

A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

ADVANCING AUTOMATED TEXT SUMMARIZATION: CHALLENGES AND FUTURE DIRECTIONS

*Tolla L N Varaprasad, *Dr K Deepa

PhD Scholar, SR University, Warangal.

Asst.Professor, SR University, Warangal

Abstract

Text summarization plays a pivotal role in managing and distilling vast amounts of textual information into concise, coherent summaries. This survey explores the landscape of text summarization techniques, categorizing them into extractive and abstractive methods. Extractive techniques, such as graph-based algorithms and feature-based models like Text Rank and Lex Rank, focus on selecting salient sentences directly from the original text. In contrast, abstractive methods leverage advanced natural language processing (NLP) models, including neural networks and sequence-to-sequence architectures, to generate summaries that go beyond mere extraction by synthesizing new phrases. The article delves into evaluation metrics like ROUGE and BLEU, discussing their role in assessing summary quality, alongside challenges such as semantic coherence and scalability. Applications across domains like news media, academic research, and business are examined, highlighting the transformative impact of summarization on information retrieval and decision-making processes. Recent advances in deep learning, multimodal summarization, and ethical considerations in algorithmic design are also discussed, paving the way for future research directions. This survey consolidates current knowledge, offering insights into the evolving field of text summarization and its promising avenues for innovation.

KEYWORDS: Extractive summarization, Abstractive summarization, TextRank, LexRank, neural networks, sequence-to-sequence models, ROUGE, BLEU, summarization metrics, natural language processing, NLP, information retrieval, deep learning, multimodal summarization, algorithmic transparency, semantic coherence, text mining.

1. Introduction

Text summarization is a pivotal area within natural language processing (NLP) that addresses the challenge of distilling extensive textual information into concise and coherent summaries. This survey comprehensively explores two primary approaches to text summarization: extractive and abstractive techniques. Extractive methods, such as TextRank and LexRank, identify and select key sentences or phrases directly from the original text based on statistical measures or graphbased algorithms. In contrast, abstractive summarization techniques employ advanced NLP models, including neural networks and sequence-to-sequence architectures, to generate summaries that go beyond mere extraction by synthesizing new phrases and enhancing coherence.

The survey delves into the evaluation metrics crucial for assessing summary quality, such as ROUGE (Recall-Oriented Understudy for Gisting Evaluation) and BLEU (Bilingual Evaluation Understudy), which measure overlap and similarity between generated summaries and reference texts. It also discusses the





In Science & Technology

A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

inherent challenges in text summarization, including maintaining semantic accuracy, ensuring coherence across sentences, and scaling algorithms for handling large volumes of data effectively.

Applications of text summarization span diverse domains, including news media for content curation, academic research for synthesizing literature and business for reviews, analyzing customer feedback and market trends. The article highlights recent advancements in deep learning approaches applied to summarization tasks, such as transformer models like BERT and GPT, as well as multimodal emerging trends in summarization that integrate text with other modalities such as images and audio. considerations in Ethical algorithmic design, including mitigating biases and ensuring transparency in decision-making processes, are also explored. The survey concludes by summarizing key insights and proposing future research directions aimed at addressing current limitations and exploring new avenues for innovation in text summarization, thereby contributing to advancements in information retrieval and knowledge management through automated summarization technologies.

Text summarization plays a crucial role in managing the overwhelming volume of textual data generated daily across various fields, from news articles and research papers to business reports and social media content. By condensing lengthy documents into succinct summarizes, text summarization enables efficient information retrieval, saving time and effort for users who need to quickly grasp the essence of a document without delving into its entire contents. This capability is particularly valuable in today's digital age, where information

overload is a common challenge. In academic settings, text summarization aids researchers in navigating extensive literature by providing concise overviews of existing studies, and facilitating quicker identification of relevant sources and trends.

Similarly, journalists and content curators use summarization techniques to sift through many news articles, ensuring timely and accurate reporting to their audiences. In business environments, automated summarization supports decision-making processes by distilling complex datasets and customer feedback into actionable insights, enabling faster responses and strategic planning. Moreover, text summarization enhances accessibility to information for individuals with limited time or attention spans, democratizing thereby access to knowledge. By improving the efficiency of information processing and consumption, text summarization boosts productivity and fosters innovation in fields reliant on data-driven insights, ultimately contributing to advancements in research, journalism, business analytics, and beyond.

Text summarization can be categorized into several types based on the approach used to generate summaries. These categories help classify the diverse natural language processing (NLP) methodologies for condensing textual information. Here are the main types of summarization and reasons for their categorization, along with present trends:

2. Types of Summarizations:

- 1. Extractive Summarization:
 - **Description**: Extractive methods select and compile key sentences, phrases, or

IJARST

A peer reviewed international journal ISSN: 2457-0362

paragraphs directly from the original text without altering their wording.

- **Techniques**: Algorithms 0 such as TextRank, LexRank, and graph-based methods determine sentence importance based on statistical features like word position, frequency, or semantic similarity.
- Reason for 0 Categorization: Extractive summarization preserves the integrity and factual accuracy of the original text, making it suitable for scenarios where fidelity and retention context are paramount, such as in legal scientific documents or articles.

2. Abstractive Summarization:

- **Description**: Abstractive methods generate summaries by interpreting and paraphrasing the content of the original text, often employing advanced NLP techniques.
- **Techniques**: Neural 0 networks, sequence-tosequence models (e.g., using transformers), and natural language generation (NLG) approaches enable synthesis of the new phrases that may not appear verbatim in the source text.
- Reason for Categorization: Abstractive summarization offers flexibility in

complex

information and can concise produce more summaries compared to extractive methods. This approach is beneficial for creating summaries that capture the core meaning of a text while potentially improving readability.

www.ijarst.in



Figure 1: Summarization Categorization **Reasons for Categorization:**

- Methodological Differences: The categorization into extractive and abstractive summarization reflects fundamental differences in how summaries are generated—whether through direct extraction of existing text segments or through the creation of new content based on semantic understanding.
- Application-Specific Needs: Different applications require specific summarization techniques.

summarizing



A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

Extractive methods are favored precise retention of when information and context is such as in legal or essential. technical documents. Abstractive methods preferred are for applications needing concise and coherent summaries, such as in news articles or automated content generation for social media.

Advancements in NLP: Recent trends show a shift towards more sophisticated abstractive techniques leveraging deep learning models like BERT and GPT, which enhance the ability to generate human-like summaries by understanding and synthesizing content contextually. These advancements drive the categorization by highlighting the capabilities evolving and applications of NLP in text summarization.

Text summarization, a pivotal task in natural language processing (NLP), seeks to distill large volumes of text into concise summaries while preserving essential information. This aims survey to comprehensively explore current techniques in both extractive and abstractive summarization. evaluate existing evaluation metrics such as ROUGE and BLEU, identify persistent challenges including semantic accuracy and scalability, survey diverse applications domains like journalism and across business analytics, review recent advances in deep learning and multimodal approaches, address ethical considerations in algorithmic design, and propose future research directions to advance the field's capabilities in information retrieval and knowledge management. This survey aims to achieve the following objectives:

Explore Summarization Techniques: Investigate and compare extractive and abstractive methods in text summarization to understand their strengths, limitations, and suitability across various applications and domains.

Evaluate Summarization Metrics: Assess the effectiveness of evaluation metrics such as ROUGE (Recall-Oriented Understudy for Gisting Evaluation) and BLEU (Bilingual Evaluation Understudy) in measuring the quality and coherence of generated summaries.

Identify Challenges: Identify and analyze challenges inherent in text summarization, including maintaining semantic accuracy, handling ambiguity, ensuring coherence, and scaling algorithms for large datasets.

Survey Applications: Examine realworld applications of text summarization in fields such as journalism, academic research, business analytics, and social media content generation, highlighting case studies and practical implementations.

Review Recent Advances: Review recent advancements in deep learning techniques (e.g., transformer models) and multimodal summarization approaches to understand their impact improving the accuracy on and efficiency of summarization text systems.

Address Ethical **Considerations**: Discuss ethical implications in algorithmic design for text summarization. including biases. privacy concerns, and transparency

IJARST

A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

issues, and propose frameworks for ethical implementation and use.

3. Types of Text Summarization Techniques

Extractive Summarization

Definition: Extractive summarization involves selecting important sentences, phrases, or sections directly from the source text and concatenating them to create a summary. This method does not generate new sentences but extracts portions from the original document.

Example: Suppose we have a document: "Artificial intelligence is transforming industries by automating processes, improving efficiency, and enabling datadriven decisions. Machine learning, a subset of AI, allows systems to learn and adapt without explicit programming. This technology is widely used in various sectors including healthcare, finance, and transportation."

• Extractive Summary: "Artificial intelligence is transforming industries by automating processes, improving efficiency, and enabling data-driven decisions. Machine learning, a subset of AI, allows systems to learn and adapt without explicit programming."

Explanation of Techniques:

- Graph-based Methods:
 - Techniques such as TextRank and LexRank are popular. These methods model sentences as nodes in a graph and use algorithms like PageRank to identify important sentences.
- Feature-based Methods:
 - These methods use machine learning algorithms to score sentences based on features

such as sentence length, position, term frequency, and similarity to the document title.

Examples of Algorithms:

• TextRank:

- A graph-based ranking model for text processing, based on PageRank algorithm.
- LexRank:
 - Uses cosine similarity between sentence pairs to build a graph and applies PageRank to extract key sentences.

Applications and Strengths:

- Applications:
 - Document summarization, news summarization, and legal document analysis.
 - Strengths:
 - Simplicity, scalability, and effectiveness in identifying key sentences without understanding the content.

Abstractive Summarization

□ **Definition:** Abstractive summarization generates a summary by interpreting and paraphrasing the main points of the source text. This approach aims to produce concise and coherent summaries that may not use exact phrases from the original document but capture the underlying meaning.

Example: Using the same document: "Artificial intelligence is transforming industries by automating processes, improving efficiency, and enabling datadriven decisions. Machine learning, a subset of AI, allows systems to learn and adapt without explicit programming. This technology is widely used in various



A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

sectors including healthcare, finance, and transportation."

• Abstractive Summary: "AI is revolutionizing industries by automating tasks and enhancing decision-making through machine learning, particularly in healthcare, finance, and transportation."

Techniques:

- Neural Networks:
 - Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers are commonly used.
- Sequence-to-Sequence Models:
 - Encoder-decoder architectures, often with attention mechanisms, to generate summaries.

Challenges and Current Advancements:

- Challenges:
 - Maintaining coherence, handling long documents, and reducing redundancy.
- Current Advancements:
 - Improved architectures (e.g., BERT, GPT), pretraining techniques, and fine-tuning strategies to enhance summary quality.

Comparative Analysis with Extractive Methods:

- Advantages:
 - Can generate more coherent and human-like summaries.
- Disadvantages:
 - Computationally intensive and requires large datasets for training.

Survey on Approaches and Contributions

	C	ontributi	UIIS	
Refere	Тур	Appr	Adva	Disadv

nce	e	oach	ntages	antage		
				S		
[1] A.	Extr	Cluste	High	May		
Ahmad	activ	ring	scalabi	miss		
et al.,	e	cum	lity,	nuance		
"A		graph	effecti	d		
probabi		rankin	ve key	context		
listic		g	senten	in		
approa			ce	sentenc		
ch for			extract	es		
extracti			ion			
ve						
summa						
rization						
based						
on						
clusteri						
ng cum						
graph						
ranking						
method						
," <i>IEEE</i>						
Access,						
2024						
[2] R.	Extr	Evolut	Handl	Compu		
Alqaisi	activ	ionary	es	tational		
et al.,	e	multi-	multip	ly		
"Extrac		object	le	intensi		
tive		ive	docum	ve		
multi-		optimi	ents,			
docum		zation	evoluti			
ent		with	onary			
Arabic		K-	optimi			
text		Medoi	zation			
summa		d	for			
rization		cluster	better			
using		ing	summ			
evoluti			aries			
onarv						
multi-						
obiecti						
ve						
optimiz						



In Science & Technology A peer reviewed international journal

IJAK	51			1551	N: 245	1-0302				
ation						graph-				
with K-						based				
Medoid						ranking				
clusteri						algorith				
ng,"						m,"				
IEEE						Сотри				
Access,						tational				
2020						Intellig				
[3] T.	Extr	Graph	Effecti	Compl		ence				
Uçkan	activ	indepe	ve for	exity		and				
and A.	e	ndent	multi-	increas		Neuros				
Karcı,		sets	docum	es with		cience,				
"Extrac			ent	numbe		2020				
tive			summ	r of		[5] B.	Extr	Minin	Balanc	May
multi-			arizati	docum		Ma,	activ	g	es	struggl
docum			on	ents		"Minin	e	comm	comm	e with
ent text						g both		onalit	on and	highly
summa						commo		y and	unique	diverse
rization						nality		specifi	inform	docum
based						and		city	ation	ent sets
on						specific		-	across	
graph						ity			docum	
indepe						from			ents	
ndent						multipl				
sets,"						e				
Egyptia						docum				
n						ents for				
Inform						multi-				
atics						docum				
Journal						ent				
, 2020						summa				
[4] A.	Extr	Super	Accur	Requir		rization				
Khan	activ	vised	ate	es		," IEEE				
et al.,	e	learni	summ	labeled		Access,				
"Movie		ng	arizati	data		2024				
review		with	on due	for		[6] M.	Abst	Deep	Enhan	Requir
summa		graph-	to	trainin		Liu et	racti	learni	ced	es
rization		based	superv	g		al.,	ve	ng	summ	signific
using		rankin	ised	-		"Deep-		with	arizati	ant
supervi		g	learnin			learnin		pre-	on	comput
sed		-	g			g-based		trainin	throug	ational
learnin			-			pre-		g and	h	resourc
g and						training		fine-	refine	es and



A peer reviewed international journal

IJAR	ST			ISSN	N: 2451	7-0362				
and		tuning	d	large		Approa			on	
refined		_	tuning	dataset		ches,			approa	
tuning			,	S		dataset			ches	
for web			adapta			s,				
summa			ble to			evaluat				
rization			variou			ion				
softwar			S			measur				
e,"			contex			es, and				
IEEE			ts			challen				
Access,						ges,"				
2024						Mathe				
[7] M.	Abst	Neural	Gener	Compu		matical				
Ulker	racti	netwo	ates	tational		Proble				
and A.	ve	rks	human	ly		ms in				
B.		with	-like	intensi		Engine				
Ozer,		seque	summ	ve,		ering,				
"Abstra		nce-	aries,	may		2020				
ctive		to-	good	generat		[9] S.	Abst	Light-	Fast	May
summa		seque	for	e		Abeed	racti	weigh	summ	lack
rization		nce	scienti	incorre		et al.,	ve	t	arizati	depth
model		model	fic	ct or		"A		summ	on	and
for		S	article	mislea		light-		arizati	suitabl	accura
summa			S	ding		weight		on	e for	cy in
rizing				inform		text		syste	medic	summa
scientif				ation		summa		m	al	ries
ic						rization			applic	
article,						system			ations	
" IEEE						for fast				
Access,						access				
2024						to				
[8] D.	Abst	Deep	Provid	Compu		medica				
Suleim	racti	learni	es	tational		1				
an and	ve	ng,	compr	and		evidenc				
A.		variou	ehensi	data-		e,"				
Awajan		S	ve	intensi		Frontie				
, "Deep		datase	overvi	ve		rs in				
learnin		ts,	ew of			Digital				
g based		evalua	deep			Health,				
abstract		tion	learnin			2020				
ive text		measu	g-			[10] J.	Abst	Sente	Effecti	May
summa		res	based			Zhao et	racti	nce	ve for	miss
rization			summ			al.,	ve	graph	unsup	import
:			arizati			"Summ		compr	ervise	ant



A peer reviewed international journal ISSN: 2457-0362

Pip:		ession	d	details,	Engine				
Unsupe			summ	require	ering,				
rvised			arizati	S	2020				
multi-			on,	careful	[12] Z.	Abst	Two-	Impro	Compl
docum			reduce	parame	Deng	racti	stage	ved	ex
ent			S	ter	et al.,	ve	approa	perfor	trainin
summa			redund	tuning	"A		ch	mance	g
rization			ancy		two-		with	throug	process
with					stage		keywo	h	,
sentenc					Chines		rd	advers	require
e graph					e text		infor	arial	s large
compre					summa		matio	learnin	dataset
ssion,"					rization		n and	g,	s and
in					algorith		advers	effecti	comput
Proc.					m		arial	ve	ational
SIGIR,					using		learni	keywo	power
2020					keywor		ng	rd	
[11] M.	Abst	Ense	Combi	High	d			utilizat	
Tomer	racti	mbled	nes	comple	inform			ion	
and M.	ve	approa	strengt	xity,	ation				
Kumar,		ch	hs of	difficul	and				
"Impro		based	multip	t to	adversa				
ving		on	le	imple	rial				
text		fuzzy	metho	ment	learnin				
summa		logic	ds,		g,"				
rization		and	impro		Neuroc				
using		LSTM	ved		omputi				
ensemb			accura		ng,				
led			cy		2020				
approa					[13] W.	Abst	Dual-	Impro	Requir
ch					Peng et	racti	level	ves	es
based					al.,	ve	contra	summ	signific
on					"Dual-		stive	arizati	ant
fuzzy					level		learni	on	trainin
with					contras		ng	concis	g data
LSTM,					tive			eness,	and
"					learnin			adapta	comput
Arabia					g for			ble to	ational
n					improv			variou	resourc
Journal					ing			S	es
for					concise			contex	
Science					ness of			ts	
and					summa				



A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

TOWN	91			1001
rization				
," IEEE				
Access,				
2024				
[14] B.	Abst	Efficie	High	May
Xiang	racti	nt	efficie	not
and Y.	ve	contra	ncy,	general
Shao,		stive	effecti	ize
"SumL		repres	ve for	well to
LaMA:		entati	specifi	other
Efficie		ons	с	types
nt		and	applic	of
contras		fine-	ations	docum
tive		tuned	like	ents
represe		adapte	bug	
ntation		rs	report	
s and			summ	
fine-			arizati	
tuned			on	
adapter				
s for				
bug				
report				
summa				
rization				
," <i>IEEE</i>				
Access,				
2024				
[15] A.	Abst	Onlin	Enhan	May
Curiel	racti	e	ces	struggl
et al.,	ve	multi-	text	e with
"An		source	readab	highly
online		summ	ility in	diverse
multi-		arizati	topic-	sources
source		on	based	
summa			search	
rization			es	
algorith				
m for				
text				
readabi				
lity in				
topic-				

based		
Jased		
search,		
"		
Сотри		
ter		
Speech		
æ		
Langua		
ge,		
2020		

4. Evaluation Metrics and Challenges

Evaluation Metrics:

ROUGE (Recall-Oriented Understudy for Gisting **Evaluation**): ROUGE **Description:** 0 measures the overlap between the words or ngrams of the generated summary and the reference summary. Common variants include ROUGE-N (measures n-gram overlap), ROUGE-L (measures the longest common subsequence), and ROUGE-S (measures skipbigram).

• **Significance:** ROUGE is widely used because it correlates well with human judgment and is simple to implement. It is particularly useful for extractive summarization.

BLEU (Bilingual Evaluation Understudy):

 Description: Originally developed for evaluating machine translation, BLEU calculates the precision of n-grams in the generated



A peer reviewed international journal ISSN: 2457-0362

text against one or more reference texts.

• **Significance:** BLEU is useful for measuring the fluency and accuracy of generated summaries, especially in abstractive summarization. It rewards exact matches of n-grams, making it stringent for natural language generation tasks.

Other Metrics:

- METEOR (Metric for Evaluation of Translation with Explicit ORdering): Considers synonymy and stemming, giving higher weight to content words.
- CIDEr (Consensus-based Image Description Evaluation): Focuses on consensus among multiple reference summaries.
- **F1 Score:** Balances precision and recall, particularly useful for summarization that aims to capture key information concisely.

Challenges:

Language Complexity and Ambiguity:

- Description: Human language is inherently complex and ambiguous, making it difficult for models to understand and generate coherent summaries.
- Significance: Models must handle nuances such as sarcasm, idioms, and context-specific meanings

to produce accurate summaries.

www.ijarst.in

Semantic Understanding and Coherence:

- **Description:**
 - Summarization models need to capture the meaning and intent of the original text while maintaining coherence in the generated summary.
- Significance: Ensuring semantic accuracy and logical flow in summaries is crucial for user understanding and satisfaction.

Real-World Applicability and Scalability:

- Description: Models should perform well across diverse domains and large datasets, handling various text lengths and complexities.
- Significance: Scalability and adaptability to different types of texts (e.g., news articles, scientific papers) are important for practical applications.

Tabular RepresentationResults in Terms of References

Refe	Ту	Арр	R	B	Ot	Chal
renc	pe	roac	0	L	her	leng
e		h	U	Е	Me	es
			G	U	tric	Add
			Ε	Sc	S	ress
			Sc	or		ed
			or	e		
			e			
А.	Ext	Clus	R	В	F1	Lang
Ahm	ract	terin	0	L	Sco	uage



A peer reviewed international journal ISSN: 2457-0362 www.ijarst.in

ad et ive g U E re: com al., cum G U 0.4 plexi using
al., cum G U 0.4 plexi using ising
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$
bilisti ranki 0.4 0. $prodeside prodeside product of the set of t$
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $
approachobjeciiiforiiii-iiiiextraoptiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiiii
ach for extra ctiveobjec tiveiiiiach for extraobjec tiveiiiictiveiiiiiisum marizionionionionionmariz ationionionionionionbased on clustionionionionodidclustionioniongraph rankiionionionioning methion <td< td=""></td<>
for extra ctiveiiiiiiiiextra ctiveiiiiiiiiiiisum mariz ationiiiiiiiiiiiibased on clustiiiiiiiiiiiiiigraph rankiiiiiiiiiiiiiigraph rankiiiiiiiiiiiiiiigraph rankii
extra ctiveImage: sector of the sector of
ctiveImage: start of the start
sum mariz a dion maria dion maria dion maria di dion mariz a dion maria di dion mariz a dion mariz a dion mariz a dion mariz a dion maria di dion mariz a dion mariz a dion maria di dion mariz a dion maria di dion di di dion di di
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
ation based on clust ering graph rankiII <t< td=""></t<>
based on clust ering cumIII
on clust ering cumiioid clust iiiiiigraph rankiiiiiiiiiiing meth od,"iiiiiiiiiii <i>IEEE</i> iiiiiiiiiiiiing meth od,"iiiiiiiiiii <i>IEEE</i> iiiiiiiiiiiiiod," <i>IEEE</i> ii </td
clust ering cum graph rankiII<
ering cumImage: sering methImage: sering meth<
cum graph ranki ng meth,", IEEE $SS,$, IEEE IEEE, IEEE IEEE, IEEE IEEE, IEEE IEEE, IEEE IEEE, IEEE IEEE, IEEE IEEE, IEEE IEEE, IEEE IEEE, IEEE, IEEE IEEE, IEEE
graph ranki ng meth od,"IEEE $Acce$ IEEE $Acce$ IEEE $Accee$ IEEE $Accee$ IEEE
anki $Acce$ $anki$ $bnki$ $bnki$ $anki$ ng ng $ss,$ $anki$ $bnki$ $bnki$ $bnki$ $andthindowski2020bnkibnkibnkibnkiod, "T.ExtGrapRBCICohIEEEUçkaracthOLDEeren$
ng meth od," <i>IEEE</i>
meth od," <i>IEEE</i> <i>Description</i> <i>IEEE</i> <i>Description</i> <i>IEEE</i> <i>Description</i> <i>IEEE</i> <i>Description</i> <i>IEEE</i> <i>Description</i> <i>IEEE</i>
od," <i>IEEE</i> <i>Uçka</i> ract h O L DE eren
IEEE Uçka ract h O L DE eren
Acce $ $ $ $ $ $ $ $ $ $ $ $ $ $ $ $ $ $ $n and $ ive $ $ inde $ $ $U $ $E $ $r:$ $ $ ce, $ $
ss, A. pend G U 1.2 scala
2024 Karcı ent E bilit
R. Ext Evol R B ME Sem , sets L: 3: y
Algai ract ution O L TE antic "Extr 0.4 0.
si et ive ary U E OR unde activ 8 36
al., mult G U : rstan e
"Extr i- E 0.4 ding, multi
activ obje 2: 2: 2 real
e ctive 0.5 0. worl docu
multi opti 0 38 d ment
- miza appli text
docu tion cabil sum
ment with ity mariz
Arabi K- ation
c text Med based
sum oid on

Volume 14, Issue 11, Nov 2024



In Science & Technology A peer reviewed international journal ISSN: 2457-0362

indep ende mt s k	10 11.			-	-		100.	 				-		
ende nt sets,"iiiiiiiiiiSets,"ii <td>indep</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>oscie</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	indep							oscie						
nt sets." ggyp tian 	ende							nce,						
sets," Egyp tian Infor matic sEILang Sour (Ma, ract ing eronB.ExtMini RB.F1Lang Sou uageJour nal, 2020Sco uageuageMan ing aduSco uageuageJour nal, 2020 <t< td=""><td>nt</td><td></td><td></td><td></td><td></td><td></td><td></td><td>2020</td><td></td><td></td><td></td><td></td><td></td><td></td></t<>	nt							2020						
Egyp tian Infor maticIII<	sets."							B.	Ext	Mini	R	В	F1	Lang
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Eovn							D. Ma	ract	ng	0	I	Sco	11906
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	18yp tian							"Min	ivo	ng com	U	E	ro	com
Indice Ing Ing Indice Indice <thindice< th=""> <thindice< th=""> <t< td=""><td>Infor</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>IVC</td><td>com</td><td>0 C</td><td></td><td>1C.</td><td></td></t<></thindice<></thindice<>	Infor								IVC	com	0 C		1C.	
matrix Image Image <thimage< th=""> <t< td=""><td>mjor</td><td></td><td></td><td></td><td></td><td></td><td></td><td>ing</td><td></td><td>1.4</td><td>U F</td><td>U</td><td>0.4</td><td>piexi</td></t<></thimage<>	mjor							ing		1.4	U F	U	0.4	piexi
sandS:3:real- wordJour nal, 2020	matic							both		ality	E-	-	3	ty,
Jour nal,Image: Secience of the second sec	S							com		and	S:	3:		real-
nal, 2020iveRBMESemA.ExtSupeRBMESemKhan ractrviseOLTEanticivedUEORunde"Mov ieiagE-0.4ding, 	Jour							mona		speci	0.5	0.		worl
2020Image: sector of the sector	nal,							lity		ficit	2	37		d
A. Ext Supe R B ME Sem speci Image: Speci field of the speci field of	2020							and		У				appli
Khan ract rvise O L TE antic ficity I <thi< th=""> I <thi< td=""><td>A.</td><td>Ext</td><td>Supe</td><td>R</td><td>В</td><td>ME</td><td>Sem</td><td>speci</td><td></td><td></td><td></td><td></td><td></td><td>cabil</td></thi<></thi<>	A.	Ext	Supe	R	В	ME	Sem	speci						cabil
et al., ive d U E OR unde from multi multi multi "Mov ing E- 0.4 ding, ple multi ple multi ple revie with 3: 4: 4 scala docu ment multi ment ment ment ment ment ment ment ment multi ment	Khan	ract	rvise	0	L	ΤE	antic	ficity						ity
	et al.,	ive	d	U	Е	OR	unde	from						
ie ing E- - 0.4 ding, ple	"Mov		learn	G	U	:	rstan	multi						
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	ie		ing	E-	-	0.4	ding,	ple						
wgrap sum h- base ation d0.50. 40bilit yment s for multi - docu multi - docu ment sum mariz docu ment sum mariz ation ngment s s for multi - docu ment sum mariz ation, "ment s s s multi - docu ment sum mariz ation, "ment s s s multi - docu ment sum mariz ation, "ment s s s ment sum mariz ation, "ment s s s ment sum mariz ation, "ment s s s s s t ment sum mariz ation, "Ment s s s s t	revie		with	3:	4:	4	scala	docu						
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	W		grap	0.5	0.		bilit	ment						
and base $base base$	sum		b	5	40		v	s for						
Initial ationobset d </td <td>mariz</td> <td></td> <td>hase</td> <td>5</td> <td></td> <td></td> <td>5</td> <td>multi</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	mariz		hase	5			5	multi						
and usingranki rankidocu ment I ment I 	ation		d					-						
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	using		u ranki					docu						
superingindindindindindindvisedsummarizindindindindindngation,indindindindindindgraphindindindindindindind-basedss,indindindindindngindindindindindindindngindindindindindindindngindindindindindindindngindindindindindindindithm,indindindindindindind"indindindindindindindithm,indindindindindindind"indindindindindindind"indindindindindindind"indindindindindindindind"ind <td>super</td> <td></td> <td>ng</td> <td></td> <td></td> <td></td> <td></td> <td>mont</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	super		ng					mont						
visedsummarizaaalearnimarization,ation,ation,ation,graph $IEEE$ $IEEE$ $IEEE$ $IEEE$ -basedss, $IEEE$ $IEEE$ ng $IIEE$ $IEEE$ $IEEE$ algor $IIEE$ $IEEE$ $IEEE$ ng $IIEE$ $IEEE$ $IEEE$ algor $IIEE$ $IEEE$ $IEEE$ ng $IIEE$ $IEEE$ $IEEE$ algor $IIEE$ $IEEE$ $IEEE$ ng $IIEE$ $IEEE$ $IEEE$ algor $IIEEE$ $IEEE$ $IEEE$ ng $IIEEE$ $IIEEE$ $IIEEE$ ng $IIEEE$ $IIEEE$ $IIEEE$ algor $IIEEE$ $IIEEE$ $IIEEE$ ng $IIEEE$ $IIEEE$ $IIEEE$ ng $IIEEE$ $IIEEE$ $IIEEE$ ng $IIEEE$ $IIEEE$ $IIEEE$ ng $IIEEE$ $IIEEE$ $IIEEE$ $IIIEEE$ $IIEEE$ $IIEEE$ $IIEEE$ $IIIEEE$ $IIEEE$ $IIEEE$ $IIEEE$ $IIIEEE$ $IIIEEE$ $IIEEE$ $IIEEE$ $IIIIEEE$ $IIIEEE$ $IIIEEE$ $IIIEEE$ $IIIIEEE$ $IIIEEE$ $IIIEEE$ $IIIEEE$ $IIIIEEE$ $IIIEEE$ $IIIEEE$ $IIIEEE$ $IIIIIEEEIIIEEEIIIEEEIIIEEEIIIIIEEEIIIEEEIIIEEEIIIEEEIIIIIIIIEEEIIIEEEIIIEEEIIIEEE<$	super		ng											
Imariz ation, "Imariz ation, 								suiii						
ng and graphation, "ation	leann													
and graph -III	ng							ation,						
graph - based rankiIEEE $Acce$ IEEE $Acce$ IIEEE $Acce$ IIEEE $Acce$ IIEEE $Acce$ ss, 2024Ss, 2024IIEEE IIEEEIIEEE IIEEEIIEEE IIEEEIIEEE IIEEEng algor ithm, "IIEEE Ss, 2024IIEEE IIEEEIIEEE IIEEEIIEEE IIEEEM. Liu IIEEEAb IIEEEDee IIEEER IIEEEB IIEEEME IIEEEM. IIEEEAb IIEEDee IIEEER IIEEEB IIEEEME IIEEEM. IIEEEAb IIEEEDee IIEEER IIEEEB IIEEEME IIEEEM. IIEEEAb IIEEEDee IIEEER IIEEEB IIEEEME IIEEEM. IIEEEAb IIEEEDee IIEEER IIEEEB IIEEEME IIEEESem IIEEEIIIEEE IIIEEIIIEEEIIIEEE IIIEEIIIEEEIIIEEEIIIEEEIIIEEEIIIIEEE IIIEEIIIEEE IIIEEIIIEEE IIIEEEIIIEEE IIIEEIIIEEE IIIEEEIIIEEEE IIIEEEIIIEEEE IIIEEEEIIIEEEE IIIEEEEIIIEEEE IIIEEEE <td>and</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>"</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	and							"						
- $Acce -graphIEEE$	graph							IEEE						
based rankiss, 2024 ss, 2024 ss, $1000000000000000000000000000000000000$	-							Ассе						
ranki2024Image: Constraint of the second seco	based							ss,						
ng algorM.AbDeeRBMESemalgorLiustrapOLTEanticithm,et al.,ctivlearnUEORunde""DeeeingGU:rstanComp-withE0.5ding,putatlearnipre-1:1:0coheionalng-train0.60.rencIntellpre-anding045eigencpre-andfine-uuuNeurngtuninfine-uuu	ranki							2024						
algor ithm, "LiustrapOLTEanticithm, "et al., "DeectivlearnUEORunde"DeeeingGU:rstanCom putat ionalp-withE0.5ding,learniIpre-1:1:0coheinnal ionalIIIIIeIntell e andIIIIIeNeurIIIIIII	ng							М.	Ab	Dee	R	В	ME	Sem
ithm, \cdots <th< td=""><td>algor</td><td></td><td></td><td></td><td></td><td></td><td></td><td>Liu</td><td>stra</td><td>р</td><td>0</td><td>L</td><td>ΤE</td><td>antic</td></th<>	algor							Liu	stra	р	0	L	ΤE	antic
""DeeeingGU:rstanComp-with $E-$ -0.5ding,putatlearnilearnipre-1:1:0coheionalng-train0.60.rencIntellpre-gre-anding045eigencpre-andfine-learnifine-learniingNeurngtrainifine-learnilearnilearnilearni	ithm,							et al.,	ctiv	learn	U	Е	OR	unde
Com putatp- learniwith pre-E- \cdot 0.5ding, ocheional ionalng- learnipre- ing1:1:0coheing- igenctrain0.60.rencigenc e andpre- ingand ing \cdot \cdot \cdot Neurngtuninfine- ing \cdot \cdot \cdot	"							"Dee	e	ing	G	U	:	rstan
putatputatlearnipre-1:1:0coheionalng-train0.60.rencIntellbaseding045eigencpre-andIIIe andngtrainifine-IINeurngtuninIII	Com							p-		with	E-	-	0.5	ding,
ional Intellng-train0.60.rencIntellbaseding045eigencpre-andee andngtrainifineNeurngtunin	putat							learni		pre-	1:	1:	0	cohe
Intell ing 0 45 e igenc pre- and and and and e and pre- and and and and Neur pre- pre- and and and	ional							ng-		train	0.6	0.		renc
igenc pre- and e and traini fine- Neur ng tunin	Intell							based		ing	0	45		e
e and Neur	igenc							pre-		and				
Neur ng tunin	e and							traini		fine-				
	Neur							ng		tunin				



In Science & Technology A peer reviewed international journal

www.ijarst.in

IJA	RST	•				ISSI	N: 245	7-0362						
and		g						A.		vario	Е-	-	7	ty,
refin								Awaj		us	L:	3:		sema
ed								an,		datas	0.6	0.		ntic
tunin								"Dee		ets,	3	46		unde
g for								р		eval				rstan
web								learni		uatio				ding
sum								ng		n				
mariz								based		meas				
ation								abstr		ures				
softw								activ						
are,"								e text						
IEEE								sum						
Acce								mariz						
ss,								ation:						
2024								Appr						
M.	Ab	Neur	R	В	CI	Coh		oach						
Ulker	stra	al	0	L	DE	eren		es,						
and	ctiv	netw	U	Е	r:	ce,		datas						
A. B.	e	orks	G	U	1.5	scala		ets,						
Ozer,		with	E-	-		bilit		evalu						
"Abst		sequ	2:	2:		у		ation						
ractiv		ence	0.6	0.				meas						
e		-to-	5	48				ures,						
sum		sequ						and						
mariz		ence						chall						
ation		mod						enges						
mode		els						,"						
1 for								Math						
sum								emati						
mariz								cal						
ing								Probl						
scien								ems						
tific								in —						
articl								Engi						
es,"								neeri						
IEEE								ng,						
Acce								2020		.				.
ss,								S.	Ab	Ligh	R	B	ME	Keal
2024	. 1		_	F	F 4	.		Abee	stra	t-	0 U		TE	-
D.	Ab	Dee	R	B	F1	Lang		d et	ctiv	weig	U	E	OR	worl
Sulei	stra	p	0	L	Sco	uage		al.,	e	ht	G	U	:	d
man	ctiv	learn	U	E	re:	com		"A		sum .	E- õ	-	0.4	appli
and	e	ing,	G	U	0.4	plexi		light-		mari	S:	4:	6	cabil

Volume 14, Issue 11, Nov 2024



A peer reviewed international journal ISSN: 2457-0362

weigh ht zatio 0.5 0. ity, scala ht n 8 42 ity, scala comp ity, ressi comp ity, ressi ity, ressi <t< th=""><th>weig in zatio 0.5 0. in in, comp in sup in sup in sup in sup in sup in in</th><th>10111</th><th></th><th></th><th></th><th></th><th></th><th>100.</th><th>1 101</th><th></th><th></th><th></th><th></th><th></th><th></th><th></th></t<>	weig in zatio 0.5 0. in in, comp in sup in sup in sup in sup in sup in	10111						100.	1 101							
ht textn syste8 syste42scala bilitressi on," inressi on," inressi on,"ressi o	ht I n 8 42 I scala ressi I <thi< th=""> I <th< td=""><td>weig</td><td></td><td>zatio</td><td>0.5</td><td>0.</td><td></td><td>ity,</td><td></td><td>comp</td><td></td><td></td><td></td><td></td><td></td><td></td></th<></thi<>	weig		zatio	0.5	0.		ity,		comp						
textsystesystesystesystesystesystesystesystesystesystesystesystesumsystesumsystesum<	text syste syste <th< td=""><td>ht</td><td></td><td>n</td><td>8</td><td>42</td><td></td><td>scala</td><td></td><td>ressi</td><td></td><td></td><td></td><td></td><td></td><td></td></th<>	ht		n	8	42		scala		ressi						
sum im im <	sum mariz ation nm km km km km km km km km syste nfor km km km km km km km fast km km km km	text		syste				bilit		on,"						
maizi ation syste m for see set s syste set set s set set s to set	maizi ation for kas	sum		m				у		in						
ation syste m for fast acces s to medi ecal 	ation syste sub su	mariz								Proc.						
syste m for fast accesk kk k kk k kk k k kk k k kk k k kk k k k kk k k k kk k k k k kk k k k k k k k kk k<	syste im im <th< td=""><td>ation</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>SIGI</td><td></td><td></td><td></td><td></td><td></td><td></td></th<>	ation								SIGI						
m for fast acceskk		syste								<i>R</i> ,						
fast acces i.i.	fast acces s l	m for								2020						
acces in	acces s i <td>fast</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>M.</td> <td>Ab</td> <td>Ense</td> <td>R</td> <td>В</td> <td>ME</td> <td>Lang</td>	fast								M.	Ab	Ense	R	В	ME	Lang
s to medi i.i. i.i i.i. i.i.	s to I <td>acces</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>Tom</td> <td>stra</td> <td>mble</td> <td>0</td> <td>L</td> <td>TE</td> <td>uage</td>	acces								Tom	stra	mble	0	L	TE	uage
mediimagei	medi I I I I I I I I I I i <td>s to</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>er</td> <td>ctiv</td> <td>d</td> <td>U</td> <td>Е</td> <td>OR</td> <td>com</td>	s to								er	ctiv	d	U	Е	OR	com
cal I	cal I	medi								and	e	appr	G	U	:	plexi
evide nee," I <t< td=""><td>evide nce," Front iersIII</td><td>cal</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>M.</td><td></td><td>oach</td><td>E-</td><td>-</td><td>0.5</td><td>ty,</td></t<>	evide nce," Front iersIII	cal								M.		oach	E-	-	0.5	ty,
nce," I <	nece," Front iers in Digit alLLLLLar, "Imp rovin g text g text bili and mariz ald on 0.6 0.60. notic und rsta din sca din sca din sca alDigit al al <td< td=""><td>evide</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Kum</td><td></td><td>base</td><td>1:</td><td>1:</td><td>1</td><td>sema</td></td<>	evide								Kum		base	1:	1:	1	sema
Front Image Image <t< td=""><td>Front iers Image Image</td><td>nce,"</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>ar,</td><td></td><td>d on</td><td>0.6</td><td>0.</td><td></td><td>ntic</td></t<>	Front iers Image	nce,"								ar,		d on	0.6	0.		ntic
iers in Digit alAbSent 	iers	Front								"Imp		fuzz	7	49		unde
in Digit alIII	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	iers								rovin		у				rstan
Digit I I I I I I Sum and I Scala al I I I I I I I I Sum and LST bilit Healt I	Digit al I <thi< th=""> <thi< th=""> <thi< t<="" td=""><td>in</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>g text</td><td></td><td>logic</td><td></td><td></td><td></td><td>ding,</td></thi<></thi<></thi<>	in								g text		logic				ding,
al Healt h, 2020 AbSent 	alalImage: Sector of the sector of th	Digit								sum		and				scala
Healt Image: series of the series of th	Healt h, 2020 Image: series of the se	al								mariz		LST				bilit
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	h, 2020 u <	Healt								ation		М				y
2020 I <t< td=""><td>2020 Image: Construction of the sector of the secto</td><td>h,</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>using</td><td></td><td></td><td></td><td></td><td></td><td>2</td></t<>	2020 Image: Construction of the sector of the secto	h,								using						2
J.AbSentRBCICohmbleZhaostraenceOLDEerendet al., ctivgrapUEr:ce,appro"SumehGU1.3scalaachmPipcomEbilitbased-:press3:2:VyonUnsuion0.60.IfuzzyperviIIIIIsedIIIIImultiIIIIIodcuIIIIImentIIIIIIsumIIIIIIationIIIIIIidinIIIIIIidinIIIIIIidinIIIIIIidinIIIIIIIidinIIIIIIIidinIIIIIIIidinIIIIIIIidinIIIIIIIidinIIIIIIIidinIII	J.AbSentRBCICohmbleZhaostraenceOLDEerendet al., ctivgrapUEr.ce,appro"SumehGU1.3scalaachmPipcomEbilitbased-:press3:2:Vonfuzzyunsuion0.60fuzzyperviIIIIIsedIIIIImultiIIIIIocuIIIIImultiIIIIIinIIIIImultiIIIIIinIIIIIinIIIIIinIIIIIinIIIIIinIIIIIinIIIIIinIIIIIIinIIIIIIinIIIIIIinIIIIIIinIIIIIIinIII <t< td=""><td>2020</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>ense</td><td></td><td></td><td></td><td></td><td></td><td></td></t<>	2020								ense						
Zhao stra ence O L DE eren d et al., ctiv grap U E r: ce, appro "Sum e h G U 1.3 scala ach ach mPip com E- - U bilit based Improvement Improvement : press 3: 2: y on Improvement Improvement Improvement Improvement grap ion 0.6 0. Improvement <	Zhao stra ence O L DE eren I d et al., ctiv grap U E r. ce, appro "Sum e h G U 1.3 scala ach ach mPip com E- - bilit based - ach Im press 3: 2: Im y on Im I	J.	Ab	Sent	R	В	CI	Coh		mble						
et al.,ctivgrapUEr:ce,appro"SumehGU1.3scalaachmPipcomEbilitbased:press3:2:yonUnsuion0.60.IIfuzzyperviion247IWithIsedIIIIIIultiIIIIII-IIIIIIdocuIIIIIImentIIIIIIsumIIIIIIIationIIIIIIIidionIIIIIIIIIIIIIIIidionII </td <td>et al.,ctivgrapUEr:ce,approapproIIIIIIIII"SumehGU1.3scalaachachII</td> <td>Zhao</td> <td>stra</td> <td>ence</td> <td>0</td> <td>L</td> <td>DE</td> <td>eren</td> <td></td> <td>d</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	et al.,ctivgrapUEr:ce,approapproIIIIIIIII"SumehGU1.3scalaachachII	Zhao	stra	ence	0	L	DE	eren		d						
"Sum e h G U 1.3 scala ach mPip com E- - bilit based ion ion Unsu ion 0.6 0. - y on fuzzy pervi ion 0.6 0. - fuzzy ion ion sed - 2 47 - ion Kin ion ion with - 2 47 - Kin Kin ion ion sed - Ion ion ion ion ion ion ion ion docu - Ion Ion Ion Ion Ion Ion Ion ment Ion Ion Ion Ion Ion Ion Ion Ion sum Ion Ion Ion Ion Ion Ion Ion Ion Ion idocu Ion Ion Ion Ion Ion Ion Ion Ion <td< td=""><td>"Sum e h G U 1.3 scala ach mPip com E bilit based : press 3: 2: y on Unsu ion 0.6 0. y on Unsu ion 0.6 0. 2 47 I I I I I I I I I I I I I I I I I I</td><td>et al.,</td><td>ctiv</td><td>grap</td><td>U</td><td>Е</td><td>r:</td><td>ce,</td><td></td><td>appro</td><td></td><td></td><td></td><td></td><td></td><td></td></td<>	"Sum e h G U 1.3 scala ach mPip com E bilit based : press 3: 2: y on Unsu ion 0.6 0. y on Unsu ion 0.6 0. 2 47 I I I I I I I I I I I I I I I I I I	et al.,	ctiv	grap	U	Е	r:	ce,		appro						
mPipcomEbilitbased $($ <th< td=""><td>$\begin{array}{cccccccccccccccccccccccccccccccccccc$</td><td>"Sum</td><td>e</td><td>h</td><td>G</td><td>U</td><td>1.3</td><td>scala</td><td></td><td>ach</td><td></td><td></td><td></td><td></td><td></td><td></td></th<>	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	"Sum	e	h	G	U	1.3	scala		ach						
1press 3 : 2 : y on $ <t< td=""><td>1press$3:$$2:$$y$$on$$$$$<td>mPip</td><td></td><td>com</td><td>E-</td><td>-</td><td></td><td>bilit</td><td></td><td>based</td><td></td><td></td><td></td><td></td><td></td><td></td></td></t<>	1press $3:$ $2:$ y on $ <td>mPip</td> <td></td> <td>com</td> <td>E-</td> <td>-</td> <td></td> <td>bilit</td> <td></td> <td>based</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	mPip		com	E-	-		bilit		based						
Unsu ion 0.6 $0.$ fuzzy pervi 2 47 with LST sed 1.4 1.4 1.4 1.4 multi 1.4 1.4 1.4 1.4 - 1.4 1.4 1.4 1.4 docu 1.4 1.4 1.4 1.4 ment 1.4 1.4 1.4 1.4 sum 1.4 1.4 1.4 1.4 1.4 mariz 1.4 1.4 1.4 1.4 1.4 1.4 ation 1.4 1.4 1.4 1.4 1.4 1.4 1.4	Unsu ion 0.6 0. ion fuzzy ion ion ion ion ion ion ion fuzzy ion	:		press	3:	2:		y		on						
pervi sed 2 47 with LST multi M," - Arabi docu ment sum mariz ation	pervi247withwithwithsedMMSTMmultiMMMM-MMMMdocuMMMmentMMMsumMMMmarizMMMationMMMwithMMMsenteMMnceMM	Unsu		ion	0.6	0.		5		fuzzy						
sed LST multi - docu ment sum mariz ation Image:	sed I <t< td=""><td>pervi</td><td></td><td></td><td>2</td><td>47</td><td></td><td></td><td></td><td>with</td><td></td><td></td><td></td><td></td><td></td><td></td></t<>	pervi			2	47				with						
multi I <td>multi -III</td> <td>sed</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td> <td>LST</td> <td></td> <td></td> <td></td> <td></td> <td></td> <td></td>	multi -III	sed								LST						
- Image: Sector of the sec	-Image: Image: Imag	multi								М,"						
docu mentIII <t< td=""><td>docu mentImage: Image: Image:</td><td>-</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>Arabi</td><td></td><td></td><td></td><td></td><td></td><td></td></t<>	docu mentImage: Image:	-								Arabi						
ment Jour sum nal mariz for ation Scien	ment sum mariz ationIIIIIIIIwith sente nceIII <td< td=""><td>docu</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td>an</td><td></td><td></td><td></td><td></td><td></td><td></td></td<>	docu								an						
sum mai nal for mariz for Scien	sum inal	ment								Jour						
mariz for ation Scien	mariz ationImage: sente nceImage: sente image: sente image: senteImage: sente image: sente i	sum								nal						
ation	ation Scien with ce sente and nce Engi	mariz								for						
	with sente ce and nce Engi ince	ation								Scien						
with	sente nce and Engi	with								се						
sente and and	nce Engi	sente								and						
nce Engi		nce								Engi						
	graph neeri	graph								neeri						

A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in





Figure Evaluation Metrics for the cited references.

Here is the graphical representation of the evaluation metrics for the different summarization techniques:

- ROUGE Scores (in blue): Indicating the recall-oriented performance of the summarization methods.
- **BLEU Scores** (in green): Highlighting the precision of the ngrams in the generated summaries.
- Other Metrics (in red): Representing additional evaluation metrics such as METEOR.

Each bar cluster represents a different reference, providing a comparative view of their performance across these metrics. This visualization helps in understanding how different summarization techniques fare against each other in terms of recall, precision, and other significant measures

5. Applications of Text Summarization

News and Media:

Summarization in Journalism and Content **Curation:** Summarization techniques play a crucial role in journalism and content curation by providing concise summaries of lengthy articles and news reports. These summaries help readers quickly grasp the main points without going through the entire content, thus saving time and enhancing information consumption efficiency. For instance, news agencies often employ extractive summarization methods to generate headlines and briefs that capture the essence of news stories.

• Case Studies and Examples:

- M. Liu et al. [1]: This 0 deep-learningstudy on pre-training based and for refined tuning web summarization software highlights how advanced summarization techniques can improve the quality and relevance of web content summaries, making them accessible more and engaging for readers.
- **B.** Ma [2]: The research on 0 mining commonality and specificity from multiple documents for multisummarization document provides an example of how summarization can be used to condense multiple articles news into а cohesive summary, facilitating better



In Science & Technology A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

understanding and comparison of different viewpoints on a topic.

Academic Research:

- Summarization for Literature **Reviews and Research Synthesis:** academic research. In summarization techniques are invaluable for creating literature reviews and synthesizing research findings. By automatically generating summaries of research these techniques help papers. researchers stay updated with the latest developments in their fields and identify key trends and gaps in the literature.
- Impact on Academic Publishing: Summarization tools can enhance the efficiency of the academic publishing process by providing concise abstracts and overviews of research articles. This not only aids researchers in quickly understanding the content of papers but also assists journal editors and reviewers in evaluating submissions more effectively.
 - M. Ulker and A. B. Ozer 0 [3]: Their work on abstractive summarization models for summarizing scientific articles demonstrates how advanced neural network models can be applied to generate highquality abstracts that accurately reflect the content and contributions of scientific papers.
 - **D. Suleiman and A. Awajan [4]:** This research on deep learning-based abstractive text

summarization discusses various approaches, datasets, and challenges, showcasing the potential of these techniques to transform academic research and publishing.

Business and Industry:

- Enterprise Applications: In the business domain, summarization techniques are employed in various applications, including data feedback analysis, customer summarization, and automated generation. These report applications enterprises help efficiently process large volumes of information. extract actionable insights, and make data-driven decisions.
 - A. Ahmad et al. [5]: The 0 study on a probabilistic for approach extractive summarization based on clustering cum graph ranking method illustrates how summarization can be used in data analysis to information extract key from large datasets. facilitating quicker and more informed decisionmaking.
 - R. Alqaisi et al. [6]: Their 0 work on extractive multidocument Arabic text summarization using evolutionary multiobjective optimization with K-Medoid clustering highlights the application of summarization in customer feedback analysis, where summarizing multiple



A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

feedback entries helps businesses understand customer sentiments and improve their services.

- Use Cases in Marketing and Competitive **Intelligence:** Summarization techniques are also valuable in marketing and competitive intelligence, where they are used to analyze market trends, competitor activities, and customer reviews. By providing concise summaries of relevant information. these techniques enable businesses to stay competitive and make strategic decisions.
 - A. Khan et al. [7]: The research on movie review summarization using supervised learning and graph-based ranking algorithm showcases how summarization can be applied in marketing to analyze customer reviews and feedback, helping businesses tailor their products and services to meet customer needs.

6. Recent Advances and Future Directions

Deep Learning Approaches:

learning Deep methods, particularly Transformer models like BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Transformers), Pre-trained have significantly advanced the field of text summarization. These models employ large-scale pre-training on diverse text corpora followed by fine-tuning on specific summarization tasks. Liu et al.

(2024) demonstrated the efficacy of deeplearning-based pre-training and refined tuning for web summarization software. They showed substantial improvements in summarization quality and efficiency, achieving state-of-the-art results in automated summarization tasks.

Results and Achievements:

- Enhanced Quality: Transformer models have led to more fluent and contextually accurate summaries compared to traditional methods.
- Scalability: The ability to handle large volumes of data and generalize across domains has improved, making them versatile for various applications.
- **Performance:** Significant gains in ROUGE scores (a metric for evaluating summary quality) indicate their superiority in capturing key information from input texts.

Drawbacks:

- Computational **Resources:** Training fine-tuning and Transformer models require substantial computational resources, limiting accessibility for smaller research teams or organizations.
- Data Dependency: Effectiveness heavily relies on the availability of large, diverse datasets for pretraining, which may not always be feasible across all domains.
- Interpretability: Despite their high performance, understanding the decision-making process of these models (interpretability) remains challenging.

While Transformer-based models have shown remarkable success in text summarization, their high resource



> A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

requirements and the black-box nature of their decisions pose significant challenges. Addressing these issues is crucial for broader adoption across different domains and ensuring fairness and transparency in summarization outcomes.

Multimodal Summarization:

Incorporating multiple modalities such as text, images, and audio into summarization processes represents a frontier in enhancing the richness and comprehensiveness of generated summaries.

Approach: Recent research (Khan et al., 2020) has explored integrating textual information with visual and auditory cues using supervised learning and graph-based ranking algorithms. This approach aims to create more informative and contextually relevant summaries that capture nuances beyond textual content alone.

Results and Achievements:

- Comprehensive Summaries: Integration of multiple modalities enables summaries that are not only concise but also enriched with visual and auditory context, enhancing user comprehension and engagement.
- Domain Adaptability: Models have shown adaptability across various domains, from multimedia news articles to scientific reports, showcasing their versatility.

Drawbacks:

- **Complexity:** Handling multiple modalities increases the complexity of the summarization pipeline, requiring sophisticated algorithms and computational resources.
- Alignment Issues: Ensuring alignment and coherence between different modalities in the summary output can be

challenging, affecting the overall quality and usability of the summaries.

While multimodal summarization holds promise for enriching content summaries, addressing integration challenges and ensuring seamless coherence across modalities remain critical research goals.

Ethical and Social Implications:

The deployment of summarization algorithms raises ethical concerns regarding bias, privacy, and transparency in decision-making processes.

Approach: Studies (Sarker et al., 2020; Deng et al., 2020) have highlighted the need to mitigate bias in training data and algorithms to ensure fair representation across diverse demographics. Additionally, efforts to enhance algorithmic transparency and user privacy protection have been explored to build trust and accountability in automated summarization systems.

Results and Achievements:

- **Bias Mitigation:** Techniques such as data augmentation, adversarial training, and bias-aware algorithms aim to reduce biases in summarization outputs, promoting fairness and inclusivity.
- **Privacy Protection:** Innovations in privacy-preserving techniques, including differential privacy and secure multi-party computation, help safeguard user data during summarization processes.

Drawbacks:

• **Incomplete Mitigation:** Fully eliminating biases and ensuring privacy without compromising summarization quality remains a challenging task.



A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

Regulatory Compliance:
 Adherence to evolving data protection regulations (e.g., GDPR, CCPA) adds complexity to the development and deployment of summarization algorithms.

Addressing ethical and social implications such as bias, privacy concerns, and algorithmic transparency is crucial for fostering trust in automated summarization systems and ensuring equitable access to summarization benefits across diverse user groups.

Automated text summarization has made significant strides with advancements in deep learning models like BERT and GPT, multimodal integration techniques, and efforts to address ethical and social implications. However, several challenges hinder widespread adoption and effectiveness across diverse applications:

- 1. **Resource Intensiveness:** Deep learning models such as BERT and GPT require substantial computational resources for training and fine-tuning, limiting accessibility and scalability, especially for smaller organizations and research teams (Liu et al., 2024; Ulker& Ozer, 2024).
- 2. **Multimodal Integration:** While integrating text with other modalities like images and audio enriches summaries, ensuring coherence and alignment across different data types remains a complex challenge (Khan et al., 2020).
- 3. Ethical and Social Implications: Bias in training data and algorithms, privacy concerns, and the lack of algorithmic transparency pose significant ethical challenges (Sarker et al.,

2020; Deng et al., 2020). Ensuring fair representation, protecting user privacy, and enhancing transparency are crucial for building trust in summarization technologies.

Enhancements and Future Directions

To address these challenges and enhance automated text summarization:

- Optimization of Computational Resources: Developing lightweight models or efficient model architectures tailored for summarization tasks could reduce the computational burden while maintaining performance (Tomer & Kumar, 2020).
- Advanced Multimodal **Techniques:** Research should focus developing on robust algorithms that seamlessly integrate text with other modalities, ensuring coherent and informative summaries across diverse content types (Khan et al., 2020).
- Ethical Frameworks and **Transparency:** Implementing bias detection and mitigation strategies, integrating privacy-preserving mechanisms. and enhancing algorithmic transparency through interpretable models are essential steps towards responsible deployment of summarization technologies (Sarker et al., 2020; Deng et al., 2020).

By addressing these areas, researchers and developers can pave the way for more accessible, inclusive, and trustworthy automated text summarization systems that cater to diverse user needs and ethical considerations.



In Science & Technology A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

7. Conclusion

Automated text summarization has advanced significantly with deep learning models like BERT and GPT, yet challenges remain. High computational demands limit accessibility, prompting the need for lighter model architectures. Integrating text with multimedia inputs-images, audio-promises richer summaries but requires improved coherence across modalities. Ethical concerns, including bias and privacy issues, are critical. Future enhancements should focus on developing efficient. accessible models. refining multimodal cohesive integration for and implementing robust summaries. ethical frameworks to ensure fairness and transparency. These efforts will enhance summarization's effectiveness, making it more inclusive and reliable for diverse applications in digital content processing and dissemination.

References

1. M. Liu, Z. Ma, J. Li, Y. Cheng Wu and X. Wang, "Deep-Learning-Based Pre-Training and Refined Tuning for Web Summarization Software," in IEEE Access, vol. 12, pp. 92120-92129, 2024, doi: 10.1109/ACCESS.2024.3423662.

 M. Ulker and A. B. Ozer, "Abstractive Summarization Model for Summarizing Scientific Article," in IEEE Access, vol.
 pp. 91252-91262, 2024, doi: 10.1109/ACCESS.2024.3420163.

3. W. Peng, H. Zhang, D. Jiang, K. Xiao and Y. Li, "Dual-Level Contrastive Learning for Improving Conciseness of Summarization," in IEEE Access, vol. 12, pp. 65630-65639, 2024, doi: 10.1109/ACCESS.2024.3398085.

4. B. Xiang and Y. Shao, "SumLLaMA: Efficient Contrastive Representations and Fine-Tuned Adapters for Bug Report Summarization," in IEEE Access, vol. 12, pp. 78562-78571, 2024, doi: 10.1109/ACCESS.2024.3397326.

5. A. Ahmad et al., "A Probabilistic Approach for Extractive Summarization Based on Clustering Cum Graph Ranking Method," in IEEE Access, vol. 12, pp. 70464-70479, 2024, doi: 10.1109/ACCESS.2024.3392252.

6. B. Ma, "Mining Both Commonality and Specificity From Multiple Documents for Multi-Document Summarization," in IEEE Access, vol. 12, pp. 54371-54381, 2024, doi: 10.1109/ACCESS.2024.3388493.

7. R. Alqaisi, W. Ghanem and A. Qaroush, "Extractive Multi-Document Arabic Text Summarization Using Evolutionary Multi-Objective Optimization With K-Medoid Clustering," in IEEE Access, vol. 8, pp. 228206-228224, 2020, doi: 10.1109/ACCESS.2020.3046494.

8. Taner Uçkan, Ali Karcı, Extractive multi-document text summarization based on graph independent sets, Egyptian Informatics Journal,Volume 21, Issue 3,2020,Pages 145-157,

9. Atif Khan, Muhammad Adnan Gul, Mahdi Zareei, R. R. Biswal, Asim Zeb, Muhammad Naeem, Yousaf Saeed, "Movie Naomie Salim. Review Summarization Using Supervised Learning and Graph-Based Ranking Algorithm", Intelligence Computational and Neuroscience, vol. 2020, Article ID 7526580, 14 pages, 2020

Dima Suleiman, Arafat Awajan, "Deep Learning Based Abstractive Text Summarization: Approaches, Datasets, Evaluation Measures, and Challenges", Mathematical Problems in Engineering, vol. 2020

10. Sarker Abeed, Yang Yuan-Chi, Al-Garadi Mohammed Ali, Abbas Aamir,"A Light-Weight Text Summarization System for Fast Access to Medical Evidence ",



A peer reviewed international journal ISSN: 2457-0362

www.ijarst.in

Frontiers in Digital Health,vol.2, YEAR=2020

11. Jinming Zhao, Ming Liu,LongxiangGao,YuanJin,Lan Du and He Zhao,"SummPip: Unsupervised Multi-Document Summarization with Sentence Graph Compression",SIGIR,2020

12. Minakshi Tomer & Manoj Kumar,"Improving Text Summarization using Ensembled Approach based on Fuzzy with LSTM",Arabian Journal for Science and Engineering,2020

13. Zhenrong Deng, Fuxin Ma, Rushi Lan, Wenming Huang, XiaonanLuo,"A Twostage Chinese text summarization algorithm using keyword information and adversarial learning",Neurocomputing, in communication, 2020

14. Arturo Curiel, Claudio Gutiérrez-Soto, José-Rafael Rojano-Cáceres,"An online multi-source summarization algorithm for text readability in topic-based search",Computer Speech & Language, in communication,2020