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Alzheimer's disease detection based on MR images using the quad convolutional layers CNN approach

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ABSTRACT

Alzheimer's disease is a progressive neurodegenerative disorder requiring early and accurate detection for effective intervention. Deep learning (DL) techniques, particularly convolutional neural networks (CNNs), have shown promise in medical image classification. However, conventional CNN models often suffer from high computational complexity and inefficiency in handling imbalanced datasets. This study proposes a quad convolutional layers-CNN (QCL-CNN) for Alzheimer's disease detection using magnetic resonance images (MRI) scans from the open access series of imaging studies (OASIS) dataset, which includes four dementia stages, non-dementia, very mild dementia, mild dementia, and moderate dementia. The QCL-CNN model employs four sequential convolutional layers for enhanced multi-level feature extraction, ensuring efficient classification while minimizing computational overhead. The experimental results demonstrate that QCL-CNN outperforms traditional CNN architectures, achieving an accuracy of 99.90%, recall of 99.89%, specificity of 99.93%, and an F1-score of 99.52%. The model surpasses VGG19, Xception, ResNet50, and DenseNet201 while maintaining a significantly lower parameter count (4.2M), making it computationally efficient. These findings confirm that network optimization is more crucial than model depth, ensuring robust performance even with fewer layers. Future research should explore multi-modal imaging, class balancing techniques, and real-world clinical validation to further improve the model's diagnostic capabilities. The QCL-CNN model offers a promising artificial intelligence (AI)-powered approach for early Alzheimer's detection, enabling precise, and efficient medical diagnosis.

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1. INTRODUCTION

According to the latest WHO report, more than fifty million individuals worldwide are currently affected by dementia, with 60–80% of cases linked to Alzheimer's [1]. This figure is expected to climb to 78 million by 2030 and 139 million by 2050, mainly driven by the extension of human lifespan and the growing proportion of elderly populations [2]. In addition to impacting individuals, Alzheimer's imposes a considerable burden on both family caregivers and healthcare infrastructures. The global cost of dementia care is projected to amount to approximately 1.3 trillion US dollars, a number that is expected to grow unless effective early detection and intervention strategies are implemented [3]. Therefore, developing faster, more accurate, and easily applicable diagnostic methods has become an urgent necessity in combating the Alzheimer's epidemic. Early diagnosis of Alzheimer's remains a major challenge as its symptoms often develop gradually and can be difficult to distinguish from normal aging [4]. Currently, the diagnostic process typically involves a combination of clinical, neuropsychological, biomarker, and brain imaging assessments such as magnetic resonance images (MRI). The MRI is widely used as a diagnostic tool because it can detect alterations in the brain's anatomical structure, particularly in the hippocampal region along with the entorhinal cortical area, which represent key regions that undergo degeneration associated with Alzheimer's disease [5]. However, interpreting MRI scans still relies on manual analysis by radiologists and neurologists, which is not only time-consuming but also introduces a degree of subjectivity. Therefore, more objective and efficient methods for analyzing brain imaging data are needed to enhance the accuracy of detecting Alzheimer's in its early stages.

Recent progress in artificial intelligence (AI) technologies, with a strong emphasis on machine learning (ML) and deep learning (DL) techniques, has led to the emergence of new opportunities in medical imaging-based diagnosis. AI algorithms can analyze MRI scans more rapidly and detect subtle patterns of brain changes that may be difficult for the human eye to recognize. Techniques such as convolutional neural networks (CNNs) have shown great potential in identifying Alzheimer's-related structural changes in the brain with high sensitivity and specificity [6]. Several studies have demonstrated that AI models can distinguish between healthy individuals, MCI patients, and Alzheimer's patients with better accuracy than conventional methods [7]. With AI, diagnosis can be performed automatically and in real-time, not only improving medical efficiency but also enabling earlier intervention for patients at high risk. Research conducted by Ebrahimi and Luo [8] explored the effectiveness of different architectures of DL models, such as two-dimensional CNNs, three-dimensional CNNs, and integrated CNN-RNN frameworks in detecting Alzheimer's from MRI. The results showed that the 3D CNN-based model with pre-trained weights gave the best results with an accuracy of 96.88%, suggesting that voxel-level analysis provides superior performance compared to approaches that rely only on slice-based imaging. Meanwhile, Al-Shoukry and Musa [9] developed an integrated AI framework merging DL methods with conventional ML such as support vector machine (SVM), Naive Bayes (NB), and XGBoost. This approach demonstrated improved diagnostic performance, reaching an accuracy as high as 94.22%, indicating that the hybrid strategy can address the inherent shortcomings of standalone AI techniques and improve early detection of Alzheimer's disease. In addition, Odusami *et al.* [10] studied the use of multimodal data by applying the integration of MRI with positron emission tomography (PET) imaging modalities to improve the precision of Alzheimer's detection. Using a modified ResNet-18 model, this study achieved an accuracy of 73.90% and emphasized the importance of XAI in enhancing the visibility of AI decisions in clinical practice.

In their research, Massoud *et al.* [11] introduced a distributed learning-based CNN classification model, achieving 94.91% accuracy in Alzheimer's detection and 96.60% validation accuracy, ensuring efficient disease classification from diverse clinical data sources. The results highlight the potential of AI-driven telemedicine in enhancing early diagnosis, optimizing treatment accessibility, and advancing healthcare solutions for improved patient outcomes. Mahanty *et al.* [12] also proposed an ensemble learning technique with the Xception model to improve the precision in identifying Alzheimer's cases. By utilizing the snapshot ensemble and blending strategies with random forest (RF) as a meta-learner, this study achieved an accuracy of 99.14%, indicating that the ensemble method can improve the reliability of neurodegenerative disease prediction. While AlSaeed and Omar [13] explored utilizing ResNet-50 as an automated feature extraction technique for diagnosing Alzheimer's from MRI. This study evaluated the performance of CNN alongside different classification techniques, including NB, SVM, and RF. The findings indicated that DL notably enhanced the predictive performance for Alzheimer's diagnosis when contrasted with conventional approaches, achieving predictive accuracies varying between 85.7% and 99% when tested on the ADNI MRI dataset. Overall, these studies show that AI and DL have made significant progress in MRI-based Alzheimer's diagnosis. However, some major challenges still need to be overcome, such as the reliance on pre-trained and ensemble learning, the problem of overfitting, and the substantial volume of parameters requiring optimization during training. Therefore, this study proposes a QCL-CNN approach for the diagnosis of Alzheimer's disease utilizing MRI data. The objective is to minimize the number of trainable parameters, speeding up model convergence and lowering computational demands.

2. METHOD

2.1. Dataset

The open access series of imaging studies (OASIS) MRI dataset is a neuroimaging corpus created to facilitate studies focused on early identification and characterization of Alzheimer's disease [14]. The dataset comprises 86,437 brain MRI scans, which are organized into four classes according to the severity of

Alzheimer’s progression, namely non-demented, very mild dementia, mild dementia, and moderate dementia (Figure 1). These categories are determined based on clinical metadata and dementia rating, allowing for in-depth analysis of the disease progression from early to advanced stages. To facilitate accessibility and compatibility with various AI models, the original data in .img and .hdr formats were converted into Nifti (.nii) format using FMRIB software library (FSL). After conversion, MRIs from 461 patients were uploaded to a GitHub repository, which can be accessed in parts to facilitate further research. In the process of training NN model, the MRI images were processed in 2D format, with the images cut along the z-axis into 256 parts. For each patient, slices between 100 and 160 were selected as model input, resulting in a more structured and optimal dataset for analysis. To improve compatibility with DL algorithms, MRI images in .nii format were then converted to .jpg format. The following are several brain MRIs of Alzheimer's patients from the OASIS dataset shown in Figure 1.

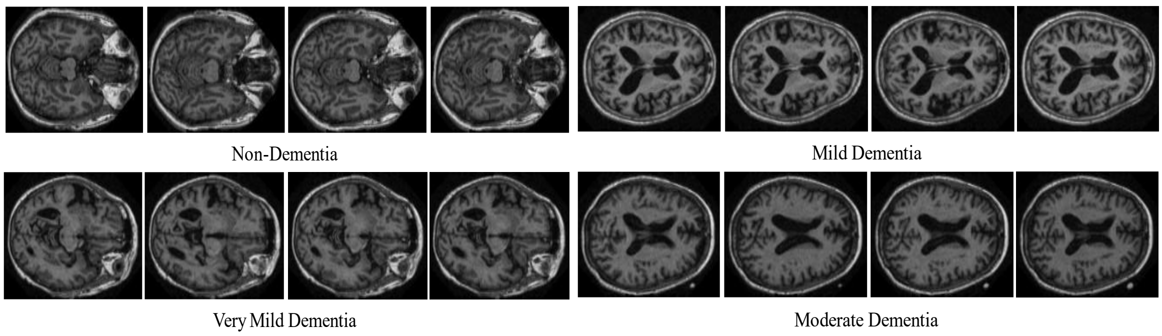

Figure 1. Example samples of the OASIS MRI dataset

2.2. Data augmentation

In the analysis of Alzheimer’s condition using the OASIS magnetic resonance imaging dataset, one of the main challenges faced is the imbalance of class distribution. This dataset shows the dominance of the non-dementia class with 67,222 samples, while the very mild dementia (13,725 samples), mild dementia (5,002 samples), and moderate dementia (488 samples) categories have much less data [14]. This disproportion may lead AI models to show higher accuracy in classifying the majority class, but less effectiveness in recognizing patients with Mild or Moderate Dementia, which are critical groups in the initial identification of Alzheimer’s cases. To mitigate this problem, different augmentation strategies are implemented to expand the dataset size and enrich the variety of features in the learning model [15]. Several augmentation approaches employed during the preprocessing phase of the OASIS MRI collection include rotation, cropping, flipping, brightness adjustment, and contrast adjustment. Rotation augmentation is applied by rotating the MRI image by ±10° to ±30°, resulting in a variety of perspectives that help the model recognize structural changes in the brain from various angles [16]. Cropping augmentation is used to focus the image on more relevant areas, such as the hippocampus and entorhinal cortex, which often experience degenerative shrinkage occurring in the initial phases of Alzheimer’s progression [17]. In addition, flipping augmentation is performed by mirroring the image horizontally or vertically, which is beneficial for enhancing the capacity of the model to identify Alzheimer’s-related patterns from different orientations without changing important anatomical information [18].

The brightness augmentation technique is applied by adjusting the brightness level of the MRI image, which aims to mimic illumination fluctuations during acquisition and help the model maintain consistent identification of Alzheimer-related characteristics [19]. Meanwhile, contrast augmentation is used to enhance the visibility of brain structures by accentuating the intensity distinction between gray and white matter, which helps the model focus more on discriminating Non-Dementia from Dementia across varying severity grades [20]. By applying this augmentation method selectively to the underrepresented categories, namely mild dementia and moderate dementia, the dataset distribution becomes more balanced, thereby preventing the model from concentrating solely on the majority class and enabling it to learn from a broader range of samples [21].

2.3. Quad convolutional layers convolutional neural network

QCL-CNN is a DL architecture that utilizes four consecutive convolutional layers to enhance the quality of feature extraction in image data [22]. This model is designed to capture more complex spatial patterns, making it highly effective for various applications, such as classification, segmentation, and detection of object, particularly in medical imaging fields like MRI and CT scans. By applying four convolutional layers sequentially, QCL-CNN can retain more information from the image without losing important details, thereby improving accuracy in image analysis. The primary function of QCL-CNN is to enhance feature representation in an image, allowing the model to recognize patterns more effectively. Each convolutional layer plays a distinct role in the feature extraction process [23]. The first layer captures basic patterns such as edges and simple textures, while the second and third layers begin to recognize object shapes and more complex structures. The fourth layer refines the previously extracted features and prepares the data for the classification stage. Additionally, the use of MaxPooling after certain convolutional layers allows the model to reduce the feature map dimensions without eliminating important information, thereby improving computational efficiency and reducing the likelihood of overfitting [24].

In terms of working principles, QCL-CNN is based on convolution operations, which apply filters or kernels to the input image to capture spatial characteristics from the input data. Each convolutional layer has its own weights and biases, which are optimized throughout the training phase to enhance predictive precision. Rectified linear unit (ReLU) or LeakyReLU activation functions are applied after each convolution operation to embed non-linear transformations, enabling the network to identify and represent intricate feature patterns [25]. Furthermore, Batch Normalization is implemented to improve training stability by maintaining an optimal data distribution, while pooling layers function to downsample the feature map by retaining either the maximum or mean value within localized pixel regions [26]. After features are extracted through four convolutional layers, the resulting data is transformed into a flattened vector representation using Flattening and then processed in a fully connected layer for classification. The model then generates final predictions using softmax for multi-class classification or Sigmoid for binary classification [27]. During the training phase, weights in each layer are updated through backpropagation and gradient descent, allowing the model to adapt based on error feedback and refine its classification accuracy [28]. The following is a proposed QCL-CNN for the identification of Alzheimer's disease.

The Table 1 presents a QCL-CNN designed for Alzheimer's disease detection. This DL architecture is organized into four convolutional layers, with every layer paired with a subsequent max pooling operation, which progressively extracts and refines image features before feeding them into fully connected layers for classification. This model is designed to categorize MRI scans into four distinct groups: non-demented, very mild dementia, mild dementia, and moderate dementia. The architecture starts with an input layer that processes input images sized at 224 by 224 pixels with three color channels. In the initial convolutional layer (Conv1), 32 filters with a kernel size of 3×3 are applied to extract primary features, including edges and surface textures. It is followed by a 2×2 max pooling layer, which compresses the spatial resolution of the data and computational load while preserving essential feature details. The second convolutional layer (Conv2) again applies 32 filters with a 3×3 kernel, further refining extracted patterns, followed by another max pooling layer to continue downsampling the feature maps. Deeper layers in the network allow for the recognition of more complex image patterns. The third convolutional layer (Conv3) expands the filter count to 64, thereby strengthening the model's capacity to identify fine-grained anatomical structures and texture details within MRI images. After another max pooling layer, the fourth convolutional layer (Conv4) utilizes 128 filters, capturing high-level abstract features indicative of structural changes in the brain caused by Alzheimer's disease. The final max pooling layer (2×2) guarantees retention of the most salient and informative features before transitioning to the fully connected layers. Following feature extraction, the Flatten layer reshapes the three-dimensional feature maps into a one-dimensional vector representation, preparing them for the fully connected (Dense) layers. The initial dense layer (Dense 1) is composed of 224 neurons utilizing ReLU activation, allowing the model to capture complex feature relationships. The second fully connected layer (Dense 2) further refines this representation with 64 neurons. Finally, the output layer uses softmax activation to classify the image into one of four categories, ensuring a multi-class classification approach. In addition, Figure 2 shows the proposed QCL-CNN with input and output vector shapes.

The Figure 2 illustrates the architecture of the proposed QCL-CNN for Alzheimer's disease detection, showcasing the representations of input and output vectors at each stage. This network is composed of four convolutional blocks, with each convolutional layer paired with a max pooling operation, ensuring efficient feature extraction while reducing spatial dimensions. The model accepts images with dimensions of 224 by 224 pixels and three channels, representing MRI scans. As the data moves through the network, the spatial resolution decreases while the feature depth increases, capturing hierarchical patterns crucial for disease classification. The first convolutional layer utilizes 32 filters to capture fundamental visual attributes like edges and surface textures, producing an output tensor of dimensions (222, 222, 32). Then, a max pooling layer is applied, decreasing the spatial resolution of the feature maps by half to (111, 111, 32). This progression continues across subsequent convolutional layers, where deeper layers increase feature complexity while further reducing spatial dimensions. The third convolutional layer expands feature representation to 64 filters, generating (52, 52, 64) before max pooling reduces it to (26, 26, 64). The fourth convolutional layer, which uses 128 filters, outputs (24, 24, 128) and is further downsampled to (12, 12, 128) via pooling. After passing through the convolution and pooling stages, the resulting feature maps are reshaped into a one-dimensional vector of 18,432 elements, serving as the input to the dense layers. The first fully connected layer compresses the representation into 224 neurons, subsequently processed by a second fully connected layer consisting of 64 neurons, refining the learned features serving as the basis for the classification process. Finally, the output layer, composed of four neurons, executes multi-class classification corresponding to the four dementia stages.

Table 1. Architecture of the proposed QCL-CNN

Layers	Layer (type)	Properties
1^{st}	Input	Input shape=224×224×3
	Convolutional 1	Kernel size=3×3, 32 filters
2^{nd}	Max-pooling	Pool size=2×2
3^{rd}	Convolutional 2	Kernel size=3×3, 32 filters
4^{th}	Max-pooling	Pool size=2×2
5^{th}	Convolutional 3	Kernel size=3×3, 64 filters
6^{th}	Max-pooling	Pool size=2×2
7^{th}	Convolutional 4	Kernel size=3×3, 128 filters
8^{th}	Max-pooling	Pool size=2×2
9^{th}	Flatten	Convert to 1d vector for dense
10^{th}	Dense 1	224 neurons, ReLU
11^{th}	Dense 2	64 neurons, ReLU
12^{th}	Output	4-class classification, softmax

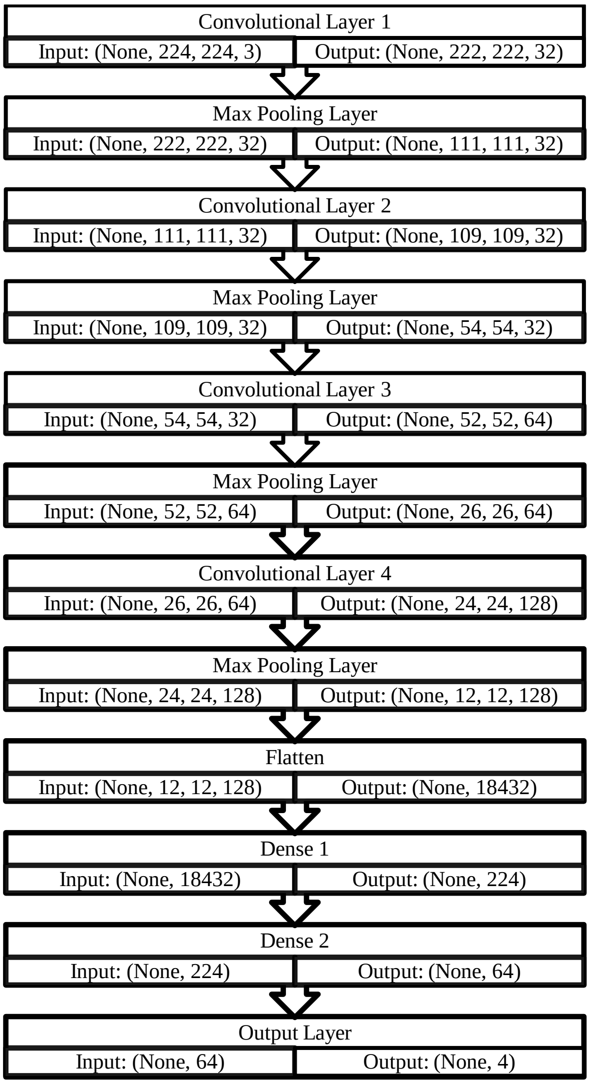

Figure 2. Proposed QCL-CNN architecture with input and output vector forms

3. RESULTS AND DISCUSSION

This study introduces a QCL-CNN approach to identify Alzheimer's disease based on MRI imaging data. The OASIS MRI dataset is chosen to support research in the initial diagnosis and detailed examination of Alzheimer's disease, providing a reliable foundation for training and testing the DL model. The dataset consists of four different classes, non-dementia (67,222 samples), very mild dementia (13,725 samples), mild dementia (5,002 samples), and moderate dementia (488 samples). The class imbalance in the dataset highlights the critical role of employing reliable DL methodologies to ensure fair and accurate classification across all categories [29]. The QCL-CNN model employs four consecutive convolutional layers, enabling a hierarchical feature extraction process that strengthens the model's capacity to distinguish among the different progression levels of Alzheimer's disease. Each convolutional layer captures spatial features from MRI scans, progressively refining extracted patterns, ranging from fundamental attributes like edges and surface textures to advanced representations such as structural irregularities in the brain. By applying multiple convolutional layers in sequence, the model preserves critical information while filtering out irrelevant noise, ultimately improving classification accuracy. The following are the performance values of the QCL-CNN approach proposed in this research.

The Table 2 presents the performance values of the proposed QCL-CNN model for Alzheimer's disease detection utilizing MRI imaging as the primary diagnostic input. The findings reveal that the model delivers outstanding predictive performance across all categories, with an overall accuracy rate of 99.90% together with an F1-score of 99.52%, confirming the robustness of the model in producing consistent and dependable classifications. The recall values, which measure the model's ability to recognize true positive instances, are 99.78% for non-dementia and very mild dementia, and 100% for mild and moderate dementia. This indicates that the model demonstrates strong sensitivity in detecting Alzheimer's disease across different stages, ensuring that almost no cases are missed. Similarly, the specificity values, which reflect the capability of the model to accurately distinguish negative instances, are consistently remarkably elevated, with an average of 99.93%, indicating a very low rate of false positives. In terms of precision, which measures the proportion of predicted positives that correspond to true positives, the model achieves an average of 99.16%, with the highest precision observed for non-dementia (99.99%) and the lowest for moderate dementia (98.18%). This slight variation suggests that while the model performs exceptionally well in classifying the majority of cases, the smaller dataset size for moderate dementia (only 488 samples) might slightly affect its predictive certainty. Nonetheless, the overall high precision indicates the model minimizes false positives, which is essential for clinical applications [30].

Table 2. Performance values of the proposed QCL-CNN

Condition	Performance evaluation (%)				
	Recall	Specificity	Precision	Accuracy	F1-score
Non-dementia	99.78	99.95	99.99	99.81	99.88
Very mild dementia	99.78	99.82	99.04	99.81	99.41
Mild dementia	100.00	99.96	99.42	99.97	99.71
Moderate dementia	100.00	99.99	98.18	99.99	99.08
Average	99.89	99.93	99.16	99.90	99.52

The accuracy values, ranging from 99.81% to 99.99%, highlight the robustness of the QCL-CNN model. The model achieves consistent performance across all dementia stages, achieving a total accuracy rate of 99.90%, thereby validating its strong capability in identifying Alzheimer's disease. Additionally, the F1-score (an evaluation metric that harmonizes precision and recall) reached an average of 99.52%, reinforcing the dependability of the model in addressing both balanced and imbalanced data distributions. These results suggest that the QCL-CNN model is highly effective for categorizing Alzheimer's disease cases through MRI-based imaging data. Its high sensitivity and specificity ensure that both positive and negative cases are accurately identified, reducing the risk of false diagnoses. In addition, the performance value of QCL-CNN is compared with several other CNN models. The following is the result of a comparative assessment of performance metrics across multiple CNN architectures with the proposed QCL-CNN.

Table 3 highlights the performance assessment of multiple CNN architectures in detecting Alzheimer's disease based on MRI imaging data. The models analyzed include VGG19, Xception, ResNet50, DenseNet201, and the proposed QCL-CNN, with key evaluation criteria including recall, specificity, precision, accuracy, and the F1-score, together with their total number of parameters. The results demonstrate that the proposed QCL-CNN outperforms alternative models across critical performance metrics while keeping the parameter count considerably lower, making it a more efficient and effective DL model for medical image classification. The proposed QCL-CNN achieves the highest recall (99.89%), indicating its ability to correctly detect almost all true positive cases of Alzheimer's disease, thereby effectively reducing the occurrence of false negatives. This aspect is especially vital in medical imaging, since misclassification errors may cause postponed treatments and potentially harmful consequences for patients [31]. Similarly, its specificity (99.93%) is the highest among all models, ensuring that non-Alzheimer's cases are correctly identified, thereby reducing false positives and preventing unnecessary medical interventions. These two metrics collectively confirm that QCL-CNN is highly reliable in distinguishing between cases diagnosed as Alzheimer's and those identified as non-Alzheimer's.

Table 3. Comparison of performance values of several CNN models

Models	Performance evaluation (%)					Total parameter
	Recall	Specificity	Precision	Accuracy	F1-score	
VGG19	97.14	99.71	99.61	99.83	98.32	20.158.788
Xception	97.58	99.82	99.35	99.89	98.44	21.395.244
ResNet50	97.98	99.82	99.01	99.89	98.49	24.121.476
DenseNet201	98.73	99.83	99.03	99.90	98.88	18.822.468
Proposed QCL-CNN	99.89	99.93	99.16	99.90	99.52	4.246.148

The accuracy of QCL-CNN reaches 99.90%, slightly surpassing VGG19 (99.83%), Xception (99.89%), and ResNet50 (99.89%), and matching DenseNet201 (99.90%). Even minor improvements in accuracy are significant in clinical applications, where every correctly classified case contributes to better patient diagnosis and treatment planning. Furthermore, the F1-score of 99.52%, which balances precision and recall, is the highest among all models, ensuring that the model maintains strong classification consistency across all categories [32]. One of the most striking advantages of QCL-CNN is its computational efficiency, as reflected in its significantly lower total parameter count. While VGG19 (20.1M), Xception (21.3M), ResNet50 (24.1M), and DenseNet201 (18.8M) require large computational resources, the QCL-CNN operates with only 4.2M parameters, making it nearly five to six times more efficient while still achieving better classification performance. This reduced number of parameters minimizes memory consumption and decreases training time. Additionally, the low parameter count of QCL-CNN makes it more suitable for edge computing and real-time applications, where models must be deployed on devices with limited processing power. Unlike heavier architectures like ResNet50 or Xception, which may require high-end GPUs for training and inference, QCL-CNN can be effectively implemented on standard computational systems, allowing faster and more accessible AI-assisted diagnostics in real-world clinical environments. The ability to deploy an efficient yet highly accurate DL model makes QCL-CNN a strong candidate for medical imaging applications, particularly for early Alzheimer's detection.

The Table 4 presents a comparative analysis of the proposed QCL-CNN in comparison with several previously developed DL models aimed at detecting Alzheimer's disease from MRI imaging. The comparison is based on the quantity of convolutional layers employed and the level of classification accuracy attained by each architecture. The results demonstrate that QCL-CNN outperforms previous architectures by achieving the highest accuracy (99.90%) while using the fewest convolutional layers (4 layers). This finding highlights the importance of network optimization and efficient feature extraction over simply increasing the depth of the model. Among the prior models, Odusami *et al.* [33] 18-layered CNN achieved 98.00% accuracy, suggesting that while deeper networks can extract complex patterns, they do not necessarily lead to superior performance. AbdulAzeem *et al.* [34] end-to-end CNN framework, which uses 8 convolutional layers, performed at 99.80% accuracy, showing that reducing the number of layers can still yield strong results. Similarly, Mandal and Mahto [35] deep multi-branch CNN (10 layers) reached 99.05% accuracy, and El-Assy *et al.* [36] deep CNN (5 layers) achieved 99.57% accuracy, further reinforcing the trend that optimized architectures perform better than excessively deep models.

Table 4. Comparison of the performance of the proposed QCL-CNN with prior work

Prior work	Models	Convolutional layers	Accuracy (%)
Odusami *et al.* [33]	18-layered CNN	18	98.00
AbdulAzeem *et al.* [34]	CNN based end-to-end framework	8	99.80
Mandal and Mahto [35]	Multi-branch CNN	10	99.05
El-Assy *et al.* [36]	Deep CNN	5	99.57
Proposed QCL-CNN	Quad convolutional layers	4	99.90

Despite having the fewest layers, the proposed QCL-CNN surpasses all previous models in accuracy, proving that deeper architectures are not always more effective. Instead, the efficiency of feature extraction and network design plays a more critical role than merely increasing depth. The quad convolutional layer structure in QCL-CNN enables multi-level feature extraction, preserving crucial spatial information while reducing computational redundancy, ultimately leading to higher classification accuracy with fewer parameters. This efficiency makes QCL-CNN an ideal solution for real-world applications, particularly in medical environments with limited computational resources. Another key insight from the comparison is that the number of convolutional layers does not directly correlate with better accuracy. The 18-layered CNN by Odusami *et al.* [33] achieves only 98.00% accuracy, while the proposed QCL-CNN with just 4 layers outperforms it with 99.90% accuracy. This indicates that a well-optimized CNN with an efficient architecture can outperform deeper models, reducing training time, computational costs, and the risk of overfitting while maintaining high classification performance.

4. CONCLUSION

This study has demonstrated the effectiveness of the QCL-CNN model to detect Alzheimer's disease through MRI-based imaging. The model achieved a remarkable accuracy rate of 99.90% alongside an F1-score of 99.52%, outperforming traditional CNN architectures while maintaining computational efficiency with only 4 convolutional layers. The results highlight QCL-CNN's high recall and specificity, ensuring accurate detection of both positive and negative classifications, while effectively reducing the incidence of false positives and false negatives. Furthermore, a comparative evaluation with other established DL architectures including VGG19, Xception, ResNet50, and DenseNet201, revealed that QCL-CNN achieves superior classification performance with significantly fewer parameters, making it a practical solution for real-world medical applications, especially within clinical settings that face limitations in computational or infrastructural resources. Despite its strong performance, there are areas for improvement and future research directions. A primary challenge arises from the uneven distribution of classes within the dataset, particularly for Moderate Dementia cases, where the limited number of available samples may slightly impact model precision. Future studies should consider data augmentation methods, synthetic data generation, or pre-trained approaches to improve classification confidence for underrepresented classes. Additionally, exploring multi-modal imaging techniques, such as integrating MRI with PET scans, may provide richer data representations and further enhance model accuracy. Another promising direction is incorporating XAI to improve interpretability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

There were no human subjects involved in this study. The data utilized were publicly available OASIS datasets.

ETHICAL APPROVAL

This paper does not involve any people participant or animal studies.

DATA AVAILABILITY

The data that support the findings of this study are openly available in OASIS at https://doi.org/10.1162/jocn.2007.19.9.1498.

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