COVID-19 PREDICTION USING DENSENET-121

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Abstract
Coronavirus 2019, also known as COVID-19, has recently had a negative influence on public health and human lives. Since the Second World War, this disastrous effect has changed human experience by bringing about a health crisis that is unpredictable and exponentially more harmful (Kursumovic et al. in Anaesthesia 75: 989-992, 2020). The global catastrophe is a serious pandemic because to COVID-19's highly contagious qualities within human groups. Early and reliable detection of the virus can be a promising method for tracking and preventing the infection from spreading (for example, by isolating the patients) due to the lack of a COVID-19 vaccine to control rather than cure the illness. This issue points to the need to improve the COVID-19 auxiliary detection method. Due of its anticipated availability, computed tomography (CT) imaging is a commonly used technology for pneumonia. The examination of photos helped by artificial intelligence may be a promising approach for finding COVID-19. In this study, convolutional neural networks (CNN) are used to provide a potential technique for predicting COVID-19 patients from the CT scan. The innovative method for forecasting COVID-19 is based on the most current modification to CNN architecture (DenseNet-121). The results exceeded 92% accuracy, and a 95% recall rate indicated that the prediction of COVID-19 performed as expected.

Keywords
DENSENET-121

I. Introduction

The 2019 coronavirus disease (COVID-19) outbreak has already been identified as a major global public health emergency. The COVID-19 virus was initially discovered in Wuhan, China, in late 2019, and it unexpectedly spread to more than 200 nations. Healthcare experts and policymakers failed to contain this severe pandemic epidemic, which led to a quick death toll, as a result of the disease's strong communicable qualities among persons in close contact. It is essential to identify and isolate the infected person as quickly as possible and institute social lockdown since secondary infections in communities are caused by intimate personal encounters.Thus, early detection of the COVID-19 incidents is a paramount option to take proactive steps to minimize risks and spread of infections, plan of clinical treatment and arrange timely care support

II. Objective

The goal of COVID-19 prediction using DenseNet-121 is to create a reliable and accurate model that can help medical practitioners identify, diagnose, and handle COVID-19 cases successfully, ultimately leading to improved patient care and outcomes for public health.

III. Literature Survey

Title

COVID-19 Detection from Chest X-ray images using deep learning and convolutional neural networks.

Description

In the research COVID-19 Detection from Chest X-ray pictures using Deep Learning and Convolutional Neural Networks, DenseNet-121 Convolutional Neural Networks are proposed as a deep learning-based method for identifying COVID-19 cases from chest X-ray pictures. Chest X-ray images from both COVID-19-positive and normal subjects are included in the study's initial collection of a sizable chest imaging dataset. To guarantee data consistency and quality, the dataset is preprocessed. Then, as the deep learning model for COVID-19 prediction, DenseNet-121, a well-liked CNN architecture known for its capacity to extract intricate information from images, is utilised. Using supervised learning, the DenseNet-121 model is trained on the dataset. The model gains the ability to automatically extract pertinent features from the chest X-ray pictures and map them to the corresponding COVID-19 or normal class labels. The study uses various performance metrics, such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve, to evaluate the model's performance.The study details the model's effectiveness at spotting COVID-19 cases in chest X-ray pictures. To assess the efficiency of DenseNet-121 in detecting COVID-19, it may also compare its performance to that of other CNN architectures or machine learning techniques. The outcomes might demonstrate the model's accuracy, sensitivity, specificity, and other performance parameters, showing that it is capable of correctly predicting COVID-19 instances from chest X-ray pictures. The study may also go through the method's shortcomings, such as potential biases in the dataset, difficulties in deciphering the findings, and the requirement for additional validation on various datasets. It may also draw attention to the possible clinical ramifications of employing the DenseNet-121 model to predict COVID-19, including early detection, effective screening, and decision assistance for healthcare professionals.

Title

COVID-19 Diagnosis from CT Scan Images using Transfer Learning with Deep Convolutional Neural Networks

Description

In a research study titled "COVID-19 Diagnosis from CT Scan Images Using Transfer Learning with Deep Convolutional Neural Networks," deep learning-based methods are suggested for identifying COVID-19 cases from CT scan pictures. Deep convolutional neural networks (CNNs) are used in this study.

A dataset of CT scan pictures is first gathered for the investigation, encompassing both normal and COVID-19-positive cases' scans. The dataset is preprocessed to guarantee data consistency and quality, and picture augmentation methods may be used to broaden the dataset's diversity. The next step is to use transfer learning, where the base model for feature extraction is a pre-trained CNN model.The basis model for transfer learning in the study is a deep CNN architecture, such as VGG-16, ResNet-50, or InceptionV3. conditioned model is fine- tuned on the CT scan images dataset, where the weights of the base model are updated during training to adapt to the specific task of COVID-19 diagnosis. The refined model gains the ability to automatically identify pertinent characteristics in CT scan pictures and link those features to the corresponding COVID-19 or normal class labels. A number of performance indicators, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve, are used to assess the model's performance. To show the usefulness of the suggested model in diagnosing COVID-19, the study may also compare its performance with that of other approaches or models already in use. The findings of the model's performance in diagnosing COVID-19 cases from CT scan pictures are reported in the study.It might go over the model's accuracy, sensitivity, specificity, and other performance metrics, showing how well it can predict COVID-19 instances from CT scan data. The practical ramifications of applying the suggested model for COVID-19 diagnosis, including the potential for early identification, effective screening, and decision support for healthcare providers, may also be included in the study. The study may also draw attention to the method's shortcomings, such as potential biases in the dataset, difficulties in interpreting the findings, and the need for more validation on a variety of datasets. The ethical issues surrounding the use of AI for COVID-19 diagnosis, such as patient privacy, fairness, and transparency, may also be covered.This research paper suggests and assesses the use of transfer learning in deep learning.It aims to contribute to the development of accurate and reliable methods for diagnosing COVID-19 cases using medical imaging data, potentially aiding in the early diagnosis and management of the disease.

Title

Deep learning-based detection and analysis of COVID-19 on chest radiographs

Description

In a research article titled "Deep learning-based detection and analysis of COVID-19 on chest radiographs," a deep learning-based method for identifying and analysing COVID-19 instances from chest radiographs (X-ray pictures) is proposed. The first step in the study is to compile a dataset of chest radiographs, which may include pictures of COVID-19-positive cases, healthy instances, and possibly other kinds of lung problems or disorders. The dataset is preprocessed to guarantee data consistency and quality, and picture augmentation methods may be used to broaden the dataset's diversity.Then, for the detection and analysis of COVID-19, a deep learning model, such as a Convolutional Neural Network (CNN), is used.Using supervised learning, the dataset is used to train the CNN, which then gains the ability to automatically identify important characteristics in chest radiographs and map those features to COVID-19 or normal class labels. Depending on the requirements of the study, other CNN architectures, such as VGG, ResNet, or DenseNet, may be used.A number of performance indicators, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve, are used to assess how well the CNN model performs. To illustrate the suggested model's efficacy in the detection and analysis of COVID-19, the study may also compare its performance with that of other techniques or models already in use. Results of the model's performance in identifying and evaluating COVID-19 cases from chest radiographs are reported in the study. It might go over the model's accuracy, sensitivity, specificity, and other performance metrics, showing how well it can reliably identify and interpret COVID-19 instances from chest radiographs. The potential clinical ramifications of applying the suggested model for COVID-19 diagnosis, such as early identification, effective screening, and decision support for medical professionals, may also be included in the study. The study may also draw attention to the approach's drawbacks, such as potential biases in the dataset, difficulties in interpreting the findings, and the need for more validation on a variety of datasets. It might also go through ethical issues like patient privacy, fairness, and transparency that come up when utilising AI for COVID-19 identification and analysis. In this research study, a deep learning strategy for COVID-19 identification and analysis from chest radiographs is proposed and evaluated. It hopes to aid in the development of precise and trustworthy techniques for identifying and analysing COVID-19 cases using data from medical imaging, thus facilitating the early diagnosis and treatment of the illness.

Title

COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-ray Images

Description

Using cutting-edge machine learning methods, COVIDX-Net is a system of deep learning classifiers that seeks to diagnose COVID-19 cases from X-ray pictures. The research report "COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-ray Images" suggests this method as a promising tool for quick and accurate COVID-19 diagnosis from X-ray pictures. The first step in the study is to compile a collection of X-ray pictures, which may include images from COVID-19-positive individuals, normal instances, and even images from other types of lung disorders or diseases. The dataset is preprocessed to guarantee data consistency and quality, and picture augmentation methods may be used to broaden the dataset's diversity. In order to diagnose COVID-19 from X-ray pictures, the study then suggests a framework of deep learning classifiers, which typically consists of numerous layers of artificial neural networks.Using a supervised learning technique, the deep learning classifiers are trained on the dataset to automatically extract pertinent features from the X-ray pictures and map them to the correct COVID-19 or normal class labels. Depending on the requirements of the study, the study may use a variety of deep learning classifiers, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), or a combination of both. To increase their accuracy and generalizability, deep learning classifiers are often trained using a large number of X-ray images. Various performance indicators, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic, are used to assess the COVIDX-Net framework's performance. To show the usefulness of the suggested framework in diagnosing COVID-19, the study may also compare its performance with that of other current approaches or models. The paper presents the outcomes of the performance of the COVIDX-Net framework in X-ray image-based COVID-19 case diagnosis. It might go over the framework's accuracy, sensitivity, specificity, and other performance metrics, which show that it can correctly identify COVID-19 instances from X-ray pictures. The study may also go through possible clinical ramifications of applying the suggested framework for COVID-19 diagnosis, including early detection, effective screening, and decision support for medical personnel. The study may also draw attention to the method's shortcomings, such as potential biases in the dataset, difficulties in understanding the findings, and the need for more validation on the ethical issues surrounding the use of AI for COVID-19 diagnosis, such as patient privacy, fairness, and transparency, may also be covered.In conclusion, the research study "COVIDX-Net: A Framework of Deep Learning Classifiers to Diagnose COVID-19 in X-ray Images" presents and assesses a framework of deep learning classifiers for COVID-19 diagnosis from X-ray pictures. It hopes to aid in the development of precise and trustworthy techniques for identifying COVID-19 instances from medical imaging data, thus facilitating the early detection and treatment of the illness.

Title

Deep learning for COVID-19 Detection and Diagnosis.

Description

Due to its capacity to automatically learn V, deep learning has emerged as a viable method for COVID-19 identification and diagnosis. complicated patterns and features from a lot of data are proposed for the system. Many research have employed deep learning models for COVID-19 detection and diagnosis, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and its derivatives. There are multiple steps in the conventional deep learning workflow for COVID-19 identification and diagnosis. First, a collection of medical images is gathered and preprocessed, such as chest X-ray, CT scan, or lung ultrasound images. The dataset can comprise instances with COVID-19 positivity, cases that are healthy, and cases with other lung disorders or diseases. Image resizing, normalisation, augmentation, and other methods of data preprocessing may be used to ensure data quality and consistency. The dataset is then used to train a deep learning model using a supervised learning strategy. The model gains the ability to automatically identify pertinent aspects in medical images and link those features to the associated COVID-19 or standard class labels. In order to increase the model's accuracy and generalizability, a huge number of photos are often used during training.Following model constraint, different performance indicators, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic (ROC) curve, are used to assess the model's performance. In order to evaluate the model's performance for COVID-19 detection and diagnosis, it may be contrasted with other currently used techniques or models. Other techniques, such as transfer learning, which enables the model to utilise pre-trained models on sizable datasets from similar tasks, may also be used to improve deep learning models for COVID-19 identification and diagnosis. The accuracy and dependability of COVID-19 detection and diagnosis may also be improved further using ensemble methods, such as integrating numerous deep learning models. Typically, the findings of studies using deep learning for COVID-19 detection and diagnosis are published, and their possible clinical implications are evaluated. These may include early detection of COVID-19 instances, effective screening of large populations, and assistance in diagnosis and treatment planning for medical experts. Deep learning's drawbacks and difficulties in COVID-19 detection and diagnosis, including potential biases in the data, interpretability issues, and ethical considerations, may also be discussed. In summary, deep learning has shown promise in COVID-19 detection and diagnosis, offering the potential for accurate and efficient methods for identifying COVID-19 cases from medical images. However, further research, validation, and integration into clinical practice are needed to fully realize the potential of deep learning in COVID-19 diagnosis.

IV. Existing systems

In summary, deep learning has shown promise in COVID-19 detection and diagnosis, offering the potential for accurate and efficient methods for identifying COVID-19 cases from medical images.The primary goal of this study is to develop trustworthy tools for applying CNN on CT images to detect COVID-19 patients. In a number of computer vision tasks, the CNN produced excellent results. Due to its self-learning capabilities, CNN has lately emerged as the leading in-depth learning method for classifying medical images. Numerous CNN-based techniques were put forth for COVID-19 identification. In contrast to other picture datasets, the medical images dataset only uses a small number of training examples. With the use of various approaches, such as data augmentation, CNNs have been amplified to attain ground-breaking efficiency on these datasets.

V. Proposed system

In summary, deep learning has shown promise in COVID-19 detection and diagnosis, offering the potential for accurate and efficient methods for identifying COVID-19 cases from medical images.In order to identify patients with COVID-19, we used CNN, a relatively recent method in which the learning process is created using an association of densely linked convolutional networks (DenseNet).The fundamental justification for using DenseNet-121 is that it reduces the issue of vanishing gradient, enhances feature reuse, and uses fewer parameters, all of which are beneficial for deep learning model training. Furthermore, based on medical imaging, DenseNet-121 has demonstrated efficacy in disease diagnosis. The idea behind operating DenseNet would be to connect each to every layer below it, hence enhancing the architecture's flow. This strategy aids CNN in making decisions based on all levels as opposed to only the top layer. Comparing DenseNet to conventional image processing, the former is more advanced and capable of capturing visual data on a wider scale.

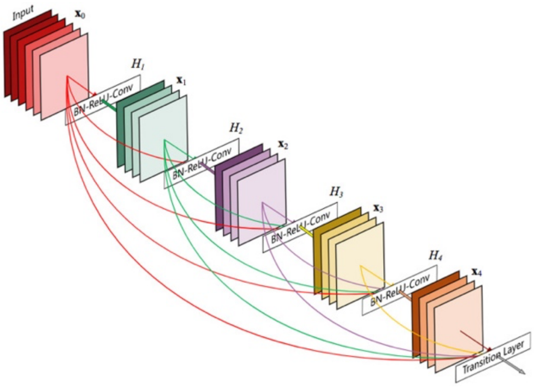
VI.Comparison between Existing system and proposed system

On the basis of various datasets, architectures, and methodologies, existing systems for COVID-19 identification and diagnosis employing deep learning and convolutional neural networks (CNNs) have been built. These systems have shown varied degrees of sensitivity, specificity, and accuracy in identifying COVID-19 instances in medical pictures such chest X-ray or CT scan images. In terms of model performance, generalisation, and clinical applicability, they might be constrained. The suggested system, COVIDX- Net, on the other hand, uses a framework of deep learning classifiers specialised for diagnosing COVID-19 from X-ray pictures.deep learning has shown promise in COVID-19 detection and diagnosis, offering the potential for accurate and efficient methods for identifying COVID-19 cases from medical images.Depending on the precise specifications of the proposed system as described in the literature, COVIDX-Net may have a number of distinctive features or advantages when compared to existing systems. Overall, the proposed COVIDX-Net system for COVID-19 identification and diagnosis using deep learning and

CNNs may have distinctive features or benefits compared to existing methods. To understand their unique characteristics and performance in detecting COVID-19 cases from X-ray pictures, the literature on both the existing methods and the proposed system must be thoroughly reviewed.

VII. System architecture

System architecture for COVID 19 prediction using densenet 121 is illustratedin the given figure.



1. Input Data: Chest X-ray photographs of patients are used as input data for the system design. These images are typically grayscale and in the JPEG or PNG format. To maintain uniformity and quality, these photos may undergo preprocessing techniques like scaling, normalisation, and augmentation.

2. DenseNet-121 Model: For image classification tasks, a deep convolutional neural network (CNN) model that has already been trained is called DenseNet-121. It is composed of a number of dense blocks, each with a number of convolutional layers and dense connections that enable effective feature reuse and minimise vanishing gradients. DenseNet-121 is suited for COVID-19 prediction since it has been demonstrated to be efficient at learning intricate patterns and characteristics from photos.

3. Feature Extraction: The input X-ray pictures are utilised to extract features using the DenseNet-121 model. The DenseNet-121 model's convolutional layers learn to separate pertinent information, such edges, textures, and patterns, from the input images. These features are then sent to the next layers for additional processing.

4. Classification Layers: Following the feature extraction, the output features from the DenseNet-121 model are flattened and passed through one or more fully connected layers, also known as the classification layers. These layers are responsible for converting the extracted features into prediction probabilities for different classes, such as COVID-19 positive, COVID-19 negative, and possibly other classes like normal or other lung diseases.

5. Activation Functions: Activation functions, such as ReLU (Rectified Linear Unit) or sigmoid, are applied to the output of the fully connected layers to introduce non-linearity into the model and improve its ability to capture complex patterns in the data.

6. Softmax Layer: The softmax layer is typically used as the final layer in the classification architecture to compute the probabilities of the different classes. The softmax function converts the prediction scores into class probabilities, where the class with the highest probability is predicted as the final output.

7. Loss Function: A loss function, such as cross-entropy, is used to measure the difference between the predicted class probabilities and the ground truth labels. The loss function is optimized during the training process to update the model parameters and improve the model's prediction accuracy.

8. Training Process: A labelled dataset of chest X-ray pictures with known COVID-19 status is used to train the system architecture. By minimising the loss function using backpropagation and gradient descent, the model learns to optimise its parameters depending on the provided labelled data during the training process

9. Evaluation Metrics: The effectiveness of the trained model in predicting COVID-19 instances from chest X-ray pictures may be evaluated using a variety of evaluation criteria, including accuracy, sensitivity, specificity, and area under the ROC curve.

10. Deployment: The algorithm can be used to forecast COVID-19 cases from fresh, previously unseen chest X-ray pictures once it has been trained and assessed. For automated COVID-19 prediction in clinical practise, this may entail integrating the trained model into a broader system or workflow, such as a hospital or healthcare system.

VIII. Modules

1.Input Data
2.Pre-Processing
3.Training The Model
4.Model File Saving
5.Real Data
6.Pre-Processing Real Data
7.Output Data

Input Data

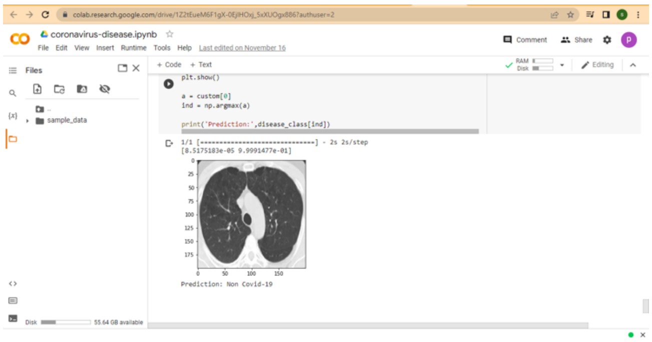
Gathering information from various datasets and sources. Since the video files in the dataset are extremely organised and have little to no fluctuation, we need to add a little amount of volatility to the data. Using a Python module and the dataset we will intentionally add variety.

Pre-Processing

Using the complete size of a huge dataset, it takes a while to calculate the gradient of the model. The image dimensions are 90 by 90 and 40 for the sequence.We have a sizable collection of pictures.The datasets include 1000 videos for each of the two classes: nonviolence and violence

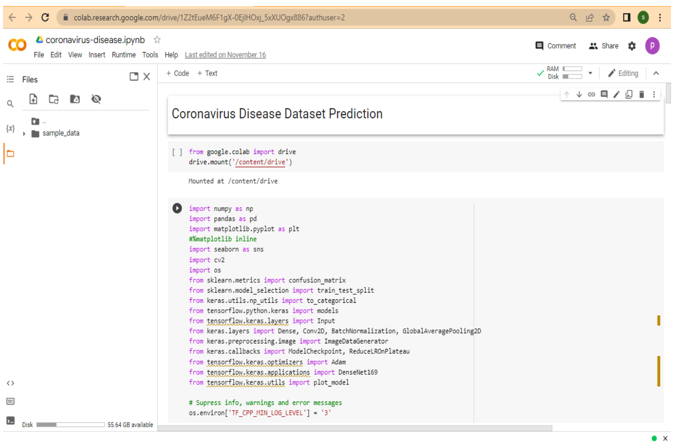
Training the model

Extracting the features from the trained dataset for the training process implementing the training procedure and classification using the scikit-learn python package and applying the extracted features



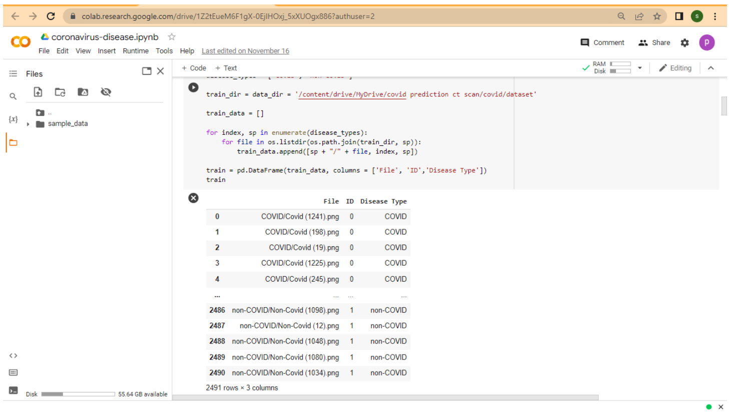
Model file saving

Saving the trained model file in h5 file with all the prediction data. Function to save the model file and the kernel size = (3, 3). Using this we can compare the real time videos



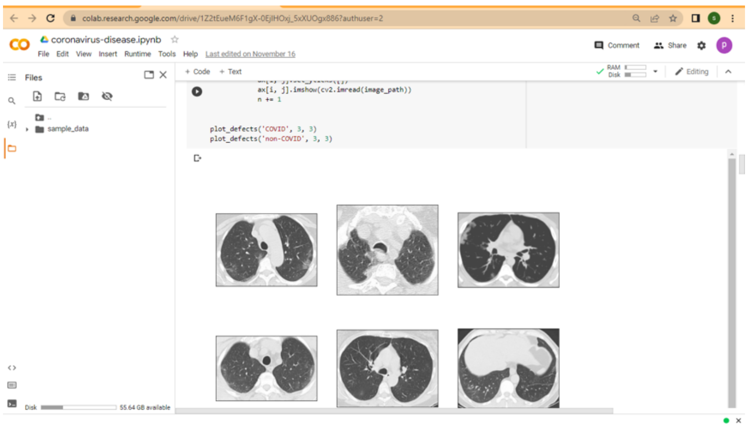
Real data

Analysing the likelihood of features taken from the real picture data and the trained model using image processing and other Python libraries and comparing the real-time data.



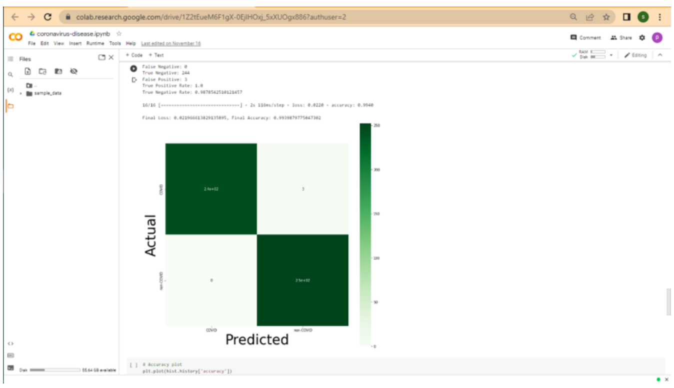
Pre-Processing real data

The process of converting unprocessed data into an image is called preprocessing. Before using the algorithms, the data's quality should be examined.



Output data

Prediction Of Videos According to The Class Declared. With Probability Of The Class Obtained The Prediction Class Is Finalised



Conclusion

In medical image analysis, the automated image classification of CT images using computer-aided systems is crucial. CT image microscopic examination is difficult and time-consuming. This study used CT image categorization based on deep learning technology, which displayed superior accuracy, to identify COVID-19 patients. Recall is 95%, while total accuracy is 92%. The average processing time for the DenseNet-121 model is 195.35s. For picture categorization, we used the DenseNet-121 deep learning architecture. For instance, several categorization models were used to support our assertion.Theoretically, the applied methodology provided an unrevealed best alternative identification technique employing a DenseNet-121 CNN with a pretty big dataset in the training phase of the DenseNet-121 model, contributing to the present growing COVID-19 literature. Due to the utilisation of the data augmentation strategy, no custom data extraction method is necessary for the applicable architecture. In the real world, this technique can be used in clinical settings to identify COVID-19 accurately. In order to obtain a true image of the infection rate, which has a high correlation with the number of daily infected cases, it would thus be beneficial to increase dependability as reflected by the computational approach for testing that has been provided. Our current investigation, however, still contains a lot of flaws. First, future network architecture and optimisation improvements might enhance categorization accuracy. Second, the absence of training data during the early stages of the COVID-19 outbreak is a problem that cannot be avoided by some places. For accurate prediction, several hundred photos might not be enough. The absence of Grad Cam visualisations of the used DenseNet-121 model, which could have improved readability, is another flaw in this study. By using different forms of architecture, such as DenseNet-161, DenseNet-169, and DenseNet-201, DenseNet can also be justified for further research and development. The implementation and testing of additional deep learning techniques or modified deep learning techniques for further research and assessment in order to more precisely identify COVID-19 patients utilising CT images. Once again, since new COVID-19 CT image datasets are being published on a timely basis, updated COVID-19 imaging datasets may be examined to enhance the efficacy of the DenseNet-121 technique.

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