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# "Artificial Intelligence" A system for identifying different types of epidemics using X-rays radiation

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**Abstract—**

The COVID-19 epidemic has put many lives in jeopardy from the very start. In order to classify epidemics, this study used the visual geometry group network (VGGNet). Pulmonary tuberculosis, normal lung, pneumonia, and COVID-19 were the four categories used to assess the 12068 chest X-ray photos collected from the Kaggle website. Using the chest X-ray pictures, we were able to identify and categorize the aforementioned condition using the VGGNet architecture. The accuracy, specificity, and sensitivity are some of the metrics used to evaluate these classes' efficacy. With regard to the parameters that were measured, the sensitivity, specificity, and accuracy were 0.98, 0.96, and 0.97, correspondingly. By correctly identifying variations in patients' X-ray pictures, our method may distinguish between various illnesses. The findings shown that when it comes to epidemic diagnosis, the VGG16 model may outperform VGG19. A quicker diagnosis and better prognosis for patients are both made possible by the VGG16-based method. In comparison to computed tomography (CT) pictures, the suggested model based on chest X-ray images is more accurate, simpler, and cheaper, according to the results.
Keywords: chest X-ray pictures, deep learning, COVID-19, image classification

## I. INTRODUCTION

The 2019 coronavirus, also known as COVID-19, is a highly contagious respiratory illness that may inflict pneumonia of varied degrees in susceptible individuals. The Chinese city of Wuhan was the first site of this pathogen's discovery in December 2019 [1, 2]. In the early stages of a COVID-19 infection, symptoms such a high temperature, dry cough, muscle pain, fatigue, shortness of breath, and loss of appetite are common. These signs and symptoms lead to the development of shock, arrhythmia, and acute respiratory distress syndrome (ARDS). It is possible to treat a mild respiratory infection caused by COVID-19 without antibiotics. Conversely, the virus is more likely to infect those who already have preexisting medical conditions, such as diabetes, chronic lung disease, or cardiovascular disease [3, 4]. Clinicians are seeking faster and more accurate methods of detecting COVID-19, as well as other viral and antibody testing alternatives, because to the increasing number of cases. Public health centers, emergency departments, and rural clinics often have X-rays and CT scans accessible, and they are affordable. They are used for the rapid diagnosis of lung infections caused by COVID-19 [5]. The RT-PCR technique requires a lot of time and only has a sensitivity of 60–70%. It is possible to guarantee early treatment by analyzing pictures of patients' lungs to identify the detrimental effects of COVID-19. Among the potential screening tools available, computed tomography (CT) scanning may be more sensitive than RT-PRC in identifying COVID-19 pneumonia. Changes in lung pathology CT scans are often done much later than when symptoms first appear [5]. In nations where testing kits are limited, X-rays and chest CT scans are typically utilized to detect COVID-19, hence clinicians are advised to rely solely on these findings when making decisions. Researchers have shown that a mix of laboratory data and clinical imaging features may help detect COVID-19 at an early stage [5]. The current testing kit shortage may be mitigated by combining CT and X-ray scan pictures of the lungs with state-of-the-art data mining and machine learning algorithms like Convolutional Neural Network (CNN). This allows for rapid and reliable diagnosis of the illness. This study recommends deep learning for COVID-19 detection in X-ray images, with a focus on transfer learning. Additional recommendations for improving VGG-16 and VGG-19 convolutional neural networks for this goal are also included. The radiologist may find this material helpful in quickly identifying the X-ray regions of interest. The paper is organized as follows: After a brief review of the relevant literature in Section 2, the methodology is laid out in Section 3, and the results of the experiments, including comparisons and evaluations of performance, are presented in Section 4. The study's conclusions, which will be used in future publications, are presented in the last part.

## II. RELATED WORK

Automated categorization of digital medical pictures makes use of many machine learning techniques. Detection, diagnosis, and classification may all benefit from the visual information that machine learning pattern recognition

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can uncover. Typically, supervised, unsupervised, and reinforcement learning are used to categorize the coaching types of ML algorithms. Acquiring experience with useable photos and using that information to anticipate new, unseen images (test data) is what supervised learning is all about [1, 2]. In order to identify COVID-19, researchers have suggested a deep learning method in [6, 7]. Patients infected with COVID-19 may be helped by using the DenseNet network trained with COVID-19 RNA sequences, according to Zhang et al. [8]. A patient with severe COVID-19 was found to have opacities in the right place, as reported by Kong et al. [9]. Also, one study by Yoon et al. [10, 11] indicated that one-third of patients had a nodular opacity in the lower left lung area. The opposite side of each lung showed four and five irregular opacities, respectively. Among the many AI techniques that have gained popularity in recent years, the Convolutional Neural Network (CNN) stands out. CNN has been successful with a variety of medical image analysis, including magnetic resonance imaging (MRI)[12,13], x-ray [14], computed tomography (CT) scans [15], ultrasound [16], and others. Among CNN's many successful applications are linguistic communication processing [17], computer vision [18], audio recognition [19], and voice recognition [20].

**III. Proposed Method**

Convolutional neural networks (CNNs) are trained in this study using the transfer learning technique. Using the transfer learning method, a CNN network that had already been trained using conserved weights from the ImageNet database was brought into this research and trained on the dataset. Since the vanishing gradient issue makes it difficult to train the network's first layers, using the transfer learning approach to train the CNN has the benefit of previously having taught them. In contrast, the network has mastered fundamentals like form detection and picture edge detection, among others. Consequently, the pre-trained model takes use of the insight obtained from the photos in the pre-existing database's fundamental learning capabilities. In figure 1 are the stages that make up the suggested approach.

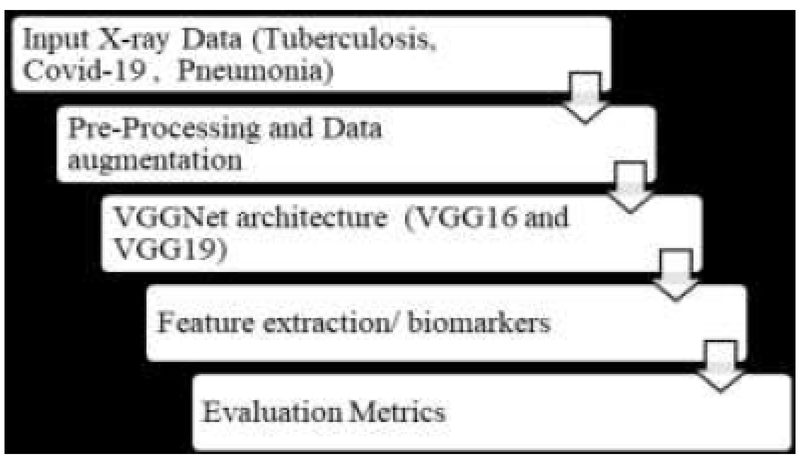


*Fig 1. Show the steps of the proposed method*

The time needed to train the network's final layers is reduced using his coaching technique [1,2,4,6,10,11] since only those levels are necessary.All of the phases of the proposed technique are shown in Figure 1, which is a flow diagram. Our tailored exploitable architecture is shown in Figure 2. By swiping the random picture fifteen degrees either way, we can verify that the proposed models generalize via data augmentation.A. A. Learning transfer The term "transfer learning" refers to the practice of using a model that has been trained on one issue to make label predictions for another problem [22]. Shortening the time it takes to train a neural network model is the biggest benefit of using transfer learning. In addition, less generalization mistakes could be the outcome. There has to be a connection between the primary and secondary concerns. In this case, we address the challenge of identifying lung illnesses by tapping into the knowledge of a model trained for general image recognition. Sixteen convolution layers, three fully linked layers, five MaxPool layers, and one SoftMax layer might make up a VGG model with nineteen members, denoted as VGG19. Variants such as VGG11 and VGG16 are also available. The FLOP count of VGG19 is 19.6 billion. It's possible that VGG-19 is a deep convolutional neural network with 19 layers. The network has already been trained on more than 1,000,000 photos and is available in the ImageNet

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database [12, 13, 23]. You will only need to import it. To implement transfer learning, we use fine-tuning. We removed the fully connected layer head and instantiated the VGG19 network with pre-trained weights on ImageNet to prepare the VGGNet model for fine-tuning. Next, we construct a new fully-connected layer head using the following layers for class prediction. Following AveragePooling2D are Flatten, Dense, Dropout, and Dense with the "softmax" activation as a last step. It is superimposed above VGG19. Next, we train just the fully connected layer head after freezing the convolutional weights of VGG19. This completes our fine-tuning setup. Figure 2 depicts the format of the suggested approach.

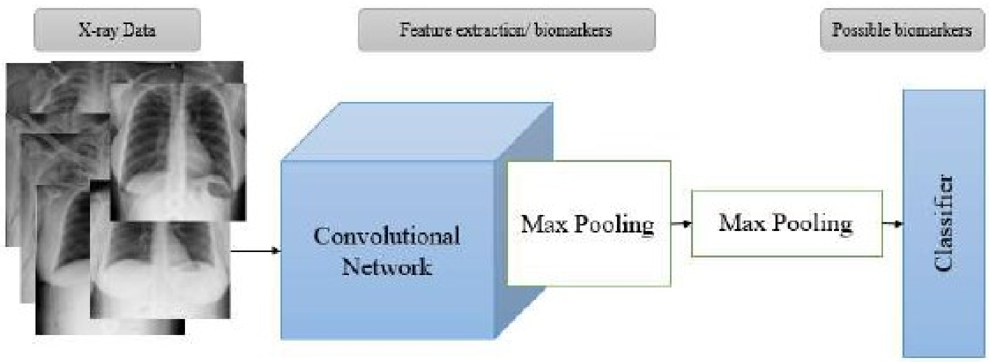


*Fig.2. Structure of proposed method*

B. Initial Steps In computer vision applications, pre-processing is often used. The picture component is prioritized by preprocessing approaches, which may aid recognition or even deep learning training. Following is the preprocessing approach used on the images taken from DICOM files: • Image pixel value normalization.• Reducing the size of the images by cropping out the white space around them. Due to the non-uniformity of the data set and the by-ray pictures' various widths, we converted all of the images to a common length of 224 by 224 pixels. This was accomplished by using RGB reordering, and the end output for the suggested model is 224 224 3 images. We only used a 20-degree rotation range for the information augmentation since the collection was small. The data set was substantially expanded by flipping the X-ray pictures horizontally and vertically. This dataset may provide coaching on new concepts using identical data sets. A dataset consisting of 12,068 chest X-rays is now being used to test and evaluate our AI system. A total of 75% of the photos in the database were chosen for model training, while 15% were used for testing and 10% were used for assessment. Training and testing sets are kept apart so as not to disturb the patients. C. Enhancing data Data augmentation is a method that significantly expands the quantity of data at your disposal. Using data from both sources, Figure 3 shows the distribution of X-ray images across four categories: normal/healthy, viral/bacterial pneumonia, and COVID-19 infection. Consequently, in order to avoid overfitting, augmentation approaches increase the quantity of pictures belonging to COVID-19 and other classes. Two methods for enhancing data were used in this research: rotation and Gaussian blur [1, 2]. D. Suggested Approach New Approach Convolutional neural networks (CNNs) are trained in this study using the transfer learning technique. This paper offers an upgraded convolutional neural network VGG-16 and VGG-19 that uses deep learning to achieve this purpose. The suggested x-ray-based epidemic screening approach is explained. In order to train the models, we made certain adjustments to the VGGNet architecture and utilized X-ray pictures taken from individuals with pneumonia, SARS-CoV-2, and otherwise good health. Following the pre-processing methods described here, the x-ray images are extracted from the datasets stated in the previous section. Finding out if chest x-rays are normal or reveal symptoms of lung disease is the goal of the suggested approach. For both models, we used a deep learning network that was trained using transfer learning and the Visual Geometry Group (VGG) models [2]. When compared to standard convolutional neural networks, the in-network depth is much better. By switching between many convolutions and nonlinear activation layers, it achieves a superior structure compared to one. By using the linear unit (ReLU) as the activation function, applying Maxpooling for low sampling, and choosing the most important value in the image region as the site's pooled value, the layer structure improves feature extraction from images. Chapter Four: Findings Table A. The three datasets that were taken into account in this study are detailed in this section. To the best of our knowledge, these are the three largest publicly available datasets. (TB) tuberculosis Database for Chest X-rays A database of chest X-ray pictures including both normal and tuberculosis (TB) positive patients has been developed by a group of researchers from the Universities of Dhaka in Bangladesh and Qatar University in Doha, Qatar. This paper's database includes 3047 pictures, including 3047

representative images and 3047 photos. Source: https://www.kaggle.com/tawsifurrahman/tuberculosis-tb-chest-xray-dataset. The COVID-19 Chest X-ray Database is also a part of the TB database. COVID-19 RADIOGRAPHY DATABASE (Recipient of the Kaggle Community's COVID-19 Dataset Award) The database of COVID-19 positive cases, normal and infected photos, was created by researchers from Qatar University in Doha, Qatar, and the University of Dhaka in Bangladesh in collaboration with colleagues from Pakistan and Malaysia and medical practitioners. The database for this paper was generated using 3006 Covid-19 photos. The data used in the database can be found at https://www.kaggle.com/tawsifurrahman/covid19-radiography-database. Covid-19 Database for Chest X-rays For the purpose of identifying this lung illness, the pneumonia database used a dataset consisting of 30,60 verified chest X-ray pictures. Data for this database came from the following source: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia. Last goodbyes
Table I summarizes the details regarding the dataset that was collected and the issues that were identified. Here we show the correlation between each class's picture count and the number of patients.

TABLE I. Datasets distribution.

| Classes | DR condition | NO. of image |
|---|---|---|
| 0 | Normal | 3047 |
| 1 | Covid-19 | 3006 |
| 2 | Pneumonia | 3060 |
| 3 | Tuberculosis | 3047 |

Measures for Assessment (B) Deep learning systems trained to identify and categorize lung nodes are evaluated using a variety of standards. We determined the accuracy, sensitivity, and specificity of our suggested CNN model to evaluate its performance.

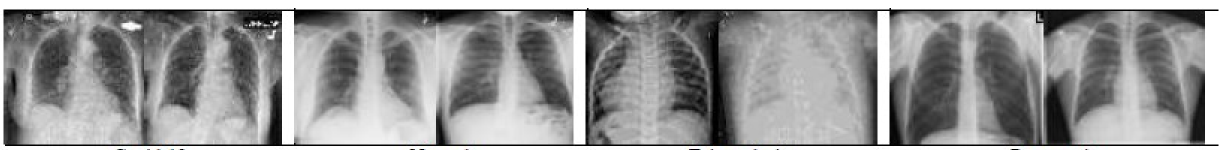

*Fig.3. Examples of images used*

For each class, you should report the accuracy as the number of "correct predictions made" divided by the number of "total predictions made" for that category [24-27, 33-35].

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

A tiny fraction of cases, as estimated below, will have a positive model result if the person's result is positive. This is known as the sensitivity, real positive rate.

$$Sensitivity = \frac{TP}{TP + FN} \quad (2)$$

Specificity: As calculated by the formula below [24-27, 33-35], the model will also have a negative outcome in a tiny proportion of circumstances if the result affects the person. This is known as the real negative rate.

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$$Specificity = \frac{TN}{TN+FP} \quad (3)$$

TABLE II. Confusion Matrix.

| Confusion Matrix | | Classified As: | |
|---|---|---|---|
| | | Negative | Positive |
| Actual Class | Negative | TN | FP |
| | Positive | FN | TP |

A matrix describing the model's overall performance is the result of the Confusion Matrix, as the name suggests.

TABLE III. SOFTWARE REQUIREMENTS.

| Distribution | Anaconda Navigator and Google Colab |
|---|---|
| API | Keras |
| Library | Tensor Flow, OpenCV |
| Packages | Matplotlib, NumPyNumPy, pandas, sci-kit learn |
| Language | Python 3.7 |
| IDE | Jupyter Notebook |
| GPU Architecture | Google Colab |
| Applications | labeling, TensorBoard |

Part C.: Conducting Experiments The paper shows how COVID-19 is often diagnosed using X-ray, ultrasound, and CT scan pictures, all of which are routinely used medical imaging modalities, by transferring learning from deep learning models. The goal is to use intelligent, deep learning image categorization algorithms to supplement the work of already overworked medical personnel. Differentiating a chest X-ray involving pneumonia from one connected to COVID-19.• Differentiating between a regular chest X-ray and one linked to lung diseases. •Here, we go over the experiment we conducted to evaluate how well the provided methods worked with regard to:

TABLE IV. VGGNET architecture results in different parameters.

| | Optimizer | Batch size | Epochs | Loss | Sensitivity | Specific | Accuracy |
|---|---|---|---|---|---|---|---|
| VGG19 | Adam | 32 | 20 | 0.6532 | 0.6515 | 0.6942 | 0.7217 |
| | Adam | 32 | 5 | 0.6969 | 0.6836 | 0.6913 | 0.7231 |
| | Adam | 16 | 10 | 1.3865 | 0.1403 | 0.1013 | 0.2493 |
| | RMS prop | 32 | 20 | 0.2502 | 0.7826 | 0.7327 | 0.7797 |
| VGG16 | RMS prop | 64 | 15 | 0.5762 | 0.7326 | 0.7592 | 0.7679 |
| | Adam | 32 | 50 | 0.0598 | 0.9826 | 0.9689 | 0.9799 |

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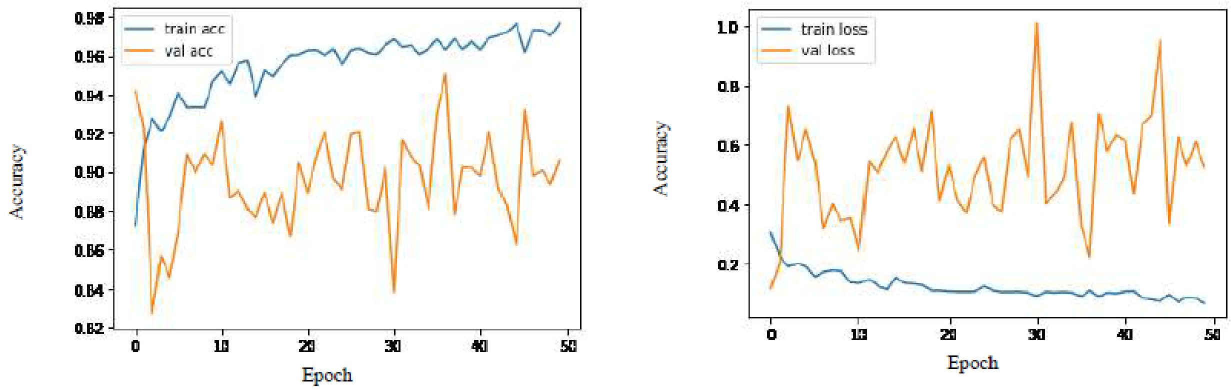


*Fig.4. Result of VGG16*

Both the train and validation sets of classification accuracy and loss curves are shown in Figure 4 throughout the CNN model training process. Performance indicators, including convergence graphs of loss functions for several transfer learning techniques, are summarized in Table IV of the experiment. Denoted by "train" and "Val," respectively, are the training and validation loss convergence curves. The VGG16 algorithm was used to classify the covid-19 X-ray picture, as shown in Figure 5. D. Radiologist's Findings: In order to gauge AI's efficacy, the study team matched its findings to those of radiologists. Radiologists prepared and used a large amount of actual data to do this. The results demonstrated that this method outperforms both experts and master radiologists, with specialists doing somewhat better. Doctors' workloads are reduced by this system. While human radiologists take an average of 6.5 minutes to scan a CT picture, AI can execute the same task in 2.73 seconds. Compared to radiologists, AI performed somewhat worse when it came to detecting pneumonia, as shown in this paper. The current model's accuracy in comparison to the real data is shown in the table below. The training of the model does not make use of this data.

TABLE V. Accuracy of the existing model relative to the actual data.

| | Sample | Radiologist | | | Model AI | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | NPV | PPV | Time | NPV | PPV | Accuracy | Sensitivity | Specific | Time |
| Normal | 50 | 0 | 50 | 15 Min | 15 | 45 | 92% | 89% | 86% | 3 Min |
| Covid-19 | 50 | 7 | 43 | 15 Min | 21 | 39 | 88% | 90% | 83% | 3 Min |
| Pneumonia | 50 | 8 | 42 | 15 Min | 19 | 41 | 91% | 88% | 90% | 3 Min |
| Tuberculosis | 50 | 19 | 31 | 15 Min | 16 | 34 | 82% | 80% | 81% | 3 Min |

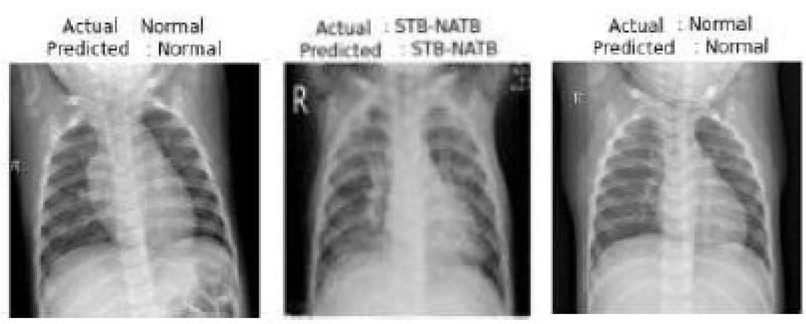


*Fig.5. Result of predicting new sample with VGG-NET*

## V. Discussion

A powerful tool for medical professionals, deep learning can interpret chest X-ray pictures and feed them into the model to diagnose illnesses. Standard chest X-rays revealed pneumonia, tuberculosis, and COVID-19. This research introduces an AI-powered approach that can reliably differentiate COVID-19 from pneumonia and pulmonary TB. In this setting, where misdiagnoses of COVID-19 are prevalent, the suggested method may aid in the identification of patients to medical professionals. Hospitals without CT scanners may find this method useful.

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More complex models, like VGG-19, lost performance because to overfitting issues and an inability to properly represent inter-category differences. Going forward, we will be looking at viral infection in the COVID-19, Pneumonia, and Tuberculosis collections using the VGG-16 model that performed the best. Instances of COVID-19 may be detected using the proposed approach, which is an alternate diagnostic tool. Last but not least, all previous studies have demonstrated promising results, therefore the present study suggests that COVID-19 should be visible using deep learning models. According to various methodologies, deep learning models are able to accurately recognize objects in photographs, which enables deep networks to properly categorize images. It will be some time before we know if deep learning algorithm findings can be relied on for accurate diagnosis.

TABLE V. Accuracy comparison of our proposed model vs. existing models.

| Study | Model | Accuracy (%) |
|---|---|---|
| Debabrata Dansana et al [28]. | VGG-19 | 91% |
| Chiranjibi Sitaula et al [29]. | VGG16 | 87.49 |
| Ayan KumarDas et al. [30]. | VGG-16 | 97.67 |
| Ki-Sun Lee [31]. | VGG-16 | 95.9% |
| Shamik Tiwari,Anurag Jain [32]. | VGG-CapsNet | 92% |
| This paper (VGG16) | VGG16 | 97.99% |

The exponential growth of COVID-19 patients is also putting a burden on healthcare systems around the globe. The restricted number of testing kits available makes it impossible to utilize traditional techniques to test every patient with the condition (RT-PCR). But this isn't enough to justify the tests' poor sensitivity and lengthy execution times. While we wait for test results, a chest X-ray may help identify probable cases of COVID-19 in high-risk quarantine patients. Due to the widespread availability of X-Ray technology in healthcare systems and the digitalization of the most recent X-Ray systems, the transportation of samples is unnecessary. Three open-source datasets and innovative methods for X-ray image classification into four groups (regular, pneumonia, TB, and COVID-19) were used to train VGGNET.

## VI. Conclusion

There was a shortage of labelled data points since the illness was in its early stages. Consequently, the amount of data points used and the dataset's size were both reduced. The possibility of overfitting exists. In most cases, better outcomes are produced by increasing the quantity of the dataset. Two independent models, each capable of performing the aforementioned classification tasks, make up our present offering. The effective grouping of chest X-rays into the suggested classes may be possible in the future with the use of an architectural framework. Our models of choice for the classification tasks were VGG-16 and VGG-19. We tested several different models, and the results were all over the map (see Table IV). In conclusion, the sensitivity rate and accuracy for identifying epidemic categories have both been enhanced by 98.26% and 97.99%, respectively, in the improved network model. It is well recognized that this enhancement has a significant effect. In addition, we have significantly reduced the parameters, and the improved VGG-16 shows great potential in identifying epidemic detection categories; it also gives a positive assurance before hospital admission. Our well-trained network is here to help with medical diagnostics, we hope. Another drawback of the research is the limited amount of COVID-19 X-ray images that were used. It is my sincere wish that more extensive COVID-19 statistics from nearby hospitals would be made public at some point so that we may enhance the precision of our planned network. Code that is currently available: To access all of the computational tools that were created for this project, as well as a tutorial on how to use them, you may visit the following repository: https://github.com/Jafar-Abdollahi/An-artificial-intelligence-system-for-detecting-the-types-of-the-epidemic-from-X-rays.

## REFERENCE

[1] Hussain, E., Hasan, M., Rahman, M. A., Lee, I., Tamanna, T., & Parvez, M. Z. (2021). CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images. Chaos, Solitons & Fractals, 142, 110495.
[2] Kamal, K. C., Yin, Z., Wu, M., & Wu, Z. (2021). Evaluation of deep learning-based approaches for COVID-19 classification based on chest X-ray images. Signal, Image and Video Processing, 1-8.

[3] Xiao, J., Wang, J., Cao, S., & Li, B. (2020, April). Application of a novel and improved VGG-19 network in the detection of workers wearing masks. In Journal of Physics: Conference Series (Vol. 1518, No. 1, p. 012041). IOP Publishing.
[4] Jain, G., Mittal, D., Thakur, D., & Mittal, M. K. (2020). A deep learning approach to detect Covid-19 coronavirus with X-Ray images. Biocybernetics and biomedical engineering, 40(4), 1391-1405.
[5] Hussain, E., Hasan, M., Rahman, M. A., Lee, I., Tamanna, T., & Parvez, M. Z. (2021). CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images. Chaos, Solitons & Fractals, 142, 110495.
[6] Kamal, K. C., Yin, Z., Wu, M., & Wu, Z. (2021). Evaluation of deep learning-based approaches for COVID-19 classification based on chest X-ray images. Signal, Image and Video Processing, 1-8.
[7] S. Wang, B. Kang, J. Ma, X. Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. Li, X. Meng, et al., A deep learning algorithm using ct images to screen for corona virus disease (covid-19), medRxiv (2020).
[8] Zhang, K. M. Saravanan, Y. Yang, M. T. Hossain, J. Li, X. Ren, Y. Wei, Deep learning based drug screening for novel coronavirus 2019- ncov (2020).
[9] W. Kong, P.P. Agarwal Chest imaging appearance of COVID-19 infection Radiology, 2 (1) (2020)
[10] 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(2), 635-640.
[11] S.H. Yoon, K.H. Lee, J. Radiol, et al. Chest radiographic and CT findings of the 2019 novel coronavirus disease (COVID-19): analysis of nine patients treated in Korea Korean, 21 (4) (2020), pp. 494-500.
[12] L. Zou, J. Zheng, C. Miao, M.J. Mckeown, Z.J. Wang 3D CNN based automatic diagnosis of attention deficit hyperactivity disorder using functional and structural MRI IEEE Access, 5 (2017), pp. 23626-23636
[13] Canayaz, M. (2021). MH-COVIDNet: Diagnosis of COVID-19 using deep neural networks and meta-heuristic-based feature selection on X-ray images. Biomedical Signal Processing and Control, 64, 102257.
[14] Liu, et al. TX-CNN: Detecting tuberculosis in chest x-ray images using convolutional neural network IEEE International conference on image processing (ICIP), Beijing (2017), pp. 2314-2318
[15] X. Zhao, L. Liu, S. Qi, Y. Teng, J. Li, W. Qian Agile convolutional neural network for pulmonary nodule classification using CT images Int J CARS, 13 (2018), pp. 585-595
[16] Liu, W. Li, N. Zhao, et al. Integrate domain knowledge in training CNN for ultrasonography breast cancer diagnosis Frangi A., Schnabel J., Davatzikos C., Alberola-López C., Alberola-Fichtinger G. (Eds.), Medical image computing and computer assisted intervention – MICCAI 2018. MICCAI 2018. Lecture Notes in Computer Science, vol. 11071, Springer, Cham (2018)
[17] A.M. Alayba, V. Palade, M. England, R. Iqbal A combined CNN and LSTM model for arabic sentiment analysis Holzinger A., Kieseberg P., Tjoa A., Weippl E. (Eds.), International cross-domain conference for machine learning and knowledge extraction, CD-MAKE Lecture Notes in Computer Science, vol. 11015, Springer, Cham (2018)
[18] X. Peng, C. Schmid Multi-region two-stream r-CNN for action detection Leibe B., Matas J., Sebe N., Welling M. (Eds.), Computer vision – ECCV 2016, ECCV, Lecture Notes in Computer Science, vol. 9908, Springer, Cham (2016)
[19] S. Zhang, S. Zhang, T. Huang, W. Gao, Q. Tian Learning affective features with a hybrid deep model for audio–visual emotion recognition IEEE Trans Circuits SystVideo Technol, 28 (10) (2018), pp. 3030-3043
[20] O. Abdel-Hamid, A. Mohamed, H. Jiang, G. Penn Applying convolutional neural networks concepts to hybrid NN-HMM model for speech recognition 2012 IEEE International conference on acoustics, Speech and Signal Processing (ICASSP), Kyoto (2012), pp. 4277-4280
[21] Dey, N., Zhang, Y. D., Rajinikanth, V., Pugalenthi, R., & Raja, N. S. M. (2021). Customized VGG19 architecture for pneumonia detection in chest X-rays. Pattern Recognition Letters, 143, 67-74.
[22] Shaha, M., & Pawar, M. (2018, March). Transfer learning for image classification. In 2018 Second International Conference on Electronics, Communication and Aerospace Technology (ICECA) (pp. 656-660). IEEE.
[23] ImageNet. http://www.image-net.org
[24] Abdollahi, J., Moghaddam, B. N., & Parvar, M. E. (2019). Improving diabetes diagnosis in smart health using genetic-based Ensemble learning algorithm. Approach to IoT Infrastructure. Future Gen Distrib Systems J, 1, 23-30.
[25] Abdollahi, J. A review of Deep learning methods in the study, prediction and management of COVID-19.
[26] Abdollahi, J., Keshandehghan, A., Gardaneh, M., Panahi, Y., & Gardaneh, M. (2020). Accurate detection of breast cancer metastasis using a hybrid model of artificial intelligence algorithm. Archives of Breast Cancer, 18-24.
[27] Abdollahi, J., & Nouri-Moghaddam, B. (2022). Hybrid stacked ensemble combined with genetic algorithms for diabetes prediction. Iran Journal of Computer Science, 1-16.

ISSN 2347–3657

Volume 13, Issue 2, 2025

[28] Dansana, D., Kumar, R., Bhattacharjee, A., Hemanth, D. J., Gupta, D., Khanna, A., & Castillo, O. (2020). Early diagnosis of COVID-19-affected patients based on X-ray and computed tomography images using deep learning algorithm. Soft Computing, 1-9.

[29] Sitaula, C., & Hossain, M. B. (2021). Attention-based VGG-16 model for COVID-19 chest X-ray image classification. Applied Intelligence, 51(5), 2850-2863.

[30] Das, A. K., Kalam, S., Kumar, C., & Sinha, D. (2021). TLCoV-An automated Covid-19 screening model using Transfer Learning from chest X-ray images. Chaos, Solitons & Fractals, 144, 110713.

[31] Lee, K. S., Kim, J. Y., Jeon, E. T., Choi, W. S., Kim, N. H., & Lee, K. Y. (2020). Evaluation of scalability and degree of fine-tuning of deep convolutional neural networks for COVID-19 screening on chest X-ray images using explainable deep-learning algorithm. Journal of Personalized Medicine, 10(4), 213.

[32] Tiwari, S., & Jain, A. (2021). Convolutional capsule network for COVID-19 detection using radiography images. International Journal of Imaging Systems and Technology, 31(2), 525-539.

[33] abdollahi jafar, amani firouz, mohammadnia alireza, amani paniz, fattahzadeh-ardalani ghasem. Using Stacking methods based Genetic Algorithm to predict the time between symptom onset and hospital arrival in stroke patients and its related factors. JBE. 2022;8(1):8-23.

[34] Abdollahi, J., & Nouri-Moghaddam, B. (2021). Feature selection for medical diagnosis: Evaluation for using a hybrid Stacked-Genetic approach in the diagnosis of heart disease. arXiv preprint arXiv:2103.08175.

[35] Abdollahi, J., Nouri-Moghaddam, B., & Ghazanfari, M. (2021). Deep Neural Network Based Ensemble learning Algorithms for the healthcare system (diagnosis of chronic diseases). arXiv preprint arXiv:2103.08182.