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Sentiment Analysis on Omicron Tweets Using Hybrid Classifiers with Multiple Feature ExtractionTechniques and Transformer Based Models

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Abstract: Since the beginning of Covid-19, the world has been in a dilemma to cope up with its effects. With time the coronavirus has evolved into variants that caused a lot of destruction to human race. One such variant is “Omicron”. This variant made its presence in many countries throughout the world. The government is left in a straining situation to curb the spread of this variant and to stop the evolution of coronavirus. Though the strict precautions were exercised, the evolution was unstoppable. To understand the thoughts and feelings of the public, twitter can be considered as one of the best platforms for sentiment analysis. Analyzing the sentiments of people across the continents is horridly difficult but with the way technology has been making advancement in the world, analyzing has become a quiet easy job. In the existing studies on Covid-19, various word embedding techniques with machine learning and deeplearning classifiers has been used for the analysis. Language based models have proven to achieve higher accuracy forsentiment analysis. Amidst these hybrid classifiers, have performed tremendously good. In the proposed work, seven Machine Learning hybrid classifiers are compared with four single classifiers using TF-IDF and Word2Vec. A proposedDeep Learning hybrid classifier is compared with two single classifiers using GloVe and FastText. Furthermore, language models like BERT and RoBERTa are employed in an effort to boost validation outcomes upto 93.39% and 93.47%.

Keywords: *Sentiment analysis, Omicron, Twitter analysis, NLP, Big Data, TextBlob, Machine learning, Deep learning, hybridclassifiers, TF-IDF, Word2Vec, GloVe, FastText, BERT, RoBERTa,*

1. Introduction

An infectious disease called COVID-19 first appeared and caused a global crisis that had profound effects on several parts of the world sectors. Among the coronavirus outbreak, the emergence of COVID-19 mutations, propagating variations as Omicron kind caused fear and terror in people. The omicron-sized SARS-CoV-2 variant was discovered on November 24, 2021, [1] in South Africa, and has expanded to numerous nations.

The effects of the omicron continue to be a concern. The population may be impacted in a similar way by the Omicron pandemic as it was by the COVID-19 pandemic in the past. With the current global spread of SAR-CoV-2, morbidity and lethality are rising sharply. As a result of genetic distortion and loss of immunity, the covid-19 disease genetic code is susceptible to aberrations. On the Google platform, there are several current researches that deal with omicron [2,3,4] sentiment analysis.

The introduction of Web 2.0 has resulted in a plethora of platforms that enable people to express their opinions on a wide range of subjects. Social media is producing a large volume of sentiment-rich data. and sentiment analysis concerns with understanding and sorting thoughts conveyed in source document. On many sites, individuals began exchanging and expressing their ideas, feelings, clarifications, and suggestions. Social media sentiment analysis is important in many different fields. Given the prevalence of slang phrases and misspelt wordson Twitter, sentiment classification of such data is particularly helpful for determining the opinions of the general public. Numerous documents can be analyzed for sentiment analysis, making it an effective process with high accuracy. Sentiment analysis is widely popular because of these factors.

To examine and investigate the public's perceptions of the COVID-19 outbreak and its evolving variants on social media platforms, numerous researches have utilized

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machine learning (ML) and deep learning (DL) approaches and algorithms. The way how the SARS CoV has been evolving and most of the information has been covered in paper [5]. Due to its scalability in processing and analyzing humongous amounts of data, sentiment analysis utilizing machine and deep learning has been increasingly popular among researchers since the rise of social media.Additionally, this assessment would give the decision-makers the real popular feelings and allow them to examinethe strategies they have previously proposed, suggestions, effectiveness messages, and modification suited to the circumstances at the time.

Article’s on COVID-19 has been a buzzing sensation among the researches since the start of pandemic. From proposing novel DL technique for prediction [6], analyzing tweets of health professionals and policymakers [7], Analyzing president trumps tweets [8] and many more.

The major goal of this research is to comprehend the opinions of the general public around the world by determining whether single classifiers and hybrid classifiers perform best in various scenarios. FIGURE 1 and illustrate how the entire study is conducted. Two months are spent gathering the dataset, which is preprocessed in accordance with the instructions provided in the relevant portion of the paper. The methodology, results, and conclusion sections come next.

2. Related Works

To acknowledge the significance of the problem, works of various authors who aimed for similar objectives or has done works in similar domain have been reviewed.

The development of New Versions of SARS-CoV-2 is elaborated and thoroughly explained in the paper [9] with the use of a family tree that summarizes the origin of the virus. Four groups are used to group the different variants. The implications of the variant's spread and the degree of their effect on the human race is discussed. Each and every variant's clinical relevance is noted.

Harleen Kaur et al. [10] discussed the effects of false information on social media platforms while examining articles that discuss the negative effects of such behaviour. A hybrid heterogenous SVM model, also known as theH-SVM method, is developed and a brief overview of deep learning algorithms like RNN is given. SVM and RNNare compared, with SVM classifying the majority of tweets as neutral and RNN classifying the majority of tweets as positive.

The Tweepy API is used by the authors in [11] to scrape two different datasets. One dataset exclusively contains tweets from India, while the other has tweets from all across the world. Using TextBlob, tweets are categorised into seven sentiments depending on their polarity. The BERT model is used, and they have been successful in achieving about 94% of validation accuracy.

The CLSTM model, which combines the advantages of both the CNN and the LSTM models, was proposed bythe Zhu Zhu [12] to introduce a study on the Chinese language. Furthermore, the SO-PMI method is used to label the data. A thorough study is carried out using various word counts. The paradigm does have certain drawbacks, and it might be challenging to interpret and understand Chinese.

A research [13] that examined movie evaluations based on information gleaned from a website. The differences between the procedures performed on the Chinese and English languages are addressed. Together with the LSTM deep learning model, Word2Vec has been deployed. The study's primary goal is to use an intelligent ML model to comprehend the sentiments of language other than English. Three different procedures are used, and the results show that 81.63% accuracy is the highest of all the approaches.

[14] intends to investigate the sentiment analysis of the twitter data using LM's like BERT. The pandemic situation in Mexico, a country in North America, is specifically being examined. The Twitter chatter dataset is a collection of 760,064,879 twitter posts concerning COVID-19 that were made in Mexico between 1 February 2020and 31 December 2020. Following pre-processing, the majority of the data was filtered out, resulting in an aggregate of 2,142,890 tweets. VADER, RoBERTa, and BERTweet are three separate tools that have been used to evaluate the sentiments based on their polarities. After doing a thorough investigation, the implementers used an ARIMA model to describe the data and outcomes by breaking down the time series.

The study [15] examined the evolution of public sentiment through time and compared it to that of other countries. Using the Textom 5.0 software, data was gathered using the terms Moderna, AstraZeneca, Janssen, andPfizer from Twitter, Naver, Daum, and Google that classifies people's feelings as positive, neutral, or negative. The writers have provided a brief justification for their decision to use these platforms and set of keywords. Preprocessing has been followed by the use of TF-IDF to understand the keyword frequencies and TF-IDF values and LDAvis is used to identify and visualize a total of 5 subjects. The quantity of information gathered from each source, as well as the keywords linked to the topic in each of the three phases, are explained in a table format representation. Results demonstrated that during the previous two years, South Koreans' attitudes toward vaccination shifted from neutral to negative and then to positive. Other countries were significantly affected by thevaccination conspiracy ideas; however South Korea was not much affected because of their optimistic expectations.

Similar to the work mentioned above, [16] conducted a research that involved the examination of COVID vaccinations using Tweets and ML techniques. Using Tweepy, 25,004 keywords, including corona vaccination and others, were extracted. Out of the two datasets used, for each vaccination, the dataset2 is separated into two separate datasets. Using TextBlob, features are selected after pre-processing tweets, and labels are already there. Decision tree produces the greatest results across all datasets when compared to SVM, Naive Bayes, Logistic Regression, and Random Forest classifiers.

Many studies that has dealt with sentiment analysis using machine learning classifiers [1724,56] came up with good accuracy scores which has been applied different types of datasets and motives. According to the survey andour best knowledge, no study has utilized a similar methodology to analyze Omicron tweets. One aspect of this work that makes it notable is the use of several feature selection techniques and hybrid classifiers to comprehend sentiments of Omicron tweets.

3. Problem Statement:

As there is already raising number of covid-19 effected patients, coronavirus has evolved in the due time into various variants. Out of which Omicron is claimed as a variant which is 'mild' yet contagious in nature. Recognizing the attitude of individuals towards the advent of this new variant has become a grueling task.

SOLUTION:

It is known that Twitter is one of the most used and effective medium to understand the sentiments of the people.Thus, information from Twitter has been gathered for the study. The study has put the following ideas to the test in order to comprehend sentiments:

- A third-party tool called TextBlob has been used to label the dataset of 36,000 tweets. • Multiple hybrid models are put forth in the machine learning and deep learning domains to find out which ones perform well when various feature extraction techniques are embedded.
- Observing that there is room for improvement in the validation accuracy, languagemodels are included.

4. Methodology:

Framework of the proposed work is exhibited in FIGURE 1**.** A. OMISENTIData Collection and Labeling:

Tweepy, considerably one of the most pronounced open-source library is used for collecting the data. As per the online stats, twitter has over 329 million users and the count will keep increasing in the future. For the analysis, 36,000 tweets are collected over the time period of 60 days when Omicron virus was spreading likea wild fire across the

world. The dataset is named as OMISENTI which is further divided into sub-datasets as OMISENTI-1, OMISENTI-2 and OMISENTI-3 according to the order of time the tweet was posted by the user with a blendof negative, neutral and positive tweets.

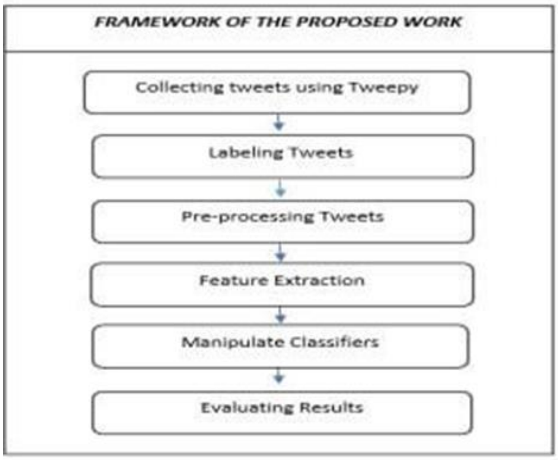


Fig 1 Framework Of The Proposed Work

1) Principles for Data Collection: The dataset, OMISENTI incorporates 36,000 unique tweets accumulated in the duration of 9th February 2022 to 9th April 2022. Solely the collection has been restricted to English tweets. The tweets are strained through a few more constraints. When using Tweepy API [11], only the tweets of the past 7 days can be fetched. Hence, data is retrieved after every seven days using python. For the full analysis, thirteen attributes were extracted. They are user_name, user_location, user_description, user_created, user_followers, user_friends, user_favourites, user_verified, date, text, hashtags, source and is_retweet.
2) Annotation Tool: By computing the value as a polarity which ranges from -1 to +1, Bandi and Fellah [25]

suggest that TextBlob can reflect a sentence's attitude. To categorize the emotional feeling into negative, neutral and positive categories, the TextBlob tool is employed. A tweet is deemed to have a negative sentiment if its polarity is less than 0.4. Coaxially, the tweet is deemed as positive when its polarity is more than 0.4. A neutral tweet has a polarity in the spectrum of -0.4 to 0.4.

TABLE 2: INSTANCES IN OMISENTI DATASET

NEGATIVE TWEET	Hospitals and ICUs are packed with people who have not received a booster dose. A booster dose is REQUIRED for immunity against the #Omicron variant.Booster does reduce the death toll. Dead people don’t shop. This is bad for businesses.
NEGATIVE TWEET	‘Beyond tragic’, says #WHO as world records half a million deaths from#Omicron variant.
NEUTRAL TWEET	It’s not over yet .. unfortunately .. Social Distancing still a norm ..
POSITIVETWEET	With #omicron spreading rapidly in #TimorLeste it's so important for people toget access to a #COVID19Vaccine which could save their life. Wherever they are from, and whatever their language.
POSITIVETWEET	positivity is great we all need it except it is in form of a virus NAAWR #OMICRON: the only positivity we don’t need

B. Data Pre-processing: Algorithms that categorize brief texts depends on pre-processing to grasp their content. Pre-processing can have such a significant influence on the system's performance. The study in

[28] outlines a methodical strategy for text pre-processing that makes use of a range of pre-processing approaches to preserve important attributes without compromising information. The Natural Language Toolkit library is a python library which is most commonly known as NLTK library is practiced in the implementation of pre-processing. NLTK library [29] is one of the best Natural Language Processing libraries out there. The steps opted for pre-processing of the tweets are as follows. Online platforms collect unstructured, loud, and informal raw data. Although hashtags are typically not required for sentiment, they can affect performance. Any extra hashtags are removed to tidy up the text. Folded in case, the text.To prevent capitalization from making the same word appear to be a separate term, all capitalised characters are folded to lower case. To separate hashtags like "coronavirus" from "corona virus," word segmentation is used. To decrease noise, stop words are frequently eliminated from textual data. Stop words have little bearing on how well a sentence conveys its message. Words undergo morphological inspection during lemmatization. after which puts them back in dictionary form. Elimination of stopwords, punctuation, white space, hyperlinks, and @mentions was the aim of the textual data analysis. Special letters, punctuation, and numerals are taken out of the original dataset because they don't help with sentiment analysis. Retweets are either omitted during data retrieval or removed after dataset collection, and repeated tweets are ruled out.

C. Investigational Study: In order to get a more thorough understanding of the OMISENTI dataset,exploratory analysis is carried out in this part.

1) Hashtags and Frequent words Analysis: Pre-processing is followed by a thorough analysis of the dataset to uncover novel insights. FIGURE 2 illustrates the distribution of the top 15 hashtags. List of termsthat appear often are provided in TABLE 3 along with the number of times the term has appeared in the OMISENTI dataset. After conducting a manual evaluation, this table was created. The most common words present in OMISENTI is depicted in FIGURE 3. The most prevalent terms in tweetsthat are present in positive, negative, or neutral tweets are displayed as a WordCloud in FIGURE 4.

Fig 2: TOP HASHTAGS

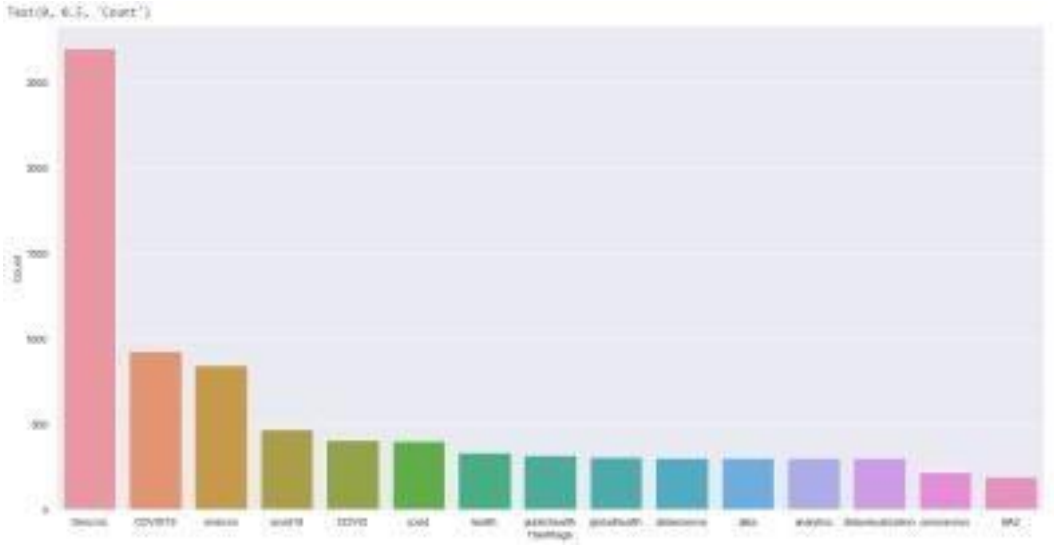


Table 3: List of Frequent Words

TERM	COUNT
omicron	41,823
covid	23,080
health	11,912
data	9,690
new	9,679
variant	9,155

Fig 3: Wordcloud Of Terms In Omisenti

Fig 4: Word Clouds Of Negative, Neutral And Positive Tweets

2) Investigating the sources: Following a thorough examination, it was discovered that users chose to tweetfrom 227 contrasting sources. The majority of sources, whose lists are in the TABLE 4, are not used to generate more than 100 tweets each. The TABLE 4 indicates the number of tweets each source has contributed to the dataset.

Table 4: List of Sources with Not More Than 100 Tweets

No. of tweets made byeach source	Total No. of sources	No. of tweets made byeach source	Total No. of sources	No. of tweets made byeach source	Total No. of sources
1	73	14	3	32	3
2	33	15	1	36	1
3	14	16	2	37	1
4	15	17	3	40	2
5	5	20	1	46	1
6	8	22	2	50	1
7	5	23	1	51	1
8	6	24	2	52	2
9	4	27	1	67	1
10	5	28	1	70	1
11	3	29	1	73	1
12	2	30	1	94	1
13	1	31	2		

The sources for the vast majority of omicron tweets are shown in the TABLE 5. It also displays the number oftweets that were generated from each source.

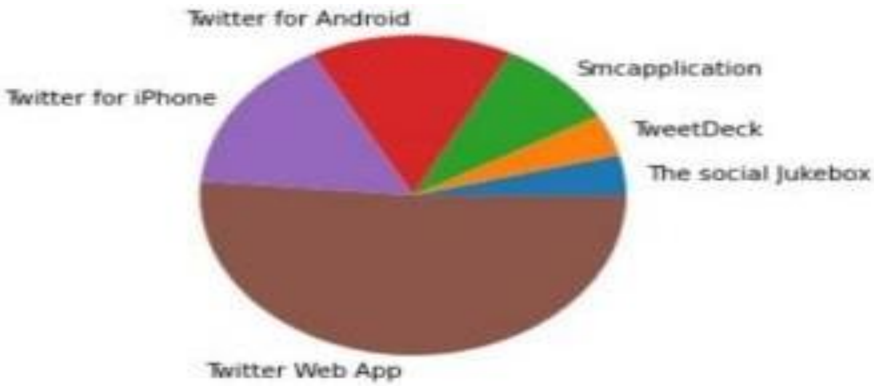
Table 5: List Of Sources With Tweets More Than 100

Sources	Number of tweets	Sources	Number of tweets
News Medical	115	Twitter for iPad	807

LinkedIn	130	Hootsuite Inc.	935
dlvr.it	161	The social Jukebox	1256
Sprout Social	176	TweetDeck	1292
VaccinationTracking	180	Smcapplication	2833
Ohhtweet	235	Twitter for Android	4743
AutoLuisAlejoVega	247	Twitter for iPhone	4866
Buffer	460	Twitter Web App	15,859

The sources that were used to create over 1,000 tweets are displayed in pie chart or FIGURE 5

Fig 5: MOST USED SOURCES



3) Topic Modeling Using LDA: The investigating of topics in OMISENTI dataset is performed by leveraging LDA. Toidentify the conceptual topics that appeared in OMISENTI dataset, statistical topic modelling has been used. Text in a document is categorised to a certain topic using the LDA [57] algorithm. Through the use of of Dirichlet distributions,it generates topic for a document and words for every topic model. Here, the number of topics is set at 10 and vectorization is carried out using the TF-IDF technique. After LDA training, topics are expressed as word distributions and document's topic distributions are acquired. The TABLE 6 below contains the top 10 words in the top 10 subjects.

Table 6: Ten Words In Top Ten Topics Of Omisenti Dataset

	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10
T1	avail	morn	district	omicron	good	teacher	trial	glass	research	Law
T2	us	make	highest	world	indic	come	would	omicron	look	Keep
T3	covid	insight	team	data	health	confirm	death	per	case	Day
T4	total	new	safe	travel	social	stay	keep	home	today	Inform
T5	omicron	variant	covid	new	case	infect	report	test	mask	China

T6	truth	lie	let	know	home	covid	strike	us	stay	Omicron
T7	franc	space	abandon	cell	airdrop	butter	spike	help	need	Aerosol
T8	omicron	case	get	covid	new	give	delta	peak	death	Reinfect
T9	canada	except	omicron	director	suffer	visit	loss	read	publish	View
T10	blood	quit	organ	sure	ba	occur	enough	sudden	unless	Flag

Following FIGURE 6 shows text clouds for each topic.

Fig 6: Textclouds Of Topics

The FIGURE 7 depicts the distribution of each topic in the OMISENTI dataset.

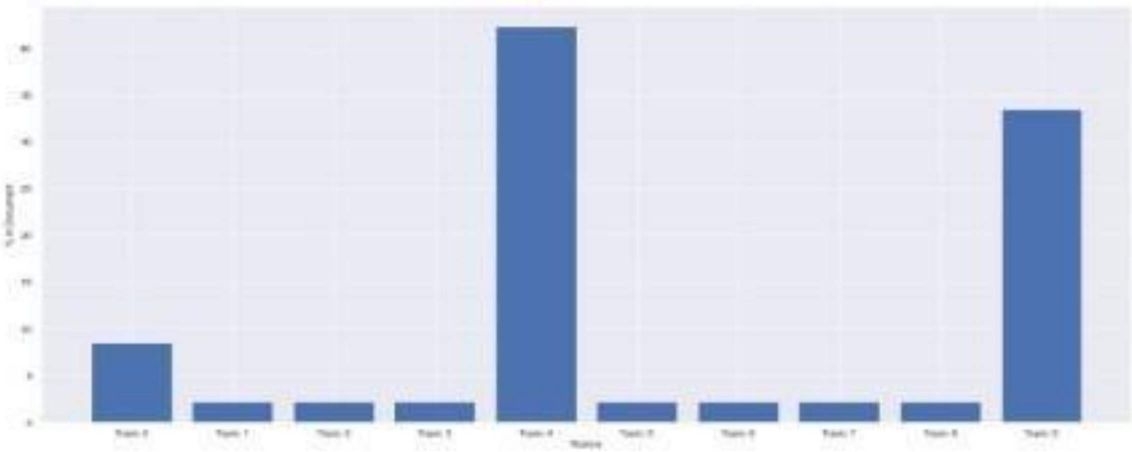


Fig 7: Distribution Of Topics

D. Feature Extraction: It entails constructing a new set of characteristics from pre-existing ones and then getting rid of some of the insignificant features. The generated set can then be used to describe the originaldata. The study employs four different kinds of feature extractions: TF-IDF, Word2Vec, GloVe and FastText. Due to their accuracy, approaches based on neural networks have gained a lot of traction in thefield of NLP. They require word embedding in order to examine texts from enormous datasets. The set of features [30] has the most impact on the classifier's performance; if the feature extracting technique works effectively, even the most basic classifier may be able to provide excellent accuracy.

- The TF-IDF, which gauges word's prominence in a group of documents, is indeed the opposite of the DF. High IDF [31] value words are uncommon in all documents, which increases their importance. It calculates the word's frequency over multiple documents, not just one. It is discovered that by utilising TF-IDF [32] vectorizer, the efficacy of sentiment analysis can be demonstrated by simulation results.

- One of the often-exploited models of word embedding is word2vec. This algorithm uses prediction to represent words as vectors with meaningful ties. It is often used in natural language processing tasks and has demonstrated a significant potential influence [33] on performance of sentiment analysis quality.

- Discrete representations, described by One Hot Code, and distributional representations, described by Global Vectors, make up the majority of the existing word embedding representation techniques (GloVe). The GloVe model [34], which is built on statistical theory, incorporates Word2vec as well as latent semantic analysis's merits. The model is better suited for large-scale corpus data sets because it also has strong scalability and ramps up the training process.

- In order for the vectors to carry as much lexical and syntactic knowledge [35] as feasible, it is vital in achieving accurate vectorization of words. A word representation method that utilizes worldwide term frequency figures is called GloVe.

- Facebook unveiled the FastText model, which is swift, effective, and accessible. FastText employs a number of techniques to enhance the model's performance. Word embeddings have been produced using FastText to explore the possibility of reducing the reliance of language processing [36] on performance of data-preprocessing on a dataset. The FastText technique has been also suggested to examine texts from enormous datasets in the study by Armand Joulin et al. [37].

- For both GloVe and FastText, deep learning models such as CNN, LSTM [38] and CNN+LSTM [17,20,39,40] are used. E. Classification:

- To assess the opinion of the general public by using Twitter application, this study includes a couple of machine learning algorithms and deep learning models. Machine learning has been coupled with word embeddings like Word2Vec and TF-IDF. While with deep learning classifiers, GloVe and FastText word embeddings have been employed. Additionally, analysis has been conducted using transformer models likeBERT [28,41,42,54] and RoBERTa [41,55]. The training and validation accuracy of single classifiers versusstacking classifiers [43] are compared in order to assess both of these metrics.

- In total, this paper includes eleven machine learning classifiers, seven of which are hybrid classifiers and four of which are single classifiers. Deep learning is employed to evaluate two single classifiers and one hybrid classifier. There are numerous existing studies, such as [18,20,39,40,44,45.46.47] that supports the claim that hybrid classifiers produce better results.

- **TF-IDF:** The four datasets are split into training and testing portions with a ratio of 75:25 for the TF-IDF feature extraction algorithm. LabelEncoder, TfidfVectorizer, models, and accuracy score are imported usingthe 'sklearn' library, and preprocessing is conducted using nltk. For the SVM model, the "linear" kernel [10]is employed, while for the Naive Bayes classifier, the "MultinomialNB" is implemented. Entropy is used asa criterion for judging the Random Forest classifier. The foundation classifier for all hybrid models is logisticregression.

- **Word2Vec:** For the purpose of extracting features using Word2Vec, all datasets are split into training and testing halves at a ratio of 75:25. Preprocessing involves importing the Gensim and Python-Levenshtein libraries. 'GaussianNB' is adopted for the Naive Bayes classifier rather than 'MultinomialNB,' while the other requirements remain similar to TF-IDF. Logistic regression serves as the hybrid models' primary classifier.

- **GloVe:** The 840B.300d file from Stanford [48] is downloaded in order to use GloVe. Deep learning modelsare preprocessed and put into use using the NLTK and Keras packages. The size of the dictionary is 76356. The code makes use of many necessary libraries, including BatchNormalization, EarlyStopping, ModelCheckpoint and RMSprop. Sparse categorical crossentropy, Adam, and accuracy are the metrics for assembling all deep learning models. For the hybrid model, CNN and LSTM are stacked with 64 filters, a kernel size of 4, a "ReLu" activation, and a dropout of 0.5.

- **FastText:** The zip file for FastText embedding can be downloaded from this URL [49]. Similar to GloVe, the dataset is split into 80:20 ratio. The weight decay is 1e-4 and the batch size is 256. For the hybrid model,64 filters, a kernel size of 3, a "ReLu" activation, and a dropout of 0.5 is considered. The metrics and imported libraries are identical to those from the previous embedding (GloVe).

- **BERT:** The BERT model is deployed with Hugging Face [50]. The model's complete description, the model's restrictions, and usage guidelines are all available on the site [51]. Imported libraries include pickle,torch ML libraries, transformers, and more. The dataset is divided into training and testing portions in a 70:30 ratio. Testing portions of the dataset are then segmented into validation and testing portions in a 50:50ratio. The optimizer is AdamW, the batch size is 16, and the learning rate is 2e-5.
- **RoBERTa:** The reference [52] contains a detailed description of the model that was employed. The trainingto testing ratio for the OMISENTI dataset is 90:10. The validation batch size is 4, whereas the training batch size is 8. Adam is the optimizer, the learning rate is 1e-05, and the loss function is cross entropy.

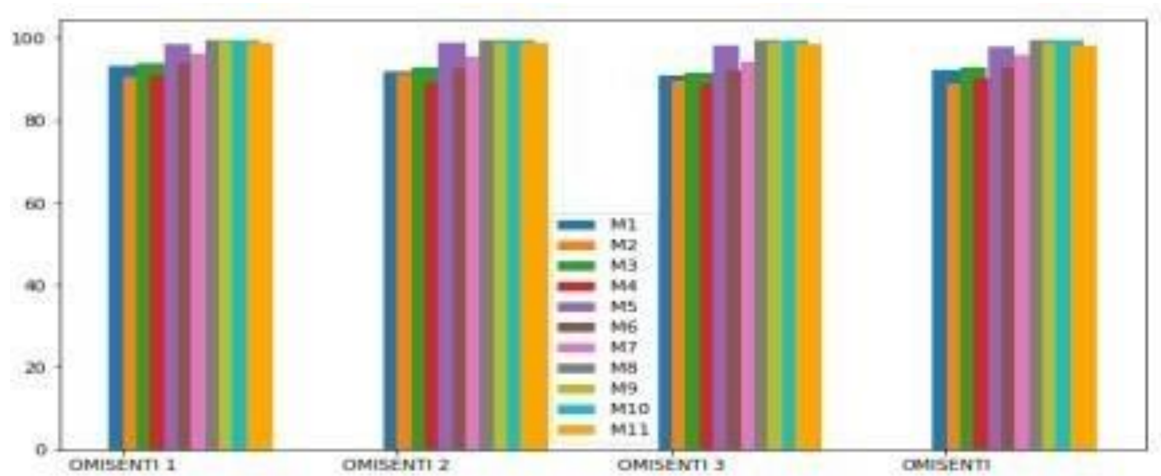
5. Results and Discussion

- The code is developed in Python. The project is successfully completed entirely via Google Colaboratory [53]. Applying python tools such as seaborn, matplotlib, and word cloud, the figures and graphs has been produced. The tables below display the findings of the analysis.
- Table 7 lists the conclusions reached from the investigation of the training accuracy of machine learning classifiers using the TF-IDF on the four datasets. The content in Table7 is visualized as a graph in Figure 8.

Table 7: Training Accuracy Of Ml Classifiers Using Tf-Idf

		OMISENTI 1	OMISENTI 2	OMISENTI 3	OMISENTI
SINGLE CLASSIFIERS					
M1	SVM	93.23	91.93	90.96	92.0
M2	Naïve Bayes	90.56	91.0	89.53	88.92
M3	Random Forest	93.8	92.7	91.5	92.74
M4	Decision Tree	90.73	89.16	88.7	90.08
HYBRID CLASSIFIERS					
M5	SVM+Random Forest	98.57	98.61	98.23	97.75
M6	SVM+Naïve Bayes	93.88	92.6	92.22	92.73
M7	SVM+Decision Tree	96.07	95.37	94.15	95.72
M8	RF+DT	**99.58**	**99.57**	**99.44**	**99.37**
M9	RF+Naïve Bayes	99.2	98.9	98.82	98.81
M10	Naïve Bayes+DecisionTree	99.56	99.47	**99.44**	**99.37**
M11	SVM+RF+DT+NAIVE	98.86	98.77	98.43	98.07

Fig 8: Graphical Representation Of Table 7



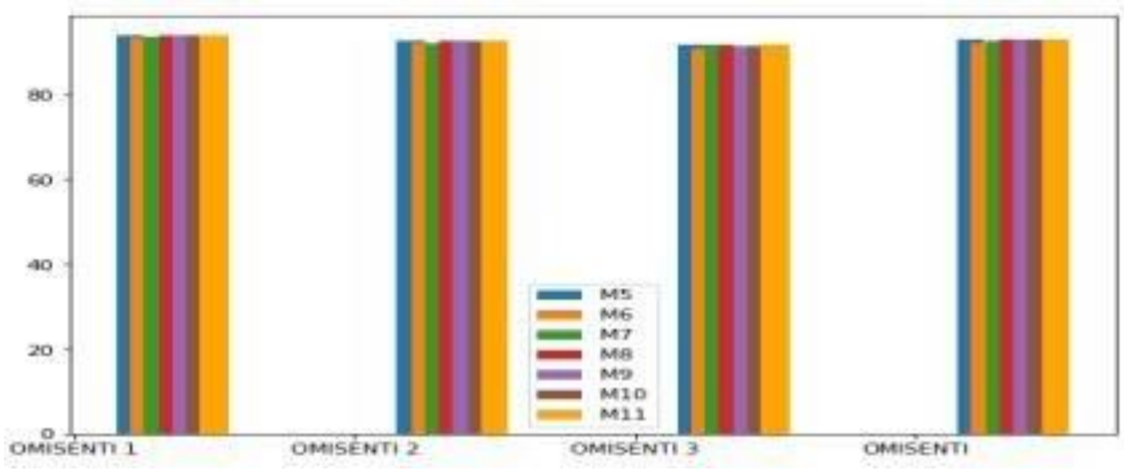
- Observing the TF-IDF results, we may draw two conclusions. One is that hybrid classifiers outperformed single classifiers in terms of performance. Another finding from the results is that M8 and M10, two hybrid classifiers, shows similar results.
- From the TF-IDF results, supplementary analysis has been conducted to determine which hybrid classifier does have the highest validation accuracy. Table 8 contains the analysis findings, while Figure 9 shows its graphical view.

Table 8: Validation Accuracy Of Ml Classifiers Using Tf-Idf

		OMISENTI 1	**OMISENTI 2**	**OMISENTI 3**	**OMISENTI**
M5	SVM+ Random Forest	93.9	92.53	**91.66**	**92.93**
M6	SVM+ Naïve Bayes	93.33	91.83	90.86	92.06
M7	SVM+ Decision Tree	93.46	92.1	91.63	92.75
M8	Random Forest+ Decision Tree	93.9	92.5	91.4	92.85
M9	Random Forest+ Naïve Bayes	93.7	**92.66**	91.33	92.88
M10	Naïve Bayes+ Decision Tree	93.9	92.36	91.5	92.81
M11	SVM+RF+DT+NAIVE	**94.0**	92.5	91.6	92.87

- According to Table 8, the models M5 for OMISENTI 3 and OMISENTI, M9 for OMISENTI 3, and M11 forOMISENTI 1 have the highest validation accuracy.

Fig 9: Graphical Representation Of Table 8



- The Word2Vec embedding has been employed association with deep learning principles for additional analysis. Single Deep Learning classifiers and hybrid Deep Learning classifiers have been used for comparative study, and Table 9 shows the training accuracy for each classifier. The exact information in Table 9 is depicted in Figure10 as a graph.

Table 9: Training Accuracy Of Ml Classifiers Using Word2vec

		OMISENTI 1	**OMISENTI 2**	**OMISENTI 3**	**OMISENTI**
SINGLE CLASSIFIERS					
M1	Svm	84.89	89.3	89.60	88.06
M2	Naïve	21.86	35.43	42.1	35.16
M3	Rf	91.76	91.0	90.76	91.92
M4	Dt	85.46	84.1	83.83	85.6
HYBRID CLASSIFIERS					
M5	Svm+rf	98.78	97.87	97.71	98.93
M6	SVM+NAÏVE	85.56	90.28	89.43	88.49
M7	SVM+DT	95.38	90.28	89.43	90.53
M8	RF+DT	99.42	**99.18**	**99.1**	**99.47**
M9	RF+NAÏVE	98.84	98.25	87.78	99.04
M10	NAÏVE+DT	**99.57**	**99.18**	**99.1**	**99.47**
M11	SVM+RF+DT+NAIVE	99.28	98.84	98.15	99.33

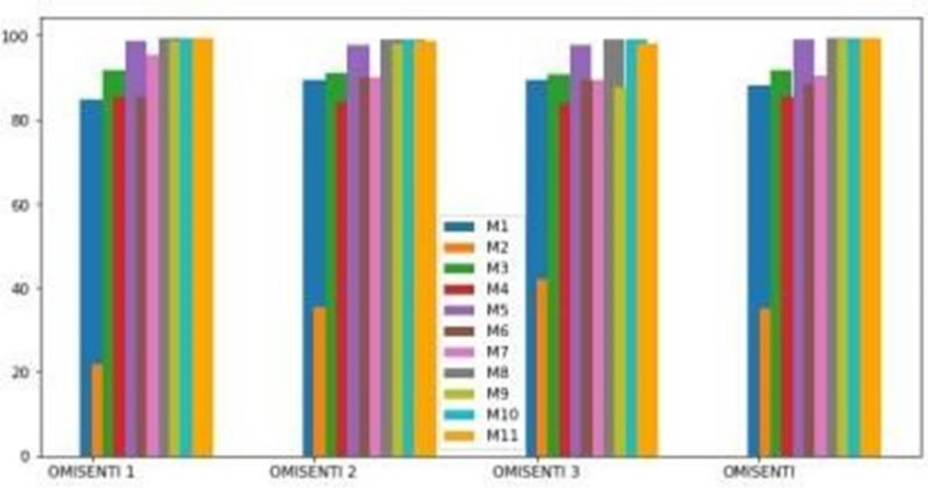


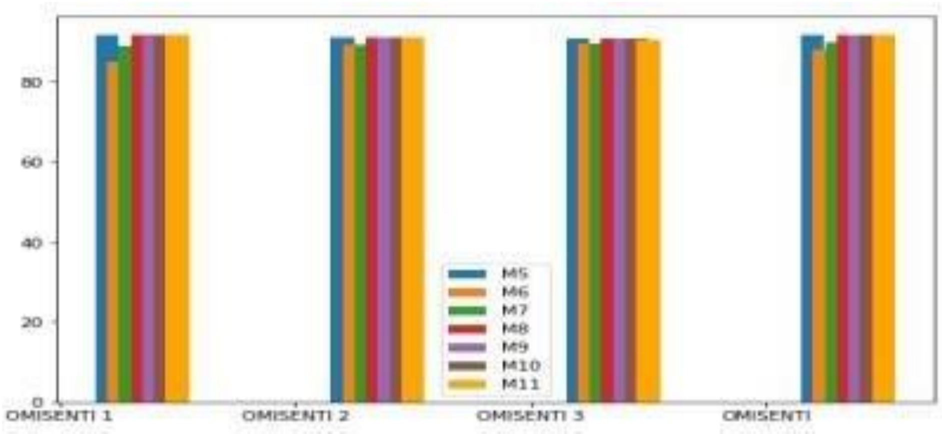
Fig 10: Graphical Representation Of Table 9

- Again, it can be inferred from Table 9 and Figure 10 that hybrid classifiers outperform single classifiers in termsof performance. The highest training accuracy is primarily found between M8 and M10 models.
- Table 10 lists and Figure 11 illustrates the hybrid machine learning classifiers validation accuracy with word2vecword embedding.

Table 10: Validation Accuracy Of Ml Classifiers Using Word2vec

		OMISENTI 1	OMISENTI 2	OMISENTI 3	OMISENTI
M5	Svm+rf	91.66	91.03	90.73	91.76
M6	SVM+NAÏVE	84.9	89.3	89.6	88.06
M7	SVM+DT	89.06	89.3	89.6	90.05
M8	RF+DT	91.6	91.13	**90.8**	**91.88**
M9	RF+NAÏVE	91.56	91.0	90.73	91.7
M10	NAÏVE+DT	91.66	91.13	90.73	**91.88**
M11	SVM+RF+DT+NAÏVE	**91.86**	**91.26**	90.66	91.71

Fig 11: Graphical Representation Of Table 10



- The chart in Figure 11 shows that the validation accuracy of the M8, M10, and M11 models is the highest.
- The investigation now shifts to the deep learning classifiers with GloVe and FastText word embeddings afterthoroughly examining the ML classifiers with other word embeddings. Both the training and validation accuracies attained following the analysis are displayed in Table 11. These results demonstrate that single classifiers have excelled hybrid classifiers in terms of their training accuracy. The hybrid classifier, however, has the highest accuracy rate when the validation accuracy of the model has been evaluated.
- The graphic depiction of the information in Table 11 is represented in Figure 12.

Table 11: Results Of Dl Classifiers Using Glove

		OMISENTI 1		OMISENTI 2		OMISENTI 3		OMISENTI	
SINGLE CLASSIFIERS		**Train**	**Val**	**Train**	**Val**	**Train**	**Val**	**Train**	**Val**
D1	CNN	**99.50**	**92.67**	**99.26**	90.54	**98.94**	90.54	**96.59**	91.12
D2	LSTM	95.18	91.92	93.05	91.04	93.26	**92.04**	95.34	91.68
HYBRID CLASSIFIER									
D3	CNN+LSTM	95.81	**92.67**	95.47	**91.50**	95.77	91.83	95.79	**92.46**

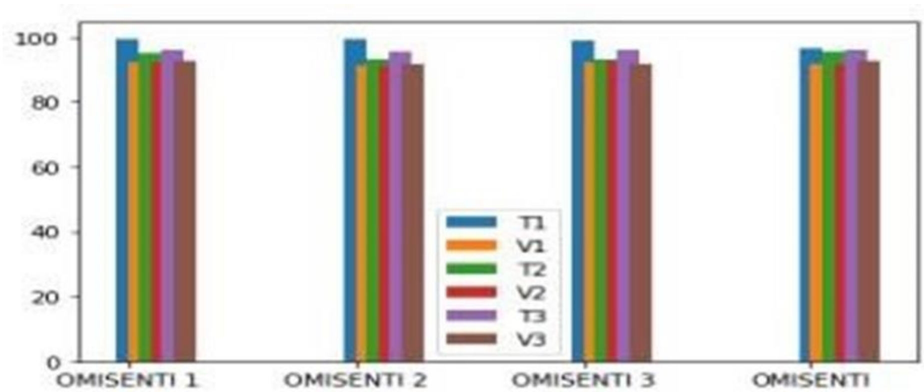


Fig 12: Graphical Representation Of Table 11

•Now that the deep learning classifiers are being used, the analysis is concentrated on using the FastText word embedding. FastText outcomes have been displayed in Table 12 in a style analogous to how the GloVe's results are presented. The findings are drawn using both the training and validation accuracies.

Table 12: Results Of Dl Classifiers Using Fasttext

		OMISENTI 1		OMISENTI 2		OMISENTI 3		OMISENTI	
SINGLE CLASSIFIERS		**Train**	**Val**	**Train**	**Val**	**Train**	**Val**	**Train**	**Val**
D1	CNN	**99.63**	92.37	**99.28**	90.50	**99.48**	91.50	**95.95**	91.87
D2	LSTM	94.14	92.25	96.86	90.42	93.94	**91.87**	94.10	89.18
HYBRID CLASSIFIER									
D3	CNN+LSTM	94.90	**92.83**	94.63	**91.08**	95.51	91.79	95.41	**93.01**

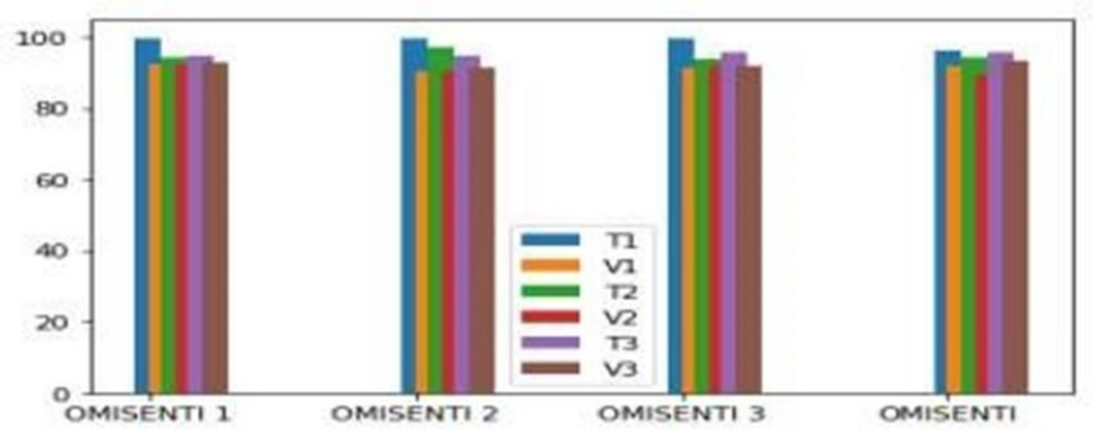


Fig 13: Graphical Representation Of Table 12

According to the data, a single deep learning classifier is winning against the hybrid classifier in terms of training accuracy. However, when the validation accuracy is assessed, the hybrid model appears to have the highest accuracy.

- FastText has demonstrated more validation accuracy rate in comparison to GloVe. • Furthermore, to delve deeper into the analysis, language models called BERT and RoBERTa are employed on the OMISENTI dataset to obtain a greater validation accuracy than the other word embeddings that have been examined thusfar.

The findings and conclusions are satisfactory, as seen in Table 13. These two transformer models appear to have adequate training accuracy, but superior validation accuracy when compared to all other applied schemes. The results acquired by the Transformer-based language models are shown in a bar chart (FIGURE 14).

Table 13: Results Of Language Models

DATASET	**OMISENTI**	
MODELS	Train	Val
BERT	97.63	**93.39**
RoBERTa	98.77	**93.47**

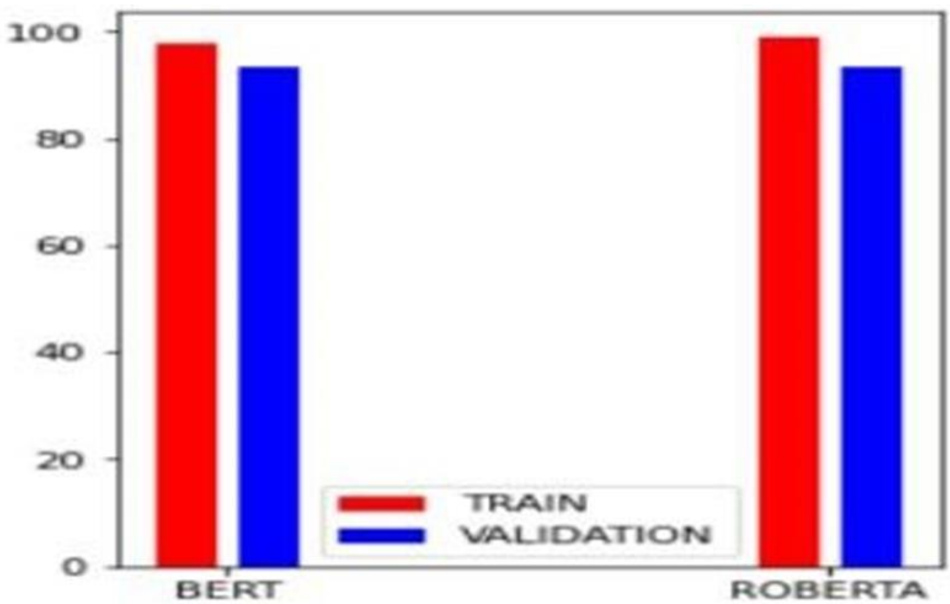


Fig 14: Graphical Representation Of Table 13

• The objective for which this additional strategy was used has been accomplished.

6. Conclusion

The proposed work leads to the conclusion that hybrid classifiers consistently offered superior outcomes in comparison to the single classifiers in terms of results. In order to determine how accurately a particular classifier will categorize fresh unused data, evaluating and assessing the validation accuracy of classifiers is crucial. Therefore, while drawing inferences, the model's validation accuracy is also taken into consideration.The hybrid models M8 (Random Forest and Decision Tree) as well as M10 (Naive Bayes and Decision Tree)are the most effective among the 11 machine learning classifiers used in terms of both TF-IDF and Word2Vec

word embeddings. After examining the validation accuracy of hybrid classifiers embedded with TF-IDF, model M5 (SVM and Random Forest) delivered 92.93% accuracy, while models M8 and M10 provided 91.88% accuracy embedded with Word2Vec. In a similar fashion, when deep learning classifiers are analyzed,it is observed that the training accuracy of a single classifier CNN embedded in GloVe and FastText is 96.59%and 95.95%, respectively, which is roughly better than the hybrid model. However, according to the assessment of validation accuracy, the hybrid model using GloVe and FastText scored 92.46% and 93.01%, respectively. The maximum validation accuracy of 93.34% and 93.47%, respectively, is reached by BERT and RoBERTa, also known as transformer models, in addition to a reasonable training

accuracy.

7. Further Research

The subsequent authors have a variety of alternatives if they want to expound on this topic further. Although the study has demonstrated to give the best outcomes, there are a few research limitations that can be addressed and rectified. To begin with, the dataset is not balanced, which is recognized as a study's limitation and needsto be resolved in order to produce much more robust results. The analysis was done using the data that was gathered in order to identify the sentiments of the populace at the pinnacle of omicron's surge.

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