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Enhancing COVID-19 Patients Detection using Deep Transfer Learning Technique Through X-Ray Chest Images

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ABSTRACT

This study addresses the urgent need for early detection of COVID-19 infection, considering its global impact. COVID-19 is caused by the severe acute respiratory syndrome Coronavirus 2 (SARS-CoV-2) and has affected more than 250 countries. Chest X-rays have been identified as a valuable tool for swift diagnosis of COVID-19 infection. In this research, we propose a composite approach to detect COVID-19 infection in its initial phases using radiographic images of the chest. To leverage existing models effectively, transfer learning is employed. Our model incorporates ensemble learning, combining transfer learning models like Efficient Net, Google Net, and XceptionNet. These models exhibit the ability to differentiate patients as COVID-19 positive, tuberculosis positive, pneumonia positive, or in good health. To evaluate the performance of our proposed model, we utilize two widely adopted datasets. Comparative analysis demonstrates that our technique surpasses current state-of-the-art models, as indicated by various performance measures.

1. Introduction

The outbreak of COVID-19, officially acknowledged by the World Health Organization (WHO) in April 2020 [1], has had significant global ramifications due to its highly transmissible nature and rapid spread. The disease caused by the SARS-CoV-2 virus is characterized by symptoms such as cough, fever, shortness of breath, and acute respiratory distress [3]. Early detection and diagnosis of COVID-19 cases are crucial for effective control of its spread and timely treatment, especially considering the absence of a medical cure [4].

In the field of medical imaging, re-searchers have explored various techniques, including chest X-rays and CT scans, for the early diagnosis and assessment of COVID-19 severity [5]. Chest X-rays are particularly favoured due to their cost-effectiveness, wider availability in hospitals, and portability in intensive care units and field hospitals [6]. Deep learning models, renowned for their success in classifying different diseases [7], including respiratory distress and pneumonia, have also been applied to classify COVID-19 from X-ray images. However, the limited availability of COVID-19 X-ray

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images compared to other diseases presents a challenge in developing effective detection techniques [9]. To overcome this challenge, researchers have pro-posed multiple techniques utilizing available data and employing models such as CNN Darknet, VGG19, MobileNet v2, Inception, and XceptionNet [10]. However, achieving better feature extraction, sufficient training data, and accurate differentiation of classes necessitate large and properly labelled datasets [11]. Medical data, including COVID-19 cases, often face limitations, imbalances, and generalization errors [12]. To address these issues, transfer learning has emerged as a valuable technique. By utilizing pre-existing models trained on extensive datasets with well-defined categories, transfer learning enables enhanced speed and precision in the classification process. Integrating transfer learning into the proposed ensemble model can facilitate the accelerated identification of potential COVID-19 cases through early diagnosis [13].

This study recognizes the urgent need for early detection of COVID-19, acknowledges the challenges posed by the limited availability of COVID-19 X-ray images, highlights the potential of deep learning models for accurate classification, emphasizes the importance of properly labeled and large datasets, and underscores the advantages of transfer learning in achieving faster and more precise results.

1.1 Related work

In 2020, Dadário and colleagues proposed a novel deep learning model that utilized a three-dimensional approach for diagnosing COVID-19. The effectiveness of the model was evaluated using 4356 chest CT scans. The experimental results showed higher sensitivity and specificity in detecting COVID-19 infection [14]. Apostolopoulos and Mpesiana conducted a study, where they developed a medical image classification algorithm using transfer learning and compared its effectiveness to other CNN-based systems. They utilized two datasets: one with 1428 X-ray images containing 225 confirmed COVID-19 cases, and another with 1442 X-ray images containing 224 confirmed COVID-19 cases. This advantageously provided a relatively large number of COVID-19 cases for training and evaluation, enabling a more comprehensive analysis of the deep transfer learning technique's performance in detecting COVID-19 patients using X-ray chest images. However, a potential disadvantage of these datasets was the relatively small number of confirmed COVID-19 cases compared to the total number of X-ray images, which could affect the model's accuracy in classifying COVID-19 patients [15].

In the same year, Singh *et al.,* proposed a system that utilized a CNN to classify chest computed tomography (CT) images and identify COVID-19 infections. They adjusted the initial parameters of the CNN using differential evolution and reported an impressive accuracy rate of 98.24% for the proposed model [16]. Wang *et al.,* developed a deep CNN model employing projection-expansion-projection (PEP) patterns to detect COVID-19. They used a large dataset of 13,975 chest X-ray images from 13,870 patients, combining five different public datasets to create a dataset specifically for COVID-19. The system achieved an accuracy of 93.3% in classifying cases and a sensitivity of 91% [17]. Shan *et al*., conducted research on segmenting regions affected by COVID-19 using a VB-Net model based on deep learning techniques. Their investigation demonstrated the commendable performance of the VB-Net model in identifying regions affected by COVID-19 [18]. Ozturk *et al.,* introduced a CNN model with automatic capabilities for the identification of COVID-19. They conducted experiments on multiclass classification datasets, including COVID-19, No-Findings, and Pneumonia. The study utilized the YOLO architecture with a DarkNet classifier, consisting of 17 convolutional layers. The DarkNet model showcased remarkable performance in the initial screening of patients [19].

1.2 Background

In this study, a robust ensemble model has been developed by integrating three transfer learning techniques: EfficientNet, XceptionNet, and GoogLeNet. This ensemble approach aims to improve outcomes and reduce errors. To enhance diagnostic accuracy, the proposed approach utilizes convolutional neural networks, pre-trained models for ensemble learning, and transfer learning methods.

1.2.1 Transfer learning

The main objective of transfer learning is to improve the performance of target learners in specific domains by leveraging knowledge obtained from related but different source domains [20]. This knowledge transfer allows for a reduction in the need for a large amount of data from the target domain when constructing target learners [21]. However, in the field of medical imaging, acquiring a substantial dataset can be particularly challenging, and this challenge is further amplified when dealing with COVID-19 data, which is scarce [23]. Consequently, obtaining satisfactory results with deep models becomes difficult. Deep learning models heavily rely on large datasets for effective training, and when working with limited datasets, these models can be prone to overfitting. To overcome these challenges, transfer learning models come into play [24]. Transfer learning utilizes pre-trained models that have already been trained on extensive image datasets. By leveraging these pre-trained models, knowledge from the source domain can be transferred to the target domain, even when limited or no sample data is available. This approach not only addresses the challenge of data training but also helps in reducing the costs associated with building new model [25].

1.2.2 Convolutional neural networks (CNN)

Convolutional neural network (CNN) models have proven to perform remarkably well in a variety of fields, including agriculture, business, and disease diagnosis. The CNN architecture draws inspiration from the visual cortex system in humans. It encompasses three primary layers: the convolution layer, pooling layer, and fully connected layer, as shown in Figure 1 above. The convolution and pooling layers play a crucial role in the learning process of the model, while the fully connected layer is responsible for classification [26].

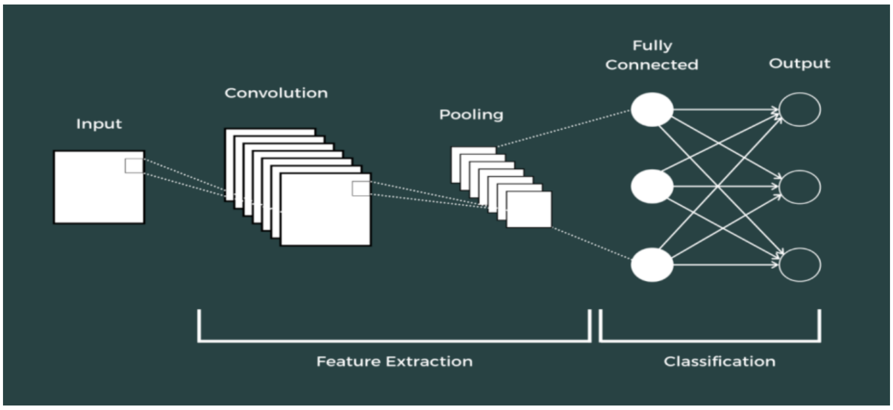

Fig. 1. Convolutional Neural Networks Architecture [27]

1.2.3 Google Net

The GoogleNet architecture is a deep neural network comprising 22 layers, including 27 pooling layers. It incorporates nine inception modules stacked linearly, with the ends of these modules connected to the global average pooling layer. This architecture allows for flexibility in selecting filter sizes within each module, enabling feature extraction at different scales from input layers of varying sizes (e.g., 1 × 1, 3 × 3, and 5 × 5). The output of the convolution kernels in these modules is then passed to the subsequent layers. The design of GoogleNet addresses challenges such as overfitting and gradient vanishing [27]. It achieves this through the creation of three groups of inception modules, with each group having its own objective function. This approach enhances the network's ability to effectively classify images. In summary, Google Net’s structure, with its stacked inception modules and flexible filter selection, enables efficient feature extraction at multiple scales, making it a powerful architecture for image classification tasks. Figure 2 despite of google net architecture [28].

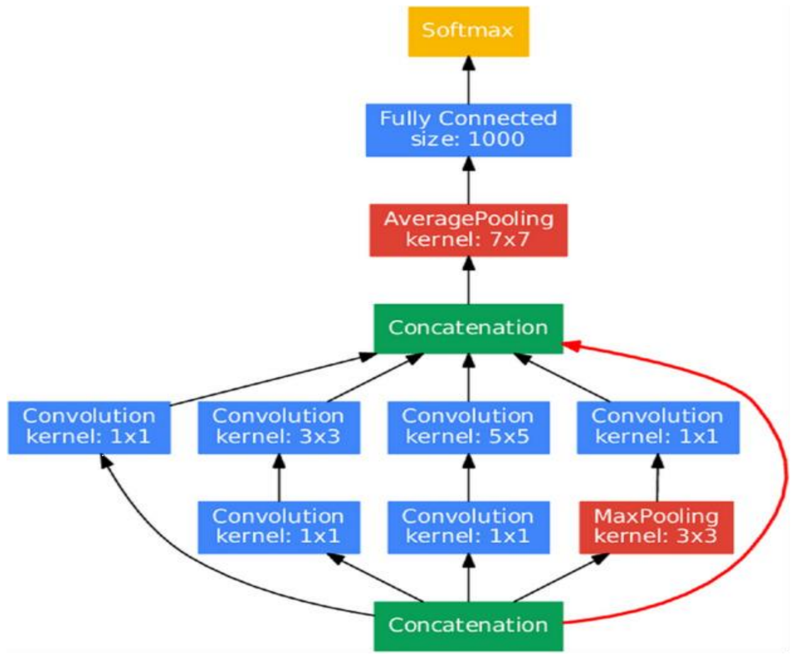

Fig. 2. GoogleNet Architecture [29]

1.2.4 EfficientNet

EfficientNet, developed by Tan and Le in 2019, was specifically designed to overcome the scalability challenges faced by convolutional neural networks (CNNs). Traditional approaches to improving accuracy in CNNs involve scaling up the width and depth of the network, which often leads to longer training and testing times. However, EfficientNet introduces a novel compound scaling method that addresses this issue. The compound scaling method employed by EfficientNet involves scaling the network dimensions in a fixed ratio, encompassing both width-wise and depth-wise scaling. Additionally, the resolution of the network is also increased. This scaling approach, as depicted in Figure 3, results in superior performance and accuracy [30].

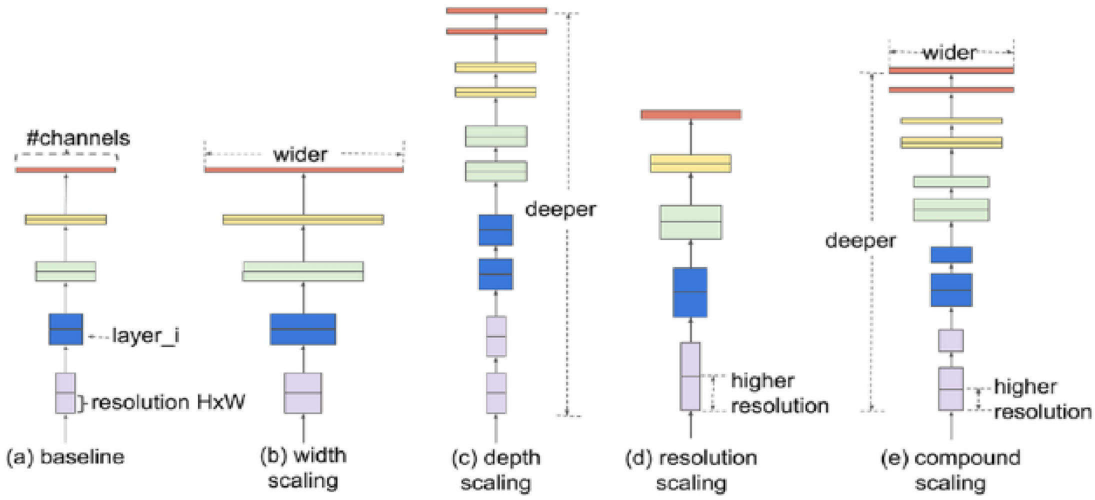

Fig. 3. The structure of the EfficientNet model that has been pre-trained [31]

1.2.5 Xception

Xception, introduced by Chollet in 2017, is an advanced deep convolutional neural network (CNN) that builds upon the Inception architecture. It enhances the inception concept by incorporating unique inception layers. The construction of these inception layers involves the utilization of depth-wise convolutions followed by point-wise convolutions [32]. This architecture is illustrated in Figure 4.

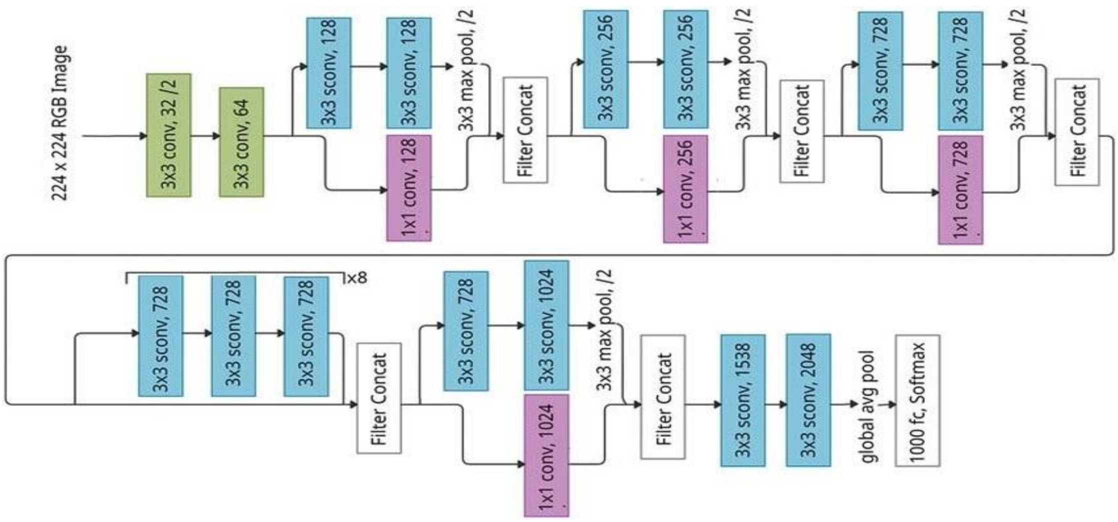

Fig. 4. The Architectural Design of The Pre-Trained Xception Deep CNN Model [32]

1.2.6 Ensemble learning

Ensemble learning is a powerful approach that enhances the accuracy and generalization of predictive models by combining multiple deep learning models. It effectively reduces errors and strengthens the overall performance. Two common methods are employed to generate base classifiers in ensemble learning. The first method involves utilizing different learning algorithms on the same dataset, creating a heterogeneous classifier. The second method employs the same learning algorithm on different datasets, resulting in a homogeneous classifier. By leveraging diverse methods, ensemble learning aims to mitigate overfitting issues and achieve optimal results. In the context of classification tasks, the final outcome is determined collectively by aggregating the decisions from multiple models using a voting mechanism [33].

2. Methodology

The methodology for developing the suggested ensemble model, which aims to classify suspected COVID-19 cases, is outlined in this section. The flow of the work is visually depicted in Figure 5. The MBConv block, an inverted residual block found in Mobile-NetV2, was used in the development of this model, along with the squeeze and excite blocks on occasion. The proposed model was designed following a series of steps, which are not explicitly stated in this section. However, the inclusion of the MBConv block and the squeeze and excite block were likely crucial steps in the development of the model, as they have been shown to be effective in other related models.

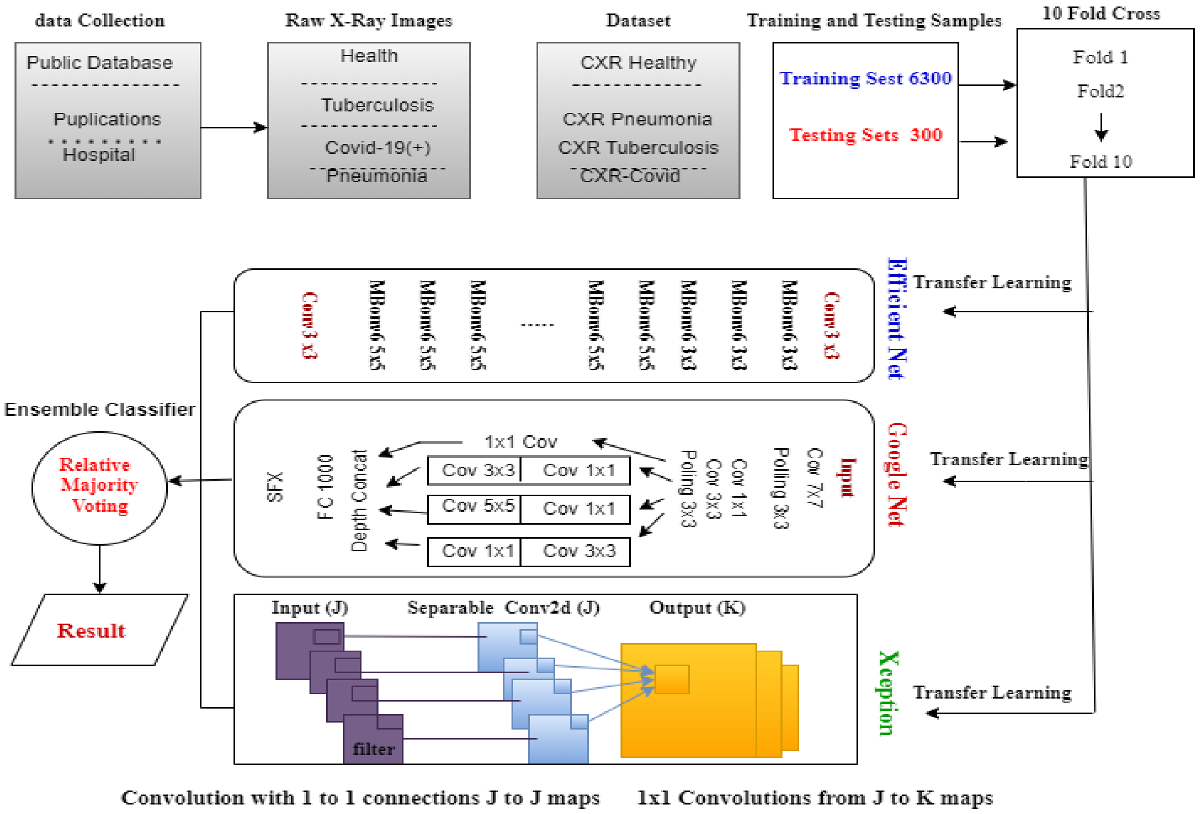

Fig. 5. The Suggested Ensemble Model

i. **Step 1:** First, load the multiclass classification dataset.

ii. **Step 2:** Four subsets were created from the chest x-ray image datasets: CXR-[Healthy, Tuberculosis, Pneumonia, and COVID], with respective sizes of 2400, 2350, 2375, and 2175. Combine these subsets into CXR-Sample: [Healthy, Tuberculosis, COVID, and Pneumonia].

iii. **Step 3:** To generate training and testing sets, perform ten-fold crossover on the CXR-Sample dataset. Utilize a partition algorithm to divide each subset into ten equal segments, creating a 10-fold Cross-SampleSet. This ensures a uniform distribution across subsets and facilitates the training and testing process. The resulting sets are referred to as CXR-Sample-Training-Set and CXR-Sample-Testing-Set: [CXR-Sample] =10-Cross [CXR-Sample] (Training-Set, Testing-Set).

iv. **Step 4:** Leverage pre-trained models (SM-EN, SM-GN, and SM-Xception) to train the network and produce distinct classifiers:
SM-EN corresponds to EfficientNet utilizing the softmax function.
SM-GN represents GoogLeNet with the softmax function, and
SM-Xception denotes Xception also using the softmax function.

v. **Step 5:** Train the classifiers for each individual SM-EN, SM-GN, and SM-Xception) using the CXR-Sample-Training Set as follows:
SM-EN=Train(SM-EN,CXR-Sample-Training-Set).
SM-GN=Train(SM-GN,CXR-Sample-Training-Set).
SM-Xception=Train(SM-Xception,CXR-Sample-Training-Set).

vi. **Step 6:** Combine the three classifiers (SM-EN, SM-GN, and SM-Xception) through ensemble learning and employ relative voting to obtain the final classifier, Ensemble-EM. The SM models (SM-EN, SM-GN, and SM-Xception) are utilized for this purpose. The sample size, CXR-Sample, is 9300 and is divided into four subsets based on the type of analysis discussed earlier.
Where*, Ensemble_EX =Ensemble (SM-EN, SM-GN, SM-EN, SM-Xception).*

3. Results and Discussions

To assess the effectiveness of the proposed model, it is evaluated against different transfer learning technique including, ResNet152V2, VGG16, and InceptionResNetV2. Detailed information about the dataset employed and a comparative analysis of these models are presented in the preceding section.

3.1 Dataset

In the study, two widely recognized datasets were utilized. Dataset 1 was acquired from Kaggle's dataset resource, specifically from Roma Gianchandani. It comprises X-ray images of individuals diagnosed with tuberculosis, pneumonia, COVID19 (+), and COVID19 (-) conditions. COVID (+) and COVID (-) images from dataset 1 were specifically chosen for the purpose of binary classification. Dataset 2, referred to as "CXR Sample," encompasses a total of 9300 images collected from diverse sources including, Qatar University, Mporas and P. Naronglerdrit, and University of Dhaka (Chowdhury 2020). Based on the image type, the dataset is partitioned into four subsets: CXR-Pneumonia, CXR-Healthy, CXR-Tuberculosis, and CXR_COVID. Each subset contains the following number of images: 2400, 2350, 2375, and 2175, respectively. Dataset 2 was utilized for performing multiclass classification. Figure 6 depicts sample images from both datasets 1 and dataset 2.

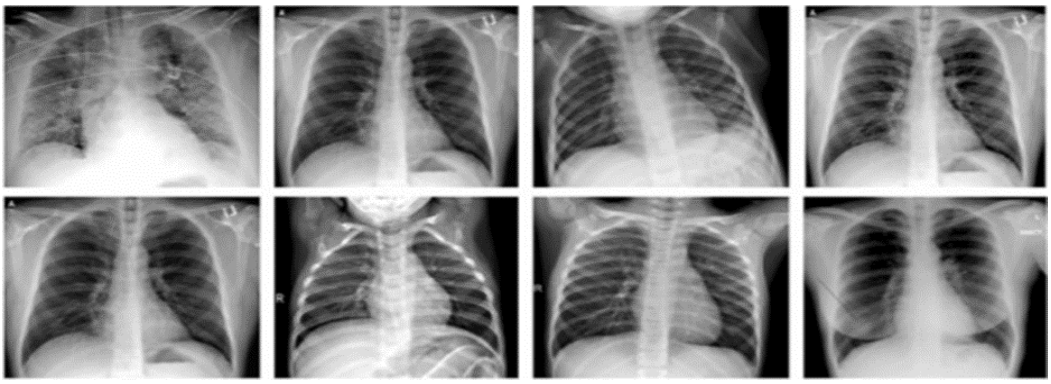

Fig. 6. Reviewing a dataset suitable for multiclass classification [34]

3.2 Data Preparation and Preprocessing

X-ray image resize of 224x224 pixel with RGB colour channels. To overcome the limited availability of data, we utilize transfer learning. This means we reuse pre-trained models that have been trained on larger datasets. Data augmentation helps improve the overall performance of a neural network by enhancing its ability to handle various types of data. When a neural network has millions of parameters, it benefits from having data in a balanced and proportional manner. Data augmentation techniques like horizontal and vertical flipping, slanted transformations, and 45-degree rotations are applied to expand the dataset. These augmented datasets are used for training and even during the validation phase to ensure the model's accuracy is tested with diverse inputs.

To improve the speed and effectiveness of network training, as well as to ensure the data falls within a specific range (0 to 1), image normalization is performed. This process helps the neural network converge more efficiently. To normalize the images, they are divided by 255. This step ensures that the pixel values fall within the range of 0 to 1. Additionally, Dataset is partitioned into three segments: Training, Validation, and Testing. Approximately, 15% of the original datasets is allocated specifically for testing, and (85%) remaining of the dataset, 17% is allocated for validation, while the majority, which is 68%, is dedicated to training the model. The larger portion is used for training because this is where the model learns and assigns weights based on the provided data. Even small changes in the proportions of training data can lead to varying results.

3.3 Experimental Analysis
3.3.1 Experimentation: Four-class classification

In order to assess the effectiveness of the proposed model, quantitative metrics were utilized and obtained from a confusion matrix. These metrics include accuracy, precision, recall, and f1-Score. These measures provide insights into how well the model performs in terms of its overall accuracy, ability to correctly identify positive instances, ability to capture all relevant instances, and the balance between precision and recall. A comparison was conducted between the suggest model (our model) and other renowned models including InceptionResNetV2, ResNet152V2, DenseNet201, and VGG16. We were able to assess the performance of the model in comparison to these competitive alternatives. Table 1 presents the performance of InceptionResNetV2 and other existing models. Among the four models, ResNet152V2 achieves the highest accuracy of 98.15%.

However, the proposed model surpasses all the pre-trained models with an impressive accuracy of 99.32These results indicate that, the proposed technique not only outperforms the current state-of-the-art techniques but also demonstrates remarkable adaptability, surpassing expectations in terms of generalization. The training process of the proposed technique takes approximately 7.4733 seconds, while the testing phase only requires 1.4343 seconds. The high precision values obtained for each class indicate, these findings suggest the proposed technique can effectively categorize other diseases associated to the chest with accuracy and efficiency. Furthermore, the exceptional validity of the suggested model is reinforced by its impressive performance in terms of macro average, f-measure, recall, and precision. Specifically, the model achieves remarkable values of 99.40% for f-measure, 99.22% for macro average precision, and 99.20% for recall. The proposed model showcases outstanding performance in contrast to existing models, showcasing enhanced generalization capabilities, swift processing times, and exceptional accuracy when classifying diverse chest-related diseases.

3.3.2 Experimentation: Tow-class classification

The base models took approximately 10 minutes to train. VGG16 and ResNet152V2 demonstrated the highest levels of accuracy for binary classification. Given the significance of COVID-19, there is a necessity to enhance the sensitivity and precision scores. Therefore, for multiclass diagnosis, an ensemble model is introduced. The proposed model exhibited superior performance compared to the base models, achieving an accuracy of 96.15%, which is approximately 1.2% higher.

Furthermore, the proposed model attained a precision value of 0.95, signifying the ac-curacy of the predicted results. These findings demonstrate that the proposed model maintains a high specificity rate, ensuring minimal false-positive pre-dictions. The elevated specificity of the system enhances its reliability, thereby assisting the healthcare system in accurately allocating testing kits to individuals who truly require them. This reliability ensures the appropriate utilization of resources, benefiting those in genuine need.

Table 1
Presents an in-depth analysis of the findings along with performance evaluation for the suggested model on 4 Class dataset

Technique	Type of Class	Precision	F-measure	Recall	Accuracy
ResNet 152v2	Normal	0.9736	0.9733	0.9722	0.984
	Pneumonia	0.9791	0.9721	0.9744	0.975
	Tuberculosis	0.9782	0.9744	0.9725	0.980
	COVID-19	0.9832	0.9791	0.9756	0.985
	[Macro average]	0.9784	0.9755	0.9734	0.981
VGG 16	Normal	0.9738	0.9838	0.9754	0.9763
	Pneumonia	0.9747	0.9856	0.9783	0.9751
	Tuberculosis	0.9728	0.9812	0.9792	0.9782
	COVID-19	0.9723	0.9754	0.9811	0.9856
	[Macro average]	0.9737	0.9816	0.9781	0.9790
DenseNet201	Normal	0.9858	0.9788	0.9862	0.9721
	Pneumonia	0.9727	0.9867	0.9762	0.9871
	Tuberculosis	0.9818	0.9786	0.9771	0.9772
	COVID-19	0.9851	0.9734	0.9723	0.9763
	[Macro average]	0.9813	0.9796	0.9780	0.9781
Inception Resnetv2	Normal	0.9749	0.9737	0.9832	0.9833
	Pneumonia	0.9757	0.9769	0.9726	0.9732
	Tuberculosis	0.9844	0.9732	0.9754	0.9782
	COVID-19	0.7365	0.9727	0.9721	0.9830
	[Macro average]	0.9851	0.9744	0.9752	0.9791
Proposed Ensemble (VGG16 + DenseNet)	Normal	0.9913	0.9951	0.9942	0.9922
	Pneumonia	0.9898	0.9922	0.9923	0.990
	Tuberculosis	0.9912	0.9922	0.9912	0.992
	COVID-19	0.9899	0.9912	0.9899	0.9910
	Macro average	0.9922	0.9932	0.9920	0.9940

3.4 An Examination of Comparative Analysis

According to the experimental results, the suggested model offers a remarkably effective and affordable solution for identifying COVID-19 through the analysis of chest X-ray images. Table 3 showcases the performance of both techniques and the proposed technique. The limited availability of training data often leads to models that struggle to generalize effectively. To address this challenge, tuberculosis infected cases were incorporated into our datasets, in addition to distinguishing between normal, COVID-19 positive, and pneumonia cases. Two datasets were employed to evaluate the performance of the proposed technique. Impressively, the model achieved remarkable accuracy rates, reaching 99.23% for multiclass classification and an impressive 98.96% for binary classification. This innovative model has recently surfaced as a notable advancement that holds great potential for health officials in addressing the urgent need for early COVID-19 detection.

Table 2
Advanced Techniques Performance Comparison: classification of binary and multi class

Technique	Author(s)	Year	Accuracy	
			Binary-class	Multi class
XceptionNet	Rahimzadeh and Attar [35]	2020	85%	92%
Inception	Szegedy, Christian [36]	2017	96.7%	92%
MobileNet v2	Howard, Andrew G [37]	2017	96.5%	94%
VGG19	Simonyan and Zisserman [38]	2014	98.12%	93%
Darknet	Tulin Ozturk [20]	2020	98.2%	87%
Proposed Model			98.96	99.23%

In this critical scenario, it can effectively aid in the prompt diagnosis of COVID-19 cases. Looking ahead, our envisioned future for this research involves broadening the horizons of our proposed work. It aims to extend its capabilities beyond merely detecting the presence of COVID-19 to also encompass predicting the level of risk and assessing the chances of survival for individuals who test positive for COVID-19. The inclusion of this additional functionality would prove immensely valuable for medical practitioners, enabling them to efficiently manage and plan the healthcare needs of infected patients.

Table 1
Specify the initial VGG-16 model established by Simonyan and Zisserman in 2014

Model	Integral of the curve	Precision	F-measure	Recall	Accuracy
ResNet 152v2	0.9765	0.9720	0.9740	0.9724	0.9778
VGG16	0.9744	0.9767	0.9740	0.9729	0.9778
DesNet201	0.9744	0.9767	0.9790	0.9757	0.9778
InceptionResNetV2	0.9765	0.9740	0.9740	0.9726	0.9778
Proposed Ensemble	0.9894	0.9950	0.9739	0.9893	0.9983

4. Conclusions

In this study, we developed a highly effective ensemble model that leverages deep transfer learning techniques, integrating EfficientNet, XceptionNet, GoogLeNet, and, for early COVID-19 diagnosis. Our pro-posed model not only detects COVID-19 but also effectively distinguishes between normal, COVID-19 positive, pneumonia, and tuberculosis cases. Through extensive testing on two datasets, our model show-cased exceptional performance, achieving an impressive accuracy of

99.23% for multiclass classification and 98.96% for binary classification. This cut-ting-edge solution holds immense potential for health officials, enabling them to facilitate early COVID-19 diagnosis during this critical situation. Looking ahead, we anticipate broadening the horizons of our research to include the prediction of risk levels and survival probabilities for patients who have tested positive for coronaviruses.

This additional capability would pro-vide invaluable support to medical practitioners in effectively managing and planning the healthcare needs of infected individuals, ultimately leading to improved patient outcomes. By incorporating predictive abilities, our proposed model not only contributes to the advancement of medical practices but also holds promise for further enhancing patient care in the field of COVID-19 management.

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