UNVEILING THE EMOTIONAL LANDSCAPE OF COVID-19: A SENTIMENT ANALYSIS STUDY

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Abstract: The COVID-19 pandemic has a rampant aftermath on the lives of human beings. The new normal i.e., the period after this horrific pandemic is not normal at all and has displayed a profound effect on the world. The impact of COVID-19 is far beyond the health sector only, huge ups and downs have taken place in every sector, especially the global economics. It has made drastic disruptions in industries causing colossal closure of businesses and job losses. The dogma of online meetings and work from home has become a common phenomenon across the globe. The social media platforms chiefly Twitter has been the weapon of mundane man to express his viewpoints (happiness, sadness or sorrow) during the lockdown and new-normal time intervals. The proposed approach focuses on conducting twitter sentiment analysis for better understanding of pandemic. Multiple machine learning and deep learning approaches are applied on two COVID-19 datasets undertaken and evaluated on the basis of evaluation metrices.

Keywords: COVID-19, Deep Learning, Machine Learning, Pandemic, Sentiment Analysis, Twitter.

1. Introduction:

COVID-19, the abbreviation for Coronavirus Disease 2019, has had a profound impact on the world since its emergence in late 2019. This highly contagious respiratory illness is caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), a novel virus that belongs to the coronavirus family. The virus spread rapidly, resulting in a global pandemic and affecting millions of people worldwide. One of the key challenges posed by COVID-19 is its transmission. The virus primarily spreads through respiratory droplets when an infected person coughs, sneezes, talks, or breathes. Close contact with an infected individual or touching surfaces contaminated with the virus and then touching the face can also lead to transmission. This mode of spread contributed to the rapid global dissemination of the virus. The symptoms of COVID-19 can range from mild to severe. Common symptoms include fever, cough, sore throat, fatigue, body aches, and shortness of breath. In some cases, individuals may experience loss of taste or smell. While most people experience mild to moderate symptoms, severe cases can lead to pneumonia, acute respiratory distress syndrome (ARDS), and organ failure, particularly in older adults and those with underlying health conditions[1].

To combat the spread of COVID-19, governments and health organizations worldwide implemented various measures. These included social distancing, travel restrictions, widespread testing, contact tracing, and the promotion of proper hand hygiene. In addition, the development and distribution of vaccines played a crucial role in controlling the pandemic. Vaccines, such as those developed by Pfizer-BioNTech, Moderna, and AstraZeneca, have been authorized for emergency use and have been administered to millions of people globally.

The impact of COVID-19 extended beyond the health sector. It significantly affected the global economy, leading to job losses, business closures, and disruptions in various industries. Education systems faced challenges as schools and universities had to adapt to remote learning. The travel and tourism industry suffered a significant blow due to travel restrictions and reduced demand. Mental health concerns also arose as people grappled with isolation, anxiety, and uncertainty[2]. Healthcare systems faced tremendous strain due to the surge in cases, with hospitals and healthcare workers working tirelessly to treat patients. The importance of personal protective equipment (PPE), such as masks, gloves, and gowns, became evident as they helped protect healthcare workers from infection. Scientific research and collaboration accelerated as experts worldwide raced to understand the virus, develop treatments, and improve testing capabilities. The figure 1 displays the clinical implications of the COVID-19 virus:

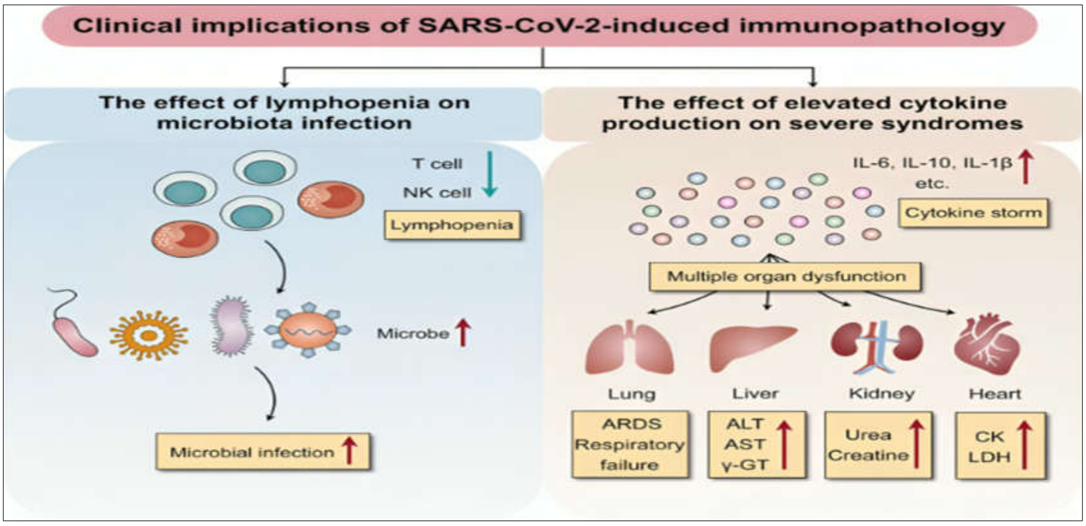

Fig 1: Clinical Implications of SARS-CoV-2 Disease [3]

The pandemic also highlighted existing societal inequalities. Certain populations, including the elderly, racial and ethnic minorities, and those with lower socioeconomic status, were disproportionately affected by COVID-19. Access to healthcare, testing, and vaccines became critical issues, and efforts were made to address these disparities.

As the world continues to battle COVID-19, ongoing vigilance and adherence to public health guidelines remain essential. Although vaccines provide hope, achieving global vaccination coverage and monitoring the emergence of new variants are ongoing challenges. It is crucial to stay informed through reliable sources, follow public health guidelines, and support each other during these trying times. COVID-19 has reshaped societies and reminded the mankind of the importance of global cooperation in combating infectious diseases[4]. It has highlighted the resilience and dedication of healthcare workers, scientists, and communities around the world. By learning from this experience and implementing effective strategies, humans can better prepare for future pandemics and work together to protect the health and well-being of humanity. The chief contribution of this research twofold: first, extrapolate sentiment-related data from tweets for automatically feature learning and second, compare the machine learning, deep learning and transformer-based approaches on data extracted from Twitter.

In the following sections, the related word will be presented in section II, followed by the data and method in section III which will give the detailed description of the datasets undertaken for the study and the proposed methodology to carry out the research. The subsequent section IV discusses the results obtained from the experiments and presents the analysis on it. Finally, section V concludes the findings and also proposes the direction of future work.

2. Literature Review:

Since the outbreak of this deadly virus from the Wuhan, China (it is still controversial to say the exact origin – animal market or laboratory), the scientists have tried to detect its actual cause, symptoms, preventions and cures. The data scientists have also poured huge effort in predicting its outreach or categorizing social media comments for checking on the mental condition of the affected people. However, it must be understood that social media messages can be very vague sometimes and need to be pre-processed before application of machine learning or deep learning tools[5]. This section details the related work using either rule-based approach, machine learning or deep learning in the recent past.

The first research is based on the data extracted from Twitter using Tweepy library based on simple hashtags related to novel coronavirus and later, used for sentiment analysis on COVID-19. Simple tools TextBlob library of Python is used for carrying out the opinion mining and also visualization is presented for better understanding[6].

The second study examined the themes and opinions on COVID-19 discussed on Twitter platform. All the collected tweets concerning COVID-19 were classified into three categories namely positive, neutral and negative. Later on, myriad feature sets and classifiers were employed to determine the sentiment behind the tweets. Out of all the classifiers, Bidirectional Encoder Representations from Transformers (BERT) model yielded the best accuracy in this study, which is 94.80%. The chief dearth in this study is the use of only accuracy as the evaluation metric instead of involving more measures like precision and recall[7].

Another research article describes a novel word-embedding methodology that employs the co-occurrence statistics of the words along with identification of contextual semantic meaning. A large text corpora extracted from Twitter platform is undertaken here and unsupervised approach is employed here in cooperation with Convolution Neural Networks (CNN) to carry out opinion mining[8].

Springer's research paper from 2018 states that due to unprecedented conditions of COVID-19, people were forbidden to go out and they spent most of their time on social media platforms. The opinion mining on this data is proposed using Hybrid Heterogeneous Support Vector Machine (H-SVM) and it is compared with other existing standards using the evaluation metrices. The experiment results reveal that the proposed approach is better than SVM and Recurrent Neural networks[9].

The authors of next study had conducted research on sentiment analysis during lockdown times in India. "Janta Curfew" was suggested by India Prime Minister in late week of March 2020 and Indians took out to online platforms to outburst their sentiments. Some of these sentiments were extracted from Twitter and mined using R language for their positive, neutral or negative sentiments. The study reveals that the Indians had a mixed emotions about the Coronavirus lockdown, social distancing and practicing the standard hygiene measures[10].

A similar kind of research was carried out in Indonesia for COVID-19 vaccine. Data scrapping tool like Rapid miner tool and Drone Emprit Academic Streaming Public Twitter were used to obtain Tweets for specific location i.e., Indonesia and specified time interval. Using Naïve Bayes machine classifier, the authors claim that most of the Indonesian people had negative opinions about the COVID vaccine[11].

A separate research article claims that most of the sentiment analysis work on COVID-19 is not consistent due to the restrictions of the lexicon approach and unstructured format of the social media messages. To handle this quandary, a special version of Bidirectional LSTM (SAB-LSTM) is utilized, and the experimental outcomes display that the envisioned method outperforms both LSTM and BiLSTM in terms of accuracy, precision, recall and F1-measure. This study was based on multiple social platforms like Facebook, YouTube, Twitter and Blogs on COVID-19[12].

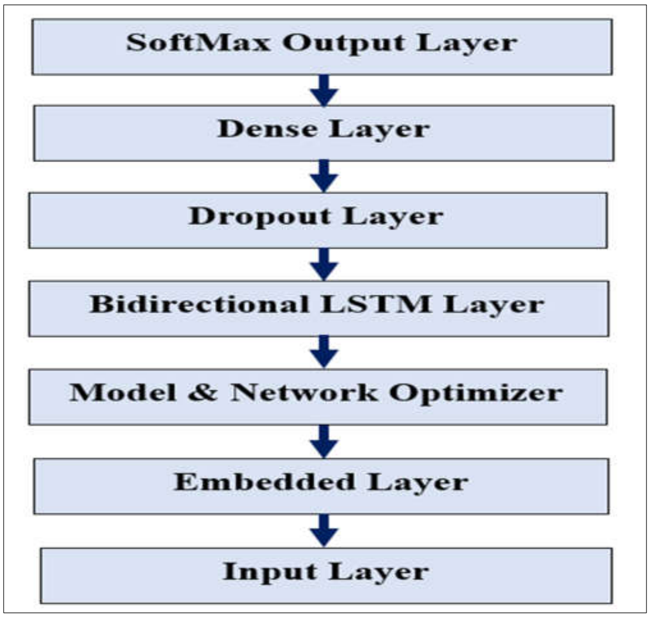

Fig. 2. Structure of SAB-LSTM[12]

The recent research on COVID-19 reveals that the deep learning classifiers are better than the natural language processing and machine learning algorithms when it comes to opinion mining of the social networking sites. The research is carried on ample datasets and in multiple languages, so that the power of deep learning can be revealed on the sentiment analysis problems[13].

Regarding research of social media messages, a study claimed that the news, awareness and gossip about the pandemic spread at more pace than the disease itself. This information flow concerning COVID-19 was captured from the earlier waves into a bigger dataset COVIDSENTI (containing approximately 90,000 tweets). Transformers like BERT, DistilBERT, ALBERT, and XLNET were employed here to set the benchmark for sentiment analysis[14].

Additionally, one research approach describes how the people belonging to different cultures respond to the COVID-19 crisis and how socio-political scenarios influence people reactions and response towards the pandemic. The study also displayed that even the people from neighbouring countries bear exactly opposite views on this ghastly disease. Here, the deep neural network like Long Short-Term Memory (LSTM) is employed for sentiment classification of data. This supervised approach is utilized on emoticons also to prove their usefulness in detecting the individual's sentiment towards COVID-19[15].

3. Data and Methods:

3.1 The Datasets

Selection of datasets is a very pivotal point in the research as a dataset should be balanced between positive and negative aspects, but it is not possible on the unsupervised data collected from Twitter. This dataset which is utilized for carrying out the opinion mining process, namely "*COVID-19 Twitter Dataset*". The first dataset contains three files containing tweets for separate lockdown periods and a total of 2,71075 tweets scrapped from the Twitter microblogging site. The APIs like Tweepy and GOT (Get Old Tweets) are exploited here for extraction of tweets from Twitter for specific time and locations[16]. It is vital to understand that the tweets in English language are only targeted here, instead of going for multiple languages. The tweets in other languages are omitted here to keep the work simple and focused.

3.2 Text Preprocessing

Information collected from social networking sites is not always structured as the individuals need not follow any specific rules except for the message length (like in Twitter). Also, the raw tweets may be informal and noisy[17]. This causes havoc for the data scientists as this data needs to be processed before going for the clustering and information extraction phases. The following steps are followed for the data preprocessing:

1) Lower the uppercase letters: In this basic step, all the letters (whether uppercase or lowercase) are converted to lowercase for easier processing of data. This is done as social media users do not follow the usual grammar rules for natural languages. For example: Twitter, twitter and TWITTER refer to the same thing, yet considered different words as most of the programming languages are case sensitive.

2) Remove the user references and hyperlinks: As the data undertaken in this study is taken mostly from the social media sites, a lot of users refer to other users for commenting or replying on their social posts. Also, some users post URLs for giving out references to some other useful websites. Both of the user references using hashtag(#) and URLs are removed from the data for a better text processing.

3) Remove digits: The text may contain random digits or numerals which do not affect the semantic meaning of the post and hence needs to be eradicated. Also, the amalgamation of letters and digits may cause bamboozlement.

4) Remove Stopwords: Stopwords are the frequent words like 'a', 'an', 'in', 'on', 'the', etc., which just add weight to the bag of words but do not actually contain valuable information. These stopwords are also deducted from the data to check for the useful words only.

5) Remove repeated letters: The users of social media write extra letters in some vital words to enhance their importance. For example: "Looovvveee the way Hritik Roshan dddannceesss" is same as "Love the way Hritik Roshan dances". Hence, to enhance the textual meaning, the repeated letters should be eliminated.

Apart from the above-mentioned ways, some other pre-processing is also done like elimination of abbreviations, shortened forms, punctuation symbols, etc.

3.3 Feature Extraction

After the pre-processing of data, it is ready for analysis and is represented as Bag-of-Words (BoW). However, some kind of processing still needs to be done like tokenization, stemming or lemmatizing of these words and also getting their related POS tags. Tokenization can be defined as a process by which the sentence is divided into small understandable chunks terms/ words. Part-of-Speech (or POS) tags identifies the type of word like noun, pronoun, adverb, adjective, etc., depending upon its definition and context. Text Lemmatization refers to the process where a word is reconverted to its root form. For example: words like "changing" and "changed" are converted to "change". Lemmatizing is considered better than stemming due to ability to consider context while word transformation[18].

After the elementary processing, the most imperative step is to extract the critical features and there are multiple approaches to achieve that. The aspect extraction techniques can be classified either as frequency based (POS tagging thresholding, PMI, TF-IDF, etc.) or Relation-based (Dependency Parser, Double Propagation, etc.) or Supervised Learning (CRF, HMM, etc.) or Unsupervised Topic Modeling (LDA, JST, ASUM, etc.). Apart from all of the above, word embedding techniques can also be employed.

The first text vectorization technique used in this study is the Term Frequency-Inverse Document Frequency (TF-IDF), which evaluates significance of a particular word in the given document. It is a statistical tool that diminishes the highly frequent stopwords and identifies the highly opinionated words that are vital for sentiment analysis. The first term (TF) is the ratio of a word's frequency in a document to the total number of words in that document. The second term (IDF) is calculated by dividing the logarithm of the total number of documents in the corpus by the quantity of documents containing the specific word[19]. Although TF-IDF proves to be a very effective technique for implementation of machine learning algorithms but is not likely the best option for deep learning algorithms and transformers. Hence, Global Vectors for word representation (or GloVe) which is an extension of Word2Vec paves the way. It was developed at Stanford University as an unsupervised learning for acquiring vector illustration of words[19].

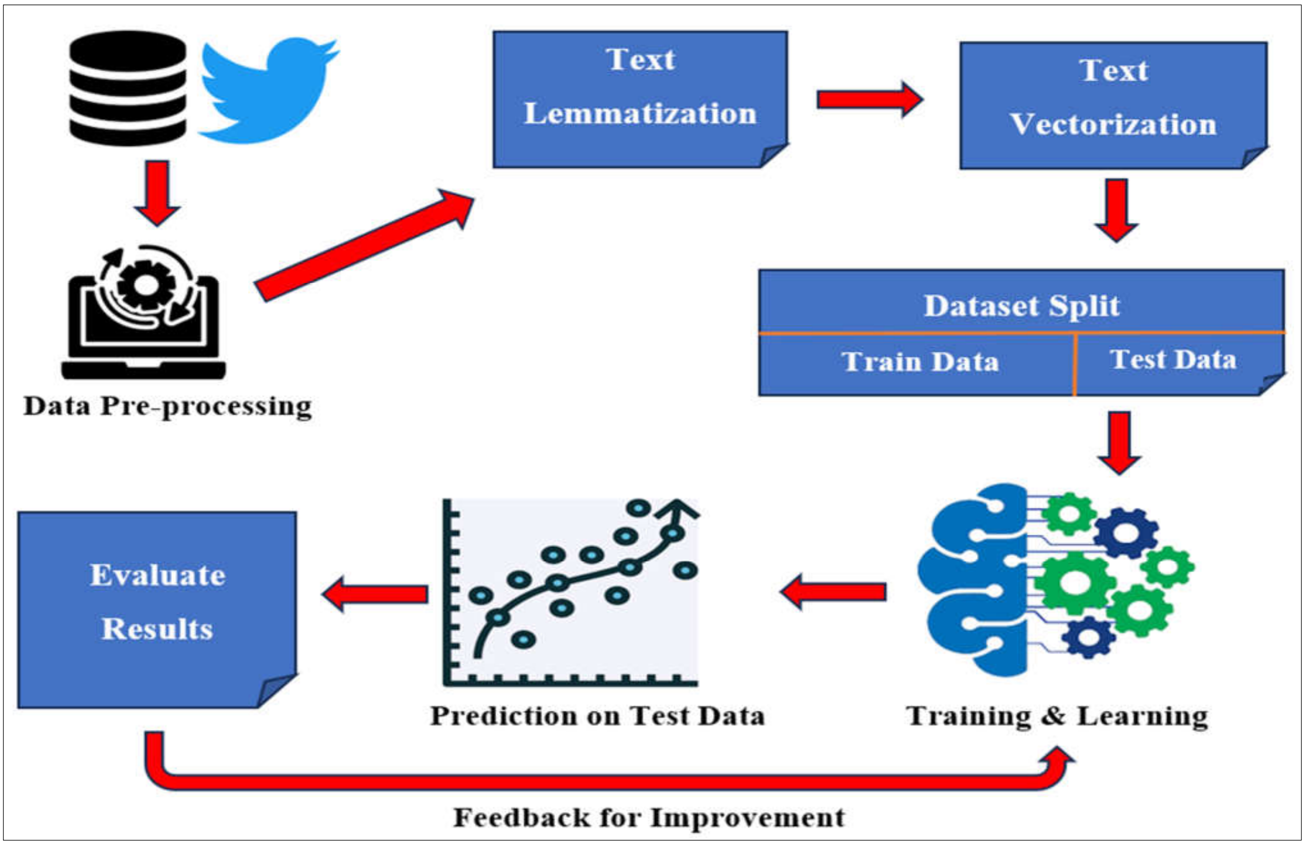

Fig 3: The Proposed Methodology

An important consideration here is that these pre-trained vectors come in various shapes and sizes; and can be easily downloaded from the internet. The GloVe embedding used in this study contains six billion words and one hundred dimensions.

3.4 Machine Learning Models

Machine learning is a specialized field of Artificial Intelligence that focuses on self-learning of computer without the need of programming. It is the force behind the chatbots, recommendation systems, autonomous vehicles, social media feeds, etc. Every corporate is utilizing this exceptional phenomenon to better understand their client requirements and also make valuable predictions. The usual programming requires a step-by-step detailed instruction, while machine learning lets the computer learn on its own. The best part about machine learning is that the input data could be anything from numbers to text to images. The computer gathers this data, trains on it and then applies its learning on test data. If the data provided for training is more, then the learning is also better compared to training with lesser data[20]. There is plethora of machine learning algorithms which are available chiefly Support Vector Machine (SVM), Naïve Bayes (NB), K-Nearest Neighbour (KNN), Decision Trees (DT), Random Forests (RF), etc. Apart from the standard machine learning algorithms, some ensemble approaches like bagging and boosting algorithms can also be utilized to boost the efficiency like adaptive boosting, Gradient and XGBoost, etc.

3.5 Deep Learning Models

Deep learning is the sub-domain of machine learning that yields even superior results for regression and classification. It can be considered as a black box compared to machine learning's white box i.e., deep learning is a complex structure based on human brain and provides an awe-inspiring approach to process unstructured data. The artificial neural network is modeled after the human neural network and this complex structure is good for natural language processing, speech recognition and digital image processing[20]. The core concept behind deep learning is the capacity of neural networks to learn from huge amounts of data and apply that learning to increase the performance manifold.

3.6 Transformer-based Language Models

Transformer-based Language Models (TLMs) or simply Transformers are defined as the enhancement of deep learning models that apply an embryonic set of statistical and mathematical functions called "self-attention" to determine the context and meaning by pursuing relationships between words of a sentence. Modern pretrained models with parallel processing and pattern-recognition features can be simply downloaded and trained using the APIs and tools provided by transformers[21]. Pretrained models are helpful in saving time, money, and resources by reducing your computing expenses. Some of widely distinguished transformers are BERT, ROBERTa, ChatGPT, XLNET, etc. One main characteristic of TLMs is the encoder-decoder structure. The former part - "encoder" takes all words of a sentence at once and converts them into sequence of numbers. This sequence is then fed to the self-attention layer which uses the data to learn and then predict about the other text from same input. At the end of this phase, the intermediate data is then passed onto a feed-forward neural network. The later part - "decoder" is similar in functionality to the encoder part. It has an additional self-attention layer that augments its ability of prediction. These language-based transformers are better as they input all words of a sentence rather than inputting only a few selected words; and this enhanced parallel processing of data makes it a more suitable choice for the tasks of natural language processing.

4. Experimental Results and Analysis:

This section weighs up the sentiment analysis on two datasets related to COVID-19 and tries to benchmark the experimental results. The implementation of this work is carried out using Google Colab so that the hardware limitation of the laptop/ computer does not affect the efficacy of the implemented algorithms. Subsequently, the data is then bifurcated into train and test data in 70:30 ratio i.e., 70% of data is used for training and the remaining 30% data is used for testing. Later on, the data is subjected to training and learning using one of the three methods (machine learning, deep learning or transformers models) and then used the derived models are used for prediction on the test data. Lastly, the results are evaluated, and the feedback is also utilized for improvement of the experimental results.

The dataset extracted using tweets contains sentiments which are classified into positive, neutral and negative using VADER. Valence Aware Dictionary for Sentiment Reasoning (VADER) is a machine learning tool that can be employed to find polarity as well as emotion's intensity. The sentiment distribution can be visualized using the figure 4 below.

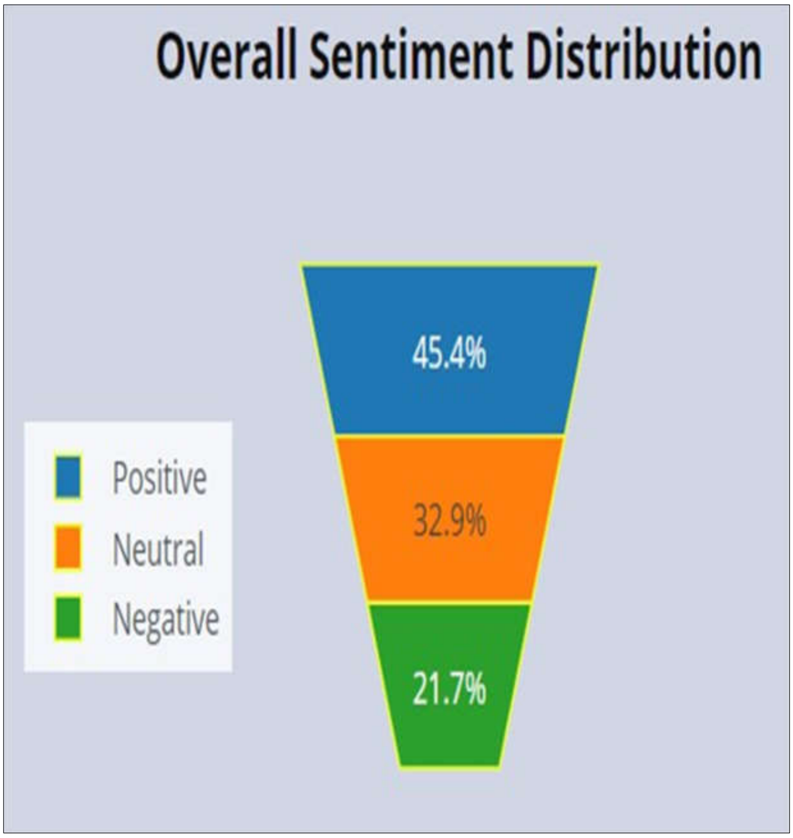

Fig. 4. Sentiment Distribution of Tweets

As clearly visible, nearly 45% of the total tweets contain a positive sentiment even in the dire and unprecedented conditions during COVID-19. Approximately, 33% of the twitter users express neutrality in their social media messages i.e., their tweets cannot be categorized into either of the positive or negative polarities. Finally, only 22% users displayed the negative opinions (approximately) regarding COVID-19 or related issues.

Consequently, the principal aspects are identified which are actually the chief features in the datasets. Some of these features are namely COVID19, pandemic, social distancing, lockdown, immune system, mask, etc., which are shown using a wordcloud in the figure 5.

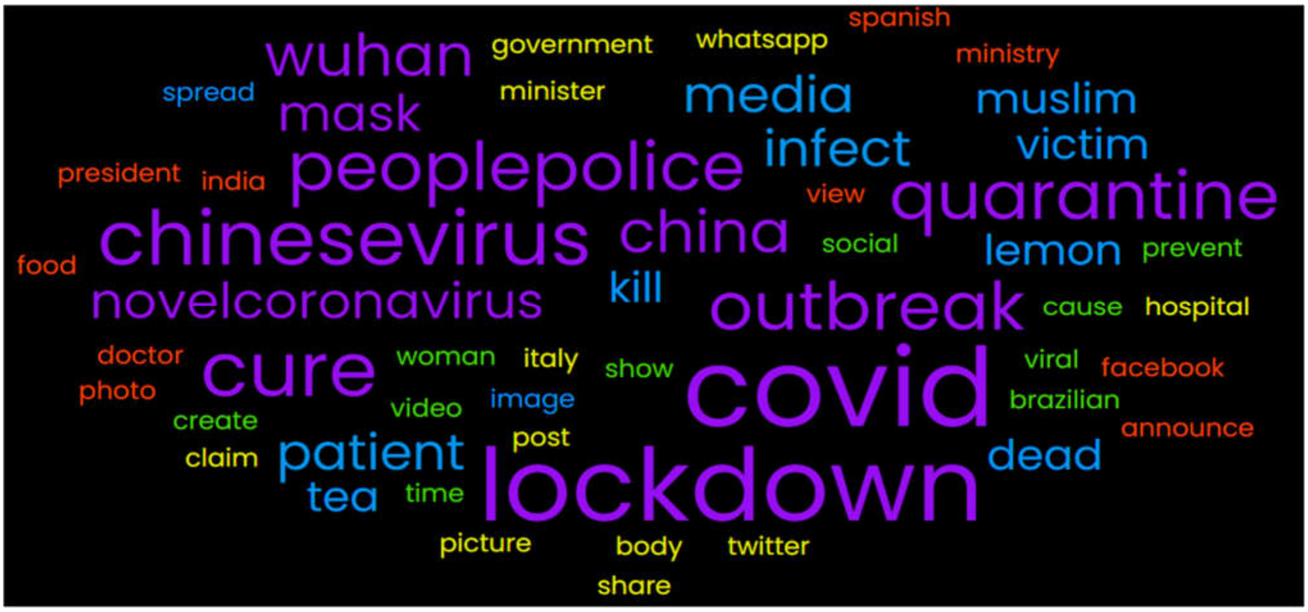

Fig 5. Wordcloud of Chief Aspects

The optimal value of hyperparameters used for the training are depicted in the table 1 below.

Table 1. Values of Hyperparameters

Number of Epochs	50
Batch Size	64
Optimizer	Adam
Learning Rate	0.001
Dropout	0.4
Output Layer Activation Function	Sigmoid
Loss Function	Binary_crossentropy
Maximum Length	148

The evaluation metrices used in this case study are Accuracy, Precision, Recall and F1-score. The next table 2 shows the evaluation measures for the machine learning algorithms. All these models have Valence Aware Dictionary for Sentiment Reasoning (VADER) used for sentiment polarity, Term Frequency-Inverse Document Frequency (TF-IDF) for text vectorization and Principal Component Analysis (PCA) for dimensionality reduction. Afterwards, the prime machine learning algorithms or classifiers like Support Vector Machine (SVM), Naïve Bayes (NB), K-Nearest Neighbour (K-NN), Decision Trees (DT) and Adaptive Boosting (AdaBoost) applied to the data. The accuracy, precision, recall and F1-score percentages are displayed in the figure 6 below. As visible from the image, the values of ensemble approach especially the AdaBoost outclasses all other conventional machine learning algorithms.

Table 2. ML Classifiers on COVID Dataset

Algorithm	Accuracy	Precision	Recall	F1-Score
SVM	83.65	90.81	88.06	89.41
NB	76.21	81.67	73.53	77.39
K-NN	79.83	83.26	85.04	84.14
DT	74.01	79.31	77.92	78.60
AdaBoost	87.31	96.06	89.28	92.55

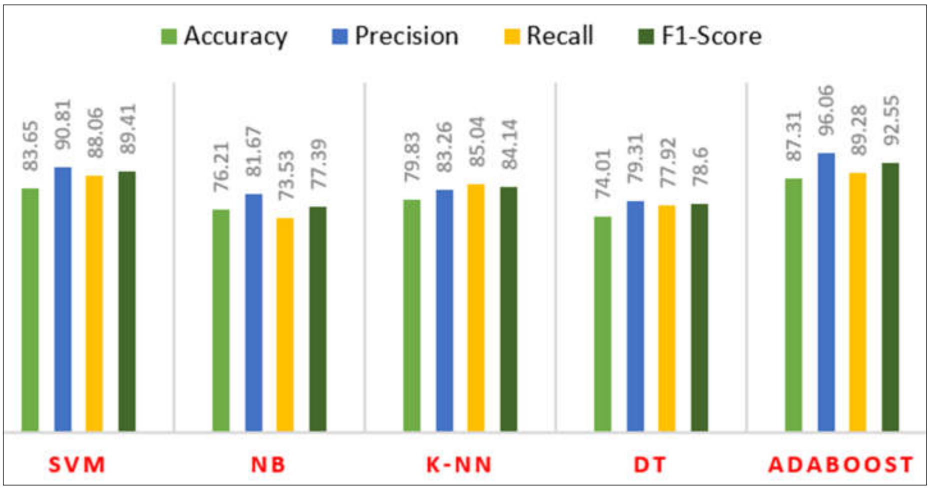

Fig. 6. Output of ML Classifiers

The deep learning classifiers are also used for training and learning on the COVID dataset to compare them against the machine learning classifiers. A slight variation is done here i.e., GloVe embeddings are used instead of TF-IDF. This embedding contains more than six billion words with one hundred dimensions. The table 3 shows the evaluation metrices for the deep learning algorithms chiefly Sequential Neural Network (SNN), Long Short-Term Memory (LSTM), Convolution Neural Network (CNN), CNN+LSTM and CNN+GRU (Gated Recurrent Unit). It is quite evident that the deep learning classifiers perform better than the machine learning classifiers. Also, the amalgamation of deep learning approaches i.e., hybrid classifiers (like CNN+GRU and CNN+LSTM) perform slightly better than the standalone deep learning classifiers. The simple sequential neural network produces the least value for all the evaluation metrices, but as the number of hidden layers and complexity increases, the performance also enhances. This phenomenon is clearly noticeable in the figure 7 displayed below.

Table 3. DL Classifiers on COVID Dataset

Algorithm	Accuracy	Precision	Recall	F1-Score
SNN	78.09	80.69	87.17	83.8
LSTM	87.86	84.76	78.72	81.63
CNN	86.09	85.24	80.45	82.77
CNN+LSTM	89.24	90.33	78.19	83.39
CNN+GRU	90.16	85.62	88.38	86.98

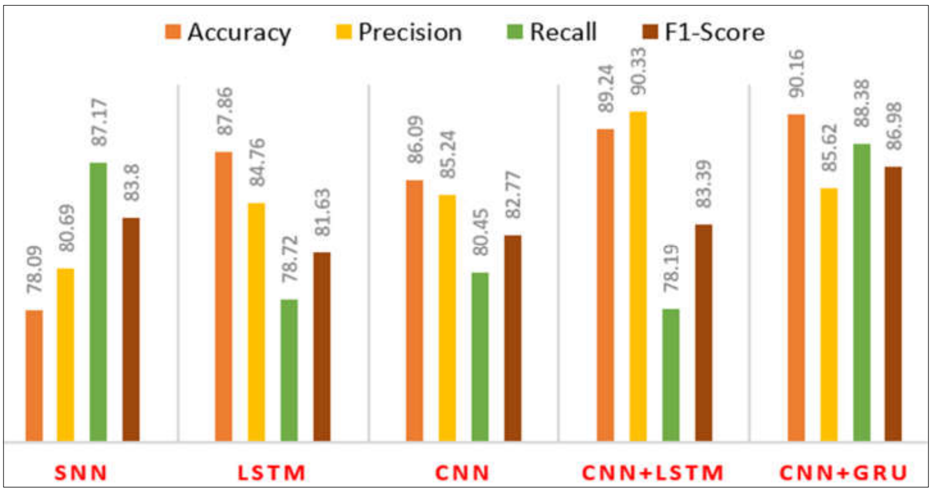

Fig. 7. Output of DL Classifiers

However, the pretrained models like BERT and ROBERTa can further augment the evaluation measures as shown in table 4 below. The visualization for the output is also presented in the figure 8, that clearly depicts that transformer-based language models supersede all the machine and deep learning algorithms for this case study.

Table 4. Hybrid Models on COVID Dataset

Algorithm	Accuracy	Precision	Recall	F1-Score
BERT	94.08	94.57	93.82	94.19
ROBERTa	95.09	94.18	95.22	94.69

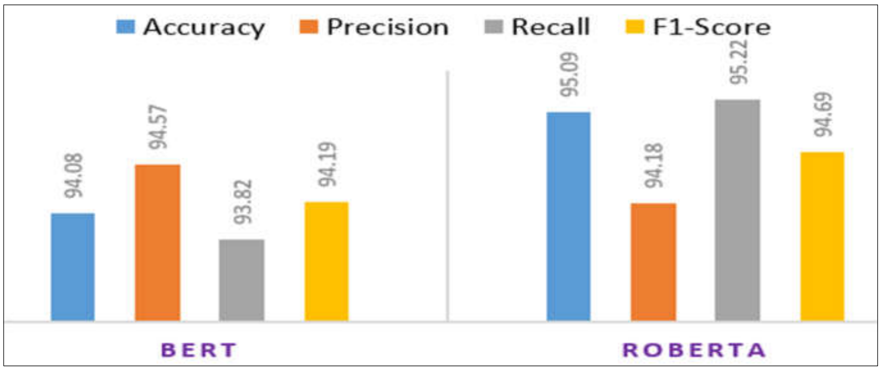

Fig. 8. Output of Transformer Models

5. Conclusion:

The expeditious outgrowth of the social networking sites users has led to the importance of sentiment analysis on the real-world data. In order to acquire the emotional state of mundane people, raw tweets (unlabeled data) were obtained from Twitter regarding the COVID-19 pandemic. However, the majority of social media data is irrelevant and needs to be preprocessed and vectorized. Practically, the cost of manual labeling of data is too high and labyrinthine, hence the automation of sentiment analysis is done. In this empirical analysis of COVID-19 data, several baseline machine learning and deep learning classifiers were employed along with the hybrid models. Among the machine learning algorithms, Adaptive Boosting showed best performance, while CNN+GRU deep learning approach slightly outdone its other deep learning counterparts. Nevertheless, the transformer-based language model ROBERTa outperformed all in terms of accuracy and F1-score.

One limitation of this work is that it is benchmarked on a single dataset and the further work can be done to extend this study on other available COVID related datasets to standardize the work. Also, attention mechanisms could be added along with deep learning classifiers to alleviate the performance.

6. References:

[1] Li, B., Yang, J., Zhao, F., Zhi, L., Wang, X., Liu, L., ... & Zhao, Y. (2020). Prevalence and impact of cardiovascular metabolic diseases on COVID-19 in China. Clinical research in cardiology, 109, 531-538.

[2] Vindegaard, N., & Benros, M. E. (2020). COVID-19 pandemic and mental health consequences: Systematic review of the current evidence. Brain, behavior, and immunity, 89, 531-542.

[3] Yang, Li, et al. "COVID-19: immunopathogenesis and Immunotherapeutics." Signal transduction and targeted therapy 5.1 (2020): 128.

[4] Taylor, A. L., & Habibi, R. (2020). The collapse of global cooperation under the WHO International Health Regulations at the outset of COVID-19: sculpting the future of global health governance. ASIL Insights, 24(15), 15.

[5] Pandey, V., Gupta, S., & Chattopadhyay, M. (2020). A framework for understanding citizens' political participation in social media. Information Technology & People, 33(4), 1053-1075.

[6] Manguri, K. H., Ramadhan, R. N., & Amin, P. R. M. (2020). Twitter sentiment analysis on worldwide COVID-19 outbreaks. Kurdistan Journal of Applied Research, 54-65.

[7] Naseem U, Razzak I, Khushi M, Eklund PW, Kim J. Covidsenti: A large-scale benchmark Twitter data set for COVID-19 sentiment analysis. IEEE TransComput Soc Syst. (2021) 8:1003–15. doi: 10.1109/TCSS.2021.3051189.

[8] Nemes, L., & Kiss, A. (2021). Social media sentiment analysis based on COVID-19. Journal of Information and Telecommunication, 5(1), 1-15.

[9] Kaur, H., Ahsaan, S. U., Alankar, B., & Chang, V. (2021). A proposed sentiment analysis deep learning algorithm for analyzing COVID-19 tweets. Information Systems Frontiers, 1-13.

[10] Barkur, G., & Kamath, G. B. (2020). Sentiment analysis of nationwide lockdown due to COVID 19 outbreak: Evidence from India. Asian journal of psychiatry, 51, 102089.

[11] Pristiyono, Ritonga, M., Ihsan, M. A. A., Anjar, A., & Rambe, F. H. (2021, February). Sentiment analysis of COVID-19 vaccine in Indonesia using Naïve Bayes Algorithm. In IOP Conference Series: Materials Science and Engineering (Vol. 1088, No. 1, p. 012045). IOP Publishing.

[12] Kumar, D. A., & Chinnalagu, A. (2020, December). Sentiment and emotion in social media COVID-19 conversations: SAB-LSTM approach. In 2020 9th International Conference System Modeling and Advancement in Research Trends (SMART) (pp. 463-467). IEEE..

[13] Yadav, A., & Vishwakarma, D. K. (2020). Sentiment analysis using deep learning architectures: a review. Artificial Intelligence Review, 53(6), 4335-4385.

[14] U. Naseem, I. Razzak, M. Khushi, P. W. Eklund and J. Kim, "COVIDSenti: A Large-Scale Benchmark Twitter Data Set for COVID-19 Sentiment Analysis," in IEEE Transactions on Computational Social Systems, vol. 8, no. 4, pp. 1003-1015, Aug. 2021, doi: 10.1109/TCSS.2021.3051189.

[15] Imran, A. S., Daudpota, S. M., Kastrati, Z., & Batra, R. (2020). Cross-cultural polarity and emotion detection using sentiment analysis and deep learning on COVID-19 related tweets. Ieee Access, 8, 181074-181090.

[16] Velev, G., & Pekova, I. (2020). Analysis of social media behavior of the 2020 presidential election candidates. Machine Learning, 3, 1.

[17] Imran, M., Castillo, C., Diaz, F., & Vieweg, S. (2015). Processing social media messages in mass emergency: A survey. ACM Computing Surveys (CSUR), 47(4), 1-38.

[18] Straka, M., & Straková, J. (2017, August). Tokenizing, pos tagging, lemmatizing and parsing ud 2.0 with udpipe. In Proceedings of the CoNLL 2017 shared task: Multilingual parsing from raw text to universal dependencies (pp. 88-99).

[19] Arroyo-Fernández, I., Méndez-Cruz, C. F., Sierra, G., Torres-Moreno, J. M., & Sidorov, G. (2019). Unsupervised sentence representations as word information series: Revisiting TF–IDF. Computer Speech & Language, 56, 107-129.

[20] Nokeri, T. C. (2021). Data Science Solutions with Python. Apress.

[21] Liu, Y., Ott, M., Goyal, N., Du, J., Joshi, M., Chen, D., ... & Stoyanov, V. (2019). Roberta: A robustly optimized bert pretraining approach. arXiv preprint arXiv:1907.11692.