International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys.13, No.1 (Mar-23)

http://dx.doi.org/10.12785/ijcds/130138

An Extractive Summarization for utilizing Learning Content using Deep Learning algorithm: Proposed Framework and Implementation

Yusra AlRoshdi[1], Mohammed AlBadawi[2], Abdullah Alhamadani[3] and Mohamed Sarrab[4]

[1,2,3]*Department of Computer Science, Sultan Qaboos University, Muscat, Oman*
[4]*Data Services Department Research Division, Organization of the Petroleum Exporting Countries (OPEC), Vienna, Austria*

Received 17 Aug. 2022, Revised 30 Oct. 2022, Accepted 5 Mar. 2023, Published 16 Mar. 2023

Abstract: Education has always been a critical factor in the long-term economic development of any society. Most educational institutions use Learning Management Systems (LMSs) to manage and organize students' learning content. These systems contain many learning materials related to a specific topic or course in different formats, such as documents, HTML pages, videos, figures, etc. However, the enormous amount of information in these materials makes it difficult for students to get what they need according to the course objectives. Therefore, summarization techniques could be one way to facilitate the learning process and provide essential content. Therefore, there is a need to summarize the learning content of the course in the guidance of the course outline. Consequently, it is important to investigate how to summarize learning content to enhance and increase students' achievement. This paper proposes a framework for a Guided Extractive Summarization of the Learning Content (GESLC). The main contribution is proposing and developing a novel framework combining several deep learning algorithms to provide efficient summarization techniques to summarize the learning content according to the course outline. Several methods are utilized in this study to evaluate the proposed Framework. As we contribute, the evaluation process shows better results in guiding instructors or students to summarize learning content according to the course objectives to finally have a perfect summary matching the learning process's objectives and enhancing the students' achievement.

Keywords: : Learning Content, Course outline, Summarization, Extractive Summarization, Knowledge Dissemination, Restricted Boltzmann Machine

1. INTRODUCTION

Nowadays, learning is a necessary process to increase the knowledge of individuals. It is acquiring new or modifying existing knowledge, behavior, skills, or values. The current generation of learners is immersed in technology and considers it a vital learning tool. Therefore, coping with this education revolution by using technology to produce e-learning concepts. E-learning, distance learning, and Blended Learning are widespread among educational institutions worldwide. Most institutions use Learning Management Systems (LMS) to provide their students with learning materials and organize the learning process. That LMS contains materials for each course, which includes a large amount of content related to a specific course. However, the regular summarization techniques summarize the content and provide a summary for all content. On the other hand, we need to summarize according to specific objectives and aims that achieve the course plan and enhance the students' achievement. Therefore, this paper focuses on proposing a framework that summarizes the course content available in LMS for a specific course according to the course outline of that course using deep learning algorithms to enhance the accuracy of the summary and provide instructors and students with an accurate summary that achieves the course objectives.

A. E-learning

There are many definitions of e-learning. For example, in the early 2000s, Pollard and Hillage defined it as "The delivery and administration of learning opportunities and support via computer, network, and web-based technology to help individuals' performance and development"[1]. E-learning systems contain many components and tools that manage any learning content. For example, educational institutions use LMS to manage online learning content for a wide range of learners anytime and anywhere.

B. Learning Content

LMS contains a massive amount of data in multiple formats [2]. For example, the learning materials in these

E-mail address: : s95653@student.squ.edu.om, mbadawi@squ.edu.om, abd@squ.edu.om, msarrab@opec.org

systems could be documents (e.g., E-books, tutorials, reports, case studies, slides), videos, figures, diagrams, etc. These learning materials contain a large amount of information, building students' knowledge. However, the massive amount of learning content makes the learning process challenging to obtain helpful information that achieves the course objectives. Therefore, effective summarization techniques will facilitate eliciting of essential information from those materials.

C. Informal and Formal Learning

There are two types of learning [3]: formal and informal. Formal learning is structured and comes from a known educational institute, i.e., the learning that is a form of courses in classrooms resulting in having grades and degrees and receiving a certificate. In informal learning, students observe, experiment, ask for help, converse, listen to stories, reflect on the day's events, and pursue general interests [3]. Learning through social media is considered informal learning because learners receive unstructured information to different knowledge, or they can ask and answer questions about anything they want to learn. Social media could build cumulative knowledge for users and change their learning culture. It supports learning through cooperative exploration, play, and innovation rather than individualized instruction [4]. Also, some researchers discuss examples of traditional knowledge repository systems such as databases, project websites, and shared whiteboards, noting that these types of systems limit social exchange benefits attributed to face-to-face communication [5]. Informal learning could be linked to formal learning through social media. It also provides employing channels to facilitate student-student, student-instructor, and student-content interactions in multimedia formats. Users are more likely to engage in the learning process and collaborate on real-life projects in this environment of involvement and creation. With social media technologies, students will be able to connect to educational environments in new and meaningful ways beyond the traditional classroom environment, blurring the line between formal and informal learning environments [6].

D. Natural Language Processing (NLP)

Natural Language Processing (NLP) is a computer science, artificial intelligence, and computational linguistics. Natural language is a language used for daily communication by a human. It refers to "computer systems that analyze, attempt to understand, or pro- duce one or more human languages, such as English, Japanese, Italian, or Russian. The input might be text, spoken language, or keyboard input" [7].

E. Automatic Text Summarization

In the past, summarization was done manually by humans. However, the enormous amount of information increases using the Internet and other electronic sources [8]. Text summarization is extracting data from a document (or documents) to generate short or concise text [9], [10]. Hovy and colleagues define a summary as a text based on one or more texts; it has the essential information of the primary texts, and its content is less than half of the primary texts [11]. When summarization is done through a computer, we call it "Automatic text summarization." It is the technique of reducing a text document to create a summary that retains the essential information of the original document. Such systems become pertinent and inevitable [12]. It automatically selects significant portions of paragraphs or sentences from a full text. It provides a short version of documents to help users capture the original documents' actual contents in a tolerable time [13]. Text summarization reduces the content of a document without compromising its essence to cut down users' time and cognitive effort [12]. The automatic text summarization generates summaries containing meaningful sentences and includes all-important, relevant information from the original documents. The area of text summarization research has been studied since the mid-20th century, which was first discussed openly by Lun (1958) with the used technique of the word frequency diagram [14]. He scored sentences of a text and ranked them to select the most important ones. Although this approach is simple, it is still used [15].

F. Types of Summarization

Summarization is one of the significant tasks of Natural Language Processing (NLP). NLP processes and analyses the human language [9]. There are many categories of text summarization. Figure 1 show those categories in detail.

1) Extractive vs. Abstractive Summarization

There are different types of summarization depending on the approach to generating the final summary:
Extractive Summarization: This type of summarization depends on selecting a sentence or phrase from the text without any modification. The summary is produced from that sentence and according to the ranking score of the most important sentence.
Abstractive summarization: this approach builds a semantic summary that depends on Natural Language Processing. It works like the human brain. It reads the whole text and produces another text with new sentences. Therefore, it generates a summary depending on understanding the main concepts and information in the source text.
This paper is focused on extractive summarization in single or multi-documents. Extractive summarization is a process that extracts the main sentence in the text according to some ranking criteria. It does not paraphrase the text to create a summary; it only selects the most substantial sentences according to some algorithms. A raw text will be the input in the extractive algorithm, and the output will be a short informative summary of the high-score sentence ranking. Extractive summarization does not create a new sentence as abstractive summarization does; it only selects the relevant information from the text, like sentences, words, and phrases [9], [14], [16]. This type of summarization uses statistical approaches such as the title, location, Term Frequency-Inverse Document Frequency (TF-IDF) method, and word method for selecting meaningful sentences or

keywords from documents [17]. The advantage of extractive summarization is that the resulting summary is guaranteed that it is grammatically correct. Also, it achieves a high score in the evaluation process [18].
Extractive techniques are split into three categories [19]:

- Word-based: each word receives a score based on some criteria, and then each sentence will score according to the words that have and sum up with the final score.
- Sentence-based: scoring and analyzing each sentence's features and relation to the whole text. It uses phrases like "it is important," "In summary: and so on.
- Graph-based: scoring each sentence in light of its relation to other sentences or phrases in the text. If there is a relation between two sentences or phrases, an edge is generated with a weight between them. Finally, all edges will be calculated, and sum up the final result.

Figure 1. Types of the Summarization

To implement the extractive summarization algorithm, three main things must be considered [20]:

1) The ranking problem is ranking the text's sentence or phrase.
2) The selecting problem: how to select the subset of these ranking sentences or phrases. And show if there is any threshold point that must consider on selecting.
3) The coherent problem is ensuring that the final summary is understandable and the full summary is readable

Extractive summarization is flexible and requires less time than abstractive Summarization [8]. Therefore, Extractive Summarization could be applied for both single and multi-documents. However, the process will be more complicated for multi-documents than a single document as it involves considering various issues such as comparison ratio, maximum relevance, and redundancy [21]. Extractive summarization could be studied for semantic and syntactic analysis of the sentences included in the final summary.
The sentence's salient degree is the sentence's degree according to sentence scoring and sentence selection steps. It can call summary worthiness. The most salient score for the sentence is selected as summary-worthy. According to the salient degree, sentence selection could be considered a machine-learning classification problem [22].
The remaining sections of the paper are as follows: Section 2 introduces the literature review on automatic text summarization and its implementation in education. Also, the deep learning algorithm that used for extractive summarization. Section 3 explains the proposed Framework and its layers. Section 4 discusses the evaluation of the proposed Framework. Section 5 discussion. Section 4 Conclusion and future work.

2. LITERATURE REVIEW

Analyzing and focusing on previous work will advance knowledge for the future [23]. Therefore, this section introduces a literature review of this automatic text summarization for utilizing learning content. This research focuses on two areas: first, the summarization techniques of a text (especially learning materials). The second is the deep learning algorithm used for Extractive Summarization.

A. Knowledge extraction in the educational area

Many researchers have studied knowledge extraction and dissemination for educational purposes. In 2019, A. Al-Abri Extracted knowledge from the collaboration tools (social media or discussion boards) and then applied some preprocessing to extract the needed information to facilitate knowledge extraction and get output from it [24]. In 2018, E. Gomede et al. suggested classifying students according to their interests into groups and aiming for each group correctly. First, they categorize them according to skills, fitness, interests, perceptions, etc. Then they personalize activities by adopting learning content [25]. In 2018, N. A. Albatayneh and his colleagues introduced a novel recommendation architecture that recommends interesting post messages to learners in an eLearning online discussion form based on semantic content-based filtering and learners' negative rating [26]. In 2017, D. Herath tried to use web-mining techniques in an e-learning environment to organize e-learning systems according to the student's navigation behavior, web content, performance, and profiles. First, the instructors provide the e-learning content, and then the recommendation system reorganizes it according to the students' interests [27], [28]. In 2006, C. Y. Yang and his colleagues proposed a web content suggestion for Distance Learning. They used the filtering content suggestion to provide and extend students' interests and enrich their knowledge [29]. In 2002, O. R. Zaïane discussed data mining and machine learning techniques to enhance web-based learning environments in a way that also allows evaluating educators better and targeting learning according to them [30].

B. History of Automatic text summarization

Most researchers define summarization as "Producing a short paragraph-length summary. It can also be constructed from keywords consisting of indicative words or phrases. By summarising single documentation, we mean the summary will be sourced from one source. Otherwise the multi-documents that indicate the original will be from various sources that discuss the same topic [14]. The automatic text summarization generates summaries containing meaningful sentences and includes all-important relevant information from the original documents. The area of text summarization research has been studied since the mid-20th century, which was first discussed openly by Lun (1958) [14]. There are two types of summarization results: extractive and abstractive results. Extractive summarization is a summary that consists of words and sentences taken entirely from the original text. In contrast, abstractive summarization produces summaries containing novel sentences, not from the original text. Abstractive summaries are very complex and relatively more difficult than extractive summarizations.
Although most research focuses on abstractive summarization and real-time summarization, the extractive summary is also receiving significant attention in addressing the problem of coherence between the summarized sentences. An abstractive summary needs NLP to solve that problem [16]. The summarization techniques will depend on the TF-IDF algorithm. First, it will rely on the keywords of the outline of the selected course. These keywords will help to summarize the necessary information from the learning content. Then it will process the frequency of these words in the given documents. Tokenization is one technique that could be used to identify sentence boundaries using the white space between words [24].

Much research is developing a general summarization system, such as the SUMMARIST [11]. However, it depends on extracting sentences from multiple language documents. There are many techniques used in text summarization, such as the statistical or weighting approach [31], [32], [33], Linguistic and Rhetorical approaches[34]. Additionally, the Graph-based ranking approach is one of them, and the TextRank system [35] is based on that.

C. Summarization for educational purposes

The goal of summarization for educational purposes is to capture important information that could help to achieve the goals and objectives of a course contained in large volumes of materials and present it in a brief, representative, and consistent summary. For example, some researchers used automatic text summarization for mobile learning to reduce the textual content to fit mobiles [36], [37].
At the same time, others used automatic text summarization to automatically summarize peer reviewers' feedback by extracting similar content to capture the strengths and weaknesses of the work [38]. Other researchers attempt to adapt the hierarchical attention networks for thread summarization of the forum discussion content [39], [40].
In 2019, CAGLIERO et al. proposed a methodology for summarizing the learning content according to the learners' needs [41].
Also, in the same year, Goulartea et al. used text summarization to automatically evaluate the students' text with the summarized text [42].
In the same year, Miller proposed service to provide students with a utility that could summarize lecture content based on their desired number of sentences using extractive summarization by a deep learning algorithm [43].

D. Deep learning for automatic summarization

[44] defined deep learning as learning that Allows computational models composed of multiple processing layers to learn data representations with various levels of abstraction. These methods have dramatically improved state-of-the-art speech recognition, visual object recognition, object detection, and many other domains, such as drug discovery and genomics. Deep learning discovers intricate structures in large data sets using the backpropagation algorithm to indicate how a machine should change its internal parameters to compute each layer's representation from the previous layer's representation.
Many researchers applied a deep learning algorithm as a summarization technique. Several deep learning techniques have been used recently in extractive text summarization. For example, many researchers implemented a deep learning algorithm for extractive Summarization [20].
Deep learning approaches have become famous for automatic summarization in general and extractive summarization in specific cases. This is because it can learn from word features automatically. In 2015, Kågebäck et al. proposed using continuous vector representations for semantically aware representations of sentences as a basis for measuring similarity [45]. In 2020 Ong et al. conducted a comparative study between 3 deep learning algorithms for extractive summarization; the result shows that [20] has the best effect on evaluation [46].
Table I introduces different implementation techniques for summarization in general and extractive or abstractive summarization in particular.

TABLE I. A DEEP LEARNING ALGORITHM FOR AUTOMATIC TEXT SUMMARIZATION

Method	Extractive/abstractive summarization	Year	Authors
Latent Semantic Analysis	Abstractive	2001	[47], [48], [49], [50]
Hidden Markov Models	Abstractive	2001	[51]
graph-based unsupervised approaches	Abstractive/ Extractive	2004	[52], [53], [35], [54], [55]
Recurrent Neural Network (RNN)	Extractive	2017	[56], [57]
Convolutional Neural Network (CNN)	Extractive	2014	[58], [59], [60]
Continuous Vector Space Models	Extractive	2015	[45], [13]
Restricted Boltzmann Machine	Extractive	2019	[20]
Bidirectional encoder Representations from Transformers (BERT)	Abstractive/ Extractive	2019	[61], [62]
Deep neural networks	Extractive	2018	[63], [64]
Autoencoder neural network	Extractive	2019	[63]
Long Short-Term Memory (LSTM)	Extractive	2019	[65]

[61] proposed and developed a general framework depending on a deep learning algorithm for extractive and abstractive summarization. Their Framework applied the BERT (Bidirectional Encoder Representations for Transformers) techniques. It is a powerful model that depends on deep learning techniques by using a pre-trained model to consider the context of the words to both the left and right of a sentence in all the layers. Furthermore, the proposed automated extractive summarizer depends on the BERT model, and they modi ed it to provide context to sentences dynamically using a machine learning algorithm [66].
There are also other deep learning algorithms used for extractive summarization, including Restricted Boltzmann Machine (RBM), Variation Auto-Encoder (VAE), and Recurrent Neural Network (RNN) [67]. They worked on extractive summarization as a sentence classi cation problem. The neural encoder creates sentence representations, and the classi er predicts which sentence should be selected as a summary [61].
Additionally, many researchers study video summarization using a deep learning algorithm. For example, in 2022, Lin and colleagues examined a video summarization task where the input was a sequence of frames, and the output was a subset of the original frame. They used the Long Short-Term Memory (LSTM) technique for video summarization[68]. Therefore, deep learning is a recent eld in eLearning to improve learning techniques [69]. Also, some research uses deep learning to enhance the MOOC environment [70].

3. PROPOSED FRAMEWORK AND ITS IMPLEMENTATION

This section provides information about a Framework proposed in light of the outcome of the literature review. As shown in gure ??, this Framework consists of four layers that interact with each other.

Input layer

Processing layer

Query-based summarization layer

Deep learning algorithm layer

A. Content Input

The rst layer is the input layer. In this layer, the Framework uses learning the content and course outline as input. It collects learning materials and extracts content as input for the data processing layer. Data Preprocessing In the second layer and after extracting the learning content, the data cleaning should be used to eliminate redundant unwanted information and stop words. It is a phase where data is prepared for the next step.
Preprocessing is one of the signi cant tasks of any text processing. It helps to remove unwanted words or punctuation for better results. There is a universal agreement on how data will be prepared before summarization techniques. Most data contain words or phrases that give ambiguity to the text and do not carry any summarisation information. Many types of research applications preprocess phase differently. For example, Verma and Delhi (2019) [20] applied this phase by conducting a document segmentation to divide the document into paragraphs, which are then divided into their root forms. Then it stops word ltering— and nally applies POS tagging. The preprocessing data is as follows:

1) Remove punctuation: removing punctuation will help focus on the words and sentence itself. It involves the removal of '?', '/', '!', and others. Also, it takes each sentence and lowercase each word.
2) Stop words removal: the words that are unlikely to help text mining, such as prepositions, articles, and pronouns—examples for stop words: the, in, a, an, with, etc. are removed from documents because those words are not processed as keywords in text mining applications. This step allows the processing to focus on the essential words by calculating their weight to produce the nal summary.
3) Sentence Segmentation (sentences boundary identi- cation).
4) Tokenization: It is the process of breaking a stream of text up into phrases, words, symbols, or other meaningful elements called tokens [71]. It is a signi cant step in the preprocessing of data. It helps to divide the sentences into a list of words for further processing. The entire document is divided into paragraphs and then into individual sentences. Most summarization methods deal with scoring sentences or clustering sentences together.
5) Part of Speech Tagging (POS): Part of speech tagging is the process of marking or classifying the words of text based on the part of speech category (noun, verb, adverb, adjectives) they belong to.

Figure 2. Overall Architecture of the Guided Framework for Extractive Summarization of Learning Content

6) Lemmatization or word stemming: is to make all words related to the same root in the same forms by removing added characters, e.g., like, liking, and likely.

In this phase, the input data is the content (i.e., PDF les, Diagrams, Slide Shows, Books, etc.). The data need to be prepared for the summarization, mainly that the extractive summarization will be applied. The proposed Framework prepared the learning material by combining the data preprocessing steps. First, document segmentation has been done to dierent segment documents of the learning materials. Second, paragraph segmentation has been applied the identify each paragraph's boundaries. Third, the word normalization is used for the content to refer to the originality of the word. Later, stop word removal was applied to clean the content of unwanted and unrelated words. Finally, the POS is used to categorize to which category they belong.

B. Course Outline Analysis

The course outline is the primary document at the beginning of the course. It contains course information and the objectives, besides other sections introducing the course. We have analyzed 50-course outline documents from di erent countries and universities for this research. In the paper, 50 dierent course outlines are studied as the following percentage: from Sultan Qaboos University 20%, from various academic institutes in Oman 30% and 50% from the international institute. , as shown in Figure 3.

Figure 3. The number of course outline from dierent universities

The analysis of those documents shows the main sections through them. The main areas and the related subsection to each one are as follow:

1) Course details or course descriptions: This section contains the following subsections in a different format:
   a) Course overview: it helps to know a general overview of the course.
   b) Course code and course name: The course name from this section will help extract general keywords about the course. For example, the course name, Software System Development, will bring information about software systems and how to develop them.
   c) Other general subsections include course code, class schedule, credit hours, prerequisites, course requirements, etc.
2) Course objectives: this is one of the main sections that will help in keyword extraction and identify the needed word list for the query input in the query-based summarization. This central section contains the following subsections in a different format:
   a) Vision and mission: it defines the course's main constraints and the main objectives to study.
   b) Purpose, objectives, and learning outcomes: these subsections will focus more on the detailed objectives that the students should achieve at the end of the course.
3) Course outline: there are two types of course outlines:
   a) The short course outline shows the course's general titles and topics covered. It is similar to course content, class topic, session topic, chapter title, etc.
   b) The detailed course outline or weekly coverage plan will provide more details about what will be covered during the course weekly. This is similar to tentative week schedules, weekly delivery plans, course working plans, key concepts, topics, etc. However, those subsections are more informative and will contain the main keywords.
4) Then other sections follow, such as:
   a) Assessment - which includes information about evaluation, grading, and corresponding assignments.
   b) Course materials include textbooks, slides, PDF files, support resources, learning resources, recommendation reading, supplementary reading, etc.
   c) Police and academic rules such as student responsibilities, fees, etc.

Figure 4 shows the percentage of each section related to the course outline in the selected outline. The Weekly coverage section shows less percentage, meaning many outlines are excluded from the description. This section shows the students' main topic each week and the key points. Additionally, most course outlines show the course objectives in brief descriptions and focus on the course's general details, as shown in Figure 4.

Figure 4. The percentage of each section related to the universities

C. Query-Based Summarization

Query-based summarization is a technique that constructs the content summary according to some keywords/keyphrases. The importance of each sentence depends on the following:

- How relevant is that sentence in the context of the input
- How appropriate is that sentence to use a question or query

Therefore, the most important thing in query-based summarization is to know the relevance of the query to the main content. We can calculate that based on the similarity of extracted sentence to the query as follows [72]:

$$X = WMD(query, sentence)$$

Where WMD stands for word mover distance score between the selected sentence and the query.

D. About BERT as a deep learning algorithm:

In this research, the query-based summarization is built on BERT. BERT stands for Bidirectional Encoder Representations from Transformers. This algorithm's summary is based on centroid sentences in a cluster. This approach has been used because the literature review shows it works effectively for extractive summarization as a comparative study done in this area [43]. In this phase, the KeyBert was used. It generates embeddings using huggingface transformer-based pre-trained models. The all-MiniLM-L6-v2 model is used by default for embedding.

```
from keybert import KeyBERT doc=""" kw_model = KeyBERT() keywords =
```

Figure 5. RBM architecture [20]

```
kw_model.extract_keywords(doc)
print(keywords)
```

Output:

[('supervised', 0.6676), ('labeled', 0.4896), ('learning', 0.4813), ('training', 0.4134), ('labels',

E. Deep Learning Algorithm for Automatic Text Summarization

Restricted Boltzmann Machine (RBM) is a neural network with random probability distributions. It is an unsupervised learning algorithm. The network contains a layer of visible neurons (input nodes) and hidden layers of hidden neurons (hidden nodes). Every input node has a bidirectional connection with every hidden node. In addition, the bias node has a connection with every hidden node [73]. However, the input nodes are not interconnected in the visible layer. Also, the hidden nodes are not interconnected in the hidden layers. Figure 5 shows the Restricted Boltzmann Machine algorithm [20].
It was used for that data in the summarization phase. It is a probabilistic model from a deep learning algorithm. The network contains a visible layer of visible neurons (input nodes) and hidden layers of hidden neurons (hidden nodes) [73]. The layer of hidden binary variables is used to model the distribution of a visible layer of variables [74]. This model has been successfully applied to text by [75], [76].

F. Sentence features:

In the second step, the sentence features will be identi- ed. These features show the importance of each sentence to be selected for the summary. A common feature could be shown in Table II:

Figure 6 shows the sentence feature extraction used to extract and rank the sentence to form the nal summary. The rst feature is sentence position, which will consider whether the sentence is the rst or last sentence. The second feature is the sentence length, which calculates the number of words in the sentence to determine which sentence will su ciently contain the information. The third feature is a numerical token which will give a score to each sentence to rank them. Finally, the TF-ISF Term Frequency-inverse document Frequency will rank the sentence according to the whole document using the keywords extracted from

TABLE II. SENTENCE FEATURES

Feature	Description	Remarks
Sentence length	The sentence length will show if this sentence should be included in the nal summary	If the sentence is longer or smaller without any value, it will not be included in the nal summary.
Sentence Position	The position of the sentence will be considered while scoring the sentence in the summarization process	If the sentence position is very important, extract it as a summary; therefore, the sentence at the beginning of the paragraph or in a particular position, such as after some keywords like to summarize or to conclude, will be included in the nal summary
Term Frequency	The intermediate-term values of words in the sentence	The sentence that has many keywords will be included in the nal summary

Figure 6. Sentence Feature Extraction

the learning content. Figure 7 shows some results of the extractive summarization in two phases, the query-based summarization, and the deep learning algorithm. The selected sentence will be included in the nal summary.

4. EVALUATION

The proposed Framework has been evaluated by applying three evaluation techniques, as shown in Figure 8:

First, use the statistical tool called ROUGE. ROUGE stands for Recall-Oriented Understudy for Gisting Evaluation. It works by comparing an automatically produced summary or translation against a set of reference summaries (typically human-produced). The Main points below show the three evaluation parameters and the equation that calculates the metrics: Recall, Precision, and F-score. The proposed Framework was trained by several reference summaries produced by humans (The instructors of the selected course as a case study), so the reference summary (human summary) was compared against the produced summary from the proposed Framework. The ROUGE algorithm takes two things as input: the reference summary and the Framework nal summary

Figure 7. Some results of the extractive summarization in two phases

Figure 8. Flowchart shows the evaluation process of the proposed Framework

Figure 9. The results of the expert's evaluation of the framework summary

to calculate their precision, recall, and F-score.

Table 3 shows the results after applying the ROUGE metrics to the proposed Framework's nal summary. In this evaluation there are two ROUGE types have been used:

ROUGE 1= Unigram, one-word sequence
ROUGE 2= Bigram, two words sequence

The ROUGE evaluation tries to nd how many n-grams in the generated summary match the n-grams in the reference summary. It means how much accuracy between them. Therefore, accuracy increases as the number approach 1. The result shows the high- e ciency and accuracy of the nal summary compared to the human summary.

$$Recall(R) = \frac{NumberOverlappingwords}{Totalreferencesummary}$$

$$Precision(P) = \frac{NumberOverlappingwords}{Totalcandidatesummary}$$

$$F\text{-}measure = \frac{1+\ ^{2}R\ P}{R+\ ^{2}\ P}$$

The second Evaluation approach is the expert evaluation—the experts from the same specialization of the learning content. The experts are from an academic

TABLE III. THE RESULT AFTER APPLYING THE ROUGE METRICS ON THE RESULT OF SUMMARIZATION

Evaluation Metrics	ROUGE-1	ROUGE-2
Precision	0.8	0.6
Recall	0.7	0.5
F-Score	0.746	0.545

TABLE IV. Shows the means of the participant before and after applying the proposed Framework

Applying Framework	Average	Count
Yes	31.04237	118
No	29.30508	118

institution in Oman. Their specializations are from commerce and management elds, the same area of the course selected as a case study. The framework summary was given to them, and they evaluated it according to some criteria, as shown in Figure 9.

The Third Evaluation approach is Knowledge evaluation using case studies in a real educational environment at SQU. In this approach, the students' achievement during the proposed Framework's implementation is tested, and the results are analyzed. This experiment was carried out for a course at the College of Economics and Political Science in spring of 2022. The experiment design is as shown in the owing gure 10. At the end of the experiment, the course's nal exam was used to measure and compare the students' achievements.

The dataset collected from Sultan Qaboos University (SQU)
College: College of Economics and Political Science
Department: Management
Course Code: MNGT2515
Course Name: International Business

The course material is collected in this experiment, and the course outline is prepared for the summarization phase. As shown in Figure 11 shows the main extracted keyword.
After that, the t-test is conducted for the student's grades in the middle half of the semester to group them properly, as shown in gure 6.15. The T-Test is used to determine if there is a signi cant dierence between the means of the two groups.

At the end of the semester, the nal exam results were analyzed for both groups, and a t-test using compare means was applied to their results, as shown in table IV and gure 13.

From the 3 evaluation techniques, the results show that the proposed Framework performs eciently to produce the nal summary that achieves the course objectives. For example, the ROUGE evaluation gives a result of 0.6 for precision and 0.7 for recall; both are considered high results using those evaluation techniques. On the other hand, the experts' evaluation evaluates the produced summary based on some criteria, as shown in gure 9. Their evaluation shows that they agree that the produced summary selects the most important sentences that achieve the course objectives. In the end, the third evaluation technique, which uses the students' achievement through one whole academic semester, shows that the performance of students that have used the produced summary as extra materials for their study achieve a higher score in the course than the others. Therefore, from the above evaluation results, the proposed Framework shows the high eciency and accuracy of the results.

Figure 10. Flowchart of the experiment

5. DISCUSSION

In recent years, tremendous data and materials have been used for learning purposes, such as e-books, academic papers, web pages, and other materials. There are many pieces of research focusing on improving summarization for di erent purposes. However, there are limitations in summary for educational purposes. There are some drawbacks to some summarized techniques. The summarized method gives missing information or not exact sentences that need to be known. Additionally, some summarization techniques can't deal with pictures and equations.
The literature review indicates that extractive summarization is more potent for extracting and summarizing the learning content because it extracts the sentence or phrase from the learning material. For example, if students want to summarize any learning content, this type of summarization will give the top-rated sentences in that content. Extractive summarization is a suitable way to summarize the learning

Figure 11. Extracted Keywords for chapters 10, 11, 12 and 13 of the selected course

Figure 12. Categorized Participants using T-Test

Figure 13. The means of the participant before and after applying the proposed Framework

content because the outcome of that summarization will be as in the materials. On the other hand, the abstractive summarization will paraphrase the learning content to produce a new summary. Deep learning techniques reduce the implementation cost and get intelligent results from summarized content. Unfortunately, automatic summarization for learning purposes in education is not studied enough.
Also, we notice that each field in education needs a different summarization model, so the summarized content will be focused on the terminology of that field. Therefore, there are several solutions to overcome those drawbacks. One is to design the evaluation metrics that fit the needed summarization purpose to produce the best-selected summaries. There are several research focus on that [59], [60], [61], [62].
Therefore, the drawback and strength of the previous topic's literature review led us to propose a guided framework that summarizes the learning content using a deep learning algorithm. The proposed Framework will rely on the most recent deep learning algorithms that make it suitable for implementation in any educational environment. The performance and evaluation of the proposed Framework show high efficiency and accuracy in the summarization of the learning content.

6. CONCLUSION AND FUTURE WORK

In conclusion, this research studies different extractive summarization techniques, focusing on the deep learning area as the implementation method. The study found that using a deep learning algorithm, the best summarization technique for summarizing educational content is the extractive summarization for single or multiple documents. Several deep learning algorithms that are applied for extractive and abstractive summarization were mentioned in this paper. The researchers proposed a framework for guided extractive summarization experiments and qualified using different deep learning algorithms for extractive summarization. In addition, using the proposed Framework, the students could receive a summary of the learning content that matches the course objectives. The results of the proposed Framework's implantation show the high efficiency and accuracy of the final results.

References

[1] E. Pollard and J. Hillage, *Exploring e-learning*. Institute for Employment Studies Brighton, 2001.

[2] E. Susnea, "Monitoring student activities in social networking," in *The International Scientific Conference eLearning and Software for Education*, vol. 1. " Carol I" National Defence University, 2017, p. 539.

[3] H. A. Aifan, "Saudi students'attitudes toward using social media to support learning," Ph.D. dissertation, University of Kansas, 2015.

[4] V. Kumar and P. Nanda, "Social media in higher education," *International Journal of Information and Communication Technology Education. https://doi. org/10.4018/ijicte*, vol. 2019010107, 2018.

[5] G.-W. Bock, R. Sabherwal, and Z. Qian, "The effect of social context on the success of knowledge repository systems," *IEEE Transactions on Engineering Management*, vol. 55, no. 4, pp. 536–551, 2008.

[6] B. Chen and T. Bryer, "Investigating instructional strategies for using social media in formal and informal learning," *International Review of Research in Open and Distributed Learning*, vol. 13, no. 1, pp. 87–104, 2012.

[7] J. F. Allen, *Natural Language Processing*. GBR: John Wiley and Sons Ltd., 2003, p. 1218–1222.

[8] K. Duraiswamy, "An approach for text summarization using deep learning algorithm," 2014.

[9] H. Gupta and M. Patel, "Study of extractive text summarizer using the elmo embedding," in *2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC)*. IEEE, 2020, pp. 829–834.

[10] H. Bakkar, A. Al-Hamad, and M. Bakar, "Multi-document summarizer," in *Intelligent Natural Language Processing: Trends and Applications*. Springer, 2018, pp. 461–478.

[11] E. Hovy, C.-Y. Lin *et al.*, "Automated text summarization in summarist," *Advances in automatic text summarization*, vol. 14, pp. 81–94, 1999.

[12] A. Kanapala, S. Pal, and R. Pamula, "Text summarization from legal documents: a survey," *Artificial Intelligence Review*, vol. 51, no. 3, pp. 371–402, 2019.

[13] M. E. Khademi, M. Fakhredanesh, and S. M. Hoseini, "Conceptual text summarizer: A new model in continuous vector space," *arXiv preprint arXiv:1710.10994*, 2017.

[14] A. P. Widyassari, S. Rustad, G. F. Shidik, E. Noersasongko, A. Syukur, A. Affandy *et al.*, "Review of automatic text summarization techniques & methods," *Journal of King Saud University-Computer and Information Sciences*, 2020.

[15] J.-M. Torres-Moreno, "Artex is another text summarizer," *arXiv preprint arXiv:1210.3312*, 2012.

[16] M. Gambhir and V. Gupta, "Recent automatic text summarization techniques: a survey," *Artificial Intelligence Review*, vol. 47, no. 1, pp. 1–66, 2017.

[17] H. Christian, M. P. Agus, and D. Suhartono, "Single document automatic text summarization using term frequency-inverse document frequency (tf-idf)," *ComTech: Computer, Mathematics and Engineering Applications*, vol. 7, no. 4, pp. 285–294, 2016.

[18] P. Lemberger, "Deep learning models for automatic summarization," *arXiv preprint arXiv:2005.11988*, 2020.

[19] G. Silva, R. Ferreira, R. D. Lins, L. Cabral, H. Oliveira, S. J. Simske, and M. Riss, "Automatic text document summarization based on machine learning," in *Proceedings of the 2015 ACM Symposium on Document Engineering*, 2015, pp. 191–194.

[20] S. Verma and V. Nidhi, "Extractive summarization using deep learning," *arXiv preprint arXiv:1708.04439*, 2017.

[21] A. K. Yadav, A. K. Maurya, R. S. Yadav *et al.*, "Extractive text summarization using recent approaches: A survey." *Ingénierie des Systèmes d'Information*, vol. 26, no. 1, 2021.

[22] B. Mutlu, E. A. Sezer, and M. A. Akcayol, "Candidate sentence selection for extractive text summarization," *Information Processing & Management*, vol. 57, no. 6, p. 102359, 2020.

[23] J. Webster and R. T. Watson, "Analyzing the past to prepare for the future: Writing a literature review," *MIS quarterly*, pp. xiii–xxiii, 2002.

[24] A. Al Abri, Y. Jamoussi, Z. AlKhanjari, and N. Kraiem, "Perlcol: A framework for personalized e-learning with social collaboration support," *International Journal of Computing and Digital Systems*, vol. 9, no. 03, 2020.

[25] E. Gomede, F. H. Gaffo, G. U. Briganó, R. M. De Barros, and L. d. S. Mendes, "Application of computational intelligence to improve education in smart cities," *Sensors*, vol. 18, no. 1, p. 267, 2018.

[26] N. A. Albatayneh, K. I. Ghauth, and F.-F. Chua, "Utilizing learners' negative ratings in semantic content-based recommender system for e-learning forum," *Journal of Educational Technology & Society*, vol. 21, no. 1, pp. 112–125, 2018.

[27] D. Herath and L. Jayaratne, "A personalized web content recommendation system for e-learners in e-learning environment," in *2017 National Information Technology Conference (NITC)*. IEEE, 2017, pp. 89–95.

[28] C. Xiong, X. Li, Y. Li, and G. Liu, "Multi-documents summarization based on textrank and its application in online argumentation platform," *International Journal of Data Warehousing and Mining (IJDWM)*, vol. 14, no. 3, pp. 69–89, 2018.

[29] C.-Y. Yang, H.-H. Hsu, J. C. Hung *et al.*, "A web content suggestion system for distance learning," *Journal of Applied Science and Engineering*, vol. 9, no. 3, pp. 243–254, 2006.

[30] O. R. Zaiane, "Building a recommender agent for e-learning systems," in *International Conference on Computers in Education, 2002. Proceedings.* IEEE, 2002, pp. 55–59.

[31] R. C. Balabantaray, D. Sahoo, B. Sahoo, and M. Swain, "Text summarization using term weights," *International Journal of Computer Applications*, vol. 38, no. 1, pp. 10–14, 2012.

[32] R. A. García-Hernández and Y. Ledeneva, "Word sequence models for single text summarization," in *2009 Second International Con-*

ferences on Advances in Computer-Human Interactions. IEEE, 2009, pp. 44–48.

[33] Y. Ledeneva, A. Gelbukh, and R. A. García-Hernández, "Terms derived from frequent sequences for extractive text summarization," in *International conference on intelligent text processing and computational linguistics*. Springer, 2008, pp. 593–604.

[34] S. Gholamrezazadeh, M. A. Salehi, and B. Gholamzadeh, "A comprehensive survey on text summarization systems," in *2009 2nd International Conference on Computer Science and its Applications*. IEEE, 2009, pp. 1–6.

[35] R. Mihalcea and P. Tarau, "Textrank: Bringing order into text," in *Proceedings of the 2004 conference on empirical methods in natural language processing*, 2004, pp. 404–411.

[36] G. Yang, N.-S. Chen, E. Sutinen, T. Anderson, D. Wen *et al.*, "The effectiveness of automatic text summarization in mobile learning contexts," *Computers & Education*, vol. 68, pp. 233–243, 2013.

[37] A. Wedi, S. Ulfa, A. Pakkawaru, and R. Bringula, "Exploring the implementation of automatic text summarization in online learning setting," in *1st International Conference on Information Technology and Education (ICITE 2020)*. Atlantis Press, 2020, pp. 5–8.

[38] F. Pramudianto, T. Chhabra, E. F. Gehringer, and C. Maynards, "Assessing the quality of automatic summarization for peer review in education." in *EDM (Workshops)*, 2016.

[39] S. Tarnpradab, F. Liu, and K. A. Hua, "Toward extractive summarization of online forum discussions via hierarchical attention networks," in *The Thirtieth International Flairs Conference*, 2017.

[40] S. Gottipati, V. Shankararaman, and R. Ramesh, "Topicsummary: A tool for analyzing class discussion forums using topic based summarizations," in *2019 IEEE Frontiers in Education Conference (FIE)*. IEEE, 2019, pp. 1–9.

[41] L. Cagliero, L. Farinetti, and E. Baralis, "Recommending personalized summaries of teaching materials," *IEEE Access*, vol. 7, pp. 22 729–22 739, 2019.

[42] F. B. Goularte, S. M. Nassar, R. Fileto, and H. Saggion, "A text summarization method based on fuzzy rules and applicable to automated assessment," *Expert Systems with Applications*, vol. 115, pp. 264–275, 2019.

[43] D. Miller, "Leveraging bert for extractive text summarization on lectures," *arXiv preprint arXiv:1906.04165*, 2019.

[44] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[45] M. Kågebäck, O. Mogren, N. Tahmasebi, and D. Dubhashi, "Extractive summarization using continuous vector space models," in *Proceedings of the 2nd Workshop on Continuous Vector Space Models and their Compositionality (CVSC)*, 2014, pp. 31–39.

[46] W. H. Ong, K. G. Tay, C. C. Chew, and A. Huong, "A comparative study of extractive summary algorithms using natural language processing," in *2020 IEEE Student Conference on Research and Development (SCOReD)*. IEEE, 2020, pp. 406–410.

[47] Y. Gong and X. Liu, "Generic text summarization using relevance measure and latent semantic analysis," in *Proceedings of the 24th annual international ACM SIGIR conference on Research and development in information retrieval*, 2001, pp. 19–25.

[48] B. Hachey, G. Murray, D. Reitter *et al.*, "The embra system at duc 2005: Query-oriented multi-document summarization with a very large latent semantic space," in *Proceedings of the Document Understanding Conference (DUC) 2005, Vancouver, BC, Canada*, 2005.

[49] J. Steinberger and K. Ježek, "Update summarization based on latent semantic analysis," in *International Conference on Text, Speech and Dialogue*. Springer, 2009, pp. 77–84.

[50] L. Cagliero, P. Garza, and E. Baralis, "Elsa: A multilingual document summarization algorithm based on frequent itemsets and latent semantic analysis," *ACM Transactions on Information Systems (TOIS)*, vol. 37, no. 2, pp. 1–33, 2019.

[51] J. M. Conroy and D. P. O'leary, "Text summarization via hidden markov models," in *Proceedings of the 24th annual international ACM SIGIR conference on Research and development in information retrieval*, 2001, pp. 406–407.

[52] R. M. Aliguliyev, "A novel partitioning-based clustering method and generic document summarization," in *2006 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology Workshops*. IEEE, 2006, pp. 626–629.

[53] C. Fang, D. Mu, Z. Deng, and Z. Wu, "Word-sentence co-ranking for automatic extractive text summarization," *Expert Systems with Applications*, vol. 72, pp. 189–195, 2017.

[54] X. Wan and J. Xiao, "Single document keyphrase extraction using neighborhood knowledge." in *AAAI*, vol. 8, 2008, pp. 855–860.

[55] G. Erkan and D. R. Radev, "Lexrank: Graph-based lexical centrality as salience in text summarization," *Journal of artificial intelligence research*, vol. 22, pp. 457–479, 2004.

[56] T. Mikolov, S. Kombrink, L. Burget, J. Černockỳ, and S. Khudanpur, "Extensions of recurrent neural network language model," in *2011 IEEE international conference on acoustics, speech and signal processing (ICASSP)*. IEEE, 2011, pp. 5528–5531.

[57] R. Nallapati, F. Zhai, and B. Zhou, "Summarunner: A recurrent neural network based sequence model for extractive summarization of documents," in *Thirty-first AAAI conference on artificial intelligence*, 2017.

[58] Y. Chen, "Convolutional neural network for sentence classification," Master's thesis, University of Waterloo, 2015.

[59] Y. Zhang, M. J. Er, R. Zhao, and M. Pratama, "Multiview convolutional neural networks for multidocument extractive summarization," *IEEE transactions on cybernetics*, vol. 47, no. 10, pp. 3230–3242, 2016.

[60] Y. Zhang, J. E. Meng, and M. Pratama, "Extractive document summarization based on convolutional neural networks," in *IECON 2016-42nd Annual Conference of the IEEE Industrial Electronics Society*. IEEE, 2016, pp. 918–922.

[61] Y. Liu and M. Lapata, "Text summarization with pretrained encoders," *arXiv preprint arXiv:1908.08345*, 2019.

[62] S. M. A.-S. Mohamed, "Extractive text summarization on single documents using deep learning," 2022.