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CNN-Based Intelligent Disease Detection and Identification Technique through Chest X-rays

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Abstract. *During a global health crisis, precise disease detection becomes crucial. This study focuses on using Convolutional Neural Networks (CNNs) for intelligent disease detection and identification using chest X-rays (CXR). The COVID-19 global impact resulted in terrible health disasters and affected millions of people worldwide. Therefore, tracking down contacts is essential to halting the disease's spread. In this article, we propose a CNN-based intelligent disease detection and diagnosis technique through chest X-rays. Our proposed methodology opens the way for faster and more accurate COVID-19 detection from chest X-rays, demonstrating the potential of intelligent healthcare systems. This approach draws on a rich research landscape and aims to improve precision, efficacy, and standards by leveraging exclusion-based performance metrics. The results show that deep learning is effective at detecting SARS-CoV-2 in CXR images, with the suggested model achieving 99% validation accuracy and 98.5% overall accuracy. The proposed model performs well compared to state-of-the-art techniques and has more efficiency than other techniques with and without self-attention by requiring fewer parameters and producing results faster.*
Keywords: Intelligent healthcare technique; deep learning; convolutional neural networks (CNNs); disease detection and diagnosis; CXR (chest x-ray) images

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1. **Introduction.** The application of deep learning (DL) techniques to medical imaging has transformed disease detection in intelligent healthcare systems. This study uses sophisticated algorithms to investigate how deep learning can improve diagnostic accuracy, operational efficiency, and accessibility. As a result, it provides a solid foundation for improving patient care effectiveness and refining outcomes in modern medical practices. The second wave of the ongoing coronavirus disease pandemic of 2019 (COVID-19) appears to be even more dangerous than the first wave, which is extremely regrettable [1, 2]. Amidst a rich research landscape, this approach aims to increase the precision and efficacy of educational reforms and standards, leveraging exclusion-based performance metrics [3]. The severe acute respiratory syndrome's second-wave coronavirus 2 has affected many nations, with India being one of the worst affected [4]. Due to their slow recovery from the first wave, Brazil and the USA are two weaker countries. 360,960 people were infected

in India as of April 26, 2021, and that number is rising quickly. SARS-CoV-2's Indian form is the most dangerous of the variations, which is upsetting for Bangladesh given the proximity of these countries geographically.

Any age can become infected with the virus, which is spreading swiftly and can cause serious disease. Since the 1918 influenza pandemic, COVID-19, an extremely contagious virus brought on by SARS-CoV-2, has decimated the global population and claimed over 2.9 million lives [5]. Patients over 60 and those with medical conditions should be thought of as having a greater chance of getting SARS-CoV-2. The number of COVID-19 cases globally is about 167,011,807, according to the WHO. In the sphere of medical science, the PCR test is frequently utilized extensively. However, since there are many cases, it is now nearly impractical to run enough PCR tests due to their time and cost requirements [6]. Therefore, an alternative test is needed so that infected individuals can be quickly identified and isolated or quarantined. The custom CNN model created achieved 99% validation accuracy and 97% accuracy. Because the percentage of accuracy of the present study's models is higher than that of past research, it is obvious that they are more trustworthy. Numerous model comparisons have proven their robustness, and the study analysis can be used to derive the scheme.

This article describes the deep learning technique for finding infected patients with SARS-CoV-2. The CNN model can extract features from the classification with high performance. The CNN model extracts features based on filters, which has the potential to be efficient for classification [7]. Images with complex identities can be categorized using CNNs. Using the CNN architecture, many weight parameters can be reduced. This study primarily uses CT scan pictures and several CNN architectures to identify COVID-19. As a sample dataset, CXR pictures were chosen in this investigation since X-ray equipment is widely available, rapid, affordable, and tiny. The quickest possible coronavirus detection from CXR images will be made possible with the aid of this system. Chest radiography is one of the most frequent radiological examinations. Thoracic illnesses are found and located using CXR analysis. This will ease the burden of expensive and time-consuming PCR testing. False negatives in PCR test results were a common problem, which is not helpful in the current circumstances. False result issues can be eliminated if a model with extraordinarily high accuracy can be created. More people might be tested right away if this test were made available, slowing the spread [8]. The chest x-ray images are shown in Figure 1.

Figure 1. Chest X-Ray Images

The novelty of the study lies in the development of a customized CNN model specifically designed for the detection and identification of diseases through chest X-rays, with a particular focus on COVID-19. This tailored CNN model achieved impressive results with 98.5% accuracy. These findings demonstrate the model's ability to accurately differentiate between positive and normal chest X-ray images, showcasing its potential for aiding in early detection and screening efforts, especially in regions with limited access to PCR testing facilities. The high accuracy and performance of the CNN model offer promising prospects for improving healthcare outcomes, especially in light of international health emergencies such as the COVID-19 pandemic. The study's contribution to the field of healthcare and medical imaging is significant.

1) We introduce a CNN-based healthcare system, designed to enhance the early detection of COVID-19 from chest X-ray (CXR) images.

2) Our model achieves a remarkable accuracy rate of 98.5%, outperforming existing methods.

3) Through rigorous validation and testing, we demonstrate the model's effectiveness in distinguishing between positive and normal CXR images.

4) The system's high accuracy and rapid prediction time contribute to its potential for improving disease management and screening efforts.

5) Our collaborative research effort underscores the significance of AI in revolutionizing healthcare diagnostics.

2. **Related work.** In 2020, Sethy and Behera [18] proposed a deep learning-based methodology to detect coronavirus-infected patients using X-ray images. Support vector machines use deep features to distinguish COVID-19-affected X-rays from others, aiding medical practitioners in diagnosis. The recommended ResNet50 plus SVM classification model achieved an accuracy, FPR, F1 score, MCC, and Kappa of 95.38%, 95.52%, 91.41%, and 90.76%, respectively, based on validated X-ray images from GitHub, Kaggle, and Open-i repositories. This approach excludes SARS and MERS ARDS detection.

In 2021, Singh et al. [19] designed and implemented a deep convolutional neural network (CNN) technique. Additionally, Multi-objective Adaptive Differential Evolution (MADE) is used to adjust CNN's hyper-parameters. Extensive experiments are conducted using the COVID-19 benchmark dataset. On some performance criteria, comparative analysis shows that the suggested method performs better than the competitive machine learning models.

Chen and Lu [31] proposed 2022 a deep learning-based method for identifying illegal content in X-ray images. The paper primarily uses the YOLO (You Only Look Once) algorithm, which views object detection as a regression task and uses one neural network to gather all data, including bounding boxes and probability. Following research, the YOLOv3 method is used in the publication, and the accuracy for the development set is 45.2813%. The number of bounding boxes for each grid in the YOLO technique and overfitting in neural network training are two other object detection tasks that are examined in the study.

Mao et al. [30] established a model in 2024 for medical insurance fraud based on machine learning. Aiming at the unbalanced distribution of fraudulent and normal samples of insured personnel, traditional over-sampling and under-sampling methods, along with synthetic samples generated by GAN (Generative Adverse Networks), are used to address sample imbalance, reducing the impact of imbalance on binary classification detection. Logistic regression and XGBoost models are used to build the fraud monitoring model, which is evaluated on the original dataset. The results show that over-sampling and GAN better preserve sample characteristics, while XGBoost outperforms logistic regression in classification and detection tasks.

In 2023, Ahmad et al. [20] designed an ULTRA-X-COVID, deep neural network designed for automated COVID-19 detection using ultra-low-dose X-ray images. It used a multinational dataset of 30,882 X-ray images from approximately 16,600 patients in 51 countries, ensuring no overlap between training and test sets. Data analysis occurred from

April 1, 2020, to January 1, 2022. The model achieved 94.3% accuracy, 88.9% specificity, a 99.0% F1 score, and an AUC of 0.968 (95% CI, 0.956–0.983). With a 0.1-second prediction time, it performed comparably to conventional doses, offering a novel COVID-19 detection method and potential for broader disease evaluation.

3. Materials and Methods.

3.1. Dataset Description. The dataset contained CXR images for two classes. The CXR scans in one class are of COVID-19 patients, whereas the CXR images in the other class are of healthy individuals. There were two subclasses of these classes. A training set is one of them, while a validation set is the other. The dataset holds 2541 images. The study contains training and test sets, with 75% (1832) of the images in the training set and 25% (609) in the test set. Without collecting new data, the variety of the data has been increased through the use of data augmentation. Figure 2 shows a CXR image affected by COVID-19, while Figure 3 shows a normal image. For the images, the model has preset forms.

To create a useful dataset, the open-source datasets from Kaggle and GitHub were combined. The dataset included CXR pictures of both healthy and COVID-19-positive individuals. To extract features, CNN was utilized. The model consists of one flattened layer, two dense layers, three Max Pooling 2D layers, four Conv2D layers, and a corrected activation function for a linear unit. The activation function was applied to the final dense layer. The last layers that may be customized are dropout, dense, flattening, and average pooling. The CNN model is appropriate for extracting image characteristics since it learns and distinguishes between pictures based on the extracted features from the provided images [9].

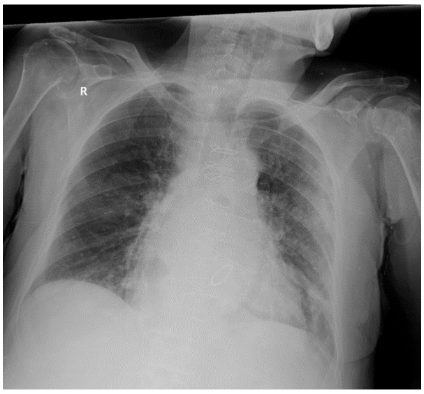

FIGURE 2. X-ray image of COVID-19 patient

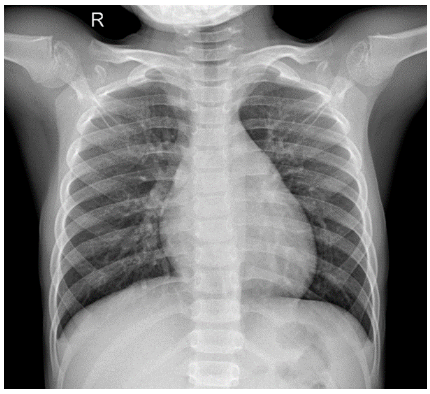

FIGURE 3. X-ray image of a normal patient

Image classification is one of computer vision's fundamental problems. Computer vision is also used in many other tasks, such as object identification, image segmentation, and detection. The process of assigning an image to one of the many preexisting categories is known as image classification. While identifying images is an easy process for humans, an automated system finds it quite difficult. Machine learning techniques can be used to classify images. These machine-learning techniques fall under the deep learning umbrella. Figure 4 shows the Convolutional Neural Network, where each layer of a neural network algorithm known as deep learning is in charge of extricating one or more image features. These nodes get input, analyze information, and then send it to a neuron in the layer below as output. Various changes may be carried out by a computing model that resembles the human brain, known as a neural network.It is a group of nodes known as neurons. Each neuron is in the layers of various levels. From the input layer to the output layer, data is transferred through several hidden layers. Convolutional Neural Networks (CNN) are a popular technique for improving picture categorization accuracy [11].

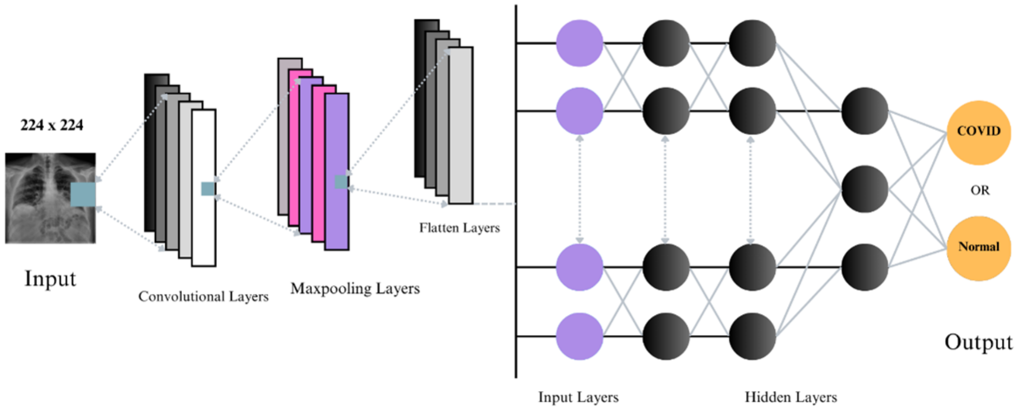

FIGURE 4. Convolutional Neural Network

Both supervised categorization algorithms and unsupervised classification methods may be used to classify images. While unsupervised classification is entirely computer-operated, supervised classification makes use of training data in addition to human interaction. The training phase and the classification phase are the two stages of supervised classification. The classifier receives class information during the training phase. It is during this stage that a model is learned [12]. In the classification step, it places the picture into one of the predetermined classes using the knowledge from the training data. For the goal of classifying images, a variety of techniques are utilized, including the minimal distance algorithm, the K-nearest neighbor algorithm, the nearest clustering algorithm, the fuzzy C-means methodology, the maximum likelihood algorithm, and more [13, 14].

The hyperparameters used in the experiment are detailed in Table 1. The original dataset consisted of 2541 X-ray images, which were transformed through data augmentation techniques to maintain the same number of images. Both datasets included labeled X-ray images categorized as COVID-19 and normal cases. The resolution of the images was 1024 × 1024 pixels. Data splitting was performed with a ratio of 75% for training and 25% for testing. Data augmentation techniques applied to the transformed dataset included rotation, flipping, and zooming. These hyperparameters were carefully selected to enhance the model's performance in accurately classifying COVID-19 from CXR images, ensuring robustness and generalization capability.

TABLE 1. Hyperparameter values of the experiment

Characteristics	**Original Dataset**	**Transformed Dataset**
Dataset size	2541 X-ray images	2541 images (after data augmentation)
Data types	CXR images, labeled	CXR images, labeled (Positive/Negative)
Image Resolution	1024 × 1024	1024 × 1024
Data Split	Training: 75%, Testing: 25%	Training: 75%, Testing: 25%
Data augmentation	None	Rotation, flipping, zooming

The computational resources employed in the study encompassed a personal GPU for dataset preparation and hardware-accelerated model training. Software-wise, Python served as the primary programming language, alongside TensorFlow and Keras for deep learning model development. Additionally, Anaconda Navigator and Jupyter Notebook facilitated dataset management and online model training, while Google Colab provided collaborative development capabilities. GitHub was utilized for version control, and Matplotlib aided in visualizing experimental findings. These resources collectively supported the efficient development, training, and evaluation of the proposed CNN model for COVID-19 identification using CXR images.

The most effective language for data analysis is Python. Python programming is very successful with deep learning-based difficulties due to Python's extensive library access. Large datasets and online model training were managed using Anaconda Navigator, Jupiter Notebook, and Google Colab, with a personal GPU being used for dataset preparation. Additionally, they were utilized to store all the data so that GitHub could be used to access it from any GPU. GitHub is appropriate for collaboration since it offers a code management and teamwork tracking system.

Images from chest X-rays of patients and healthy people are included in this collection. The dataset consists of CXR pictures from various sources, and each image is given ground truth labels indicating whether it conforms to the positive or normal class. Table 2 presents the dataset details.

Table 2. Prepared Dataset

Dataset Details	**Count**
COVID-19	531
Normal	87
Total of Images	609

3.2. **Data preprocessing.** A crucial step in getting the datasets ready for the CNN model's training is data preparation. This stage involves several procedures to make sure the data is in a format that the neural network can understand and to increase the model's effectiveness. The preprocessing of the data is briefly mentioned in the study. The following are typical data preparation processes for the CXR images.

(1). **Data Augmentation.** Data augmentation is a method for growing the dataset without adding any new information. It entails giving the already-existing images arbitrary adjustments including rotation, flipping, and zooming. The model's capacity to generalize to several iterations of the same picture is improved as a result of this approach.

(2). **Splitting the Dataset.** The dataset is typically divided into training, validation, and testing sets. The CNN model is tested using the testing set to evaluate the performance of the model on untrained data, validated using the validation collection to adjust the hyperparameters, and trained using the training set.

3.3. **Block Diagram.** The block diagram in Figure 5 shows the process for classifying CXR images to differentiate between positive and negative cases. The process begins with the input of CXR images from a dataset, which are then preprocessed to ensure uniformity and prepare them for model training. Preprocessing steps include loading images of a specific size, partitioning the dataset, and applying data augmentation techniques to enhance model generalization. The labeled dataset is used to train a model capable of making decisions about the presence of COVID-19. Fine-tuning techniques are applied to optimize model performance. The trained model then evaluates new images, and post-processing steps such as confidence scoring calculation may occur. This comprehensive approach ensures that the system provides accurate classifications of COVID-19-affected and normal cases based on input CXR images.

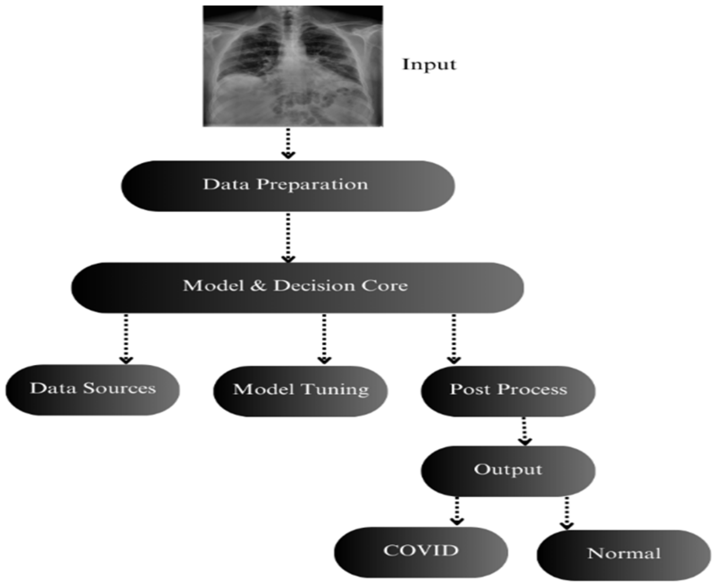

Figure 5. Block diagram of the system

3.4. **System Architecture.** System architecture gives a review of the entire system. A CXR image serves as the input, and a prediction of the image serves as the output in this design. In this instance, it will forecast whether the image is impacted by COVID-19. Figure 6 depicts the system architecture of the CNN used for classifying CXR images as affected or normal.

The input form measures 224×224 and has three channels. In the first two layers of the intended design, the filter size is 32 with padding, the kernel size is 3, and the activation function is ReLU. Next, a first max-pooling layer with 2 pool sizes and 2 strides is applied. The following layer is a flat layer that creates a single column of features from pooled data.

Eventually, two broad layers were visible. While ReLU is the activation function of the first layer, softmax is the activation function of the least dense layer. Following preprocessing, the network gains new features. The architecture is shown in Figure 6.

3.5. **Convolutional Layer.** The convolutional layer is CNN's foundational layer. The design attributes are determined by this. In this layer, a filter is utilized to the input image. Convolution is the result of the same filters, and it creates the function map. A convolution operation multiplies weight sets with the input [15]. An array of input data and a two-dimensional collection of weights are combined to create a filter [16]. A single value is obtained by multiplying an equal-sized input and filter patch to form a dot product. This product is applied between the filter and the filter-sized patch of the input. The filter is used to multiply the input from several places; it is also smaller than the input. The filter is created as a unique method to recognize particular elements as it meticulously goes through the entire image.

- **Pooling Layer.** The down-sampling of characteristics is allowed by the pooling layer, which summarizes their presence. It frequently follows some spatial invariance

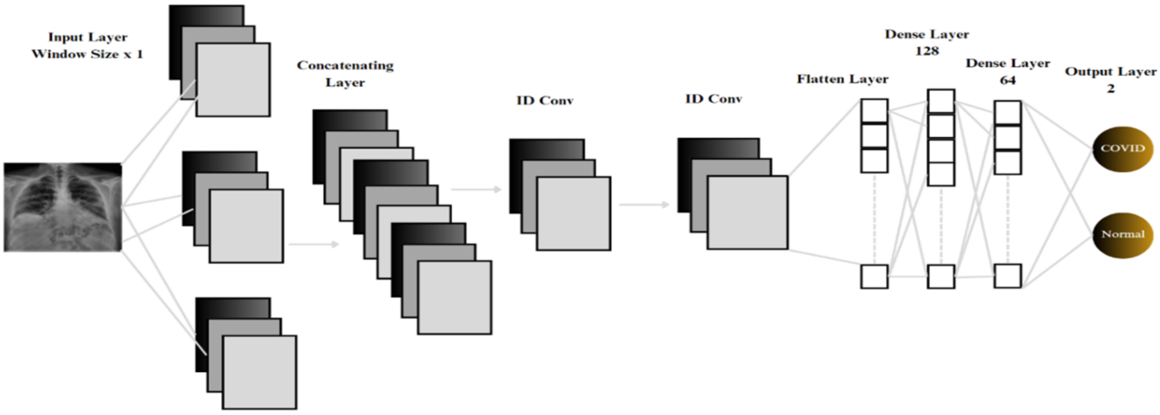

FIGURE 6. System architecture

and a convolution layer. Average pooling and max pooling, two widely used pooling approaches, are used to highlight a function's average presence and its most active existence.

- **Flattened Layer.** The completely linked layer uses the flattened layer to construct a single vector to transfer data into an array with one dimension for usage inside the matrix. A long, narrow one-dimensional feature must be used. If desired, vectors may be flattened. In the end, the single vector is connected to the last step of the classification model, also referred to as a completely linked layer.
- **Fully Connected Layer.** The fully connected layers that CNNs primarily use are particularly beneficial for computer vision image categorization and recognition. The CNN method splits the image into features and processes each one individually. The first two steps in this process are convolution and pooling. The flattening of input connects every neuron within a completely linked layer to every other neuron. One often-used entirely linked layer is the ReLU activation function.

4. Experimental Results and Analysis.

4.1. Experimental Environment and Performance Indicators. By utilizing various methodologies, we developed a thorough strategy to choose the ideal model for the classification problem. TensorFlow and the Keras library from Python were used to run the simulations. The model's accomplishments were visualized using the Matplotlib library in Python using experimental findings. The suggested model's output was evaluated using extensive experimental findings and debate.

Accuracy, precision, recall, and F1-score as shown in Equations (1), (2), (3), and (4) are utilized to evaluate the efficacy of the proposed model. These performance metrics were evaluated in accordance with the confusion matrix result, which produced four distinct outcomes. Here, the terms true positive (TP) and true negative (TN) relate to the number of CXR that were predicted to be positive for COVID-19, the number that was predicted to be normal, the number that was predicted to be positive for COVID-19 but was actually normal, and the number that were expected to be negative for COVID-19 but were normal.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\text{-}Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

Equation illustrates accuracy as a metric for rating classification models. The model's accuracy reveals how many accurate predictions it produced. Accuracy for binary classification is evaluated using positive and negative values. The ratio of situations that are accurately predicted as positive as specified in the Equation is determined to determine precision [17]. Recall, also referred to as sensitivity, is assessed as part of the CNN evaluation to determine the proportion of COVID-19 positive instances that are anticipated to be positive, also shown in Equation. As indicated in Equation, measuring the F1-score is another crucial component of the evaluation because it helps to determine the proper ratio of precision to recall. Figure 7's confusion matrix reveals that the tailored CNN model correctly predicted 98 TP and TN events. According to this confusing graph, the suggested customized CNN model did an excellent job of forecasting TN cases.

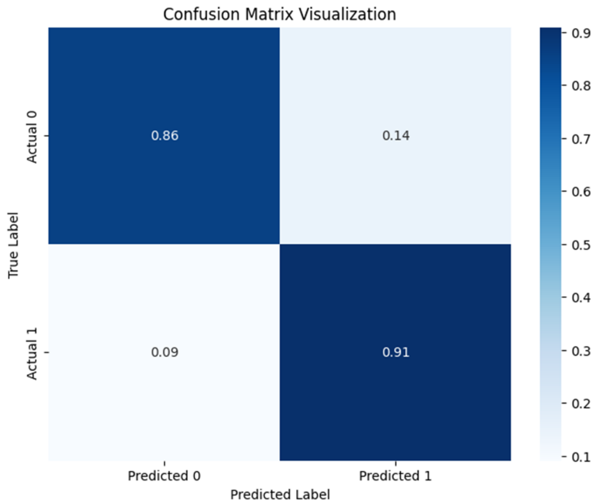

Figure 7. Confusion matrix

In our evaluation of the diagnostic model, we assessed key performance metrics including recall (sensitivity), precision, and accuracy. The recall metric reflects the model's ability to correctly identify positive cases, while precision indicates the proportion of correctly predicted positive cases among all predicted positives. An overall assessment of the model's accuracy in predicting both positive and negative cases is given by the accuracy metric. Our model excelled with a recall (sensitivity) of 98%, precision of 98%, and accuracy of 98.5%, demonstrating its effectiveness in clinical diagnostics.

Comparative analysis of existing models going beyond mere accuracy figures, our study compares favorably against previously published models targeting COVID-19 identification from CXR images. As shown in Table 3, our proposed CNN model excelled with an F1-Score of 98% and an impressive Accuracy rate of 98.5%, outperforming several established techniques in this domain. This comparative analysis underscores the efficacy of our approach in addressing the challenges posed by infectious disease detection through medical imaging.

In the realm of medical image analysis, measures such as specificity, sensitivity (recall), and area under the ROC curve are critical for understanding model performance in a clinical context. While our evaluation primarily focused on recall, precision, and accuracy.

Table 3. Performance Table

Accuracy	Precision	Sensitivity	F1-Score
98.5%	98%	98%	98%

To double-check the results produced by the model, additionally, some arbitrary picture samples were considered. Figure 8 represents the discrepancy between the predicted output and the true labels. Where in Figure 9 model accuracy is a performance metric that evaluates how well the model performs on a given dataset. Figure 10 shows the ROC Curve. Figures 11 and 12 give examples of the model's output generated during testing. Figure 12 displays typical X-ray samples and the accompanying forecasts, along with information on the X-ray output size in the prediction column. Figure 11 shows X-ray samples of COVID-19 and the accompanying predictions, together with the size of the output images. Even though the images utilized in this cross-check procedure were not preprocessed, the model identified the images accurately.

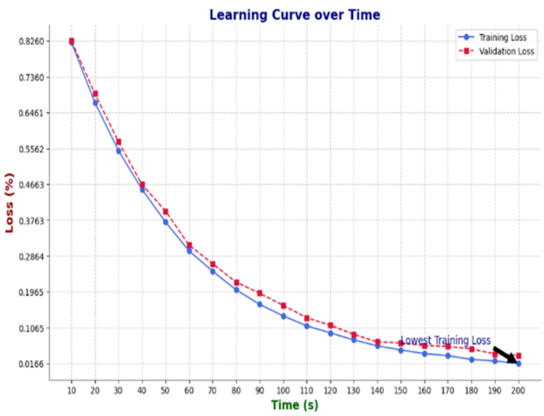

Figure 8. Model Loss

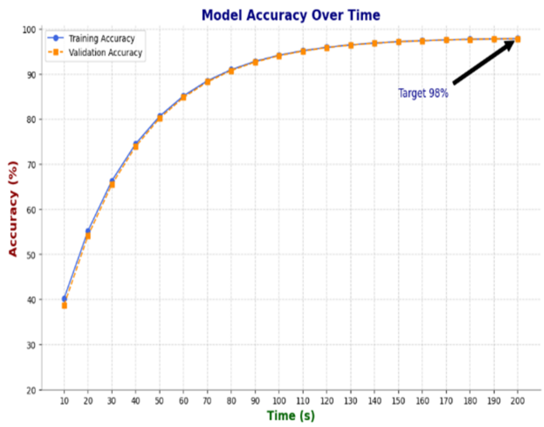

Figure 9. Model Accuracy

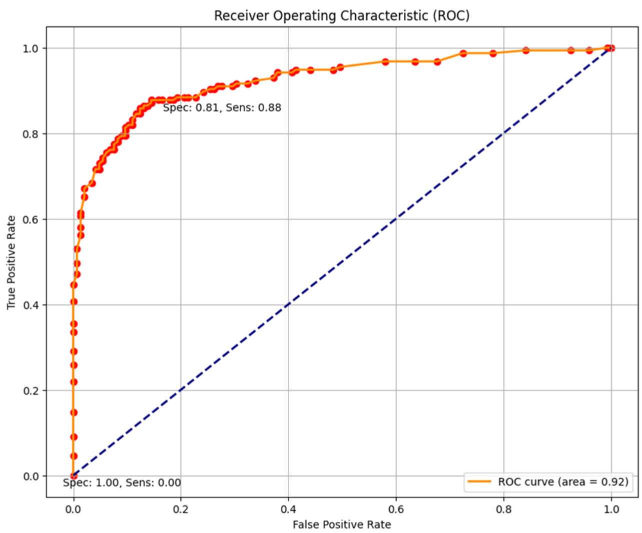

Figure 10. ROC Curve

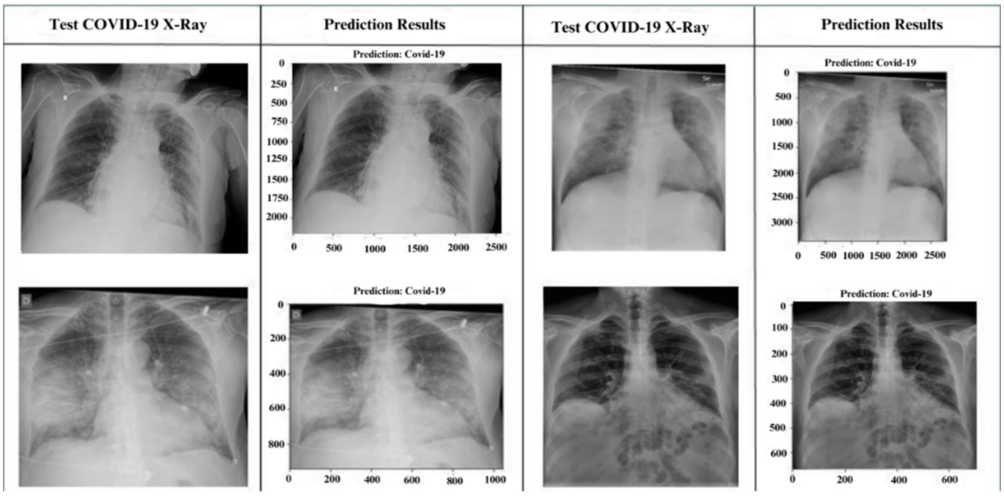

FIGURE 11. COVID-19 X-rays produced by the model underwent testing

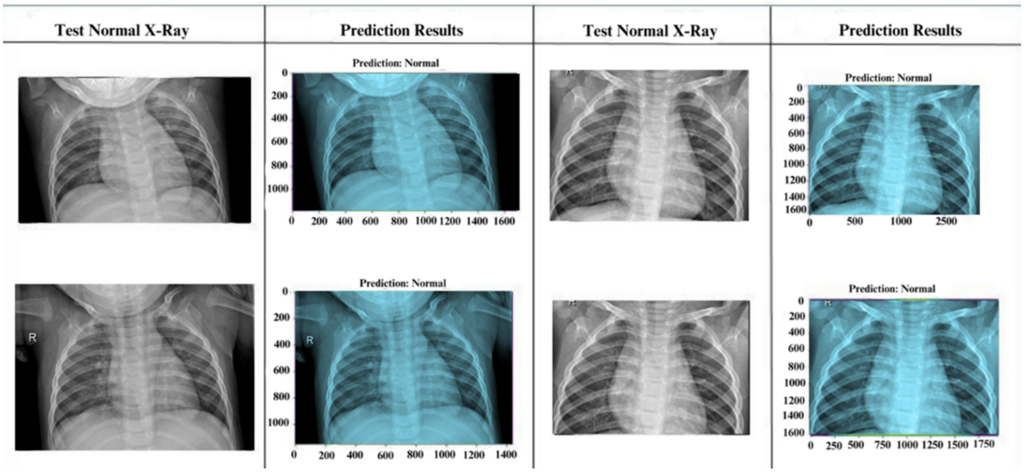

FIGURE 12. Normal X-Ray and Output Procedure by the Model

4.2. **Comparison with Previous Published Models.** Table 4 shows the comparison of model accuracy rates. The proposed model in our study showcases exceptional performance, achieving an outstanding F1-Score of 98% and an impressive Accuracy rate of 98.5%. This surpasses the performance of many models presented in prior research. For instance, the ULTRA-X-COVID Net achieved a commendable Accuracy rate of 98%, while models such as ResNet50, SVM, and MADE-CNN reported Accuracy rates of 95.38% and 94.4%, respectively. Furthermore, the Efficient NetB0 model demonstrated an Accuracy rate of 92.93%, indicating a notable performance gap when compared to our proposed CNN model. These findings underscore the efficacy of our proposed approach in addressing the challenges posed by the task at hand, positioning it as a promising solution in the realm of image classification for COVID-19 identification.

5. **Discussion and Limitations.** The SARS-CoV-2 is the cause of the global health emergency known as COVID-19 [?]. A CNN was developed in this study to identify COVID-19 from CXR images to provide faster and more accurate diagnostic testing. The CNN model produced highly accurate results, and its prospective uses in healthcare are encouraging. To guarantee the validity and application of the model, a few restrictions must be accepted [25].

Table 4. Comparisons with Previous Published Model

Previous Study	Model	F1-Score%	Accuracy%
Sethy and Behra [18]	ResNet50, SVM	95.52	95.38
Singh et al. [19]	MADE-CNN	93.9	94.4
Ahmad I.S, et al. [20]	ULTRA-X-COVID Net	98	98
L. Gaur et al. [21]	Efficient NetB0	88	92.93
Zhou et al. [22]	ResNet-SVM	93.6	93
Hemdan et al. [23]	AlexNet	89	90
Our Proposed	**CNN**	**98**	**98.5**

The customized CNN model performed admirably, obtaining 98.5% accuracy, 98% precision, 98% recall (sensitivity), and an F1-score of 98%. These good findings imply that the model can distinguish between positive and normal CXR pictures. The model is a strong contender for aiding early detection and screening efforts because of its high accuracy, particularly in areas without easy access to PCR testing facilities.

Our commitment to ensuring the validity and reliability of our findings through robust validation techniques and mitigation strategies. We acknowledge the importance of model validation and the risk of overfitting, particularly in the context of deep learning-based disease detection tasks. To address these concerns, we employed rigorous validation strategies throughout our study. Our model underwent thorough validation using cross-validation techniques, with the dataset split into training and testing sets at a ratio of 75% to 25%. This made it possible for us to analyze the model's broad generalization capabilities and performance on untested data. Furthermore, we conducted a detailed analysis of model complexity, considering factors such as architecture depth and parameter count. This analysis helped us strike an optimal balance between model complexity and performance, thereby reducing the risk of overfitting.

To mitigate overfitting during model training, we incorporated regularization techniques such as dropout and weight decay. These techniques were carefully tuned and evaluated to ensure their effectiveness in preventing overfitting. Our results demonstrate the model's strong ability to generalize well to unseen data, providing confidence in its reliability and effectiveness. However, we recognize the ongoing need for continuous improvement and exploration of novel techniques to further enhance our model's capacity to generalize and reduce the risk of overfitting.

Regarding the importance of clinical validation and collaboration with medical professionals, we engaged with Dr. Muhammad Faheem Khan at the Women and Children Hospital in Bannu to discuss our model. Dr. Khan, in charge of the Ultrasound/X-ray Section, appreciated our work and expressed satisfaction with the model's real-world applicability and accuracy in clinical diagnostics. This positive interaction underscores the significance of engaging healthcare experts to validate and refine AI models for practical use. Moving forward, we are formalizing collaboration with Dr. Khan and the hospital to conduct rigorous clinical validation studies to evaluate the performance of the model in real clinical scenarios and contribute to advancing AI applications in healthcare.

Our collaboration with Dr. Khan and the Women and Children Hospital reflects our commitment to ensuring that our diagnostic model meets the highest standards of accuracy and reliability, guided by input from medical professionals. We are dedicated to conducting robust studies to validate and enhance the utility of our model and to make meaningful contributions to the field of AI-driven healthcare diagnostics.

Given the CNN model's promising performance, it is essential to clinically evaluate it against established diagnostic procedures such as PCR testing. The accuracy and safety of the model will be proven through extensive clinical testing and collaboration with medical specialists. CNNs are one type of deep learning model that may be computationally and resource-intensive. The concept may be difficult to implement in areas with low resources or inaccessible high-end computing equipment. The model's accessibility can be increased by creating lightweight copies of the model or investigating edge computing options.

6. **Conclusions.** The objective of this study was to use CXR images and deep learning algorithms to develop a classification system for COVID-19 diagnosis. A tailored CNN model was suggested for early identification of COVID-19 utilizing CXR pictures to achieve this objective. The X-ray images' intricate details were enhanced by preprocessing the data utilized for training, testing, and validation [26]. Cross-dataset analyses are carried out to assess the suggested model's adaptability in a real-world setting. The model was trained and validated using two datasets that were available to the public. The model was designed with nine layers specifically to deliver precise and effective outcomes. Three carpooling layers, four convolution layers, two dense (ANN) layers, and a total of nine layers are used to extract local data, reduce the size of the feature maps produced by convolution layers, and differentiate between COVID-19 and standard CXR images [27]. The tailored CNN model obtained an accuracy of 98.5%, a precision of 98%, a recall (sensitivity) of 98%, and an F1-score of 98.5%, for COVID-19 and conventional CXR images, respectively. To balance the quantity of accuracy and samples with other models, a comparison table was created. Our system performed the COVID-19 classification job with more efficiency than other techniques with and without self-attention by requiring fewer parameters and producing results faster. The results of the tests demonstrated that our method worked better than existing COVID-19 screening techniques [28]. Millions of people have already died because of COVID-19 worldwide, and populations are still at risk [29]. A technique for automatic diagnosis offers quicker and simpler screening predictions. We predict that our proposed approach, which may be a competitor in early COVID-19 detection in hospitals, will be successful and have a significant impact in high-risk locations with a lack of resources and diagnosis facilities.

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