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Entropy State-Regularized Recurrent Neural Network- Long Short Term Memory (ESRRNN-LSTM) and Classifier for COVID-19 Vaccine

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Abstract

Background: The subject of why some people refuse to receive certain vaccines during an ongoing public health crisis is particularly relevant because low vaccination rates will prolong the time it takes for many countries to recover from the coronavirus disease 2019 (COVID-19) pandemic. Thus, the prediction of user opinion who is taking COVID-19 vaccinations plays a significant role. Existing classification methods has the issue of handling larger dataset, and it becomes increased time complexity. Deep Learning (DL) model is solution for analyzing user opinions with increased tweets, and produces better performance. **Objective:** The major objective of the work is to design a new methodology for the prediction of user opinion using DL. DL is used to predict the evolution of the user opinion to coronavirus vaccination. **Findings:** Covid-19 Twitter Dataset has been collected from Kaggle. It consists of 2,35,240, 3,20,316, and 4,89,269 tweets for first, second, and third phase. Results of proposed ESRRNN-LSTM classifier is compared with existing methods like Modified Long Short-Term Memory (MLSTM) and Bi-LSTM. Results of classifiers are measured in terms of precision, recall, f-score, and accuracy. Proposed system has the highest results in terms of accuracy of 91.20%, precision of 90.00%, recall of 88.00% and F-Score of 87.00%. The five fold cross validation has been also performed to classifiers. **Novelty:** this work is resulted in developing an Entropy State-Regularized Recurrent Neural Network- Long Short Term Memory (ESRRNN-LSTM) for vaccination prediction from user opinion tweets. Parameters of classifier are optimized using the entropy function.

Keywords: COVID19; Sentiment Analysis; Twitter; Deep Learning; Entropy State

1 Introduction

Ending 2019 with a pandemic, the novel coronavirus disease 2019 (COVID-19) presented a significant hurdle for many, if not all, of the world's nations due to its quick emergence, which included issues in the political, economic, social, and security domains [(1)]. As a result, national governments are now compelled to use a variety of strategies to address this situation [(2,3)]. In particular, COVID-19 vaccination technology into the human body has a demonstrably higher resistance to COVID-19 [(4,5)]. People all throughout the world express their opinions and general thoughts about the pandemic that has interfered with their daily lives on social media, both generally and during lockdown periods. One of the most widely used social media sites is Twitter, which in a short amount of time exhibited a sharp rise in coronavirus-related tweets, including good, negative, and neutral ones [(6,7)].

Online social media platforms are full with noisy data, which makes it difficult to separate meaningful material from enormous amounts of noisy data. However, once the noisy data has been cleaned up, it contains human feelings, expressions, and thoughts. Careful analysis reveals a great deal about the current state of mind, mindset, and character of a sizable human group. The number of people using social media is growing over time as a result of their reliance on the platform for educational content, and data volume is also rising. This study concentrated on the effective extraction of meaningful information from social media using Natural Language Processing (NLP) with various techniques. However, the difficulties in evaluating a part of content's intrinsic value when utilizing NLP-strategies such as words and phrases in context, ambiguity in speech or text make the application of machine learning (ML)-based algorithms. DL classifiers become the best solution to test the short and long text information.

DL and lexicon-based algorithms were used to classify the thoughts [(8)]. The BERT model, a new DL model for analyzing texts and performance, was used to analyze the data, and it was evaluated against three other approaches: Logistic Regression (LR), Support Vector Machine (SVM), and Long-Short Term Memory (LSTM) [(9)]. The present research is more significant since it represents the collected view of Indian people, which is diverse in nature [(10)].

Throughout the study, there was more talk about vaccine rejection and hesitation than about vaccination interest, but the trend varied by country [(11)]. Author investigated the COVID-19 vaccination topic discovered on Twitter from December 15th, 2020 to December 31st, 2021, every message about the COVID-19 vaccine was gathered using the Twitter API, and the unsupervised learning VADER model was used to assess the feeling groups and determine the sentiment score of the dataset. The Latent Dirichlet Allocation (LDA) model is used for acquiring themes and keywords after determining the total amount of topics [(12)].

Deep Predictor which is a combination of LSTM and RNN were used in classifying social media tweets regarding COVID vaccination and it gave accuracy of 99.50% to 99.93% [(13)]. In 2023 the author used multiclass sentiment analysis to identify people's opinions regarding COVID-19 vaccines from extracted tweets using machine and deep learning methods, and also analyzed the negative tweets using LDA approaches. ML in deep learning gave best results obtaining accuracy of 96%. Finally, the LSTM model in DL demonstrated 91.66% accuracy [(14)].

The concept of AI integrating with RNN plays a vital role in predicting efficient visulalization is been carried out. Two well-known techniques namely attention and permutation has been implemented to get a clear visulalization prediction [(15)]. To maximize prediction outcomes, this work establishes the optimum activation function for M-LSTM, especially a deep reinforcement learning method. Modified LSTM model is used to optimize COVID-19 pandemic in order to determine various challenges in covid-19 [(16)].

The author evaluated people's attitudes toward various vaccinations, which were measured using the NLP tool and VADER. Feelings are categorized into positive, negative, and neutral for classification of tweets. This study enhances public perception of COVID-19 vaccinations and contributes to the goal of eliminating corona virus from the planet [(17)]. Text classification plays a good role in predicting the words during a strong sentiment analysis. Two deep learning algorithms namely LSTM and RNN were implemented in text classification. Result shows that LSTM gave accuracy of 86% and RNN gave accuracy of 83% in classifying social media tweets regarding COVID vaccination [(18)].

1.1 Research Gap

Careful analysis reveals a great deal about the current state of mind, mindset, and character of a sizable human group. The number of people using social media is growing over time as a result of their reliance on the platform for educational content, and data volume is also rising. This study concentrated on the effective extraction of meaningful information from social media using Natural Language Processing (NLP) with various techniques. However, the difficulties in evaluating a part of content's intrinsic value when utilizing NLP-strategies such as words and phrases in context, ambiguity in speech or text make the application of machine learning (ML)-based algorithms. DL classifiers become the best solution to test the short and long text information.

2 Proposed Methodology

Three different approaches were compared using a Twitter dataset to tackle this sentiment evaluation in the COVID-19 time. Entropy State-Regularized Recurrent Neural Network-Long Short Term Memory (ESRRNN-LSTM) classifier is introduced for SA. SRRNN is done on a Twitter dataset who tweeted after vaccination during COVID. Finally, it is evaluated that the proposed architecture is outperforming conventional architectures like DBN and TG-ML concerning precision, recall, F-measure, and accuracy. Figure 1 shows the overall flow of the proposed system.

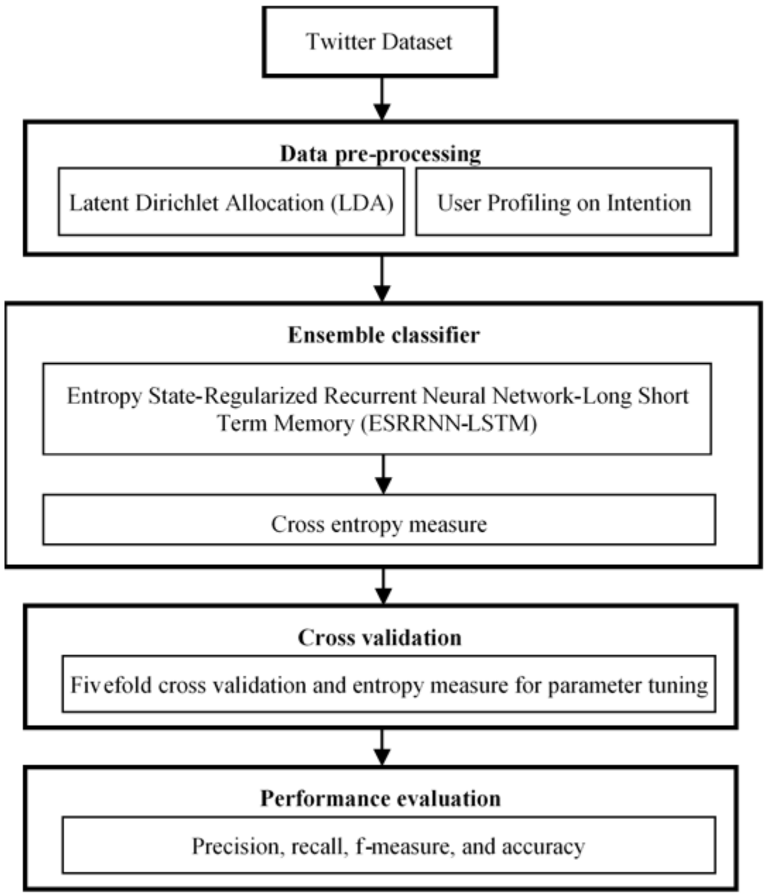

Fig 1. Proposed Twitter Opinion Analysis System

2.1 Dataset

This proposed method has implemented using Python Version 3.8 using Spyder environment with Windows 10 system OS, Intel® Core^{TM} i3-1005G1 CPU @ 1.20GHz based processor with 4 GB RAM.

COVID-19-related English tweets are gathered for the dataset at a rate of nearly 10,000 per day over the course of three phases: April–June 2020, August–October 2020, and April–June 2021. Initial phase dataset, which included roughly 235k tweets gathered between April 19, 2020, and June 20, 2020. After a month, dataset gathering tweets from Twitter once more because the pandemic was still spreading fatally at that point. For the second phase dataset, from August 20 to October 20, 2020, gathered close to 320k tweets. Ultimately, nearly 489k tweets from April 26, 2021, to June 27, 2021 were gathered for the third phase dataset after 6 months. https://www.kaggle.com/datasets/arunavakrchakraborty/covid19-twitter-dataset has been used for dataset collection.

2.2 Data Pre-processing

It consists of user profiling, and LDA algorithm for pre-processing.

2.2.1 User profiling

Online Social Network composed of user information and user-generated content. The invention of vaccine was a god's gift and many had positive and negative feedback for it. Deep Belief Network (DBN) in classifying social media tweets regarding COVID vaccination. The combination of Tokenization, filtering, stemming are some of the preprocessing techniques and DBN are applied categorize the tweets for quick convergence to optimality[19]. To extract the opinion of the user, user profiling has to be obtained based on the various implicit and explicit attributes as follows,

$$U_p = \{U1\ , U2, U3.....\ Un\} \tag{1}$$

- **User Profiling:** The User profiling extract the opinion and intention of each user in the social networks including implicit and explicit attributes contexts on multiple domain category. User Adaption to the COVID vaccine is represented as,

$$UA = \{Ua1, Ua2, Ua3, \ ....Uan\} \tag{2}$$

The Adaption rate of the user to the COVID vaccination is computed using the Mean Field Game.

- **Latent Dirichlet Allocation (LDA):** Furthermore, LDA has been employed to determine the latent factor of the user for the particular context. User experience for specified behavior characteristics is described as follows,

$$SUe = \frac{1}{n}\int u\left(\frac{dy}{dx}\right)^{-2}\sum_{x\varepsilon C}^{n} E \tag{3}$$

User experience for complete behavior characteristics,

$$CUi = \int Cu\left(\frac{dy}{dx}\right)^{-2} \sum\nolimits_{x\varepsilon C}^{1} E \tag{4}$$

Optimal Latent behavior for the sentiment analysis is computed by utilizing a discrete matrix provided by user Discrete Matrix on dynamic state behavior,

$$DSi = \int D\left(\frac{dy}{dx}\right)^{-2} Si \tag{5}$$

The discrete State Matrix containing the user profile has been processed using a transformation matrix through matrix normalization[20] on the selected user pool with similar characteristics.

2.3 ESRRNN-LSTM Classifier

Entropy State-Regularized Recurrent Neural Network- Long Short Term Memory (ESRRNN-LSTM) classifier merges their individual decisions to classify new tweets as positive, negative, and neutral. The combination is typically done by cross entropy function. Regularization is used by ESRRNN-LSTM to the recurrent setting. The no. of hidden states is regulated to a restricted no. of states. An ESRRNN cell is made up of two parts. The initial component, known as the recurrent component, performs the function of a typical RNN cell,

$$u_t = f(h_{t-1}, c_{t-1}, x_t) \tag{6}$$

incorporate the cell state c, which is absent from RNN that do not have 1-memory. The stochastic component is the name given to the second element. In order to allow the RNN to transition implicitly between a limited no. of states, it is in charge of modeling the probabilistic state transitions. Let d is denoted as the hidden state vector size. Furthermore, let,

$$\triangle^D := \{\lambda \in \mathbb{R}_+^D : \|\lambda\| = 1\} \tag{6}$$

$\triangle^D$be the (D -1) probability simplex. The k learnable centroids $s_1, \ldots, s_k$ of size d are preserved by the stochastic component and often represented as the column vectors of a matrix $S \in R^{d\times k}$. The output u_t of the recurrent component is used to compute a discrete probability distribution at each time step t.

$$\alpha = \omega\{S, u_t\}, \alpha \in \triangle^k \tag{6}$$

Most importantly, samples of ω need to be differentiable for continuous training. Traditionally, the function ω relies on the dot-product, which is then transformed into a probability distribution.

$$\alpha_i := \frac{exp((u_t.s_i)/\tau)}{\sum_{i=1}^{k} exp((u_t.s_i)/\tau)} \tag{7}$$

Here, τ is a temperature parameter and E the inner product of two vectors that can be used to anneal the behavior of probabilistic state transitions. The more α resembles the centroid one-hot encoding, the lower τ. The more identical something becomes, the higher τ. ESRRNN concentrate to the k centroids to calculate transition probability. At every time step, state h_{t-1} and reading input symbol x_t, the probability for transitioning to state s_i is α_i. Consequently, in its second phase, the stochastic part calculates the hidden state h_t at time step t from the distribution α and the matrix S with a probably stochastic mapping $h : \triangle^k \times R^{d\times k} \to R^d$. However, the ESRRNN is not continuous differentiable when arg max is applied directly. First, a low temperature parameter τ can be used to compute arg max using Equation (8); as τ gets closer to 0, α approximates an onehot distribution.

$$\alpha = One\_Hot\left(\underset{i}{arg\,max}\left(\frac{exp\left(\frac{u_t.s_i}{\tau}\right)}{\sum_{j=1}^{k} exp\left(\frac{u_t.s_i}{\tau}\right)}\right)\right) \tag{8}$$

The softmax function is able to compute the categorical distribution z[21]. With $\alpha \in \triangle^{k-1}$representing the $\triangle^{k-1}$ is the (k-1) dimensionality probability simplex to symbolize a k-dimensional sample vector. Each instance $\alpha_i \in \alpha$ is assigned probability,

$$\alpha_i = \frac{exp((((u_t.s_i) + g_i)/\tau)}{\sum_{j=1}^{k} exp\left(\frac{((u_t.s_j) + g_j)}{\tau}\right)} \tag{9}$$

where τ is represented as temperature and z as $\tau \to 0$. In this case, a global state of the ESRRNN is an l-tuple related to the centroids of the l^{th} layer. Cell state of a LSTM include forget, input and output gates,

$$fo_t = \sigma\left(W^{fo}x_t + R^{fo}h_{t-1} + p^{fo} \odot c_{t-1} + b^{fo}\right) \tag{10}$$

$$in_t = \sigma\left(W^{in}x_t + R^{in}h_{t-1} + p^{in} \odot c_{t-1} + b^{in}\right) \tag{11}$$

$$out_t = \sigma\left(W^{out}x_t + R^{out}h_{t-1} + p^{out} \odot c_t + b^{out}\right) \tag{12}$$

where h_{t-1} is the output of the earlier cell's stochastic part; $W^s \& R^s$ are the matrices of the unique LSTM; the p^s are the parameters of the keyhole connections; and $\odot$ is the element wise multiplication. The weight and the parameters of the keyhole connections are optimized using the entropy function. In DL, a loss function can be defined using cross-entropy. The given distribution, q_i, represents the expected value of the current DL model, while the true probability, p_i, is the true label. Cross-entropy is to measure of dissimilarity among p and q,

$$H(p,q) = -\sum_i p_i log q_i = -y log\widehat{y} - (1-y)\, log(1-\widehat{y}) \tag{13}$$

This strategy makes use of DL methods, notably RNN using LSTM cells. ESRRNN-LSTM has been tested on the Twitter dataset. LSTM is an appropriate option for sentiment analysis on Twitter data because it is able to handle the analysis of sequential data[22]. Table 1 illustrates the Hyper Parameter Tuning of SRRNN-LSTM.

Table 1. Hyper Parameter Tuning of ESRRNN-LSTM

Network Parameter	Values
Batch size of the Model	158
Data Learning Rate	0.01
Number of Epoch	50
Word Length	500
Activation Function	Sigmoid
Error function	Cross entropy

3 Results and Discussion

Experimental analysis of ESRRNN-LSTM architecture has been implemented to twitter dataset for COVID vaccination. Twitter dataset related to COVID-19 tweets is crawled and transformed using data transformation and normalization approaches. Training data is utilized to train the model and test data is to predict the result. Validation data is used to cross-fold validation. In this work, 5-fold validation is carried out using a confusion matrix to compute the performance of the prediction model on precision, recall, and f-measure metrics.

- **Precision Analysis :** It is the ratio of relevant user intention to the retrieved user intention to the particular content. It is measured concerning the true positive and false positive values of the confusion matrix.

$$Precision = \frac{True\ positive}{True\ positive + False\ Positive} \tag{14}$$

- **Recall Analysis:** Recall is the ratio of irrelevant user intention to the retrieved user intention to the particular content.

$$Recall = \frac{True\ positive}{True\ positive + False\ negative} \tag{15}$$

- **F measure Analysis:** It is considered as several correct user predictions to the sentiment classes among the total number of users on a particular category of data. The multiple-user intention computed may have multiple-user adoption rates.

$$F - measure = \frac{2 * Precision * Recall}{Precision + Recall} \tag{16}$$

- **Accuracy Analysis:** An indicator of the model's performance across every category is accuracy. It is measured as the proportion of correctly predicted events to all predicted events.

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Positive + True\ Negative + False\ Negative} \tag{17}$$

Figure 2 provides a performance evaluation of the DL methods like MLSTM, Bi-LSTM and ESRRNN-LSTM on precision. From the above Table 2 and graph the precision obtained by proposed ESRRNN-LSTM is 90.00% which is very higher when compared to MLSTM and Bi-LSTM precision by 85.00%, and 87.00%.

Figure 3 provides a performance evaluation of the methods on recall. Table 2 and graph the recall obtained by proposed ESRRNN-LSTM is 88.00% which is very higher when compared to MLSTM and Bi-LSTM recall by 83.00%, and 85.00%. From this it's proved that ESRRNN-LSTM works better than other algorithms in terms of recall.

Figure 4 illustrates the performance of the DL approaches based on f-measure against conventional approaches to estimate the adaption rate for user sentiments. Table 2 and graph the F Measure obtained by proposed ESRRNN-LSTM is 87.00% which is very higher when compared to MLSTM of 84.00% and Bi-LSTM of 86.00%.

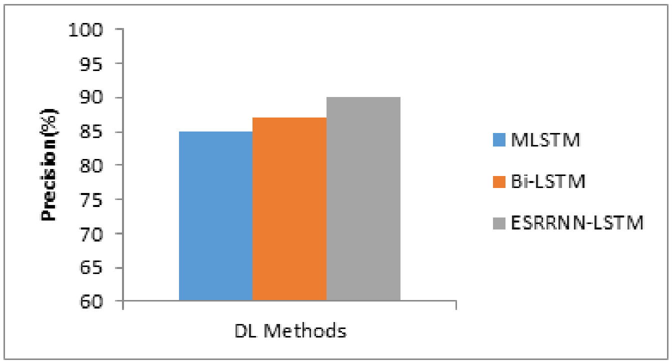

Fig 2. Precision Comparison with DL Models

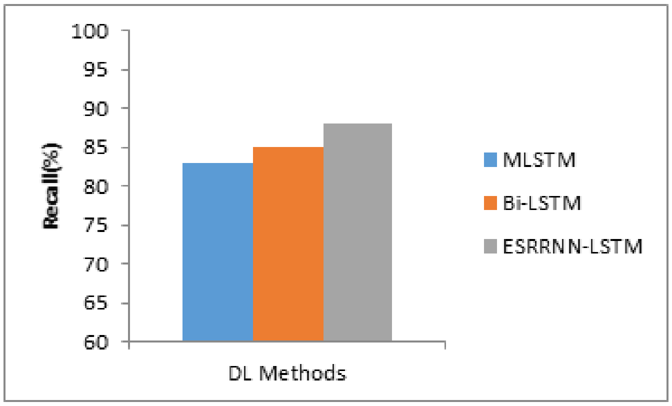

Fig 3. Recall Comparison with DL Models

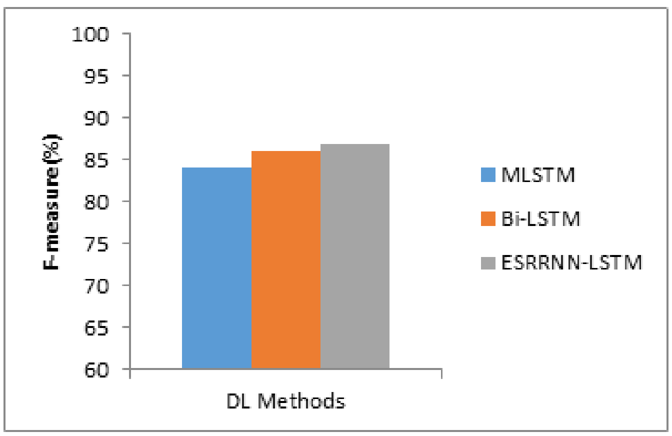

Fig 4. F-measure Comparison with DL Models

Table 2. Performance Analysis

Architecture	Precision (%)	Recall (%)	F-Measure (%)	Accuracy (%)
MLSTM	85.00	83.00	84.00	86.50
Bi-LSTM	87.00	85.00	86.00	88.70
ESRRNN-LSTM	90.00	88.00	87.00	91.20

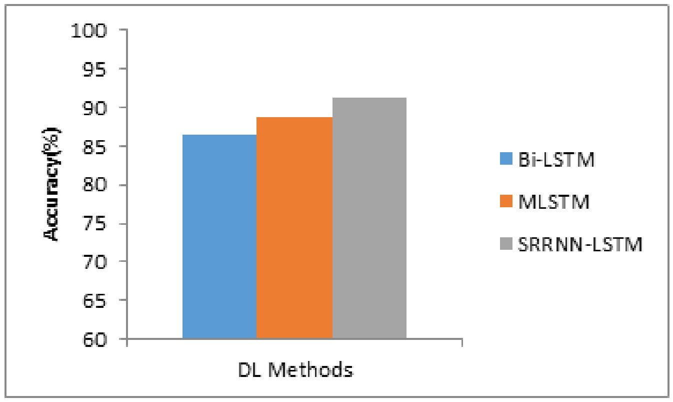

Fig 5. Accuracy Comparison with DL Models

Table 2 and graph the accuracy obtained by proposed ESRRNN-LSTM is 91.20% which is very higher when compared to MLSTM and Bi-LSTM accuracy of 88.70%, and 86.50%. From this it's proved that ESRRNN-LSTM works better than other algorithms in terms of accuracy.

Findings of Research Work: Table 2 demonstrates the performance analysis of various sentiment analysis techniques to determine user similarities and user opinion evolution.

Table 3 provides the performance evaluation of the multiple-fold validation on the confusion matrix.

Table 3. Performance Analysis on Cross Fold Validation

Validation Data	Predicted adaption to COVID Vaccination		Precision (%)	Recall (%)	F-Measure (%)	Accuracy (%)
	Adapted	Not Adapted				
Fold 1	10000	6000	91.00	89.00	90.00	91.21
Fold 2	8000	8000	91.00	89.00	90.00	91.05
Fold 3	4000	12000	90.00	88.00	88.00	90.98
Fold 4	12000	2000	89.00	87.00	88.00	90.85
Fold 5	2000	14000	89.00	87.00	89.00	90.50

In this research around 5 Folds have been used. In Fold 1 the Predicted adaption to COVID Vaccination (Adapted-10000 and Not Adapted-6000) gives the accuracy of 91.21%, 91.00% by precision, 89.00% by recall, and 90.00% by F-Measure. In Fold 2 the Predicted adaption to COVID Vaccination (Adapted-8000 and Not Adapted-8000) gives the accuracy of 91.05%, 91.00% by precision, 89.00% by recall, and 90.00% by F-Measure. In Fold 3 the Predicted adaption to COVID Vaccination (Adapted-4000 and Not Adapted-12000) gives the accuracy of 90.98%, 90.00% by precision, 88.00% by recall, and 88.00% by F-Measure. In Fold 4 the Predicted adaption to COVID Vaccination (Adapted-12000 and Not Adapted-2000) gives the accuracy of 90.85%, 89.00% by precision, 87.00% by recall, and 88.00% by F-Measure. In Fold 5 the Predicted adaption to COVID Vaccination (Adapted-2000 and Not Adapted-14000) gives the accuracy of 90.50%, 89.00% by precision, 87.00% by recall, and 89.00% by F-Measure. Proposed ESRRNN-LSTM system has the highest results for vaccination prediction from user opinion tweets. Parameters of classifier are optimized using the entropy function. The classifier parameters like weight, bias, parameters of the keyhole connections are optimized using the cross entropy function. Due to parameters tuned by entropy function it has highest results when compared to other classifiers. The results of proposed classifier are compared with the existing methods like MLSTM [23], and Bidirectional Long Short-Term Memory (Bi-LSTM) [24].

4 Conclusion and Future Work

In this paper, Entropy State-Regularized Recurrent Neural Network-Long Short Term Memory (ESRRNN-LSTM) classifier is introduced for SA to the COVID-19 tweet. The major novelty of the work is to tune the parameters of ESRRNN-LSTM classifier by entropy function. ESRRNN-LSTM classifier is used for high representative prediction of the adoption rate of the user to the COVID vaccination on different time frames based on sentiment attached to user intention. Furthermore, the activation function and loss function imposed on the hyperparameter are tuned layers of the network to provide optimal prediction accuracy. Finally, results of the proposed system, and existing classifiers are measured using the metrics like precision, recall, f-measure, and accuracy. From the results it shows that the proposed system has the highest results of 90.00%, 88.00%, 87.00%, and 91.20% for precision, recall, f-measure, and accuracy. The ESRRNN-LSTM system has the highest f-measure of 87.00%, MLSTM of 84.00% and Bi-LSTM of 86.00%. This has been helpful for early insights into new patterns and feelings that will enable them to respond proactively to the changing conversation surrounding vaccines. The present system directly applied for high dimensional dataset, it doesn't focus on the reduction of the dimensionality of features from the dataset. It has been considered as scope of future work, and it reduces the computational complexity of the classifier.

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