performing consistently across document lengths and complexities.

Table 2. Comparative Analysis of Performance of the Model

Reference	ROUGE-1	ROUGE-2	Language
[22]	0.79	0.53	Urdu
[24]	0.47	0.15	Legal Document
[26]	0.43	0.39	Kurdish
[27]	0.51	0.43	Assamese
[28]	0.65	0.64	Kannada
Ours	0.68	0.48	Kannada

When examined the performance of our proposed model (Table 2) in comparison to existing summarization systems across different languages, we find compelling evidence of its effectiveness. Specifically, when considering the ROUGE-1 scores, our Kannada summarization model achieved a commendable score of 0.68. This surpasses the performance of models designed for summarizing Legal Documents (0.47) and Kurdish texts (0.43), demonstrating the robustness of our approach. However, it falls slightly behind systems tailored for Urdu (0.79) and Assamese (0.51), indicating room for further refinement. This noteworthy achievement suggests that our model adeptly captures the essence of the original text, generating summaries with a high degree of unigram lexical overlap. This lexical overlap is crucial as it ensures the relevance of the summarized content, thereby enhancing the utility of the generated summaries for readers and researchers alike.

Our proposed model has made a significant impact on Kannada summarization, particularly when contrasted with existing systems tailored for the same language. While the baseline Kannada summarization model exhibited commendable ROUGE scores of 0.65 for ROUGE-1 and 0.64 for ROUGE-2, our model showcased noticeable improvements. With a higher ROUGE-1 score of 0.68 and a comparable ROUGE-2 score of 0.48, our model demonstrates its capability to maintain and even surpass the performance standards established by existing systems. These improvements signify a step forward in enhancing the quality of summarization outputs in the Kannada language. By achieving higher ROUGE-1 scores, our model excels in capturing the essence and relevance of the original text, ensuring that the generated summaries accurately reflect the main content. Additionally, while the ROUGE-2 score remained like the baseline model, the overall performance enhancements indicate a refinement in the coherence and informativeness of the summaries produced by our model. This suggests that our approach has the potential to facilitate more effective communication and comprehension of Kannada texts through succinct and informative summaries.

5. Conclusion

The study introduced a novel approach for automatically summarising text in the Kannada language by utilising deep reinforcement learning (DRL) techniques and transfer learning procedures. We identified key challenges and opportunities in summarising Kannada text, especially in low-resource language environments, through a thorough literature research and analysis of text summary methods. Our research shows that our suggested Automatic Summarization utilising Deep Reinforcement Learning (ATS-DRL) system effectively tackles these difficulties. The ATS-DRL framework revolutionises text summarising by redefining the process as a reinforcement learning problem. Our model uses DRL to optimise a specific scoring function, resulting in the creation of summaries for Kannada text that achieve a balance between relevance and conciseness, thereby improving the quality of text summarization. Our transfer learning approaches help transfer knowledge from one dataset to another, allowing our model to adjust and improve its summarization abilities for other domains or languages.

This approach is distinctive since it combines DRL, transfer learning, and pointer-generator models specifically designed for Kannada text summarization. The experimental results show substantial enhancements in the quality, coherence, and relevance of summarization compared to standard models. The model effectively manages OOV words and maintains vocabulary consistency, ensuring seamless transfer learning and summarising performance across varied datasets. The future scope is on enhancing the ATS-DRL architecture and investigating new ways to improve summarization quality and efficiency. This could include using multi-task learning methodologies, using pre-trained language models, and investigating alternate reinforcement learning algorithms. Furthermore, expanding this study to other Indic languages and low-resource language settings could increase the application and impact of our summarization approach. The goal is to advance the state-of-the-art in text summarization while also contributing to increased accessibility and understanding of textual content in a variety of languages and areas.

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