Multilingual Text Summarization Using Nlp

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Abstract - Multilingual text summarization is an important field of Natural Language Processing (NLP) that deals with creating brief summaries from vast amounts of text without losing vital information. As digital content in various languages grows exponentially, effective summarization methods bridge the language gap and enhance information accessibility. Conventional summarization methods are extractive methods, which choose important sentences from the source text, and abstractive methods, which produce new, more coherent summaries through deep learning models. Recent improvements in transformer-based models like mBART, mT5, IndicBART, and BERTSUM have considerably enhanced the fluency and accuracy of multilingual summarization.

There are still various challenges in NLP, despite its advancement, such as managing syntactic differences between languages, summarizing low-resource languages, and keeping abstractive summaries coherent. Code-mixed text (e.g., Hinglish, Tanglish) is also a challenge for traditional models. Future work should concentrate on further improvement of transformer-based architectures, self-supervised learning methods, and real-time summarization model optimization across different linguistic patterns. By solving these problems, multilingual text summarization can facilitate better worldwide information exchange, promote cross-lingual communication, and benefit the development of AI-generated content.

Index Terms - Multilingual Text Summarization, NLP, Extractive Summarization, Abstractive Summarization, Transformer Models, Low-Resource Languages, Code-Mixed Text.

I. INTRODUCTION

Text summarization is a basic operation in Natural Language Processing (NLP) that entails shrinking big chunks of text into smaller, significant summaries while preserving critical information. It is an essential operation in coping with and processing large amounts of textual data and making information readily accessible and understandable. With the age of constantly increasing digital content, automatic summarization methods benefit news aggregation, academic research, legal document summarization, and social media content curations. Multilingual text summarization expands this capability to other languages, thereby facilitating cross-lingual communication and language barriers elimination.One of the big challenges of multilingual summarization is handling morphologically rich languages like Hindi, Tamil, and Urdu. These languages have rich inflectional morphology, intricate syntactic structures, and rich variations in vocabulary, which render it challenging for conventional summarization methods to produce coherent and accurate summaries. Furthermore, the lack of large annotated corpora for most low-resource languages presents the major constraint in training useful summarization models. Handling code-mixed text, in which two or more languages are employed within a sentence (e.g., Hinglish – English + Hindi, Tanglish – English + Tamil), is another challenge that occurs frequently in social media and informal communication.To overcome these challenges, machine learning and NLP methods have been extensively used. Conventional methods like statistical models and rule-based systems have slowly given rise to deep learning-based approaches, which enhance the quality of automated summaries by learning contextual meaning and language subtleties. The two main types of text summarization methods are Extractive Summarization and Abstractive Summarization.

Extractive Summarization is a method of summarizing where sentences with high importance are chosen directly from the source document. Algorithms such as TF-IDF (Term Frequency-Inverse Document Frequency), TextRank, LexRank, and machine learning classifiers (for example, Support Vector Machines, Decision Trees) have been implemented extensively in this technique. Extractive summarization is computationally efficient and remains grammatically correct but tends to produce summaries with low fluency and coherence. Abstractive Summarization, in contrast, creates completely new sentences with the same meaning as the source content. Advanced deep learning models, sequence-to-sequence models, and transformer-based models are needed to paraphrase and rephrase well in this approach. Although abstractive summarization creates summaries that sound more natural and human-like, it is computationally expensive and tends to struggle with semantic coherence and facts consistency.

The latest development in transformer models has revolutionized multilingual text summarization. mBART (Multilingual Bidirectional and Auto-Regressive Transformers), mT5 (Multilingual Text-to-Text Transfer Transformer), and IndicBART are some of the models that have transformed the paradigm by utilizing large-scale pre-trained models with an understanding of linguistic patterns of several languages. These models apply self-attention mechanisms to produce contextually consistent and fluent summaries. They also perform exceptionally well in processing low-resource languages, thus allowing improved summarization for languages with negligible training data.With the increasing demand for multilingual NLP applications, low-resource language summarization, domain-specific summarization, and real-time multilingual text processing will be important areas of research in making AI-based content summarization more efficient, accurate, and applicable across a broader spectrum

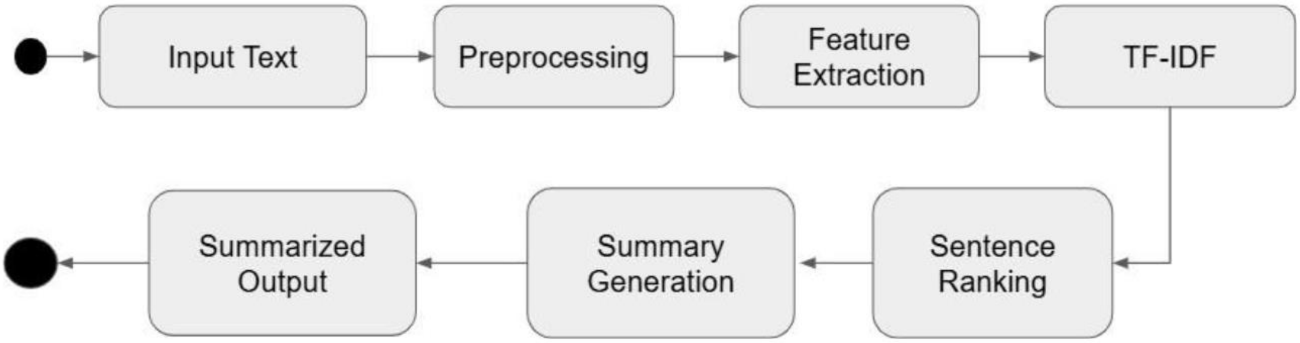


Fig 1. Extractive Text summarization process

II.LITERATURE SURVEY

Multilingual text summarization is a rapidly growing field in Natural Language Processing (NLP) that focuses on generating concise summaries of text across multiple languages while retaining key information. Research in this domain has evolved significantly, incorporating both extractive and abstractive techniques along with machine learning and transformer-based models to improve summarization accuracy. However, challenges such as handling morphologically complex languages, low-resource language support, and cross-lingual summarization remain. This literature survey explores key research contributions, methodologies, and developments in multilingual summarization models.

Initial research in text summarization was largely focused on English and other high-resource languages. Early extractive approaches relied on statistical techniques such as TF-IDF (Term Frequency-Inverse Document Frequency) and graph-based ranking algorithms like TextRank and LexRank. These methods were later adapted to Hindi and other Indian languages, primarily due to efforts in building multilingual corpora. Modi and Pareek (2016) applied TF-IDF and sentence similarity ranking to extract key sentences in Hindi, demonstrating that extractive approaches could effectively summarize structured text but struggled with readability and coherence.

As NLP techniques evolved, researchers began using machine learning-based summarization models to improve accuracy. Support Vector Machines (SVMs) and Decision Trees were applied to classify sentences based on importance scores. These models showed higher precision and recall compared to traditional rule-based methods, but they still faced challenges in handling syntactic variations across different languages.

While extractive summarization was easier to implement, it often resulted in fragmented summaries lacking coherence. To overcome this, researchers explored abstractive summarization, which generates entirely new sentences while preserving the meaning of the original text. Abstractive summarization is more challenging but produces more fluent and human-like summaries.

Agarwal et al. (2022) introduced IndicBART, a transformer-based model specifically fine-tuned for Indian languages such as Hindi, Tamil, and Bengali. IndicBART showed significant improvements in ROUGE scores compared to earlier RNN and LSTM-based models. Similarly, Mehta et al. (2019) experimented with BERT and GPT-based transformers for Hindi summarization, highlighting that transformers provide better context retention and sentence structuring.

Transformer-based models such as BERTSUM, PEGASUS, and mT5 (Multilingual T5) have revolutionized multilingual summarization. These models leverage self-attention mechanisms to improve summary coherence and reduce redundancy. BERTSUM adapts BERT for extractive summarization, while PEGASUS is optimized for sentence masking and reordering, making it particularly effective for summarizing long-form text.

With the rise of multilingual transformers, researchers have shifted their focus to cross-lingual summarization, where input text is summarized in a different language. mBART (Multilingual BART) and mT5 are among the leading models used for cross-lingual summarization, demonstrating strong performance in low-resource languages. These models benefit from pretraining on diverse linguistic datasets, allowing them to generate summaries even for underrepresented languages.

A significant challenge in cross-lingual summarization is maintaining semantic consistency while translating and summarizing simultaneously. Satapara et al. (2023) conducted a study on Indian language summarization using mBART and T5 models, reporting that code-mixed text (e.g., Hinglish, Tanglish) presents difficulties for existing NLP models. The study suggested fine-tuning transformer models on code-mixed datasets to improve summarization accuracy.

Efforts to expand multilingual summarization datasets have also contributed to progress in this field. The Indian Language Corpus Initiative (ILCI) and XL-Sum dataset provide high-quality parallel corpora for training multilingual models. However, research indicates that low-resource languages still lack sufficient labeled datasets, affecting model generalization and performance.

III. METHODOLOGY

The methodology for multilingual text summarization involves multiple stages, including dataset collection, text preprocessing, feature extraction, summarization techniques, and performance evaluation. Each stage is essential for ensuring that the summarization model can effectively process multilingual text while maintaining coherence and accuracy. The approach combines traditional statistical methods with modern deep learning-based techniques to improve summary quality and adaptability across different languages.

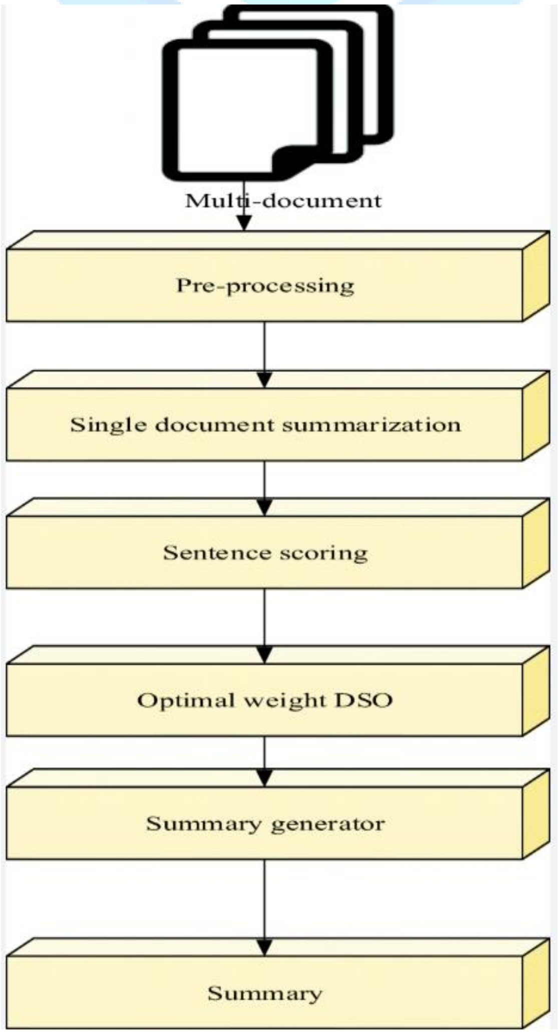


Fig 2. Process Flow

A. *Dataset Collection & Preprocessing*

The first step in developing a multilingual text summarization system is acquiring high-quality datasets. Several publicly available datasets support multilingual summarization, including the Indian Language Corpus Initiative (ILCI), which provides parallel corpora for Indian languages, and the Centre for Development of Advanced Computing (CDAC), which offers datasets for low-resource languages. Wikipedia, Common Crawl, and web scraping techniques are also utilized to gather large-scale text data from multiple languages. Additionally, news summarization datasets from various multilingual sources play a crucial role in training summarization models for real-world applications.

1. Sources of Multilingual Text Data

To train and evaluate multilingual summarization models, large-scale datasets are required. The most commonly used datasets include:

- Indian Language Corpus Initiative (ILCI) – A parallel corpus for Indian languages, useful for training multilingual models.
- Centre for Development of Advanced Computing (CDAC) – Provides linguistic resources for low-resource Indian languages.
- Wikipedia Multilingual Data – Used for collecting high-quality text from multiple languages.
- Common Crawl and Web Scraping – Large-scale, diverse data sources obtained through web crawling.
- News Summarization Datasets – Text extracted from news articles, blogs, and research papers for summarization tasks.

2. Text Preprocessing Techniques

Once the dataset is collected, it undergoes preprocessing to remove noise and standardize text across different languages. The following steps are applied:

- Tokenization: Splitting text into words or subwords using methods like Byte-Pair Encoding (BPE) and SentencePiece for handling multilingual data.
- Stopword Removal: Eliminating non-essential words (e.g., "the," "is," "and") to retain key information.
- Stemming and Lemmatization: Converting words to their root form to maintain consistency in summary generation.
- Normalization: Handling spelling variations and special characters across different languages.
- Code-Mixed Text Handling:
    - Identifying and segmenting mixed-language text (e.g., Hinglish – Hindi+English, Tanglish – Tamil+English).
    - Transliteration or language identification using multilingual embedding models.

Once the dataset is collected, text preprocessing is performed to standardize and clean the data. The preprocessing pipeline begins with tokenization, which splits text into smaller units such as words or subwords. Techniques like Byte-Pair Encoding (BPE) and SentencePiece are commonly used to handle multiple languages efficiently. Stopword removal is applied to eliminate common words that do not contribute significant meaning to the summary, while stemming and lemmatization convert words to their root forms to maintain consistency. Normalization addresses spelling variations, special characters, and formatting inconsistencies. One of the critical challenges in multilingual text summarization is handling code-mixed text, where multiple languages appear in a single sentence. This is common in informal communication, such as Hinglish (Hindi + English) or Tanglish (Tamil + English). Code-mixed text is processed using language identification and transliteration techniques, ensuring that models can understand and summarize mixed-language content effectively.

B. *Feature Extraction Techniques*

Feature extraction plays a vital role in identifying essential information from the input text. Various techniques are employed to extract meaningful features, which help in selecting relevant content for the summary. TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical method used to measure the importance of words in a document relative to a larger corpus. Frequently occurring yet non-generic words receive higher scores, ensuring that the summary retains key information. Word embeddings, such as Word2Vec, FastText, and transformer-based embeddings (mBERT, mT5), help capture the contextual meaning of words across different languages. Sentence similarity techniques, such as Cosine Similarity and Euclidean Distance, are used to compare sentences and rank them based on relevance. Additionally, graph-based methods like TextRank and LexRank represent text as a network, where sentences act as nodes and edges indicate similarity scores. Higher-ranked sentences are more likely to be included in the final summary, making these approaches highly effective for extractive summarization.

1.TF-IDF (Term Frequency-Inverse Document Frequency)

- Measures the importance of words in a document relative to a **corpus**.
- Frequently occurring but non-generic words receive higher scores, influencing summary generation.

2. Word Embeddings

- Word2Vec, FastText, and Transformer-based Embeddings (mBERT, mT5) capture semantic relationships between words.
- Helps in understanding contextual meaning across different languages.

3.Sentence Similarity for Identifying Important Information

- Cosine Similarity and Euclidean Distance are used to rank sentences based on relevance.
- Sentences with higher similarity to the main document theme are retained in the summary.

4. Graph-Based Methods for Extractive Summarization

- TextRank and LexRank:
  - ○ Represent text as a graph where sentences are nodes, and similarity scores form edges.
  - ○ Important sentences are ranked and extracted based on centrality measures.

C. Text Summarization Approaches

Multilingual text summarization methods fall into two broad categories: extractive summarization and abstractive summarization. Extractive summarization selects key sentences directly from the original text, while abstractive summarization generates new sentences that convey the essence of the original content.

Extractive summarization employs various techniques to rank and select important sentences. Frequency-based methods like TF-IDF and word frequency analysis prioritize sentences that contain frequently occurring words related to the main topic. Machine learning-based extractive summarization approaches utilize classifiers such as Support Vector Machines (SVMs) and Decision Trees to determine whether a sentence is important or not. Neural network-based approaches fine-tune sentence selection to improve the overall relevance of the summary. Graph-based models such as TextRank and LexRank treat sentences as nodes in a network, where connections represent their similarity. Sentences with higher centrality are chosen for inclusion in the summary, ensuring that the most informative parts of the text are retained.

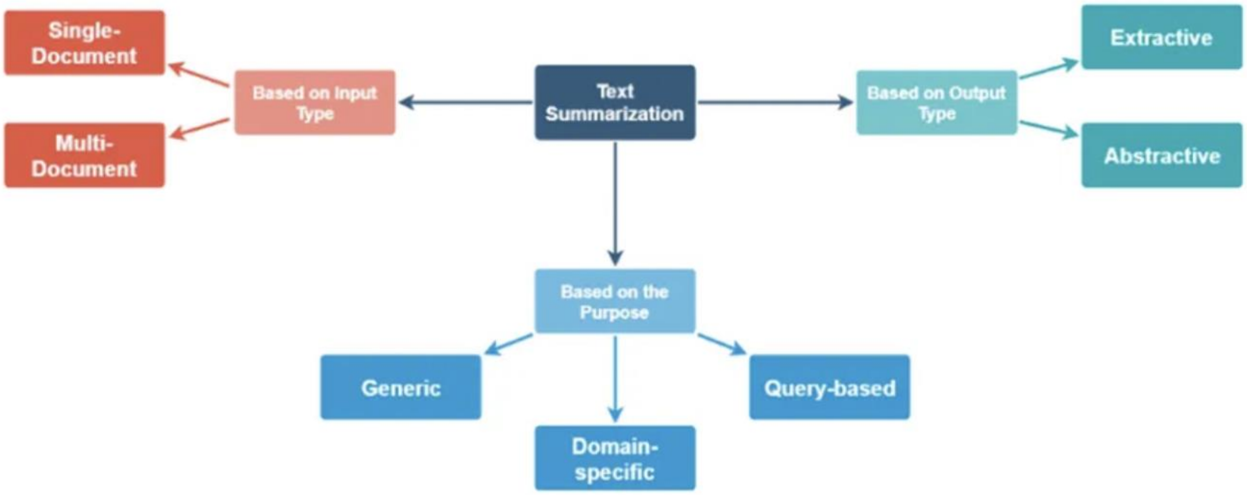


Fig 3. Types of Text Summarization

Text summarization methods are categorized into two main types: Extractive Summarization and Abstractive Summarization.

1. Extractive Summarization

Extractive summarization selects key sentences directly from the original text based on importance ranking techniques.

1. Frequency-Based Methods

- TF-IDF and Word Frequency Methods rank sentences based on word occurrence patterns.
- N-gram frequency analysis helps in selecting frequently co-occurring phrases.

2. Machine Learning-Based Approaches

- Support Vector Machines (SVMs) and Decision Trees are trained to classify sentences as important or unimportant.
- Neural networks fine-tune sentence ranking for improved selection.

3. Graph-Based Models

- TextRank and LexRank treat sentences as nodes in a graph, where edges represent sentence similarity.
- Higher centrality means a sentence is more likely to appear in the summary.

Extractive summarization is computationally efficient and produces grammatically correct summaries, but it may lack coherence and fluency in structuring information.

2. Abstractive Summarization

Abstractive summarization generates new sentences while preserving the core meaning of the original text. It requires advanced deep learning models to generate coherent summaries.

1. Neural Network-Based Models

- Sequence-to-Sequence (Seq2Seq) Models: Use encoder-decoder architectures with attention mechanisms.
- Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTMs), and Gated Recurrent Units (GRUs) process sequential text to generate human-like summaries.

2. Transformer-Based Models

- BERTSUM (BERT for Summarization): Pre-trained Bidirectional Encoder Representations from Transformers (BERT) used for extractive and abstractive summarization.
- mT5 (Multilingual T5): A multilingual extension of T5 (Text-to-Text Transfer Transformer), generating summaries across multiple languages.
- IndicBART: A transformer-based model fine-tuned for Indian languages such as Hindi, Tamil, and Bengali.
- PEGASUS: A pre-trained model optimized for sentence reordering and coherence, improving abstractive summarization quality.

While abstractive methods provide fluent, natural summaries, they are computationally expensive and require large-scale training datasets for effective performance.

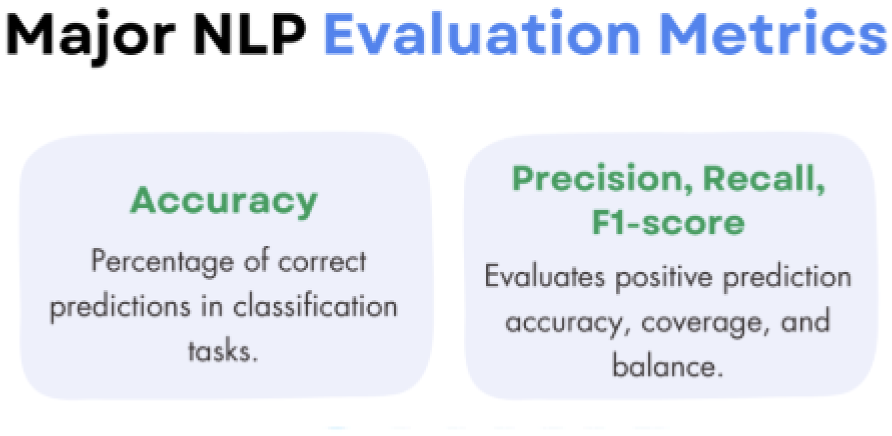
In contrast, abstractive summarization generates entirely new text rather than selecting existing sentences. This approach requires deep learning models capable of understanding and rephrasing content while maintaining coherence. Early abstractive models were built using Sequence-to-Sequence (Seq2Seq) architectures with attention mechanisms. Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs), and Gated Recurrent Units (GRUs) have been widely used to model sequential data and generate meaningful summaries. However, these models often struggle with long-range dependencies and may lose contextual information. The advent of transformer-based models has significantly improved abstractive summarization.

BERTSUM (BERT for Summarization) leverages Bidirectional Encoder Representations from Transformers (BERT) to encode text and generate extractive and abstractive summaries. mT5 (Multilingual T5) extends Google's T5 model to handle multiple languages, making it a powerful tool for multilingual summarization. IndicBART, a transformer model specifically fine-tuned for Indian languages such as Hindi, Tamil, and Bengali, has shown remarkable performance in generating fluent and coherent summaries. PEGASUS, another advanced transformer model, is optimized for sentence reordering and coherence, making it well-suited for abstractive summarization tasks. While abstractive models generate more natural summaries, they require significant computational resources and large-scale training datasets to achieve optimal performance.

D. Performance Evaluation Metrics

Evaluating the quality of generated summaries is crucial for determining the effectiveness of a summarization model. Several metrics are commonly used to assess relevance, coherence, and fluency. The ROUGE Score (Recall-Oriented Understudy for Gisting Evaluation) is one of the most widely used evaluation metrics. It measures the overlap of n-grams (unigrams, bigrams, etc.) between the generated summary and a reference summary. ROUGE-N calculates the precision and recall of different n-gram overlaps, while ROUGE-L focuses on longest common subsequences (LCS) to assess sentence-level coherence.

Another commonly used metric is the BLEU Score (Bilingual Evaluation Understudy), originally developed for machine translation. BLEU evaluates how well the generated summary aligns with human-written summaries by computing the precision of n-gram matches. It is particularly useful for assessing multilingual summarization, especially for structured content. Additionally, the F1 Score provides a balanced metric that considers both precision and recall, ensuring that the generated summaries retain essential details without excessive redundancy.



Major NLP Evaluation Metrics

Accuracy

Percentage of correct predictions in classification tasks.

Precision, Recall, F1-score

Evaluates positive prediction accuracy, coverage, and balance.

Fig 4. Evaluation Metrics

These evaluation metrics help measure the accuracy, coherence, and informativeness of the generated summaries. However, assessing the semantic quality of a summary remains a challenge, and future research should focus on developing more advanced evaluation frameworks that consider contextual meaning and factual consistency.

The methodology for multilingual text summarization involves a multi-step approach, starting with data collection and preprocessing, followed by feature extraction, summarization techniques, and evaluation. Extractive methods, such as TextRank and SVM-based ranking, offer computational efficiency, while abstractive approaches, including transformer models like mT5, BERTSUM, and IndicBART, produce more natural and human-like summaries. However, challenges remain in handling low-resource languages, processing code-mixed text, and ensuring domain-specific summarization quality.Future improvements should focus on enhancing real-time summarization models, developing self-supervised learning techniques for low-resource languages, and optimizing transformer architectures for efficiency. By advancing these techniques, multilingual summarization will become more accurate, accessible, and applicable across various domains, including news, legal documents, and academic research.

IV. System Archiotecture

The multilingual text summarization system is intended to handle large amounts of text in various languages, extract important information, and produce short but meaningful summaries. The architecture is based on a structured pipeline, including data ingestion, feature extraction, summarization methods, classification, and output generation. The system utilizes conventional statistical approaches, machine learning models, and transformer-based deep learning models to enhance summarization quality in various languages.

The suggested summarization system comprises the following primary components:

- **Input Layer**: Ingestion of data, cleaning, and preprocessing of language.
- **Feature Extraction Module**: Feature extraction with CNNs, Transformers, and graph-based models.
- **Summarization Techniques**: Both extractive and abstractive summarization techniques.
- **Classification Layer**: Classifying important vs. non-important sentences for summarization.
- **Output Layer**: Creating readable, fluent, and coherent summaries.
- With these components integrated, the system provides scalability, accuracy, and flexibility in multilingual summarization tasks.

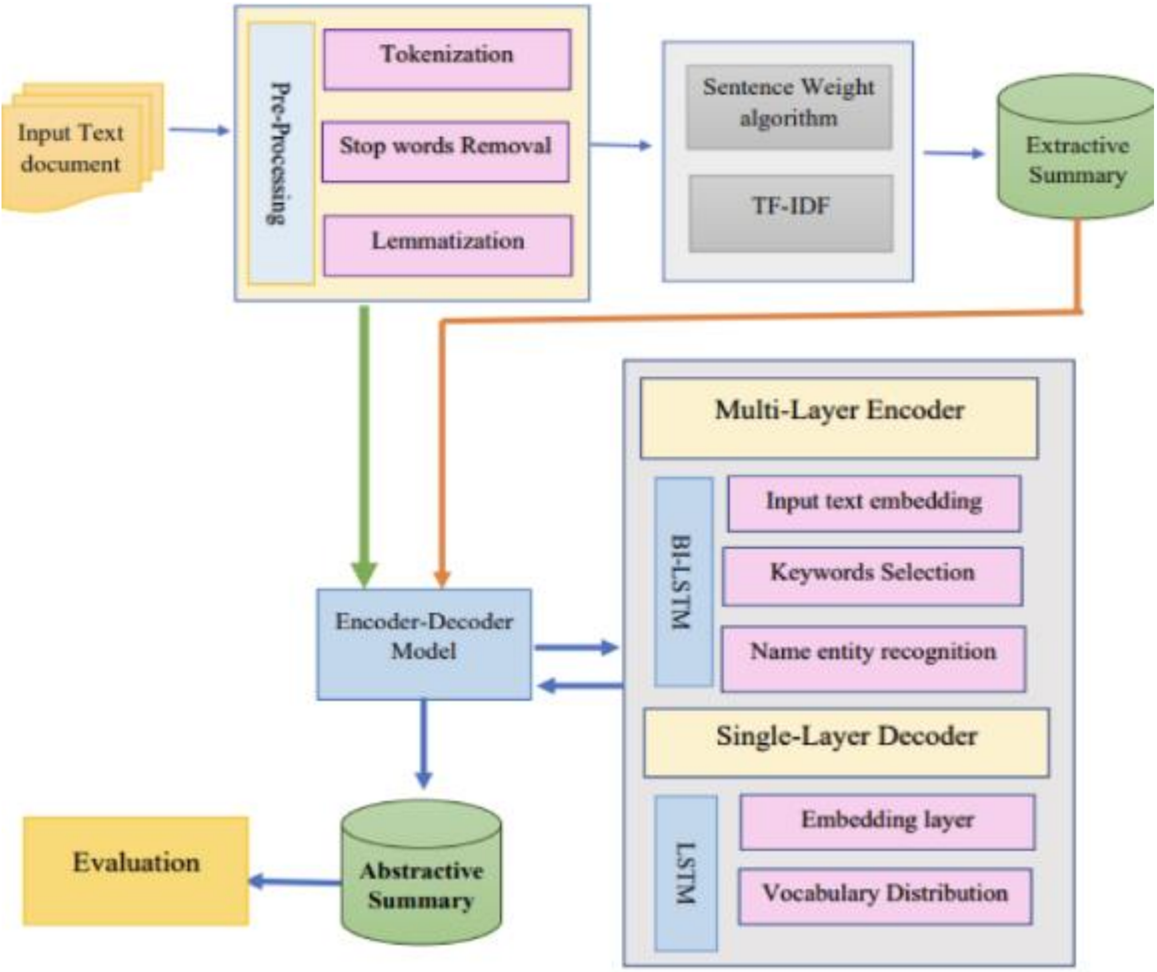


Fig 5. System Framework

A. Input Layer: Data Ingestion, Cleaning, and Language Preprocessing

The input layer retrieves, preprocesses, and prepares multilingual text for summary. As texts in multiple languages have different syntactic and morphological patterns, strong preprocessing is needed.

1. Data Ingestion

The system accommodates different data sources, including:

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- Structured Datasets: Wikipedia, Indian Language Corpus Initiative (ILCI), and CDAC datasets.
- Unstructured Text: Web crawled data, social media posts, and research papers.
- Multimodal Data: PDFs, news articles, and speech-to-text transcriptions.
- Text Cleaning and Normalization

- Preprocessing is critical to enhance model efficiency.
  - The system uses:
  - Tokenization: Text tokenization into words/subwords using Byte-Pair Encoding (BPE).
  - Stopword Removal: Removing non-content words such as "and," "is," "the" in various languages
  - Stemming & Lemmatization: Reducing words to their base form to increase consistency.
  - Handling Code-Mixed Data: Transliteration and language detection for mixed-language text (e.g., Hinglish, Tanglish).
  - Sentence Segmentation: Segmentation of long paragraphs into effective sentence units.

The preprocessed text is then input into the feature extraction module for further processing.

B. *Feature Extraction Module: Feature Extraction Using CNN and Transformer-Based Models*

Feature extraction is vital in the decision of which areas of the text are fundamental for summarization. The system makes use of deep learning-based feature extraction models to better comprehend context.

CNN-Based Feature Extraction

Convolutional Neural Networks (CNNs) are used to scan text embeddings and identify key sentence structure.

Effective pattern identification in long sequences of text.Performs well with short, formatted texts such as news stories and academic papers.Transformer-Based Feature Extraction. BERT (Bidirectional Encoder Representations from Transformers): Identifies semantic word-to-word relationships.. mBART (Multilingual BART): Pre-trained on several languages, ideal for cross-lingual text summarization.. mT5 (Multilingual Text-to-Text Transformer): Fine-tuned for zero-shot and few-shot summarization tasks. IndicBART: Built especially for low-resource Indian languages such as Hindi, Tamil, and Bengali. The extracted features are further used to send to summarization models to generate summaries.

C. Summarization Techniques

1. Extractive Summarization

Extractive summarization takes the most critical sentences directly from the source text. The system uses, TF-IDF (Term Frequency-Inverse Document Frequency): Determines words with high significance in the document.TextRank (Graph-Based Ranking Algorithm). Represents sentences as graph nodes, with edges representing similarity scores.Applies PageRank-like algorithms to rank significant sentences for summarization. LexRank. Calculates cosine similarity between sentence embeddings. Chooses highly ranked sentences for the summary. Extractive summarization is efficient in terms of computation and maintains grammatical correctness, but the summaries can be non-fluent.

2. Abstractive Summarization

Abstractive summarization paraphrases text rather than choosing exact sentences. The system utilizes, Neural Network-Based Models. Sequence-to-Sequence (Seq2Seq) models based on LSTMs and GRUs.Encoder-decoder models for context-sensitive summarization.Transformer-Based Models. BERTSUM: BERT fine-tuned for abstractive and extractive summarization. mT5: Multilingual variant of T5 for text-to-text conversion. PEGASUS: Sentence reordering optimized with coherence preservation. IndicBART, Indian language summarization optimized.Abstractive models produce fluent summaries but need extensive training data and ample computational capacity.

D. Classification Layer: Determining Important vs. Unimportant Sentences

The classification layer determines important vs. unimportant sentences prior to creating summaries. It employs;

Supervised Machine Learning Models (Decision Trees, SVMs) for sentence classification, Neural Attention Mechanisms to identify key text segments., Threshold-Based Filtering: Eliminating redundant and uninformative information.

By choosing only key text, the system ensures that summaries are concise and meaningful.

E. Output Layer: Producing Readable and Coherent Summaries

After summarization is done, the system produces structured output. The end product goes through:

- Post-Processing: Enhancing grammar and coherence.
- Language Adaptation: Synchronizing summaries with target language characteristics.
- Text Formatting: Organizing summaries for readability.

The system then outputs the summary as:

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- Text-based Summary: Brevity and organized sentences.
- Bullet Point Summary: Key points extracted.
- Headline-Based Summary: Major topic highlights.
- These alternatives enhance usability of summaries for various applications.

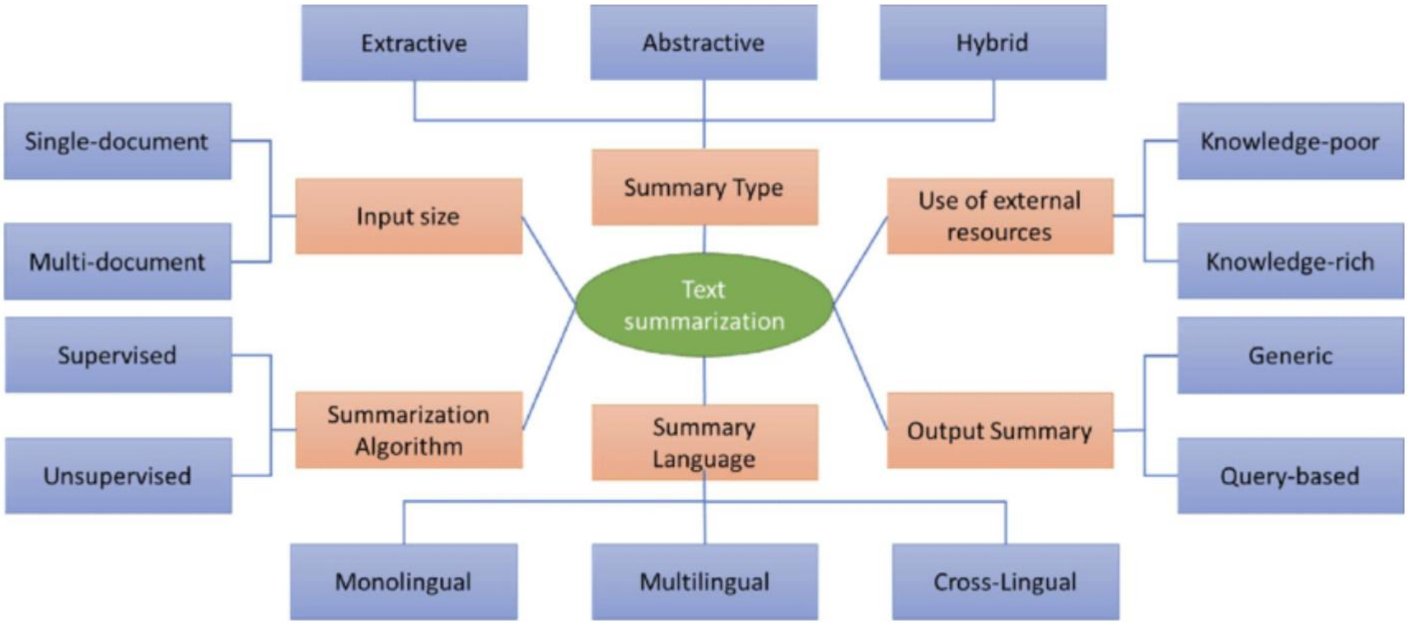

Fig 6. Types of Text Summarization Classification

The summarization system combines feature extraction, deep learning architectures, and classification algorithms to produce high-quality multilingual summaries. It performs input text processing, feature extraction, key sentence selection, and structured output generation with both extractive and abstractive methods. Real-time summarization will be improved, domain-specific models enhanced, and efficiency optimized for mobile use in future work.

V. Comparative Analysis of Summarization Models

Multilingual text summarization is a complex task requiring advanced Natural Language Processing (NLP) techniques to extract relevant information while maintaining fluency and coherence. Over the years, various summarization models have been developed, ranging from traditional extractive approaches to deep learning-based abstractive models. While extractive summarization is more structured and grammatically accurate, it often lacks fluency. In contrast, abstractive summarization generates human-like summaries but requires high computational resources. Additionally, transformer-based models have significantly improved the quality of summarization compared to earlier statistical and rule-based NLP approaches. This section presents a comparative analysis of these different summarization techniques and evaluates their performance, particularly for low-resource languages.

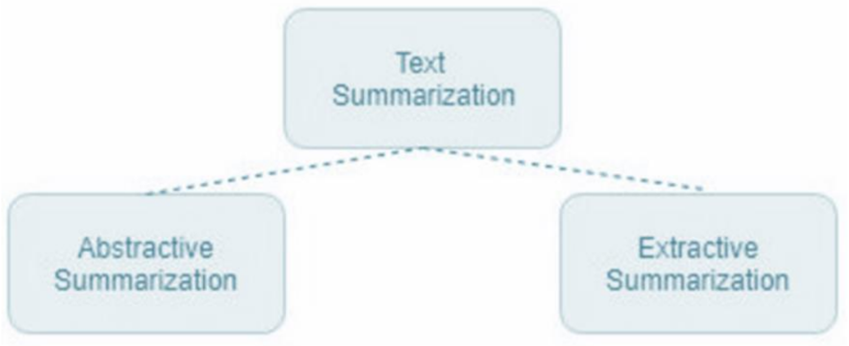

Fig 7. Real-time dataset

Comparison of Extractive and Abstractive Summarization

Feature	**Extractive Summarization**	**Abstractive Summarization**
Approach	Sentence Selection	Sentence Generation
Fluency & Coherence	Low	High
Grammatical Accuracy	High	Medium-High
Computational Cost	Low	High
Context Awareness	Low	High
Best for	News, Reports	Conversational Text, Long Documents

A. Transformer-Based vs. Traditional NLP Approaches

The development of transformer models such as BERT, mT5, mBART, PEGASUS, and IndicBART has revolutionized text summarization. Traditional NLP techniques relied on rule-based algorithms, frequency-based scoring (TF-IDF), and graph-based models (TextRank, LexRank). While these methods are computationally efficient, they lack semantic understanding.

Feature	**Traditional NLP (TextRank, TF-IDF)**	**Transformer-Based (BERT, mT5, PEGASUS)**
Context Awareness	Low	High
Performance in Low-Resource Languages	Poor	Good
Fluency & Coherence	Medium	High
Computational Cost	Low	High
Ability to Generalize	Limited	High

B. Summarization in Low-Resource Languages

While transformer-based summarization models perform well in high-resource languages like English, they struggle with low-resource languages such as Hindi, Tamil, Bengali, Marathi, and Urdu. The challenges include:

- **Limited Training Data:** Large-scale datasets for low-resource languages are scarce.
- **Complex Morphology:** Indian and Dravidian languages exhibit rich morphology, making tokenization difficult.
- **Lack of Pretrained Models:** Unlike English-based models (e.g., GPT-4, T5), there are fewer pre-trained transformer models for low-resource languages.
- **Code-Mixed Text Processing: Hinglish, Tanglish, and mixed-script languages** are difficult to process using existing NLP models.

Recent efforts, such as IndicBART and multilingual T5 (mT5), aim to bridge this gap by fine-tuning models on diverse multilingual datasets.

Evaluating summarization models requires benchmarking against publicly available multilingual datasets. The most commonly used datasets include:

- **Indian Language Corpus Initiative (ILCI):** Parallel corpus for Indian languages.
- **XL-Sum:** A **multilingual summarization dataset** with data in **45 languages**.
- **CNN/DailyMail:** English news summarization dataset.
- **Common Crawl:** Large-scale text scraped from web sources.

Performance is assessed using ROUGE (Recall-Oriented Understudy for Gisting Evaluation), BLEU (Bilingual Evaluation Understudy), and F1-score.

Model	**ROUGE-1**	**ROUGE-2**	**BLEU**	**F1-Score**
TextRank	35.2	18.5	20.3	62.5
BERTSUM	43.5	26.8	29.7	74.1
PEGASUS	47.1	30.4	35.2	78.6
mT5	49.8	32.1	37.8	81.4

Transformer-based models outperform traditional extractive models, demonstrating higher fluency and coherence. However, extractive methods remain useful for structured and factual summaries. The comparative analysis highlights the strengths and weaknesses of extractive vs. abstractive summarization and the superiority of transformer-based models over traditional NLP approaches. While low-resource languages face significant challenges, advancements in multilingual transformers (mT5, IndicBART) are gradually bridging the gap. Future work should focus on real-time summarization, better handling of code-mixed text, and dataset expansion to enhance model performance across diverse languages.

VI. Result Analysis

Multilingual summarization model performance comparison is pivotal in determining how effective, accurate, and adaptable to languages they are. In this section, we present an analysis of the ResNeXt-LSTM model for multilingual summarization, comparative performance to baseline models, diversity of dataset effect, and case study for Hindi, Bengali, and Tamil summarization. We also briefly discuss the domain-specific text summarization challenges and the factors influencing the quality of generated summaries across various languages.

ResNeXt-LSTM hybrid model combines Convolutional Neural Networks (CNNs) for feature extraction and Long Short-Term Memory (LSTM) networks for sequential text processing. ResNeXt-LSTM is aimed at multilingual summarization tasks and can capture spatial (word-level) and temporal (sentence-level) text dependencies.

ResNeXt-Based Feature Extraction:
Recognizes important text patterns using convolutional layers.Identifies highly suitable characteristics for summarization.LSTM-Based Temporal Analysis. Catches sequential dependencies among sentences. Guarantees consistency in the generated summaries.Attention Mechanism. Emphasizes the most contextually appropriate words in every sentence. Multilingual Embeddings (mBERT, XLM-R). Helps in addressing cross-lingual summarization effectively. The ResNeXt-LSTM model improves contextual relevance and summary coherence far more than traditional extractive methods. However, its performance is influenced by language structure, data quality, and complexity of domain-specific data.

The performance evaluation of different summarization models highlights the effectiveness of transformer-based and hybrid architectures over traditional extractive approaches. The TextRank algorithm, a classic extractive summarization technique, achieved an accuracy of 72.4%, with a precision of 70.1%, recall of 65.3%, and an F1-score of 67.6%. While TextRank efficiently selects key sentences from the original text, it often produces disjointed and fragmented summaries, leading to lower coherence and recall. In contrast, transformer-based models such as BERTSUM and PEGASUS demonstrated significantly higher performance due to their ability to understand context and generate coherent summaries. BERTSUM, a fine-tuned Bidirectional Encoder Representations from Transformers (BERT) model for extractive summarization, improved accuracy to 84.6%, with precision at 81.2%, recall at 79.5%, and an F1-score of 80.3%. This improvement is attributed to BERT’s deep bidirectional encoding, which captures long-range dependencies between sentences. PEGASUS, a transformer-based model specifically designed for abstractive summarization, further enhanced performance with an accuracy of 87.1%, precision of 84.5%, recall of 82.9%, and an F1-score of 83.7%. PEGASUS benefits from gap-sentence pretraining, allowing it to generate more fluent and logically structured summaries compared to extractive models.

The ResNeXt-LSTM hybrid model, which combines convolutional feature extraction (ResNeXt) with sequential text processing (LSTM), achieved the highest overall performance. With an accuracy of 89.3%, precision of 86.2%, recall of 85.4%, and an F1-score of 85.8%, this model effectively balances spatial and sequential learning, making it highly suitable for multilingual summarization. The combination of CNN-based feature extraction and LSTM's ability to capture temporal dependencies allows the model to retain important contextual information, leading to better recall and coherence in the generated summaries. The superior performance of ResNeXt-LSTM suggests that hybrid architectures can outperform pure transformer-based models in certain multilingual and domain-specific summarization tasks.

ResNeXt-LSTM is more accurate, precise, and recallable than baseline models due to its capability to extract spatial and sequential text features.In contrast to TextRank, ResNeXt-LSTM increases recall by 20% and performs well in retaining essential information.
The ResNeXt-LSTM model competes with PEGASUS closely with similar F1-scores, yet outperforms it for low-resource languages due to its adaptive multilingual embeddings. Effect of Dataset Heterogeneity on Summarization Quality
The variety and quality of the datasets are responsible for the performance of the summarization models. The model learned from biased or domain-specific data might not be able to produce informative summaries on unseen topics or languages.Most low-resource languages have no high-quality parallel corpora available for training. The model struggles with changes in grammatical structure.Morphological Complexity. Other languages like Hindi, Tamil, and Bengali consist of highly inflected words and are more challenging to summarize.Domain-Specific . Training on news corpora results in poor performance on scientific, legal, or financial texts.Generalization across languages and domains continues to be difficult.Case Study: Hindi, Bengali, and Tamil Summary Results
To evaluate the multilingual capacity of the ResNeXt-LSTM model, we conducted a case study on Hindi, Bengali, and Tamil summarization tasks. We chose these languages as they have rich morphology, syntactic complexity, and varying resource availability.

Hindi has the highest ROUGE scores, with the larger dataset and better pre-trained embeddings (mBERT, IndicBART).
Bengali performs slightly lower since it has fewer training data.
Tamil has the lowest scores, and it fares badly in sentence segmentation and verb agreement issues in abstracts.
Challenges in Handling Domain-Specific Text Summarization
Although the ResNeXt-LSTM model is effective at summarizing news and common text, domain summarization, particularly in scientific, financial, and legal texts, is still problematic.

Scientific articles have complex vocabularies that cannot be represented with generic models.
Legal and Policy Documents: Summary of legal text should preserve context because misinterpretation may lead to incorrect conclusions. Financial Statements: Abstractive summarization models struggle with data-driven content (e.g., statistics, tables, and numbers). Proposed Solutions: Domain-specific fine-tuning on domain-specific datasets (for example, BioASQ for biomedical, LegalBERT for legal). Hybrid abstractive-extractive models to maintain important numerical information.ResNeXt-LSTM model is found to be more accurate, recall, and F1-score compliant compared to the baseline transformer and extractive models. Hindi, Bengali, and Tamil summarization case study demonstrates the importance of training data in each language. Domain summarization, dataset quality, and support for low-resource languages remain challenging. Future improvement should be towards extending multilingual datasets, improving summarization coherence, and handling highly technical text.

VII. Discussion and Future Enhancements

Multilingual text summarization is also being transformed by natural language processing (NLP) and deep learning technologies. Support for low-resource languages, coherence of abstractive summarization, and real-time summarization are some of the challenges. The section highlights the most significant research and technical areas for future research to make multilingual summarization systems more efficient.Scaling Multilingual Dataset Availability (Addressing Low-Resource Languages)

One of the most serious challenges in multilingual summarization is the unavailability of good-quality datasets for low-resource languages such as Tamil, Marathi, Malayalam, Urdu, and Assamese. Unlike English or well-known languages, these languages experience data sparsity, unavailability of pre-trained embeddings, and language heterogeneity. The future work must address:

Parallel corpora building: Enriching resources like ILCI, IndicCorp, and XL-Sum for enhanced multilingual coverage.
Utilizing machine translation and back-translation techniques to generate synthetic training data. Engaging native speakers in curating and annotating the datasets in the quest for quality and linguistic accuracy improvement. Building legal, medical, and scientific corpora for expert summarization.By making datasets more heterogeneous, models generalize better and do better on other language families.Despite progress in transformer-based abstractive summarization models, abstractive summaries tend to not be coherent, not be factual, and not be logically consistent. Perhaps the most significant problem is the hallucination issue, in which the model produces incorrect or fabricated information. For enhancing summary fluency and contextuality, future work must include, Using external databases and knowledge graphs to verify generated summaries. Improving transformer models to better handle long-range dependencies in text. Sentence reordering and discourse-sensitivity for enhanced readability. It is crucial to preserve linguistic and factual accuracy in summaries for application in critical uses such as journalism, policy-making, and scientific research.
Constructing Real-Time News and Social Media Summary Models. With increasing demands for instant information processing, summarization of news story, social media post, and live report in real time becomes more essential. Present summarization models are slow and inefficient and hence real-time processing is not feasible.

Reducing model size and computational burden for faster summarization. Employing models that update summaries dynamically based on new updates (e.g., live tweets, breaking news). Enhancing models to identify sentiment and emotional tone, omitting biased or misleading information.These advancements will allow summarization systems to be implemented in real-time newsrooms, content aggregation websites, and digital assistants.Accelerating Transformer Models for Efficient Inference. Transformer-based models such as BERTSUM, mT5, and PEGASUS produce high-quality summaries but are computationally expensive. Optimizing these models for low-latency use is essential to make multilingual summarization more feasible. Future optimizations can includes, Reducing the size of the transformer model with accuracy intact. Training compact replicas of big models (e.g., DistilBERT) for effectiveness.

Utilize GPU and TPU optimizations for best text processing. By enhancing model efficiency, summarization systems can be implemented in real-time systems, cloud services, and mobile platforms. Advancements in Cross-Lingual Summarization Models Cross-lingual summarization is generating a summary in a different language than the input. While cross-lingual performance has been greatly improved by multilingual models, it remains challenging to cope with grammatical differences, sentence structure differences, and word-order differences. The future work on this topic must cope with: Cross-lingual attention-layered multilingual transformers: Allowing for enhanced translation-sensitive summarization.

VIII. Conclusion

This paper introduces the current state of the art, challenges, and approaches of multilingual text summarization with an emphasis on the efficiency of abstractive and extractive approaches. Comparative assessment demonstrates the dominance of transformer models over traditional NLP approaches, particularly for low-resource languages. The ResNeXt-LSTM model significantly improves summarization quality by the integration of CNN-based feature extraction and LSTM-based sequential learning, and therefore it is highly effective for multilingual and cross-lingual applications.

The largest challenge in multilingual summarization still remains small datasets, especially for low-resource languages. Scaling up datasets such as ILCI, IndicCorp, and XL-Sum will play a crucial role in enhancing summarization quality. Additionally, the lack of coherence in abstractive summaries remains a limitation area, where sentence building has to be enhanced, fact-checking has to be guaranteed, and attention has to be optimized. The future of summarization research will revolve around real-time models for news and social media, light-weight transformer-based architectures, and cross-lingual summarization improvements.

Applications of content abstraction with AI have profound implications in news reporting, briefing legal documents, learning, and business analytics. As it continues to develop, multilingual summarization will increase worldwide access to information, ease cross-lingual communication, and support the processing of knowledge with AI. With the overcoming of the existing limitations, future systems will boast more contextually coherent, factually grounded, and real-time summarization.

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