Predicting the COVID-19 Outspread in Andhra Pradesh Using Hybrid Deep Learning

Bhimavarapu Usharani

Abstract COVID-19 is one of the major health care challenges around the world today. Physical detection of COVID-19-positive patients is time consuming due to the limited data sources. The deep learning classifiers and the blood test parameters perform a significant part in the prediction of the disease and death rate of COVID-19. Parameters such as age, gender, lactic dehydrogenase (LDH), and lymphocyte count reports the severity of COVID-19. The features lactic dehydrogenase (LDH), C-reactive protein (CRP), and lymphocyte count predicts the mortality of the COVID-19 patients with accuracy. Deep learning classifiers can detect nonlinear relationships and interactions between parameters, explaining better performance.

Keywords Artificial neural network · Coronavirus · COVID-19 · Deep learning classifiers · Gated recurrent unit

1 Introduction

The full form of COVID-19 is the coronavirus disease of 2019. The International Committee on Taxonomy of Viruses (ICTV) authoritatively identified the 2019 novel coronavirus as a Severe Acute Respiratory Syndrome Coronavirus-2 (SARS-CoV-2) [1, 2]. COVID-19 was officially named by the WHO on 11 February 2020 [3] in the International Classification of Diseases (ICD). The COVID-19 virus emerged in Wuhan, China, on 19 December 2020 and mushroomed all around the globe, becoming a major health issue [4, 5]. In Wuhan during the first week of January 2020 one adult tested positive, and three adults tested positive during the second week of January 2020 [6]. Coronaviruses are zoonotic, and this human-to-human transmission of COVID-19 is due to unprotected contact [3]. The COVID-19 cases that were reported in India by 28 September 2020 numbered 60,73,348 and the death rate stood at 95,574 [7]. The state of Andhra Pradesh stood in second place with confirmed positive cases being 675,674 [7]. The second wave of COVID-19 is very

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dangerous and the top ten confirmed COVID-19 cases for 6 April 2021 is given in Fig. 1.

India has the third largest number of coronavirus cases in the world, and its infection numbers are rising again. Some of India's neighbours are also experiencing a rise in infections. South Asian countries hold ramped over checking out then Sri Lanka, India, or Pakistan at present study inside the measure deemed ample by way of the WHO. As of March 2021, according to COVID-19 statistics, the highest number of mortalities are noted in India, Iran, Indonesia, Turkey, and Iraq along extra than three lakhs' mortalities combined. State-wise confirmed and recovered cases in India are represented in Fig. 2.

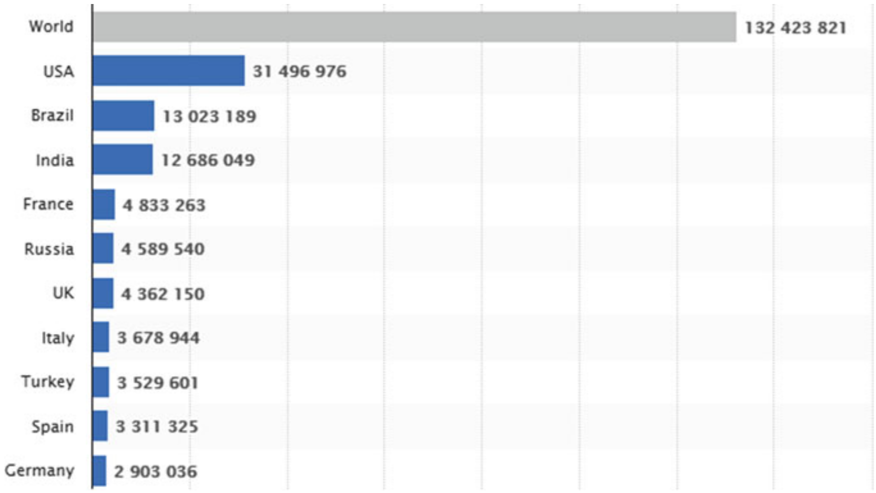


Fig. 1 Total top ten COVID-19 cases in the world as on 6 April 2021

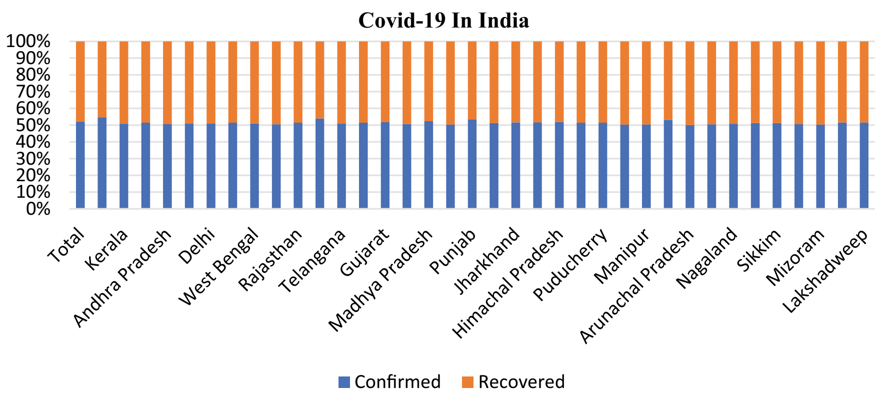
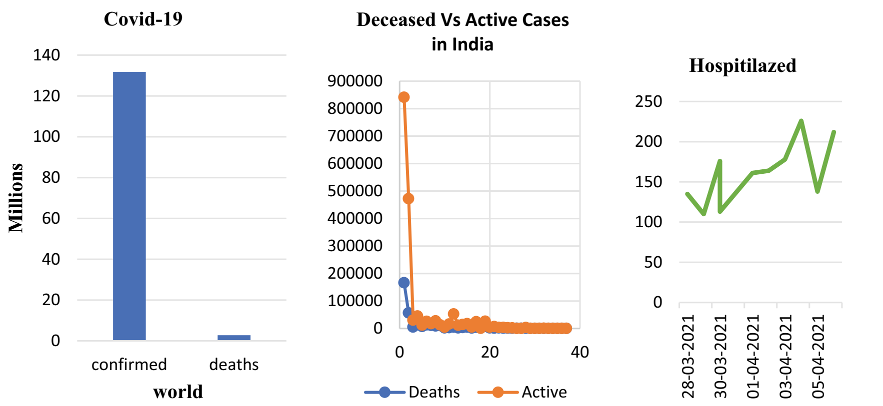


Fig. 2 COVID-19 in Indian States on 6 April 2021



(a) Covid-19 cases in the world as on 06/04/2021

(b) Deceased vs active covid cases in India on 06/04/2021

(c) Hospitalized in Krishna District in Andhra Pradesh up to Aril 06,2021

Fig. 3 COVID-19 cases as on 6 April 2021

The per-period instances attenuate mid-September among India with 90,000 instances referred to per time or have because occur below to under 15,000 as regarding January 2021. On 4 April 2021, India became the 2nd USA, into the submitted extra than one lakh cases in a single day, afterward USA. Reported COVID-19 cases in exceptional regions durability are shown in Fig. 3.

The COVID-19 pandemic in Southeast Asia is shared over the continuous worldwide contagion of coronavirus sickness 2019 (COVID-19) generated by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). As of 7 April 2021, Indonesia has the highest number of cases or deaths, ahead about the Philippines within each aspect's stability. A report on Asian countries showing confirmed cases as of 7 April 2020 is shown in Fig. 4.

At present, current improvements within machine learning, mainly deep learning (DL) techniques using convolution neural network and ConvLSTM partake in the proven hopeful overall performance in recognizing, categorizing, and measuring disorder outlines into health snapshots [8–14], especially for detection concerning COVID-19 [15, 16]. For example, Rajaraman et al. [15] introduced a procedure using a convolution neural network for COVID-19 exposure. They conveyed their procedure outdoors over a kind of X-ray image called CXR images. They acquired better precision for classifying COVID-19 statistics. The authors [15] advanced an approach for computerized reckoning concerning COVID-19 as the use of an extreme study deep convolutional neural network (DCNN) created using Inception V3 mannequin or heart X-ray images. They acquired far better accuracy for their findings regarding COVID-19. The author [16] employed a discipline approach because of the array of COVID-19, pneumonia, or breast X-ray graphs. They mated the beneficial common precision because of validation so 0.9725 stability.

The uniqueness of this study is recapped as follows.

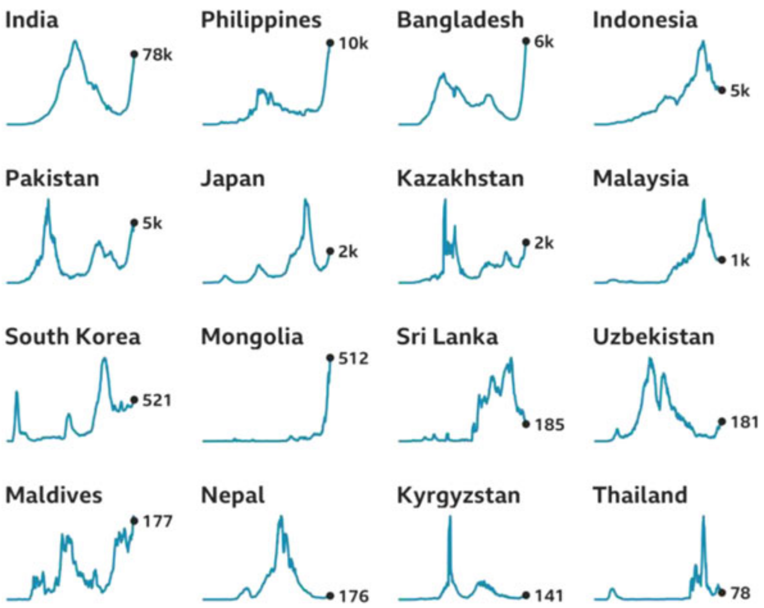


Fig. 4 Countries with the highest number of cases on the Asian continent as of 7 April 2020

- Forecast of COVID-19 infection with deep learning.
- To determine the diagnostic accuracy of a deep learning classifier built for the identification of COVID-19 utilizing results of the blood tests.

In this paper, there is an automated prediction of COVID-19 using a deep learning technique, habits, and food diet. For this, applied hybrid deep learning pretrained modes were used to obtain a higher prediction accuracy. This research may encourage the researchers to innovate the models by using the blood sample data. The balance of the paper is planned as support. Section 2 recaps the earlier deep techniques for COVID-19 and other medical images. Section 3 discusses the suggested approach. Performance measures are examined in Sect. 4. Finally, this paper is summarized in the Conclusion section.

2 Related Work

The authors identified the CD39 (Cluster of Differentiation 39) in the blood of COVID-19-confirmed individuals [17]. For COVID-19 there was a reduction in NK units in the life blood of COVID-19 patients.

2.1 Anomaly Detection

Anomaly detection also helps to detect COVID-19. Convolution neural networks established generative types such as Generative Adversarial Networks [18] and Variational Auto Encoders [19] that are used for unsupervised anomaly detection. The expansions such as the context encoder [20], Constrained Variational Auto Encoders [20], Adversarial Auto Encoder [21] and Bayesian Variational Auto Encoders [22] improves the accuracy of the projections. The authors [23] proposed a CAAD (Confidence Aware Anomaly Detection) model and a confidence prediction network for viral pneumonia screening and achieved accuracy of 83.61%.

2.2 Deep Learning Techniques

The authors [24] established a deep neural network architecture to recognize the greatest mortality prognostic variables from the clinical variables. The authors identified D-miner, O2 index, CRP and diarrhoea as the top predictors to predict the mortality rate. The authors [25] applied the deep CNN model to uncover COVID-19 and this deep CNN model consists of five convolution layers. Features are extracted from deep CNN and used the machine learning algorithms KNN, SVM, decision tree. The authors obtained the highest accuracy of 98.97% for SVM by using the COVID-19 radiology dataset. The authors [26] used the MobileNetV2, SqueezNet together with Social Mimic Optimization (SMO) method. To pre-process the images fuzzy colour techniques have been used and to reconstruct the images image-stacking has been used. The X-ray images were categorized using the support vector machine technique and accomplished accuracy of 99.27%. Kumar et al. [27] uses the techniques VGG, DenseNet, AlexNet, MobileNet, Resnet and capsule Network to acknowledge the models in lung screening. They proposed a technique to share the patient's data securely with the assimilation of the amalgamated learning and the blockchain. The proposed deep learning model, i.e. the capsule, network achieved an accuracy of 83% and sensitivity of 96.7%. Medical imaging has been used to become aware of cardiovascular illnesses [28], Genius tumours [29], yet nowadays clinical imaging is also life saving because of detection regarding COVID-19.

The major issue over function extraction may be tackled through making use of state-of-the-art extreme discipline methods. SqueezeNet, along Bayesian optimization regarding constraints certain as like researching percentage then momentum have been employed in [30]. Transfer discipline over pre-trained Xception CNN structure is exploited with the aid of authors of [31] in imitation of X-ray images of four categories, specifically COVID 19, pneumonia viral, pneumonia bacterial and normal. The mannequin obtained a better precision about 4 organization class arrangement. In [32], ResNet was employed because of characteristic abstraction on which an array standard is utilized in conformity with marshal image so COVID and nonCOVID.

This pattern accomplishes an exactness and a 121-layered pretrained Densenet structure called Chexnet, employed in [33] to notice pneumonia between 112,120 X-ray photographs on 30,805 exceptional patients. That technique is prolonged after observing fourteen diseases between X-ray images. In [34], a pretrained InceptionV3 was employed because of the abstraction of an image embedding. The acknowledged configuration was able to register unique respiratory illnesses expertly or carried out an exceptionally excessive accuracy regarding the illness. A deep adaption algorithm used to be recommended between [35]; the authors of that procedure offered a pneumonia classifier in accordance with observing the COVID-19 disorder by means of working usage of both mutual and awesome functions on COVID-19 yet pneumonia. In [36], the authors applied a pretrained Resnet50 for characteristic abstraction or support vector machine because of alignment and did a truth about 95% regarding geminate classification. In [37], they used Darknet or different filtering of each stratum then carried out a proprietary at about 98.08% regarding binary classification and 87% of the alignment on X-ray pics as like pneumonia, COVID-19 then normal. A stacked version containing a pretrained VGG19 paradigm or an instant 30-layered COVID discovery mannequin is recommended in [38] because of function abstraction, while the Logistic regression procedure is employed because of categorization on X-ray photographs and discovery about COVID-19. The authors of [39] did an assessment of several pretrained fashions or past to that amount Resnet50 achieves the maximum accuracy about 98% among the discovery about COVID-19 among InceptionV3 and ResNetV2. In [40], they anticipated a sound instruction pattern because inspection regarding COVID-19 using pre-processing picture methods established totally about HU values, yet 3D convolution neural network fashions for function origin beyond X-ray illustrations. In [41], a pretrained Chexnet model was used for spotting anomalies within thorax X-rays after aligning into usual pneumonia, COVID-19. A SE-ResNext101 encoder along SSD RetinaNet is employed [42]. This mannequin was adjusted regarding a database including heart X-rays over 26,684 special patients. Every illustration is labelled including certain three one-of-a-kind lessons from the related radiological [43] reviews: No Lung Opacity (or) Not Normal, Normal, Lung Opacity, in view that lung imprecision is a considerable symptom of pneumonia. The authors among [43] aged convolution neural network architectures, inclusive of InceptionV3, InceptionResnetV2, yet Xception because of alignment regarding chest X-ray images while numerical procedures, like, Markov chain Monte Carlo (MCMC) yet genetic algorithms are aged in imitation of note the hyperparameters regarding the representations. In [44] the developers pretrained convolutional neural network techniques as Alexnet, VGG16, VGG19 for characteristic abstraction. The characteristics presented out of the patterns stated upon have been afterwards reduced with the assistance concerning minimal dismissal maximum relevance sets of rules.

3 Methodology

The methodology that was followed in this present work is depicted in Fig. 5.

3.1 *Deep Learning Classifiers*

Deep learning techniques have risen quickly then have been extended for purposes in more than a few scientific or industrial domains. Healthiness informatics [45], power [46], municipal informatics [47], security [48], protection [49], hydrological systems modelling [50], pecuniary [51], bioinformatics [52], and computational mechanism [53] have been among the most requested areas on deep learning. Deep learning is a subgroup concerning machine learning, and refers after the utility of a embark concerning algorithms known as neural networks and their variants.

3.1.1 ANN

Artificial Neural Networks is an AI model inspired by the framework of biological human neurons. It has been applied to different fields. ANN provides a correlation among the input and the output data, for this it is essential to be trained using a set of data involving input and the subsequent output statistics. ANN includes three layers: (1) input layer; (2) hidden layer; (3) output layer. The Activation Functions are given as:

$$a_j(t+1) = f\left(a_j(t), p_j(t), \theta_j\right) \tag{1}$$

$$o_j(t) = f_{\text{out}}\left(a_j(t)\right) \tag{2}$$

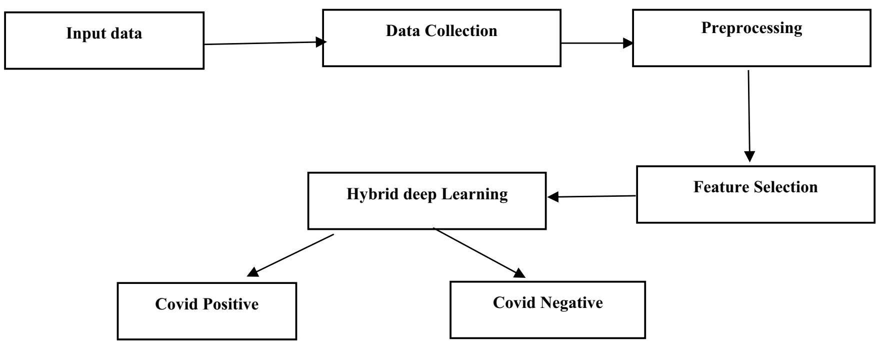


Fig. 5 Proposed methodology flow chart

$$p_j(t) = \sum o_i(t) w_{ij} \tag{3}$$

$$p_j(t) = \sum o_i(t) w_{ij} + w0_j \tag{4}$$

3.1.2 GRU

G is a simple modification of the LSTM that has two gates: one is the update gate and reset gate, update gate which contains of input, forget gates. GRU has no extra memory to maintain the info, so it can regulate data within the unit, where:

$$t = \sigma(Wzxt + Uzht - 1 + bz) \tag{5}$$

$$rt = \sigma(Wzxt + Uzht - 1 + bz) \tag{6}$$

$$\hat{h}t = \varphi(Whxt + Uh(rtht - 1) + bz) \tag{7}$$

$$ht = (1 - zt) \circ ht - 1 + zt\hat{h}t \tag{8}$$

xt	input data.
ht	output data.
$\hat{h}t$	Candidate activation function.
zt	update gate data.
rt	rest gate data.
W, U, b	Parameter matrices data.

3.2 Data Pre-processing

The imported data may consist of unfilled data. To complement the incomplete clinical measures the"− 1" padding technique was used.

3.3 Feature Selection

Algorithm 1: COVID-19 Analytics Algorithm

Result: Prediction of COVID-19

Initialization.

1. Acquire the data from the database.
2. Apply the data filtering technique. Select only those blood test parameters at the final diagnosis as the subset.
3. Perform data pre-processing techniques such as handling the missing values and remove the erroneous values or outliers. The missing data were padded with"−1".
4. Use the ANNGRU predictive model.

The COVID-19 analytics algorithm is a deep learning-based algorithm consisting of five steps. The steps are as follows: the first step is the data acquisition step, i.e. gathering the data from the dataset; the second step is the data training and it consists of the blood test parameters obtained from the patient's final diagnosis; the third step is the data pre-processing that handles the missing values and removes the erroneous values or outliers. The missing data were padded with"− 1″. The fourth step is building the diagnostic model using the deep learning algorithm; the final step is evaluating the model using the stratified tenfold cross validation. In the evaluation method, the hybrid models used were the Artificial Neural Network (ANN) and Gated Recurrent Unit (GRU).

4 Performance Measures

4.1 Experiment Setup

The integration of the sixteen blood test parameters might achieve the high-level performance to precisely distinguish the morbidity of COVID-19. The COVID-19 dataset that is used in this research is available in IRCSS [54]. The dataset consists of 279 records. This data is extracted from hospital patients that were admitted between February to mid-March 2020. It is important to select the appropriate number of parameters for the prediction of the disease and deaths from COVID-19. The sixteen parameters were carefully selected as the final indicators for input as described in Table 1.

Table 1 Laboratory findings in the dataset

Laboratory findings	Gender, age, white blood cells, Piastrine, Neutrofili, Linfociti, Monociti, Eosinofili, Basofili, C-reactive protein, Aspartate aminotransferase, Alanine aminotransferase, Alkaline phosphatase, Gamma glutamyl transferase, Lactate dehydrogenase, target

4.2 Performance Metrics

The accomplishment of the deep learning classifiers on the test set is measured by applying the metrics sensitivity, specificity, precision and accuracy. The formulas for the sensitivity Eq. (9), specificity Eq. (10), precision Eq. (11) and accuracy Eq. (12) are given below.

$$\text{Sensitivity}(\text{or Recall}) = \frac{\text{tp}}{(\text{tp} + \text{fn})} * 100 \tag{9}$$

$$\text{Specificity} = \frac{\text{tn}}{(\text{tn} + \text{fp})} * 100 \tag{10}$$

$$\text{Precision} = \frac{\text{tp}}{(\text{tp} + \text{fp})} \tag{11}$$

$$\text{Accuracy} = \frac{\text{tp} + \text{tn}}{(\text{tp} + \text{fp} + \text{tn} + \text{fn})} * 100 \tag{12}$$

4.3 Performance Results

The test set was completely independent of the training set to prove the stability and reliability of the deep learning classifiers. The parameter target is binary; if it is 0 it means no COVID-19 infection, while 1 means a COVID-19 infection is present. When the coronavirus infection penetrates the human physique, the alignment of the plasma varies, and the parameters discussed in Table 1 play a vital role on identifying the morbidity rate of COVID-19. For COVID-19-tested confirmed individuals there is an increased aspartate aminotransferase, reduction of white blood cell numbers, improved alanine aminotransferase, enhanced lactate dehydrogenase and increased C-reactive protein. Parameters such as age, gender, lactic dehydrogenase (LDH), C-reactive protein (CRP) and lymphocyte count reports the severity of COVID-19. The features lactic dehydrogenase (LDH), C-reactive protein (CRP) and lymphocyte count predicts the mortality of the COVID-19 patients with accuracy. The accuracy rates for survival, morbidity and mortality are shown in Fig. 6.

The first parameter, gender, plays an important role—male patients were more expected to be affected by COVID-19 than female patients. During the COVID-19 pandemic the vulnerability of males has been higher than for females. Thus there was a correlation between gender and the mortality rate of COVID-19. The total number of patient records in the dataset was 279. Out of the 279 records, 188 were men and 91 women. The average age of the corona-infected individuals in the dataset was 61.34 years. The missing data were padded with“-1″. White blood cells play a vital role in the human immune system. The white blood cells recognize when the

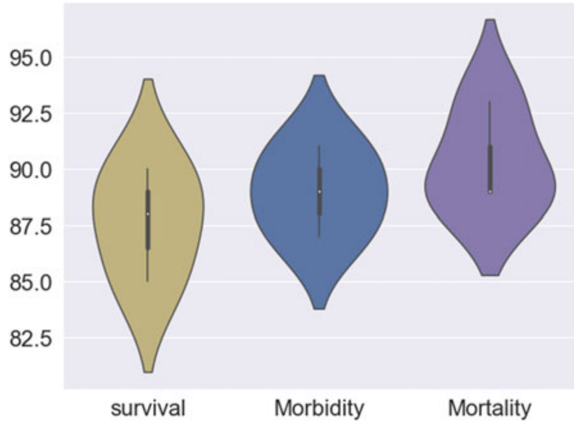


Fig. 6 Plot for performance on testing data

virus or bacteria enters the bloodstream and they destroy the harmful particles that can cause disease. A low white blood cell count (WBC) has the potential to become life threatening in infectious diseases such as COVID-19. The performance of the Mean in the deep learning classifiers in discriminating mortality outcomes is shown in Fig. 7.

WBC is a strong predictor of mortality rate. Ten distinct deep learning application versions are employed as classifiers. Predictions were presented and the accomplishment of these ten different classifiers was evaluated. In terms of performance, the best identified model in the LSTM family is the GRU for predicting the COVID-19 disease. The execution of the algorithms was tested using the 75–25 train test split methodology. Table 2 shows the performance outcomes of different deep learning

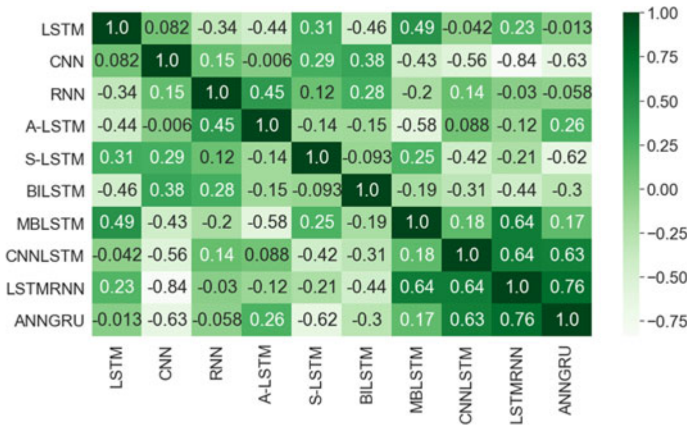


Fig. 7 Performance of the mean of the deep learning classifiers in discriminating mortality outcomes

Table 2 Results of deep learning classifiers on the test data

	Precision	Recall	Accuracy	$F1$-score	AUC
LSTM	0.8675	0.9942	0.8666	0.9189	0.6250
CNN	0.8948	0.9248	0.8800	0.8913	0.6147
RNN	0.8785	0.9598	0.8506	0.9058	0.5245
A-LSTM	0.8708	0.9857	0.8775	0.9234	0.6150
Stacked LSTM	0.8783	0.9581	0.8568	0.9054	0.5248
Bi-LSTM	0.8695	0.9932	0.8623	0.9389	0.6550
MBLSTM	0.8758	0.9548	0.8056	0.9138	0.5278
CNNLSTM	0.8926	0.9218	0.8416	0.9001	0.5889
LSTMRNN	0.8977	0.9423	0.8568	0.9120	0.6408
ANNGRU	0.9195	0.9948	0.9456	0.9423	0.9178

classifiers with the train test separation approach. The most excellent execution was obtained with the ANNGRU hybrid model at 94%.

In Table 2 the exactness outcomes of all deep learning classifiers were achieved above 80%. ANN provides a robust result, and it does not impose any restriction on the input. ANN can produce robust output even in the case of missing information. GRU train the data fast and outperforms better for large datasets. In experiments for GRU the number of neurons taken are 1,632,664,128, the learning rate is 0.001, the activation function used is RELU, the optimizer used is Adam, batch size is 10, the number of epochs taken is 500 and the time step is 3. The performance measures considered in this paper are precision, recall, accuracy, $F1$-score and AUC. Precision can be characterized as the ratio of the accurately predicted positive case to the aggregate predictive positive cases. In this research the precision obtained high to the ANNGRU with 0.9195. Recall is the proportion of correctly predicted positive cases to the total number of cases. In this research the high recall obtained to the ANNGRU with 0.9948. $F1$-score is the weighted average of the precision and recall values. The performance of standard deviation of the deep learning classifiers in discriminating mortality outcomes is shown in Fig. 8.

The $F1$-score obtained with ANNGRU is 0.9423 and is the best when compared to the remaining classifiers. AUC is a measure to identify which of the classifiers predicts the best score. The obtained AUC score with ANNGRU is 0.6578. In this research, a deep learning classifier is used. The comparison of different classifiers measures is compared in Table 3 and the outcomes of deep learning classifiers on the test data is exhibited in Fig. 9.

Ten different classifiers are used; ANNGRU obtained the best performance measures. The performance measures from Table 3 elucidate that the deep learning approaches are more powerful than the machine learning approaches. Deep learning classifiers are employed to the patient dataset and test a mortality and morbidity prediction with high accuracy. The comparison results of classifiers is shown in Fig. 10.

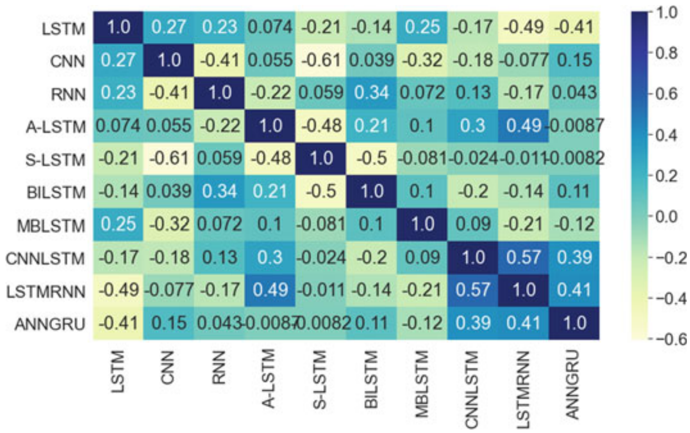


Fig. 8 Performance of standard deviation of the deep learning classifiers in discriminating mortality outcomes

Table 3 Comparison results of classifiers

Study	Classifier	Accuracy	AUC	$F1$-score
[55]	SVM, RF	–	0.87	0.72
[56]	XGBOOST	–	0.66	–
[57]	SVM	0.80	–	–
Present work	ANNGRU	0.94	0.91	0.94

This work shows that the input of the clinical parameters for a patient, such as white blood cells, with the ANNGRU, accurately classifies patients as likely to live or die. This model is the automatic mortality and morbidity prediction model of a patient with COVID-19. Predicting the mortality and morbidity rates for India is shown in Fig. 11.

Andhra Pradesh stood at the fourth place in COVID-19 cases in India as of 7 April 2021. The large population is one of the major factors of the COVID-19 spread in Andhra Pradesh. Predictions for the mortality and morbidity rates in Andhra Pradesh and its capital district Krishna are shown in Fig. 12.

Air pollution also one of the factors affecting the spread of COVID-19 infections. According to the USA Environmental Science and Forestry, an increase in hazardous air pollutants is a correlation in around 20% of human COVID-19 cases. Figure 13 shows the COVID-19 mortality levels associated with high levels of hazardous air pollution.

According to the Andhra Pradesh government reports as of 7 April 2021, the mortality rate in the Krishna district is high and stood in second place in Andhra Pradesh. The COVID-19 cases report for Andhra Pradesh is shown in Fig. 14.

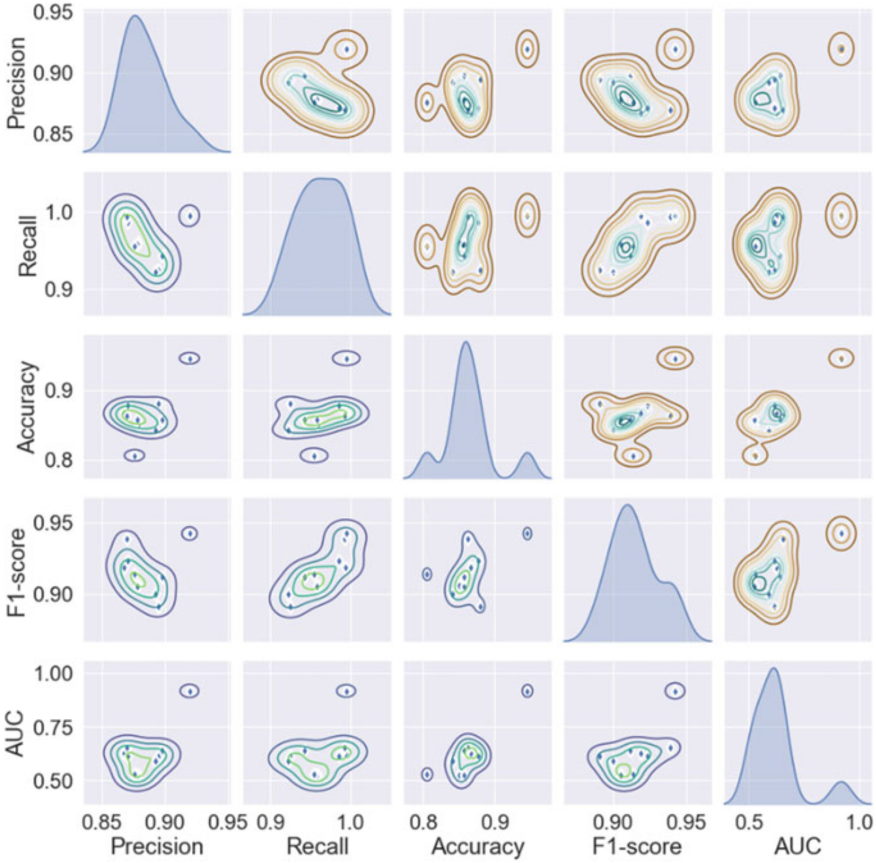


Fig. 9 Results of deep learning classifiers on the test data

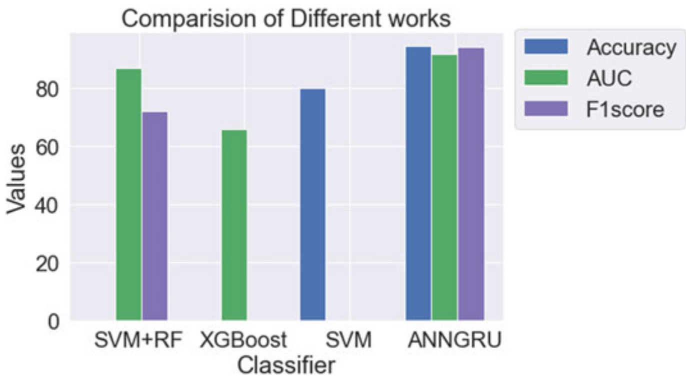
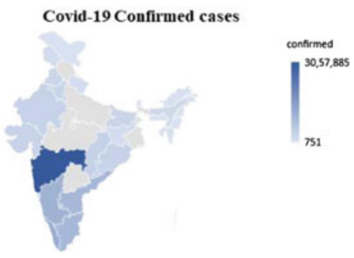
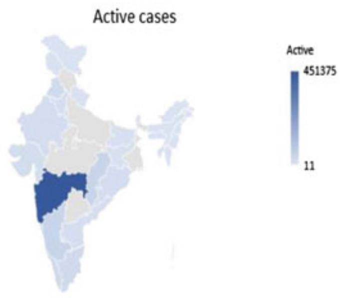


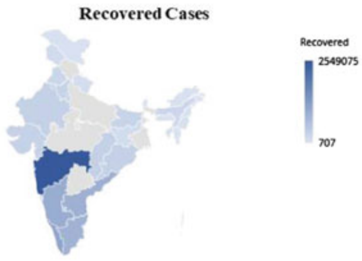
Fig. 10 Comparison results of classifiers



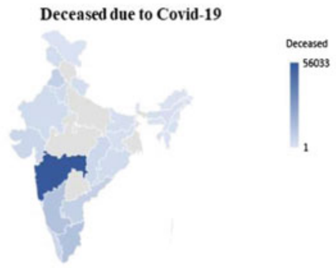
(a) Predicted Confirmed Cases



(b) Predicted Active Classes

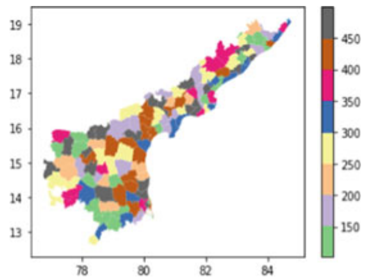


(c) Predicted Recovered Cases

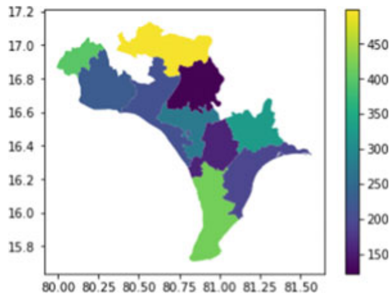


(d) Predicted Deceased Cases

Fig. 11 Predicted COVID-19 mortality and morbidity in India

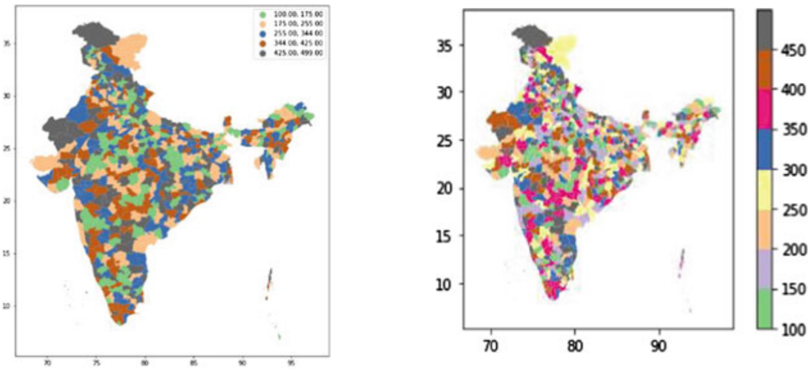


(a) Predicting Covid -19 in Andhra Pradesh



(b) Predicting Covid-19 in Krishna District in Andhra Pradesh

Fig. 12 Predicted COVID-19 mortality and morbidity in Andhra Pradesh and Krishna district in Andhra Pradesh



(a) Covid-19 Cases in India Population Wise (b) Covid-19 Cases in India pollution wise

Fig. 13 Predicting the mortality and morbidity rates by using air pollution in India district-wise

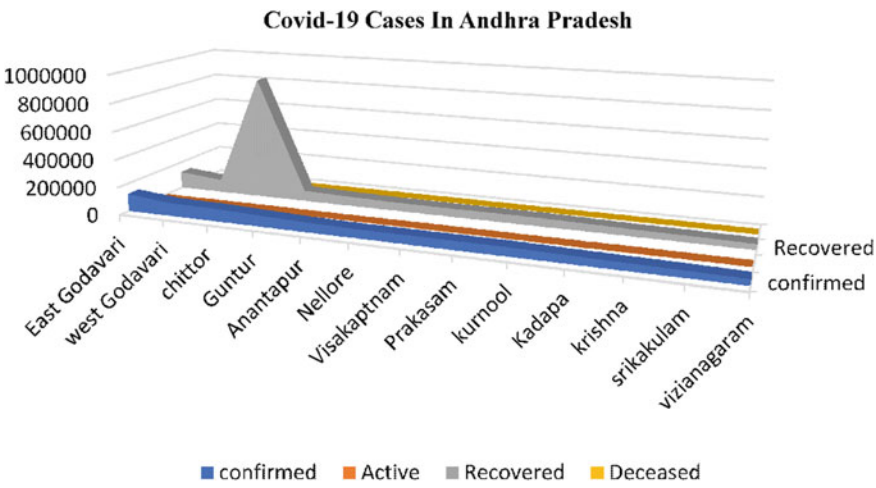


Fig. 14 COVID-19 morbidity cases in Andhra Pradesh district-wise

In this paper, there is an automated estimate of COVID-19 employing a hybrid deep learning technique. For this, applied ANNGRU deep learning pretrained modes were used to obtain higher accuracy.

5 Conclusion

Symptoms that were diagnosed for COVID-19, and also for patients with other diseases or infectious diseases, were studied. In this study the ANNGRU model was composed and compared to the most accurate stand ANN patterns for assessing the morbidity and mortality rates of COVID-19 cases. The conclusions indicate that implementation of the ANN GRU-based prediction model led to more accurate estimations. For the results, it is confirmed that the more accurate confirmed cases are estimated.

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