J. Electrical Systems 20-10s (2024): 5637-5647

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Hybrid Gradient Descent-tuned Recurrence Net-based Classification of COVID-19 using Chest X-ray images

Abstract: - The COVID-19 pandemic has underscored the importance of rapid and accurate diagnosis to mitigate its spread. Chest X-ray (CXR) images have proven to be invaluable tools for identifying pulmonary abnormalities associated with COVID-19. We propose a novel Hybrid Gradient Descent-tuned Recurrence Net (HGD-TRN) approach based on deep learning (DL)regarding the categorization ofCOVID-19. We collected a "dataset of CXR images, including COVID-19 and images of healthy lungs" from Kaggle. The distinction between COVID-19 and healthy patients in this study was made using CXR images. Using the Min-Max Normalization technique, the gathered CXR images are pre-processed. After that, we can obtain images of the lungs by utilizing the Edge-Based Segmentation, which can be used to delineate object boundaries. Next, significant points were extracted from the segmented lung images using Principal Component Analysis (PCA) is an area that uses medical imaging to extract several statistical components, including intensity, shape and texture features. Finally, we usedthe Hybrid Gradient Descent-tuned Recurrence Net (HGD-TRN) method to classify the images into COVID-19 and healthy lung images. The proposed model's performance isevaluated using the Python platform and compared to that of the existing used COVID-19 detection methods. The accuracy 98%, F1 scores 98%, precision 99%,recall 98.90%,Root Mean Squared Error (RMSE) of 0.021and Mean Squared Error(MSE) 0.147, was key examination metrics used to examine the performance of our model. In conclusion, our novel approachHGD-TRN, based on DL techniques, has showcased its potential as an efficient and accurate diagnostic tool for COVID-19 using CXR images.

Keywords: deep Learning (DL), COVID-19, Edge-Based Segmentation, Principal Component Analysis (PCA), Chest X-RayImages (CXR), Image Classification, Hybrid Gradient Descent-tuned RecurrenceNet (HGD-TRN)

1. Introduction

Medical researchers and IT companies across the world have been working around to find a solution to the COVID-19 pandemic, which was triggered by the new corona virus SARS-CoV-2 [1]. A key component of these efforts is the use of CXR imaging for the recognition and tracking of COVID-19 infections. The fight against the virus has shifted its focus to this fusion of innovative medical scanning technologies with the essential need for quick and precise diagnoses. A non-invasive and effective way to determine how COVID-19 affects the respiratory system is using CXR. Inflammation and fluid accumulation in the lungs, symptoms similar to pneumonia, are characteristic of the condition [2]. By carefully analyzingCXR images, healthcare providers can quickly detect possible instances of COVID-19 and distinguish them from other respiration disorders due to this specific pattern.The combined efforts to tackle the COVID-19 pandemic are highlighted by this multidisciplinary strategy, which merges the domains of medicine and science [3].

To distinguish between COVID-19 positive and negative instances, DL techniques trained on extensive information can acquire complex patterns that are characteristic of the virus [4]. Not only does this aid in early treatment and better patient care, but it speeds up the diagnostic procedure. There are a number of critical phases involved in creating and deploying DL algorithms for COVID-19 recognition utilizing CXR images. Collecting broad and informative records, including a range of COVID-19 patients and other respiratory illnesses, is a first step. These statistics are essential for building strong models that can apply patterns to different patient populations and medical problems. An advanced indication of how technology and medicine are coming together is the use of DL with CXR images for the recognition of COVID-19. This strategy might have far-reaching consequences for medical imaging, going beyond resolving the pandemic's critical problems [5].

We propose a novel Hybrid Gradient Descent-tuned Recurrence Netapproach based on DL for COVID-19 using Chest X-ray images.

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2. Related works

Study [6] presented a “Domain Extension Transfer Learning (DETL)” as a method for screening COVID-19 by extracting distinctive characteristics from CXRs images. Research [7]proposed an automated deep learning (DL) classification technique to identifiedCOVID-19 from CXR images, employing “convolutional neural networks (CNN)”.Article [8] presented a deep neural network using the “Transfer Learning (TL)” technique to recognize cases of “COVID-19 pneumonia”, “non-COVID-19 virus pneumonia” and “microbial pneumonia(MP)”.Paper [9] presented DL algorithms for evaluated query CXR images, intending to provide accurate solutions for healthcare practitioners in testing for COVID-19 and identifying verified cases. Study [10] presented "deep convolutional neural network (DCNN)" with the intention of detecting COVID-19 utilizing “chest radiographs(CR)”.

Research [11] presented a DL model that had been developed and assessed using CXR to support medical operations and decrease the pressure on medical personnel in managing COVID-19.Paper [12] presented DL algorithms that were pre-trained on ImageNet, to classify CXR images.Article [13] presented a CNN model based on "deep convolutional generative adversarial networks (DCGAN)" that created synthetic CXR images. Study [14] presented the DL model using the ResNet-101 CNN structure. Their algorithm was fine-tuned to detect anomalies in CXR images after that were trained to detect particles in a collection of 1 million images. Research [15] proposed a deep transfer learning approach that utilized“CXR images of both COVID-19-afflicted patients and non-COVID-19 individuals” to autonomously identify the condition.

3. Methodology

In this work, the HGD-TRN approach to classify COVID-19 depends on CXR images. Min-max normalization is used for data pre-processing, Edge-based segmentation is applied to identifyboundaries in images and PCA is employed to extract features to improve the performance of classifications. Figure 1 shows the overview of the methodology.

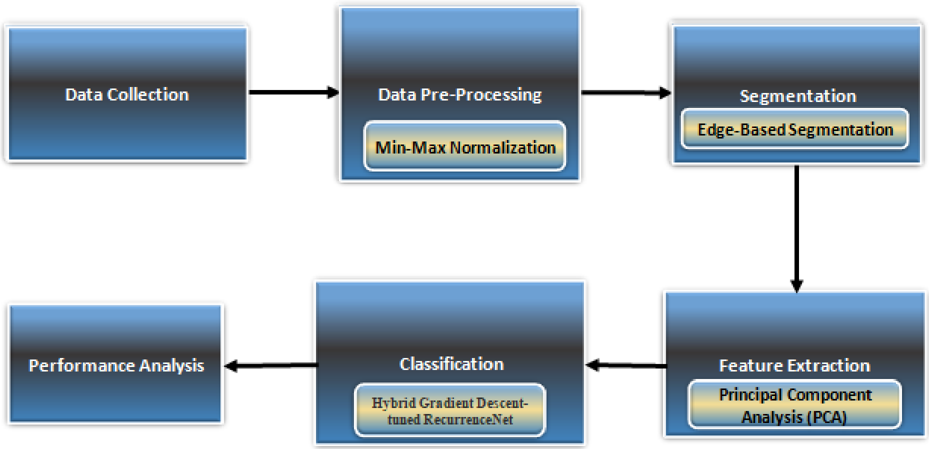

Figure 1: Overview of methodology

(Source: author)

3.1 Data collection

We gathered a dataset from kaggle,https://www.kaggle.com/discussions/general/160302.The diagnosis of COVID-19 can be aided by CXR. A database of CXR images of individuals with COVID-19 and “pneumonia”. The collection includes 6432 “CXR images of normal chests, COVID-19 cases and pneumonia”. All of these images are sourced from the general field. If everyone is curious about COVID-19 and pneumonia prediction using CXR images, they might examine the statistics.

3.2 Data pre-processing

Pre-process the image quality normalization, image resizing, classification imbalance handling, data splitting image augmentation for more variation and resolve missing or noisy input to enhance the effectiveness of COVID-19 identification utilizing CXR images.

3.2.1 Min-Max-Normalization

This approach is a method that converts the characteristics or outcomes from one number of variables to another number of variables in a linear manner. Typically, the variables are converted to break between the range of 0 and 1, or -1 and 1. The process of rescaling is accomplished by the use of a quadratic transformation, as expressed by the following equation (1):

$$Z = \frac{(w - \min(w))}{\max(w) - \min(w)} \quad (1)$$

Let min and max represent the lowest and highest values in w, which is the collection of observable numbers of w. By deducting the smallest value of w from the greatest value of w, or $max(w) - min(w)$, one could determine the range of w. The benefit of this normalization approach stems from the precise preservation of all connections in the information. Figure 2 shows the result of CXRs.

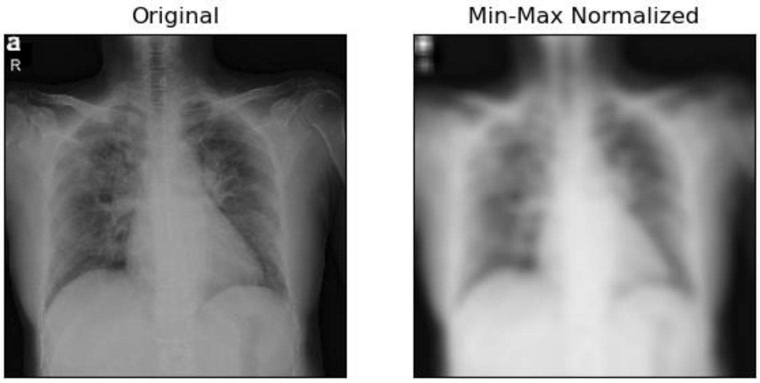

Figure 2: Min-Max-Normalization of CXRs

(Source: author)

3.3 Segmentation

Edge-based segmentation is a method used in image recognition and computer vision to segment or characterize items in an image by detecting their edges.

3.3.1 Edge-Based-Segmentation

The variation in intensity could be detected by subtracting surrounding images. Convolving the filter with the image is a method used to compute the initial degree component. The edge sensors, namely Robert, Prewitt, Sobel and Canny, are classed based on the values specified in the filters. These edge sensors recognize the edges in the horizontal and vertical orientations. Two distinct templates are used to ascertain the horizontal and vertical borders. The comprehensive edge map is obtained by combining the horizontal and vertical sides.

Edge recognition processors such as Robert and Sobel do not include edge connection. The visibility of the object boundaries can be obscured. The Canny edges detection recognizes edges in an image by applying smoothing, localizing the borders and thresholding to locate the genuine edges. The noise images are comprised of seabed and sediment characteristics. These entities are observed as interconnected elements, resulting in inelegant boundaries.

3.4 Feature extraction

Extract characteristics from CXR images to detect COVID-19, facilitating precise categorization and assisting in the creation of reliable diagnostic instruments for enhanced healthcare results.

3.4.1 Principal Component Analysis (PCA)

PCA model states that d-dimensional vectors w are obtained from lesser k-dimensional vectors$x$ by a linear transformation (G,n) together with the addition of a noise vector f. Mathematically, this relationship can be expressed as$f$: $w = Gx + n + f$.Figure 3 shows the PCA components. Both the noise and the main component vector were assumed to follow a spherical Gaussian distribution as shown in Equation (2-6):

$$o(f) \sim \mathcal{N}(0, uJ_c),\ o(x) \sim \mathcal{N}(0, J_l) \quad (2)$$

The measurement w follows a Gaussian distribution.

$$o(w|G, n, u) \sim \mathcal{N}(n, GG^S + uJ) \quad (3)$$

The purpose of PCA is to determine the basis matrices G and the noise variances u from giveninformation C, which consists of elements$C = \{W_1, \dots W_M\}$. The possibility of the information is,

$$o(C|G, n, u) = (2\pi)^{-\frac{Mc}{2}} |GG^S + uJ|^{-\frac{M}{2}} \exp\left(-\frac{1}{2} tr((GG^S + uJ)^{-1}T)\right) \quad (4)$$

$$T = \sum_j (W_j - n)(w_j - n)^S \quad (5)$$

The estimations obtained by the method are:

The orthogonal matrices V comprise the leading Leigenvectors of $^T/_M$, the diagonal matricesΛcomprise the associated Eigenvalues and Q is any arbitrary orthogonal matrices.

$$\hat{n} = \frac{1}{M} \sum_j W_j\ \hat{u} = \frac{\sum_{j=l+1}^{c} \lambda_i}{c-l} \hat{G} = V(\Lambda - \hat{u}J_l)^{1/2} Q \quad (6)$$

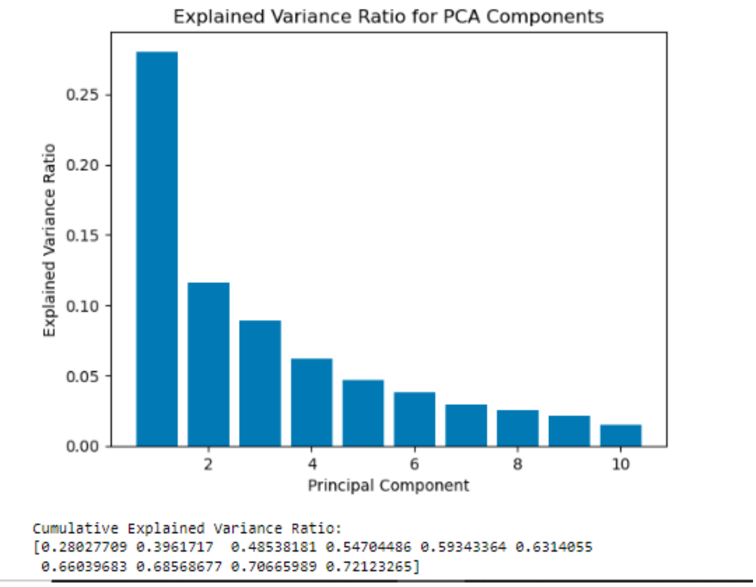

Figure 3: PCA components

3.5 Hybrid Gradient Descent-tuned RecurrenceNet (HGD-TRN)

This approach integrates Hybrid Gradient Descent optimization with recurrence Net, therefore improving the efficiency in identifying COVID-19. The use of these methodologies enhances the effectiveness of training and facilitates more precise identification of COVID-19 patterns in CXR data, leading to improved diagnostic capabilities.

3.5.1 Hybrid Gradient Descent (HGD)

The HGD method is a simplified version. Instead of calculating the gradient of $F_m(e_u)$each variation approximate this gradient using a randomly selected sampley_s as shown in Equation (7):

$$x_{s+1} = x_s - \gamma_s \Delta_x R(y_s, x_s) \quad (7)$$

The stochastic procedure $\{x_s, s = 1, \ldots\}$is influenced by the randomly selected samples at each execution. There is a (7) thatwill exhibit behaviour similar to what is anticipated, even with the interference caused by this reduced approach.

Due to its stochastic nature, the method does not need the retention of information about visited cases, allowing it to analyze examples in real time inside a deployed system. Under these circumstances, stochastic gradient descent minimizes the anticipated risk by directly considering instances randomly selected from the momentum distributions.

The propagation of stochastic gradient descent has been well investigated in stochastic approximations science. Convergence findings need the use of diminishing gains that fulfil the requirements $\sum_s \gamma_s^2 < \infty and \sum_s \gamma_s < \infty$ .The Robbins-Siegmund theorem allows for the establishment of virtually guaranteed convergence, even in circumstances where the loss function lacks differentiability throughout, by imposing moderate constraints.

The rate at which stochastic gradient descent converges is constrained by the imprecise estimation of the actual gradient. When the rate of increase of gains is sluggish, the rate of reduction of the variance of the component estimation x_s is slow. When the rate of increase diminishes rapidly, it takes a significant amount of time for the parameter estimate x_s to converge to the optimal value. When certain regularity constraints are satisfied, the optimal rate of convergence is attained by employing gains that follow a $\gamma_s \sim S^{-1}$, pattern. The residual error expectations drop at a comparable rate, namely$\mathbb{E}_\rho \sim s^{-1}$.

The second-order stochastic gradient descent (2SGD) algorithm applies positively definite matricesγ_s, which approximates the inversion of the Hessian, to the gradients in Equation (8):

$$x_{s+1} = x_s = \gamma_s \Gamma_s \Delta_x R(y_s, x_s) \tag{8}$$

Regrettably, this adjustment does not diminish the random noise and hence does not enhance the variance ofx_s. While the constants have been enhanced, the residual error's anticipated reduction follows a s^{-1} trend, denoted as $\mathbb{E}_\rho \sim s^{-1}$.

3.5.2 Tuned recurrenceNet (T-RN)

The Tuned Recurrent Neural Network (T-RNN) utilizes the sequential data included in CXR images to recognize COVID-19.T-RNNscan be seen as a specialized variant of feed-forward networks. Given that each neuron unit has an internal storage to store information from past and present input, the T-RNN is very advantageous for processing data sequences. The efficacy of T-RNNs depends on their ability to retain an internal state, known as memory tissues, which are used to analyze sequences incrementally and then reused in subsequent iterations. The input to the T-RNN consists of the optimum features, denoted as $\{E_1^{opt}, E_2^{opt}, \ldots, E_m^{opt}\}$, together with their corresponding labels, denoted as$\{Z_1, Z_2, \ldots, Z_m\}$. The output is obtained by conducting a series of operations on the hidden vectorhid_s, resulting in a sequence of numbers from 1 to 2. The mathematical representation of T-RNN can be expressed as equations (9) to (11) correspondingly as shown in Equation (10-11):

$$hid_s = e_{hid}\left(hid_{s-1}, E_s^{opt}\right) \tag{9}$$

$$Z_s = e_Z(hid_s) \tag{10}$$

The stimulation valuee_{hid} relates to the hidden levels whereas the activation variable $e_Z$equates to the output levels. The loss equation K of T-RNN is calculated using the Mean Squared Error (MSE) function.

$$K = \frac{1}{N} \sum_{j=1}^{N} \sum_m \frac{\left(z_{(m)}^j - P_{(m)}^j\right)^2}{N * X_m} \tag{11}$$

In this context, N represents the number of samples and refers to the actual output,$z_{(m)}^j$and $P_{(m)}^j$represent the projected result. Furthermore, M represents the number of classes.

3.6. Proposed technique

This hybrid design employs the advantages of Gradient Descent optimization and fine-tuned recurrence networks to augment the overall effectiveness of the systems. The HGD-TRN model utilizes Gradient Descent optimization to adjust the model variables, resulting in accelerated resolution during development. This optimization strategy effectively fine-tunes the values of the system, enhancing the model's capability to extract pertinent characteristics from CXR images linked to COVID-19. The combination of these two elements produces a stable hybrid model that specializes in acquiring complex spatial and temporal structures, eventually resulting in more precise and dependable detection of COVID-19 from CXR images. The HGD-TRN model shows potential for enhancing the timely and precise identification of COVID-19, thereby assisting healthcare practitioners in managing patients and implementing containment methods.

4. Result and discussion

We used Python 3.11, Tensor Flow 1.14.0 and Jupyter2019.07 to develop the proposed technique. Windows 10, an Intel i5 and 8 GB of RAM are the characteristics of this laptop. The outcomes of the proposed technique is analyzed in terms of various parameters, including Accuracy, Precision, Recall,F1score, RMSE and MSE to examinethe efficacy of the proposed techniquewith traditional methods. We use existing methods such as Attention-based VGG(AB-VGG)[16], Inception V3 with Transfer learning(IV3-TL)[16], Transfer learning with Resnet18(TL-R18)[16], Custom CNN(C-CNN)[16],Random Forest (RF) [17], Logistic Regression (LR) [17], K-Nearest Neighbours (KN-N)[17], Naive Bayes(NB)[17], Masked Auto-encoder for Distribution Estimation - Deep Belief Network (MADE -DBN)[18].

The confusion matrix assists investigators in identifying the data groupings that have been most inaccurately categorized, hence facilitating the improvement of classification systems. The rows of the matrix display actual classifications, while the columns represent predictions. The total of accurate vs inaccurate forecasts is calculated. The system achieves optimal efficiency when the ratios of categorization decline in a consistent manner along the diagonal of the matrices. Misclassification occurs when there is a deviation from the diagonal divisions. The confusion matrix's output is displayed in Figure 4.

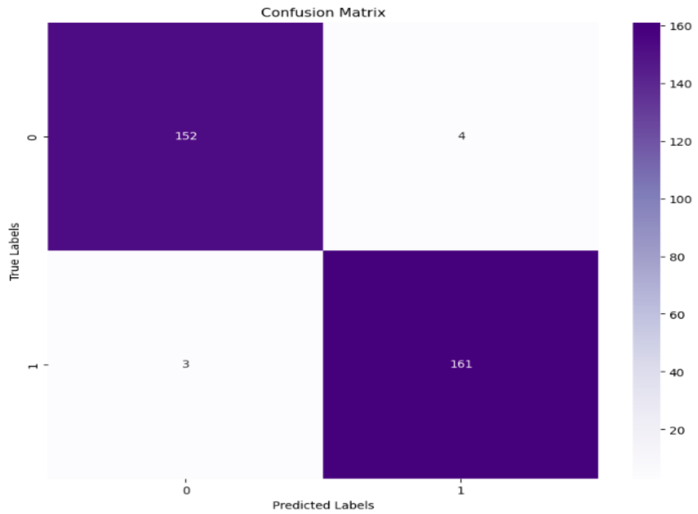

Figure 4: Result of confusion matrix

(Source: author)

ROC matrices examine the model's capacity to distinguish between COVID-19 and non-COVID-19 instances by comparing the TP rate to the FP rate. Figure 5 provides the output of ROC.Our proposed technique has obtained the value of 0.98. This indicates that our suggested strategy is more effective.

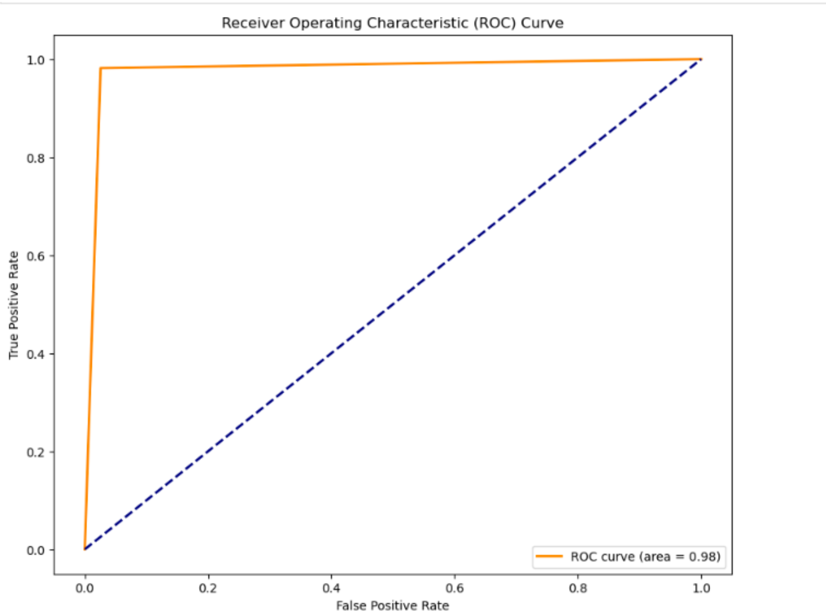

Figure 5: Output of ROC-AUC

(Source: author)

Accuracy measures are used to assess the efficacy of the model in separating COVID-19 instances from non-COVID-19 cases using CXRimages. Figure 6 provides the accuracy comparison. Comparatively, the performance of the existing approaches, AB-VGG (84.43%), IV3-TL (93%), TL-R18 (91.60%)and C-CNN (95.94%) in terms of accuracywhile our proposed approach has HGB-TRN(98%).The outcomes indicate that our proposed method has a much higher accuracy compared to the existing approach.

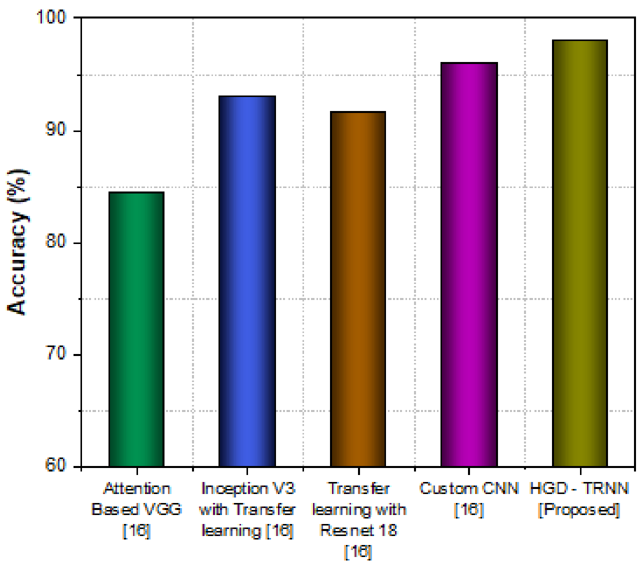

Figure 6: Result of accuracy

(Source: author)

Precision is essential for constraining misdiagnoses and guaranteeing accurate identification of COVID-19 patients using CXRimaging. Figure 7 presents a comparison of precision. Comparatively, the performance of the existing approaches, RF (94.67%),LR (95.58%), KNN (95.89%) and NB (92.11%) in terms of accuracy while our proposed approach is HGB-TRN(99%). The findings indicate that the method we have proposed exhibits a greater level of precision in comparison to the existing methods.

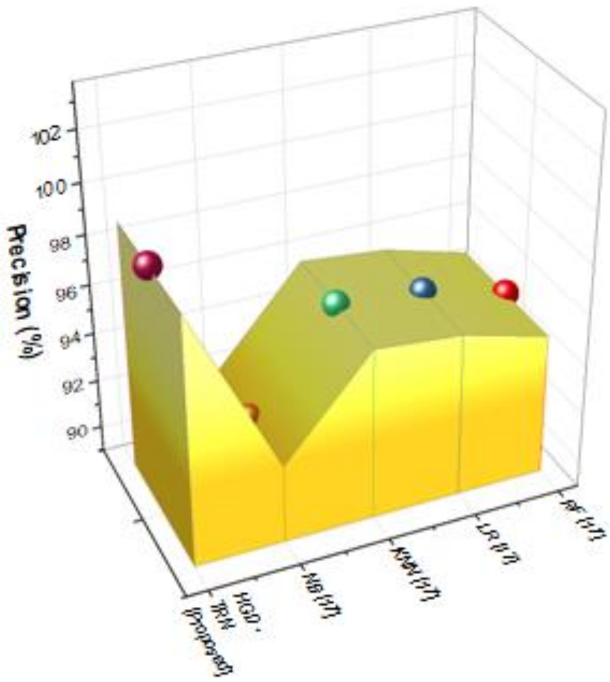

Figure 7: Result of precision

(Source: author)

Recall measures for COVID-19 recognition using CXRimages evaluate the technique capacity to recognize positive instances among all the true positive cases. Figure 8 displays the comparative evaluation of recall. When comparing the proposed approach HGB-TRN (98.90%) with the existing method RF (98.61%), LR (95.83%), KNN (97.22%) and NB (97.22%), As a result, in each instance, the efficacy of our proposed technique offers a greater advantage.

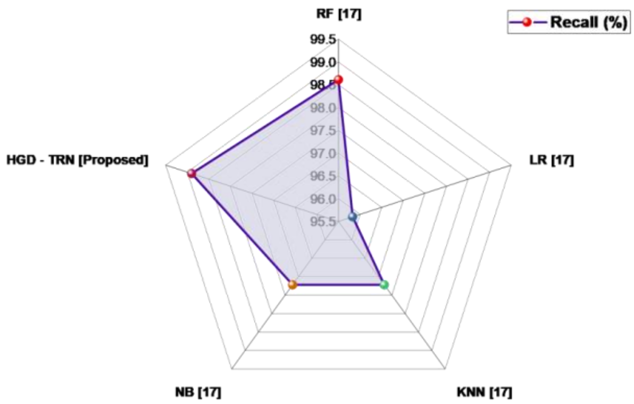

Figure 8: Result of recall

(Source: author)

The F-score is a quantitative measure used to evaluate the effectiveness of a COVID-19 classification technique by analyzingCXRimages.In Figure 9when comparing the proposed method HGB-TRN(98%) with the existing method RF (96.60%), LR (95.83%), KNN (96.55%)and NB (94.59%) shows that our suggested approach is better than the existing approach. This indicates that our suggested strategy is more effective.

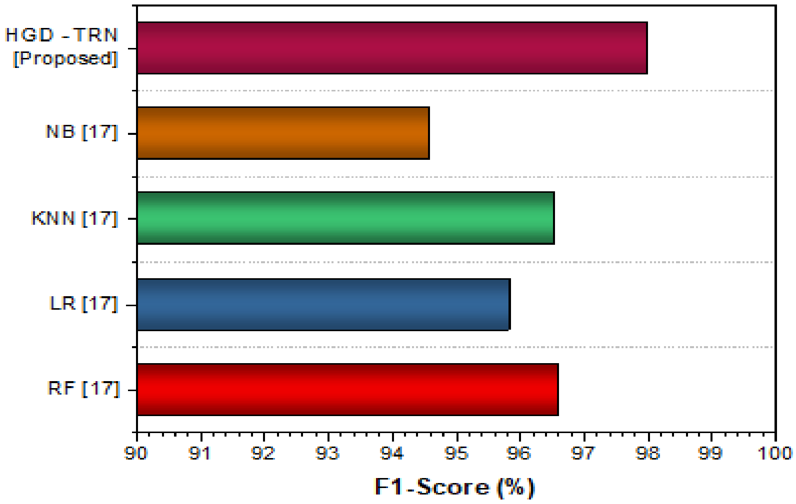

Figure 9: Result of F-score

(Source: author)

RMSE is a quantitative measure used to assess the reliability of predictions to categorization of COVID-19 utilizing CXRimages. RMSE comparison is displayed in Figure 10. In comparison the performance of the existing technique areRF (0.181), LR (0.198), KNN (0.181) and NB (0.229)while our suggested solution is HGB-T-RN (0.021). The outcomes demonstrate that our suggested approach has a lower RMSE in comparison with the existing methods.

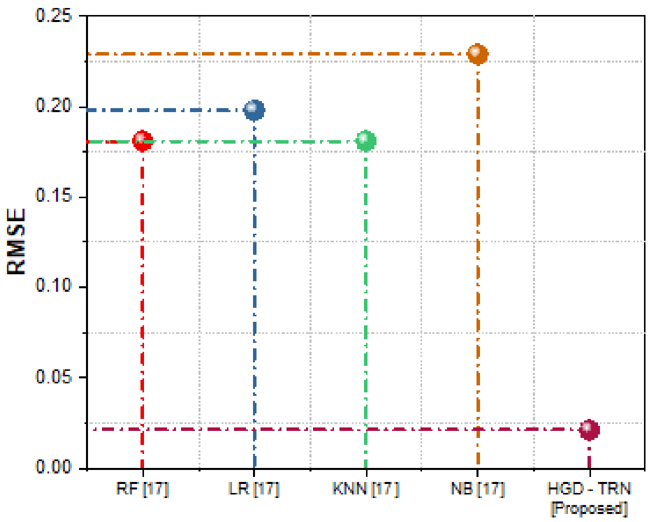

Figure 10: Output of RMSE

(Source: author)

MSE serves as a measure of the model's ability to reliably reconstruct pictures, which is crucial for ensuring dependable diagnosis and classification in healthcare imaging situations. Figure 11depicts the MSE comparison and the outcomes of the existing method RF (0.329), LR (0.395), KNN (0.329) andNB (0.526)while our proposed method is HGB-TRN (0.147). The outcomes demonstrate that our suggested approach has a lower MSE in comparison with the existing methods.

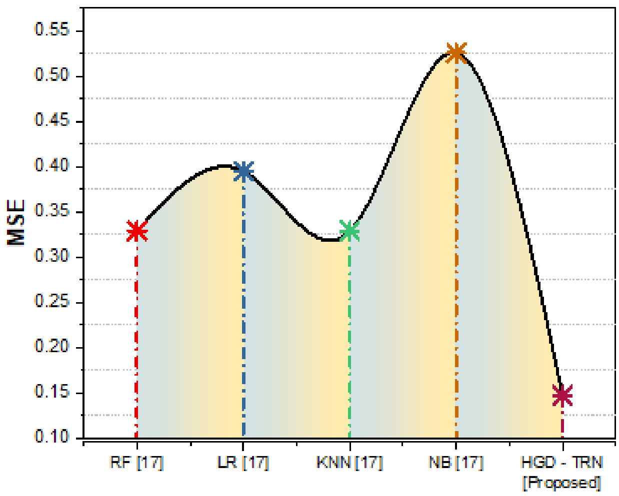

Figure 11: Output of MSE

(Source: author)

5. Conclusion

The COVID-19 pandemic emphasizes highlighted the requirement of immediate and precise recognition to reduce its transmission.The revolutionary Hybrid Gradient Descent-tuned Recurrence Net utilizes DL to depend on CXR images as a resource for identifying COVID-19-related lung anomalies. We gathered Kaggle dataset that included CXR images of both infected and COVID-19 organs. We used pre-processing methods such as Min-Max Normalization and Edge-Based Segmentation on a significant characteristic might be extracted with the use of Principal Component Analysis (PCA). Analytical measures including Accuracy (98%), Precision (99%), Recall (98.90%), F1-score (98%), RMSE (0.021) andMSE (0.147) demonstrated higher performance in the implementation of our suggested technique. We demonstrate that our methodology is a powerful diagnostic tool by doing extensive testing on the Python framework and comparing it to other approaches. The constraints of COVID-19 recognition using CXR images involve the possibility of inaccurate positive or negative results, dependence on image clarity and require for skilled interpreting. Future developments for COVID-19 recognition utilizing CXR images include breakthroughs in artificial intelligence to enhance diagnostic accuracy, connection with healthcare networks to facilitate wider screening and continuous research to enhance awareness and supervision of therapy.

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