

Using Convolutional Neural Networks (CNN) for Medical Image Classification

Name: Areej Abdulaziz Alotaibi

Research Problem

The role of medical image classification in contemporary healthcare is critical since it allows making an early diagnosis and facilitating clinical decision-making. Despite the fact that Convolutional Neural Networks (CNNs) have made tremendous breakthrough in this field through better image parting, feature incorporation and enhanced image classification, the system still faces a number of limitations that negatively impact the system in practical use. Available literature indicates that CNNs are capable of effectively learning spatial hierarchies and intricate patterns of medical images, but most of the studies lack empirical support, work with small datasets, or do not focus on issues regarding generalization and interpretability (Kshatri and Singh, 2023). Also, a majority of CNN-based models do not perform well when used in other imaging modalities or with heterogeneous sources of data, and their clinical effectiveness is diminished (Sarvamangala and Kulkarni, 2021).

Hybrids and ensemble systems, e.g., CNN-LBP feature fusion or stacking-based systems, have been shown to improve accuracy and robustness and obtain significant gains in specialized datasets (Rocha et al., 2023; Müller et al., 2024). The methods are however usually tested on small datasets and it is hard to make generalization on the large medical setting. Computational complexity is also a limiting factor, especially in situations that require CNNs in a healthcare setting characterized by time sensitivity (Nirthika et al., 2022). Moreover, optimization pooling strategy and domain adaptation mechanisms are not integrated in many models, and as a result, they do not have much adaptability.

Consequently, it is evident that research is necessary to come up with optimized CNN-based classification methods which combine hybrid feature extraction, ensemble-based learning, and better architectural design. By filling such gaps, one can improve accuracy in diagnosis and the robustness of the models, as well as facilitate the practical use of CNN models in various medical imaging contexts (Al-Zubaidi and Mijwil, 2021).

Research Objectives

Primary Goal:

To construct the ideal CNN-based medical image classification model that increases diagnostic accuracy, robustness, and computational efficiency.

Specific Objectives:

- To examine the shortcomings of the currently employed CNN based methods of medical image classification in terms of accuracy, generalizability, and interpretability.
- To investigate how optimizations of architecture like hybrid feature extraction and improved pooling can affect CNN performance.
- To assess ensemble learning strategies (e.g. stacking, bagging) to enhance reliability of CNN classification in separate medical imaging data.
- To design and propose the most efficient CNN-based classification model and incorporates the efficient hybrid, pooling, and ensemble methods.
- To prove the proposed model on the basis of several medical image datasets and to compare its results with the existing state-of-the-art CNN-based solutions.

Literature Review

The initial article by Kshatri & Singh (2023) gives a literature on convolutional neural networks (CNNs) used in medical image processing, specifically in preprocessing, segmentation, and diagnosis of MRI. The authors underline the fact that CNNs with the help of convolution and pooling and backpropagation layers successfully learn the spatial hierarchy of medical images and make efficient classification and feature retrieval. Their review also classifies CNN-based research by their usage as pattern recognition and classifies medical images processing with a taxonomy. The review concludes that CNNs have made new breakthroughs in the field of medical imaging because segmentation and noise reduction processes have been automated, which significantly enhances diagnostic accuracy. Nevertheless, even though the paper is written in a highly technical way, it is not quantitatively evaluated and experimentally attested. The second weakness that limits the generalization of the findings is the lack of analysis of the transfer learning and domain adaptation methods.

The second research, by Rocha et al (2023). suggests a hybrid CNN-based model named as Hybrid CNN Ensemble (HCNNE) to classify medical images. This model combines deep CNN features with Local Binary Pattern (LBP) features which are handcrafted in order to enhance medical image texture based discrimination. The features extracted are trained with multilayer perceptrons and ensemble classifiers yielding 10% accuracy improvement compared to the earlier models of the state-of-the-art modeling odontogenic cyst histological images. The study shows that the high-level and low-level features used together are beneficial to increase the performance of classification with low cost in terms of computation. However, the primary weakness of the study is that it was only validated on one dataset and therefore it cannot be applied widely to other medical imaging fields. Its strength, however, is that hybrid feature fusion is effective in balancing accuracy and efficiency in CNN-based classification systems.

The third article by Muller et al (2024). discusses how ensemble learning techniques may be used to achieve optimal CNN performance in medical image classification pipelines. This paper

explores various ensemble methods, such as stacking, bagging, and augmenting, and it was used with nine CNNs and four medical imaging datasets of different complexity. By empirically assessing the methods, the authors show that the stacking method provides the best improvement and the F1-score can be improved by up to 13% and then bagging and augmenting, which are more effective at generalization and robustness. Surprisingly, the study also concludes that simple statistical pooling functionality tends to be more efficient than the complex learning-based pooling functionality, such as a support vector machine. The advantages of this work are the thoroughness of the experimental design and reproducibility, which provide viable insights on CNN ensemble optimization. Nevertheless, it does not discuss the issue of computational trade-offs and interpretability, which is vital in clinical acceptance.

In the fourth paper, Nirthika et al (2022). provide a comprehensive survey and empirical results of the pooling methods in CNNs in terms of their effects on medical image classification problems. The authors survey several pooling mechanisms such as max, average, stochastic and spatial pyramid pooling and provide a comparison experiment of HEp-2 cell and diabetic retinopathy data. Their results show that pooling plays an important role in CNN performance because the type of pooling to use should be related to the magnitude and distribution of class-specific features relative to image size. The experiment also shows that the application of optimized pooling strategies based on the ResNet architecture can bring new state-of-the-art results. Although the paper presents excellent theoretical foundations and experimental support, its weakness is that it has limited number of datasets, which limits the generalizability. However, it gives useful recommendations in the choice of pooling activities in future CNN-based medical applications.

The fifth article by Sarvamangala & Kulkarni (2021) provides a comprehensive review of how CNNs can be used to understand medical image, which includes classification, segmentation, localization, and detection of different types of diseases involving the brain, breast, and the lungs. The authors claim that CNNs outperform the conventional methods of diagnosis, and even humans, in a number of recognition tasks because they are able to learn complex spatial features automatically. The paper includes a brief description of CNN architectures and their award-winning structures, which also furnishes evidence that CNNs enhance diagnostic performance and lower the workload of clinical personnel. Nevertheless, issues like interpretability, data imbalance, and computational costs are also revealed by it, and they are still not resolved in clinical practice. Although conceptually deep and all-encompassing, the research lacks the latest developments such as attention-based networks or transformers, which restricts its ability to capture the latest trends in CNN.

Lastly, Al-Zubaidi & Mijwil (2021) use a practical CNN model to classify COVID-19 medical images with the help of the GoogleNet architecture. The model was trained using 425 CT-coronavirus

images to help in early detection of an infection. The CNN had a validation accuracy of 82.14% using a total training time of about 74 minutes which shows the possibility of the model to be used in automated pandemic diagnostics. The study also emphasizes the fact that CNNs can exploit features that are directly extracted out of medical data and classify them without much preprocessing. The main merit of the work is the fact that it can be applied in real life and that CNN is efficient in a time-sensitive medical environment. Nevertheless, this makes the dataset rather small and presents a risk of overfitting, and the absence of an external validation restricts its clinical applicability. Even with these constraints, the study has a good evidence of the effectiveness of CNNs in the rapid detection of diseases in emergency situations.

Taken together, these six papers indicate the increased maturity of CNN research in medical image classification. They show a steady tendency to combine hybrid architecture, ensemble learning and optimization methods to achieve better diagnostic precision. Nevertheless, general difficulties remain throughout the literature, such as the lack of data diversity, interpretability, and computational requirements, implying the possibility of future research.

Synthesis of Findings

In all the explored researchers, CNNs are repeatedly determined as an effective method of classifying medical images automatically. Kshatri & Singh (2023) and Sarvamangala & Kulkarni (2021) presented the background theoretical viewpoints regarding CNN architecture and its usage, whereas Rocha et al. (2023) and Muller et al. (2024) break the ice and consider the hybrid and ensemble improvements. In the meantime, Nirthika et al. (2022) add some architectural ideas with the focus on pooling mechanisms, and Al-Zubaidi and Mijwil (2021) prove CNNs in a realistic healthcare environment. The papers taken as a whole demonstrate the power of CNNs in feature selection and pattern recognition but show a variation in their priorities: some of them put more emphasis on accuracy and robustness via intricate architectures, and others tend to focus on the value of computational efficiency and flexibility. Although the approaches may vary, the necessity of CNNs in the progress of diagnostic imaging is unanimous, and the research requirements of the future should revolve around explainability, cross-domain generalization, and real-time deployment issues.

Summary Table of Reviewed Papers

No .	Author(s) & Year	Title	Methodology	Key Findings	Weaknesses/Limitations
1	Kshatri & Singh (2023)	CNN in Medical Image Analysis: A Review	Systematic literature review	CNNs improve segmentation and diagnostic accuracy	No empirical validation; lacks transfer learning discussion
2	Rocha et al. (2023)	Medical Image Classification Using Hybrid CNN Ensemble	CNN + LBP hybrid with ensemble classifiers	+10% accuracy improvement with hybrid features	Dataset-specific; low generalization
3	Müller et al. (2024)	Ensemble Learning Optimized Medical Image Classification	Comparison of stacking, bagging, augmenting	Stacking yields +13% F1-score improvement	No computational analysis or interpretability study
4	Nirthika et al. (2022)	Pooling in CNNs for Medical Image Analysis	Empirical study on pooling methods	Pooling selection affects task-specific accuracy	Limited datasets; narrow scope
5	Sarvamangala & Kulkarni (2021)	CNNs in Medical Image Understanding	Literature survey	CNNs outperform human experts in diagnosis	Lacks discussion of new architectures
6	Al-Zubaidi & Mijwil (2021)	COVID-19 Classification Using CNNs	GoogLeNet model on CT dataset	82.14% validation accuracy	Small dataset; possible overfitting

Conclusion

The literature reviewed proves the outstanding performance of CNNs in medical image classification both in theory and practical clinical environment implementation. Such innovations as hybridization and ensemble learning increased the robustness and accuracy of the models considerably. Nevertheless, there still remain challenges such as incomplete cross-domain adaptability, lack of explainability and data scarcity that prevent full clinical deployment. The way forward must focus on explainable AI, federated learning to maintain data privacy, and the integration of multimodal CNN to make sure that medical image classification systems are both diagnostic and ethically transparent.

References

- Al-Zubaidi, E. A., & Mijwil, M. M. (2021). *Medical image classification for coronavirus disease (COVID-19) using convolutional neural networks*. *Iraqi Journal of Science*, 62(8), Article 27. <https://doi.org/10.24996/ij.s.2021.62.8.27>
- Kshatri, S. S., & Singh, D. (2023). *Convolutional neural network in medical image analysis: A review*. *Archives of Computational Methods in Engineering*, 30, 2793–2810.
- Müller, D., Soto-Rey, I., & Kramer, F. (2024). *An analysis on ensemble learning optimized medical image classification with deep convolutional neural networks*. *IEEE Access*.
- Nirthika, R., Manivannan, S., Ramanan, A., & Wang, R. (2022). *Pooling in convolutional neural networks for medical image analysis: A survey and an empirical study*. *Neural Computing and Applications*, 34, 5321–5347.
- Rocha, M. M. M., Landini, G., & Florindo, J. B. (2023). *Medical image classification using a combination of features from convolutional neural networks*. *Multimedia Tools and Applications*, 82, 19299–19322.
- Sarvamangala, D. R., & Kulkarni, R. V. (2021). *Convolutional neural networks in medical image understanding: A survey*. *Evolutionary Intelligence*, 15, 1–22.