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Diagnose COVID-19 by using hybrid CNN-RNN for chest X-ray

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ABSTRACT

Combating the COVID-19 epidemic has emerged as one of the most promising healthcare the world's challenges have ever seen. COVID-19 cases must be accurately and quickly diagnosed to receive proper medical treatment and limit the pandemic. Imaging approaches for chest radiography have been proven in order to be more successful in detecting coronavirus than the (RT-PCR) approach. Transfer knowledge is more suited to categorize patterns in medical pictures since the number of available medical images is limited. This paper illustrates a convolutional neural network (CNN) and recurrent neural network (RNN) hybrid architecture for the diagnosis of COVID-19 from chest X-rays. The deep transfer methods used were VGG19, DenseNet121, InceptionV3, and Inception-ResNetV2. RNN was used to classify data after extracting complicated characteristics from them using CNN. The VGG19-RNN design had the greatest accuracy of all of the networks with 97.8% accuracy. Gradient-weighted the class activation mapping (Grad-CAM) method was then used to show the decision-making areas of pictures that are distinctive to each class. In comparison to other current systems, the system produced promising findings, and it may be confirmed as additional samples become available in the future. For medical personnel, the examination revealed an excellent alternative way of diagnosing COVID-19.

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1. INTRODUCTION

COVID-19 has expanded swiftly by person-to-person transfer, wreaking havoc on world health. COVID-19 infected around 16.89 million people worldwide, resulting in close to 663,476 deaths [1]. Because of the scarcity of intensive care units (ICUs), all countries' healthcare systems have collapsed. Patients with acute illnesses who have been infected with the Coronavirus are referred to ICUs. To prevent the epidemic from spreading from person to person, many governments advocated a 'lockdown' to ensure population 'social separation' and 'isolation' [2]. The indicators of the coronavirus can range from a cold to a high temperature, Shortness of breath, and acute respiratory illness [3]. The most critical step is to detect COVID-19 as soon as possible and isolate those who are infected from the rest of the population. The Chinese government has identified RT-PCR as a significant indicator for diagnosing COVID-19 patients [4]. It's also, a time-consuming procedure with a considerable risk of error [5]. Because of low sensitivity, the coronavirus may not be appropriately recognized in so many cases. Deep learning applications appear to have arrived at the right time in the previous five years. Deep learning is a collection of machine learning methods primarily aimed at automatically extracting and classifying features from images, with applications ranging from object identification to the classification of medical images [6]. Machine learning and deep learning have established themselves as established fields for extracting, analyzing, and recognizing patterns from data using artificial intelligence. As new data becomes available, reclaiming those fields' gains for the patient, it's becoming more difficult to reap the benefits of clinical decision-making and computer-assisted systems [7]. The role of medical imaging technologies in combating this pandemic has sparked a lot of attention [8]. Due to their high sensitivity, chest radiographs, including chest X-rays and computed tomography, can both detect COVID-19 (CT), which is already being examined as a standard detection approach for pneumonia illness [9]. When it comes to identifying pneumonia, computed tomography is more reliable than chest X-rays, because chest X-rays are less expensive, faster, and use less radiation [10]. To interpret complex medical images, deep learning is frequently used in the medical industry [11]. Instead of manually constructed features, deep learning approaches rely on automatic feature extraction. It's already conducted a thorough investigation of categorization and segmentation issues [12]. In this article, we describe a framework that combines CNN and recurrent neural networks for exploiting chest X-rays to identify coronavirus patients. We examined four well-known CNN models that had been pre-trained with RNN, including DenseNet121, InceptionV3, and Inception-ResNetV2 among the VGG19, in order to identify the optimal CNN-RNN architecture within the dataset limitations. The models InceptionV3, DenseNet121, and Inception-ResNetV2. This system's foundation is a CNN that was pre-trained to extract important features from images. Then, using the features gathered, we applied COVID-19 cases found by an RNN classifier. The article's organization is outlined below. In Section 2, there is a brief summary of relevant studies. Data gathering, the formation of merged networks, and the efficiency evaluation standards are all explained, along with the materials and methods used in Section 3. A thorough analysis of the outcomes is provided in Section 4, along with pertinent comments. The article's conclusion is presented in Section 5.

Several attempts were made to build a system for COVID-19 diagnosis utilizing artificial intelligence approaches such as machine learning and deep learning in response to the COVID-19 outbreak [11], [13]. This section contains the full overview of the newly developed systems for diagnosing COVID-19 patients. Luz *et al*. [14]. To analyze the lung condition utilizing X-ray pictures, and enhanced efficient net convolutional network architecture-based model was introduced. A model classified coronaviruses with 93.9 percent accuracy and 80% sensitivity using 183 COVID-19 samples. Minaee *et al*. [15] used 71 COVID-19 samples to present a deep transfer learning architecture for distinguishing infected regions from other lung illnesses. To distinguish coronavirus cases, the design achieved a sensitivity score of 97.5% as well as a specificity of 90%. Khasawneh *et al*. [16] 284 COVID-19 samples a deep convolutional neural network (CNN) was trained to diagnose coronavirus illness. The proposed model detected coronavirus with a precision of 97 percent and an accuracy of 89.5 percent. Apostolopoulos and Mpesiana [17] presented a coronavirus infection detection technique based on transfer learning. With a precision of 93.48%, a specificity of 92.85 %, and a sensitivity of 98.75 %, the VGG19 outperformed the competition. Bharati *et al.* [18]. For the detection of COVID-19, the best result for VGG19 was 83 % recall and eighty -three percent precision, which was accomplished using a deep transfer learning-based approach. Lakshmanaprabu *et al*. [19] categorized corona virus-infected patients. Researchers employed nine pre-trained CNNs, and a support vector machine was used in a transfer learning system. With an accuracy of 95.38%, the ResNet50-SVM outperformed all other models. Karakanis and Leontidis [20] COVID-19 detection from the chest X-ray dataset was proposed using the transfer learning method. With 89 COVID-19 samples, the system achieved 98.18 percent accuracy and a 98.19% F1 score. Singh *et al*. [21] X-ray pictures were used to detect corona virus cases using a CNN and LSTM architecture. In this study 421 datasets were used, including 141 COVID-19 cases, then had a 97% accuracy, 91% specificity, and 93% sensitivity.

2. METHODS

Even thoughmany existing systems have yielded encouraging results, the COVID-19 has a tiny dataset because the mutable quality of such datasets stayed not taken into account. It was pointed out that the dataset used in person's studies was exceedingly unrepresentative, which might lead to the majority class being over-classified at the price of a minority class being under-classified. Because COVID-19 photos were taken from different parts of the world, they were highly inconsistent, while in previous investigations, pneumonia and normal photos were homogeneous and well-curated. The COVID-19 samples had the majority of adult patients, while the pneumonia dataset contained largely children. Inside the existing systems, these disparities are usually disregarded. As a result, our suggested method using the balanced dataset includes photos of both adult and children patients to understand a disease's genuine properties. The suggested approach, as depicted in Figure 1, includes various phases for COVID-19 infection diagnosis. To begin, X-ray samples from the chest were scaled, in the shuffled and normalized preprocessing pipeline to determine the true features and reduce picture noise. The dataset was then divided into exercise and testing groups.

We selected four CNN architectures with recurrent neural network (RNN) classifiers that have been pre-trained on a training dataset. After each epoch, the accuracy and loss of training datasets were computed, and the validation loss and accuracy were determined using the five-fold cross-validation technique. The confusion matrix was utilized to evaluate the system's performance, accuracy, precision, recall, area under curve (AUC), and F1-score are among the measures available.

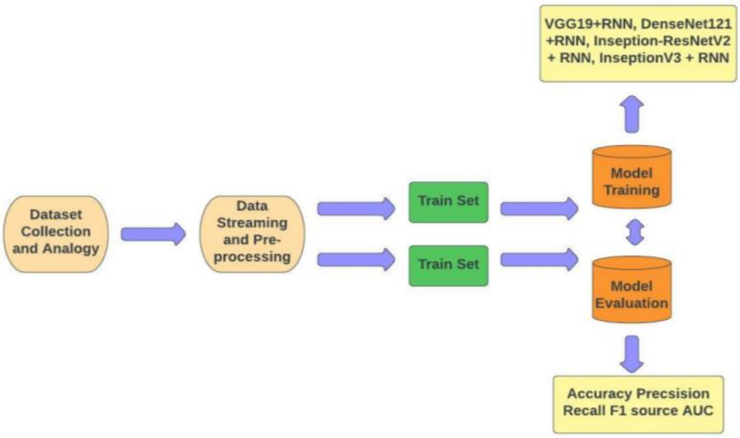

Figure 1. The COVID-19 diagnosis framework's overall system architecture [22]

2.1. Dataset of the study

In this study, we used a variety of datasets from diverse sources. The COVID-19 Radiography database is one of these databases, the CoronaHack-Chest X-Ray dataset, the COVID Chest X-Ray dataset, and the COVID-19 X-Ray dataset. The COVID-19 Radiography database is the winner of the COVID-19 dataset on Kaggle [23]. Qatar University researchers cooperated with clinical professionals to construct a chest X-ray picture for COVID-19 in this dataset. These COVID-19 datasets include 1231 normal, 1235 viral pneumonia, and 1042 healthy pictures. The COVID Chest X-ray dataset is a public collection of patient chest X-rays and CT pictures [23]. A Chinese team created the COVID-19 X-ray dataset to investigate chest CT image anomalies [23]. To identify the X-ray pictures, the CoronaHack-Chest X-Ray dataset was created [24].

2.2. CNN and deep transfer learning

In this method, transfer learning the data from one field is moved to a domain with a similar name [24]. When a dataset is insufficient to train the variables of any network, this method is used. This section provides a brief overview of the CNNs used for automatic recognition. The CNNs that were employed in the classification process, as well as the parameters set for transfer learning, are listed in Table 1. The parameters were defined after multiple experiments, but there is a plethora of other options that might be studied in a future study to see if they contribute to performance improvement. Starting at the bottom of the CNN, the Layer Cutoff parameter specifies the number of layers that are not trainable. To extract more information from the late convolutional layers, the rest of the layers that are closer to the output features are made trainable. The CNN's classifier is located at the top to execute the classification of the features that have been retrieved and is referred to by a parameter Neural Network. It is defined by the total number of hidden layers and the total number of nodes.

Some hyper-parameters are shared by all CNNs. The rectified linear unit (ReLU) is responsible for activating all convolutional layers [7]. The dropout [25] layer has been added to neural networks with two hidden layers to avoid overfitting [23]. The CNNs were generated using the Adam [23] method of optimization. Table 1 also illustrates the features of four pre-trained CNN designs, which were trained using a batch size of 64 for 10 epochs.

- Inception-ResNetV2: An Inception-ResnetV2 network combines inception and residual connections in a single network. Litjens *et al*. [26], using 164 deep layers. It avoids a degradation problem by using different-sized convolution filters that have been trained on millions of photos.

- InceptionV3: By extending a network's breadth and depth, InceptionV3 [27] improves computing resources. That has 48 layers with missed connections that can be used as a fundamental component. It was trained on a million images in 1000 different categories. To reduce dimensionality, Max-pooling is used to recreate the inception module.
- DenseNet121: The dense convolutional network utilizes dense associates between hidden layers rather than direct connections [28]. Each layer in the DenseNet architecture is related to the following layer to carry data throughout the network. Only a few parameters are used for training the mouth maps, which stand sent straight to altogether following layers. For short datasets, thick connections reduce over fitting of a model. DenseNet121 is made up of 121 layers, each of which is filled with weights from the Image Net dataset.
- VGG19: the VGG19 is the deep network architecture-based variant of Karen Simonyan and Andrew Zisserman's visual geometry group network (VGG) [29]. To execute on the ImageNet dataset, it has a total of 19 layers, 16 convolutional layers and three fully-connected layers are included [30]. VGG19 employed a three-dimensional with a stride of one, a convolutional filter is used., After that, there is a slew of non-linear layers. VGG19 uses max pooling to minimize the image's volume size while maintaining good image organization accuracy.

Table 1. Showsthe characteristics of four CNN architectures that have pre-trained

Networks	Distance	Parameters (106)
Inception-ResNetV2	164	56.0
InceptionV3	48	23.6
DenseNet121	121	8.0
VGG19	19	144.0

2.3. Recurrent neural network (RNN)

The RNN is a sort of extensible feedforward neural network that handles sequential data and has one or more feedback loops [31]. An RNN generates an output sequence (y1,...,yt) using the formulas below, as illustrated in Figure 2, given an input sequence (x1,...,xt).

$$ht=sigm (Whxxt + Whhht-1) \quad (1)$$

$$yt=Wyhht \quad (2)$$

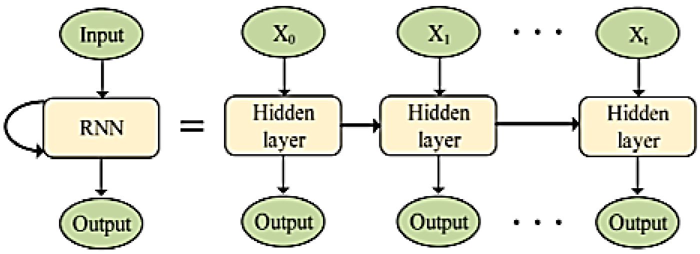

Figure 2.Recurrent neural networks' structural [32]

When a time and capacity-based input-output relationship is discovered, it can be used to manage long-term dependency, and RNN is applied [33]. The technique for modeling sequences uses an RNN to feedstuff the input arrangement into a course with a defined size, which is then mapped to a softmax layer. However, when the gradient vectors grow and shrink inexorably over time, a problem emerges with RNN. Because of the vanishing gradient and exploding problems [33], learning long-range associations from RNN architecture sequences is difficult. The long short-term memory (LSTM) [34] is a type of short-term memory, on the other hand, capable of successfully solvingsuch a long-distance reliance issue. The fundamental distinction between LSTM and Recurrent neural networks stays that LSTM has a discrete memory lockup state for storing long-term states that it updates or exposes as needed. An LSTM is composed of the following gates: inputs gates, output gates, and forgotten gates, at each time step t, ft stands for forgetting gate, Ot for output gate, ct for the memory cell, and ht for a hidden state. The LSTM transitional representations are listed in:

i=∂(wi xt + Uiht-1 + Vict-1) (3)

f=∂(wi xt + Uiht-1 + Vict-1) (4)

O=∂(wi xt + Uiht-1 +Vict-1) (5)

C=∂(wi xt + Uiht-1 +Vict-1) (6)

Ct=∂(wi xt + Uiht-1 +Vict-1) (7)

h=∂(wi xt + Uiht-1 +Vict-1) (8)

The current input is denoted by xt, σsigmoid denotes the sigmoid function, andʘ element-wise multiplication denotes the multiplication of elements.

2.4. Hybrid CNN-RNN architectures

In this article, a hybrid technique based on using three different types of X-ray samples, CNN, and Recurrent neural networks were created to identify COVID-19. DeneNet121, InceptionV3, and Inception-ResNetV3 are VGG19 were used for extract complex features from 224 224 3 sized data. To distinguish Normal cases, COVID-19, and pneumonia, the collected features were fed into an RNN classifier. Figure 3 depicts the COVID-19 classification, CNN-RNN network is used, and includes:

- Step 1: To extract critical information from X-ray pictures, use a variety of pre-trained CNN models.
- Step 2: Reorganize the feature map so that it fits in order.
- Step 3: Set a multi-layered RNN's feature map as the input.
- Step 4: To categorize COVID-19 chest X-ray pictures, use a softmax classifier.

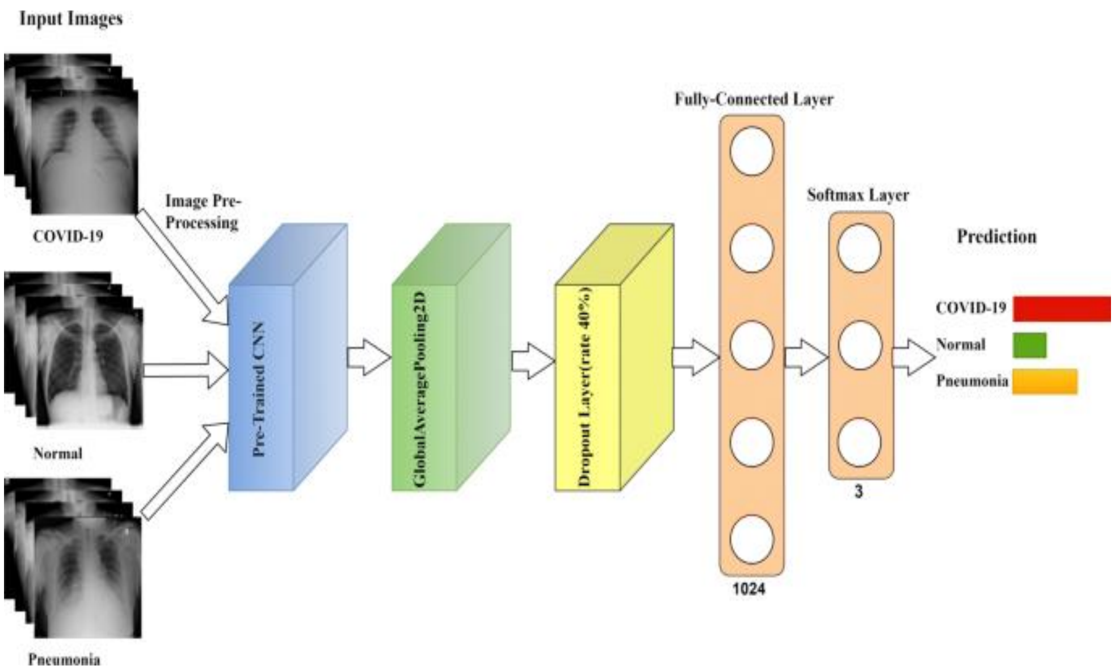

Figure 3. Shows the COVID-19 diagnosing workflow using the CNN-RNN architecture [35]

The rectified linear unit (ReLU) was utilized to activate the convolutional layers [36]. The Dropout layer [37] was employed to avoid the model overfitting [38]. RMSprop [39] was used to train the CNN architectures, which had a total of 150 epochs, a batch size of 32, a learning rate of 0.00001, and a batch size of 32. Figure 4 depicts the construction of the hybrid CNN-RNN.

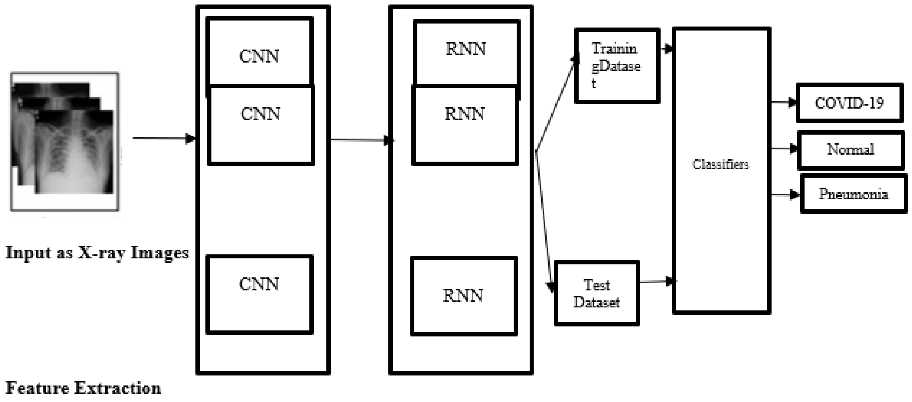

Figure 4. Illustrations of COVID-19 were diagnosed using a hybrid CNN-RNN architecture

2.5. Criteria for evaluation

The developed system's AUC, accuracy, precision, and recall are all utilized to assess its performance. The following is a mathematical representation of the evaluation metric parameters. true positive (TP) denotes correctly identified COVID-19 instances, true negative (TN) denotes correctly categorized pneumonia or normal cases, COVID-19 cases identified erroneously are referred to as false +ve (FP), and false -ve (FN) refers to pneumonia or normal instances that have been wrongly classified.

$$\text{Recall} = TP/\ (TP + FN) \quad (9)$$

$$\text{Precision} = TP/\ (TP + FP) \quad (10)$$

$$\text{Accuracy} = (TP + TN)/\ (TN + FP + TP + FN) \quad (11)$$

3. RESULTS AND DISCUSSION

The accuracy is shown in Figure 5 during the training and validation periods. At epoch 200, the maximal training and validation accuracy of the VGG19-RNN architecture is 97.8 % and 97.74 %, respectively. The InceptionV3-RNN network, on the other hand, has the lowest training and validation accuracy (95.14 % and 93.01 %, respectively). In this study, a combination of four CNN and RNN stayed used to diagnose COVID-19 contamination. The findings showed that VGG19-RNN is more successful than other deep learning architectures in identifying COVID-19 patients as pneumonia and normal patients, and it is now regarded as a key deep learning architecture. Table 2 shows a comparison of basic CNN-based classifier networks with our research. It has been demonstrated that the VGG19-RNN network outperforms CNN networks that have been pre-trained. Eventually, Table 3 shows another comparison between current studies and our research. Existing technologies can diagnose coronavirus infections with an accuracy of 82.3% to 98.5%, according to research. The VGG19-RNN network, on the other hand, achieved 97.8% accuracy, and it improves other current systems. The VGG19-RNN networks performed well in comparison to previous research.

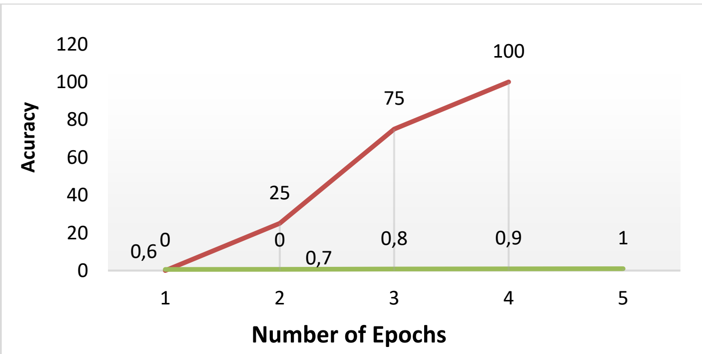

Figure 5.CNN-RNN architectures' accuracy

Table 2. Using COVID-19 patients, compares the designs of classifier CNN and CNN-RNN

Classifier	Accuracy	Precision	Recall
DenseNet121	98.04%	98.15 %	98.08%
VGG-19	98.03%	98.01%	98.61 %
Inception-ResNetV2	98.09%	98.40 %	96.03%
InceptionV3	98.15%	96.61 %	96.82%
VGG19-RNN	98.39%	98.53%	98.08%

Table 3. Shows a comparison of the proposed CNN-RNN architecture to previous work in terms of accuracy

Works	Design	COVID-19Accuracy (%)	Accuracy (%)
Lakshmanaprabu *et al.* [19]	Xception - ResNet50V2	96.7	90.5
Islam *et al*. [22]	Xception	94.5	87.3
Mastouri *et al.* [23]	Tailored CNN	79.0	90.5
Litjens *et al.* [26]	Inception-ResNetV2	-	90.1
Yasar and Ceylan [24]	DenseNet	77.3	85.6
Asnaoui [31]	Sgdm-SqueezeNet	94.1	96.2
Chouhan *et al.* [33]	CNN-LSTM	-	96.2
Proposed System	VGG19-RNN	97.8	97.8

4. CONCLUSION

Using deep learning techniques for COVID-19 diagnosis has become a critical problem during the COVID-19 epidemic to deal with a lack of medical resources. The major contribution we used is a combination between a CNN and an RNN that uses deep transfer learning to categorize us divided X-ray samples into three groups: COVID-19 pneumonia then normal in this paper.The four well-known to extract features CNN networks were utilized, and an RNN networks was utilized to categorize distinct classes based on those characteristicsalso comparing the suggested model's performance measure to those of existing pertained models revealed that the proposed model is more efficient than the others.It should, perhaps, lessen the doctor's burden while testing COVID19 patients. Our proposed system does have certain drawbacks. To begin, the COVID-19 samples are modest, and additional samples are needed to verify our suggested methodology. Second, only a posterior-anterior chest X-ray picture is suitable for this investigation, thus it can't categorize other perspectives like apical and so on. Third the results of our test are not likened to those of radiologists which is something we want to do in the future.

REFERENCES

[1] R. Naik, T. Wani, S. Bajaj, S. Ahir, and A. Joshi, “Detection of lung diseases using deep learning,” *SSRN Electronic Journal*, vol. 4, no. 9, pp. 2019–2021, 2020, doi: 10.2139/ssrn.3568730.

[2] Q. K. Kadhim, “Classification of human skin diseases using data mining,” *International Journal of Advanced Engineering Research and Science*, vol. 4, no. 1, pp. 159–163, 2017, doi: 10.22161/ijaers.4.1.25.

[3] E. Matsuyama and D.-Y. Tsai, “Automated classification of lung diseases in computed tomography images using a wavelet based convolutional neural network,” *Journal of Biomedical Science and Engineering*, vol. 11, no. 10, pp. 263–274, 2018, doi: 10.4236/jbise.2018.1110022.

[4] S. Candemir and S. Antani, “A review on lung boundary detection in chest X-rays,” *International Journal of Computer Assisted Radiology and Surgery*, vol. 14, no. 4, pp. 563–576, 2019, doi: 10.1007/s11548-019-01917-1.

[5] E. Hussain, M. Hasan, M. A. Rahman, I. Lee, T. Tamanna, and M. Z. Parvez, “CoroDet: A deep learning based classification for COVID-19 detection using chest X-ray images,” *Chaos, Solitons and Fractals*, vol. 142, p. 110495, 2021, doi: 10.1016/j.chaos.2020.110495.

[6] Q. K. Kadhim, “Image compression using discrete cosine transform method,” *International Journal of Computer Science and Mobile Computing*, vol. 5, no. 9, pp. 186–192, 2016.

[7] S. Taha Ahmed and S. Malallah Kadhem, “Using machine learning via deep learning algorithms to diagnose the lung disease based on chest imaging: a survey,” *International Journal of Interactive Mobile Technologies (IJIM)*, vol. 15, no. 16, p. 95, 2021, doi: 10.3991/ijim.v15i16.24191.

[8] K. Purohit, A. Kesarwani, D. Ranjan Kisku, and M. Dalui, “COVID-19 detection on chest X-Ray and CT scan images using multi-image augmented deep learning model,” *bioRxiv*, pp. 395–413, 2022, doi: 10.1007/978-981-16-6890-6_30.

[9] M. Tabaa, H. Fahmani, M. El Ouakifi, and H. Bensag, “COVID-19’s rapid diagnosis open platform based on X-ray imaging and deep learning,” *Procedia Computer Science*, vol. 177, pp. 618–623, 2020, doi: 10.1016/j.procs.2020.10.088.

[10] X. Wu, C. Chen, M. Zhong, J. Wang, and J. Shi, “COVID-AL: The diagnosis of COVID-19 with deep active learning,” *Medical Image Analysis*, vol. 68, p. 101913, 2021, doi: 10.1016/j.media.2020.101913.

[11] V. Mergen *et al*., “Deep learning for automatic quantification of lung abnormalities in COVID-19 patients: First experience and correlation with clinical parameters,” *European Journal of Radiology Open*, vol. 7, 2020, doi: 10.1016/j.ejro.2020.100272.

[12] H. H. N. Pham, M. Futakuchi, A. Bychkov, T. Furukawa, K. Kuroda, and J. Fukuoka, “Detection of lung cancer lymph node metastases from whole-slide histopathologic images using a two-step deep learning approach,” *American Journal of Pathology*, vol. 189, no. 12, pp. 2428–2439, 2019, doi: 10.1016/j.ajpath.2019.08.014.

[13] M. Ajin and L. Mredhula, “Diagnosis of interstitial lung disease by pattern classification,” *Procedia Computer Science*, vol. 115, pp. 195–208, 2017, doi: 10.1016/j.procs.2017.09.126.

[14] E. Luz *et al*., "Towards an effective and efficient deep learning model for COVID-19 patterns detection in X-ray images," *Research on Biomedical Engineering*, vol. 38, no. 1, pp. 149–162, 2022, doi: 10.1007/s42600-021-00151-6.
[15] S. Minaee, R. Kafieh, M. Sonka, S. Yazdani, and G. Jamalipour Soufi, "Deep-COVID: Predicting COVID-19 from chest X-ray images using deep transfer learning," *Medical Image Analysis*, vol. 65, pp. 1–9, 2020, doi: 10.1016/j.media.2020.101794.
[16] N. Khasawneh, M. Fraiwan, L. Fraiwan, B. Khassawneh, and A. Ibnian, "Detection of covid-19 from chest x-ray images using deep convolutional neural networks," *Sensors*, vol. 21, no. 17, pp. 1–15, 2021, doi: 10.3390/s21175940.
[17] 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*, vol. 43, no. 2, pp. 635–640, 2020, doi: 10.1007/s13246-020-00865-4.
[18] 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, doi: 10.1016/j.imu.2020.100391.
[19] S. K. Lakshmanaprabu, S. N. Mohanty, K. Shankar, N. Arunkumar, and G. Ramirez, "Optimal deep learning model for classification of lung cancer on CT images," *Future Generation Computer Systems*, vol. 92, pp. 374–382, 2019, doi: 10.1016/j.future.2018.10.009.
[20] S. Karakanis and G. Leontidis, "Lightweight deep learning models for detecting COVID-19 from chest X-ray images," *Computers in Biology and Medicine*, vol. 130, no. September 2020, p. 104181, 2021, doi: 10.1016/j.compbiomed.2020.104181.
[21] D. Singh, V. Kumar, Vaishali, and M. Kaur, "Classification of COVID-19 patients from chest CT images using multi-objective differential evolution–based convolutional neural networks," *European Journal of Clinical Microbiology and Infectious Diseases*, vol. 39, no. 7, pp. 1379–1389, 2020, doi: 10.1007/s10096-020-03901-z.
[22] M. M. Islam, M. Z. Islam, A. Asraf, and W. Ding, "Diagnosis of COVID-19 from X-rays using combined CNN-RNN architecture with transfer learning," *medRxiv*, vol. 9, pp. 1–16, 2020, doi: 10.1101/2020.08.24.20181339.
[23] R. Mastouri, N. Khlifa, H. Neji, and S. Hantous-Zannad, "Deep learning-based CAD schemes for the detection and classification of lung nodules from CT images: A survey," *Journal of X-Ray Science and Technology*, vol. 28, no. 4, pp. 591–617, 2020, doi: 10.3233/xst-200660.
[24] H. Yasar and M. Ceylan, "A new deep learning pipeline to detect Covid-19 on chest X-ray images using local binary pattern, dual tree complex wavelet transform and convolutional neural networks," *Applied Intelligence*, vol. 51, no. 5, pp. 2740–2763, 2021, doi: 10.1007/s10489-020-02019-1.
[25] H. Panwar, P. K. Gupta, M. K. Siddiqui, R. Morales-Menendez, P. Bhardwaj, and V. Singh, "A deep learning and grad-CAM based color visualization approach for fast detection of COVID-19 cases using chest X-ray and CT-Scan images," *Chaos, Solitons and Fractals*, vol. 140, no. August, p. 110190, 2020, doi: 10.1016/j.chaos.2020.110190.
[26] G. Litjens *et al*., "A survey on deep learning in medical image analysis," *Medical Image Analysis*, vol. 42, pp. 60–88, Dec. 2017, doi: 10.1016/j.media.2017.07.005.
[27] J. Ma, Y. Song, X. Tian, Y. Hua, R. Zhang, and J. Wu, "Survey on deep learning for pulmonary medical imaging," *Frontiers of Medicine*, vol. 14, no. 4, pp. 450–469, 2020, doi: 10.1007/s11684-019-0726-4.
[28] M. A. Khan et al., "Prediction of COVID-19 - Pneumonia based on selected deep features and one class kernel extreme learning machine," *Computers and Electrical Engineering*, vol. 90, no. June 2020, p. 106960, 2021, doi: 10.1016/j.compeleceng.2020.106960.
[29] S. Röhrich, T. Schlegl, C. Bardach, H. Prosch, and G. Langs, "Deep learning detection and quantification of pneumothorax in heterogeneous routine chest computed tomography," *European Radiology Experimental*, vol. 4, no. 1, 2020, doi: 10.1186/s41747-020-00152-7.
[30] J. Wu and T. Qian, "A survey of pulmonary nodule detection, segmentation and classification in computed tomography with deep learning techniques," *Journal of Medical Artificial Intelligence*, vol. 2, no. April, pp. 8–8, 2019, doi: 10.21037/jmai.2019.04.01.
[31] K. El Asnaoui, "Design ensemble deep learning model for pneumonia disease classification*," International Journal of Multimedia Information Retrieval*, vol. 10, no. 1, pp. 55–68, 2021, doi: 10.1007/s13735-021-00204-7.
[32] W. Chen, L. Zhang, J. Song, Y. Wang, and Y. Li, "Polarimetric radar target recognition framework based on LSTM," *The Journal of Engineering*, vol. 2019, no. 21, pp. 8089–8092, 2019, doi: 10.1049/joe.2019.0747.
[33] V. Chouhan *et al*., "A novel transfer learning based approach for pneumonia detection in chest X-ray images," *Applied Sciences (Switzerland)*, vol. 10, no. 2, 2020, doi: 10.3390/app10020559.
[34] H. Wang, H. Gu, P. Qin, and J. Wang, "CheXLocNet: Automatic localization of pneumothorax in chest radiographs using deep convolutional neural networks," *PLoS ONE*, vol. 15, no. 11 November, pp. 1–15, 2020, doi: 10.1371/journal.pone.0242013.
[35] M. Chakraborty, S. V. Dhavale, and J. Ingole, "Corona-Nidaan: lightweight deep convolutional neural network for chest X-Ray based COVID-19 infection detection," *Applied Intelligence*, vol. 51, no. 5, pp. 3026–3043, 2021, doi: 10.1007/s10489-020-01978-9.
[36] W. Setiawan and F. Damayanti, "Layers modification of convolutional neural network for Pneumonia detection," *Journal of Physics: Conference Series*, vol. 1477, no. 5, 2020, doi: 10.1088/1742-6596/1477/5/052055.
[37] N. Magnavita, G. Tripepi, and R. R. Di Prinzio, "Symptoms in health care workers during the covid-19 epidemic. A cross-sectional survey," *International Journal of Environmental Research and Public Health*, vol. 17, no. 14, pp. 1–15, 2020, doi: 10.3390/ijerph17145218.
[38] M. M. Rahaman *et al*., "Identification of COVID-19 samples from chest X-Ray images using deep learning: A comparison of transfer learning approaches," *Journal of X-Ray Science and Technology*, vol. 28, no. 5, pp. 821–839, 2020, doi: 10.3233/XST-200715.
[39] A. Haghanifar, M. M. Majdabadi, Y. Choi, S. Deivalakshmi, and S. Ko, "COVID-CXNet: Detecting COVID-19 in frontal chest X-ray images using deep learning," *Multimedia Tools and Applications*, vol. 81, no. 21, pp. 30615–30645, 2022, doi: 10.1007/s11042-022-12156-z.

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