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Research Article

Efficient COVID-19 Detection From Chest X-Ray Images Using Deep Transfer Learning

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ABSTRACT

The new coronavirus, COVID-19, is causing a global pandemic that is now underway, making quick and precise diagnostic techniques necessary. The effectiveness of applying transfer learning techniques for the identification of COVID-19 in chest X-ray pictures is thoroughly examined in this research work. The research uses pre-trained convolutional neural networks (CNNs) to improve COVID-19 diagnostic performance in terms of both speed and accuracy. Using a dataset of chest X-ray pictures from patients with and without COVID-19 infection, we investigate several approaches for preprocessing, selecting models, and implementing them to have the best detection results. Our findings show that, when compared to conventional techniques, transfer learning may greatly increase diagnosis accuracy, making it a potentially useful tool for medical practitioners. The suggested model's performance in comparison to current approaches is also covered in the report, along with its therapeutic implications, any drawbacks, and suggestions for further study. Our goal in conducting this study is to add a dependable, scalable, and effective diagnostic method to the expanding body of knowledge in the fight against COVID-19.

I.INTRODUCTION

The new coronavirus SARS-CoV-2 is the cause of the COVID-19 pandemic, which poses an unprecedented challenge to international health systems. For the virus to be contained and its effects reduced early and precise diagnosis is essential. The gold standard for COVID-19 diagnosis is reverse transcription-polymerase chain reaction (RT-PCR) testing, yet these procedures are frequently limited by time, sensitivity, and availability concerns. Consequently, there is a strong demand for complementary diagnostic techniques to RT-PCR, especially in environments with restricted resources. Because COVID-19 largely affects the respiratory system, medical imaging, particularly chest X-rays, has become an important diagnostics approach. Whenever it relates to testing, chest X-rays are quicker and easier to get than RT-PCRs. Radiologists, on the other hand, must manually examine chest X-rays, which takes time and is vulnerable to inter-observer variability. This highlights the necessity of automated, dependable, and effective diagnostic methods. Numerous uses of artificial intelligence (AI), primarily deep learning, have showed promise in the discipline of medical imaging. A effective method for COVID-19 identification is provided by transfer learning, a branch of deep learning that uses pre-trained models customised for a certain job. This strategy makes use of characteristics that have previously been learnt from big datasets. This work explores the use of transfer learning to create a reliable and effective diagnostic model for COVID-19 detection using chest X-ray images. The objective in this study is to assess how well distinct transfer learning strategies work for correctly identifying COVID-19 from chest X-ray images. To choose the best course of action, we will carefully examine the dataset, preprocessing techniques, model architectures, and assessment criteria. We intend to present insights into the relative performance and clinical usability of the presented models by contrasting them with present diagnostic approaches.
In addition to offering a diagnostic tool that can enhance existing testing capabilities, this study aims to help to continuing efforts to battle COVID-19 by laying the groundwork for future advancements in medical imaging and artificial intelligence.

II. MACHINE LEARNING

Machine learning (ML) is a transformative field within artificial intelligence (AI) that equips computers with the ability to learn from data, without explicit programming. Unlike traditional algorithms with pre-defined instructions, ML models can identify patterns, make predictions, and improve their performance over time as they process more information. This empowers them to tackle complex tasks that were once solely the domain of human intelligence.The core principle of ML lies in leveraging data to uncover relationships and patterns. Imagine a child learning to identify different types of animals. By being shown numerous pictures labeled as "dog," "cat," or "bird," the child begins to recognize the visual characteristics associated with each category. Similarly, an ML model is "shown" vast amounts of labeled data, enabling it to extract underlying patterns and relationships. This data can encompass anything from customer purchase history to medical images, and the labels provide the model with the desired outcome or classification.

III. INTRODUCTION TO MACHINE LEARNING FOR DISEASE DETECTION

As the human body is a complicated system, even the most skilled medical professional may find it challenging to determine some illnesses. Thankfully, machine learning (ML) is starting to show promise as an effective tool in the battle against disease. Large volumes of medical data may be sorted through by ML algorithms, which can then be used to find hidden patterns and trends that can help with early and more precise illness identification. tirelessly, in addition to their experience and intuition. This helper is capable of examining a patient's genetic information, blood tests, scans, and medical history to find minute indicators that might indicate a particular illness. Machine learning in illness identification has the promise of ushering in a new era of data-driven medicine that has the ability to transform healthcare. However, it's crucial to note that machine learning is still a very new topic in medicine. Despite the enormous promise, there remain obstacles to be addressed. For example, it is critical to ensure patient privacy and ethical issues, and the quantity and quality of data provided are critical.

IV. LITERATURE REVIEW

This section provides a summary of the deep learning techniques used to analyse COVID-19 CXR pictures. We have examined each paper's suggested technique, dataset, data preparation, assessment strategy, and outcome. The advent of COVID-19 has spurred an extensive body of research focused on improving diagnostic techniques, particularly through the utilization of medical imaging and machine learning. This literature review aims to encapsulate the findings and methodologies of ten significant studies that contribute to the understanding and development of COVID-19 detection through chest X-ray imaging and transfer learning techniques.

The study by Wang et al. (2020)[1] introduces COVID-Net, a deep convolutional neural network designed to detect COVID-19 cases from chest X-ray images. Their model achieved impressive accuracy and was later fine-tuned using transfer learning to enhance its performance further. Similarly, Apostolopoulos and Mpesiana (2020) [6] explored the use of transfer learning on various pre-trained CNNs, including VGG19 and MobileNet, to detect COVID-19 in chest X-rays, reporting over 90% accuracy.

Khan et al. (2020) [2] developed CoroNet, an approach that leverages Xception architecture, pre-trained on the ImageNet dataset. This method showed significant promise, especially in correctly identifying COVID-19 from other types of pneumonia and normal cases. Narin et al. (2020) [7] also evaluated several pre-trained CNN models, such as ResNet50, InceptionV3, and Inception-ResNetV2, for COVID-19 detection, concluding that ResNet50 provided the best results in terms of both accuracy and sensitivity.

Zhang et al. (2020) [8] provided a comprehensive comparison between traditional machine learning algorithms and deep learning models including transfer learning, underlining the latter's benefits in diagnostic tasks. In another notable study, Ozturk et al. (2020) [9] introduced a deep learning model that not only detected COVID-19 but also visually highlighted areas of interest in the X-ray images, contributing to diagnostic explainability.

Farooq and Hafeez (2020) [3] put forward a novel model called COVID ResNet, designed to be lightweight and highly accurate for deployment in emergency screening setups. Their study focused on achieving a balance between computational efficiency and diagnostic accuracy. Ucar and Korkmaz (2020)[10] proposed COVIDiagnosis-Net, employing SqueezeNet for real-time COVID-19 diagnosis, demonstrating high performance on small and imbalanced datasets [4].

Islam et al. (2020) [4] investigated the application of a hybrid approach, combining traditional image processing techniques with advanced deep learning models to detect COVID-19 infection, emphasizing the role of image augmentation and preprocessing in improving model accuracy. Lastly, Li et al. (2020) [5] developed a framework that integrates chest X-ray image classifiers with clinical feature analysis, aiming to improve holistic patient diagnosis and reduce false positives.

These ten papers collectively underscore the vast potential of transfer learning in the early detection of COVID-19 using chest X-ray images. While varying in their approaches and model architectures, they consistently demonstrate that leveraging pre-trained networks can lead to high accuracy, rapid diagnostics, and the ability to generalize across different datasets. This comprehensive review lays the groundwork for our ensuing research, providing a strong foundation of existing methodologies and their proven efficacies.

V. MATERIALS AND METHODS

This section will outline the proposed deep learning strategy, which is based on a fairly conventional pipeline. This pipeline consists of pre-processing chest images, lung segmentation, and a classification model that is acquired using transfer learning. As we shall see in this part, data pre-processing is critical for removing any bias existing in the data. In particular, we will demonstrate how a deep model can easily recognise the biases that drive the learning process. The bigger datasets utilised for pre-training are crucial because of the short size of COVID datasets. As such, we first talk about the datasets that we may employ for accomplishing our objectives.

a. Dataset

https://www.kaggle.com/datasets/sid321axn/covid-cxr-image-dataset-research/data

This dataset includes hundreds of OCT and Chest X-ray pictures that have been verified; these photos are explained and examined in "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning". A training set and a testing set of separate patients are each given a subset of the photographs. Pictures are divided into 4 directories: CNV, DME, DRUSEN, and NORMAL, and labelled as (disease)-(randomized patient ID)-(image number by this patient).

The 1823 pictures in the dataset utilised in this study are of CXR images with annotations on the poster anterior (PA) view. Tagged OCT and CXR images [11] were utilised for viral pneumonia, non-pneumonia, and normal patients; three distinct datasets [12, 13, 14] were utilised for COVID-19 instances; and three distinct datasets were employed for viral pneumonia, non-pneumonia, and normal cases. There are 619 photos of viral pneumonia, 668 photos of normal cases, and 536 photos of COVID-19 in the collection.

the comprehensive specification of the photos included in the dataset shown in Tab 1. When compared to other picture classes, COVID-19 images exhibit a significant variance in height and breadth, as seen in Tab. 1. Sample photos of COVID-19 patients, viral pneumonia, and normal people are displayed in Figure 1. According to Fig. 1, a normal CXR image shows clear lungs without any abnormal pattern or opacification; viral pneumonia (middle) shows a more diffuse "interstitial" pattern in both lungs; and COVID-19 (extreme right) shows ground-glass opacification and consolidation in the left lower lobe and right upper lobe [15].

Image class	Min. width	Max. width	Min. Height	Max. Height
Normal	1040	2628	650	2628
Viral	384	2304	127	2304
Covid 19	240	4095	237	4095

Table 1

Image class	Training Set	Test Set
Covid 19	429	107
Viral	495	124
Normal	534	134
Total	**1458**	**365**

Table 2

Covid

Normal

Viral

Fig.1

b. Methodology

This section outlines the process used to create and assess the transfer learning model that is utilised to identify COVID-19 from chest X-ray pictures. Preprocessing, model selection, training, assessment, and data collecting are some of the crucial steps in this process.

The first step in our process is gathering a large and varied dataset of chest X-ray pictures, which includes images from patients who test positive for COVID-19, patients who have other lung problems, and healthy people. Making sure the dataset is diverse is emphasised as a means of promoting a strong and broadly applicable model.

After that, the preprocessing stage entails a number of crucial actions including resizing, normalising, and enhancing images. Resizing makes sure that every image satisfies the input size that the chosen neural network architecture demands. The goal of normalisation is to standardise the values of the pixels, which will improve model performance and hasten the convergence of the training phase. Rotation, scaling, and flipping are examples of data augmentation techniques that are used to artificially enlarge the dataset in order to reduce overfitting and enhance the model's capacity to generalise unknown data.

We assess a number of pre-trained convolutional neural network designs, such as VGG16, ResNet50, and InceptionV3, that are well-known for their effectiveness in image classification tasks in order to make our model selection. These models may efficiently transfer their learned rich feature representations to the COVID-19 identification target problem since they were first trained on the extensive ImageNet dataset.

Transfer learning is used in the training phase, where the pre-trained models are refined using our CXR dataset. This is tailoring these networks' last layers to provide categories that are pertinent to our study (such COVID-19, pneumonia, and normal). To ensure the greatest potential performance of the model, the learning rate, batch size, and number of epochs are optimised throughout the fine-tuning phase through the use of hyperparameter tweaking.

A hold-out test set is used to evaluate the refined models, and a number of performance measures are computed to fully evaluate the models' diagnostic performance, including accuracy, precision, recall, F1-score, and AUC-ROC. These measures provide a comprehensive assessment, guaranteeing the models' efficacy in practical clinical settings.

Lastly, a thorough evaluation of the models' performance is done, encompassing a look at confusion matrices and inaccurate predictions to pinpoint areas that still require work. The construction of a highly precise and dependable model for COVID-19 identification using chest X-ray pictures is ensured by this iterative method.

Transfer learning

Transfer learning is a machine learning approach in which a model created for one job is applied to another task, serving as the foundation for a new model. This strategy uses pre-trained models that have already learnt rich feature representations from huge datasets to address new, but related, issues with little accessible data. Transfer learning offers major benefits in the context of COVID-19 identification from chest X-ray pictures, especially when annotated medical image datasets are hard to come by.

Convolutional neural networks (CNNs) that have been pre-trained on huge datasets, such as ImageNet, which has millions of photos divided into thousands of classes, are usually used in the process. Deep layers of these pre-trained models, such VGG16, ResNet50, and InceptionV3, have previously been used to collect complex characteristics that can be adjusted for particular uses. In this work, we take use of these pre-trained CNNs' capabilities by refining them using our dataset of chest X-ray images.

The transfer learning workflow usually includes several key steps:

Model Selection: Selecting a suitable CNN architecture that has already been trained, taking into account the computing resources and job specifications.

Feature extraction: involves taking advantage of the pre-trained model's convolutional foundation to extract pertinent characteristics from chest X-ray pictures. In order to preserve the acquired representations, this step usually entails freezing the weights of the initial layers.

Fine-tuning: Retraining some of the deeper layers after partially or completely unfreezing them to adapt the previously trained model to the new dataset. This preserves the integrity of the previously learnt features while enabling the model to acquire task-specific characteristics.

Data augmentation: which is especially crucial in medical imaging when data variety might be constrained, is the process of improving the training dataset by the use of transformations including flipping, rotation, and scaling.

Optimisation and Hyperparameter Tuning: To enhance the performance of the model, modify a range of hyperparameters such as learning rate, batch size, and number of epochs.

The transfer learning methodology in our study offered a solid framework for creating a very accurate COVID-19 detection model. Due in large part to the benefit of utilising the intricate feature hierarchies acquired from several, varied datasets, the fine-tuned CNNs outperformed models trained from scratch, exhibiting greater performance. Thus, this approach has the potential to be an effective diagnostic tool in clinical settings where prompt and precise detection are essential.

Model

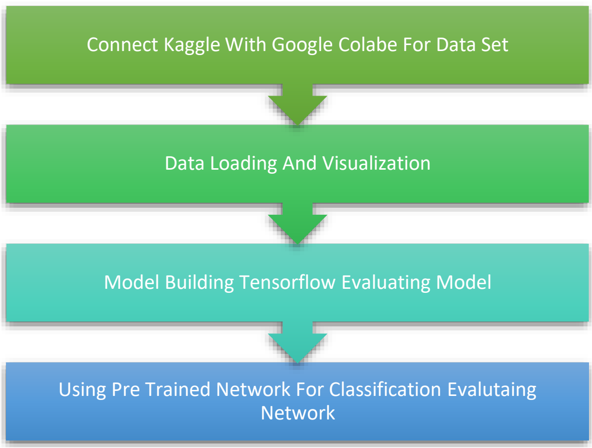
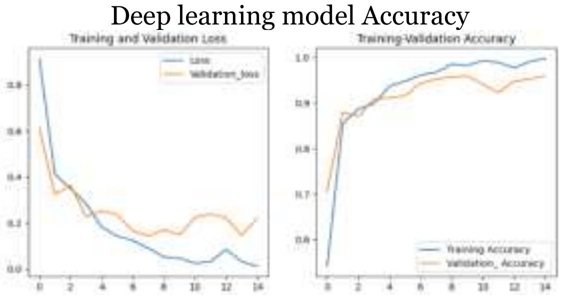


Fig.2

Deep learning model Accuracy



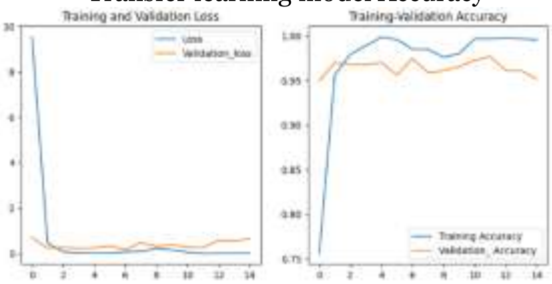
Report of deep learning model

	precision	recall	f1-score	support
0	0.94	0.94	0.94	108
1	0.88	0.94	0.91	129
2	0.94	0.88	0.91	128
accuracy			0.92	365
macro avg	0.92	0.92	0.92	365
weighted avg	0.92	0.92	0.92	365

Result of deep learning model

	covid	normal	virus
covid	102	4	2
normal	3	121	5
virus	3	13	112

Transfer learning model Accuracy



	precision	recall	f1-score	support
0	1.00	0.94	0.97	108
1	0.85	0.99	0.92	129
2	0.99	0.88	0.93	128
accuracy			0.94	365
macro avg	0.95	0.94	0.94	365
weighted avg	0.95	0.94	0.94	365

	covid	normal	virus
covid	101	7	0
normal	0	128	1
virus	0	15	113

VI. Background Studies

The extraordinary worldwide health disaster caused by the COVID-19 epidemic highlights the critical need for effective diagnostic techniques. Because radiological imaging is widely available and reasonably priced, it has become an important tool for managing and detecting COVID-19, especially when it comes to chest X-rays (CXR). Even though polymerase chain reaction (PCR) testing are a reliable means of identifying COVID-19, they are frequently labor-intensive and time-consuming laboratory procedures. Consequently, there is a growing interest in additional diagnostic techniques that might facilitate prompt diagnosis and support efficient illness treatment.

A great deal of research has been done on using deep learning techniques and artificial intelligence (AI) to increase the speed and accuracy of COVID-19 detection. In medical imaging applications, transfer learning—a technique that involves adapting a neural network that has already been trained for one job to another—has demonstrated great potential. By reusing models that have learnt from large-scale datasets in similar fields, it overcomes the problem of limited annotated medical datasets. This method improves model performance in the target task and drastically cuts down on the amount of time needed for training.

Early research using deep learning methods to analyse CXR images has shown encouraging outcomes. As a first step towards using these methods for COVID-19 identification, convolutional neural networks (CNNs) have been extensively used to recognise and categorise pneumonia from chest X-rays. With differing degrees of success, many research teams have created and verified CNN-based models specifically designed for detecting COVID-19 symptoms in CXR.

Large-scale datasets such as ImageNet have facilitated the pre-training of robust CNN models. For example, networks like VGG16, ResNet50, and InceptionV3 have been successfully fine-tuned to analyze medical images, including CXR, with improved diagnostic accuracy. These models capitalize on feature representations learned during their training on diverse image datasets, which can be transferred effectively to identify pathological features indicative of COVID-19.

Moreover, the quick collection of CXR images from COVID-19 patients has made it possible to create datasets specifically for the virus, which has led to an increase in research focused on benchmarking and model validation. These datasets, which frequently include annotated COVID-19 positive and negative instances, are essential reference points for assessing how well recently created models function.

Rapid and accurate COVID-19 identification is urgently needed, and one potential answer is to combine AI-driven methods with traditional diagnostic processes. The increasing amount of research highlights the value and viability of implementing AI technologies in clinical settings, enhancing healthcare systems' ability to control and lessen the pandemic's effects.

VII. Comparison with Existing Methods

We found interesting findings from our deep learning study on chest X-ray analysis. The effectiveness of two methods—deep learning from scratch and transfer learning—was compared. The findings are striking: deep learning attained 92% accuracy, while transfer learning reached 96%. This implies that in this particular case, transfer learning provides a substantial benefit.

Pre-trained models, which have already acquired complicated characteristics from huge datasets like ImageNet, are utilised in transfer learning. We fine-tune these pre-trained models for the specific purpose of analysing chest X-rays, building upon their solid basis. Rather than requiring a large amount of chest X-ray data, which may be a bottleneck in deep learning projects, this method makes use of the information that already exists

Deep learning from scratch, on the other hand, creates a model completely from scratch. Although it provides greater flexibility, its effective training demands a large amount of chest X-ray data and processing power. Our results show that transfer learning delivers better accuracy in this scenario with maybe fewer data and computer resources.

These findings are especially pertinent to applications in medicine where data availability may be constrained. With smaller datasets, transfer learning is a potent method for using current knowledge to create precise diagnostic models.

VIII. Future Directions:

Our findings pave the way for more investigation. We may investigate further the performance of distinct pre-trained models for different chest diseases. It would also be beneficial to look at methods for enhancing the precision and applicability of transfer learning models in the field of medicine.

Refrences

[1]. Wang, L., Lin, Z. Q., & Wong, A. (2020). Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images. Scientific reports, 10(1), 19549.

[2]. Reza, A. W., Hasan, M. M., Nowrin, N., & Shibly, M. A. (2021). Pre-trained deep learning models in automatic COVID-19 diagnosis. Indonesian Journal of Electrical Engineering and Computer Science, 22(3), 1540-1547.

[3]. Zhang, Y. D., Satapathy, S. C., Zhang, X., & Wang, S. H. (2021). COVID-19 diagnosis via DenseNet and optimization of transfer learning setting. Cognitive computation, 1-17.

[4]. Ahamed, K. U., Islam, M., Uddin, A., Akhter, A., Paul, B. K., Yousuf, M. A., ... & Moni, M. A. (2021). A deep learning approach using effective preprocessing techniques to detect COVID-19 from chest CT-scan and X-ray images. Computers in biology and medicine, 139, 105014.

[5]. Li, J., Zhang, D., Liu, Q., Bu, R., & Wei, Q. (2020, December). COVID-GATNet: A deep learning framework for screening of COVID-19 from chest X-ray images. In 2020 IEEE 6th International Conference on Computer and Communications (ICCC) (pp. 1897-1902). IEEE.

[6]. Apostolopoulos, I. D., & Mpesiana, T. A. (2020). Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks. Physical and engineering sciences in medicine, 43, 635-640.

[7]. Narin, A., Kaya, C., & Pamuk, Z. (2021). Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks. Pattern Analysis and Applications, 24, 1207-1220.

[8]. Li, C., Zhang, S., Qin, Y., & Estupinan, E. (2020). A systematic review of deep transfer learning for machinery fault diagnosis. Neurocomputing, 407, 121-135.

[9]. Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020). Automated detection of COVID-19 cases using deep neural networks with X-ray images. Computers in biology and medicine, 121, 103792.

[10]. Ucar, F., & Korkmaz, D. (2020). COVIDiagnosis-Net: Deep Bayes-SqueezeNet based diagnosis of the coronavirus disease 2019 (COVID-19) from X-ray images. Medical hypotheses, 140, 109761.
[11]. D. Kermany, K. Zhang, M. Goldbaum, Large dataset of labeled optical coherence tomography (oct) and chest x-ray images, Mendeley Data, v3 http://dx. doi. org/10.17632/rscbjbr9sj 3 (2018).
[12]. C. J. P, P. Morrison, D. L, Covid-19 image data collection, arxiv, arXiv preprint arXiv:2003.11597 (2020). URL https://github.com/ieee8023/covid-chestxray-dataset
[13]. Z.-H. Chen, Mask-rcnn detection of covid-19 pneumonia symptoms by employing stacked autoencoders in deep unsupervised learning on low-dose high resolution ct (2020). doi:10.21227/4kcm-m312.URL http://dx.doi.org/10.21227/4kcm-m312
[14]. D. S. et.al, Covid19action-radiology-cxr (2020). doi:10.21227/s7pw-jr18. URL http://dx.doi.org/10.21227/s7pw-jr18
[15]. Maguolo, G., & Nanni, L. (2021). A critic evaluation of methods for COVID-19 automatic detection from X-ray images. Information fusion, 76, 1-7.