DEEP LEARNING TECHNIQUES FOR COVID-19 DETECTION: A FOCUS ON DENSENET ARCHITECTURE

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ABSTRACT

According to World Health Organization statistics, COVID-19 has been the most challenging pandemic to date, spreading to nearly every nation on the earth and killing millions of people. Reverse transcription-polymerase chain reaction (RT-PCR), a prolonged and extortionate technique, is mostly used in the diagnosis of this disease. Presently, the infectious disease diagnosis often relies on reverse transcription-polymerase chain reaction (RT-PCR), a method that is both time-intensive and exorbitant. Detecting COVID-19 accurately and swiftly is crucial for effective disease management and treatment. Deep learning methods for COVID-19 identification with increased accuracy are examined in this study and DenseNet-169 model with fine-tuned hyper parameters is selected as the optimal architecture for the same. The chest X-Ray images dataset taken are preprocessed and augmented to avoid over fitting. Also transfer learning is exploited since the dataset is limited. Experimentation of the DenseNet-169 model using the public dataset showed that it can be chosen as the best architecture for detecting COVID-19. The performance is assessed against popular deep learning models including DenseNet-101, ResNet-50, EfficientNet-B0 and EfficientNet-B1. To assess the model's effectiveness, metrics such as accuracy, precision, recall, and F1-score are used. The DenseNet-169 model achieves a commendable accuracy of 89% in distinguishing COVID-19 cases. The findings support ongoing efforts to create robust and efficient diagnostic tools for COVID-19 aiming to support early detection and prompt medical intervention.

1. *INTRODUCTION*

COVID-19 pandemic triggered by the novel coronavirus SARS-CoV-2 was revealed in December 2019 in Wuhan, China. The disease was formally named so by the World Health Organization on February 11, 2020. According to the World Health Organization, the epidemic has spread to nearly every country and killed billions of human beings by June 2021[1]. To detect the presence of SARS CoV-2 ribonucleic acid (RNA) in respiratory tract samples, the polymerase chain reaction and reverse transcriptase (RT-PCR) method [2] is adopted as the main technique. In case of people with strong respiratory symptoms, faster and more reliable medical imaging techniques are used to help doctors to identify diseases and their effects more quickly. The aim is to improve the effectiveness of medical treatments and increase the chances of survival without the need for intensive care. These patients first undergo an X-ray imaging, and if further detail is needed, a CT scan (computed tomography) is performed. Thus, CT scan and X-ray images are being widely used for detecting COVID-19 since they can complement or replace PCR testing [3]. Between these two modalities, X-ray imaging is the one most frequently used by medical experts to aid in diagnosing COVID-19. This is due to the inexpensive nature and easy availability of X-ray imaging system as it is an indispensable part of universal health care. Also X-Rays were used for the detection of Pneumonia and other respiratory infections.

Computer-aided detection and diagnosis must be utilized to assist radiologists in managing the overwhelming number of COVID-19 patients. With the rapid advancement of machine learning, automated detection methods offer promising avenues to enhance diagnostic accuracy and efficiency. Machine learning researchers and computer scientists play a crucial role during the global spread of COVID-19. Recent years saw the advancements of deep learning applications, primarily due to the growing computational power. Deep learning techniques, like Convolutional neural network (CNN) model extracts discriminative features automatically and is efficient than traditional feature extraction models. This motivated the authors to perform a thorough study on popular deep learning models for Covid-19 detection and selected Densenet-169 for implementation. A benchmarking study of the Densenet model is performed with recent methods to find out which model achieves superior accuracy in diagnosis of COVID-19 using chest X-ray images. The models selected for comparative study are DenseNet-101, ResNet-50, EfficientNet-B0 and EfficientNet-B1. Evaluation of the results indicate that DenseNet-169 outperforms competing approaches. This study have the following objectives:

- Model Selection: DenseNet-169 model is taken as the optimal deep learning architecture for Covid-19 detection.
- Comprehensive Analysis: A thorough analysis of literature is done and five deep learning models used in COVID-19 patient diagnosis is experimented on chest X-ray image datasets and evaluated to find that DenseNet-169 is the best performing model for Covid-19 detection.

From Extensive experimentation on these five models using chest X-Ray data set, it is identified that DenseNet-169 model is a robust choice for this task, demonstrating an accuracy of 0.89 and F1-score of 0.89. Fine- tuning of the model and increase in dataset may improve the performance parameters further. Automated classification models trained on datasets of chest X-ray images play a pivotal role in distinguishing COVID-19 cases from other respiratory conditions. This study aims to contribute to the ongoing efforts in medical imaging and public health. Also it demonstrates the efficacy of various deep learning algorithms for COVID-19 diagnosis from medical images. This article promotes researchers to create a sophisticated solution for COVID-19 detection. By automating and optimizing the diagnostic process, the researchers can assist clinicians in early detection, prompt medical intervention, and eventually increase accurate outcomes.

The rest of this paper is ordered as given below: Section 2 gives recent literature review, while Section 3 is dedicated to the methodology part, Section 4 showcases the experimental setup and Section 5 demonstrates results and discussions. Finally, the conclusion is provided in Section 6.

2. *RELATED WORKS*

Jaime Ramírez and Govardhan Jain et al., [4] presented a two-stage deep learning strategy for detecting COVID-19 from chest X-ray images, differentiating COVID-19 cases from bacterial and viral pneumonia, as well as healthy individuals, with high accuracy. The proposed model, utilizing ResNet50 and ResNet-101 architectures, demonstrates promising results and contributes to the rapid and accurate detection of COVID-19, aiding in the pandemic response. Limitations include the need for better network design, limited COVID-19 images for training, and potential extension to other viruses.

Mohd Zulfaezal Che Azemin et al., [5] explored deep learning techniques to predict COVID-19 from chest X-ray images using the ResNet-101 architecture. The model, retrained with radiologist-adjudicated chest X-ray images, shows a 71.9% accuracy, 77.3% sensitivity and 71.8% specificity. The study highlights the importance of high-quality training data and emphasizes the significance of data quality, model selection, and cautious result interpretation.

Shervin Minaee et al., [6] utilized deep transfer learning with models like ResNet18, ResNet50, SqueezeNet, and DenseNet-121 to predict COVID-19 from chest X-ray images. Using the COVID-Xray-5k dataset, DenseNet-121, achieved 98% sensitivity and 92%. Specificity. This article emphasizes the potential of deep learning for early and accurate diagnosis of COVID-19 through chest X-ray analysis.

Emtiaz Hussain et al., [7] developed the CoroDet model, a deep learning-based classification method that outperforms existing techniques for COVID-19 detection, achieving high accuracy rates: 91.2% for 4-class classification, 94.2% for 3-class classification, and 99.1% for 2-class classification. The large dataset used for training enhances its effectiveness as a valuable tool for clinicians.

Mohit Kumar et al., [8] introduced the Hybrid Convolutional Neural Network (HDCNN), which combines CNN and RNN architectures for COVID-19 detection. The model achieved a 98.20% accuracy rate, leveraging transfer learning through Grad-CAM. The dataset included 6000 X-ray images, and future work aims to explore other deep learning models and imaging modalities.

S. Tabik et al., [9] developed the COVID-SDNet methodology using the COVIDGR-1.0 dataset to classify COVID-19 severity levels. The model achieved high accuracy, especially in moderate and severe cases, with accuracy rates 78.18%, respectively. The methodology outperformed other models, providing a valuable tool for healthcare professionals.

Hanan S. Alghamdi et al., [10] reviewed various deep learning methods for COVID-19 detection using chest X-ray images, emphasizing the importance of CXR imaging and the role of deep learning. It highlights the need for a public comprehensive COVID-19 dataset and standardized evaluation metrics. The survey underscores the potential and challenges of deep learning in medical imaging for COVID-19 diagnosis.

Aras M. Ismael et al., [11] evaluated three deep learning methods for COVID-19 detection: deep feature extraction, fine-tuning pretrained CNNs, and end-to-end training of a custom CNN model. The combination of ResNet50 and SVM resulted in the attainment of the highest accuracy of 94.7%. The study highlights the efficacy of deep learning for COVID-19 detection and suggests further research with larger datasets and deeper CNN models.

Sushavan Mondal et al., [12] focused on developing a deep learning model to classify chest X-ray images for identifying various diseases using the Xception model. The study utilized a subset of the NIH Clinical Center dataset, consisting of 5,606 images from 30,805 unique patients, and aimed to predict 14 categories of diseases. The Xception model attained accuracy rate of 88.76%, indicating the potential of deep learning in medical diagnostics.

Fátima A. Saiz and Iñigo Barandiaran, [13] proposed a deep learning approach for COVID-19 detection using chest X-ray images. Their model attained 94.92% sensitivity and 92% specificity. The dataset combined COVID-19 images from GitHub and pneumonia images from a Kaggle challenge, totaling 513 images for training and 887 for testing. Histogram equalization (CLAHE) was applied for image normalization, enhancing model training and reducing false positives. The model employed was SDD300, using transfer learning with VGG-16 weights pre-trained on ImageNet. The results demonstrated improved detection accuracy, with 94.92% accuracy for normal images and 92.00% for COVID-19 images. The study highlights the robustness of their model in distinguishing COVID-19 from other conditions.

Talukder et al., [14] investigated the potential of X-rays with deep learning algorithms to accurately identify COVID-19 patients. Experiments performed on a COVID-19 X-ray dataset comprising of 2000 images using Xception, InceptionResNetV2, ResNet50, ResNet50V2, EfficientNetB0 and EfficientNetB4 showed an accuracy rate of 99.55%, 97.32%, 99.11%, 99.55%, 99.11% and 100% respectively. EfficientNetB4 achieved the highest accuracy score. The outcomes obtained emphasize the effectiveness of fine-tuned transfer learning for effective COVID-19 diagnosis using X-ray images. Further investigations could integrate deep learning with machine learning models and moreover, expanding the study to include a larger dataset of multi-class MRI and CT images.

Srivastava et al., [15] performed a comparative study on many traditional pre-trained models. Modified InceptionV3, along with Modified EfficientNet B0 & B1, achieved 99.78% accuracy for bi-variate classification. The curated dataset comprises of 3270 normal, 1656 viral-pneumonia-infected and 1281 COVID-19 chest X-ray images. ResNetV2 achieved a 97.90% classification accuracy for 3-class classification. A novel CNN-based model, CoviXNet, was proposed with 15 layers, demonstrating a 99.47% accuracy for bi-variate classification and 96.61% accuracy for 3-class classification, with minimal computational cost. This study, along with the proposed CoviXNet model, can aid medical experts in the effective diagnosis of the Coronavirus.

The review reveals that the classification performance of deep learning network architectures is heavily influenced by the number of images used for training and testing. Limitation of labeled datasets results in over fitting. Transfer learning can be employed to enhance the speed and performance of deep learning models where the dataset is limited. The necessity for a better network design for detection of Covid-19 is evident from the surveyed articles. Also, if the hyper parameters are properly tuned, performance can be improved. The survey highlights the advantages of the DenseNet-169 architecture in COVID-19 image classification. This article investigates ways to enhance existing deep learning architectures for improved COVID-19 detection.

3. *METHODOLOGY*

In this research article, the implementation details of DenseNet-169 [16] based classification for Covid-19 detection are presented. The key steps are Data collection, Data Pre-processing, Data Loading, Model Setup, Model Compilation, Model Training and Performance Evaluation. DenseNet-169 Covid-19 Classification model is given in Fig. 1.

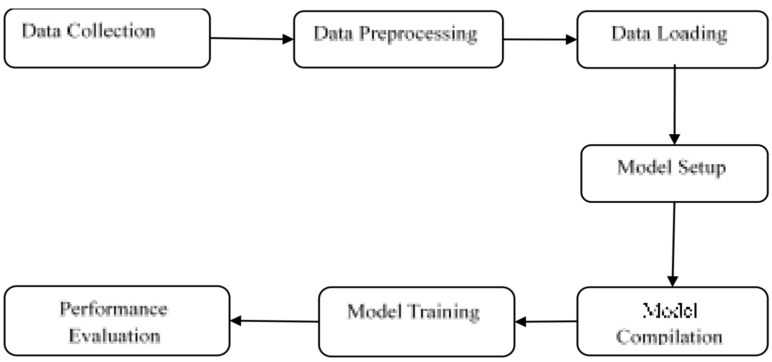

Fig 1. COVID-19 Classification model

The first step is to gather the dataset of images needed for the classification task. A public dataset of 852 chest X-Ray images are used for both training and validation [9]. It contains 426 positive and negative cases of Covid-19. These images are organized into subdirectories for two classes of COVID-19 positive and negative. This data provides the basis for training and assessing the model. Data preprocessing is essential for preparing images for model training and involves two key steps: augmentation and normalization. As the dataset is limited in number, Data

Augmentation methods such as Rotation with a range of 30, Zoom in the Range of 0.8 and 0.9, Feature-wise Centering, Feature-wise Standard Normalization, Sample-wise Centering, and Sample-wise Standard Normalization are applied. Pixel values are rescaled from the range [0, 255] to [0, 1] by dividing by 255, ensuring consistent input and accelerating training convergence. After preprocessing, images are divided into training and validation sets in the range 80:20, ready for model input. With the data preprocessed, the next step is to load it into a format suitable for training. This is accomplished using ImageDataGenerator from Keras. Train Generator applies the previously defined augmentation settings to produce batches of varied training images. Validation Generator processes validation images by normalization only, providing a method to evaluate the performance of the model on new data. Both generators deliver batches of images and labels for the training and evaluation phases.

In the second phase, the DenseNet169 model, pre-trained on ImageNet, is utilized. The DenseNet169 model is loaded without its top layers allowing it to function as a feature extractor. The weights of the DenseNet169 layers are set as non-trainable to retain the learned features from ImageNet and prevent overfitting on the smaller dataset. Additional layers are added to adapt the model for binary classification. These include a GlobalAveragePooling2D layer for dimensionality reduction, a Dense layer with 256 units and ReLU activation used to capture intricate patterns, and a final Dense layer having sigmoid activation function to output probabilities for the binary classification task (COVID-19 positive or negative).

The model compilation is done to define the training process. Adam Optimizer is selected due to its adaptive learning rate, which facilitates faster convergence. Binary cross-entropy is used as the loss function, which is appropriate for bi-variate classification tasks, as it evaluates how well the predicted probabilities align with the actual labels. Then the training data is used for training the model for 50 epochs and validation data is used for validating the model. During the process of training, the model updates its weights according to the loss function and optimizer to minimize prediction errors. After every epochs, the performance of the model is assessed on the validation set to track its ability to generalize to unseen data.

After training, the model's performance is evaluated through several key steps. For visualizing the model's performance over epochs, both training and validation accuracy as well as training and validation loss are plotted. Next, the accuracy of the model on the validation set is computed to provide a final performance measure. Additional metrics, including F1-score, precision and recall, are computed to provide a complete evaluation of the model's capability to accurately classify positive cases. Finally, a confusion matrix is created to display the true positives count, false positives count, true negatives count, and false negatives count, aiding in the diagnosis of any classification issues.

3.1. *DenseNet-169*

DenseNet-169 is a member of the DenseNet family with 169 layers, is used to improve the performance and efficiency of CNNs in object recognition tasks [16]. The dense block, a vital component of the DenseNet architecture, is composed of multiple convolutional layers. Each layer in the dense block accepts as input all the feature maps from the preceding layers and output k new feature maps. The growth-rate parameter k indicates the quantity of new information introduced by each layer. This design enhances the flow of information and gradients across layers, promoting the reuse of learned features. It has significantly fewer trainable parameters compared to other DenseNet architectures with fewer layers. DenseNet-169 effectively address the vanishing gradient problem, have robust feature propagation, minimize the number of trainable parameters, and encourage feature reuse, making them highly reliable deep learning architectures. Figure 2 shows the DenseNet-169 architecture.

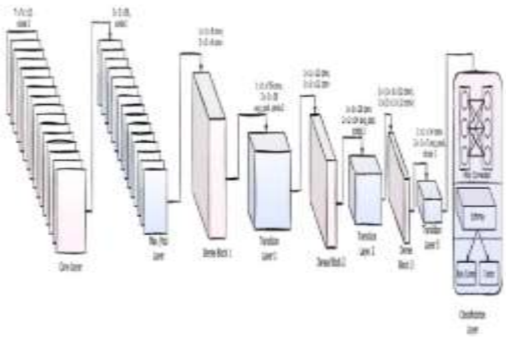

Fig 2. DenseNet-169 Architecture

Initial Convolution Layer performs a 7x7 convolution with a stride of 2, generating 112 feature maps. It takes elementary features from the input image. Max Pooling Layer applies a 3x3 max pooling operation with stride 2 for dimensionality reduction of feature maps and computational load while conserving major features. Since each layer takes input from all previous layers within the block, access is allowed to feature maps from every preceding layer rather than just the immediately prior one. The block includes multiple convolutional layers, such as 1x1 convolutions to reduce feature map dimensions and 3x3 convolutions to produce new feature maps. After processing, the outputs are concatenated with the previous layer's inputs, enabling the preservation and integration of features learned throughout the block.

Transition Layers in DenseNet play a crucial role in managing feature map complexity and size. They generally include a 1x1 convolution, which decreases the number of feature maps and simplifies the model, along with a pooling operation such as 2x2 average pooling with a stride of 2, which downscales the spatial dimensions of the feature maps. By performing these functions, Transition Layers effectively balance the model's complexity and computational requirements between Dense Blocks, ensuring efficient processing and feature management throughout the network. Global Average Pooling Layer reduces each feature map to a single value by averaging the values across the feature map, which minimizes the parameters and mitigates overfitting. Fully Connected Layer processes the pooled features through a set of fully connected neurons to generate the final classification output. Finally, the softmax function is employed to convert the output into probabilities for different classes, facilitating multi-class classification.

3.2. Models for Comparison

3.2.1 DenseNet-101

DenseNet-101 is a type of convolutional neural network (CNN) known for its dense connectivity pattern [17]. Unlike traditional CNNs, where each layer has its own inputs from the previous layer and outputs to the next layer, DenseNet-101 connects every layer to every other layer in a feed-forward fashion. This design enhances the flow of information and gradients throughout the network, which helps in reducing the vanishing gradient problem, improving feature reuse, and increasing model efficiency. DenseNet-101, specifically, refers to a version of DenseNet with 101 layers, striking a balance between depth and computational efficiency, making it well-suited for various computer vision tasks such as image classification and detection.

3.2.2. ResNet-50

ResNet-50, is a convolutional neural network (CNN) model with a 50-layer deep architecture [6]. Its vital feature is the use of residual blocks, which effectively address the vanishing gradient issue found in deep neural networks. These blocks connect activations from earlier layers to later ones, skipping some layers and allowing gradients to flow more smoothly, which aids in training deeper networks. ResNet-50's architecture comprises convolution layers for initial feature extraction, convolution blocks for higher-level feature refinement with normalization and activation functions, and fully connected layers for making final predictions.

Trained on extensive datasets like ImageNet, ResNet-50 excels in visual recognition tasks, standing out for its robustness and efficiency in deep learning applications.

3.2.3. EfficientNet-B0

EfficientNet-B0 introduces a unique compound scaling method that adjusts the network's depth, width, and resolution in a balanced manner, boosting both accuracy and efficiency [14]. Utilizing the Mobile Inverted Bottleneck MBConv structure with squeeze-and-excitation enhancements, EfficientNet-B0, though the smallest in its family, achieves remarkable performance. It sets new benchmarks for accuracy on datasets like ImageNet while maintaining computational efficiency, redefining standards for scalable and efficient deep learning models.

3.2.4. EfficientNet-B1

EfficientNet-B1 enhances the EfficientNet-B0 model by utilizing compound scaling, which adjusts the network's depth, width, and resolution for better accuracy and efficiency [15]. Featuring the Mobile Inverted Bottleneck MBConv architecture with squeeze-and-excitation optimization, EfficientNet-B1 delivers superior performance while being computationally efficient. This makes it an excellent choice for image recognition tasks and establishes new benchmarks in deep learning model scalability and performance.

4. EXPERIMENTAL SETUP

All experiments were performed using the with Intel® Core system i7-8550U CPU @ 1.99 GHz processor, NVIDIA® GeForceMX130 graphics card and 8 GB RAM. Experiments were conducted using a Python-based deep learning framework Keras with Tensorflow as the back end in Google Colab with GPU support.

4.1 Dataset

A public dataset of 852 chest X-Ray images have been identified from the limited publicly available data sources [9]. It contains 426 positive cases and 426 negative cases of Covid-19. These images are organized into subdirectories for two classes of COVID-19 positive and negative. This data is used for the experimentation of DenseNet-169 and other selected models. The images are preprocessed Viz., normalized and augmented before training. From the chest X-ray dataset split, 80% of images are designated for training purposes, and 20% are set aside for testing.

4.2 Training and Optimization

During training process, weights are initialized with the Glorot-uniform weight initializer. Adam Optimizer is selected due to its adaptive learning rate, which facilitates faster convergence. The parameter values set in Adam optimizer are learning rate - 0.001, batch size - 8, beta1 value 0.9 and beta2 value 0.999. The model has been trained for 50 epochs. If the epochs are increased further, training loss decreases, but validation loss increases.

Proper selection of loss function is essential for an efficient model. So. Binary cross-entropy is employed as the loss function, appropriate for binary classification. During training, the model adjusts its weights based on the loss function and optimizer to minimize prediction errors. Following each epoch, the performance of the model is assessed on the validation set to observe its generalization to unseen data.

For the evaluation of the machine learning model, 5 - fold cross-validation is adopted.

4.3 Performance Evaluation

After training, the model's performance is evaluated as follows. The plots of training and validation accuracy and loss provide a visual representation of the model's performance across epochs, which helps in identifying any issues like over fitting or under fitting.

The performance of the model is validated using metrics including accuracy, F1-score, recall and precision [18] to find out whether it correctly classify positive cases. Let TP represent the total count of true positive pixels, TN the total count of true negative pixels, FN the total count of false negative pixels, and FP the total count of false positive pixels. The mathematic expression of the performance metrics for evaluation of various Covid-19 classification models is shown in table 1.

Table 1. Performance Metrics for the evaluation of Various Covid-19 Classification models

Performance Metric
$Accuracy = \frac{TP+TN}{TN+FN+TP+FP}$
$Precision = \frac{\lvert TP\rvert}{\lvert TP\rvert+\lvert FP\rvert}$
$Recall = Sensitivity = \frac{\lvert TP\rvert}{\lvert TP\rvert+\lvert FN\rvert}$
$F - score = \frac{2*Precision*Recall}{Precision+Recall}$

5. *RESULTS AND DISCUSSION*

For the performance analysis of the DenseNet-169 model in classifying COVID-19, chest X-Ray images were used. To assess its performance in comparison to other deep learning architectures, we evaluated DenseNet-169 against ResNet-101, ResNet-50, EfficientNetB0, and EfficientNetB1. The performance curve of DenseNet169 is given in figure 3. The average values of performance metrics obtained is given in Table 2. DenseNet-169 model achieved an accuracy rate of 89%, F1-score of 89% Precision value of 79% and Recall value of 91%. This high accuracy and F1-score values reflects the model's effectiveness in distinguishing between positive and negative COVID-19 cases. Accuracy can be further improved by expanding the training dataset with additional images and by increasing the number of training epochs. If the number of epochs is increased while using a smaller training dataset, the model may risk overfitting. Thus, it is evident that DenseNet-169 demonstrated superior performance over these models, indicating its advanced capability in feature extraction and accurate classification. This outcome highlights the model's significant potential in medical imaging and COVID-19 detection. Future work could explore incorporating additional data sources or using ensemble methods to enhance accuracy even further.

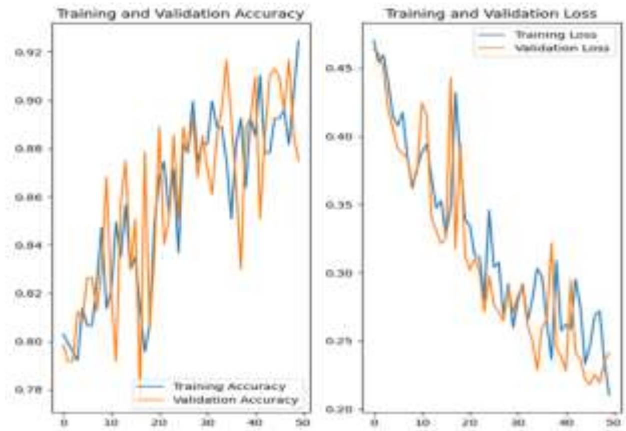

Fig 3. Performance Curve of DenseNet169

Table2. Performance Comparison of DenseNet-169 with various deep learning models for Covid-19 detection

Model	Accuracy	Precision	Recall	F1-Score
DenseNet-169	0.89	0.79	0.91	0.89
DesNet-101	0.81	0.76	0.90	0.88
ResNet-50	0.81	0.79	0.80	0.89
EfficientNet-B0	0.80	0.78	0.83	0.88
EfficientNet-B1	0.78	0.79	0.89	0.88

6. CONCLUSION

In recent years, deep learning has advanced significantly beyond traditional machine learning algorithms, playing a pivotal role in automating various aspects of our daily lives. This article demonstrated the effectiveness of DenseNet-169 model in detecting COVID-19 from X-Ray images. The performance is evaluated by comparing with popular deep learning algorithms, including ResNet-50, ResNet-101, EfficientNet-B0, and EfficientNet-B1. Extensive experimentation of the above models revealed that DenseNet-169 has superior performance in accurately identifying COVID-19 cases. These results indicate that deep learning techniques, can significantly enhance early detection and diagnosis, aiding in timely medical intervention and treatment. To enhance the robustness and generalizability of deep learning models for COVID-19 detection, future efforts should emphasize on increasing the dataset to include a diverse range of X-ray images from various demographics, age groups, and stages of the disease. Integrating these images with other clinical data, such as patient symptoms, lab results, and medical history, will improve diagnostic accuracy and provide a more comprehensive understanding of patient conditions. Additionally, real-time deployment of these models in clinical settings, including integration with hospital systems and portable X-ray machines, will enable rapid and precise on-site diagnoses, significantly improving healthcare response times and patient outcomes and also need to look into more advanced deep learning techniques that can effectively handle complicated health care data.

Conflicts of interest. The authors Shereena V B and Hajarommabi P A declare that they have no conflicts of interest.

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Ethical approval. All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent. Informed consent was obtained from all individual participants included in the study.

REFERENCES

[1] World Health Organization. Weekly epidemiological update on COVID-19—29 June 2021, 46th edn. https://www.who.int/publications/m/item/weekly-epidemiological-update-on-covid-19-20-july-2021.

[2] Dumakude A, Ezugwu AE. Automated COVID-19 detection with convolutional neural networks. Scientific Reports [Internet]. 2023 Jun 30 [cited 2024 Apr 6];13(1):10607. Available from: https://www.nature.com/articles/s41598-023-37743-4

[3] 1.Yang D, Martinez C, Visuña L, Khandhar H, Bhatt C, Carretero J. Detection and analysis of COVID-19 in medical images using deep learning techniques. Scientific Reports [Internet]. 2021 Oct 4;11(1):19638. Available from: https://www.nature.com/articles/s41598-021-99015-3

[4] Jain G, Mittal D, Thakur D, Mittal MK. A deep learning approach to detect Covid-19 coronavirus with X-Ray images. Biocybernetics and Biomedical Engineering. 2020

Oct;40(4):1391–405.

[5] Che Azemin MZ, Hassan R, Mohd Tamrin MI, Md Ali MA. COVID-19 Deep Learning Prediction Model Using Publicly Available Radiologist-Adjudicated Chest X-Ray Images as Training Data: Preliminary Findings. International Journal of Biomedical Imaging. 2020 Aug 18;2020:1–7.

[6] Minaee S, Kafieh R, Sonka M, Yazdani S, Jamalipour Soufi G. Deep-COVID: Predicting COVID-19 From Chest X-Ray Images Using Deep Transfer Learning. Medical Image Analysis. 2020 Jul;101794.

[7] Hussain E, Hasan M, Rahman MA, Lee I, Tamanna T, Parvez MZ. CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images. Chaos, Solitons & Fractals. 2020 Nov;110495.

[8] Kumar M, Shakya D, Kurup V, Suksatan W. COVID-19 prediction through X-ray images using transfer learning-based hybrid deep learning approach. Materials Today: Proceedings. 2021 Dec;

[9] Tabik S. COVIDGR dataset and COVID-SDNet methodology for predicting COVID-19 based on Chest X-Ray images. IEEE Journal of Biomedical and Health Informatics. 2020;1–1.

[10] Alghamdi HS, Amoudi G, Elhag S, Saeedi K, Nasser J. Deep Learning Approaches for Detecting COVID-19 From Chest X-Ray Images: A Survey. IEEE Access. 2021;9:20235–54.

[11] Ismael AM, Şengür A. Deep learning approaches for COVID-19 detection based on chest X-ray images. Expert Systems with Applications. 2021 Feb;164:114054.

[12] Mondal S, Agarwal K, Rashid M. Deep Learning Approach for Automatic Classification of X-Ray Images using Convolutional Neural Network. 2019 Nov 1;

[13] Saiz F, Barandiaran I. COVID-19 Detection in Chest X-ray Images using a Deep Learning Approach. International Journal of Interactive Multimedia and Artificial Intelligence. 2020;InPress(InPress):1.

[14] Md. Alamin Talukder, Md. Abu Layek, Kazi M, Md. Ashraf Uddin, Aryal S. Empowering COVID-19 detection: Optimizing performance through fine-tuned EfficientNet deep learning architecture. Computers in Biology and Medicine. 2024 Jan 1;168:107789–9.

[15] Srivastava G, Chauhan A, Jangid M, Chaurasia S. CoviXNet: A novel and efficient deep learning model for detection of COVID-19 using chest X-Ray images. Biomedical Signal Processing and Control. 2022 Sep;78:103848.

[16] Bohmrah MK, Kaur H. Classification of Covid-19 patients using efficient Fine-tuned Deep learning DenseNet Model. Global Transitions Proceedings. 2021 Aug;

[17] Kong L, Cheng J. Classification and detection of COVID-19 X-Ray images based on DenseNet and VGG16 feature fusion. Biomedical Signal Processing and Control. 2022 Aug;77:103772.

[18] Rahman MdA, Sadi MS. IoT Enabled Automated Object Recognition for the Visually Impaired. Computer Methods and Programs in Biomedicine Update. 2021 May;1:100015.