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Sentiment Classification of COVID-19 Tweets using BERT

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Abstract: The COVID-19 has instigated anxiety with loss of lives. This could have been avoided if the spread was noticed in the early stages of the pandemic. Sentiment analysis is a technique to find out individual's emotion by investigation on social media. In this paper, a methodology is proposed to carry out multi-label classification of COVID-19 tweets using Bidirectional Encoder Representation from Transformer (BERT). The proposed work compares the accuracy of BERT models on the SenWave dataset. The outcomes are indicated by heatmap representation of tweets across labels. The results specify that the greater part of the tweets were joking, empathetic, optimistic, and pessimistic during the COVID-19. The carried work examines the occurrence of Unigrams, Bi-grams with comparative performance of BERT, TinyBERT and DistilBERT.

Keywords: BERT, TinyBERT, DistilBERT, Heatmap, Tweets, COVID-19.

1. Introduction

The COVID-19 sudden occurrence affected people on a massive scale and has disturbed human lives. The COVID-19 pandemic has created challenges in monetary access, food and supply chain, global health, and the work-life balance. Nowadays social media platforms are being processed for extracting the people's opinions about a particular situation.

The attitude or sentiment plays a decisive role in evaluating the behavior of a person. The sentiments can be interpreted and classified into different categories accordingly. Hence, a real time analysis provides insight to the current scenario to make decisions. Sentiments or feelings have been important fraction of public for knowing their activities Coronavirus has also posed a challenge in terms of safety, control, readiness and action by various governments. This has led to a crisis and has triggered the issue of relocation adaptability for health communities. SenWave dataset is designed by collecting millions of tweets to assess the overall increase and drop of sentiments during the outbreak of pandemic. BERT is a deep learning algorithm and applied on text to achieve better results and has sparked a revolution in transfer learning.

The ruthless acute respiratory syndrome coronavirus-2 (SARS-CoV-2) is responsible for the contagious virus known as Coronavirus disease 2019. The first case of the disease was originated in Wuhan, China, in December 2019, and it is thought to have come from there. Since then, the disease has become a major health issue all over the world. After the virus's genome was sequenced, it was discovered that it was genetically related to the 2003 SARS pandemic, which is why it is called SARS-CoV-2. It is not clear where the virus came from. Due to the 96% genome sequence similarity between SARS-CoV-2 and another Coronavirus prevalent in bats, it is speculated that it originated in bats[1-4]. Jain et.al.[5] investigated various measures for twitter emotion assessment utilizing decision tree models and multinomial naive baye’s models. The choice tree acquires the best outcomes with improvement in accuracy and F1-score. Researchers from various nations have attempted to converge and distribute COVID twitter datasets. Pokharel et al.[6] discussed Nepalese attitude towards the COVID outbreak. The tweets from May 21-31, 2020 were collected and specific keywords like CORONAVIRUS and COVID-19 were used.

The transformer is a recurrent or convolution neural network-free sequence and transduction model. The process of transforming a sequence of input of type X into output of type Y is known as transduction. For instance, a sentence can be translated from English to Hindi. The attention mechanism is used by the transformer to model the long-term dependencies between input and output. This indicates that a long sentence's word-to-word relationships has been learned to outline the sequence's context during training. Modeling long-term dependencies with an attention mechanism involves storing network states independently and switching attention between them. First, the encoders store the hidden layer states, and then data from the encoders is sent to the decoding layers. By highlighting some features, this filtering procedure adds context to the decoder. Self-attention tries to figure out how each input in the sequence relates to the other words to boost an improved understanding as stated by the authors [7-13]. Emotions such as anger, fear, joy and sadness, were analyzed using the Indian Twitter data. Additionally, the three other models were compared to the obtained results: LSTM, logistic regression (LR) and support vector machine (SVM). The BERT model had an accuracy of 89 percent, while the other models had an accuracy of 75%, 74.75 % and 65 %, respectively by the authors [14].

A transformer-based BERT model, known as CT-BERT, was applied by the authors[15]. In terms of accuracy of classification, this model outperformed the BERT-LARGE model by 10-30%. The COVID-19 Category dataset had the accuracy value of 94.9% when the CT-BERT was tested on diverse data sets. The authors[16] used the COVIDSENTI data set and found that among transformer-based models (XLNET, BERT, ALBERT and DistilBERT), the BERT model had the highest accuracy of 94.8%. In a similar vein, the Bidirectional LSTM extension was utilized by the authors[17] to develop multi-class sentiment assessment model (SAB-LSTM). In comparison to the LSTM and BLSTM models, this model performed better on news articles and long texts posted on shared media. The addition of additional layers assisted the models in avoiding issues with over fitting and dynamically optimized the model parameters for the given dataset. BERT language model-based sentiment investigation was carried for various geographical related dataset in china, Australia and Nepal, where greater part of sentiment was fear[18]. The authors [19] designed neural network for emotion classification of documents. In a cross-language based sentiment analysis of European tweets, it was found that the lockdown information was correlated with deterioration of mood.

The paper is organizedas follows: Section 2 discusses the steps involved in proposed methodology. Section 3, provides the analysis of experimental outcomes and Section 4 concludes the paper.

2. Proposed Methodology

BERT

BERT model was announced in 2018 by Google. This model distinguishes itself from other models by evaluating the sentence both left-to-right and right-to-left. This guarantees a better comprehension of the word relationships. Masked Language Modeling (MLM) and Next Sentence Prediction (NSP) are the two techniques used to train the BERT. 15% of the sentence's words are replaced with mask tokens. The context is then used by the model to predict those words' original value. Additionally, 10% of the words are substituted at random, while the other 10% percent remain unchanged. Making connections between words is the primary goal of MLM. The embedding matrix is multiplied with the output to obtain vocabulary, and an additional layer is added to the encoder's output to accomplish this. Finally, word probability is calculated using softmax.

NSP exploits the association between sentences, whereas MLM establishes on the relationship between the words in the sentence. Pairs of sentences are fed during the training. NSP anticipates whether the second sentence pursues the first sentence. However, before the model receives the entire sentence, 50% of it is randomly altered. The optimization is carried out with the intention of reducing the overall loss by combining MLM and NSP.

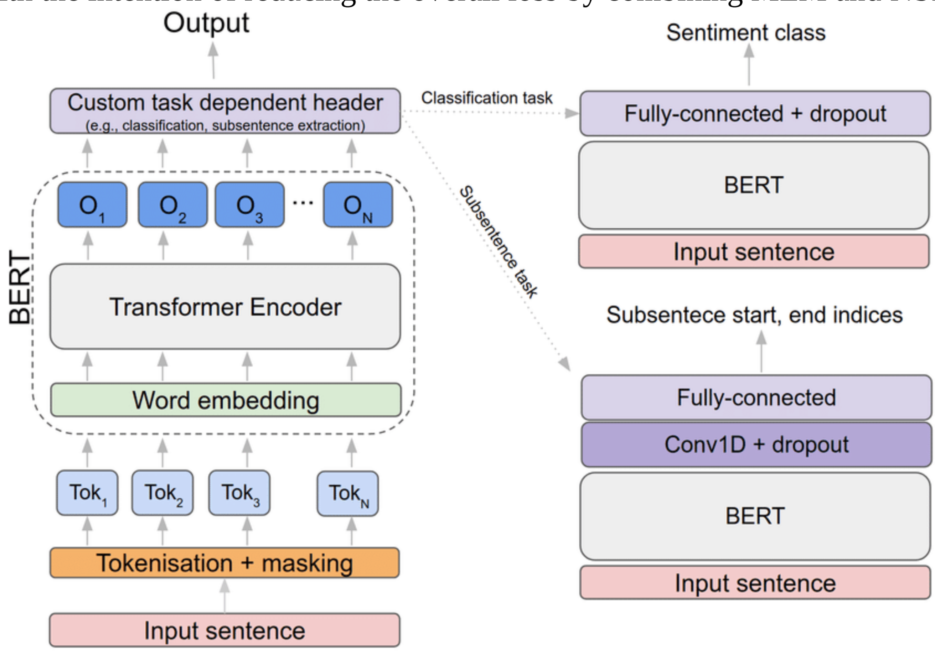


Figure 1. Architecture of BERT Model

Algorithm for Multi Label Sentiment Classification :

Input : Senwave Dataset (Approx 1000 English tweets).
Output : Computing accuracy of BERT Models.
Step 1 : Pre-processing of dataset by removing stop words and lemmatization.
Step 2 : To obtain a plot of Unigrams and Bi-grams from March to July’2020.
Step 3 : To split dataset into train(70%) and test set(30%).
Step 4 : Apply the BERT variants and obtain the heatmap representation.
Step 5 : To assess the accuracy of multi-label classification
End

3. Experimental Results

A. Analysis of tweets by BERT

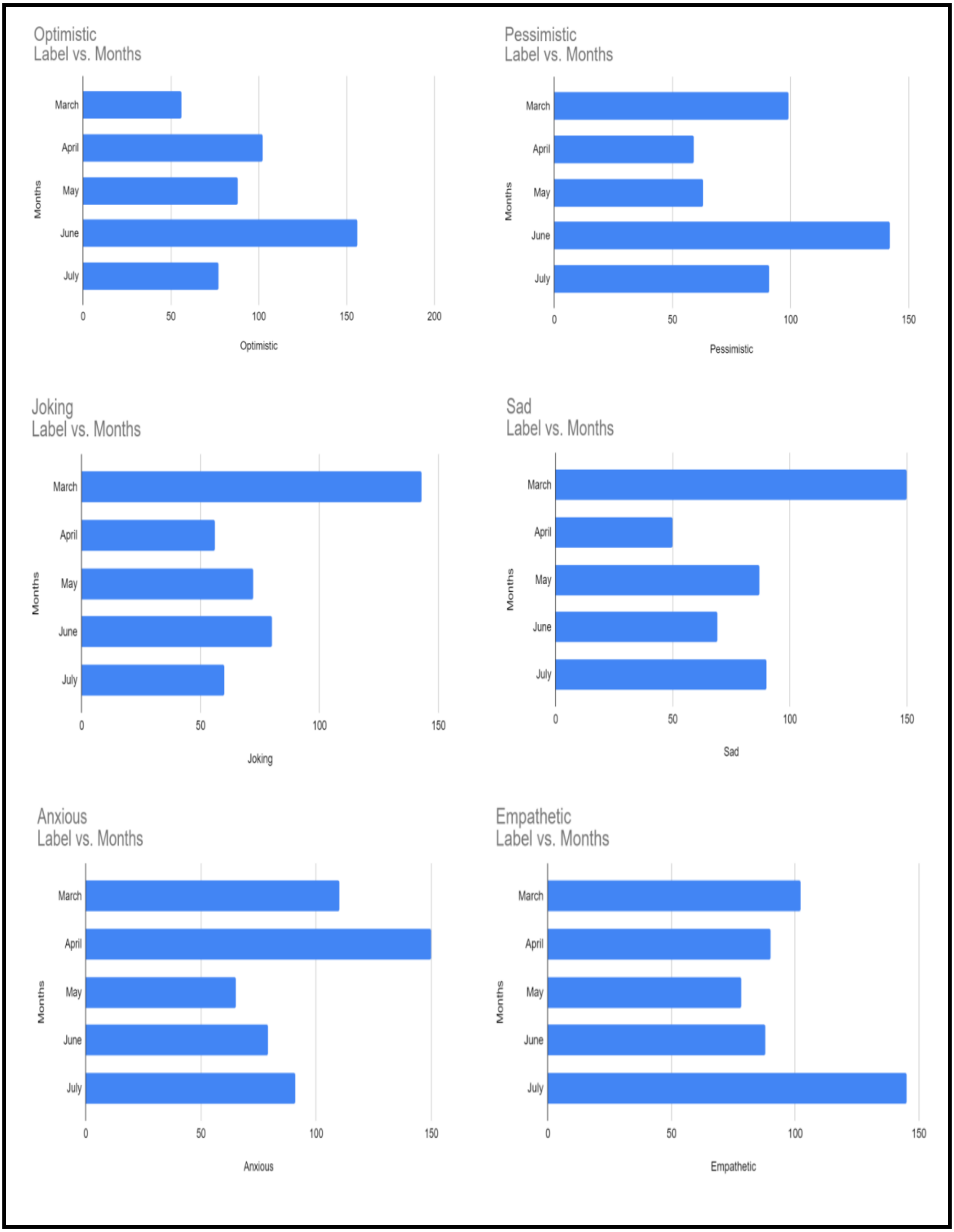


Figure 2. BERT based sentiment occurrence in SenWave dataset from March to July of pandemic.

	Optimistic	Pessimistic	Joking	Sad
Optimistic	70	119	32	97
Pessimistic	119	44	90	110
Joking	32	90	140	60
Sad	97	110	60	77

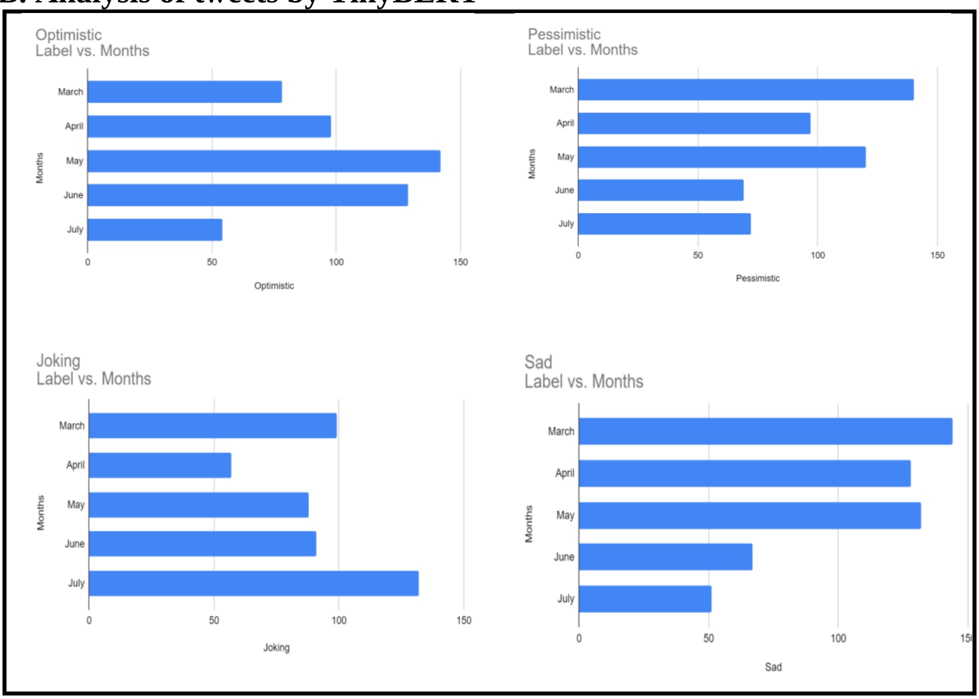
	Optimistic	Pessimistic	Joking	Sad	Anxious
Optimistic	102	92	41	88	9
Pessimistic	92	57	69	130	107
Joking	41	69	137	45	99
Sad	88	130	45	110	49
Anxious	9	107	99	49	168

	Optimistic	Pessimistic	Joking	Sad	Anxious	Surprise
Optimistic	33	170	77	32	40	55
Pessimistic	170	88	65	110	139	45
Joking	77	65	150	43	80	99
Sad	32	110	43	100	120	50
Anxious	40	139	80	120	99	67
Surprise	55	45	99	50	67	160

	Optimistic	Pessimistic	Joking	Sad	Anxious	Empathetic	Surprise
Optimistic	95	88	70	46	44	50	130
Pessimistic	88	99	56	110	78	39	60
Joking	70	56	170	27	77	67	92
Sad	46	110	27	65	81	93	60
Anxious	44	78	77	81	55	42	106
Empathetic	50	39	67	93	42	142	33
Surprise	130	60	92	60	106	33	167

Figure 3. BERT based sentiment heatmap with 4-7 sentiments for 1000 tweets on SenWave dataset

B. Analysis of tweets by TinyBERT



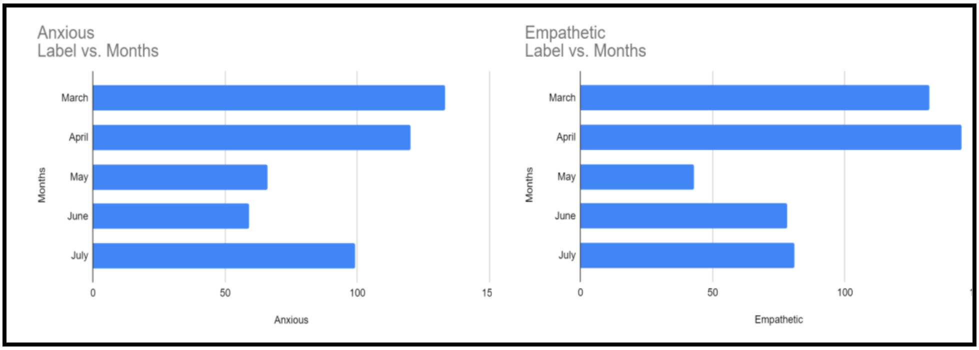


Figure 4. TinyBERT based sentiment occurrence in SenWave dataset from March to July of pandemic.

	Optimistic	Pessimistic	Joking	Sad
Optimistic	67	33	99	44
Pessimistic	33	81	43	156
Joking	99	43	102	76
Sad	44	156	76	119

	Optimistic	Pessimistic	Joking	Sad	Anxious
Optimistic	167	37	164	44	52
Pessimistic	37	44	78	57	132
Joking	164	78	83	66	94
Sad	44	57	66	99	81
Anxious	52	132	94	81	102

	Optimistic	Pessimistic	Joking	Sad	Anxious	Surprise
Optimistic	55	43	31	47	90	32
Pessimistic	43	107	57	88	63	95
Joking	31	57	81	143	33	50
Sad	47	88	143	92	41	166
Anxious	90	63	133	41	69	49
Surprise	32	95	50	166	49	100

	Optimistic	Pessimistic	Joking	Sad	Anxious	Empathetic	Surprise
Optimistic	99	67	34	51	49	76	66
Pessimistic	67	103	122	33	61	103	90
Joking	34	122	166	81	70	143	27
Sad	51	33	81	59	92	60	50
Anxious	49	61	70	92	47	64	29
Empathetic	76	103	143	60	64	70	144
Surprise	66	90	27	50	29	144	81

Figure 5. TinyBERT based sentiment heatmap with 4-7 sentiments for 1000 tweets on SenWave dataset.

C. Analysis of tweets by DistilBERT

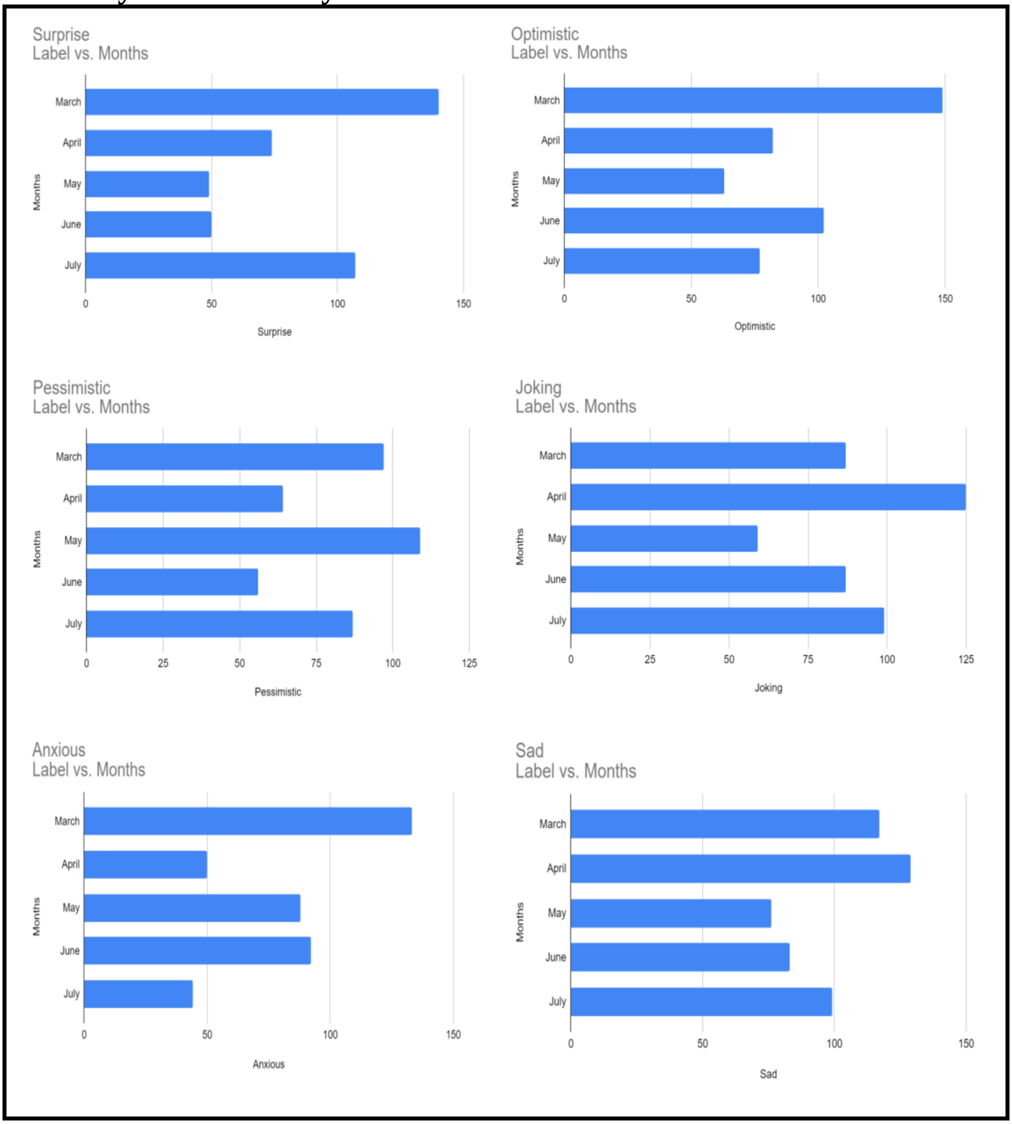


Figure 6. DistilBERT based sentiment occurrence in SenWave dataset from March to July of pandemic.

	Optimistic	Pessimistic	Joking	Sad
Optimistic	100	34	78	43
Pessimistic	34	159	65	88
Joking	78	65	163	45
Sad	43	88	45	99

	Optimistic	Pessimistic	Joking	Sad	Anxious
Optimistic	99	55	43	78	37
Pessimistic	55	137	83	62	73
Joking	43	83	156	87	102
Sad	78	62	87	100	94
Anxious	37	73	102	94	76

	Optimistic	Pessimistic	Joking	Sad	Anxious	Surprise
Optimistic	65	49	119	57	77	40
Pessimistic	49	117	123	33	56	89
Joking	119	123	170	132	78	29
Sad	57	33	132	55	154	31
Anxious	77	56	78	154	67	77
Surprise	40	89	29	31	77	80

	Optimistic	Pessimistic	Joking	Sad	Anxious	Empathetic	Surprise
Optimistic	44	27	67	55	91	147	33
Pessimistic	27	120	42	60	49	73	47
Joking	67	42	144	29	39	167	101
Sad	55	60	29	77	44	51	55
Anxious	91	49	39	44	98	79	85
Empathetic	147	73	167	51	79	75	120
Surprise	33	47	101	55	85	120	99

Figure 7. DistilBERT based sentiment heatmap with 4-7 sentiments for 1000 tweets on SenWave dataset

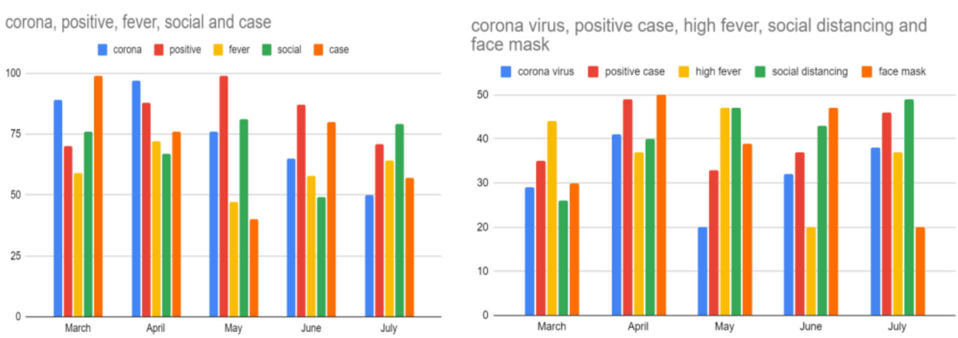


Figure 8. Plot of Unigrams and Bigrams from the dataset.

Table I. Sentiment occurrence from March to July 2020.

BERT	Optimistic	Anxious	Pessimistic	Empathetic	Joking	Surprise	Sad
March	56	110	99	102	143	74	150
April	102	150	59	90	56	98	50
May	88	65	63	78	72	56	87
June	156	79	142	88	80	66	69
July	77	91	91	145	60	41	90

Tiny BERT							
March	149	133	97	129	87	90	117
April	82	50	64	102	125	88	129
May	63	88	109	132	59	145	76
June	102	92	56	67	87	100	83
July	77	44	87	80	99	61	91
Distil BERT							
March	78	133	140	132	132	140	144
April	98	120	97	144	144	74	128
May	142	66	120	43	43	49	132
June	129	59	69	78	78	50	67
July	54	92	72	81	81	107	51

Table II. Performance metrics of the models

Models	Accuracy
BERT	77%
TinyBERT	72%
DistilBERT	74%

4. Discussion

Figure 2, 4 and 6 provide the number of occurrences of a given sentiment from March to July 2020. Figure 3, 5 and 7 provide a co-occurrence to the rest of the sentiments. It was found that some of the prominent sentiments were *joking*, *pessimistic* and s*ad*. Also it was found that most tweets that were associated with *joking* are either *sad.* About 21% of the tweets have two sentiment associated to them and 7% have no sentiment. An insignificant number of tweets have 3 or more emotions associated to them which indicate that populace does not show multiple emotions at the same time. The accuracy with BERT is relatively significant than the other BERT variants.

5. Conclusion

In this paper, a method is proposed to perform multi-label classification of COVID-19 tweets using Bidirectional Encoder Representation from Transformer (BERT). The proposed work compares the accuracy of BERT models on the SenWave dataset. The outcomes are indicated by heatmap representation of tweets across labels. The results specify that the greater part of the tweets have been empathetic, joking, optimistic and pessimistic during the COVID-19 period. The carried work examines the occurrence of Unigrams, Bi-grams, and sentiment labels during the pandemic period.

As a part of future work, the proposed work can be extended for different for geographical places to know their behavior.

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