

DEEP LEARNING FOR HEALTHCARE APPLICATIONS

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ABSTRACT:

The COVID19 pandemic is an existential global health emergency affecting the entire planet. Countless individuals have died as a result of COVID, which is still present and spreading in nations including the United States, India, and Russia. Positive cases are increasing despite the fact that there are currently multiple vaccines available. So that a suspected COVID-19 patient can be saved, there is an urgent need for quick infection diagnosis with good visualisation. Results from procedures like Polymerase chain reaction (PCR) and Lateral flow tests (LFTs), which must be sent to a laboratory for examination, may not be available to patients for a few days. The outcomes, though, aren't always accurate. Despite CT scan images being a common imaging modality among previously accessible, generally available, and less priced materials, deep learning algorithms have achieved progressive performance in computer-aided medical diagnosis. In order to discriminate between COVID-19 and non-COVID 19 in CT scan images, our study will use a range of deep learning techniques. The developed models' respective levels of accuracy for diagnosing COVID-19 were 85.34%, 87.46%, and 88.15%. COVID-19 automated diagnostic using CT scan pictures is a quick and effective method for COVID-19 screening that doctors can use.

Keywords: Antibody, Corona virus, Community spread, Social Distance, Surgical mask.

INTRODUCTION:

Since it spreads mostly through human contact, COVID-19, also known as SARS-CoV-2 and 2019-nCoV, is a virus that is having an impact on the entire world. In December 2019, Wuhan, China, reported the first corona virus case. Every continent has since experienced the virus's global expansion. When people are crowded together, it spreads from one to another individual. COVID-19 was recognised as a global

pandemic on March 11, 2020. As of November 19 2021, this terrible virus had infected 251,310,000 persons, and over 51.3 lakh of those patients have passed away. This contagious virus swept across all continents and afflicted 193 countries. The most common symptoms of this viral infection include a cough, cold, fever, bone pain, and respiratory problems. Fatigue, a sore throat, muscle pain, and a loss of taste or smell are further symptoms that patients with the corona virus may encounter. A patient may occasionally contract the corona virus without displaying any of the preceding symptoms. Individual transmission is believed to work in a manner similar to that of influenza and other respiratory viruses, with respiratory droplets being formed when an infected person coughs or sneezes within 6 feet of someone who isn't ill. Before entering the lungs, these droplets may come into contact with mucosal surfaces on the mouth, nose, and eyes. When infected surfaces are handled and a person touches their own mouth, nose, or eyes, or when they eat with dirty hands, contact transmission occurs. The virus is predicted to be present on clean surfaces for only a short time. Although the lifespan of the virus that causes COVID-19 to emerge on surfaces is unknown, it seems to function in a manner similar to that of other corona viruses. Recent research has revealed that human corona viruses can live on surfaces for anywhere between 2 hours and 9 days. The type of surface, temperature, relative humidity, viral strain, and others all have an impact on how long a virus can persist. The same research found that simple disinfectants like sodium hypochlorite and 70% ethanol can efficiently inactivate bacteria in under a minute.

LITERATURE SURVEY:

The picture normalisation process is integrated into the Fast Ai library before the model is trained. With an accuracy of 93.11%, the first stage model does a good job at differentiating between pneumonia caused by a virus, pneumonia caused by bacteria, and pneumonia in healthy individuals. With 97.22 percent accuracy, the second stage model for detecting COVID-19 performs remarkably well.

The author suggested a deep transfer learning method that uses chest CT and X-ray pictures to more quickly identify COVID-19 patients. This is due to the fact that early chest X-ray (CXR) screening for COVID-19 can help identify patients who may have the disease. They looked at three different datasets: Images of chest X-rays associated with pneumonia, a SARS-COV-2 CT scan, and a COVID chest X-ray are shown in order. They calculated the sensitivity and specificity of the proposed model using the provided data. Sensitivity and specificity for the proposed model are 76.19 and 97.22 percent, respectively.

The MeCas12a system, an improved version of the Cas12a detection system, can identify as little as five copies of SARS-CoV-2 RNAs, according to the study. In contrast to PCR-based methods, Cas12 and Cas13 detection of SARS-CoV-2 needed at least 10 copies of the viral genome. As a result, in terms of sensitivity, MeCas12a beats the other techniques. MeCas12a is also quite specific, discriminating between SARS-CoV-2 and MERS-CoV, as well as SNPs with single nucleotide changes. They also demonstrated that MeCas12a has a high sensitivity and specificity for detecting SARS-CoV-2 in 24 COVID-19 patient samples in 45 minutes.

For distinguishing COVID-19 CT images from other community-acquired pneumonia and/or healthy CT images, the researchers suggest a lightweight Convolution Neural Network (CNN) architecture based on the Squeeze Net model. The design calls for a 3.2 percent improvement in the first dataset arrangement and a 2.1 percent improvement in the second dataset, with an accuracy requirement of 85.03 percent in the first dataset arrangement and about 2.1 percent in the second dataset arrangement.

To develop and evaluate a fully automated method for COVID-19 detection using chest CT: The study comprised a total of 3,322 people and 4356 chest CT scans. The patients' average age was 49.15 years, and there were somewhat more men than women among them (1838 vs. 1484; p-value=0.29). With an AUC of 0.96 and a p-value of 0.001, the independent test set's per-exam sensitivity and specificity for diagnosing COVID19 were, respectively, 114 of 127 (90 percent [95 percent CI: 83 percent, 94 percent]) and 294 of 307 (96 percent [95 percent CI: 93 percent, 98 percent]), for the disease. In the independent test set, the per-exam sensitivity and specificity for diagnosing CAP were 87 percent (152 of 175) and 92 percent (239 of 259), respectively. The suggested CNN-2 performs better than the original Squeeze Net on both dataset sets. For instance, the F1-Score for the NN-2 model is 85.03 percent accuracy, 87.55 percent sensitivity, 81.95 percent specificity, and 86.20 percent. Using a 3D deep learning architecture, COVID-19 was found. Both 2D local and 3D global representative features can be provided using this technique. In the discipline of radiology, deep learning has overtaken the use of conventional techniques.

In this article, chest X-rays are preferred over CT scans. The reason for this is that practically all hospitals have X-ray equipment. CT scanners are more expensive than X-ray devices. Chest X-ray self-analysis was performed using deep learning-based algorithms. Deep transfer learning approaches were able to train network weights on large datasets as well as refine the weights of pre-trained networks on small datasets. A wide range of performance metrics, including accuracy, f-measure, sensitivity, specificity, and kappa statistics, have been used in extensive comparative analyses to assess the performance of the suggested model.

A three-dimensional deep learning method was published by Xu et al. (Xu et al.), which identified CT scans as COVID19 pneumonia-positive or viral pneumonia-positive. They trained a location-attention categorization model, and then used the estimated probability to create a forecast using a Bayesian function. Their top model needed to be confirmed in many clinical studies and had an 86.7 percent recall rate. UNet++ was used by Chen et al. (Chen et al., 2020a) to build a model. Wang and others (Wang et al., 2020b) used a modified Inception neural network architecture to obtain an accuracy of 79.3%.

CovidAID: The authors introduce COVID-19 AI Detector, a novel deep neural network-based model for stratifying patients for appropriate diagnostics. Using the publicly available COVID-chest ray-dataset, our model accurately predicts the COVID-19 infection with a sensitivity (recall) of 100% and a specificity (accuracy) of 90%. We significantly outperform Covid-findings on the same dataset. Net's Due of the lack of X-Ray data (particularly pneumonia caused by bacteria and viruses), it is challenging to train a deep neural network from scratch. We use a pre-trained backbone that has been trained on a large dataset as a consequence. The methods leverage the CheXNet pre-trained model developed by Weng et al.

The researcher created the COVID-CT dataset, which includes 463 non-COVID-19 CT scan images in addition to 349 COVID19 CT scan images from 216 patients. The importance of this dataset has been confirmed by a well-known radiologist who has been identifying and treating COVID-19 patients ever since the pandemic began. We also carry out practical studies to demonstrate the use of this dataset for developing COVID-19 AI-based diagnostic algorithms. Author develops diagnostic methods based on self-supervised learning and multi-task learning with an F1 of 0.90, AUC of 0.98, and accuracy of 0.89 using this dataset.

Microsoft Azure's proprietary vision software, which is based on machine learning techniques, is utilised to train and test the suggested solution. The proposed method achieves an overall accuracy of about 91 percent for COVID-19 classification. The system is trained using specialised vision software based on machine learning methods, such as Microsoft Azure's residual neural network (ResNet) architecture. ResNet is used to construct networks that are more complicated than other simple networks and to determine the optimum number of layers to prevent the vanishing gradient issue.

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According to the findings, the MeCas12a system, an enhanced variation of the Cas12a detection system, can recognise as few as five copies of SARS-CoV-2 RNAs. Unlike PCR-based techniques, Cas12 and Cas13 need at least 10 copies of the viral genome to identify SARS-CoV-2. As a result, MeCas12a outperforms the other approaches in terms of sensitivity. In addition to distinguishing between SARS-CoV-2 and MERS-CoV as well as SNPs with single nucleotide alterations, MeCas12a is also quite specific. Additionally, they demonstrated that MeCas12a can quickly and accurately identify SARS-CoV-2 in 24 COVID-19 patient samples.

The RT-PCR test, also known as reverse transcription-polymerase chain reaction, takes a lot of time and skill to do. Because of this, it's crucial to develop an automated early diagnosis system that can make judgements quickly while significantly lowering diagnostic error. A potential solution for COVID-19 screening has recently emerged using images from chest CT scans and contemporary artificial intelligence (AI) approaches, in particular Deep Learning (DL) algorithms. A number of researchers modified pre-trained deep learning architectures like ResNet50, InceptionV3, and VGG19. They employed the openly available. They are widely accessible today, making the use of this deep learning technology to identify patient photos crucial.

EXISTING SYSTEM:

According to earlier investigations, the CT imaging of COVID-19 exhibits a variety of different symptoms. Focal ground glass shadows, which are mostly found in the bilateral lungs, multiple consolidation shadows with the "halo sign" of surrounding ground glass shadows, mesh shadows, bronchiectasis, and inflating signs inside the lesions, and multiple consolidation of various sizes and grid-shaped high-density shadows are some of the manifestations. However, using simply human sight to separate COVID-19 from other illnesses is not unbiased or reliable. By digitising and standardising the visual information, deep learning system-based screen models, in contrast, produced findings that were more precise and trustworthy. As a result, they can help doctors make an immediate clinical decision that is more accurate, which will aid the management of suspected patients.

In this study, a classification network for differentiating COVID-19 from influenza-A viral pneumonia was designed using deep learning technology. The traditional ResNet was employed for feature extraction in terms of the network structure. The network model was contrasted with and without the additional location-attention mechanism. The test demonstrated that the proposed mechanism could more effectively identify COVID-19 cases from other cases.

The symptoms of COVID-19 and other pneumonias, including organic pneumonia, eosinophilic pneumonia, and influenza-A viral pneumonia, may overlap in some cases. The COVID-19 clinical diagnosis is required. to incorporate the patient's earliest symptoms, laboratory test, contact history, and travel history. The number of model samples used in this investigation was constrained. Therefore, to increase accuracy going forward, the number of samples used for training and testing should be increased. To deal with the complex clinical condition, more multi-center clinical investigations should be carried out. Additionally, the segmentation and classification model has to be improved. The segmentation and classification accuracy of the model should be increased, a better exclusive model should be created for training, and a larger data set should be used to verify the generalisation performance of this technique.

They have provided a cutting-edge technique in this multi-center case study that could totally automate the screening of COVID-19 using deep learning technologies. A promising supplemental diagnostic tool for front-line clinical practitioners, models with locationattention mechanisms could more effectively classify COVID-19 at chest radiography with an overall accuracy rate of 86.7%.

PROBLEM STATEMENT:

A prevalent and harmful virus called COVID19 has the potential to seriously harm people. There may not be any warning signs or symptoms when a person has a virus like this. Many of the individuals who have been infected by this virus are on the verge of death. As a responsible member of society and in response to the daily rise in instances, we have developed a method to identify the COVID19 virus as early as possible in order to rescue the patient.

PROPOSED SYSTEM:

In this proposed model, convolution neural networks are employed as a component of deep learning techniques. This model's main objective is to evaluate algorithms and determine which one offers the highest level of precision in order to detect the corona virus early in the body. The accuracy should be high because even one inaccurate prediction could have catastrophic consequences.

A Convolution Neural Network (CNN), which is a Deep Learning algorithm, can take an image as input, assign significance (learnable weights and biases) to different aspects/objects in the picture, and distinguish between them, as shown in Figure 3.1. In comparison to other classification methods, a CNN requires significantly less pre-processing. While manual filter engineering is required for simple techniques, Convents with adequate training may learn these filters/characteristics. A CNN's structure is modelled after how the visual cortex is organised and resembles how neurons are connected in the human brain. Only in a limited region of the visual field known as the Receptive Field are individual neurons capable of responding to inputs. If similar fields overlap, the entire visual field will be covered. In neural networks, the method is frequently referred to as a convolution. Although cross-correlation is a related operation, mathematically speaking, it is a cross-correlation rather than a convolution. Only the indices in the matrix are impacted, which has an impact on which index gets which weights.

The use of the same weights for two levels of the model is referred to as "sharing weights." Simply said, this means that the system will represent two different transformations using the same parameters. Essentially, this means that the same matrix elements may undergo several updates during back propagation from different gradients. Instead of the usual transformations from a single layer, the same set of elements will enable transformations at several layers.

Convolution is the name given to the method in neural networks. It's a cross-correlation mathematically speaking, not a convolution, even if they are related operations. Only the indices in the matrix are impacted, which has an impact on how much weight is given to each index.

The input is a tensor with the following dimensions: (number of photos) x (image width) x (image height) x (number of pictures) x (number of pictures) x (number of pictures) x (number of pictures) x (number of pictures) x (number of pictures) (image depth). Convolution kernels (how many there are). Hyper settings for kernel width and height are required, and kernel depth must match image depth. An input and output layer, as well as multiple hidden layers, make up a convolution neural network.

In a CNN's hidden layers, convolution layers, RELU layers (activation function), pooling layers, fully connected layers, and normalisation layers are frequent.

ARCHITECTURE:

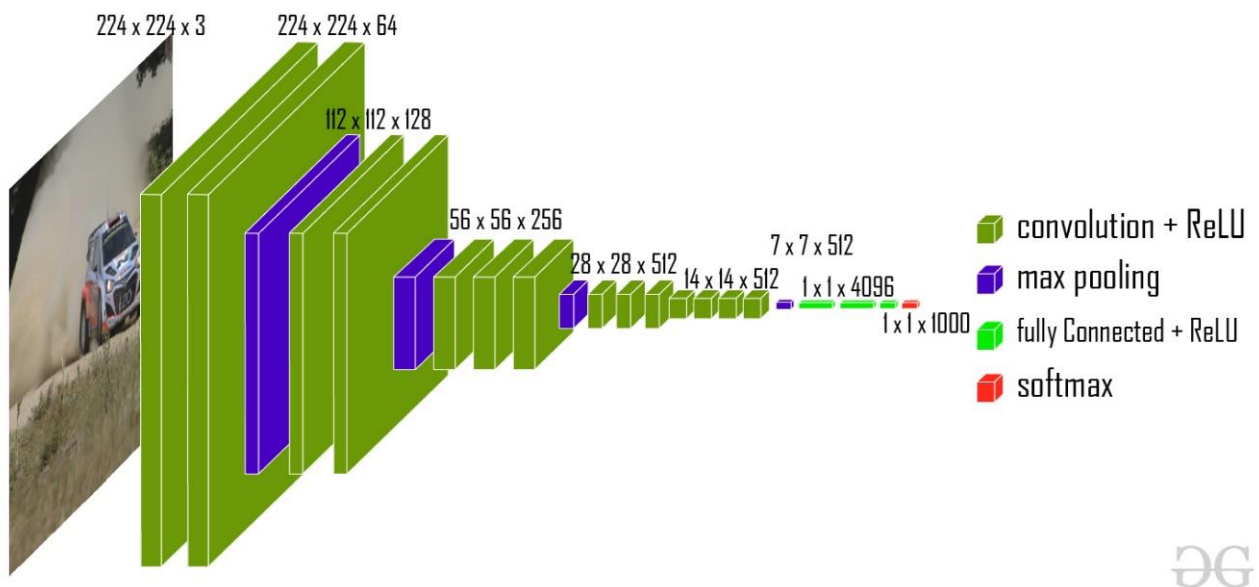


Fig 1.VGG-16 architecture

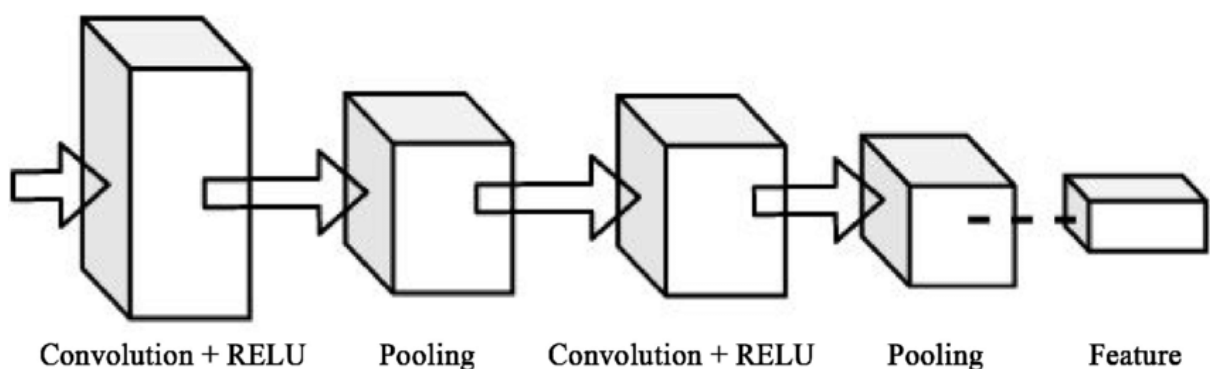


Fig 2. CONVOLUTION+ RELU BLOCK DIAGRAM

ALGORITHMS:

VGG-16 is the name of a convolutional neural network with 16 layers. A persistent version of the network that has been trained on more than a million photos is present in the ImageNet database [1]. A number of animals, a keyboard, a mouse, and a pencil are among the 1000 different item categories that the pertained network can classify images into. As a result, the network now has comprehensive feature representations for a range of photos. Images having a resolution of 224 by 224 are supported by the network. for more networks that have been trained in MATLAB.

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an annual contest for computer vision. Each year, teams compete in two challenges. Object localization, the initial phase, is identifying objects in an image that belong to 200 lessons. The second method includes classifying each image into one of a thousand groups. VGG 16 was proposed by Karen Simonyan and Andrew Zisserman in the 2014 book "VERY DEEP CONVOLUTIONAL NETWORKS FOR LARGE-SCALE IMAGE RECOGNITION" from the Visual Geometry Group Lab at Oxford University. This model placed first and second in the aforementioned categories of the 2014 ILSVRC challenge. Big data sets are being raised by the hub authority.

Convolutional neural networks, a subset of artificial neural networks, are also referred to as ConvNets. A convolutional neural network is made up of an input layer, an output layer, and numerous hidden layers. The CNN (Convolutional Neural Network) variation known as VGG16 is one of the best computer vision models available today. This model showed a significant improvement over the state-of-the-art setups by analysing the networks and enhancing the depth using an architecture with exceptionally small (3 3) convolution filters. With yielding, the depth was increased to 16–19 weight layers. Machine learning has a subset called deep learning that only uses artificial neural networks. Deep learning is also a human brain mimic because neural networks are made to resemble the human brain.

VGG16 is an object identification and classification algorithm that, when used to classify 1000 images into 1000 separate categories, has an accuracy rate of 92.7%. It is a popular method for categorising photos and is easy to use with transfer learning.

RESULTS:



POSITIVE COVID-19 CT SCAN IMAGES



NEGATIVE COVID-19 CT SCAN IMAGES

CONCLUSION:

In this study, the suggested strategy is paired with a convolution neural network. But it is noted that deep learning approaches outperform approaches with a semantic emphasis in terms of accuracy. Deep learning approaches, however, require more training time. The primary objective of the suggested model is to suggest an effective technique for identifying the lethal virus. To ensure that our deep learning algorithms (Convolution neural networks) could achieve good performance on the suggested dataset, we conducted multiple experiments. On the suggested dataset, trials have been run, and accuracy has been calculated for each algorithm separately. As a result, both filters' accuracy is as follows. Gaussian filter: 84.66 percent, Gabor filter: 86.18%, and bilateral filter: 85.34. We may therefore conclude from a comparison of the filters that the Gabor filter has the highest accuracy when compared to the other two filters. Therefore, we can confidently assert that the Gabor filter has the best likelihood of discovering the corona virus identification and can be used to save people's precious lives.

REFERENCES:

1. Jain, Govardhan, Madhup K. Mittal, Deepti Mittal, and Daksh Thakur. The phrase "A deep learning approach to detect Covid-19 corona virus with X-ray images." 40, no. 4 (2020): 1391–1405 for Biocybernetics and Biomedical Engineering.
2. Harsh Panwar, P. K. Gupta, Mohammad Khubeb Siddiqui, Ruben Morales Menendez, Prakhar Bhardwaj, and Vaishnavi Singh are some of the authors. The phrase "A deep learning and gradCAM based colour visualisation approach for fast detection of COVID-19 cases using chest X-ray and CT-Scan images." *Chaos, Solitons & Fractals* 140: 110190 (2020).
3. *Advanced science* 7, no. 20 (2020): 2001300. Ma, Peixiang, Qingzhou Meng, Baoqing Sun, Bing Zhao, Lu Dang, Mingtian Zhong, Siyuan Liu, et al. "MeCas12a, a Highly Sensitive and Specific System for COVID-19 Detection."
4. Matthew Polsinelli, Luigi Cinque, and Giuseppe Placidi, "A light CNN for detecting COVID-19 from CT scans of the chest." *Letters* 140 (2020) on pattern recognition: 95–100.
5. Khaled Rabie, Halgurd S. Maghded, Kayhan Zrar Ghafoor, Ali Safaa Sadiq, Kevin Curran, and Danda B. Rawat. a brand-new framework for coronavirus diagnosis powered by AI.
6. 2020 IEEE 21st International Conference on Information Reuse and Integration for Data Science (IRI), pp. 180–187. COVID-19 employing smartphone embedded sensors: design study. IEEE, 2020.
7. Youbing Yin, Xin Wang, Bin Kong, Junjie Bai, Li, Lin, Lixin Qin, Zeguo Xu, and others are all mentioned. On a chest CT, artificial intelligence can tell COVID-19 from community-acquired pneumonia. *Imaging* (2020).
8. Dilbag Singh, Manjit Kaur, Naresh Kumar, Vijay Kumar, and N. Narayan Das. the phrase "Automated deep transfer learning-based approach for detection of COVID-19 infection in chest X-rays." *IRBM* (2020).
9. Amit Kharat, Ashrika Gaikwad, Viraj Kulkarni, Lokwani, Rohit, and Aniruddha Pant. "Convolution neural networks for automated detection of COVID-19 from CT scans." Preprint for the arXiv is 2006.13212 (2020).

10. Arpan Mangal, Surya Kalia, Harish Rajgopal, Krithika Rangarajan, Vinay Namboodiri, Subhashis Banerjee, and Chetan Arora, "CovidAID: COVID19 detection using chest X-ray." (2020) arXiv preprint arXiv:2004.09803.
11. Yang, Xingyi, Pengtao Xie, Xuehai He, Jinyu Zhao, Yichen Zhang, and Shanghang Zhang. A CT scan dataset about COVID-19 is known as "COVID-CT-dataset." The 2020 arXiv preprint is 2003.13865.
12. Sakshi Ahuja, Bijaya Ketan Panigrahi, Nilanjan Dey, Venkatesan Rajinikanth, and Tapan Kumar Gandhi are among the list. "Automatic detection of COVID-19 from lung CT scan slices using deep transfer learning." 51, no. 1 (2021), Applied Intelligence, pp. 571–585.
13. Sachin Sharma, "Drawing insights from COVID-19-infected patients using CT scan images and machine learning techniques: a study on 200 patients." Environmental Science and Pollution Research, Volume 27, Number 29, 2020, Pages 37155–37163.
14. Seemab Zakir, Talha, and Anwar. "Deep learning-based diagnosis of COVID-19 using chest CT-scan images." In the 1–5 pages of the 2020 IEEE 23rd International Multitopic Conference (INMIC). IEEE, 2020.
15. Himadri, Mukherjee, Subhankar Ghosh, Kaushik Roy, Ankita Dhar, Sk Md Obaidullah, and K. C. Santosh. Applied Intelligence 51, no. 5 (2021): 2777–2789. "Deep neural network to detect COVID19: one architecture for both CT Scans and Chest X-rays."
16. Chuansheng, Xianbo Deng, Qing Fu, Qiang Zhou, Jiawei Feng, Hui Ma, Wenyu Liu, and Xinggang Wang are among the names mentioned. The phrase "Deep learning-based detection for COVID-19 from chest CT using weak label." 2020's MedRxiv.