Enhancing chest image classification using PCA and CNN model

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ABSTRACT

Deep learning (DL) has a significant impact on X-ray images for diagnosing and categorizing a range of lung disorders. The proliferation of extensive annotated image datasets has resulted in the emergence of convolutional neural networks (CNNs) as a useful instrument for the tasks of image recognition and categorization. Despite this abundance, the primary challenge in medical diagnosis continues to be the classification of these images. This research aims to enhance image classifiers by using the CNN model; both training and testing datasets underwent analysis using the suggested CNN system. An analysis and comparison are conducted on the impact of feature extraction using the Principal Components Analysis (PCA) technique. The study attains maximal classification efficiency by preparing images through dimensionality reduction before classification, concurrently enhancing the efficacy of CNNs in feature extraction. The optimal tuning strategies for enhancing the performance of the proposed CNN were found to include boosting the number of epochs, changing the optimizer, and decreasing the learning rate, as well as improving algorithm gains by using pre-trained weights. The suggested system outperforms previously utilized approaches like VGG or DenseNet, with more than 99.80 percent accuracy, precision, recall, and F1-score values. The suggested methodology demonstrates considerable promise for enhancing the efficacy and precision of lung disease diagnoses derived from chest X-ray images, thereby offering clinicians beneficial decision support and accelerating the implementation of treatment strategies. Furthermore, the developed model facilitates the identification of pulmonary ailments, encompassing critical conditions like COVID-19, thereby facilitating timely and efficacious patient care.

1. Introduction

Pneumonia is a serious pulmonary illness that impacts individuals. The pneumonia infection may be caused by fluid building up in the alveoli, which may lead to a number of breathing problems, as well as a temperature and chest discomfort. There are several germs that may cause pneumonia, such as bacteria, viruses, and fungus. This problem has to be diagnosed and treated correctly. has to be diagnosed early and correctly since it is so bad for kids, old people, and those with weak immune systems. It is essential to identify the pneumonia and the microorganisms responsible for the illness in order to plan and provide the requisite therapy [1], [2]. The detection of lung disorders via the use of chest X-ray images provides a considerable amount of potential for the improvement of patient care and healthcare practices [3].

Traditionally, X-rays of the chest have been the most important diagnostic technique for pneumonia. On the other hand, the interpretation of these pictures is greatly reliant on the competence of radiologists, which might result in a possibility for variability in diagnosis. Recent developments in artificial intelligence (AI) and DL, in particular CNNs, have shown that they have the potential to automate the processing of medical pictures. This would result in improved diagnosis accuracy and a reduction in the workload of healthcare personnel [4]. As a result, the field of medical image analysis has seen a remarkable transformation [5]. Successful applications of AI have included the treatment of skin cancer and chronic disorders [6]. In the search for a cure for the new coronavirus, scientists now expect AI to play a vital role and, in doing so, help ease the related fear that is afflicting people all over the world [7].

However, the recent COVID-19 pandemic has placed severe strains on the healthcare system as it attempts to meet the costs associated with an ever-growing number of patients and their requirements. Because of this, the healthcare industry must adopt a new mentality in light of the recent effects of COVID-19. Thus, it is crucial to use cutting-edge tech like AI to create healthcare solutions that are both intelligent and self-sufficient [8], [9]. In the process of categorizing COVID-19 pneumonia, the performance of a deep learning-based strategy that is implemented by Convolutional Neural Networks (CNNs) increases [10]. On the other hand, the limitation of CXR image datasets and the pressing need for more effective methods is highlighted by the difficulty of generalizing deep neural network classifiers [11].

Pneumonia continues to be a serious worldwide health concern, particularly in poor countries. It is also a contributor to a substantial number of fatalities each year, particularly among children who are under the age of five [12]. The chest X-ray, also known as a CXR, is a diagnostic imaging method that is frequently used. These images provide greater clarity to the targeted parts and organs. These organs include the lungs, the heart, and the ribs. The identification of important signs of pneumonia, such as lung inflammation, fluid buildup, and infection, is vital for determining the degree and severity of the illness. Chest X-rays are necessary for this identification [13].

Through improvements in diagnostic accuracy and efficiency, machine learning (ML) has brought about a revolution in the processing of medical pictures, notably chest X-rays (CXRs). When it comes to automating CXR interpretation, ML algorithms and deep learning models in particular play a crucial role. This enables the diagnosis of a variety of thoracic illnesses, such as pneumonia, TB, and lung cancer, via the use of machine learning algorithms [14]. The introduction of deep learning in recent years has resulted in a paradigm change in the field of medical image analysis. The use of deep learning (DL) for image processing has resulted in revolutionary improvements, which have made it possible to achieve capabilities that were previously unattainable using conventional methods [15], [16].

The aim of this study is to enhance the diagnosis outcomes of chest diseases across various datasets and to solve the fundamental issues that are involved in distinguishing chest X-ray images for various disorders, which include COVID-19, pneumonia, and other conditions [17]. Significantly, this study has made noteworthy contributions through utilizing a variant of CNN for both training and fine-tuning network weights on large and small datasets. Additionally, to enhance the overall effectiveness of the recommended method and reduce overfitting, a unique training process is employed, using the assistance of a variety of alternative organizational structures for training, such as validation patience and data augmentation. Furthermore, to evaluate the effectiveness of the suggested method, this research compares its results across several important measures, such as accuracy, precision, recall, specificity, and F1-score.

Furthermore, the research is presented in six sections. Section 2 provides a literature overview on the application of AI in medical imaging, along with brief explanations of the various DL methods used. Section 3 describes the methodology used to build the platform and its subcomponents. The metrics utilized for evaluation purposes are laid out in Section 4. Section 5 will discuss the outcomes achieved by the suggested CNN model. The final section of this study is the conclusion and discusses some potential future applications of the system.

2. Related Work

Radiology is a crucial component of contemporary medical treatment, yet ongoing difficulties persist in the form of an increasing demand for services and a scarcity of personnel. There is a possibility that the most recent developments in the field of artificial intelligence may provide assistance to radiologists and contribute to the resolution of these issues [18]. The literature surrounding the use of AI algorithms in various medical imaging applications will be covered in this section. Related to chest medical diagnosis, this section will also discuss other computer vision and image processing techniques. Image categorization is the process of assigning each image to one of many categories. Computer vision encompasses a fundamental issue that serves as the basis for other related operations, including detection, segmentation, and localization.

In the year 2025, Oltu et al. [19] introduced a deep learning (DL) model that has been automated. This model is superior to a number of other state-of-the-art approaches when it comes to making diagnoses of chest diseases. The suggested system utilizes a dataset consisting of 21,165 chest X-rays and employs DenseNet201 for feature extraction and average clustering for the retention of important spatial information. As a consequence of this combination, a strong categorization system is created that achieves exceptional accuracy. A total accuracy rate of 97.87 percent is an impressive feat that has been accomplished by the framework that was put out.

Bahram et al. (2025) [20] conducted a comparison of various deep learning models for the purpose of classifying chest X-rays that exhibited several diseases. Their primary objective was to achieve balanced improvement of many illness categories. The purpose of the research was to determine which design would be the most appropriate for clinical deployment, and therefore it included both transformer-based designs and standard convolutional neural networks. The findings showed that each and every one of the models attained a high level of classification accuracy, with all of them surpassing the 95% mark. EfficientNetV2-M outperformed all of the other models in terms of accuracy, reaching a score of 96.02%, and it also earned a robust F1-score of 90.08%. MobileNetV2, while it is somewhat less precise, was able to deliver the most efficient and quickest prediction in terms of resources.

Awotunde et al. (2025) [21] propose an improved convolutional neural network (CNN) that is coupled with principal component analysis (PCA). The suggested model makes use of principal component analysis (PCA) for dimensionality reduction while simultaneously influencing the strengths of CNNs in feature extraction. Experiments were carried out on a dataset consisting of chest X-ray pictures representing pneumonia. To preprocess the input data, a multi-layered CNN architecture that was enhanced using principal component analysis was used. There is a 98% degree of accuracy shown by the findings. To improve the detection of pneumonia using medical imaging, artificial intelligence applications and the use of mobile devices and networks can be leveraged in several areas [22]. Similarly, cloud computing technologies enable remote access to data through web tools and applications [23], [24]. Furthermore, proper resource management contributes to improving the digital environment, especially in the educational and medical fields [25], [26].

A DL anomaly detection model was created by Zhang et al. [27], It is imperative to have swift and dependable methods for COVID-19 triage. The GitHub website furnished one hundred chest X-ray (CXR) images obtained from seventy patients diagnosed with COVID-19, while the ChestX-ray14 website offered an additional 1,431,000 images acquired from 1008 patients suffering from diverse pneumonia types. Zhang's model involves a primary network along with classification and anomaly detection heads. The first segment of the CXR analyzer extracts advanced features utilized in both classification and anomaly detection functions. When using a value of 0.25 for the study's parameter T, this work had a sensitivity of 90% and a specificity of 87.8%, for a total of 96% and 70.6%, respectively (when parameter T was 0.15). Nonetheless, the model had 30% false positives and missed 4% of COVID-19 cases.

The study by Polus (2025) [28] proposes a method for the categorization of chest X-ray images that involves the combination of Generalized Extreme Value (GEV) probability density functions (PDFs) and Convolutional Neural Networks (CNNs). The old technique is connected to the way we have presented it, and the results demonstrate considerable improvements in key performance indicators because of this connection. When compared to the previous technique, which achieves an accuracy of 89.85%, the suggested method achieves a greater accuracy of 91.95%, which often results in improved skills in correct categorization. The precision of the suggested technique is greater, coming in at 91.13%, which highlights its ability to accurately detect affirmative situations. On the other hand, the suggested technique has a higher level of specificity (67.22%) in comparison to the conventional approach (61.20%). The suggested technique has an F1-score of 95.01%.

Research by Buriboev et al. (2025) [29] presents a method for the binary classification of pneumonia in chest X-ray images. Utilizing adaptive tile scaling, variance-guided clipping, and entropy-weighted redistribution, the enhancement model is an upgrade over the conventional contrast-limited methodologies. Its purpose is to optimize image quality for the purpose of pneumonia diagnosis. When applied to the Chest X-Ray Images (Pneumonia) dataset, which contains 5856 images, the upgraded images make it possible for the CNN to attain an accuracy of 98.7%, a precision of 99.3%, a recall of 98.6%, and an F1-score of 97.9%. Other researchers [30] have focused on the shift in the use of digital tools in multiple fields, including health and education. The research conducted by Kadhim et al. (2023) [31] utilizes transfer learning, a widely used methodology. The process entails the transfer of the weights or information obtained from the solution of one problem to another that is closely related. When using CNN, transfer learning entails training a model on another dataset while keeping the features (neuron weights) obtained in the first dataset.

3. Method

Classifying medical images, detecting viruses like COVID-19, and measuring the severity of lung infections are critical during this pandemic. The absence of sufficient health care providers, facilities, and early disease diagnosis among a large population was the impetus for this strategy. This paragraph discusses the CT-based classification system suggested for lung diseases. The proposed CNN model consists of three stages, starting with preprocessing, then feature extraction, and the third is classification. The PCA technique serves as a feature extraction stage. In contrast, a sigmoid function layer follows one or more fully connected layers in the classification stage (see Fig. 1).

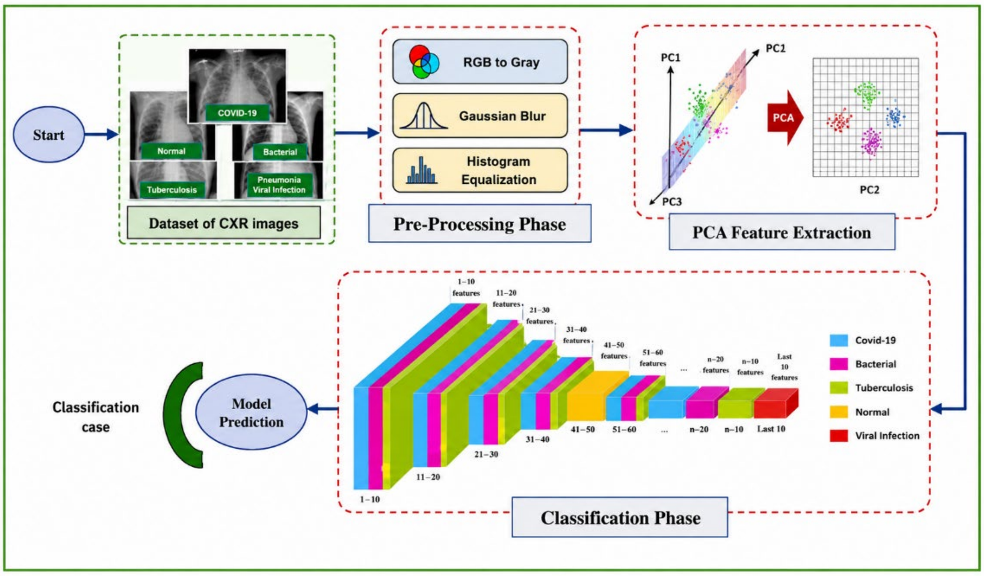

Fig. 1. The methodology diagram is used for image classification

3.1. Dataset

This particular investigation made use of a dataset that was composed of five distinct classes, which were primarily created from three distinct parent datasets. The data were gathered from the extensive collection of X-ray and CT images that were compiled by Calgua [32]. These photos included a variety of lung illnesses. This database is constantly being updated and now has 752 X-ray pictures that are up to date until the 15th of June, 2020. The bulk of these photos, 435, reflect instances of COVID-19. This study did not contain lateral X-rays or CT scans, and insufficient metadata omitted gender information for forty-three photos. Additionally, this investigation did not include additional photographs. The patients have an average age of 54, with about 256 men and 136 women affected. On average, the patients come from the United States. Fig. 2 illustrates the construction details and balanced composition of the COVID-19 five-class dataset obtained through these efforts.

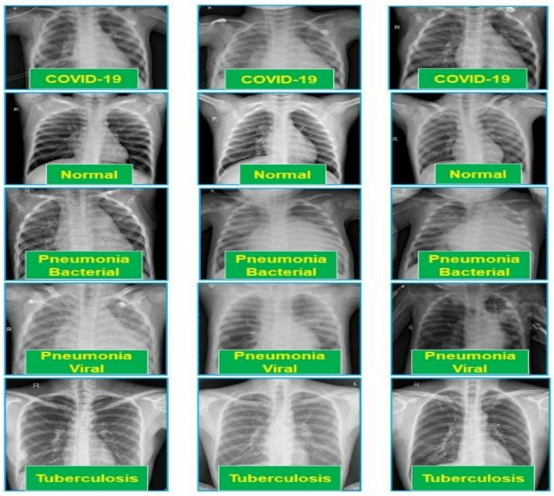

Fig. 2. Images from each of the five X-ray classes

The second source that was employed for the purpose of producing balanced sets of pneumonia-positive radiographs (normal bacterial viral) and normal pictures was acquired from a different dataset that had around 5,863 images [33]. On the other hand, the dataset has a significantly lower number of TB X-ray images when contrasted with other classifications; hence, it is possible that class imbalance will have an effect on the detection performance. Several X-ray images were chosen at random and then resized using augmentation methods to remedy this problem.

3.2. Pre-Processing Phase

In the domain of DL approaches, this is the most frequently employed strategy for reducing background noise, highlighting regions of an image that may be useful in an identification task, or lending a hand during the learning phase. Through the use of this preprocessing procedure, all of the superfluous data and noisy values are eliminated. It is necessary to perform pixel force normalization in the interval [0, 1] in order for the model to converge. CNN models were supported by the resized response images, which operated in conjunction with the design of the system. To easily take advantage of higher-quality response images, EfficientNets have a low computational cost in terms of memory and latency. Hence, the impact of adjusting the response determination on the model's precision. The steps below describe the preprocessing phase of the procedure:

- Produce a grayscale image by converting the RGB color image. Since a grayscale image just has a single channel of information, it can be processed more quickly than a color image, which has many more (three channels). This procedure is carried out utilizing Eq. (1):

$$Grayscale\ (i,j) = (0.2989 \times r) + (0.5878 \times g) + (0.1140 \times b) \tag{1}$$

- In order to remove noise or sharpness, soften, and blur features that may have been present in the original image, the image is then smoothed out using a method known as Gaussian blur, as in Eq. (2):

$$Gb(i,j) = \frac{1}{2\Pi\sigma^2} e^{\frac{-i^2+j^2}{2\sigma^2}} \quad (2)$$

In the context of this description, x represents the displacement along the horizontal axis from a reference point at zero. Similarly, y corresponds to the deviation in the vertical direction relative to said reference position. Additionally, σ denotes the standard deviation associated with a Gaussian distribution.

- The use of a histogram equalization strategy is recommended in order to produce a better contrast in the picture. This approach is designed to improve visual clarity by increasing the difference between the regions that are the brightest and the darkest. This results in darker blacks and brighter whites, as shown in Equation (3):

$$Hist(v) = cut\left(\frac{(cdf_{(v)} - cdf_{min}}{(m*n)-1}\right) * (L-1) \quad (3)$$

The Cumulative Distribution Function (CDF) is determined in accordance with the number of pixels present in the picture, which are designated as m and n, respectively. The range of gray levels employed, which amounts to 256 levels, is represented by L.

- Either reduce the picture size or rearrange its proportions resulting from the preceding processes. These actions are typically conducted to enhance computing efficiency, although they include trade-offs concerning data quality and model effectiveness, as shown in Eq. (4):

$$J_{reshape(x.y)} = \sum_{h=1}^{x} \sum_{w=1}^{y} j\_Gray(x.y) \quad (4)$$

where the width of the original image is w=96, the height of the original image is h=103, the width of the image after it has been resized to x=20, and the height of the image after it has been resized to y=20.

PCA is appropriate to use when the data is not labeled or for preprocessing to remove noise and speed up subsequent algorithms. In the case of labeled data, LDA is used, and the main objective is to achieve classification or maximize class separation. The use of autoencoders is in situations where the connection in the data is non-linear and complicated, and when the data and computer resources are available to train a neural network

3.3. Feature Extraction

Machine learning algorithms rely on correct feature extraction, presenting considerable difficulties in the exact diagnosis of lung disorders from X-ray images. Improperly selected features may provide a poor data representation, hence resulting in ineffective classification. PCA is used for numerous feature extraction applications and is a cornerstone for further improving machine learning models in X-ray image-based diagnostics. PCA relies on extracting features from principal components by reducing the dimensions of the dataset. Simultaneously, a new set of principal components is extracted from the original features by reducing the dimensions of the dataset [33]. At the same time, d is taken into account as a data point, where n is the total number of dimensions, considering that the information provided is $z_1,\ z_2,\ z_d \in \mathbb{R}^n$, and this algorithm is implemented through the following steps.

- The mean vector MV in m dimensions is calculated as:

$$MV = \frac{1}{d}\sum_{i=1}^{d} z_i \quad (5)$$

- For the observations, the covariance matrix CM is:

$$CM = \frac{1}{d}\sum_{i=1}^{d} (z_i - MV)(x_i - MV)^d \quad (6)$$

CM is used to calculate the eigenvalues and eigenvectors.

- Performed through the PCA method in order to decrease the dimensionality of the data, which requires linear transformations.

$$y_d = a_{d1}z_1 + a_{d2}\, z_2 + \ldots + a_{dd}\, z_d \tag{7}$$

3.4. The Proposed CNN-Deep model

Architects of DL have yet to reach consensus on the actual impact of DL on many sectors. Healthcare professionals are familiar with DL's stance because it has been applied to the study of several different illnesses. After features have been extracted, they are fed into a separate network that handles categorization. As retraining a very deep network from scratch might be prohibitively expensive computationally, this method is often used to either retain the useful feature extractors trained in the first phase or train a new network from scratch. Typical network layers, such as input, convolution, max-pooling, and completely linked, are used in the suggested architecture.

Additionally, the implementation of a rectified linear unit (ReLU) activation function following the completion of each dense layer (fourth, seventh, and eighth), a ReLU activation function is first implemented after each convolution layer (first through seventh). A dropout rate of twenty percent was applied to the model's one fully connected layer in order to reduce the likelihood of the model overfitting the data. The trained model surpasses other adaptive approaches that are currently in use because it has a higher convergence rate. This, in turn, minimizes the possibility of making a mistake and increases the likelihood of achieving accurate convergence. Fig. 3 demonstrates the proposed CNN architecture.

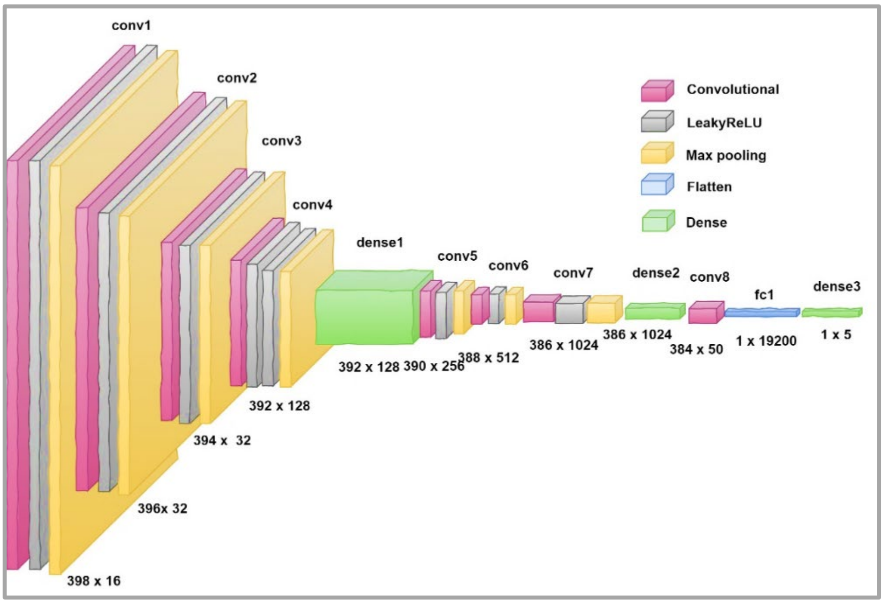

Fig. 3. Layers of the proposed model

3.5. Evaluation Metrics

Work at this step entails determining the classifier's accuracy rate. To evaluate the classifier's efficacy, it must be established how well all predicted and observed class labels match up. Counting the percentage of training data that is successfully classified is just one technique to measure classification accuracy (true positives), the number of well-recognized examples that are irrelevant to the class (true negatives), and the number of incorrectly classified examples (false positives) or unclassified examples (false negatives) [31], [34]. To achieve the highest possible level of transparency, the study uses repeated K-fold cross-validation, which involves several runs and multiple folds, to reveal not only the mean performance of the model but also its standard deviation (stability of performance). The following are the measurements for the quantitative analysis.

- Accuracy, or how many forecasts were accurate relative to how many total predictions, also referred to as high model viability, is as follows:

$$Accuracy = (TP + TN) / (TP + TN + FP + FN) \tag{8}$$

- The precision of a classification system is measured by how accurately a set of documents describes the category to which it has been assigned. Class precision is quantified as

$$Precision = TP / (TP + FP) \tag{9}$$

- Recall is the degree to which a classifier can recognize things that fall under a certain category. It is possible to count the recall of class by:

$$Recall = TP / (TP + FN) \tag{10}$$

- The F1 metric assesses how quickly the precision and recall are synced. If F1 is high, the system's overall performance is satisfactory. As stated in:

$$F1\, Score = 2x\, ((Precision\, x\, Recall)) / ((Precision + Recall)) \tag{11}$$

4. Results and Discussion

The system of this study uses the Python language and the Keras library; the proposed CNN model was developed and trained on the COVID-19 5-class dataset. Input parameter values were determined with consideration of available hardware performance capabilities, resulting in an optimal batch size of 20 for inputs sized at 20 by 20. The input parameters underwent testing over a span of 100 epochs, as shown in Fig. 4, where precision and F-score findings indicated superiority. To evaluate network performance across various scenarios, fresh image samples were utilized while altering parameters within the COVID-19 5-class dataset; this process occurred ten times overall. The highest-performing network based on accuracy during the testing phase among all runs was selected for validation purposes moving forward.

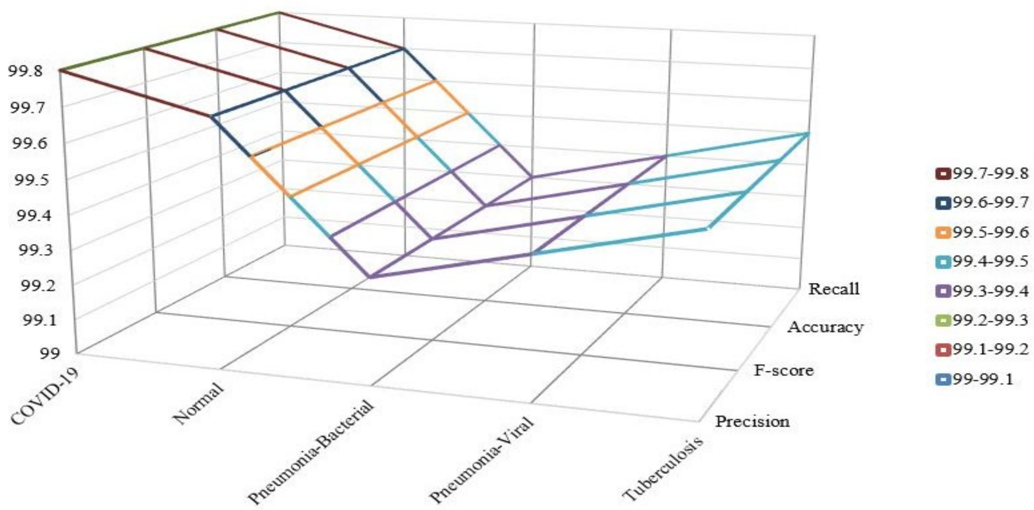

Fig. 4. Analysis of Classifier Efficiency

Table 1 shows the outcomes of several dataset processing strategies. Exactly where the proposed accuracy and recall performance are displayed in Fig. 5 and Fig. 6.

Table 1. Evaluation of Classifier Performances

Ref.	Method	Accuracy	Recall
Suliman et al. (2024) [10]	CNN (deeplearning)	0.857	0.837
Bundea and Danciu (2024) [1]	DenseNet201	0.960	0.960
An et al. (2024) [35]	E-B0&D-121	0.951	0.938
Bhatt and Shah (2023) [36]	CNN	0.841	0.992
Sharma and Guleria (2023) [37]	VGG16	0.921	0.931
Goyal and Singh (2023) [38]	F-RRN-LSTM	0.943	0.954
Ali et al. (2025) [33]	ML+DT+PCA	0.880	0.880
Awotunde et al. (2025) [21]	CNN+PCA	0.980	0.960
Jaganathan et al. (2024) [39]	Modified LeNet + revised ReLU	0.960	0.960
Chandranegara et al. (2024) [40]	ResNet-RS CNN	0.920	0.915
Song et al. (2024) [41]	Transfer learning + pre-trained CNN model	0.900	0.900
Mardianto et al. (2024) [42]	CNN	0.920	0.930
Nithya et al. (2023) [43]	GANs	0.960	0.960
Shiferaw et al. (2025) [44]	CNN	0.934	0.948
Proposed	**CNN**	**0.998**	**0.998**

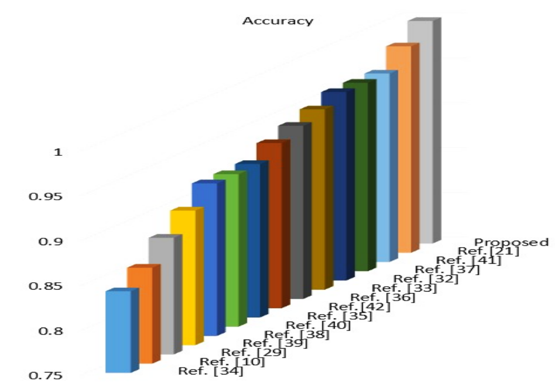

Fig. 5. Accuracy Analysis of Classifier Efficiency

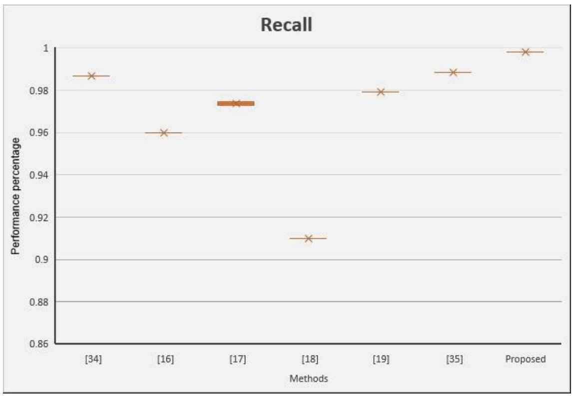

Fig. 6. Recall Analysis of Classifier Efficiency

The findings indicate that the suggested CNN model outperforms alternative approaches in terms of classification accuracy. These results provide strong evidence that DL with CNNs may greatly improve automatic feature detection and extraction from the use of X-ray images to diagnose lung diseases. Additional patient data, particularly from those who have lung diseases, is required for deeper exploration. A technique that distinguishes between individuals with moderate symptoms and those with pneumonia symptoms, even if the latter may not be accurately evident on X-rays, could be useful in future research. As for the execution time for various epochs, it is presented in Fig. 7.

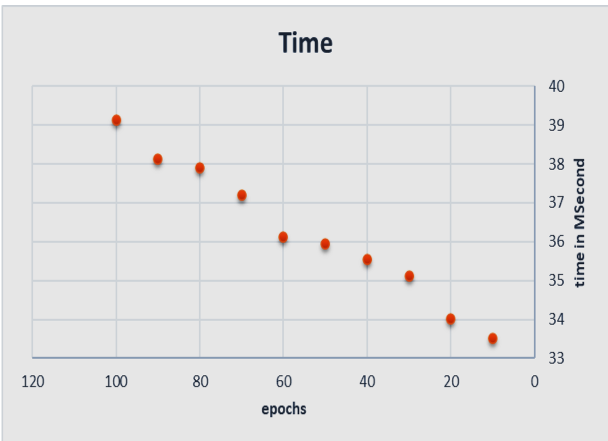

Fig. 7. Time Analysis of Classifier Efficiency

To make the suggested method work better and avoid overfitting, a special training process is used that includes different training strategies, like validation patience and data stimulation. Furthermore, it is imperative to develop models that can accurately differentiate COVID-19 from other similar viral infections, such as SARS, and distinguish the disease from common pneumonia or even normal physiological X-rays. The automated diagnoses solely rely on medical scans without incorporating pertinent patient information, which may be crucial in assessing the risk of contracting the illness. Nonetheless, this study enhances the feasibility of rapid and cost-effective detection of coronavirus disease through automatic means. On the other hand, there are a number of significant constraints that make it challenging to use this in clinical settings. As a result, future research will concentrate on developing systems that are easier to comprehend and have several facets in order to determine whether or not the characteristics discovered by CNNs can be relied upon as valid indications for diagnosing lung instances.

5. Conclusion

Chest disorders are among the most common health concerns globally; they may be life-threatening conditions affecting organs such as the heart and lungs. A substantial volume of patients necessitates a swift and efficient diagnostic procedure. Many individuals have succumbed and been admitted to ICUs due to flawed and inefficient testing protocols, inadequate facilities, and the failure to identify numerous chest ailments at an early stage. Chest radiographs are crucial in diagnosing pneumonia. The results of a study in which simulated images of the lungs were used to distinguish between those of people with disease and those of healthy individuals provide evidence for this. The outcomes show that the suggested approach works, with an acceptable degree of precision. Early stages of disease are detected using the DL architecture. The false-negative rate in image classification systems has been effectively lowered by the use of approaches with a high percentage of classification accuracy. Even yet, the suggested model achieves a very high degree of accuracy (99.8%) in its predictions. The chest x-ray, on the other hand, could not show any abnormalities in instances of mild pneumonia or early pneumonia; hence, alternative imaging modalities might be more effective in identifying the new radiological alterations.

Declarations

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