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DETECTION OF OMICRON VIRUS BASED ON CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

COVID-19, an upper respiratory viral infection, is spreading too quickly and is now found almost everywhere on the planet. A chest x-ray and RT-PCR are used to confirm Covid-19. However, resource constraints in developing countries make this difficult. This paper aims to monitor infection in Egyptian's lungs using chest X-rays and convolutional neural networks in the early-stage detection. The omicron chest X-ray dataset is gathered from public records along with hospital and doctor arrangements that are approved by their patients to achieve our goal. The classification mission's backbone is a classic neural network (CNN), which benefited from its speed while deep networks are being trained and reduced the impact of vanishing gradient problems. Images are resized and pre-processed to improve sharpness and contrast before being used to validate the proposed system. Meanwhile, by feeding images into a deep neural network, infectiousness can be predicted.

The deep learning measurement's receiver operating characteristics (ROC) region under the curve is 0.9888, with 96.2 percent sensitivity, 98 percent accuracy, and 100 percent precision, according to the findings. It has been demonstrated that the proposed system can be easily modified to increase efficiency by adding additional images (normal and infected). As a quick alternative to the current PCR-based method, the proposed system offers a significant advantage to all nations in terms of screening and diagnosing OMICRON.

Keywords: *COVID-19, OMICRON, CNN, Dimension Reduction, Haar, Image Classification, X-RAY.*

1. INTRODUCTION

The coronavirus disease (COVID-19) pandemic began in Wuhan, China, in December 2019 and quickly spread around the world [1, 2].

The virus that causes COVID-19 epidemic disease is SARS-CoV-2 (severe acute respiratory syndrome coronavirus-2). Coronaviruses (CoV) are a large virus family responsible for diseases such as Middle East Respiratory Syndrome (MERS-CoV) and SARS (Severe Acute Respiratory Syndrome) (SARS-CoV). COVID-19, according to preliminary evidence, causes mild symptoms in about 99 percent of cases, with the remaining cases being serious or critical [3-4]. Not all COVID-19 versions have not yet been diagnosed or treated with a drug till now [5].

Chest radiography (X-ray) is one of the most common methods for diagnosing pneumonia all over the world [6-7]. The chest X-ray is a quick, low-cost [8] and widely used clinical method [9-10]. In comparison to computed tomography (CT) and magnetic resonance imaging (MRI), a chest X-ray exposes the patient to less radiation [11]. DNA polymerase is used in the polymerase chain reaction (PCR), which is an in vitro replication of specific DNA sequences. The power of PCR stems from the fact that the amount of matrix DNA is not a limiting factor in theory [12]. A chest X-ray is much more difficult to diagnose than other imaging modalities like CT, MRI, or PCR [13].

In the field of medical services, neural network algorithms are becoming more popular due to their ability to deal with massive datasets that exceed human capacity [14]. Integrating computer-aided design (CAD) methods into radiologist diagnostic systems reduce doctors' workload while increasing accuracy and quantitative analysis [15].

The studies using chest X-rays to diagnose covid-19 are the starting point for this paper. Our research exploit CNN architecture which has been chosen because it is the most widely used in biomedical imaging. Although authors faced a number of challenges in collecting consistent and quality data, collected X-RAY pictures are classified by CNN using image data from medical Egyptian institutions for non-vaccinated patients, and then a deep convolutional neural network is used to classify COVID-19 X-ray images accurately and quickly.

At this work an AI-based method was developed to determine whether or not a person is an omicron patient. The proposed model adapted X-ray images with high accuracy to be trained for omicron identification because of the limited availability of omicron selected samples. The most significant accomplishment of this research is that the proposed system performance indicates measured admirably in terms of precision, sensitivity, and accuracy.

Paper is organized as follows; the main section 3, presents the proposed model which consists of three stages employed to improve this study and achieve better outcomes. Section 4 presents the experimental results for 915 images. Section 4 closes with a conclusion.

2. RELATED WORK

COVID-19 is diagnosed using chest X-rays in studies with binary or multiple classifications. Raw data is used in some studies, while feature extraction is used in others. The number of data points used in studies varies as well.

Qin et al. (2020) [16] Performed a clinical analysis of lung CT images from four patients with Covid-19 disease, two men and two women. The findings show that patients with pneumonia have a high level of involvement in lung lesions caused by Covid-19.

Lin et al. (2020) [17] looked at how the CT scans of a 61-year-old male Covid-19 patient's lungs changed as the disease progressed. Lung involvement increases as the disease progresses, according to the study's findings.

Li et al. (2020) [18] evaluated CT scans of the lungs of five Covid-19 patients ranging in age from ten months to six years in a similar evaluation. Two of the patients exhibited no indication of disease on CT scans of their lungs, but three of them exhibited substantial abnormalities, according to the study.

CT images of the lungs of 50 Covid-19 patients are examined clinically by Xu et al. (2020) [19], with 9 in the mild range, 28 in the moderate range, 10 in the extreme range, and 3 in the critical range. During the assessments conducted as part of the analysis, it is confirmed that no alterations in radiological images occurred in 9 individuals.

Asymmetrical lesions appeared in 26 cases, while symmetrical lesions appeared in 15 cases. In addition, the study's discussion section decided that frequent CT scanning is an effective tool for assessing illness development and providing timely Covid-19 therapy.

Xia et al. (2020) [20] evaluated CT images of 20 Covid-19-diagnosed pediatric patients in a publication. According to the data, many of the patients in the sample had sub-pleural lesions.

Huang et al. (2020) [21] looked examined clinical evidence from people who had been diagnosed with Covid-19. According to the findings, lung abnormalities are observed in 40 of the 41 Covid-19 individuals investigated in the study, with bilateral involvement. In a study conducted by Hu et al. (2020) [22], CT scans of two Covid19 patients' lungs are evaluated. While the disease symptoms improved after two days of medication, the CT imaging of the lungs revealed inconsistencies with this improvement. A clinical analysis of CT scans of the lungs from 73 Covid-19 cases with varying degrees of severity is carried out, according to Liu et al. (2020) [23]. Except for 8% of patients with moderate pneumonia, all patients showed abnormal CT scans of the lungs, according to the study's findings. In a paper published by Xu et al. (2020) [24], the clinical data histories of 90 Covid-19 patients are examined.

According to the findings of the study, Covid-19 patients experienced multiple patchy ground-glass opacities on CT images. Pan et al. (2020) [25] used the clinical data of 63 Covid-19 patients to perform a similar analysis, and irregularities are discovered in CT images of the patients' lungs.

The lesion levels in CT images of 44 Covid-19 patients' lungs are labeled by radiologists and computers.

Li et al. (2020) [26] did a clinical assessment of CT images of the lungs taken during the course of pneumonia owing to Covid-19 illness. This article emphasized the necessity of CT imaging of the lungs in assessing the impact and course of the Covid-19 sickness.

For Taiwan's first Covid-19 incidence, Wang et al. (2020) [27] undertook a similar investigation. In this regard, the findings of Lim et al. (2020) [28], Li et al. (2020) [26], Sakagianni et al. (2020) [29], and Hu et al. (2020) [20] research are higher. The findings are similar to Liu et al. [30], but they fall short of Long et al. (2020) [31] and Apostolopoulos et al. (2020) [32].

It should be emphasized, however, that the determination of 6060 ROI areas on the image is done manually in Ardakani et al (2020) [33]'s study, and dense areas are marked for precise comparison. While Jaiswal et al. (2020) [34] utilized similar transfer learning methods; the results are insufficient because the entire picture is utilized.

In their investigation, they also classified images as a whole. One of the most noteworthy findings of this study is that when texture function photographs are used instead of or in addition to the original photographs, significant modifications in the study outcomes can be accomplished. This scenario holds for other high-results research.

It is expected that by doing so, the findings of a previous study will be bolstered even more. Using deep learning algorithms to scan CT images of the lungs to diagnose Covid-19 disease, according to the findings, would speed up the diagnosis and considerably lessen the strain on healthcare workers.

Valdiviezo-Diaz (2021) [35] Using an available dataset with day-level information on COVID-19 impacted cases in China; this article uses data mining approaches to forecast COVID-19 infected patients' recovery. COVID-19 patients' recovery is predicted using data mining algorithms. Using the R programming language, the methods of logistic regression, decision trees, and neural networks are applied to the COVID-19 patient dataset. The outcome of the experiment in comparison to previous methods, experimental results revealed that the neural network has a reduced error rate and improves classification accuracy significantly. The use of neural networks on a balanced dataset revealed that their efficiency is not influenced by majority class values. Other methodologies for data missing imputation, such as a k-nearest neighbor, will be used as future work. Other prediction methods, such as Naive Bayes and Support Vector Machine, are also available [35].

Karami (2021) [36] his study gathered 9298 publications from COVID-19 research that is published between May 5, 2020, and May 5, 2021. They employed frequency analysis to identify the most common symptoms and therapeutic compounds, demonstrating the significance of the two biomedical ideas. Topic modeling is also used in this study, which resulted in 25 categories displaying relationships between the two overarching categories.

Their paper outlines a well-thought-out research strategy that will greatly aid COVID-19 researchers in streamlining their publication search to make timely, well-informed decisions. A deeper grasp of COVID-19 literature should help people to understand biomedical principles and prepare us for future COVID-19 and other infectious disease outbreaks [36].

Alsunaidi et al. (2021) [37] Big data analytics are essential for acquiring the knowledge needed to make decisions and take preventative measures. Given the vast amount of data about COVID-19 available from a variety of sources, it is vital to revisit the role of big data analysis in limiting COVID-19's spread, as well as describe the major issues and directions in COVID-19 data analysis the difficulties faced when evaluating COVID-19 data are discussed in this study. The outcomes of this study point to crucial areas for further research and application.

In this work, they provided a study of several COVID-19 data analysis applications, in addition to a taxonomy structure that classified COVID-19's potential applications into four categories. Some of the subjects covered include diagnosing, estimating, or predicting risk scores, healthcare decision-making, and medications. The study described the major aspects of a number of data analysis tools. They also offered important details regarding a number of concerns that could hinder COVID-19's use of data analytics tools. Patients' cooperation in sharing some of their medical information, as well as concerns about healthcare data security and patient privacy, that's beside difficulty of sharing data with researchers, and lack of data validation for some studies, leads to biased results [37].

Ahouz (2021) [38] COVID-19 has emerged as a new pandemic due to its widespread distribution. Predicting its global prevalence and incidence is crucial for guiding health professionals in making important decisions. The purpose of this research is to anticipate COVID-19 occurrence within two weeks in order to better manage the condition. The Johns Hopkins University COVID-19 databases, which have been updated daily since January 22, 2020, offer information on COVID-19 instances in various geographic regions. Data from 252 such regions has been evaluated as of March 29, 2020, with 17,136 records and four variables: latitude, longitude, date, and records. Two weeks before the design, information about the region and its nearby areas is gathered to create the incidence pattern for each geographic region. The model is then developed using a Least-Square Boosting Classification method to estimate the occurrence rate for the next two weeks.

The model is shown for three incidence rate groups: less than 200, 200 to 1000, and 1000 and above. The mean absolute error of model evaluation is 4.71, 8.54, and 6.13 percent, respectively. When the prediction results are compared to the actual values for the time period in issue, the suggested model correctly anticipated the number of globally verified COVID-19 cases with a very high accuracy of 98.45 percent.

Using data from different geographical locations within a country and determining the pattern of prevalence in a region and its nearby areas, their boosting-based model can accurately forecast the occurrence of COVID-19 within two weeks. [38].

Nahe. (2021) [39] Covid-19 was a serious pandemic by 2020, according to the researchers. The most frightening term heard that year was "Covid-19 positive," which caused terror all around the world. Early detection will lessen the threat because it is an infectious pandemic. The most difficult part is detecting it. To identify Covid-19, a person needs wait a lengthy period for the results of a blood test. Using Deep Learning algorithm CNN and Machine Learning algorithm Logistic Regression, authors can detect Covid-19 immediately. These techniques use radiological data such as CT-Scan and X-ray images as input. With the help of this model, Covid19 positive cases will be detected more quickly.

Prediction of Covid-19 as soon as possible is required to halt its spread. When compared to blood tests, Covid-19 with radiological data such as CT-Scan and X-ray images using deep learning and machine learning techniques such as CNN and Logistic Regression can be predicted. Many models have been proposed; among them, our proposed model could detect covid-19 positive or negative with reasonable and greater accuracy than other models for both CT-Scan and X-ray datasets, when compared to other models. If COVID-19 positivity is detected in the future, the severity of the condition can be determined [39].

Bhargava. (2021) [40] the worldwide spread of pandemic COVID-19 (Coronavirus) necessitates an immediate commitment to the fight across the whole human population. For this sudden outbreak and abandoned environment, human health care emergencies are restricted. In this case, ingenious automation such as computer vision (machine learning, deep learning, artificial intelligence), and medical imaging (computed tomography, X-Ray) has developed a promising remedy against COVID-19. Various experts have been working on image processing approaches in recent months. A comprehensive examination of picture acquisition, segmentation, diagnosis, avoidance, and management is described in this study. For coronavirus, an analytical evaluation of the numerous proposed algorithms by researchers is carried out, as well as in-depth assessments of machine learning strategies for dealing with the COVID-19 (Coronavirus) outbreak. [40].

Our current findings could serve as a starting point for future researchers looking to create new strategies for predicting coronavirus patient recovery.

To improve these studies and produce better results, it is critical to enhance the radiological and clinical data available for Covid-19 patients and make them openly accessible to researchers as in Figure 1.

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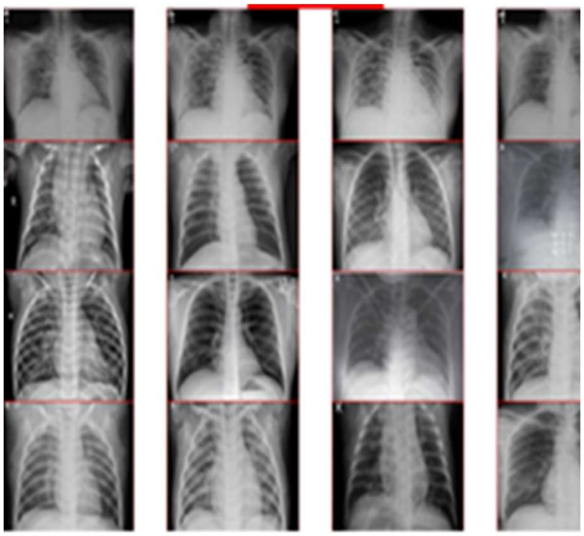

Figure. 1: Sample of used chest x-ray images.

3. PROPOSED MODEL

The image preprocessing stage, dimension reduction and feature extraction stage, and classification stage are the three stages of the proposed model. The structure of these stages is as in Figure 2.

After applying the median filter to the noisy image, the X-RAY images are now ready for the dimension reduction step. The proposed method's block diagram illustrated in figure 4.

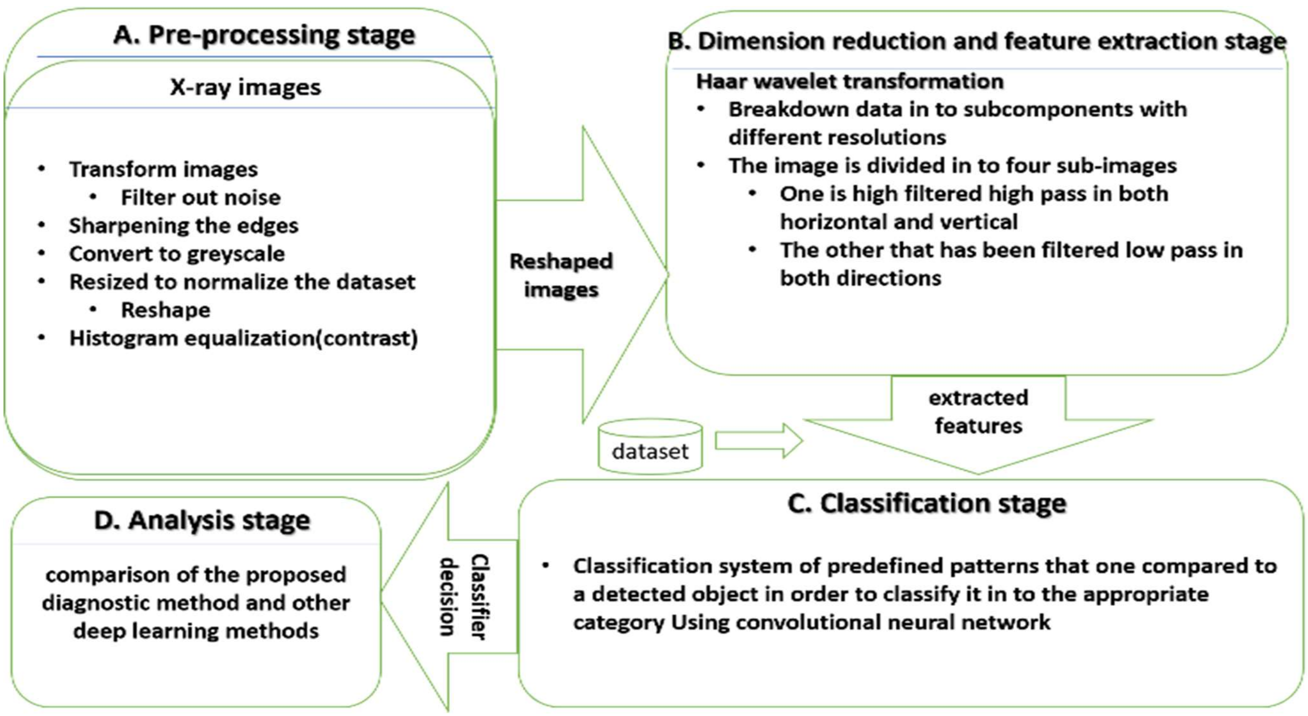

Figure 2: The proposed framework

a. Image Preprocessing Stage

The image is transformed in the pre-processing stage to meet the requirements of the next stage. It sharpens the edges while filtering out noise and other objects in the image. X-Ray images are reshaped here as well. It has a noise-reduction median filter.

Convert the chest X-Ray image from eight-bit to double-precision pattern in the preprocessing stage to obtain a high-resolution image of the x-ray while remaining non-invasive. Although the goal of this paper is to detect, segment, and classify the omicron cells, but noise removal is required to finish the process. To get the best X-Ray image quality, a median filter is used to remove any noise from the original image as in Figure 3.

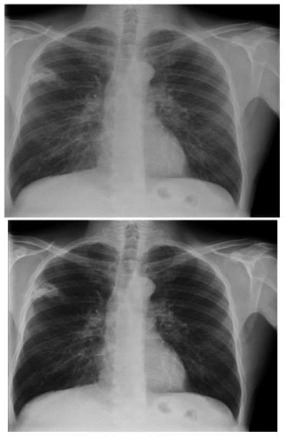

Figure 3. (A): The Original X-ray image with noise.

(B): The same image after applying the median filter.

Some of the photographs appeared to be three-dimensional. To normalize the dataset, they are resized to 400*400 pixels. Histogram equalization is used to boost the contrast of all images to improve detection.

Again, Figure 3 shows a comparison of two images before and after applying the median filter to remove any noise. This procedure is applied to the initial dataset to increase the dataset size and avoid over-fitting.

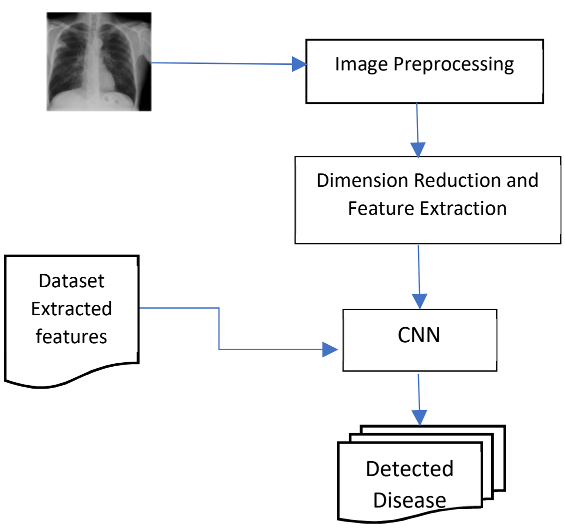

Figure 4: Proposed model block diagram.

b. DIMENSION REDUCTION AND FEATURE EXTRACTION STAGE

The local features are discovered after the local chest pattern, which is a 400*400 image, is discovered. However, because this feature vector is too large to be used in the classification process, the Haar wavelet transform is used to reduce it to a one-dimensional feature vector. Data in the chest area can be broken down into sub-components with different resolutions using the Haar wavelet. The chest image is subdivided into four sub-images. These images are made up of two high-resolution images, one with a high pass filter in both horizontal and vertical directions and the other with a low pass filter in both directions as in Figure 5.

Using the Haar wavelet transform successfully reduces the feature vector, affecting the overall performance of the device and reducing the overall time of the classification process, in contrast to other approaches.

The output of this stage is a MATLAB file containing only the features selected from each image for comparison with the dataset mat file in the next stage.

c. CLASSIFICATION STAGE

Image classification is the process of categorizing images

In to one of many predefined groups. A classification system consists of a database of predefined patterns that are compared to a detected object to assign it to the correct category. In a variety of applications, image recognition is a Critical and difficult task.

Image classification is a method of image processing that distinguishes between distinct types of objects based on features exhibited in image data. The classification findings, as well as the categorization of picture classification, are highly diverse. Based on multiple visual semantics, images can be classified as object classification, scene classification, event classification, and emotion classification.

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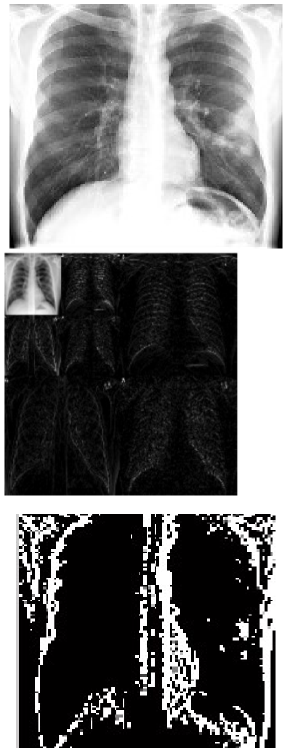

Figure 5. (A) Original x-ray image (B) the image after the Haar with different resolution (C) the same image after applying Haar wavelet

The key steps in image classification are picture preprocessing, image feature definition and extraction, and classifier building. To make further processing of the target image easier, image filtering (such as median filtering, mean filtering, and Gaussian filtering) and dimensional normalization operations are utilized in preprocessing. Each image has its own characteristics, and feature extraction, that is, according to the character, is a description of the prominent traits or attributes. The classifier is an algorithm that categorizes the target image based on the defined criteria; the appropriate features are identified and extracted efficiently. Images are becoming increasingly important in people's lives. A fundamental part of pattern recognition is image classification. The issue of collecting meaningful data is a serious one that needs to be addressed.

The feature extraction problem, which is at the heart of the image classification algorithm, is inextricably linked to the classification problem, as shown in Figure 6.

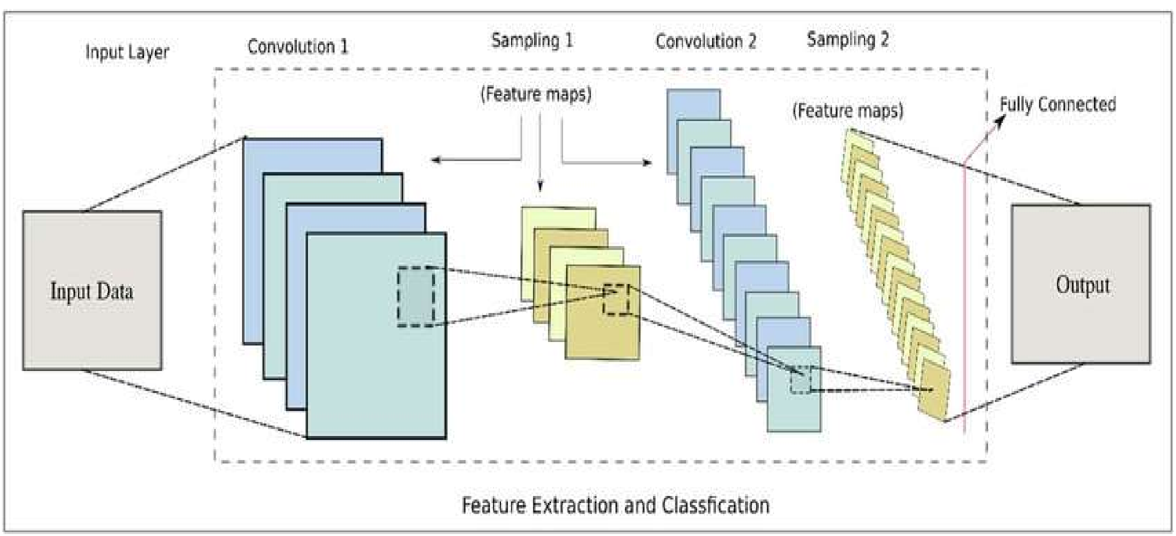

Figure 6: The general architecture of CNN

Various categorization jobs should have different feature needs and feature extraction methodologies.

The basic CNN architecture consists of an input layer, an output layer, and a series of hidden layers. The hidden layers are the convolution layer(s), pooling layer(s), and completely linked layer(s). The convolution layer selects the kernels that are most relevant to the application. The pooling layer

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reduces dimensionality by obtaining the mean or limit of the image patches.

At the end of CNN, fully connected layers produce a tensor, which is then transformed into a vector.

4. EXPERIMENTAL RESULTS

In this section, the results of using an image database are presented. Present the database that is used in the experiments first, and then the results using the framework that is used.

a. Dataset

The information is obtained through agreements with Egyptian hospitals and doctors, as well as patient consent. As shown in Figs. 7 and 8, the data is divided into two categories: common cases and COVID-19 cases. The 'jpeg' format contains 915 images with sizes ranging from 461*431 to 4284*3480 pixels. These images are divided into three groups: 70% for preparation, 15% for testing, and 15% for validation.

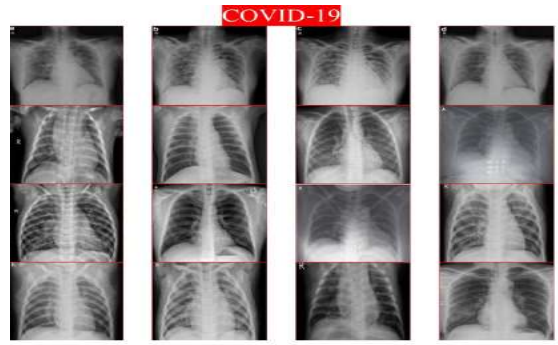

Figure 7: Omicron Virus Cases.

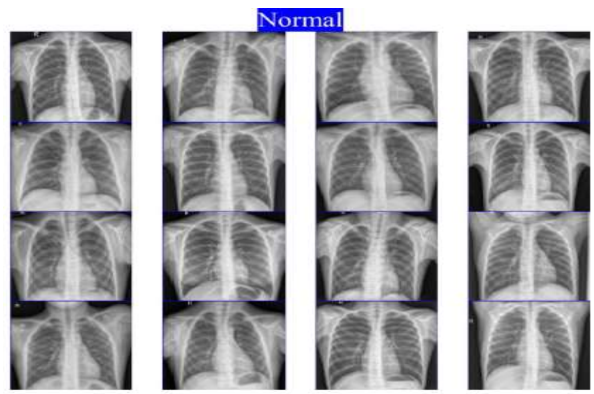

Figure 8: Sample of the dataset images

Figure 9: The confusion matrix for the 2 classes curve

b. Comparative Analysis

In the uncertainty matrix, false positive (FP), false negative (FN), true positive (TP), and true negative (TN) cases are listed. A false positive resulted from normal cases being misclassified and misrepresented as infectious cases. Omicron cases that have been correctly identified are true positives. In true negative cases, standard cases are correctly classified as non-infectious. A false negative, in which omicron cases are incorrectly classified as regular, is the worst-case scenario. As in Figure 10, the confusion matrix. It can calculate sensitivity, precision, accuracy, specificity, and negative predictive value.

$$Sensitivity=TPTP+FN \quad (1)$$

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

$$Accuracy=TP+TNTP+TN+FP+FN \quad (3)$$

$$Negative\quad Predictive\quad Value=TNTN+FN \quad (4)$$

The proposed algorithm has a sensitivity of 96.2 percent, precision of 100 percent, specificity of 100 percent, and a negative predictive value of 96 percent. The accuracy of the proposed method is found to be 98 percent, indicating that true outcomes, whether true positive or true negative, are fairly normal. The COVID-19 diagnosis necessitates extreme precision. Furthermore, 96.2 percent sensitivity is appropriate because it ensures a low number of false-negative results, which are a major source of infection. The proposed method can be used in both real-time and non-real-time applications. The processing time is 0.56 seconds on a computer with a Core i7 processor and 8 GB RAM. As a result, the proposed method can be used in clinical settings. The area under the curve and the receiver operating characteristics (RoC) curve, which could aid physicians in selecting the operating region using FP and detection rate, are both deemed important performance indicators (AUC). This is a crucial field because it is unaffected by size. It evaluates how well forecasts are organized, regardless of their absolute values. Furthermore, the classification threshold does not affect AUC. The AUC is calculated and discovered to be 0.9888.

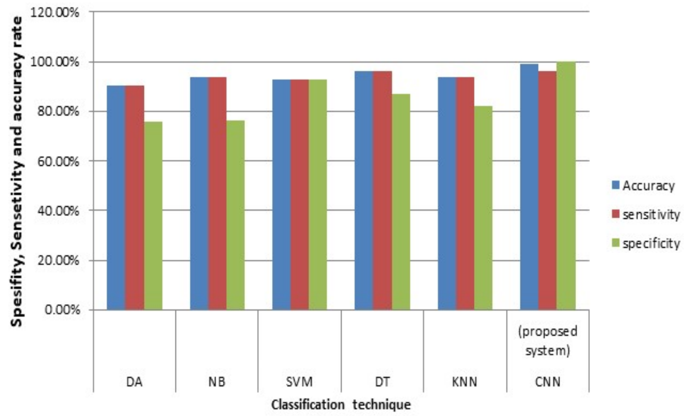

Figure 10. Classification results in terms of specificity and sensitivity.

Table. 1 shows a quick comparison of other deep learning approaches. This shows that the proposed system outperformed other recently published systems in terms of classification rate (accuracy).

TABLE 1: Comparison of the Proposed Diagnostic Method and Other Deep Learning Methods

Study	Accuracy
Ioannis et al.	93.48%
Wang and Wong	92.4%
Sethy and Behra	95.38%
Hemdan et al.	90.0%
Hossam et al.	98%
Proposed System	99.1%

Table. 2 shows a brief comparison of using CNN versus other machine learning algorithms on the same COVID 19 dataset, with CNN being the best algorithm, with an accuracy of 99.1 percent, which is higher than the other algorithms as in Figure 11.

Table 2 shows the comparison between these algorithms according to sensitivity and specificity and the table show that using CNN achieving the higher sensitivity and specificity compared with the other techniques, which make the proposed system achieving the higher accuracy compared with other techniques.

Table 2: The accuracy of the classification Techniques

Classifier	DA	NB	SVM	DT	KNN	CNN (proposed system)
Accuracy	90.12 %	93.52 %	92.59 %	96.19 %	93.7%	99.10%
Sensitivity	90%	93%	92.%	96%	93 %	96.20%
specificity	75.93 %	76.08 %	92.59 %	87.04 %	82.30 %	100%

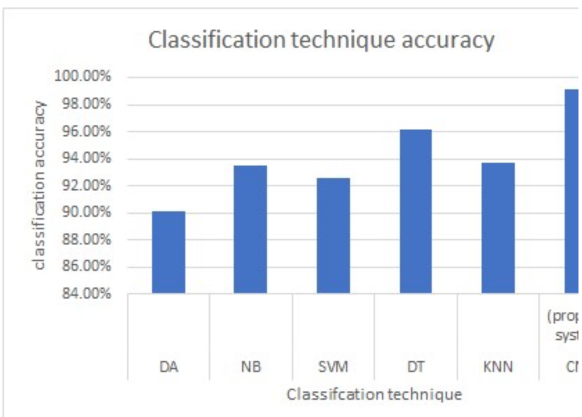

Figure 11: The accuracy of classification techniques.

Table. 3 states the comparison of classification techniques based on classification time. It is clear that CNN is not the best classification algorithm in terms of classification time, and that KNN is the best algorithm in terms of classification time as in Figure 12.

Table3: The Classification Techniques Classification Time.

Classification Technique	Classification Time (seconds)
DA	760.8
CNN (proposed system)	754.3
NB	11.6
SVM	735.7
DT	11.06
KNN	0.03

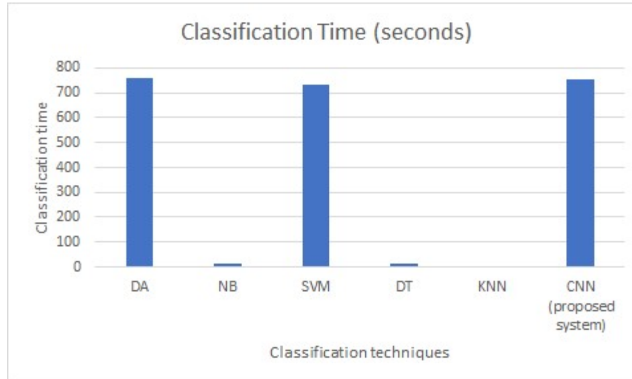

Figure 12: A comparison between classification techniques according to classification time.

According to tests, the CNN algorithm achieved the highest detection rate. At 99.1% of the time with correct classified. When it came to computational efficiency, the K-Nearest Neighbor technique was found to have a faster build time (the time it takes to create a model using network training data) of 0.03 seconds and a detection rate of 93.7 percent, as seen in the table. 1. With a detection rate of 93.52 percent, Naive Bayes achieved the second-best built time of 1.6 seconds. When it comes to the real-time classification of possibly hundreds of network traffic streams, computational performance is important. Due to its relatively high detection rate, CNN looks to be the best choice for real-time classification duty, according to this research.

5. CONCLUSION

Neural networks have distinct advantages in the field of picture categorization, thus Images can be utilized directly as input data since convolutional. The X-RAY image classification algorithm based on convolutional neural networks is discussed in this research. Several basic picture data preprocessing approaches are introduced by demonstrating the advantages of convolutional neural networks in image classification processing. The X-RAY pictures are classified by CNN using image data from several medical institutions, consequently, good results are produced. Finally, the results of the standard gradient technique and the Adam algorithm are compared to various commonly used grayscale photographs.

It can be inferred that the CNN model, when combined with the feature reduction approach, improves X-RAY image categorization accuracy and speed. First and foremost, the neural network's basic structure is described. The pooling layer and the convolution layer are two of the convolution neural network's unique features. The benefits of using a convolutional neural network for image processing, classification, and classification are demonstrated. The feature extraction of X-RAY images is then performed using the Haar wavelet transform as the feature classifier of the CNN model, and the X-RAY pictures are then classified using CNN.

Second, based on the analysis of CNN's X-RAY classification effect and CNN's X-RAY classification accuracy, it can be concluded that when feature reduction is used to optimize CNN's training process, the classification accuracy of the obtained features is comparable to the accuracy of X-RAY image classification using the momentum-based CNN model algorithm. The adaptive moment estimate method can significantly speed up the model's training process. However, because using non-parallel training and detection methods will take a long time; this research achieves CNN training and detection parallelization.

A deep convolutional neural network is used to classify Omicron X-ray images accurately and quickly. The CNN architecture is chosen because it is the most widely used in biomedical imaging. The implemented system performed admirably in terms of precision, sensitivity, accuracy, specificity, RoC, and AUC. The deep learning measurement's receiver operating characteristics (ROC) region under the curve is 0.9888, with 96.2 percent sensitivity, 98 percent accuracy, and 100 percent precision. Additionally, by incorporating more images into the algorithm can improve efficiency (normal and omicron). As a faster alternative to the existing PCR-based process, the proposed system offers a significant advantage to all nations in terms of screening and diagnosing omicron virus.

Although, the CNN method has produced good results for several simple image classification tasks, it has to be enhanced for some complicated picture classifications. The algorithm developed in this paper has good X-RAY image classification properties. However, there are flaws in the system. The model's generalization ability must still be tested due to the small number of samples, and the sparse technique can be improved. As a result, to better identify X-RAY scans, these aspects must be investigated further.

6. FUTURE WORK:

Suggest to apply this method on vaccinated patient shows positive tests after vaccination, also we looking forward to apply gens impacts on our results and compare between different nations…..and so on we have to say anything about vaccination here.

7. ACKNOWLEDGMENT

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8. CONFLICT OF INTEREST:

The paper authors have no conflict of interest exists

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