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RESEARCH ARTICLE

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MULTICLASS-SUBJECTIVITY FEATURE CLUSTERING BASED TWITTER SENTIMENT ANALYSIS USING CONTENT BASED DEEP FEATURED NEURAL NETWORK FOR COVID-19 WAVE OPINIONS

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ABSTRACT

Recent day's social media is big discussion area for content discussion on social media have sentiment facts depending on the user opinions because of different user have different opinion to share in twitter tags. Due to improper analysis in content analysis, the subjectivity of original information be varied due to opinion projection of words are trajectory. So, the prediction of the trajectory contents failed to produce classification in accuracy in the sense of precision rate. To resolve this problem, we propose a Multiclass-Subjectivity Feature Clustering (MSFC) Based Twitter Sentiment Analysis (SA) Using Content Based Deep Featured Neural Network (DFNN) for Covid-19 Wave Opinions to find the positive, negative opinions. This estimates the Hashtag Content Indexing Rate (HTCIR) depends on the user tweet tags accumulation carried out tagging speech of words. Then the tweet term sentiment was observed by lexical analysis using Lexical Subject Impact Score (LSIC). From the sentiment score lexical features point are averaged into mean depth threshold values and considering features are grouped into clustering using MSFC. Then the cluster be ranked using Opinion Ranking Weight (ORW). Once trained as a DFNN, it can classify the terms and select features based on the references. This proposed system produces higher efficiency compared to the other system as well in SA attains high calcification and precision accuracy than other methods.



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I. INTRODUCTION

Social media information is transformed into global big data through big data forums. Data analysis reveals that the processed data is vast and can take many forms worldwide. In addition, all of these movements can have a negative impact on human fitness. Their actions on social media reflect their opinions. Social cognitive analysis identifies positive, negative, or neutral behavior [1]. By conducting SA on Twitter comments, we can gain insights into public opinion on Covid-19. Big data analysis can be based on SA feedback to derive insights about user sentiment, depending on the data processing method. User feedback is critical for products, and older people can try out reviews of their products before processing them through Natural Language Processing (NLP) into a broader concept known as sentiment mining or SA. This process, also referred to as "reputation analysis," helps to evaluate the overall sentiment of the reviews received. Large tags ad discussion can't easily analyze this data every day due to the huge amount of data. The tweet tags contain different dimension and different point of view to produce the meaning, which is support with help of map reducing framework to analyses.

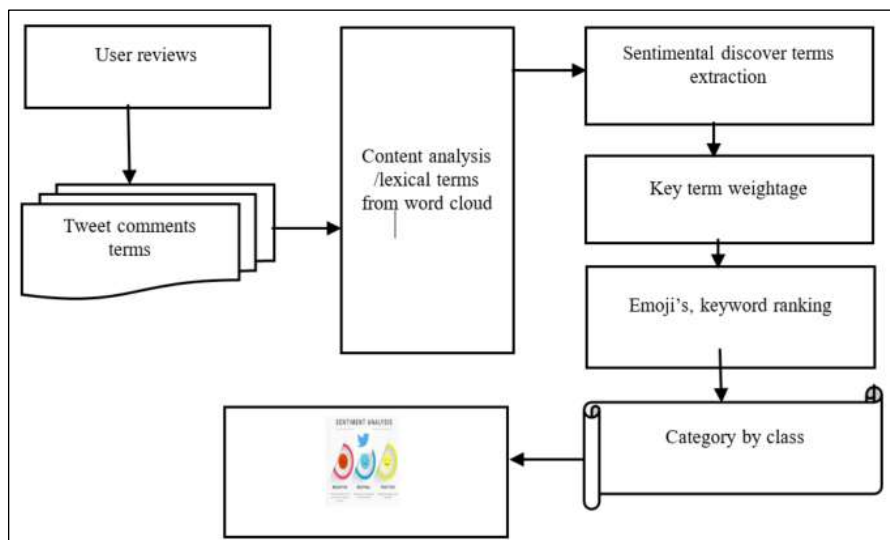


Figure 1: Process of tweet SA.

Source: Authors, (2026).

The subjectivity of a word depends on the context of the phrase. The target document may also contain subjective sentences. To overcome these difficulties, we also implement the proposed system, which improves the accuracy of reviews. In addition to that, precision can be evaluated using parameters such as recall, F-measure, and precision. The audit pole is also calculated by the computer, which provides a better estimate of accuracy compared to other measurements. These concepts cannot be used to tackle complex, big data problems such as unstructured data, where relationships need to be created. Twitter data is a good example of unstructured data. Content Analysis techniques normally used are bag of words, part of speech, machine learning, statistical dependency and relations, keyword filtration, lexical affinity, concepts, presence of particular of word, syntactical representation, human judgment factor is also very important along with computational system which may not precise estimation analysis of tendency of text generated by author. Dealing with data which is generated by social media is involves Stop word removal, substitution, sentence completion (for incomplete sentence) are applied to complex structured data retrieved for analysis. To resolve the problems of substitution, number of rule based, prediction based or relation-based approaches are applied to SA. Tree traversal techniques also are used to parse the tree in a syntactic form to trace out the topic of sentiment in domain communication. Similarly, Dictionary-based polarization approaches can be evaluated by implementing commonly used methods in SA. Lexicon-based techniques, also known as lexical approaches, use precomputed polarity dictionaries or lexical term predictors. Either a manual dictionary or one created from another available corpus can be utilized. Subjectivity knowledge is the underrating of keyword expose term from the accuracy of their heuristically selected features and the training machine learning algorithms. Agnostic learning content extraction method can be used with algorithms like Support Vector Machines (SVM) and Particle Swarm Optimization (PSO) to prevent biases in the learning algorithm and interaction process. An Artificial Neural Network (ANN) classification algorithm can be developed and a reputation analysis filtering method can be applied. Contributions are, Understand the concerns and questions raised about the existing facilities regarding the Covid-19 pandemic and the vaccination operation. Errors about vaccines to reduce the problems. Take appropriate action to create awareness about the current situation. The improve precision, recall and accuracy values. In addition, a reduce time and error rate for predicting the result.

II. RELATED WORK

Social media is a substantial part of the content debate, and consuming online media can be daunting [1]. Emotional analysis is a technique that uses text analysis to analyze and classify emotions [2]. So this work uses emotional analysis. In this article, we present a text analysis of Twitter information and a general view of monitoring the progression of fear directly related to the widespread infection of the corona virus [3]. To address the noise, slang, and spelling variants that often occur due to the informal nature of social media, a variety of normalization approaches have been applied to a dataset obtained from Twitter. Proper normalization has enhanced the effectiveness of the preprocessing stage and, in turn, assist to produce more accurate results in text mining and sentiment analysis [4]. Social media has become an integral part of our lives, generating an enormous volume of information and opinions on various topics. In order to manage this vast amount of data, researchers are now exploring ways to extract useful information from it. SA is one such method that enables the tracking of personal evaluations with a degree of confidentiality [5]. Most classification algorithms are designed to predict data labels with a nominal focus. Many researchers are working in this area. Alyssa et al. We extracted several tweets and provided the design of the emotional mine [6]. They categorized customer reviews as positive and negative through tweets. Hashtag status emotion mining are content analysis to get predations during news observation. The result is a general perception analysis of a particular hashtag over a period of time. This is particularly different from conventional sentence and statement-level emotional studies [7]. He emphasized the importance of ideological research in forecasting [8]. As of today, all humans in the world work under the COVID-19 epidemic state. Concealment level perception at the classification level considers analytical shortcomings. Mostly SVM, naive Bayes, and Solution Client are mainly used to improve classification impression analysis capability [9]. To examine how people reacted to the COVID-19 unlock phase and their emotional responses, researchers utilised machine-learning methodologies to analyse tweets. The findings of this study provided evidence that social media is a valid data source for assessing public opinion on large-scale major changes in society [10].

There are unstructured textual information, criticism, or opinion mining ideas (recognition and classification) of SA. SA on previous research has mainly on the process of manually extracting text [11]. Recently, the manual embedding of neural words has been used to represent the demanding representation of functional engineering. Most of these words are embedded and ignore the grammatical information of the sample words in the emotional context [12]. These applications include the social network analysis of social networks, which plays an important role in one of the most important areas of corporate finance, investment, and big data. So this defined the took advantage of the Joint Social Data Analysis and Feedback Information (SDAFI). Therefore, assessing people's beliefs about this condition helps to maintain a positive environment [13]. So with this in mind, we make emotional awareness of the same thing. The majority of algorithms for categorization concentrate on forecasting nominal data labels. On the other hand, considerable knowledge concerns are involved in convention nomenclature predicate categories at the sequence level [14]. Continuous regression or continuous categorization are terms used to describe this kind of issue. However, the practice also encounters problems, such as advanced vocabulary, complex enhancement, vocabulary transcription, and retrieval complexity, because of the enlargement and massive text data on various topics on social networks [15], and cover various word senses. The limitation are direct extension or a time-consuming and inefficient method of pertinence, which leads to a lack of adequate flexibility and communication. . SA on previous research has mainly on the process of manually extracting text.

III. MATERIAL AND METHODS

The importance of content analysis, the subjectivity of original information be varied due to opinion projection of words are trajectory. So the prediction of the trajectory contents failed to produce classification in accuracy in the sense of precision rate. To resolve this problem we propose a MSFC Based Twitter SA Using Content Based DFNN for Covid-19 Wave Opinions to find the positive, negative opinions.

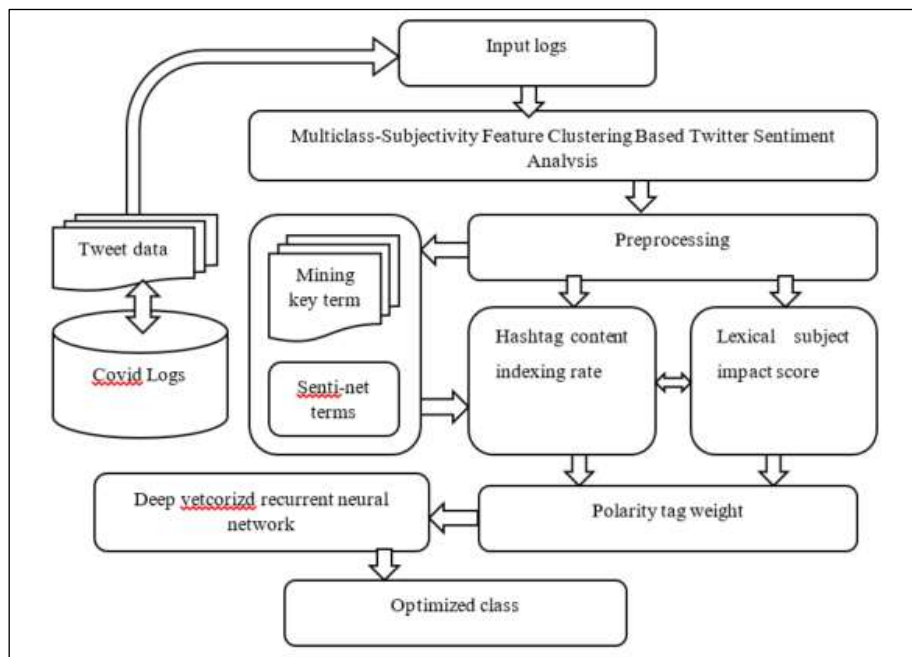


Figure 2: proposed Architecture of MSFC-DFNN.

Source: Authors, (2026).

SA can accurately extract positive or negative sentiment from unstructured review texts, but more care is needed for very fine, very negative, negative, and neutral categories. Figure 2 shows the proposed Architecture of MSFC-DFNN. In general target less impression analysis, a call signifies overall emotional well-being throughout the text. A call-to-work analysis of another impression, identifying emotions for the entity or feature, which is analyzing the impression of the target orientation or feature level. Our research focuses on less common goal influencer research. There are two general methods of reputation analysis. Is a rule-based approach. Machine learning is available, including other deep learning method

III.1 DATASET DESCRIPTION

Tweets were collected using Twitter API and script using Python. A query for this high frequency tag (#covid19) is performed every day over a period of time to gather a large sample of tweets.

user_name	user_location	user_description	user_created	user_follower	user_follower	user_follower	user_verified	date	text	hashtags	source	is_retweet
#Kazda	astrowork	wednesday	#####	624	950	18775	FALSE	#####	If I smelled the scen	Twitter fo	FALSE	FALSE
Tom Basil	New York	Husband,	#####	2253	1677	24	TRUE	#####	Hey @Yankees @Yar	Twitter fo	FALSE	FALSE
Time4fisti	Pewee Va	#Christian	#####	9275	9525	7254	FALSE	#####	@diane34 [COVID19	Twitter fo	FALSE	FALSE
ethell mer	Stuck in th	#Brown's	#####	197	987	1488	FALSE	#####	@brookbs [COVID19	Twitter fo	FALSE	FALSE
DIPR-J&K	Jammu an	BY-Si, Off	#####	101009	168	101	FALSE	#####	25 July: [CoronaV	Twitter fo	FALSE	FALSE
BY21 Franz	BB&B&B&B&B&B	#OC	#####	1180	1071	1287	FALSE	#####	#coronavi [coronavi	Twitter W	FALSE	FALSE
hr bartent	Gainesvill	Workplac	#####	79956	54810	3801	FALSE	#####	How #CO [COVID19	Buffer	FALSE	FALSE
Derbyshire	LPC		#####	608	355	95	FALSE	#####	You now have to we	TweetDec	FALSE	FALSE
Prathamesh	Bendre	A poet, re	#####	25	29	18	FALSE	#####	Praying [covid19,	Twitter fo	FALSE	FALSE
Member c	BY*BY*lo	Just as the	#####	55201	34239	29802	FALSE	#####	POPE AS	Hurrican	Twitter fo	FALSE
Voice Of	CBSE Students		#####	8	10	7	FALSE	#####	49K+	Twitter W	FALSE	FALSE
Creativegi	Dhaka, Bar	f'm	#####	241	1694	8443	FALSE	#####	Order [Yogo], gr	Twitter W	FALSE	FALSE
SEXXYLYPI	Hotel Jivir	My link	#####	0	8	32	FALSE	#####	BY*BY*BY*BY*BY*	[COVID19	Twitter W	FALSE
Africa You	Africa	Official ac	#####	830	254	3692	FALSE	#####	Let's all [COVID19	Twitter W	FALSE	FALSE
Dailyadda	New Delh	Breaking r	#####	546	29	88	FALSE	#####	Rajasthan Governme	Twitter W	FALSE	FALSE
Dimapur 2	Nagaland,	strive to	#####	274	32	378	FALSE	#####	Nagaland [Covid19	Twitter fo	FALSE	FALSE
ChennaiCity	Now	Individual	#####	3987	53	749	FALSE	#####	July 25 [COVID19	Twitter fo	FALSE	FALSE
marc goov	Brussels	Progressi	#####	283	1432	1546	FALSE	#####	Second in [COVID19	Twitter fo	FALSE	FALSE
Dorian Aur			#####	46	108	453	FALSE	#####	It is [light]	Twitter W	FALSE	FALSE
Coronavir	Florida, U	COVID-19	#####	14	24	74	FALSE	#####	COVID Update: The i	Twitter fo	FALSE	FALSE
The Voice of	GenX		#####	292	1037	58	FALSE	#####	@EvanAK	Twitter fo	FALSE	FALSE
APO Grou	AFRICA	#Latest #AF	#####	10661	6	2037	TRUE	#####	Coronavirus - South	Africa Nev	FALSE	FALSE

Figure 3: Dataset description.
Source: Authors, (2026).

III.2 PREPROCESSING

We collect data on non-searched, less emotive words like links, hashtags beginning with # and tags beginning with (@), single letter words, and Twitter-specific phrases such as numerals.

$$N = \frac{c - \mu}{\sigma}$$

When classifiers are being trained and tested, terms like these can have a significant impact. Before feeding the labelled dataset into the classifier, noise needs to be eliminated in order to enhance the classifier's performance.

III.2.1 Vector processing

Non-numeric languages cannot be entered into machine learning classifiers. Textual data needs to be transformed into features before being used in predictive modelling is analysis the size and diversity.

Input tweets dataset

$X \leftarrow \text{Clean_tweets}$

$X \leftarrow X.lower$

$\text{Tokens} \leftarrow \text{wordTokenize}(X)$

For each token

No stop words []

If token is not in stop words.

$\text{No_stopwords.add}(\text{Token})$

$\text{Tokens} = \text{no_stopwords}$

$\text{Stopped_tokens_append}(\text{vectorized_tokens})$

End

End

To determine word frequency, employ the feature extraction programmer CountVectorizer.

III.3 MINING COVID KEY-TERMS

Sentiment analysis mainly focuses on analyzing text data, which involves complex text processing. In this study, we created test data for three frequently used search terms - "Covid," "Coronavirus," and "Covid-19." Social media users commonly use these keywords, and hence, we used them as search strings for the work.

III.4 SUBJECTIVITY ANALYSIS

In Figure 1, we can implement a word cloud generated from the tweet database, which can show how often the word “COVID” occurs on Twitter. By using the word cloud, the frequency of the keyword “Covid” can be observed. The values of the two constants can be displayed in the database in terms of subjectivity and polarity using Cartesian coordinates. Polarization refers to whether a term is subjective or objective, while polarization suggests positive and negative human behavior associated with each keyword. There is a "zero" point in the polar column. Therefore, all points on the map to the left of zero indicate non-positive comments, and positive comments to the right are zero.

III.5 POLARITY MEASURE

When performing sentiment analysis, it is crucial to distinguish between subjective and objective sentences. If a sentence is objective, no further analysis is necessary. However, if the sentence is subjective, it is important to determine its polarity, whether it is positive, negative, or neutral.

III.6 HASHTAG CONTENT INDEXING RATE

At this point, the system will read the hashtags and extract the text words from the record depends on the opinion. Then, for each period of extraction of the key terms, the method goes through a pause removal and steaming process to get the posteriors word relationally the subjectivity points. This method maintains a list of meaningless stop words and removes the content from the stop word. They extract the subject point verbs, objects, entities, pronouns and the dictionary of relational dependencies.

Input: preprocessed tweet data's and hashtag under covid discussions

Output: objective terms (Ot)

Step 1: initialize dataset Twt ($n \rightarrow tw1, tw2...$)

Check relative key term log Covid ($RL(Tw-1)$)

Extract the key terms and its subjective $Ks(tw) = \sum Text \in (RL(Tw - 1))$

Step 2 Identify the subjective terms pint covid ($Cst \rightarrow RL(T, Cs(Tw))$)

Estimate the number of count Terms (Cv as tweet Tag (Tg))

Step 3 Splits the tags support $Tg(n)$.

$Ts = \sum(RL(Ts) \in Ht) \cap CV$

Compute the Nous and subjective hash terms verbs (Cv and Ts)

Accomplish Covid tweet of each tag (Cti).

$Cti = Tag(Tw)$.

Check if $Ts \leftarrow$ relative speech term (tw)

Return objective points ($Op \rightarrow tw$)

Else

Extract the actual subjectivity tweets ($Ats(Tw)$)

Generate subjectivity hash index ($Shi \leftarrow Ats$)

Return objectives terms ($Ot(Shi)$)

End

End

Stop.

After pre-processing, these words will be arranged in structural processing by processed their data to extract the hash terms. This reduce the dimensionality of the Tweet datasets which is redundant to make easy process. This process reduces the time complexity of Tweet pattern investigation because of the least selected feature used to make efficient Tweet analysis. This find the behavioral of data originate the main key terms

III.7 FEATURE SELECTION USING LEXICAL SUBJECT IMPACT SCORE (LSIS)

According to Feature selection using text granularity, lexical based text contents are analysed for key terms present and point of reference to the sentiment terms are extracted. The extracted terms are subjects to the subject to the Main term in word level sense for topic discussion. Lexical Word SA is a prerequisite for sentence reputation analysis.

A more critical debate of reality terminology takes place in the context of the presentation of reality labels. It locates relative subjectivity between opponents in terms of dominance. The opposite acronym for mean sentence importance is this mirror race. In order to forecast contextual phrases, this abstract model determines the frequency of relationships between real and non-real terms. Based on the opinions of the terms dependencies of the key terms are categorized on sentiment terms related to subjective pointing reference.

Input: subjectivity sentiment term S_i , tweet processed dataset (tDs)
Output: Subjectivity Impact Score (SGS).
Step 1: calculate the dataset.
 Extract term lexical sentiment set (Tss) and tweets words
 Create similar set G_s .
 Observe each ecological term (t_{Di}) from the set of t_{Ds} of the objective relations
 Sentiment context words $T = \text{predicted identity of subjective words } (S_t \leftarrow t_{Ds})$
Step 2: compute the relation term from relative identity
 Relative subjected sentiment term $S_s = (\sum (n=1) \wedge (\text{Mutual data term}(Ds) \text{ extract relative } \epsilon Di) \times \text{categorize("covid")}) \text{ topic}$
 keyterm
 Calculate the subjectiveness of each term TS_i from the perception of S_i
Step 3: compute term index G_i .
 $CT_i = \text{Terms}@S_i$ Estimating long-range frequencies from the environment set
 For each term T_n from CT_i to find difference
 Check if T_s as rational term
 Compute term index count $T_i = T_i \text{ } \& \text{ } T_n$
 Else
 Check relative term
Step 4: Extract the mirrored object from the real-world counterpart
 Check if the max count term
 Return Sentient S_i
 End
 End
 Check for subject T_k from T_i
 Extract the subject term to S_i
 $S_i = \sum (\text{tweets} \epsilon) + \text{Negative term equivalence } (N_i).$
 End.
Step 5: compute to relative subject R_s .
 For each decision support, the trust term consists of a lexical term L_t
 If $D_i \epsilon L_t$ then find R_s
Step 6: Identifying sentiment words from contextual subjective support values
 Contextual inverse support value $R_s = \sum (\text{Concepts} \epsilon \text{ relation } D_i) + \text{computed inverse mirrored value } C_i.$
 Extract the term index support weight LS_i
 End for
 End for each
 End if
 Stop

From a subjective point of view, the pre-processing of textual documents includes related entities and unrelated entities. The lexical features generate semantic equivalence based on the mirrored terms from the subjectivity to identify the relational lexical terms as lexical features. To determine the results of sentence-level analysis chapter level emotional ways. The conclusions of the sentences are a comprehensive one with the results of the research. On the other hand, chapter-level emotional tendencies are based on contextual semantic relationships. Based on the textual analysis, the word emotion is the determinant of emotional tendencies. So it is very meaningful

III.8 OPINION RANKING WEIGHT (ORW)

When categorizing tweet tags using comment points based on opinion ranking, input data should be chosen to contain as much information as possible, while most tags contain important keywords related to the subject. One of the methods used to measure the information of any variable used for this purpose is the feedback rank weight. When the modulation scheme information used by the transmitter is specified by c , the interaction between the i -th function and the volume c is defined as follows.

$$I(x_i; c) = \iint P(x_i, c) \log \frac{P(x_i, c)}{P(x_i)P(c)} dx_i dc,$$

$P(x_i, c)$ is the joint probability distribution of the corresponding terms x_i and c . The higher mutual information value helps the finite value because this feature contains a lot of information about the module covid relative forum from the tag.

III.9 MUTUAL INFORMATION QUANTITY

In this stage, the preprocessed LSIS and optimize ORW weight be a further process in taken opinion ranking process. By dividing the scaling weights based on the features, we can detect and predict their correlations. Moreover, we can implement a feature subclass to browse the related weights and create variation relationships between them. Additionally, the surf factor can identify feature weights and selectively measure values between class decision edges. We can sort the weights of the feature visits into key period subgroups of the tweet based on internal and external subgroups. Furthermore, it helps us select polar biases to eliminate undesired deterministic values.

Input R-FD_s dataset.
Select Label Properties
Estimate the marginal weights of the measurement values $MG_w \leftarrow R - FD_s\{dr_1, dr_2\}$
Estimate sub-attribute distributions for each data $MG_w \rightarrow 1 = 0,1,2,$
Compute the relational range of class labels $I_m \rightarrow \{Fuel, speed, brake \dots\}$
Compute Low if weight scale mean rate (I_m)
 $M_R \rightarrow$ Inner feature $O_t(i * MG_w) =$ all partitions excluding i .
Similarly as where outer set $\rightarrow O_t(i)$, Inner set $\rightarrow I(i)$
Development up to $O_t(i)$, = the i 'th partition as M_R
Compute initialization for $j = 0, 1 \dots M$
Calculate the common conduct distance S_t Measure (F_s) with j intnte featyre set $F_s \ I \rightarrow i + F_s; J$ loop
End
Progress Ratings are the biggest features from the IF_s
Return the IF_s feature

To select values in redundant feature dimensions, it's necessary to sort the features. The above algorithm can be implemented to define interactions based on access groups. Furthermore, weights can be aggregated based on the multiple frequently accessed features. Even if the feature weights are small, subsequent accesses of feature key weights can be selected.

III.10 DEEP VECTORED RECURRENT NEURAL NETWORK

These classifiers can be classified into logical activation phase and deep recurrent neural network classification which are follows as

III.11 LOGICAL ACTIVATION PHASE

In this case, the sigmoid activates and determines the patient's risk profile based on the activation process and the clinical recommendations made by that class. The activation function based on softmax logical condition to attain the logical contains from feature inputs. This select to train the features from the threshold conditions the features re get categorized in neural network. A RNN can be trained using an adaptive algorithm obtained from an optimized feedforward network. Neurons can also be adjusted based on their closest weight predictions. In this phase actual output are observed logically to activation for making decisions to create successive weights prediction. This integrate the watchcase key term prediction approach based on feature selective on decision support.

The activation function trains remains the $f(x) = \begin{cases} y = 1 & \text{if } \sum_{i=1}^n w_i x_i \geq b \\ y = 0 & \text{otherwise} \end{cases} \dots (9)$ the infraclass definition variables $f(x)$ and x be the features to create transformation logical condition weight, $w_{(t+1)} = w_t - \mathbb{N} \Delta w_t$ and $b_{(t+1)} = b_t - \mathbb{N} \Delta b_t$.

The iteration are formulated by attaining mean weigh closes to the successive function from the weight $w(t)$ at trains 't' at $N \rightarrow$ number of neurons activation links are checked. This creates logical representation based on the weightage of features be trained into the neurons. The Weight 'w' at 'i' and 'j' remains the max limit of the features weight to predict the category, however the function 'y' remains the training level from the feature of 'x'. A fully integrated feed-forward of the neuron is illustrated in the construction of the network

$$net_{i(t)} = \sum_{j=1}^j w_{ij} y_{j(t)} + x_{i(t)}, i = 1 \dots j \text{ and}$$

$$Ti \frac{dy(t)}{dt} = -yi(t) + \varphi(net_i) + x_{i(t)}, i = 1 \dots j$$

The neural layer $net_{i(t)}$ is obtained by optimizing weights from the function "x," which is trained on the logical function "y." The neuron weights are typically fixed at T_i which balances the bandwidth allocation based on the state of service according to the average weight $W_{(i)}$ calculated from $X_{(i)}$ and $Y_{(i)}$.

III.12 DEEP VECTORIZATION RNN

Ideal neural algorithms are synthetic neurons that execute functions based on deep neural network called Deep featured recurrent neural network, including hidden layers, for binary classification problems. Perceptron uses a functional function based on a neuron-bi-neuron.

By the definition of classifier, the selected features are clustered into input layer processed to decision through logical activation function. This create logical decision by determining feature weights attain in each hidden layer progressed into neurons. The features are selectively defined into threshold margins. Each features be verified with search optimization between the selective relative groups. The relative groups are average into the scaling levels to create winner class by class by reference. The marginal weights are get classified by each iteration to the activation to split category by class.

Algorithm: Spectral RNN (SRNN)

Input: Feature values $\rightarrow F_v(F_{rc} - I_{ds})$
Output: Recommended categories of twitter
Calculate hidden layer structure as F_v
Create an input progression and code the feature FI_p
A feedforward layer of neuron logic $R8 \times C16$ can be created using the inter-segment constructor.
For perform FI_p as redundant connection
Advanced connectivity can be extended and linked with clusters of groups.
The F index can be sorted into cluster F_c with respect to all features

$$FI_p \rightarrow (y + b)^n = \sum_{i=0}^n \binom{b}{y} y^k w^{n-k} + c \sum_{l=1}^n \epsilon l t_s$$

Calculate the dense lattice weights at each measured threshold
For all scalar j in cluster c_i
For all term index changed weight x
Check neural layers
If layer exceed Forward $\rightarrow$ new $X_{new}, C_i, jw_{(t+1)} = w_t - N \Delta W_t(net_{i(t)})$
Compute the IRP_i characteristic scaling of class C_i
Fix margin winner period Y new $FS_i = b \cdot \text{Relative weight}, FS_i$
Feature index spread $b_{(t+1)} = b_t - N \Delta b_t$
End for each
End for
End if
Compute implementations for hidden layer iterations
 $F \rightarrow FS_i$ Make the maximum layer as forward weight at each node,
For each close design of related connection, each pattern p
 a_{ss} Categorize the features based on each similarity.
 $Pfs = \frac{\sum_{i=1}^{size(p)} \sum P(i) == S_{cs}(i)}{size(p)}$. To split the class polarity
End for
Compute cumulative $PFS = \frac{\sum_{i=1}^{size(pps)} Pfs}{size(pps)}$. positive, negative. Nuetralize class
End
Step 7: Return FS_i class by reference a_s .

The iterative activation function in hidden layer create 20 sub structure for connective groups of neurons conating the threshold margins are active class function. Based on feature training and adaptive weights the feature index get updated to change the c =values of the neurons. Then the neural get active weighted features for conditional verification from the input features. The active weights are get trained with fitness evaluation thi categories the feature limits to training layers. At the active trains features are spread into comparative trained features values based on the margin class, threshold values split the margins depend on the risk values attacks are split into positive, negative and neutral and low margin are classified into tweet class

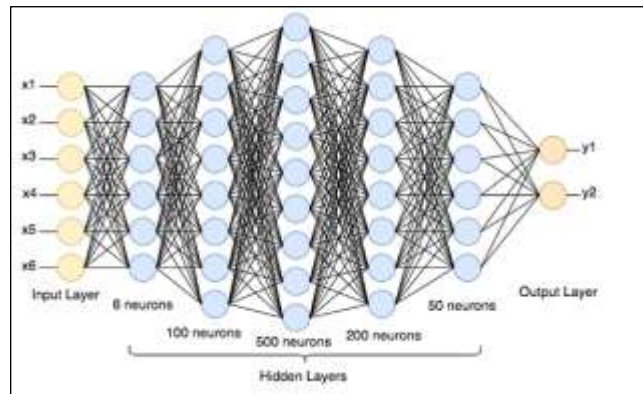


Figure 4: DFNN Architecture.
Source: Authors, (2026).

A deep neural network (DNN) is a collection of completely connected layers that classifies the output value, which is sequentially computed in network layers, based on the features of each compound as input. The input vector representing the output value of each unit in the preceding layer is multiplied by the weight vector of each unit in the current hidden layer to determine the weighted total for each layer. An input layer (L_0), an output layer (L_{ut}), and H hidden layers (L_h ; $h \in \{1, 2, \dots, H\}$) positioned between the input and output layers make up the fundamental DNN architecture. A vector $a_h \in \mathbb{R}^{|L_h|}$ can be structured as follows: Here, $|L_h|$ denotes the number of units in each hidden layer L_h , which is a set of units.

IV. RESULT AND DISCUSSION

The Twitter sentiment analysis based on MSFC employs a content-based DFNN to analyze tweets from real organizations collected from a tweet repository in the Twitter dataset. The analysis helps in predicting the sentiment of these tweets. Additionally, the sentiment words extracted from the comment dataset affect the tweet positions depending on the relevant datasets. The table below displays the processed parameters and their corresponding values.

Table 1: Evaluation of simulation parameter in dataset.

Simulation	Values
Usage of Datasets	Twitter dataset of covid forums
Class Statement	Positive negative, neutral
No of tweets logs	3000
Terms of Content	Attribute text

Source: Authors, (2026).

Twitter analysis is a useful tool that can be used to determine the number of posts. To accomplish this, the features are extracted into three categories: positive, negative, and neutral. Table 1 shows the parameters and values processed in Twitter analysis. The affective attitude toward a keyword can be accurately measured using this method. Additionally, it has been demonstrated that relationship closeness can be measured by the number of words in tweets.

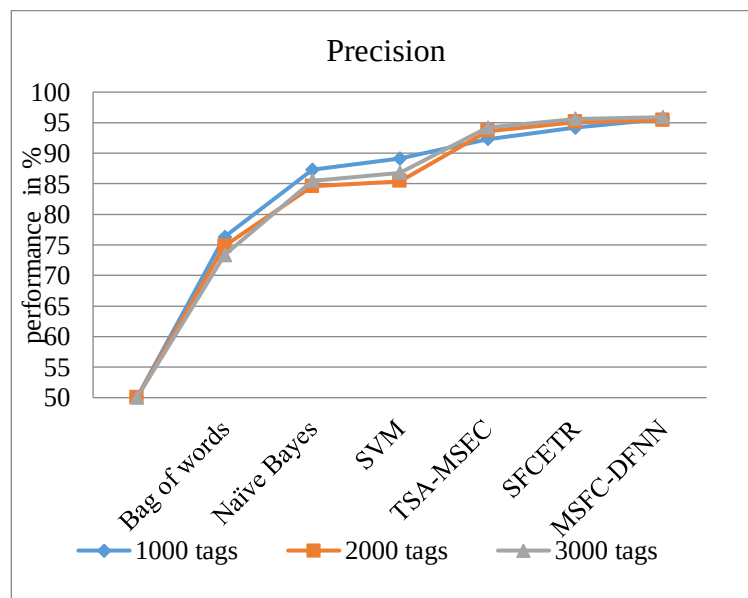


Figure 5: Performance of precision rate.

Source: Authors, (2026).

A comparison between the precision sensing approach and other different methods is illustrated in Figure 5. Furthermore, the accuracy rate can be significantly improved by implementing the proposed system. Based on these selected features, they are more noticeable and give more results.

Table 2: Performance of precision.

Methods/number of tweets	Performance of precision in %					
	BW	Naïve Bayes	SVM	TSA-MSEC	SFCETR	MSFC-DFNN
1000 tags	76.3	87.3	89.1	92.3	94.2	95.6
2000 tags	74.8	84.6	85.4	93.6	95.1	95.4
3000 tags	73.2	85.5	86.8	94.2	95.6	95.9

Source: Authors, (2026).

The table 2 presented above provides a comparison of the accuracy of sentiment word analysis from tweet comment data. According to the table, the precision of Naïve Bayes is 8.35%, while the accuracy of SVM is 89.1%. The proposed MSFC-DFNN has the highest accuracy rate of 95.9%, making it 95.6% more efficient than the other methods.

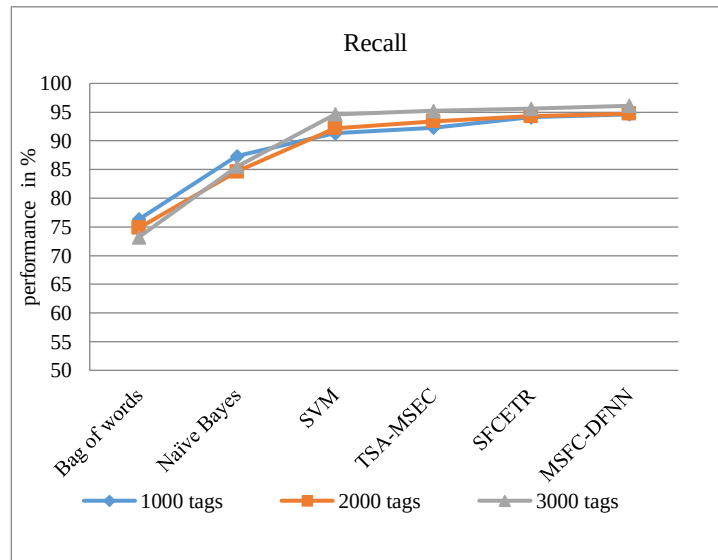


Figure 6: Performance of recall.
Source: Authors, (2026).

Figure 6 above illustrates an efficient approach to creating effective recall. The efficiency of this processing has more elevated results compared to other different methods.

Table 3: Performance of recall.

Methods/ number of tweets	Performance of recall in %					
	BW	Naïve Bayes	SVM	TSA- MSEC	SFCE TR	MSFC - DFNN
1000 tags	76.3	87.3	91.3	92.3	94.1	94.6
2000 tags	74.8	84.6	92.2	93.4	94.3	94.7
3000 tags	73.2	85.5	94.6	95.2	95.6	96.1

Source: Authors, (2026).

Table 3 above presents the effects of an iterative examination of recall status to describe the relevant patterns. The efficiency of MSFC-DFNN for the objective technique system is % higher than that of different methods.

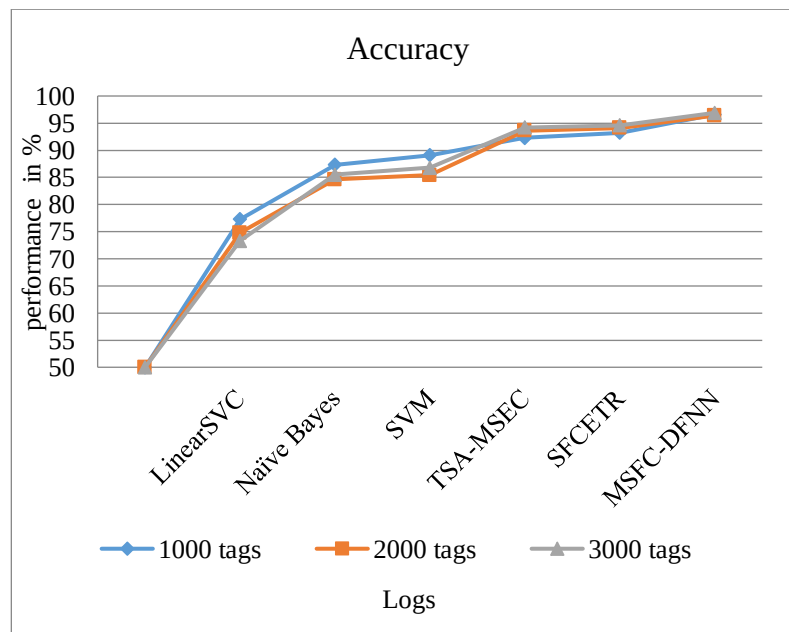


Figure 7: Performance of precision rate.
Source: Authors, (2026).

A comparison between the accuracy sensing approach and other different methods is illustrated in Figure 7. Furthermore, the accuracy rate can be significantly improved by implementing the proposed system. Based on these selected features, they are more noticeable and give more results.

False extraction Ratio

$$= \sum_{k=0}^{k=n} \times \frac{\text{total dataset failed tweets (Fer)}}{\text{Total no of extratedrate(Fr)}} * 100$$

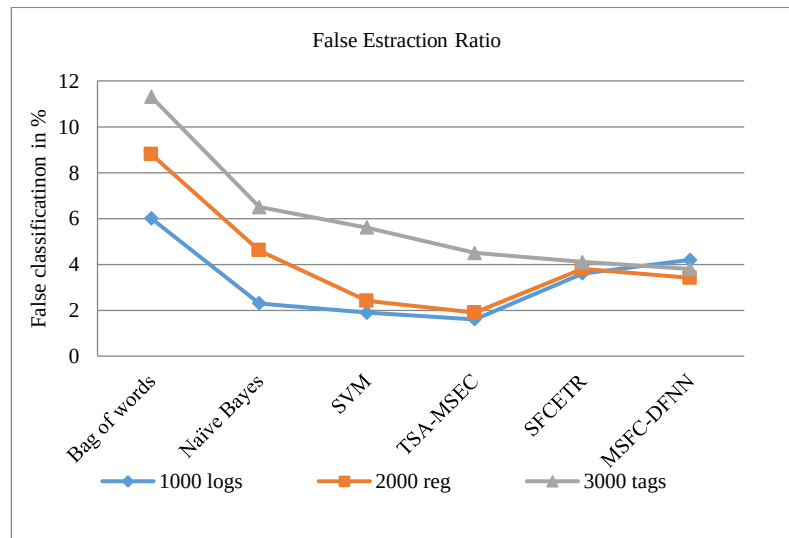


Figure 8: Performance of false extraction.
Source: Authors, (2026).

Figure 8 above compares and demonstrates the misclassification of different methods. Furthermore, the objective MSFC-DFNN method can produce lower misclassification rates compared to different methods.

Table 4: Performance of false extraction.

Methods/number of tweets	Evaluation of false extraction in %					
	BW	Naïve Bayes	SVM	TSA- SEC	SFCETR	MSFC-DFNN
1000 tags	6.6	5.3	5.2	4.4	3.6	4.2
2000 tags	8.8	4.6	4.4	4.3	3.8	3.4
3000 tags	11.3	6.5	5.6	4.5	4.1	3.8

Source: Authors, (2026).

As described above, different methods can produce different classifications of Naïve Bayes 5.3 %, as described in Table 4. Also, different methods can be compared with different preferred performance levels. The misclassification rate of the proposed MSFC-DFNN method is reduced to 3.8%.

Variant types for classification results. Time complexity (Tc) = $\sum_{k=0}^{k=n} \times \frac{\text{total tweets handeletd to process in dataset}}{\text{Time taken(Ts)}}$

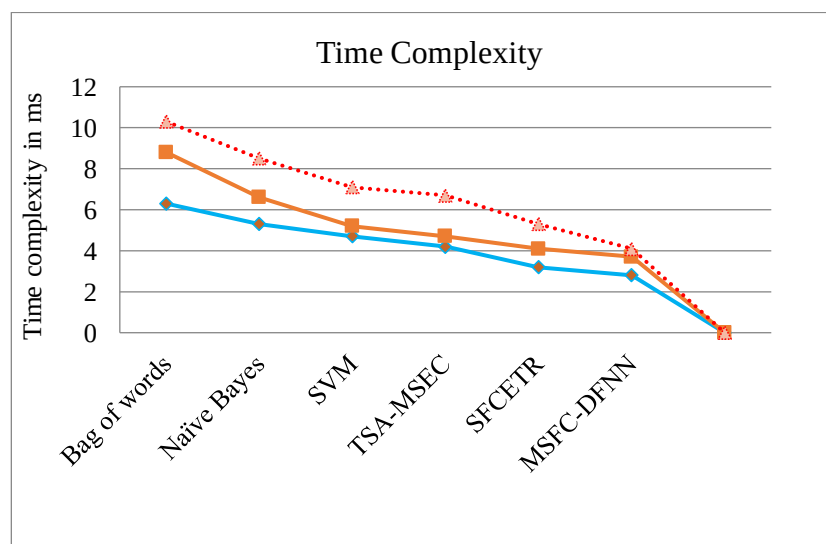


Figure 9: Performance of time complexity.
Source: Authors, (2026).

The above figure 9 resemble the various dissimilar comparison of time complexity compared to the proposed system. The proposed MSFC-DFNN implementation produce the maintained mean time performance as good than dissimilar methods.

Table 5: Performance of time complexity.

Methods/number of tweets	Evaluation time complexity in seconds (ms)					
	BW	Naïve Bayes	SVM	TSA-MSEC	SFCETR	MSFC-DFNN
1000 tags	6.3	5.3	4.7	4.2	3.2	2.8
2000 tags	8.8	6.6	5.2	4.7	4.1	3.7
3000 tags	10.3	8.5	7.1	6.7	5.3	4.1

Source: Authors, (2026).

In the table 5 mentioned above, it can be observed that processing the terms in the tweet dataset is a time-consuming task. Moreover, the feature classifiers can only combine these terms with redundant ones, which further adds to the processing time. However, the implementation of the proposed MSFC-DFNN can significantly reduce the execution time to as low as 2.8 milliseconds, as compared to other available methods. This makes the proposed model highly efficient in terms of execution time.

V. CONCLUSION

To conclude, the amount of people who use social networking sites on a daily basis has significantly increased. Individuals would rather openly express their ideas on social media than in person. We investigate popular perceptions of the Indian government's shutdown amid the coronavirus pandemic using tweets. Motivated by the contrasting responses that India received following the announcement of the lockdown, we gathered tweets from the country's second lockdown phase. The proposed algorithm uses MSFC-based Twitter SA to process Covid-19 wave feedback using content-based DFNN to perform positive, negative, and neutral classification based on Twitter SA to achieve predictions of COVID-19 tweet data. The first process of pre-processing is used to remove noise symbols. To identify the content process of a hashtag in a tweet, feature selection uses lexical content terms. This method is more effective than other existing methods and provides better results. The proposed classification accuracy performance is 95.9%, with a recall performance of 96.1%, a classification precision performance of 95.8%, and an F-measure result of 3.8%. Additionally, the time complexity is 4.1ms. For future research, it is worth experimenting with variations and combinations of the models proposed in this study to consider whether this could further improve accuracy. In addition, the existing classifiers can be tested on larger datasets to verify the high level of accuracy achieved in emotion detection. In addition to increasing the size of the dataset, it is important to include more datasets.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: P. Kavitha, R. Renuga Devi, V. Ruckmani.

Methodology: P. Kavitha, R. Renuga Devi, V. Ruckmani.

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