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Automatic Detection of Covid-19 from Chest X-Rays using Weighted Average Ensemble Framework

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Abstract: COVID-19 stands as one of the most serious diseases resulting from the novel corona virus. Chest x-rays (CXR) have gained widespread recognition as an effective screening tool for lung-related diseases due to their simplicity and cost-effectiveness. Radiologists find CXR image interpretation straightforward and affordable due to its low cost and fast results. In this study, we introduce an innovative approach to improve the detecting and classification of Covid-19 by analyzing their chest x-rays(CXR). Our model includes pretrained architectures like VGG16, ResNet50, and InceptionV3 to create a Weighted Average Ensemble Model. Despite the limitation of dataset our model has achieved an accuracy rate of 98.33%. These results confirm the potential of weighted average ensemble models in contribution to identifying Covid-19 through chest x-ray-based classification.

Keywords: *Covid -19 , VGG16, ResNet50, InceptionV3, weighted average ensemble model*

1. Introduction

COVID-19, a novel corona virus, initially emerged in China in 2020 and quickly spread worldwide, posing a significant global health crisis [1–3]. On January 30, 2020, the World Health Organization (WHO) publicly designated COVID-19 a global public health emergency. [4]. then it declared pandemic on March 11,2020. This virus primarily targets the respiratory system, often leading to severe and potentially deadly respiratory syndromes [5] "Real-Time Polymerase Chain Reaction" (RT-PCR) is used to examine Covid-19" [6]. However, many researchers have recently attempted to use x-ray scans to automate the diagnosis of disease. [7]. Although many imaging modalities are available, According to studies [8, 9], chest radiography has a sub-optimal sensitivity for significant clinical findings given its integral role in healthcare worldwide; X-ray imaging is a mode that medical experts generally use. With the ready accessibility of X-ray machines, their utilization becomes vital for detecting Covid-19 cases, mainly because of comprehensive screening facilities. Analysis of X-ray images reveals that during the early phases of Covid-19, In the lungs, specifically in the lower lobes and posterior segments, with an outlying and sub-pleural circulation, different effects may be seen. However, a substantial encounter arises from the time-consuming process of examining each X-ray image and extracting critical answers, requiring the expertise of medical professionals in the field. Therefore, Computer-assisted solutions are urgently required to assist healthcare providers in the detection of COVID-19 cases through the analysis of Chest X-Ray images.

Deep learning approaches, integrated into computer-aided methods, have made essential upgrades in analyzing medical images, exhibiting remarkable performance. Hence, this study introduces a deep learning-based weighted average ensemble model designed to classify Covid-19 cases using Chest X-ray images."

The main contributions of this research study are summarized below:

- The weighted average ensemble model is combined with pre-trained deep learning models (VGG16, ResNet50, and InceptionV3) for a multi-class classification.
- State-of-the-art deep learning models are then compared with the currently developed ensemble model.

2. Related Work

There are two subsections for related work. In Section 2.2 The studies related to weighted average ensemble(WAE) model for disease diagnosis is covered 2.1, the research studies using the deep learning models for Covid-19 are discussed.

2.1. Studies Related To Deep Learning Models

Castiglioni et al. [11] proposed an ensemble-based model containing ten pre-trained CNNs, achieving a sensitivity rate of 80%. Ozturk et al. [12]"implemented DarkCovidNet, a deep CNN model for automated COVID-19 detection using chest X-ray images. DarkCovidNet is developed to make available precise diagnoses for both multi-class classification (COVID vs. Normal vs.

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Pneumonia) and binary arrangement (COVID vs. Normal), achieving classification accuracies of 87.02% for multi-class cases and 98.08% for binary cases ". Nigam et al. [13] proposed a Coronavirus diagnostic scheme utilizing pre-trained CNN models, including VGG16, DenseNet121, Xception, NASNet, and EfficientNet-B7. Among these, EfficientNet-B7 received an accuracy of 93.48% for classifying chest x-ray images into COVID, normal and Pneumonia. Kumar et al. [14] proposed a deep Convolutional network-based system for Covid-19 detection using X-ray images, achieving an accuracy of 95.38%. Their model was trained on GitHub, Kaggle, dataset. Jain et al. [15] utilized a Chext X-Rays dataset of 6431 from public repositories like kaggle and developed InceptionV3, Xception, and ResNeXt models. Xception model received better accuracy of 97.67% compared to other models., they have used LeakyReLU as an activation function. However, they cautioned that the high accuracy observed could potentially result from overfitting and suggested validating their model with larger datasets in the future. A dataset comprised of 2504 Covid-19 and 6807 non-COVID-19 images was compiled from six publically accessible sources by Narayan et al.[16] and used for Covid-19 detection. Through 10-fold cross-validation, their tests revealed that ResNet50 achieved better results in comparison to Inception-v3, DenseNet201, and Xception, with a detection rate of 99.34%. Gopatoti and others[17] introduced CXGNet, a deep learning architecture for classifying two, three, and four classes, attaining accuracy rates of 100% for two class model 97.05% for the 3-class model, and 94.00% for the 4-class model.

2.2 Studies related to Weighted average ensemble model

According to Kunwar et al. [18]"developed an ensemble framework of state of art three deep learning models, namely VGG-19, EfficientNet-B4", and DenseNet-121. By utilizing the grid search technique, they enhanced the outcomes produced by a weighted average ensemble model. The researchers achieved an accuracy of 100% for binary classification and 95.29% for multi-class classification. they classified Covid-19 using ECG images" In another work of Aimon Rahman et al.[19] three distinct techniques were proposed: a tradition CNN network, transfer learning with VGG16, and CNN-SVM. to enhance prediction accuracy and reduce generalization error, an ensemble learning method was employed. The outcomes of the three networks were combined, and a final prediction was made. weighted average ensemble model, resulted in an impressive accuracy of 97.77%.

Pradeek Kumar Roy et al.[20] introduced a ensemble learning framework consists of ResNet50, DenseNet201, InceptionV3, VGG-19, VGG-16, Xception, and MobileNetV2 are seven transfer learning architectures for Covid-19 classification from chest X-rays. While all models exhibited some false-positive predictions individually, an ensemble learning-based architecture was created to mitigate this issue. This ensemble learning model uses the predictions from individual transfer learning1models and a probability averaging of ensemble technique is determined. The precision, recall, and F1-score values for the developed ensemble learning are 1.00, 1.00, and 1.00, respectively.

3. Materials and Methodology

Section 3.1 discusses the Covid dataset and the pre-processing, while Sections 3.2 and 3.3 covers the methodology.

3.1. Dataset Collection and Preprocessing

In the initial phase, we initiate data preprocessing for the images for three distinct classes. Our approach begins with data augmentation, which serves to expand the training dataset effectively. Subsequently, we adjust the images to 224 x 224 to the appropriate dimensions and randomize their order to prepare them as suitable inputs for the neural network. Moreover, we employ data augmentation as a means to report the challenge posed by the limited dataset availability of Covid-19 CXR images, thereby augmenting the sample complexity necessary for neural network training. This augmentation process involves applying various transformations to the images. the total dataset taken for this proposed model was discussed in the table no: 1, and the images was collected from publicly available data sources like kaggle and github.

3.2. Methodology

3.2.1 Transfer learning approach.

A machine learning technique called transfer learning i.e. the process of using knowledge obtained from one activity to help in solving another, related problem. [21]. This approach has gained popularity in the development of ML models, especially when faced with limited data availability, avoiding the need for an extensive dataset [22]. Deep learning models, with their numerous parameters, typically necessitate millions of images for effective training. However, in medical image analysis, privacy concerns often restrict access to large datasets suitable for training deep learning models. as a result, researchers frequently turn to transfer learning as an indispensable tool for model training in such scenarios.

In our research, we used pre-trained models for example VGG-16, ResNet50, and InceptionV3 to construct an ensemble framework for multiclass classification. To optimize these models for our specific task, we removed their fully-connected layers, thus reducing the parameter count. We then introduced new dense layers with fewer parameters tailored to our classification needs. In this regard, a well-established method involves the pre-trained model weights are freeze to avoid weight alterations during the fine-tuning procedure and then trained only added layers to obtain the final classification results.

3.2.2 VGG16

The Visual Geometry Group (VGG) at Oxford University developed the convolution neural network (CNN) model i.e.VGG16" [23]. It represents an evolution from the earlier AlexNet, which was introduced in 2012. convolution blocks (8 layers), fully connected (three layers), max-pooling(five layers), and softmax layer "are included in the architecture of the VGG16, the architecture has total 11 layers it Originally crafted for the ImageNet challenge, the architecture follows a unique pattern: the width of the convolution blocks begins with starting at 64 in the initial layer, and is incrementally doubled after each max-pooling operation till it spreads 512. .Further specifics of the architecture include an input image size of 224 × 224, with stride of 1and kernel size of 3 × 3. Spatial padding is employed to maintain the image's spatial resolution. Max-pooling operations utilize a pool size of 2 × 2 with a stride of 2. the first two layers possess a size of 4096, while the final fully connected layer consists of 1000 units. This size corresponds to the 1000 classes within the ImageNet classification task. In our current work, we have made enhancements to the VGG16 architecture. We introduced a 2D average pooling layer and a flatten layer, then dense layer with 128 units, utilizing the ReLU activation function. Moreover, we applied a dropout rate of 0.2. The final dense layer comprises three units, utilizing the Adam optimizer and definite cross-entropy as the loss function, with a learning rate set at 0.0001.

3.2.3 ResNet50

ResNet50 architecture has 48 Convolution layers and 1 MaxPooling layer and 1 Average Pool layer make up the model. Conventional assumptions is that improving the accuracy of models should result from adding more convolutional layers. but, it has been found that as more layers are added, difficulties like overfitting and vanishing gradient problems may cause the model's to ineffectiveness. ResNet introduces skip connections before applying ReLu, these skip connections sole the vanishing gradient issue, by providing a different shortcut channel for gradient flow, As a result, higher layers perform comparatively better as lower layers. They also enable the model to evolve into an identity function. The ResNet50 model is intended to process images with 224 224 pixels in size. It is divided into five stages, each of which include blocks for convolution and identification. Three layers make up each convolution block, while three levels make up each identity block. An typical pooling layer follows a fully-connected (FC) layer with 1000 neurons at the network's edge. We have modified the ResNet50 model specifically for this model. We used global average pooling, then a 512-unit dense layer with a 0.4 dropout rate. Further, the third class are added in the final dense layer for classification.

3.2.4. InceptionV3

Inception Net holds significant importance as it addressed a fundamental challenge in neural network architecture. Prior to its introduction, models relied on stacking numerous layers to achieve better performance. However, this approach had its drawbacks, especially when dealing with limited training data, which often led to overfitting. To tackle this problem, a shift was made from fully connected (FC) architectures to closely connected architectures, where information from various kernels (e.g., 1 × 1, 3 × 3, 5 × 5) was concatenated. InceptionV3, designed to accept images with dimensions of 299 × 299, introduced the concept of the inception layer. This innovative layer allowed internal layers to dynamically select the most suitable filter size for learning essential information from the input image. In InceptionV2, two 3 × 3 convolutions replaced the 5 × 5 convolutions, primarily for parameter reduction. This change contributed to better computational efficiency, as 3 × 3 convolutions outperformed their 5 × 5 counterparts. In our specific study, we have tailored the InceptionV3 model by introducing global average pooling in 2D, then by a dense layer with 512 units and ReLU activation, followed by a dropout rate of 0.4. The model was tailored for a classification task with three classes.

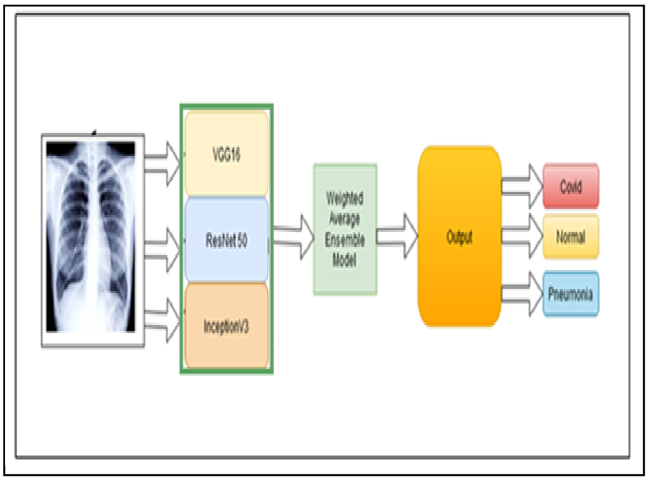
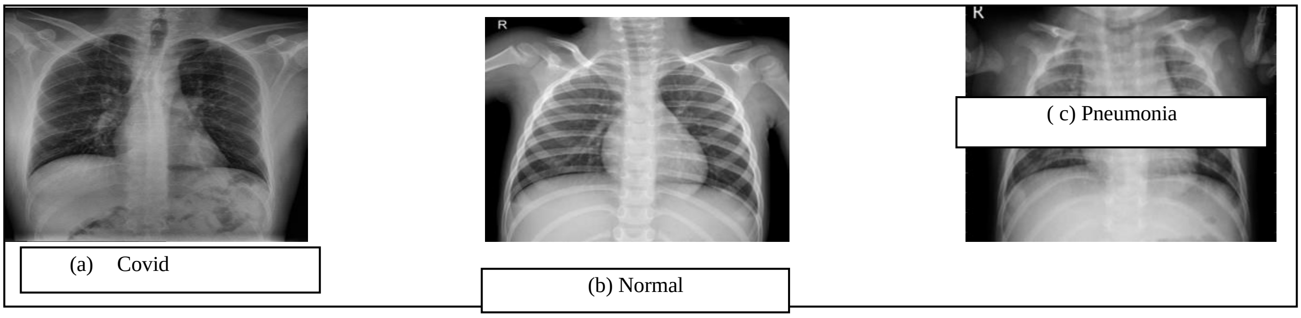


Fig 1. Proposed Ensemble Model Framework for Covid-19 Disease Detection

Table 1. The dataset description

	Covid	Normal	Pneumonia	Total
Train	877	1083	1076	3036
Test	220	267	269	756
Total	1097	1350	1345	3792

Fig 2. Chest X-Rays of Covid, Normal and Pneumonia



3.3 Weighted Average Ensemble Method

In many research papers, classification outcomes predominantly rely on a single model, despite substantial evidence demonstrating the superior performance of ensemble models [24]. Investigators frequently use groups made up of various models to improve their performance in general since they are aware that a single model would not be able to properly extract the complex features present in a dataset. For multi-class classification in this study, we use an optimal weighted average ensemble model. The standard regular ensemble technique, which uses all models similarly to generate classification results, serves as the key for this improved ensemble strategy. The significance of each model's contribution is assessed using particular weights in the weighted average ensemble technique. This approach effectively enhances accuracy and performance, particularly in addressing intricate and noisy problems. Furthermore, it aids in mitigating the risks of overfitting and underfitting by achieving a balanced trade-off between bias and variance. mathematically ensemble model is defined as follows: let models are ($M1$,$M2$,$M3$,…,Mm) having n classes The probability values of each classes for ith input (xi) with model $M1$,.M2 and M3 can be expressed as:

$$o_{M1}^{(i)} = (P_{1M1,}^{i} P_{1M1,}^{i}, P_{1M1,}^{i} .. P_{nM1}^{i}) \quad (1)$$

$$o_{M2}^{(i)} = (P_{1M2,}^{i} P_{1M2,}^{i}, P_{1M2,}^{i} .. P_{nM2}^{i}) \quad (2)$$

$$o_{M3}^{(i)} = (P_{1M3,}^{i} P_{1M3,}^{i}, P_{1M3,}^{i} .. P_{nM3}^{i}) \quad (3)$$

The Equation :4. can be used to express the final prediction score acquired from probability averaging.

$$O_{Ensemble} = \left[\frac{\sum_{k=1}^{m} P_{1MK}^{i}}{m}, \frac{\sum_{k=1}^{m} P_{2MK}^{i}}{m}, \frac{\sum_{k=1}^{m} P_{3MK}^{i}}{m}, \ldots\ldots\ldots \frac{\sum_{k=1}^{m} P_{nMK}^{i}}{m}\right] \quad (4)$$

$= [0_{1,}\ 0_{2,}\ 03,\ldots 0_{n,}]$

Table 2.

Performance evaluation of the recommended ensemble model in contrast to the developed and current models

Author	Data type	Model	Classes	Accuracy
Castiglioni et al [11]	CXR	Ensemble of Ten Models	Multi Class Classification	80.0%
Ozturk et al [12]	CXR	DarkNet	Multi Class Classification	87.02 %
Nigam et al [13]	CXR	Transfer learning Models	Multi Class Classification	93.48 %
Kumar et al. [14]	CXR	ResNet +SVM	Multi Class Classification	95.38 %
Jain et al. [15]	CXR	InceptionV3, Xception, ResNext	Multi Class Classification	97.97 %
Gopatoti et al. [17]	CXR	CXGNet	Multi Class Classification	97.05 %
P.V.Naresh et.al [25]	CXR	PSO –CNN –SVM	Multi Class Classification	97.42 %
P.V.Naresh et. at [26]	CXR	VGG16+ ResNet50+ CNN	Multi Class Classification	97.00 %
Proposed Model	CXR	VGG16+ResNet 50+ InceptionV3	Multi Class Classification	98.33 %

4. Results

The experimental evaluations and their outcomes are described in this section. It includes a description of the classification model that was tested and employed to categorize chest X-ray pictures. The primary measures used to assess performance are precision, recall, F1-score, and accuracy. (Eq. (5) to (8)) These are described as follows:

4.1. Evaluation Metrics

1. Accuracy: Accuracy is commonly computed by dividing the count of accurately predicted instances by the overall number of instances within a dataset:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

2. Precision: Precision measures how many of the things a model predicts as positive are actually correct, relative to all the things it predicted as positive

$$\text{Precision} = \frac{TP}{TP+FP} \quad (6)$$

3. Recall: Recall, also recognized as sensitivity, is the ratio of accurate positive forecasts made by the model to all possible positive predictions.

$$\text{Recall} = \frac{TP}{TP+FN} \quad (7)$$

4. F1-score: The F1 is the harmonic mean of metric precision and recall .

$$\text{F1 – Score} = \frac{2* Precision*Recall}{Precision+Recall} \quad (8)$$

True Positive: True Positive (TP) refers to instances correctly predicted as positive in a classification, indicating the model's accurate identification of the positive class..

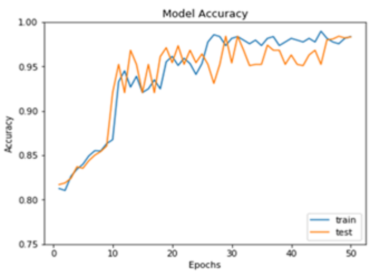
True Negative: True Negative (TN) refers to instances correctly predicted as negative in a classification, indicating the model's accurate identification of the negative class

False Positive: False Positive (FP) refers to instances incorrectly predicted as positive in a classification, indicating that the model wrongly classified a negative instance as positive.

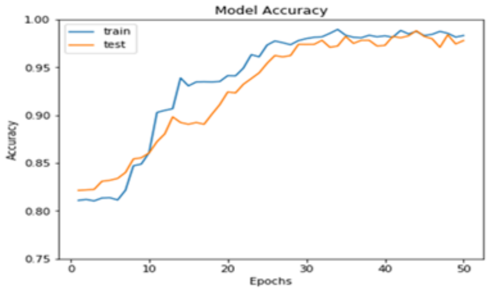
False Negative: False Negative (FN) refers to instances incorrectly predicted as negative in a classification, indicating that the model wrongly classified a positive instance as negative.

4.2 Experimental Setup

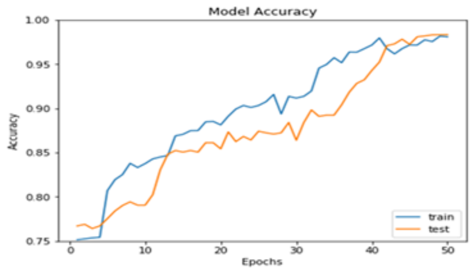
The models are tested and trained on the Google Colab platform. It offers NVIDIA Tesla K80 GPU and 12.68 GB RAM for 12 hours. The Adam optimizer is employed in this investigation with a learning rate of 0.001. For multi-class classification, definite cross-entropy loss functions are employed.



VGG16



ResNet 50



Inception V3 Model

Fig. 3 Multiclass Classification: Epochs Vs Accuracy Graphs

	Precision	Recall	F1- Score	Support
Covid – 19	0.97	1.00	1.00	220
Normal	0.97	1.00	0.98	267
Pneumonia	1.00	0.94	0.97	269
Accuracy			0.98	756
Macro avg	0.98	0.99	0.98	756
Weighted avg	0.98	0.98	0.98	756

Fig 4 . Classification Report Of Proposed Ensemble Model**.**

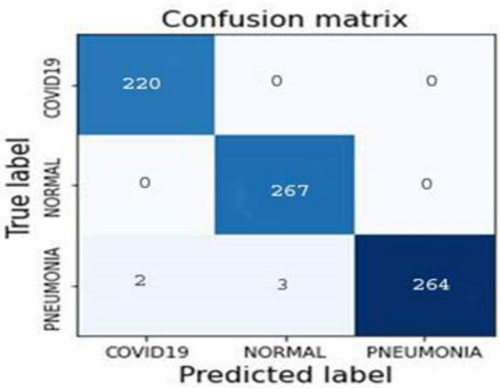


Fig 5. Confusion Matrix

We have covered the results in this section. First, we have developed three fine tuned deep learning architectures for multi-class classification ie.: VGG-19, ResNet50, and InceptonV3. and these three models are then combined to create weighted average ensemble model . the weight assigned to improve the performance are = [0.4, 0.3, 0.3]. in weighted average ensemble model each individual model's prediction is assigned a specific weight. whereas in average ensemble model all the individual models contribute equally to the final prediction. The final prediction is a weighted sum of the individual models' predictions, where each prediction is multiplied by its respective weight. the model achieved an overall accuracy of 98.33%

5. Conclusion

In this study, three pre-trained deep learning models are taken and modified the layers according to our requirement to create an weighted average ensemble learning model . the model has achieved better accuracy of 98.33% compare to other state of art models.

References

[1] C.D.C. COVID, R. Team, Severe outcomes among patients with coronavirus disease 2019 (COVID-19)—United States, February 12–March 16, 2020, MMWR Morb. Mortal Wkly. Rep. 69 (2020) 343–346.

[2] A. Remuzzi, G. Remuzzi, COVID-19 and Italy: what next? Lancet (2020). E. Mahase, Coronavirus: covid-19 has killed more people than SARS and MERS combined,

[3] World Health Organization. “Public health emergency of international concern (PHEIC),” who. 2020. p. 1–10 [Online]. Available: https://www.who.int/publications/m/item/COVID-19-public-health-emergency-of-international-concern-(pheic)-global-research-and-innovation-forum. [Accessed 2 August 2021]. accessed.

[4] C. Huang, Y. Wang, X. Li, L. Ren, J. Zhao, Y. Hu, L. Zhang, G. Fan, J. Xu, X. Gu, Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China, Lancet 395 (2020) 497–506.

[5] V.M. Corman, O. Landt, M. Kaiser, R. Molenkamp, A. Meijer, D.K.W. Chu, T. Bleicker, S. Brünink, J. Schneider, M.L. Schmidt, Detection of 2019 novel coronavirus (2019-nCoV) by real-time RT-PCR, Eurosurveillance 25 (2020), 2000045.

[6] O. Gozes, M. Frid-Adar, H. Greenspan, P.D. Browning, H. Zhang, W. Ji, A. Bernheim, E. Siegel, Rapid ai development cycle for the coronavirus (covid-19) pandemic: initial results for automated detection & patient monitoring using deep learning ct image analysis, ArXivPrepr. ArXiv2003.05037. (2020).

[7] Annarumma M, Withey SJ, Bakewell RJ, Pesce E, Goh V, Montana G. Automated triaging of adult chest radiographs with deep artificial neural networks. Radiology 2019;291 (1):196–202. http://dx.doi.org/10.1148/radiol.2018180921

[8] Mazurowski MA, Buda M, Saha A, Bashir MR. Deep learning in radiology: an overview of the concepts and a survey of the state of the art with focus on MRI. J Magn Reson Imaging 2019;49(4):939–54.

[9] http://dx.doi.org/10.1002/jmri.26534

[10] I. Castiglioni, D. Ippolito, M. Interlenghi, C.B. Monti, C.Salvatore, S. Schiaffino, A. Polidori, D. Gandola, C. Messa, F. Sardanelli, Artificial intelligence applied on chest x-ray can aid in the diagnosis of covid-19 infection: a first experience from lombardy, italy, medRxivdoi: 10.1101/ 2020.04.08.20040907.

[11] Ozturk T , Talo M , Yildirim EA , Baloglu UB , Yildirim O , Acharya UR . Automated detection of COVID-19 cases using deep neural networks with X-ray images. Comput Biol Med 2020:103792.

[12] Nigam B, Nigam A, Jain R, Dodia S, Arora N, Annappa B. Covid-19: Automatic detection from x-ray images by utilizing

[13] deep learning methods. Expert Syst Appl 2021;176 . https:// doi.org/10.1016/j.eswa.2021.114883 114883.

[14] Kumar P. and Kumari S. Detection of coronavirus disease (COVID-19) based on deep features. preprints.org, no. March, p. 9, Mar. 2020.

[15] R. Jain, M. Gupta, S. Taneja, D.J. Hemanth, Deep learning based detection and analysis of COVID-19 on chest X-ray images, Appl. Intell. 51 (3) (2021) 1690–1700.

[16] Narayanan BN, Hardie RC, Krishnaraja V, Karam C, Davuluru VSP. Transfer-to-transfer learning approach for computer aided detection of covid-19 in chest radiographs. AI 2020;1(4):539–57.

[17] AnandbabuGopatoti a, P. Vijayalakshmi “ CXGNet: A tri-phase chest X-ray image classification for COVID-19 diagnosis using deep CNN with enhanced grey-wolf optimizer” Biomedical Signal Processing and Control 77 (2022) 10380

[18] Kunwar Prashant , Prakash Choudhary,b, Tarun Agrawal , Evam Kaushik , “OWAE-Net: COVID-19 detection from ECG images using deep learning and optimized weighted average ensemble technique”, Intelligent Systems with Applications 16 (2022) 200154, https://doi.org/10.1016/j.iswa.2022.200154

[19] A. Rahman, H. Zunair, M. Sohel Rahman, J. Quader Yuki, S. Biswas, M. Ashraful Alam, N. Binte Alam, M.R.C. Mahdy, Improving Malaria Parasite Detection from Red Blood Cell Using Deep Convolutional

Neural Networks, 2019 arXiv Preprint arXiv:1907.10418.

[20] Pradeep Kumar Roy, Abhinav Kumar, “Early Prediction of Covid-19 using ensemble of transfer learning”, Computers and Electrical Engineering 101 (2022)10818, https://doi.org/10.1016/j.compeleceng.2022.108018

[21] G. Ayana, K. Dese, S. Choe, Transfer learning in breast cancer diagnoses via ultrasound imaging, Cancers 13 (2021) 738.

[22] Transfer learning. Available online: http://www.isikdogan.com/blog/transfer-learning.html (accessed on 15 March 2022).

[23] Simonyan, K. & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

[24] Ekbal, A., & Saha, S. (2013). Stacked ensemble coupled with feature selection for biomedical entity extraction. Knowledge-Based Systems, 46, 22–32.

[25] P.V. Naresh, R. Visalakshi, B.Satyanarayana,” PSO Optimized CNN-SVM Architecture for Covid - 19 Classification”, International Journal on Recent and Innovation Trends in Computing and Communication, Volume: 11 Issue: 5s, https://doi.org/10.17762/ijritcc.v11i5s.6646

[26] P.V. Naresh, R. Visalakshi, B.Satyanarayana,”A Light Weight Grid Search Based Ensemble Model for Covid-19 Classification in Chest X-Rays” Intelligent Systems and applications in engineering,”Volume 11 issue : 3.