TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 22, No. 5, October 2024, pp. 1187~1195
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v22i5.26017

A high accuracy of deep learning based CNN architecture: classic, VGGNet, and RestNet50 for Covid-19 image classification

Ibnu Utomo Wahyu Mulyono[1], Eko Hari Rachmawanto[1], Christy Atika Sari[1], Md Kamruzzaman Sarker[2]
[1]Study Program in Informatics Engineering, Faculty of Computer Science, University of Dian Nuswantoro, Semarang, Indonesia
[2]Department of Computer Science, Bowie State University, Bowie, United States

Article Info

Article history:

Received Jan 29, 2024
Revised Jun 23, 2024
Accepted Jul 12, 2024

Keywords:

Classic convolutional neural network
Convolutional neural network
Covid-19
RestNet-50
VGGNet

ABSTRACT

This research paper provides a detailed examination of different convolutional neural network (CNN) structures used in Covid-19 image classification tasks. The study thoroughly investigates the performance of classic CNN, visual geometry group (VGG), and ResNet-50 architectures across a variety of datasets. The analysis focuses on evaluating the efficacy of each architecture by considering metrics such as accuracy, precision, recall, and F1-Score. The experimental results reveal that the ResNet-50 architecture achieves the highest performance with an accuracy rate of 96.63%, outperforming both VGG and classic CNN models. This finding emphasizes the importance of architectural choices and hyperparameter selection in achieving optimal performance in image classification tasks. The combination of the ResNet-50 architecture with the Adam optimizer demonstrates its effectiveness in improving classification accuracy. These findings contribute to the field of deep learning by providing valuable insights into the performance analysis of CNN architectures and highlighting the significance of selecting appropriate hyperparameters for optimal model performance. The selection of VGG and ResNet-50 architectures was based on their strong feature extraction capabilities, proven state-of-the-art performance, and their suitability for transfer learning. VGG and ResNet-50 also have widely available pre-trained models, facilitating their usage and experimentation.

Corresponding Author:

Christy Atika Sari
Study Program in Informatics Engineering, Faculty of Computer Science, University of Dian Nuswantoro
Imam Bonjol 207, Semarang, 50131, Central Java, Indonesia
Email: christy.atika.sari@dsn.dinus.ac.id

1. INTRODUCTION

Covid-19 pandemic has garnered global attention since its emergence in early 2020 [1]. This novel coronavirus, also known as SARS-CoV-2, has had far-reaching and significant impacts worldwide [2]. Its rapid and easily transmissible nature has led to alarming increases in cases and fatalities, as well as severe social, economic, and health consequences [3]. The declaration by the World Health Organization (WHO) of Covid-19 as a global public health emergency has had a profound impact on almost every aspect of human existence [4]. Governments across the globe continue to implement various measures, including vaccine development and restrictive policies, in their ongoing efforts to curb the spread of the virus. Nevertheless, the Covid-19 situation remains a complex and evolving challenge, with long-term implications that are still not fully understood [3], [4].

Medical technologies like computed tomography (CT) scans and magnetic resonance imaging (MRI) have played a crucial role in diagnosis and monitoring [5], [6]. CT scans have played a crucial role in identifying lung abnormalities associated with the virus, enabling healthcare providers to evaluate the extent of infection and deliver suitable medical interventions [7]. The use of high-resolution CT scans has been instrumental in identifying the distinct ground-glass opacities and consolidations in the lungs, facilitating early detection and prompt intervention for Covid-19 cases [8]. Similarly, MRI technology has proven valuable in assessing the impact of Covid-19 on other organs and systems, such as the cardiovascular and nervous systems [9]. By providing detailed anatomical and functional information, MRI scans aid in identifying potential complications and guiding therapeutic decisions [10]. These advanced imaging techniques have revolutionized the understanding and management of Covid-19, empowering healthcare providers to deliver more accurate and targeted care to those affected by the virus.

The adoption of convolutional neural network (CNN) techniques has demonstrated significant effectiveness in enhancing the classification of individuals with Covid-19, community-acquired pneumonia (CAP), and non-Covid conditions. This approach has proven to be highly effective in improving the accuracy of distinguishing between these different medical conditions [11], [12]. CNN is an advanced deep learning algorithm that has been specifically developed to excel in image processing and pattern recognition tasks. Its architecture is designed to effectively analyze and extract features from images, making it particularly well-suited for various visual recognition tasks [13]. These layers are designed to identify patterns and structures within the images, enabling the CNN to learn and recognize meaningful features that can aid in accurate medical diagnoses [14]. By training the CNN model on a large dataset of labeled images, it can learn to differentiate distinct patterns and characteristics associated with Covid-19, coronary artery disease (CAD), and non-Covid conditions [14], [15]. This trained model can then be applied to classify new medical images, enabling accurate and efficient diagnosis. The incorporation of CNN into medical imaging analysis holds significant potential in enhancing the identification and differentiation of these conditions, ultimately leading to more timely and targeted medical interventions [16], [17].

2. METHOD

2.1. Related research

This section presents a literature survey on various techniques employed in the development of ResNet, VGGNet, and classic layers based on CNN, along with their advantages and limitations. Showkat and Qureshi [18] represented an important contribution in the field of chemometrics and analytical chemistry. In their study, focused on developing a novel approach for multivariate calibration using deep learning techniques. The researchers introduced a novel deep CNN architecture that combined the ResNet architectures with traditional layers. This integration was aimed at improving the predictive performance of chemometric models. By incorporating ResNet structures into the CNN, the researchers sought to enhance the ability of the model to accurately predict and analyze chemical data. The combination of these architectures allowed for the extraction of both low-level and high-level features from spectral data, enabling more accurate and robust calibration models. The authors demonstrated the effectiveness of their approach through extensive experiments on various chemical datasets, achieving superior performance compared to traditional chemometric methods. Paymode and Malode [19] represented an important milestone in the field of artificial intelligence and image analysis. In their study, explored the application of VGGNet architectures in the context of facial recognition systems. By leveraging the depth and skip connections of the stacked convolutional layers of VGGNet, they aimed to improve the accuracy and robustness of facial recognition algorithms. Through extensive experiments on benchmark datasets, they demonstrated the superiority of their proposed approach compared to traditional methods. However, their research also highlighted certain limitations, such as the computational complexity associated with deeper networks and the need for a significant amount of labeled training data. In this study,we focused on investigating the integration of VGG, ResNet, and classic CNN architectures to improve the overall performance of CNNs in image classification tasks. We explored how combining these different architectures can enhance the capabilities of CNNs and potentially achieve better results in accurately classifying images. By combining the strengths of these three architectures, we aimed to leverage the deep feature extraction capabilities of visual geometry group (VGG), the skip connections of ResNet for improved gradient flow, and the simplicity and efficiency of classic CNN layers. The experimental results on a benchmark image dataset demonstrated that the fused architecture outperformed individual architectures in terms of accuracy and robustness.

2.2. Proposed method

In this study, we propose a hybrid method that combines the strengths of classic CNN architectures, namely VGG and ResNet, to enhance the performance of image recognition tasks. Our approach leverages the deep feature extraction capabilities of VGG, which excels in capturing fine-grained details, with the skip connections of ResNet, which allows for efficient propagation of gradients during training. To assess the performance of the proposed method, we conducted comprehensive experiments on widely recognized benchmark datasets. Our objective was to evaluate how the method performed in comparison to individual

VGG and ResNet models. Through these experiments, we aimed to quantify the improvements achieved by our approach and provide a comparative analysis of its performance against the standalone VGG and ResNet models as shown in Algorithm 1, Algorithm 2, and Figure 1.

Algorithm 1. VGG architecture
1. Image Input Layer $\leftarrow Width_{in} \times Height_{in} \times Dimension_{in} \leftarrow 200 \times 200 \times 1$
2. Convolutional Layer 1:
   – Convolution operation with a filter size $3 \times 3 \times 8\, Filters$.
   – Padding $\leftarrow$ $'same'$.
   – ReLU function is Actived.
3. Max Pooling Layer: Max pooling size $\leftarrow 2 \times 2$ with a stride $\leftarrow 2$.
4. Convolutional Layer 2:
   – Convolution operation with a filter size $3 \times 3 \times 16\, Filters$.
   – Padding $\leftarrow$ $'same'$.
   – ReLU function is Actived.
5. Max Pooling Layer: Max pooling size $\leftarrow 2 \times 2$ with a stride $\leftarrow 2$.
6. Convolutional Layer 3:
   – Convolution operation with a filter size $3 \times 3 \times 16\, Filters$.
   – Padding $\leftarrow$ $'same'$.
   – ReLU function is Actived.
7. Convolutional Layer 4:
   – Convolution filter size: $3 \times 3 \times 32\, Filters$.
   – Padding $\leftarrow$ $'same'$.
   – ReLU function is Actived.
8. Max Pooling Layer: Max pooling size $\leftarrow 2 \times 2$ with a stride $\leftarrow 2$.
9. Convolutional Layer 5:
   – Convolution filter size: $3 \times 3 \times 64\, Filters$.
   – Padding $\leftarrow$ $'same'$.
   – ReLU function is Actived.
10. Max Pooling Layer: Max pooling size $\leftarrow 2 \times 2$ with a stride $\leftarrow 2$.
11. Fully Connected Layer 1:
   – Matrix multiplication $\leftarrow 4096\, neurons$.
   – ReLU function is Actived.
12. Dropout Layer 1: Dropout rate $\leftarrow 0.5$.
13. Fully Connected Layer 2:
   – Matrixmultiplication $\leftarrow 4096\, neurons$.
   – ReLU function is Actived.
14. Dropout Layer 2: Dropout rate $\leftarrow 0.5$.
15. Fully Connected Layer 3: Matrix multiplication with $3\, neurons$ (replace 3 with the number of classes).
16. Softmax Layer: Softmax activation function to generate class probabilities.
17. Classification Layer: Classification layer for multi-class classification.

Algorithm 2. Resnet-50 architecture
1. Image Input Layer $\leftarrow Width_{in} \times Height_{in} \times Dimension_{in} \leftarrow 200 \times 200 \times 1$
2. Convolutional Layer:
   – Convolution filter size: $7 \times 7 \times 64\, filters$.
   – Stride $\leftarrow$ 2.
   – Padding $\leftarrow$ 3.
3. Batch Normalization Layer: Normalization operation of the previous layer.
4. ReLU Layer: Element-wise ReLU of the previous layer.
5. Max Pooling Layer:
   – Max pooling size $\leftarrow 3 \times 3$.
   – Stride $\leftarrow$ 2.
   – Padding $\leftarrow$1.
6. Convolutional Layer of Residual Blocks 1:
   – Convolution filter size:$1 \times 1 \times numFilters1 \leftarrow 1 \times 1 \times 128\, filters$
   – Stride $\leftarrow$ $'stride'$.
   – Padding $\leftarrow$ 0.
7. Convolutional Layer of Residual Blocks 2:
   – Convolution filter size:$1 \times 1 \times numFilters1 \leftarrow 1 \times 1 \times 256\, filters$
   – Stride $\leftarrow$ $'stride'$.
   – Padding $\leftarrow$ 0.
8. Convolutional Layer of Residual Blocks 3:
   – Convolution filter size:$1 \times 1 \times numFilters1 \leftarrow 1 \times 1 \times 512\, filters$
   – Stride $\leftarrow$ $'stride'$.
   – Padding $\leftarrow$ 0.
9. Average Pooling Layer:

   – Average pooling size ← [1 1].
10. Fully Connected Layer: Matrix multiplication with 3 *neurons* (replace 3 with the number of classes in your case).
11. Softmax Layer: Softmax activation of the previous layer to generate class probabilities.
12. Classification Layer: Classification layer for multi-class classification.

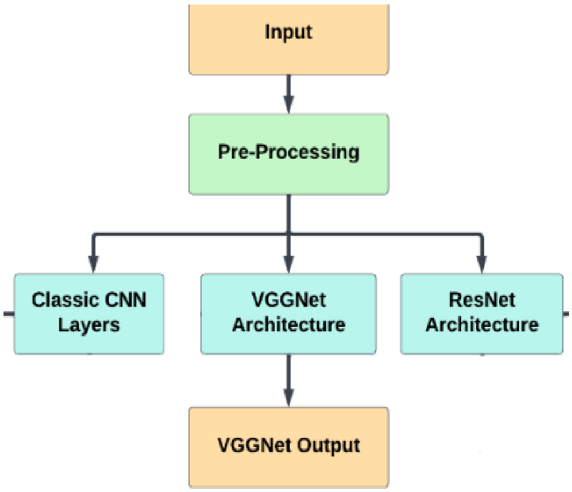


Figure 1. Flowchart of proposed hybrid method

The difference between the provided mathematical expressions lies in the architecture and ordering of the layers. The first expression reflects an architecture inspired by the VGG network with repeated convolutions and several fully connected layers, while the second expression represents a simple residual block structure within a network. The first mathematical expression incorporates convolutional layers, pooling layers, fully connected layers, and activation layers like ReLU and softmax. In contrast, the second expression consists of convolutional layers, batch normalization layers, and ReLU layers, reflecting a residual block commonly found in deep network architectures like ResNet. Comparing the two expressions, the first one is more intricate and suitable for general classification tasks with extensive datasets. On the other hand, the second expression, with its residual block structure, is commonly used in deeper and more complex network architectures like ResNet. Based on layers CNN can be seen in Figures 2 and 3, where Figure 2 represent VGGNet layers, and Figure 3 represent ResNet layers.

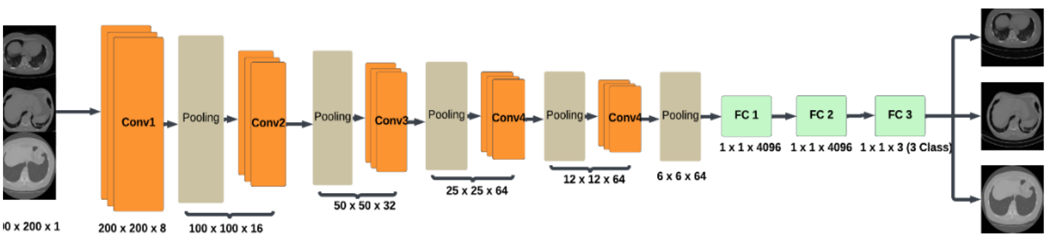


Figure 2. Proposed VGGNet architecture layers based on Algorithm 1

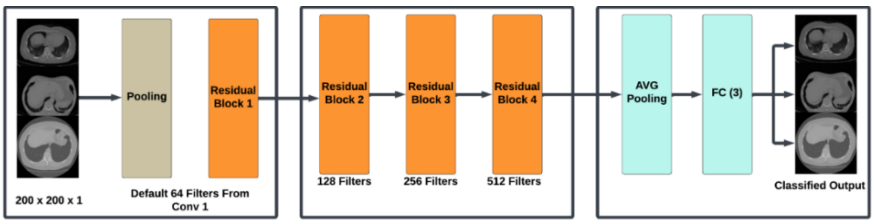
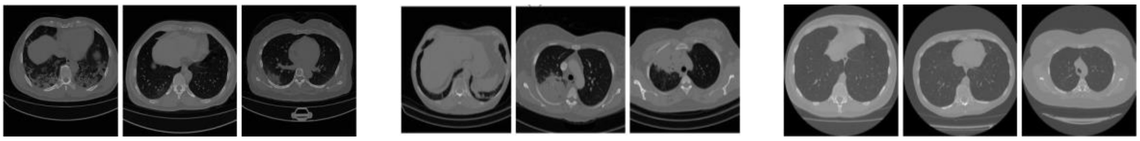


Figure 3. Proposed ResNet-50 architecture layers based on Algorithm 2

2.3. Dataset

The dataset used in this study was obtained from Kaggle and consisted of medical images obtained through CT scans [20]. The initial size of the images was 512×512×1, but they were resized to 200×200×1 during preprocessing. The dataset comprised a total of 17,103 data samples, which were further filtered down to 16,169 samples for analysis. The dataset was divided into three distinct classes for classification purposes. These images offer detailed visual information that can be leveraged to train and test algorithms, advancing the field of medical imaging and enabling more accurate diagnoses and treatments. In Figures 4(a)-(c), there are 9 sample data instances selected as a representation of the total dataset consisting of 16,169 samples image. These samples serve as representative examples, offering a glimpse into the overall dataset's composition. Each sample exhibits unique characteristics and features, showcasing the diversity present within the dataset. By visually examining these selected examples, one can gain an understanding of the range of patterns and variations that the models are expected to accurately classify.



(a) (b) (c)

Figure 4. Sample of visualzation Covid-19 dataset; (a) Covid-19, (b) CAP, and (c) non Covid-19

2.4. CNN

CNN is an advanced deep learning algorithm explicitly developed for analyzing visual data, including images. It is extensively employed in computer vision tasks such as image classification, object detection, and image segmentation [21]. CNNs are constructed with specialized layers that effectively capture local patterns and spatial hierarchies present in the input data. The fundamental components of a CNN include convolutional layers, pooling layers, and fully connected layers. Convolutional layers utilize filters to extract relevant features from input images, enabling them to capture both low-level details and high-level representations. Pooling layers perform downsampling on the obtained feature maps, reducing their spatial dimensions while preserving essential information. Fully connected layers establish connections between the extracted features and the final output layer, facilitating tasks like classification or regression. Training a CNN involves employing backpropagation and gradient descent algorithms to adjust the network's weights and biases, with the aim of minimizing the discrepancy between predicted and actual outputs.

2.5. Result analysis

Confusion matrix is a crucial tool for evaluating the performance of a classification model. It is used to present a tabular representation of predicted and actual labels, enabling a detailed analysis of the model's accuracy. The matrix consists of four main metrics: true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). TP indicate the number of correctly predicted positive instances, FP represent the number of incorrect positive predictions, TN are the number of correct negative predictions, and FN are the number of incorrect negative predictions. It is important to note that the ResNet and VGG architectures mentioned earlier may yield different results when evaluated using the confusion matrix due to their unique architectural designs and parameter configurations as in (1)-(4).

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

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

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

$$F1 - score = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \quad (4)$$

In the context of a confusion matrix, TP denotes the number of positive samples that the model accurately classified. FP represents the number of negative samples that were incorrectly classified as positive. FN indicates the number of positive samples that were inaccurately classified as negative. Lastly, TN signifies the number of negative samples that the model correctly classified. These metrics help assess the performance of a classification model and evaluate its ability to distinguish between different classes accurately.

3. RESULTS AND DISCUSSION

In this study, the data used for analysis was obtained from Kaggle, a popular platform for sharing and exploring datasets. The dataset was carefully filtered and refined, resulting in a final sample size of 16,169 instances, as discussed in subsection 2.3. The analysis focused on various aspects, including feature extraction, model training, and performance evaluation. The results obtained from the analysis provide valuable insights into the effectiveness of the proposed approach. The discussion revolves around the accuracy of the models, the impact of different architectural choices, and the significance of the findings in addressing the research objectives. Based on proposed method (1) to (4), results of this study using classic layers, VGGNet architecture, and ResNet architecture method can be seen below. Based on the evaluation results presented in Table 1, to assess the performance of the models, a comparative analysis was conducted, evaluating metrics such as accuracy, precision, recall, and F1 score. The results of this analysis indicated significant variations in these performance measures across the different approaches.

Table 1. A result from our proposed method

CNN architecture	Optimization	Accuracy (%)	Recall (%)	Precision (%)	Specificity (%)	F1-Score (%)
Classic layers	Adam	93.32	100	100	100	100
	SGDM	93.29	98.43	99.40	99.74	98.92
VGGNet	Adam	95.70	99.61	97.20	98.79	99.62
	SGDM	94.92	99.81	99.05	99.58	99.43
ResNet-50	Adam	96.63	99.23	100	100	99.62
	SGDM	96.11	98.13	99.36	100	98.88

Based on Figure 5, the evaluation results obtained from the various CNN architectures demonstrate a consistent performance across the board, with all architectures achieving accuracy rates above 90%. Among the evaluated architectures, ResNet-50 emerged as the most effective in terms of overall performance. ResNet-50 achieved an impressive accuracy of 96.63%, along with excellent recall, precision, specificity, and F1-Score values. This indicates its ability to correctly classify instances and maintain a high level of precision in predicting positive cases. The performance of ResNet-50 showcases the benefits of utilizing its deep residual structure, which enables the model to effectively capture intricate features and improve the discriminative power of the network. Therefore, based on these evaluation results, ResNet-50 proves to be the most suitable and effective architecture for the given task, surpassing the performance of both the classic layers and VGGNet architectures. Based on experiments listed in Table 2, it is remarkable to note that each classification attempt achieved a perfect accuracy rate of 100%. This signifies that none of the classification experiments resulted in any failures or false predictions.

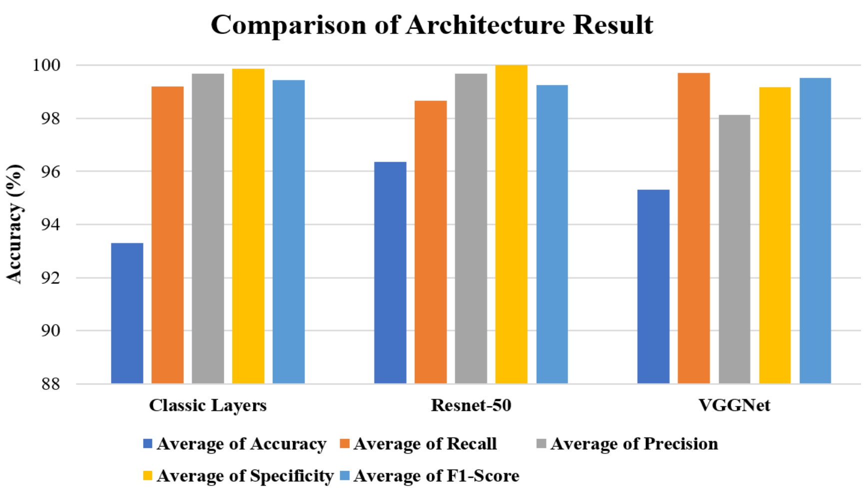


Figure 5. Results of CNN architecture

Table 2. Testing results of classification

CNN	Optimization	Prediction	Actual class
Classic layers	Adam	Covid (True)	Covid
	SGDM	Covid (True)	Covid
	Adam	CAD (True)	CAD
	SGDM	CAD (True)	CAD
	Adam	Non Covid (True)	Non Covid
	SGDM	Non Covid (True)	Non Covid
VGGNet	Adam	Covid (True)	Covid
	SGDM	Covid (True)	Covid
	Adam	CAD (True)	CAD
	SGDM	CAD (True)	CAD
	Adam	Non Covid (True)	Non Covid
	SGDM	Non Covid (True)	Non Covid
ResNet-50	Adam	Covid (True)	Covid
	SGDM	Covid (True)	Covid
	Adam	CAD (True)	CAD
	SGDM	CAD (True)	CAD
	Adam	Non Covid (True)	Non Covid
	SGDM	Non Covid (True)	Non Covid

In comparison phase based on Table 3, a comparative analysis of various methods based on previous research efforts. Mukherjee *et al*. [22] employed a deep neural network (DNN) approach, achieving an accuracy of 96.28%. Their method demonstrated high recall (97.92%) and precision (94.81%), along with notable specificity (94.64%) and an F1-Score of 96.34%. Shorfuzzaman *et al*. [23] utilized a combination of deep artificial neural network (ANN) and ResNet-50V2, achieving an accuracy of 95.49%. Their model exhibited excellent recall (99.19%) and precision (96.85%), alongside high specificity (98.27%) and an F1-Score of 98%. Shankar and Perumal [24] implemented deep CNN with InceptionV3 (GoogleNet), achieving an accuracy of 94.08%. Their method showed balanced recall (93.61%) and precision (94.85%), with specificity at 94.56% and an F1-Score of 93.20%. In the study by Punitha *et al*. [25], an attention-based convolutional neural network (ABCNN) yielded an accuracy of 92.37%, with no reported recall or precision metrics. Lastly, the proposed method in this study combined deep CNN with ResNet-50, achieving the highest accuracy of 96.63%. This method demonstrated superior recall (99.23%), precision (100%), specificity (100%), and an impressive F1-Score of 99.62%.

Table 3. Several comparison results based on previous research

Author	Method	Accuracy (%)	Recall (%)	Precision (%)	Specificity (%)	F1-Score (%)
Mukherjee *et al*. [22]	DNN	96.28	97.92	94.81	94.64	96.34
Shorfuzzaman *et al*. [23]	Deep ANN+ResNet-50V2	95.49	99.19	96.85	98.27	98
Shankar and Perumal [24]	Deep CNN+InceptionV3 (GoogleNet)	94.08	93.61	94.85	94.56	93.20
Punitha *et al*. [25]	ABCNN	92.37	-	-	-	-
Proposed method	Deep CNN+ResNet-50	96.63	99.23	100	100	99.62

Among the various architectures employed in the study, the most outstanding research finding was achieved using the ResNet architecture, which obtained an impressive accuracy of 96.63%. This result showcases the superiority and effectiveness of the ResNet model in accurately classifying the given dataset. In comparison to other researchers in the field, the accuracy attained by the ResNet model surpasses many previous studies. It demonstrates the capability of ResNet to effectively capture intricate features and achieve superior performance in image classification tasks. The remarkable accuracy achieved by the ResNet model solidifies its position as a state-of-the-art architecture for image classification, highlighting its significance in advancing setting a new benchmark for future research.

4. CONCLUSION

The evaluation and comparison of different CNN architectures conducted in this study indicate that the classic CNN and VGG architectures do not outperform the ResNet-50 architecture in terms of image classification performance. The results of the study suggest that the ResNet-50 architecture exhibits superior performance and accuracy when applied to image classification tasks compared to the classic CNN and VGG architectures. The results consistently show that ResNet-50 outperforms both classic CNN and VGG, achieving a significantly higher accuracy rate of 96.63%. This finding highlights the limitations of the classic CNN and

VGG architectures in capturing intricate features and achieving optimal classification accuracy. Therefore, for image classification tasks, the ResNet-50 architecture should be considered as the preferred choice due to its superior performance and ability to effectively classify images. This conclusion emphasizes the importance of selecting appropriate architectures in deep learning models and highlights the significance of the ResNet-50 architecture in advancing image classification tasks. For future research, there are several areas that can be explored to further enhance the development of image classification models. Firstly, investigating the application of transfer learning techniques with the ResNet-50 architecture could prove beneficial. By leveraging pre-trained models on larger datasets, the model's generalization and performance on specific image classification tasks can be improved. Additionally, exploring ensemble methods, such as combining multiple CNN architectures or incorporating additional classifiers, may lead to even higher accuracy rates.

ACKNOWLEDGEMENTS

We would like to thank Dian Nuswantoro University for supporting the progress of this research, providing facilities for programming and funding for this research collaboration.

REFERENCES

[1] S.-C. Ma, C.-Y. Su, S.-F. Chen, S. Sato, and S.-M. Ma, "Analysis of COVID-19-Related User Content on the Baseball Bulletin Board in 2020 through Text Mining," *Behavioral Sciences*, vol. 13, no. 7, p. 551, Jul. 2023, doi: 10.3390/bs13070551.

[2] A. Raihan and H. A. Himu, "Global impact of COVID-19 on the sustainability of livestock production," *Global Sustainability Research*, vol. 2, no. 2, pp. 1–11, Mar. 2023, doi: 10.56556/gssr.v2i2.447.

[3] O. Damette and T. L. D. Huynh, "Face mask is an efficient tool to fight the Covid-19 pandemic and some factors increase the probability of its adoption," *Scientific Reports*, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-34776-7.

[4] Md. A. Rahman, S. Cronmiller, Y. Shanjana, M. A. Bhuiyan, and Md. R. Islam, "The WHO announced COVID-19 is no longer a global public health emergency amid the spreading of arcturus variant: a correspondence evaluating this decision," *International Journal of Surgery*, May 2023, doi: 10.1097/JS9.0000000000000522.

[5] K. D. Pithani, K. D. Pithani, and R. Vadhi, "Enhanced Non-Alcoholic Fatty Liver Detection: CT Scan Image Analysis and Noise Reduction with Morphological Dilation," *Research Square (preprint)*, 2023, doi: 10.21203/rs.3.rs-3049270/v1.

[6] A. Harry, "The Future of Medicine: Harnessing the Power of AI for Revolutionizing Healthcare," *International Journal of Multidisciplinary Sciences and Arts*, vol. 2, no. 1, pp. 36–47, Jun. 2023, doi: 10.47709/ijmdsa.v2i1.2395.

[7] R. Hasweh *et al*., "Radiological Differences in COVID-19 Related Lung Manifestations Between Smokers and Non-smokers: A Single-Center Retrospective Study in Jordan," *Cureus*, May 2023, doi: 10.7759/cureus.38437.

[8] A. Prabhakar, N. Prabhakar, M. Garg, and A. Kumar, "The Integral Role of Radiology in the Diagnosis and Management of COVID-19–Associated Mucormycosis Infections," *American Journal of Tropical Medicine and Hygiene*, vol. 106, no. 4, pp. 1022–1025, Apr. 2022. doi: 10.4269/ajtmh.21-1135.

[9] N. L. DePace and J. Colombo, "Long-COVID Syndrome and the Cardiovascular System: A Review of Neurocardiologic Effects on Multiple Systems," *Current Cardiology Reports*, vol. 24, no. 11, pp. 1711–1726, Nov. 01, 2022. doi: 10.1007/s11886-022-01786-2.

[10] E. Melotti *et al*., "The Role of Multimodality Imaging for Percutaneous Coronary Intervention in Patients With Chronic Total Occlusions," *Frontiers in Cardiovascular Medicine*, vol. 9. May 2022, doi: 10.3389/fcvm.2022.823091.

[11] T. Streba, N. Ullah, J. A. Khan, S. El-Sappagh, N. El-Rashidy, and M. S. Khan, "A Holistic Approach to Identify and Classify COVID-19 from Chest Radiographs, ECG, and CT-Scan Images Using ShuffleNet Convolutional Neural Network," *Diagnostics*, vol. 13, p. 162, 2023, doi: 10.3390/diagnostics13010162.

[12] J. L. Gayathri, B. Abraham, M. S. Sujarani, and M. S. Nair, "A computer-aided diagnosis system for the classification of COVID-19 and non-COVID-19 pneumonia on chest X-ray images by integrating CNN with sparse autoencoder and feed forward neural network," *Computers in Biology and Medicine*, vol. 141, Feb. 2022, doi: 10.1016/j.compbiomed.2021.105134.

[13] J. Gupta, S. Pathak, and G. Kumar, "Deep Learning (CNN) and Transfer Learning: A Review," in *Journal of Physics: Conference Series, Institute of Physics*, 2022, doi: 10.1088/1742-6596/2273/1/012029.

[14] A. W. Salehi *et al*., "A Study of CNN and Transfer Learning in Medical Imaging: Advantages, Challenges, Future Scope," *Sustainability (Switzerland)*, vol. 15, no. 7, Apr. 2023, doi: 10.3390/su15075930.

[15] M. H. Alshayeji, S. C. Sindhu, and S. Abed, "CAD systems for COVID-19 diagnosis and disease stage classification by segmentation of infected regions from CT images," *BMC Bioinformatics*, vol. 23, no. 1, Dec. 2022, doi: 10.1186/s12859-022-04818-4.

[16] M. Radak, H. Y. Lafta, and H. Fallahi, "Machine learning and deep learning techniques for breast cancer diagnosis and classification: a comprehensive review of medical imaging studies," *Journal of Cancer Research and Clinical Oncology. Springer Science and Business Media Deutschland GmbH*, 2023, doi: 10.1007/s00432-023-04956-z.

[17] B. Mueller, T. Kinoshita, A. Peebles, M. A. Graber, and S. Lee, "Artificial intelligence and machine learning in emergency medicine: a narrative review," *Acute Medicine & Surgery*, vol. 9, no. 1, Jan. 2022, doi: 10.1002/ams2.740.

[18] S. Showkat and S. Qureshi, "Efficacy of Transfer Learning-based ResNet models in Chest X-ray image classification for detecting COVID-19 Pneumonia," *Chemometrics and Intelligent Laboratory Systems*, vol. 224, May 2022, doi: 10.1016/j.chemolab.2022.104534.

[19] A. S. Paymode and V. B. Malode, "Transfer Learning for Multi-Crop Leaf Disease Image Classification using Convolutional Neural Network VGG," *Artificial Intelligence in Agriculture*, vol. 6, pp. 23–33, Jan. 2022, doi: 10.1016/j.aiia.2021.12.002.

[20] M. Maftouni, "Large COVID-19 CT scan slice dataset." [Online]. Available: https://www.kaggle.com/datasets/maedemaftouni/large-covid19-ct-slice-dataset. (Accessed: Jul. 06, 2023).

[21] N. R. D. Cahyo, C. A. Sari, E. H. Rachmawanto, C. Jatmoko, R. R. A. Al-Jawry, and M. A. Alkhafaji, "A Comparison of Multi Class Support Vector Machine vs Deep Convolutional Neural Network for Brain Tumor Classification," in *2023 International*

Seminar on Application for Technology of Information and Communication (iSemantic), IEEE, Sep. 2023, pp. 358–363, doi: 10.1109/iSemantic59612.2023.10295336.
[22] H. Mukherjee, S. Ghosh, A. Dhar, S. M. Obaidullah, K. C. Santosh, and K. Roy, "Deep neural network to detect COVID-19: one architecture for both CT Scans and Chest X-rays," *Applied Intelligence*, vol. 51, no. 5, pp. 2777–2789, May 2021, doi: 10.1007/s10489-020-01943-6.
[23] M. Shorfuzzaman, M. Masud, H. Alhumyani, D. Anand, and A. Singh, "Artificial Neural Network-Based Deep Learning Model for COVID-19 Patient Detection Using X-Ray Chest Images," *Journal of Healthcare Engineering*. vol. 2021, 2021, doi: 10.1155/2021/5513679.
[24] K. Shankar and E. Perumal, "A novel hand-crafted with deep learning features based fusion model for COVID-19 diagnosis and classification using chest X-ray images," *Complex and Intelligent Systems*, vol. 7, no. 3, pp. 1277–1293, Jun. 2021, doi: 10.1007/s40747-020-00216-6.
[25] S. Punitha, T. Stephan, R. Kannan, M. Mahmud, M. S. Kaiser, and S. B. Belhaouari, "Detecting COVID-19 From Lung Computed Tomography Images: A Swarm Optimized Artificial Neural Network Approach," *IEEE Access*, vol. 11, pp. 12378–12393, 2023, doi: 10.1109/ACCESS.2023.3236812.

BIOGRAPHIES OF AUTHORS

Ibnu Utomo Wahyu Mulyono received a Bachelor's degree at the Department of Informatics Engineering from Dian Nuswantoro University, Semarang, Indonesia, in 2001 and a Master's degree from the Department of Informatics Engineering, Dian Nuswantoro University, Semarang, Indonesia, in 2013. He is currently the lecturer and researcher at the Faculty of Computer Science, Dian Nuswantoro University, Semarang, Indonesia. His research interests include image processing, machine learning, and data mining. He can be contacted at email: ibnu.utomo.wm@dsn.dinus.ac.id.

Eko Hari Rachmawanto received a Bachelor's degree at the Department of Informatics Engineering Dian Nuswantoro University, Semarang, Indonesia, in 2009 and a dual Master's degree in the Department of Informatics Engineering, Dian Nuswantoro University, Semarang, Indonesia and in Faculty of Computer Science and Information, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia, in 2012. He is currently the lecturer and researcher at the Faculty of Computer Science, Dian Nuswantoro University, Semarang, Indonesia. He has authored or co-authored more than 100 refereed journal and conference papers. He is also a reviewer of more than 10 Scopus-indexed journals indexed by Scopus. His research interests include image processing, especially data hiding, cryptography, image processing, and machine learning deep learning. He can be contacted at email: eko.hari@dsn.dinus.ac.id.

Christy Atika Sari received a Bachelor's degree at the Department of Informatics Engineering Dian Nuswantoro University, Semarang, Indonesia, in 2010 and a dual Master's degree in the Department of Informatics Engineering, Dian Nuswantoro University, Semarang, Indonesia and in Faculty of Computer Science and Information, Universiti Teknikal Malaysia Melaka, Melaka, Malaysia, in 2012. She is currently the lecturer and researcher at the Faculty of Computer Science, Dian Nuswantoro University, Semarang, Indonesia. She has authored or co-authored more than 90 refereed journal and conference papers. She is also a reviewer of more than 10 Scopus-indexed journals indexed by Scopus. Her research interests include especially security data, image processing, quantum security, machine learning, and deep learning. She can be contacted at email: atika.sari@dsn.dinus.ac.id.

Md Kamruzzaman Sarker received his Ph.D. in Computer Science focusing on artificial intelligence (AI) in 2020 from Kansas State University. After his Ph.D., he also worked as a postdoc at the same university's Center for Artificial Intelligence and Data Science. He obtained his M.S. in Computer Science in 2018 from Wright State University and a B.Sc. in Computer Science and Engineering from Khulna University of Engineering and Technology. Now, he is Assistant Professor of Computer Science at the Bowie State University. He also worked at Intel Corporation and Samsung Electronics. Furthermore, he has authored over 30 peer-reviewed papers and edited a book. He can be contacted at email: mdkamruzzamansarker@gmail.com.