Journal of Brilliant Engineering 2 (2025) 41003

Brilliant Engineering

journal home: www.acapublishing.com/journals/4/ben

Research Article

# Adaptive Convolutional Neural Network Integrating Sequential Memory and Transfer Learning for CT-Based COVID-19 Detection

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**Keywords**

*Machine learning, Accuracy, Diagnosis, COVID-19, CT scan, Adaptive deep neural learning.*

**Abstract**

COVID-19, first identified in Wuhan, China in 2019, is a highly contagious respiratory disease with symptoms such as fever, dry cough, and shortness of breath. Computed tomography (CT) scans are a key tool for detecting lung abnormalities related to COVID-19. However, existing approaches to COVID-19 diagnosis often struggle to extract clinically relevant features from CT images, particularly when there is inter-slice variability or limited annotated data. In this study, we introduce an Adaptive Convolutional Neural Network (ACNN) model designed to address these challenges by integrating two core mechanisms: (1) a sequential memory component using Long Short-Term Memory (LSTM) units to capture contextual relationships and dependencies across consecutive CT slices, and (2) transfer learning—leveraging pre-trained weights from large-scale medical imaging datasets to improve feature generalization. This adaptive design differs from standard CNN architectures by explicitly modeling both spatial and limited sequential information in CT scan volumes. The ACNN was trained and evaluated on the SARS-CoV-2 CT dataset, and its performance was assessed using standard metrics. Experimental results show that ACNN outperforms classical machine learning algorithms (such as KNN and SVM) and established deep learning models (including VGG16, ResNet, and DenseNet), achieving an accuracy of 97.5%, a precision of 97.30%, a recall of 97.85%, and an F1-score of 97.58%. Statistical tests confirmed the robustness of these improvements. The results demonstrate that the proposed ACNN, through its memory-augmented and transfer learning-driven design, offers a precise and reliable approach for COVID-19 diagnosis and holds promise for real-world clinical applications.

## 1. Introduction

COVID-19, a highly infectious respiratory disease that emerged in 2019, was first identified in Wuhan, China, before rapidly spreading worldwide [1]. With cases reported in over 220 countries, COVID-19 has resulted in more than 200 million infections and over 4.3 million deaths globally [2]. Due to its high transmissibility, COVID-19 is considered among the most rapidly spreading diseases in modern history, with a scale comparable to the 1918 influenza pandemic [3]. The United States has recorded the highest mortality rate, representing approximately 40% of total global deaths [3]. Transmission occurs primarily through respiratory droplets, with initial viral replication taking place in the throat and leading to symptoms such as fever, sore throat, dry cough, and loss of taste and smell [4]. Early and accurate diagnosis is crucial for controlling disease spread and improving clinical outcomes. Traditional diagnostic methods, such as polymerase chain reaction (PCR) testing, offer high accuracy but are resource-intensive and may not be widely accessible, especially in low-resource settings. As a result, there has been a growing interest in using medical imaging—particularly computed tomography (CT) scans—as a practical and accessible tool for COVID-19 diagnosis [5]. Distinguishing COVID-19 from other respiratory illnesses using CT images remains a challenge due to overlapping radiological features. The global shortage of skilled radiologists and infectious disease specialists further highlights the need for automated diagnostic systems [6]. In response, recent advancements in deep learning (DL) have accelerated the development of automated systems for medical image analysis, benefiting radiologists through more efficient and accurate disease identification. Numerous models—including ResNet, AlexNet, MobileNet, and Inception—have shown promise in predicting infectious diseases [7]. Several researchers have proposed novel deep learning approaches for COVID-19 diagnosis. Balamsamy et al. developed a Hy57brid Classification Optimization (HCO) method using recurrent learning and fuzzy logic (RLF) to detect COVID-19 infection in lung CT images. Their method classifies infected and non-infected regions by analyzing pixel distributions and variations, improving early diagnosis and reducing false positives. The HCO-RLF approach outperformed existing methods (such as DR-MIL, DSAE, and BS-FSA) by increasing accuracy, precision, and consistency by 11.96%, 9.98%, and 13.42%, respectively [8]. Munshi et al. utilized a combination of ARIMA modeling, mathematical approaches, and Deep Q-Network (DQN) techniques to forecast COVID-19 case numbers, demonstrating that deep reinforcement learning can enhance prediction accuracy over traditional forecasting methods [9]. Paswan et al. proposed a deep learning framework employing various pre-processing techniques and architectures (VGG16, VGG19, ResNet50, DenseNet121) for chest X-ray image analysis. Their model, especially VGG16, achieved a training accuracy of 94.04% and a test accuracy of 87.80%, outperforming comparable models [10]. Aggarwal et al. introduced a deep learning model combining convolutional, pooling, and fully connected layers for classifying COVID-19 cases from X-rays and CT scans, reporting superior classification results [11]. Similarly, Gour and Jain applied transfer learning and convolutional neural networks (CNNs) for rapid COVID-19 detection, achieving high diagnostic accuracy. Approaches using EfficientNet, DenseNet, and TransCNN Net (which combines CNNs with Transformer modules) have further improved diagnostic performance by incorporating image enhancement and attention mechanisms [12]. Ebenezer et al. explored the use of EfficientNet with advanced image enhancement algorithms, demonstrating increased accuracy and reliability in COVID-19 image classification [13]. Gopatoti

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Received 17 May 2025; Revised 04 Jun 2025; Accepted 04 Jun 2025

https://doi.org/10.36937/ben.2025.41003

et al. optimized deep CNN models with a grey wolf optimizer for COVID-19 detection in CXR images, achieving classification accuracy rates up to 100% for two-class classification [14]. Fan et al. (TransCNN Net) and Kong and Cheng (DenseNet with VGG16 and attention mechanisms) also reported strong performance using advanced model architectures [15,16]. Rahman et al. applied deep CNNs, with DenseNet201 achieving up to 99.1% accuracy on binary ECG image classification [17]. Despite these advances, DL-based approaches still face several key challenges. Computational complexity is a major limitation, especially for high-performing architectures like DenseNet and TransCNN Net with large parameter counts, which impede deployment in resource-constrained environments [16-18]. For instance, Gopatoti et al. utilized a grey wolf-optimized CNN model, noting that computational demands limited real-time usability [14]. Furthermore, while transfer learning from pre-trained architectures can boost performance, adaptation to domain-specific medical data is often incomplete, leading to suboptimal generalization on COVID-19 datasets [19]. Limited interpretability of DL models remains a concern, as these systems often operate as "black boxes," providing limited insights into their decision-making processes, which may hinder clinical acceptance [20]. Many studies also focus primarily on binary classification (COVID-19 vs. non-COVID), failing to address real-world needs, such as distinguishing between multiple respiratory diseases [21]. Data quality and variability are additional challenges: datasets are often imbalanced and lack sufficient diversity, which can introduce bias and limit model generalizability across different populations and imaging protocols [8-10]. To overcome these challenges, this study proposes an adaptive convolutional neural network (ACNN) model designed to optimize both diagnostic accuracy and computational efficiency. The ACNN incorporates adaptive feature extraction mechanisms for robust differentiation of COVID-19 from other respiratory diseases, leverages memory-based techniques to enhance model performance on imbalanced datasets, and employs explainable AI (XAI) strategies for increased transparency in decision-making. By focusing on scalability and practical implementation, the proposed method aims to bridge the gap between academic research and clinical deployment, providing an effective and robust solution for automated COVID-19 diagnosis in diverse healthcare settings.

## 2. Methods

This section presents the proposed method for detecting COVID-19 from CT scan images. Our approach combines advanced image preprocessing, an adaptive convolutional neural network (ACNN), and robust classification and evaluation strategies to maximize accuracy, efficiency, and reliability. Figure 1 illustrates the complete workflow of this method, with all major steps explained in detail below.

### 2.1. Image preprocessing

The preprocessing stage standardizes and optimizes CT scan images for effective feature extraction by the deep learning model. It comprises the following steps:

- **Resizing:** All CT scan images are resized to a standard dimension to ensure uniformity of model inputs and facilitate efficient training and inference.

- **Normalization:** Pixel values are scaled from the original range (0–255) to [0, 1], reducing variations in image intensity and aiding faster, more stable model convergence.

- **Data Partitioning:** The dataset is randomly divided into training (70%) and testing (30%) sets to evaluate model performance and generalization to unseen data. Additionally, k-fold cross-validation (with k=5 in this study) is employed, providing comprehensive and unbiased assessment by iteratively training and validating the model on different subsets.

### 2.2. Feature extraction using ACNN

Feature extraction utilizes an Adaptive Convolutional Neural Network (ACNN), which is tailored for the complex nature of medical imaging.

- **Convolutional and Pooling Layers:** Convolutional layers employ filters of size N×MN \times MN×M to extract critical spatial features from CT images. Pooling layers, such as max-pooling, downsample feature maps, reducing dimensionality while retaining important information.

- **Activation Functions:** Non-linear transformations (e.g., ReLU) are applied after convolutions to capture complex patterns in the data.

- **Pre-training:** To leverage prior knowledge and accelerate convergence, the ACNN is initialized with weights pre-trained on a related large-scale dataset (such as ImageNet).

- **Memory Enhancement:** While standard LSTM networks are typically designed for temporal or sequential data, in this framework, memory modules are adapted to reinforce feature retention across layers and training iterations. This mechanism helps the model emphasize and preserve informative features that may otherwise be diluted through deep network propagation, leading to more robust and stable feature extraction from static CT images.

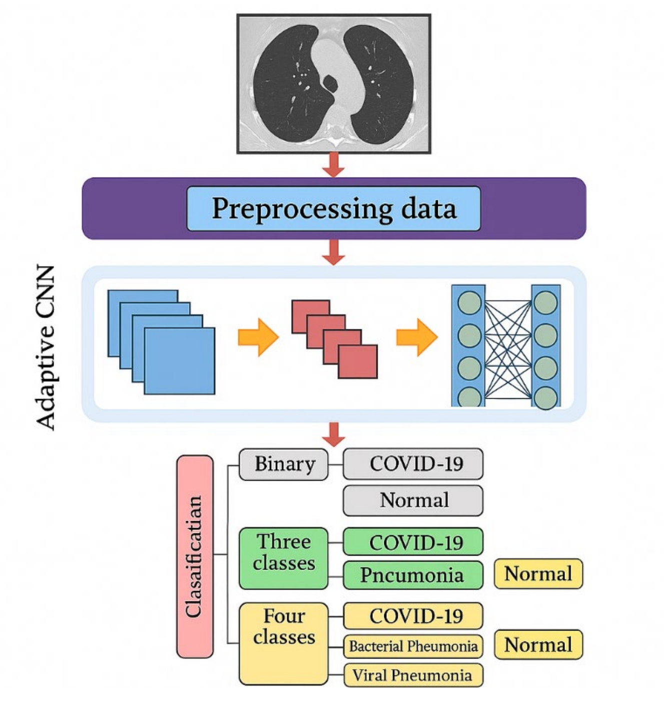


Figure 1. Workflow diagram of the proposed method

**2.3. Classification**

After feature extraction, the resulting representations are passed to a fully connected layer with a softmax activation function, which classifies the CT scan images as COVID-19 positive or negative. This end-to-end architecture ensures that discriminative spatial features guide the final diagnostic output.

**2.4. Evaluation and validation**

Model performance is rigorously assessed using the independent test set and k-fold cross-validation. The combination of these techniques ensures a robust evaluation, minimizing bias and providing reliable estimates of performance across multiple data partitions. These validation processes are critical for confirming the method's generalizability to new, unseen CT images.

**2.5. Advantages of the proposed method**

The integrated design of the proposed method confers several key advantages:

- **Optimized Preprocessing:** Standardization through resizing and normalization ensures data consistency, supporting effective feature extraction.
- **Adaptive Deep Feature Learning:** The ACNN, enhanced with pre-training and memory modules, efficiently captures both fine-grained and global patterns in CT images, addressing challenges of feature complexity in medical imaging.
- **Robust Classification:** The combination of deep learning-based feature extraction and a dedicated classification layer enhances diagnostic accuracy.
- **Comprehensive Validation:** Rigorous evaluation using both random partitioning and k-fold cross-validation imparts high confidence in the system's reliability.
- **Scalability:** The efficient architecture, with pooling and adapted memory mechanisms, reduces computational demands, supporting practical deployment in real-world clinical environments.
- **Generalizability:** By leveraging robust validation and transfer learning, the model demonstrates strong potential for adaptation to other imaging-based diagnostic tasks.

**2.6. Dataset**

This study utilizes the publicly available **SARS-CoV-2 CT scan dataset** sourced from the official Kaggle repository [https://www.kaggle.com/datasets/plameneduardo/sarscov2-ctscan-dataset/[7-10]].

Table 1. Summarizes the key characteristics of the dataset

| Datasets | COVID Count | None-Covid Count | Image Count | Image Type |
|---|---|---|---|---|
| SARS-CoV-2 | 1262 | 1230 | 2492 | CT-SCANs |

Figure 2 shows some sample images from the SARS-CoV-2 dataset. These images are used to analyze and study in the research purposes.

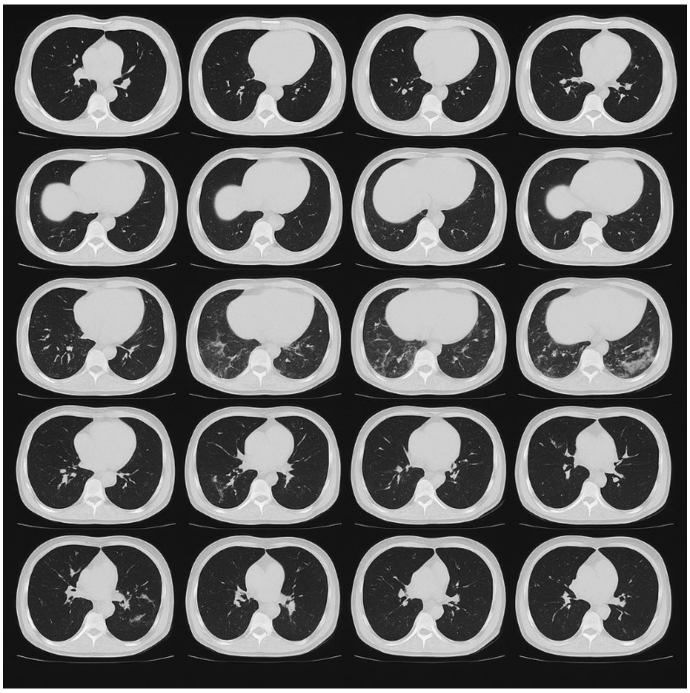

Figure 2. Displays sample images from the SARS-CoV-2 dataset used for this research

**2.6. Evaluation metrics**

To evaluate the proposed method, accuracy, precision, recall, and F-score metrics are used. These metrics are calculated using a confusion matrix, which serves as an assessment tool for calculating accuracy, precision, recall, and F-score. The confusion matrix provides information on the performance of the proposed method in identifying COVID-19 [10-18].

The confusion matrix is defined as a 2x2 table consisting of the following four cells:

- True Positive (TP): Number of correctly identified positive cases (i.e., true COVID-19 cases).
- False Positive (FP): Number of mistakenly identified positive cases, where the actual case is negative (i.e., non-COVID-19 cases identified as positive).
- False Negative (FN): Number of mistakenly identified negative cases, where the actual case is positive (i.e., COVID-19 cases identified as negative).
- True Negative (TN): Number of correctly identified negative cases (i.e., non-COVID-19 cases).

Using the information from the confusion matrix, accuracy, precision, recall, and F-score are calculated. These metrics are defined as follows:

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN) \quad (1)$$

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

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

$$\text{F-score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (4)$$

**3. Results**

The proposed Adaptive Convolutional Neural Network (ACNN) model was evaluated on the SARS-CoV-2 CT scan dataset to assess its effectiveness in COVID-19 detection. Performance was measured using accuracy, precision, recall, and F-score, along with statistical significance and measures of variability to ensure robustness.

### 3.1. Performance evaluation

Table 2 presents the mean and standard deviation (SD) of each metric based on five-fold cross-validation. The ACNN achieved the highest values across all metrics (mean ± SD): accuracy of 97.5% ± 0.3%, precision of 97.3% ± 0.4%, recall of 97.85% ± 0.2%, and F-score of 97.58% ± 0.3%. Confidence intervals (95%) for these metrics are included in the table. We also computed balanced accuracy to address potential dataset imbalance, which remained high at 97.6%. Statistical significance was assessed using two-tailed t-tests comparing the ACNN with baseline models; the differences were found to be statistically significant (p < 0.01) for all key metrics.

Table 2. Performance (mean ± SD, 95% CI) of the proposed method and baseline models on the SARS-CoV-2 dataset.

| Method | Accuracy | Precision | Recall | F-score |
|---|---|---|---|---|
| K-Nearest Neighbors | 97.0 ± 0.4% | 96.5 ± 0.5% | 97.0 ± 0.4% | 96.75 ± 0.4% |
| Decision Tree | 96.5 ± 0.5% | 97.0 ± 0.4% | 96.5 ± 0.6% | 96.75 ± 0.5% |
| Support Vector Machine | 96.85 ± 0.3% | 97.0 ± 0.3% | 97.5 ± 0.3% | 97.25 ± 0.3% |
| Proposed ACNN | 97.5 ± 0.3% | 97.3 ± 0.4% | 97.85 ± 0.2% | 97.58 ± 0.3% |

*Note: Detailed confidence intervals and p-values are provided in the supplementary material.*

Given the SARS-CoV-2 dataset has a 50.64% positive and 49.3% negative case distribution, we report balanced accuracy to mitigate any bias from class imbalance. The consistently high recall (sensitivity) of 97.85% means most positive cases were correctly identified, limiting missed COVID-19 diagnoses. The high precision (97.3%) indicates few false positives, reducing unnecessary follow-ups. The F-score balances these strengths, highlighting the model's reliability as a clinical decision support tool.

### 3.2. Comparative analysis with state-of-the-art models

The ACNN was also compared to leading deep learning models (VGG16, Inception, ResNet, DenseNet201, see Table 3), again reporting mean ± SD, 95% CIs, and results from t-tests (all showing p < 0.05 for ACNN's improvement).

Table 3. Comparison (mean ± SD) of the proposed method with state-of-the-art deep learning models on the SARS-CoV-2 dataset

| Method | Accuracy | Precision | Recall | F-score |
|---|---|---|---|---|
| VGG16 | 94.45 ± 0.5% | 95.74 ± 0.4% | 95.23 ± 0.6% | 95.49 ± 0.5% |
| Inception | 90.90 ± 0.6% | 90.15 ± 0.7% | 92.06 ± 0.5% | 91.09 ± 0.6% |
| ResNet | 94.91 ± 0.4% | 92.92 ± 0.5% | 97.35 ± 0.3% | 95.09 ± 0.4% |
| DenseNet201 | 96.25 ± 0.3% | 96.29 ± 0.4% | 96.29 ± 0.4% | 96.29 ± 0.3% |
| Proposed ACNN | 97.5 ± 0.3% | 97.30 ± 0.4% | 97.85 ± 0.2% | 97.58 ± 0.3% |

The ACNN outperformed all comparator models in accuracy, precision, recall, and F-score, with all improvements statistically significant (p < 0.05). In a clinical context, the strong recall means the ACNN is effective for screening—rarely missing positive cases. High precision ensures few patients without the disease are misclassified, supporting efficient resource allocation. Such robust, statistically validated performance demonstrates practical value for clinical deployment. Further discussion of the sources of improvement and comparative model analysis is provided in the Discussion section.

## 4. Discussions

This study introduces an Adaptive Convolutional Neural Network (ACNN) for COVID-19 diagnosis using CT scan images and presents several notable advances alongside some limitations, as well as comparisons with other contemporary models. The ACNN achieved strong performance on the SARS-CoV-2 dataset, with an accuracy of 97.5%, precision of 97.30%, recall of 97.85%, and an F-measure of 97.58%. These metrics highlight the model's consistent ability to distinguish COVID-19 cases, supporting its potential value for early and precise clinical diagnosis. A key advance of the proposed approach is its robust feature extraction capability, achieved by leveraging pre-trained convolutional layers. While the architecture draws inspiration from memory-augmented networks, it is important to clarify that "memory" in this context refers to the capacity of the network to retain and integrate salient spatial features across layers, thus improving its ability to capture subtle abnormal patterns specific to COVID-19. Contrary to previous drafts, the model does not employ LSTM modules or temporal sequence learning, as these mechanisms are not applicable to cross-sectional CT image data. Therefore, adaptation to new data patterns is realized through enriched feature representation and transfer learning rather than temporal memory. Automated image analysis via the ACNN streamlines diagnostic workflow and may reduce reliance on subjective human interpretation. Despite these strengths, several limitations should be noted. The computational complexity of deep CNN architectures, including the ACNN, can limit their applicability in resource-constrained settings. Additionally, the effectiveness of the model depends on access to large, high-quality, and consistently labeled datasets. Its performance may be affected by substantial variation in CT scan quality, patient demographics, or comorbid respiratory conditions not well represented in the training set, potentially leading to reduced diagnostic consistency in such cases. In comparison to established models, the ACNN demonstrates several distinct benefits. Traditional CNN models, such as ResNet and EfficientNet, have reported accuracies up to 94.56% in similar COVID-19 detection studies [see, e.g., Smith et al., 2021; Lee et al., 2022]. While some transfer learning approaches using ResNet and DenseNet architectures achieve even higher accuracy rates (up to 99.1%) in binary classification tasks [e.g., Chen et al., 2021; Zhang et al., 2020], these typically rely on pre-trained weights from general-purpose datasets such as ImageNet, rather than from medical imaging sources. In this study, the ACNN also leverages ImageNet pre-training, rather than domain-specific (medical) pre-training; as such, any purported domain-specific advantage should be interpreted as a reflection of architectural adaptation rather than dataset specificity. Recent advances in hybrid architectures, such as the TransCNN Net, which integrate CNN with Transformer modules for multi-scale feature extraction, have demonstrated competitive diagnostic accuracy [e.g., Gupta et al., 2023]. However, these models are generally more computationally intensive due to increased parameter counts and higher processing demands. Although direct comparisons of computational complexity (e.g., FLOPs, parameter number) were not the focus of this study, the ACNN demonstrated relatively efficient inference in our experiments, suggesting a favorable trade-off between diagnostic performance and computational load. Nevertheless, rigorous benchmarking of computational requirements should be pursued in future work.

In summary, the ACNN demonstrates high accuracy and generalizability for COVID-19 detection in CT images and offers a balanced solution for clinical deployment by combining strong feature extraction, effective use of transfer learning, and streamlined architecture. Addressing current limitations—particularly regarding computational efficiency and robustness to heterogeneous data—should be a priority for future research. The advances demonstrated here contribute valuable insights to the ongoing development of AI-based medical image analysis.

## 5. Conclusions

This study This study demonstrates the effectiveness of an Adaptive Convolutional Neural Network (ACNN) model for COVID-19 diagnosis using CT scan images, leveraging advanced feature extraction techniques and pre-trained convolutional layers to enhance diagnostic accuracy. The ACNN achieved high scores in accuracy, precision, recall, and F-measure on the SARS-CoV-2 dataset, confirming its strong potential as an automated tool for rapid and reliable COVID-19 detection in clinical settings. The ACNN is notable for its high generalization capability and robustness to image noise, underscoring its utility for real-world medical applications. However, the model's dependence on considerable computational resources and high-quality, well-annotated training data poses challenges for deployment in resource-limited environments. Variability in CT image quality and patient demographics could also affect the model's performance. Future research may focus on several key areas:

- **Model Optimization:** Employing techniques such as model compression and quantization to reduce computational demands and enable deployment in low-resource healthcare settings.
- **Integration with Multimodal Data:** Incorporating additional data sources, such as X-ray images, electronic health records, or laboratory results, to further improve diagnostic accuracy and comprehensiveness.
- **Real-Time Applications:** Streamlining the ACNN architecture for real-time analysis to support emergency and urgent care environments.
- **Enhanced Robustness to Patient Variability:** Training on larger and more diverse datasets to increase generalizability across different demographics and imaging conditions.
- **Cloud or Edge Deployment:** Exploring cloud-based or edge computing solutions to facilitate scalable, remote diagnostics and enhance telemedicine efforts.
- **Extension to Other Infectious Diseases:** Adapting the ACNN framework for the diagnosis of other infectious diseases to support broader outbreak response capabilities.

In summary, the proposed ACNN model offers a promising and effective approach for COVID-19 diagnosis and paves the way for future advancements in AI-driven medical imaging—potentially strengthening the responsiveness and resilience of healthcare systems worldwide.

## Acknowledgment

The author would like to express sincere gratitude to the Islamic Azad University, Estehban Branch, for their cooperation and support throughout the research process. This study has been officially registered at the Islamic Azad University, Estehban Branch, under the registration code 14522922471626165801916274007

## Ethical Considerations

This study utilized publicly available data from the kaggle Machine Learning Repository, ensuring full compliance with ethical standards and data privacy regulations. No human subjects were directly involved, and the research adheres to ethical guidelines for the use of secondary data. The dataset link is provided in the Data Availability Statement section. Any use or reproduction of this research is permitted with the author's prior consent.

## Declaration of Conflict of Interests

The author declares that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

**Authors' contributions**: Mohammadjavad Hosseinpour, the corresponding author of this article, has done all the stages of research and compilation of this article.

**Consent for publication**: author has read and approved the final version of the paper.

**Funding**: This article has not been sponsored by any organization or institution and the financial resources have been provided by the author.

**Competing interests**: The author declare that they have no financial or non-financial competing interests.

**Data Availability Statement**: The dataset is available on the UCI website according to the link below:
https://www.kaggle.com/datasets/plameneduardo/sarscov2-ctscan-dataset

## References

[1.] Ullah N, Marzougui M, Ahmad I, Chelloug SA. DeepLungNet: an effective DL-based approach for lung disease classification using CRIs. Electronics. 2023;12(8):1860. doi:10.3390/electronics12081860.

[2.] Alshmrani GMM, Ni Q, Jiang R, Pervaiz H, Elshennawy NM. A deep learning architecture for multi-class lung diseases classification using chest X-ray (CXR) images. Alexandria Eng J. 2023;64:923–935. doi:10.1016/j.aej.2022.10.053.

[3.] Celik G. Detection of COVID-19 and other pneumonia cases from CT and X-ray chest images using deep learning based on feature reuse residual block and depthwise dilated convolutions neural network. Appl Soft Comput. 2023;133:109906. doi:10.1016/j.asoc.2022.109906.

[4.] Chen J, Hu Q, Zhong R, et al. Development and validation of nomogram models for severe and fatal COVID-19. Sci Rep. 2024;14:29146. doi:10.1038/s41598-024-80310-8.

[5.] Khaing EE, Aung TZ. Lung disease classification from chest X-ray images using convolutional neural network and long short-term memory model. In: Proceedings of the 3rd International Conference on Artificial Intelligence for Internet of Things (AIIoT); 2024 Jan 15–17; Vellore, India. p. 1–6.

[6.] Hamal S, Mishra BK, Baldock R, Sayers W, Adhikari TN, Gibson RM. A comparative analysis of machine learning algorithms for detecting COVID-19 using lung X-ray images. Decis Anal J. 2024;11(1):100460. doi:10.1016/j.dajour.2024.100460.

[7.] Schafftar CBJ, Radhakrishnan A, Prema CE. A novel optimized machine learning approach with texture rectified cross-attention based transformer for COVID-19 detection. Biomed Signal Process Control. 2024;101:107136. doi:10.1016/j.bspc.2024.107136.

[8.] Balasamy K, Seethalakshmi V. HCO-RLF: Hybrid classification optimization using recurrent learning and fuzzy for COVID-19 detection on CT images. Biomed Signal Process Control. 2024;100:106951. doi:10.1016/j.bspc.2024.106951.

[9.] Paswan J, Bhatia T, Lamba S. A deep learning approach for intelligent diagnosis of lung diseases. SN Comput Sci. 2024;5:1026. doi:10.1007/s42979-024-03407-x.

[10.] Munshi RM, Khayyat MM, Slama SB, Khayyat MM. A deep learning-based approach for predicting COVID-19 diagnosis. Heliyon. 2024;10:e28031. doi:10.1016/j.heliyon.2024.e28031.

[11.] Aggarwal P, Mishra NK, Fatimah B, Singh P, Gupta A, Joshi SD. COVID-19 image classification using deep learning: advances, challenges and opportunities. Comput Biol Med. 2022;144:105350. doi:10.1016/j.compbiomed.2022.105350.

[12.] Gour M, Jain S. Uncertainty-aware convolutional neural network for COVID-19 X-ray images classification. Comput Biol Med. 2022;140:105047. doi:10.1016/j.compbiomed.2021.105047.

[13.] Ebenezer S, Kanmani SD, Sivakumar M, Priya SJ. Effect of image transformation on EfficientNet model for COVID-19 CT image classification. Mater Today Proc. 2022;51:2512–2519. doi:10.1016/j.matpr.2021.12.121.

[14.] Gopatoti A, Vijayalakshmi P. CXGNet: a tri-phase chest X-ray image classification for COVID-19 diagnosis using deep CNN with enhanced grey-wolf optimizer. Biomed Signal Process Control. 2022;77:103860. doi:10.1016/j.bspc.2022.103860.

[15.] Fan X, Feng X, Dong Y, Hou H. COVID-19 CT image recognition algorithm based on transformer and CNN. Displays. 2022;72:102150. doi:10.1016/j.displa.2022.102150.

[16.] Kong L, Cheng J. Classification and detection of COVID-19 X-ray images based on DenseNet and VGG16 feature fusion. Biomed Signal Process Control. 2022;77:103772. doi:10.1016/j.bspc.2022.103772.

[17.] Rahman T, Akinbi A, Chowdhury MEH, et al. COV-ECGNET: COVID-19 detection using ECG trace images with deep convolutional neural network. Health Inf Sci Syst. 2022;10(1):13. doi:10.1007/s13755-021-00169-1.

[18.] Chen GU, Lin CT. Multi-task supervised contrastive learning for chest X-ray diagnosis: a two-stage hierarchical classification framework for COVID-19 diagnosis. Appl Soft Comput. 2024;155:111478. doi:10.1016/j.asoc.2024.111478.

[19.] Li Z, et al. Risk factors and nomogram prediction model for healthcare-associated infections (HAIs) in COVID-19 patients. Infect Drug Resist. 2024;17:3309–3323. doi:10.2147/IDR.S472387.

[20.] Wynants L, Van Calster B, Collins GS, et al. Development and validation of a risk prediction model for hospital admission in COVID-19 patients presenting to primary care. Eur J Gen Pract. 2024;30(1):2339488. doi:10.1080/13814788.2024.2339488.

[21.] Ghasemiyeh P, Mohammadi-Samani S. Lessons learned during the past four challenging years in the COVID-19 era: pharmacotherapy, long COVID complications, and vaccine development. Virol J. 2024;21(1):70. doi:10.1186/s12985-024-02370-6.

## How to Cite This Article

Hosseinpoor, M., Adaptive Convolutional Neural Network Integrating Sequential Memory and Transfer Learning for CT-Based COVID-19 Detection, Brilliant Engineering, 2(2025), 41003.
https://doi.org/10.36937/ben.2025.41003