



# 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]**

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**RCC Institute of Information Technology**

# Introduction

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- 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

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- The Novel Coronavirus (COVID-19) was identified in 31<sup>st</sup> Dec, 2019 in Wuhan, Hubei Province, China [\[1\]](#).
- WHO announced Covid-19 outbreak as pandemic on 11<sup>th</sup> 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

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**“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

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**“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

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**“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

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**“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

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**“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

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**“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

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- **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

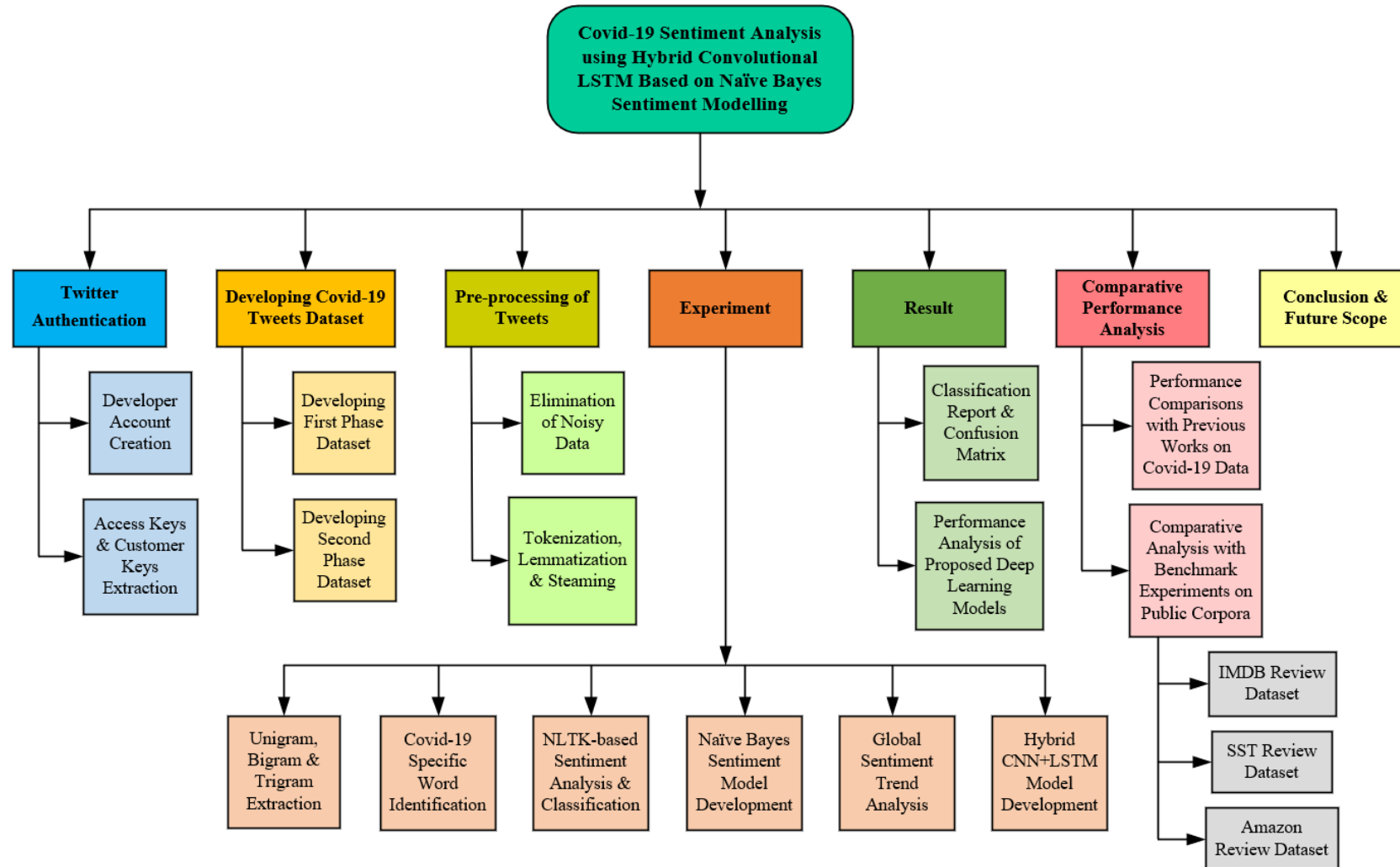
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- Covid-19 Specified Word Identification
- N-gram Model
- NLTK-based Sentiment Analysis
- Naïve Bayes Sentiment Model
- Sentiment Modelling using Hybrid Convolutional LSTM

# Design Methodology



- **Work Breakdown Structure**



# Design Methodology



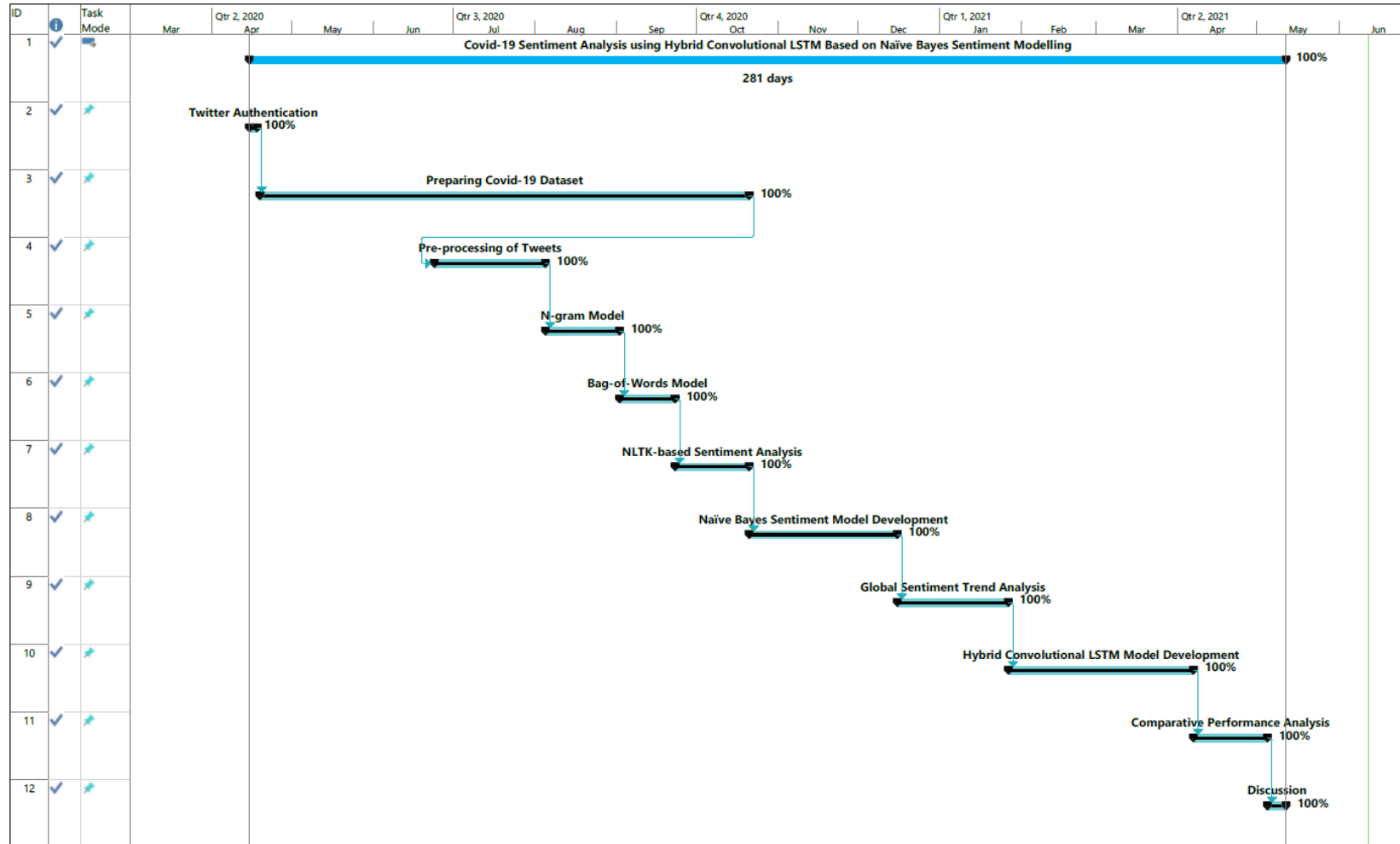
## • Timeline Task Sheet

ID	Task Mode	Task Name	Duration	Start	Finish	Predecessors
1	✓	<b>Covid-19 Sentiment Analysis using Hybrid Convolutional LSTM Based on Naïve Bayes Sentiment Modelling</b>	281 days	Wed 15-04-20	Tue 11-05-21	
2	✓	<b>Twitter Authentication</b>	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	✓	<b>Preparing Covid-19 Dataset</b>	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	✓	<b>Pre-processing of Tweets</b>	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	✓	<b>N-gram Model</b>	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	✓	<b>Bag-of-Words Model</b>	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	✓	<b>NLTK-based Sentiment Analysis</b>	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	✓	<b>Naïve Bayes Sentiment Model Development</b>	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	✓	<b>Global Sentiment Trend Analysis</b>	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	✓	<b>Hybrid Convolutional LSTM Model Development</b>	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	✓	<b>Comparative Performance Analysis</b>	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	✓	<b>Discussion</b>	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





# 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 @NGvisior	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 @GlblCtn	en	0	4	Macgirl730	Together,	GlblCtn	Menomonee Falls, WI

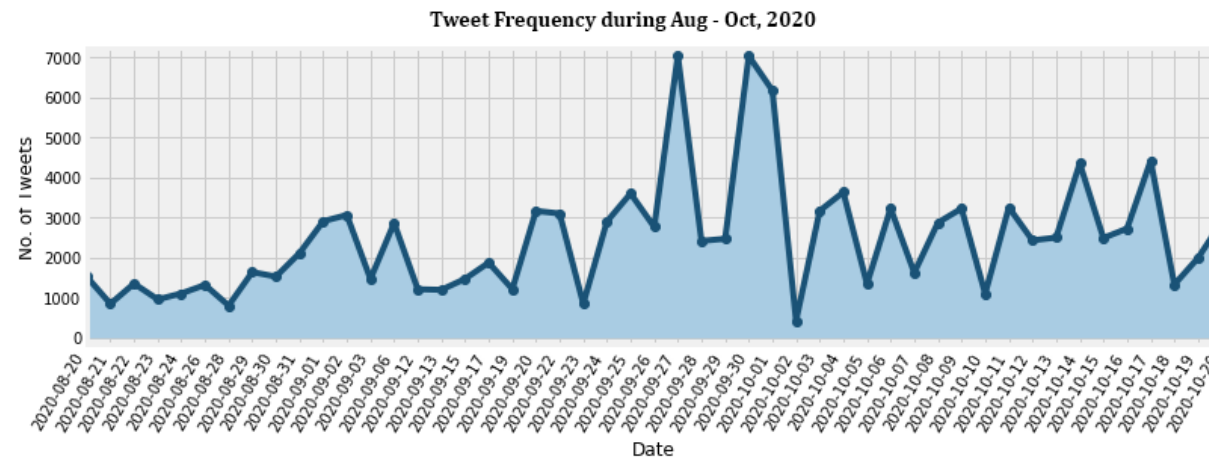
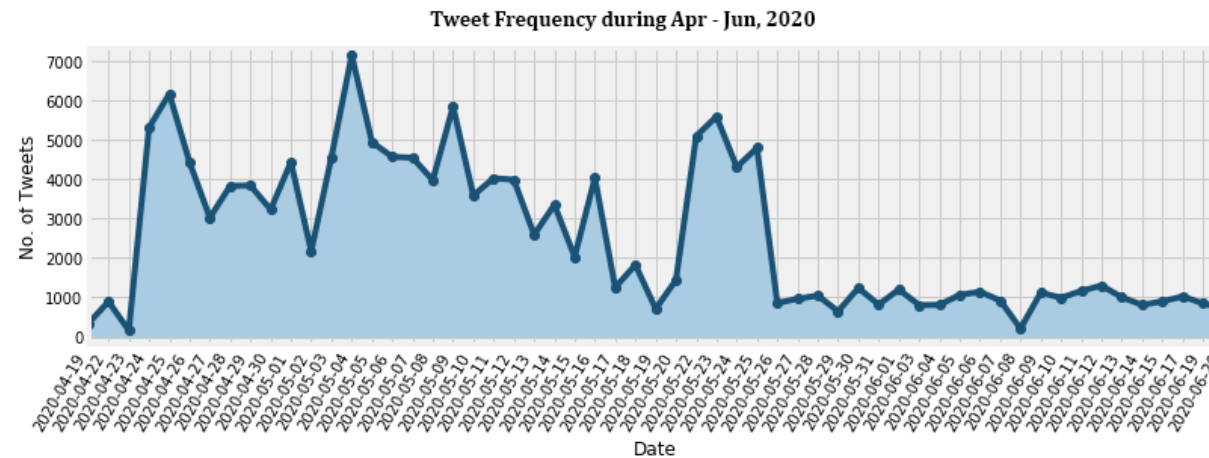
- [4] [www.statista.com](http://www.statista.com)



# 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

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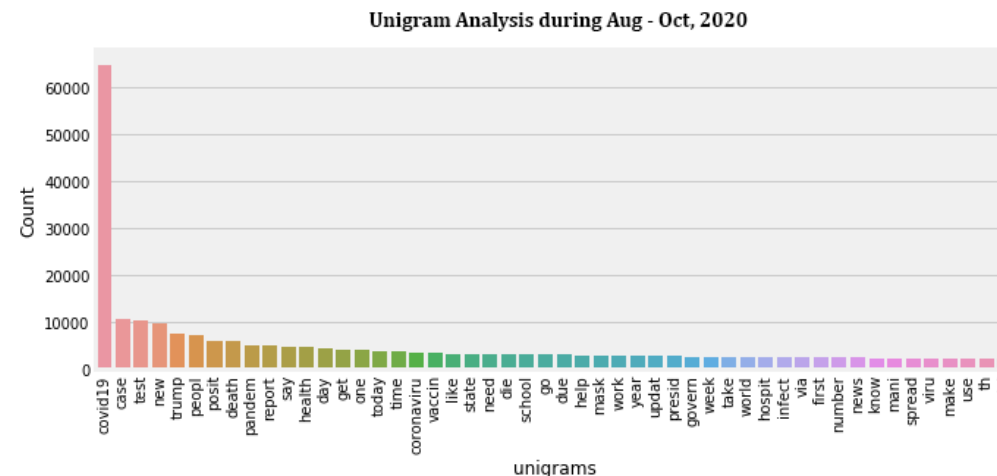
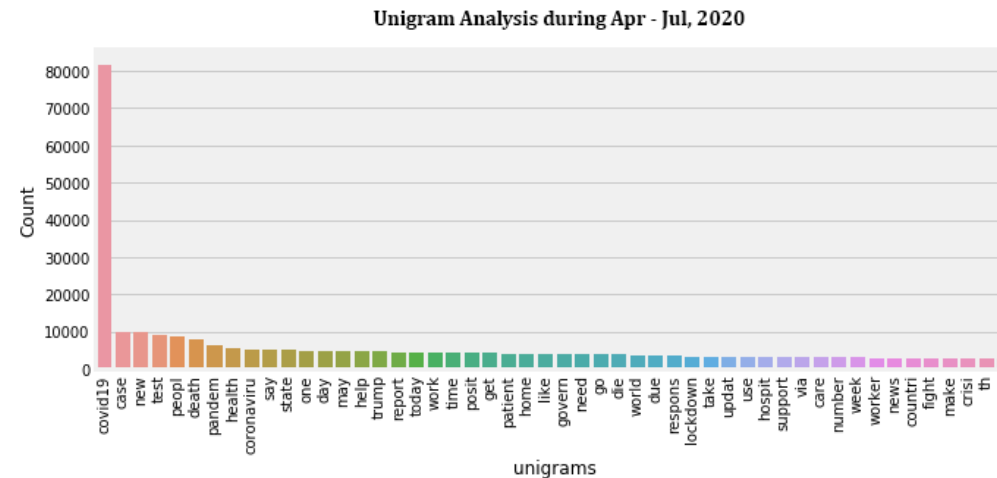


- The pre-processing function follows the following steps to clean raw tweets-
  1. *Convert the whole tweet into lower case.*
  2. *Remove all URLs from the tweet.*
  3. *Remove all punctuations from the tweet.*
  4. *Remove all stop words from the tweet.*
  5. *Tokenize the tweet to split each of the 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**

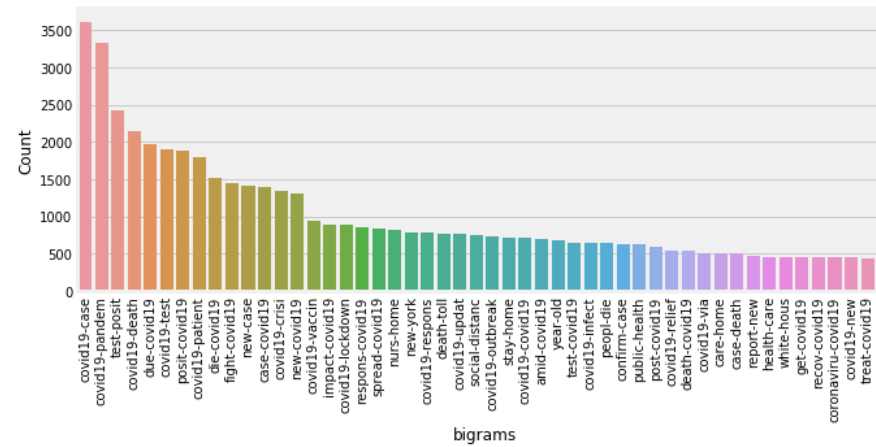


# Feature I : Word Trend Detection using N-gram

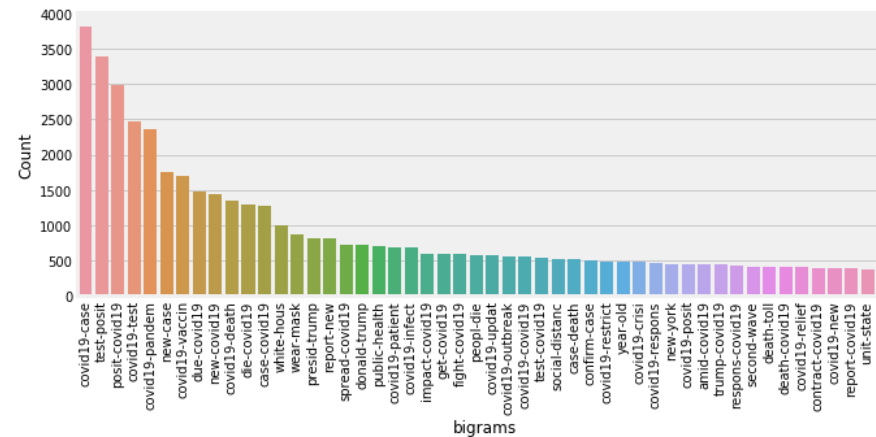


- **Bigram Analysis**

Bigram Analysis during Apr - Jul, 2020



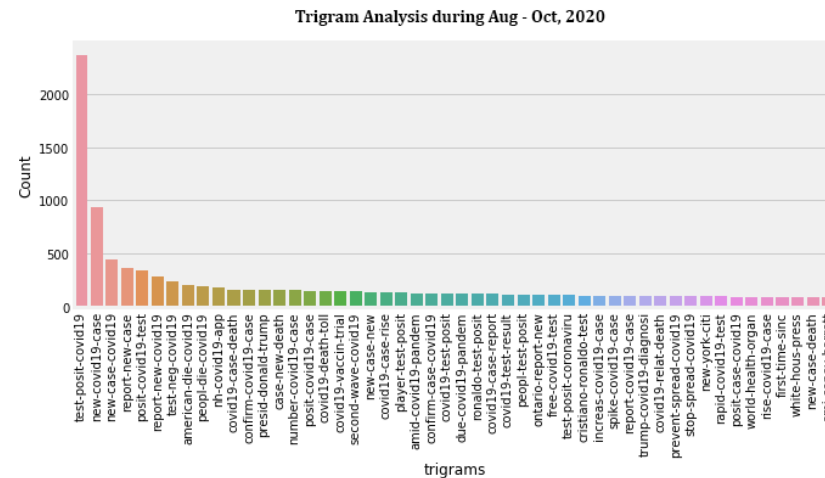
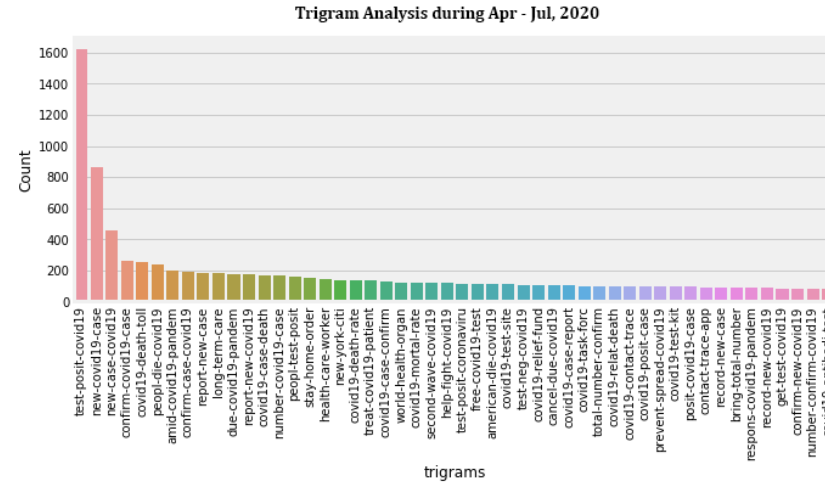
Bigram Analysis during Aug - Oct, 2020



# Feature I : Word Trend Detection using N-gram

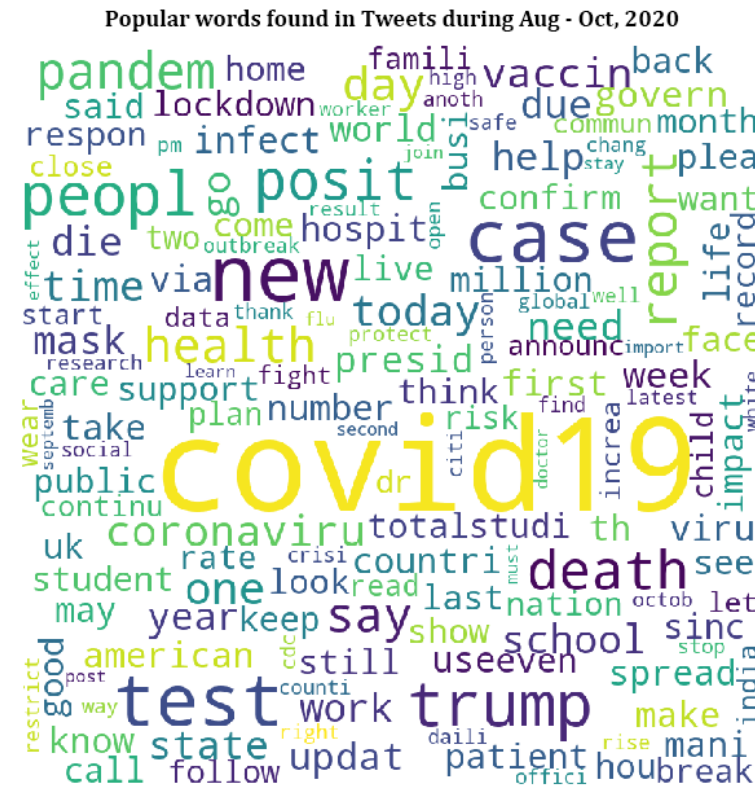
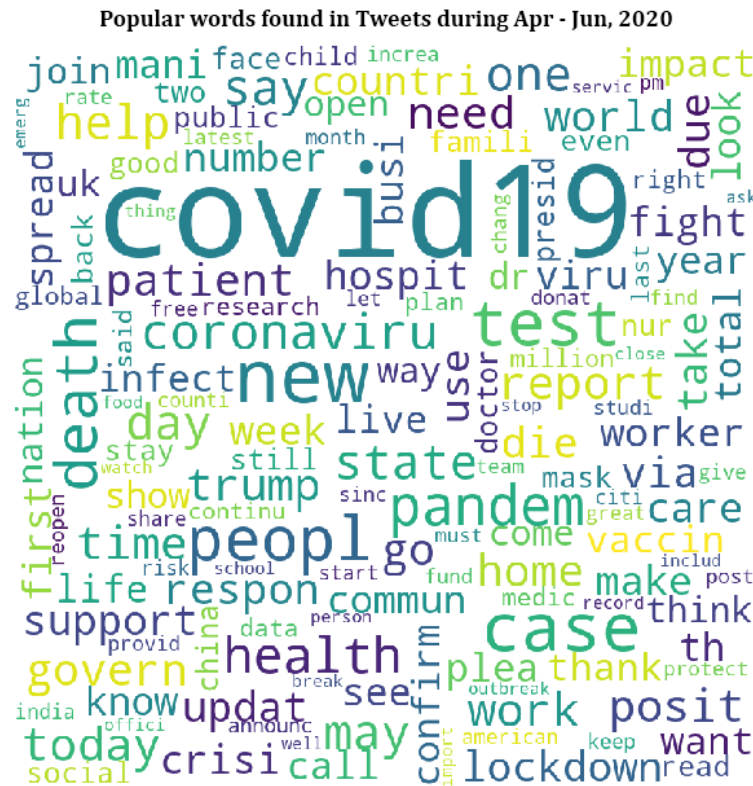


- **Trigram Analysis**



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

- [illegible]

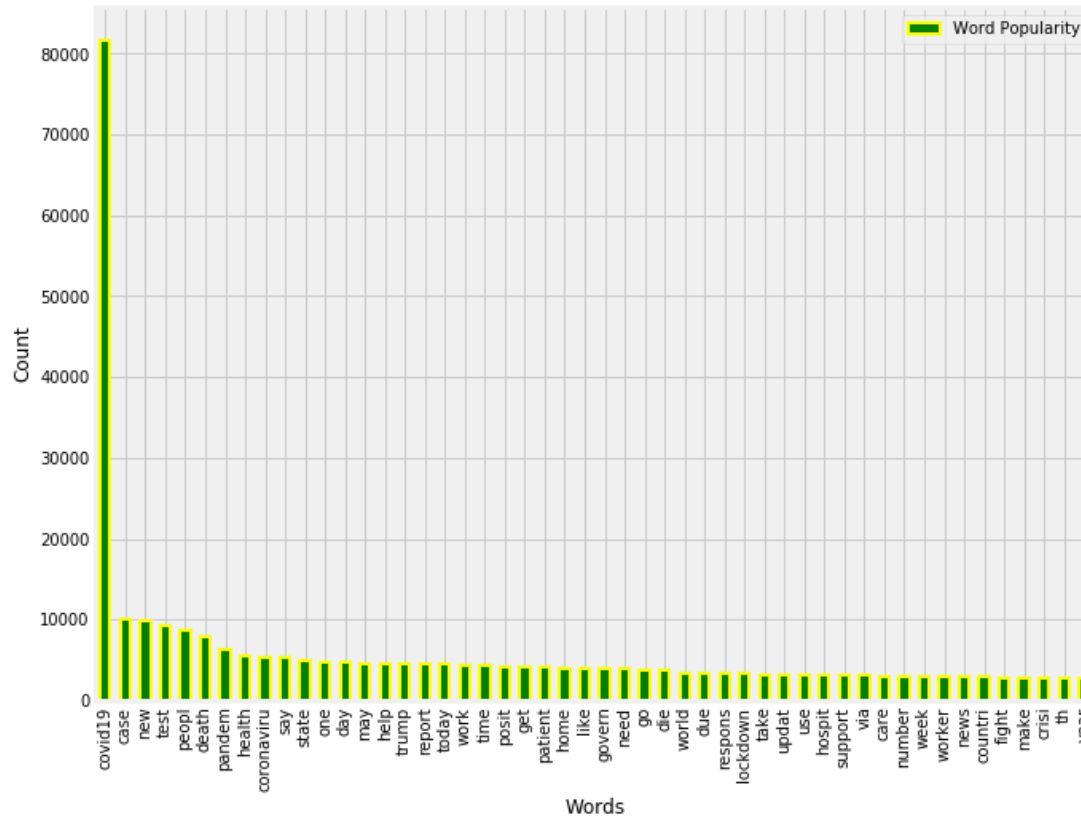


# Feature II : Covid-19 Specified Word Identification

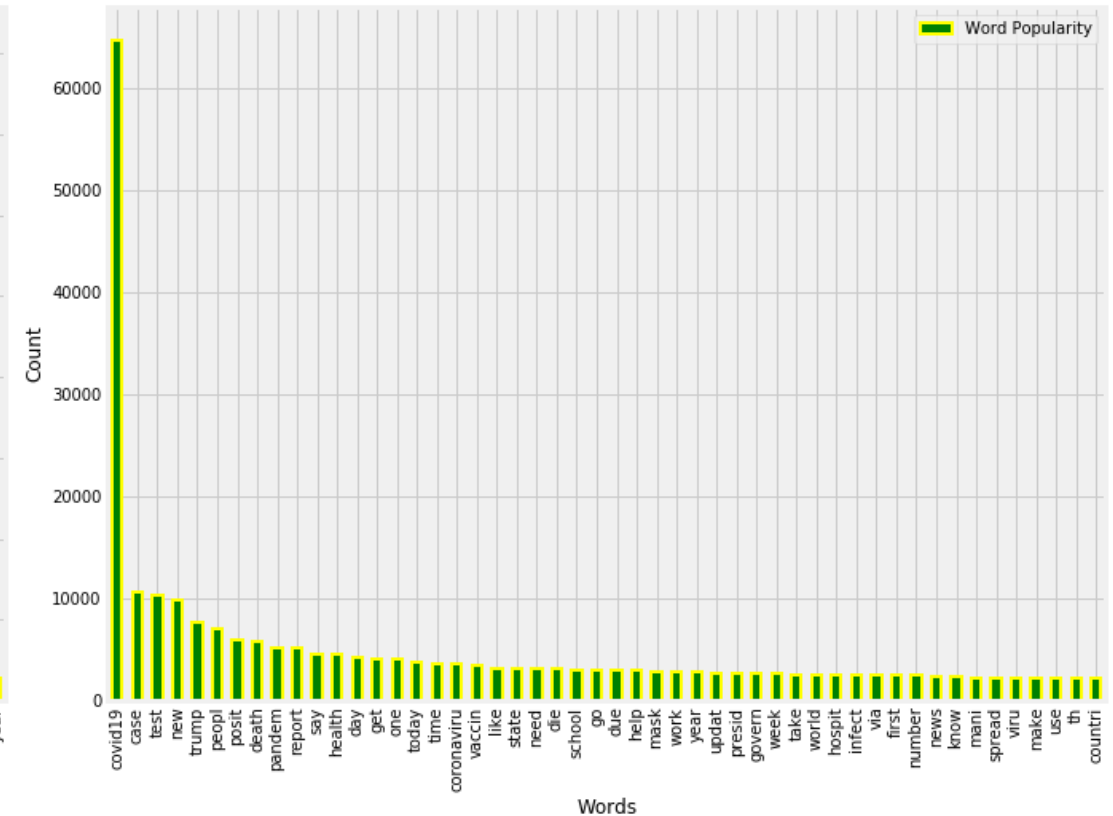


- From the obtained list of most popular Covid-19 exclusive words we have found the frequency for the recurrence of each words.

Frequency of Covid-19 specific words during Apr - Jun, 2020



Frequency of Covid-19 specific words during Aug - Oct, 2020





## 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.

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

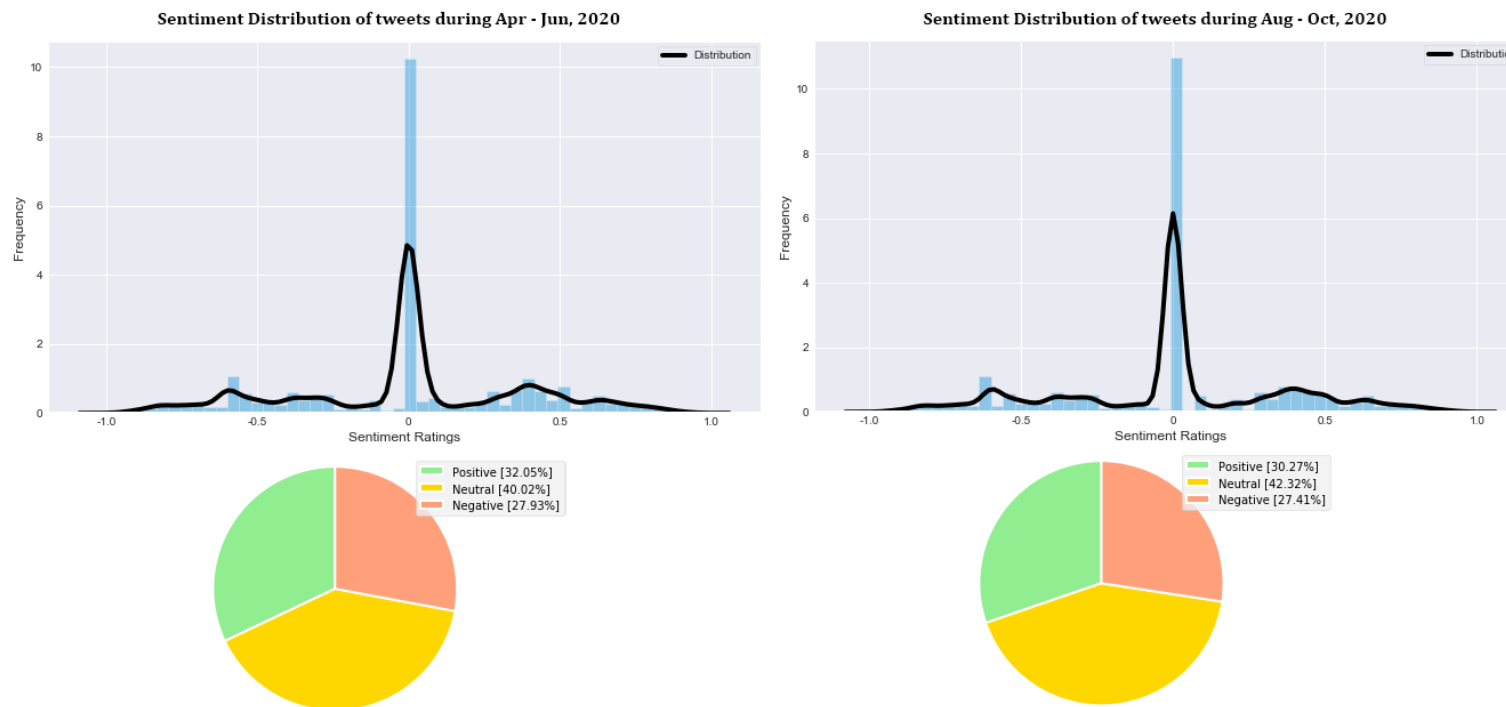
- We represented the popularity and probability of recurrence for top five most frequent Covid-19 related words.

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

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- 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.

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**Algorithm Fine-Grained Sentiment Classification (sentiment, refined\_sentiment):**

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

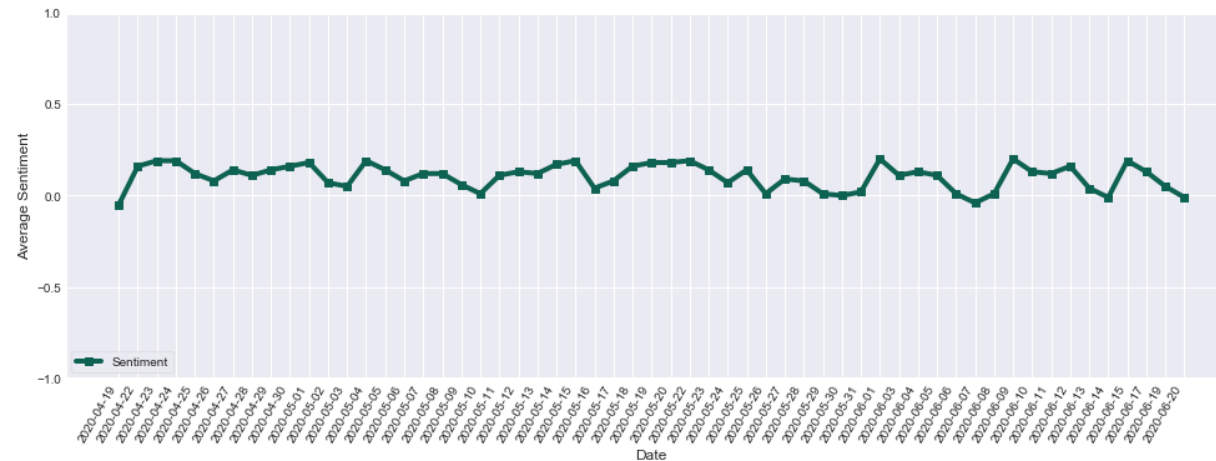
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# Global Sentiment Trend Analysis

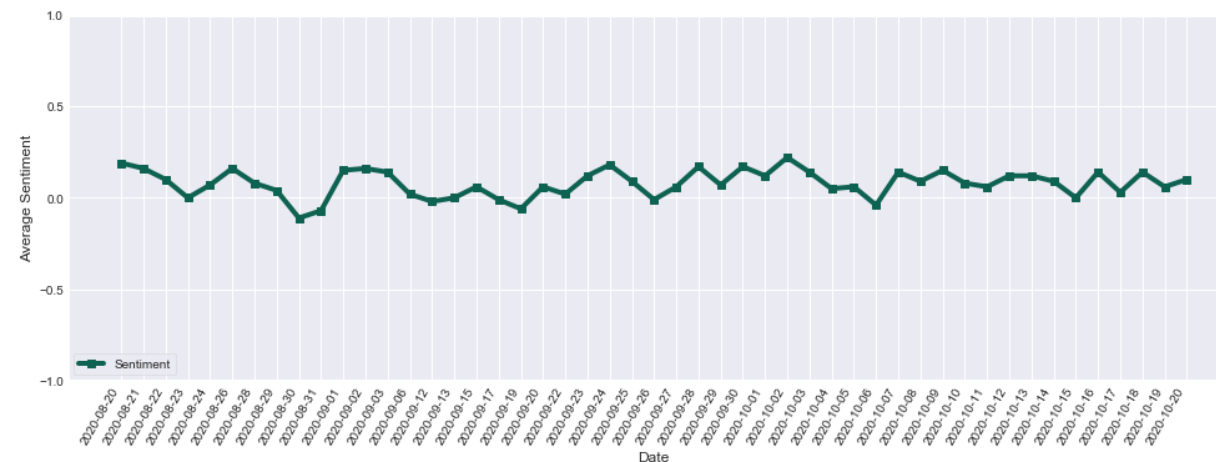


- Overall Average Sentiment Trend throughout the world.

Average Sentiment Trend of Covid-19 during Apr - Jun, 2020



Average Sentiment Trend of Covid-19 during Aug - Oct, 2020



# Global Sentiment Trend Analysis



- Some Covid-19 tweets from different sentiment classes.

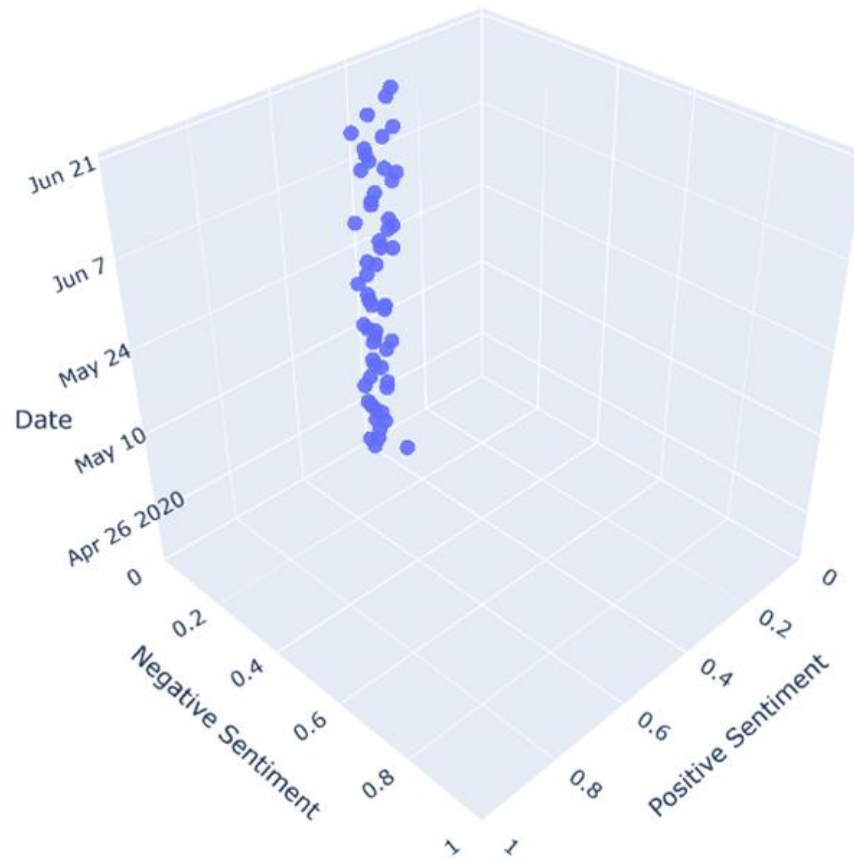
Date	Original Tweet	Naïve Bayes Sentiment Rating	Refined Sentiment Rating	Sentiment Class
05-05-2020	<b>Barbara Walton #FBPE @LesTroisChenes</b> More Than 60 Doctors in Italy Have Died in COVID-19 Pandemic. Why? Lack of PPE and information. UK just a fraction behind them - far ahead of other countries. We threw our health worker under the #COVID bus and then clapped for them.	0.24	-1	Most Negative
27-04-2020	<b>Elizabeth Stein @lizstein</b> 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	<b>Volker Stollorz @Stollovo</b> “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	<b>Muh’d @smj_esq</b> 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	<b>CNN Philippines @cnnphilippines</b> 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

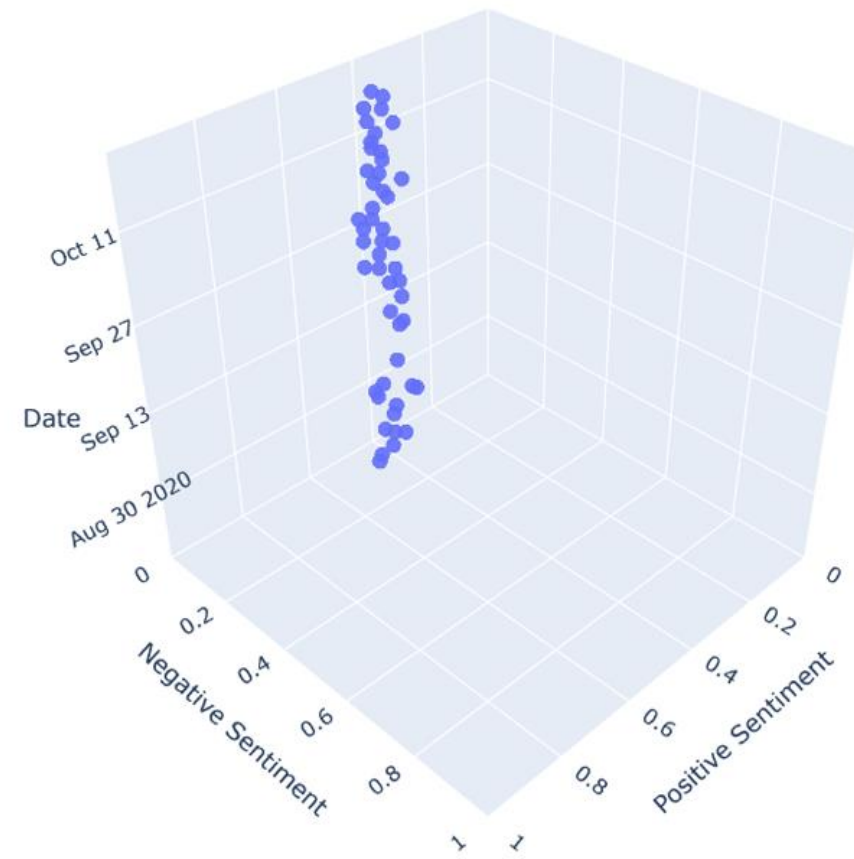


- Worldwide Average Sentiment Trend Shift Detection.

Average Sentiment Trend Shift during Apr - Jun, 2020



Average Sentiment Trend Shift during Aug - Oct, 2020



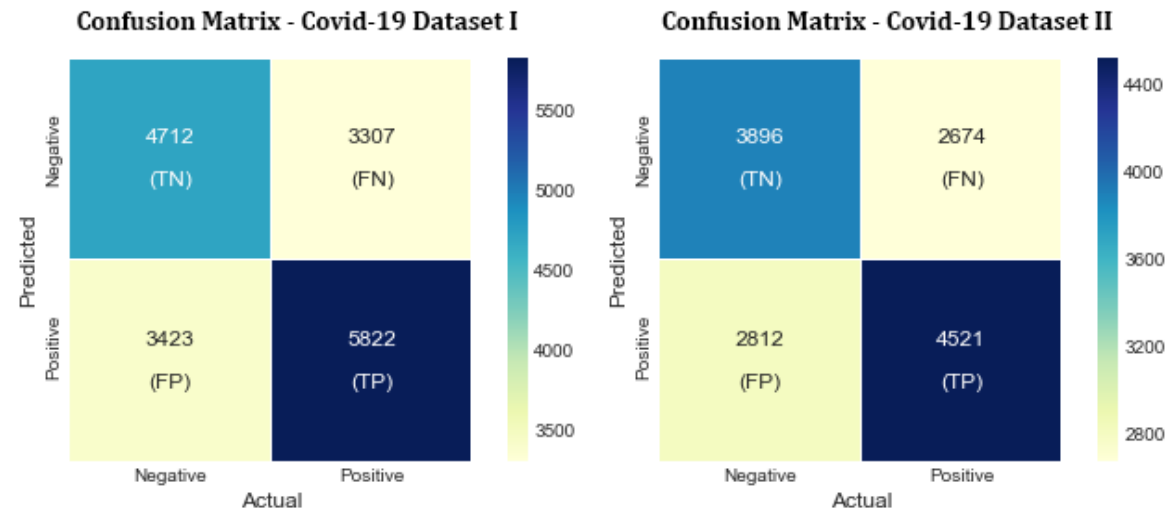
# Classification Report & Confusion Matrix



- 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	<b>0.61</b>	<b>0.61</b>	<b>0.61</b>	<b>17264</b>
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	<b>0.61</b>	<b>0.61</b>	<b>0.61</b>	<b>13903</b>

- Confusion Matrix

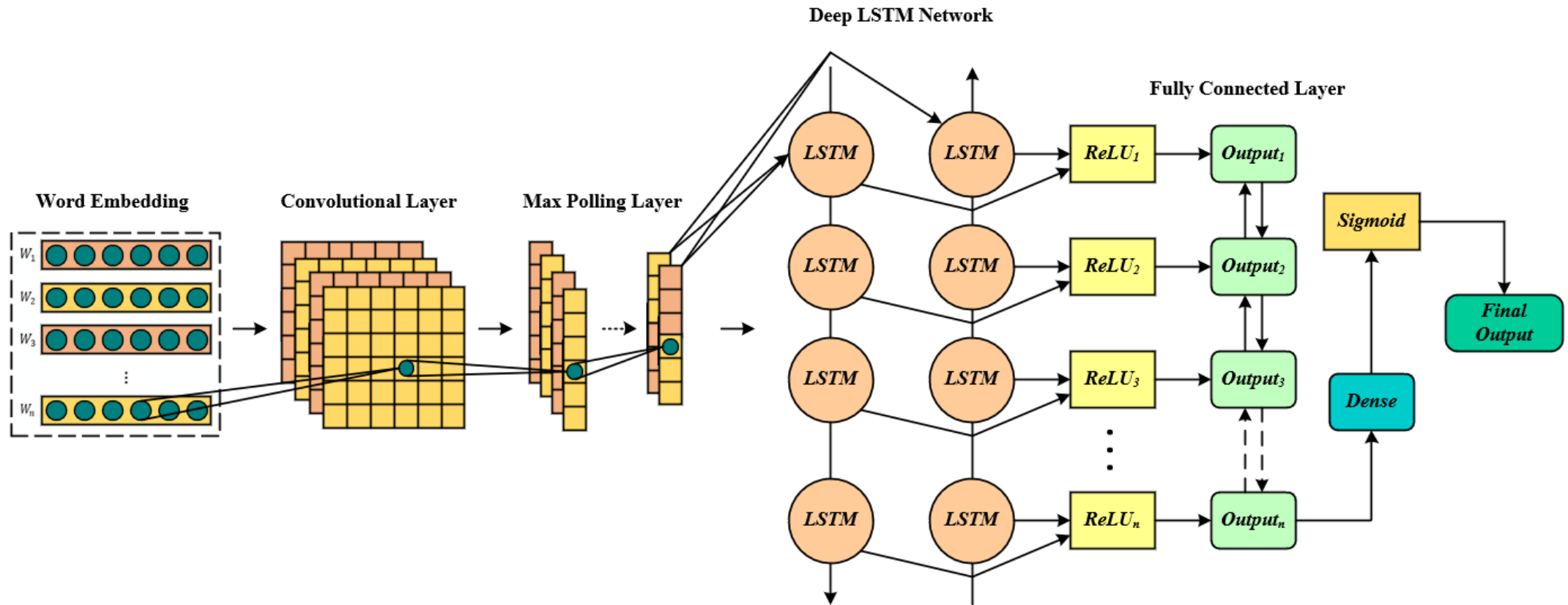




# Sentiment Modelling using Hybrid Convolutional LSTM



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



# Sentiment Modelling using Hybrid Convolutional LSTM

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- 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

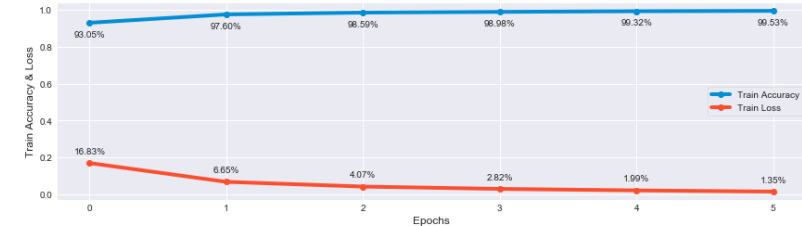


- Training accuracy vs. loss, validation accuracy vs. loss using **CNN + Seq-LSTM** network.

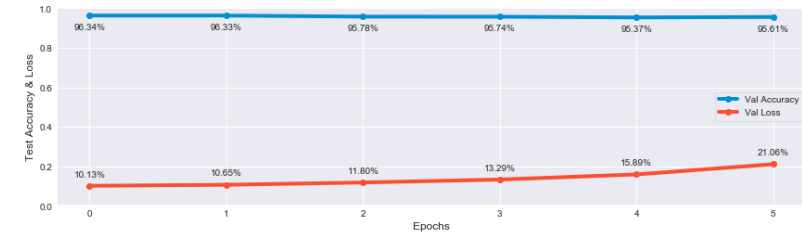
	Epochs	Train Loss	Train Accuracy	Val Loss	Val Accuracy
<b>Covid-19 Dataset I</b> <b>(Apr – Jun, 2020)</b>	<i>Initially</i>	16.83%	93.05%	10.13%	96.34%
	<i>2<sup>nd</sup></i>	06.65%	97.60%	10.65%	96.33%
	<i>3<sup>rd</sup></i>	04.07%	98.59%	11.80%	95.78%
	<i>4<sup>th</sup></i>	02.82%	98.98%	13.29%	95.74%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

Performance Evaluation of Convo-Sequential LSTM Model on Covid-19 Data during Apr - Jun, 2020

Training Accuracy & Loss in per Epochs using CNN + Seq-LSTM

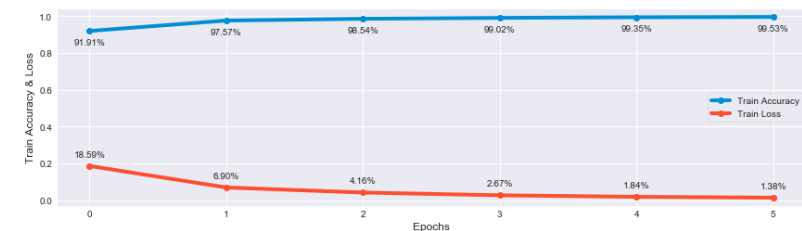


Validation Accuracy & Loss in per Epochs using CNN + Seq-LSTM

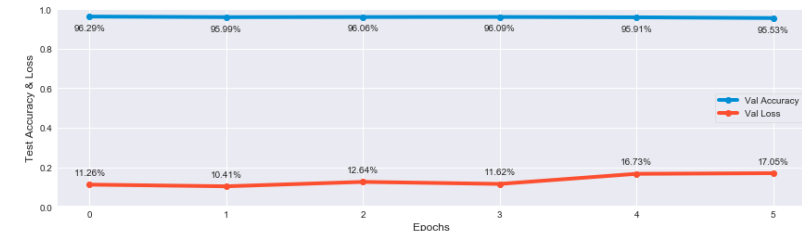


Performance Evaluation of Convo-Sequential LSTM Model on Covid-19 Data during Aug - Oct, 2020

Training Accuracy & Loss in per Epochs using CNN + Seq-LSTM



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

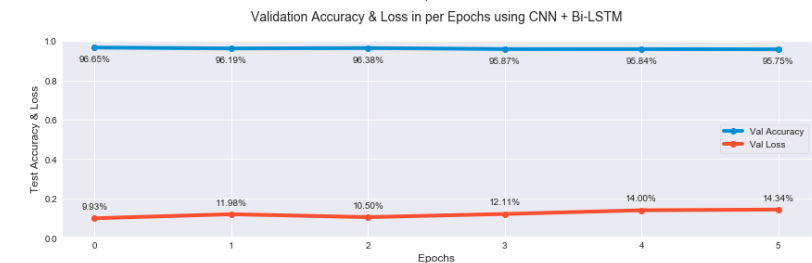
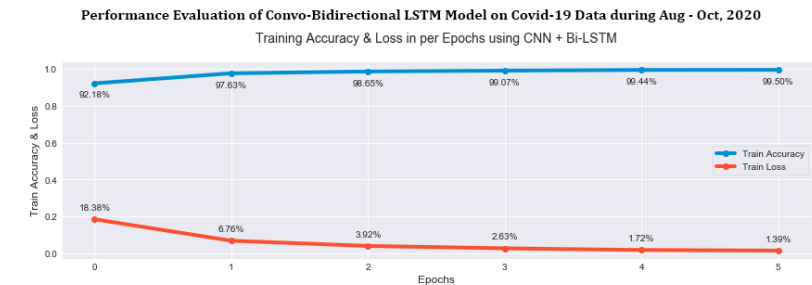
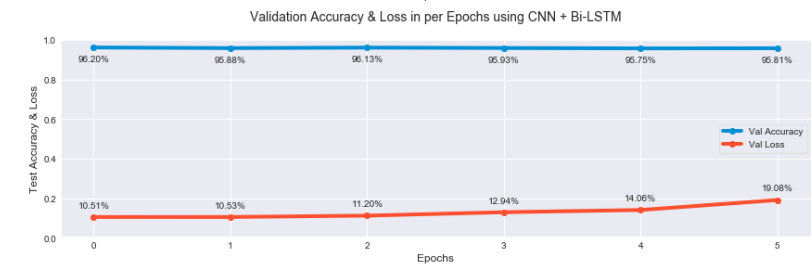
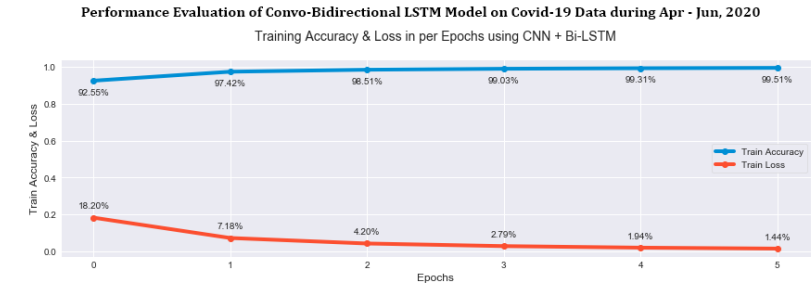


# Sentiment Modelling using Hybrid CNN + Bi-LSTM



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



# 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 <a href="#">[19]</a>	95.62%
CNN + Seq-LSTM w. Naïve Bayes Sentiment Model	95.61%
CNN w. <i>GloVe</i> Embeddings <a href="#">[13]</a>	90.67%
Bayesian Regression w. Tf-Idf <a href="#">[17]</a>	89.40%
ERNIE on Chinese Weibo message <a href="#">[18]</a>	88.00%
Bert on Chinese Weibo message <a href="#">[18]</a>	83.00%
Random Forest <a href="#">[17]</a>	82.20%
LDA + Deep LSTM <a href="#">[14]</a>	81.15%
Logistic Regression w. trigrams + Tf-Idf <a href="#">[15]</a>	81.00%
SVM w. Gaussian Membership based Fuzzy logic <a href="#">[15]</a>	79.00%
LSTM on Chinese Weibo message <a href="#">[18]</a>	78.00%
Deep RNN Model <a href="#">[16]</a>	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	90.44%
CNN + Seq-LSTM w. Naïve Bayes Sentiment Model	90.26%
Ensemble LSTM + CNN <a href="#">[25]</a>	90.00%
CNN + LSTM w. Combined Kernels <a href="#">[21]</a>	89.50%
CNN <a href="#">[25]</a>	89.30%
CNN - LSTM <a href="#">[23]</a>	89.20%
LSTM <a href="#">[25]</a>	89.00%
CNN + LSTM w. Vanilla or Multiword Pre-processing <a href="#">[24]</a>	88.90%
CNN w. Multiword Pre-processing <a href="#">[24]</a>	87.90%
CNN <a href="#">[23]</a>	87.70%
MLP <a href="#">[23]</a>	86.74%
Vanilla Neural Network <a href="#">[22]</a>	86.67%
LSTM <a href="#">[23]</a>	86.64%
LSTM w. Tuning and Dropout <a href="#">[26]</a>	86.50%
SA-LSTM w. Joint Training <a href="#">[26]</a>	85.30%
Recursive RNN <a href="#">[20]</a>	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% <a href="#">[27]</a>	99.91%	99.92%
Stanford Sentiment Treebank (SST) dataset	86.99% <a href="#">[28]</a>	90.07%	90.25%



# Recent Achievement

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- 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](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

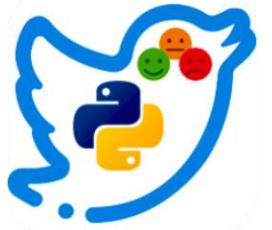
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- For the future work, we will extract the tweets from the datasets for which the Convo-Bidirectional LSTM model performs better than Convo-Sequential LSTM model.
- Further we will use fine-grained classified tweets to train the hybrid deep learning models to ensure the versatility of my proposed system.

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