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An Efficient Ensemble Model for Diagnosing Covid-19 and Pneumonia Using Chest X-Ray Images

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Abstract

Objectives : To propose an ensemble machine learning model for early identification of COVID-19 and pneumonia lung infections by analyzing the chest X-ray images. **Methods:** RGDSoft model is proposed for image classification which is a soft voting ensemble deep transfer learning strategy with pre-trained classifiers ResNet-18, GoogLeNet, and DenseNet-121. The model is tested on COVID-19 dataset having 1143 positive COVID-19, 1341 normal, and 1345 pneumonia images, and the Kermany dataset which has 5856 chest X-ray images divided into two groups: ”Pneumonia” and ”Normal”. Out of these image-set 80% of images are used for training and 20% for testing purposes. To demonstrate the efficiency of the proposed model, python is used for implementation. Performance results are evaluated and compared with the existing pre-trained models like GoogLeNet, ResNet18 and DensNet121. **Findings:** Efficiency of the proposed ensemble model is achieved with 98.1% accuracy level, 98.8% precision, 98.8% recall on kermany dataset whereas 94% accuracy, 96% precision and 96% recall on COVID-19 dataset which is optimum as compared with the most state-of-art models discussed in literature. **Novelty:** According to the findings of the comprehensive study, the proposed RGDSoft model not only outperforms most of the classifiers like GoogLeNet, ResNet18 and DenseNet121 in terms of combinations of accuracy, precision and recall but is so generic model which shows very good results on different datasets.

Keywords: Machine Learning; Deep Learning; Covid19; Pneumonia; xray images; googlenet; resnet18; densenet121; ensemble

1 Introduction

As the need to early identify COVID-19 infections develops, the usage of CNN-based AI systems is rapidly rising. The main reason for this discipline's success is because it will help to speed up medical image analysis. It is critical to utilise chest X-ray recognising since it is the most reliable tool for identifying and diagnosing pneumonia and other infections with similar symptoms. It is also used to characterise and diagnose infections caused by COVID-19[1]. Authors in[2] investigated the use of CNN technique for coronavirus detection and automated lung segmentation. The usage of computed tomography (CT) and X-rays has been thoroughly investigated in this investigation. Similarly, in[3,4] estimated modified pre-trained AlexNet and changed the CNN model using their CT checkup dataset and chest X-ray. Furthermore, researchers investigated three pre-trained models that employed ImageNet weights (equivalent to Inception v3, ResNet50, and Inception- ResNet v2) and had two alternative pictures ordering in mind: normal pictures and coronavirus disease-19. It achieved the highest level of delicacy, estimated to be more than 98 percent[5–9].

To analyse pneumonic chest X-ray images, authors in[10] created primitive CNN infrastructures. They used data augmentation to compensate for the absence of data. Sharma et al. achieved a delicacy rate of 90.68 percent using the dataset supplied by Kermany et al. [11]. Researchers in[12] acquired a delicacy rate of 93.73 percent. Data addition, on the other hand, only supplies a little amount of fresh data for CNNs to train on, and so may not greatly improve their performance. Authors in[13] used the DenseNet-121 CNN model for the pneumonia bracket, but only received a 76.8 F1- score. They concluded that a lack of patient history was a key reason in the poor performance of both their deep literacy model and the radiologists with whom they compared it.

According to the literature study, most techniques are based on the use of a single model rather than an ensemble. Nonetheless, some of the methods compute on the ensemble[14,15]. The ensemble model has also been designed to provide a variety of benefits in terms of minimising computing error, making it the most adaptable approach. In a paper[16], reported on an ensemble of CNNs based on EfficientNet for detecting coronavirus disease-19 infection. This study makes extensive use of chest X-rays. During the disquisition, the open-access X-ray collection was updated and pre-trained weights for EfficientNet were uploaded to ImageNet. The top layers were likewise well-tuned, and the chest X-ray matches were classified using an ensemble of model photographs. Authors in[14] used ensembles of multiple models, including ResNet18, DenseNet161, and VGG19, in one of their studies. The strategy, on the other hand, has a number of limitations. Each model, in particular, must learn a vast number of parameters, each of which necessitates a separate training session. Following suit, researchers in[15] ran an ensemble on a single model. It did, however, use a variety of visual judgments. It generates forecasts by creating a new model for each resolution. This approach is time-consuming and computationally intensive. Using the massive coronavirus disease-19 database, Wang et al. built and evaluated a sophisticated custom CNN armature (COVID-Net).

Research Gap: Most of the study is based single model and are trained specifically for specified dataset, and on variety of circumstances, the model's calculation overhead were discovered to be extremely large. As a result of these findings and extensive comprehensive study we found that there is lots of work needs to be done on ensemble modeling as they are robust in nature. Therefore, we have proposed an ensemble technique 'RGDSoft' to identify COVID-19 and pneumonia from X-ray images.

Rest of the paper is presented in four more sections. In section 2 Methodology of the model and explanation is presented, in section 3 descriptions of the evaluation matrices is included, section 4 comprises of result and discussion and finally conclusion is given in section 5.

2 Methodology

Architecture of the model architecture is multi-leveled. At the most fundamental level, we used two publicly available databases. The obtained chest X-ray images are then pre-processed at second level. The proposed ensemble machine learning model's third level of functionality is in charge of selecting the features from preprocessed chest X-ray images, while in the end level of functionality is in charge of creating and implementing the ensemble machine learning paradigm. Finally, the model's usefulness and efficacy in identifying coronavirus disease-19 and pneumonia were experimentally evaluated using cutting-edge approaches. Figure 1 depicts the proposed ensemble model of machine learning.

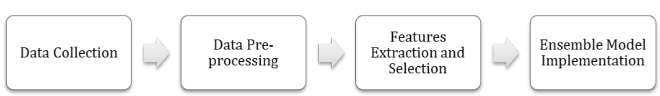

Fig 1. Ensemble Machine Learning model

2.1 Dataset

This section displays the results of the evaluation of the recommended system. Two freely accessible chest X-ray datasets were used for COVID-19 and pneumonia. The COVID-19 dataset comprises 1143 positive COVID-19 pictures, 1341 normal images, and 1345 pneumonia images, whereas the Kermany dataset[11] has 5856 chest X-ray images from a wide population of both

Table 1. Summary of some literature worked on detecting lung diseases

Method	Approach	Merits	Demerits
Sharma et al. [10]	Devised a CNN model for classification of X-ray images	Automatic feature learning for complex tasks	Simple linearly progressing CNN model increases computation cost without providing strong boost to performance
Albahli et al. [17]	Transfer Learning using InceptionResNet-V2	Reuse of models pre-trained on a large dataset	Oversimplified for a complex pattern recognition task; Performance obtained is poor and not fit for practical use
Chandra et al. [18]	Segmentation of lung X-rays using image processing, Extraction and classification of eight statistical features	Segmentation of lungs before classification allows localization of the disease	The use of handcrafted features limits its ability to perform in complex pattern recognition tasks; Evaluation on a small dataset (412 images) cannot be generalized
Kuo et al. [19]	Used 11 features from patient data to fit traditional classifiers	Use of 10-fold cross validation with 3 repeats avoids over-fitting	Patient data are often private and not publicly available to fit to classification models
Yue et al. [20]	Segmented lung lobes using U-Net Extracted and classified radiomic features from CT-scan images	Segmentation before classification helps extract important features for radiologists and allows localization of the disease	Method evaluated on a small dataset (72 lesion segments) and thus difficult to generalize
Janizek et al. [21]	Developed a deep learning framework based on adversarial optimization	Adversarial optimization removed dependency on the source of the dataset and view of the X-rays for classification	Results (AUC 74.7%) are not fit for deployment in the field
Zhang et al. [22]	Developed a confidence-aware module for anomaly detection in lung X-ray images	Posing the detection task as a one-class problem helped improve the model performance	The sensitivity obtained on the dataset was too low (71.70%) for practical use
Jaiswal et al. [23]	Developed a mask region-based CNN for segmentation. Used an ensemble model for image thresholding	Use of threshold value in background boosts the performance	An irregular trend was observed, where results of the training set were lower than those of the testing set
Gabruseva et al. [24]	Localized pulmonary opacity based on a single-shot detector Used a snapshot ensemble model for Segmentation	One-shot detector alleviates the problem of scarcity of data	Irregular trend of validation loss over epochs during model training
Wang, et al. [25]	new CNN framework named COVID-Net and the large chest X-ray benchmark dataset "COVIDx	the predictions of COVIDNet-CT via explainability-driven performance validation to ensure that its predictions are based on relevant image features and to better understand the CT image features associated with COVID-19 infection	COVIDNet-CT is not yet suitable for clinical use and also generalizability is a big question.

adults and children, evenly divided into two groups: "Pneumonia" and "Normal." To illustrate the superiority of the proposed system, it was compared to existing models and frequently used ensemble methods published in the literature. In addition, we evaluated our approach using a kermany dataset of 5863 images divided into two categories: normal and pneumonia.

2.2 Proposed method

In this section proposed 'RGDSoft' model is presented, we used a soft voting ensemble approach to construct an ensemble framework (Figure 2) that contained three classifiers: GoogLeNet [26], ResNet-18 [27], and DenseNet-121 [28].

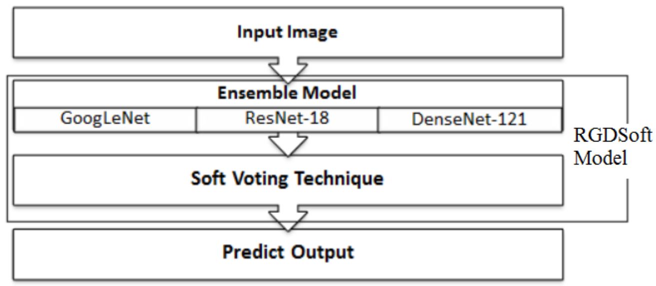

Fig 2. The proposedRGDSoft model.

2.2.1 GoogLeNet

In their GoogLeNet design, Szegedy et al.[26] describe a deep neural network made up of "inception modules" rather than uniformly increasing layers. Due to the increasing number of parameters, an inception block allows several units at each level by hosting concurrent convolution and pooling layers. To manage computational complexity, the GoogLeNet model employs dimension reduction inception blocks rather than the naïve inception blocks used in[29]. GoogLeNet's performance, which introduced the inception block, demonstrates that an optimal sparse architecture constructed from accessible dense building blocks improves artificial neural network performance for computer vision applications.

2.2.2 ResNet-18

He et al.[27] proposed the ResNet-18 model, which is based on a residual learning framework that enhances deep network training efficiency and has been hailed as the world's first of its type at the National University of Standards and Training for Artificial Intelligence. In contrast to the native unreferenced mapping in continuous progressive convolutions, the residual blocks in ResNet models allow for network augmentation, which improves model accuracy. These residuals, also known as "skip connections," enable identity mapping without the use of extra parameters or processing complexity.

2.2.3 DenseNet-121

The model[28] has fewer trainable parameters and is more computationally efficient. The feature mappings of each DenseNet model layer are conjugated with those of previous layers. Feature representation is also improved by concatenating feature maps from previous layers with the current layer.

2.2.4 Ensemble scheme

In the Ensemble ML paradigm, a number of categorization algorithms are combined to form one model. We employed soft voting in this study to combine the predictions of three categorization algorithms. So, the propose scheme gives result according to the following equation:

$$f_{comb}(x_n) = \sum_{t=1}^{T} \alpha_t f_t(x_n), \quad f_t \in (0,1],$$

Suppose we have t number of base classifiers h_t, which are trained with classifier specific weights α_t. Let $f_t(x_n)$ represents the output of tth classifier for input (xn).Where, $f_{comb}(x_n)$ is the weighted linear combination of the T base classifier, α_t is the weight for classifier h_t.

3 Evaluation metrics

Four traditional assessment criteria were utilised to evaluate the suggested approach on the two chest disease datasets: accuracy (Acc), precision (Pre), recall (Rec), and f1-score (F1). To begin, we'll define the words "True Positive," "False Positive," "True Negative," and "False Negative," as well as the phrases "True Positive," "False Negative," and "False Negative."

Assume the two classes in the dataset are labeled "positive" and "negative" for a binary classification job. The following are definitions for the concepts stated above. True Positive (TP) is a positive-class sample that has been successfully classified by a model. False positive (FP) is a sample that should have been labeled as negative but was instead classified as positive. True Negative (TN) refers to a sample that falls into the negative category and is correctly detected by the model. False Negative (FN) refers to a sample that should have been classified as negative but was instead classified as positive.

4 Results and Discussion

This section displays the results of the evaluation of the recommended 'RGDSoft' system. As discussed in the previous section RGDSoft system is an ensemble of three classifiers viz. ResNet18, GoogLeNet and DenseNet-121 with soft-voting technique. The system was applied on two freely available chest radiograph datasets for detecting novel coronavirus (COVID-19) and pneumonia. To illustrate the superiority of the proposed system, it was compared to existing models and some ensemble methods published in the literature. Figure 3 displays the results analysis of proposed 'RGDSoft' method with existing methods on kermany[11] dataset. It is clearly visible that our proposed model has outperformed all the existing models and achieved with 98.1% accuracy level, 98.8% precision, 98.8% recall and 98.79% F1 score which is clearly standout and comes out to be best model among all others.

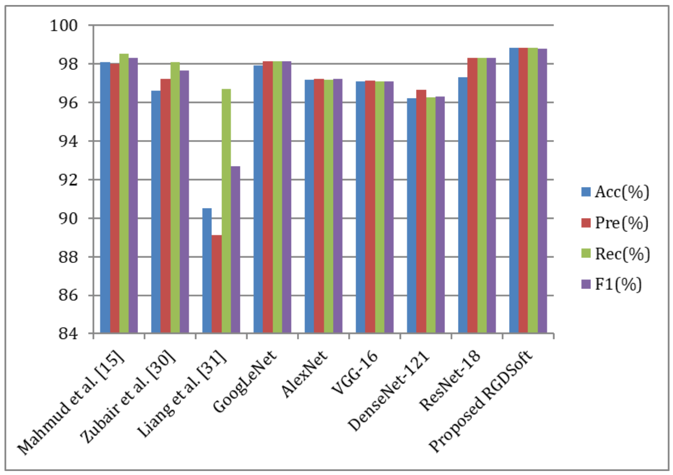

Fig 3. Comparison of Proposed RDGSoft method with other existing methods on the Kermany dataset[11]

In Figure 4 results analysis of proposed RGDSoft mode with other existing models on Covid-19 datasets are displays in graphical way. Here it is evident that our proposed RGDSoft model outperforms many state-of-art models with 94% accuracy, 96% precision and 96% recall. The comparative models which are showing nearly 100% accuracy are shows that they are over-fitted and will give very bad results if they are applied on different dataset. This clearly gives an indication that our proposed model is generic in nature and it can be applied on different dataset to achieve concrete results among its competitors.

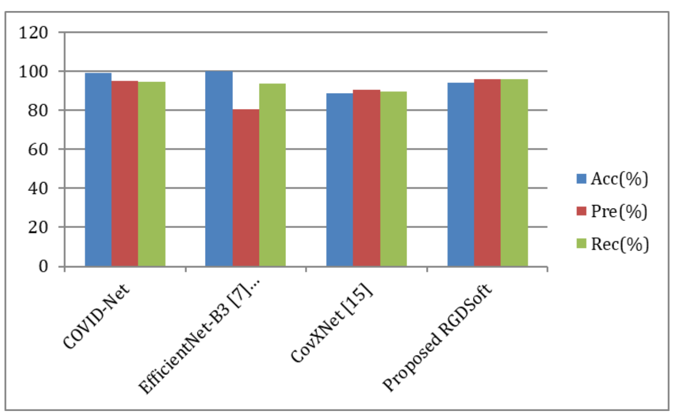

Fig 4. Proposed method was compared to existing methods On the COVID-19 dataset

5 Conclusion and Future Work

This study proposed an ensemble approach RGDSoft for identifying lung disease such as COVID-19 and pneumonia [30] from chest X-ray images. When compared to other well-known methods, the proposed ensemble model captures COVID-19 infection more effectively and performs better. The decision scores of three CNN models were combined to produce a soft voting ensemble: GoogLeNet, ResNet-18, and DenseNet-121. Our method was applied to the Covid-19 dataset and the Kermany [11] dataset. On covid-19 dataset we obtained 94% accuracy, 98.1% precision and 96% recall whereas on kermany [11] dataset 98.1% accuracy, 98.82% precision, 98.80% recall and 98.79% f1 score was obtained, outperforming most state-of-the-art models. Similarly, because the proposed ensemble model is so generic, it may be used for a wide range of computer vision problems.

In the future, we may look at tactics such as image discrepancy improvement or other pre-processing processes to improve image quality. We may also partition the lung picture before categorising it to help the CNN algorithms value extra information. Similarly, because the proposed ensemble requires the training of three CNN models, the computation cost is larger than in previous CNN instances. In the future, we may try to minimise processing conditions by using approaches similar to shot ensembling.

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