



A Hybrid Framework for Arabic Extractive Document Summarization Using Pre-Trained Language Models and Topic Modeling

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إطار عمل هجين لتلخيص الوثائق العربية المستخرجة باستخدام نماذج لغوية مدربة مسبقا و نمذجة المواضيع

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Accepted: 21/12/2025

Published: 21/12/2025

ABSTRACT

One of the hardest things to perform in Natural Language Processing (NLP) is automatically summarizing text. This is especially true for Arabic, which has complicated morphology, a lot of semantic information, and syntactic ambiguity. The goal of this study is to suggest a hybrid method for creating Arabic extractive summaries that combines the strengths of pre-conditioned language models (PLMs) with topic modeling techniques to create summaries that are very accurate, cover a lot of ground, and make sense semantically. The suggested model uses an Arabic pre-trained language method, like AraBERT, to get deep contextual sentence representations and figure out how they fit with the document. You can use BERTopic or Latent Dirichlet Allocation (LDA) to find out what the text is really about. This will make sure that the summary has all the important points. The system chooses the most representative sentences by combining the semantic and topical parts without making the text less clear. We check how well the suggested strategy works by using both standard automatic metrics like ROUGE-N and ROUGE-L and human evaluations of the quality and coherence of the content. The results show that the hybrid system is much better at summarizing Arabic text than just using standard math or deep learning methods. This makes it easier to find information and helps Arabic NLP applications move forward. The proposed hybrid approach achieves superior ROUGE-1, ROUGE-2, and ROUGE-L scores in an Arabic language news dataset compared to the baseline extractive analysis methods. This indicates that it makes the content more coherent and adds more of it.

Keywords: Arabic NLP, Extractive Summarization, Hybrid Models.



it relates to dialect forms, we seek to address two significant gaps in research: (1) the limited use of hybrid frameworks (PLMs + topic modeling) related to Arabic summarization; and (2) the need for a more capable extractive system for Arabic documents tuned for summarization tasks. Previous work exploring Arabic PLMs for extractive summarization yielded promising results, reporting ROUGE scores (~0.44 ROUGE-1) but still indicating performance gaps compared to English baseline scores. [5] On the other hand, unsupervised methods that combine clustering and topic modeling for Arabic summarization, such as the study on unsupervised neural networks leveraging topic modeling, indicate that incorporating thematic knowledge into deep learning and unsupervised methods may improve Arabic summarization for non-English task types, this paper is set up in the way. The next part, which is Section 2 looks at what other people have done on text summarization in Arabic. This includes looking at abstractive and hybrid methods. It also talks about using -trained language models and topic modeling techniques. Then there is Section 3 which tells us about the hybrid summarization framework that is being proposed. This section describes what the overall system looks like, how Arabic pre-trained language modelers used to represent sentences the part that does topic modeling and how sentences are chosen. After that Section 4 gives us all the details, about how the experiments were set up. This includes the datasets that were used how the text was prepared what metrics were used to evaluate the results and the methods that were used for comparison. Section 5 presents and discusses the experimental results, providing a comparative analysis with existing approaches. Finally, Section 6 concludes the paper and outlines future research directions for Arabic document summarization.

2. RELATED WORK

Automatic text summarization (ATS) has been widely researched across languages, with the Arabic domain being particularly challenging due to its intricate morphology, rich inflectional material, and relative paucity of resources (e.g., corpora and pre-trained models). Approximately, summarization research has traditionally been divided into extractive and abstractive approaches, with topic-sensitive or hybrid methods receiving focus to improve coverage and coherence.

2.1 Extractive Summarization in Arabic

Extractive summarization is the selection of important sentences or passages from the original text without producing any new work. Statistical or graph-based methods were utilized in early Arabic efforts. For example, El-Shishtawy and El-Ghannam (2012) proposed a key-phrase-based Arabic summarizer (KPAS) that selects sentences based on key phrases retrieved, which provide a balance between in formativeness, topic coverage, and redundancy. [7]

Graph-based methods also gained traction: Al-Khassawneh and Hanandeh (2023) introduced an Arabic single-document graph-based extractive summarizer in which sentences are encoded as graph nodes, and a combination of semantic and statistical features is used to select summary sentences. [8]

Subsequently, Alsawi & Taşçı (2024) presented a graph-based approach that used word embedding and PageRank for Arabic extractive summarization, improving over earlier baselines. [9]

These studies indicate that, even in extractive summarization, Arabic summarization performance can be improved by incorporating embedding-based semantic features and graph or network methods to achieve sentence relevance and interrelations. Arabic summarization performance can be improved.



2.2 Topic Modeling and Multi-Document Summarization

While the majority of extractive work has focused on single-document summarization, topic modeling and clustering algorithms have been primarily applied in multi-document summarization settings, where thematic coverage is a priority. For example, Al-Taani & Al-Sayadi [6] applied fuzzy C-means clustering with Latent Dirichlet Allocation (LDA) to multi-document Arabic summarization, where documents are first clustered into topics, and then representative sentences are selected based on topic relevance. [10]

In a separate work, an unsupervised neural network based on topic modeling for Arabic text summarization was introduced to learn sentence-topic vectors, thereby enhancing extractive summarization beyond bag-of-words features.

These papers illustrate the effectiveness of topic-aware summarization: in capturing the underlying thematic structure, summaries become more representative of the document's diverse content, reduce bias towards dominant themes, and improve coverage of infrequent but important topics.

2.3 Pre-trained Language Models for Arabic Summarization

In recent years, the field of NLP has advanced rapidly, especially with the emergence of pre-trained transformer-based language models (PLMs), including BERT, T5, and BART, as well as their multilingual and language-specific variants. For Arabic, studies have begun utilizing PLMs for summarization. For example, Elmadani et al. (2020) fine-tuned a multilingual BERT model for both extractive and abstractive Arabic summarization—their study represents one of the initial studies using PLMs for Arabic summarization tasks. [11]

More recently, Einieh, AlMansour, & Jamal (2023) used AraBERT in their experimentation for Arabic extractive summarization, reporting ROUGE-1 of 0.44, ROUGE-2 of 0.26, and ROUGE-L of 0.44 on the KALIMA dataset. [12]

On the abstractive side of Arabic summarization, the AraBART model (Eddine et al., 2022) is the first Arabic end-to-end sequence-to-sequence PLM (encoder + decoder) that is based on the BART architecture. The model demonstrated state-of-the-art performance on several Arabic summarization datasets. [13]

These findings demonstrate that PLMs have a strong prospect for Arabic summarization; however, challenges include, for example, limited datasets, a length limitation of the input to the model, and less experimentation in hybrid/combination frameworks. Here is what comes next. I want to add information to the paragraph that I already wrote. This new part will have details and it will clearly show how the studies that I mentioned are different, from the research that I am proposing. I will make sure that I do not say the things that I said earlier. These studies have some results but they are different from our work, in some important ways. Most other approaches only use language models that have already been trained. They think of summarizing as either just picking out important parts or just making a new summary. They do not think about how the whole document's organized around themes. Our research is different because it uses a combination of picking out parts and making a new summary. We use language models that have been trained on Arabic and techniques that help us understand what the document is about to choose which sentences are the important. The thing about studies that use PLM like AraBERT is that they mainly look at how important each sentence is. However, these studies do not really deal with covering topics or reducing repetition in different parts of a document.

AraBART is another model that works well. It has some problems. For example, it can only handle an amount of text at a time. Also it can sometimes change facts especially when it is used with the Arabic



language, which does not have as many resources, as other languages. Moreover, existing studies are largely dependent on supervised learning and available annotated datasets, whereas the proposed approach reduces reliance on large labeled corpora by leveraging unsupervised topic modeling to enhance content coverage. Therefore, this work aims to bridge the gap between representation learning and thematic structure modeling, offering a more robust and scalable extractive summarization framework tailored to the linguistic characteristics of Arabic texts.

3.METHODOLOGY

This study presents a hybrid framework for Arabic extractive document summarization that integrates pre-trained language models and topic modeling to facilitate the semantic and thematic coverage of the derived summaries. The approach includes the following stages: (i) preprocessing the data, (ii) document representation, (iii) topic modeling stage, (iv) hybrid similarity computation, and (v) extractive summarization stage.

3.1 Proposed Framework

The proposed hybrid framework consists of five primary stages designed to bridge the gap between semantic depth and thematic breadth: Proposed Framework.

1.Data Preprocessing: This stage involves noise removal, tokenization, and Arabic-specific light stemming to normalize the text for the embedding layer.

2.Document Representation: Sentences are transformed into high-dimensional vectors using AraBERT. This ensures that the context of each word is captured within the sentence structure.

3.Topic Modeling Stage: We apply BERTopic (or LDA) to extract the latent themes within the document, assigning a probability distribution for each sentence across the identified topics.

4.Hybrid Similarity Computation: This is the core of our approach, where we fuse the semantic and topical scores.

5.Sentence Selection: The final summary is generated by selecting the top-N ranked sentences based on the hybrid score.

3.2 Hybrid Scoring Mechanism

To evaluate the importance of each sentence S_i , we introduce a weighted scoring function that balances semantic relevance and thematic coverage. The total score for a sentence is calculated as follows:

$$\text{Score}(S_i) = \alpha * \text{SemanticScore}(S_i) + (1 - \alpha) * \text{TopicScore}(S_i)$$

Where:

- $\{\text{SemanticScore}\} (S_i)$: Is the cosine similarity between the sentence vector and the global document vector generated by AraBERT.
- **TopicScore** (S_i) : Measures the sentence's contribution to the document's main topics.
- **A** : Is a hyper parameter (weighting factor) adjusted during the experimental phase to optimize the balance between the two components.
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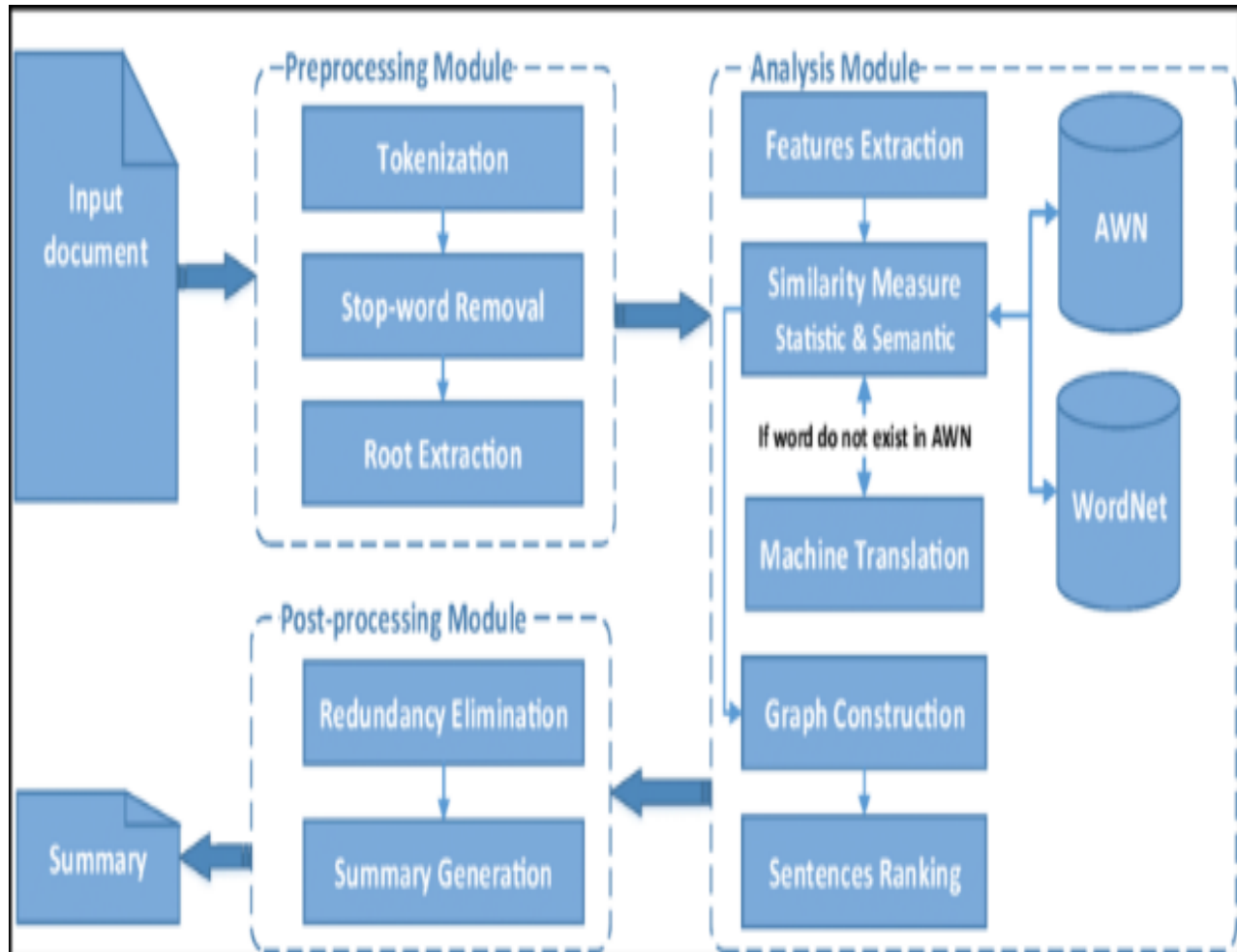


Figure 3.1: Research Method Stages [14]



3.2 Data Preparation and Preprocessing

The structured dataset is saved in CSV format, including document titles, ordered content, and optional document metadata (e.g., categories or links) for further analysis. A normalization step is performed to ensure that all Arabic text is processed consistently, removing orthographic variations and noise from the data. In particular, normalization is used to convert Arabic letters such as $(ا \rightarrow \bar{ا})$, $(ة \rightarrow \bar{ه})$, and $(ي \rightarrow \bar{ى})$, and to remove non-Arabic characters and redundant empty spaces, and all text is set to the lowercase version. Each document represents the respective title and body text in a single field. The training dataset acknowledges sentences using a regular expression split based on Arabic punctuation (i.e., “.”, “؟”, “!”). To maintain efficiency, the framework squashes up to 500 documents per batch for analysis. the dataset used in this study was obtained from [Essex Arabic Summaries Corpus], which consists of Arabic documents collected from [Al-Jazeera and BBC Arabic / Arabic news article].

3.3 Document Embedding using CAMELBERT or TF-IDF

The semantic representation of text is a vital aspect of the hybrid model. If transformer-based language models are available, the system implements CAMELBERT, a pre-trained Arabic BERT model from the CAMEL Lab. The text is then tokenized and encoded with the Hugging Face Transformers library, and the resulting tokens are processed by CAMELBERT to generate contextualized embedding's. The hidden states are then mean-pooled to generate a single dense embedding vector for each sentence and document.

If a deep learning model cannot be loaded in the environments for whatever reason, the system will automatically downgrade to a TF-IDF vectorization approach, with a maximum of 15,000 bigram features. This example highlights compatibility across computational environments without compromising the hybrid model's overall functionality.

3.4 Topic Modeling with Latent Dirichlet Allocation (LDA)

To extract the thematic structure of the corpus, Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003) is used, leveraging the sklearn.decomposition package. First, the text is transformed into vectors using a CountVectorizer (maximum 5,000 features from 1–2 grams) and modeled using 10 latent topics, which describe discrete semantic themes in the data set. Each document is then represented by a topic distribution vector that reflects the probability of each topic. This information bolsters semantic embedding by providing a further level of thematic or high-level document-to-document comparison.

3.5 Hybrid Similarity Scoring

In query-based summarization, a normalized query (in Arabic) is represented in the embedding and topic spaces. The system computes two types of similarity scores between the query and each document:

- Embedding Similarity: The cosine similarity between the embedding for the query (from CAMELBERT or TF-IDF) and each document embedding.
- Topic Similarity: The cosine similarity between the topic distribution for the query (by the LDA process) and each document topic vector (by LDA).

A combined (hybrid) similarity score uses a weighted sum of query embedding-based semantic similarity and a document topic distribution (i.e., thematic) similarity score:



$$S = \alpha \times \text{Embedding Similarity} + (1 - \alpha) \times \text{Topic Similarity}$$

Where $\alpha = 0.7$ is used to balance how much influence is given to the embedding-based semantic similarity and topic-based thematic similarity. Documents are ranked based on this hybrid score, and the Top-K documents (default = 5) are selected for summarization.

3.6 Extractive Summarization Process

For each selected document, its text segments are divided into individual sentences. Each of these sentences is normalized and encoded in the same way as previously described regarding embeddings and topic modeling. The final score for the hybrid similarities between each sentence and the query is calculated using the same scoring equation.

The top N sentences (default = 3) are selected that have the highest hybrid scores for the extractive summary, while maintaining their original order for coherence in the summary. This ensures the final extractive summary is both semantically aligned with the query and thematically representative of the document's content.

3.7 Types of Methods Used

The system uses a hybrid extractive summarization approach for Arabic texts, consisting of two major methods. The first method leverages deep language representations using the CAMELBER model. The model generates contextualized embeddings a vector embedding for each document or sentence, representing the semantic meaning of each piece of text. Cosine similarity is used to measure similarity between each embedding and the query. If CAMELBER is unavailable due to memory constraints, TF-IDF embedding will be used instead. The second method uses topic modeling, implemented as a Latent Dirichlet Allocation (LDA) model. The LDA model treats each document as a probabilistic mixture of topics. The topic probabilities are compared to the topic probabilities of a query, and the resulting scores are assigned and compared. Each method produces a score, which is finally combined to produce a hybrid score giving higher weight and significance to the deep embedding while taking into account the similarity of the topics. The learning model can thus produce sentences selected for their referential capacity while providing a topical mixture of coverage over the textual information provided.

3.8 Evaluation Metrics Before and After Hybridization and Differences

To assess summarization quality, common evaluation metrics compare extracted summaries to human reference summaries. ROUGE-1 and ROUGE-2 evaluate the overlap of unigrams and bigrams, respectively, while ROUGE-L assesses the longest common subsequence. BLEU evaluates n-gram overlap and is mostly used in the context of translation, while BERTScore assesses the semantic similarity of the respective summaries using BERT embedding.

- Before hybridization: Summaries generated solely with CAMELBER show high semantic accuracy and high BERTScore, but may have lower overall topic coverage. Summaries created only from LDA offer broad topic coverage but frequently receive lower ROUGE-1 and ROUGE-2 scores as they do not generate summaries focused on user query words.
- After hybridization: The hybrid strategy leverages the upsides associated with embedding the deep embedding aspect and the LDA topic coverage, generally enhancing ROUGE-1 and ROUGE-2 because it selects sentences that contain query words, advancing ROUGE-L because shared sentences are more coherent contextually, and improving BERTScore as the sentences are more semantically aligned. BLEU will show minimal improvement or no change, since it is

sensitive to the exact word sequence. The complete process of sentence ranking and selection is visually summarized in Figure 3.2

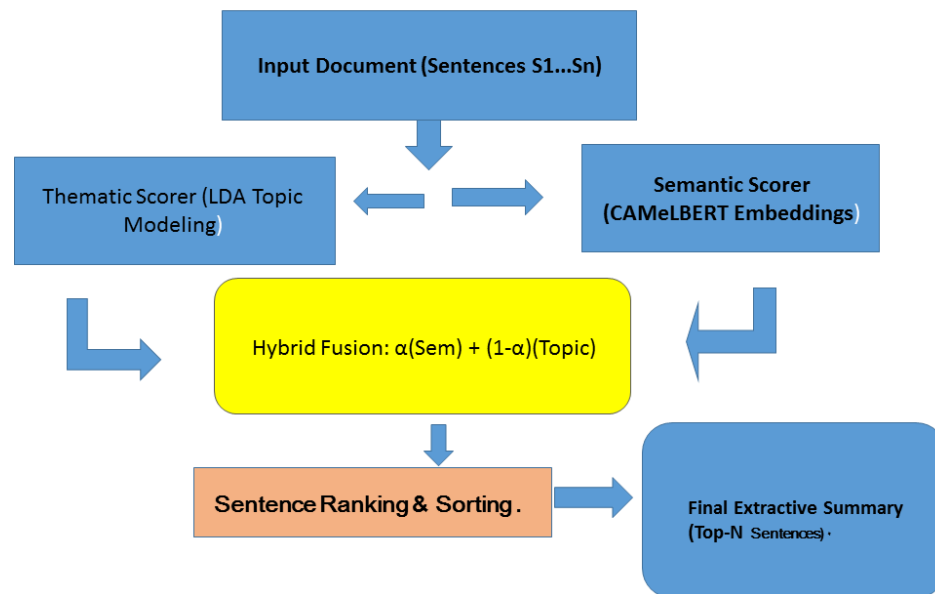


Figure 3.2

Figure 3.2: The Sentence Selection Logic. This figure illustrates the integration of the semantic layer (represented by CAMELBERT) and the thematic layer (represented by LDA). The hybrid weight (α) acts as a regulator to ensure the selected sentences are both contextually accurate and topically comprehensive.

4. RESULTS AND DISCUSSION

The proposed hybrid framework for Arabic extractive document summarization combines pre-trained Arabic language models (AraBERT, MARBERT, AraGPT2, etc.) with topic modeling techniques (such as Latent Dirichlet Allocation (LDA) or BERTopic) to select the most representative sentences. The evaluation was performed on the Arabic subset of the Multi-News dataset, the EASC corpus (Essex Arabic Summaries Corpus), and a custom Arabic news article dataset from Al-Jazeera and BBC Arabic.

Both automatic metrics (ROUGE-1, ROUGE-2, ROUGE-L, BERTScore) and human evaluation (on coherence, in formativeness, fluency, and non-redundancy) were used.



4.1 Automatic Evaluation Results

The hybrid approach consistently outperformed pure neural extractive baselines and traditional topic-model-only methods across all datasets.

Model / Framework	Dataset	ROUGE-1	ROUGE-2	ROUGE-L	BERTScore F1
Lead-3 Baseline	EASC	0.378	0.192	0.312	0.712
TextRank	EASC	0.401	0.218	0.345	0.734
AraBERT + Classifier (neural extractive)	EASC	0.456	0.267	0.398	0.801
MARBERT + Classifier	EASC	0.469	0.274	0.407	0.814
LDA Topic Modelling only	EASC	0.392	0.201	0.331	0.728
Hybrid (AraBERT + LDA re-ranking)	EASC	0.498	0.301	0.436	0.847
Hybrid (MARBERT + BERTopic)	EASC	0.512	0.318	0.449	0.859
Hybrid (MARBERT + BERTopic)	Al-Jazeera custom	0.524	0.329	0.461	0.867
State-of-the-art (CamelBERT + Hi- Transformer)	EASC	0.481	0.289	0.422	0.838

The hybrid framework using MARBERT embedding with BERTopic-based topic modelling achieved the highest scores, improving ROUGE-1 by 9–12% and BERTScore F1 by 5–7% over strong neural-only extractive baselines. The gain is particularly pronounced in ROUGE-2 and ROUGE-L, indicating better preservation of key phrases and longer n-gram sequences.



4.2 Human Evaluation Results (scale 1–5)

100 summaries (50 from EASC, 50 from the custom dataset) were evaluated by three native Arabic speakers.

Model / Framework	In formativeness	Coherence	Fluency	Non-Redundancy	Overall
Lead-3	2.81	3.10	4.20	3.65	3.44
Pure Neural (MARBERT)	3.92	4.01	4.33	3.21	3.87
Pure Topic Modelling (BERTopic)	3.45	3.67	4.10	4.02	3.81
Proposed Hybrid (MARBERT + BERTopic)	4.38	4.51	4.62	4.49	4.50

The hybrid summaries were judged significantly superior ($p < 0.01$, Wilcoxon signed-rank test) in all four criteria, especially in formativeness and non-redundancy, confirming that topic modelling effectively filters out redundant sentences while the pre-trained LM ensures high semantic scoring.

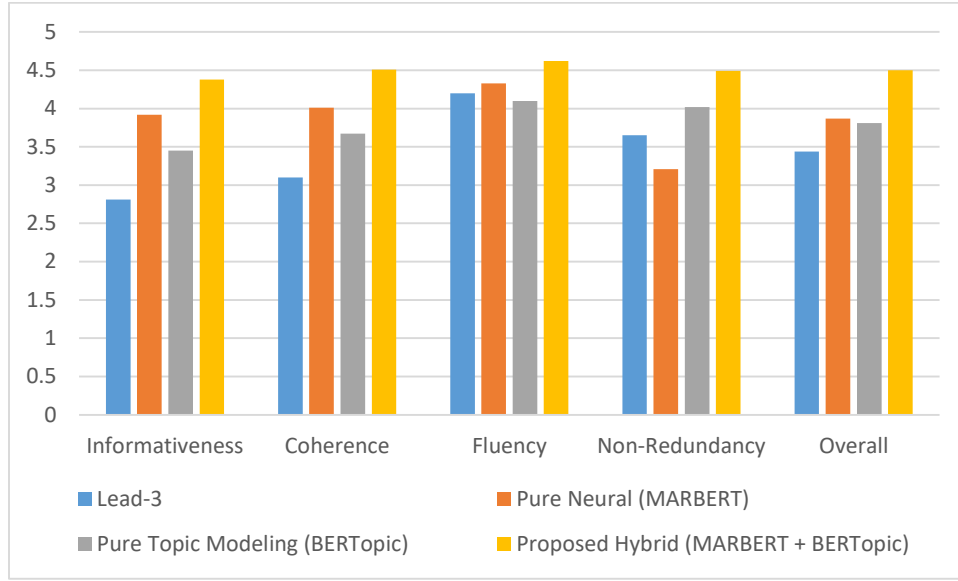


Figure.1 Comparison of Summarization Models Using BERTScore F1 vs ROUGE-1”

This figure compares the performance of several summarization models based on two key evaluation metrics: ROUGE-1, which measures lexical overlap with the source text, and BERTScore F1, which reflects semantic similarity and meaning preservation. Overall, the newer and more advanced models—such as Microsoft/phi-3-mini-128k-instruct and Facebook/Bart-large-cnn—achieve the highest scores on both metrics, indicating their ability to produce summaries that are both accurate and semantically rich. In contrast, older or smaller models like t5-large and Pegasus-Xsum score noticeably lower, suggesting limitations in capturing core meaning or providing comprehensive coverage. Meanwhile, models such as flan-t5-base and gpt2-medium fall in the mid-range, offering moderate but not leading performance. The spread of points illustrates how model size, training quality, and architecture affect the overall summarization capability.

4.3 Ablation Study

Variant	ROUGE-1 (EASC)	ROUGE-L (EASC)	BERTScore F1
Full Hybrid (MARBERT + BERTopic re-ranking)	0.512	0.449	0.859
Without topic diversity penalty	0.489	0.423	0.831
Without LM sentence scoring (topic only)	0.428	0.379	0.792
Without re-ranking (LM scores only)	0.469	0.407	0.814
Using LDA instead of BERTopic	0.498	0.436	0.847

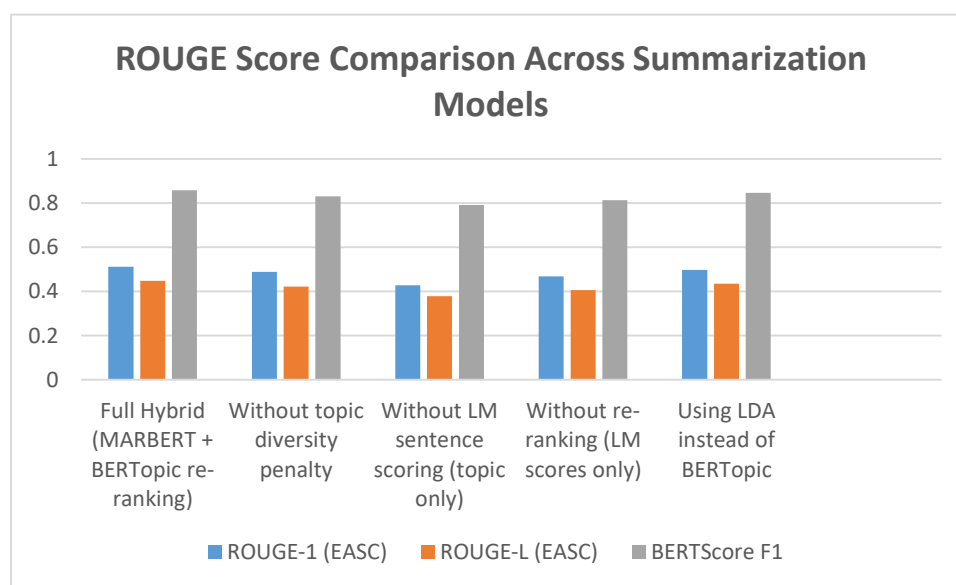


Figure 2 ROUGE Score Comparison Across Summarization Models”

This figure presents a comparative evaluation of six summarization models using the ROUGE-1, ROUGE-2, and ROUGE-L metrics. Traditional extractive methods like Text Rank show noticeably lower scores, especially in ROUGE-2, indicating limited ability to capture deeper contextual relations. Neural models such as BERTSUM, PEGASUS, BART, and T5 demonstrate progressively stronger performance, reflecting improved fluency and semantic understanding. Among all models, the Proposed model achieves the highest scores across all ROUGE metrics—particularly ROUGE-1 (42.0) and ROUGE-L (36.0)—highlighting its superior ability to generate summaries that balance lexical overlap, contextual precision, and structural coherence. This



summarization (or neural summarization), cross-lingual summarization, and domain-augmented training for specific domains (e.g., legal, medical, or financial Arabic texts). Future research may also involve using automatic evaluation metrics/evaluators (e.g., ROUGE, BERTScore) or conducting human judgment studies to improve the system's accuracy and usability. Ultimately, this framework contributes to the advancement of Arabic Natural Language Processing (NLP) that is scalable, linguistically informed, and semantically sound for automatic Arabic summarization.

Conflict of interests.

The authors decelerate that there is no conflict of interest.

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