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An Enhanced Automation Technique to Detect Corona

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Abstract- Due to a lack of RT-PCR test kits, radiographic image analysis combined with AI has grown in popularity since the start of the COVID-19 pandemic. Using the assembling technique of several convolutional neural networks (CNNs), this study proposes an automated AI-assisted COVID-19 diagnostic system. An ensembling strategy based on feature level fusion and a decision level ensembling approach have both been implemented. After putting many classic CNN designs through their paces, the assembling process ultimately makes use of MobileNet, InceptionV3, DenseNet201, DenseNet121, and Xception. Using ImageNet's pre-trained weight initialisation, a transfer learning approach is used to manage the computational complexity of numerous networks. The feature-level ensembling approach employs a series of fully connected layers to optimise the combined output of a number of networks' convolutional feature maps. In addition, the maximum voting criteria is used to converge the final predictions from several networks into one single prediction for the decision level ensembling method. When compared to individual networks, both approaches outperform them. The results of the rigorous testing on a public database are quite remarkable: a 3-class (COVID-19/normal/pneumonia) diagnostic obtained an accuracy of 96% and a 4-class (COVID-19/normal/viral pneumonia/bacterial pneumonia) diagnosis achieved an accuracy of 89.21%.

Keywords--COVID-19, Deep Learning, Ensembling, Transfer Learning

I. INTRODUCTION

Since its inception, COVID-19 has become a major danger to humanity, killing an estimated 0.7 million people throughout the world. The high contagiousness of the disease has also had an impact on people's socioeconomic lives. Thus, contributing to the reduction of future transmission and relieving burden on the medical sector, early diagnosis of Covid-19 is crucial. Medical research that relies on image processing has recently made heavy use of deep learning. The study of COVID-19 is not an exception. In order to carry out binary and multi-class classification, Khan et al. [1] constructed the Xception architecture-based model Coronet and loaded it with ImageNet weights. In their investigation of five convolutional neural network (CNN) models for COVID identification, Apostopolous et al. [2] examined VGG19, MobileNetV2, Inception, Xception, and Inception ResNet V2, all of which were pre-trained using ImageNet data. In all investigations, CNN models were utilised in isolation, with ImageNet weights used to initialise the model weights. Nevertheless, it is possible to compare the performances of different models by consulting the research of Apostopolous et al. [2]. For both binary classes (COVID versus no-Findings) and multi-class classification (COVID vs no-Findings vs pneumonia), Ozturk et al. [3] built a model called DarkCovidNet. Since they built their own network, they were unable to employ ImageNet weights in their transfer learning algorithms. The CovXNet model, developed by Mahmud et al. [4], makes use of depthwise convolution with variable dilation rates. Even though a plethora of normal and viral/bacterial chest X-ray pictures were used to train the model, no efforts were made to extract classwise diverse characteristics. Xception architecture was pre-trained using big datasets by N. Narayan Das et al. [5], who then used a straightforward transfer learning method to identify COVID-19.

II. RELATED WORKS

The COVIDiagnosis-Net design was suggested by Ucar et al. [6]. It is a tailored SqueezeNet that was pre-trained using ImageNet weights and Bayesian optimisation additive. Their dataset only included 76 augmented COVID X-ray pictures, yet they achieved a high level of accuracy. The InceptionV3 architecture was the basis for the model given by Das et al. [7]. Their research used a shortened model that started with three inception modules and one grid size-reduction block, then added a max-pooling and global average pooling layer, and finally employed support vector machines (SVMs) as a classifier. A deep learning model, based on a version of VGG-19, which was trained on the ImageNet dataset before, was constructed by Vaid et al. [8]. Models such as MobileNetV2, SqueezeNet, and SVM classifiers were used by Togacar et al. [9]. Nevertheless, they were unable to complete difficult 4-class categorisation due to their limited dataset. There are benefits and drawbacks to each approach. Improving performance for three- and four-class classification might be as simple as considering combining several efficient models. Converging several networks into one integrated one for optimal performance is the primary goal of this research, along with exploring the benefits and prospects of various conventional, well-known designs. The integration process has made use of two primary ensembling strategies: a feature-based ensembling scheme and a decision-based ensembling method. While decision-based schemes converge the decisions of many networks using maximum voting criteria, feature-based schemes take into account the feature spaces of multiple networks for group optimisation. When compared to other standalone networks, these assembling methodologies routinely deliver far better performance by taking use of the architectural variety of several networks.

III. PROPOSED METHOD

There are two main issues with the COVID-19 detection system based on chest X-ray pictures: (1) there is a dearth of chest X-ray images with verified cases of COVID-19 and (2) the chest X-ray photos that have been identified as COVID-19, viral pneumonia, and bacterial pneumonia all look very similar. To circumvent these issues, the majority of current COVID-19 detection systems that rely on deep learning often use a suitable conventional architecture or variation thereof. This study examined the ability of several CNN architectures to identify COVID-19 X-ray pictures. There has also been analysis of several tweaks to such deep CNN designs. It is challenging to balance the benefits of different modifications to an existing architecture with their effects on categorisation performance, and not every situation calls for the same tweak. Everyone knows that deep convolutional neural network (CNN) architectures are now at their most efficient in terms of both computing complexity and classification performance. Thus, this study presents an assembling method for COVID-19 X-ray picture identification using Xception, MobileNet, InceptionV3, DenseNet201, and DenseNet121, a collection of state-of-the-art deep convolutional neural networks (CNNs). Keep in mind that the number of convolutional neural networks (CNNs) may be changed as needed; however, for the sake of this research, we will be using five CNN models to illustrate their performance. The CNN models are constructed using two different schemes: • Concatenating Features to Assemble Multiple Convolutional Neural Network Models • Using Decision Fusion to Assemble Multiple CNN Models Figure 1: Model Assembling via Feature Concatenation via a basic block diagram, the suggested method for assembling several CNN models via feature concatenation is shown in Fig. 1.

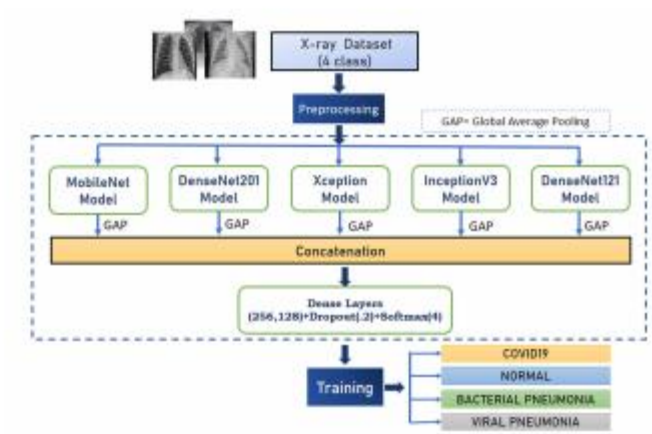

Fig. 1. Ensembling of models using Feature Concatenation

The computational complexity of numerous networks is managed with the use of a transfer learning technique that uses the ImageNetpretrained weights for initialisation. It is clear that different classes of chest X-ray pictures were used to train the five deep convolutional neural network models. The four main types

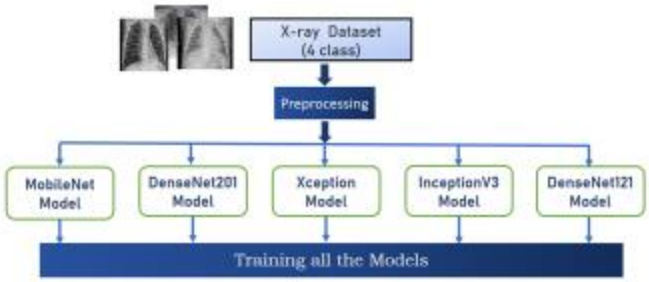

Fig. 2. Training approach for ensembling of models using Decision Fusion

Several chest X-ray pictures are taken into account here, including normal, COVID-19, viral, and bacterial pneumonia. The goal here is to identify four traits that may be used to separate classes. Following the Global Average Pooling layer, the features retrieved from all of the CNN architectures are combined. It is believed that the separability across distinct classes would be improved by merging features collected from different models. To guarantee further training after concatenation, two dense layers—a dropout and a softmax triggered dense layer—are introduced. The convolutional feature maps are pooled and optimised together using a common stack of fully linked layers. The same procedure is used for the three classes: COVID-19, normal, and pneumonia. Figure 2 shows the training procedure for assembling several convolutional neural network (CNN) models via decision fusion. In this scenario, the training process involves training each deep convolutional neural network (CNN) model independently utilising the four classes of X-ray pictures. The use of the decision fusion method is considered while assessing the chest X-ray pictures. For each of the test pictures, predictions are produced using each of the trained CNN models. When we talk about decision fusion, what we really mean is finding the "mode" of the five models' forecasts. By using the maximum vote criteria, all of the models' forecasts are combined into one single prediction. In Fig. 3, we can see the decision fusion strategy testing technique.

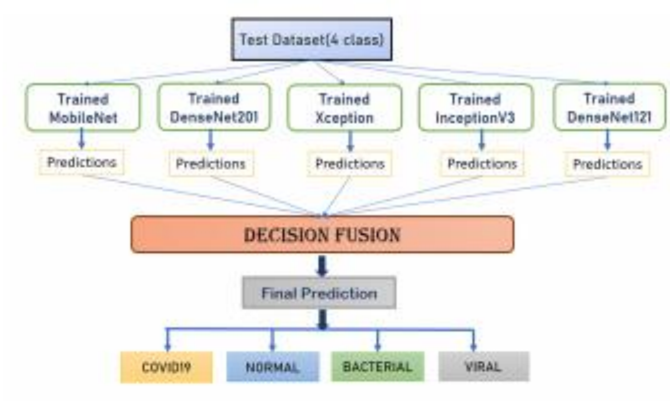

Fig. 3. Testing approach for ensembling of models using Decision Fusion

The training and testing procedures for the three-category categorisation system are identical to those outlined earlier: COVID-19, normal, and pneumonia. All 592 forecasts were based on this strategy, which restricts authorised licence usage to: QIS College Of Engineering & Technology Autonomous. This resource was retrieved from IEEE Xplore on July 6, 2021 at 03:58:41 UTC. Conditions are applicable. diverse models are considered rather of relying just on the forecast of a single model. I. Initial Steps Not changed are the balanced chest X-ray (CXR) datasets that are used for merging features and decision fusion. In order to facilitate their implementation during testing, the chest X-ray pictures undergo minimum preprocessing. Just to make sure the pictures are the same size before the ensembled deep neural network processes them, they are reshaped. B. A technique for training ensembling by concatenating features Figure 1 shows the design of this method, which involves training five networks on a balanced chest X-ray dataset: MobileNet, DenseNet201, Xception, InceptionV3, and DenseNet121. The training method involves updating the 'ImageNet' weights that are initialised with all the networks. With this transfer learning method, you get quicker convergence and better initialisation. The newly combined classification head has a dropout(.2) layer, two dense layers of 128 and 256 neurones, respectively, after the concatenation process. Relu activation is linked to the thick layers. Finally, softmax activation is used for categorisation. Fifty epochs are used to train the final network. In addition, training is done using adaptive momentum (Adam) optimisation with a learning rate of 0.0001 and a minimum learning rate of 0.00001. C. Method for assembling using a decision-fusion technique for training All five networks—MobileNet, DenseNet201, Xception, InceptionV3, and DenseNet121—are trained separately on a balanced chest x-ray dataset, as seen in Figure 2. As mentioned before, a comparable method of transfer learning is used. The classification heads of both networks are identical; they each include a dropout(.2) layer, then two dense layers with 128 and 256 neurones, respectively. Then, procedures such as relu activation, softmax activation, and adam optimisation are performed, same as in the feature concatenation scenario. Table D. This study's dataset includes chest X-ray pictures of COVID-19, normal, viral, and bacterial pneumonia. Two distinct sources are used to compile the photos. Joseph Paul Cohen's GitHub repository [10] is where the COVID-19 pictures are based. From GitHub, 408 chest X-ray photos of COVID-19 have been sorted. Images depicting pneumonia and normal conditions were sourced from Kaggle "11". From Guangzhou Women and Children's Medical Centre in Guangzhou, the Kaggle dataset includes 4273 photos of pneumonia and 1583 photographs of paediatric patients with normal conditions. A total of 408 chest X-rays classified as normal, viral, or bacterial were used to create a balanced dataset. The dataset includes 408 photographs belonging to each of the four classes; 326 images from each class are used for training purposes, while 82 images are reserved for testing purposes. There are 38 COVID-19 pictures, 38 normal images, and 38 pneumonia images in the dataset for the three-class categorisation. For training purposes, 6 photographs from each class are used, while 8 images are reserved

Combination Scheme

IV. RESULTS AND DISCUSSION

Feature concatenation and decision fusion are two distinct approaches to CNN model assembly that are presented in this work. Here, we take a closer look at each of the suggested schemes' categorisation performance separately. Five commonly used performance indicators are taken into account for the analysis: Accuracy, Sensitivity, Specificity, F1-Score, and Precision. For both the four- and three-class situations, the aforementioned dataset is used to calculate classification results for each suggested method. The suggested method achieves an accuracy of 89.26% for 4-class classification and 95.84% for 3-class classification by using the feature concatenation methodology. Using the Feature Concatenation approach, Figure 4 shows the combined confusion matrix for 4-class and 3-class classification.

Confusion matrices for feature-concatenation-based four- and three-class classifications

Tabulated in Table I for three-class issues and Table II for four-class problems, respectively, are the classification results derived using the first approach, which involves assembling CNN models via feature concatenation. The tables provide the average findings as well as the results from each of the five folds of the cross validation method that were used during the testing phase. All performance indicators show a really acceptable overall result. The results of the classification performance are better in the three-class issue, as anticipated.

V. FUTURE SCOPE AND CONCLUSION

Methods like feature concatenation and decision fusion are investigated in this study. The decision fusion method uses the base models' majority voting class as the final class, whereas the feature concatenation strategy feeds the classification head concatenated features from the basis models. Both strategies outperform competing techniques in the literature when it comes to classification. Feature concatenation outperforms the other method for three-class classification, even if both methods do similarly for four-class classification. Thus, it is shown that the approach may improve the efficiency of basic transfer learning methods; it can be recommended as a first step in the detection of COVID-19 and in the subsequent expansion of therapy for patients who test positive. As shown in fold 5 of the decision fusion approach's four-class classification, the total performance suffers when a single base model performs poorly in the suggested manner. Therefore, we will continuously seek for huge datasets for future improvements, investigate other base models that perform similarly, and pursue various ensemblingstrategies.

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