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Deep Learning Based On Different Methods For Text Summary: A Survey

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ABSTRACT

Abstract—in today's rapidly growing information age, text summary has become a critical and important instrument for help understanding text information. it is really hard for human beings to physically summarize huge textual documents also there is an abundance of text content available online. text summarization is an active research field that works on compressing large pieces of text into smaller texts that preserve relevant information. text summary classified as extractive or abstractive. methods of extractive summarization working by deciding important text sentences and choosing them as a summary. that method based only on sentences from the source text. methods of abstractive summarization aim to paraphrase important information in a new form like that of humans. text summary can be achieved using different deep learning techniques, such as: fuzzy logic, Convolutional Neural (CNN), transformers, neural network, reinforcement learning, etc. in the past three years, the research trend in text summarization has also undergone a slight change, where new trends have appeared that are trends that lead to enhancement, how to improve the efficiency of text summarization to obtain high accuracy. we have made several attempts in this paper to discuss the various techniques used on the basis of deep learning for text summary in these years and observe the new trends in the field of deep learning.

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1. Introduction

People used to summarize the text document by themselves for a very long period of time, but today it is difficult for people to deal with the huge volume of data because of increasing data and articles, news, posts, information and massive amounts of textual data are available online. To treat this problem text summarization is needed and became a very important task.

The importance of a summary of texts is due to multiple factors, including the retrieval of essential information with a short period of time, from a large text, the fast and easy loading of the most important data, and the resolve of the issues related to the requirements Necessary for the summary evaluation [1]. Due to the development and production of automated approaches of text summarization that have produced substantial findings in many languages, it is appropriate to review and summarize them. There are a wide variety of applications of text summarization, including text media monitoring, such as notifications, marketing inquiries, and searches, bots used for answering questions, managing the internal flow of documents at work, reviewing legal contracts, social networking marketing, the power to overload email, class tasks and e-learning. Deep learning enables the rapid advancement of artificial intelligence (AI), as well as its development has led to practical applications in a wide range of domains [20]. Swarm intelligence and deep learning have been successfully applied in many fields in today's world, including image classification, pattern recognition, and intrusion detection systems [21]. Text summary in this process the extracted data is presented as a summary report after retrieving the relevant and essential data from the original text [2]. The text summary is classified as Extraction or Abstractive summarization. Extractive summary, a summary that selects the important sentences of the document, and puts them in accordance with a particular arrangement [2][3]. Extractive summarization tries to detected sentence attributes then it assigns scores these sentences then generate the summarization. The result for this summary relies upon the attributes collected from the phrases of the document [4]. The extractive summary has the main drawback Some time all the information and expertise in a sentence will be inserted in the summary when it is chosen irrespective of its significant relevance [3]. Abstract summarization works to produce new sentences from the beginning and then configure the summary and give it to the user which categories it into two classes semantic-based methods and structured base method. the main drawback of abstractive summarization that it has one relevance problem that the meanings of the newly created sentences may not become the same as were intended in the original document text. Sometimes, less relevant secondary information in the document may be chosen by the summary produced. Abstractive summary mostly performed on text of small documents, Therefore, the techniques for a large text remains a major challenge [3] [2]. The most widely used text summary approaches are Machine Learning-based method (ML), Graph-based summarization, Genetic Algorithm (GA), General Statistical Method (GSM), Fuzzy Logic (FL), Semantic Approach, Neural Network for text summarization, Vector space model, Deep learning, transformers, Reinforcement learning, Multi-Objective Artificial Bee Colony(MOABC), and so on.

We aimed to learn the various text summary techniques in this paper that have been implemented over the previous three years. (2020,2019,2018) by different researchers and to prepare a succinct analysis of which methods are more useful and more favored and why.

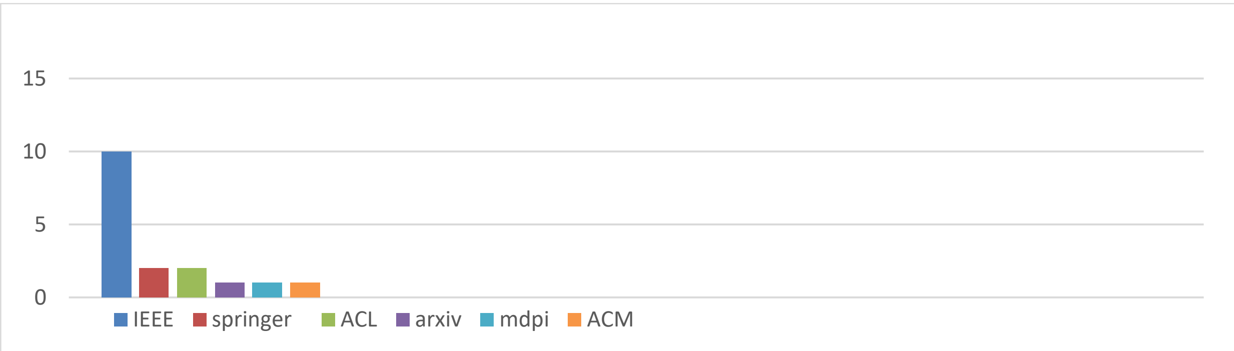

Fig 1. Division of research papers studied from different online Sources

Fig. 1. has explained from where the research papers to be studied have been selected. Study papers have been gathered from IEEE, Springer, ACL, arivx , mdbi ,ACM library.

The structure of the paper is described in the following: there is an introduction to the text summary in section 1, related work has been discussed in section 2, The paper ends with section 3 of Conclusion and Future Work, and the references in section 4.

2. Related work

Nikhil S. Shirwandkar and Dr. Samidha Kulkarni proposed a methodology that is designed to summarize the text in an extractive manner, the summarization process is executed on a single document, two mechanisms have been combined in order to select important sentences from the text in order to produce a meaningful summary. Restricted Boltzmann Machine and Fuzzy Logic are the methods used to select sentences from the text. In the beginning fuzzy logic and The Restricted (Boltzmann) Machine are used to produce two summaries for each document. Then the results of both summaries are then combined and processed using a separate set of operations to get the final summary from the document provided. The results showed that the proposed designed strategy overcomes and solves the problem of text overloading by providing a good and efficient summary. Ten English documentation from a dataset of news articles from Kaggle have been used for this study and the proposed method the ROUG matrices achieves (F measure = 0.84, precision = 0.88 Recall = 0.80) [2].

Shengli Song et al proposed an LSTM-CNN-based abstract text summary (ATSDL) framework which can generate new phrases through investigating more fine-grained segments than phrases, conceptual words, and more explicitly. ATSDL has two steps, the first of which extracts sentences from the original sentences, three sub-steps are used in phrase extraction: phrase acquisition, refinement of phrases, and combination of phrases and the second by use LSTM-CNN model produce text summaries, Experimental outcomes for ROUGE matric indicate that R-1= 34.9, R-2= 17.8 = 17.8 on daily mail and CNN datasets [5].

Afsaneh Rezaei et al proposed to use deep learning to generate an extractive multi-document summary when deep learning was in the form of a deep belief network and a deep neural auto-encoder network. These frameworks are constructed on the DUC2007 dataset and validated with the ROUGE metrics. In this study, after data normalization and extraction of features, the feature-sentence matrix was introduced into the neural networks and the value of sentences was determined based on network output scores. In general, the network of autoencoders has better performance than DBN. The ROUGE2 for an autoencoder equal to 0.088 and DBN with a mean of R-2 equivalent to 0.0899 illustrate better performance compared to other systems. Besides, the ROUGE-1 values obtained from these systems are appropriate and accurate [6].

Wen Xiao and Giuseppe Carenini proposed for large documents an extractive summary model of a novel neural single-document that integrates both the local scope inside the current topic and the global scope of the entire document. On of scientific articles dataset arXiv and PubMed then test the model where It exceeds prior work, Each abstractive and extractive models on Rouge-1, Rouge-2 and METEOR ratings. The first to be extended for text summary is LSTM-minus, LSTM-minus is a form of Embedded learned text spans, Basic components are included in this proposed model: Sentence encoder, document encoder, and classifier of sentences, in sentences encoder they use Average word embedding the purpose of the sentence encoder is to map word embedded sequences to a vector of a fixed length. At Document Encoder the use the bi-directional gated recurrent units (GRU) which it output Comprising two hidden states to every statement, Hidden state, as forward and backward, both. Once for the sentence representation, for its subject segment, and for the document has been obtained, these are in order to make a final prediction pi, three factors are combined on whether the sentence should be included in the text summary or not .the Outcome for arXiv dataset to attentive context model is R-1, R-2, R-L and METEOR (43.58, 17.37,29.30,21.71) and for concat model is R-1, R-2, R-L and METEOR is (43.62, 17.36,29.14,21.78), and the result for PubMed dataset to attentive context model is R-1, R-2, R-L and METEOR (44.81, 19.74, 31.48,20.83) and for concat model is R-1, R-2, R-L and METEOR is (44.85, 19.70, 31.43,20.83) [7].

Rajeev Kumar Singh at el proposed model summarizing news articles and producing an accurate and crisp headline, a new method called SHEG has been proposed by them. This method has exceeded state-of-the-art frameworks and is one of its type models creating both an abstract summary and a related headline associated with it. This model was learned, checked, and validated through the use of CNN/Daily Mail, Gigaword, and Newsroom datasets. CNN and RNN are used in the extractive mechanism to achieve word-level and sentence-level attention and to use a novel controlled actor-critical (CAC) model to train the pointer-generator network to strike a balance between variance and bias in the reinforced abstractive mechanism [8].

Within Table 1, we have described very brief the articles that were studied, considering a year of publication, the used methods, Datasets, remarked notes, and high scores achieved for ROUGE matric to the method that used in the paper compared with scores that achieved for other methods in the same paper.

Table1 Overview of an Examined Articles

Authors	**Year**	**Methods Used**	**Dataset**	**Notes**	**ROUGE matrices**
Zepeng Hao , at el [9]	2020	Two function capture networks are used: the non-local network , the memory network	CNN/ Daily Mail .	Experimental results indicate that the suggested model is more powerful than the baseline model.	On three Rouge-1, Rouge-2 and Rouge-L metrics, ROUGE matrices increased by 5.6 %, 5.3%, 6.2 %.
Min Yang at el [10]	2020	They introduce an HH-ATS that comprises three key components, — for example a knowledge-based hierarchical attention framework, a DD-GAN framework and a multitask framework.	CNN/ Daily Mail and Gigaword	Experimental results indicate that the suggested model achieves higher ROUGE matrices scores than the baseline methods of the state of the art.	The result of cnn/daily mail is R- 1=43.16 R-2 =20.32 R- L=39.14 the results on Gigaword Rouge1=38.43 Rouge 2 =19.75 RougeL=36.11
Aniruh Srikanh et al [11]	2020	The BERT model and the embedding of sentences by K means clustering	CNN/ Daily Mail	The key drawback of the current model was that a smaller number of sentences could not reflect the whole context of the document to be summarized.	This Model Accomplishments Compared with state-of-the-art models I : R-1(F1)= 41.4 , R-2(F1)= 17.9 R-L(F1)= 37.9
Ajay Dhruv et al[12]	2020	(BERT) transformers	CNN/ Daily Mail Highlight s News.	When the subject has a heavy overlap in the news, a better summary appears to be provide for that system. Device uses real-time information as inputs to achieve dynamic outcomes.	41.72, 19.39, 38.76 score for R-1, R-2, and R-L
Pooja Vinod [13]	2020	BERTSUMEXT	Data in the textual clinical report issued by the local	The approach resulted in a clear improvement on all nine ROUGE criteria.	R-1, recall, precision and F measure have been enhanced by (2.09, 0.8 ,1.44). R-2, The recall, precision and F measure have been enhanced by (2.38, 0.746 ,1.51). R-L, The recall, precision and F measure have been enhanced by(2.13, 0.84 ,1.48)

			hospital		
Rajeev Kumar Singh [8]	2020	For extractive they use Word embedded, cnn gated recurrent units (GRU) RNNs, CAC to Reinforced abstractive mechanism they use bidirectional LSTM encoder	Gigaword , NEWSROOM and CNN/ Daily Mail.	this model has outpaced state-of -heart models and is one of its type models, creating both an abstract summary and correspond headline.	NEWSROOM for SHEGE Abstract summary outcomes to abstractive and extractive is 28.2, 14.7, 25.9 for Rouge 1, Rouge 2, Rouge L. Results on NEWSROOM headline 13.81 ,7.94, 11.42 for Rouge1, Rouge 2 Rouge L Comparative results of different models of headline generation on the Gigaword 31.82 ,13.2 ,28.80 for R-1, R-2, R-L. Comparative results of different models of headline generation frame works on CNN/Daily Mail 40.67, 17.74 ,36.69 for R-1, R-2, R-L. Result Comparative of different extractive frameworks on CNN/ Daily Mail (42.5, 17.6 ,35.6) for R-1, R-2, R-L.
Yong Zhang [14]	2019	Seq2seq convolutional model. CNN model with GLU.	DUC and GigaWord	They also incorporate a copy method for extracting OOV words from of the original text.	DUC corpus 29.74 ,9.85 ,25.81 to R- 1, R- 2, R- L Gigaword 37.95, 18.64 ,35.11 to R- 1, R- 2, R- L
Afsaneh Rezaei et al [6]	2019	auto encoder neural network and deep belief network	DUC 2007 dataset	In general, against DBN, the auto encoder network has better performance.	Comparable to other method result DBN on R-1=0.391 R-2=0.089 And Auto encoder on R-1=0.398 R-2=0.092
Wen Xiao et al[7].	2019	LSTM-minus, bi-directional gated recurrent units (GRU)	arivx and PubMed	This model creates a new extractive neural single-document summary framework that incorporates both the local context within the current topic and the entire document's global context. And it use for large document.	for arXiv dataset to attentive context model is R-1, R-2, R-L and METEOR (43.58, 17.37,29.30 ,21.71) and for concat model is R-1, R-2, R-L and METEOR is (43.62, 17.36 ,29.14 ,21.78), the result for PubMed dataset to attentive context model is R-1 ,R-2 ,R-L and METEOR (44.81, 19.74, 31.48 ,20.83) and for concat model is R-1, R-2 ,R-L and METEOR is (44.85, 19.70, 31.43 ,20.83)

Abdullah Al Munzir et al [15] .	2019	It used LSTM and Gated Recurrent Units based RNN.	dataset of Two hundred Bengali news articles with 3 summary sets per article type	This proposed model has some drawbacks, including the need for a large amount of training data, high training time and hardware costs.	average F1 scores is - 0.63, 0.59, 0.56 for R-1, R-2 and R-3
Amr M. Zaki et al [16] .	2019	Using several methods to go to Pointer-Generator, starting that with simpleSeq2seq with models of attention,To use a method called Scheduled-Sampling for curriculum learning,Once the latest methods to integrating reinforcement learning with seq2seq are achieved,	CNN- Daily Mail , Arabic news and Saudi newspapers	The result of this work reveals the possibility of implementing the same architectures in various languages by representing the dataset through word-embedding.	For English dataset Methods 1-Corner-Stone (6.48 ,0.76 ,05.31) to Rouge1, Rouge 2, Rouge L 2-Pointer-Generator (30.84 ,9.82, 21.39) to Rouge1, Rouge 2, Rouge L 3-Scheduled-Sampling (34.18 12.47 23.68) to Rouge1, Rouge 2, Rouge L 4-Policy-Gradient (33.26 10.97 23.28) to Rouge1, Rouge 2, Rouge L For Arabic dataset for advanced cleaning 1-Corner-Stone 60.79, 41.28, 50.08to Rouge1, Rouge 2, Rouge L 2-Pointer-Generator 48.78 ,32.13 ,41.63 to Rouge1, Rouge 2, Rouge L 3-Scheduled-Sampling 52.97, 36.68 ,45.82 to Rouge1, Rouge 2, Rouge L 4-Policy-Gradient 43.08, 27.92, 37.34 to Rouge1, Rouge 2, Rouge L
shengli Song1 et al [5] .	2018	LSTM-CNN	Daily Mail and CNN	ATSDL contains of 2 steps, the 1- extracts sentences from the original phrases 2- generates text summaries by using the deep learning Approaches.	Experimental outcomes indicate that R-1= 34.9, R-2= 17.8 = 17.8

Sangaraju et al [4].	2018	CNN has been used to solve a regression problem for the ranking of phrases. The selection of phrase is based on the sentence ranks using the ILP approach.	the DUC 2007 dataset	This model has been discovered for achieve competitive effectiveness with the state-of-the-art methods, even with a very fundamental CNN design	Comparative analysis of findings of the Duc 2007 Multi Document Text summary Systems for mv-cnnn R-1=40.92 R-2=9.11 For CNN-ILP R-1= 39.68, R-2= 10.26
Nikhil S. Shirwandkar et al [2].	2018	RBM (Restricted Boltzmann Machine) , Fuzzy Logic	Ten English documentation from a dataset of news articles from Kaggle	The connectivity of the sentences has improved using features such as thematic words and Sentence-Centroid similarity.	the ROUGE matrices for proposed method is Is precision = 0.88, Recall = 0.80 , F measure = 0.84
Li Wang1 et al [17].	2018	self-critical sequence training (SCST) for optimizing and convolutional Sequence-to-sequence model	the Gigaword , DUC-2004, and LCSTS datasets	On different benchmark datasets, The advancement of the proposed model advances state-of-the-art approaches .Furthermore, this framework can generate summaries with better formability, coherence, and diversity.	High degree ROUGE For datasets 1- Gigaword (36.92 ,18.29 ,34.58) to Rouge1, Rouge 2, Rouge L 2-internal test set of Gigaword (46.92, 24.83, 44.04) to Rouge1, Rouge 2, Rouge L 3- DUC-2004 (31.15 ,10.87 ,27.68) to Rouge1, Rouge 2, Rouge L 4- LCSTS (39.93/45.12 21.58/33.08 37.92/42.68) to Rouge1, Rouge 2, Rouge L * On left, the word-level ROUGE ,On the right the character-level
Yuliska et al [18]	2019	Query Focused Extractive Summary for multi-document based on Deep Learning techniques	DUC 2005, DUC 2007	They compared six deep learning methods and they found that the best one is Bi-LSTM.	High degree for Bi-LSTM Max on DUC2005-2007 is (43.53 11.40 18.67) for ROUGE-1 ROUGE-2 ROUGE-L
Paolo Rosso et al[19]	2018	Graphs-based method for extractive summary	DUC 2002	The key contribution of the research is to they do study of the influence of a known algorithm for social network analysis, which enables large graphs to be analyzed accurately.	The score of the Betweenes Cent(Euclidean) method is (0.3833 , 0.5581 for $ROUGE-1$,BLEU matrices

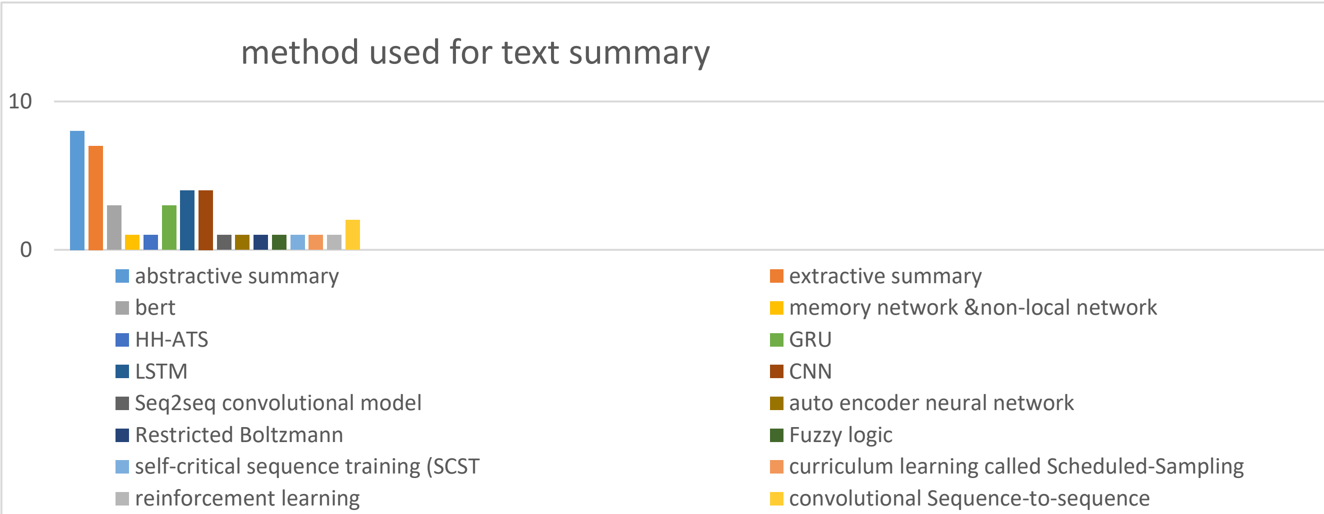

Fig 2 Variation of methods that is used in the research papers

In figure 2 The range of summary text techniques used in the 17 articles which have been examined was described accurately, which include Gated Recurrent Units (GRU), Boltzmann Machine, Fuzzy Logic, reinforcement learning, etc.

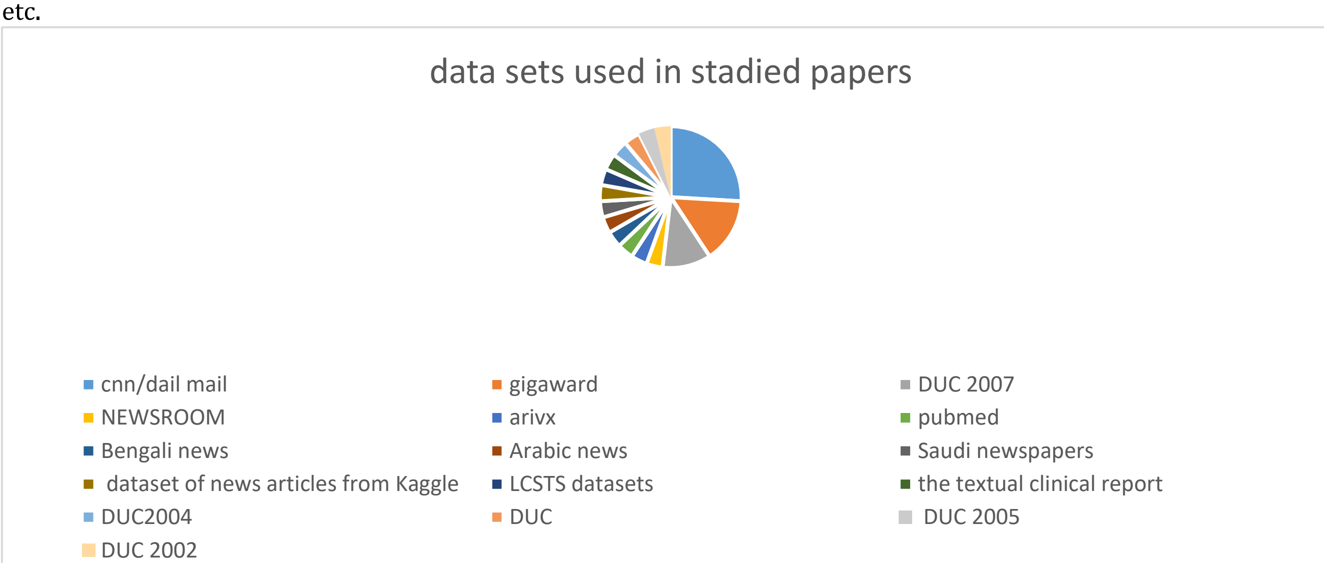

Fig 3 Variation of the datasets that is used in research

Fig. 3 consists of a graph that displays the number of datasets used in the articles that were examined. Scientists have used data from various resources such as online networks and social media posts, while some have used daily mail and CNN or gigaword , DUC 7, etc. data. It is possible to read the other details from Fig. 3.

3. CONCLUSION AND FUTURE WORK

In latest years, the significance of the text summary process has increased due to the large amount of information available on the Internet. The analysis of the methods examined yielded a range of conclusions. The deep learning strategies most widely used were the Recursive neural network(RNN). Some approaches used LSTM to solve the problem of gradient disappearance, while other approaches used Gated Recurrent Units (GRU) and transformers. The sequence-to-sequence framework has also been used for abstractive summarization. From this paper we can see the different summary text techniques, such as transformers like (BERT), Restricted Boltzmann Machine, Fuzzy Logic, LSTM-CNN, Gated Recurrent Units (GRU) based RNN, Seq2seq convolutional model, Word embedded and RNNs using any of these approaches. Also, ROUGE1, ROUGE2, and ROUGE-L have been used to determine the Efficiency of the summaries. Through Fig 3 we can see the most deep learning approaches which include extractive and abstract methods. The best results for both extractive summary and abstract summary based on the results shown in table 1 when they have been using transformers such as Bidirectional Encoder Representations from Transformers (BERT) which treat many problems like long documents and enhance the summarization process accuracy. In the past three years, the extractive method has stayed very desirable since extraction is simpler than abstract and the ability to combine techniques is still available and it has an attractive result. we intend in this article to analyze the various trends in the field of text summary. The data obtained from 17 research papers were compiled and presented in a tabulated form as seen in Fig 1. And from the observation of the results of examined papers lead it's possible to raise more suggestions for future work and extend the scope of future research to develop the methods of text summary and increase its efficiency.

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