

COVNET: AN INTELLIGENT MULTI-MODAL IMAGING SYSTEM FOR COVID-19 SEVERITY DETECTION

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Abstract – COVID-19 is a viral respiratory illness that causes characteristic lung changes on chest X-ray (CXR) and CT such as patchy opacities and diffuse inflammation. Imaging features of COVID-19, such as ground-glass opacities, are non-specific and can overlap with other lung infections, making it difficult to confirm the disease based on imaging alone. To overcome these challenges, a novel DL-based COVNET approach is proposed for COVID-19 severity detection using multi-modality images (CXR and CT). Initially, the gathered multi-modality images are pre-processed by Adaptive Wienmed (ADW) filter for denoising the input images. The noise-free images are fed into the Dual-stream EfficientNet (DSE-Net) for extracting the structural and textural features. That extracted structural and textural features are fused and fed into Deep Belief Network (DBN) for classifying the COVID-19 cases such as normal and COVID-19. The proposed COVNET model is evaluated based on its f1 score (F1), specificity (SP), precision (PR), recall (RE) and accuracy (AC). The classification AC of 99.14% for the proposed DBN are highly reliable for publicly available dataset. The proposed COVNET model achieves the overall AC by 2.82%, 5.14%, and 1.46% comparing to the existing method such as MIn-V3, CoroDet and nCOVnet respectively.

Keywords –COVID-19, Deep learning, Adaptive Wienmed filter, Dual-Stream EfficientNet, Deep Belief Network.

1. INTRODUCTION

In late 2019, the virus known as the severe acute respiratory syndrome coronavirus 2 was identified [1]. The virus that started in China is now responsible for Corona Virus Disease 2019, or COVID-19. In March 2020, the disease was deemed a pandemic by the World Health Organization [2]. Millions of people worldwide were impacted by the epidemic, according to reports released and updated by state governments and international healthcare organizations. Pneumonia is the most severe infection linked to COVID-19 that affects the lungs [3]. The illness can cause a wide range of symptoms, such as coughing, runny nose, high temperature, and dyspnea. The most typical way to diagnose these situations is to use CXR imaging analysis to check for abnormalities [4]. Since a CXR shows the image

of the thoracic cavity, which includes the bones of the chest and spine as well as the soft organs like the lungs, blood vessels, and airways, it is used to identify conditions connected to the chest, such as pneumonia and other lung disorders [5].

These benefits include its low cost, noninvasiveness, reduced time consumption, affordability of the gadget, and the wide availability of X-ray facilities [6]. In general, handcrafted-based machine learning (ML) techniques have not fared as well as deep learning (DL) approaches [7]. Recently DL, ML and computer vision have been used to automatically diagnose a variety of human diseases, advancing smart healthcare [8]. At the same time, the most recent automated methods, namely DL, have sought to decrease radiologists' workload and improve X-ray imaging efficiency. Convolutional neural network (CNN) methods have outperformed conventional AI methods in DL when it comes to diagnosing different medical images [9,10]. Limiting the transmission of COVID-19, facilitating treatment, and developing therapeutic protocols all depend on prompt and precise detection and classification of the virus [11]. Imaging features of COVID-19, such as ground-glass opacities, are non-specific and can overlap with other lung infections, making it difficult to confirm the disease based on imaging alone. To overcome these challenges, a novel DL-based COVNET approach is proposed for COVID-19 severity detection using multi-modality images. The key contributions of this work are summarized as,

- The multi-modality images are pre-processed by ADW filter for denoising the input images.
- The denoised images are processed by the DSE-Net, which extracts structural features from CXR images and textural features from CT images to enhance the accuracy of lung abnormality detection.
- The extracted structural and textural features are fused and given to the DBN, which

classifies the cases into normal or COVID-19 categories.

- The efficiency of the proposed COVNET was assessed utilizing the specific metrics like AC, F1, SP, PR and RE.

The structure of the paper is organized as follows, section-2 defines the literature survey, the proposed COVNET was explained in section-3 and Section-4 includes the final results and discussion. Lastly, conclusion enfold in section-5.

2. LITERATURE SURVEY

In recent years, the adoption of computer-assisted software in the medical field has gained important attention due to the development of computerized methods for COVID-19. These advancements expedite medical treatment and reduce patient delaying times. A summary of some existing DL and ML models is provided below.

In 2023 Thangaraj, R., et al., [12] proposed Modified-Inception V3 (MIn-V3) model to categorize a variety of illnesses, such as bacterial pneumonia, COVID-19, pneumonia, and normal pneumonia. By contrasting MIn-V3 with pre-trained DL models like Inception-ResNet V2, Inception V3 and MobileNet V2 its performance is evaluated. With a classification accuracy of 96.33% experimental findings show that the MIn-V3 model outperforms other pre-trained models.

In 2022 Ayalew, A.M., et al., [13] proposed DL based histogram of oriented gradients (HOG) and CNN for COVID-19 detection. CXR pictures gathered from the University of Gondar and internet databases used to assess the diagnostic efficacy of the hybrid CNN model and HOG-based approach. Using HOG, the suggested model's accuracy was 98.5%.

In 2021 Kalane, P., et al., [14] proposed an automated Covid-19 identification method that trains the DL based U-Net architecture utilizing Computer Tomography (CT) images. One thousand chest CT scans were used to assess the suggested system's performance. With an overall accuracy of 94.10%, the suggested method has attained sensitivity and specificity of 94.86% and 93.47%, respectively.

In 2021 Ismael, A.M. and Şengür, A., [15] suggested a CNN model for the identification of COVID-19. The study's performance was evaluated using classification accuracy. According to experimental research, DL has promise for detecting COVID-19 from CXR images. The deep features extracted from the ResNet50 model and SVM classifier with the Linear kernel function produced a 94.7% accuracy score, which was the highest among all the obtained results.

In 2021 Hussain, E., et al., [16] proposed a CoroDet use raw CXR and CT scan image for automatic COVID-19 detection. For two class classifications, three class classifications and four class classifications. The suggested model generated a classification accuracy of 99.1% for two class classification, 94.2% for three class classification, and 91.2% for four class classification.

In 2020 Panwar, H., et al., [17] proposed nCOVnet, a DNN-based technique for COVID-19 identification. Based on the test data set's confusion matrix, we were able to attain a sensitivity of 97.62% and a specificity of 78.57%. We know that we have reached an accuracy of 97.62% in the case of COVID-19 positive patients, and we have accurately predicted a COVID-19 patient with an error of only 2.03% in less than 5 seconds.

In 2020 Alom, M.Z., et al., [18] proposed a multitask DL technique for detecting COVID-19 using CT and CXR scans. It employs the NABLA-N network model for COVID-19 region segmentation and the Inception Residual Recurrent CNN with Transfer Learning (TL) technique for COVID-19 detection. The detection model's testing accuracy from CXR is around 84.67%, while its accuracy from CT images is approximately 98.78%.

In the literature review, the above existing techniques were developed utilizing various DL and ML approaches to the classification of COVID-19. One key limitation in COVID-19 classification is the class imbalance in datasets, where severe cases are underrepresented, leading to biased model predictions and reduced AC for critical stages. Imaging features of COVID-19, such as ground-glass opacities, are non-specific and can overlap with other lung infections, making it difficult to confirm the disease based on imaging alone. In this research, the COVNET model was proposed for classifying COVID-19.

3. PROPOSED COVNET METHODOLOGY

In this research, a novel COVNET model is proposed for COVID-19 classification. Figure 1 shows the COVNET proposed methodology.

3.1 Dataset description

This research, utilized a database [19] that included 623 chest CT scan images of COVID-19 patients and 3,000 normal chest CT scan images. Dr. Jkooy's open-source GitHub repository provided these images. 325 chest CT scan images of COVID-19 patients and 408 chest CT scan images of healthy patients were used. Additionally, we used 500 CXR pictures of healthy people and 500 CXR pictures of COVID-19 patients that we found on Kaggle. Eighty percent of the dataset was used for training, and the remaining twenty percent was used for testing.

3.2 Pre-processing using ADW filter

The Wiener and median filters are combined to create the ADW filter. These two filters work well together to effectively reduce noise dispersion and edge faults. Replacing nearby and noisy image pixels, which were previously organized based on image intensity is the primary goal of a filter. After applying the Wienmed filter on the dataset, a pre-processed image is produced. The mean m in each pixel is found and expressed in equation (1).

$$K = \frac{1}{gh} \sum_{g,h \in p} q(g,h) \quad (1)$$

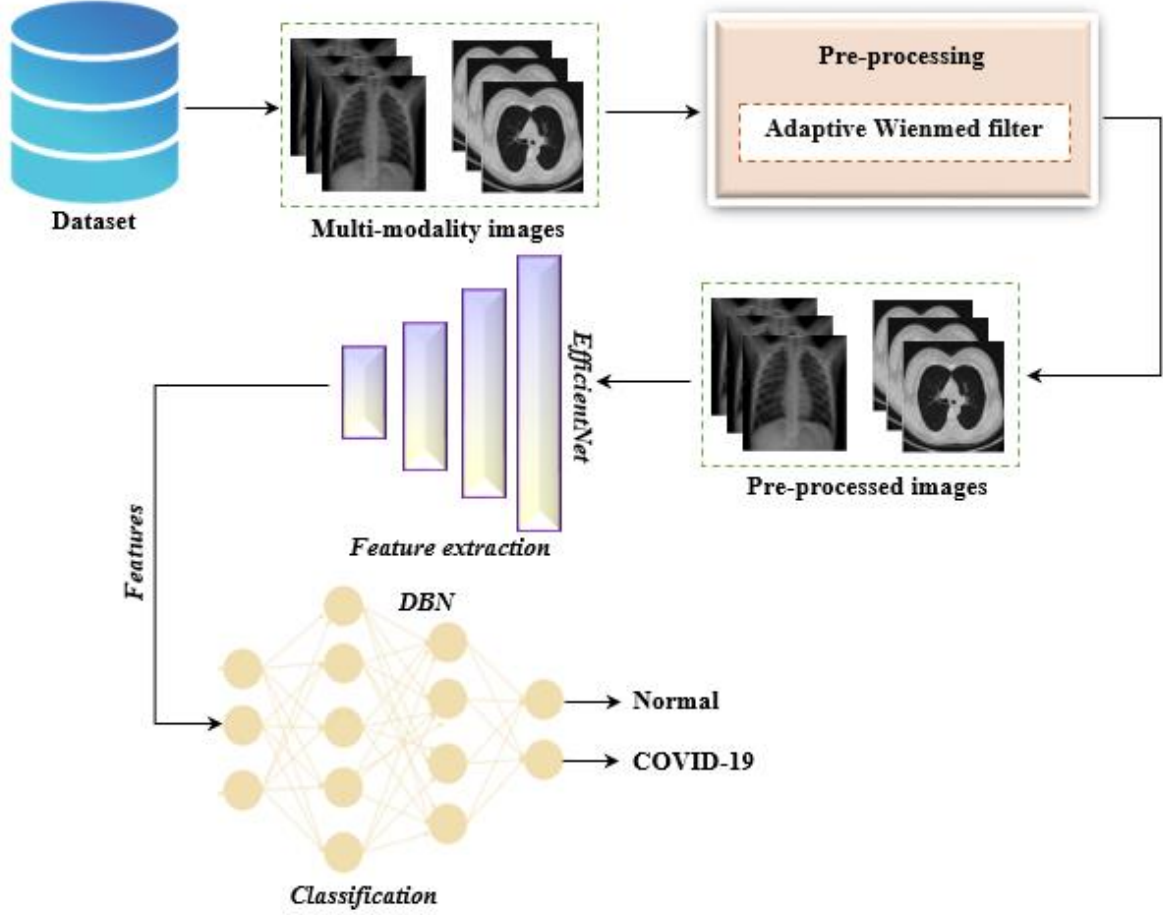


Figure 1. Proposed COVNET methodology

In this case, k represents each image, g denotes its pixel dimensions, and p is a pre-processed satellite image. Equation (2) also provides Gaussian noise variation, where σ^2 denotes the variance of Gaussian noise is calculated as.

$$\sigma^2 = \frac{1}{gh} \sum_{g,h \in p} q(g, h) - n^2 \quad (2)$$

Where g and h represent the pixel dimensions width and height of the image patch p , and $q(g, h)$ refers to the intensity value at each pixel location (g, h) . The term n represents the mean intensity value computed over the patch, and its square n^2 is subtracted to determine the variance.

$$T(g, h) = \sigma^2 [K - q(g, h)] \quad (3)$$

Here, $T(g, h)$ represents the filtered output at pixel location (g, h) is calculated. This formulation adjusts each pixel by the deviation from the mean, scaled by the estimated noise variance, thereby enhancing image quality by suppressing noise. As a result, the Wienmed filter eliminates noise from frames, and the obtained images proceed to the feature extraction stage.

3.3 EfficientNet for structural and textural feature extraction

In this section, DSE-Net is used for extracting the structural and textural features from the multi-modality images. One EfficientNet is used for extracting the structural

features from the CXR image and another for textural features from the CT image. CNN using the DSE-Net design aim to achieve great performance with the least amount of processing power. It makes use of a cutting-edge compound scaling technique that balances the network's depth, width, and resolution unlike traditional approaches that scale only one dimension at a time. This balanced scaling allows DSE-Net to achieve greater accuracy while maintaining efficiency, making it appropriate for use in resource-constrained settings, such as those of mobile devices. Bottlenecks that link MBConv blocks which are composed of a layer that first expands and then compresses the channels are connected directly significant smaller number of channels than expansion layers. Compared to typical layers, computation is reduced by almost a factor of k , the kernel size denoted by k . The compound coefficient is used in compound scaling to adjust depth, width, and resolution equally ϕ in conjunction with the principles outlined in Equations (4, 5, 6).

$$\text{depth: } d = \alpha^\phi \quad (4)$$

$$\text{Width: } w = \beta^\phi \quad (5)$$

$$\text{resolution: } r = r^\phi \quad (6)$$

where α , β , and γ are grid search-determined constants. ϕ , α , β , and γ determine which the network's breadth, depth, and resolution are given more resources respectively, while

is a user-defined coefficient that regulates the number of resources are available to scale the model. This efficient scaling enables DSE-Net to deliver improved outcomes in a variety of models while maintaining a balance between accuracy and resource utilization. Weighted average fusion is used for combining the structural and textural features to improve detection accuracy.

3.4 Classification

DBN is used to detect the COVID-19 namely Normal and COVID-19. DBN is a type of RBM designed to integrate low-level features with additional nonlinear transformations. This DL model combines Neural Networks with Backpropagation Neural Networks (BPNN) to effectively learn and represent high-level abstract features. In COVID classification, DBN has ability to learn high-level intellectual features from complex datasets. DBN integrates Neural Networks and BPNN, enabling them to perform both unsupervised and supervised learning tasks. A SoftMax output layer is added at the top of the DBN, the model facilitates supervised learning for COVID classification. This setup allows for the effective evaluation and analysis of patient data, providing accurate classification and prediction of cardiovascular conditions. The proposed classification of a DBN consisting of multiple layers, including visible layers v and hidden layer h , with connections between adjacent layers. to depict the random variable x , it was split up into groups: $x = \{x_1, x_2, \dots, x_n\}$, $y = \{y_1, y_2, y_3, \dots, y_m\}$, and

several links within the hidden and visible levels were left out. Its energy function could be shown as follows:

$$E(V, x) = -(\sum_{i,j=1}^{m,n} V_i W_{ij} x_j + \sum_{j=1}^n C_j x_j) \quad (7)$$

The final version of the probability density function is obtained by substituting the energy function RBN:

$$P(x) = P(y, x) = \frac{1}{Z} \cdot e^{\sum_{i,j=1}^{m,n} y_i W_{ij} x_j + \sum_{i=1}^m b_i y_i + \sum_{j=1}^n c_j x_j} \quad (8)$$

Reverse supervised fine-tuning of each layer's initial settings was carried out in conjunction with labeled data. The hidden layer's activation state was used as the input for the backward transmission procedure during the reconstruction phase. Comparable to the forward transmission process's weight adjustment on weight modifications, mistakes were backpropagated and rebuilt. Errors were reduced by recurrent learning until convergence was achieved. DBN offer a robust and efficient framework for COVID-19 classification by selecting features and combining unsupervised and supervised learning. Their adaptability and high AC make They are a potentially useful instrument for enhancing patient care and early diagnosis in COVID-19.

4. RESULTS AND DISCUSSIONS

In this section, the proposed COVNET is implemented using MATLAB (2020b) and operates on a server configured with an Intel Xeon F8 CPU running at 3.5 GHz, 64 GB of RAM and an NVIDIA GPU with an 11 GB graphics card. The COVNET is assessed by various measures like PR, AC, SP, RE and F1.

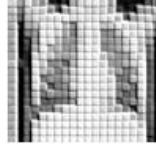
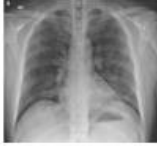
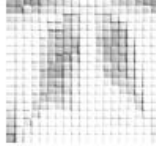
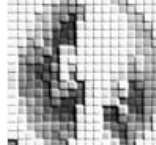
Patient	Input image	Pre-processing	Feature extraction	Classification
1				Normal
				
2				COVID-19
				

Figure 2. Experimental result of the proposed COVNET

Figure 2 illustrates the simulation result of the proposed COVNET with the different patient multi model image samples. The input images (column 2) from the gathered dataset are pre-processed using Adaptive Wienmed filter as displayed in column 3. Feature extraction image is shown in

column 4 and finally the column 5 displayed the classification results such as normal and COVID-19.

4.1 Performance analysis

A proposed COVNET model was assessed based on fl score, specificity, recall, accuracy and precision.

$$SP = \frac{T_{neg}}{T_{neg} + F_{pos}} \quad (9)$$

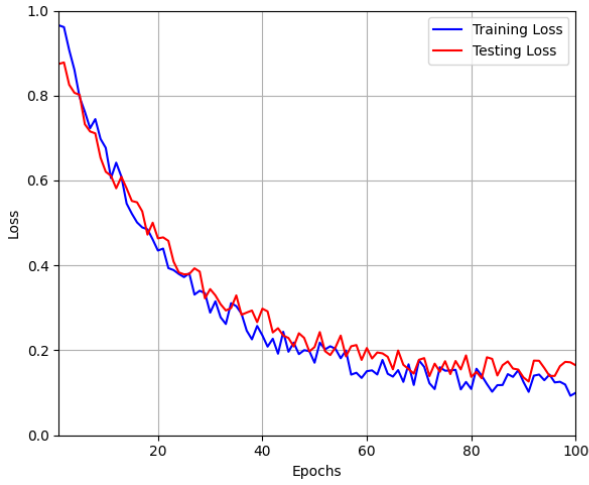
$$PR = \frac{T_{pos}}{T_{pos} + F_{pos}} \quad (10)$$

$$RE = \frac{T_{pos}}{T_{pos} + F_{neg}} \quad (11)$$

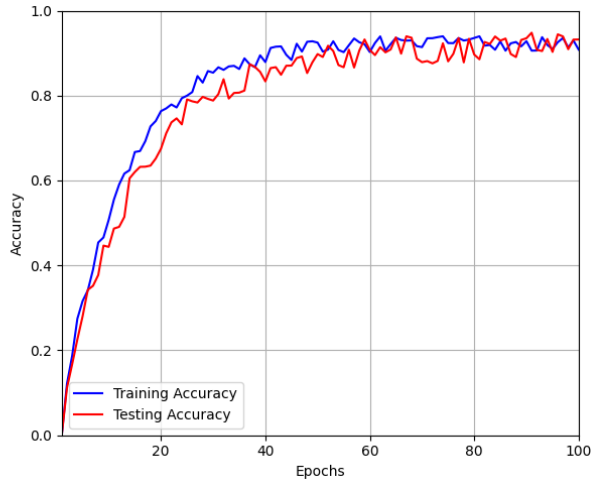
$$AC = \frac{T_{pos} + T_{neg}}{\text{Total no. of samples}} \quad (12)$$

$$F1 = 2 \left(\frac{\text{Precision} + \text{Recall}}{\text{Precision} + \text{Recall}} \right) \quad (13)$$

Where T_{neg} and T_{pos} specifies true negatives and true positives of the sample images, F_{neg} and F_{pos} specifies false negatives and false positives of the sample images.



(a)



(b)

Figure 3. Accuracy and loss curve of the proposed COVNET model

Figure 3 a) depicts the AC curve, shows the AC range on the vertical axis against the number of epochs on the horizontal axis. When the number of epochs raises, the proposed COVNET demonstrates an enhancement in AC. Figure 3 b) displays as the epochs and loss increase, the COVNET experiences a decrease in loss. Based on the gathered multi modal images, the proposed COVNET model proved to be effective in accurately classifying COVID-19 cases. According to the findings, the COVNET achieves substantial performance in classification accuracy of 99.14%.

4.2 Comparative analysis

In this analysis, the competence of suggested and existing models was estimated using different metrics. The comparison assessment was competed among the proposed DBN with different classification techniques. The contrast of traditional classification networks is illustrated in table.2.

Table 1. Performance assessment of the proposed

COVNET model

Classes	AC	SP	PR	RE	F1
Normal	99.53	97.90	95.42	94.18	89.30
COVID-19	98.76	96.23	96.67	95.79	93.62
Overall	99.14	97.06	96.04	94.98	91.46

Table 1 shows the efficiency of the proposed COVNET model to categorize the different COVID-19 classes. A 99.14% accuracy rate is achieved by the proposed model.

Table 2. Comparison of traditional models for classification

Models	AC	SP	PR	RE	F1
DenseNet	93.71	90.42	93.36	90.57	89.56
LeNet	95.40	91.61	90.70	92.62	90.49
ShuffleNet	97.73	93.40	95.23	89.21	85.13
DBN	99.14	97.06	96.04	94.98	91.46

Table 2 presents a comparison of various conventional DL networks, identifying the best classification accuracy achieved. Though, despite their utilization, classic DL networks didn't yield superior outcomes in comparison to the proposed DBN. The suggested DBN increases the overall AC by 5.79%, 3.92% and 1.44% better than DenseNet, LeNet and ShuffleNet respectively

Table 3. Accuracy assessment among Proposed and Existing models

Authors	Methods	Accuracy
Thangaraj, R., et al., [12]	MIn-V3	96.33%
Hussain, E., et al., [16]	CoroDet	94.2%
Panwar, H., et al., [17]	nCOVnet	97.62%
Proposed	COVNET	99.14%

Table 3 illustrates the assessment of the COVNET model with prior models based on the gathered dataset. The proposed COVNET model advances the overall AC by 2.82%, 5.14%, and 1.46% better than MIn-V3, CoroDet and nCOVnet respectively. Though, the existing networks not performed well when related to the suggested network. So, the estimated fallouts of the proposed COVNET are extremely consistent for classifying the COVID-19 in its early stages based on retinal images from the gathered datasets.

5. CONCLUSION

This research proposed a novel DL-based COVNET approach for COVID-19 classification. The gathered multi-modality images are pre-processed by ADW filter for denoising the input images. The noise-free images are fed into the DSE-Net for extracting the structural and textural features. That extracted structural and textural features are fused and fed into DBN for classifying the COVID-19 cases such as normal and COVID-19. The proposed DBN outperforms DenseNet, LeNet and ShuffleNet by 5.79%, 3.92% and 1.44% respectively, in terms of overall accuracy range. As a result of the experiment, the proposed method performed 99.14% more accurately than previous method to classifying the classes of COVID-19. The proposed COVNET model achieves the overall accuracy by 2.82%, 5.14%, and 1.46% comparing to the existing method such as better than MIn-V3, CoroDet and nCOVnet respectively. In future, the COVNET model can be extended by incorporating clinical data and temporal imaging sequences to further improve diagnostic accuracy and robustness in COVID-19 classification.

CONFLICTS OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

FUNDING STATEMENT

Not applicable.

ACKNOWLEDGEMENTS

The author would like to express his heartfelt gratitude to the supervisor for his guidance and unwavering support during this research for his guidance and support.

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Arrived: 03.01.2025

Accepted: 21.02.2025