Identification of COVID-19 in CT Images using Deep Learning Model

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***Abstract*— Worldwide, COVID-19 has had a substantial impact on patients and hospital systems. Early identification and diagnosis are essential for regulating the growth of COVID-19. The input CT screening images are initially segmented into various regions using the Fuzzy C-means (FCM) clustering technique. Next, region-based image quality enhancement employs a histogram equalization method. Furthermore, certain necessary data is represented in a new image using the Local Directional Number technique. Lastly, the input images are portioned with the help of a traditional convolutional neural network model. The proposed convolutional neural network based system was able to give an accuracy of 98.60%, and the results revealed that methods for detecting COVID-19 impact from CT scan images must be developed significantly before considering it as a medical choice. Moreover, many diverse datasets are essential to assess the processes in a real-world setting.**

Keywords*— *COVID-19, Fuzzy C-means, Histogram Equalization, Convolutional Neural Network, Local Directional Number, Deep Learning

I. Introduction

In the end of 2019, Wuhan a city of China, an illness without recognized causes was identified and it was spreading among humans in a short duration. In January 2020, the pandemic had infected 106 persons in 19 countries and killed 213 persons in China, where it had infected 9720 people [1]. A few days later, numerous independent agencies determined that a new coronavirus was the root cause of this unexplained pneumonia. The illness that induces coronavirus sickness is the SARS-CoV-2 virus. Furthermost virus-affected people will have moderate to severe lung infections, but they will make progress deprived of the requirement for extra care. Nevertheless, certain individuals will get serious illnesses and need medical care [2]. The older person with severe medical illnesses, such as malignancy, diabetes, cardiovascular disease, or severe lung disorders, suffer from severe disease.

COVID-19 can make anyone sick or a source of demise at any age. The most excellent way to preclude or halt the spread is to equip yourself with the condition. We can avoid disease by maintaining a space of at least one meter from people, wearing a mask, and frequently cleaning our hands [3]. When an affected person spits, sniffles, talks, sings, or breathes, the virus may develop from their mouth or nose in minute liquid particles. More substantial respiratory droplets to minute particulates, these particles vary. According to studies, there is no variation in infectious burden among individuals, which reveals more extensive viral passes in the nasal passages related to the throat [4]. Patients may still be contagious even after their symptoms have subsided. The virus is also thought to be present in the sewage, contaminate the water supply, and then spread orally or through nebulization. The most frequent clinical signs and symptoms are fever, congestion, dry mouth, migraine, and exhaustion.

COVID-19 is one of the illnesses demonstrated to be the most severe and hazardous to human society. Since digital technology has advanced over the recent decades, creative approaches that use sophisticated medical equipment and facilities have been developed to help with diagnostic techniques, treatment, and management [5]. Although there are several lab tests are available to diagnose the infections, doctors used imaging results such as CT scans and X-ray pictures were considered as the most efficient ways of diagnosing COVID-19. CT screening is chosen over X-rays due to its flexibility and 3D view, even though X-rays are generally more accessible and less expensive. These conventional techniques are essential for managing the pandemic [6]. After artificial intelligence application were introduced to medical field, machine learning and deep learning based models were widely applied in almost most of the medical diagnosis and treatments. In-depth learning Based support systems are created employing CT and X-ray samples for COVID-19 diagnosis. The primary goal of the research is to develop a deep learning based model which could assist the medical practitioner to identify Covid-19 in a patient.

II. Literature survey

Deep learning algorithms can learn from simplistic representations to understand complicated issues. The ability to learn accurate representations and the ability to learn the data in a profound manner using numerous layers consecutively are the significant characteristics that have made deep learning approaches popular. Data collection, preparation, feature extraction and classification, and outcome evaluation are typically included in deep learning-based systems. ResNet50 is a CNN version that Wu et al. [7]used to introduce a coronavirus detection system. The hospitals in

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China are where the dataset was gathered. For training, testing, and validation, the dataset is partitioned into portions of 80%, 10%, and 10%, respectively. Before the network is built, each image is downsized to 256 X 256. The performance of the system was evulated interms of accuracy, sensitivity and specificity and it was found to be 76%, 81.1% and 61.5% in the test dataset used. Li et al. [8] used ResNet50 to show an automatic system for coronavirus identification from CT scans. The hospitals provided the dataset. The dataset needed to be divided into training, testing and validating datasets, and hence a test ratio of 90:10 was followed for training and testing of the model. similarly like all the works the proposed system was measured in terms of sensitivity and specificity and the model was well performing with 90% and 96% [9]. A deep convolutional neural network-based system completed the challenging multi-class diagnosis task and the model performance was equally good having AUC score of 97.81% on testing 3,199 CT-scan images.

This study provides a deep learning-based algorithm based system which was able to identify if the piblic are wearing face masks in public places which was then the better way to prevent the spread of coronavirus. The proposed model was developed based on ensemble algorithms. the performance of the developed model was measured in terms of detection speed and prediction accuracy which was found to be good as fast as 0.05 seconds for detection and 98.2% accuracy. The model results from a face mask-centric dataset that was created using highly balanced random oversampling and data augmentation [10]. Implementing the bounding box affine transformation and transfer learning are two more features that helped build the highly efficient model. The deep learning-based method for diagnosing coronavirus-affected patients using X-rays images of the patients are elaborated in the work. For the effective detection of sick patients, the in-depth feature of X-ray images is classified using a decision tree approach. This study uses X-ray images to construct 11 distinct CNN models for classifying patients [11].

First, utilizing CT scans, we created a deep learning integrated model to identify COVID-19 among patients. While using CT images, infected lesions (ROIs) were automatically segmented using a pre-trained DL algorithm. Four machine learning algorithms and five feature selection approaches were combined to create radionics models. The multi-layer perceptron (MLP) classifier, trained with features chosen by L1 regularised logistic regression, displayed the best efficiency with AUC of 0.922 and 0.959, sensitivity of 0.879, specificity of 0.900, and 0.887 [12]. To identify COVID-19 affected patients, a deep learning integrated CT diagnosis method was created. The study outcomes demonstrated that the model accurately distinguishes among COVID-19 patients and patients with bacterial pneumonia, with an AUC of 0.95, recall, and precision of 0.96. The algorithm extracted key lesion characteristics, particularly the ground-glass opacity, which aids physicians in diagnosing [13].

A hybrid model comprising bidirectional gated recurrent network and 1D convolution algorithms was build. To identify the affected percentage and forecast the pandemic risk, the laboratory based methods of detecting coronavirus was directly incorporated. A trained model which was build on attention mechanism was used for determining the optimum performances [14]. The synthetically harmful data created by swapping out the spike protein's coding sequence was likewise correctly anticipated. To define whether a person is positive for COVID-19, the person's imaging data is analyzed using a layered technique. A deep learning model which utilizes the combined power of RNN and CNN were used to perform a fast coronavirus detection among patients [15]. Here, X-ray and CT image classifications are measured so that the threshold value can be used to determine a person's health at any stage, from the mildest to the most severe. The following are this paper's main contributions:

- We proposed a model of effective COVID-19 detection techniques based on CNN and texture descriptors.
- We present a unique dataset that combines CT images from cases with and without COVID-19.
- We obtain high accuracy on data based on CNN and texture descriptors.

The rest of this paper is organised as follows. The proposed model are described in detail in Section 3. In section 4 the experimental setup, the dataset used , and performance metrics which was used to evaluate the proposed methods are presented. The results, performance of the system, conclusion and further scope are presented in last section..

III. Methodology

A detailed strategy is used in the proposed procedure to identify the COVID-19 disease. First, the CT images received from a public dataset were subjected to the pre-processing approach [16]. The Fuzzy C-mean is used to cluster each one of the CT images (FCM). A histogram equalization strategy improves the intended region of photos. After that, a new image is produced using the enhanced images using the texture descriptor approach known as Local Directional Number (LDN). The CNN for COVID-19 feature extraction and classification is used to produce results with high accuracy. The proposed methodology is diagrammatically represented in Fig. 1. and briefed in the following sections.

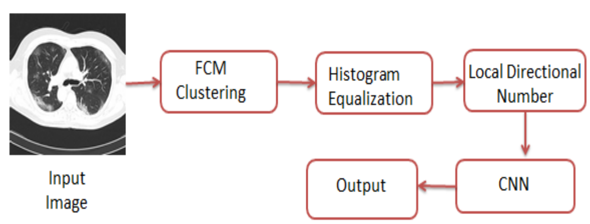

Fig. 1. Proposed Method

A. Dataset

There are 2482 CT scans in the COVID-19 dataset [17] from 120 patients scanned using 1252 CT scans. Information was gathered from Sao Paulo, Brazil, hospitals. These are digital scans of the images; there is no established criterion for image size. A COVID-19 CT image example is shown in Fig. 2. The dataset is partitioned into training and testing in the ratio 80:20. The dataset is available open sourced and researchers could use it [17]. Healthy and non-covid patient images are gathered from databases like the LUNA and MedPix datasets.

B. Fuzzy C-means

Using fuzzy C-Means (FCM) method, every piece of information might belong to two or more clusters by being divided into separate portions. The soft c-means clustering approach has a version called FCM [18]. In the FCM technique, the cluster centre of every segment is found by updating the weights of each pixel's membership level.

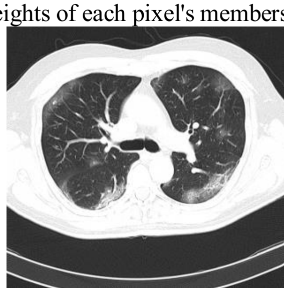

Fig. 2. Sample COVID-19 CT image

The fuzzy c-means primary goal is to reduce the resulting objective function:

$$X = \sum_{a=1}^{m} \sum_{b=1}^{n} Y_{ab} ||P_a - Q_b||^2 \quad (1)$$

$$Y_{ab} = 1 \Big/ \left(\sum_{i=1}^{m} \left(\frac{P_a - Q_k}{P_a - Q_s}\right)\right)^x \quad (2)$$

P and Q denote the pixel abbreviations and center in the above equations. Y_{ab} is the integrated value of the b_{th} trial in the a_{th} cluster. m shows specific clusters, and n signifies some pixels.

C. Histogram Equalization

The primary purpose of any image enhancement algorithm will be boosting the perception of the data in the image and to reveal the features which helps to increase the effectiveness of the model. Conventional histogram equalization is the most widely used technique due to its efficiency and simplicity. Conventional histogram equalization modifies the image contrast by changing the histogram's intensity distribution [19]. When the image's data collected is considered to be adequate values, this method typically increases the overall contrast of numerous images. The intensities on the histogram can be more evenly spread by making this adjustment. As a result, areas with less local contrast can acquire greater contrast [20]. The most frequent pixel intensities are efficiently distributed via histogram equalization to achieve this. The implementation of this method is as follows:

Step 1: calculating the probability that an event will take place at the a-th pixel level in the grayscale image of i.

$$P_a(x) = P(i = x) = {n_a}/{n}, 0 \leq a \leq k \quad (3)$$

where n_a represents the gray-level occurrences, n represents the pixels in the image, and k occurrence of grey levels in the image. Additionally, $p_a(x)$ is the histogram for pixel value x.

Step 2: The normalized accumulative distribution function corresponding to P_a

$$F(i) = \sum_{j=0}^{x} P_a\,(a = j) \quad (4)$$

Step 3: Create a new image with a flat histogram.

$$F(i) = iP \quad (5)$$

Where P is a constant value.

Step 4: Converting F(i) based on features of the cumulative distribution function.

$$X = A(s) = F(i) \quad (6)$$

Where s lies in [0,m] and A(s) maps the level in [0,1].

Step 5: We apply the following transformation to map the values to the original range.

$$x^1 = X.(\max\{a\} - \min\{a\}) + \min\{a\} \quad (7)$$

This research proposes an efficient region-based histogram equalization used on brain CT images. Fig. 3. Shows histogram equalization image.

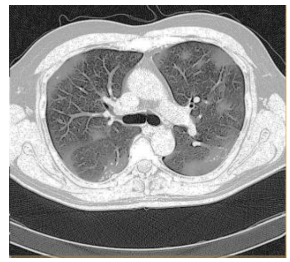

Fig. 3. Histogram Equalization Output

D. Local Directional Number

A feature vector comprising numerous details about an image makes up a texture descriptor. In this study, the Local Directional Number (LDN) technique encodes a neighborhood's structure by examining its directional data [21]. LDN constructs an image from elements of the same kind, assessing an image's algebraic, geometric, statistical, differential, or spatial qualities. LDN equation is shown in (8):

$$F(l, m) = (P_{cl,cm}) + (n_{cl,cm}) \quad (8)$$

where $P_{cl,cm}$ is the highest positive value and *(cl, cm)* denotes the neighborhood's mid-pixel. Additionally, the negative response's minimum value is the $n_{cl,cm}$.

E. Convolutional Neural Network Architecture

The CNNs are made up of many illusionary neuronal layers. A grid-patterned deep learning framework called CNN is used to process data, including image data. CNN is used to automatically learn spatial feature topologies by backpropagation utilizing different building blocks. This feature extraction, prediction, and classification structure contain some weights and biases. The convolutional layer converts an input into a heap of feature mappings of the information, referred to as the fundamental component of any CNN. It is regarded as the initial layer to extract features and is often present at the start of the CNN pipeline.

Convolution, pooling, and fully connected layers are the considered as the building elements of CNN based model. Convolution and pooling layers, the first two layers, serve as feature extraction layers. In contrast, the fully connected layer, the third layer, translates the extracted feature matrices into the outcome. A convolution layer comprises a stack of mathematical operations like convolution, a specific kind of linear operation. Convolutional neural networks inevitably acquire numerous patterns in parallel is their crucial innovation.

Some significant elements of the texture are extracted using a convolution layer. With a wide receptive field, the convolutional layer can reliably detect across a greater area, but the interpretation is less accurate. This study uses narrow receptive fields to distinguish between different regions accurately and identify significant traits. The convolutional layer can more precisely identify minute variations since it has a narrow perceptron and can identify stimuli over a focused area. The CNN design employs the pooling layer to lessen the spatial dimension. As the number of parameters reduces, the pooling layers can lower the spatial information, improve computation speed, and reduce the chance of a fitting problem. The CNN design uses activation layers to narrow the enormous number of output features to just those appropriate for object identification. The activation function selection will determine how effectively the structure understands the training samples. The CNN model's ability and working are inclined by the activation function selected, and diverse activation functions can be used in other regions of the structure.

We employed MaxPooling and ReLU activation layers in this paper. The input image is subjected to the dot product and the resulting binary mask. The features are combined to form a 1D vector. This research chooses a patch size of 35x35 for every pixel inside the images. All pixels within the images go through this procedure again and again. Convolutional layers can capture both temporal and spatial dependencies, resulting in a feature map. When computing the dot product between a filter with any perceptron and associated pixels in an image, the convolutional operation multiplies the input data. A MaxPooling layer was added after each convolutional layer. This spatial pooling layer reduces the dimension of the prior feature matrix acquired in the preceding layer by choosing the most significant value inside a 2x2 window. The 2D feature maps are converted to 1D and combined to create a 1D feature vector. The Fully-Connected layer, positioned before a CNN's classification output, is essential for getting additional high-level information. The Softmax layer is the used as the final layer of the CNN architecture that generates results with a probabilistic meaning. This layer uses logistic regression in its design. If fair values are used, the learning period for the features lengthens. Different learning rate values were used to get the classifier's optimum performance while training. Fig. 4 shows diagrammatically shows the working of CNN architecture.

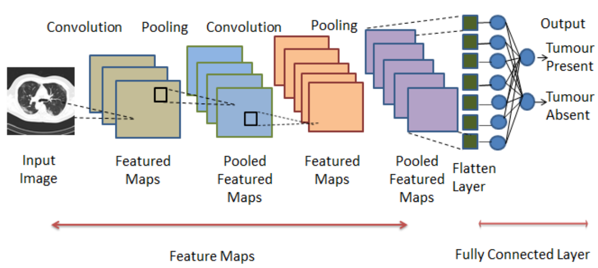

Fig. 4. Workflow of CNN Architecture

IV. Experimental Results and Discussions

We utilized the statistical inference analysis to determine the precision after training it. Five-fold cross-validation technique was used to load the test data and evaluate the effectiveness of the developed model. The criteria in this study include accuracy, sensitivity, and specificity. It is used to assess the proposed's efficiency and accuracy model. The percentage of precise predictions for the test data is what accuracy means. It is calculated by distributing the number of correct predictions by the total number of predictions. The ratio of positives that are effectively distinguished is measured by sensitivity. The percentage of successfully distinguished negatives is a measure of specificity. In this study openly available datasets were used to develop a deep learning model for COVID-19 identification. The training set and validation set were created by randomly dividing the images using train-test inbuilt method.

$$Accuracy = \frac{TPS+TNS}{TPS+FPS+TNS+FNS} \quad (9)$$

$$Sensitivity = \frac{TPS}{TPS+FNS} \quad (10)$$

$$Specificity = \frac{TNS}{TNS+FPS} \quad (11)$$

where,
TPS is True Positives
TNS is True Negatives
FPS is False Positives
FNSis False Negative

TABLE 1. Summarization of the existing work

Author	Dataset	Accuracy	Sensitivity	Specificity
Khair Ahammed et al. [22]	COVID-19 Radiography Database	94.03%	94.03%	97.01%
Talal S. Qaid et al. [23]	COVID-19 Radiography Database, Asir Hospital (Saudi Arabia)	97.8%		
Shuai Wang et al.[24]	Xi'an Jiaotong University Hospital	89.5%	88%	87%
Abolfazl Karimiyan Abdar et al.[25]	Alinasab Hospital of Tabriz	90%	90%	91%
Tarun Agrawa et al.[26]	Kaggle, SIRM, RSNA	95.20%	95.20%	
Joy Iong-Zong Chen et al.[27]	Cohen's dataset	85%		

COVID-19 has an impact on daily lives all over the globe, and assessment is a strategy to stop the disease from spreading. The patient can use health advice to stop the epidemic when the sickness is detected during its early stages. In the current study, we suggested employing an FCM, Histogram Equalization, Local Directional Number, and Convolutional Neural Network to swiftly and automatically detect an individual using CT images. We distinguished between infected and non-infected individuals based on the affected portions located in the CT scans of COVID-19 patients.

We trained our models with a batch size of 32 to fulfill our automatic CT image classification objective. It was developed using Python 3 and the Keras library. It was made with the aid of Google Colab. We intended to create a COVID-19 automated identification system to assist medical professionals in conducting a thorough assessment of COVID-19 patients. Our findings demonstrate the COVID-19 classification's high accuracy. It is found to be ideal. one of the primary objective of the work is to reduce the wrongly identified COVID-19 patients. The validation parameters namely accuracy, sensitivity and specificity of some of the methods discussed in the related works are tabulated in Table 1. The proposed model was performing good with a good accuracy score near to 98%. Fig. 5. displays the accuracy of the proposed system.

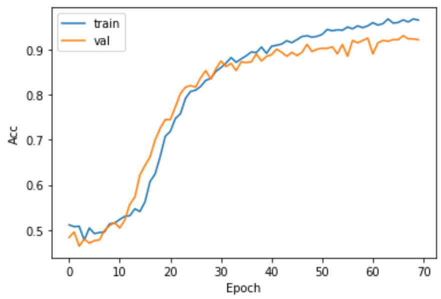

Fig. 5. Model Accuracy

V. CONCLUSION

This paper proposes a technique for identifying the infection caused by COVID-19 on CT images based on the CNN technique. The input image's quality is raised through the application of histogram equalization. A new image was created using the LDN textural descriptor method based on the modified images. CNN uses the resulting images for steps in feature extraction and classification. The network's training procedure doesn't need a lot of data because it uses the LDN technique and extracts other crucial information. An exhaustive analysis has shown the effectiveness of the suggested strategy when compared to recently released frameworks. The system was performing good calculating the performance parameters namely accuracy, sensitivity and specificity and it was measuring 98.60%, 98.10%, 97.80%.. Future research is advised to employ a powerful pre-processing technique that may effectively eliminate the most unimportant portions of an image before feeding it into a CNN model.

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