Spring 5-24-2021

AUTOMATING TEXT ENCAPSULATION USING DEEP LEARNING

Anket Sah

AUTOMATING TEXT ENCAPSULATION USING DEEP LEARNING

A PROJECT

Presented to

The Faculty of the Department of Computer Science

San Jose State University

In Partial Fulfillment

Of the Requirements for the Degree

Master of Science

by

Anket Sah

May, 2021

The Designated Project Committee Approves the Project Titled

AUTOMATING TEXT ENCAPSULATION USING DEEP LEARNING

by

Anket Sah

APPROVED FOR THE DEPARTMENT OF COMPUTER SCIENCE

San Jose State University

May 2021

Dr. Robert Chun	Department of Computer Science
Dr. Navrati Saxena	Department of Computer Science
Mr. Mayur Barge	Software Engineer, Cisco

ABSTRACT

Data is an important aspect in any form be it communication, reviews, news articles, social media data, machine or real-time data. With the emergence of Covid-19, a pandemic seen like no other in recent times, information is being poured in from all directions on the internet. At times it is overwhelming to determine which data to read and follow. Another crucial aspect is separating factual data from distorted data that is being circulated widely. The title or short description of this data can play a key role. Many times, these descriptions can deceive a user with unwanted information. The user is then more likely to spread this information with his colleagues/family and if they too are unaware, this false piece of information can spread like a forest wildfire. Deep machine learning models can play a vital role in automatically encapsulating the description and providing an accurate overview. This automated overview can then be used by the end user to determine if that piece of information can be consumed or not. This research presents an efficient Deep learning model for automating text encapsulation and its comparison with existing systems in terms of data, features and their point of failures. It aims at condensing text percepts more accurately.

Keywords: Deep learning, Text Encapsulation, system, dataset, features, automated, model, machine learning

ACKNOWLEDGEMENTS

I would like to thank Dr. Robert Chun for his constant support and guidance throughout the research and implementation of this project. I would also like to thank my committee members Dr. Navrati Saxena and Mr. Mayur Barge for their inputs and valuable feedback on the project.

Lastly, I would like to thank my family and friends for their endless support and motivation along the way.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

I. INTRODUCTION

Data is being generated and consumed in order of several terabytes each day. There is a dramatic increase in the influx of data sources. For a consumer airline, there is approximately half a terabyte of flight data that is generated during a single flight duration. As per research, by 2025 the number of connected devices is forecasted to reach 75 billion [12]. All these devices generate and consume data. A single user consumes approximately 2.9 GB of data per day which includes social media, news, scientific articles, banking and navigation data. As per Bloomberg, 69% of the data that is being consumed by an average user mainly consists of news articles, and for tech savvy audiences, this can go up to 87% [10].

As per New York Times, a user selects a news article to read based on the title or heading rather than the content [7]. The content itself can be misleading. For instance, an article distributed in the Times Daily under the title “The benefits of ginger for adults” was deluding. This article actually referenced that, “The investigation shows that ginger could probably affect serotonin and aid in concentration improvement but ginger’s chemical composition can severely affect dopamine exclusively due to the presence of phenolic compounds”. The article examines the slight possibility of the constructive outcomes of ginger on adults; however, the heading has an alternate meaning. A robust deep learning model to encapsulate this content, as well as automate the process that captures the exact holistic meaning of this content, becomes a necessity.

1.1 Research Objective

The goal of this research is to automate the text encapsulation process by making use of a dual LSTM (Long Short-Term Memory) encoder-decoder deep learning model. The current text summarizers are naïve and lack accuracy. A significant performance improvement can be attained by incorporating new modifications. These modifications include:

- improving the data pre-processing stage to attain accurate data free from outliers
- automating the text encapsulation for the entire cleaned dataset
- incorporating dual long short term memory network in the process pipeline
- performance comparison of the system developed with existing models

The intent in using a dual LSTM deep learning system is to encapsulate the text without changing the universal interpretation of the entire content. Also, the aim is to automate this task of encapsulation and reduce manual effort.

1.2 Motivation

If we take a look at the very fundamental level of computer science, we can find encapsulation in object-oriented programming and in object-oriented system design. Encapsulation simply means restricting the direct access to some of the object's components without changing the meaning or object’s functionality. In the real world too, depicting the exact meaning that the content carries are as important as encapsulation in object-oriented system design. Identifying the content and

accurately condensing it to form an appropriate heading is a crucial aspect of text encapsulation. Preserving the exact meaning of the entire content is of essence.

The present machine learning models require some amount of manual effort and many of these models simply compress the text by removing commonly used words. With the spread of covid-19, the blame game of governments has started. This has provided a platform for netizens to feed on fake news and irrelevant articles which might not be scientifically true. Among the overall audiences, 29% of these consumers include elders and some youth that are not scientifically literate and are more prone to spreading false information. With the unregulated and free use of social media, people even vent out their frustration on other users due to misleading content that is wrongly summarized and lure the users into reading that content.

II. RELATED WORK

Automating the text encapsulation using deep learning is a relatively new concept. There isn't much research performed on this exact NLP problem, but there are related text summarization techniques explored over the years. In the year 2001, Nomoto et al. [1] made use of the C4.5 decision tree algorithm, generalized by the Concept of Minimal Definition Span (MDS) and equated it with unsupervised approaches. The approach had an error rate of 49%. This results in a distorted sentence sequence which is vaguely different in meaning than the actual content. The researcher Shuhua Liu, in a 2005 IEEE conference [2] suggested a two-phase topic guided text condensation technique. In the first phase, passages are extracted from a public file, and in the second phase, text comprehension and merging of data is performed. This merging is assisted by syntactic and semantic tools to form a meaningful description. This paper provides better accuracy for a single keyword extraction but performs at 57% accuracy for key phrase extraction and summarization.

Zhang et al [3] describe a three-step approach for text summarization in the 2009 IEEE CSIT conference. They first grouped the sequences in the text; then measured the total statistical correlation on every group depending on the multi-feature set; and finally picked the subject phrase by following their established guidelines. The researchers performed their experiment on the DUC2003 document dataset. Nomoto et al. [1] attained an F1 measure of 0.432 and Zhang et al [3] achieved a score of 0.475. This means that this approach [3] can retain the meaning of summarized text with 21% higher accuracy than the approach described by Nomoto [1]. Thakkar

et al. [4] take a graph-based approach for summarizing text. The researchers suggest the use of a shortest path algorithm as it creates a seamless text snippet as opposed to keyword scoring algorithms from the previous approaches.

Another graph-based approach for text summarization is discussed by Reategui et al. [5]. This approach uses a text mining tool named Sobek that is developed using an N-simple version of an interval network. This network consists of nodes that include key words given in the text, and the edges represent data regarding adjacency. Sobek tool counts the total occurrences of each word, assigns a weight to those words and generates a summary that is somewhat in line with the content. On the other hand, in 2014, Ferreira et al. [6] suggested combining the sentence scoring methods for summarizing text. The two approaches for consolidating the sentence scoring techniques discussed in the paper include: (I) By Ranking: Every assistance chooses the primary text sequence and the client consolidates it in some way or another; (II) By Accentuation: The administration scores every text sequence and returns one sequence with refreshed scores. The accuracy for this approach wherein the expected output matches the actual output is 78%.

One of the other approaches to solving the problem of text summarization is an extractive summarization. Moratanch et al. [7] perform a survey on all the extractive summarization methods and put forward their results. The basic principle behind the working of extractive summarization is that it depends on the retrieval of multiple sections from a sequence of text, such as sentence sequences and its dependent phrases, and combine everything with each other to create a short description.

For example, given a text sequence: Covid-19 has spawned multiple global health crisis some have dubbed coronasomnia -- an inability to fall asleep or get good quality sleep during the pandemic. Along with this, there are multiple levels of stress associated with the pandemic – financial, health care related and social isolation. All these damage mental health, threaten health and quality of life for upto 45% of world's population. (source CNN news dataset)

Extractive summary: 'Coronasomnia' -- an inability to fall asleep

The terms have been derived and merged to generate a description as seen above, but the interpretation can be syntactically and grammatically odd.

2.1 Scoring Sentences based on the Word-Frequency

This technique assigns weights to every single word that occurs in the text. For example, if the word 'research' appears 5 times in the text body, a weight of 5 is assigned to the word. Similarly, a holistic score based on the word appearance is assigned to every sentence that occurs in the text body. The sentences that have a higher score are then picked up and displayed as summarized text.

2.2 Universal Sentence Encoder for Text Ranking

Text Ranking is similar to PageRank used by Google. PageRank creates a matrix of pages that will be most likely visited next by the user. Similarly, TextRank uses cosine function to determine the similarity of 2 sentences to each other. This cosine linear similarity matrix is then

used to build a tree. The PageRank rating equation is then added to the tree in order to determine rankings for each statement.

2.3 Unsupervised Learning using K-means Clustering

Every text has some central theme around which the content revolves. This theme word appears multiple times in the text and helps understand what the text is about. This word is taken as a center, weight is assigned to it and the nearest K-words are chosen from the clusters. These K-words are then displayed as summarized text. This method has high error rate as the training data is unlabeled.

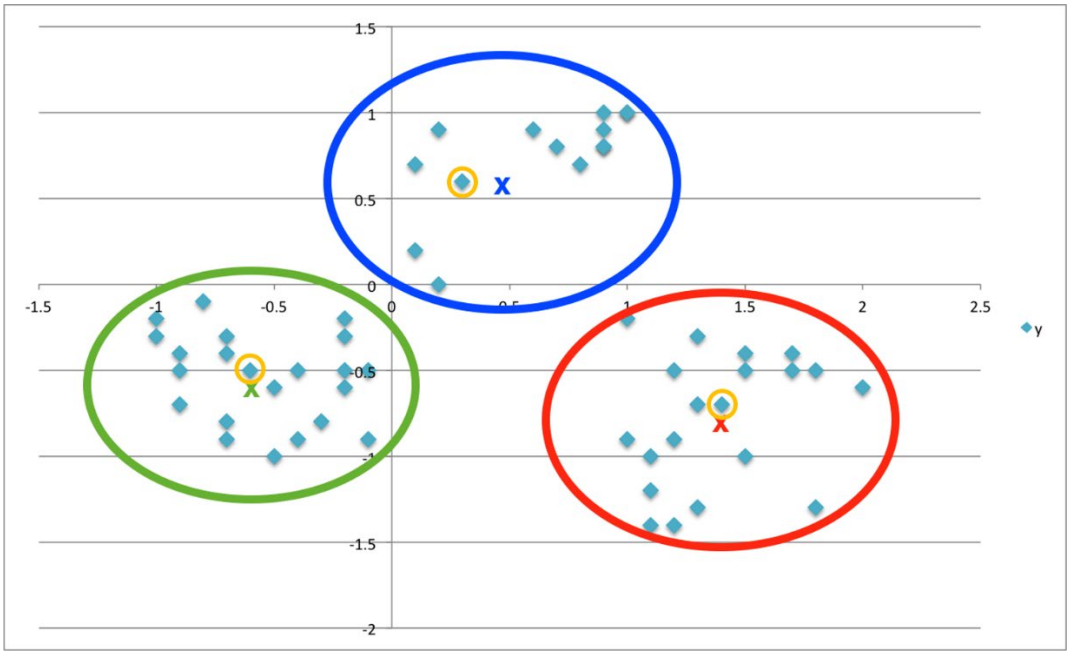


Figure 1: Unsupervised Learning using K-means

III. DATASET

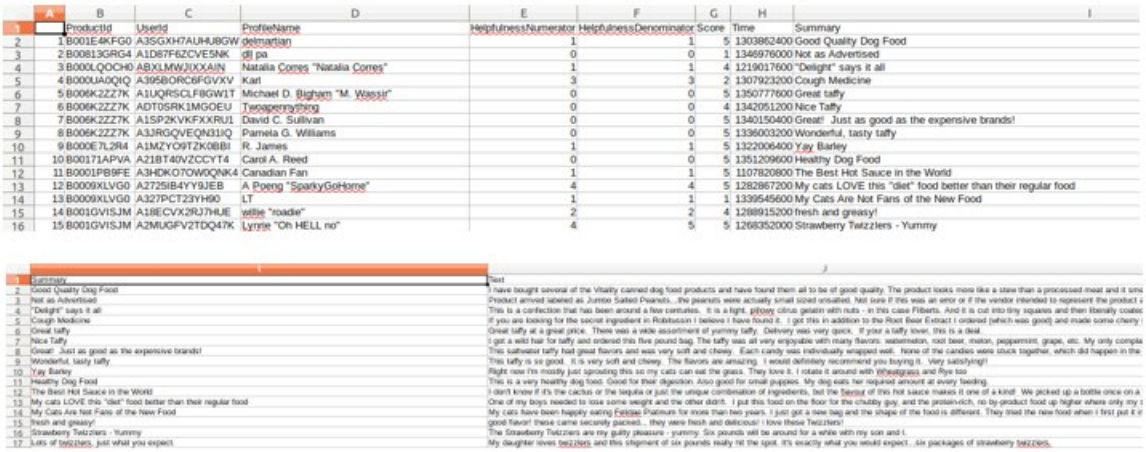
Two datasets that include the CNN News Dataset and the Amazon reviews dataset, provide an accurate set of input data required to train the model. Here are their descriptions:

3.1 Amazon Reviews Dataset

The researchers from the Department of Computer Science at the University of California, Berkeley have created a text summarization dataset in 2020. During the covid-19 pandemic, purchase of essentials such as toilet papers, tissues, eateries skyrocketed due to public induced fear of lockdown. This is a reason why it can provide a good source of most recent data from public, news houses and scientists about the products used by them daily. This dataset contains Amazon ratings and reviews of all the stated essentials purchased during the covid pandemic. Additionally, the dataset includes data that spans more than a decade, with all 1 million reviews up to October 2012 included. Product and usage stats, scores, and a simple text summary are also used in reviews. It also contains ratings from all of Amazon's other categories.

The following are some of the characteristics of this dataset that make it suitable for this project:

- The dataset is sufficiently broad for the algorithm to be efficiently trained. A model's performance improves when it is exposed to heterogenous data.
- The model’s encapsulation will improve as the dataset contains unrelated user data and reviews.
- The reviews are simple text, meaning that most scripting frameworks can tokenize them.



	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	5	1303862400	Good Quality Dog Food
2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	1	1346976000	Not as Advertised
3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	4	1219017600	"Delight" says it all
4	B000UA0QIQ	A395BORC6FGVXV	Karl	3	3	2	1307923200	Cough Medicine
5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	5	1350777600	Great taffy
6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	4	1342051200	Nice Taffy
7	B006K2ZZ7K	A1SP2KVKFXXRU1	David C. Sullivan	0	0	5	1340150400	Great! Just as good as the expensive brands!
8	B006K2ZZ7K	A3JRGQVEQN31IQ	Pamela G. Williams	0	0	5	1336003200	Wonderful, tasty taffy
9	B000E7L2R4	A1MZYO9TZK0BBI	R. James	1	1	5	1322006400	Yay Barley
10	B001771APVA	A21BT40VZCCYT4	Carol A. Reed	0	0	5	1351209600	Healthy Dog Food
11	B0001PB9FE	A3HDKO7OW0QNK4	Canadian Fan	1	1	5	1107820800	The Best Hot Sauce in the World
12	B0009XLVG0	A2725IB4YY9JEB	A Poeng "SparkyGoHome"	4	4	5	1282867200	My cats LOVE this "diet" food better than their regular food
13	B0009XLVG0	A327PCT23YH90	LT	1	1	1	1339545600	My Cats Are Not Fans of the New Food
14	B001GVISJM	A18ECVX2RJ7HUE	willie "roadie"	2	2	4	1288915200	fresh and greasy!
15	B001GVISJM	A2MUGFV2TDQ47K	Lynne "Oh HELL no"	4	5	5	1268352000	Strawberry Twizzlers - Yummy

	Summary	Text
2	Good Quality Dog Food	I have bought several of the Vitality canned dog food products and have found them all to be of good quality. The product looks more like a stew than a processed meat and it sme
3	Not as Advertised	Product arrived labeled as Jumbo Salted Peanuts...the peanuts were actually small sized unsalted. Not sure if this was an error or if the vendor intended to represent the product a
4	"Delight" says it all	This is a confection that has been around a few centuries. It is a light, pillowy citrus gelatin with nuts - in this case Filberts. And it is cut into tiny squares and then liberally coate
5	Cough Medicine	If you are looking for the secret ingredient in Robitussin I believe I have found it. I got this in addition to the Root Beer Extract I ordered (which was good) and made some cherry
6	Great taffy	Great taffy at a great price. There was a wide assortment of yummy taffy. Delivery was very quick. If your a taffy lover, this is a deal.
7	Nice Taffy	I got a wild hair for taffy and ordered this five pound bag. The taffy was all very enjoyable with many flavors: watermelon, root beer, melon, peppermint, grape, etc. My only compla
8	Great! Just as good as the expensive brands!	This saltwater taffy had great flavors and was very soft and chewy. Each candy was individually wrapped well. None of the candies were stuck together, which did happen in the
9	Wonderful, tasty taffy	This taffy is so good. It is very soft and chewy. The flavors are amazing. I would definitely recommend you buying it. Very satisfying!!
10	Yay Barley	Right now I'm mostly just sprouting this so my cats can eat the grass. They love it. I rotate it around with Wheatgrass and Rye too
11	Healthy Dog Food	This is a very healthy dog food. Good for their digestion. Also good for small puppies. My dog eats her required amount at every feeding.
12	The Best Hot Sauce in the World	I don't know if it's the cactus or the tequila or just the unique combination of ingredients, but the flavour of this hot sauce makes it one of a kind! We picked up a bottle once on a
13	My cats LOVE this "diet" food better than their regular food	One of my boys needed to lose some weight and the other didn't. I put this food on the floor for the chubby guy, and the proper-ich, no by-product food up higher where only my
14	My Cats Are Not Fans of the New Food	My cats have been happily eating Felidae Platinum for more than two years. I just got a new bag and the shape of the food is different. They tried the new food when I first put it i
15	fresh and greasy!	good flavor! these came securely packed... they were fresh and delicious! i love these Twizzlers!
16	Strawberry Twizzlers - Yummy	The Strawberry Twizzlers are my guilty pleasure - yummy. Six pounds will be around for a while with my son and I.
17	Lots of twizzlers, just what you expect.	My daughter loves twizzlers and this shipment of six pounds really hit the spot. It's exactly what you would expect...six packages of strawberry twizzlers.

Figure 2: Amazon reviews Dataset (Row Headers: ProductId, UserId, Score, Time, Summary, Text)

3.2 CNN News Dataset

This is a custom dataset that has been created by scrapping news data from CNN using a python script. The url used to scrape data (https://www.cnn.com/specials/world/coronavirus-outbreak-intl-hnk) contains most recent world news related to Covid-19 pandemic. The dataset comprises of over 10,000 records, with an average of 400 words per record. The characteristics of this dataset that make it suitable for this project include:

- Large number of words per record that helps test the performance of model as the dataset size increases.
- A combination of news data from different categories that include covid-19 pandemic, national news, sports and lifestyle news.

IV. DATA PREPARATION

4.1 Data Quality Issues

4.1.1 Manual Data Entry Errors

People are prone to making mistakes, and a simple set of data containing manually entered data is likely to produce errors. Typos, data entered in the incorrect sector, missing entries, and other mistakes are almost unavoidable.

4.1.2 Lack of complete information

There can be some records in the dataset with missing fields. For example, in a dataset containing the username and reviews posted by that user, the reviews or username might be missing which makes the dataset lack vital information. These fields can be filled with null values or the entire record can be removed.

4.2 Contraction Mapping

The news articles and reviews are raw thoughts expressed by the writer. This is why it can have slangs and words like isn't, needn't, shan't and so on. The root words are required to have a well-trained model. As a result, these slangs and compressed words must be mapped to actual words. For example, isn't → is not, needn't → need not, shan't → shall not and so on.

4.3 Outlier Identification

An outlier is a particular occurrence that tends to differ significantly from the rest of the data. The following are some of the reasons why finding possible outliers is crucial. An outlier may be a sign of skewed results. For instance, data may have been wrongly interpreted, or a text could contain numbers and special characters.

4.4 Remove Duplicates and Filter Stopwords

Drop_duplicates() and dropna() functions help eliminate duplicates. Natural language toolkit contains stop words such as commonly occurring pronouns which get filtered out. Converting all text to lowercase, splitting individual strings to aid tokenization are some methods that are used to prepare data before training the model.

V. ALGORITHMS

5.1 Naïve Bayes

Naive bayes algorithm is based on the rule that all features of each category are independent.

The stages involved in Naïve Bayes summarization include:

1. Extract features
2. Count the number of features
3. Calculate probability
4. Generate Summary

Each individual sentence is a feature in each category. It calculates the number of features in each category and records this amount. A weight is then assigned to each sentence. Each Key is an independent sentence, and value is the number of times that sentence occurs in the text.

For example, {“sentence_1”, 2} means that “sentence_1” appears 2 times in the whole text and is assigned more weight.

Next it calculates the probability of feature occurrence in each category. Based on this relative probability, a summarization for a piece of text is generated.

5.2 Extractive Summarization using BERT

The job of extractive summarization is a daunting one which has gradually emerged as feasible. One explanation for this development, as with many items in NLP, is the advanced mappings

provided by converter templates like BERT. Using BERT sentence encoding and two supervised models, this method builds an extractive summarizer. Only encodings and their variations are considered in the first model. This is consistent with an intuition that a strong parser could parse context and can pick sentences solely based on the article's inner core. Another model uses data patterns and builds on the popular Lead3 phenomenon, which is unique to newspaper corpora. The Lead3 phenomenon is based on the concept that the first three sentences of an essay usually summarize it well. Most authors, in reality, implement this technique directly.

5.3 TF-IDF

TF-IDF stands for Term Frequency – Inverse Document Frequency. This algorithm summarizes articles and text based on the weight assigned to each word in the document. It weighs down commonly occurring words like he, the, they, them and all the pronouns and weighs up less frequently occurring words. Based on the weights of each of the words, top weighted words are chosen and a summary is generated by using those words. This summary is more focussed on the keyword extraction rather than capturing the holistic meaning of the text. This is why the summary generated can be very vague in meaning as compared to the original text.

5.4 Latent Semantic Analysis

Latent semantic examination (LSA) is an algorithm for extracting a portrayal of text articles dependent on the noticed words. The initial step is to construct a term-sentence grid, where each line is a word from the data (n words) and every segment is a sentence. Every passage of the grid

is the heaviness of the word i in sentence j processed by the TFIDF method. Now, Solitary Val Decomposition (SVD) is utilized on the grid that changes the underlying grid into three grids: a term-theme grid having loads of words, a corner-to-corner grid where each column relates to the heaviness of a subject, and a point sentence grid. By increasing the corner-to-corner grid with loads and the subject sentence network, the outcome will portray how much a sentence represents a theme, in other words, the heaviness of the topic i in sentence j.

VI. EVALUATION

6.1 Evaluation Metrics

One of the difficulties in evaluating encapsulated text is that it needs the presence of a collection of reference, or short descriptions. These aren't typically accessible for many of these articles, which is why analysis is dominated by newspaper texts and academic articles. Research journals have manuscripts, whereas media outlets typically use roundups or banners for their pages. To evaluate the performance of the system developed, a combination of bleu measures to measure the preciseness and rouge measures to measure recall can be used.

Bleu measures precision: how many terms (n-grams) from the computer-generated encapsulations are present in the human description summaries

Rouge measures recall: how many terms (n-grams) from the human description summaries are present in the computer-generated encapsulations

These outputs closely accompany each other. If there are multiple n-grams from the computer output present in the human summaries, the Bleu is high. If there are multiple n-grams from the human summaries present in the computer output, the Rouge is high.

To address this, there is a concept named brevity penalty that can be added to Bleu implementations. It imposes a penalty on computer outcomes that are less than a reference's average length. This is in comparison to the n-gram parameter method, which incentivizes longer than reference outcomes by increasing the denominator as the computer results gets longer.

Finally, to make the metrics work together, an F1 measure is calculated given by the formula:

F1 = 2 x (Bleu x Rouge) / (Bleu + Rouge)

An alternative evaluation method can use the number of sentences against the total number of sentences to validate results, for example,

Precision = Number of important sentences / Total number of sentences summarized.

Recall = Total number of important sentences Retrieved / Total number of important sentences present.

F1 Score = 2 x (Precision x Recall / Precision + Recall)

Compressed Rate = Total number of words in the summary / Total number of words in original document.

VII. IMPLEMENTATION

7.1 Choosing the Corpus of Data

Choosing the right data set is a crucial step in creating a consistent deep learning system. The very first step is to consolidate data from different sources. These include Amazon reviews dataset and a CNN news dataset. The CNN news dataset is created by scrapping news with the help of a python script. This dataset contains world news pertaining to the topic of Covid-19. These 2 datasets are ideal for testing the model as they contain most recent data that is entered by users, journalists, and writers. It covers covid news and reviews of products used by people during lock-downs. As this data covers a wide range of topics, it is heterogeneous and can test the developed model well.

B	C	D	E
Published Date	Author	Text	Source
		(CNN) A growing number of Americans have missed their scheduled second dose of a Covid-19 vaccine, according to data from the US Centers for Disease Control and Prevention.	
		The vaccines by Pfizer/BioNTech and Moderna require two doses -- administered three and four weeks apart, respectively -- to be considered fully effective. But data shows about 8% of Am	
		It's not an exact count. The CDC is collecting data on vaccinations, but states don't report information immediately and must gather it from mass vaccination sites, retail pharmacies and vario	
		"If a person received the two doses from different reporting entities, those two doses may not have been linked together," a CDC spokesperson said.	
		"For example, if a person received their first dose at a clinic run by the state, and second dose from a tribal health clinic, they might not be linked and it could look like they missed the secon	
		The news comes as the United States continues its effort to vaccinate as many Americans as quickly as possible. The CDC reported Sunday that 95 million people -- about 28.5% of the pop	
		Dr. Anthony Fauci, director of the National Institute of Allergy and Infectious Diseases, told CNN's Jim Acosta on Sunday he was not surprised some people are missing the second dose, sa	
		"Obviously whenever you have a two-dose vaccine, you're going to see people who for one reason or other -- convenience, forgetting, a number of other things -- just don't show up for the	
		"I'd like it to be a 0%," he said, "but I'm not surprised that there are some people who do that."	
		Similarly, the CDC said Americans missing second doses was expected. Groups initially prioritized for vaccination, such as health care workers, were more likely to get vaccinated at their work	
		"The reasons behind the delayed or missed second doses, however, require further analysis," the spokesperson said, and officials should work to understand whether this is due to access c	
		Covid-19 vaccinations declined last week	
		About 229 million doses of Covid-19 vaccines have been administered in the United States, according to CDC data published Sunday -- about 3 million more administered doses reported sir	
		That puts the seven-day average of administered doses at about 2.8 million doses per day, a slight drop from earlier in the month, when the average pace of new doses administered peake	
		Saturday, the CDC's Dr. Amanda Cohn said the recent pause on the Johnson & Johnson Covid-19 vaccine had contributed to the decline.	
		"Last week was the first week that we saw a decline in vaccination, in terms of the total number of people who got vaccinated over the course of the week, and there is clearly the contributo	
		The CDC and the US Food and Drug Administration paused use of the vaccine following reports of a rare blood clotting syndrome among six women who were recently vaccinated.	
		Further search turned up a total of 15 cases out of nearly 7 million people vaccinated, and Friday, the agencies gave the OK for use of the vaccine to continue , saying the vaccine label wo	
		JUST WATCHED Rutgers official: Vaccine is the game-changer for us Replay More Videos ... MUST WATCH Rutgers official: Vaccine is the game-changer for us 03:02	
		Some place see 'unsettling gaps' in vaccine coverage	
		After several weeks of reporting concerning Covid-19 case increases , the United States could be seeing the beginning of a hopeful trend, a leading health official says.	
		The country's seven-day average of new reported infections is going down, CDC Director Dr. Rochelle Walensky said at a White House Covid-19 briefing Friday.	
		Former US Food and Drug Administration Commissioner Dr. Scott Gottlieb believes that decline could stick this time, telling CBS's "Face the Nation" Sunday that even hard-hit areas such as	
		"Right now, the declines that we're seeing we can take to the bank," he said. "I think we can feel more assured because they're being driven by vaccinations and greater levels of population	
		"Some areas are doing very well with greater than 65% coverage for those over the age of 65 ... but many areas have far less coverage, less than 47%," she said. "Because this virus is an	
		"I think it's really important to understand that vaccines work best at a population level, not at the individual level," infectious diseases specialist and epidemiologist Dr. Celine Gounder told C	
		"Really the best way to reduce the risk for all of us is for as many people to get vaccinated as possible," Gounder added.	
		A person walks to the former Stein Mart store on Washington Road in Augusta, Georgia, on March 25, 2021, for Augusta University's Covid-19 vaccination clinic.	
		Reports warn of vaccine 'tipping point'	
		And in just a few weeks' time, the US could hit a "tipping point" on vaccine enthusiasm and supply will likely outstrip demand, a Kaiser Family Foundation report said.	
		"Once this happens, efforts to encourage vaccination will become much harder, presenting a challenge to reaching the levels of herd immunity that are expected to be needed," the report s	
		Some experts, including Fauci, have estimated somewhere between 70% to 85% of Americans need to have immunity to the virus -- either through vaccination or previous infection -- to cont	
		Behind the slowing vaccine demand are several factors, experts say, including vaccine hesitancy.	
		In its latest Covid-19 briefing, the University of Washington's Institute for Health Metrics and Evaluation wrote that the "slow erosion of vaccine confidence unfolding over the last two or more	
		"Facebook runs a survey every day, and we look at that data on a daily basis and that's shown that vaccine confidence in the US has been slowly but steadily going down since February,"	
2021-04-25 00:00:00	list_authors	"There's a lot of people out there, and it's a growing fraction of people, who are not sure they want to get the vaccine, and that's really important that we overcome that," he added.	https://www.cnn.com/specials/world/coronavirus-outbreak-intl-h

Figure 3: CNN news dataset (Row Headers: Published Date, Author, Text, Source)

7.2 Preprocessing / Data Cleaning

This is a very important step in creating a fault-tolerant deep learning system which is mostly ignored by professionals. The price paid is a deep learning model that considers outliers such as blank spaces and special characters as important aspects and keeps including them in the output (which should not be included in the ideal output). This is why it is of utmost importance to eliminate the blank spaces and special characters. To clean the content, the following steps are involved that include:

- Eliminating additional void areas
- Expanding Contractions
- Eliminating special characters and uncommon strings
- Converting all characters to lowercase

This data pre-processing can be performed using some pre-existing tools such as openrefine or weka. However, these tools fail to perform well in case of the dataset used in this system. Openrefine and weka tools can handle small datasets and fail in case of large datasets. These tools throw an outOfMemoryError() when the dataset size increases beyond kilobytes. The developed system makes use of NLP toolkit that consists of stop words and a custom coded function. The NLP toolkit removes pronouns and commonly occurring repeated words as it encounters them. The custom coded function converts all uppercase letters to lowercase, eliminates blank spaces and deletes special characters on parsing the input.

7.3 Data Splitting

Preprocessing provides a dataset that is free from outliers. This data can now be divided into 2 sets:

- Training data set
- Test data set

The dataset division is done in such a manner that 75% of input data is chosen as training dataset and the remaining 25% dataset is chosen as the test dataset. If we use the entire dataset that is 100% as a training dataset, then there can be a problem of overfitting. Overfitting happens when a function is prepared too well on a restricted arrangement of information. At that point, when a model gets trained with so much information, it begins learning from the noise and inaccurate information. For example, consider a model that is trained to detect animals. But if this model is trained only on the images of cats and dogs and we pass an image of black bear during evaluation, the model will classify that bear as a dog.

7.4 Deep learning model

The deep learning model developed, consists of an encoder-decoder architecture at its heart.

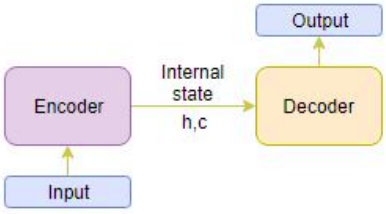


Fig. 4: Deep Learning Model Architecture

This model comprises three fundamental components that include: the encoder, an intermediate vector and the decoder.

7.4.1 The Encoder

The encoder essentially includes a sequence of stacked neurons from LSTM. The training set is taken by the encoder and this data is summarized into internal state sequences. The decoder then utilizes the sources of the encoder and the series of inner states. The input data is a list of all the keywords from the content that must be condensed in our text encapsulation system. Each keyword is portrayed as k_i where the order of this keyword is i.

7.4.2 The Intermediate Vector

This is the actual concealed state created from the model's encoder. It is processed utilizing the equation (1) given below. In efforts to support the decoder to make valid inferences, this variable (vector) attempts to summarize the data for all input components. It functions as the initial concealed portion of the model that makes up the decoder.

7.4.3 The Decoder

The decoder consists of a multi-recurrent system array where each array calculates a value y_t at time phase t. Each multi-recurrent unit embraces a concealed state and outputs a result along with its own concealed state from the previous module. The result stream is a list of all the keywords from the condensed content in the developed encapsulation system. Each keyword is denoted as y_i, where the order of this keyword is i.

For computing any initial concealed state h_i, the formula in [13] is used:

$$h_t = f(W^{(hh)} h_{t-1}) \quad (1)$$

Here, it is evident that a prior concealed state is used to calculate the next one.

The output y_t at a time instant t can be calculated using the formula in [13]:

$$y_t = softmax(W^S h_t) \quad (2)$$

The result is then computed by utilizing the concealed state at the present time phase along with the associated weight W^s. Softmax is utilized to generate a likelihood vector which will assist us in deciding the final result (for example, a single keyword answer in the question-answering problem).

7.5 Encapsulator

The DL model then generates an encapsulator that is capable of condensing the content without changing the exact meaning of the text. Its performance can be tested using the test dataset. The encapsulator generated has a content aware consciousness that plays a key role in keeping the meaning of the text intact.

Content Aware Consciousness (CAC): The key idea behind this mechanism is how much focus should be kept on every phrase in the input data so as to create a keyword at time phase t. For example:

> Question: What are the **factors** that have impacted mental health during the **pandemic**?
>
> Answer: ***Covid-19*** *has spawned multiple global health crisis some have dubbed* ***coronasomnia*** *-- an inability to fall asleep or get good quality sleep during the pandemic. Along with this, there are multiple levels of stress associated with the pandemic –*

financial, health care related *and* ***social isolation****. All these damage mental health, threaten health and quality of life for upto 45% of world's population. (source CNN news)*

In the inquiry above, the 12th word 'pandemic' is related to 'Covid-19' and the 4th word 'factors' is related to 'Coronasomnia', 'financial', 'health', 'social isolation'.

In this way, rather than taking a gander at all the keywords in the input arrangement, the significance of explicit pieces of the text can be emphasized that generate the ideal result. This is the fundamental idea behind the Content Aware Consciousness.

Based on the manner in which the background variable is extracted, there are 2 distinct classes of consciousness:

7.5.1 Global Content Aware Consciousness

The emphasis is laid on all the positions (all sentences) of the source. In other terms, for extracting the supported context variable, all the concealed states of the encoder are taken into account. The system uses this global content aware consciousness.

7.5.2 Local Content Aware Consciousness

The emphasis is laid on only a few positions (2-5 crucial sentences) of the source. For extracting the supported context variable, only a few concealed states of the encoder are taken into account.

This is how the CAC works:

- The encoder generates the concealed state (h_j) for each time phase j in the source series
- Likewise, the decoder generates the concealed state (s_i) for each time phase i in the target series

- The arrangement score (e_{ij}) is calculated based on the source series which is aligned with the target series using a function for score estimation. The arrangement score is calculated from the source concealed state h_j and target concealed state s_i using the score function, which is given by:

$$e_{ij} = \text{score}(s_i, h_j)$$

where e_{ij} indicates the arrangement score for target time phase i and source time phase j

- The arrangement scores are then normalized by using the softmax function to extract the CAC weights (a_{ij}):

$$a_{ij} = e^{eij} / \sum_{k=1}^{Tx} e^{eik}$$

- Now the CAC context variable (C_i) is calculated from the summation of CAC weights and concealed states of encoder h_j

$$C_i = \sum_{j=1}^{Tx} a_{ij} h_j$$

- The concealed variable V_i is generated by integrating the CAC context variable and the concealed state of the decoder at time phase i:

$$V_i = \text{integrate}(s_i, C_i)$$

- To create the final output y_i, the concealed variable V_i is further loaded into the deep network,

$$y_i = \text{deepNet}(V_i)$$

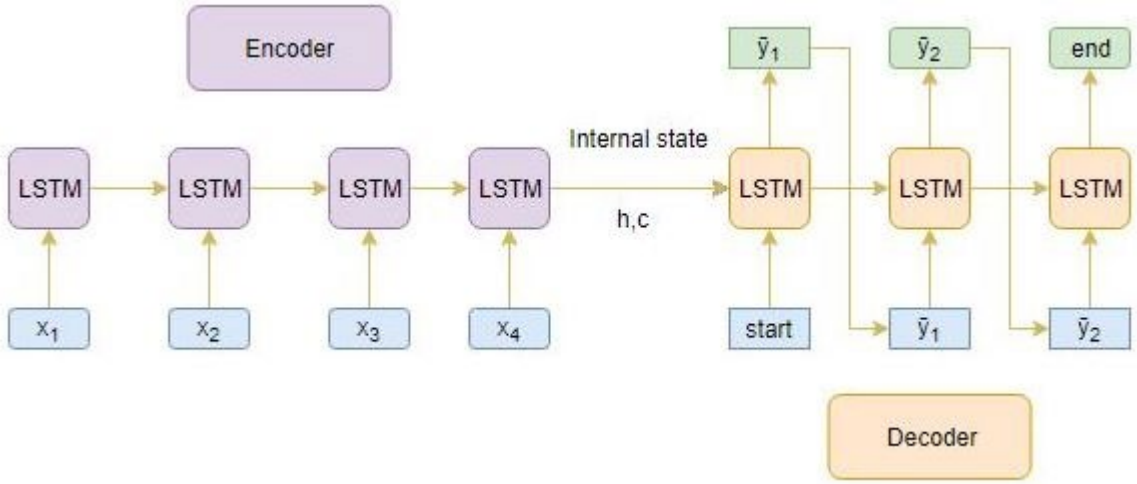


Figure 5: System Depicting Encoder, Internal State and Decoder

With the aid of an example, let's comprehend the above-mentioned CAC process. Consider [x_1, x_2, x_3, x_4] as the input content and [y_1, y_2] as the output encapsulated text.

- For each time phase t, the encoder scans the complete input series and produces a set of concealed states h_1, h_2, h_3, h_4

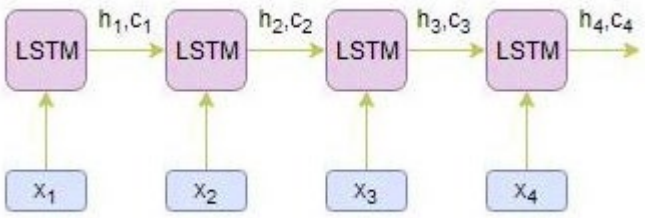


Figure 6: Data Flow in Encoder

- The decoder scans one time phase offset of the complete target series, and produces the concealed state for each time phase s_1, s_2, s_3

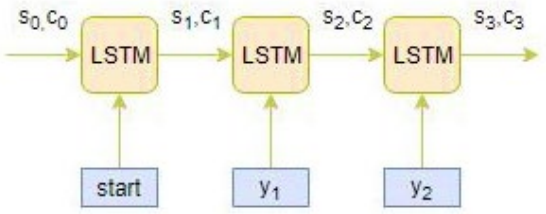


Figure 7: Data Flow in Decoder

- The arrangement scores e_{1j} are determined using the score function from the concealed input state h_i and target concealed state s_1:

$$e_{11} = \text{score}(s_1, h_1)$$

$$e_{12} = \text{score}(s_1, h_2)$$

$$e_{13} = \text{score}(s_1, h_3)$$

$$e_{14} = \text{score}(s_1, h_4)$$

- The arrangement scores are then normalized by using the softmax function to extract the CAC weights (a_{ij}):

$$a_{11} = e^{e11} / (e^{e11} + e^{e12} + e^{e13} + e^{e14})$$

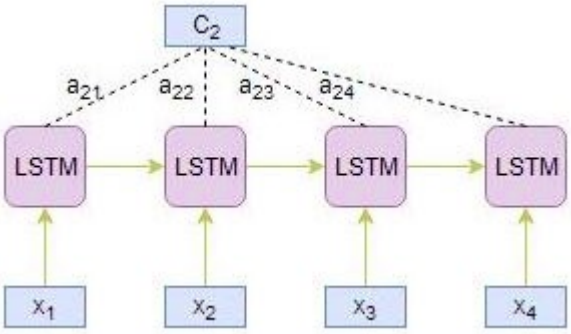
$$a_{12} = e^{e12} / (e^{e11} + e^{e12} + e^{e13} + e^{e14})$$

$$a_{13} = e^{e13} / (e^{e11} + e^{e12} + e^{e13} + e^{e14})$$

$$a_{14} = e^{e14} / (e^{e11} + e^{e12} + e^{e13} + e^{e14})$$

- Now the CAC context variable (C_i) is calculated from the multiplication of CAC weights a_{ij} and concealed states of encoder h_j

$$C_2 = h_1 * a_{21} + h_2 * a_{22} + h_3 * a_{23} + h_4 * a_{24}$$



- Concealed variable V_i is generated by integrating the CAC C_2 variable and the concealed state s_2

$$V_2 = \text{integrate}([s_2; C_2])$$

- The concealed variable V_2 is further loaded into the deep network to generate output y_2

$$y_2 = \text{deepNet}(V_2)$$

y_3, y_4 and so on are calculated in a similar fashion as shown below.

```
Model: "model"
_________________________________________________________________________________________________
Layer (type)                 Output Shape              Param #     Connected to
=================================================================================================
input_1 (InputLayer)         [(None, 80)]              0
_________________________________________________________________________________________________
embedding (Embedding)        (None, 80, 500)           2558500     input_1[0][0]
_________________________________________________________________________________________________
lstm (LSTM)                  [(None, 80, 500), (N 2002000     embedding[0][0]
_________________________________________________________________________________________________
input_2 (InputLayer)         [(None, None)]            0
_________________________________________________________________________________________________
lstm_1 (LSTM)                [(None, 80, 500), (N 2002000     lstm[0][0]
_________________________________________________________________________________________________
embedding_1 (Embedding)      (None, None, 500)         537500      input_2[0][0]
_________________________________________________________________________________________________
lstm_2 (LSTM)                [(None, 80, 500), (N 2002000     lstm_1[0][0]
_________________________________________________________________________________________________
lstm_3 (LSTM)                [(None, None, 500),  2002000     embedding_1[0][0]
                                                              lstm_2[0][1]
                                                              lstm_2[0][2]
```

Figure 8: Deep Learning Model network

VIII. RESULTS AND OBSERVATIONS

To evaluate the output of each of the approaches, a recent news snippet is chosen with over 1250 words, related to Covid-19 as shown below:

(CNN) The US will likely soon come up against a significant obstacle in the fight against the Covid-19 pandemic -- more doses of the vaccines than people who are willing to receive them, according to data that is worrying experts. "We actually think that (vaccine) supply will outstrip demand ... in probably the middle of May," Dr. Chris Murray, chair of the Institute for Health Metrics and Evaluation (IHME) at the University of Washington, told CNN Friday. The foundation cited the percentage of survey respondents that said they've already received the vaccine or would get it as soon as they could – 62%. Weighing that against the daily rate of vaccinations, and the CDC's data showing more than 41% of US adults already have had at least one dose, it's possible that the vast majority of US adults who presently want a first dose will have received them by early- to mid-May, the KFF said. One modifying factor, the foundation said, would be how many of the people who say they'll "wait and see" -- 13% -- decide to get a vaccine in the next few weeks. Murray cited different data -- daily Facebook surveys, watched by his institute, that he said showed a decline in percentage of adults wanting the vaccine since February: About 67%, down from around 75%. But both Murray and KFF have said their different indicators point to a significant slowdown in new vaccinations sometime in May -- and experts have said more people will need to be persuaded to get one, and more people will need to be made eligible, to be assured of herd immunity. Health officials -- including Dr. Anthony Fauci -- estimate that somewhere between 70% to 85% of the country needs to be immune to the virus -- either through inoculation or previous infection -- to suppress its spread. Currently, no Covid-19 vaccine is authorized in the US for people younger than 16. Vaccine makers have been studying their efficacy and safety in younger people, and Pfizer has asked the FDA to authorize its product for ages 12-15 . Expanding vaccine eligibility will be key to stamping out the pandemic, Dr. Leana Wen told CNN. "It's going to be very difficult, if not impossible, for us to reach herd immunity unless our children are also vaccinated," Wen, a CNN medical analyst and a former Baltimore health commissioner, said Saturday. The average number of Covid-19 vaccinations administered in the US per day has been falling recently. The average was 2.86 million a day as of Friday morning, down from a record 3.38 million on April 13, according to CDC data. Already, the military is seeing a surplus of doses and a steady decline in the rate at which they are used. "We have heard anecdotally that younger people may feel that they're not as vulnerable to Covid and that perhaps the risk of getting vaccination is higher than getting the disease, which of course we know not to be true," Terry Adirim, acting assistant defense secretary for health affairs, told reporters this week. Model predicts declining deaths, but vaccine hesitancy could hurt Daily Covid-19 deaths in the US should continue to decline in the coming months, though that could change if vaccine hesitancy rises, Murray's IHME said Friday. The country averaged 704 Covid-19 deaths a day across the last week, according to Johns Hopkins University data -- down from the 3,000s in parts of January and February. An IHME model projects that average will dip to around 425 by June 1, and 105 by August 1, the institute said Friday. Recent vaccine expansion and mask usage have helped death rates decline even as more contagious coronavirus variants -- such as B.1.1.7 -- have spread, the IHME said. But in a worst-case scenario, daily deaths could stay in the 700s in May and June, and in the 600s through July, the IHME predicts. That scenario involves a fast decline in mask use and an increase in mobility, the institute said. Vaccine hesitancy also would be troublesome, the IHME said. "Given how central vaccination is to the US strategy to control the B.1.1.7 potential surge, the slow erosion of vaccine confidence unfolding over the last two or more months is cause for concern," the IHME said. Lifting of J&J pause is welcome news, CDC director says On Friday, the CDC and the Food and Drug Administration lifted their recommended pause on the use of the Johnson & Johnson vaccine . The agencies had recommended the pause April 13 after learning of cases a rare blood

clotting syndrome among women who had recently received the vaccine. After examining data about the cases, the CDC's vaccine advisory committee voted to recommend lifting the pause, essentially deciding the benefits of the vaccine outweighed the risks. But the FDA will update the vaccine's label, indicating women under the age of 50 should be aware of a risk of the rare blood clotting syndrome linked to that product. The CDC said it has collected reports of 15 such cases, all in women and 13 of them in women under 50. At most, resuming administration of the J&J vaccine would result in a few dozen rare blood clots while saving hundreds of lives, a CDC analysis showed. "When resuming vaccination among all persons at least 18 years, we expect 26 to 45 TTS cases depending on vaccine uptake," CDC's Dr. Sara Oliver said, referring to the rare blood clots known as thrombosis-thrombocytopenia syndrome. But 600 to 1,400 deaths from Covid-19 would be prevented, and as many as 3,500 ICU admissions would be prevented. The CDC's director, Dr. Rochelle Walensky, said Friday the lifted pause is "welcome news for many, as many have wanted the Johnson & Johnson vaccine to fill an important need in vaccination efforts here and around the world." "I think we have to do extraordinary outreach to clinicians -- as we have been doing this past week; we already have plans to start that on Monday to public health officials -- and then we have to do extraordinary outreach to patients, to meet people where they're at, to educate them" about Covid-19 vaccines, Walensky said at a joint conference held by the CDC and the FDA. "Overall, I actually think that this pause conveyed that we are taking every one of these needles in haystacks that we find seriously -- that we're really examining, scrutinizing the data that we're seeing." The Moderna and Pfizer/BioNTech vaccines have not been associated with blood clots, a CDC's vaccine advisory committee was told Friday Study shows how to reduce infections in children While vaccines remain unavailable to children, new research suggests that testing in school and the vaccination of adults may lower infections in children. So far, no vaccines are authorized for people younger than 16, but a study published in the medical journal JAMA Network Open on Friday showed that quickly identifying and contact tracing children to identify "silent infections" of Covid-19, where the disease is either presymptomatic or asymptomatic, combined with vaccination of 40-60% adults could significantly reduce the amount of disease. In a different scenario, where silent infections remained undetected, researchers estimated that children would need an 81% vaccination rate, in addition to 40% of adults being vaccinated, in order to achieve a similar infection rate. As more students return to the classroom, the study provides a road map to continuing reducing the spread of the virus even before children are eligible for the shots.

Original Title: No vaccine for younger adults despite of excessively produced number of doses

8.1 Approach 1 – Scoring Sentences based on the Word-Frequency

This technique assigns weights to every single word that occurs in the text. For example, if the word ‘research’ appears 5 times in the text body, a weight of 5 is assigned to the word. Similarly, a holistic score based on the word appearance is assigned to every sentence that occurs in the text body. The sentences that have a higher weight are then picked up and used to summarize the text.

```
# Method to score sentences based on word frequency
def stm_score(stms, count_chart):
    val_stm = {}

    for st in stms:
        num_count_in_stm = len(word_tokenize(st))

        for wordVal in count_chart:

            if wordVal.lower() in st.lower():
                if st in val_stm:
                    val_stm[st] += count_chart[wordVal]
                else:
                    val_stm[st] = count_chart[wordVal]

        val_stm[st] = val_stm[st] // num_count_in_stm
    return val_stm

# To return the average score
def cal_mean_score(val_stm):
    summation = 0

    for entry in val_stm:
        summation += val_stm[entry]

    mean = int(summation/len(val_stm))

    return mean
```

As shown in the snippet above, the words are tokenized, weights are assigned to all the words and the sentence score is computed. To generate the overview, we'll take the top N statements which have a score higher than all the other statements. These statements are then chosen to generate the encapsulations.

```
def summary_generator(stms, val_stm, threshold):
    num_stm = 0

    summary_result = ''

    for st in stms:
        if st in val_stm and val_stm[st] > threshold:
            summary_result += " " + st
            num_stm += 1

    return summary_result
```

The generated encapsulated text:

```
Currently, no Covid-19 vaccine is authorized in the US for people younger than 16. Vaccine makers
have been studying their efficacy and safety in younger people, and Pfizer has asked the FDA to
authorize its product for ages 12-15 . Expanding vaccine eligibility will be key to stamping out the
pandemic, Dr. Leana Wen told CNN. The average number of Covid-19 vaccinations administered in the US
per day has been falling recently. An IHME model projects that average will dip to around 425 by June
1, and 105 by August 1, the institute said Friday. Recent vaccine expansion and mask usage have
helped death rates decline even as more contagious coronavirus variants -- such as B.1.1.7 -- have
spread, the IHME said. That scenario involves a fast decline in mask use and an increase in mobility,
the institute said. Vaccine hesitancy also would be troublesome, the IHME said. After examining data
about the cases, the CDC's vaccine advisory committee voted to recommend lifting the pause,
essentially deciding the benefits of the vaccine outweighed the risks. The CDC said it has collected
reports of 15 such cases, all in women and 13 of them in women under 50. But 600 to 1,400 deaths from
Covid-19 would be prevented, and as many as 3,500 ICU admissions would be prevented.
```

8.2 Approach 2 – Universal Sentence Encoder for Text Ranking

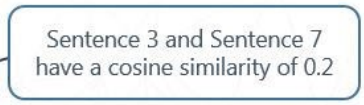
Text Ranking is similar to PageRank used by Google. PageRank creates a matrix of pages that will be most likely be visited next by the user. Similarly, TextRank uses cosine function to determine the similarity of 2 sentences to each other. This cosine linear similarity matrix is then used to build a tree. The PageRank rating equation is then added to the tree in order to determine rankings for each statement.

```
from sklearn.metrics.pairwise import cosine_similarity
import networkx as nx

# To create the cosine similarity matrix
mx = cosine_similarity(message_embeddings)

# To generate graph and scores from the textrank method
nx_gh = nx.from_numpy_array(mx)
score = nx.pagerank(nx_gh)

stm_rank = sorted(((score[i],s) for i,s in enumerate(stm)), reverse=True)
num_of_stm = 2

result = " ".join([i[1] for i in stm_rank[:num_of_stm]])
print(result)
time_elapsed = datetime.now() - start_time
print('Time elapsed (hh:mm:ss.ms) {}'.format(time_elapsed))
```

The table below shows the cosine matrix which is used to build a tree for the PageRank algorithm:

TABLE 1: COSINE SIMILARITY MATRIX

	S1	S2	S3	S4	S5	S6	S7	S8
S1	1.00	0.15	0.74	0.00	0.85	0.00	0.20	0.25
S2	0.15	1.00	0.15	0.71	0.26	0.59	1.00	0.00
S3	0.74	0.15	1.00	0.00	0.57	0.00	0.20	0.57
S4	0.00	0.71	0.00	1.00	0.00	0.80	0.00	0.00
S5	0.85	0.26	0.57	0.00	1.00	0.00	0.34	1.00
S6	0.00	0.59	0.00	0.80	0.00	1.00	0.59	0.80
S7	0.20	1.00	0.20	0.00	0.34	0.59	1.00	0.00
S8	0.25	0.00	0.57	0.00	1.00	0.80	0.00	1.00



The generated encapsulated text:

```
Model predicts declining deaths, but vaccine hesitancy could hurtDaily Covid-19 deaths in the US
should continue to decline in the coming months, though that could change if vaccine hesitancy rises,
Murray's IHME said Friday. So far, no vaccines are authorized for people younger than 16, but a study
published in the medical journal JAMA Network Open on Friday showed that quickly identifying and
contact tracing children to identify "silent infections" of Covid-19, where the disease is either
presymptomatic or asymptomatic, combined with vaccination of 40-60% adults could significantly reduce
the amount of disease.
```

8.3 Approach 3 – Dual bi-directional LSTM

From the previous 2 approaches we can infer that no new text is generated but simply sentences are chosen based on the assigned weights and ranks. The sentences are then displayed as output. However, these sentences do not capture the essence of the input text and sound vaguely odd when read by the user. This is where the developed system beats all the existing systems. This is due to use of three lstm layers out of which two are bidirectional and all the layers are interlinked to each other. The input text is given to LSTM layer 1 which generates intermediate return sequences along with the return state. This is then fed to LSTM layer 2 which generates a new set of sequences and state and is then parsed by the LSTM layer 3. The LSTM layer 3's output is then

used as input by decoder that uses SoftMax activation function along with CAC and generates new text that captures the holistic meaning of the entire input text.

```
lDim = 500

# Get the input to Encoder
ips = Input(shape=(max_len_text,))
bedd = Embedding(x_voc_size, lDim,trainable=True)(ips)

# 1 LSTM
en_ls1 = LSTM(lDim,return_sequences=True,return_state=True)
en_op1, is1, stc1 = en_ls1(enc_emb)

# 2 LSTM
en_ls2 = LSTM(lDim,return_sequences=True,return_state=True)
en_op2, is2, stc2 = en_ls2(en_op1)

# 3 LSTM
en_ls3=LSTM(lDim, return_state=True, return_sequences=True)
en_op, iS, stc= en_ls3(en_op2)

# To configure the decoder.
dc_ips = Input(shape=(None,))
dcBedd = Embedding(y_voc_size, lDim,trainable=True)
dc = dcBedd(dc_ips)

# The initial state of the LSTM as encoder states
drLs = LSTM(lDim, return_sequences=True, return_state=True)
dr_op,dr_stF, dr_stB = drLs(dc,initial_state=[iS, stc])

# Context Aware Consciousness
intermediate_sequence = 3
cac = AttentionLayer(name='attention_layer')
cac_op, cac_st = cac([en_op, dr_op])

# Concat attention output and decoder LSTM output
dr_Cip = Concatenate(axis=-1, name='concat_layer')([dr_op, cac_op])

# Dense layer
den = TimeDistributed(Dense(y_voc_size, activation='softmax'))
dr_op = den(dr_Cip)

# Define the model
model = Model([ips, dc_ips], dr_op)
model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================================
input_1 (InputLayer)            [(None, 80)]         0
__________________________________________________________________________________________________
embedding (Embedding)           (None, 80, 500)      25785500    input_1[0][0]
__________________________________________________________________________________________________
lstm (LSTM)                     [(None, 80, 500), (N 2002000     embedding[0][0]
__________________________________________________________________________________________________
input_2 (InputLayer)            [(None, None)]       0
__________________________________________________________________________________________________
lstm_1 (LSTM)                   [(None, 80, 500), (N 2002000     lstm[0][0]
__________________________________________________________________________________________________
```

The generated encapsulated output:

```
The US may have more vaccines than people who want them by mid-May. Here's why that's a big problem.
```

To understand how the model performs on both the datasets, analysis of distribution of text length is performed and a graph is plotted using matplot. Y-axis represents the total number of statements X-axis represents the number of words.

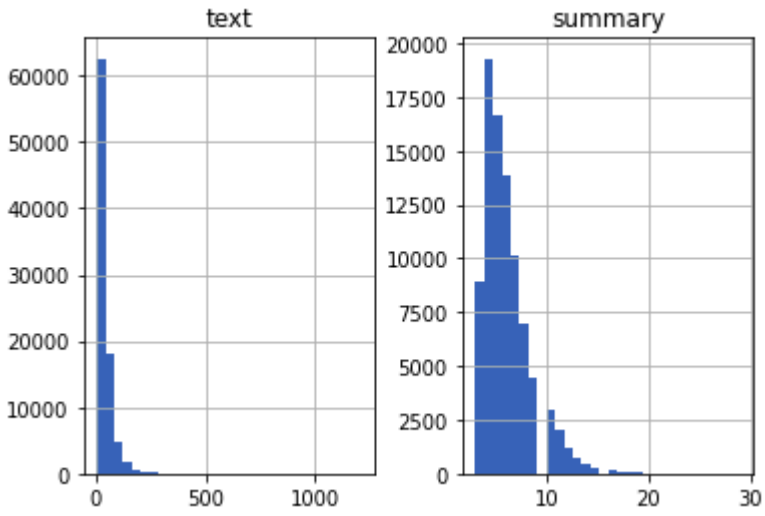


Figure 9: Distribution of text length for Amazon Reviews Dataset

As seen in figure 9, the average length of reviews ranges from 200 – 400 words per review.

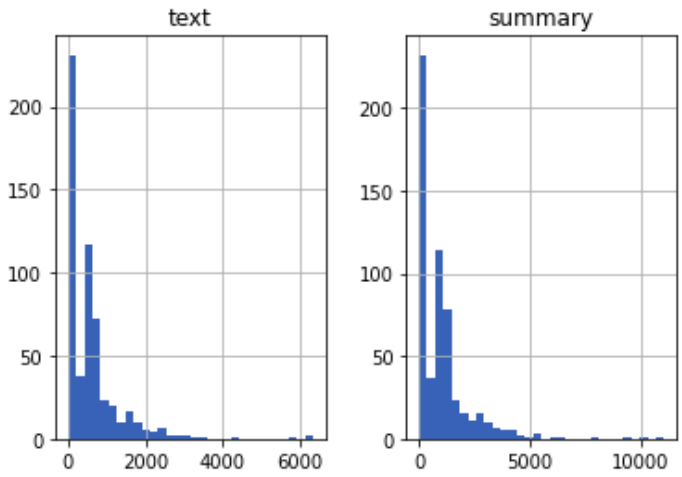


Figure 10: Distribution of text length for CNN News Dataset

As seen in figure 10, the average length of news articles ranges from 1000 – 2500 words per article.

Sample outputs generated for Amazon Reviews dataset with the help of approach 3:

Original Summary: bars tasty really taste like brownie certainly chocolatey yummy good amount protein good afternoon snack trying gain muscle mass best thing workout contain almost carbs know proper
Generated Encapsulation: pretty good for protein bar

Original Summary: really like taste powder great protein shake especially banana blended issue shelf life product container lasts long time container purchased amazon expired less month purchase date
Generated Encapsulation: good in smoothies but why the short shelf life

Original Summary: self respecting cat picky eater never met cat likes whiskas choice cut foods mainly gravy sometimes meat magnificent wonderful likes beef gravy tuna truth told dry crunchie really
Generated Encapsulation: good cat food without smelly cans

Original Summary: better mayo one market also one made without sugar complete miracle way mayo made also great spices tangy taste perfect would expect lemon mayonnaise whole foods near home carried
Generated Encapsulation: best mayo on the market

Original Summary: shipping fine one packs see costco placed box shipment good deal around dollar bottle drink made splenda plenty sweet almost taste like regular juice drink one better tasting diet
Generated Encapsulation: best tasting splenda drink with no after taste

Original Summary: diet fresh easy neighborhood grocery looking possible diet foods wanted things tasty non fat low calories came home dozen items discovered farms pickled crispy asparagus
Generated Encapsulation: my idea of good diet food

Original Summary: ordered line received days tea excellent price right
Generated Encapsulation: good tea

Original Summary: organic market bought two bottles cost three dollars fell love instantly drink delicious taste yerba mate acai juice like slightly bitter chocolate honey tea sensitive sucralose
Generated Encapsulation: best energy shot have ever tasted

Original Summary: bought years grocery store none carry anymore ended getting great price bulk package highly recommended kool aid type drink
Generated Encapsulation: one of the best drinks mixes out there

Original Summary: great brownies happen gluten free everyone loves including wheat eaters celiacs disease cannot eat gluten get ill never gotten ill brownies means gluten free safe gluten free diets
Generated Encapsulation: great brownies that just happen to be gluten free

Original Summary: local eat regularly use kinds foods love hot without flavor like sauces burn taste burn awesome flavor surprised find amazon would highly recommend anyone likes good hot sauce
Generated Encapsulation: love this stuff

Original Summary: good even store brand oatmeal requiring preparation still mccann good gets instant oatmeal even better organic natural brands tried varieties mccann variety pack taste good microwave
Generated Encapsulation: best of the instant

Original Summary: spicy chips lot great flavor left breath afterwards first time ate night even could taste mouth next morning careful eat especially people later day
Generated Encapsulation: tasty but make sure you have gum

Original Summary: quaker oatmeal cookies tastey make easy snack work individually wrapped put bag cookie soft nice bits nuts chocolate little dry perfect milk brainer good cookie individually wrapped l
Generated Encapsulation: good cookie for on the go

Original Summary: popchips really great snack alternative regular chips full replacement far concerned taste texture great jalapeno ones hate greasy fried chips often switch baked version chips another
Generated Encapsulation: great alternative to regular chips

Sample outputs generated from CNN news Dataset:

Original title: soon start selling rights shoot many elephants year country announced week spokesman zimbabwe parks wildlife management authority told cnn thursday declining tourism revenue owing coronavirus pandemic among main
Generated Encapsulation: decision to allow elephant hunting was appalling read more

Original title: wrote first time seen man smile since wife died dan peterson lost beloved wife march fell deep depression six months later chance encounter store day going day self pity feeling sorry told cnn changed
Generated Encapsulation: how you can positively impact life tara wood said

Original title: granted temporary residency allowing right work began four year long process gain full citizenship navigating complexities financial costs american immigration bureaucracy arriving new country thought activism
Generated Encapsulation: trump emphasis on fighting for ordinary americans read more

Original title: may tract symptoms get cnn health weekly newsletter sign get results sanjay gupta every tuesday cnn health team parent keep watch symptoms reach immediately health care provider emergency room one last important
Generated Encapsulation: close contact with your child school and your pediatrician

Original title: responsibility enabling government said report published monday april july people slaughtered mainly ethnic minority also message foreign affairs minister today key step getting two countries closer french presid
Generated Encapsulation: france role in connection with the genocide read more

Original title: way allows seen said share back see connection sharing story creating shared vision together says managing loneliness post pandemic world simply take time effort people talk makes realize going try start said
Generated Encapsulation: that as we emerge from pandemic we emerge together

Original title: allowed observe understand catherine mayer monarchy ultimate exclusive club sovereign born reign subjects citizens hardly obvious qualifications performing key role head state queen nevertheless largely succeeded
Generated Encapsulation: to covid restrictions it must seem proportionate read more

Original title: weeks world health organization warned virus sweeps hotspots several corners globe million new cases recorded last week single week since pandemic began director general tedros adhanom ghebreyesus said news
Generated Encapsulation: these deaths is tragedy for families communities and nations

Original title: deadly tesla crash texas raised questions tesla autopilot feature consumer reports released video showing someone might trick autopilot system operate without driver
Generated Encapsulation: autopilot system to operate without driver source cnn business

As seen from the output above, the original titles and summaries may not depict the exact information that the text carries. The encapsulation that is generated using the deep learning model captures the holistic meaning of the text. Some outputs generated with this approach may not be precise or some might be blank. This is due to the loss encountered during the model training and validation phases.

8.4 Model Training and Validation Loss

The observations from experiments provide a deep insight into the results. There is a notable performance difference between the 3 approaches. The first methodology generates moderate results with a marginal score of 67 percent using Word-frequency as a measure, the second methodology performed better with the Text Ranking algorithm with a good accuracy of 78 percent, and the third method has a 93 percent accuracy using the proposed LSTM network.

The training and test phase losses for each of the models decreases gradually as we move from Epoch 1 to Epoch 10. An insight into losses for each of these models helps better understand why the approach 3 has high accuracy. For approach 1 and 2, a significant change in validation loss even after 10 epochs cannot be seen.

TABLE 2: Training and Validation Loss per Epoch for Scoring Sentences (Approach 1)

EPOCHS	TRAINING LOSS	VALIDATION LOSS
1/10	8.933	8.900
2/10	7.297	7.013
3/10	6.662	6.190
4/10	6.288	6.121
5/10	6.088	5.759
6/10	5.407	5.366
7/10	5.328	5.049
8/10	5.076	5.003
9/10	4.891	4.558
10/10	4.322	4.219

TABLE 3: Training and Validation Loss per Epoch for Text Ranking (Approach 2)

EPOCHS	TRAINING LOSS	VALIDATION LOSS
1/10	8.323	8.157
2/10	8.091	8.073
3/10	7.866	7.739
4/10	7.600	7.577
5/10	4.945	4.825
6/10	4.507	4.447
7/10	4.226	4.140
8/10	3.505	3.428
9/10	3.110	3.107
10/10	3.086	3.079

TABLE 4: Training and Validation Loss per Epoch for Dual LSTM (Approach 3)

EPOCHS	TRAINING LOSS	VALIDATION LOSS
1/10	6.913	6.125
2/10	6.856	5.751
3/10	4.909	3.297
4/10	3.485	2.741
5/10	3.143	2.729
6/10	3.077	2.620
7/10	2.971	2.594
8/10	2.950	2.524
9/10	2.854	2.405
10/10	2.831	2.463

8.5 Run-Time Analysis

The model training sequence is the most time consuming step as the model is being trained to read unknown sequences of text and generate a precise output. For the first approach that involves scoring sentences based on the word frequency, the time required for model training and evaluation is the least. This is why it has the least accurate output. For the covid news snippet with over 1250 words, end to end run with the approach 1 takes approximately 25 seconds to generate output. Approach 2 which uses text ranking, performs better in terms of generating a precise output but its model training and evaluation requires more time as compared to the first approach. For the news snippet above, end to end run with the approach 2 takes approximately 30 seconds to generate output text.

For approach 3, in the very first training phase, the developed system requires the largest amount of time to train and evaluate the model. In this first phase, the model training and evaluation takes approximately 42 seconds on a small Amazon reviews dataset with over 1300 records. From the second phase onwards, the run-time decreases as the model gets trained on more new data. This model training and evaluation takes approximately 16 seconds to complete in the second run. The larger Amazon dataset is over 300MB in size and consists of 100,000 reviews. The model training and validation on this dataset takes approximately 22 minutes. Although the time required to train the model is more, it generates a precise output. For the covid news snippet above, the approach 3 takes approximately 2 milliseconds to generate the encapsulated text. The table 2 displays the runtime analysis information for all the approaches.

TABLE 5: Run-time Analysis

Input Data	Approach	Total Run-time for Model Training and Evaluation [Time elapsed (hh:mm:ss.ms)]	Time to generate Output (Seconds)
	Scoring Sentences based on the Word-Frequency	0:00:24.746911	24.746911
News Snippet	Universal Sentence Encoder for Text Ranking	0:00:30.07571	30.07571
	Dual bi-directional LSTM	0:00:30.07571	2.097957
Amazon Reviews Dataset 1	Dual bi-directional LSTM	0:00:42.349841	1.086803
Amazon Reviews Dataset 2	Dual bi-directional LSTM	0:22:46.944088	12.744386
CNN News Dataset	Dual bi-directional LSTM	0:03:48.934982	1.097957

8.6 Comparison of the Results

All the above approaches performed differently with different algorithms used in each implementation. The accuracy is a good measure for evaluating the models, along with the F1 scores that can be used for comparison. The comparisons of accuracy and F1 scores from the results of each approach, led to insightful conclusions. Scoring Sentences based on the Word-Frequency in approach 1 has a low performance and accuracy of 67%. In the second approach, Universal Sentence Embeddings have a slightly higher performance as compared to approach 1

with an accuracy of 78%. The LSTM model in approach 3 performed the best as it closely resembles a human summary and has the highest accuracy of 93% with high F1 scores.

TABLE 6: Comparison between Three Approaches

	Accuracy	**Precision**	**Recall**	**F1**
Scoring Sentences based on the Word-Frequency	67% (+/- 0.537)	65%	61%	66%
Universal Sentence Encoder for Text Ranking	78% (+/- 0.029)	77%	75%	76%
Dual bi-directional LSTM	93% (+/- 1.046)	92%	91%	93%

The following remarks can be drawn from the findings:

Remark 1: The first approach simply scores all the sentences and selects the highest weighted sentences to display as summarized output. We can infer from Table 2 that since the training and validation phase losses are high, this model has an average precision score of 65%. The holistic meaning of the text might not be captured by this method. Even though it has a good F1 score, the recall is pretty poor for this approach.

Remark 2: The second approach has a good accuracy of 78% due to moderate training and test phase losses during the 10 Epochs. This is mainly because of the Text Ranking grid matrix. Text Ranking uses cosine function to determine the similarity of 2 sentences to each other. This cosine

linear similarity matrix is then used to build a tree. The PageRank rating equation is then added to the tree in order to determine rankings for each statement. The summaries generated by this approach has low recall but high precision and F1 scores of 77% and 76% respectively.

Remark 3: The proposed approach as demonstrated in the experiments, has the highest accuracy out of the 3 approaches. This is because it has the lowest training and validation phase losses during the 10 epochs. This approach generates sentences based on the natural language understanding with the help of SoftMax and CAC. This approach more closely resembles a human approach rather than a machine generated approach. This is why it has a high precision of 92% and F1 score of 93%. Even though the recall is less, the overall accuracy of the approach turns out to be greater than 93%.

IX. CONCLUSION AND FUTURE WORK

The modern age of innovation has begun as a result of the rapid advancement in the realms of deep learning. Most of these innovations are automated and require little to no human intervention in generating precise output. Text encapsulation means capturing the meaning of the sequence of text rather than just summarizing the text. Existing text summarization systems like approaches 1 and 2 simply remove pronouns, some random words and summarize the articles based on sentence weights. These summarizations can be completely different in meaning when compared with the original article. The developed model captures the exact meaning of the entire text by parsing the input data through multiple LSTM layers and generates its own encapsulated text. Since this model has high precision of 92% and F1 score of 93%, the generated text closely resembles a human generated one or in some cases even better than the human generated ones.

In a world where pandemic is prevalent for a long time and news with mis represented headings lure people into disappointment, it is more important than ever to have a robust text encapsulation system. The developed model can be further refined by using a large dataset in combination with a quadri-bidirectional LSTM network. By making use of the beam scanning technique, this model can be further improved, loss can be reduced and higher output accuracy can be attained. The developed system's applications can be extended to academia as well where it can be used by budding researchers to encapsulate brief articles into some well-structured short descriptions or titles. This research project provides an overview on existing systems and proposes an approach to automate the text encapsulation process. The series of tests performed on the developed model using heterogeneous datasets make it robust, consistent and highly efficient as compared to existing systems.

REFERENCES

[1] T. Nomoto and Y. Matsumoto, "An experimental comparison of supervised and unsupervised approaches to text summarization," Proceedings 2001 IEEE International Conference on Data Mining, San Jose, CA, USA, 2001, pp. 630-632, doi: 10.1109/ICDM.2001.989585.

[2] Shuhua Liu, "Enhancing e-business-intelligence-service: a topic-guided text summarization framework," Seventh IEEE International Conference on E-Commerce Technology (CEC'05), Munich, Germany, 2005, pp. 493-496, doi: 10.1109/ICECT.2005.45.

[3] P. Zhang and C. Li, "Automatic text summarization based on sentences clustering and extraction," 2009 2nd IEEE International Conference on Computer Science and Information Technology, Beijing 2009, 167-170, doi: 10.1109/ICCSIT.2009.5234971.

[4] K. S. Thakkar, R. V. Dharaskar and M. B. Chandak, "Graph-Based Algorithms for Text Summarization," 2010 3rd International Conference on Emerging Trends in Engineering and Technology, Goa, 2010, pp. 516-519, doi: 10.1109/ICETET.2010.104.

[5] E. Reategui, M. Klemann and M. D. Finco, "Using a Text Mining Tool to Support Text Summarization," 2012 IEEE 12th International Conference on Advanced Learning Technologies, Rome, 2012, pp. 607-609, doi: 10.1109/ICALT.2012.51.

[6] R. Ferreira et al., "A Context Based Text Summarization System," 2014 11th IAPR International Workshop on Document Analysis Systems, Tours, 2014, pp. 66-70, doi: 10.1109/DAS.2014.19.

[7] N. Moratanch and S. Chitrakala, "A survey on extractive text summarization," 2017 International Conference on Computer, Communication and Signal Processing (ICCCSP), Chennai, 2017, pp. 1-6, doi: 10.1109/ICCCSP.2017.7944061.

[8] M. Afsharizadeh, H. Ebrahimpour-Komleh and A. Bagheri, "Query-oriented text summarization using sentence extraction technique," 2018 4th International Conference on Web Research (ICWR), Tehran, 2018, pp. 128-132, doi: 10.1109/ICWR.2018.8387248.

[9] S. Abujar, M. Hasan, M. S. I. Shahin and S. A. Hossain, "A heuristic approach of text summarization for Bengali documentation," 2017 8th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Delhi, 2017, pp. 1-8, doi: 10.1109/ICCCNT.2017.8204166.

[10] R. Zhang, W. Li, D. Gao and Y. Ouyang, "Automatic Twitter Topic Summarization With Speech Acts," in IEEE Transactions on Audio, Speech, and Language Processing, vol. 21, no. 3, pp. 649-658, March 2013, doi: 10.1109/TASL.2012.2229984.

[11] R. A. García-Hernández and Y. Ledeneva, "Word Sequence Models for Single Text Summarization," 2009 Second International Conferences on Advances in Computer-Human Interactions, Cancun, 2009, pp. 44-48, doi: 10.1109/ACHI.2009.58.

[12] Alam, Tanweer, (2018), "A Reliable Communication Framework and Its Use in the Internet of Things," (IOT3).

[13] W. Zhao, G. Zhang, G. Yuan, J. Liu, H. Shan and S. Zhang, "The Study on the Text Classification for Financial News Based on Partial Information," in IEEE Access, vol. 8, pp. 100426-100437, 2020, doi: 10.1109/ACCESS.2020.2997969.

[14] Thu, Ha. (2014). An Optimization Text Summarization Method Based on Naïve Bayes and Topic Word for Single Syllable Language. Applied Mathematical Sciences. 8. 10.12988/ams.2014.36319.

[15] Hermann, K. M., Kocisky, T., Grefenstette, E., Espeholt, L., Kay, W., Suleyman, M., & Blunsom, P. (2015), Teaching machines to read and comprehend, In Advances in Neural Information Processing Systems (pp. 1684-1692)

[16] S. Brin, ''Extracting patterns and relations from the world wide web,'' in Selected Papers from the International Workshop on The World Wide Web and Databases, ser. WebDB '98. London, UK, UK: Springer-Verlag, 1999, pp. 172--183. [Online]. Available: http://dl.acm.org/citation.cfm?id=646543.696220

[17] S. Strassel, A. Mitchell, and S. Huang, ''Multilingual resources for entity extraction,'' in Proceedings of the ACL 2003 Workshop on Multilingual and Mixed-language Named Entity Recognition - Volume 15, ser. MultiNER '03. Stroudsburg, PA, USA: Association for Computational Linguistics, 2003, pp. 49--56. [Online]. Available: https://doi.org/10.3115/1119384.1119391

[18] J. N. Madhuri and R. Ganesh Kumar, "Extractive Text Summarization Using Sentence Ranking," 2019 International Conference on Data Science and Communication (IconDSC), Bangalore, India, 2019, pp. 1-3, doi: 10.1109/IconDSC.2019.8817040.

[19] C. Lakshmi Devasena and M. Hemalatha, "Automatic Text categorization and summarization using rule reduction," IEEE-International Conference On Advances In Engineering, Science And Management (ICAESM -2012), Nagapattinam, India, 2012, pp. 594-598.

[20] D. Gunawan, S. H. Harahap and R. Fadillah Rahmat, "Multi-document Summarization by using TextRank and Maximal Marginal Relevance for Text in Bahasa Indonesia," 2019 International Conference on ICT for Smart Society (ICISS), Bandung, Indonesia, 2019, pp. 1-5, doi: 10.1109/ICISS48059.2019.8969785.

[21] S. R. Rahimi, A. T. Mozhdehi and M. Abdolahi, "An overview on extractive text summarization," 2017 IEEE 4th International Conference on Knowledge-Based Engineering and Innovation (KBEI), Tehran, Iran, 2017, pp. 0054-0062, doi: 10.1109/KBEI.2017.8324874.

[22] C. HARK, T. UÇKAN, E. SEYYARER and A. KARCI, "Graph-Based Suggestion For Text Summarization," 2018 International Conference on Artificial Intelligence and Data Processing (IDAP), Malatya, Turkey, 2018, pp. 1-6, doi: 10.1109/IDAP.2018.8620738.

[23] A. R. Mishra, V. K. Panchal and P. Kumar, "Extractive Text Summarization - An effective approach to extract information from Text," 2019 International Conference on contemporary Computing and Informatics (IC3I), Singapore, 2019, pp. 252-255, doi: 10.1109/IC3I46837.2019.9055636.

[24] X. -y. Jiang, X. -Z. Fan, Z. -F. Wang and K. -L. Jia, "Improving the Performance of Text Categorization Using Automatic Summarization," 2009 International Conference on Computer Modeling and Simulation, Macau, China, 2009, pp. 347-351, doi: 10.1109/ICCMS.2009.29.

[25] C. Wang, L. Long and L. Li, "HowNet based evaluation for Chinese text summarization," 2008 International Conference on Natural Language Processing and Knowledge Engineering, Beijing, China, 2008, pp. 1-6, doi: 10.1109/NLPKE.2008.4906789.