Sentiment Analysis on Large-Scale Covid-19 Tweets using Hybrid Convolutional LSTM Based on Naïve Bayes Sentiment Modelling

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Project – Part 2 (Dissertation II + Defence of Project – II) [PGCSE 491]

Presented By:

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Course – MTech (CSE); **Year –** 2^{nd}; **Semester –** 4^{th}; **Roll No. –** MCS2019/001
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Introduction

- Sentiment Analysis is a type of Data Mining that measures the inclination of people's opinions through Natural Language Processing (NLP), computational linguistics and text analysis [2].
- By using sentiment analysis on social media, we can get incredible insights on a particular topic or incident what is happening around the world.
- This is often used to identify and extract human sensations within a given text across blogs, reviews, social media, forums, news etc.
- Using the sentiment analysis, we can analyze and extract subjective information from the social media to determine whether the data is *positive*, *negative* or *neutral* [3, 10].

Motivation & Objectives

- The Novel Coronavirus (COVID-19) was identified in 31st Dec, 2019 in Wuhan, Hubei Province, China [1].
- WHO announced Covid-19 outbreak as pandemic on 11th March, 2020.
- Several countries implemented strict lockdowns to prevent spread of disease by stopping chains of transmission of COVID-19 [2].
- Lot of people shared their expression on Twitter on this pandemic during this lockdown period [3].
- The motivation behind this work is to analyze the irrational behaviors of people throughout the world.
- We used Sentiment Analysis to measure the trend of public opinions throughout the world [9].

Related Work I

“Analysis of Twitter Data Using Evolutionary Clustering during the COVID-19 Pandemic” ***By*** *Ibrahim Arpaci, Shadi Alshehabi, Mostafa Al-Emran, Mahmoud Khasawneh, Ibrahim Mahariq, Thabet Abdeljawad and Aboul Ella Hassanien*, **2020**. [6]

- **Proposed Methodology:** Evolutionary K-means Clustering Model.
- **Purpose:** Analyse the public attention during the epidemic.
- N-gram Model for identification of tweet patterns.
- **Result:** The difference between the occurrences of n-gram.

Related Work II

“Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India” ***By*** *Parul Arora, Himanshu Kumar and Bijaya Ketan Panigrahi,* ***2020***. [5]

- **Proposed Methodology:** Covid-19 trend prediction model.
- **Purpose:** Predicting the COVID-19 trend for positive cases in different states of India.
- **Training:** Different LSTM variants such as stacked, convolutional and bi-directional LSTM used for training on historical data.
- **Result:** The proposed Bi-LSTM model gives more accurate results over other LSTM models.

Related Work III

“Datastories at semeval-2017 task 4: Deep LSTM with Attention for Message-level and Topic-based Sentiment Analysis” ***By*** *Baziotis Christos, Nikos Pelekis and Christos Doulkeridis*, **2017**. [8]

- **Proposed Methodology:** Message-level and Topic-based sentiment analysis.
- **Purpose:** The proposed deep learning system used for -
  - ✓ Short-text sentiment analysis using an attention mechanism.
  - ✓ Topic-based sentiment analysis, with a context-aware attention mechanism utilizing the topic information.
- **Training:** The LSTM network augmented with two kinds of attention mechanisms.

Related Work IV

"Long Short Term Memory Hyperparameter Optimization for a Neural Network Based Emotion Recognition Framework" ***By*** *Bahareh Nakisa, Mohammad Naim Rastgoo, Andry Rakotonirainy, Frederic Maire and Vinod Chandran*, **2018**. [9]

- **Proposed Methodology:** The Deep Neural Network-based Emotion Recognition framework.
- **Purpose:** To find an optimized LSTM classier with high performance in the context of emotion classification.
- **Training:** LSTM Deep Neural Network.
- **Result:** Optimized LSTM classifier achieved 77.68% accuracy by using the Differential Evolution algorithm.

Related Work V

“COVID-19 Public Sentiment Insights and Machine Learning for Tweets Classification” ***By*** *Jim Samuel, G. G. Md. Nawaz Ali, Md. Mokhlesur Rahman, Ek Esawi and Yana Samuel*, **2020**. [11]

- **Purpose:** Comparative analysis of four different machine learning classifiers on Coronavirus Tweets data.
- **Machine Learning Classifiers:** Naïve Bayes classifier, Logistic Regression.
- **Result:** Naïve Bayes classifier achieved 91% classification accuracy for short Tweets whether using the Logistic Regression classifier provides classification accuracy of 74% on the same number of tweets.

Related Work VI

“Deep Sentiment Classification and Topic Discovery on Novel Coronavirus or COVID-19 Online Discussions: NLP Using LSTM Recurrent Neural Network Approach” ***By*** *Hamed Jelodar, Yongli Wang, Rita Orji and Shucheng Huang*, **2020**. [12]

- **Proposed Methodology:** Sentiment Evaluation using deep learning model.
- **Purpose:** To detect the topics on Coronavirus related issues from online healthcare forums.
- **Training:** LSTM Recurrent Neural Network.
- **Result:** The proposed model achieved 81.15% of classification accuracy on COVID-19 comments for classifying them into positive, negative and neutral classes.

Novelty of Our Work

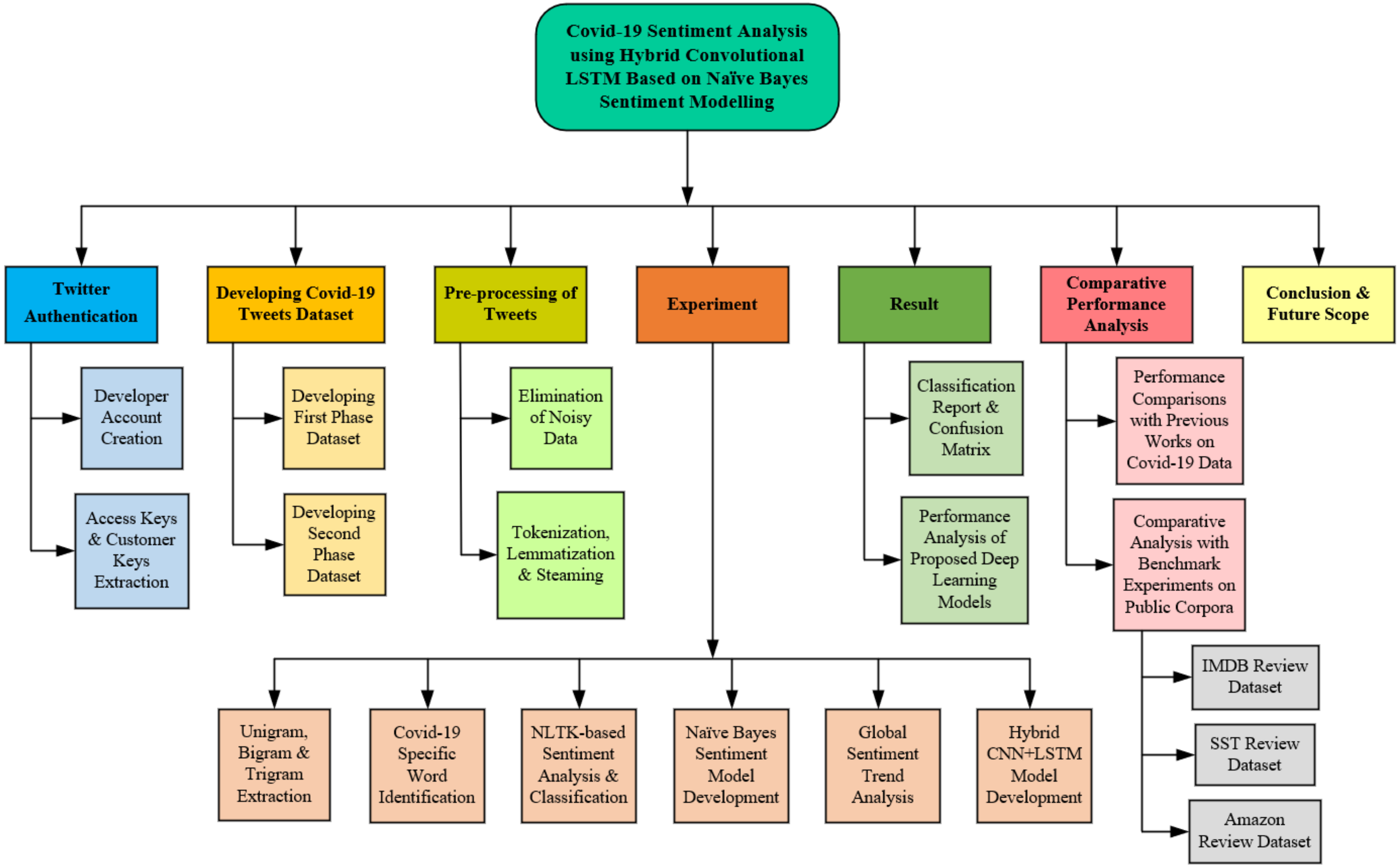
- **Originality :** Till now there are only few numbers of significant research works demonstrating the public sentiments on Covid-19 pandemic all over the world.
- **Preparing real time dataset :** We have started streaming tweets from the twitter after WHO declared Covid-19 as pandemic. We have collected almost 235k and 320k worldwide English tweets related to Covid-19 during April – June, 2020 and August – October, 2020.

Contribution

- Covid-19 Specified Word Identification
- N-gram Model
- NLTK-based Sentiment Analysis
- Naïve Bayes Sentiment Model
- Sentiment Modelling using Hybrid Convolutional LSTM

Design Methodology

- **Work Breakdown Structure**



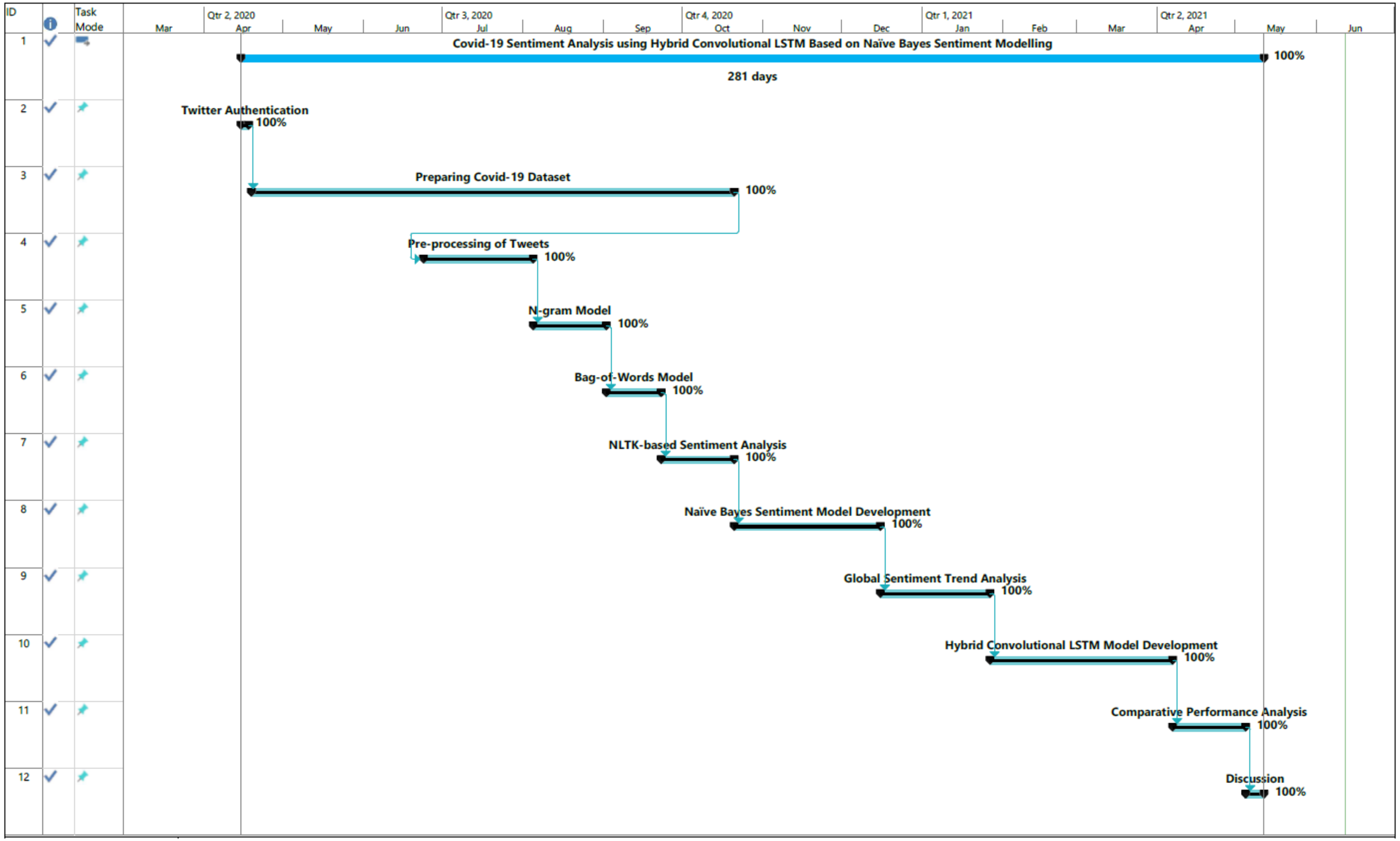
Design Methodology

- **Timeline Task Sheet**

ID		Task Mode	Task Name	Duration	Start	Finish	Predecessors
1			**Covid-19 Sentiment Analysis using Hybrid Convolutional LSTM Based on Naïve Bayes Sentiment Modelling**	**281 days**	**Wed 15-04-20**	**Tue 11-05-21**	
2			**Twitter Authentication**	**3 days**	**Wed 15-04-20**	**Fri 17-04-20**	
3			Developer Account Creation	2 days	Wed 15-04-20	Thu 16-04-20	
4			Access Keys & Customer Keys Extraction	1 day	Fri 17-04-20	Fri 17-04-20	3
5			**Preparing Covid-19 Dataset**	**133 days**	**Sun 19-04-20**	**Tue 20-10-20**	**2**
6			Construction of First Phase Dataset	46 days	Sun 19-04-20	Sat 20-06-20	4
7			Construction of Second Phase Dataset	44 days	Thu 20-08-20	Tue 20-10-20	6
8			**Pre-processing of Tweets**	**30 days**	**Wed 24-06-20**	**Tue 04-08-20**	**6**
9			Elimination of Noisy Data	20 days	Wed 24-06-20	Tue 21-07-20	6
10			Tokenization, Lemmatization & Steaming	10 days	Wed 22-07-20	Tue 04-08-20	9
11			**N-gram Model**	**20 days**	**Wed 05-08-20**	**Tue 01-09-20**	**8**
12			Unigram Extraction & Visualization	8 days	Wed 05-08-20	Fri 14-08-20	10
13			Bigram Extraction & Visualization	6 days	Sat 15-08-20	Mon 24-08-20	12
14			Trigram Extraction & Visualization	6 days	Tue 25-08-20	Tue 01-09-20	13
15			**Bag-of-Words Model**	**15 days**	**Wed 02-09-20**	**Tue 22-09-20**	**11**
16			Covid-19 Specific Word Identification	10 days	Wed 02-09-20	Tue 15-09-20	14
17			Word Popularity & Probability, Visualization	5 days	Wed 16-09-20	Tue 22-09-20	16
18			**NLTK-based Sentiment Analysis**	**20 days**	**Wed 23-09-20**	**Tue 20-10-20**	**15**
19			Sentiment Classification & Distribution	15 days	Wed 23-09-20	Tue 13-10-20	17
20			Visualization	5 days	Wed 14-10-20	Tue 20-10-20	19
21			**Naïve Bayes Sentiment Model Development**	**40 days**	**Wed 21-10-20**	**Tue 15-12-20**	**18**
22			Naïve Bayes Sentiment Classifier Implementation	20 days	Wed 21-10-20	Tue 17-11-20	20
23			Fine-grained Sentiment Classification	6 days	Wed 18-11-20	Wed 25-11-20	22
24			Peperation of Final Data	8 days	Thu 26-11-20	Mon 07-12-20	23
25			Confusion Matrix & Classification Report	6 days	Tue 08-12-20	Tue 15-12-20	24
26			**Global Sentiment Trend Analysis**	**30 days**	**Wed 16-12-20**	**Tue 26-01-21**	**21**
27			Overall Average Sentiment Trend	10 days	Wed 16-12-20	Tue 29-12-20	25
28			Average Sentiment Trend Shift Detection	15 days	Wed 30-12-20	Tue 19-01-21	27
29			Visualization	5 days	Wed 20-01-21	Tue 26-01-21	28
30			**Hybrid Convolutional LSTM Model Development**	**50 days**	**Wed 27-01-21**	**Tue 06-04-21**	**26**
31			Model Creation & Data Fitting	35 days	Wed 27-01-21	Tue 16-03-21	28
32			Sentiment Prediction, Error Analysis & Visualization	15 days	Wed 17-03-21	Tue 06-04-21	31
33			**Comparative Performance Analysis**	**20 days**	**Wed 07-04-21**	**Tue 04-05-21**	**30**
34			Previous Works on Covid-19 Data	5 days	Wed 07-04-21	Tue 13-04-21	32
35			IMDB Movie Review Dataset	5 days	Wed 14-04-21	Tue 20-04-21	34
36			SST Review Dataset	5 days	Wed 21-04-21	Tue 27-04-21	35
37			Amazon Customer Review Dataset	5 days	Wed 28-04-21	Tue 04-05-21	36
38			**Discussion**	**5 days**	**Wed 05-05-21**	**Tue 11-05-21**	**33**
39			Final Result & Conclusion	3 days	Wed 05-05-21	Fri 07-05-21	37
40			Future Scope	2 days	Sat 08-05-21	Tue 11-05-21	39

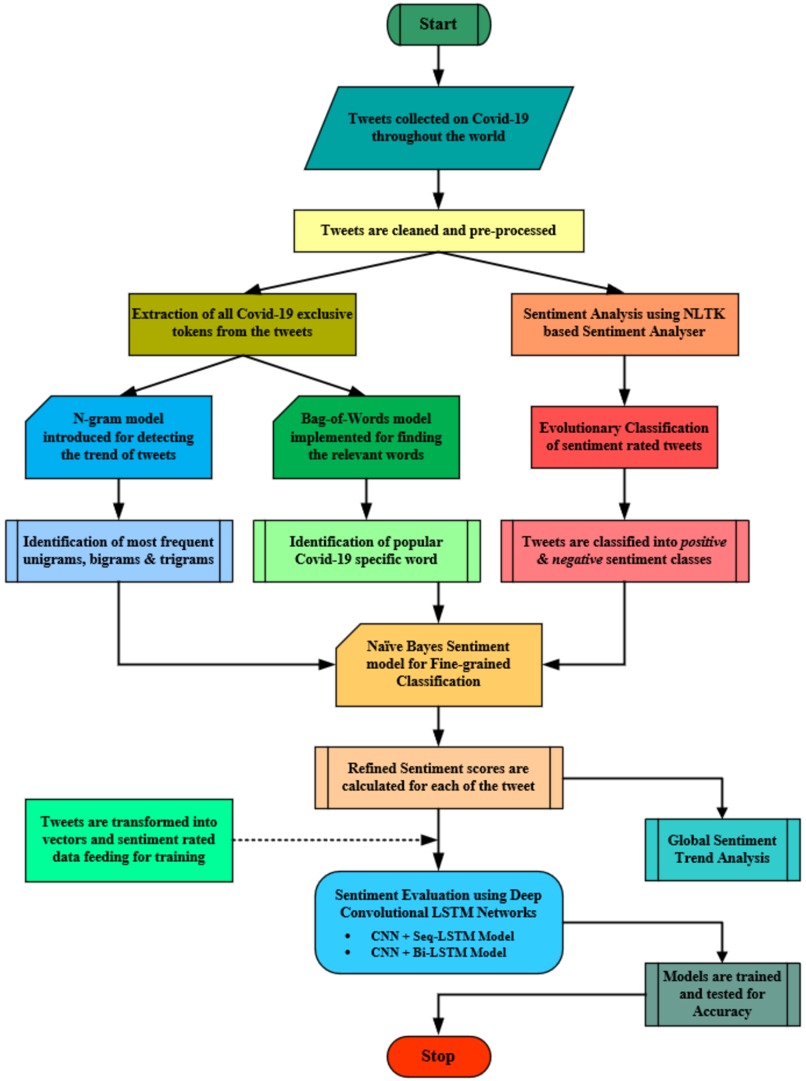
Design Methodology

- **Gantt Chart**



Design Methodology

- **Proposed Methodology**



Developing Covid-19 Dataset

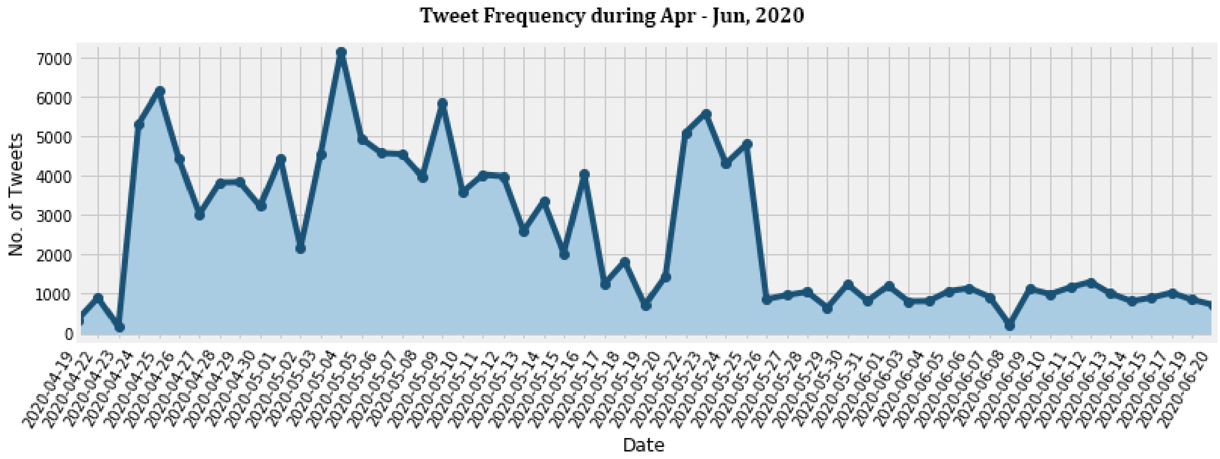
- In 2020, out of 320 million active Twitter users from all over the world, India has 18.9 million active Twitter users, i.e. currently the third highest in the world [4].
- Twitter API mostly allows the users to live stream only 1-2% of the total tweets on a particular keyword [3].
- However, we have collected 2,35,240 tweets for first phase dataset and 3,20,316 tweets for second phase dataset containing the hash-tagged keywords like – ***#covid-19***, ***#coronavirus***, ***#covid***, ***#covaccine***, ***#lockdown***, ***#homequarantine***, ***#quarantinecenter***, ***#socialdistancing***, ***#stayhome***, ***#staysafe*** etc.

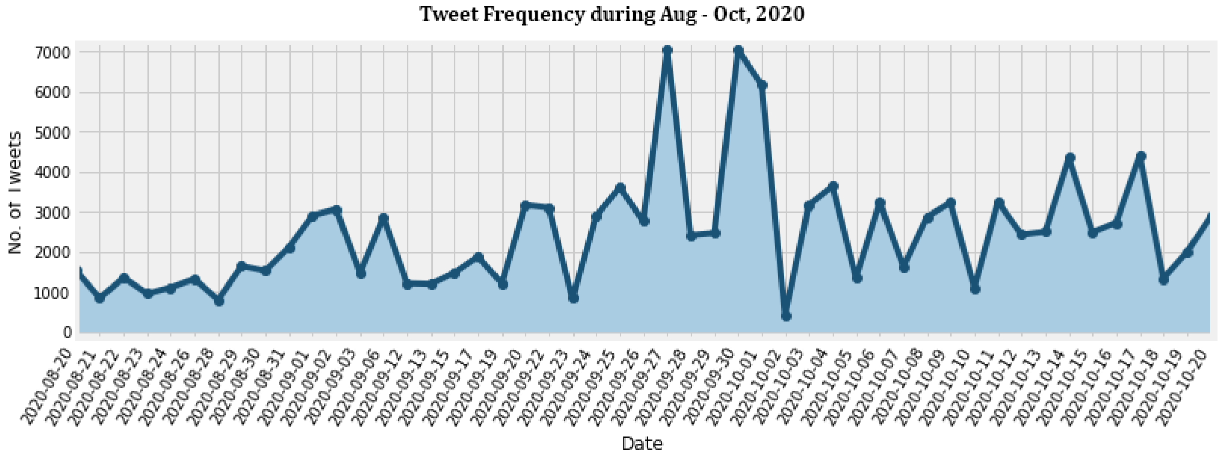
id	created_at	source	original_text	lang	favorite_count	retweet_count	original_author	hashtags	user_mentions	place
12519347672113	Sun Apr 19	<a href="http:	RT @Ash_The	en	0	705	EmpoweringGo	Jehanaba	Ash_TheLoneW	Panjim Goa India
12519347333171	Sun Apr 19	<a href="http:	RT @NGvisior	en	0	2646	Ibilola_Amao	lockdown	NGvision2020	London, England
12519346661830	Sun Apr 19	<a href="http:	RT @Barnes_	en	0	5593	cliff_skidmore		Barnes_Law	Texas, USA
12519346075592	Sun Apr 19	<a href="http:	RT @Joelpatri	en	0	108	GMA4Trump_	Covid_19	Joelpatrick1776	Choctaw, OK
12519345822927	Sun Apr 19	<a href="http:	RT @GlblCtzn	en	0	4	Macgirl730	Together	GlblCtzn	Menomonee Falls, WI

- [4] www.statista.com

Data Pre-Processing

- Initially, we removed all duplicate tweets from the datasets and found 1,43,903 and 1,20,509 tweets from first phase and second phase Covid-19 datasets.





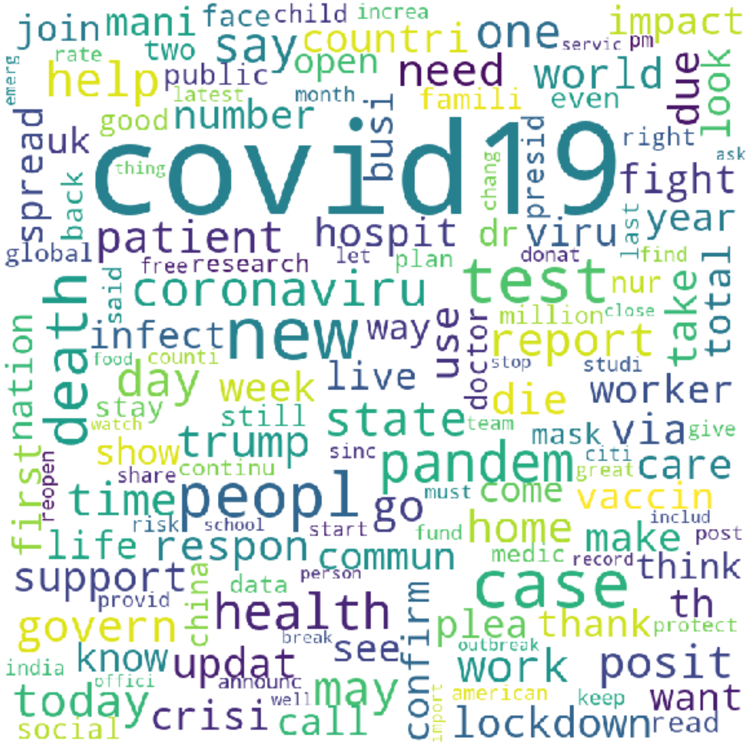
Data Pre-Processing

- The pre-processing function follows the following steps to clean raw tweets-
  1. *Convert the whole tweet into lower case.*
  2. *Remove all URLs from the tweet.*
  3. *Remove all punctuations from the tweet.*
  4. *Remove all stop words from the tweet.*
  5. *Tokenize the tweet to split each of the sentence into smaller parts of word.*
  6. *Stemming used to reduce inflected words to their word stem.*

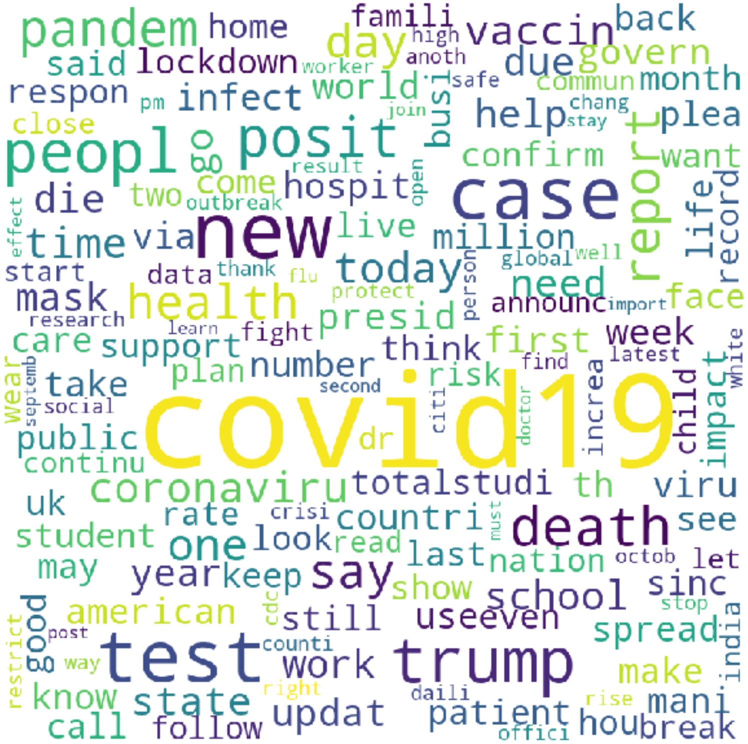
Covid-19 Specified Word Identification

- The **Bag-of-Words** (BOW) model used to identify frequently occurred grams from the word lexicon.
- Finally, we obtained a list of most frequent Covid-19 exclusive words.

Popular words found in Tweets during Apr - Jun, 2020

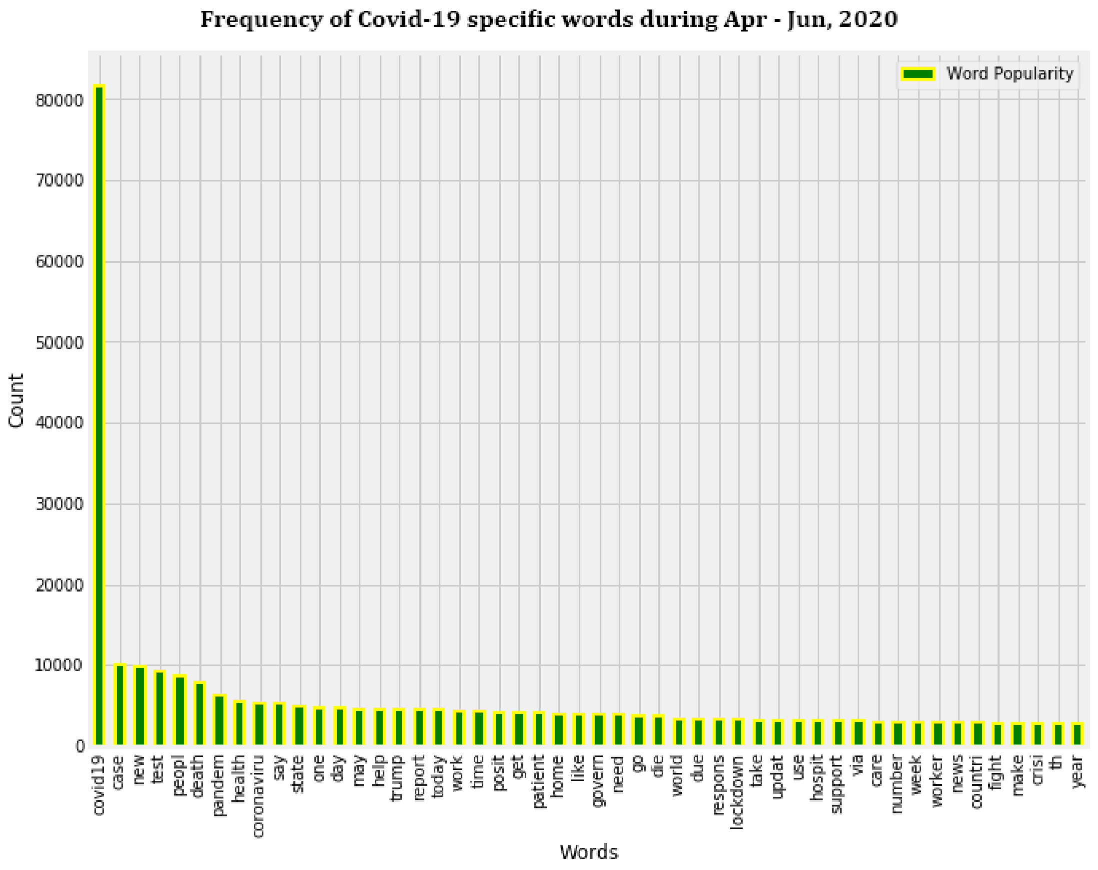


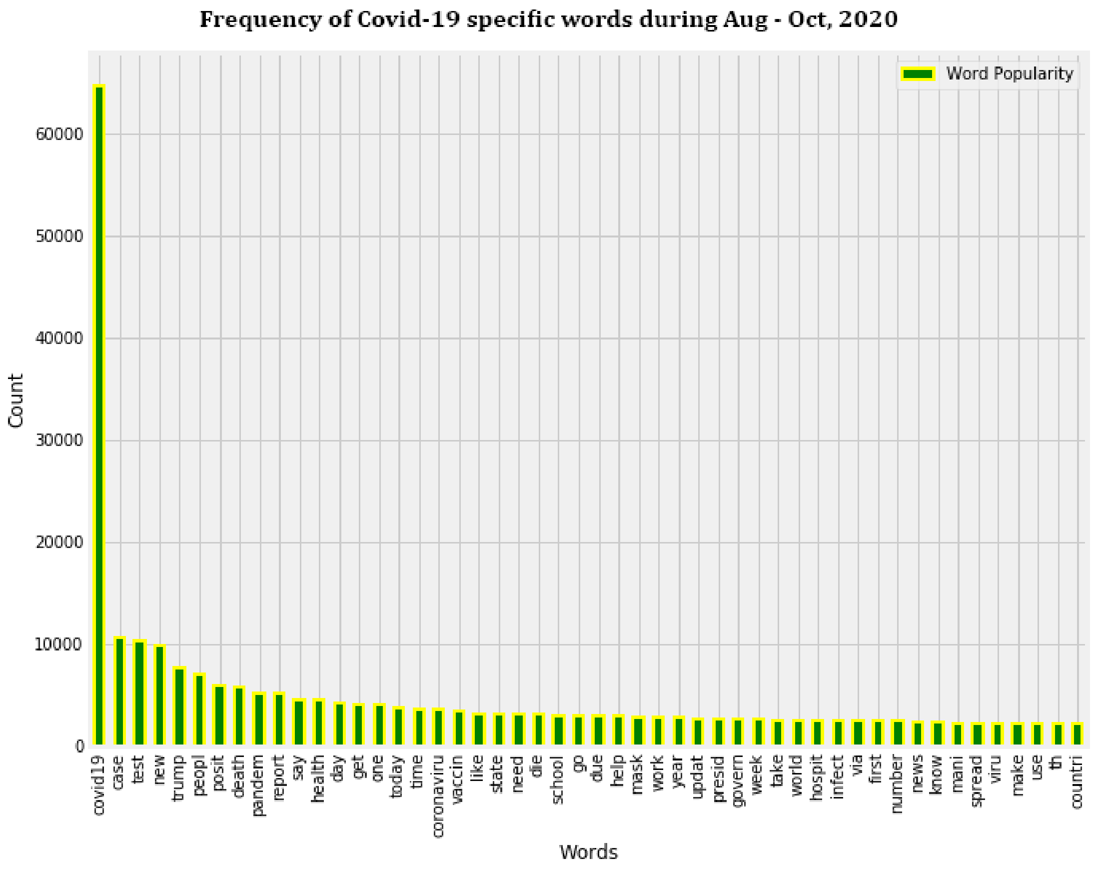
Popular words found in Tweets during Aug - Oct, 2020



Covid-19 Specified Word Popularity

- From the obtained list of most popular Covid-19 exclusive words we have found the frequency for the recurrence of each words.





Covid-19 Specified Word Popularity

- Probability of repetition for each word on the basis of total 13,79,835 and 11,33,188 words from both of the generated corpora.

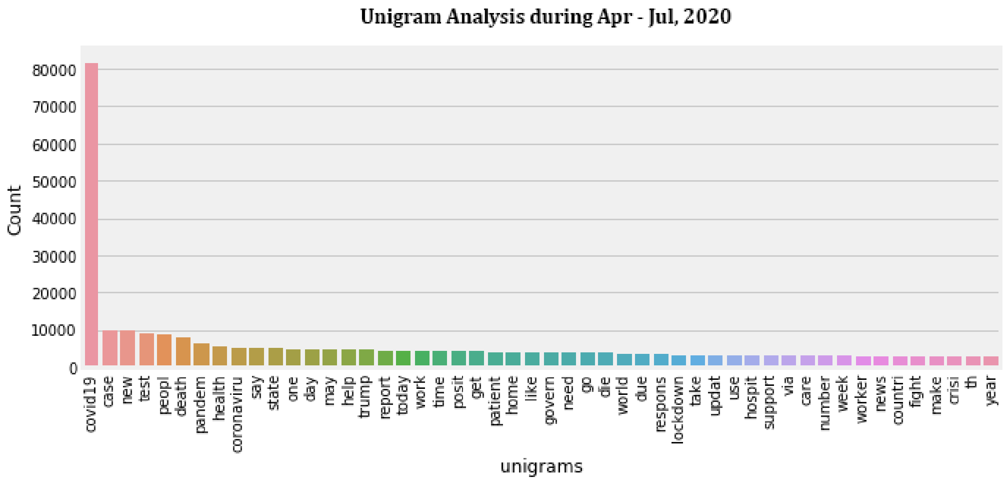
$$P(W_i) = \frac{count(W_i)}{\sum_{i=0}^{n} count(W_{i=0}^{n})} \quad (1)$$

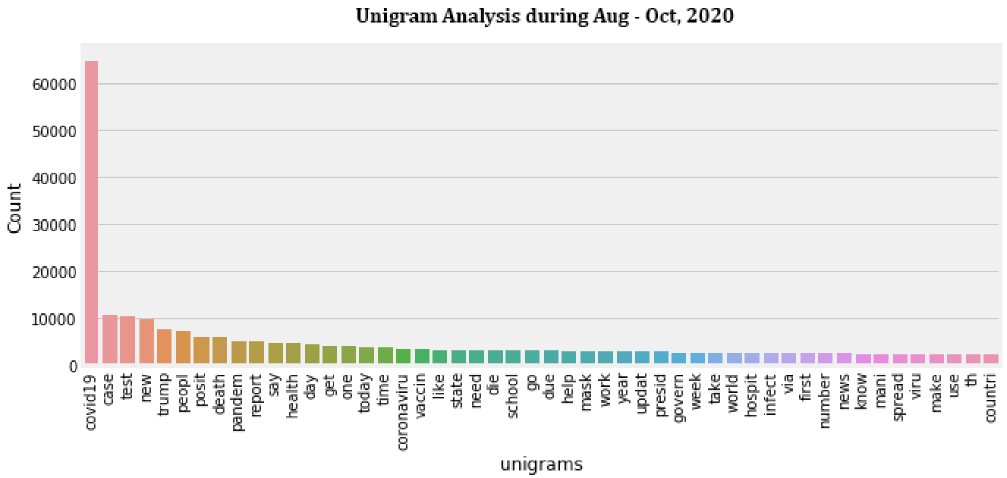
- We represented the popularity and probability of recurrence for top five most frequent Covid-19 related words.

	Covid-19 Dataset I (Apr – Jun, 2020)				Covid-19 Dataset II (Aug – Oct, 2020)		
	Words	**Popularity**	**Probability**		**Words**	**Popularity**	**Probability**
1	covid19	81696	0.059207	**1**	covid19	64672	0.057071
2	case	10001	0.007248	**2**	case	10656	0.009404
3	new	9875	0.007157	**3**	test	10323	0.009110
4	test	9204	0.006670	**4**	new	9797	0.008646
5	peopl	8624	0.006250	**5**	trump	7605	0.006711

Word Popularity Detection using N-gram

- **lexical n-gram model** used for Identification of the most popular unigrams, bigrams and trigrams within our corpus.
- **Unigram Analysis**

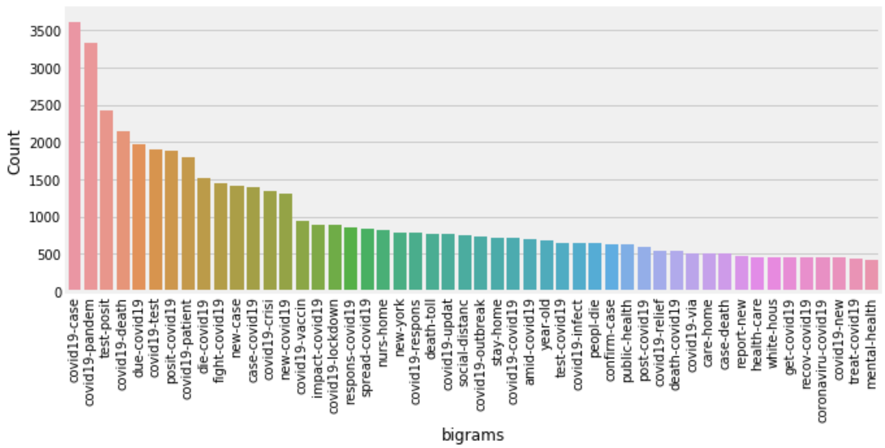




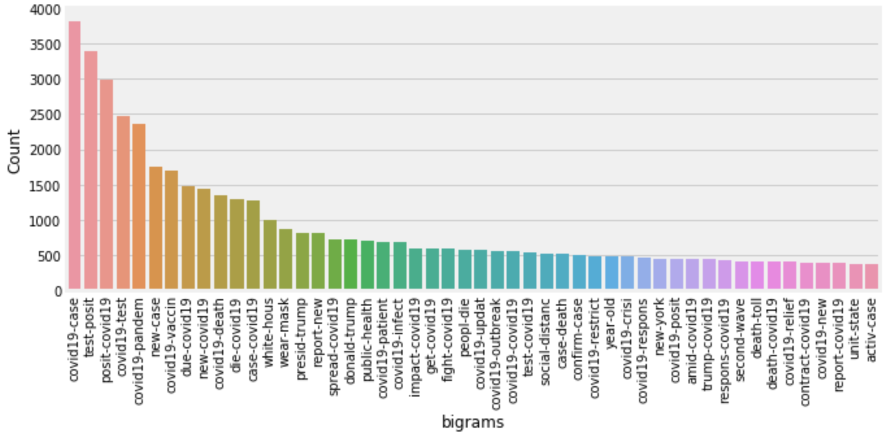
Word Popularity Detection using N-gram

- **Bigram Analysis**

Bigram Analysis during Apr - Jul, 2020



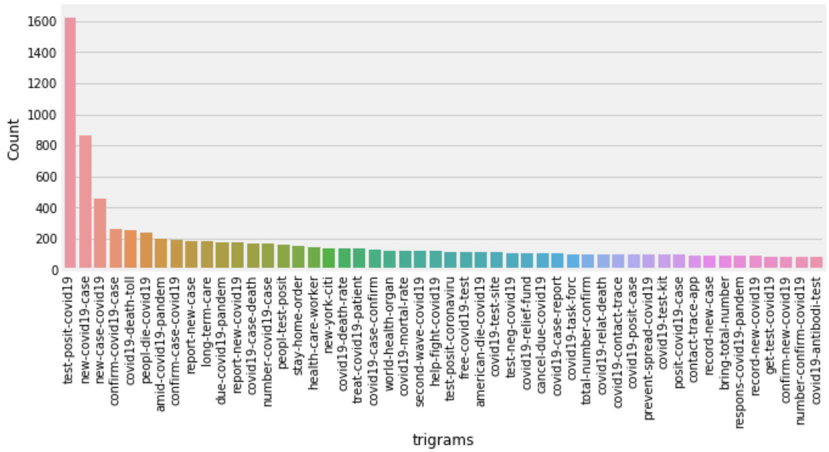
Bigram Analysis during Aug - Oct, 2020



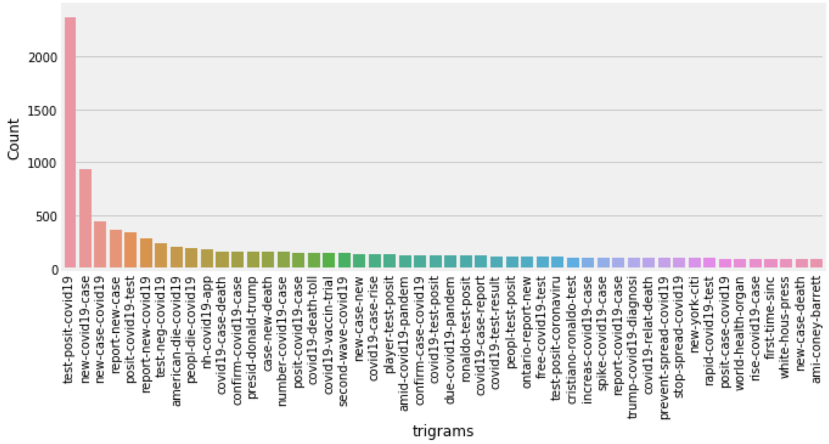
Word Popularity Detection using N-gram

- **Trigram Analysis**

Trigram Analysis during Apr - Jul, 2020



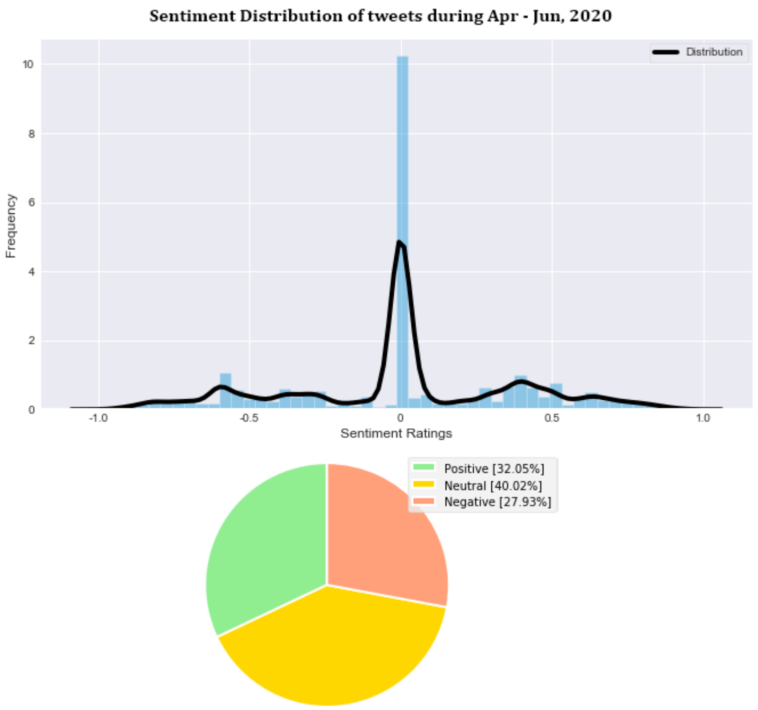
Trigram Analysis during Aug - Oct, 2020

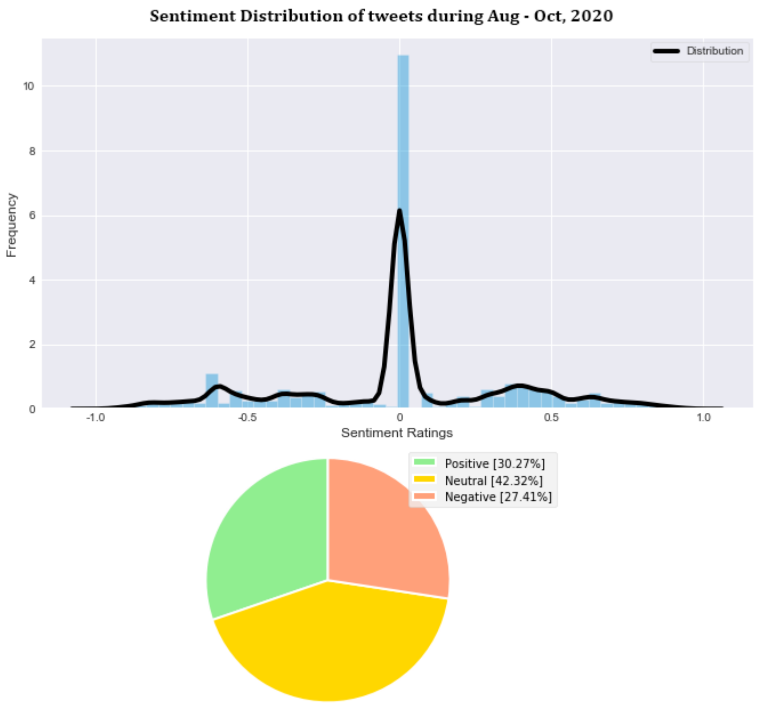


- According to the n-gram model, the popularity of trigrams is lesser than that of bigrams and the unigrams popularity is the highest.

NLTK-Based Sentiment Analysis & Classification

- Evaluation of Sentiment polarity for each preprocessed tweets.
- Classification of tweets into ***positive***, ***negative*** and ***neutral*** classes based on their sentiment score.
- Sentiment distribution of three class polarity along with the percentage of Covid-19 tweets occurred from each class.





Naïve Bayes Sentiment Analysis

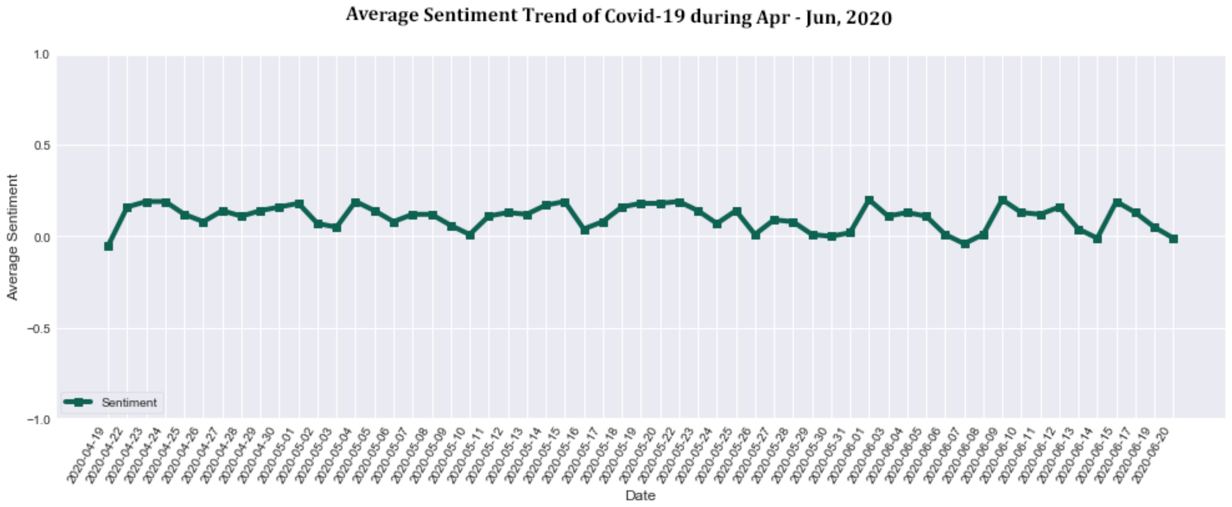
- Evaluation of refined Sentiment ratings for each classified tweets on the basis of extracted features.
- Classification of tweets into ***most positive (1.0)***, ***positive (0.5)***, ***neutral (0.0)***, ***negative (-0.5)*** and ***most negative (-1.0)*** classes based on their sentiment score.

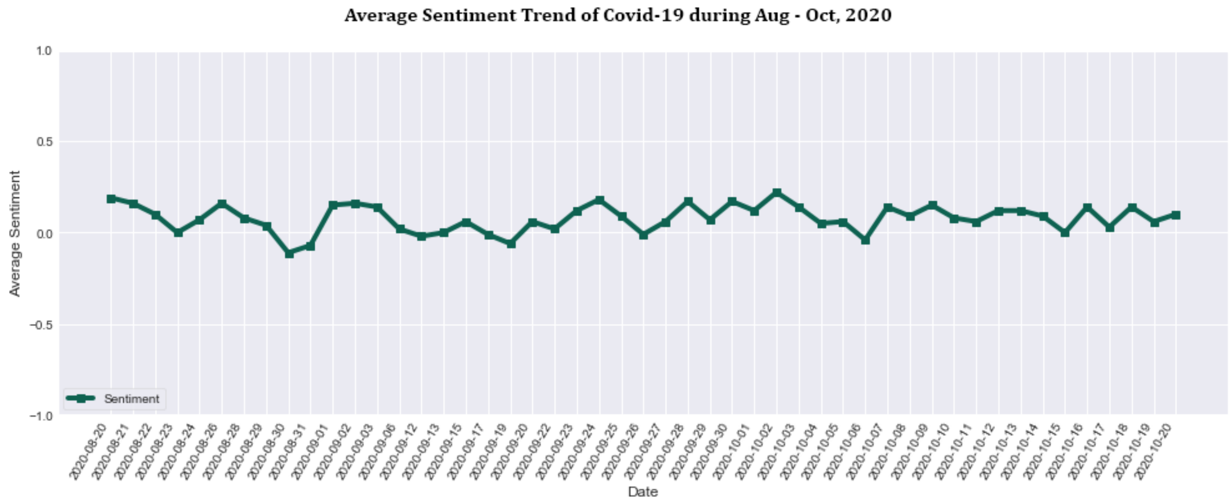
Algorithm Fine-Grained Sentiment Classification (sentiment, refined_sentiment):

```
for each i in range (0, len(tweet.index)):
  if tweet_i[sentiment] >= 0.0 and tweet_i[sentiment] < 0.25:
    tweet_i[refined_sentiment] ← -1.0      # assigned -1.0 for Most Negative Tweets
  elif tweet_i[sentiment] >= 0.25 and tweet_i[sentiment] < 0.5:
    tweet_i[refined_sentiment] ← -0.5      # assigned -0.5 for Negative Tweets
  elif tweet_i[sentiment] == 0.5:
    tweet_i[refined_sentiment] ← 0.0       # assigned 0.0 for Neutral Tweets
  elif tweet_i[sentiment] > 0.5 and tweet_i[sentiment] <= 0.75:
    tweet_i[refined_sentiment] ← 0.5       # assigned 0.5 for Positive Tweets
  else:
    tweet_i[refined_sentiment] ← 1.0       # assigned 1.0 for Most Positive Tweets
end
```

Global Sentiment Trend Analysis

- Overall Average Sentiment Trend throughout the world.





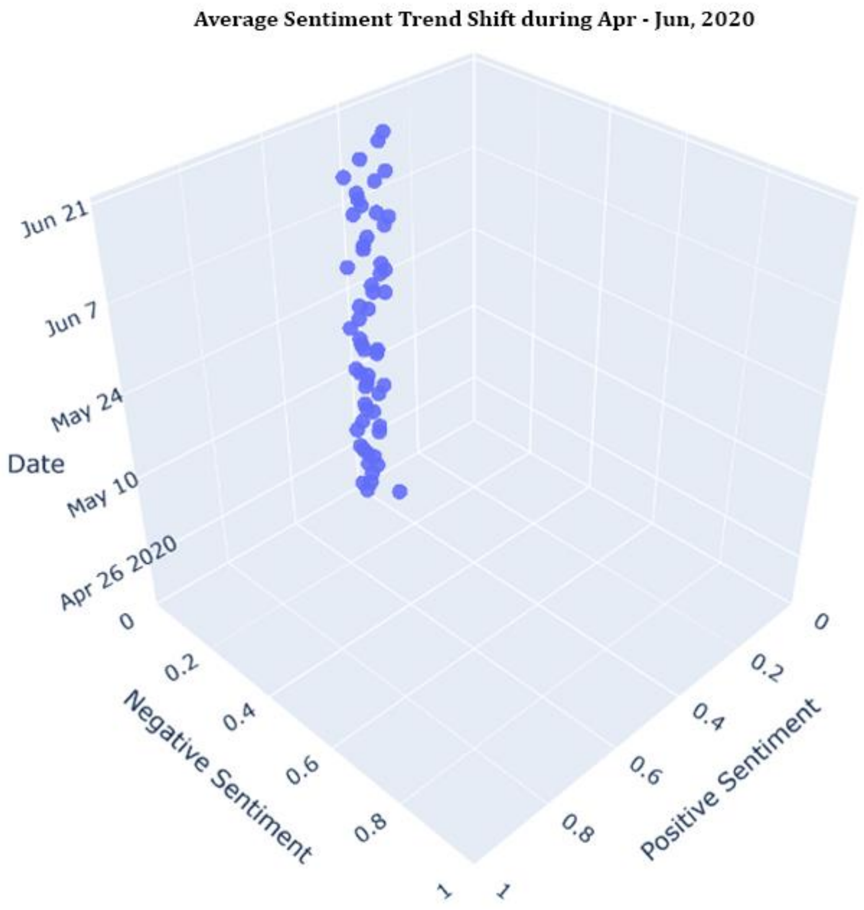
Global Sentiment Trend Analysis

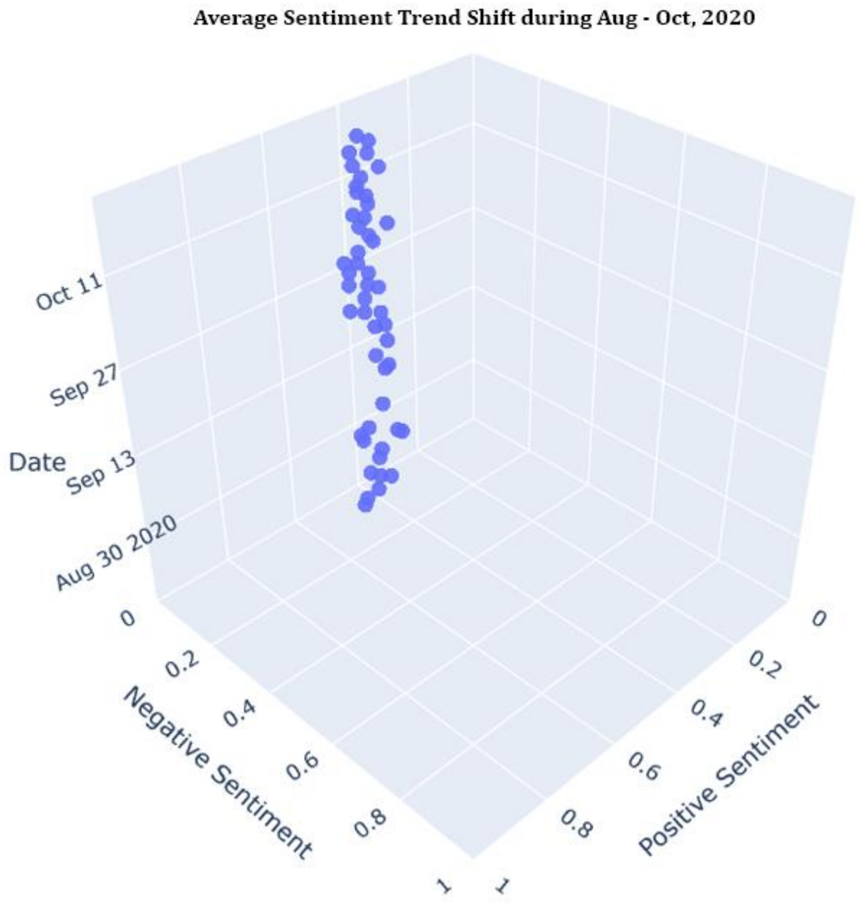
- Some Covid-19 tweets from different sentiment classes.

Date	Original Tweet	Naïve Bayes Sentiment Rating	Refined Sentiment Rating	Sentiment Class
05-05-2020	**Barbara Walton #FBPE @LesTroisChenes** More Than 60 Doctors in Italy Have Died in COVID-19 Pandemic. Why? Lack of PPE and information. UK just a fraction behind them - far ahead of other countries. We threw our health worker under the #COVID bus and then clapped for them.	0.24	-1	Most Negative
27-04-2020	**Elizabeth Stein @lizstein** A tale of two cities. “More than fifteen thousand people in New York are believed to have died from covid-19. Last week in Washington State, the estimate was fewer than seven hundred people.”	0.26	-0.5	Negative
10-05-2020	**Volker Stollorz @Stollovo** “Anyway, I remain a born optimist. And now that I have faced death, my tolerance levels for nonsense and bullshit have gone down even more than before. So, I continue calmly and enthusiastically, although more selectively than before my illness” #COVID19	0.50	0.0	Neutral
26-04-2020	**Muh’d @smj_esq** People are recovering from COVID-19 and it’s a good development. I think Government should tell the public the drugs administered on the recovered patients. Just my own thoughts though!	0.73	0.5	Positive
07-05-2020	**CNN Philippines @cnnphilippines** There are now more than 400 health personnel who have recovered from the coronavirus disease, the Department of Health says.	0.10	1.0	Most Positive

Global Sentiment Trend Analysis

- Worldwide Average Sentiment Trend Shift Detection.



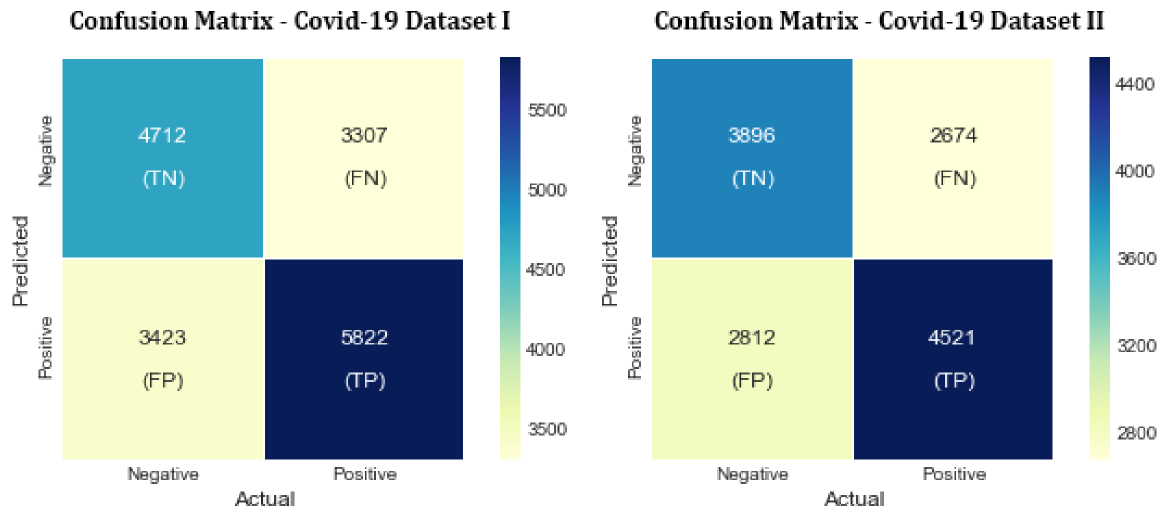


Classification Report & Confusion Matrix

- **Classification Report**

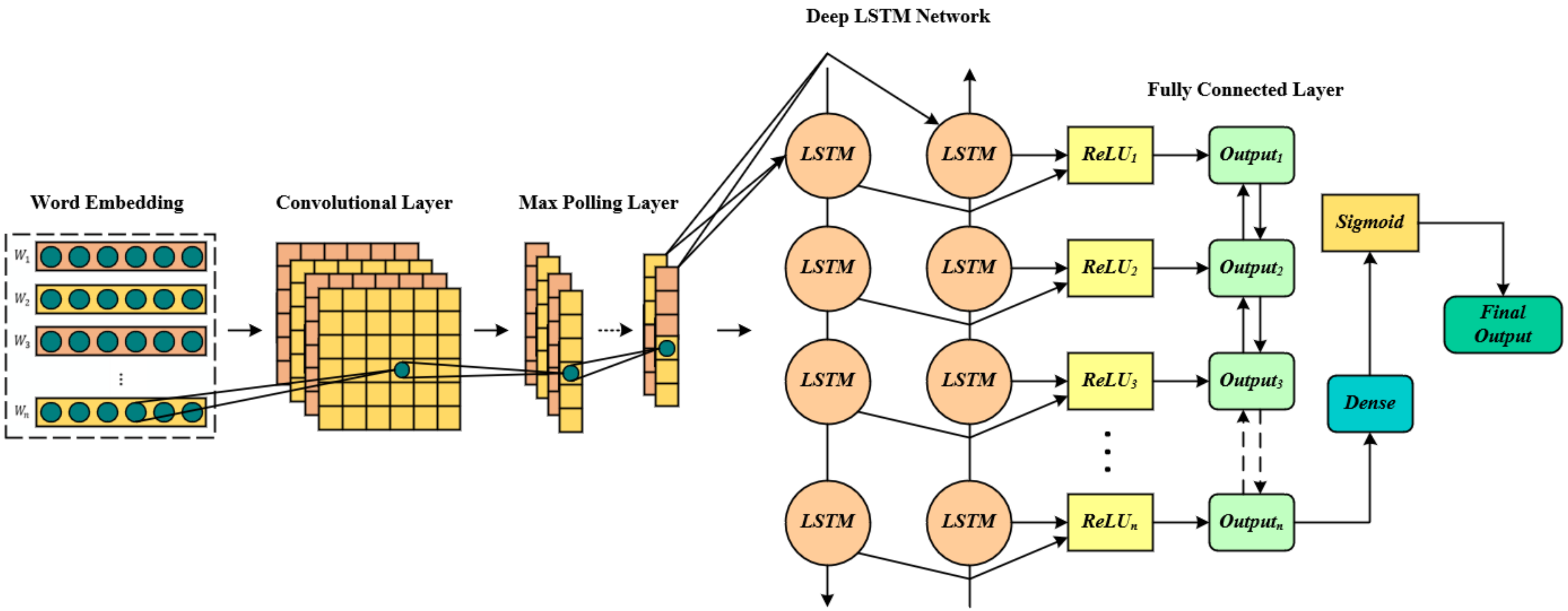
		Precision	Recall	F1-Score	Support
Covid-19 Dataset I (Apr – Jun, 2020)	*Positive (1.0)*	0.64	0.63	0.63	9245
	Negative (0.0)	0.58	0.59	0.58	8019
	Avg. / Total	**0.61**	**0.61**	**0.61**	**17264**
Covid-19 Dataset II (Aug – Oct, 2020)	*Positive (1.0)*	0.63	0.62	0.62	7333
	Negative (0.0)	0.58	0.59	0.59	6570
	Avg. / Total	**0.61**	**0.61**	**0.61**	**13903**

- **Confusion Matrix**



Sentiment Modelling using Hybrid Convolutional LSTM

- Proposed System Architecture of **Hybrid Convolutional LSTM model** for sentiment prediction of Covid-19 tweets.



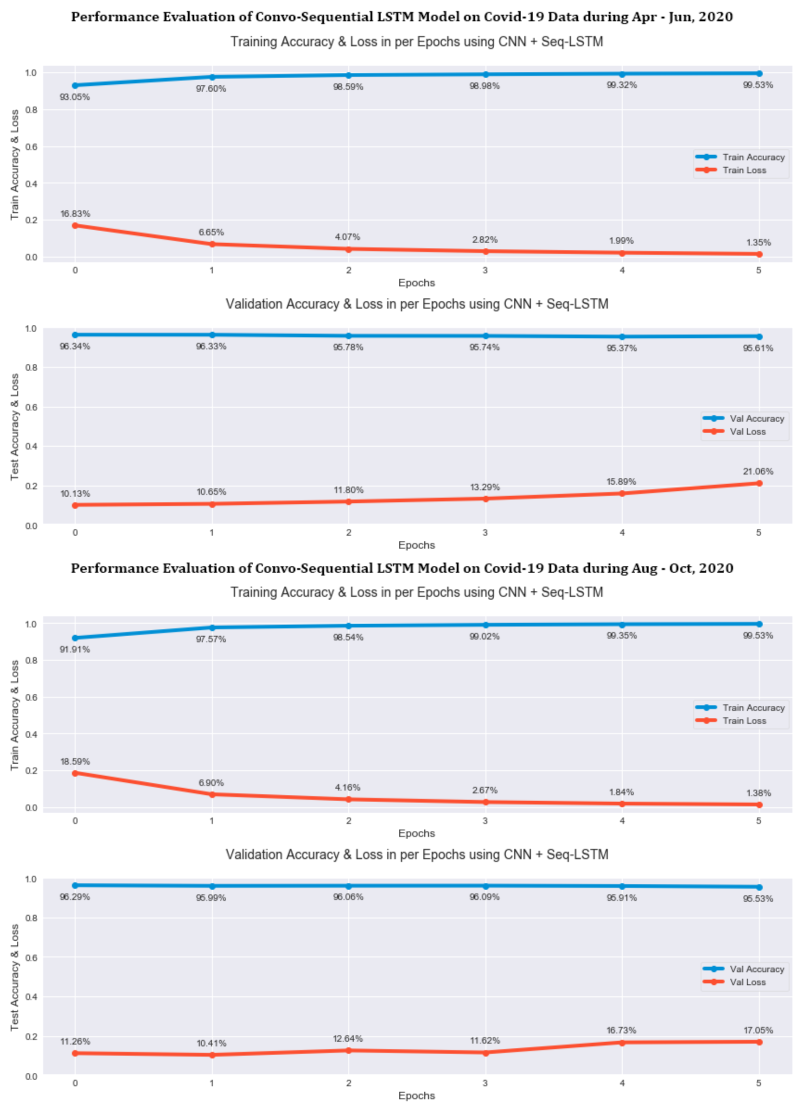
Sentiment Modelling using Hybrid Convolutional LSTM

- The new dataset contains all preprocessed tweets along with their corresponding ***positive*** (1.0) and ***negative*** (0.0) sentiments.
- We split the dataset into **80:20** ratio. i.e., **80%** for **training** and **20%** for **validation** purposes respectively.
- Word vectors are calculated for each Covid-19 exclusive words.
- ***TensorFlow*** framework and ***keras*** library are used to add ***Sequential*** and ***Bidirectional LSTM*** models with ***Embedding***, ***Convolutional***, ***Max Pooling*** and ***Dense*** layers.
- The **Convo-Sequential LSTM** and **Convo-Bidirectional LSTM** models trained for **6 epochs** on certain parameters**.**
- We have finally achieved **95.61%** and **95.81%** of **validation accuracy** for **first phase dataset** whereas on the **second phase dataset** these models obtained the validation accuracy as **95.53%** and **95.75%** respectively.

Sentiment Modelling using Hybrid CNN + Seq-LSTM

- Training accuracy vs. loss, validation accuracy vs. loss using **CNN + Seq-LSTM** network.

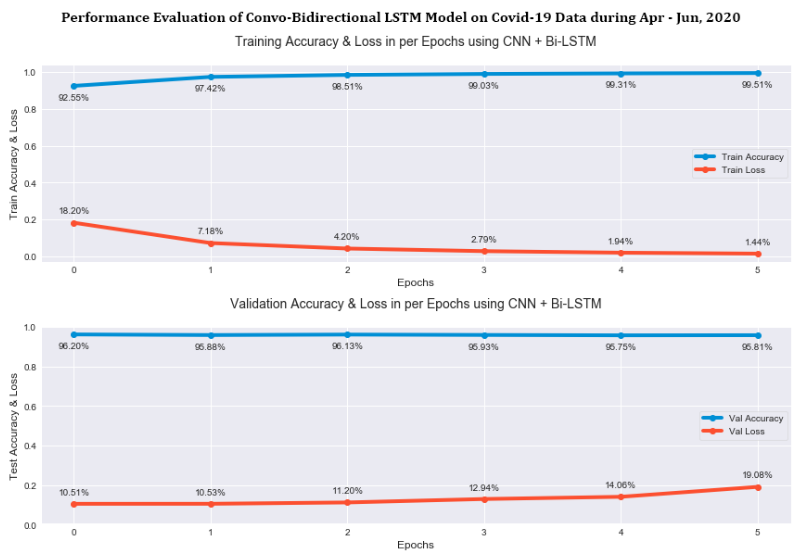
	Epochs	Train Loss	Train Accuracy	Val Loss	Val Accuracy
Covid-19 Dataset I (Apr – Jun, 2020)	*Initially*	16.83%	93.05%	10.13%	96.34%
	2nd	06.65%	97.60%	10.65%	96.33%
	3rd	04.07%	98.59%	11.80%	95.78%
	4th	02.82%	98.98%	13.29%	95.74%
	5th	01.99%	99.32%	15.89%	95.37%
	6th	01.35%	**99.53%**	21.06%	**95.61%**
Covid-19 Dataset II (Aug – Oct, 2020)	*Initially*	18.59%	91.91%	11.26%	96.29%
	2nd	06.90%	97.57%	10.41%	95.99%
	3rd	04.16%	98.54%	12.64%	96.06%
	4th	02.67%	99.02%	11.62%	96.09%
	5th	01.84%	99.35%	16.73%	95.91%
	6th	01.38%	**99.53%**	17.05%	**95.53%**

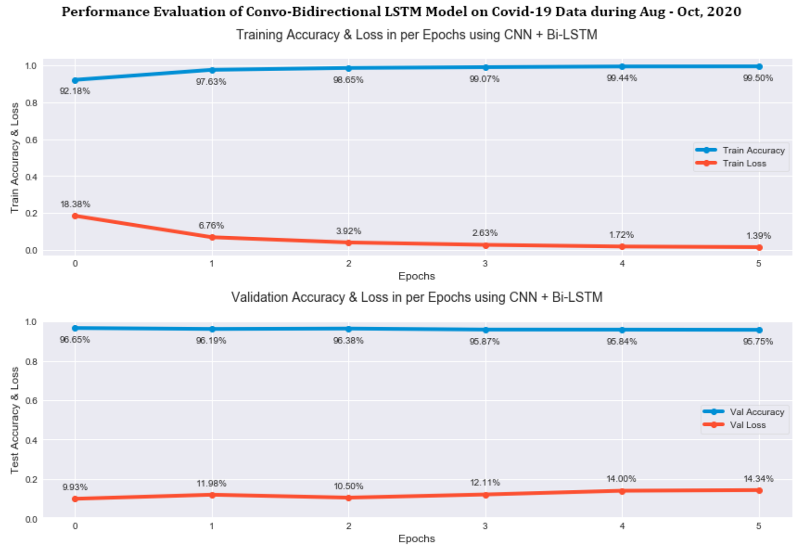


Sentiment Modelling using Hybrid CNN + Bi-LSTM

- Training accuracy vs. loss, validation accuracy vs. loss using **CNN + Bi-LSTM** network.

	Epochs	Train Loss	Train Accuracy	Val Loss	Val Accuracy
Covid-19 Dataset I (Apr – Jun, 2020)	*Initially*	18.20%	92.55%	10.51%	96.20%
	2nd	07.18%	97.42%	10.53%	95.88%
	3rd	04.20%	98.51%	11.20%	96.13%
	4th	02.79%	99.03%	12.94%	95.93%
	5th	01.94%	99.31%	14.06%	95.75%
	6th	01.44%	**99.51%**	19.08%	**95.81%**
Covid-19 Dataset II (Aug – Oct, 2020)	*Initially*	18.38%	92.18%	09.93%	96.65%
	2nd	06.76%	97.63%	11.98%	96.19%
	3rd	03.92%	98.65%	10.50%	96.38%
	4th	02.63%	99.07%	12.11%	95.87%
	5th	01.72%	99.44%	14.00%	95.84%
	6th	01.39%	**99.50%**	14.34%	**95.75%**





Comparative Performance Analysis I

- Benchmark Comparison of NLP based Experiments on **Covid-19**.

Machine Learning or Deep Neural Network Models	Prediction Accuracy
CNN + Bi-LSTM w. Naïve Bayes Sentiment Model	**95.81%**
Multilingual BERT on single-level classification [19]	95.62%
CNN + Seq-LSTM w. Naïve Bayes Sentiment Model	**95.61%**
CNN w. *GloVe* Embeddings [13]	90.67%
Bayesian Regression w. Tf-Idf [17]	89.40%
ERNIE on Chinese Weibo message [18]	88.00%
Bert on Chinese Weibo message [18]	83.00%
Random Forest [17]	82.20%
LDA + Deep LSTM [14]	81.15%
Logistic Regression w. trigrams + Tf-Idf [15]	81.00%
SVM w. Gaussian Membership based Fuzzy logic [15]	79.00%
LSTM on Chinese Weibo message [18]	78.00%
Deep RNN Model [16]	76.71%

Comparative Performance Analysis II

- Comparative Analysis of State-of-Art Experiments on **IMDB Dataset**.

Machine Learning or Deep Neural Network Models	Prediction Accuracy
CNN + Bi-LSTM w. Naïve Bayes Sentiment Model	**90.44%**
CNN + Seq-LSTM w. Naïve Bayes Sentiment Model	**90.26%**
Ensemble LSTM + CNN [25]	90.00%
CNN + LSTM w. Combined Kernels [21]	89.50%
CNN [25]	89.30%
CNN - LSTM [23]	89.20%
LSTM [25]	89.00%
CNN + LSTM w. Vanilla or Multiword Pre-processing [24]	88.90%
CNN w. Multiword Pre-processing [24]	87.90%
CNN [23]	87.70%
MLP [23]	86.74%
Vanilla Neural Network [22]	86.67%
LSTM [23]	86.64%
LSTM w. Tuning and Dropout [26]	86.50%
SA-LSTM w. Joint Training [26]	85.30%
Recursive RNN [20]	83.88%

Comparative Performance Analysis III

- Comparisons with Benchmark Experiments on **Other Public Corpora**.

Public open-source corpora	Previous Benchmark results	Our results	
		CNN + Seq-LSTM	CNN + Bi-LSTM
Amazon customer review dataset	90.00% [27]	99.91%	99.92%
Stanford Sentiment Treebank (SST) dataset	86.99% [28]	90.07%	90.25%

Recent Achievement

- Regarding the progress of this research work so far I like to inform you that my paper has been accepted in the **First International Conference on Research and Applications in Artificial Intelligence (RAAI 2020)** organized by *Dept. of Information Technology, RCC Institute of Information Technology, A Unit of an Autonomous Society of Department of Higher Education. Govt. of West Bengal, India.*
- The paper is entitled as : **Chakraborty, A.K.**, Das, S. and Kolya, A.K., 2021. Sentiment Analysis of Covid-19 Tweets Using Evolutionary Classification-Based LSTM Model. In *Proceedings of Research and Applications in Artificial Intelligence* (pp. 75-86). Springer, Singapore. https://doi.org/10.1007/978-981-16-1543-6_7
- This paper has received **Best Paper Award** for the respective track in the **International Conference on Research and Applications in Artificial Intelligence (RAAI 2020).**

Conclusion and Future Scope

- For the future work, we will extract the tweets from the datasets for which the Convo-Bidirectional LSTM model performs better than Convo-Sequential LSTM model.

- Further we will use fine-grained classified tweets to train the hybrid deep learning models to ensure the versatility of my proposed system.

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References

1. Tuli, S., Tuli, S., Tuli, R. and Gill, S.S., 2020. Predicting the Growth and Trend of COVID-19 Pandemic using Machine Learning and Cloud Computing. *Internet of Things*, p.100222.

2. Dubey, A.D., 2020. Twitter Sentiment Analysis during COVID19 Outbreak. *Available at SSRN 3572023*.

3. Das, S., Das, D. and Kolya, A.K., 2020. Sentiment classification with GST tweet data on LSTM based on polarity-popularity model. *Sadhana*, *45*(1).

5. Arora, P., Kumar, H. and Panigrahi, B.K., 2020. Prediction and analysis of COVID-19 positive cases using deep learning models: A descriptive case study of India. *Chaos, Solitons & Fractals*, *139*, p.110017.

6. Arpaci, I., Alshehabi, S., Al-Emran, M., Khasawneh, M., Mahariq, I., Abdeljawad, T. and Hassanien, A.E., 2020. Analysis of Twitter Data Using Evolutionary Clustering during the COVID-19 Pandemic. *CMC-COMPUTERS MATERIALS & CONTINUA*, *65*(1), pp.193-203.

7. Jurafsky, D., 2000. *Speech & language processing*. Pearson Education India.

8. Baziotis, C., Pelekis, N. and Doulkeridis, C., 2017, August. Datastories at semeval-2017 task 4: Deep lstm with attention for message-level and topic-based sentiment analysis. In *Proceedings of the 11th international workshop on semantic evaluation (SemEval-2017)* (pp. 747-754).

9. Nakisa, B., Rastgoo, M.N., Rakotonirainy, A., Maire, F. and Chandran, V., 2018. Long short term memory hyperparameter optimization for a neural network based emotion recognition framework. *IEEE Access*, *6*, pp.49325-49338.

10. Wang, J.H., Liu, T.W., Luo, X. and Wang, L., 2018, October. An LSTM approach to short text sentiment classification with word embeddings. In *Proceedings of the 30th conference on computational linguistics and speech processing (ROCLING 2018)* (pp. 214-223).

11. Samuel, J., Ali, G.G., Rahman, M., Esawi, E. and Samuel, Y., 2020. Covid-19 public sentiment insights and machine learning for tweets classification. *Information*, *11*(6), p.314.

12. Jelodar, H., Wang, Y., Orji, R. and Huang, S., 2020. Deep sentiment classification and topic discovery on novel coronavirus or covid-19 online discussions: Nlp using lstm recurrent neural network approach. *IEEE Journal of Biomedical and Health Informatics*, *24*(10), pp.2733-2742.

13. Das, S., Kolya, A.K.: Predicting the pandemic: sentiment evaluation and predictive analysis from large-scale tweets on Covid-19 by deep convolutional neural network. *Evolutionary Intelligence*. 1–22 (2021).

References

14. Jelodar, H., Wang, Y., Orji, R. and Huang, S., 2020. Deep sentiment classification and topic discovery on novel coronavirus or covid-19 online discussions: Nlp using lstm recurrent neural network approach. *IEEE Journal of Biomedical and Health Informatics*, *24*(10), pp.2733-2742.

15. Chakraborty, K., Bhatia, S., Bhattacharyya, S., Platos, J., Bag, R. and Hassanien, A.E., 2020. Sentiment Analysis of COVID-19 tweets by Deep Learning Classifiers—A study to show how popularity is affecting accuracy in social media. *Applied Soft Computing*, *97*, p.106754.

16. Al-Shaher, M.A., 2020. A hybrid deep learning and NLP based system to predict the spread of Covid-19 and unexpected side effects on people. *Periodicals of Engineering and Natural Sciences (PEN)*, *8*(4), pp.2232-2241.

17. Serrano, J.C.M., Papakyriakopoulos, O. and Hegelich, S., 2020, July. NLP-based feature extraction for the detection of COVID-19 misinformation videos on Youtube. In *Proceedings of the 1st Workshop on NLP for COVID-19 at ACL 2020*.

18. Yang, Q., Alamro, H., Albaradei, S., Salhi, A., Lv, X., Ma, C., Alshehri, M., Jaber, I., Tifratene, F., Wang, W. and Gojobori, T., 2020. Senwave: Monitoring the global sentiments under the covid-19 pandemic. *arXiv preprint arXiv:2006.10842*.

19. Li, I., Li, Y., Li, T., Alvarez-Napagao, S., Garcia-Gasulla, D. and Suzumura, T., 2020, December. What Are We Depressed About When We Talk About COVID-19: Mental Health Analysis on Tweets Using Natural Language Processing. In *International Conference on Innovative Techniques and Applications of Artificial Intelligence* (pp. 358-370). Springer, Cham.

20. Timmaraju, A. and Khanna, V., 2015. Sentiment analysis on movie reviews using recursive and recurrent neural network architectures. *Semantic Scholar*, pp.1-5.

21. Yenter, A. and Verma, A., 2017, October. Deep CNN-LSTM with combined kernels from multiple branches for IMDb review sentiment analysis. In *2017 IEEE 8th Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)* (pp. 540-546). IEEE.

22. Shaukat, Z., Zulfiqar, A.A., Xiao, C., Azeem, M. and Mahmood, T., 2020. Sentiment analysis on IMDB using lexicon and neural networks. *SN Applied Sciences*, *2*(2), pp.1-10.

23. Ali, N.M., Abd El Hamid, M.M. and Youssif, A., 2019. Sentiment analysis for movies reviews dataset using deep learning models. *International Journal of Data Mining & Knowledge Management Process (IJDKP) Vol*, *9*.

24. Camacho-Collados, J. and Pilehvar, M.T., 2017. On the role of text preprocessing in neural network architectures: An evaluation study on text categorization and sentiment analysis. *arXiv preprint arXiv:1707.01780*.

References

25. Minaee, S., Azimi, E. and Abdolrashidi, A., 2019. Deep-sentiment: Sentiment analysis using ensemble of cnn and bi-lstm models. *arXiv preprint arXiv:1904.04206*.
26. Dai, A.M. and Le, Q.V., 2015. Semi-supervised sequence learning. *arXiv preprint arXiv:1511.01432*.
27. Guner, L., Coyne, E. and Smit, J., 2019. Sentiment analysis for Amazon. com reviews.
28. Dong, X.L. and De Melo, G., 2018, July. A helping hand: Transfer learning for deep sentiment analysis. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)* (pp. 2524-2534).