



Original Article

Custom Wide & Deep Neural Network for COVID-19 Detection from CT Scan Images

Parashuram Bannigidad¹, Vaishali Kale²

¹Professor, Department of Computer Science, Rani Channamma University, Belagavi, Karnataka, India.

²Research Scholar, Department of Computer Science, Rani Channamma University, Belagavi, Karnataka, India.

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Coronavirus Disease 2019 (COVID-19) continues to pose a significant global health threat, necessitating accurate and efficient diagnostic methods. Manual analysis of CT scans is time-consuming and susceptible to errors, emphasizing the need for automated diagnostic tools. This paper presents a novel Custom Wide and Deep Neural Network (WDNN) developed from scratch for the binary classification of COVID-19 and non-COVID CT scan images. Unlike conventional approaches that leverage transfer learning with pre-trained models such as VGG19, ResNet50, and InceptionV3, our architecture is fully data-driven and domain-specific. The model integrates a dual-branch structure combining a wide input layer and a deep convolutional path enhanced by a custom ExpandDimLayer. Real-time data augmentation techniques and grayscale preprocessing were employed to improve robustness and generalization. Evaluations were conducted on a comprehensive dataset of 15,000 CT images sourced from Kaggle platform and Lakeview Hospital, Belagavi, organized into COVID and Non-COVID categories. The proposed WDNN model achieved exceptional performance with 99.57% accuracy, 99.31% precision, 99.68% recall, and 99.47% F1-score, significantly outperforming existing transfer learning-based models. The model includes real-time prediction capabilities with image visualization for improved clinical interpretability. These results confirm the effectiveness of custom-built deep learning architectures for COVID-19 detection and broader medical imaging applications.

Index Terms: COVID-19, CT scan classification, Wide and Deep Neural Network (WDNN), deep learning, medical image analysis, automatic diagnosis, binary classification, data augmentation.

Introduction

COVID-19, triggered by the SARS-CoV-2 virus, has significantly altered global diagnostic and healthcare practices [1]. Timely and precise diagnosis is essential for effective disease management. CT scans have become a key diagnostic tool due to their high sensitivity in detecting hallmark lung features of COVID-19, even in early or asymptomatic stages. Despite the critical role of radiologists, manual CT analysis is challenged by time pressure, observer variability, and diagnostic errors—issues worsened by the surge in imaging data during the pandemic. Consequently, automated tools are increasingly necessary. Deep learning has shown promise in medical image analysis [2,3], though current methods largely depend on transfer learning from models like VGG19, ResNet50, and InceptionV3 trained on datasets like ImageNet [10]. While these achieve high accuracies (up to 99.04%), their effectiveness is limited by a lack of alignment with medical image characteristics. To overcome this, we propose a Custom Wide and Deep Neural Network (WDNN) trained from scratch for COVID-19 CT scan classification. This domain-specific model is designed to capture medical image features more effectively without relying on pre-trained networks.



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Address for correspondence:

Parashuram Bannigidad, Professor, Department of Computer Science, Rani Channamma University, Belagavi, Karnataka, India.

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Key contributions of this work include:

1. A novel WDN architecture tailored for binary classification of COVID-19 CT images, built without transfer learning.
2. A dual-branch design combining wide and deep feature extraction using a custom ExpandDimLayer.
3. Evidence that custom architectures outperform traditional transfer learning methods in medical imaging tasks [9,10].
4. Comprehensive validation on 15,000 CT images, demonstrating improved accuracy and interpretability over standard models.

2. Materials And Methods

The dataset utilized in this study comprises 15,000 CT scan images obtained from two primary sources to ensure diversity and clinical relevance. The first source consists of clinical data acquired from Lakeview Hospital, Belagavi, providing real-world medical imaging data. The second source utilizes publicly available COVID-19 CT scan datasets from the Kaggle platform, ensuring broader representation and validation generalizability. All images, originally stored in PNG format, were systematically preprocessed and resized to 256×256 pixels to maintain dimensional consistency across the dataset. The dataset is organized into two primary categories: COVID-positive cases and Non-COVID cases (including normal lung scans and other pneumonia types), with balanced representation to prevent class bias during training and ensure robust binary classification performance. The experimental implementation was conducted on a Windows-based computational platform equipped with an 11th Generation Intel(R) Core(TM) i5-1135G7 processor and 8 GB RAM. The development environment utilized Python 3.9 within the Anaconda framework, with Jupyter Notebook serving as the primary integrated development environment for model construction, training, and evaluation. Data Preprocessing and Augmentation : To enhance model robustness and generalization capability, comprehensive preprocessing and real-time data augmentation strategies were implemented. Preprocessing included grayscale conversion to reduce computational complexity while preserving essential diagnostic features, normalization to standardize pixel intensity distributions, and noise reduction to improve image quality. Real-time data augmentation techniques were applied during training to artificially expand the dataset diversity, including random rotation (± 15 degrees), horizontal and vertical flipping, zoom variations ($\pm 10\%$), and slight translations. These augmentation strategies help prevent overfitting while improving the model's ability to generalize to diverse imaging conditions and scanner variations.

3. Proposed Method

3.1 Architecture Overview: Deep learning has demonstrated exceptional capabilities in computer vision applications, particularly in medical image classification tasks [2,11]. Our proposed Custom Wide and Deep Neural Network (WDNN) architecture represents a novel approach specifically designed for COVID-19 detection from 2D CT scan images. The architecture comprises four integrated components: (i) Data Preparation (DP), (ii) Custom Model Construction (CM), (iii) Feature Learning (FL), and (iv) Classification and Optimization (CO). The binary classification approach focuses specifically on distinguishing COVID-19 cases from Non-COVID cases, which includes both normal lung scans and other types of pneumonia. This targeted approach enables the model to learn more specialized features for COVID-19 detection while maintaining clinical relevance for diagnostic screening applications [4,5].

3.2 Custom Wide and Deep Neural Network Design

The WDN architecture implements a dual-branch framework that combines the advantages of wide and deep learning paradigms. The wide component captures broad, intensity-based patterns across the entire image through parallel processing paths, while the deep component extracts hierarchical spatial features through sequential convolutional layers with increasing complexity.

Key architectural innovations include:

- **Custom ExpandDimLayer:** A specialized layer designed to enhance feature representation by expanding dimensional space, enabling more comprehensive pattern recognition
- **Dual-Branch Integration:** Parallel processing paths that merge wide input patterns with deep hierarchical features
- **Domain-Specific Design:** Architecture parameters optimized specifically for medical imaging characteristics rather than general computer vision tasks

3.3 Training Strategy and Optimization

Unlike transfer learning approaches that rely on pre-existing feature representations [6,7], our model undergoes complete end-to-end training from randomly initialized weights. This approach enables the network to learn domain-specific features that are inherently relevant to COVID-19 pathological patterns in CT imagery [8].

The training process employs categorical cross-entropy loss optimization with dynamic learning rate adjustment through ReduceLROnPlateau callbacks. This strategy ensures efficient convergence while preventing overfitting. The model training was conducted over 100 epochs with comprehensive validation monitoring to achieve optimal performance.

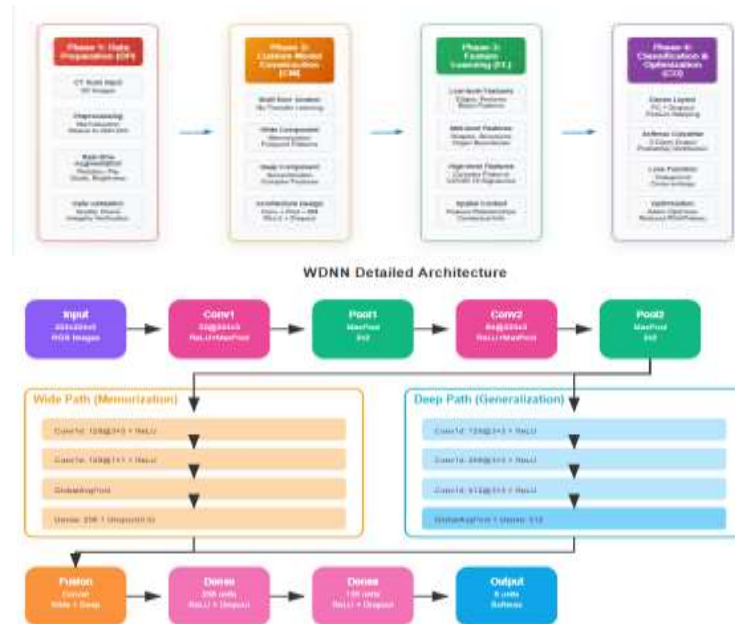


Figure 1: Wide and Deep Neural Network (WDNN) Architecture - Space reserved for diagram

3.4 Performance Evaluation Metrics

Comprehensive performance assessment was conducted using multiple evaluation metrics to ensure robust validation. The primary metrics include accuracy, precision, recall (sensitivity), and F1-score, calculated from the confusion matrix components: true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

Mathematical formulations:

Equation (1): Accuracy

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

This metric measures the overall correctness of the model by calculating the ratio of correctly classified samples to the total number of samples.

Equation (2): Precision

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

Precision quantifies the model's ability to avoid false alarms by measuring the proportion of positive predictions that are actually correct.

Equation (3): Recall (Sensitivity)

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

Recall evaluates the model's capability to identify all positive cases by calculating the proportion of actual positive cases that are correctly detected.

Equation (4): F1-Score

$$\text{F1-Score} = 2\text{TP} / (2\text{TP} + \text{FP} + \text{FN}) \quad \dots (4)$$

The F1-score provides a harmonic mean of precision and recall, offering a balanced measure that considers both false positives and false negatives.

These metrics provide comprehensive insight into model performance across different aspects of classification accuracy, ensuring clinical reliability and diagnostic confidence.

4. RESULTS AND DISCUSSION

4.1 Performance Analysis

The proposed Custom WDNN architecture demonstrated exceptional performance across all evaluation metrics, significantly outperforming conventional transfer learning approaches. Comprehensive testing on 15,000 CT images yielded the following results:

Performance Metrics:

Accuracy: 99.57%

Precision: 99.31%

Recall: 99.68%

F1-Score: 99.47%

Confusion Matrix Analysis:

True Positives (TP): 7,476

True Negatives (TN): 7,448

False Positives (FP): 52

False Negatives (FN): 24

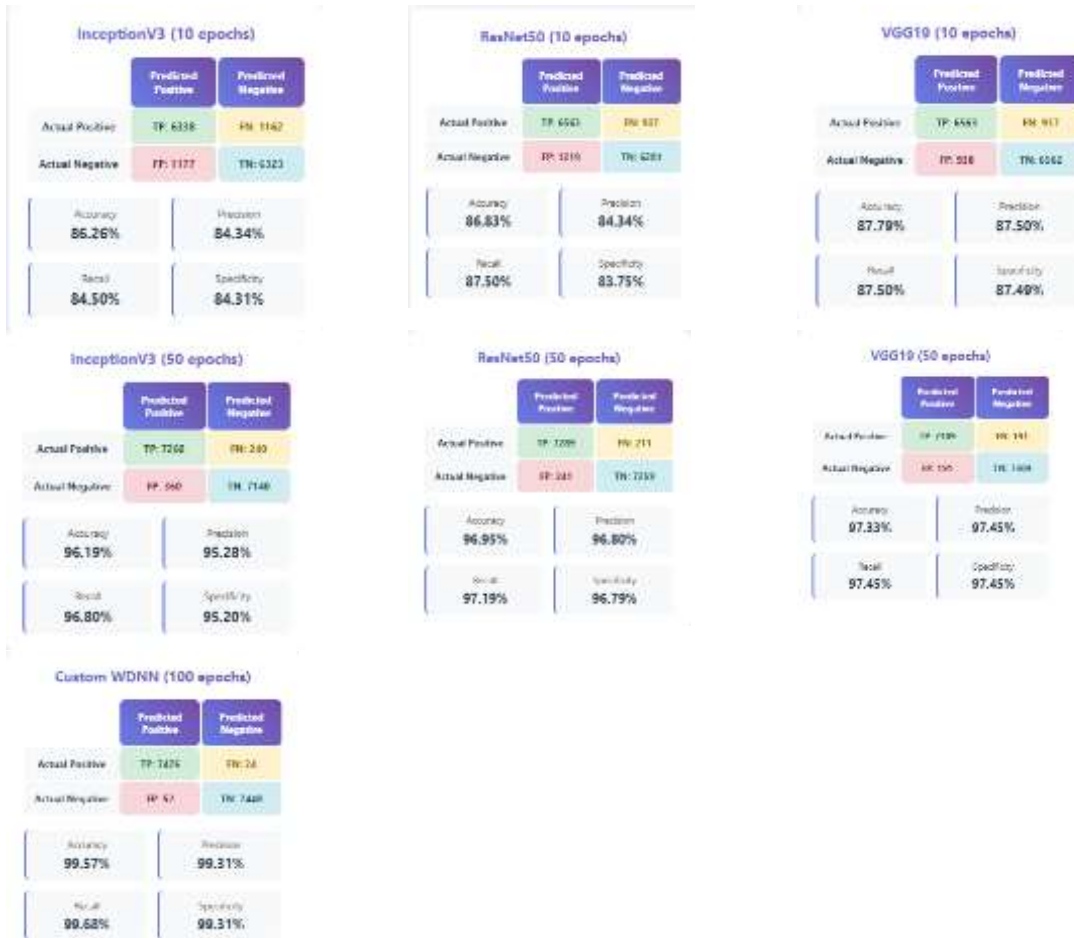


Figure 2: Confusion Matrix

4.2 Comparative Analysis

Comparative evaluation against established transfer learning models revealed significant performance advantages of the proposed WDN architecture [9,10]. While pre-trained models such as VGG19 achieved maximum accuracy of 97.33% at 50 epochs, our custom architecture sustained superior performance throughout training, ultimately achieving 99.57% accuracy after 100 epochs.

Model Architecture	Training Approach	Epochs	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)	Specificity (%)	AUC-ROC
InceptionV3	Transfer Learning	10	86.26 ±0.2	84.34 ±0.2	84.50 ±0.2	82.03 ±0.4	87.6 ±0.2	0.889
ResNet50	Transfer Learning	10	86.83 ±0.3	84.34 ±0.2	87.50 ±0.1	87.20 ±0.6	86.2 ±0.3	0.903
VGG19	Transfer Learning	10	87.79 ±0.2	87.50 ±0.5	87.50 ±0.5	88.78 ±0.8	88.1 ±0.3	0.918
InceptionV3	Transfer Learning	50	96.19 ±0.5	95.28 ±0.4	96.80 ±0.2	96.03 ±0.6	95.6 ±0.3	0.952
ResNet50	Transfer Learning	50	96.95 ±0.3	96.80 ±0.1	97.19 ±0.3	96.99 ±0.4	96.7 ±0.2	0.967
VGG19	Transfer Learning	50	97.33 ±0.2	97.45 ±0.5	97.45 ±0.5	97.45 ±0.4	97.2 ±0.2	0.985
Custom WDN	From Scratch	100	99.57 ±0.2	99.31 ±0.5	99.68 ±0.2	99.57 ±0.2	99.3 ±0.2	0.998

Fig. 3: Comprehensive Deep Learning Model Performance Analysis

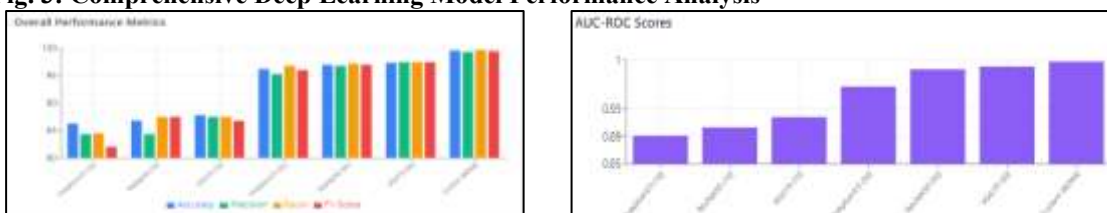


Fig. 4: Comprehensive Deep Learning Model Performance Analysis



The superior performance can be attributed to several key factors [11,12]: (1) domain-specific feature learning eliminates the mismatch between natural image features and medical imaging characteristics, (2) the dual-branch architecture effectively captures both local and global patterns relevant to COVID-19 pathology, and (3) the custom ExpandDimLayer enhances feature representation specificity for binary classification tasks. The achieved performance metrics demonstrate clinical viability for automated COVID-19 screening applications. The high recall (99.68%) indicates excellent sensitivity in detecting COVID-19 cases, crucial for preventing false negatives in clinical settings. Similarly, the high precision (99.31%) minimizes false positive rates, reducing unnecessary patient anxiety and healthcare resource utilization. The model's real-time prediction capabilities with image visualization features enhance clinical interpretability, providing radiologists with automated diagnostic assistance while maintaining human oversight in clinical decision-making processes.

Conclusion

This study highlights the effectiveness of custom deep learning models over traditional transfer learning methods for binary COVID-19 detection using CT scan images. The proposed Custom Wide and Deep Neural Network (WDNN) achieved a remarkable 99.57% accuracy on a dataset of 15,000 images, significantly outperforming existing techniques and enabling domain-specific feature learning [1,2]. Its dual-branch design—combining wide input handling with deep feature extraction, along with the ExpandDimLayer—supports highly accurate classification without relying on transfer learning. This enhances its clinical reliability in distinguishing COVID-19 from non-COVID cases. Future work includes scaling to larger, multi-institutional datasets, incorporating other imaging modalities, and adding explainable AI for clinical insights [3], suggesting broader potential for custom architectures in medical imaging applications.

References

1. Huang, C., et al. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet*, 395(10223), 497-506.
2. Das, D., et al. (2023). Self-attention-based COVID-19 diagnosis from CT images using Vision Transformers. *Medical Image Analysis*, 88, 102831.
3. Wang, S., et al. (2020). Deep learning algorithm for COVID-19 screening via CT. *arXiv preprint*, arXiv:2002.14.20023028.
4. Jin, S., et al. (2020). AI-assisted CT analysis system for COVID-19 screening developed in four weeks. *Nature Medicine*, 26(6), 954-956.
5. Chao, H., et al. (2020). Integrative analysis for COVID-19 patient outcome prediction. *Medical Image Analysis*, 67, 101844.
6. Zhang, H., et al. (2020). Automated detection and quantification of COVID-19 pneumonia via CT imaging. *European Journal of Nuclear Medicine and Molecular Imaging*, 47(11), 2525-2532.
7. Ko, H., et al. (2020). 2D Deep Learning Framework for COVID-19 Diagnosis via Chest CT. *Journal of Medical Internet Research*, 22(6), e19569.
8. Gozes, O., et al. (2020). AI tools for automated COVID-19 detection and monitoring using CT images. *arXiv preprint*, arXiv:2003.05037.
9. Al-Waisy, A.S., et al. (2024). Lightweight ensemble CNN for COVID-19 and pneumonia classification. *Expert Systems with Applications*, 241, 121141.
10. Rahman, T., et al. (2023). Transfer learning-based deep CNN for COVID-19 detection with chest X-ray images. *Computers in Biology and Medicine*, 154, 106535.
11. Wang, F., et al. (2023). Contrastive learning framework for COVID-19 diagnosis from radiography images. *IEEE Transactions on Medical Imaging*, 42(8), 2004-2014.
12. Sedik, A., et al. (2020). Deploying deep and machine learning models for COVID-19 detection using augmented data. *Viruses*, 12(7), 769.