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CVD-HNet: Classifying Pneumonia and COVID-19 in Chest X-ray Images Using Deep Network

S. Suganyadevi[1] · V. Seethalakshmi[1]

Abstract

The use of computer-assisted analysis to improve image interpretation has been a long-standing challenge in the medical imaging industry. In terms of image comprehension, Continuous advances in AI (Artificial Intelligence), predominantly in DL (Deep Learning) techniques, are supporting in the classification, Detection, and quantification of anomalies in medical images. DL techniques are the most rapidly evolving branch of AI, and it's recently been successfully pragmatic in a variety of fields, including medicine. This paper provides a classification method for COVID 19 infected X-ray images based on new novel deep CNN model. For COVID19 specified pneumonia analysis, two new customized CNN architectures, CVD-HNet1 (COVID-HybridNetwork1) and CVD-HNet2 (COVID-HybridNetwork2), have been designed. The suggested method utilizes operations based on boundaries and regions, as well as convolution processes, in a systematic manner. In comparison to existing CNNs, the suggested classification method achieves excellent Accuracy 98 percent, F Score 0.99 and MCC 0.97. These results indicate impressive classification accuracy on a limited dataset, with more training examples, much better results can be achieved. Overall, our CVD-HNet model could be a useful tool for radiologists in diagnosing and detecting COVID 19 instances early.

Keywords Deep learning · COVID 19 · CNN · X-ray · Accuracy · Matthews correlation coefficient

1 Introduction

With the rapid advancement of artificial intelligence, an increasing number of researchers are focusing on intelligence, deep learning-based diagnostic approaches. A few of them have produced some very impressive outcomes. DL (Deep Learning) techniques are the significant contributor to the current emergence of AI in practically every aspect of life [1].

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It's a direct result of current achievements in a wide range of scientific domains, including chemical structure analysis, Particle Physics, Computer Vision, Natural Language Processing, DNA analysis, brain circuit's studies. It has recently stimulated the importance of clinical imaging investigators, indicating which it holds enormous promise for the field's future [2]. The Deep Learning model enables machines that can learn extremely complicated data representational mathematical models, which can then be utilised to do precise data analysis [3]. These methods perform linear functions and/or non-linear of the input image or data which are weighted with the model parameters in a hierarchical fashion [4]. Deep learning approaches have a common aim of continuously learning the features of a computer model using training datasets, so that the model improves over time at performing a specified task, such as classification and detection, over that datasets under a stated metrics [5].

Machine Learning has been employed in the medical imaging sector since the 1960s. However, it was in the 1990s that the first major contributions relating to contemporary Deep Learning techniques appeared in the Medical Imaging field [6]. In recent decades, medical imaging modalities including X-ray, Magnetic Resonance (MR), Mammography, Computed Tomography (CT), Positron Emission Tomography (PET) and ultrasound had grown more significant in early disease detection, diagnosis, and treatment. Today's Medical imaging techniques including MRI/fMRI, X-ray, CT, and PET scanners provide a plethora of complicated and highly useful images to computer-aided diagnosis (CAD) [6, 7].

Appropriate feature extraction [8] or feature illustration is at the core of machine learning's attainment in completing specified jobs. Relevant features were traditionally defined by medical specialists depending on their understanding of the aim of the field, making it difficult for non-experts [9] to use machine learning models for their own research. Deep learning models, on the other hand, has overcome these challenges by integrating the feature engineering process into a learning phase. That example, inspite of manually extracting features, DL techniques just necessitates a collection of image data's and some basic pre-processing [10].

The current technological improvements have resulted in the combination of DL classifiers and medical images providing greater impressive outcomes comparable to conventional RT-PCR screening while increasing the accuracy of COVID 19 case prediction and diagnosis. From December 2019, a novel coronavirus (SARS-CoV-2) had spread across Wuhan to the rest areas of China and numerous other nations. And over 230 million cases have been confirmed, with approximately 5 million deaths had been recorded worldwide by October 1 2021. (https://www.worldometers.info/coronavirus). Figure 1 shows the Global Situation of COVID-19 Total Cases, Total Deaths and Recovered Cases taken by World meter. Which has far implications on people's daily lives, global economy and public health. It's critical to identify confirmed cases as quickly as possible to stop the outbreak from growing faster and to help patients as quickly as possible [11]. The demand of supplemental diagnostic equipment has grown since there are no effective automated toolkits available. Such images convey essential information regarding the COVID-19 virus, as according latest researches obtained employing radiological imaging techniques. Improved AI based techniques paired with imaging techniques can help to detect exact disease, along with solve the issue of a physician scarcity in rural regions [12].

One among the most vital significant drawbacks of chest x-ray analysis is their being unable to recognise COVID-19 in its early phases due to a lack of sensitivity while performing GGO detection [13–15]. Deep learning models that have been well-trained, on the other hand, can concentrate on details which the human eye misses, potentially reversing this view.
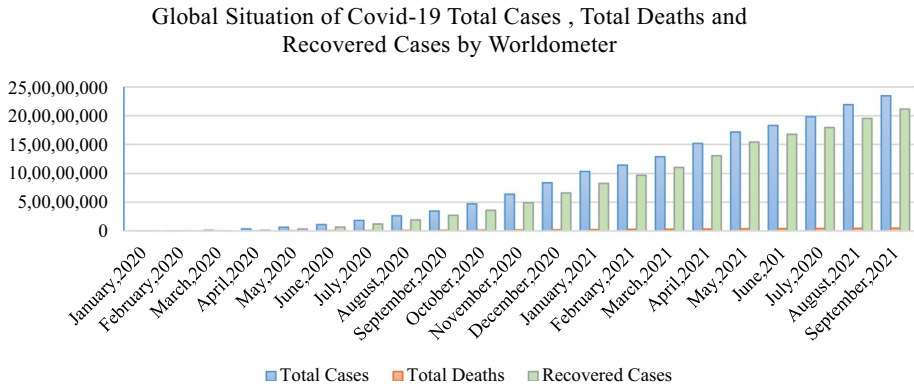
Global Situation of Covid-19 Total Cases , Total Deaths and
Recovered Cases by Worldometer

Fig. 1 Global Situation of COVID-19 Total Cases, Total Deaths and Recovered Cases by Worldometer

In Sect. 2 we present some general classifications of learnings, In Sect. 3 we cover the principles of extracting high-level representations from data using neural networks and deep architectures such as Artificial Neural Network (ANN), Recurrent Neural Network (RNN) and Convolutional Neural Network (CNN) [11]. Section 4 covers classification approach based on Proposed COVID-HNet (COVID-HYBRIDNet). Finally, in Sect. 5, we summarise the study patterns of one of application of deep learning such as COVID19 classification and finally in Sect. 6 we present conclusions and make some recommendations for future improvements.

2 Learning Types

The following are the 14 categories of learning that we must be acquainted with as AI specialists. Figure 2 shows the various kinds of learnings available in machine learning.
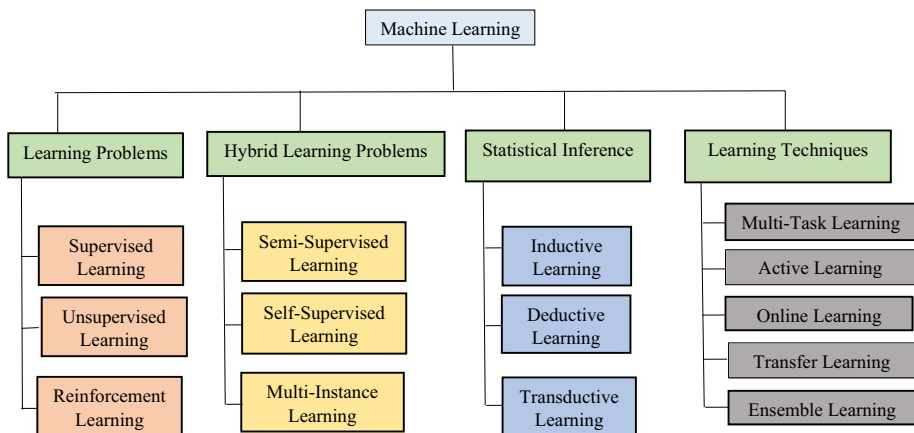

Fig.2 Learning Types

2.1 Supervised Learning

Supervised learning is among the most prevalent types of Machine Learning (ML). In this instance, the algorithm is given training on annotated data. In spite of the fact that appropriate annotated data is mandatory used for this method to work, this kind of learning can be extremely effective while utilised under the right situations [12–14].

The environment has a set of data inputs and resulting data outputs $(x_t, y_t) \sim p$ when contemplating such a technique. If the input is x_t, the smart agent will assume $y_{t^\wedge} = f(x_t)$ and return $(y_{t^\wedge}, y_t)$ as a loss value [15]. In this classification scenario, normally y would be a class value which is always scalar but it could be a vector of continuous data in a regression setting [16].

Deep Neural Networks (DNNs), Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) are examples of supervised learning techniques for DL. Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) techniques are also included in the RNN category [17]. The primary benefit of this technology is the capacity to gather data or develop a data output using prior knowledge. The downside of this strategy is that when the training set lacks samples that should be in a class, the decision boundary may be overstrained. In general, this strategy is easier to learn than other high-performance learning techniques [18].

2.2 Unsupervised Learning

Unsupervised learning algorithms are trained to discover patterns in unlabelled data, such as latent subspaces. Conventional unsupervised methods includes Principal Component Analysis (PCA) and clustering approaches. This implies that no human labour is necessary to make the dataset machine-readable, enabling the programme to work on much larger datasets [19].

When compared to supervised learning, unsupervised learning algorithms allow users to complete more complicated processing tasks. However, when compared to other natural learning methods, unsupervised learning is more unpredictable [20]. Clustering, anomaly detection, and neural networks are examples of unsupervised learning methods [21].

Some of the most newly invented elements of the DL category, such as Deep Boltzmann Machines, Auto-Encoders, and Generative adversarial Network, have fared well along nonlinear dimensionality reduction (DR) and clustering issues [22]. RNNs including LSTM and GRUs approaches, have now been employed used in a variety of applications for unsupervised learning. Unsupervised learning's key drawbacks are its inability to give precise data sorting information and its computational complexity. Clustering is one of the most often used unsupervised learning techniques [23].

2.3 Reinforcement Learning

Reinforcement Learning (RL) is based on interacting with the environment, whereas supervised learning is based on a set of data that is presented. This method was created in 2013 with the help of Google Deep Mind. As a result, numerous improved reinforcement learning approaches have been developed [24].

Reinforcement learning is a machine learning training strategy that involves rewarding specific behaviours while punishing unwanted ones [25]. A reinforcement learning

agent can observe and comprehend its surroundings, execute actions, and learn through trial and error in general. There is no answer in reinforcement learning, but the reinforcement agent decides how to complete the job. It is obligated to learn from its experience in the absence of a training dataset.

Since the reinforcement learning technique does not have a straightforward loss function, it is far more difficult to perform than typical supervised techniques [25, 26]. Furthermore, There have been two key differences among supervised and reinforcement learning. first, there is no comprehensive availability towards the function, necessitating optimization, suggesting that it should be questioned such as through interaction, and second, the state has been interacted with is based on a surroundings, with the data relying on previous actions [27].

3 Deep Models

Hinton and Salakhutdinov released an article in the science journal in 2006 that ushered in the DL era [28]. They demonstrated that a neural network with hidden layers was crucial in boosting learning's features' power [29].The accuracy of these algorithms can be improved while classifying different types of data [30]. Figure 3 describes the general classification of machine learning model [31].

3.1 Artificial Neural Network (ANN)

A single perceptron or neuron could be thought of a Regression Model. At each layer of an ANN, there are numerous perceptron's/neurons [31]. Because data inputs are exclusively processed in the forward direction, that ANN is furthermore known as a Feed-Forward Neural Network. ANN comprises of 3 layers explicitly Input, Hidden and Output layer
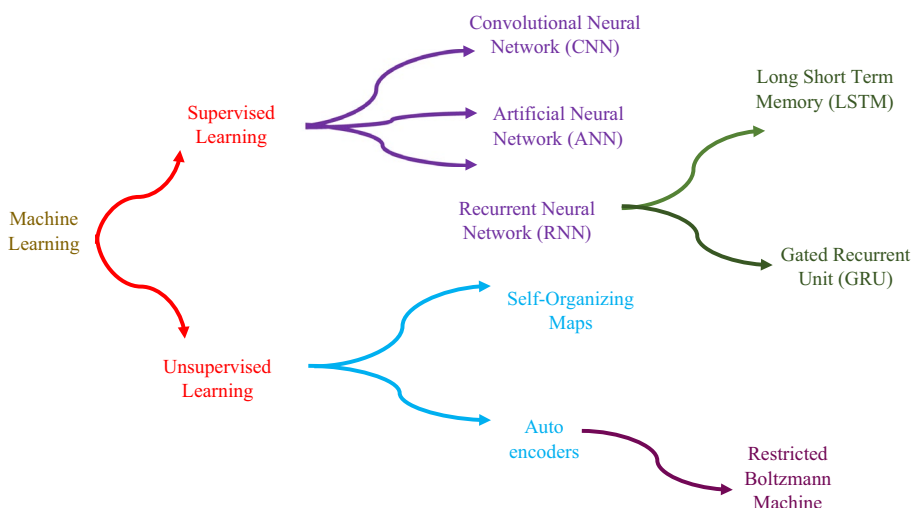

Fig.3 General Classification of Machine Learning

[32]. The data is received by the input layer, evaluated by the hidden layer, and synthesized by the output layer. In essence, each layer is attempting to learn specific weights [33].

3.1.1 Advantages

Artificial Neural Network learns any non—linear function. As a result, these networks are commonly referred to as Universal Function Approximators [34]. An artificial neural network (ANN) can train weights that map every input to the desired output. One of its primary reasons for universal approximation would be the activation function [35]. Activation functions are used to establish the network's non-linear properties. This makes it easier for the network to learn any complicated input–output connection [36].

3.1.2 Challenges

Before training an ANN model in solving picture classification challenge would be to transform a two-dimensional picture into a one-dimensional vector [37]. This has some disadvantages, as the image size grows larger, the number of trainable parameters grows dramatically. The spatial properties of an image are lost while using ANN. Spatial characteristics pertain to how pixels are arranged in an image [38].

In most of these Neural Network models, the Vanishing and Exploding Gradient will be a frequent problem. Back propagation algorithm is also linked with this issue [39]. This Back propagation algorithm finds the gradients and updates the weights of a neural network. As a result, when a highly deep neural network (DNN) propagates backward, the gradient vanishes and bursts, resulting in vanishing and exploding gradients [40]. ANN does not capture sequence information in the data input, which is required for handling with sequence data sets [41].

3.2 Recurrent Neural Network (RNN)

Recurrent Neural Networks are used to address problems involving time series data, text data, and audio data. RNNs were originally designed for the analysis of discrete sequence of data [42]. It will be seen of a generalisation of Multilayer perceptron since both input, output could be of various lengths, making them appropriate for applications like machine translation, where the input and output are a phrase from the source and target languages, respectively [43]. The model learns a distribution across classes $P(y|x_1, x_2, \dots x_{T)}$ from a series $x_1, x_2, \dots x_T$ instead of only one vector x in a classification context [44].

At time t, the basic RNN keeps a hidden or latent state h, which is the result of a nonlinear mapping between its prior state h_{t-1} and input x(t). Here R and W are weight matrices shared among time shown in Eq. (1) [45].

$$\sigma\left(Wx_t + \mathrm{R}h_{t-1} + \mathrm{b}\right) = h_t \tag{1}$$

3.2.1 Advantages

During making predictions, RNN preserves the sequence data available in the input datasets, which is the dependent seen among words in the text [45]. The parameters of RNNs

are shared between time steps. This is commonly referred to as parameter sharing. As a result, there are lesser factors to train and the computing cost is lower [46].

3.2.2 Challenges

The vanishing and exploding gradient issue is a prevalent issue in all forms of Neural Networks, and it also affects deep RNNs that is RNNs with higher number of time steps [47].

3.3 Convolutional Neural Network (CNN)

In DL community, Convolutional Neural Networks (CNN) are all the rage right now [48]. These CNN models are employed in a variety of regions and applications, but they are particularly common in picture and video dealing out projects [49]. Filters, often known as kernels, are the building components of CNNs. The kernels are utilised to extract relevant information from input by using convolution approach. Even though CNNs had been developed to handle issues with image data, they can function well with sequential inputs [50]. The inputs to SAE, DBN, and DBM deep models are always in vector form. However, structural data among surrounding pixels is a significant source of data for medical pictures [51]. As a result, image vectorization invariably eliminates structural and configurable information. A CNN is meant to best utilize spatial and setup information by taking 2-dimensional and 3-dimensional images as input [52]. In the structure of a CNN, convolutional layers are alternated with pooling levels, preceded by fully connected layers, as in a traditional multilayer neural network. The working model of the basic structure for a CNN is shown in Fig. 4 [53].

3.3.1 Advantages

CNN automatically learns the filters without revealing them. These filters aid in the extraction of the most relevant and appropriate features from the incoming data [54]. The spatial features of a picture is acquired by CNN. The pattern of pixels and their interrelation in an image are referred to as spatial characteristics [55]. They assist us in precisely identifying an object, as well as its location and relationship to other things in a picture. The concept
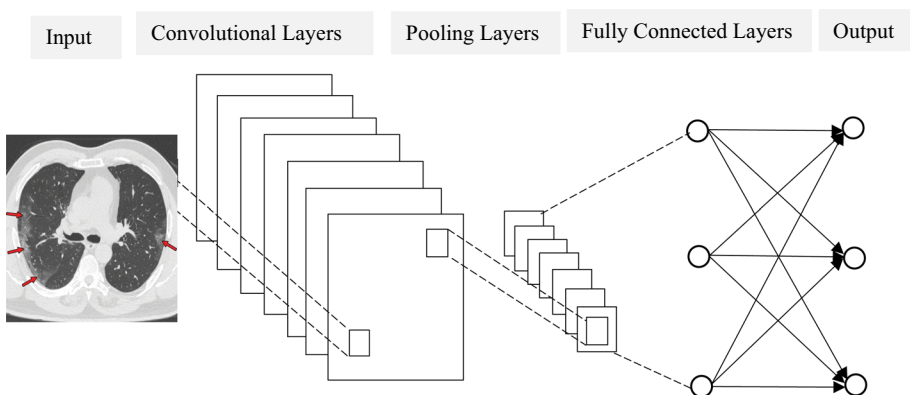

Fig.4 General Architecture of CNN

of parameter sharing is also used by CNN. A feature map is created by applying a single filter to various portions of an input [56].

3.3.2 Challenges

After a sample of data has been prepossessed, backprob is a way for determining the influence of each weight in the error, and most good optimization algorithms like SGD, ADAM, etc. uses to find the gradients [57]. Back propagation has performed admirably in recent years, but it is not an effective method of learning because it necessitates a large dataset [58].

When we talk about translational invariance, we mean that if an object's orientation or position changes significantly, the neuron that is meant to detect that object may not fire [59]. The problem is partially solved through data augmentation, but it is not completely solved [60].

Pooling layers is a huge mistake since it loses a lot of useful information and ignores the relationship between the parts and the whole [61]. For example, if we're talking about a face detector, we need to combine various traits (mouth, two eyes, a face oval, and a nose) to declare it's a face. Table 1 provides a comparison between ANN, RNN and CNN [62]. Various Processes involved in CNN model is shown in Fig. 5.
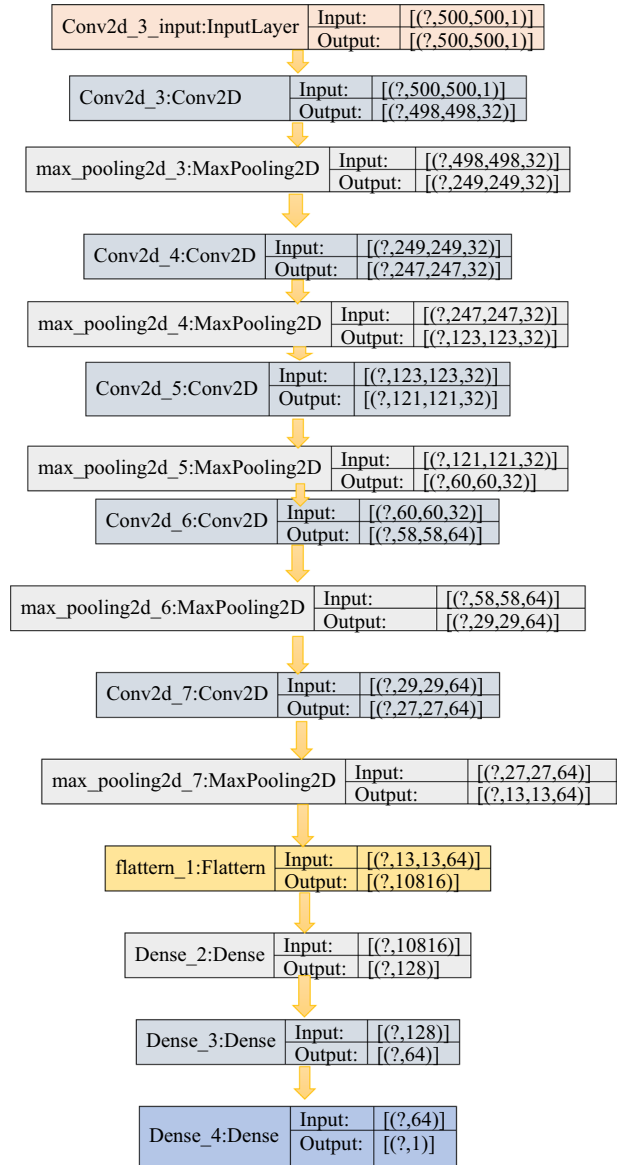
4 Deep CVD-HNet Architecture and Classification

We used a new novel deep CNN models to identify the clear COVID 19 Pneumonia abnormalities in chest X-ray images in this work. Because of their high capacity for learning prominent features and patterns revealed by images, deep CNN models have been widely used in image recognition and classification. CNNs are employed for both feature creation and classification because of their high learning capabilities. We termed CVD-HNet1 (COVID-HybridNet1) and CVD-HNet2 (COVID-HybridNet2) are two new Convolutional Neural network designs depends on boundaries and regions based procedures for COVID 19 specialized pneumonia in X-ray samples. These approaches are tuned from beginning to end to acquire pneumonia-specialized data from X-ray pictures. The recommended deep CNN designs use fully—connected layers for categorization [63]. The subsequent subsections summarise the design features.

Table 1 Comparison between ANN, RNN and CNN

	ANN	RNN	CNN
Data (Input)	Tabular data	Sequence data (i) Time Series (ii) Text (iii) Audio	Image data
Recurrent Connections	Not Available	Available	Not Available
Parameter sharing	No	Yes	Yes
Spatial relationship	No	No	Yes
Vanishing & exploding gradient	Yes	Yes	Yes

Fig.5 Process of the CNN model

| Conv2d_3_input:InputLayer | Input: | [(?,500,500,1)] |
| | Output: | [(?,500,500,1)] |

| Conv2d_3:Conv2D | Input: | [(?,500,500,1)] |
| | Output: | [(?,498,498,32)] |

| max_pooling2d_3:MaxPooling2D | Input: | [(?,498,498,32)] |
| | Output: | [(?,249,249,32)] |

| Conv2d_4:Conv2D | Input: | [(?,249,249,32)] |
| | Output: | [(?,247,247,32)] |

| max_pooling2d_4:MaxPooling2D | Input: | [(?,247,247,32)] |
| | Output: | [(?,123,123,32)] |

| Conv2d_5:Conv2D | Input: | [(?,123,123,32)] |
| | Output: | [(?,121,121,32)] |

| max_pooling2d_5:MaxPooling2D | Input: | [(?,121,121,32)] |
| | Output: | [(?,60,60,32)] |

| Conv2d_6:Conv2D | Input: | [(?,60,60,32)] |
| | Output: | [(?,58,58,64)] |

| max_pooling2d_6:MaxPooling2D | Input: | [(?,58,58,64)] |
| | Output: | [(?,29,29,64)] |

| Conv2d_7:Conv2D | Input: | [(?,29,29,64)] |
| | Output: | [(?,27,27,64)] |

| max_pooling2d_7:MaxPooling2D | Input: | [(?,27,27,64)] |
| | Output: | [(?,13,13,64)] |

| flattern_1:Flattern | Input: | [(?,13,13,64)] |
| | Output: | [(?,10816)] |

| Dense_2:Dense | Input: | [(?,10816)] |
| | Output: | [(?,128)] |

| Dense_3:Dense | Input: | [(?,128)] |
| | Output: | [(?,64)] |

| Dense_4:Dense | Input: | [(?,64)] |
| | Output: | [(?,1)] |

The suggested CVD-HNets design is inspired by traditional image processing methods [64] and also is built on the concept of leveraging fundamental features in images. In order to efficiently learn the COVID 19 unique patterns of pneumonia, we rigorously synergized the usage of boundaries and regions based procedures, along with convolutional processes in CNN to evaluate the advantages of this suggested boundaries and region based approach in information extraction with CNN models, we employed VGG 16 and ResNet 18 as baseline methods [65, 66]. In this study, we gathered 7000 pictures from the Open Source GitHub and Kaggle repositories, which included 3500 COVID 19 patients and 3500 healthy people. VGG 16 can

be a state-of-the-art CNN that uses mean pooling throughout design to regulate picture size and convolution operations for feature extraction. Rather than pooling, ResNet 18 employs strided convolution for picture down sampling, taking benefit of convolution in tandem with the Relu activation function enabling feature extraction. Four convolution blocks make up the proposed CVD-HNet1. Batch normalisation, a convolutional layer (Eq. (2)) and also ReLU as an activation function are all included in every block. After each convolutional block, average (Eq. (3)) and max pooling (Eq. (4)) are used to perform boundaries and regions based procedures. These methods improve the image's region-specific qualities and boundaries data, whilst the convolutional process extracts the image's sequence features. The proposed model employs fully—connected layers, as shown in Eq. (5), to produce goal information for classification. The setup of the proposed CVD-HNet architecture for the COVID 19 dataset is summarised in Fig. 6.

$$f_{x,y} = \sum_{a=1}^{p} \sum_{b=1}^{q} f_{x+a-1,y+b-1} K_{a,b} \tag{2}$$

$$f_{x,y}^{avg} = \frac{1^2}{W} \sum_{a=1}^{w} \sum_{b=1}^{w} f_{x+a-1,y+b-1} \tag{3}$$

$$f_{x,y}^{max} = max_{a=1,\dots w, b=1,\dots w} f_{x+a-1,y+b-1} \tag{4}$$

```
Layer (type)                    Output Shape              Param #
=================================================================
conv2d (Conv2D)                 (None, 150, 150, 16)      448

max_pooling2d (MaxPooling2D)    (None, 75, 75, 16)        0

dropout (Dropout)               (None, 75, 75, 16)        0

conv2d_1 (Conv2D)               (None, 75, 75, 32)        4640

max_pooling2d_1 (MaxPooling2     (None, 37, 37, 32)        0

conv2d_2 (Conv2D)               (None, 37, 37, 64)        18496

max_pooling2d_2 (MaxPooling2     (None, 18, 18, 64)        0

dropout_1 (Dropout)             (None, 18, 18, 64)        0

flatten (Flatten)               (None, 20736)             0

dense (Dense)                   (None, 512)               10617344

dense_1 (Dense)                 (None, 1)                 513
=================================================================
Total params: 10,641,441
Trainable params: 10,641,441
Non-trainable params: 0
```

Fig. 6 Model Summary and Training Parameters of CVD-HNet Architecture

Table 2 Comparison among CVD-HNets in contrast to baseline methods

Deep models	Accuracy	F score	MCC	Depth
VGG16	96.16	0.98	0.95	18
Resnet18	96.21	0.98	0.96	16
CVD-HNet1	97.46	0.99	0.97	10
CVD-HNet2	97.75	0.99	0.97	08

Table 3 ADAM based Learning capability assessment using baseline approaches and proposed CVD-HNets

Deep Models	Accuracy	Sensitivity	Specificity	TP	FP	FN	TN	MCC	F Score
VGG16	95.90	0.96	0.96	639	26	28	625	0.95	0.96
Resnet18	96.64	0.97	0.97	641	21	23	628	0.96	0.97
CVD-HNet1	98.09	0.98	0.98	651	12	13	636	0.97	0.99
CVD-HNet2	98.84	0.99	0.99	660	8	7	628	0.98	0.99

$$v = \sum_{d}^{D} \sum_{c}^{C} u_d f_c \tag{5}$$

The regions operator helps to smooth out region variances through average pooling (Eq. (3)), and so functions as a noise suppression for X-ray imaging aberrations. The edge operators, on the other hand, uses the max pooling operation to promote CNN to acquire effective feature and narrow features (Eq. (4)).To limit the possibilities of overfitting, dropout is given to the fully-connected layers. CVD-HNet-2, on the other hand, is built on the same concept but with more depth.

COVID-HNet-2 is made by 4 convolutional blocks and each with distinct no. of operations. Table 2 provides the performance comparison of suggested CVD-HNETs and Existing CNNs. By features extraction from the proposed COVID-penultimate HNet's layer and assigning it to the ADAM classifier, the suggested COVID-mapping HNet's capability is tested and it's shown in Table 3.

4.1 Implementation of Existing Standard CNNs

VGG, Inception, GoogleNet, ResNet, SqueezeNet, Xception and DenseNet [67–75] were used to compare several existing state-of-the-art deep CNN algorithms. These CNNs were employed extensively for a broad range of picture classification issues, including COVID 19 X-ray classification by numerous studies. These methods differ in blocks architecture and design, but they all used a unique unit of pooling process for complexity regulation or substituted the pooling process with a strided convolutional. These CNNs were implemented in end-to-end manner for classification, with extra Fully Connected and classification layer introduced to adjust them for COVID 19 infected categorization based on X-rays. According to the standard metrics accuracy, MCC and F-score, Table 4 reveals that the suggested 2 new novel CVD-HNet1 and CVD-HNet2 architectures could better distinguish the COVID 19 abnormalities from datasets.

Table 4 Proposed CVD-HNets versus Existing CNNs

Deep models	Accuracy	Sensitivity	Specificity	TP	FP	FN	TN	MCC	F score
Inceptionv3	96.82	0.97	0.97	626	20	21	624	0.94	0.97
DenseNet201	96.51	0.97	0.96	627	26	19	618	0.94	0.98
Google net	95.59	0.96	0.96	641	30	29	640	0.94	0.96
Squeeze Net	95.99	0.96	0.96	629	25	27	618	0.94	0.96
Xception	96.29	0.97	0.96	626	27	21	620	0.94	0.97
Resnet50	96.52	0.96	0.96	630	23	22	620	0.95	0.96
CVD-HNet1	98.15	0.97	0.98	640	9	17	635	0.97	0.97
CVD-HNet2	98.85	0.99	0.98	645	8	7	645	0.97	0.99

4.2 The Proposed Technique's Transfer Learning Based Optimization

Transfer learning is used to train the planned CVD-HNet1 and CVD-HNet2 using the X-ray dataset. CNNs are parametric, and best performance necessitates high volume data, but training with lesser X-ray images may result in convergence issues [76]. When a large dataset is unavailable, Transfer learning can be a methodology that has demonstrated favourable outcomes for CNN architectures. It allows the weight space of previously trained models to be reused and minimises overfitting in highly specified algorithms by giving a better initial set of weights [77]. As a result, we routinely used the concept of Transfer learning in this approach to accomplish significant results. In this case, we used the parameter space of the pre-trained model to initialise the weights of the suggested CVD-HNets [78]. Similarly, we are using the same training technique for existing CNN models to ensure a fair comparison. These models have now been optimised with X-ray images by applying domain adaptation enabled Transfer learning to modify the ImageNet pre trained techniques for categorization of COVID 19 specific pneumonia for the dataset. [79].

4.3 Proposed Methodology

The entire dataset has been split into two separate groups, each having an 80:20 percent ratio for the train and test sets (70% of X-ray pictures of the chest are used for training, 10% for validation purpose, and 20% for testing purpose). The fivefold cross validation technique was used to optimise the architectures parameters. SGD was utilised as an optimizer with a momentum of 0.94 during CNN training. Here learning rate was fixed as 0.0001 as well as weight decay was set as 0.0005. The model has been trained over ten epochs. For smooth training, a mini batch training has been used with batch size of 15 photos per epoch. Softmax can be utilised as activation function for all deep CNNs, and they were all optimised for picture classification by minimising cross-entropy loss. For the machine learning based classification analysis, ADAM was applied [80–85]. MATLAB 2019b was used to run all of the simulations. For MATLAB simulations, a 2.90 GHz Dell 8th gen intel core-7500 processor as well as a Multi core Nvidia GTX 1060 Tesla has been used. The models were trained for around 12 h. On the Nvidia Tesla K80, one epoch took 30–60 min to train. Figure 7. Provides the Performance analysis of proposed CVD-HNet1 and CVD-HNet2 models with Existing CNNs.
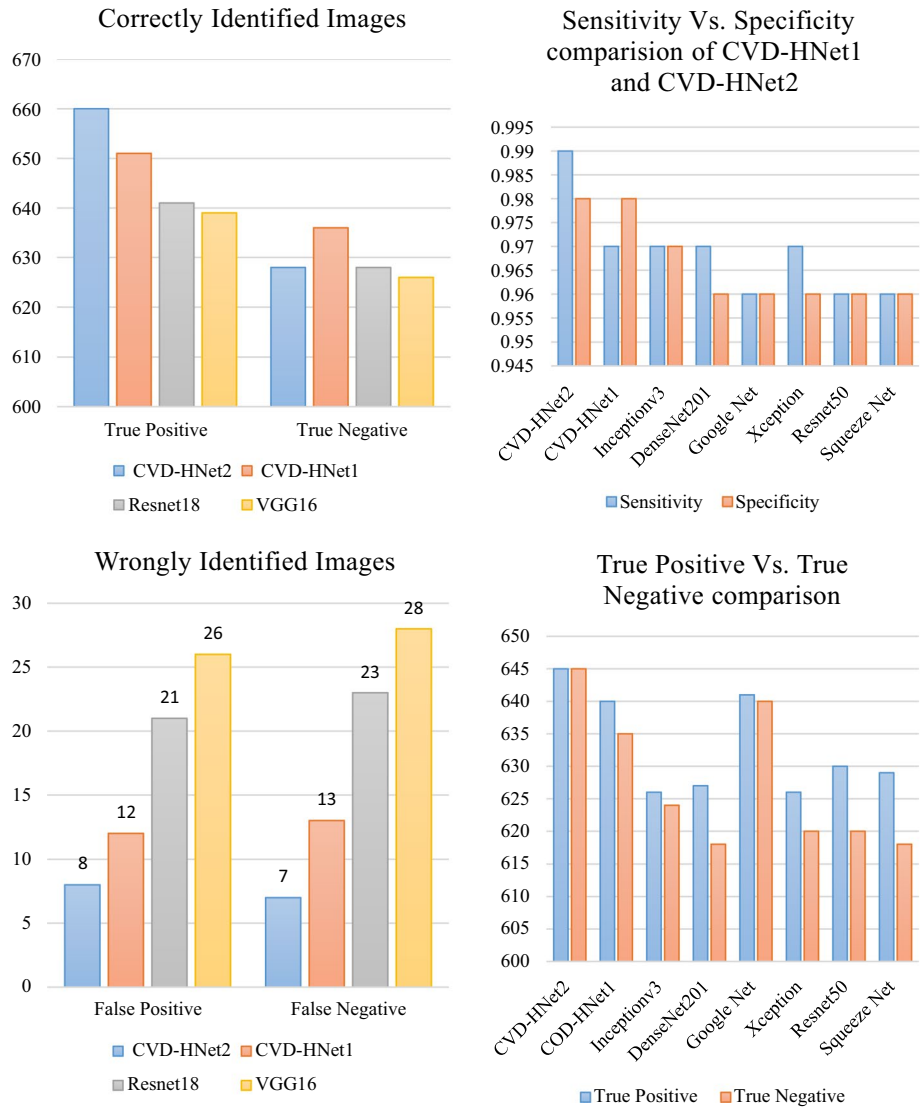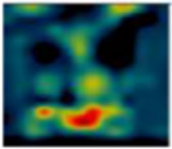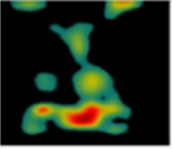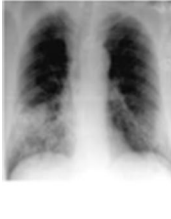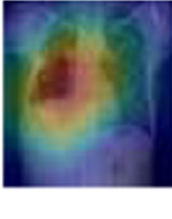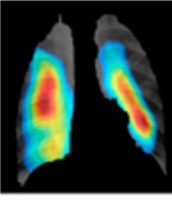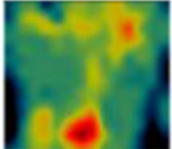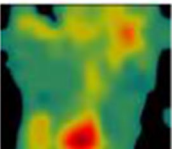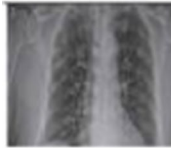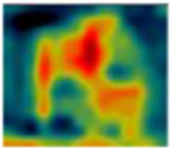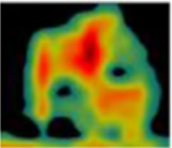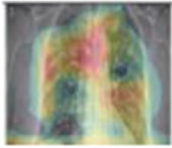
Fig. 7 Performance analysis of CVD-HNet1 and CVD-HNet2 with Existing CNNs

5 Results and Discussions

Utilizing chest X-ray images, this research describes a new novel deep CNN model for distinguishing COVID 19 affected cases. Two experiments have been carried out to empirically assess the efficiency of the suggested model. We looked at the benefits of synchronising employing max and average pooling in CVD-HNets for region classification in the first experiment shown in Table 5. The second section compares results to popular state-of-the-art methods in order to make a broad assessment of the COVID 19 identification challenge shown in Table 6.

Table 5 Correctly identified images

Classified image	Test image	Activation map	Segmented activation map	Composite image
Normal				
Bacterial pneumonia				
Viral pneumonia				
Covid 19 pneumonia				
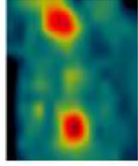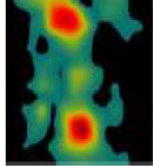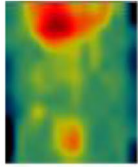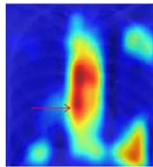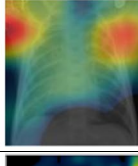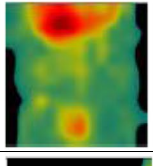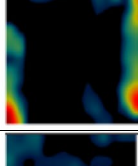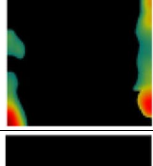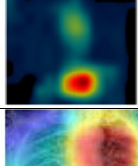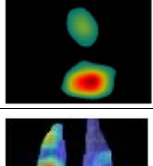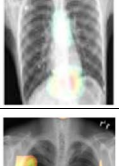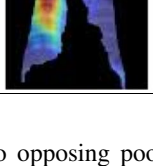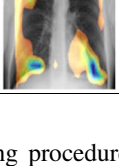
5.1 Performance Analysis of the Proposed CVD-HNets

There are a variety of metrics that may be used to assess the effectiveness of categorization models, including accuracy, sensitivity, specificity, F-score, precision, confusion matrix. Table 7 provides a mathematical description of the various measurements [86–90].

Here suggested CVD-HNet1 and CVD-HNet2 models are assessed using Accuracy, Matthews Correlation Coefficient and F score, which are conventional measurements in medical image diagnosis systems, on an unknown test dataset. Unlike Accuracy, both F score and Matthews Correlation Coefficient give recall and precision equal weight. 642 images of COVID 19 and normal people were accurately identified using the suggested CVD-HNet1 model. Similarly, the suggested CVD-HNet2 functions admirably, properly categorizing 631 COVID 19 afflicted and 636 normal people. The detection rate for COVID-19 tends to enhance when the depth is increased. Misclassification is most likely caused by lighting variations, low contrast areas, and a complex regions of images. In order to increase generalisation and improve robustness to unseen images, we used multiple data augmentation procedures during training (Fig. 8).
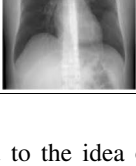
Benchmarking the feasibility of the suggested model against ResNet and VGG is used to assess its efficiency. ResNet-18 and VGG 16, the two baseline methods, are about as deep as CVD-HNet1 and CVD-HNet2. VGG 16 model uses a unique sort of pooling operators, whereas ResNet 18 employs strided convolution operation instead of pooling down,

Table 6 Wrongly identified images

Classified image	Test image	Activation map	Segmented activation map	Composite image	Results
Normal					Predicted class: Covid 19 pneumonia Predicted score: 0.9132
					Predicted class: Bacterial pneumonia Predicted score: 0.9241
					Predicted class: Viral pneumonia Predicted score: 0.9129
Pneumonia					Predicted class: Normal Predicted score 0.7123
					Predicted class: Covid 19 Predicted score: 0.7255
					Predicted class: Normal Predicted score 0.7436

as opposed to the idea of employing two opposing pooling procedures in CVD-HNets. Table 2 shows the results comparison including Accuracy-98%, Matthews Correlation Coefficient -0.97 and F score-0.99 both CVD-HNets outperform ResNet 18 and VGG 16, according to performance analysis. In comparison to existing VGG16 and ResNet 18, the suggested CVD-HNets importantly enhance the metrics for both COVID 19 affected cases and healthy people.

In assessing the learning potential of deep CNN models, extracting feature is crucial. The contribution of the proposed model's feature set in learning class specified mappings is assessed using the traditional ML model. By extracting features from the proposed CVD-HNet's penultimate layer and allocating it to the ADAM classifier, mapping capacity of the suggested CVD-HNet is tested. Table 3 reveals that the sequence lent by proposed CVD-HNet1 and CVD-HNet2 can be used to distinguish COVID 19 cases from normal patients in two classes. Quantitative examination of Accuracy-98.84%,

Table 7 Performance matrices for classification

Sl. No	Metrics	Formula
1	TP	If COVID-19 is identified in a COVID-19 affected person
2	TN	If an individual is identified as NONCOVID-19 correctly
3	FP	Depicts an inaccurate identification in which a healthy person is found to have COVID-19
4	FN	Indicates an inaccurate identification in which a person affected with COVID-19 is mistakenly identified as a healthy person
5	Accuracy	$\dfrac{\text{No. of Images Correctly predicted as both COVID} - 19 \text{ and Non COVID}}{\text{Total No.of Images}}$ $= \dfrac{TP + TN}{(TP + TN + FP + FN)}$
6	Sensitivity/Recall	$\dfrac{\text{No. of Images Correctly predicted as COVID} - 19}{\text{Total No. of COVID} - 19 \text{ Images}} = \dfrac{TP}{(TP+FN)}$
7	Specificity	$\dfrac{\text{No. of Images Correctly predicted as Non COVID} - 19}{\text{Total No. of Non COVID} - 19 \text{ Images}} = \dfrac{TN}{(TN+FP)}$
8	Precision	$\dfrac{\text{No. of Images Correctly predicted as COVID} - 19}{\text{Total No. of predicted Positive Images}} = \dfrac{TP}{(TP+FP)}$
9	F-Measure	$2 \times \dfrac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}$
10	Confusion Matrix	

	Predicted Class	
Actual Class	True Positive (TP)	False Negative (FN)
	False Positive (FP)	True Negative (TN)

Fig. 8 Confusion matrix
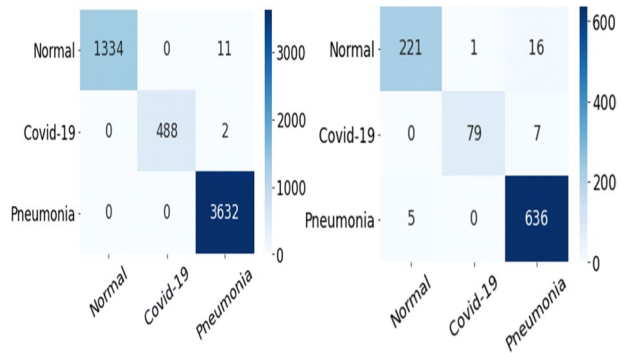
Matthews Correlation Coefficient-0.98, F score -0.99, and suggests that this technique outperforms ResNet 18 (Accuracy-96.64%, Matthews Correlation Coefficient-0.96, F score-0.97) and VGG-16 (Accuracy-95.90%, Matthews Correlation Coefficient -0.95, F score-0.96).

For a thorough empirical evaluation, we compared the proposed technique to popular CNN architectures on unseen chest X-ray pictures. Accuracy, MCC, AUC-ROC, F-score, precision and sensitivity used to evaluate the outcomes.

5.1.1 Performance Comparison with Existing CNNs

The suggested CVD-HNet1 and CVD-HNet2 are compared to DenseNet-201, GoogleNet, ResNet-50, InceptionV3, Xception, SqueezeNet, and in terms of performance [91–100]. In accordance with the standard performance metrics Accuracy, MCC, F score, and the performance analysis demonstrates that suggested CNN designs CVD-HNet1 and CVD-HNet2 could better distinguish the COVID 19 unique pneumonia affected regions from X-ray pictures. This increase the speed due to the proposed CNN architecture's systematic usage of max and average pooling operations.

6 Challenges and Future Directions

On ImageNet Challenger, the most important picture classification and segmentation challenge in the image analysis field, a considerable result was achieved using the numerous CNN-based deep neural networks constructed. The primary benefit of CNN over its counterparts is that it could detect critical properties without human assistance [101]. Table 6 shows how several classification models produced various performance indicators such as Accuracy, Sensitivity/Recall, Precision, Specificity, Receiver Operating Characteristic (ROC) Curves and F-measure. We may evaluate the best CNN model according to these performance metrices [102].

In recent days we've seen so much about imbalanced datasets, lack of confidence intervals [103], and also improperly labelled data in deep learning-related Medical Imaging literature which it is simple to label it the core obstacle while fully investigating Deep Learning (DL) breakthroughs [104–110]. The number of image samples and cases in database searches now available for diagnostic imaging activities is limited, with the exception of a few datasets. When compared with datasets for basic Computer Vision challenges that typically ranges from some few thousand to millions of labelled images [111], medical imaging datasets are far too small. Alternatively, now we are seeing a rising trend in the community of medical imaging professionals to learn deep models end-to-end, similar to what we're seeing in the wider Pattern Recognition community. Alternatively, the wider community has traditionally supported as such endeavours because large-scale labelled datasets are a required condition for producing correct DL models [112]. As an outcome, its unknown how well end-to-end certified DL models can execute medical image diagnosis activities without overfitting to training examples. Principal Component Analysis (PCA), Image flipping, image cropping, padding, and adversarial training are some of the basic data augmentation techniques we've created. These techniques, however, aren't as sophisticated as the Generative Adversarial Network when it comes to augmenting dataset images [113–115].

A further big stumbling block would be the usage of black boxes, the legitimate implications of black box functionality would be a disincentive, as Medicare practitioners could not trust on it. If the decision was unfavourable, who may be held liable? The hospital may be hesitant to utilise a black-box technique which could allow hospital to track that a certain outcome came from an optometrist, owed to the sensitivity of this location [116]. The black-box problem is an important research topic, and deep learning researchers are striving to address it [117].

Furthermore, teaching deep learning models is a very expensive endeavour due to the complicated data structures. They frequently demand high-end GPUs and hundreds of computers, raising the cost to users [118].

Because the increased complexity of numerous layers needs a large computing burden, training performance degrades as a result. To fight vanishing gradient and over-fitting concerns, researchers have used improved activation functions, drop-out techniques and cost function design [119]. High computational load has been addressed with the use of massively parallel technologies like GPU's and batch normalization [120]. The construction of an interdisciplinary data repository is made possible by the presence of a huge volume of electronic healthcare data.

7 Conclusion

Medical image diagnosis is a vital technology which bridges the gap between scientific and societal needs, and it has the potential to produce a substantial synergy that will benefit each of these sectors. Our investigation revealed the current state-of-the-art, which may be valuable to radiologists all over the world, according to the latest 120 medical imaging research papers. In this research, two new customized deep CNN methods are proposed to distinguish COVID 19 infected pneumonia cases from healthy people in X-ray pictures. The proposed COVID 19 classification method is compared against existing CNN models to see how well it performs. The proposed CVD-HNet1 and CVD-HNet2 models outperform existing CNN models and baseline in terms of Accuracy, MCC and F score according to experimental results. The proposed method is intended to aid physicians in the analysis of COVID 19 affected individuals. Furthermore, it provides a great potentiality in analysing various sorts of chest X-ray image anomalies. We discussed the current obstacles, main issues, and future directions.

Declarations

Conflicts of interest The authors have no competing interests to declare that are relevant to the content of this article.

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