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Article

Deep-COVID: Detection and Analysis of COVID-19 Outcomes Using Deep Learning

Muhammad Ibrahim Khalil [1], Saif Ur Rehman [1,*], Mousa Alhajlah [2], Awais Mahmood [2], Tehmina Karamat [3], Muhammad Haneef [4] and Ashwaq Alhajlah [5]

1 Institute of Information Technology, PMAS Arid Agriculture University, Rawalpindi 46000, Pakistan
2 Computer Science and Information Systems Department, Applied Computer Science College, King Saud University, Riyadh 12571, Saudi Arabia
3 Department of Software Engineering, Foundation University Islamabad, Islamabad 44000, Pakistan
4 Department of Electrical Engineering, Foundation University Islamabad, Islamabad 44000, Pakistan
5 Saudi Authority for Data and Artificial Intelligence, Riyadh 12571, Saudi Arabia
* Correspondence: saif@uaar.edu.pk

Abstract: The coronavirus epidemic (COVID-19) is growing quickly around the globe. The first acute atypical respiratory illness was reported in December 2019, in Wuhan, China. This quickly spread from Wuhan city to other locations. Deep learning (DL) algorithms are one of the greatest solutions for consistently and readily recognizing COVID-19. Previously, many researchers used state-of-the-art approaches for the classification of COVID-19. In this paper, we present a deep learning approach with the EfficientnetB4 model, centered on transfer learning, for the classification of COVID-19. Transfer learning is a popular technique that uses pre-trained models that have been trained on the ImageNet database and employed on a new problem to increase generalization. We presented an in-depth training approach to extract the visual properties of COVID-19 in exchange for providing a medical assessment before infection testing. The proposed methodology is assessed on a publicly accessible X-ray imaging dataset. The proposed framework achieves an accuracy of 97%. Our model's experimental findings demonstrate that it is extremely successful at identifying COVID-19 and that it may be supplied to health organizations as a precise, quick, and successful decision support system for COVID-19 identification.

Keywords: computed tomography; deep learning; transfer learning; convolutional neural network; chest X-ray; deep transfer learning

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1. Introduction

The COVID-19 epidemic, which began on December 31, 2019, with the revelation of nonspecific pneumonia indications in Wuhan, China, swiftly became a significant outbreak, with great ramifications worldwide [1]. COVID-19 is causing discord on the public's lifestyles and public healthcare arrangements all around the globe. The majority of coronaviruses attack animals; however, due to their zoonotic characteristics, they may potentially infect people [2]. At the start of the outbreak, medical centers lacked adequate test kits, and these produced a high proportion of false negative findings; thus, clinicians' were advised to rely, for their evaluations, only on symptomatic and chest computed tomography (CT) reports [3,4]. According to the researchers, incorporating clinical imaging characteristics with test data might aid in the timely analysis of COVID-19 [5,6].

The fast worldwide expansion of COVID-19 placed medical systems under severe strain; however, this expansion might be considerably halted if an efficient screening methodology for COVID-19 cases is developed. Researchers and clinicians faced a formidable task in finding techniques to promptly identify the disease [7,8]. A COVID-19 infection may result in significant complications such as abrupt renal failure, pulmonary edema, and heart attack. Early discovery and inaccessibility of infected individuals is important in governing and handling the COVID-19 pandemic. COVID-19 is also discovered and detected utilizing radiometric testing processes such as CT [9]. Chest X-ray (CXR) has been identified as among the most successful procedures for detecting pneumonia worldwide since it is a quick, affordable, and widely used clinical approach that exposes the patient to less radiation than CT [10].

Given that the majority of COVID-19-positive individuals were reported with pneumonia, diagnostic imaging exams might be beneficial for illness characterization and advance monitoring. With the first patient manifestation, chest CT testing outperformed sensitivities [11]. As a result, the majority of current COVID-19 medical research has been on CT results. As the frequency of COVID-19 rises, the frequent practice of CT causes a significant load on radiology sections and poses a risk of infestation in CT rooms; hence, the necessity to detect COVID-19 characteristics on CXR rises [12,13]. Reports on the frequency of COVID-19 occurrence in the world's most impacted countries indicate that the United States tops the globe in terms of reported diseases, accounting for 27,007,399 cases out of a total of 69,065,018 cases as shown in Figure 1 [14].

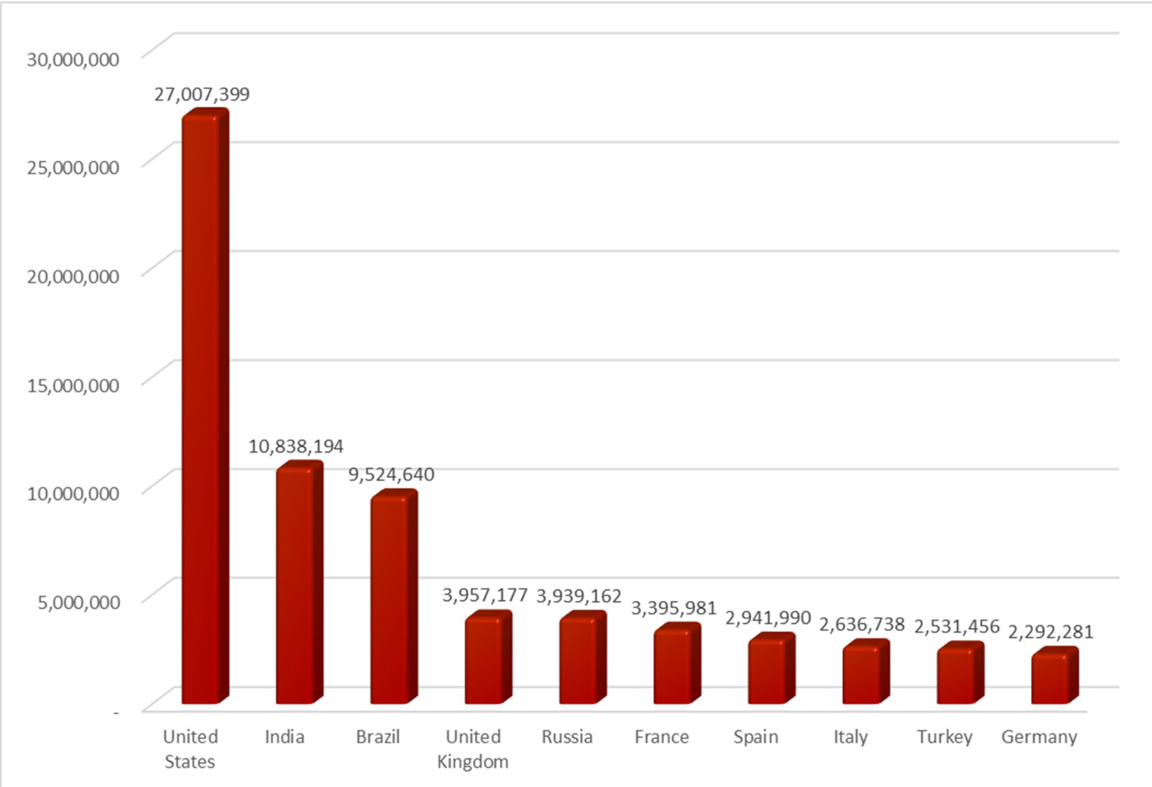

Figure 1. Countries with COVID-19 case statistics [14].

Numerous disorders are now being detected using artificial intelligence, which has shown its simplicity of use and superior performance in computerized image classification tasks utilizing multiple machine learning (ML) algorithms. [15]. Furthermore, ML refers to frameworks that can learn and draw conclusions based on enormous quantities of incoming data samples. Based on the analysis of the incoming data, artificial intelligence (AI) accomplishes activities that require human intellect, such as voice recognition, interpretation, sensory processing, and others [16,17]. DL is an amalgamation of ML approaches that primarily concentrates on the automated extraction of features and categorization of visuals; it has shown significant success in a variety of industries, particularly in medical services [18–20]. DL has been recommended for several key reasons. It also is connected to the rise in available data in today's digital era, since massive data collections are employed in the learning of these methodologies [21].

The generic workflow of COVID-19 detection using DL is presented in Figure 2. Many academics and data professionals are working to develop extremely precise and dependable DL-based diagnosis approaches for COVID-19. Scholars are concentrating on DL approaches for identifying characteristics in COVID-19 patients' CXR and CT images. [22]. Medical experts have a difficult problem when attempting to recognize COVID-19 from CXR pictures. They must distinguish characteristic features of the illness, which are mostly similar to other varieties of viral pneumonia, which leads to diagnostic mistakes. Various breakthroughs in scientific journals have been reported in relation to the automated classification of COVID-19 [23].

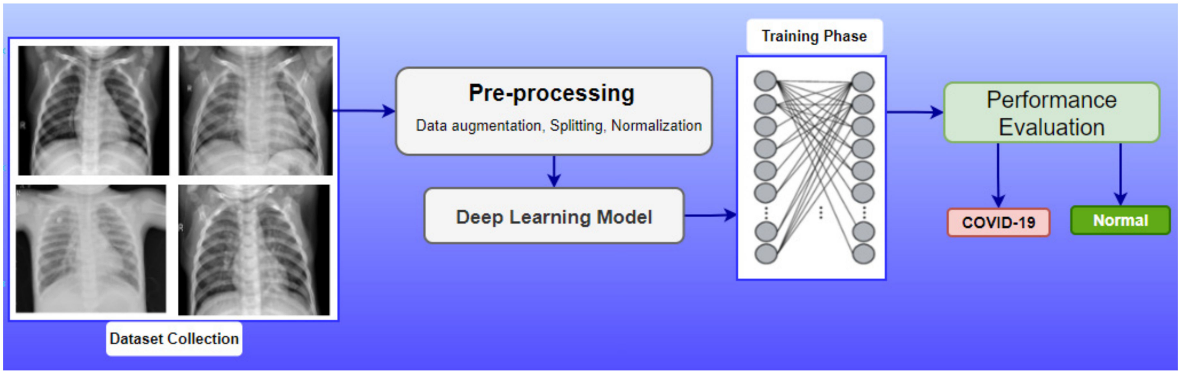

Figure 2. COVID-19 detection process.

DL applications to combat COVID-19 are appealing; however it is important to gain an understanding of the downsides of DL. Adding to the challenge is the absence of a dependable indicator of uncertainty. In this study, the following are the most significant contributions:

- By analyzing CXR images, the DL mode using TL is employed to categorize COVID-19-infected individuals.
- The recommended model is used to automatically extract features from the ImageNet dataset employing its weights and a model structure.
- Thorough experiments are carried out to assess the efficiency of the proposed solution using the COVID-19 CXR dataset.
- The aim of this study is to propose a robust DL architecture that can also be used for other clinical datasets.
- Comparative analysis is also presented by taking into account various renowned supervised learning approaches for COVID-19 detection.

The remaining divisions of this article are as follows: Section 2 is a brief review of current studies; Section 3 presents the proposed model for COVID-19 detection, and its design criteria; Section 4 describes the experimentation work; and Section 5 presents conclusions and outlook for future work.

2. Literature Review

In recent months, there has been a great amount of research on COVID-19 identification and diagnosis. COVID-19 is now a worldwide epidemic due to its rapid dissemination. It is difficult to discover exposed individuals since illness indicators do not appear quickly. As a result, in order to take the required precautions, it is important to develop a system for predicting the number of possibly affected people on a frequent basis. As a solution to conventional time-consuming and costly procedures, AI may be used to evaluate a patient for COVID-19. Although there have been various researches regarding COVID-19, this research focuses on the application of AI in anticipating COVID-19 infections and identifying COVID-19 infection using chest X-ray images.

Pathak et al. [24] present a DTL algorithm utilized to categorize COVID-19-affected individuals. A top-2 smoothing loss function with cost-effective features is also used to solve disruptive and unbalanced COVID-19 data challenges. A pre-trained ResNet-50 network is employed in DTL, scores an accuracy of 93% on the training set. Hyperparameter collection is not included in this study; thus, other methods, such as evolutionary algorithms and non-dominated sorting evolutionary algorithms, will be developed in the future.

Following the abrupt and rapid appearance of COVID-19, this study provides an innovative modelling framework that is centered on capsule networks presented by Afshar, P. et al. [25], known as the COVID-CAPS, possessing a much smaller number of learnable parameters than its peers. Pre-training and TL constructed on newer data created from an outside dataset of X-ray images are used to further enhance the diagnosing ability of the COVID-CAPS architecture. COVID-19 identification using pre-training based on real-world images is a departure from previous research.

Three modes of technique were suggested by Brunese et al. [26]. The first module is to determine the existence of pneumonia in the dataset containing chest X-rays. The next is to discriminate among COVID-19 and pneumonia. The third stage is to identify the regions in the X-ray which are indicative of the existence of COVID-19. The methodology uses the VGG-16 DL model and achieves an accuracy of 96%. This research advocated the use of DL for COVID-19 identification from X-rays in order to provide a totally automated and quicker diagnosis.

The CoroNet technique was presented by Khan et al. [27]. It is a DNN model which efficiently detects the existence of the COVID-19 disease from chest X-ray data. The suggested model is built on the pre-trained Xception framework and then trained on the dataset made up of COVID-19 and further chest pneumonia X-rays from two publicly accessible sources. CoroNet was trained and evaluated on the preprocessed data, and the experiment findings demonstrate that our suggested model attained an accuracy rate of 89.6%. CoroNet produced encouraging results on a limited dataset, indicating that with additional data, the suggested model may provide superior results with minimal data pre-processing.

Essam H. et al. [28] presented hybrid quantum-classical CNN that reached an overall accuracy of 88.6%. The HQCNN model's fundamental concept is built on hybrid computing to improve the effectiveness of classical works. The suggested model is divided into two sections: the quantum component, which makes use of the quantum conventional part; and the traditional section with the CNN architecture. The HQCNN approach outscored traditional CNNs and other multiclass techniques on the binary COVID-19 databases.

Ioannis D et al. [29] presented a cutting-edge CNN named Mobile Net, used and trained from the ground up to examine the significance of the recovered characteristics for the classifying problem. The dataset used to train MobileNet v2 contains 3905 X-ray pictures belonging to six illnesses, and has been shown to perform well in related work. Training CNNs from the beginning surpasses the other TL approaches in differentiating X-rays across the seven classes, both among COVID-19-infected individuals and normal individuals.

Y Oh et al. [30] presented the pre-trained model ResNet-18, which performs pre-processing for data normalization. A classification model is employed to categorize the related illnesses from the fragmented lung region using patch-by-patch learning and interpretation, and the final conclusion is determined relying on a majority vote. Because of two factors, the relatively basic ResNet-18 was chosen as the foundation of the classification technique. A foremost priority was to prevent overfitting, which is known to be associated with the use of an excessively sophisticated model used on a limited number of data points. Additionally, to account for the low number of training data, TL was used with pre-trained values. It was discovered that using these strategies keeps training steady even though the data is limited.

Kishore Medhi et al. [31] presented a DNN technique for quickly and reliably identifying the COVID-19 virus from individual chest X-ray data. Data include more than 150 verified COVID-19 cases from the Kaggle repository, utilized in the experiments to test the efficacy of the proposed framework. The findings reveal that the suggested method correctly detects the cases, reached an accuracy of 93%. The outcomes of this study will assist physicians and other health experts in making appropriate decisions in a timely manner.

Toraman et al. [32] presented a technique intended to provide rapid and precise diagnosis of COVID-19 disorders using binary classification and multi-class categorization. Capsule networks were built to store the locations and attributes of items in an image, as well as to simulate their hierarchy connections. A novel network structure with five convolution layers is presented. The purpose of adding additional convolution layers is to produce a more optimized feature pattern as a feed to the main layer. The presented method's effectiveness was assessed employing a 10-fold cross-validation procedure. The collected data was separated into ten sections, nine of which were utilized for training and last one for testing. This procedure was repeated for each component, and the method's effectiveness was determined by considering the mean of all components.

Kevser Sahinbas et al. [33] described a deep CNN approach that is built on raw chest X-ray data of COVID-19 participants and is openly accessible on GitHub. There are 50 positive and 50 non-COVID-19 X-ray cases for training, as well as 20 positive and 20 negative cases for testing. The approach employed five distinct structures of very well-pre-trained networks to classify COVID-19, since the intricate composition of the images necessitates a DL framework. When matched with the other four methods, the pre-trained VGG16 has the greatest classification score (80%), and may be utilized by medical experts as a useful tool. With a larger COVID-19 dataset, the suggested model provides more efficient findings.

According to the detailed study, the DL models may obtain effective production for COVID-19 discovery from CXR and CT scans as shown in Table 1. The DL models may provide considerable results, but the outcomes may be enhanced substantially by using effective feature-extraction methods. Transfer learning may also be used to fine-tune DL models. As a result, the fundamental objective for this study is the creation of a robust DTL mode for COVID-19 classification.

Table 1. Comparative analysis of COVID-19 diagnostic techniques.

Article	Methodology	Total Classes	Research Findings	Accuracy
Pathak et al. [24]	ResNet-50	2	Lightweight DL model.	93.0189%
Afshar, P. et al. [25]	Capsule-based network	2	Modified loss function to handle class imbalance.	97.2%
Brunese et al. [26]	VGG-16	3	Decreases the time window around 2.5 s.	96%
Khan et al. [27]	CoroNet	4	Improves on existing radiology-based methods for smaller datasets.	89.6%
Essam H. et al. [28]	CNN based on hybrid quantum	3	Integrates the random quantum circuits with CNNs.	88.6%
Ioannis D et al. [29]	MobileNet V2	3	Trained the CNN from scratch for detection of COVID-19.	97.36%
Y Oh et al. [30]	ResNet-18	3	Patch-based CNN with comparatively few trainable parameters.	88.9%
Kishore Medhi et al. [31]	Deep CNN	2	COVID-19 classification with the DNN approach as quick and reliable.	93%
Toraman et al. [32]	Capsule networks	2	Convolutional CapsNet method employed to facilitate fast screening for COVID-19.	97.24%
Kevser Sahinbas et al. [33]	VGG-16	2	DTL approach with multiple DL models scores considerable results on limited data.	80%

3. Proposed Methodology

The proposed study presents a deep transfer learning (DTL) method for detecting COVID-19 infection using CNNs. In transfer learning (TL), a vast quantity of data is used to complete initial training and categorization. The first module contains CXR datasets from COVID-affected and healthy patients. In the second phase, the data set is pre-processed and separated into training and test sets. In the third step, the pre-trained DL model EfficientNetB4 is used as a backbone model, and its final layers are fine-tuned. The thorough training and assessment measures establish the classification sores. Figure 3 depicts the design of the proposed methodology.

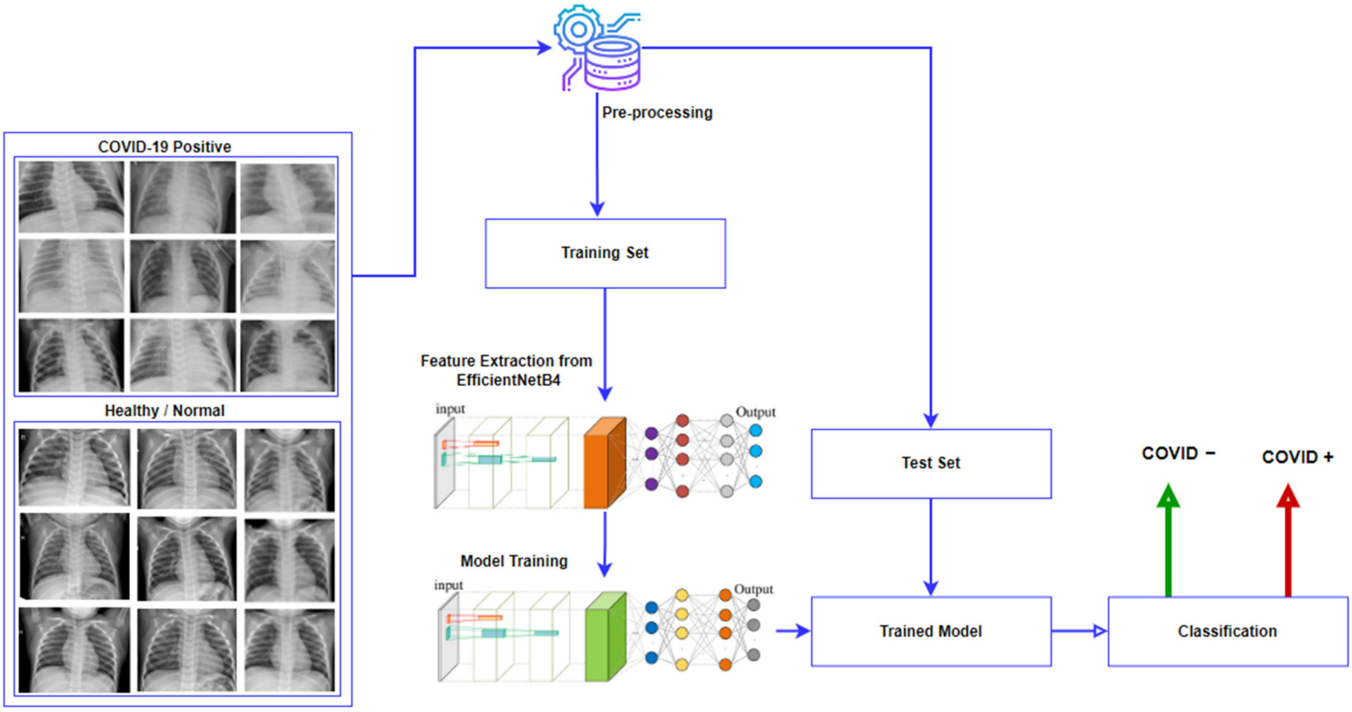

Figure 3. Proposed methodology workflow.

TL is an approach in which the information extracted by a CNN from provided data is transmitted to tackle a separate but similar job using new data, which is typically of a relatively small data size, in which case the model is trained from scratch. In DL, this technique entails training a CNN for a classification job using huge databases. Because CNN may learn to extract major properties of an image, the presence of data for preliminary training is the significant component for effective learning. It is determined if this model is acceptable for TL based on the CNN's capacity to recognize and extract the most noteworthy visual characteristics. The proposed methodology workflow is shown in Algorithm 1.

Algorithm 1: Proposed methodology steps

Let d = dataset, α = augmentation, i = image, pp = pre-Processing, r = rotate s = scale, sm = shifting methods, ia = image augmentation
Begin
1: Get(d)
2: α(i) w.r.t. r, s, st
3: Perform (pp (i))
3.1. Perform (ia)
3.2. Resize
3.3. Normalize (i)/interval [0, 1]
3.3.1. Conversion
3.3.2. Computation (mean)
3.3.3. Scaling(i)
3.3.4. Conversion back
3.4. Dataset splitting for training, testing, and validation
3.5. Feature extraction from EfficientNetB4
3.6. Optimize (epochs, batch size, model layers, learning weights)
Step 4: Evaluation metrics (accuracy, precision, F1 score, and recall)
End

In the next stage, the CNN is used to analyze a fresh batch of pictures of a different kind and features extracted based on the expertise of its feature extractor gained during the original training. There are two commonly used methods for using the pre-trained CNN's properties. The first method, termed feature mining through TL, refers to how the pre-trained structure retains both its fundamental architecture and all learned weights. As a consequence, the pre-trained architecture is only used to gather features; the extracted properties are then entered into a new framework that performs the classification process. This method is often employed to reduce the processing costs involved with training very deep structures from the start, or to retain the important characteristics produced during the initial stage.

The core architecture of the proposed solution is centered on the EfficientNetB4 as a backbone model. The most challenging difficulty when employing DL approaches is determining the enormous quantity of components and hyperparameters (e.g., batch size, frozen layers' numbers, total epochs, learning rate, etc.). The implications of different hyperparameter values on the effectiveness of the suggested systems are studied. The profound concept is to link all layers directly with one another in a feed-forward manner to enhance details and gradient transfer across layers, as shown in Figure 4. Pre-trained methods are often trained on enormous datasets that serve as a common standard in the field of image processing. Weights derived from the classifiers may be used to other imaging applications. These algorithms may be used independently to anticipate new tasks or included into the learning phase of a new classifier. Incorporating pre-trained models into a model reduces the training process and generalization errors. The EfficientNet architectures were designed to use as few resources as possible while maintaining great accuracy and using minimal memory and learning time. For classifying issues, TL approaches have been a typical addition to DL solutions. This work examines the use of pre-trained EfficientNets and additional fine-tuning for COVID-19 disease identification, as well as data improvement using min-max normalization. Moreover, including normalization in the preprocessing step strengthens the approach.

The EfficientNet architectures are built on very simple and efficient compounded scaling techniques. This strategy allows one to increase the ConvNet base exponentially to any goal-restricted capacity while retaining the network function used for training data transfer.

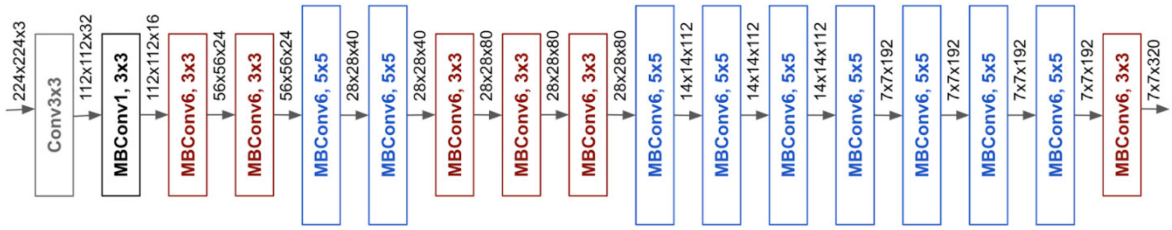

Figure 4. EfficientNet architecture.

4. Experiment and Results

The experimentation work was conducted at the university using the Anaconda 3 software environment. Experiments were performed in Keras using a TensorFlow2 on the backend. The experiments were performed using a publicly accessible dataset and the suggested DL method based on TL, employing the EfficientNetB4 architecture with hyperparameters including batch size 64, the learning rate of 0.000001, and Adam as an optimizer. There are several EfficientNet variations, with a unique set of parameters that range from 5.3 million to 66 million. Performance measurements were employed on the COVID-19 dataset to evaluate and verify our proposed approach. The following evaluation criteria were mainly utilized to assess the proposed methodology:

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + False\ Negative + True\ Negative + False\ Positive}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

$$F1\ Score = 2 * \frac{Precision *\ Recall}{Precision + Recall}$$

Figures 5 and 6 show the accuracy and loss variability during the training and validation procedures of the EfficientNetB4 model learning process. In clinical research, particularly for crucial disorders such as COVID-19, it is critical to capture accuracy and loss variability in order to reduce falsely positive and falsely negative outcomes. For obvious reasons, false denials must be kept to a minimum, since misclassifying any COVID-19 positive might have significant ramifications for our civilization. It is particularly crucial to limit the false positive rate, since misclassifying a COVID-19 negative as a COVID-19 positive might result in severe emotional stress. Figure 7 depicts the proposed model accuracy score with other DL approaches on COVID-19 classification, and the presented models in [25,26,29] are trained on the smaller datasets and achieve moderate results. The proposed method obtains 97% accurate classification outcomes shown in Table 2 while minimizing the impact of falsely positive and falsely negative findings. It is clear that the suggested technique has a lower false prediction rate. Given the potential for overfitting, the evaluation metrics of the system are biased. The significant correlations that one is attempting to predict, along with a number of other particular factors specific to the conditions underlying the dataset's gathering, have an impact on the facts we observe. Although the modelling may incorporate these traits, predictor variables are responsible for the outcome's prediction accuracy.

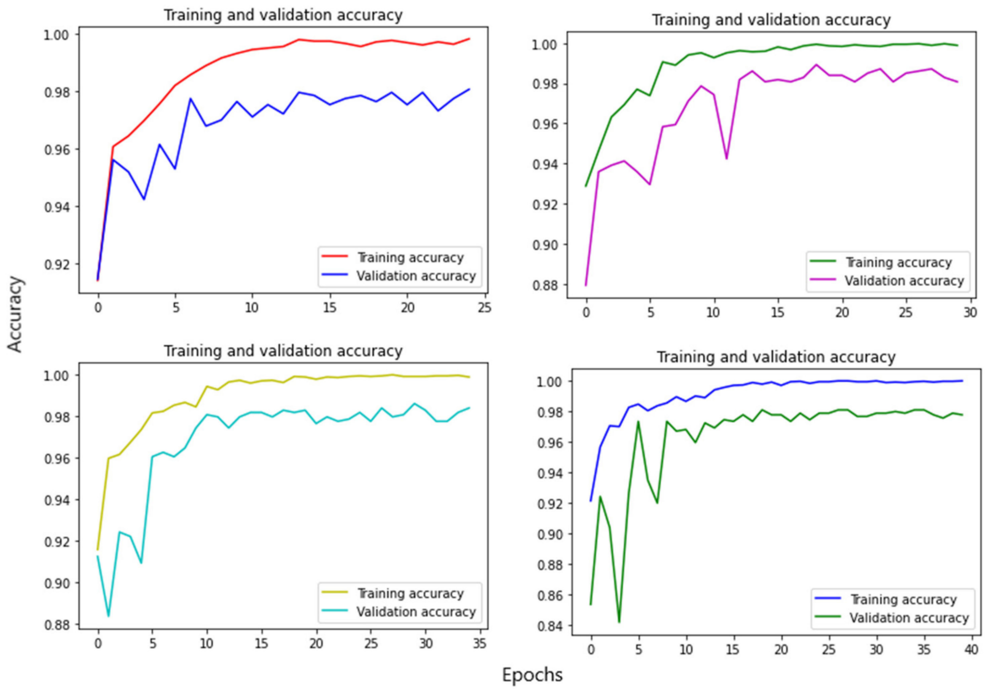

Figure 5. Model EfficientNetB4 training and validation accuracy graphs.

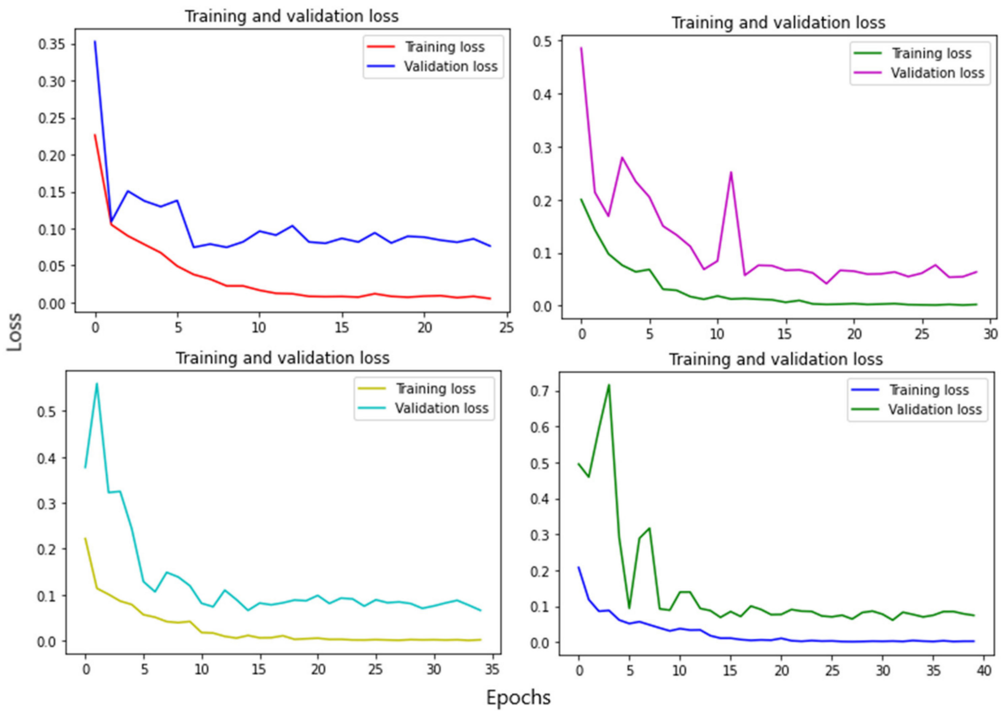

Figure 6. Model EfficientNetB4 training and validation loss graphs.

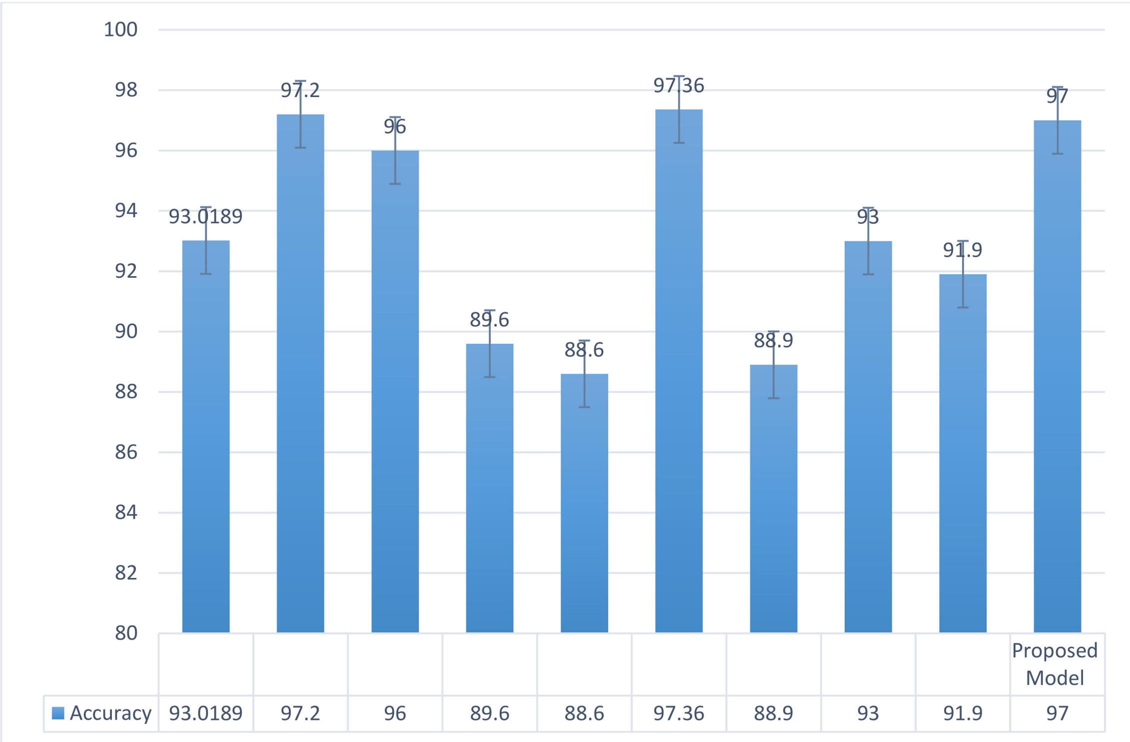

Figure 7. Results of the accuracy comparison [24–31,33].

Table 2. Results with EfficientNetB4 model.

Evaluation	**Results**			
Accuracy	0.97			
	precision	recall	f1-score	support
COVID	0.96	0.97	0.97	217
NORMAL	0.96	0.99	0.99	1580
PNEUMONIA	0.96	0.97	0.98	423

The superiority of the proposed classifying framework over existing supervised COVID-19 classifications techniques is measured through the use of a confusion matrix using a set of evaluation indicators. Accuracy, specificity, precision, sensitivity, and negative prediction are among these measurements, as shown in Figure 8. False negative projections must be avoided in the medical environment since they may result in diagnosis and medication delays, unsatisfactory medical results, emotional suffering of patients, general loss of trust in health services, and regulatory ramifications. It was discovered that the suggested model learns effectively while incurring the fewest losses and with the least difference between validating and training accuracies. Overall, the outcomes indicate that the DL model performed well.

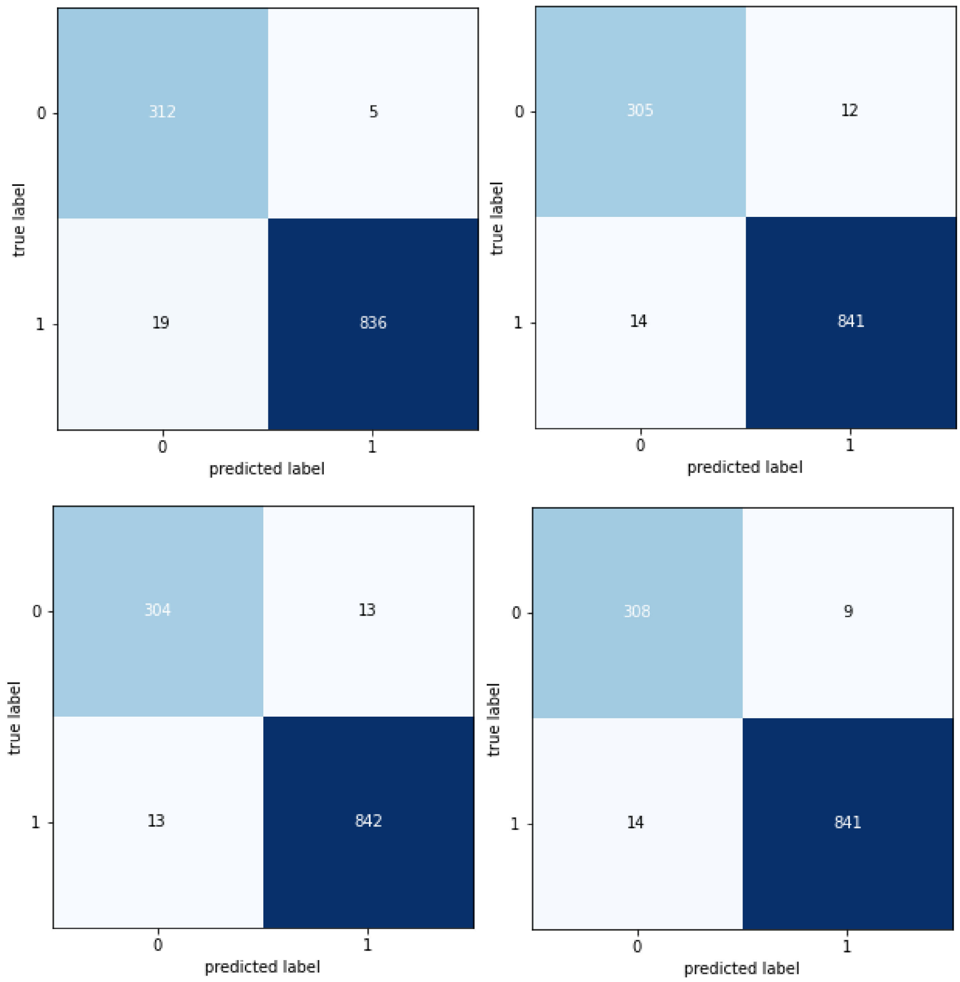

Figure 8. Model EfficientNetB4 confusion matrix at various epochs.

5. Conclusions

It is critical to appropriately identify these illnesses early to select the appropriate therapy and to isolate COVID-19 individuals in order to prevent the infection from spreading. In this research, a new DTL model for the classification of COVID-19 outcomes is developed using the pre-trained EfficientNetB4 model. Comparative evaluations indicated that the EfficientNetB4-based CNN outperforms many well-known DTL models. The proposed model achieves 97% accuracy. In comparison to previous supervised learning techniques, experimental findings prove that the proposed DTL-based model produces efficient results. When compared to competing models, the suggested model is a significant improvement. Furthermore, if we can implement the suggested approach in a wider population, the efficiency increase may result in the saving of many lives. More data may be integrated in future work for improved outcomes, which would enhance the proposed framework even more.

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