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An Enhanced Convolutional Neural Network with Principal Component Analysis for Pneumonia Diagnosis Classification from Medical Images

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Abstract

Pneumonia is a lung infection that causes inflammation in the air sacs and is one of the leading causes of death worldwide for children under the age of five. The increasing prevalence of pneumonia, coupled with the critical need for accurate diagnostic tools, drives the development of advanced Machine Learning models. Therefore, this study presents an enhanced convolutional neural network (CNN) integrated with Principal Component Analysis (PCA) to improve pneumonia diagnosis from medical images. The proposed model influences the strengths of CNNs in feature extraction while employing PCA for dimensionality reduction, thus optimizing computational efficiency and reducing overfitting. We conducted experiments on a pneumonia dataset of chest X-ray images, implementing a multi-layered CNN architecture augmented with PCA to preprocess the input data. Performance metrics for evaluation were systematically evaluated against the CNN baseline model. The results demonstrate significant improvements in classification performance with an accuracy of 98%, highlighting the effectiveness of combining enhanced CNNs with PCA. This approach not only enhances diagnostic accuracy but also facilitates quicker and more efficient analysis of medical images, potentially aiding radiologists in clinical decision-making. The findings suggest that integrating traditional machine learning techniques like PCA with modern deep learning frameworks can yield robust solutions for complex medical imaging challenges.

Keywords: Machine learning; Deep learning; Pneumonia; Principal component analysis; Feature selection; Pneumonia, Medical images; Medical diagnostics.

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1. Introduction

Pneumonia is an infection that attacks the air sacs in your lungs, causing them to become inflamed. This can lead to coughing, trouble breathing, fever, and chest pain [1]. Different germs can cause pneumonia, including viruses, bacteria, fungi, and even parasites. While it can range from mild to severe, pneumonia can be very risky for young children, babies, older adults, and people with compromised immune systems [2]. The number of people with pneumonia can fluctuate significantly across geographic regions. Factors such as age distribution, socioeconomic status, healthcare access, and the presence of risk factors like smoking, air pollution, and compromised immune systems all contribute to this variation. Worldwide, pneumonia remains a major contributor to both illness and death, particularly for susceptible populations, such as small children, the elderly, and people with underlying medical issues. 740,180 children under the age of five died from pneumonia in 2019 [3], which makes up 14% of all pediatric cancer deaths. Beyond mortality, pneumonia also creates a significant burden of illness. This includes hospital admissions, doctor visits, and healthcare expenses. The occurrence and prevalence of pneumonia can fluctuate seasonally, with colder months and regions lacking access to vaccines, antibiotics, and healthcare seeing higher rates (WHO) [4].
One area of artificial intelligence is machine learning (ML). The primary objective is to develop models and methods for computers to learn from data and make judgments [5]. Many different studies have shown that ML models are good at diagnosing pneumonia. These algorithms are trained on massive collections of medical information, including chest X-rays, and can be very accurate at finding the illness [6]. This makes things faster and easier for doctors and potentially leads to detecting pneumonia earlier. One such study by Rajpurkar et al. (2017) [7] developed a program called CheXNet, which attained results comparable to radiologists when it came to spotting pneumonia on X-rays. Another study, in [8] investigated using a complex ML tool called a deep learning algorithm to examine chest X-rays for diagnosing pneumonia. The authors in [9] used CNN to analyze chest X-rays. This model achieved an impressive accuracy rate of nearly 96% in identifying cases of pneumonia. These studies highlight the exciting possibilities of machine learning for diagnosing pneumonia more accurately and efficiently.
An enhanced CNN integrated with PCA is a robust framework for pneumonia diagnosis from medical images, particularly chest X-rays. CNNs are powerful DL models that automatically extract hierarchical features from images, making them highly effective for medical image classification. However, large datasets can contain redundant and noisy data, potentially reducing CNN performance. PCA, a dimensionality reduction technique, addresses this issue by transforming the dataset into a set of orthogonal components, capturing the most significant variance while discarding irrelevant information. In this enhanced model, PCA is applied to the input data to reduce its dimensionality before feeding it into the CNN. This results in a more computationally efficient system, reduces the risk of overfitting and accelerates the training process. Additionally, by focusing only on the most relevant features, CNN can better learn to distinguish between pneumonia and non-pneumonia cases. This hybrid approach not only improves the classification accuracy of pneumonia diagnosis but also reduces the overall complexity of the model. It helps in achieving faster, more reliable, and more interpretable results, making it a valuable tool in medical imaging for early and accurate diagnosis of pneumonia. The following are the key contributions of this study:

I. the model was enhanced with PCA feature extraction to bring about efficiency in the classification of pneumonia
II. to reduce the model complexity, a new enhanced CNN-PCA was used for discriminant features. The enhanced CNN was employed to extract features from the raw data, and PCA was subsequently applied to those extracted features.
III. compare the performance of the developed model with existing pneumonia prediction models.

The rest of the paper is organized as follows: section 2 presents the materials and methods used in this study. Section 3 discusses the implementations and the results obtained from the paper. Finally, section 4 concludes the paper with future work.

2. Literature Review

Pneumonia is a life-threatening infection affecting the lungs, and its early detection is critical to improving patient outcomes. In recent years, artificial intelligence (AI) and machine learning (ML) have played pivotal roles in automating and enhancing diagnostic processes, particularly through imaging technologies such as chest X-rays. AI refers to the broader field of creating machines that can mimic human intelligence. In the context of pneumonia diagnosis, AI-powered systems integrate various ML techniques to analyze medical data, improving diagnostic accuracy and enabling early intervention. ML a subset of AI, involves creating models that can learn from data and make predictions. ML models, particularly DL models like CNNs, are revolutionizing pneumonia diagnosis by offering automated, scalable, and accurate solutions. CNNs and PCA are integral tools in AI and ML models, often applied to medical diagnosis, including pneumonia detection from chest X-rays. CNNs are a class of DL models specifically designed for image recognition tasks. In pneumonia diagnosis, CNNs automatically learn features from chest X-ray images, such as patterns and abnormalities associated with the chest.

Research in neural networks however has produced encouraging outcomes when interpreting medical images for various tasks, including detecting pneumonia. Because of its exceptional capacity to automatically extract layered information from pictures, CNNs have become the preferred option. This makes them exceptionally successful in recognizing pneumonia patterns within chest X-rays and CT scans [10]. These algorithms automate disease diagnosis by finding patterns and deviations in images like X-rays and Magnetic Resonance Imaging (MRIs), helping healthcare professionals make accurate and fast diagnoses [11]. Therefore, this study aims to show that the use of CNNs for diagnosing pneumonia marks a major leap in healthcare technology, simplifying diagnostic procedures and boosting the efficiency of respiratory disease management. As CNN technology keeps developing, it has the potential to radically revolutionize the detection of pneumonia and enhance global healthcare delivery.
An enhanced CNN integrated with PCA can significantly improve pneumonia diagnosis from medical images, particularly chest X-rays. This approach leverages the strengths of deep learning for feature extraction and classification while utilizing PCA for dimensionality reduction. In pneumonia diagnosis, CNNs can automatically learn important features from chest X-ray images, such as the presence of lung opacities, which are indicative of pneumonia. By training on large datasets of labeled medical images, CNNs have been shown to outperform traditional methods in diagnosing pneumonia with high accuracy. The proposed CNN architecture effectively classifies chest X-ray images, achieving high accuracy rates (up to 99.82%) in pneumonia detection [13]. The architecture typically includes convolutional layers followed by max pooling and dense layers, utilizing ReLU and sigmoidal activation functions to optimize performance [13-15].
PCA a dimensionality reduction technique, helps simplify complex datasets by extracting the most significant features. In medical imaging, PCA can reduce the computational load and highlight the most relevant aspects of X-ray images, making subsequent CNN processing faster and more efficient without losing essential diagnostic information. PCA can be employed to reduce the dimensionality of the input data, which helps minimize overfitting and improve computational efficiency without significant loss of information [16]. By focusing on the most significant features, PCA enhances CNN's ability to generalize from training data to unseen images [17]. Studies report median accuracy rates of 96.5% and F1-scores of 0.938, indicating the robust performance of CNNs in pneumonia classification [18]. The integration of PCA can further refine these metrics by streamlining the input data [13]. While most existing ML models are accurate, they lack transparency, making it extremely hard to understand how they arrive at a risk score.

3. Methodology

3.1 Data Collection

This study investigates the potential of using enhanced CNNs and PCA to automate pneumonia diagnosis from chest X-ray images. It aims to construct a model that can assist healthcare professionals in diagnosing pneumonia with improved accuracy and efficiency. Figure 1 shows the proposed framework.

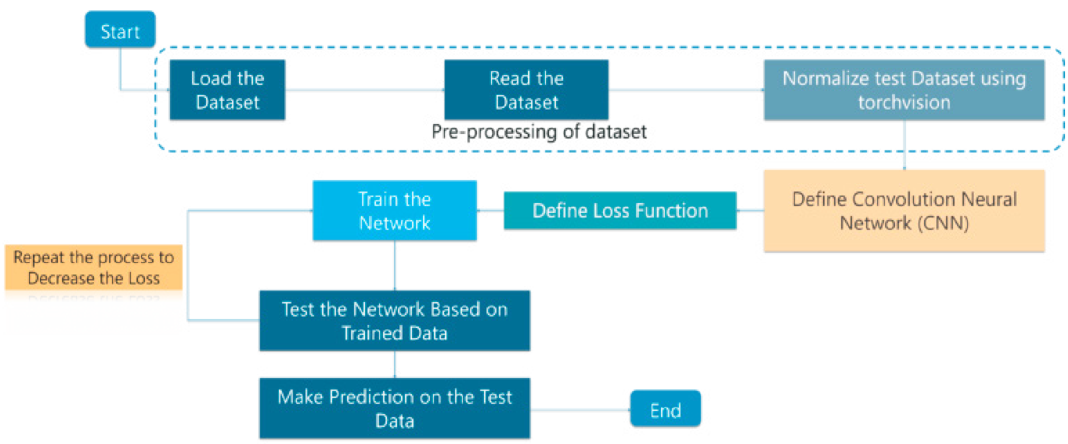

Figure 1. CNN flowchart diagram

3.2 Data Pre-Processing
Once the data is collected, we will perform essential pre-processing steps to prepare it for model training. This will involve techniques like resizing, normalization, and maybe adding more data to increase the size and stability of the collection. Typically, before training a model, the dataset must be pre-processed to ensure optimal performance and minimize errors. In this study, the original RGB images were converted to grayscale and resized to 180 × 180 pixels.

3.2.1 Image Resizing
Chest X-ray pictures vary in size and resolution, necessitating a standardized approach to ensure consistency across the dataset. All images are resized to a fixed dimension, in this case, 150x150 pixels, to match the input requirements CNN model. This resizing helps maintain uniformity, enabling the model to learn and extrapolate the data more effectively.

3.2.2 Normalization
To scale the picture pixel values to a range of 0 to 1, normalization is applied. The pixel values are divided by 255, changing their range from 0–255 to 0–1. The highest value possible for an 8-bit image, in this operation. Normalization helps speed up the convergence of the neural network during training by making certain that the scale of the supplied data is the same. This normalization prevents larger values from disproportionately affecting the model's learning, which is expected to improve the model's performance.

3.3 Principal Component Analysis (PCA) for Feature Extraction
Principal Component Analysis (PCA) is a dimensionality reduction technique that transforms high-dimensional data into a lower-dimensional space while retaining most of the original information. In pneumonia diagnosis, PCA can be applied to extract relevant features from chest X-ray images, reducing noise and redundancy, and improving the performance of classification models by focusing on the most discriminative features.

Data standardization, which involves scaling each feature to have a zero mean and unit variance through feature standardization, significantly impacts PCA. Scaling is crucial because it affects the covariance matrix, which determines the correlation between features through element-wise multiplication. If features are not scaled to the same range, the covariance matrix's purpose becomes inconsistent. After extracting 512 features using PCA, standardization (feature scaling) was performed on the data using equation 1.

$$x' = \frac{x - x'}{\sigma} \quad (1)$$

where x is the original feature vector, x' represents the mean of the feature vector, and σ denotes the standard deviation.

3.4 CNN Framework
The CNN framework illustrated in the diagram follows a structured process for feature extraction and classification. Initially, the input image is passed through several convolutional layers, where filters detect various features like edges, textures, and patterns. This step is crucial for extracting meaningful features from the image. After convolution, the data is passed through pooling layers, which reduce the spatial dimensions and help in retaining the most significant information, improving the model's efficiency and reducing its propensity for overfitting. Following the feature extraction process, the final classification is carried out by fully connected layers using the characteristics that have been collected from the data. Figure 2 displays the CNN framework.

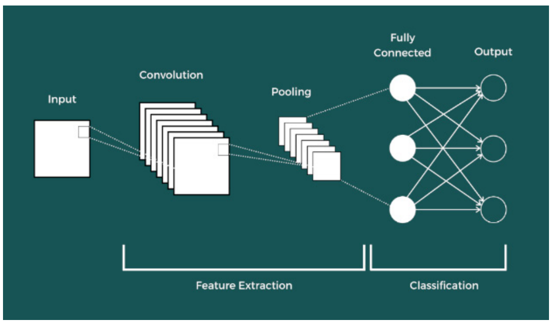

Figure 2. CNN Framework.

3.5 Dataset Description

The study primarily utilized the dataset published by Kermuny et al. in 2018 [12], comprising 5863 JPEG x-ray images categorized into normal and pneumonia cases, derived from children aged 1 to 5 years at the Guangzhou Women and Children's Medical Center. These chest x-ray images were obtained as part of routine clinical care [12]. To enhance analysis and evaluation accuracy, a total of 5856 chest x-ray images were collected and quality-screened. Considering external factors like scanning location, personal habits, and the patient's medical history, which could contribute to image clarity issues, image enhancement techniques were employed to improve readability during the research process. The dataset was divided as follows:

Training Set: Used to train the model. It consists of most data and includes a diverse range of images to help the model learn the underlying patterns and features. The training set was further split into training and validation subsets to fine-tune the model and prevent overfitting.

Test Set: Used to evaluate the final performance of the model. To enable an objective evaluation of the model's accuracy and capacity for generalization, the test set is kept apart from the training and validation sets. Table 1 shows the dataset distribution for the normal and pneumonia images. Figure 3 shows the normal and pneumonia chest X-ray images Patient.

Table 1: Dataset Distribution

Dataset	**Normal**	**Pneumonia**	**Total**
Training	1349	3884	5233
Testing	234	390	624
Total	1583	4274	5857

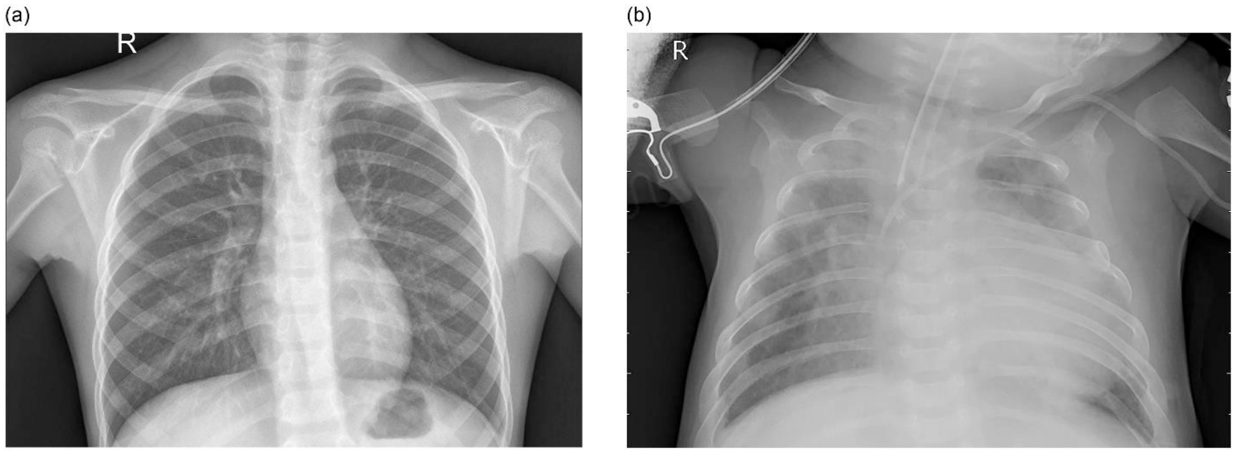

Figure 3. (a) Patient with normal X-ray chest image, (b) Patient with pneumonia X-ray chest image.

2.6 Model Performance and Analysis

Once training is complete, the model's performance will be evaluated on the held-out testing set using the following metrics:

Accuracy: Accuracy is a measure of the total effectiveness of a model. Out of all the cases, it determines the percentage of accurately anticipated instances. Even while accuracy is a valuable indicator, it can be deceptive when datasets are unbalanced and one class is more frequent than the other. The formula is:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2)$$

Precision: The precision of the positive predictions is measured. Good accuracy is correlated with a low false positive rate. The representation is:

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

Recall: Out of all actual positive occurrences, it calculates the percentage of accurately anticipated positive instances The formula is:

$$Recall = \frac{TP}{TP+FN} \quad (4)$$

F1-score: The F1-score is a statistic that provides a balance between accuracy and recall, calculated as the harmonic mean of the two.

$$F - measure = \frac{2*Precion*Recall}{Precision+Recall} \quad (5)$$

ROC AUC: The whole two-dimensional area beneath the ROC curve, which displays the true positive rate (recall) against the false positive rate (1-specificity), is measured by the ROC AUC (Area Under the Curve).

4 Implementation, Results, and Discussion

The study experimentation setups are as follows: Intel core i7 processor with 8GB RAM and GPU of 4GB. The model has been implemented using the Python programming language. The numpy pandas matplotlib sci-kit-learn tensorflow keras opencv-python were used for implementation.

4.1 Model Performance and Evaluation

The enhanced CNN with PCA was implemented using the Keras library, a powerful and user-friendly DL model framework built on top of TensorFlow. Keras allows for rapid prototyping and experimentation due to its simplicity and extensibility. Table 2 displays a summary of the proposed model architecture and its performance metrics:

Table 2. Performance results of the metrics of the proposed model.

Class	Precision	Recall	F1-Score	Support
Normal	97	94	96.3	234
Pneumonia	98	96	97.4	374
Accuracy		98		608
Macro Avg	98	95	96	608
Weighted Avg	97	96	97	608

4.2 Confusion Matrix

The confusion matrix is a specific table layout that allows visualization of the effectiveness of an algorithm, usually one that uses supervised learning. The examples in a predicted class are represented by each column of the matrix, and the occurrences in an actual class are represented by each row (or vice versa). Figure 4 shows the confusion matrix of the proposed model.

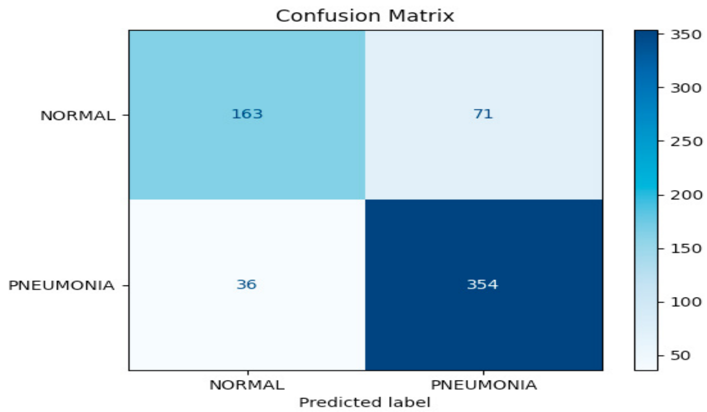

Figure 4. Confusion Matrix of the Proposed Model

The enhanced CNN with the PCA model achieved an impressive accuracy of 98%. This high level of accuracy underscores the effectiveness of deep learning techniques and PCA in medical image analysis, particularly in the automated detection of pneumonia. In addition, the high precision and recall values for both classes reflect the model's ability to minimize false positives and false negatives, ensuring reliable predictions. This makes the enhanced CNN with PCA model a valuable tool in medical diagnostics, potentially aiding healthcare professionals in making timely and accurate decisions.

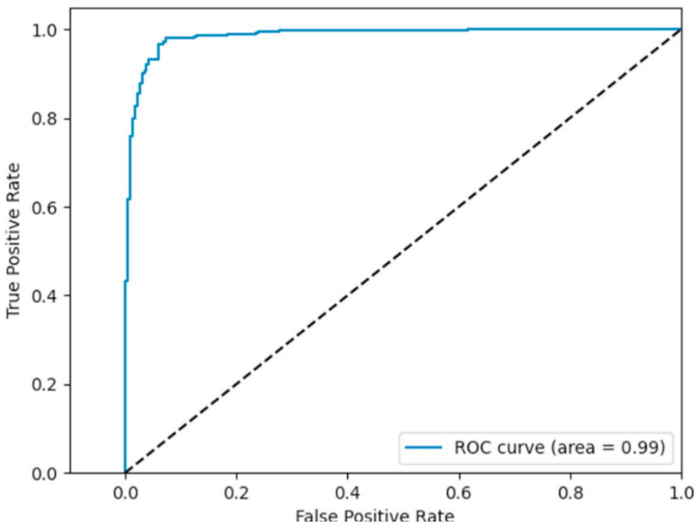

Figure 5. The ROC of the Proposed Model

Figure 6 displays the ROC of the proposed model, a random classifier that visualizes true and negative class rates. The larger FTR value indicates more positive and negative samples, while TPR indicates more positive classes. The ROC curve is stable.

4.3 Comparison of the Proposed Model with the CNN model

Table 3 provides a comparative overview of the performance metrics for the proposed model with the CNN model. The findings show a better performance when compared with the CNN-based model. Although the CNN-based model performance is good, the proposed model shows a better performance across all the performance metrics. This comparison shows the importance of feature extraction in the classification of pneumonia, showing that DL models and PCA for feature extraction provide better accuracy and resilience than old methods, even though traditional techniques are still useful.

Table 3. Comparison of the Proposed model with the CNN model

Metric	CNN	CNN + PCA
Accuracy	91%	98%
Precision	90%	97%
Recall	96%	96%
F1-Score	93%	97%

The study proposes an enhanced CNN combined with PCA for pneumonia diagnosis from medical images. The PCA reduces the dimensionality of the input data, improving computational efficiency. The enhanced CNN architecture achieves higher accuracy in classifying pneumonia by effectively extracting relevant features from images. The method outperforms traditional CNN models, offering a promising approach for accurate and efficient pneumonia diagnosis. Figure 6 displays the comparison of the proposed model with the CNN model.

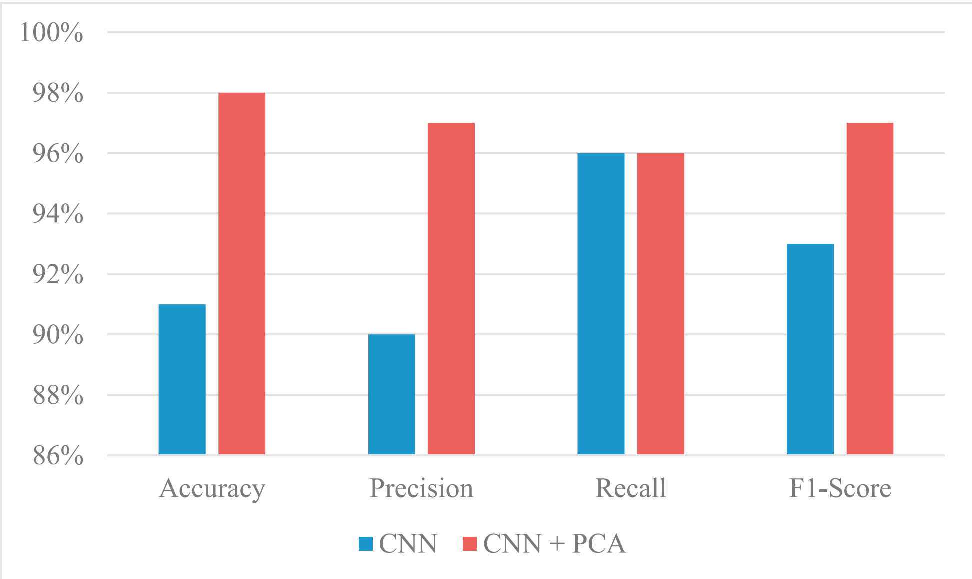

Figure 6. The comparison of the proposed model with the CNN algorithm

4.4 Comparison with Existing Models

Table 3 shows the comparison of the proposed model with some recent work in the area of pneumonia diagnosis. Various CNN architectures, such as ResNet50, LeNet, and VGG19, have shown high accuracy in pneumonia detection, with models achieving up to 96% accuracy [13, 14, 16, 17]. The integration of transfer learning has been effective, allowing models to fine-tune pre-trained parameters, which improves classification performance, especially in imbalanced datasets achieving up to 93% [15, 19]. An enhanced CNN combined with PCA significantly improves pneumonia diagnosis from medical images. This approach utilized the strengths of CNNs in feature extraction and classification while exploiting PCA for dimensionality reduction, enhancing model efficiency and interpretability. The proposed model results show better performance in terms of accuracy with an increase of 2% to the existing models.

Table 4. Comparison of the Proposed model with existing models

Authors	methods	Results (Accuracy)
Jaganathan et al., (2024) [13]	Modified LeNet + revised ReLU	96%
Chandranegara et al., (2024) [14]	ResNet-RS CNN	92%
Song et al., (2024) [15]	Transfer learning + pre-trained CNN model	90%
Mardianto et al., (2024) [16]	CNN	92%
Jain et al., (2020) [17]	CNN	96%
Nithya et al., (2023) [18]	GANs	96%
Gill et al., (2023) [19]	Transfer learning	93%

4.5 Discussion

In this study, we developed an enhanced CNN integrated with PCA to classify pneumonia from medical images, achieving impressive metrics: an accuracy of 98%, precision of 97%, recall of 96%, and an F1-score of 97%. These results indicate not only the model's efficacy in identifying pneumonia cases but also its reliability in minimizing false positives and negatives, which is critical in clinical settings.
When compared to recent studies, our model demonstrates superior performance. For instance, Jaganathan et al., (2024) [13] reported an accuracy of 96% using traditional CNN architectures without dimensionality reduction techniques, indicating that PCA significantly enhances classification performance by reducing noise and computational complexity. Similarly, Jain et al., (2020) [17] and Nithya et al., (2023) [18] both achieved an accuracy of 96% using CNN and GANs models respectively; however, the proposed model not only outperforms their results but also simplifies the model by reducing the number of parameters through PCA, making it more efficient for real-time applications.

Furthermore, the high precision and recall values suggest that the proposed model is well-suited for deployment in healthcare settings, where misdiagnosis can lead to severe consequences. The integration of PCA also allows for improved interpretability of features, enabling healthcare professionals to gain insights into the decision-making process of the model. Overall, the findings contribute to the ongoing advancements in medical image classification, suggesting that enhanced CNN architectures combined with PCA are promising avenues for future research in pneumonia diagnosis.

5. Conclusion

Integrating Enhanced CNN with PCA presents a promising approach for diagnosing pneumonia from medical images. This method leverages the multi-layered feature extraction capabilities of CNNs while utilizing PCA to reduce data dimensionality, enhancing classification performance. The proposed method achieves high accuracy and outperforms existing methods for Pneumonia diagnosis classification. Furthermore, we conduct extensive experiments and provide detailed analysis to validate the effectiveness of our approach. This novel method has the potential to greatly improve the diagnosis and treatment of Pneumonia, ultimately improving patient outcomes and reducing healthcare costs. CNNs excel in automatically extracting complex features from chest X-ray (CXR) images, significantly improving diagnostic accuracy. PCA effectively reduces the feature space, leading to faster processing times and improved model performance. This is crucial in medical imaging, where high-dimensional data can complicate analysis. The combination of PCA with enhanced CNNs has enhanced interpretability and efficiency, allowing for quicker clinical decision-making. while the proposed method shows significant promise, challenges remain in ensuring model interpretability and handling diverse datasets, which can affect generalizability across different populations and imaging conditions.

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