

A Review: Detection of Respiratory Diseases Using CNN

Mrs. Chandra Prabha R¹, Shubham Kulkarni², Akshaya Subrahmanya E³, Devaraj⁴, Akhil M P⁵

¹Assistant Professor, Dept. of Electronics & Communication Engineering, BMS Institute of Technology and Management, Bengaluru, India

^{2,3,4,5}Dept. of Electronics & Communication Engineering, BMS Institute of Technology and Management, Bengaluru, India

ABSTRACT

Convolutional Neural Networks (CNNs) have emerged as powerful tools within medical imaging, offering significant advancements in the detection and diagnosis of respiratory diseases such as COVID-19 and pneumonia. This research paper provides a comprehensive comparison of various studies that utilize CNNs for these purposes. The paper analyzes methodologies, datasets, network architectures, performance metrics, and results across multiple research papers. The aim is to pinpoint the strengths and weaknesses of different approaches, highlight the most effective practices, and deliberate on prospective domains for future investigation. Our discoveries suggest that although CNNs show high accuracy and efficiency in detecting respiratory diseases from medical images, challenges such as data quality, generalizability, and computational requirements remain critical considerations for real-world applications.

Keywords— Convolutional Neural Network (CNN), COVID-19, Deep Learning, InceptionV3, Mobile Net, Pneumonia, ReLU, ResNet50, Softmax

INTRODUCTION

The outbreak of the COVID-19 pandemic has underscored the urgent need for efficient and accurate diagnostic tools. Traditional diagnostic methods, while effective, often face limitations in terms of speed, accessibility, and scalability. In the present context, Convolutional Neural Networks (CNNs) have attracted considerable attention for their potential to revolutionize medical diagnostics, especially in identifying of respiratory diseases like COVID-19 and pneumonia. CNNs, a type of deep learning models, excel at recognizing patterns in visual data, rendering them ideal for analyzing medical images such as chest X-rays.

Recent studies have demonstrated the feasibility of using CNNs to assist for the early detection and diagnosis of respiratory conditions. These models have demonstrated potential in enhancing diagnostic accuracy, reducing the burden on healthcare professionals, and potentially improving outcomes. However, the efficacy of CNNs in medical applications depends on several factors, including the quality and dataset size, the architecture of the neural network, and the robustness during the training process. Research paper aims to compare various research efforts that employ CNNs for detecting COVID-19 and pneumonia. By systematically reviewing and synthesizing findings from multiple studies, the paper seeks to provide an overall view of the current state of CNN applications in the field of medical image evaluation. The research will also explore different methodological approaches, evaluate their performance, and discuss the practical implications of deploying these models in clinical settings. Ultimately, our goal is to identify best practices and find the areas where additional research is required to overcome existing challenges and enhance the use of CNNs in respiratory disease diagnosis.

DEEP LEARNING

Deep learning, a branch of machine learning, utilizes multi-layered neural networks to analyze extensive datasets and uncover complex patterns. This technique, which emulates human decision-making processes, has transformed fields such as image recognition, speech processing, and autonomous driving. In contrast to conventional methods, deep learning excels in managing unstructured data, enabling more detailed and sophisticated interpretations. With the continuous growth of computational resources, deep learning is set to revolutionize technology and provide profound insights across various industries.

A. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are advanced deep learning models tailored for analyzing grid-structured data types like images. By employing convolutional and pooling layers, CNNs can efficiently extract hierarchical features, identifying spatial patterns and relationships. This capability allows them to excel in functions such as image classification, object detection, and semantic segmentation, as they can recognize edges, textures, and shapes. Because of their effectiveness and widespread adoption, CNNs are pivotal in various modern artificial intelligence applications, including healthcare diagnostics and autonomous vehicles.

B. MobileNet

MobileNet is specifically engineered for mobile and embedded vision applications where computational resources are constrained. It achieves efficiency through employing depthwise separable convolutions, which break down the standard convolution into a depthwise convolution followed by a pointwise convolution. This approach drastically reduces the parameter count and computations needed while still maintaining competitive accuracy. The general architecture of MobileNet is illustrated in Figure 1.

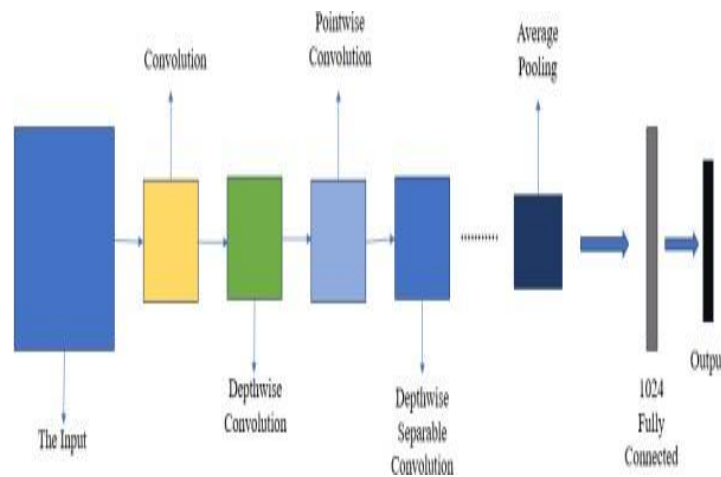


Figure 1 General Architecture of MobileNet

C. InceptionV3

Inception modules, also known as GoogleNet, were created to improve the computational efficiency of CNNs by incorporating various kernel sizes within a single layer. The primary innovation of Inception modules lies in their parallel convolutional pathways, which utilize different kernel sizes to capture features at multiple scales effectively. The general architecture of InceptionV3 is depicted in Figure 2.

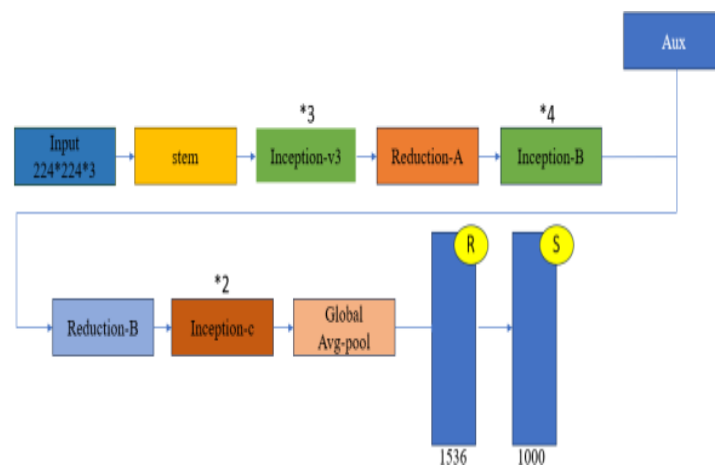


Figure 2 General Architecture of InceptionV3

D. ResNet50

ResNet50 introduced residual learning to tackle the challenge of vanishing gradients in deep neural networks. It achieves this by incorporating skip connections or shortcuts, which facilitate the direct flow of gradients during training. This design allows for the effective training of very deep networks, extending to hundreds of layers. The general architecture of ResNet50 is illustrated in Figure 3.

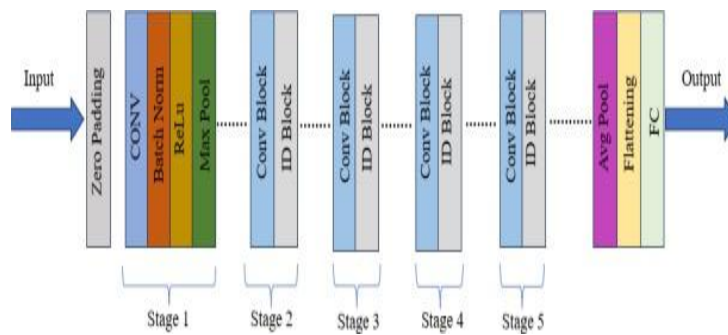


Figure 3 General Architecture of ResNet50

LITERATURE REVIEW

The study by M. M. R. Khan *et al.* explores the application of deep neural networks (DNNs) for the automated identification of COVID-19 in chest X-ray images. Six DNN models were evaluated, with ResNet-50 exhibiting the highest performance, achieving a classification accuracy of 96.91%. The dataset comprises 2905 chest radiographs categorized into COVID-19 affected, Viral Pneumonia affected, and Normal cases. Methodology involves analyzing performances of DNNs through transfer learning to fine-tune pre-trained models. Tools utilized include Python with Keras on TensorFlow backend, operating on an NVIDIA GeForce RTX 2080Ti GPU supported by stochastic gradient descent (SGD) optimizer. Architectures evaluated include ResNet-50, InceptionResNetV2, InceptionV3, DenseNet201, and MobileNetV2. ResNet-50 demonstrated superior performance, followed closely by DenseNet201 and MobileNetV2. Recommendations for further enhancement include dataset expansion, hyperparameter fine-tuning, exploration of ensemble methods, and continuous validation on new data. [1]

F. Marwa and M. Machhout developed a real-time CNN- based application to detect COVID-19 from chest X-rays. Using Rmsprop and SGD with momentum, their model achieved 99.22% accuracy, 99.65% specificity, and 99.45% sensitivity. The dataset, containing 12,056 images from Kaggle and GitHub, was augmented with rotation, scaling, and noise. Split into training, validation, and test sets, it supports comprehensive evaluation. The CNN, with 23 layers, conducts feature extraction and classification, optimized for CPU and GPU processing. Evaluation metrics include accuracy, specificity, sensitivity, and cross-entropy curves. Recommendations for improvement include advanced augmentation, hyperparameter tuning, and transfer learning for better generalization. [2]

The research paper by Nafisah *et al.* (2023) uses the COVID-QU-Ex dataset, consisting of 21,165 chest X-ray images (10,192 healthy, 7,357 viral pneumonia, and 3,616 COVID-19). The methodology involves preprocessing the images, segmenting the regions of interest using a UNet model, and applying rotation augmentation. The study compares the efficiency of CNN models (like EfficientNetB7) and Vision Transformers (like SegFormer) in detecting COVID-19. Findings suggest that EfficientNetB7 achieved the highest accuracy at 99.82%, with both CNN and ViT models performing comparably well. [3]

The study by M. Shorfuzzaman, M. Masud, H. Alhumyani,

D. Anand, and A. Singh presents the development of a deep learning framework for automatic detecting of COVID-19 from chest X-ray images, comparing various convolutional neural network (CNN) architectures and fusion techniques. The study focuses on ResNet50V2, addressing data scarcity challenges and emphasizing model interpretation and clinical validation. Data consists of labeled chest radiographs representing COVID-19, bacterial pneumonia, viral pneumonia, and healthy cases. Methodology involves data collection, model selection (ResNet50V2, VGG-16, InceptionV3), transfer learning, fusion framework development, evaluation, and model interpretation using techniques like Grad-CAM. Results show promising metrics for the fusion model, with accuracy (95.4%), sensitivity (99.1%), specificity (98.2%), AUC (95.4%), and F1-score (98.0%). Comparison with existing studies validates the fusion model's effectiveness, and visualization aids model interpretation. Recommendations for enhancement include Dataset expansion, incorporation of metadata for disease stage identification, cross-dataset validation, collaboration with domain experts, and integration of multimodal data for improved prediction accuracy. [4]

This study by J. Kodi, J. B. V. Siva, S. N. Sai, A. Raju, D. Reddy, and P. K. Bhanu explores AI's role in detecting COVID-19 from chest X-ray images and disease spread forecasting. It trains CNN models (ResNet50, VGG19, MobileNet) for detection and logistic regression, Prophet, and SEIRD models for forecasting. ResNet50 demonstrates superior accuracy in detection (98.5%), while SEIRD excels in forecasting (96.43%). The study emphasizes AI's crucial support in healthcare decision-making during the pandemic. Future research may focus on model optimization and integration for enhanced effectiveness. Tools include Python, TensorFlow, Keras, PyTorch, Scikit-learn, and Prophet.

Results underscore AI's potential in disease management, urging continued advancements in AI technologies for efficient pandemic response. [5]

The study by M. K. Delimayanti, A. Mardiyono, B. Warsuta, E. S. Puspitaningrum, R. F. Naryanto, and A. Naryaningsih outlines the implementation of a CNN for COVID-19 screening via X-ray images, covering data preprocessing, CNN architecture, and performance evaluation. The study achieves high accuracy, sensitivity, specificity, and precision in identifying cases of COVID-19 cases. It advocates for further exploration of deep learning methods to enhance diagnostic accuracy in COVID-19 detection. Chest radiographs obtained from Kaggle, including normal and COVID-19 cases, are utilized for training and evaluating the CNN model. Preprocessing involves lung area separation and Gaussian filtering. The CNN architecture, based on VGG-16, is implemented using TensorFlow, Matplotlib, Numpy, and Keras. Performance metrics assess model effectiveness. CNN model attains 98.13% accuracy, 98.79% precision, 87.76% sensitivity, and 98.9% specificity in classifying X-ray images. [6]

The study by M. K. Delimayanti, A. Mardiyono, B. Warsuta, E. S. Puspitaningrum, R. F. Naryanto, and A. Naryaningsih introduces the MNRSC model for detecting COVID-19 from chest X-ray images, addressing challenges in diagnosis. It combines MobileNet with residual separable convolution blocks for enhanced feature extraction and classification. Evaluation on COVID5K and COVIDRD datasets shows high accuracy and sensitivity, especially on balanced datasets like COVIDRD. Comparative analyses with state-of-the-art models validate its effectiveness, with compatibility demonstrated on low-scale devices. The methodology involves CNNs, TensorFlow or PyTorch frameworks, and preprocessing techniques. Results indicate excellent performance across diverse datasets and input sizes, promising efficient COVID-19 detection. However, challenges like detecting disoriented images and handling imbalanced datasets remain. The study indicates potential avenues for future research for improving model robustness and clinical utility in COVID-19 diagnosis. [7]

The study by A. Sharma, A. Kodipalli and T. Rao compares the performance of ResNet-16 and Inception-V4 convolutional neural networks in identifying COVID-19 from X-ray radiographs. Inception-V4 exhibits superior accuracy, approximately 83%, attributed to its deeper architecture compared to ResNet-16. The urgency for accurate diagnostic tools amid the pandemic underscores the significance of machine learning in symptom identification. Utilizing Python and TensorFlow, the models undergo transfer learning using pre-trained weights on ImageNet, alongside data augmentation techniques for enhanced generalization. The results highlight Inception-V4's potential for swift and accurate virus identification, crucial for effective containment measures. While showcasing the promising role of deep learning architectures in COVID-19 diagnosis, further evaluation with additional metrics and larger datasets is warranted for comprehensive insights into their performance and applicability in healthcare settings. [8]

The study by P. M, S. Sreekumar, and A. S compares the effectiveness of Convolutional Neural Networks (CNN) and ResNet-50 models in identifying COVID-19 in chest X-ray images. Methodologies involve pre-processing, segmentation, and model training, with assessment based on metrics such as accuracy, precision, recall, and F1-score. Both models achieve a 96% accuracy, with ResNet-50 slightly outperforming in real-world tests. The dataset includes COVID-19 positive and negative chest X-ray images, pre-processed and segmented using U-Net. TensorFlow and OpenCV are utilized for implementation, with Python as the primary language. Results demonstrate promising performance for both models, highlighting their potential in automated COVID-19 detection. Future research may focus on enhancing CNN architectures and expanding dataset sizes for improved accuracy and reliability. The study underscores the importance of deep learning architectures in medical imaging analysis for disease diagnosis. [9]

The study by X. Cai, Y. Wang, X. Sun, W. Liu, Y. Tang, and W. Li evaluates ResNet-18, ResNet-34, and ResNet-50 for COVID-19 diagnosis using CT scans. With 3227 CT scans, including 1601 COVID-19 positive and 1626 negative cases, models were trained and tested. ResNet-34 exhibited the best performance, with precision (0.971), accuracy (0.943), F1-score (0.942), sensitivity (0.914), specificity (0.973), and AUC (0.985) on the testing set. Implementation utilized PyTorch on a GTX 1060 6G GPU, with Grad-CMA for model analysis. ResNet-34's superior performance suggests its potential as a backbone network for medical tasks, despite ResNet-18's lightweight nature. However, concerns regarding dataset size and model computational complexity warrant further research for improved model robustness and mobile device suitability in COVID-19 screening. [10]

This study by Y. Khurana and U. Soni explores the efficacy of the Inception ResNet-v2 architecture in detecting COVID-19 from chest X-rays. By employing transfer learning and fine-tuning pre-trained weights, the model achieved an impressive accuracy of 0.966, demonstrating its potential for rapid and efficient screening. Despite running for only 29 epochs, the results underscore the efficacy of artificial intelligence, specifically deep learning, in disease diagnosis. The methodology involved leveraging Python, TensorFlow or PyTorch, and standard data preprocessing techniques to formulate a robust classification model. Promising outcomes suggest the utility of AI as a supplementary tool in medical diagnosis, particularly during pandemics like COVID-19. However, further validation and testing are essential to guarantee the model's reliability in clinical settings, emphasizing the necessity for continual research and refinement. [11]

This paper by M. Soni, A. K. Singh, K. S. Babu, S. Kumar, A. Kumar, and S. Singh explores CT scans image segmentation for COVID-19 detection using CNN models, highlighting the significance of computer-aided diagnosis systems. It presents a CNN-based approach with Adam and Adadelta optimizers, achieving impressive accuracies of 99.54% for training and 99.65% for validation, surpassing existing results. The dataset comprises 160 CT scans images, including lung masks and infection masks, divided into training, testing, and validation sets. Implementation leverages TensorFlow, Keras, and Python libraries on Linux OS with GPU acceleration. Results demonstrate high accuracy (99.65%) on the test dataset and low mean squared error (MSE), indicating precise COVID-19 region identification. While specific IOU values aren't provided, model performance is compared with U-Net and SegNet architectures. Recommendations for enhancement include incorporating diverse datasets, fine-tuning hyperparameters, and exploring ensemble learning techniques or advanced architectures like attention mechanisms. [12]

The study by M. K. Jalehi and B. M. Albaker compares the efficacy of four pre-trained CNN models—ResNet50V2, NASNetMobile, MobileNetV2, and EfficientNetB0—in detecting COVID-19 from chest X-rays using six public datasets. Images were resized, normalized, and augmented to enhance training and reduce overfitting. ResNet50V2 achieved the highest level of accuracy of 96.6%, highlighting the importance of dataset size, preprocessing, and model selection. The study highlights the potential of ResNet50V2 in clinical diagnostics, emphasizing the necessity for careful dataset preparation and overfitting mitigation to enhance the robustness and reliability of AI-based COVID-19 detection tools. [14]

This study by N. Ilma Progga, M. Shahadat Hossain, and K. Andersson presents a modified MobileNet architecture for diagnosing COVID-19 and pneumonia from chest radiographs, addressing limitations of traditional testing methods. Using a balanced dataset of 3,990 images split into training (3,192), validation (399), and testing (399) sets, images were resized to 128x128 pixels. The modified MobileNet employs depthwise separable convolutions for efficiency, global max-pooling, LeakyReLU activation, a fully connected layer, and dropout to prevent overfitting. Achieving high classification accuracy, this approach showcases superior performance and computational efficiency, highlighting its potential for swift and precise clinical diagnosis of COVID-19 and pneumonia. [15] The research by A. K. A. Raheem, M. Zuhair, and Hajer. A.

A. Ameri employs a deep transfer learning approach to diagnose COVID-19 utilizing chest radiographs, utilizing VGG-16, VGG-19, and MobileNetV2 models enhanced by adaptive histogram equalization for image preprocessing. The dataset includes 219 COVID-19, 400 viral pneumonia, and 400 normal images, augmented to 2038 images. VGG-16 achieved the highest accuracy at 98.75%, followed by VGG-19 at 97% and MobileNetV2 at 92.65%. Tools like MATLAB, TensorFlow, and Keras were used for preprocessing and model training. The paper underscores the possibilities of transfer learning and image enhancement in improving diagnostic accuracy for COVID-19 from chest X-rays. [16]

This study by K. Jahnavi, N. S. Sandeep, R. Deepika, V. S. Josthna Battu, R. Anitha, and K. B. Prakash explores COVID-19 detection and forecasting using models of machine learning. ResNet50, VGG19, and MobileNet were used for detection, achieving accuracies of 98.5%, 97.68%, and 93.94% respectively. For forecasting, Prophet, logistic regression, and SEIRD models were employed, with SEIRD achieving 96.43% accuracy, Prophet 94.57%, and logistic regression 72.34%. The dataset includes 285 chest X-rays (90 COVID, 100 normal, 95 viral pneumonia), split into 178 training and 107 testing images. Tools used include TensorFlow, Keras, and Tableau. The study underscores the potential of deep learning and statistical models in healthcare, recommending further research for enhanced accuracy. [17]

The study by S. Saha, R. Bhadra, and S. Kar utilizes the Inception v3 to detect COVID-19 from chest X-rays and CT scans, attaining high accuracy, precision, recall, and F1-scores. Using datasets from IEEE 802.3 and UCSD-AI4H, images were preprocessed and augmented. The Inception v3 model, fine-tuned on medical images, demonstrated over 95% accuracy in distinguishing COVID-19 cases from other conditions. The study emphasizes the potential of AI in medical imaging diagnostics, suggesting deep learning algorithms are capable of enhance diagnostic accuracy and support radiologists in identifying COVID-19 swiftly. [18]

DISCUSSION

The literature review highlights a diverse range of studies exploring utilizing deep neural networks (DNNs) and convolutional neural networks (CNNs) for the automated identification of COVID-19 from chest X-ray images. Notably, Khan et al. evaluated six DNN models, with ResNet-50 achieving the highest accuracy of 96.91% on a dataset comprising 2905 images categorized into COVID-19, viral pneumonia, and normal cases. This study employed transfer learning to fine-tune pre-trained models using Python and Keras on a Tensor Flow backend, with ResNet-50 outperforming other architectures such as DenseNet201 and MobileNetV2. Similarly, Marwa and Machhout developed a real-time CNN-based application attaining a level of accuracy of 99.22%, utilizing a dataset of 12,056 images and employing advanced augmentation techniques for comprehensive evaluation.

Several studies focus on comparing different CNN architectures and methodologies to optimize COVID-19 detection. Nafisah et al. used the COVID-QU-Ex dataset containing 21,165 images and compared CNN models like EfficientNetB7 and Vision Transformers such as SegFormer. Their results showed EfficientNetB7 achieving the utmost accuracy of 99.82%, demonstrating the capacity of both CNN and Vision Transformer models in COVID-19 detection. Shorfuzzaman et al. compared various CNN architectures and fusion techniques, highlighting ResNet50V2 for its high performance in a fusion framework, achieving metrics like 95.4% accuracy and 99.1% sensitivity. These studies underscore the importance of careful dataset preparation, model selection, and preprocessing in improving the accuracy and robustness of AI models for medical diagnostics.

Moreover, other research emphasizes the incorporation of AI into clinical settings and the continuous improvement of diagnostic models. Kodi et al. trained CNN models (ResNet50, VGG19, MobileNet) for COVID-19 detection and used logistic regression and SEIRD models for forecasting, with ResNet50 demonstrating superior detection accuracy (98.5%). Delimayanti et al. proposed a CNN-based approach achieving high accuracy and specificity in detecting COVID-19 cases from Kaggle datasets, suggesting further investigation into deep learning methodologies. The studies collectively recommend enhancements such as dataset expansion, hyperparameter fine-tuning, advanced augmentation techniques, and continuous validation on new data to improve model performance and reliability in real-world clinical applications. This comprehensive review highlights the significant advancements and ongoing efforts in utilizing AI for effective COVID-19 diagnosis as well as the necessity for further research to refine these technologies for better healthcare outcomes.

CONCLUSION

The conclusion drawn from the reviewed studies underscores the substantial progress and potential of deep learning architectures in diagnosing COVID-19 from chest X-ray images. The findings consistently demonstrate that models such as ResNet-50, EfficientNetB7, and Vision Transformers achieve high accuracy, sensitivity, and specificity, underscoring their effectiveness in medical diagnostics. The superior performance of these models, particularly ResNet-50, which achieved an accuracy of 96.91%, and EfficientNetB7 with 99.82%, highlights the importance of selecting appropriate model architectures and employing advanced preprocessing and augmentation techniques to enhance detection accuracy.

Despite these promising results, the studies emphasize the necessity for further research to address existing challenges and improve model robustness. Recommendations include expanding datasets to ensure diversity and representativeness, fine-tuning hyperparameters for optimized performance, and exploring ensemble methods for better generalization. Continuous validation incorporating fresh data is vital for maintain the models' relevance and reliability in real-world clinical settings. Subsequent studies should also prioritize integrating multimodal data and collaborating with domain experts to refine AI models, ensuring their clinical applicability and effectiveness in supporting healthcare decision-making during pandemics like COVID-19.

REFERENCES

- [1]. M. M. R. Khan et al., "Automatic Detection of COVID-19 Disease in Chest X-Ray Images using Deep Neural Networks," in 2020 IEEE 8th R10 Humanitarian Technology Conference (R10-HTC), Kuching, Malaysia: IEEE, Dec. 2020, pp. 1–6. doi: 10.1109/R10-HTC49770.2020.9357034.
- [2]. F. Marwa and M. Machhout, "Real-Time Application for Covid-19 Class Detection based CNN Architecture," Aug. 2021. doi: 10.1109/DTS52014.2021.9498055.
- [3]. S. I. Nafisah, G. Muhammad, M. S. Hossain, and S. A. AlQahtani, "A Comparative Evaluation between Convolutional Neural Networks and Vision Transformers for COVID-19 Detection," *Mathematics*, vol. 11, no. 6, Art. no. 6, Jan. 2023, doi: 10.3390/math11061489.
- [4]. M. Shorfuzzaman, M. Masud, H. Alhumyani, D. Anand, and A. Singh, "Artificial Neural Network-Based Deep Learning Model for COVID-19 Patient Detection Using X-Ray Chest Images," *Journal of Healthcare Engineering*, vol. 2021, p. e5513679, Jun. 2021, doi: 10.1155/2021/5513679.
- [5]. J. Kodi, J. B. V. Siva, S. N. Sai, A. Raju, D. Reddy, and P. K. Bhanu, "Detection of COVID-19 using ResNet50, VGG19, MobileNet, and Forecasting; using Logistic Regression, Prophet, and SEIRD Model," *IEEE Conference Proceedings*, vol. 2023, no. ICCMC, pp. 1538–1542, 2023.
- [6]. M. K. Delimayanti, A. Mardiyono, B. Warsuta, E. S. Puspitaningrum,
- [7]. R. F. Naryanto, and A. Naryaningsih, "Implementation of Convolutional Neural Network for COVID19 Screening using X-Rays Images," in 2023 International Conference on Computer Science, Information Technology and Engineering (ICCoSITE), Feb. 2023, pp. 398–403. doi: 10.1109/ICCoSITE57641.2023.10127845.
- [8]. V. S. K. Tangudu, J. Kakarla, and I. B. Venkateswarlu, "COVID-19 detection from chest x-ray using MobileNet and residual separable convolution block," *Soft Comput*, vol. 26, no. 5, pp. 2197–2208, Mar. 2022, doi: 10.1007/s00500-021-06579-3.
- [9]. A. Sharma, A. Kodipalli, and T. Rao, "Performance of Resnet-16 and Inception-V4 Architecture to Identify

- Covid-19 from X-Ray Images,” in 2022 IEEE 9th Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON), Dec. 2022, pp. 1–6. doi: 10.1109/UPCON56432.2022.9986372.
- [10]. P. M, S. Sreekumar, and A. S, “Detection of Covid-19 from the Chest X-Ray Images: A Comparison Study between CNN and Resnet-50,” in 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), Oct. 2022, pp. 1–7. doi: 10.1109/MysuruCon55714.2022.9972488.
- [11]. X. Cai, Y. Wang, X. Sun, W. Liu, Y. Tang, and W. Li, “Comparing the performance of ResNets on COVID-19 diagnosis using CT scans,” in 2020 International Conference on Computer, Information and Telecommunication Systems (CITS), Oct. 2020, pp. 1–4. doi: 10.1109/CITS49457.2020.9232574.
- [12]. Y. Khurana and U. Soni, “Leveraging deep learning for COVID-19 diagnosis through chest imaging,” *Neural Comput & Applic*, vol. 34, no. 16, pp. 14003–14012, Aug. 2022, doi: 10.1007/s00521-022-07250-0.
- [13]. M. Soni, A. K. Singh, K. S. Babu, S. Kumar, A. kumar, and S. singh, “Convolutional neural network based CT scan classification method for COVID-19 test validation,” *Smart Health (Amst)*, vol. 25, p. 100296, Sep. 2022, doi: 10.1016/j.smhl.2022.100296.
- [14]. L. Di Biasi, F. De Marco, A. Auriemma Citarella, M. Castrillón- Santana, P. Barra, and G. Tortora, “Refactoring and performance analysis of the main CNN architectures: using false negative rate minimization to solve the clinical images melanoma detection problem,” *BMC Bioinformatics*, vol. 24, no. 1, p. 386, Oct. 2023, doi: 10.1186/s12859-023-05516-5.
- [15]. M. K. Jalehi and B. M. Albaker, “A Comparison of Different Chest X-ray Datasets with Fast Pre-Trained CNN Models in the Detection of Covid-19 Infection,” in 2022 2nd International Conference on Advances in Engineering Science and Technology (AEST), Oct. 2022, pp. 769–773. doi: 10.1109/AEST55805.2022.10413022.
- [16]. N. Ilma Progga, M. Shahadat Hossain, and K. Andersson, “A Deep Transfer Learning Approach to Diagnose Covid-19 using X-ray Images,” in 2020 IEEE International Women in Engineering (WIE) Conference on Electrical and Computer Engineering (WIECON- ECE), Dec. 2020, pp. 177–182. doi: 10.1109/WIECON-ECE52138.2020.9398037.
- [17]. A. K. A. Raheem, M. Zuhair, and Hajer. A. A. Ameri, “COVID-19 Detection Based on Chest X-Rays and CT Scans Using Inception v3 Deep Learning Algorithm,” in 2023 International Conference on Engineering, Science and Advanced Technology (ICESAT), Jun. 2023, pp. 47–51. doi: 10.1109/ICESAT58213.2023.10347317.
- [18]. K. Jahnvi, N. S. Sandeep, R. Deepika, V. S. Josthna Battu, R. Anitha, and K. B. Prakash, “Detection of COVID-19 using ResNet50, VGG19, MobileNet, and Forecasting; using Logistic Regression,
- [19]. Prophet, and SEIRD Model,” in 2023 7th International Conference on Computing Methodologies and Communication (ICCMC), Feb. 2023, pp. 1538–1542. doi: 10.1109/ICCMC56507.2023.10083564.
- [20]. S. Saha, R. Bhadra, and S. Kar, “Diagnosis of COVID-19 & Pneumonia from Chest x-ray Scans using Modified MobileNet Architecture,” in 2021 IEEE Mysore Sub Section International Conference (MysuruCon), Oct. 2021, pp. 793–798. doi: 10.1109/MysuruCon52639.2021.9641739.