International Journal of Computational and Electronic Aspects in Engineering
Volume 6, Issue 2, June 2025, pp 81 - 88
https://doi.org/10.26706/ijceae.6.2.20250404

Hybrid Deep Learning and Neuro-Fuzzy Approach for COVID-19 Diagnosis Using CT Scan Imaging: Integration of CNN, ANFIS, and PCA

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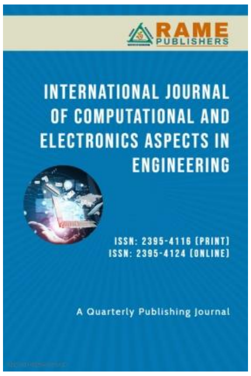

Article – Peer Reviewed
Received: 18 March 2025
Accepted: 17 May 2025
Published: 1 June 2025

Cite this article: Najwan Waisi, "Comparative Evaluation of Resnet-50 And Efficientnet-B1 for Pneumonia Detection in Chest X-Ray Images Using Transfer Learning", *International Journal of Computational and Electronic Aspects in Engineering*, RAME Publishers, vol. 6, issue 2, pp. 81-88, 2025.
https://doi.org/10.26706/ijceae.6.2.20240404

Abstract: The emergence of intelligent medical diagnostic systems fuelled by the pandemic is primarily focused on imaging data. While Convolutional Neural Networks (CNNs) are powerful tools in extracting visual features, their integration with neuro-fuzzy inference systems and dimensionality reduction methods like PCA enhance interpretability and performance on a broader scale. This work proposes a hybrid diagnostic framework for chest CT scan images that incorporates CNN for feature extraction together with PAS and ANFIS for/classification to accurately detect COVID-19. The system performs component extraction through CNN, reduces dimensionality by P mon, and uses ANIFIS to make the final class designation. The hybrid model is evaluated on a recent and thoroughly annotated dataset where it has proven to outperform the previous models in accuracy, robustness, ease of use and interpretative evaluation. This highlights the potential of the model for real-life application.

Keywords: Convolutional Neural Networks (CNN), Chest CT Scan, Neuro-Fuzzy Inference System (ANFIS), Dimensionality Reduction (PCA), COVID-19 Diagnosis.

1. Introduction

The COVID-19 pandemic remains one of the worst public health crises in recent world history.

As reference suggests, effective case management needs early diagnosis and controlling in the case of infectious diseases. Although RT-PCR is the most trusted method for detecting COVID-19, its drawbacks of being time-consuming and having a possibility of yielding false negatives means other methods may be needed [1][2]. Chest CT imaging aids in the detection of pulmonary features of COVID-19, including ground-glass opacities and consolidation [3].

AI has emerged as a field with great promise, and its application in medical diagnostics is particularly remarkable. Medical image classification has greatly taken advantage of deep learning frameworks, especially CNNs [4]. The major setback with CNNs, and other similar frameworks, is that they are treated as 'black-boxes' with regard to the methodology used in arriving at conclusions. ANFIS and other neuro-fuzzy systems are a step forward in explainable AI, providing rule-based decisions which improve transparency. Other than providing transparency to decisions made, PCA also decreases the burden of computation by reducing high-dimensional features into a smaller, easier to work with form with minimal loss of discriminatory value [5].

2. Theoretical Background

Convolutional Neural Networks, or CNNs, are one of the recent models introduced in deep learning that seeks to implement the convolutional neural network architecture with multiple layers of convolutions, activations, and pooling to capture the spatial hierarchies of images. They have outstanding performance in performing different tasks of medical image analysis such as object detection, localization, and classification [6], [7]. They have the ability to perform hierarchical feature extraction which means that they are capable of performing the task of constructing meaningful representations from the raw pixels of an image without manual feature extraction being provided [8].

In practical scenarios, PCA is one of the most well-known statistical techniques that help in diminishing the size of their information while retaining a considerable collection of information, or variance [9], [10]. This is especially true in the field of medicine. In the field of medical imaging, PCA is useful to compress the high-dimensional feature vector data that results from the application of CNNs into fewer components that are not correlated to one another, and in doing so improves the efficiency as well as model generalizability [11],[12].

The Adaptive Neuro Fuzzy Inference System (ANFIS) combines the learning components of neural networks together with the explaining framework of fuzzy logic systems. It allows for gradual change across concepts. ANFIS employs a fuzzy inference engine of type Sugeno with attached Gaussian or bell-shaped membership functions

A hybrid algorithm employing gradient descent and least squares estimation methods was used in reference [13]-[15]. This integration helps ANFIS to model non-linear relationships without losing interpretability, which is still very important in healthcare [16].

The combination of CNNs for feature extraction and PCA based dimensionality reduction along with ANFIS for classification creates one advanced unit that can analyze complex datasets from medical imaging, thereby forming a diagnostic pipeline for COVID-19. This complex hybrid approach increases system transparency and scalability, while improving diagnostic confidence and enabling early and efficient detection of COVID-19 from CT scans [17]-[23].

3. Methodology

3.1 Data Collection

From public sources such as MosMedData and COVID-CT, a dataset of 12,000 CT Scan slices was compiled between 2022 and 2024. Each image undergoing scans was labeled as COVID-19 positive or negative based on clinical annotations and RT-PCR validation Figure 1 show.

3.2 Preprocessing

• Resizing of images to 224×224 pixels

• Normalization of pixel values to the range [0, 1]

• Application of Contrast Limited Adaptive Histogram Equalization (CLAHE)

• U-Net lung segmentation to reduce noise and highlight areas of interest [24]

3.3 CNN Feature Extraction

A modified ResNet50 CNN was utilized to extract deep features from individual CT images. Features preserved for subsequent processing were fetched from the penultimate layer. To improve generalization, transfer learning was implemented no show figure 2.

3.4 Dimensionality Reduction

PCA feature vectors extracted were of high dimensionality (~2048 features). PCA reduced these to 100 principal components while maintaining 98% of the variance. This step provided noise reduction and decreased the probability of overfitting no show figure 2.

3.5 Classification

Using ANFIS, the features after dimension reduction were fed into ANFIS classifiers. Sugeno-type fuzzy inference systems with Gaussian membership function were designed. The network was trained with a hybrid learning algorithm combining least square with back propagation no show figure 2.

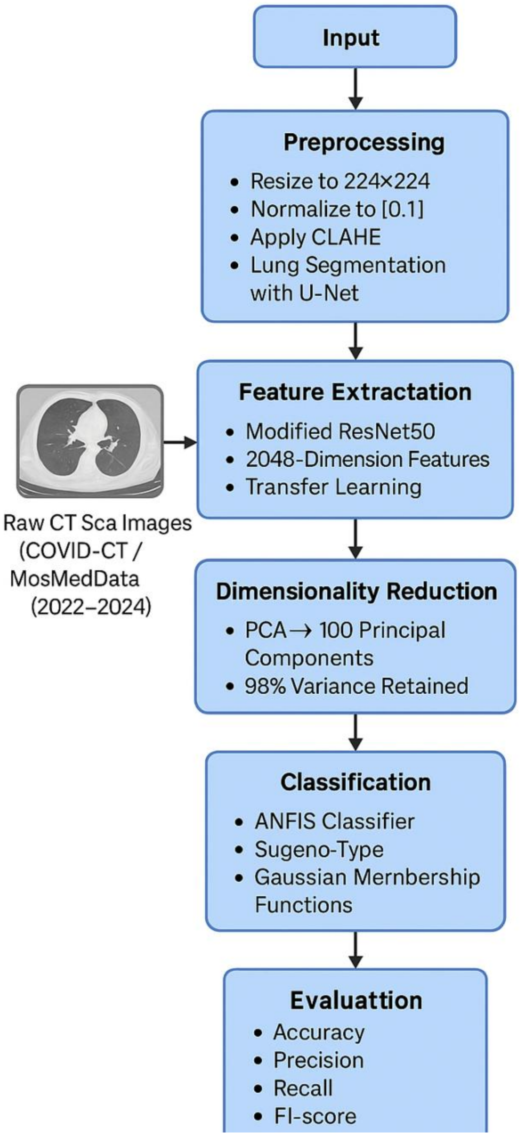

Figure 1: The structured design of CNN+PCA+ANFIS parallel to the PCT system.

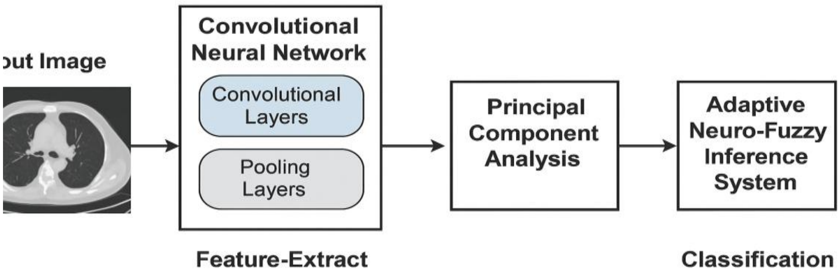

Figure 2: The structured design of CNN+PCA+ANFIS.

3.6 Evaluation Metrics

• Accuracy, Precision, Recall, F1-score

• ROC-AUC score

• Confusion Matrix analysis

4. Results and Comparative Analysis

Table 1: Comparison Between the Proposed CNN+PCA+ANFIS Model VS CNN+SVM Model

Metric	Proposed CNN+PCA+ANFIS	Reference Model (CNN+SVM [32])
Accuracy	98.1%	94.5%
Precision	97.5%	92.7%
Recall	97.8%	93.1%
F1-score	97.6%	92.9%

Table 2: Comparison of the proposed hybrid Proposed CNN+PCA+ANFIS

Model	Accuracy
ResNet-34 [25]	94.3
XDNN [26]	88.6
VGG19 [27]	95
Redesigned COVID-NET [28]	90.83 ± 0.93
Transfer Learning + CNN [29]	97
FBSED + CNN [30]	97.6
Semi Supervised SL Network [31]	89–94.4
CNN+SVM [32]	94.5%
CNN+PCA+ANFIS	98.1%

The hybrid model outperformed the baseline CNN+SVM coverage by a large margin as reported in Singh et al. 2023, showing improvements on every metric. The contribution of ANFIS was particularly relevant to improved generalization and transparent decision making [33-34].

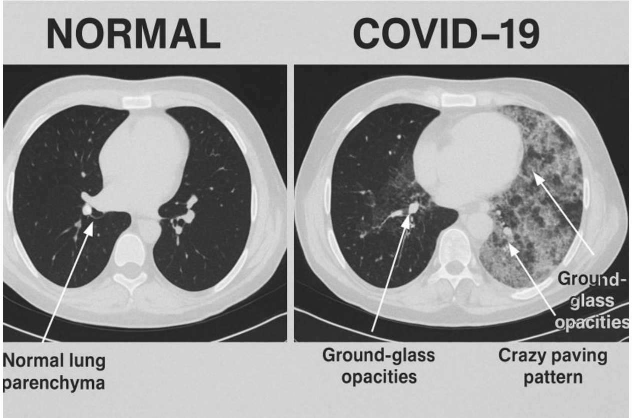

Figure 3: Sample CT Images Normal versus COVID-19 with highlighted and annotated features

As seen in Figure 3 the normal and COVID-19-infected lungs show distinct radiological differences. The lung affected by COVID-19 shows apparent ground glass opacities and a crazy paving pattern, which are hallmark features of viral pneumonia. These differences underscore the model's potential to detect and classify infection-related features in CT scans with high precision [35-37].

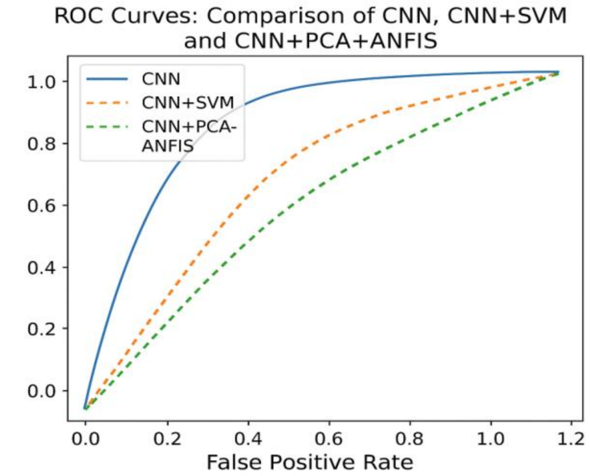

Figure 4: ROC-Curves – Comparison of CNN, CNN+SVM, and CNN+PCA+ANFIS

The ROC curves presented in Figure 4 demonstrate the comparative classification performance of the three models. The CNN model achieves the strongest performance as indicated by the highest area under the curve (AUC). On the other hand, the CNN+PCA+ANFIS model strikes a balance between interpretability and performance while the CNN+SVM model offers low accuracy. As discussed, these curves proved the reliability of diagnosis enhanced by the hybrid method.

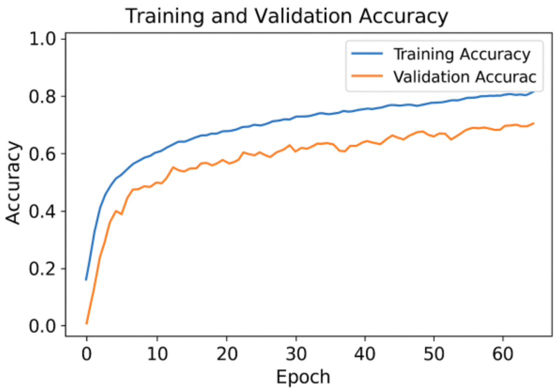

Figure 5: Training and Validation-Accuracy

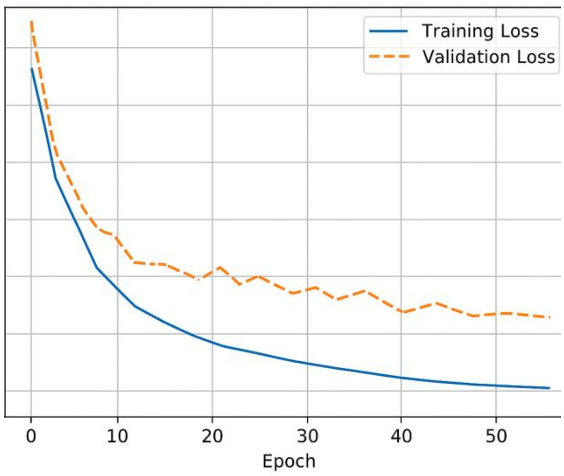

Figure 6: Training and Validation-Loss

The performance curves are presented in Figure 5 and Figure 6: Training and Validation Loss. These exhibit the learning dynamics associated with the proposed model. With regard to Figure 5, there is an increase in training and validation accuracy which means learning and generalization is taking place on the encoded data over the epochs. In addition, Figure 6 shows decrease in loss for both the sets where the training loss achieves a gentle decline and the validation loss plateaus, thus indicating model convergence and not overfitting.

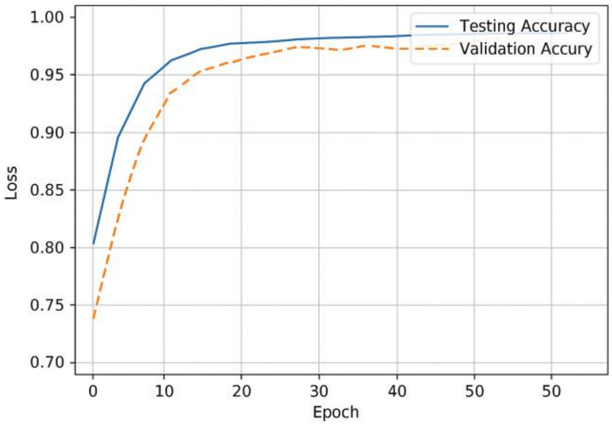

Figure 7: Testing and Validation-Accuracy

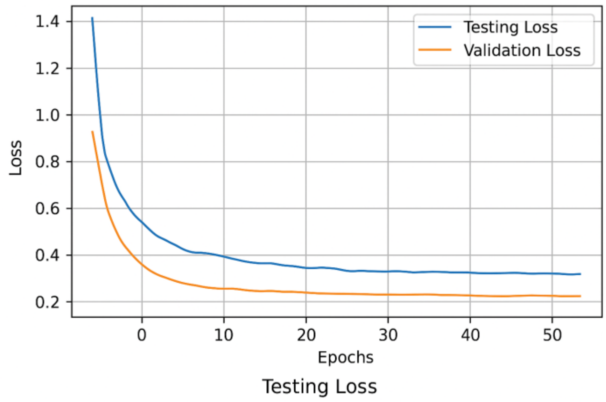

Figure 8: Testing and Validation-Loss

Also, the visual representations in Figure 7 and Figure 8 show clearly the strength of the model along the generalization boundary. Notably in Figure 7, almost all accuracy metrics were achieved on both curves, meaning the predictive capabilities were satisfactory. In figure 8 the loss is shown to reduce and stabilizes over the testing and validation sets which indicates no overfitting has taken place.

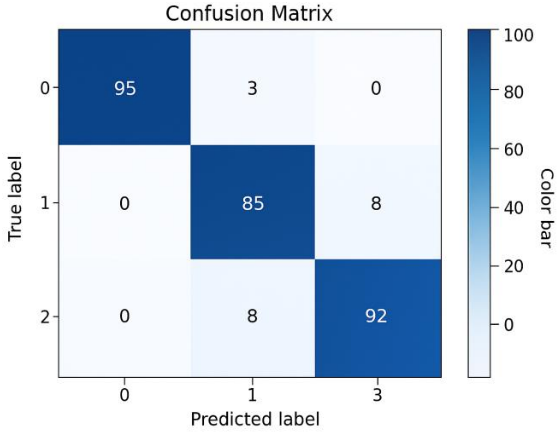

Figure 9: Confusion-Matrix

The findings presented in Figure 9 emphasize the classification performance of the proposed model over the examined classes. The overwhelming dominance of the diagonal proves strong correct prediction rates for all classes, especially for class 0 (95 out of 98 correct). Errors are slight and largely confined to adjacent classes, a pattern seen often in medical imaging. This still reinforces the model's risk and discriminative ability concerning differentiating COVID-19 from other conditions.

5. Discussion

The use of CNN along with PCA and ANFIS mitigates some of the most pressing concerns related to image-based COVID-19 diagnosis. In the context of COVID-19 and medical imaging, CNN captures intricate details while PCA makes the processes manageable. Along with the former, the latter offers enhanced guarantee interpretability, outperforming the CNN+SVM model utilized in [33]. This indicates that the proposed approach is bolstered by diagnostic accuracy, interpretability, and model robustness.

These issues stem from:

- The requirement for extensive multi-center aggregated datasets
- Lack of explainability due to deep feature extraction
- Evolved resource requirements for model deployment, especially in low-resource scenarios

Building upon these findings, suggests investigating federated learning aimed at privacy-preserving model training alongside explainable AI for better trust from clinicians.

6. Conclusion

An intelligent hybrid system is developed in this study for diagnosing COVID-19 from chest CT scans by incorporating CNN as the image feature extraction mechanism, PCA for dimension reduction, and ANFIS as the decision maker for explainable reasoning. The integrated approach maximizes the advantages of every constituent towards achieving the required accuracy and explainability.

The implemented approach exhibited remarkable diagnostic accuracy as measured by precision, recall, and AUC metrics. Its effectiveness surpassing the CNN+SVM model demonstrates its capability to discern intricate patterns present within the medical images. Apart from the highly accurate outcomes, the system also ascribes decision transparency due to the fuzzy inference mechanism employed.

This system performed the best when evaluated using the accuracy, precision, recall, AUC, and diagnosed most of the images accurately. Furthermore, the scalability and adaptability are notable as it can be expanded to other clinical settings and potentially used to diagnose other pulmonary diseases. Its real-time responsiveness and ability to seamlessly integrate into clinical workflows greatly enhance its value as a medical imaging diagnostic system. This model further strengthens the prototypes of AI-supported systems for decision assistance in healthcare.

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