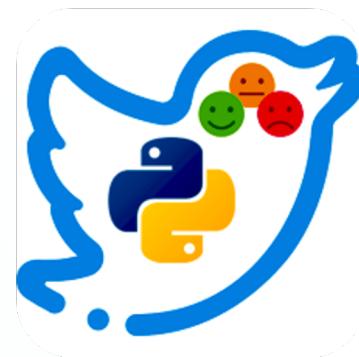




Sentiment Analysis on Large-Scale Covid-19 Tweets using Hybrid Convolutional LSTM Based on Naïve Bayes Sentiment Modelling



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

Presented By:

Arunava Kumar Chakraborty

Course – MTech (CSE); Year – 2nd; Semester – 4th; Roll No. – MCS2019/001

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RCC Institute of Information Technology

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 Arpacı, 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 classifier 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.

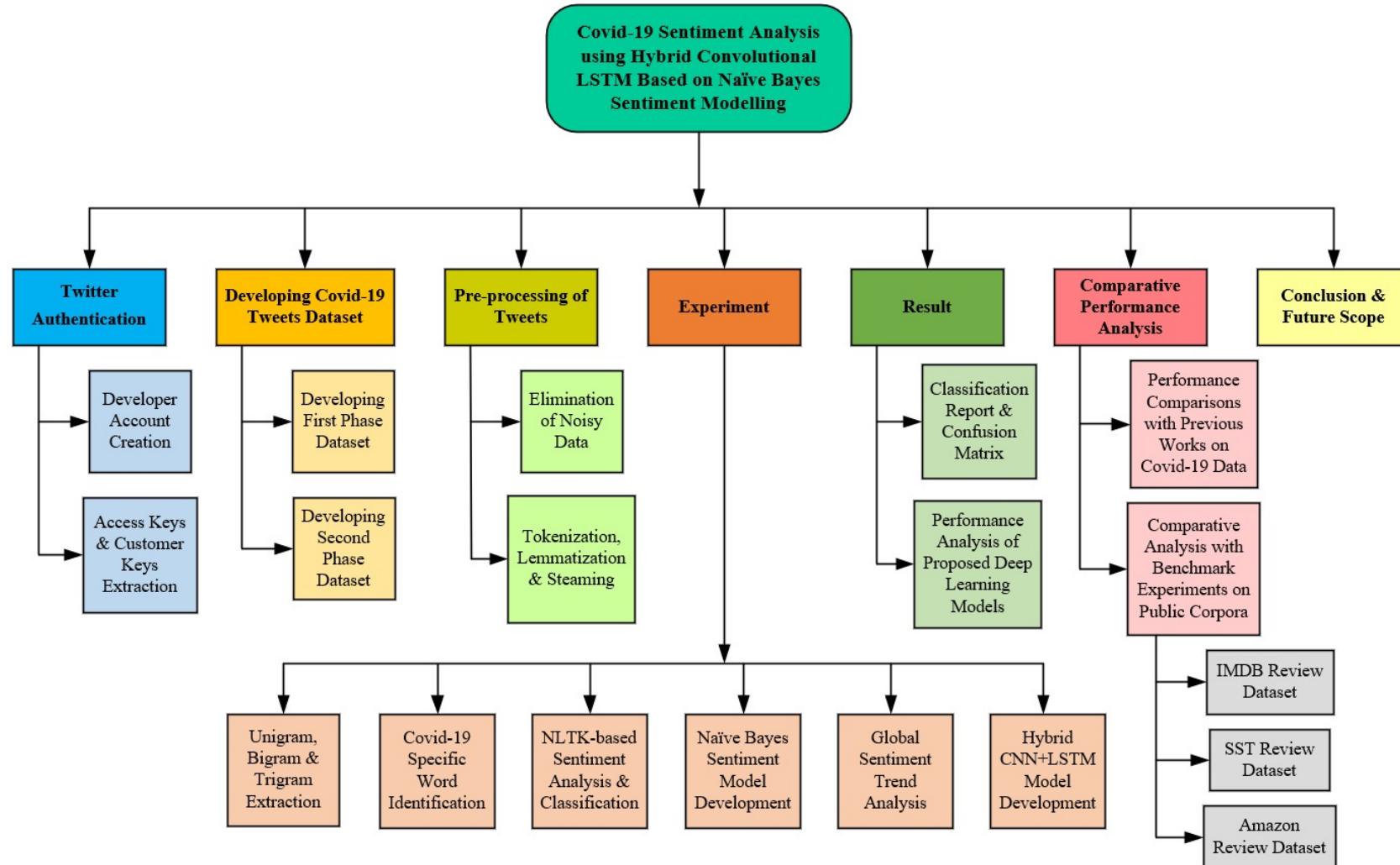
Contribution

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

Design Methodology



- Work Breakdown Structure



Design Methodology



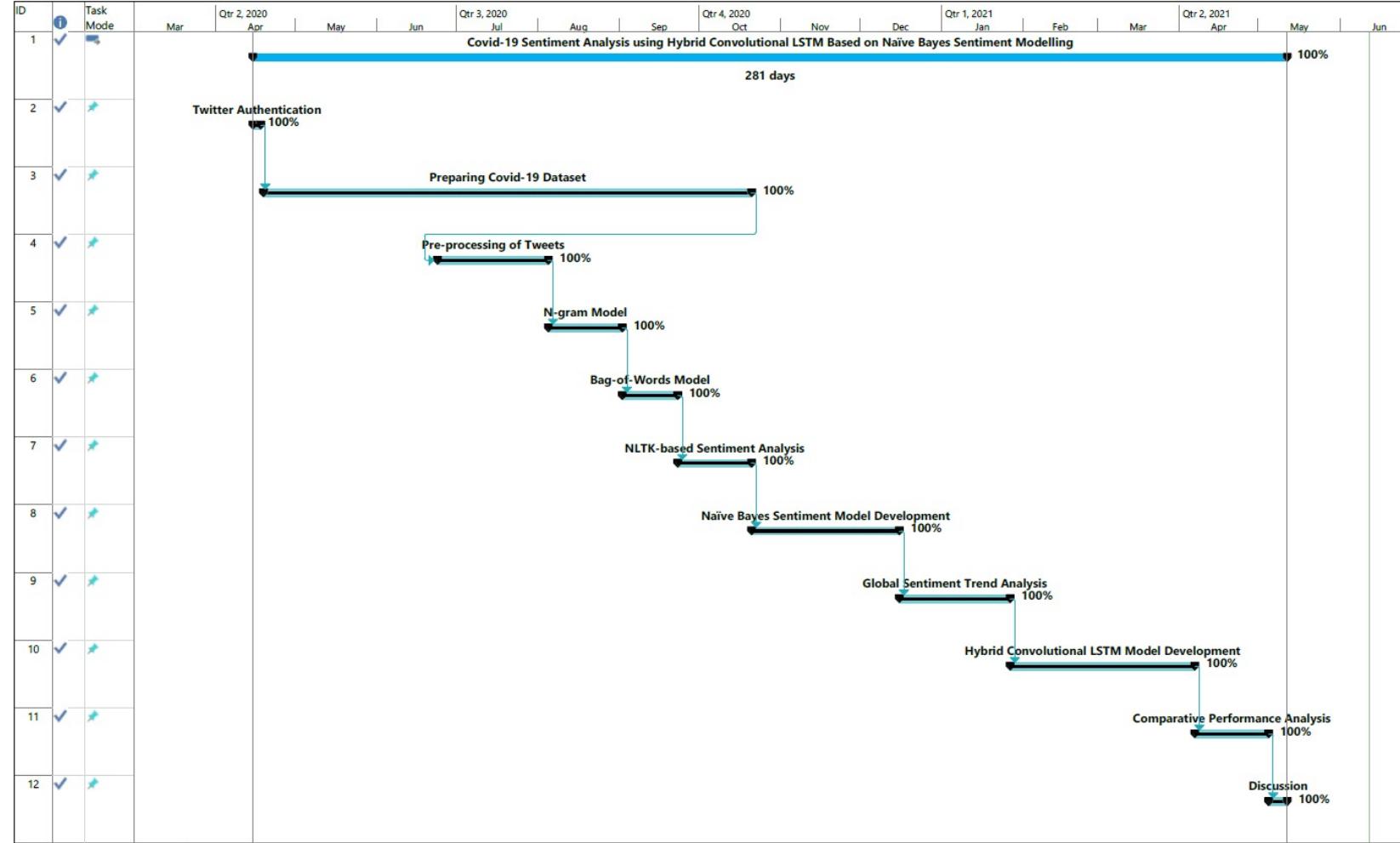
- Timeline Task Sheet

ID	Task Mode	Task Name	Duration	Start	Finish	Predecessors
1	✓	Covid-19 Sentiment Analysis using Hybrid Convolutional LSTM Based on Naive 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



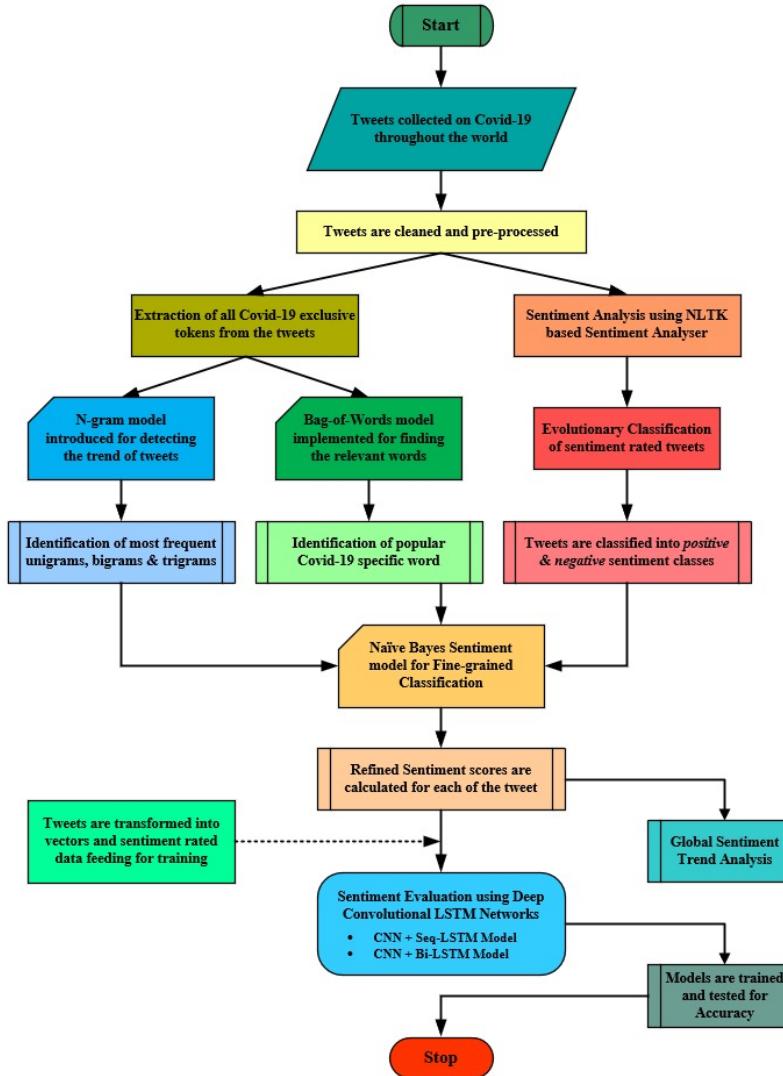
- Gantt Chart



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.

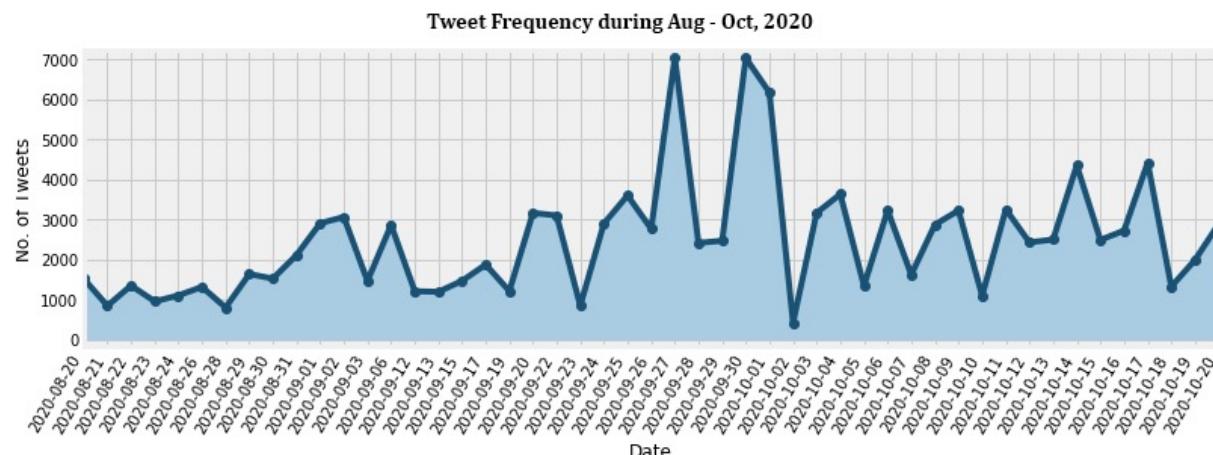
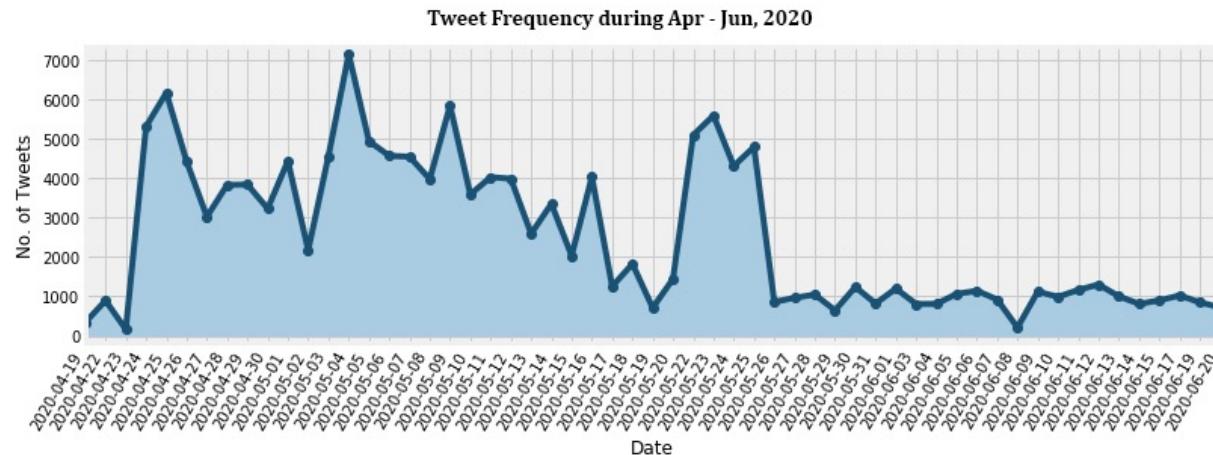
id	created_at	source	original_text	lang	favorite_count	retweet_count	original_author	hashtags	user_mentions	place
125193476721131	Sun Apr 19	<a href="http:	RT @Ash_The	en	0	705	EmpoweringGo	Jehanaba	Ash_TheLoneW	Panjim Goa India
125193473331715	Sun Apr 19	<a href="http:	RT @NGvisor	en	0	2646	Ibilola_Amao	lockdown	NGvision2020	London, England
125193466618305	Sun Apr 19	<a href="http:	RT @Barnes_	en	0	5593	cliff_skidmore		Barnes_Law	Texas, USA
125193460755922	Sun Apr 19	<a href="http:	RT @Joelpatri	en	0	108	GMA4Trump_	Covid_19	Joelpatrick1776	Choctaw, OK
125193458229277	Sun Apr 19	<a href="http:	RT @GlbICtzn	en	0	4	Macgirl730	Together	GlbICtzn	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

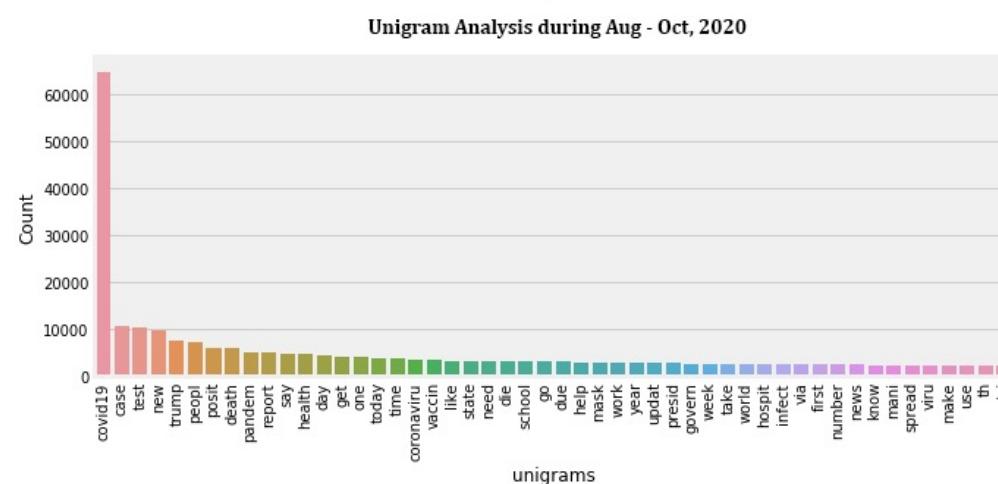
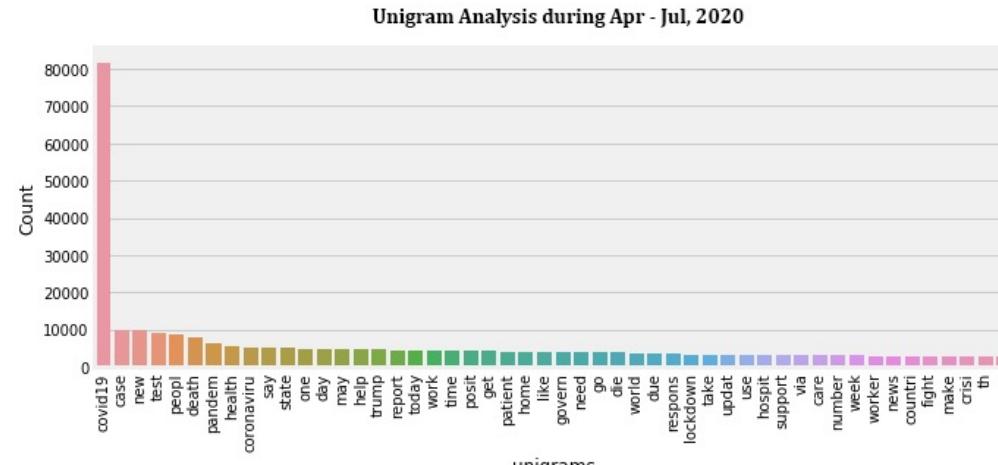


- The pre-processing function follows the following steps to clean raw tweets-
 1. *Convert the whole tweet into lower case.*
 2. *Remove all URLs from the tweet.*
 3. *Remove all punctuations from the tweet.*
 4. *Remove all stop words from the tweet.*
 5. *Tokenize the tweet to split each of the sentence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

Feature I : Word Trend Detection using N-gram



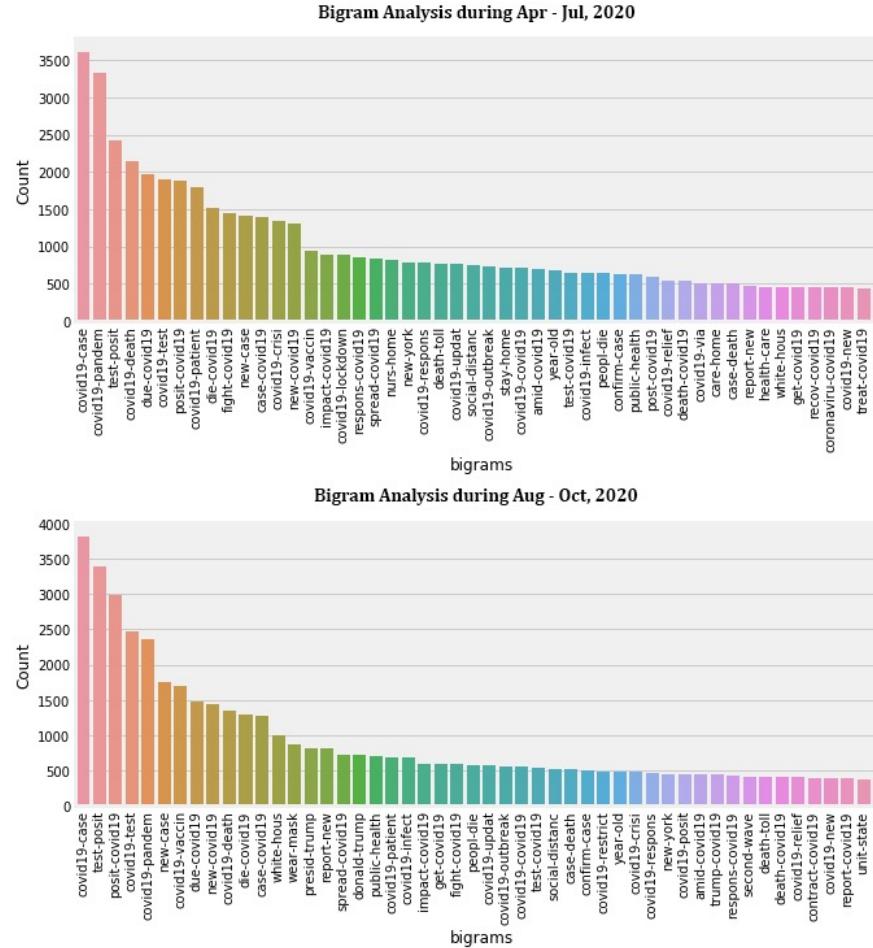
- **lexical n-gram model** used for Identification of the most popular unigrams, bigrams and trigrams within our corpus.
- **Unigram Analysis**



Feature I : Word Trend Detection using N-gram



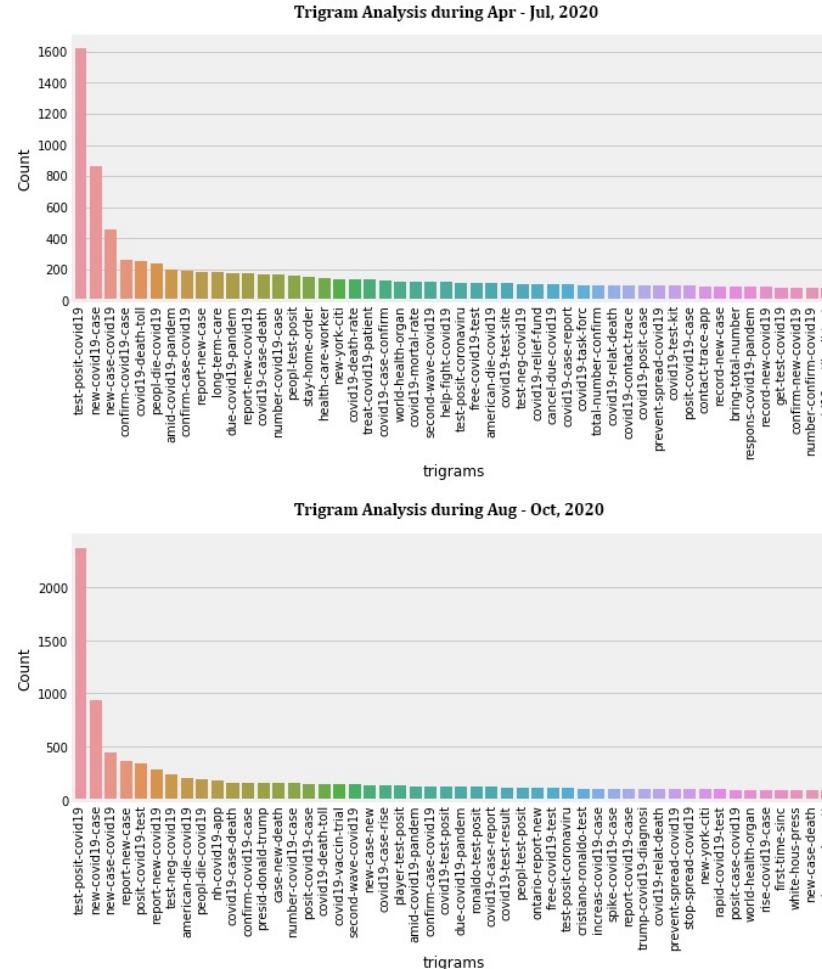
- **Bigram Analysis**



Feature I : Word Trend Detection using N-gram



- Trigram Analysis

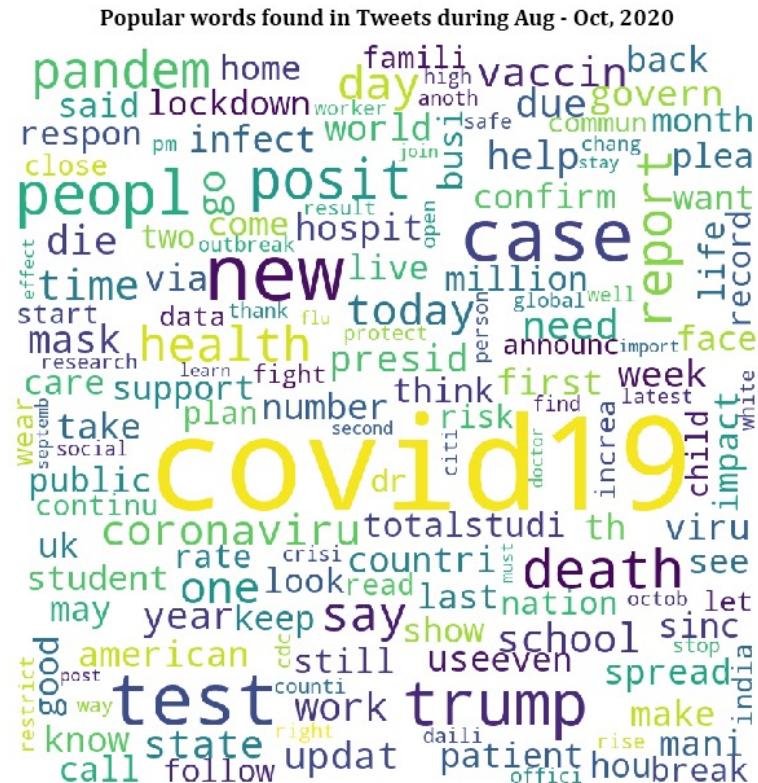
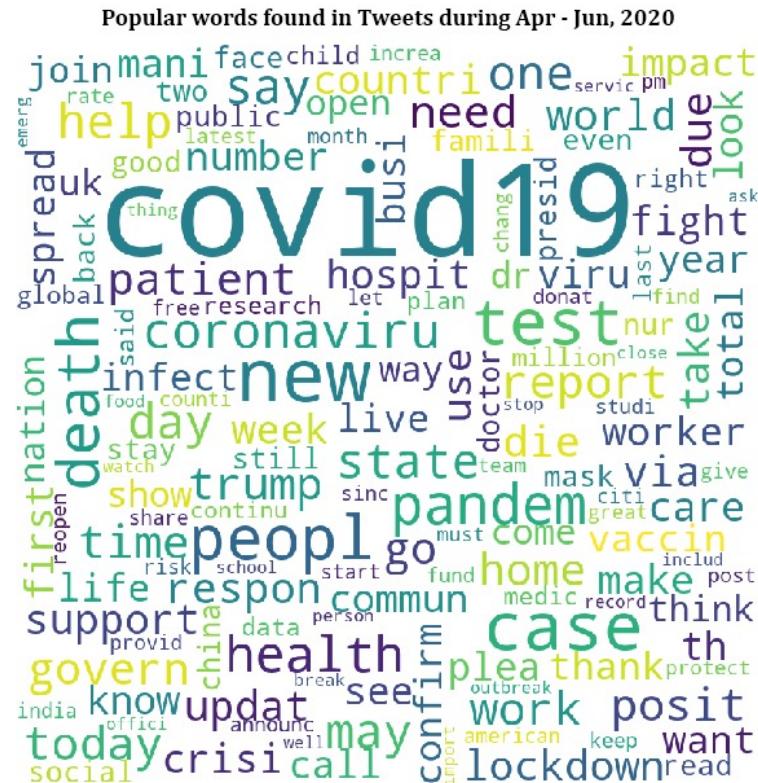


- According to the n-gram model, the popularity of trigrams is lesser than that of bigrams and the unigrams popularity is the highest.

Feature II : Covid-19 Specified Word Identification



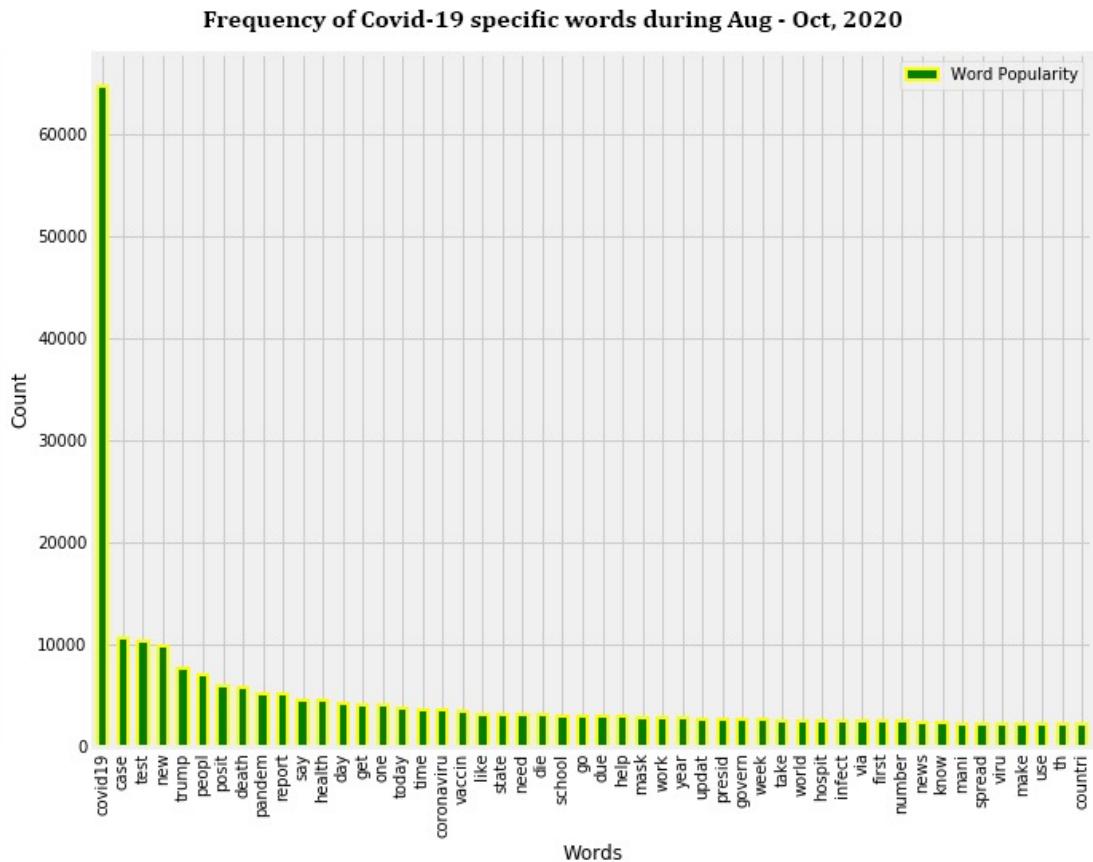
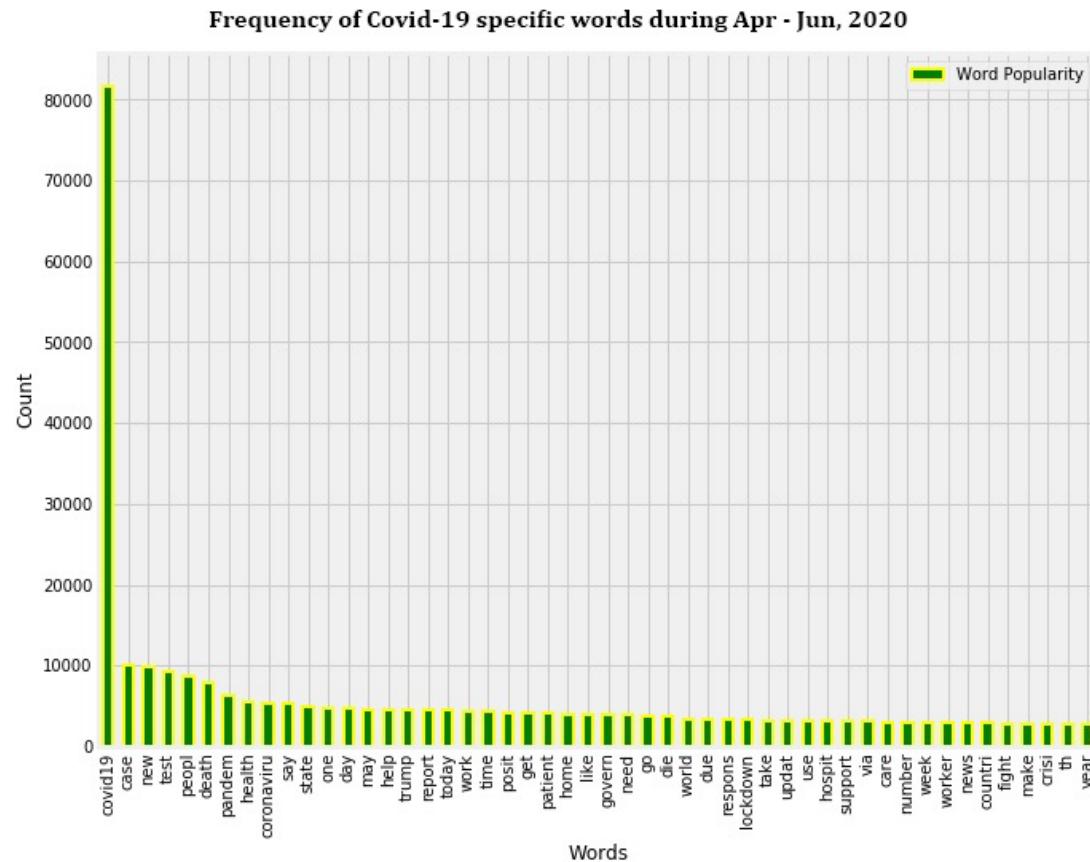
- The **Bag-of-Words** (BOW) model used to identify frequently occurred grams from the word lexicon.
- Finally, we obtained a list of most frequent Covid-19 exclusive words.



Feature II : Covid-19 Specified Word Identification



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



Feature II : Covid-19 Specified Word Identification



- 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.

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

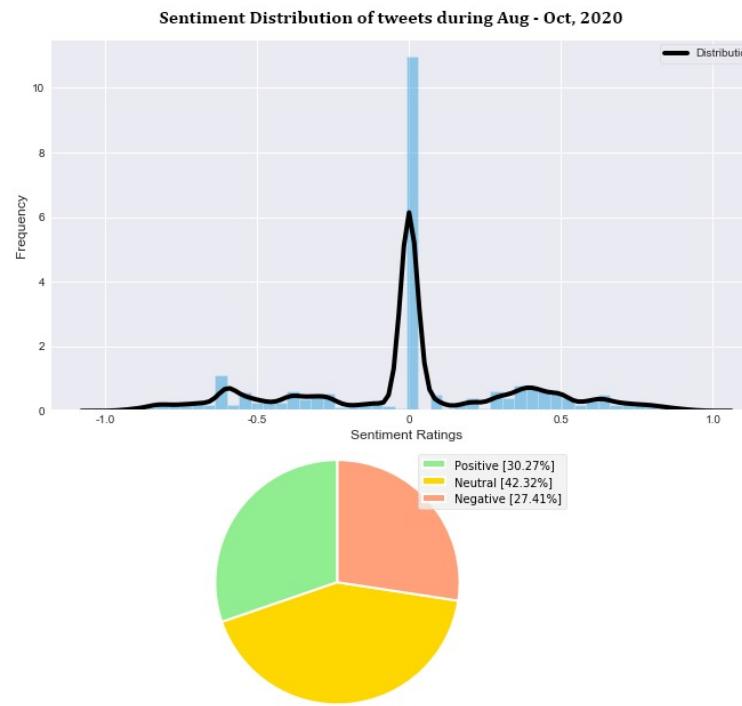
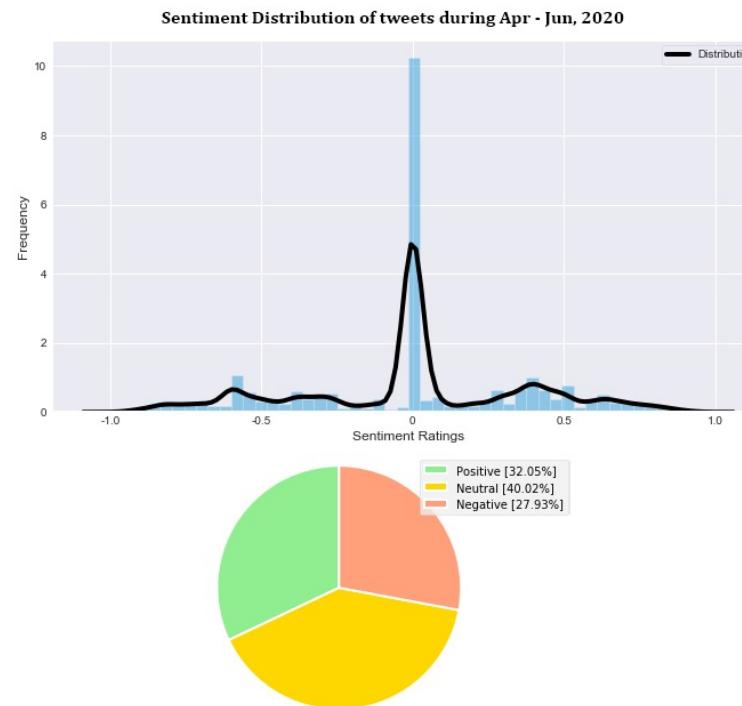
- We represented the popularity and probability of recurrence for top five most frequent Covid-19 related words.

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

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.

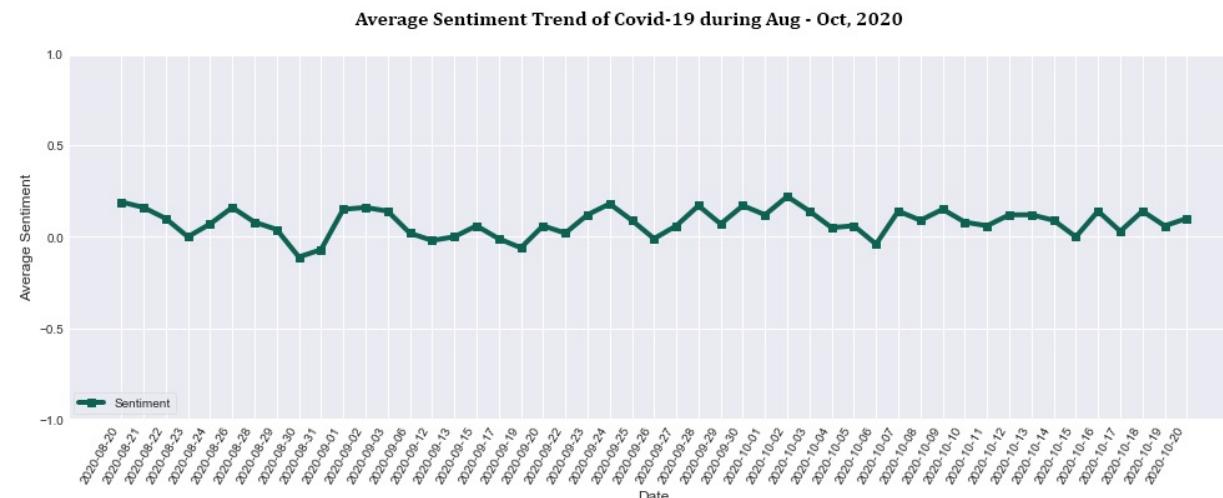
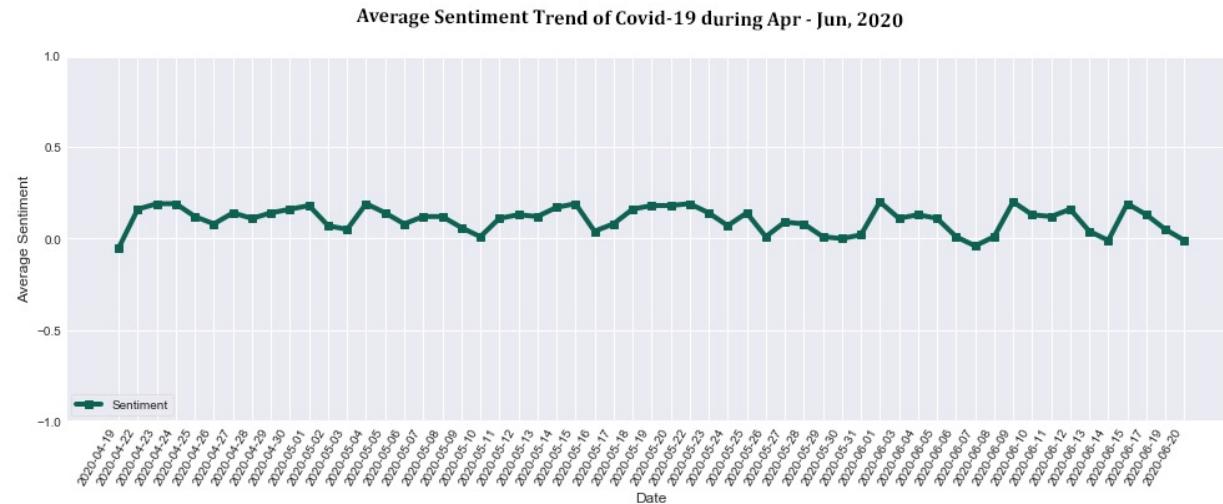
Algorithm Fine-Grained Sentiment Classification (sentiment, refined_sentiment):

1. *for each i in range (0, len(tweet.index)):*
2. *if tweet_i[sentiment] >= 0.0 and tweet_i[sentiment] < 0.25:*
3. *tweet_i[refined_sentiment] ← -1.0 # assigned -1.0 for Most Negative Tweets*
4. *elif tweet_i[sentiment] >= 0.25 and tweet_i[sentiment] < 0.5:*
5. *tweet_i[refined_sentiment] ← -0.5 # assigned -0.5 for Negative Tweets*
6. *elif tweet_i[sentiment] == 0.5:*
7. *tweet_i[refined_sentiment] ← 0.0 # assigned 0.0 for Neutral Tweets*
8. *elif tweet_i[sentiment] > 0.5 and tweet_i[sentiment] <= 0.75:*
9. *tweet_i[refined_sentiment] ← 0.5 # assigned 0.5 for Positive Tweets*
10. *else:*
11. *tweet_i[refined_sentiment] ← 1.0 # assigned 1.0 for Most Positive Tweets*
12. *end*

Global Sentiment Trend Analysis



- Overall Average Sentiment Trend throughout the world.



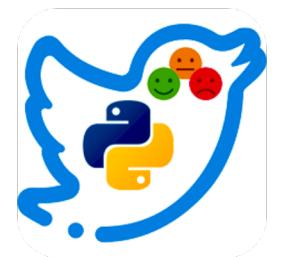
Global Sentiment Trend Analysis



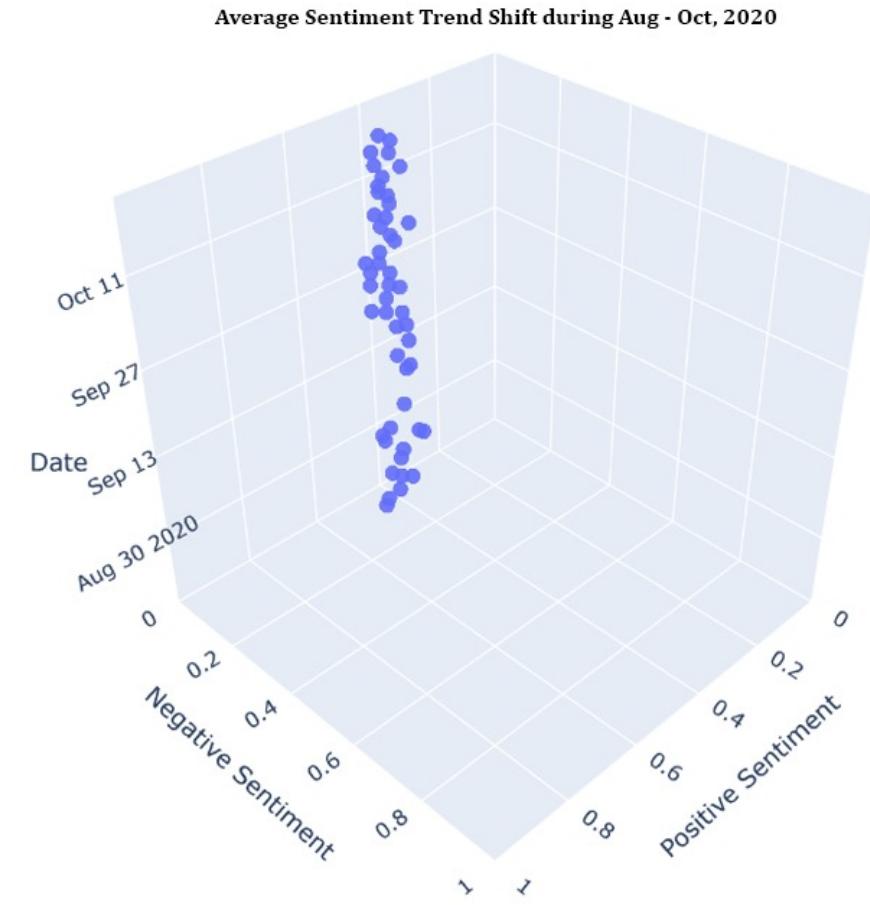
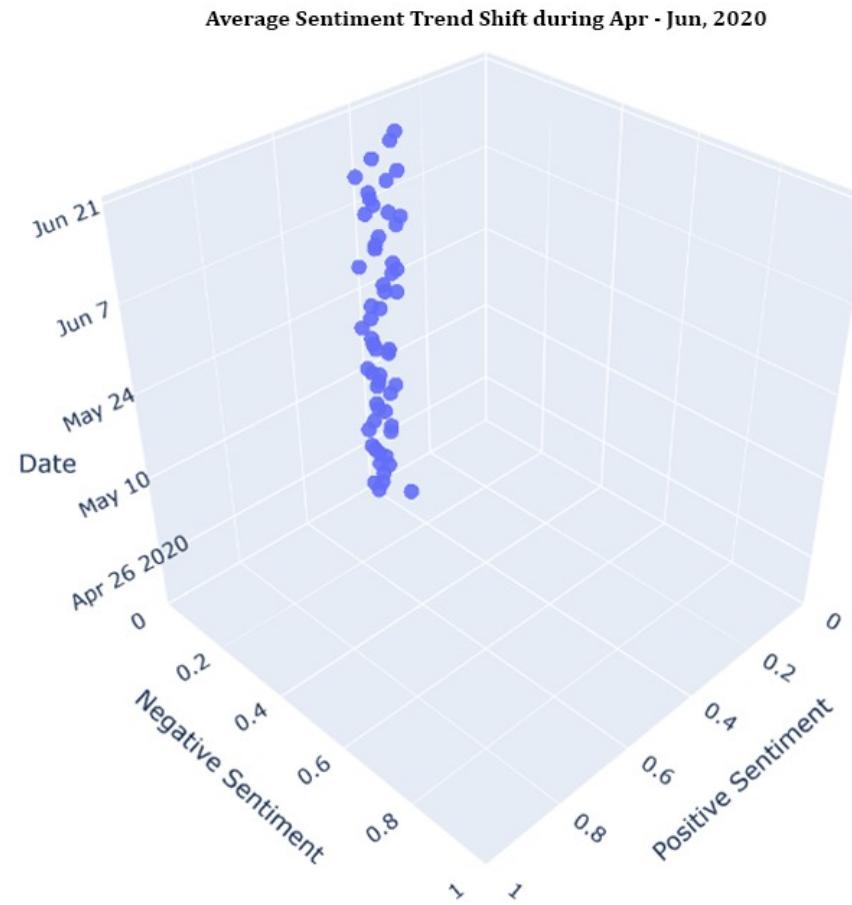
- Some Covid-19 tweets from different sentiment classes.

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

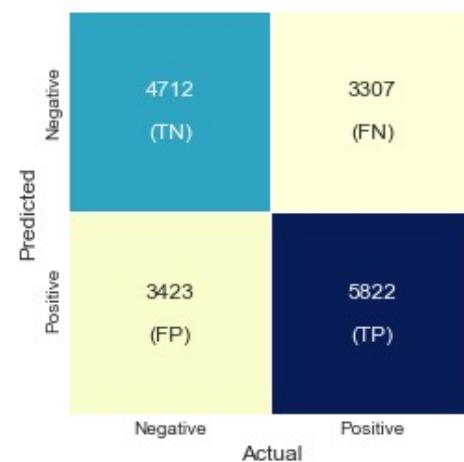


• Classification Report

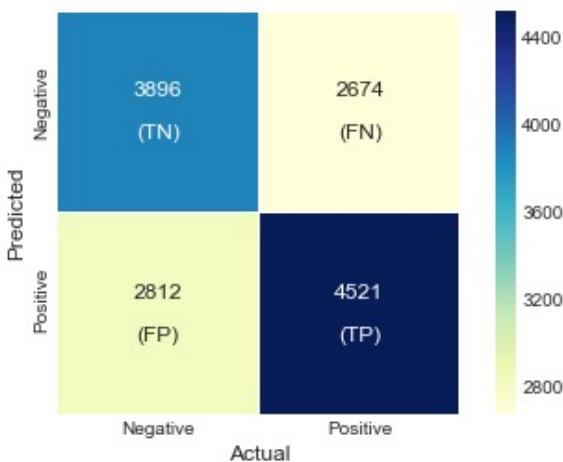
		Precision	Recall	F1-Score	Support
Covid-19 Dataset I (Apr - Jun, 2020)	<i>Positive (1.0)</i>	0.64	0.63	0.63	9245
	<i>Negative (0.0)</i>	0.58	0.59	0.58	8019
	Avg. / Total	0.61	0.61	0.61	17264
Covid-19 Dataset II (Aug - Oct, 2020)	<i>Positive (1.0)</i>	0.63	0.62	0.62	7333
	<i>Negative (0.0)</i>	0.58	0.59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

• Confusion Matrix

Confusion Matrix - Covid-19 Dataset I



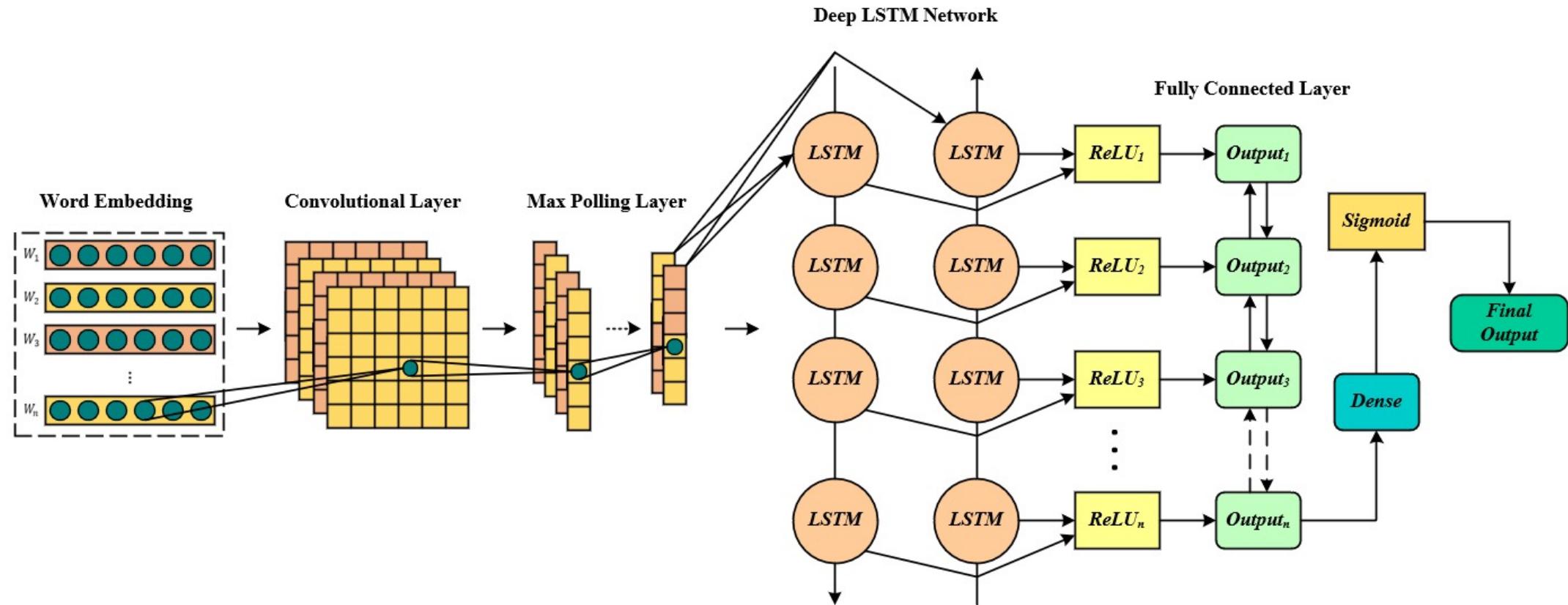
Confusion Matrix - Covid-19 Dataset II



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



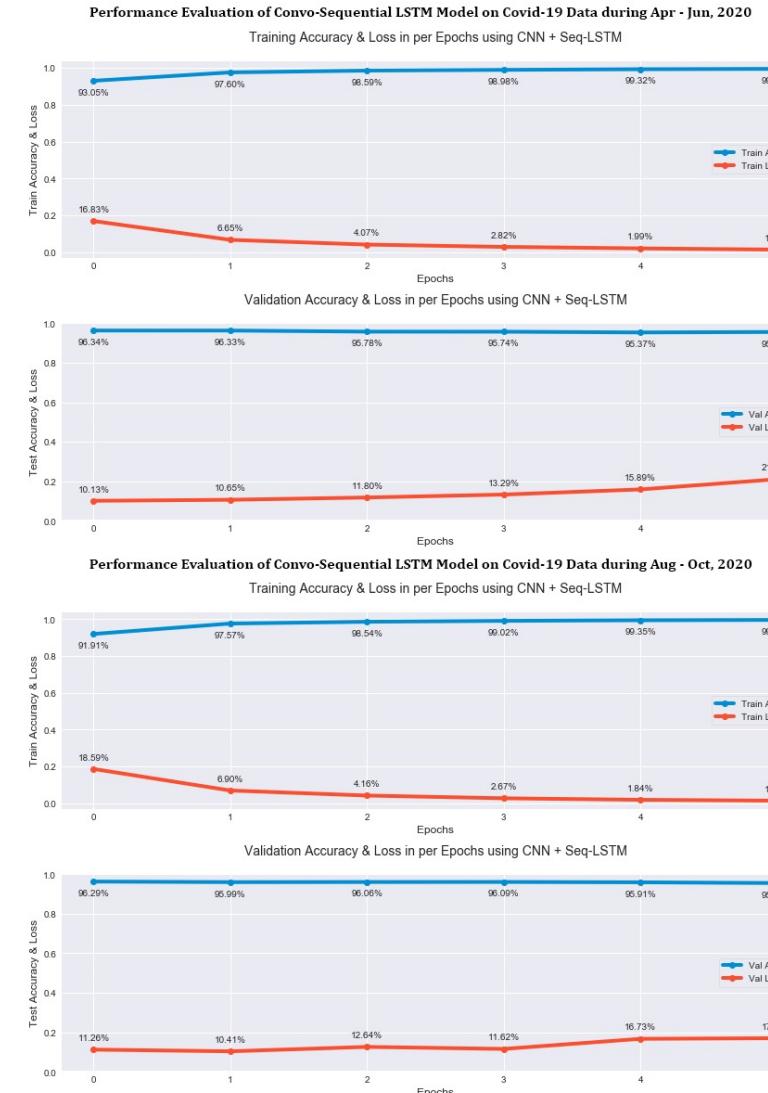
- The new dataset contains all preprocessed tweets along with their corresponding ***positive*** (1.0) and ***negative*** (0.0) sentiments.
- We split the dataset into **80:20** ratio. i.e., **80%** for **training** and **20%** for **validation** purposes respectively.
- Word vectors are calculated for 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)	<i>Initially</i>	16.83%	93.05%	10.13%	96.34%
	2 nd	06.65%	97.60%	10.65%	96.33%
	3 rd	04.07%	98.59%	11.80%	95.78%
	4 th	02.82%	98.98%	13.29%	95.74%
	5 th	01.99%	99.32%	15.89%	95.37%
	6 th	01.35%	99.53%	21.06%	95.61%
Covid-19 Dataset II (Aug - Oct, 2020)	<i>Initially</i>	18.59%	91.91%	11.26%	96.29%
	2 nd	06.90%	97.57%	10.41%	95.99%
	3 rd	04.16%	98.54%	12.64%	96.06%
	4 th	02.67%	99.02%	11.62%	96.09%
	5 th	01.84%	99.35%	16.73%	95.91%
	6 th	01.38%	99.53%	17.05%	95.53%



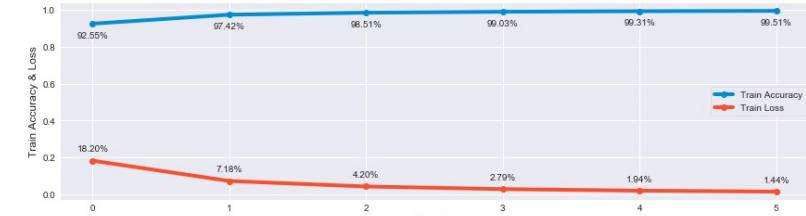
Sentiment Modelling using Hybrid CNN + Bi-LSTM



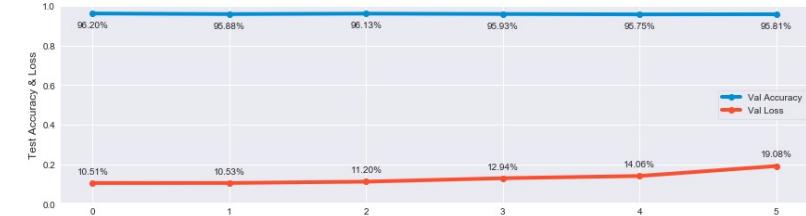
- Training accuracy vs. loss, validation accuracy vs. loss using CNN + Bi-LSTM network.

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

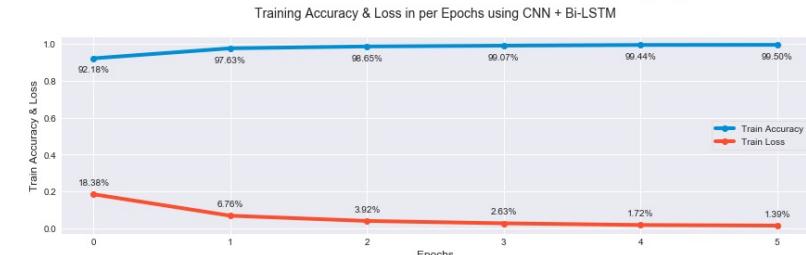
Performance Evaluation of Conv-Bidirectional LSTM Model on Covid-19 Data during Apr - Jun, 2020
Training Accuracy & Loss in per Epochs using CNN + Bi-LSTM



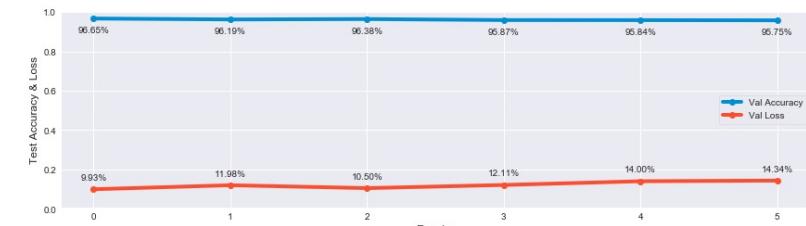
Validation Accuracy & Loss in per Epochs using CNN + Bi-LSTM



Performance Evaluation of Conv-Bidirectional LSTM Model on Covid-19 Data during Aug - Oct, 2020



Validation Accuracy & Loss in per Epochs using CNN + Bi-LSTM



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 (Ours)	95.81%
Multilingual BERT on single-level classification [19]	95.62%
CNN + Seq-LSTM w. Naïve Bayes Sentiment Model (Ours)	95.61%
CNN w. <i>GloVe</i> 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.

Deep Neural Network Models	Prediction Accuracy
CNN + Bi-LSTM w. Naïve Bayes Sentiment Model (Ours)	90.44%
CNN + Seq-LSTM w. Naïve Bayes Sentiment Model (Ours)	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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