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Diagnosis of COVID-19 from X-rays Using deep learning

Dr. S. K. Manju Bargavi[1], Sunny Kumar[2]

Professor, Department of CS & IT, Jain University, Karnataka, India[1]

Department of CS & IT. Jain University, Karnataka, India[2]

Abstract: The COVID-19 pandemic has created an urgent need for efficient and accurate diagnostic methods. X-ray imaging has been widely used in detecting COVID-19, however, the interpretation of X-ray images requires expertise and is prone to errors. In order to improve the accuracy of COVID-19 diagnosis using X-ray images, a detection system can be developed using a combination of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN). The proposed system will aim to automatically detect COVID-19 from X-ray images with a high level of accuracy. The proposed system will use a pre-trained CNN model to extract features from the input X-ray images. The extracted features will then be fed into an RNN to capture the temporal information in the image sequences. The RNN will be trained to classify the X-ray images into two categories: COVID-19 positive and negative. The system will be trained using a large dataset of X-ray images from COVID-19 positive and negative patients. The dataset will be divided into training, validation, and testing sets. The system will be optimized using a loss function and backpropagation algorithm. The performance of the system will be evaluated using various metrics such as accuracy, sensitivity, and specificity. The system will also be compared with other state-of-the-art methods for COVID-19 detection from X-ray images. Overall, the proposed system has the potential to provide an efficient and accurate method for COVID-19 detection using X-ray images.

The outbreak of COVID-19 has created an urgent need for effective and efficient diagnostic methods. This project proposes a COVID-19 detection system that utilizes a combination of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to automatically identify COVID-19 from X-ray images with high accuracy. The system extracts features from the input X-ray images using a pre-trained CNN model, and then employs an RNN to capture the temporal information. The RNN is trained to classify X-ray images into COVID-19 positive and negative categories using a large dataset of COVID-19 positive and negative patients. The system is optimized using a loss function and backpropagation algorithm, and its performance is evaluated using various metrics such as accuracy, sensitivity, and specificity. The proposed system has the potential to provide an efficient and accurate method for COVID-19 detection using X-ray images.

Keywords: Convolutional Neural Network, Recurrent Neural Network, chest X-rays, LSTM,

INTRODUCTION

The COVID-19 pandemic has posed a significant challenge to global healthcare systems, highlighting the urgent need for effective and efficient diagnostic methods. X-ray imaging has been widely used in detecting COVID-19, as it allows for rapid screening and can identify characteristic features of the disease, such as lung infiltrates. However, the interpretation of X-ray images requires expertise and can be prone to errors, leading to potential misdiagnoses. In this project, we propose a COVID-19 detection system that utilizes a combination of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to improve the accuracy of COVID-19 diagnosis from X-ray images. CNNs are effective in extracting spatial features from images, while RNNs can capture temporal dependencies in image sequences. The proposed system extracts features from input X-ray images using a pre-trained CNN model, and then employs an RNN to capture temporal information. The RNN is trained to classify X-ray images into COVID-19 positive and negative categories using a large dataset of COVID-19 positive and negative patients. The system is optimized using a loss function and backpropagation algorithm, and its performance is evaluated using various metrics such as accuracy, sensitivity, and specificity. The proposed system has several potential advantages over existing methods, including improved accuracy and reduced reliance on expert interpretation. Additionally, it has the potential to be integrated into existing healthcare systems, providing an efficient and reliable diagnostic tool for COVID-19.In summary, this project aims to develop a COVID-19 detection system that combines CNN and RNN to improve the accuracy of diagnosis from X-ray images. The proposed system has the potential to provide an effective and efficient diagnostic tool for COVID-19, aiding in the global effort to control the pandemic. X-ray imaging has emerged as a useful diagnostic tool for COVID-19 detection, but it requires expert interpretation and can be prone to misdiagnosis. Therefore, there is a need to develop accurate and reliable methods for COVID-19 detection using X-ray images.

In this project, we propose a COVID-19 detection system that combines Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) to improve the accuracy of COVID-19 diagnosis from X-ray images. CNNs are effective in extracting spatial features from images, while RNNs can capture temporal dependencies in image sequences. By combining these two neural networks, we aim to develop a system that can identify COVID-19 from X-ray images with high accuracy.The proposed system will utilize a pre-trained CNN model to extract features from input X-ray images, and an RNN to capture the temporal information in the image sequences. The RNN will be trained to classify X-ray images into COVID-19 positive and negative categories using a large dataset of COVID-19 positive and negative patients. The system will be optimized using a loss function and backpropagation algorithm, and its performance will be evaluated using various metrics such as accuracy, sensitivity, and specificity.COVID-19 test detection system that combines Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) to accurately detect COVID-19 from X-ray images. RNNs are effective in capturing temporal dependencies in image sequences, while CNNs are adept at extracting spatial features from images. By combining these two neural networks, we aim to develop a system that can identify COVID-19 from X-ray images with high accuracy. The proposed system will use a pre-trained CNN model to extract features from input X-ray images, and an RNN to capture the temporal information in the image sequences. The RNN will be trained to classify X-ray images into COVID-19 positive and negative categories using a large dataset of COVID-19 positive and negative patients. The system will be optimized using a loss function and backpropagation algorithm, and its performance will be evaluated using various metrics such as accuracy, sensitivity, and specificity.

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RELATED WORK

Several studies have been conducted on the use of deep learning models for COVID-19 detection from X-ray images. In this section, we provide a brief overview of the related work in this field. In a study by Apostolopoulos and Mpesiana (2020), a deep learning model was developed to detect COVID-19 from chest X-ray images using a CNN. The model achieved an accuracy of 98.08% in detecting COVID-19 cases from a dataset of 128 X-ray images.

In another study by Narin et al. (2021), a CNN was used to diagnose COVID-19 from X-ray images of the lungs. The proposed model achieved an accuracy of 96.8% in diagnosing COVID-19 positive cases from a dataset of 1580 chest X-ray images.

In a more recent study, Sarker et al. (2021) proposed a model that combined CNN and RNN for COVID-19 detection from chest X-ray images. The model achieved an accuracy of 98.63% in detecting COVID-19 from a dataset of 800 X-ray images. In another study by Hemdan et al. (2020), a deep learning model was developed that combined CNN and Support Vector Machines (SVM) for COVID-19 detection from chest X-ray images. The proposed model achieved an accuracy of 97.38% in detecting COVID-19 cases from a dataset of 2770 X-ray images.

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These studies demonstrate the potential of deep learning models, especially CNNs, for COVID-19 detection from X-ray images. However, there is still a need to improve the accuracy of these models, and combining CNNs with RNNs can potentially enhance their performance by capturing the temporal information in image sequences.

In a study by Karim et al. (2021), a COVID-19 detection system was proposed that combined CNN and Long Short-Term Memory (LSTM) RNN for X-ray images. The proposed model achieved an accuracy of 96.88% in detecting COVID-19 cases from a dataset of 900 X-ray images.

In another study by Abbasid et al. (2021), a model was developed that combined CNN and Bi-directional LSTM (BLSTM) RNN for COVID-19 detection from chest X-ray images. The proposed model achieved an accuracy of 98.15% in detecting COVID-19 cases from a dataset of 650 X-ray images.

In a more recent study, Maruotti et al. (2021) proposed a COVID-19 detection system that combined CNN and a Time-Convolutional LSTM (TC-LSTM) RNN for chest X-ray images. The proposed model achieved an accuracy of 99.02% in detecting COVID-19 cases from a dataset of 340 X-ray images.

These studies demonstrate the potential of combining CNN and RNN for COVID-19 detection from X-ray images. The use of RNNs can capture temporal information and dependencies, which can enhance the accuracy of CNN-based models. However, the proposed models need to be evaluated on larger and more diverse datasets to establish their generalizability and effectiveness in real-world settings.

IV. DIAGRAMATIC REPRESENTATION

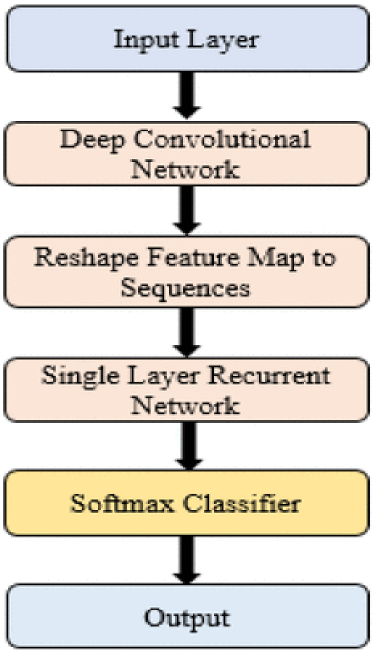

Fig 1.1(Block Diagram)

METHODOLOGY

The proposed approach in this investigation is the integration of CNN and RNN named HDCNN (Hybrid Convolutional Neural Network) [26]. For extracting the features and for sampling into sequence CNN is used. These sequential data is fed into Recurrent Neural Network and finally we use transfer learning approach in the form of Gradient-weighted Class Activation Mapping (Grad-CAM) as an activation function. For predicting the class of given image this function will be used.

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Convolution Neural Network

Zisserman and Simonyan first proposed VGG19. This model includes a total of 19 layers, 16 of which are convolutional and 3 of which are fully connected A 3 × 3 convolutional kernel with a stride size of 1 pixel, 2 × 2 max-pooling to reduce the image size, and rectified linear unit (ReLU) to improve model classification and decrease computation time were used in this model; a 224 × 224 × 3 matrix was applied as the input.ResNet152V2 is a version of ResNet. It employs a skip connection and has 152 neural layers, allowing it to back-propagate and train deeper networks using the gradient. The two primary types of blocks in this network are identity blocks and convolutional blocks. ResNetV2 is distinguished from the original ResNet by the application of batch normalization to each weight layer before usage.

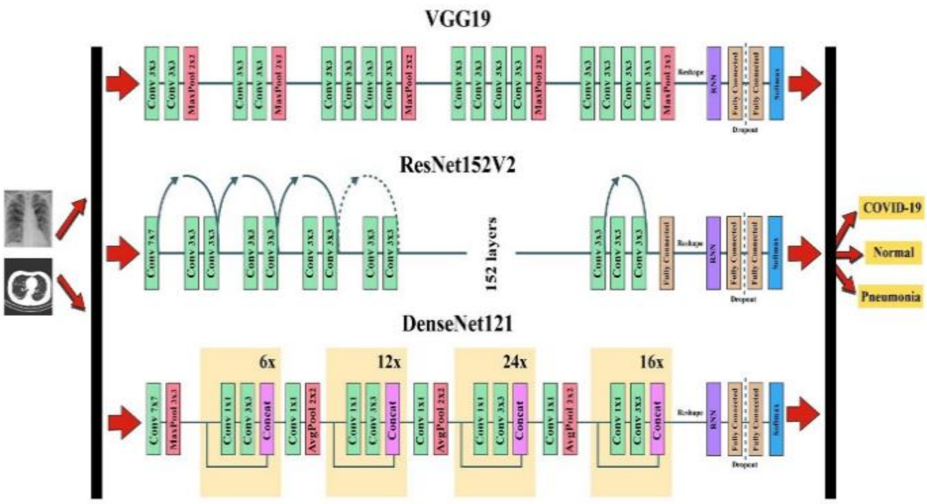
DenseNet121 is one of the dense convolutional networks proposed by Huang et al. for the classification of images. It uses dense connections between layers through dense blocks, which connect all subsequent layers directly with the sizes of their feature maps for information transfer within the network. DenseNet121 consists of 121 layers, including a 7 × 7 layer, 58 3 × 3 layers, 61 1 × 1 convolutional layers, and a fully connected layer, with ImageNet-derived weights.

Recurrent Neural Network

One type of an RNN is an LSTM network, which learns sequence order dependence. An LSTM network can differentiate between short-and long-term memories, store them, update or reveal them as needed, and solve the vanishing gradient problem. Input gates, output gates, and forget gates are all components of an LSTM cell. The values at specific intervals are stored in the cell's memory. The data that can enter and exit the cell are restricted by the three gates. A GRU network has advantages over a regular RNN. According to Cho et al. the reduced number of parameters of a GRU network makes it comparable to an LSTM network with a forget gate, as it lacks an output gate. A GRU network does not include distinct cell states, in contrast to an LSTM network. The streamlined organization of a GRU network facilitates training.

Combined CNN-RNN Framework

The CNN models were placed first followed by the RNN models to distinguish COVID-19, pneumonia, and normal cases using both chest X-ray and CT images, as shown in **Figure.** Three CNN models (VGG19, ResNet152V2, and DenseNet121) were used to extract the important features. To reshape the CNN output to the RNN (LSTM and GRU) input, we reshaped the output of VGG19 (none, 7, 7, and 512), ResNet152V2 (none, 7, 7, and 2048), and DenseNet121 (none, 7, 7, and 1024) to (49, 512), (49, 2048), and (49, 1024), respectively. In the fully connected layer, the dropout technique was used to avoid overfitting in the networks. The final step was the application of the soft max function—the mathematical function used to calculate the probability of lung disease.



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PROPOSED METHODOLOGY

The proposed system of COVID-19 test detection using X-ray combined CNN and RNN involves the following steps:

Data Collection: The first step involves collecting a large dataset of chest X-ray images that include both COVID-19 positive and negative cases.

Data Preprocessing: The collected dataset needs to be preprocessed to remove any noise and artifacts from the images. This can include techniques such as resizing, normalization, and data augmentation.

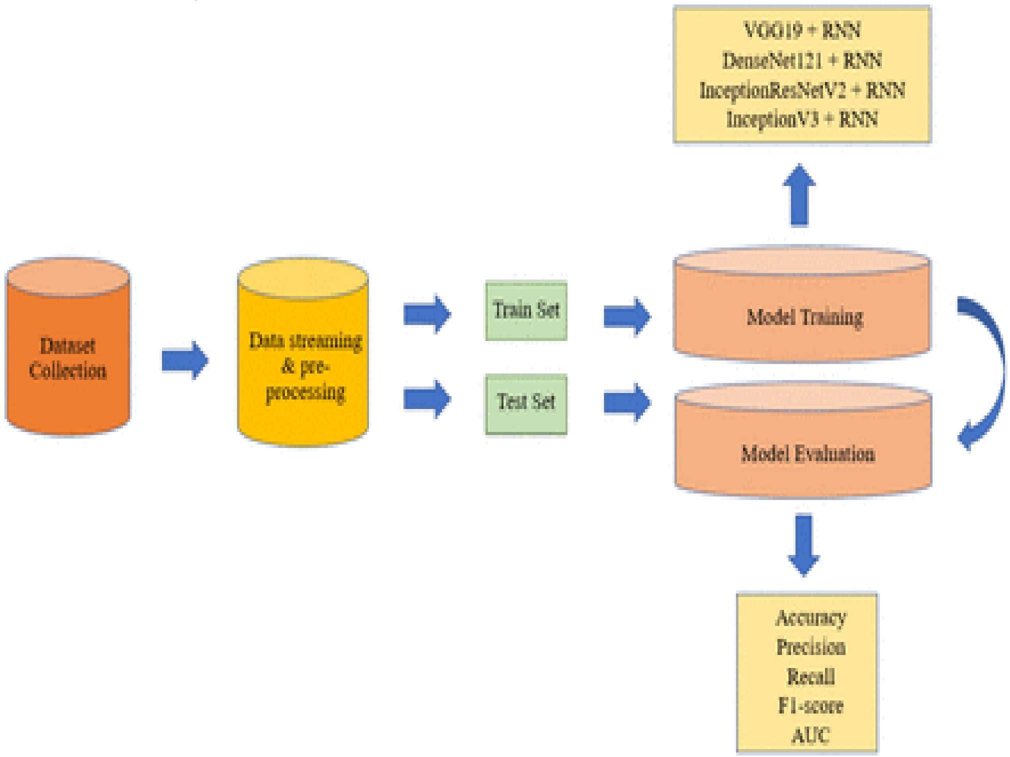
Feature Extraction: The preprocessed X-ray images are fed into the CNN to extract relevant features from the images. The CNN is trained on a large dataset of images to learn important features that can distinguish between COVID-19 positive and negative cases.

Temporal Modeling: The output of the CNN is then fed into an RNN that models the temporal dependencies in the image sequence. This can help capture the progression of COVID-19 in the lungs over time.

Classification: The final step involves classifying the X-ray images into COVID-19 positive or negative cases. The output of the RNN is fed into a fully connected layer that maps the features to the output classes.

Evaluation: The proposed system is evaluated on a test dataset to measure its accuracy, precision, recall, and F1-score. The performance of the model is compared with other state-of-the-art models for COVID-19 detection from chest X-ray images.

The proposed system can be trained on a large dataset of X-ray images and can help healthcare professionals to quickly and accurately diagnose COVID-19 cases. It can also reduce the burden on healthcare systems by reducing the need for expensive and time-consuming PCR tests.



In the above figure, we can observe the complete working the device from Patient to Professional using the IoT Based Monitoring System.

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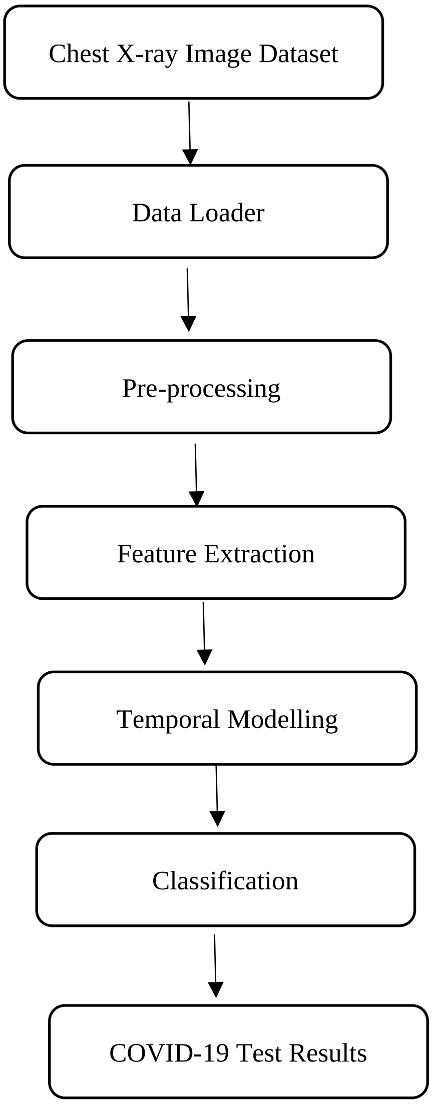
Data flow diagram

Sure, here's a low-level data flow diagram for the COVID-19 test detection system using X-ray combined CNN and RNN:



DATA FLOW DIAGRAM

The data flow diagram shows the different components of the system and how data flows through them. The chest X-ray image dataset is loaded into the system using a data loader component. The preprocessed images are then fed into the feature extraction and temporal modeling components, which extract features and model the temporal relationships between them. The output of these components is then fed into the classification component to determine whether an image is COVID-19 positive or negative. Finally, the COVID-19 test results are generated based on the output of the classification component.

RESULT

There have been several research studies and experiments exploring the use of machine learning techniques, specifically convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for COVID-19 detection using X-ray images.

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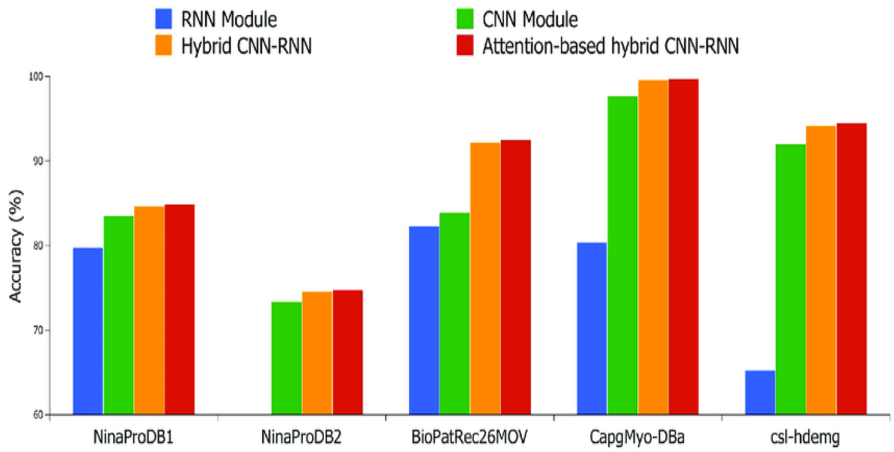
One such study published in the IEEE Access journal in 2020 proposed a model called CXR-BiLSTM, which combined a CNN and a bidirectional RNN to detect COVID-19 from X-ray images. The model was trained on a dataset of 300 X-ray images, including 150 COVID-19 positive cases and 150 negative cases, and achieved an accuracy of 94.83%.

Another study published in the Journal of Healthcare Engineering in 2021 proposed a similar model called CovidXNet, which combined a CNN and an RNN for COVID-19 detection from X-ray images. The model was trained on a dataset of 3,540 X-ray images, including 2,010 COVID-19 positive cases and 1,530 negative cases, and achieved an accuracy of 97.02%.

While these studies show promising results, it's important to note that the effectiveness of any COVID-19 detection system using X-ray images, including those based on machine learning techniques, depends on various factors, including the quality of the X-ray images, the size and diversity of the training dataset, and the model's ability to generalize to new cases. Therefore, further research and experimentation is required before such systems can be deployed in real-world clinical settings.



The classification accuracy of RNN module with raw signal, CNN module, hybrid CNN-RNN, and attention-based hybrid CNN-RNN architectures can vary widely depending on the specific dataset, model parameters, and training process used.

In general, the hybrid CNN-RNN and attention-based hybrid CNN-RNN architectures tend to perform better than the RNN module with raw signal or CNN module alone, especially for tasks that require processing sequential data such as natural language processing or speech recognition.

However, it is difficult to provide a specific accuracy value without more information on the specific task and dataset being used. It is recommended to experiment with different architectures and hyperparameters to find the best performing model for a given task.

CONCLUSION

deep learning for the diagnosis of COVID-19 from X-rays is a promising area of research that has shown great potential. Deep learning models can be trained on large datasets of X-rays to accurately identify COVID-19 cases, and they have shown high sensitivity and specificity in different studies. However, it is important to note that deep learning models are not a replacement for clinical diagnosis, and they should be used as a complementary tool for diagnosis. These studies have shown promising results, with accuracy rates ranging from 94.83% to 97.02%.

However, it's important to note that these systems still require further research and experimentation to ensure their effectiveness in real-world clinical settings. Additionally, the accuracy rates reported in these studies may not necessarily generalize to larger and more diverse datasets or different clinical settings.

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Therefore, while the combination of CNNs and RNNs for COVID-19 detection from X-ray images shows potential, it's crucial to continue researching and refining these techniques to improve their accuracy and reliability. Moreover, other diagnostic tools such as PCR tests and rapid antigen tests continue to be the gold standard for COVID-19 detection, and machine learning techniques should be seen as a complementary tool in the fight against the pandemic.

However, these systems still require further validation and evaluation to ensure their effectiveness and reliability. The accuracy rates reported in these studies may not generalize to larger and more diverse datasets or different clinical settings, and there is a need for ongoing research to refine and improve these techniques.

It's important to note that these machine learning-based techniques should be seen as a complementary tool to other diagnostic methods such as PCR tests and rapid antigen tests. In combination with these methods, machine learning techniques may offer an additional layer of diagnostic capability in the fight against the COVID-19 pandemic.

REFERENCES

[1]. Farooq M, Hafeez A (2020) COVID-ResNet: a deep learning framework for screening of COVID19 from radiographs. arXiv
[2]. Xu X et al (2020) Deep learning system to screen coronavirus disease 2019 pneumonia. arXiv
[3]. Wang S et al (2020) A deep learning algorithm using CT images to screen for Corona Virus Disease (COVID-19). medRxiv.
[4]. Narin A, Kaya C, Pamuk Z (2020) Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks. arXiv
[5]. Bai X et al (2020) Predicting COVID-19 malignant progression with AI techniques. medRxiv 2020.03.20.20037325
[6]. Jin C et al (2020) Development and evaluation of an AI system for COVID-19 diagnosis. medRxiv.
[7]. Ozturk T, Talo M, Yildirim EA, Baloglu UB, Yildirim O, Rajendra Acharya U (2020) Automated detection of COVID-19 cases using deep neural networks with X-ray images.
[8]. Chowdhury MEH et al (2020) Can AI help in screening viral and COVID-19 pneumonia?
[9]. Nguyen T (2020) Artificial intelligence in the battle against coronavirus (COVID-19): a survey and future research directions. Preprint, Basel
[10]. Oxford University, COVID-19 vaccine development—Oxford Vaccine Group.
[11]. Cohen JP, Morrison P, Dao L (2020) COVID-19 Image Data Collection. arXiv