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A Robust and Computationally Faster Approach to COVID-19 Diagnosis using Shallow Convolutional Neural Architecture

Adil Khadidos[1*]

[1] *Department of Information Technology, Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, SAUDI ARABIA.*

**Corresponding Author (Email: akhadidos@kau.edu.sa).*

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Abstract

The ongoing COVID-19 pandemic has infected millions of people worldwide, overwhelming health infrastructures. The common symptoms are fever, cough, sore throat, muscle pain, headache, nausea, vomiting, and diarrhea, similar to the symptoms of common flu in mild and moderate cases. The distinguishing signs of common flu from that of COVID-19 are invisible until patients start feeling shortness of breath when the infection attacks the respiratory system in severe cases. At this stage, patients require immediate medical attention and hospitalization. In developing countries where health facilities are not adequate and costlier radiological tests like computed tomography (CT)-scans are scarce, diagnosis becomes a challenging task. The clarity comes only when a COVID-19 test is conducted, which has its own time limitations depriving the patient of specialized treatment until the patient tests positive. In far to reach rural areas identification of COVID-19 induced pneumonia cases with the help of chest X-rays is more difficult with substandard medical infrastructure and a handful of expert radiologists available. This work detects COVID-19 induced Pneumonia with the help of chest X-rays. The used dataset includes COVID-19-infected patients' chest X-ray images as well as normal non-COVID chest X-Ray images. A Lightweight Stacked Convolutional Neural Network was created to extract fine details and information from images, assisting in the detection of COVID-19 caused pneumonia cases. For evaluation, we assessed the developed Neural Network model on a test validation set consisting of hundreds of chest X-Ray images. The suggested Neural Network's average test accuracy was determined to be 98.76%, with per-class accuracy of 99.40% for detecting COVID-19 cases and 98.42% for detecting normal cases.

Disciplinary: Healthcare Management, Applied Information Technology.

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1 Introduction

COVID-19 infections have reached more than 24 million globally and have claimed more than eight lakhs lives. Due to its highly infectious nature detection and contact tracing seems to be the only solution currently to control it. Considering no vaccine in sight anytime soon, accurate detection of infected cases and isolating them to stop the further spread of infections is the only strategy. In general, there are three types of tests used to detect infection Molecular test, Antigen test, and Antibody test. While the Molecular test is highly accurate, it may take days to get the test results. The Antigen and Antibody tests take less time to test, but getting false-negative results is relatively high[1,2]. Fever, cough, myalgia, headache, and other flu-like symptoms are common in those infected with SARS-CoV-2. The symptom becomes severe in some cases of comorbidities or lowered immunity, such as breathing trouble [3]. COVID caused Pneumonia occurs when the infection enters the afflicted person's lungs, necessitating rapid medical attention.

In developing countries like India, when there is a Monsoon season around this time of the year, it brings along the seasonal flu and common Pneumonia caused by pathogens. This creates stress on already weak medical infrastructures in rural areas. As many parts around the world lack adequate access to testing, proper image examination through Chest X-Rays, a commonly performed X-Ray diagnostics examination that can prove to be a potential first-line tool to detect and diagnose Novel Coronavirus Infected Pneumonia (NCIP). This approach can particularly distinguish the signs of infection caused due to seasonal flu from that of Pneumonia as a complication from viral infections such as COVID-19. Intelligent methods for early prediction and diagnosis are extremely desirable since they can assist limit the spread of the virus and enable the selection of specialist medical care. Prediction and screening of the COVID-19 pandemic were accomplished using ML, DL, mathematical and statistical methodologies from earlier studies [4,5]. The computed CT scans of 416 COVID-19 patients and 412 patients diagnosed with non-COVID-19 pneumonia were analyzed using AI systems that included a multi-scale convolutional neural network (MSCNN). Using only a small number of training data, the AI method was found to have a promising diagnostic performance in recognising COVID-19 and separating it from other frequent Pneumonias [6]. This method showed great accuracy in detecting Pneumonia from normal Chest X-ray (CXR) radiographs and was also able to distinguish between bacterial and viral pneumonia [7]. Differential evolution is used to modify Manta-Ray Foraging Optimization and select the most important features. Two COVID-19 X-ray datasets were used to test the approach. 96.9% and 98.9% of the first and second datasets were correctly predicted using this method [8].

The proposed Lightweight Stacked Convolutional Neural Network Architecture in this paper adds a new dimension to COVID-19 diagnostics. Image testings that corroborate COVID-19 through specific image results are supported by the detection approach used in this study. The proposed Neural Network not only provides the highest recall value of 99.39% which is better than the existing models and architectures proposed in previous works. The distinguishing factors of this Lightweight Neural Network Architecture with others are the reduced Time Complexity and memory requirements.

2 Materials and Methodology

The entire dataset as well as the proposed technique are detailed in this section. This section is divided into two parts: the first explains the dataset used in the suggested scheme, and the second discusses the core model's main premise.

2.1 Dataset Details and Preparation

An open-source dataset used in this work can be found at this Github repository (https://github.com/education454). Chest X-ray images from COVID-19 and NORMAL subjects are included in this dataset. For the training and validation sets, this dataset contains 545 COVID-19 chest X-Ray images and 1266 NORMAL chest X-Ray images. Figure 1 shows the images of the COVID-19 and NORMAL chest X-Rays.

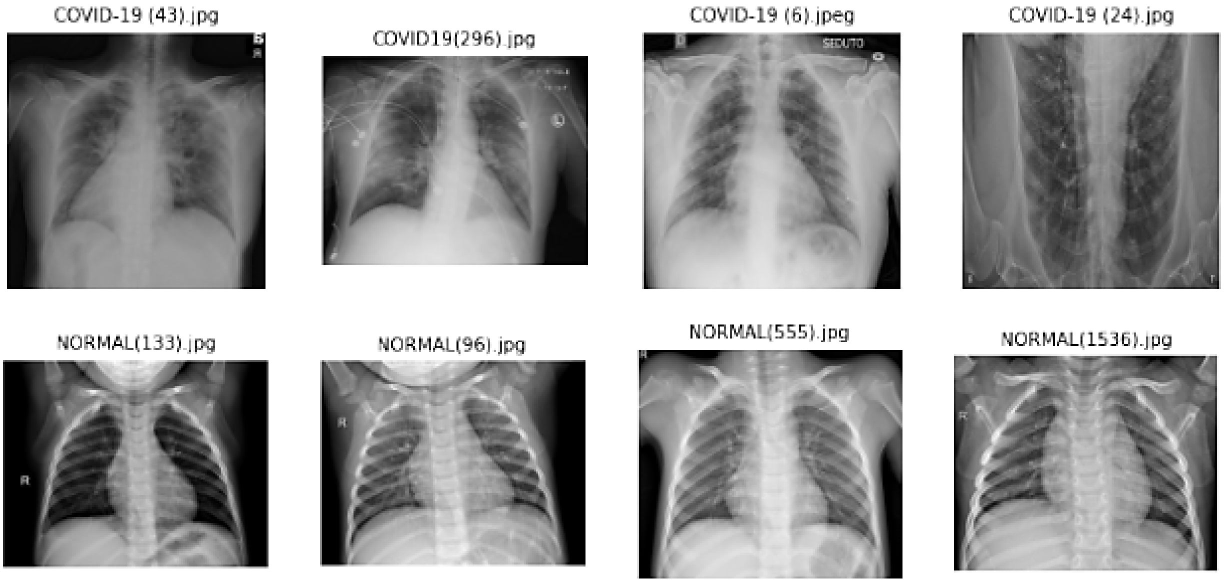

Figure 1: NORMAL and COVID-19 chest X-Ray images.

As we see from the dataset, it is a case of imbalanced data and if we deal with this kind of dataset in our designed neural network, then, it would lead to improper and inaccurate detection of COVID-19 and NORMAL cases. As a result, balancing the dataset and training the network with roughly equal quantities of data from each category is the optimum solution to this problem. The network will be able to recognize all classes this way. We are unable to increase this class data since we do not have access to additionally available datasets of COVID-19 and NORMAL cases. Hence, we apply the technique of the Image Augmentation Approach.

Image data augmentation [9] is an approach that is utilized to artificially enhance the dataset's size used for making altered variants of images in the dataset. For deep learning neural network models to develop stronger and augmentation algorithms to make images that boost the fit models' capacity to establish what they have learnt from fresh images, more data is needed. Transforms combine an array of actions in the area of image handling, such as shifts, flips, zooms, and many other actions. The purpose is to enlarge the training dataset with newer conceivable patterns. This means variations of the training set image are anticipated to be seen by the model. In this paper, the process of Image Augmentation is carried out by zooming in and zooming out the images by 20% and also by creating Horizontal Flips of the Dataset Images.

2.2 Proposed Algorithm and Architecture

In this paper, an efficient algorithm. for analysis and COVID-19 detection in Chest X-Rays has been proposed. A robust Lightweight Stacked Convolutional Neural Network has been designed for efficiently dealing with any amount of dataset and with any type of noise (problem faced by the conventional methods), thus enabling detection with the highest accuracy (**Overall Average Accuracy: 98.76%**) and proving response with very less Time Complexity (**240 milliseconds**) as well as occupying very less memory (very less Space Complexity), therefore making the computation process of the algorithm smooth and highly efficient.

The individual and working of the different layers of the Stacked Convolutional Neural Network are described the next subsection.

2.2.1 Stacked Convolutional Neural Network

Convolution, Pooling, Dropout, Flattening, and Fully Connected Layers comprise the first four tiers of the Stacked Convolutional Neural Network.

The entire system's core is designed using Convolutional Neural Networks (CNN). As a typical deep learning technique [10], the Convolutional Neural Network (CNN) can be used to separate images using features extracted from the images for fine-tuning and computer vision-based tasks. The use of a multi-layer perceptron architecture to analyze images and videos using various feature detection operations and filters to perform tasks like image classification, image segmentation, and object recognition can be beneficial for automated drone control and robotic vision-based applications. Deep learning applications in healthcare, like medical imaging, can also make use of CNN.

Major Components of CNN:

Image features and fine details can be retrieved from the image using a convolution layer.

In order to anticipate the best image description, the convolution layer's output is transferred to this fully linked layer.

It is based on the visual cortex's organisation and interplay and is intended to mirror the connectivity patterns of the neurons present in the human brain in its structure and operation.

Three-dimensional subdivisions of the neurons in a CNN allow it to focus on discrete areas of an image. A second possibility is that each cluster of neurons focuses on a certain aspect of the image, making it easier to spot any patterns that could be there. With CNN, layers' procrastinations produce the desired result: a vector of probable values showing the likelihood that a given component is part of a particular class.

Multi-layers CNN:

- Fully linked input layer: Connects each neuron to the deeper and hidden layers of the neural network, allowing the feature extraction operations to be combined in order to obtain the features by the later layers.
- Convolutional layer: Builds feature maps by applying a filter that scans the entire image, a few pixels at a time, extracting small details and numerous features from the image, such as corner features, edge features, and so on.
- Pooling layer: To decrease the number of parameters and computations in the network, this function performs a Down sampling operation and gradually reduces the spatial scale of the illustration. The pooling layer takes each feature map into account on its own. Min pooling, average pooling, Global Average Pooling, and other variants are all forms of pooling.
- Dropout layer: The function of the Dropout Layer is to introduce regularization into the working of the Neural Network in order to prevent the problem of Overfitting. It helps to randomly activate and deactivate neurons in the CNN Architecture, thus, helping to extract the features from the images effectively.
- Flatten Layer: As a result of flattening, each layer's input is transformed into a one-dimensional array. As a result of the convolutional layers, we straighten their output to produce a lengthy feature vector. Additionally, a "fully-connected layer" connects it to the final classification model.
- Fully connected layer: Links the feature maps together to extract correlation and inter-relationship within the feature maps by applying weights to the feature analysis input to anticipate an accurate label.
- A completely linked output layer: Generates the final probability for determining a specific class for the output image.

The stacking of the different layers of the Convolutional Neural Network and their corresponding interactions with each other is given in Figure 2. The working of each section of the Neural Network is given in Figures 3, 4, 5, and 6.

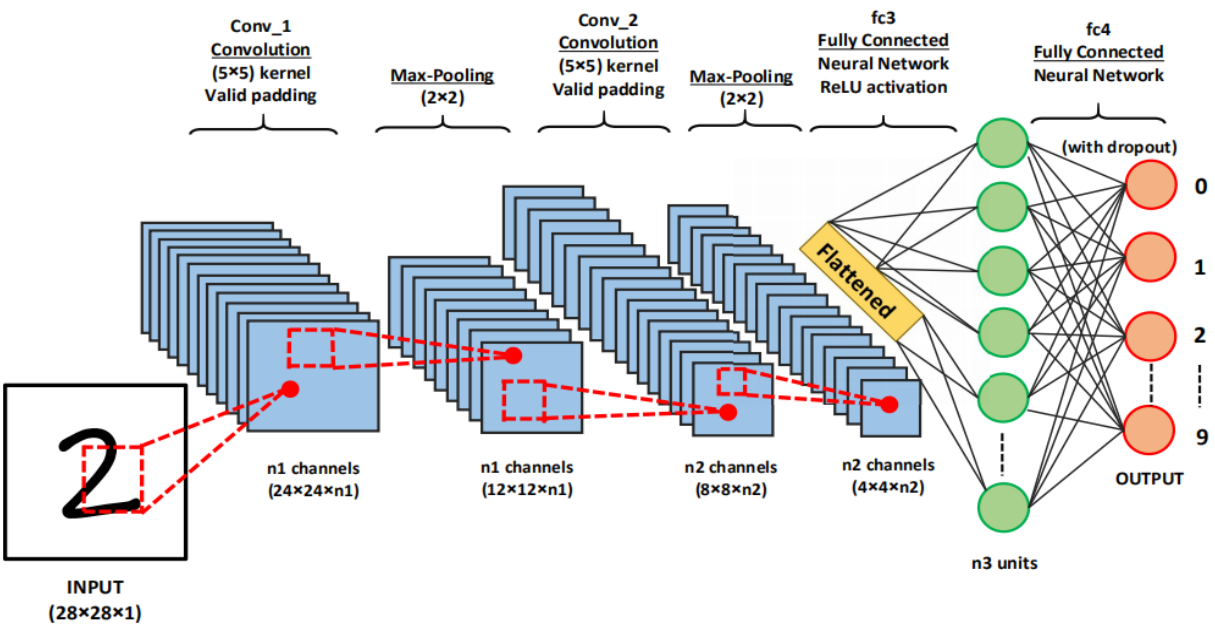

Figure 2: Working of Convolution Neural Network.

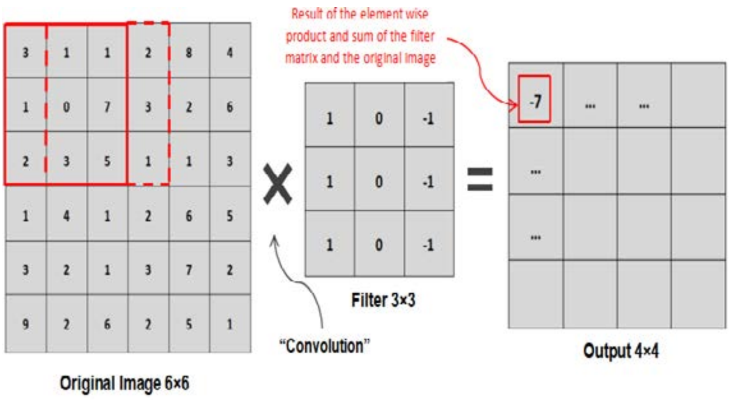

Figure 3. Convolution Layer.

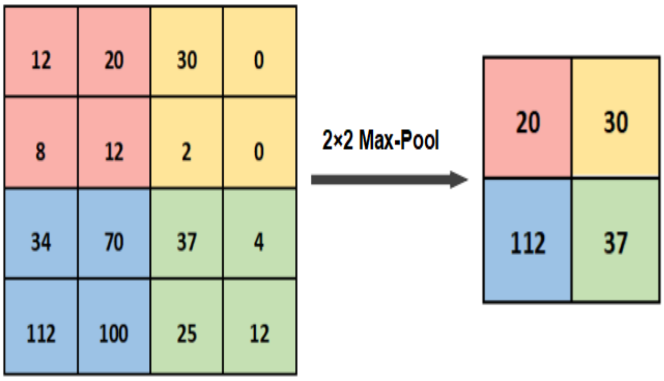

Figure 4. Max-Pooling Layer.

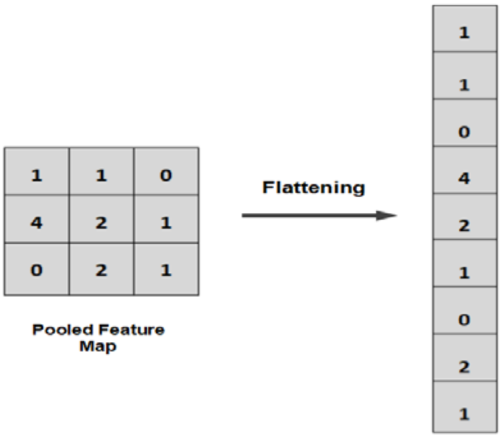

Figure 5. Flattening Layer.

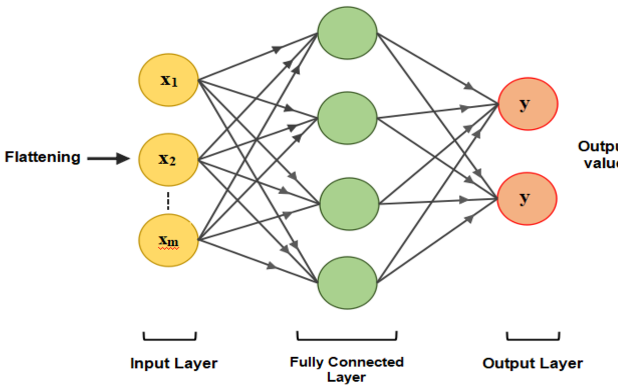

Figure 6. Fully Connected and Output Layer.

2.2.2 Proposed Lightweight Stacked CNN Architecture

To detect COVID-19 in chest X-Rays, the proposed Lightweight Convolutional Neural Network accepts images of chest X-Rays, and the many layers in its design help extract characteristics for effective illness diagnosis. The proposed model consists of two Convolutional Layers along with two Max-Pooling and Dropout Layers followed by Flattening and Dense Layers which is shown in the flow diagram given in Figure 7.

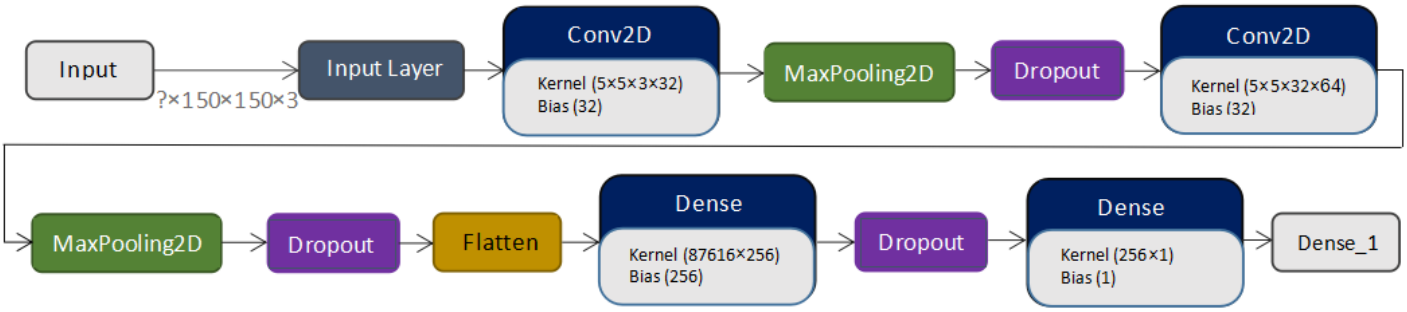

Figure 7. Flow Diagram of the Stacked Convolutional Neural Network.

X-ray images are supplied into the Lightweight Stacked Convolutional Neural Network, which helps extract fine details and features from the various chest X-ray images and hence aids in the automatic detection process [11] for both detecting COVID-19 and assessing NORMAL chest X-ray images. The working of the various layers and their corresponding interactions and roles in developing feature maps are explained as follows:

1) Chest X-Ray images of dimension: (150 x 150 x 3) are fed into the Neural Network. The images may consist of some amount of noise which can be well handled by the Neural Network.

2) The next layer of the Neural Network is a Convolution Layer consisting of 32 filters. A (5 x 5) kernel is used as a window in this case for extracting the fine details & features from the input image. Zero Padding is also used in these two layers in order to preserve the information in the later layers. Moreover, the L1 Regularization technique also called Lasso Regularization [12] is embedded within each of the convolution layers in order to enable the model to learn all the hyperparameters in a fine-tuned and well-defined manner and overcome the problem of Overfitting providing Low Bias and Low Variance to the model. The Activation Function used after each of the two layers is Leaky ReLU (Leaky Rectified Linear Unit)[$\boldsymbol{Leaky\ ReLU : max\ (0.01\ , x)}$] [13], this aids in the extraction of the image's non-linear features.

3) The third layer is a Pooling Layer. Max Pooling layer is used in this case in order to perform spatial down-sampling. The kernel used in this layer is of size (2 x 2). The high-intensity fine details are extracted in the process in order to develop the feature maps and thus, develop the Encoder part of the network. In this case, Zero Padding (SAME) is again used in order to preserve the details of the image. Dropout regularization is applied after this layer. Dropout is a training approach in neurons are ignored which chosen randomly . They are "disappeared" at random. This means that on the forward pass, their contribution to downstream neuron activation is momentarily removed, and any weight modifications are not applied to the neuron on the backward trip. In this example, a p = 0.5 (50 percent) dropout is applied.

4) The fourth layer again consists of a Convolution Layer each consisting of 64 filters. A (5 x 5) filter is used in this case for extracting further features from the input image like multiple edges, contours, texture, shapes, corners, etc. Again, Zero Padding (SAME) is used in this layer in order to preserve the spatial information in the later layers. L1 Regularization technique is also embedded with the two layers to further diminish overfitting problems. After this layer, the Leaky ReLU (Leaky Rectified Linear Unit) Activation function is applied once again to help extract non-linear characteristics from the image. For all positive values, the Leaky ReLU is linear (identity), whereas for all negative values, it has a tiny value of 0.01. Because it does not have the Vanishing Gradient problem, Leaky ReLU is employed repeatedly in the process [14].

5) Next, Max Pooling layer with kernel size (5 x 5) is used in the fifth layer in order to perform further spatial down-sampling and thus, helps in order to extract the most important fine details and features from the image like the edge features, corner features, morphological features and other important features like the blur and sharpening features form the image. Dropout regularization is again applied after this layer in order to randomly activate and deactivate the neurons and thus, helps in extracting the important features and also preventing overfitting problems from the system.

6) Next, the High Dimensional feature maps are converted into a One Dimensional vector in the Flattening Layer by the process of Vector-Space Transformation. Next, a Dense Layer is created by the interconnection of each neuron. There are a total of 256 feature maps present in this layer that are subjected to non-linear operations by introducing a Leaky ReLU Activation Function. Again, dropout p = 0.5 is used after this layer in order to regularize the process.

7) Finally, the output layer consists of one neuron whose result is governed by the presence of a Sigmoid Activation Function. 7. A sigmoid function, also known as a sigmoid curve, is a mathematical function that has an unique "S"-shaped curve [15]. Because there are two points in the sigmoid function, it is employed (0 to 1). As a result, it is especially beneficial in models where the probability has to be

anticipated as a result.. This activation function has a 0.5 cutoff, with a probability greater more than 0.5 indicating the NORMAL scenario and a probability less than 0.5 indicating COVID-19.

The functioning and interworking of the different layers of the proposed Lightweight Stacked Convolution Neural Network used in this paper are shown in Figure 8.

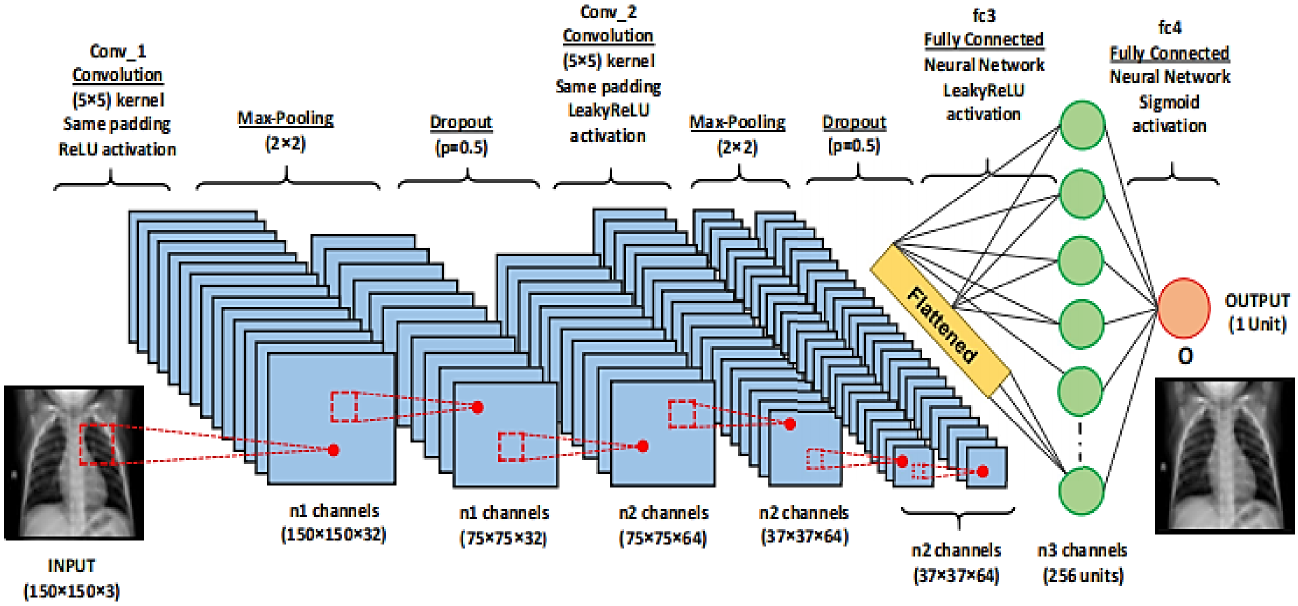

Figure 8. Lightweight Stacked Convolutional Neural Network.

8) The output image is compared to the original labelled image after the final layer of training to assess the training loss. Using a binary cross-entropy loss function [16], this network calculates the amount of loss created. Equation 1 depicts the loss function.

$$H_p(q) = -\frac{1}{N}\sum_{i=1}^{N} y_i \,.log\left(p(y_i)\right) + (1 - y_i).log\left(1 - p(y_i)\right) \qquad (1),$$

where y is the label and p(y) is the predicted probability of the point.

Back propagation is used to reduce loss with the use of an Adaptive Delta Optimizer (to reach the Global Minima) and to update each and every element in the network's filters. As a result, the loss decreases over time, and the output is finally obtained with maximum value. In their 2015 ICLR work, titled "Adam, (poster): Diederik Kingma from Open AI and Jimmy Ba from the University of Toronto presented "A Stochastic Optimization Method." When it comes to solving non-convex optimization issues, Adam is a go-to choose for many in the scientific community, [17]. Hyper-parameters are easy to comprehend and typically only require modest modifications.

9) During the training, a total of 30 Epochs were used. An epoch is a unit of measurement for the amount of training vectors needed to adjust the weights just once. Before the weights are changed in batch training, each of the training datasets goes through one period of learning. The Learning Rate is set to 0.001 in this neural network. The Learning Pace parameter, in essence, defines the rate at which the derivative of the Neural Network's Loss Function hits zero and the Global Minima Position is reached, thus optimizing the entire network.

10) During the training process of this Neural Network, the k-Fold Cross-Validation Technique is utilized to properly evaluate the performance of the Neural Network. In this paper, the value of k is 10. Thus, through the continuous training process, the 10-Fold Cross-Validation helps to calculate the Validation accuracy apart from the training accuracy which helps to give us a clear picture of whether the model is overfitting or not. The overall average Validation accuracy achieved due to the application of the Light Weight Stacked Convolution Neural Network is 98.76%. As a result of this research, a novel interpretation of the Convolution Neural Network Mechanism is provided using the laws of thermodynamics and the principles of gas kinetic theory. According to Maxwell, Gibbs, and Boltzmann, among many other notable scientists. This study uses thermodynamics-based approaches to provide a new perspective on the workings of neural networks [18], which eventually enhances the ways of conceiving and characterizing different neural connections in the network.

An Energy-Based Model is used to explain the Convolutional Neural Network Networks presented in the paper (EBM). This is impossible because the thermodynamics and kinetic theory of gases across the universe relies on gas molecules in the surrounding space achieving a minimum energy state. Because all particles in the universe can achieve Zero Entropy by achieving their lowest energy state, this idea has some basis in reality. The Boltzmann Distribution for Gaseous Particles [19] outlines the concept, which is universal and applies to all particles in the universe. Both the Kinetic Theory of Gases and the Law of Thermodynamics, which both rely on gas molecules in the surrounding space, lead to the same minimum energy state for all particles in the universe (EBM). All particles in the universe can attain zero entropy by lowering their energy levels to the lowest possible level. The Boltzmann Distribution for Gaseous Particles [19] explains the principle, which applies to every particle in every place in the states.

3 Discussion

This section contains a detailed outcome analysis of the suggested scheme and algorithm. The Neural Network was trained using a set of 545 COVID-19 cases and 1266 NORMAL cases during the training process (Data Imbalance is being handled by Image Augmentation), the overall average training set accuracy was found to be 9 NORMAL cases is 98.42%. In order to gain deeper insight regarding the performance of the proposed deep learning model, several other evaluation metrics and strategies are being taken into consideration and presented 7.24%. Validation of this proposed Lightweight Stacked Convolutional Neural Network is done on a test validation set consisting of 167 COVID-19 cases and 317 NORMAL cases. Overall validation accuracy is 98.76%, with per-class accuracy of 99.40% for detecting COVID-19 instances and for detecting in this study.

Confusion Matrix [20] has been developed for the detailed evaluation of the model from where we get to calculate the Recall Score (Sensitivity), Precision Score, and $\boldsymbol{F_\beta}$ Score [21]. A confusion matrix, also known as an error matrix, is an individual table arrangement that permits the visualisation of the performance of an algorithm, often a supervised learning one, in the context of machine learning. Furthermore, we will do a detailed examination of the two major types of errors: There are two types of errors: Type 1 and Type 2. The evaluation results based on various metrics used for the proposed algorithm are taken from Equations (1), (2), (3), and (4).

$$\text{Accuracy (overall average)} = \frac{\boldsymbol{TP+TN}}{\boldsymbol{TP+FP+TN+FN}} \quad (2).$$

$$\text{Recall (Sensitivity)} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FN}} \quad (3).$$

$$\text{Precision} = \frac{\boldsymbol{TP}}{\boldsymbol{TP+FP}} \quad (4).$$

$$\boldsymbol{F_\beta}\ \text{Score} = (\boldsymbol{1} + \boldsymbol{\beta^2}) \left[\frac{\boldsymbol{Precision \times Recall}}{\boldsymbol{\beta^2\ (Precision + Recall)}}\right] \quad (5)$$

Since the problems which are dealt in this paper are related to medical applications, so the value of Recall is very important. Which indicates the value of β to be taken as 0.5, which leads to the calculation of $F_{0.5}$a Score whose value must be greater than 2 and is a robust metric of evaluation given as

$$\boldsymbol{F_{0.5}}\ \text{Score} = \boldsymbol{5} \left[\frac{\boldsymbol{Precision \times Recall}}{\boldsymbol{(Precision + Recall)}}\right] \quad (6).$$

For each class, there are TP (True Positives), FP (False Positives), FN (False Negatives), and TN (True Negatives), which represent the number of relevant classification techniques used, FP (False Positives), FN (False Negatives), and TN (True Negatives), which represent the number of images from that class that were incorrectly classified as belonging to another class. The classifier's capacity to detect all positive samples is represented by the classifier's ability to detect these samples. Choosing between 1 and 0 gives you the best and the worst results. An accurate classifier is described as one that does not mistakenly classify a negative sample as positive. There are two values for an F-beta score: one that is the weighted harmonic mean of precision and recall, whereas the other is zero. The aggregate score is weighted according to the beta parameter. The confusion matrix is depicted in Figure 9 and the evaluation metrics are tabulated in Table 1.

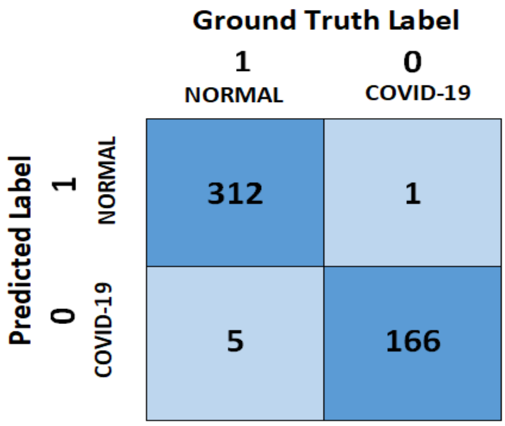

Figure 9. Confusion Matrix.

Table 1: Evaluation Metrics Table.

Model Name	NORMAL Correct Detected (TN)	NORMAL Not Detected (FP)	COVID-19 Correct Detected (TP)	COVID-19 Correct Detected (FN)
Lightweight Stacked CNN	312	5	166	1

The values of **True Positives (TP)**, **True Negatives (TN)**, **False Positives (FP)** and **False Negatives (FN)** are seen from the above Confusion Matrix and Evaluation Metrics Table 1, where **TP** = 166, **TN** = 312, **FP** = 5 and **FN** = 1.

True Negative (TN) signifies that a Chest X-Ray image is recognized (predicted) to be a NORMAL case and is also a NORMAL case in this study's COVID-19 detection from Chest X-Ray images. **True Positive (TP)** refers to the detection of the Chest X-Ray image as COVID-19 and is also originally a COVID-19 case. Again, **False Positive (FP)** indicates the detection of the Chest X-Ray image as COVID-19 but is originally a NORMAL case. And lastly, **False Negative (FN)** means the detection of an image has NORMAL but is originally a COVID-19 case.

From the Confusion Matrix and the Evaluation Metrics Table 1, the value of the metrics are calculated which are as follows:

$$\text{Accuracy (overall average)} = \frac{\mathbf{166 + 312}}{\mathbf{166 + 312 + 1 + 5}} = 0.9876 = 98.76\ \%$$

$$\text{Recall (Sensitivity)} = \frac{\mathbf{166}}{\mathbf{166 + 312}} = 0.9939 = 99.39\ \%$$

$$\text{Precision} = \frac{\mathbf{166}}{\mathbf{166 + 5}} = 0.9705 = 97.05\ \%$$

$$\boldsymbol{F_{0.5}}\ \text{Score} = \mathbf{5}\left[\frac{\mathbf{0.9705 \times 0.9939}}{\mathbf{0.9705 + 0.9939}}\right] = 2.45 \qquad (> 2.0)$$

$$\text{COVID-19 class accuracy} = \frac{\mathbf{166}}{\mathbf{166 + 1}} = 0.9940 = 99.40\ \%$$

$$\text{NORMAL class accuracy} = \frac{\mathbf{312}}{\mathbf{312 + 5}} = 0.9842 = 98.42\ \%$$

The value of Recall Score is far more important than all the other evaluation metrics in this case since the value of False Negative (FN) cases has to be as minimum as possible (FN = 1) which in turn, indicates that the value of Recall Score has to be higher than precision which is clearly shown in the results above. We conclude that the values of the various evaluation metrics calculated in the paper are in good agreement with each other, and the values of the three main evaluation parameters, namely, Recall Score (99.39%), F0.5 Score (2.45), and COVID-19 class accuracy (99.40%), are the highest achieved to the best of our knowledge and literature survey.

Multiple optimization functions were studied in this research while the Algorithm was being trained in order to evaluate the model's efficacy in detecting COVID-19-induced Pneumonia. Many different optimization techniques were employed, including Adaptive Momentum and Stochastic Gradient Descent with Momentum. A sufficient degree of smoothness in an objective function can be achieved using repeated stochastic gradient descent [22], e.g. differentiable and/or sub differentiable. Stochastic approximation of gradient descent optimization is so named because it substitutes an estimate for the actual gradient from the entire data set (calculated using a portion of the data chosen at random). A reduced convergence rate is swapped for faster iterations in high-dimensional optimization problems, minimizing the processing cost. It's one of the most widely used and oldest optimization techniques available, aside from Adam Optimizer. RMSProp [23] uses the magnitudes of the most recent gradients to normalize gradients. When splitting a gradient, a moving average over the root mean squared (or RMS) gradients is always employed as a basis. This Optimization Algorithm is more precise than SGD Optimizer, but not quite as precise as Adam Optimizer.

The performance of the different optimization functions and the validation overall average accuracy achieved after their respective application is given in Table 2.

Table 2: Optimization Algorithms vs Accuracy Score

Optimization Algorithm	Score for Validation Accuracy (%)
Adaptive Momentum	98.76
Adaptive Gradient	97.21
Adaptive Delta	95.45
RMSProp	91.39
Stochastic Gradient Descent with Momentum	87.45

The Adaptive Momentum (Adam) Optimization Algorithm integrates both the Stochastic Gradient Descent with Momentum (SGDM) and the RMSProp methods, as shown in Table 2. It helps achieve the maximum validation accuracy of 98.76 percent by assisting in the optimal weight and parameter optimization. Moreover, the purpose of this Lightweight Neural Network model is to boost the performance and the response time for the detection of COVID-19 induced Pneumonia from Chest X-Ray images. Therefore, taking into consideration the Time Complexity as well as the Space Complexity factor, the time taken by the model to perform the detection process is only **240 milliseconds**, and the memory utilized by the model during runtime is only **275KB**. Thus, the architecture suggested in this study paper offers a new dimension in the field of medical science by taking into account all of the different elements for evaluating a Neural Network model before putting it in production and application.

The application and scope of the Lightweight Stacked Convolutional Neural Network architecture are not only limited to the detection of binary use cases but it can also be applied for multi-Class detection processes. The area of work of this Neural Network can be extended for the detection of general Pneumonia cases along with COVID-19 and NORMAL cases [24]. Moreover, this architecture can also help to diagnose several other medical conditions from CT scan, Mammographic scan, Ultrasonography oriented images, and Blood Sample images. Apart from these, this proposed Neural Network model can also help in the identification and classification of different Protein Structure images, thus helping in the detection of various diseases. Due to its lightweight architecture, it can be easily deployed on a basic computer or a smartphone.

4 Conclusion

This paper explores a wide range of possibilities for using supervised Stacked Convolutional Neural Networks in medical and biomedical research. In contrast to all previous research on COVID-19, the work given in this study takes a completely new strategy, attaining the best accuracy while requiring the least amount of Time Complexity and Memory. Amongst all the recent advancements in the development of Deep Neural Network architectures for achieving higher accuracies, this Lightweight Stacked CNN architecture proposed in this paper offers an out-of-the-blue Shallow Learning Approach, which not only achieves a good accuracy but also brings about tremendous efficiency in response time and computation. The efficient Lightweight architecture proposed in the paper plays a vital role in accelerating and boosting up the response time for the diagnosis of COVID-19.

5 Availability of Data and Material

Data can be made available by contacting the corresponding author.

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Dr. Adil Khadidos is an Assistant Professor at the Faculty of Computing and Information Technology, King Abdulaziz University, Jeddah, Saudi Arabia. He received a B.Sc. degree in Computer Science from King Abdulaziz University, Jeddah, Saudi Arabia, and an M.Sc. degree is in Internet Software Systems from the University of Birmingham, Birmingham, United Kingdom, and a Ph.D. degree in Computer Science from the University of Southampton, Southampton, United Kingdom. His main research interests include the areas of Computer Swarm Robotics, Entomology Behavior, AI in Deep Learning and Machine Learning, Image Analysis, Self-distributed Systems, and Embedded Systems.