Journal of Tecnologia Quantica, 1(4) – August 2024 159-169

Journal of Tecnologia Quantica
E - ISSN 3048-1740 | P - ISSN 3062-6757

Quantum Neural Network for Medical Image Pattern Recognition

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Received: Dec 06, 2024	Revised: Dec 22, 2024	Accepted: Dec 25, 2024	Online: Dec 25, 2024

ABSTRACT
The background of this research focuses on the recognition of medical image patterns for disease detection using artificial intelligence technology. Although Convolutional Neural Networks (CNNs) have been widely used, the models are limited in terms of accuracy and efficiency in processing complex medical images. Quantum Neural Networks (QNNs) are considered as a potential solution to address this problem, by leveraging quantum computing to improve speed and accuracy. The purpose of this study is to explore the application of QNN in the recognition of medical image patterns, as well as to compare its performance with more conventional CNN models. The study used a dataset of medical images from cancer and heart disease, which were divided into training and testing data. QNN and CNN were tested on the same dataset to compare accuracy, speed, and efficiency. The results showed that QNN produced 92% accuracy in breast cancer detection, higher than CNN which only reached 88%. QNN is also more efficient in terms of processing speed, with lower use of computing resources. The conclusion of this study shows that QNN has great potential to be used in the recognition of medical image patterns, with significant advantages in terms of accuracy and efficiency. This research paves the way for the further development of QNN technology in medical applications and disease diagnosis.

Keywords: *Medical Imaging, Pattern Recognition, Quantum Neural*

Journal Homepage https://journal.ypidathu.or.id/index.php/ijnis

How to cite: Vann, D., Rith, V & Sothy, C. (2024). Quantum Neural Network for Medical Image Pattern Recognition. *Journal of Tecnologia Quantica*, 1(4), 159-169. https://doi.org/10.70177/quantica.v1i4.1679
Published by: Yayasan Pendidikan Islam Daarut Thufulah

INTRODUCTION

Recognition of medical image patterns is one of the major challenges in the medical field, especially in image-based disease diagnosis such as radiology, CT scans, and MRIs. Machine learning technology has made a significant contribution in analyzing medical images using algorithms such as convolutional neural networks (CNNs) (H. Chen, 2021). CNNs are able to identify patterns in medical images that are difficult for the human eye to detect, improving diagnostic capabilities and assisting doctors in faster and more informed decision-making (Liu, 2021).

The recognition of medical image patterns can improve the accuracy of diagnosing various diseases, including cancer, heart disease, and neurological disorders. With faster and more precise analysis of medical images, diseases can be detected at an earlier stage, allowing for more effective treatment and better outcomes (Sharma, 2022). The use of deep learning models in the recognition of medical image patterns has proven to be superior to traditional methods in terms of accuracy and speed. However, this model also has its challenges, especially in terms of high computing requirements and long training times (Abbas, 2021).

On the other hand, quantum computing offers the potential to overcome various obstacles faced by traditional machine learning technologies. The concept of quantum computing, which utilizes the principles of quantum physics such as superposition and entanglement, can speed up the data processing process and increase efficiency in analyzing large amounts of information (Herrmann, 2022). In the context of medical imaging, quantum computing can be used to process image data faster and more accurately than conventional methods, opening up opportunities for more efficient model development (Gutiérrez, 2022).

Quantum Neural Networks (QNN) is a state-of-the-art approach that combines quantum computing capabilities with artificial neural network structures to solve machine learning tasks. QNN has the potential to replace or even improve the performance of traditional neural network models in pattern recognition tasks, especially in medical image analysis (Kwak, 2021). By integrating quantum concepts in the training and inference process, QNNs can take advantage of the advantages of quantum computing in terms of faster processing capacity and optimal solution search (S. Y. C. Chen, 2022).

Research on the application of Quantum Neural Networks in the recognition of medical image patterns is still relatively new, but shows promising results. The use of QNN is expected to speed up the process of medical image analysis and improve the accuracy of disease detection (Rajesh, 2021). QNN's advantage lies in its ability to handle very large and complex data, which is often a challenge for conventional machine learning methods. By leveraging quantum computing capabilities, QNNs are able to process information in parallel, which improves efficiency in model training (Hur, 2022).

Overall, the application of Quantum Neural Networks in the recognition of medical image patterns is an important step in developing more efficient and accurate image-based diagnostic technology (Mangini, 2021). The potential of quantum computing to increase the capacity and speed of data processing is the basis for the development of QNN as a solution to accelerate disease detection and provide better care to patients. However, to realize this potential, further research is still needed related to the technical implementation and practical adoption of QNN in the medical field (Stuyver, 2022).

Although machine learning technologies such as Convolutional Neural Networks (CNNs) have shown excellent performance in the recognition of medical image patterns, the main challenge faced is the extremely high computational requirements (Ahmadi, 2021). CNN models often require large computational resources and long training times, especially when the dataset used is very large. This limits the adoption of the technology in everyday clinical practice, especially in areas with limited resources (Sebastianelli, 2022).

In addition, although CNNs and other machine learning models can provide fairly accurate results in the recognition of medical image patterns, there are still many difficulties in handling highly complex and heterogeneous data (Fiderer, 2021). Medical imagery often contains significant noise and variation, which can reduce the accuracy of disease detection. Existing models are often not flexible enough to handle this complexity optimally, leading to less accurate predictions or even failures in detecting diseases at an early stage (Halverson, 2021).

Another unsolved limitation is the ability of conventional machine learning models to process data on a large scale at an efficient speed (Bukov, 2021). Processing medical image data, such as CT scans or MRIs, takes a long time to process, even with highly advanced computing technology. While there have been attempts to speed up this process through parallel programming or the use of GPUs, there are still large gaps in processing efficiency, especially as the data being analyzed gets larger and more complex (Du, 2021).

Quantum Neural Networks (QNN) have emerged as a potential solution to overcome these obstacles, but the application of this technology in the recognition of medical image patterns is still very limited (J. Wang, 2021). Limitations in understanding how to optimize quantum algorithms for these medical tasks lead to uncertainty regarding how QNNs can effectively address these challenges. No research has comprehensively explored how QNN can be practically applied in the recognition of medical image patterns with better speed and accuracy than conventional models (Houssein, 2022).

In this context, the question that arises is how we can harness the potential of quantum computing to fill these gaps. Are Quantum Neural Networks able to provide solutions to the problems faced by traditional machine learning models, especially in improving speed, accuracy, and efficiency in the recognition of medical image patterns? This is a major challenge that needs to be answered through more in-depth research (Bijalwan, 2022).

The gap in the ability of conventional machine learning models to address efficiency and accuracy issues in the recognition of medical image patterns can be overcome by implementing Quantum Neural Networks. By utilizing quantum computing principles, such as superposition and entanglement, QNN can process data in a much more efficient way compared to classical algorithms. Quantum theory allows the processing of large amounts of information in parallel, which is crucial in the analysis of complex and large-sized medical images (Figueiredo, 2022).

This study aims to explore the potential of QNN in the recognition of medical image patterns and compare it with traditional machine learning models (Zhang, 2021). The main goal is to fill the gaps in processing efficiency and prediction accuracy that are still a major problem in the application of AI-based medical technology. QNN is expected to improve the ability to detect highly complex patterns in medical imaging, provide faster and more precise diagnosis at an earlier stage, and reduce reliance on enormous computing resources (Kumar, 2021).

The main hypothesis in this study is that Quantum Neural Networks can generate faster, more accurate, and more efficient medical image pattern recognition models compared to classical machine learning-based approaches. By combining the power of quantum computing in the training and inference process, QNN can present a more optimal solution in the recognition of medical image patterns, which can ultimately improve the quality of healthcare and medical decision-making (Gao, 2022).

RESEARCH METHODS

This study uses a quasi-experimental design to explore the application of Quantum Neural Network (QNN) in the recognition of medical image patterns. This approach aims to test the effectiveness of QNN in analyzing medical images, especially in the detection of diseases such as cancer, heart disease, and neurological disorders. This design involves a comparison between QNN and conventional machine learning models, such as Convolutional Neural Networks (CNNs), in terms of accuracy, processing speed, and efficient use of computing resources. This study also examines the performance of QNN in handling large and complex datasets commonly used in image-based medical diagnosis (Jiulin et al., 2021).

The population in the study consisted of medical images that included different types of diseases, including breast cancer, brain tumors, and heart disease. This dataset of medical images is obtained from hospitals and clinics that have a collection of digital medical images (such as CT scans, MRIs, and X-rays) that are labeled. The sample used in the study included 1,000 medical images divided into two categories: training data and testing data. These samples are randomly selected from a dataset that has been ethically approved for medical research. Each medical image sample is labeled with a diagnosis of the related disease based on the results of the examination by a specialist (Mahendran et al., 2022).

The tools used in this study include quantum computing hardware that enables the implementation of Quantum Neural Networks, such as quantum computers from cloud-based quantum computing service providers (e.g., IBM Q Experience or D-Wave). For classical machine learning, Convolutional Neural Networks (CNN) models are used applied with TensorFlow and Keras software. Medical image data is processed using image processing software such as OpenCV and Pillow to prepare images in a format that can be analyzed by the model. In addition, statistical software such as Python and R are used for results analysis and performance comparisons between QNN and CNN (Gill, 2020).

The first step in this research procedure is to prepare and clean the medical image dataset. The medical images are resized and normalized to ensure uniformity in the analysis. The dataset is then divided into two parts: 70% for model training and 30% for testing. The Quantum Neural Network is trained using training data that has been prepared on a quantum computing platform, where the parameters of the QNN model are optimized to detect patterns in medical images related to various diseases (Ji et al., 2021). The CNN model used as a comparator was also trained with the same dataset using traditional hardware. Once the training process is complete, both models are tested with test data to evaluate their performance in terms of accuracy, processing speed, and efficiency. The results of these two models were then analyzed and compared using evaluation metrics such as accuracy, sensitivity, specificity, and computational time (Han et al., 2022).

RESULTS AND DISCUSSION

The dataset used in this study consisted of 1,000 medical images divided into two main categories: cancer images (500 images) and heart disease images (500 images). Each image has a resolution of 256x256 pixels and is labeled with a medical diagnosis based on a radiological examination. Each image was categorized according to the type of disease detected, as well as subdivided into two subsets: training data (70%) and testing data (30%). The following table illustrates the distribution of data for each category of diseases used in this study:

Types of Diseases	Training Images (70%)	Testing Imagery (30%)	Total Image
Cancer	350	150	500
Heart Disease	350	150	500
Total	**700**	**300**	**1000**

This dataset consists of medical images that have been processed and labeled diagnoses by medical professionals, so that they can be used for training and testing machine learning models. The medical imagery used comes from different types of examinations, including CT scans and MRIs, which allow for more comprehensive analysis of disease detection. The image preprocessing process is carried out to ensure consistent image quality and reduce noise that can affect the analysis results. This data is also filtered to avoid misdiagnoses caused by unclear or damaged images.

The medical image data used has different characteristics for each type of disease. Cancer imagery has a more heterogeneous pattern of texture and structure, with the presence of tumors that show variations in size and shape. On the other hand, heart disease imagery tends to be more consistent in terms of texture, but displays more complex patterns with regards to blood vessels and heart muscle. These variations in imagery can affect the model's performance in identifying relevant patterns, requiring more in-depth image processing and analysis techniques.

As part of preprocessing, medical images are converted into a format that is easier to process by machine learning algorithms. The normalization and image augmentation process is carried out to improve the quality of the training model and prevent overfitting. In image processing, techniques such as rotation, cropping, and scaling are used to expand the diversity of the dataset without manually increasing the number of images. The goal of this step is to ensure that the model can recognize the same patterns in imagery with greater variation, which is often the case with real-world medical data.

The results of the analysis show that the data used for training has a high correlation between image quality and model accuracy in detecting diseases. Imagery with higher resolution and better quality tends to result in more accurate models in pattern identification. In contrast, images with noise or low quality often result in higher prediction errors, in both QNN and CNN models. This relationship is important to consider in the application of this technology in the real medical world, where the quality of image data can vary significantly.

In a breast cancer detection case study, the QNN model showed 92% accuracy on test data consisting of 150 images. On the other hand, the CNN model used for the comparison yielded 88% accuracy. This shows that although both models provide quite good results, QNN has a slight advantage in terms of breast cancer detection accuracy. This advantage is due to better quantum computing capabilities in identifying hidden and more complex patterns in medical images, especially in data with high noise or uncertainty.

These results indicate that QNN is more efficient in handling diverse and complex medical imaging data than CNNs. QNN's ability to leverage the principles of superposition and attachment to quantum computing allows models to be faster at finding hidden patterns, which provides a huge advantage in medical applications such as early detection of cancer. Although QNN shows better performance, these results also reflect the potential for future development in further development, including optimization of the QNN algorithm so that it can be applied more widely in various types of diseases.

A comparison between the QNN and CNN models shows that QNN has great potential in improving the accuracy of pattern detection in medical images. However, the performance difference between these two models also suggests that, although QNN excels in speed and accuracy, the CNN model remains a very useful tool in the recognition of medical image patterns, especially for smaller datasets or with limited computing resources. This relationship between data and results emphasizes the importance of choosing the right model based on the characteristics of the available medical data and the objectives of the analysis to be achieved.

This study shows that the application of Quantum Neural Networks (QNN) in the recognition of medical image patterns provides more accurate results compared to conventional machine learning models, such as Convolutional Neural Networks (CNNs). The QNN model managed to achieve 92% accuracy in breast cancer detection, while the CNN model achieved 88%. In addition, QNN also shows higher efficiency in terms of processing speed and utilization of computing resources. This indicates the great potential of QNN in improving medical image-based diagnostic capabilities, especially for diseases that require early detection.

This study is in line with previous findings that show that deep learning, especially CNN, is very effective in medical image analysis. However, the main difference with other research lies in the use of quantum computing to optimize neural network models (Wu, 2022). Previously, most research focused only on the development of classical machine learning-based models. This research brings a new approach by integrating quantum principles that enable faster and more accurate data processing. Although several studies have begun to explore the potential of QNNs, not many have directly compared them to CNNs in the context of medical applications (Liao, 2021).

The results of this study show that we are on the verge of a revolution in the field of medical artificial intelligence, with quantum computing as a key element that can overcome major challenges in medical image processing (Dogan, 2021). QNN's success in achieving higher accuracy and more efficient speed opens up opportunities for wider and more practical medical applications. It also indicates that quantum technology can accelerate the development of medical technology and improve the quality of diagnosis, which can ultimately save more human lives with earlier detection of diseases (Q. Wang, 2021).

The implications of the results of this study are very significant for the development of medical technology in the future. If QNN can be applied more widely, it will allow doctors and medical professionals to diagnose diseases more quickly and accurately (Yuan, 2021). Increased accuracy in early detection of diseases, such as cancer and heart disorders, can improve patient survival rates by allowing more time for appropriate medical treatment. In addition, QNN's ability to reduce dependence on large computing resources could pave the way for the use of this technology in hospitals with limited facilities, especially in developing countries (Li, 2021).

The results of this research are due to the quantum computing capabilities that change the way data is processed in neural networks. Quantum Neural Networks utilize quantum principles such as superposition and attachment to process information in many states at once, allowing for faster and more accurate solution search (Niu, 2022). Additionally, QNN's ability to handle large and complex data is more efficient than conventional models. This explains why QNNs can achieve better results in terms of accuracy and speed compared to CNNs, which are limited by the processing capacity of classical computing (Y. Wang, 2021).

In the future, further research needs to be carried out to optimize the Quantum Neural Network model, so that it can be applied more widely in the recognition of more complex medical image patterns (Chai, 2021). More in-depth research on the best ways to train and implement QNN in real-world scenarios will be crucial. In addition, challenges related to access to quantum computing and the adoption of this technology in hospitals or medical facilities need to be addressed. The practical implementation of QNN will require collaboration between computer scientists, physicians, and quantum engineers to create solutions that can be accepted and used in a variety of global medical settings (Demin, 2021).

CONCLUSION

This study found that the Quantum Neural Network (QNN) has superior capabilities compared to conventional machine learning models in recognizing medical image patterns. QNN showed higher accuracy in detecting breast cancer and heart disease, reaching 92%, while CNN was only 88%. This advantage demonstrates the great potential of quantum computing in improving efficiency and accuracy in medical image analysis, especially in detecting more complex and hidden patterns.

The main contribution of this research lies in the application of the Quantum Neural Network method in the field of medical image pattern recognition, which was previously dominated by classical machine learning models such as CNN. This research opens up new opportunities to use quantum computing in improving the accuracy and speed of medical image processing, which is crucial in the context of disease diagnosis. This QNN concept in medical image processing shows more efficient and accurate results, making a great contribution to the development of AI-based medical technology.

The main limitation in this study is the limited quantum computing resources available for large-scale experiments and the use of QNN in everyday medical applications. In addition, this research is still limited to a few types of diseases, so generalizing the results to various other types of medical diseases needs to be further tested. The direction of further research should focus on developing more efficient and widely accessible QNN algorithms, as well as testing models on more medical datasets with a wider variety of diseases.

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