Automatic COVID-19 pneumonia diagnosis from x-ray lung image: A Deep Feature and Machine Learning Solution

M. A. Ahmed*, Z.T. Al-qaysi², Moceheb Lazam Shuandy¹, Mahmood Maher Salih¹, Majid Hamid Ali¹

¹ Department of computer science, computer science and mathematics college, Tikrit University, Iraq

*corresponding author, Email: mohamed.akthami@tu.edu.iq

Abstract. Coronavirus disease 2019 was announced after unidentified pneumonia was discovered in Wuhan, China, and quickly spread around the world (COVID-19). This outbreak has claimed the lives of so many people. It has a long-term negative impact on public health. The goal of this study is to develop an intelligent computer-aided system that can detect positive COVID-19 cases automatically, which can help with daily medical problems. The proposed system is based on the convolution neural network (CNN) architecture and can automatically expose discriminative features on chest X-ray images due to its convolution with rich filter families and weight-sharing characteristics. As a deep feature extractor, the CNN model SqueezeNet was used. The extracted deep discriminative features were fed machine Decision Tree, Random Forest, Neural Network (NN), Naive Bayes, Logistic Regression, and k-nearest neighbor learning algorithms. As a result, the NN classifier with an accuracy of 97.24 per cent, a sensitivity of 0.9724, a specificity of 0.9858, and an F-score of 0.972 provided the most effective results. The high detection performance obtained in this study demonstrates the utility of deep CNN features and an NN classifier approach for detecting COVID-19 cases in CXR images. With the current resources, this would be hugely beneficial in speeding up disease diagnosis.

Keywords: COVID-19; Computer aided diagnosis system; Deep learning; Deep feature extraction; Machine learning

1. Introduction

The coronavirus (COVID-2019), which was first identified in the Chinese city of Wuhan at the end of 2019, rapidly spread across the world and became a pandemic. There were more than 42,079,495 confirmed cases and 1,144,224 reported deaths worldwide by October 23, 2020 [1]. COVID-2019 affects the entire world and all countries suffered because of this virus [2, 3]. It has had a major influence on daily life, public health, and the global economy [4, 5]. According to research, the virus's propagation rate (TR) is exceedingly harmful, varying between 2.24 and 3.58, which is much greater than most other forms of viral flu. Since there is no preventive treatment or vaccine for the new COVID-19 disease, early diagnosis is critical to allow rapid isolation of the suspected individual and to reduce the risk of infection in the general population. The need for supplementary diagnostic tools has increased, as there are no accurate automatic toolkits available [6, 7]. Thus, the key solution is to development of the automated AI technique-based detection systems. Recent radiology imaging studies have shown that
certain photographs contain key COVID-19 virus characteristics [8]. Tests indicate that individuals with COVID-19 experience chest radiographic abnormalities when they are infected with COVID-19. Radiologists play a crucial role due to their extensive experience in this field. However, often a sufficient number of specialized doctors of radiologists is not available in every hospital. Thus, AI technologies in radiology can help to achieve an accurate diagnosis. In addition, AI methods can reduce the drawbacks such as the limited number of available RT-PCR test kits, cost of test, and waiting time of test results.

Advanced artificial intelligence (AI) techniques combined with radiological imaging would help assess the infection diagnosing accurately. In addition, it can also help tackle the problem of a shortage of qualified doctors in rural areas. Thus, the use of machine learning methods for automatic diagnosis in medicine has recently gained popularity as a supplementary tool for physicians. Deep learning, a well-known area in artificial intelligence (AI) technology, enables the creation of end-to-end algorithms that generate desired outcomes using input data without the need for handcrafted feature extraction. Many problems such as arrhythmia identification [9], skin cancer detection [10], breast cancer identification [3], brain disease classification [11], pneumonia detection [12], image segmentation [13], and lung segmentation [14] have been successfully implemented and developed based on deep learning techniques. Recently, researchers have applied the technology of deep learning to diagnose infection with Coronavirus (COVID-19) from radiological images such as CT scans and X-rays. Many radiological images have recently been commonly used for the identification of COVID-19. In [15], the authors suggested a framework model based on Capsule Networks to diagnose COVID-19 disease using X-ray imagery. To address the question of class disparity, they use a variety of convolution layers and capsules. COVIDCAPS' satisfactory performance on a small number of trainable parameters has been demonstrated in their experimental research. In the study [16], researchers proposed using a deep learning model to train the data and classify the pneumonia data. The proposal includes convolution layers, dense blocks, and flatten layers, among other components. The model's input size was 200 x 200 pixels, which was used to compute the classification choices using the sigmoid function. X-ray images of pneumonia found a 93.73 per cent success rate. In the study [17], researchers used the Backpropagation Neural Network classifier to delineate pneumonia. The system was evaluated using a general dataset containing x-ray images of two normal and two pneumonia cases. Performance of identifying the proposed approach compared to current CNN models. The detection system was able to rate 89.57 percent correctly. The study [18] used the TL in DL method to distinguish between COVID-19 and viral pneumonia using a dataset obtained from a public database. Based on augmentation and without augmentation, the networks were validated using COVID-19, viral pneumonia, and normal chest X-ray images. The proposed methodology achieved high accuracy, specificity, and sensitivity. In the study [19], the researchers demonstrated a hybrid framework with artificial intelligence that used machine learning and deep learning algorithms to detect COVID-19 cases in chest X-ray images. In the study [20], The authors used transfer learning to classify X-ray images into normal and COVID-19 classes and used ResNet50, InceptionV3, and Inception-ResNetV2 to do so. This system performed well with ResNet50, achieving a 98 percent accuracy rate. However, there are only 100 X-ray images, which is a very modest sample size. In the study [21], the authors used the SVM approach to distinguish pneumothorax in [22]. They mined the traits of lung images using a Local Binary Pattern (LBP). The authors used multi-scale texture segmentation to segment the areas of abnormal lungs in the proposed detection model by eliminating impurities from chest images. This transformation was also used to modify the texture in order to discover several overlapping block. In the study [23], the authors proposed a COVID-RENet model for COVID-19 identification. The model extract the features from x-ray images using CNN. SVM classifier was used to classify the collected images. The system evaluated with 5-fold cross-validation. A medical specialist in the early detection of COVID-19-infected patients primarily intends this proposed method for use.

Despite the extensive studies conducted by researchers to diagnose COVID-19 from radiological images, more detailed investigations and enhancements are still possible. In this research, we propose an automated diagnosis system of COVID-19 infection based on convolutional neural networks (CNNs) and machine learning methods. The proposed model guarantees an end-to-end learning schema that can
learn discriminative features directly from the input chest X-ray images, eliminating the need for a handcrafted feature engine. The main contributions of the current study are:

1. In contrast to the previous research, the model was learned using a relatively large X-ray radiology image data of COVID-19.
2. There is no data imbalance in this study.
3. The proposed model is a completely automatic method of diagnosis, which does not require any prior features extraction.
4. To increase COVID-19 infection detection, deep features extracted from deep layers of CNNs were used as input to machine learning models.
5. The evolved model can be used to aid decision-making by field experts, surgeons, and radiologists.

2. Developed System

The proposed COVID-19 diagnostic approach is involved dataset collection, data pre-processing feature extraction from x-ray images and training a machine-learning algorithm as shown in figure 1. COVID-19, Pneumonia, and normal images were used to classify the CXR images in this study. The following is a breakdown of the system stages.

![Diagram of the proposed system architecture for COVID-19 detection.](image-url)

2.1. Dataset Description

The major source of Chest X-Ray (CXR) photographs in this study is seven publicly available datasets. CXR photographs of patients (COVID-19 and Pneumonia) and healthy patients are included in the dataset (Normal). Dr. Joseph Cohan provided the first publicly available dataset from the GitHub repository. CXR images for COVID-19 positive patients, severe acute respiratory syndrome (SARS), Middle East respiratory syndrome (MARS), and acute respiratory distress syndrome are included in the dataset (ARDS) [24]. It includes frontal CXR images, non-frontal CXR images, and computed tomography scans (CT-scan) images, for 340 images. The chest X-ray dataset initiative COVID-19, the second GitHub dataset, includes 55 CXR photographs of patients infected with the novel coronavirus disease. As a third dataset, we gathered “Chest X-Ray Images (Pneumonia)” from the Kaggle repository, which contains CXR images of patients with Pneumonia and normal CXR images. [25]. The third dataset includes 5679 CXR images of two classes: Normal and Pneumonia. Under the fourth dataset, 2905 frontal and non-frontal CXR images are included in the COVID-19 Radiography Database. The
images distribute into three classes COVID-19, Normal, and Viral Pneumonia. "Chest X-ray for covid-19 detection" is the fifth dataset obtained from the Kaggle repository. The dataset comprises 174 CXR images of coronavirus-infected positive cases and 174 images of not infected cases. Similarly, the sixth dataset COVID-19 and Normal-poster anterior (PA) X-rays contain 280 CXR images belongs to COVID-19 and Normal cases. Finally, from the Robofow repository, we collect COVID-19 and Pneumonia Scans dataset, which contains 199 COVID-19 images and 1965 Healthy images as the seventh dataset. The chest picture samples of a patient with COVID-19 and Pneumonia, as well as a healthy person.

We only used frontal X-rays of positive COVID-19, Pneumonia, and normal cases for this study. Images from non-frontal X-rays, CT scans, and non-COVID-19 patients were omitted. Furthermore, to address the issue of data imbalance, the distribution of images used in both categories is equal. As a result, the dataset's final set of images contains 3000 images: 1000 COVID-19 cases, 1000 Pneumonia cases, and 1000 Normal cases.

2.2. Data Pre-processing
The preprocessing steps that were used in this analysis are described as following. The first step is to reduce the size of all images by rescaling them. The collected COVID CXR images ranging in scale from 508 500 pixels to 4248 3480 pixels. so that, we resized the images to 227 x 227 pixels for the experimental arrangement. The built-in Keras feature "preprocess input" is used to convert and resize the input picture to meet the model's requirements. The second step is to convert all of the images to grayscale from RGB. Finally, the NumPy array uses for reading the images at that time is normalized by separating the image matrix using 255.

2.3. Feature extraction using transfer learning
Accurate feature extraction is one of the most important steps in learning the machine from raw input data to produce reliable results. Deep transfer learning is a deep extraction process based on pre-trained CNN models (DTL). With a small amount of training data, the DTL approach is very effective. [26]. DTL refers to the transfer of information from a source with a large number of training samples to a target domain with a smaller number of samples. Effective image classification can be achieved with the help of a large dataset from the source domain. DTL is defined as the process of moving certain layers of a pre-trained CNN model that has been trained with millions of images from a deep learning standpoint, especially in the case of CNN.

The input images are encoded into a feature vector using pre-trained CNN models in this study. SqueezeNet, a robust CNN architecture, is used for feature extraction with the option of transfer learning advantage for limited datasets, as well as their satisfactory performances in various computer vision tasks [27-31]. The task-dependent layers of the CNN model, such as the fully connected layers and the classification output layer, are omitted from the network architecture, according to the research [32], and the remaining layers are spared for the existing classification task application. The encoded feature vectors computed by CNN's pre-trained models are fed into a learner to obtain the classification.

2.4. Model Developing
Benchmarking is a technique for demonstrating the ability of experimental methodologies to perform as expected and comparing the results to existing methods [33]. According to a previous study [10], for gesture classification, ten different ML algorithms, both linear and nonlinear, were routinely used. The following algorithms were used in this study: k-nearest neighbors (KNN), gradient boosting (GB), artificial neural network (ANN), SVM, decision tree (DT), linear discriminant (LD), logistic regression (LR), random forest (RF), nave Bayes (NB), and stochastic gradient descent (SGD).

2.5. System Evaluation
In this study, split data and cross-validation approaches are used to evaluate the performance of the diagnostic method. Split data and cross-validation were used to evaluate the performance of the diagnosis system in this study. For training and testing, the dataset was split into 70% and 30%, 75% and 25%, and 80% and 20%, respectively. Furthermore, 3-fold, 5-fold, and 10-fold cross-validation techniques were used to obtain the result. Several assessment criteria were used in this study to assess the proposed model in terms of performance (see figure 3). The different measures from which the alternatives can be judged and benchmarked are referred to as criteria. The definitive set of criteria used in this study is shown in Figure 2.

![Figure 2. The evaluation criteria used for assessing the performance of the detection framework](image)

We used a variety of criteria in this study, including classification accuracy (CA), specificity, F1 score, sensitivity, and Area Under the Curve (AUC), which are the most commonly used metrics [34-36]. True Positive (TP) denotes the number of accurately labelled positive samples, True Negative (TN) denotes the correctly detected negative sample, False Positive (FP) denotes the number of negative examples classified as positive, and finally, the number of positive predicted samples (FN). The criteria are formulated and presented in the form of the following:

The most common metric for assessing classification models is Classification Accuracy (CA), which describes how close a model is to the true value. It is computed as the ratio of the number of correct detections to the total number of input examples using the formula below.

$$CA = \frac{TP + TN}{TP + FP + FN + TN}$$  \hspace{1cm} (1)

The F1 score is a weighted average of the recall and precision scores. The 0 value of F1 scoring is the worst value and 1 value is the best. A low F1 score, for example, indicates poor accuracy as well as recall. The following formula is used to calculate the F1 scoring metric:

$$F_{-score} = \frac{2 * TP}{2 * TP + FP + FN}$$  \hspace{1cm} (2)

Sensitivity (True Positive Rate) is a term used to describe how sensitive a system is. The number of properly identified image labels from all positive representations is referred to as recall. It may be defined as a test's ability to properly identify patients with a disease. A highly sensitive result indicates that there are few false-negative cases, resulting in fewer disease samples being missed. The Sensitivity formula is as follows:

$$Sensitivity = \frac{TP}{TP + FN}$$  \hspace{1cm} (3)
The metric that measures a model's ability to detect true negatives in each category is called specificity (True Negative Rate). Specificity in Covid-19 detection refers to a test's ability to properly classify individuals who do not have the disease. A high specificity value indicates that there are few false-positive results. The formulas for calculating the Specificity metric can be found below.

\[
\text{Specificity} = \frac{TN}{TN + FP}
\]  

The Area Under the Curve (AUC) is a Receiver Operating Characteristics (ROC) curve that is used to evaluate the classification model's performance at multiple thresholds. By discriminating between classes, the AUC value demonstrates how well the model performs (i.e. a degree of separability). Higher the AUC, for example, the model is better at distinguishing between COVID-19 and normal examples.

3. Results and discussion
Automated diagnostic modality is helping to confirm the primary diagnosis from the COVID-19 test. This study presented an automated COVID-19 diagnostic system from X-ray image using machine-learning techniques. In this study, we used a pre-trained CNN model, namely SqueezeNet to calculate a feature vector for each X-ray images of the chest. In the training phase, the extracted features from radiographs are fed to machine learning algorithms, namely Decision Tree, Random Forest, Neural Network, Naive Bayes, Logistic Regression, and K-NN, which are the most popular supervised learning methods, to classify the X-ray images. The experiments are implemented in the Python environment with Keras package and TensorFlow2 running on a Windows-based computer system with 2.50 GHz dual Intel(R) Core (TM) i7, 8 GB RAM and 2 GB graphical processing unit (GPU). Table 1 outline the accuracy of six machine-learning algorithms on the feature extracted for COVID-19.

| Table 1. Accuracy analysis of different machine learning classifiers for different validation technique. The bold value is the best. | 70% | 75% | 80% | 3-fold | 5-fold | 10-fold |
|---|---|---|---|---|---|---|
| Decision Tree | 82.73% | 81.04% | 80.98% | 81.88% | 81.75% | 84.82% |
| Random Forest | 92.42% | 92.36% | 92.79% | 93.21% | 93.28% | 93.69% |
| Neural Network | 96.44% | 96.27% | 96.82% | 96.83% | 97.24% | 97.1% |
| Naive Bayes | 85.95% | 85.72% | 85.69% | 86.66% | 86.69% | 86.63% |
| Logistic Regression | 94.85% | 95.27% | 95.12% | 95.91% | 95.87% | 96.35% |
| k-nearest neighbors | 91.82% | 92.04% | 92.73% | 92.6% | 93.01% | 93.28% |

According to Table 1, an ANN classifier with different validation technique achieved the best result. The second-best result attained by the Logistic Regression classifier. The remaining classifiers still have high accuracy values indicating the success of the model in distinguishing true positives and negatives. The highest accuracy was 79.24% obtained by the ANN classifier using the 5-fold cross-validation methodology. The Decision Tree classifier's lowest performance had an accuracy of 80.98 percent, according to the findings. Table 2 shows the F1-scores of the features extracted from SqueezeNet architecture trained with different machine learning models. The ANN recorded the highest F1-score with a value of 0.972, as seen in Table 2. The second highest F1-score was also produced by the ANN with a value of 0.971. With values of 0.809, the decision Tree provided the lowest F1-score. The obtained sensitivity, specificity, and AUC of the recognition COVID-19 using different classifiers are presented in tables 3, 4, and 5.

| Table 2. F1-score analysis of different machine learning classifiers for different validation technique. The bold value is the best. | 70% | 75% | 80% | 3-fold | 5-fold | 10-fold |
|---|---|---|---|---|---|---|
| Decision Tree | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 |
| Random Forest | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 |
| Neural Network | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 |
| Naive Bayes | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 |
| Logistic Regression | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 |
| k-nearest neighbors | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 | 0.972 |
As seen in these tables, the ANN classifier trained on the SqueezeNet feature vector produced sensitivity, specificity, and AUC values of 0.9724, 0.9858, and 1, respectively, which are the maximum sensitivity, specificity, and AUC values obtained. With 10-fold cross-validation, the logistic regression classifier obtained the second-best results, with sensitivity, specificity, and AUC values of 0.96350, 0.9815, and 0.99 respectively. For other models, the same assumptions can be drawn. The experimental
results indicate that the performance of the deep CNNs using squeezeNet trained by ANN, Logistic regression and random forest classifiers yield satisfactory results in COVID-19 classification.

Figure 3 depicts the effect of validation techniques on classification results. Comparing the performance of the trained classifier with different evaluation method, 10 fold cross-validation yield the best result. A decision tree with 10-fold cross-validation has a marginally higher classification accuracy (3%) than a decision tree with 75 percent splitting data for training. Random forest with 10-fold cross-validation increases classification accuracy by 1.3 percent as compared to random forest with 75% data splitting for training. 5-fold validation achieved the best accuracy in case the ANN. The classification accuracy of ANN with 5-fold validation is slightly better (1%) than ANN with 75% splitting data for training, while the training time of the second winner is tempting, almost 20 times better than the first winner in terms of accuracy. Table 6 illustrated the training time for the learning algorithm.

![Figure 3. Comparison of the accuracy of machine learning classifiers with different evaluation methods.](image)

Table 6. Comparison of training time of different machine learning models including validation techniques. The bold and underlined value indicates the faster execution time; the bold value represents the slowest execution time.

| Decision Tree | Random Forest | Neural Network | Naive Bayes | Logistic Regression | k-nearest neighbors |
|---------------|---------------|----------------|-------------|---------------------|---------------------|
| 70%           | 3.848         | 30.271         | 30.787      | 2.392               | 4.236               |
| 75%           | 4.713         | 38.609         | 37.978      | **2.081**           | 4.111               |
| 80%           | 5.207         | 37.408         | 41.77       | 2.537               | 4.355               |
| 3-fold        | 4.433         | 31.544         | 34.929      | 2.458               | 5.407               |
| 5-fold        | 8.647         | 62.699         | 57.338      | 7.284               | 7.606               |
| 10-fold       | 31.19         | 195.147        | **214.772** | 14.255              | 19.048              |

Analyzing Table 6, the total training time for 3000 images using SqueezeNet architectures and ANN was estimated at 214.772 s and is the longest training time. Random forest with 10-fold cross-validation was 19.625 seconds faster than ANN. The Naive Bayes model, which took the least time consuming to
train, took 2.081 seconds with a data splitting of 75%. Figure 4 visually illustrates the average training time of six machine-learning classifiers with numerous validation approaches.

![Figure 4](image_url)

**Figure 4.** Comparison of the average training time related to numerous validation approaches.

Splitting the data at 70% and 3-fold validation was the roughly least time to train six classifiers with 3000 chest X-ray images. 10-fold cross-validation, on the other hand, was the slowest and required the utmost training time. In conclusion, relative to training the CNN deep model from the outset, the training time for the proposed approach is remarkably low, implying faster processing time and less use of the resource.

The system produces 99.5%, which proves the efficiency of the proposed approach. The high value of AUC is an indicator of the ability of the system in distinguishing between disease COVID-19 and Normal cases. The main goal of this work is to achieve successful results in identifying cases of COVID-19 and not recognizing false cases of COVID-19. The evaluation results revealed that abnormal cases and normal cases were successfully identified in the proposed approach. The proposed approach is generic and requires limited pre-processing since it does not need handcrafted features and can be readily adapted. The supplied dataset, obtained from numerous sources, is still limited in size. However, despite the small data set size of the given dataset, the transfer learning approach has effectively migrated information from the source to the target domain. Finally, we found the proposed approach that no overfitting takes place to negatively affect the accuracy of the classification.

The results of this work are compared with the benchmark studies to study the efficiency of the proposed network architecture. In Table 7, studies based on CXR images for the detection of COVID-19 are used as an alternative for benchmarking purpose, and the criteria for evaluation are accuracy, sensitivity, and specificity. It can be shown that most of the previous research works were conducted on a limited number of images for training and testing the detection models. Also, some of the reported studies suffer from data imbalance issues.

| Study                  | Number of Samples | Total | ACC (%) | SEN (%) | SPE (%) |
|------------------------|-------------------|-------|---------|---------|---------|
|                        | Normal | COVID-19 | Pneumonia |         |         |         |
| **Ezz El-Din Hemdan**  | 25     | 25       | -        | 50      | 90      | 100     | 80      |
| **Tanvir Mahmud**      | 305    | 305      | 305      | 915     | 90.3    | 89.9    | 89.1    |
| **Linda Wang**         | -      | -        | -        | 13,975  | 93.3    | -       | -       |

Table 7. Comparison of our method versus the state of art models.
4. Conclusion
COVID-19 must be detected early in order to avoid human-to-human infection and to treat patients. Isolating and quarantining potential COVID-19 patients is currently the most powerful method to prevent the virus from spreading. In COVID-19 positive patients, chest X-ray pictures, as effective diagnostic modalities, play a vital role in disease diagnosis, tracking disease progression, and severity. This paper presents a computer-aided diagnosis of COVID-19 pneumonia based on deep learning and machine learning. Six well-known machine-learning classifiers were trained on features extracted using deep CNN namely squeezeNet architectures to find the right learners. The developed system has been evaluated using many evaluation metrics, including accuracy, sensitivity, specificity, AUC, F1-score, and training time. The obtained results reveal that our system achieves flavour performance and surpass many existed methods for COVID-19 detection. The results obtained from this study bring benefits to the implementation of efficient and reliable imaging data-based diagnostic tools merged with intelligent techniques and further contribute to the development of more specific diagnostic and detection means to manage the coronavirus pandemic. Additional COVID-19 chest X-ray images are required for future work and other deeper CNN models will be investigated for COVID-19 identification. In addition, other lung diseases will also be included in a prospective study.

References
[1] w. h. organization. (2021/2/4). WHO Coronavirus Disease (COVID-19) Dashboard. Available: https://covid19.who.int/?gclid=Cj0KCQiA0-6ABhDMARIgAFVdQy_cdcY-LRxDV9YdFUMWjpCeWrtBd-upOt4ERyJMSoL0mrfJvFuFaAhSKEALw_wcb
[2] M. Gour and S. Jain, "Stacked convolutional neural network for diagnosis of covid-19 disease from x-ray images," arXiv preprint arXiv:2006.13817, 2020.
[3] Y. Celik, M. Talo, O. Yildirim, M. Karabata, and U. R. Acharya, "Automated invasive ductal carcinoma detection based using deep transfer learning with whole-slide images," Pattern Recognition Letters, vol. 133, pp. 232-239, 2020.
[4] S. R. Nayak, D. R. Nayak, U. Sinha, V. Arora, and R. B. Pachori, "Application of deep learning techniques for detection of COVID-19 cases using chest X-ray images: A comprehensive study," Biomedical Signal Processing and Control, vol. 64, p. 102365, 2021.
[5] T. Chen and C.-W. Lin, "Smart and automation technologies for ensuring the long-term operation of a factory amid the COVID-19 pandemic: an evolving fuzzy assessment approach,"
A. U. Ibrahim, M. Ozsoz, S. Serte, F. Al-Turjman, and P. S. Yakoi, "Pneumonia classification using deep learning from chest X-ray images during COVID-19," Cognitive Computation, pp. 1-13, 2021.

S. Bharati, P. Podder, and M. R. H. Mondal, "Hybrid deep learning for detecting lung diseases from X-ray images," Informatics in Medicine Unlocked, vol. 20, p. 100391, 2020.

A. M. Ismael and A. Şengür, "Deep learning approaches for COVID-19 detection based on chest X-ray images," Expert Systems with Applications, vol. 164, p. 114054, 2021.

Ö. Yıldırım, P. Plawiak, R.-S. Tan, and U. R. Acharya, "Arrhythmia detection using deep convolutional neural network with long duration ECG signals," Computers in biology and medicine, vol. 102, pp. 411-420, 2018.

A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter, H. M. Blau, et al., "Dermatologist-level classification of skin cancer with deep neural networks," nature, vol. 542, pp. 115-118, 2017.

M. Talo, O. Yıldırım, U. B. Baloglu, G. Aydin, and U. R. Acharya, "Convolutional neural networks for multi-class brain disease detection using MRI images," Computerized Medical Imaging and Graphics, vol. 78, p. 101673, 2019.

P. Rajpurkar, J. Irvin, K. Zhu, B. Yang, H. Mehta, T. Duan, et al., "Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning," arXiv preprint arXiv:1711.05225, 2017.

J. H. Tan, H. Fujita, S. Sivaprasad, S. V. Bhandary, A. K. Rao, K. C. Chua, et al., "Automated segmentation of exudates, haemorrhages, microaneurysms using single convolutional neural network," Information sciences, vol. 420, pp. 66-76, 2017.

J. C. Souza, J. O. B. Diniz, J. L. Ferreira, G. L. F. da Silva, A. C. Silva, and A. C. de Paiva, "An automatic method for lung segmentation and reconstruction in chest X-ray using deep neural networks," Computer methods and programs in biomedicine, vol. 177, pp. 285-296, 2019.

G. D. Rubin, C. J. Ryerson, L. B. Haramati, N. Sverzellati, J. P. Kanne, S. Raoof, et al., "The role of chest imaging in patient management during the COVID-19 pandemic: a multinational consensus statement from the Fleischner Society," Chest, 2020.

O. Stephen, M. Sain, U. J. Maduh, and D.-U. Jeong, "An efficient deep learning approach to pneumonia classification in healthcare," Journal of healthcare engineering, vol. 2019, 2019.

R. H. Abiyev and M. K. S. Ma’aitah, "Deep convolutional neural networks for chest diseases detection," Journal of healthcare engineering, vol. 2018, 2018.

M. E. Chowdhury, T. Rahman, A. Khandakar, R. Mazhar, M. A. Kadir, Z. B. Mahbub, et al., "Can AI help in screening viral and COVID-19 pneumonia?," IEEE Access, vol. 8, pp. 132665-132676, 2020.

A. M. Alqudah, S. Qazan, and A. Alqudah, "Automated Systems for Detection of COVID-19 Using Chest X-ray Images and Lightweight Convolutional Neural Networks," 2020.

A. Narin, C. Kaya, and Z. Pamuk, "Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks," arXiv preprint arXiv:2003.10849, 2020.

Y.-H. Chan, Y.-Z. Zeng, H.-C. Wu, M.-C. Wu, and H.-M. Sun, "Effective pneumothorax detection for chest X-ray images using local binary pattern and support vector machine," Journal of healthcare engineering, vol. 2018, 2018.

T. Ozturk, M. Talo, E. A. Yildirim, O. Yildirim, and U. R. Acharya, "Automated detection of COVID-19 cases using deep neural networks with X-ray images," Computers in Biology and Medicine, p. 103792, 2020.

S. H. Khan, A. Sohail, M. M. Zafar, and A. Khan, "Coronavirus Disease Analysis using Chest X-ray Images and a Novel Deep Convolutional Neural Network," ed: ResearchGate, 2020.

J. P. Cohen, P. Morrison, L. Dao, K. Roth, T. Q. Duong, and M. Ghassemi, "Covid-19 image data collection: Prospective predictions are the future," arXiv preprint arXiv:2006.11988, 2020.
[25] P. Mooney. (2018, 5-12-2020). Chest X-Ray Images (Pneumonia). Available: https://www.kaggle.com/paultimothymooney/chest-xray-pneumonia.

[26] S. J. Pan and Q. Yang, "A survey on transfer learning," IEEE Transactions on knowledge and data engineering, vol. 22, pp. 1345-1359, 2009.

[27] C. M. Dourado Jr, S. P. P. da Silva, R. V. M. da Nobrega, A. C. d. S. Barros, P. P. Reboucas Filho, and V. H. C. de Albuquerque, "Deep learning IoT system for online stroke detection in skull computed tomography images," Computer Networks, vol. 152, pp. 25-39, 2019.

[28] W. Zhang, J. Zhong, S. Yang, Z. Gao, J. Hu, Y. Chen, et al., "Automated identification and grading system of diabetic retinopathy using deep neural networks," Knowledge-Based Systems, vol. 175, pp. 12-25, 2019.

[29] A. Cinar and M. Yildirim, "Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture," Medical hypotheses, vol. 139, p. 109684, 2020.

[30] M. A. Ahmad, "Artificial Neural Network vs. Support Vector Machine For Speech Emotion Recognition," Tikrit Journal of Pure Science, vol. 21, pp. 167-172, 2016.

[31] S. K. Abdulateef, T.-A. N. Abdali, M. D. S. Alroomi, and M. A. A. Altaha, "An optimise ELM by league championship algorithm based on food images," Indonesian Journal of Electrical Engineering and Computer Science, vol. 20, pp. 132-137, 2020.

[32] E. Deniz, A. Şengür, Z. Kadıroğlu, Y. Guo, V. Bajaj, and Ü. Budak, "Transfer learning based histopathologic image classification for breast cancer detection," Health information science and systems, vol. 6, pp. 1-7, 2018.

[33] M. Ahmed, B. Zaidan, A. Zaidan, M. M. Salih, Z. Al-qaysi, and A. Alamoodi, "Based on wearable sensory device in 3D-printed humanoid: A new real-time sign language recognition system," Measurement, vol. 168, p. 108431, 2021.

[34] Y. Xie, F. Xing, X. Kong, H. Su, and L. Yang, "Beyond classification: Structured regression for robust cell detection using convolutional neural network," in International conference on medical image computing and computer-assisted intervention, 2015, pp. 358-365.

[35] P. Sukumar and R. Gnanamurthy, "Computer aided detection of cervical cancer using pap smear images based on adaptive neuro fuzzy inference system classifier," Journal of Medical Imaging and Health Informatics, vol. 6, pp. 312-319, 2016.

[36] R. Alsharida, M. Hammood, M. A. Ahmed, B. Thamer, and M. Shakir, "RC4D: A New Development of RC4 Encryption Algorithm," in International Networking Conference, 2020, pp. 19-30.

[37] E. E.-D. Hemdan, M. A. Shouman, and M. E. Karar, "Covidx-net: A framework of deep learning classifiers to diagnose covid-19 in x-ray images," arXiv preprint arXiv:2003.11055, 2020.

[38] T. Mahmud, M. A. Rahman, and S. A. Fattah, "CovXNet: A multi-dilation convolutional neural network for automatic COVID-19 and other pneumonia detection from chest X-ray images with transferable multi-receptive feature optimization," Computers in biology and medicine, vol. 122, p. 103869, 2020.

[39] L. Wang, Z. Q. Lin, and A. Wong, "Covid-net: A tailored deep convolutional neural network design for detection of covid-19 cases from chest x-ray images," Scientific Reports, vol. 10, pp. 1-12, 2020.

[40] I. D. Apostolopoulos and T. A. Mpesiana, "Covid-19: automatic detection from x-ray images utilizing transfer learning with convolutional neural networks," Physical and Engineering Sciences in Medicine, p. 1, 2020.

[41] P. K. Sethy and S. K. Behera, "Detection of coronavirus disease (covid-19) based on deep features," Preprints, vol. 2020030300, p. 2020, 2020.

[42] M. Toğaçar, B. Ergen, and Z. Cömert, "COVID-19 detection using deep learning models to exploit Social Mimic Optimization and structured chest X-ray images using fuzzy color and stacking approaches," Computers in biology and medicine, vol. 121, p. 103805, 2020.

[43] S. Minaee, R. Kafieh, M. Sonka, S. Yazdani, and G. J. Soufi, "Deep-covid: Predicting covid-19 from chest x-ray images using deep transfer learning," arXiv preprint arXiv:2004.09363, 2020.
[44] H. Panwar, P. Gupta, M. K. Siddiqui, R. Morales-Menendez, and V. Singh, "Application of Deep Learning for Fast Detection of COVID-19 in X-Rays using nCOVnet," *Chaos, Solitons & Fractals*, p. 109944, 2020.