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Enhanced convolutional neural network enabled optimized diagnostic model for COVID-19 detection

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ABSTRACT

Computed tomography (CT) films are used to construct cross-sectional pictures of a particular region of the body by using many x-ray readings that were obtained at various angles. There is a general agreement in the medical community at this time that chest CT is the most accurate approach for identifying COVID-19 disease. It was demonstrated that chest CT had a higher sensitivity than reverse transcription polymerase chain reaction (RT-PCR) for the detection of COVID-19 illness. This article presents gray-level co-occurrence matrix (GLCM) texture feature extraction and convolutional neural network (CNN)-enabled optimized diagnostic model for COVID-19 detection. In this diagnostic model, CT scan images of patients are given as input. Firstly, GLCM algorithm is used to extract texture features from the CT scan images. This feature extraction helps in achieving higher classification accuracy. Classification is performed using CNN. It achieves higher accuracy than the k-nearest neighbors (KNN) algorithm and multi-layer preceptor (MLP). The accuracy of GLCM based CNN is 99%, F1 score is 99% and the recall rate is also 98%. CNN has achieved better results than MLP and KNN algorithms for COVID-19 detection.

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1. INTRODUCTION

Around the end of 2019, the SARS-like coronavirus (COVID-19) was initially identified in Wuhan City, China, and swiftly spread across the rest of the globe. The COVID-19 pandemic has expanded to more than 220 nations and territories across the globe and has had an effect on every facet of our day-to-day lives. In spite of the virus's high level of pathogenicity, it is often transmitted from person to person via the air [1]. In contrast to the other respiratory disorders, the SARS-CoV-2 seemed to be transmitted by the oral-faecal route, according to the findings of prior research. The stool specimens of 71 persons who were infected with COVID-19 were analysed in a recent research [2]. Of these 71 patients, 39 were positive for COVID-19 RNA, providing credibility to the concept that fecal-oral contamination may constitute an additional pathway for the transmission of the disease [3]. The most typical signs of COVID-19 are a hacking cough, a high temperature, and extreme fatigue [4]. People who were infected with the virus had a broad variety of gastrointestinal symptoms, some of which included nausea, lack of appetite, and diarrhoea. It is essential to bear in mind that asymptomatic people might be a possible source of sickness transmission, thus it is essential to remember this fact [5].

There has been a recent surge in the use of artificial intelligence (AI) in the realm of medicine. Because of recent advancements in computer infrastructure, machine learning (ML), and digitalized data collecting, AI applications may now be discovered in domains that were previously thought to be inaccessible to computers [3]. On real CoV datasets (like MERS-CoV), only a few research have used diverse data mining strategies and ML classifiers. The development of prediction algorithms that are able to accurately detect and identify viruses of this kind continues to be a tough endeavor. The development of AI-driven solutions for the early identification of epidemiological hazards will be an important factor in the future enhancement of global health risk prediction, prevention, and detection [4]. Through reading the literature on data mining and ML, they gained additional knowledge about the CoV family as well as the methods that have been used in previous research to approach prediction, regression, and classification processes in the context of the CoV family. Researchers are seeking for answers to problems such whether or if the algorithms are genuine in their implementation, whether or not there are many various sorts of applications, and how ML and data mining are applied and assessed. These questions may be found in the ML literature.

Identifying COVID-19 is often accomplished by the use of reverse transcription polymerase chain reaction (RT-PCR). In this particular biological process [4], the nucleic acid ribonucleic acid (RNA) is employed as the starting point rather than deoxyribonucleic acid (DNA). RNA is put to use in the process of reverse transcription, which is carried out by the chemical known as reverse transcriptase. This allows for the production of a matching piece of discarded DNA [6]. In order to become ready for a polymerase chain reaction, the freshly synthesised single-stranded DNA is first transformed into double-stranded DNA. There have been several efforts made to increase the number of daily polymerase chain reaction (PCR) testing; nonetheless, there are still certain restrictions associated with this method [7]. The inaccessibility of PCR reagent kits, the large amount of time that is necessary for contact, and the very high risk of false-negative results in individuals who are recognising COVID-19. In this kind of circumstance, more accurate procedures or practises are predicted to be able to assist in identifying people who are infected with COVID-19 [8], [9]. Imaging methods used in clinical practise play an essential part in this scenario, playing an important part both in identifying patients who were picked from a first-response medical emergency and in displaying pulmonary inclusion of COVID-19. The contribution that clinical imaging has made to the battle against the COVID-19 pandemic is described, as are the findings obtained from a variety of imaging techniques [10].

Chest x-rays have a strong correlation with computed tomography (CT) diagnoses, making them a potentially valuable tool for identifying COVID-19 infections, which are rather common in the medical industry owing to the nature of the work they do. In a number of countries, including Spain [11], the primary imaging tool that is used for the diagnosis of COVID-19 infected individuals is the x-ray. GGO, lung nodules, and interstitial changes may often be seen on the x-ray pictures of persons who have COVID-19. Patients who have ground glass opacities have an increased lung thickness, yet their bronchial designs and the visibility of their blood vessels are not obstructed. It is possible that x-rays will play a pivotal part in stopping the further spread of illness in light of the anticipated rise in the number of infectious cases. It is possible that this may be a challenge for CT analysis, in particular in nations in which the RT-PCR technology is not commonly accessible. On the other hand, an RT-PCR test and CT scans are obligatory for patients who are in the most critical condition.

CT films are used to construct cross-sectional pictures of a particular region of the body by using many x-ray readings that were obtained at various angles. There is a general agreement in the medical community at this time that chest CT is the most accurate approach for identifying COVID-19 disease. Despite the fact that there are several early prognostic tests for viral infections, such as RT-PCR and biomarkers [12], [13]. Additionally, it is advised for asymptomatic persons who have negative nucleic acid testing due to the fact that CT scans give greater proof of the spread of the infection. It was demonstrated that chest CT had a higher sensitivity than RT-PCR for the detection of COVID-19 illness. Furthermore, it was demonstrated by a study of 1,014 individuals with a positive RT-PCR result that CT scans of the chest have a sensitivity of 97% for the detection of COVID-19 [14], [15].

This article presents gray-level co-occurrence matrix (GLCM) texture feature extraction and convolutional neural network (CNN) enabled optimized diagnostic model for COVID-19 detection. In this diagnostic model, CT scan images of patients are given as input. Firstly, GLCM algorithm is used to extract texture features from the CT scan images. This feature extraction helps in achieving higher classification accuracy. Classification is performed using CNN. It achieves higher accuracy than the k-nearest neighbors (KNN) algorithm and multi layer preceptor (MLP).

2. LITERATURE SURVEY

The most significant benefit of ML is that it may serve as a basis for the development of prediction approaches. This is better to just possessing any essential technologies that are either little discussed or poorly understood. The functioning of these systems is based on the development of sophisticated patterns from enormous amounts of noisy or detailed input. The individuality issue may be reduced by using master models, which means that predictive algorithms may be able to give greater assistance with medical prognostication. In the field of clinical imaging study and prediction, ML approaches have previously been used to identify pandemic tendencies [16]. A suitable data preparation strategy, automation, iterative learning, testing, scalability, and ensemble modelling are all necessities for a classification approach. In light of this, a number of different investigations have employed various ML approaches for predicting and prognosticating COVID-19. These methods include random forest (RF), decision tree (DT), support vector machine (SVM), logistic regression (LR), naive Bayes (NB), and so on.

One definition of ML is the process of constructing a mathematical model of some type via repeated iteration and correction of inputs. This is an example of what is meant by the phrase “correcting inputs”. As inputs, we use the features that were retrieved from the COVID-19 radiology image collections. Improved generalisation is the consequence of applying a validation set to a model that has already been trained. The subsequent labour and errors provide feedback that is used to further develop and improve the model. After the model has been trained and fine-tuned across a number of iterations, the effectiveness of the model is evaluated using test data that has never been seen before [17]. It is the new image, not the database, that serves as the catalyst for the generalisation of the learning experience in order to provide correct outcomes.

The very first artificial neural network (ANN) was created in 1950, and it is now widely regarded as the cornerstone of contemporary ML. It is a close approximation of the way in which information is processed and evaluated by the human brain. The data (features) are first sent to the input layers, which are then followed by the hidden layer and the output layer. The layers are made up of neuronal components, which function as computer units. The network is trained using those features as well as an objective function, and the training is done by taking features from images that are stored in a database. In order to strengthen the neurons, many iterations of altering the parameters are performed multiple times until good prediction results are generated. The learned model may be efficiently applied to new, unfamiliar photos with very little to no further training required.

The computational complexity of ANN is high, and they are very adaptive. It is recommended that the training set make use of a greater number of photographs than there are parameters available in the ML algorithm. When we speak about “fitting” a model, what we mean is finding the pattern in the data that corresponds to the model. The statistical matches might be utilised as a guidance by the algorithms that power ML. If your model is underfitting, it won’t be able to learn from new data since it already has all the information it needs. Low performance in classification is supplied, and the classification pattern is not recorded. When a model is overfit, it narrows its focus to a single dataset and becomes very data dependent. When evaluating the model with newly collected data, it does not provide the kind of results that are desired. An adequate fit provides a more general model that is capable of handling an unknown input [18]. This is accomplished by finding a balance between overfitting and underfitting, which describes the two extremes of the fitting process.

A fundamental description-learning strategy is referred to as a deep learning (DL) method. However, by using non-linear elements, we are able to move the presentation from one intellectual level to another [19]. This allows for more flexibility in the presentation. Because of the naturally complex design of the DL approaches, they were able to successfully identify the difficult AI problems. In the field of biomedical informatics, DL approaches are increasingly being used to test out innovative events because to the many benefits they provide, including improved performance, end-to-end learning patterns that amalgamate joined feature learning, and the management of composite and multi-modal data. Utilize DL techniques in order to effectively classify the COVID-19 outbreak cases and conduct an analysis of the clinical pictures that accompany each case.

CNN, long short-term memory (LSTM), generative adversarial network (GAN), recurrent neural network (RNN), and autoencoder are only some of the DL approaches that have been employed in a number of articles to detect and predict the COVID-19 diagnosis. DL is an area of ML that shows a lot of promise for addressing problems connected to AI. A database-dependent deep neural network is utilised. DL excels in a number of different domains, including non-linearity, generalisation, harmony, fault tolerance, parallelism, and learning. It is a carefully guarded secret as to which real layers of the neural network are responsible for the data learning process. Each level is related to the one directly underneath it as well as the one that came before it. Because of everything that has been sent into the system, there is a far better chance that the output will be correct. Depending on the weights and activation functions that are input into the neural network as well as the learning process, a variety of distinct deep neural network (DNN) designs may be formed. DL is able to draw conclusions and useful representations directly from the raw data that was used to create the image. This eliminates the requirement for a separate procedure that would extract the features from the picture. Automated feature representation learning and learning are both processes that take place inside the layers [20].

In the realm of medicine, the usage of databases of retinal imaging, chest x-rays, and CT scans containing high-quality pictures has shown to be beneficial, with enhanced relative accuracy attained via the use of DL processes and AI [21]. Because of this, there have been many good consequences. Hospitals and other types of healthcare facilities often make use of x-ray and CT scan scanners due to the speed and accuracy with which they can diagnose a wide range of problems affecting human organs.

Lung ultrasonography is quickly becoming one of the most prominent diagnostic and therapeutic tools that clinicians utilize at the point of care for the management of acute respiratory failure. In addition, LUS does not need the radiation or laborious process of CT [22], and it is also as effective as or more so than chest x-rays for diagnosing the majority of acute respiratory illnesses. The reason for this is because LUS does not need the utilization of ultrasonic waves. In addition, because of its low cost and the fact that it is battery-regulated, LUS has the potential to be used in a wide range of settings due to it is adaptability. In the presence of disinfectants, LUS exhibits the classic B line reaction. This disease might have been brought on by pulmonary emphysema or the noncardiac consequences of interstitial syndromes. It is generally agreed that pneumonia and acute respiratory distress syndrome are both examples of this latter category.

3. METHOD

This section presents GLCM texture feature extraction and CNN enabled optimized diagnostic model for COVID-19 detection. Figure 1 represents this diagnostic model. In this diagnostic model, CT scan images of patients are given as input. Firstly, GLCM algorithm is used to extract texture features from the CT scan images. This feature extraction helps in achieving higher classification accuracy. Classification is performed using CNN. It achieves higher accuracy than the KNN algorithm and MLP.

Feature extraction is a technique that is used in all classification methods to reduce the amount of superfluous input data. It is necessary to evaluate the extracted features for characteristics such as sparseness, dispersal, overlap, presence of outliers, Gaussianity, non-Gaussianity, linearity, and non-linearity in order to determine which classifiers are the most effective for a specific classification problem. Only then can the most effective classifiers be identified. GLCM has minimum root mean square error among available feature selection techniques. Similarly, CNN achieves best accuracy for the image classification.

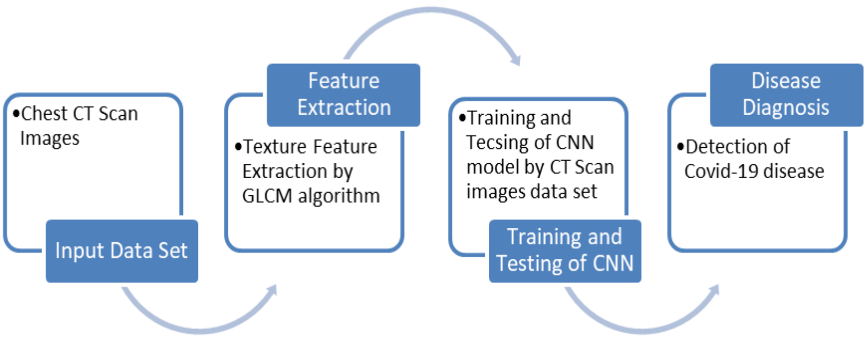

Figure 1. GLCM texture feature extraction and CNN enabled optimized diagnostic model for COVID-19 detection

Through the use of the GLCM [23], statistical information on the texture of any order may be derived from photos (GLCM). The grey level correlation matrix is a matrix that indicates the frequency with which one grey level appears in close proximity to another grey level. The number of rows and columns in a GLCM matrix is equivalent to the number of different tones of grey or pixels in an image. It has been shown to be an efficient method for classifying the textures of images, and the central component of this method, which consists of a two-dimensional histogram plot of grey levels for a pixel pair with a known spatial link, is easy to put into practise. Using the GLCM's extracted textural features, one may obtain insight into the specifics of the overall picture's content in order to better understand it. The medical image feature vectors that are derived using GLCM have the potential to differentiate between normal and diseased situations. A statistical analysis of the texture that is sensitive to the way pixels interact with one another spatially is made available by the GLCM.

In the field of AI, CNN [24], is a powerful and well-known DL algorithm that can take input images and perform segmentation, feature extraction, and classification. Architecture is shown in Figure 2. Feed-forward ANNs are the kind that CNN belongs to. CNN was built such that its architecture could take use of the 2D structure of the images it was given as input. A conventional multilayer neural network is similar to a CNN in that it consists of one or more convolutional layers followed by one or more fully connected layers. A CNN, however, consists of more than one convolutional layer. The output picture is created by first extracting, mapping, and then grouping the characteristics of the input image whenever that image is provided. There is no need for any further post-processing of the output picture since CNNs work on intensity information that has been conventionally pre-processed and applied.

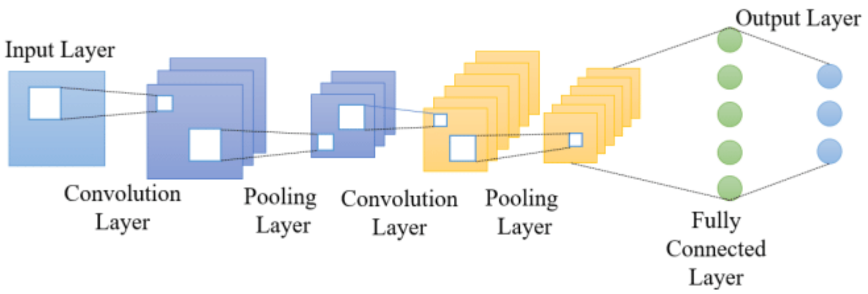

Figure 2. CNN architecture

3.1. Convolutional layer

At the point when the input picture is being received, the characteristics of the image are recognised and mapped using a matrix format. In this process, edges are enhanced, pictures may be blurred depending on their quality, and edge detection and enhancement take place simultaneously. This initial preprocessing step lays the foundation for subsequent image analysis and feature extraction. After this initial preprocessing, the image data is ready for more advanced tasks such as object recognition, pattern analysis, or further image manipulation as required for the specific application.

3.2. Maximum pooling

CNN also makes use of the power tool known as pooling. Pooling is a method that takes enormous photos and reduces their size while retaining the majority of the information that is contained within them. The mathematics involved in pooling is, at best, appropriate for second graders. It involves moving a tiny window over a picture in steps and calculating the greatest value that can be obtained from the window at each of those steps. A non-linear down sampling method is used to activation maps by the pooling layer. The practise of pooling is considered to be aggressive; thus, the current tendency is to employ lower filter sizes and give up pooling.

3.3. Flattening

The process of flattening involves transforming the data into a one-dimensional array so that it may be entered into the subsequent layer. The output of the convolutional layers is flattened by the system, which results in the creation of a single lengthy feature vector. It is linked to the final classification model, making it what is known as a fully connected layer

3.4. Fully connected

Layers that are fully connected are linked together such that every neuron in one layer is coupled to every neuron in the next layer. In general, it functions in the same manner as the conventional multi-layer perceptron neural network (MLP). In order to identify the pictures, the flattened matrix travels through a layer that is completely linked.

4. RESULTS AND DISCUSSION

For experimental set up, 500 images are collected from openly available data set [25]. 300 images are related to COVID-19 patients and remaining 200 images are normal images. Out of these 500 images 400 images are used to test CNN model. Remaining 100 images are used to test CNN classification model. Firstly, GLCM algorithm is used to extract texture features from the CT scan images. This feature extraction helps in achieving higher classification accuracy. Results are shown in Figure 3.

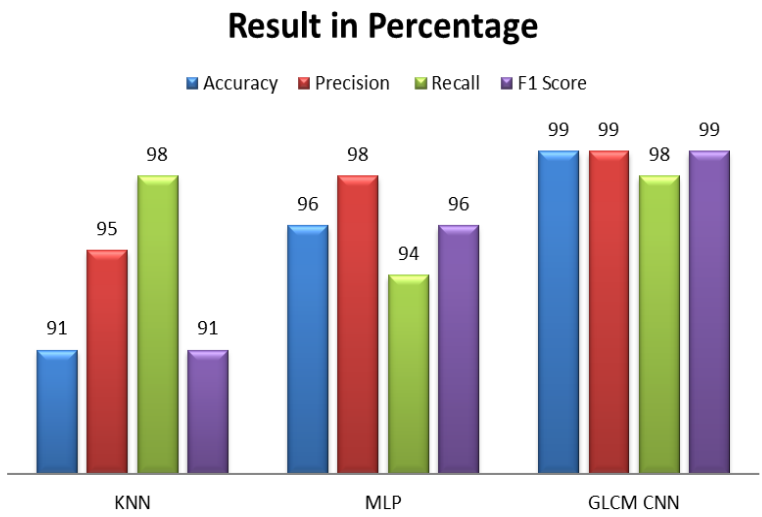

Figure 3. CNN architecture

The ratio of the number of photos that were successfully categorised to the total number of test images generated by the classification models is the definition of classification accuracy. The accuracy of the categorization might vary anywhere from 0% all the way up to 100% of the time. The accuracy of the classification approaches may be determined by using (1):

$$\text{Accuracy} = (\text{TP} + \text{TN})/(\text{TP} + \text{TN} + \text{FP} + \text{FN}) \quad (1)$$

The number of properly recognised results is divided by the combined total of the number of correctly identified and correctly rejected outcomes that are predicted by the model. This is how precision is calculated. In order to determine the appropriate ratio of identifications, precision is required. The value of the accuracy might vary anywhere from 0 to 1, inclusive. The value of maximum precision exemplifies the superiority of the classification methods' ability to make accurate predictions. The accuracy value of the various classification methods may be computed using (2):

$$\text{Precision} = \text{TP}/(\text{TP} + \text{FP}) \quad (2)$$

The recall is calculated by dividing the number of outcomes that were properly recognised by the total number of results that were either successfully identified or mistakenly rejected across all relevant sample data. The recalls are used to calculate the percentage of real positives that were detected accurately. The recall value of categorization methods may vary anywhere from 0 to 1, with 0 being the most common. The maximum recall value is used to quantify the accuracy of the classification methods' predictions. The recall value of the various classification approaches may be computed using (3):

$$\text{Recall} = \text{TP}/(\text{TP} + \text{FN}) \quad (3)$$

The F1 score is one of the measures that is often used in the process of evaluating the effectiveness of ML algorithms. The F1 score is defined as the harmonic mean between the recall and the accuracy categories. The F1 score may vary anywhere from 0 up to 1, inclusive. The value of the F1 score reflects the advantage in terms of prediction possessed by the categorization methods. The F1 score for each of the classification methods may be found by using (4):

$$\text{F1 Score} = 2\text{TP}/(2\text{TP} + \text{FP} + \text{FN}) \quad (4)$$

5. CONCLUSION

CT films are used to produce cross-sectional images of a particular region of the body by making use of several x-ray readings that were obtained at a range of angles. After that, the diagnostic process begins with analyzing these photographs. The majority of medical experts working in the area of medicine have come to the conclusion that chest CT is the technique that provides the most accurate and trustworthy findings when it comes to the diagnosis of COVID-19 sickness at this point in time. It was shown that chest CT had a higher level of sensitivity than RT-PCR when it came to the detection of COVID-19 illness. The goal of this article is to provide an ideal diagnostic model for the detection of COVID-19 using GLCM texture feature extraction and CNN technology. CT scan images collected of the patients in question serve as the diagnostic model's primary source of data input. In order to extract the textural features from the CT scan photographs, the first phase of the method involves applying the GLCM algorithm on the pictures. The extraction of these characteristics helps to increase the accuracy of the classification process as a whole. The procedure of categorization is carried out with the assistance of a CNN. It generates an accuracy that is superior to that produced by the KNN technique as well as the MLP. In future, methodology proposed in this article may be extended to classify real time images.

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