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NEURO-Q-NET: Quantum-Enhanced Ensemble for Neurodegenerative Disease Detection

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Abstract. Neurodegenerative diseases are a group of progressive disorders that affect the nervous system, characterized by a gradual deterioration in mental and physical functions. In the domain of neurodegenerative diseases, Alzheimer's disease (AD) and Parkinson's disease (PD) are some of the most prevalent diseases that are very difficult to diagnose in advance stages. In order to address the issue of the present methods that are currently practiced for the diagnosis of neurodegenerative diseases, a novel diagnostic approach, termed as Neuro-Q-Net, is proposed in the developmental work of this study that possesses the capability to diagnose more than one neurodegenerative disease at a time using the Fluorodeoxyglucose Positron Emits Scan images taken from the brain of a human. In order to address the issue of unavailability of imbalanced scans in the domain of medicine, the utilization of a novel approach in computer science, termed as a Generational Adversarial Network (Gan), is suggested that assist in generating high-quality images to increase the efficiency of neural networks. We use deep convolutional neural networks for feature identification, followed by Quantum Machine Learning. Our experiments show that this approach outperforms existing models in accuracy, specificity, and sensitivity. The proposed system offers an effective clinical tool for diagnosing neuro- degenerative illnesses.

Keywords: Neurodegenerative Diseases, FDG-PET, Deep Learning, GAN, Quantum Machine Learning, Ensemble Models.

1 INTRODUCTION

Neurodegenerative disorders are one of the significant global health issues, which are on a rise with an irreversible nature. Indeed, the progressive alteration of neuronal architecture and functionality because of neurodegenerative disorders renders impressive advancements of impairment of mental functions, motor deficits, and psychiatric problems [1]. Cumulatively taken, Alz-heimer's and Parkinson's disease affect a considerable number of patients worldwide, thus plac-ing a substantial socioeconomic load on them [2].

Early detection of such a management holds the key to slowing the progression of the disease, optimizing treatment schedules, and even ensuring improved survival of the patients [11]. However, the early detection of the disease holds the key because of the non-specific clinical symptoms of the disease. The conventional method of detection of the disease includes clinical examina- tion and imaging studies for a particular disease, which does not provide a means of distin- guishing among the different diseases [3].

The consequent outcome is an improvement in healthcare by creating a high-precision diagnos- tic analysis of brain scans using artificial intelligence [10]. In particular, the FDG-PET technique possesses a high potential in the detection of

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metabolic disorders associated with neurodegener- ative diseases [4]. Moreover, certain limitations such as a shortage of labeled data in the healthcare domain, as well as class imbalance, illustrate that deep learning is incapable of providing satis-fying results.

This paper puts forward Neuro-Q-Net, which is a hybrid diagnostic model that combines deep, generative, and quantum-inspired ensemble models for dealing with these issues. By dealing with these issues, the proposed model intends to enhance diagnostic accuracy, quality, and practicality by diagnosing Alzheimer's and Parkinson's diseases simultaneously using FDG- PET images.

2 RELATED WORK

In recent years, there has been considerable progress in the diagnosis of neurodegenerative disorders using machine learning and deep learning algorithms [9]. Convolutional Neural Networks have been chiefly employed for the classification of Alzheimer's Disease using MRI and PET scans, and have been proven better than the various traditional machine learning algorithms [14].

There are several studies on the use of deep learning techniques to identify Parkinson's disease based on the metabolic pattern of the disease identified through PET and SPECT scans [5]. These methods deal only with a particular disease.

Data scarcity and imbalance are long-term problems in the field of medical image processing. This is addressed by the usage of Generative Adversarial Networks that produce novel images to enhance the robustness of models to overfitting [6].

Quantum machine learning emerged quite recently, merging the fields of quantum computing and machine learning [7]. Ensemble quantum classifiers proved their efficacy in decision boundaries and robustness in solving classification problems, but their applications in the diagnosis of neurodegenerative disorders remain unexplored.

The proposed Neuro-Q-Net model brings forth novel advances in the community by combining data augmentation using GANs, feature learning using DCNNs, and quantum learning in an ensemble method for multi-disease classification.

3 PROBLEM DEFINITION

The Neurodegenerative disorders include a collection of chronic progressive disorders, which are distinguished by an irreversible loss of neuronal structure and function. Alzheimer's disease and Parkinson's disease are a few examples of neurodegenerative dis- orders that display progressive manifestations of mental, behavioral, or motor dysfunction. Such disorders significantly affect patients' quality of life while also creating a heavy toll on healthcare systems worldwide because one of the primary issues with man- aging such disorders is accurately identifying them in their early stages since overlap- ping symptoms concurrently pose a high risk of inaccurate diagnosis.

The current state-of-the-art techniques used for diagnostics are dominated by the clinical, cognitive, and visual analysis of the neuroimages. Even though these techniques have been of great help, they are still mainly dependent upon the human expertise. This gives rise to the observer variation, and hence, there are discrepancies in the diagnosis acquired. Most of the current automated techniques are designed for the diagnosis of the single disease, which is insufficient for the diagnosis, since there are often several neurological illnesses which have to be diagnosed together.

Another significant limitation involves the limited availability of imaging data in healthcare. Neuroimaging datasets are typically small, imbalanced, and expensive to ac- quire, which leads to biased learning and limited generalization in deep learning models. This challenge underscores the need for a robust, data-efficient, and multi-disease diagnostic tool. To address these issues, the proposed Neuro-Q-Net model utilizes generative modeling, deep learning, and ensemble classification with a quantum-inspired approach. Through the integration of synthetic data generation and advanced feature learning, Neuro-Q-Net seeks to enhance diagnostic accuracy while maintaining scalability and clinical relevance.

4 PROPOSED METHODOLOGY

This paper proposes Neuro-Q-Net, a unified diagnostic tool that aims to identify and differentiate various neurodegenerative diseases using FDG-PET brain images. While creating a unified diagnostic tool, various challenges in medical imaging, such as dealing with limited sample data, imbalance in classes, and similarities among classes, are treated in Neuro-Q-Net. The proposed unified diagnostic tool combines three aspects: generative models, deep convolutional networks, and ensemble quantum machine learning [8].

First, the raw FDG-PET images are standardized through preprocessing. Then, Generative Adversarial Networks are applied for creating new images, and hence, diversity in the data is increased. Hierarchical models for Alzheimer's and Parkinson's diseases are learned through Deep Convolutional Neural Networks. Decisions from different models are taken using an ensemble quantum classifier, which boosts the certainty of decisions. This reduces potential uncertainties. Each step in this process has been designed for facilitating multi-class diagnostic accuracy and also for making sure that everything re- mains scalable.

4.1 Dataset Acquisition and Preprocessing

The FDG-PET brain scan datasets representing Alzheimer's disease, Parkinson's disease, and healthy controls will be obtained from publicly available authenticated repositories according to the ethical standards.

All scans are anonymized to maintain patient privacy according to established ethical guidelines for medical data use. The preprocessing will include the application of a string of procedures to the acquired scans to ensure consistency and high quality for further analyses.

Smoothing and denoising filters, such as the Gaussian filter, are used to reduce noise and remove scanner-specific artifacts and random noise [15]. Intensity normalization is done through standardization of voxel intensities based on a z-score, so that the ranges of intensity will be the same in all images. Spatial normalization incorporates all scans to one common template by using both affine and nonlinear transformations, taking into account possible variations in patient positioning and brain anatomy. Finally, images are resized to fixed dimensions in accordance with the input requirements of the DCNN while keeping structures intact for computational efficiency.

These are the preprocessing procedures that reduce intra-class variability, enhance the reliability of feature extraction, and further provide standardized input toward modeling.

4.2 Data Augmentation with GANs

The Data Augmentation with GANs aims to alleviate dataset imbalance and further enhance the diversity in training by the generative adversarial network. GANs work especially well in the field of medical imaging since these are capable of synthesizing high-dimensional data with the preservation of realistic features of specific diseases. Genera- tor Network: The generator network is first taught the generation of synthetic FDG-PET images taken from a vector of random noise. It iteratively enhances its capability for reproducing even the subtleties of metabolic patterns that could give insight into each neurodegenerative condition in question.

Discriminator Network: This acts to tell the difference between real images and syn- thetic, feeding this as information so that the generator can produce high-quality output.

Adversarial Training: The generator and discriminator are competitively trained in a min-max optimization framework, whereby the generator tries to mislead the discriminator and the discriminator tries to correctly classify between real vs. generated images. This adversarial process generates high-quality synthetic images to augment the training dataset, especially for under-represented disease classes. It significantly improves model generalization by reducing overfitting and enabling the DCNN to learn robust and di- verse features

4.3 Deep Convolutional Neural Network Architecture

A Deep Convolutional Neural Network is designed to learn hierarchical spatial and structural features from the FDG-PET scans:

1. Consecutive convolutional layers will detect local features in the form of edges and textures and minute variations in intensities corresponding to metabolic changes due to disease conditions.
2. Batch Normalization: This is applied after every convolutional layer to stabilize and speed up the training, hence reducing the internal covariate shift.
3. Pooling Layers: This is used for the max-pooling operation, down sampling feature maps to reduce their dimensionality in space and introduce translational invariance.
4. Fully Connected Layers: Dense layers increase the extracted features and perform high-order representation learning on multi-class classification.
5. ReLU Activations: These introduce non-linearity within the network, enabling it to capture complex relationships between features.
6. Regularization: Dropout layers are used in order to avoid overfitting, something quite important when dealing with neuro imaging data, which is relatively small.

This augmented dataset is used for training the DCNN to capture subtle metabolic vari- ations and disease-specific patterns that distinguish between Alzheimer's disease, Park- inson's disease, and healthy subjects

4.4 Quantum Ensemble Classification

In order to increase the level of accuracy, robustness, as well as confidence in the results, a Quantum Machine Learning (QML) approach using an ensemble technique combines the predictions of multiple independently trained models of DCNN as follows:

- Quantum-Inspired Feature Mapping: The produced probability distributions by all DCNNs are represented in a high-dimensional space named as quantum-inspired feature space, which enables the model to learn complex dependencies between features, that might not be captured by conventional models.

- Ensemble Aggregation: The predictions made by several. The aggregation of DCNN models happens through a majority voting approach, which is weighted by confidence scores obtained from quantum representation.

- Variance Reduction and Robustness: the impact of the noisy or uncertain pattern in the input is reduced because of the ensemble approach; the prediction variance is there- fore reduced while the generalizability of the model improves.

It tends to combine the process of feature detection in deeper layers with the capabilities of quantum-inspired ensemble-based classification, thus guaranteeing the development of a highly accurate diagnostic system. The overall architecture of the proposed Neuro-Q-Net system is shown in Fig. 1.

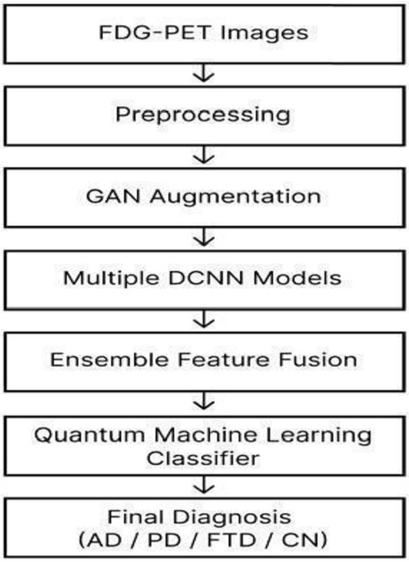

Fig. 1. System Architecture of Neuro-Q-Net

5 CLINICAL SIGNIFICANCE

Neurodegenerative conditions such as Alzheimer's disease and Parkinson's disease pre- sent significant diagnostic and therapeutic challenges due to their progressive nature and overlapping clinical manifestations. Early and accurate diagnosis of these conditions is essential for initiating timely interventions that may slow disease progression and im- prove patient quality of life. The Neuro-Q-Net framework offers substantial clinical value by providing a reliable, fully automated, multi-disease diagnostic support system utilizing FDG-PET brain imaging.

In contrast to traditional diagnostic methods that typically identify only a single neuro- logical disorder, Neuro-Q-Net is designed to differentiate among multiple neurodegen- erative diseases within a unified framework. This capability is particularly valuable in clinical practice, as patients often present with ambiguous or overlapping symptoms dur- ing the early stages of disease. The system assists clinicians in reducing diagnostic un- certainty and minimizing the risk of misclassification by leveraging disease-specific metabolic patterns identified through FDG-PET imaging.

Generative Adversarial Networks address common challenges of data scarcity and im- balance in medical datasets by enhancing model robustness. This improvement enables better generalization across diverse patient populations and varying imaging conditions. The ensemble-based quantum learning component further enhances diagnostic confi- dence by integrating multiple predictive perspectives, thereby reducing variability and improving stability in clinical decision making. This stability is critical in clinical con texts where diagnostic accuracy directly influences treatment planning and patient out- comes.

Neuro-Q-Net can be easily integrated into the current practices in the medical field to aid in decision-making, such that the insights obtained will complement and not replace the substantial inputs provided by the neurologist and radiologist. The proposed model has the capability to aid neurologists and radiologists in the screening, staging, and lon- gitudinal observation of patients suffering from neurological disorders. The distributable nature of the architecture will enable the quick addition of new disorders, multimodal imaging, and biomarkers.

The proposed system provides a notable enhancement in smart and technology-sup- ported health care by showing the capability of using sophisticated computational meth- ods for accuracy enhancement in the diagnostic process. Such an enhancement helps in performing early intervention and the design of personalized treatment plans for patients with neurodegenerative diseases.

6 ETHICAL CONSIDERATION AND DATA PRIVACY

Neuro-Q-Net is developed with the primary goal of ensuring the appropriate use of the patient data. Anonymized data sets are used in the project and are obtained from public sources that follow the appropriate guidelines for the use of the data in research projects. Anonymized data sets are used in the project such that they are not associated with personally identifiable information in any way during the development process of the model. The project aims to develop an assistant diagnostic model that does not replace human decision-making abilities.

Strategies for mitigating biases have been incorporated to ensure fairness in model out- puts for different groups of people. Moreover, this framework is consistent with general principles of data protection that promote responsible and transparent use of artificial intelligence in health informatics.

7 . PERFORMANCE ANALYSIS

The effectiveness of the proposed Neuro-Q-Net model was tested based on some standard metrics for classification, which also included sensitivity, specificity, precision, re- call, accuracy, and F1-score. These metrics were used to establish the model's effective- ness on the lesions in FDG-PET brain scan images from Alzheimer's and Parkinson's diseases.

Neuro-Q-Net exhibits strong classification performance with a pretty decent result in identifying AD versus PD. The model's performance was considerably enhanced by the data augmentation with GAN. Moreover, Neuro-Q-Net showed more stable predictive performance than the hybrid model.

The model reaches a high sensitivity, demonstrating good detection of neurodegenerative disorder patients. High sensitivity is very important, especially in early diagnosis, as any missed cases lead to adverse outcomes. The deep convolutional neural network is effective in identifying metabolic shifts, enhancing early-stage disorder detection.

Neuro-Q-Net model has a high level of specificity, which means the outcome will not be mislabeled as a human who is healthy or has non-target diseases. This is further enhanced through the ensemble learning method which prevents misclassification of data due to a positive predictive result.

The performance metrics of the proposed model are summarized in Table 1.

Table 1. VALUE TABLE OF NEURO-Q-NET

	Precision	Recall	F1-score	Support
0	0.99	0.96	0.97	360
1	0.98	1.00	0.99	317
2	0.93	0.95	0.94	107
Accuracy			0.97	784
Micro Average	0.96	0.97	0.97	784
Weighted Average	0.97	0.97	0.97	784

The values of precision suggest that the results from this model are reliable since there are few cases of false negatives with respect to disease prediction. High values of recall further emphasize the effectiveness of this system with respect to true disease cases. There is a good combination of values of recall and precision.

The F1-Score, which combines both precision and recall, remains relatively constant for all classes of diseases. This consistency indicates that Neuro-Q-Net performs well on multi-class classification, which has overlapping diseases and metabolic patterns, without significantly affecting precision and recall.

Synthetic images generated with the help of the GAN add significantly to the improvement in performance. The addition to the dataset brings about an improvement in generalization and reduces the problem of overfitting while training solely with the real images.

The quantum-inspired classifier improves the classification accuracy by navigating the high-dimensional feature space effectively. It enables clear differentiation among the features of diseases and thus makes one more confident about the results.

Neuro-Q-Net allows for hybrid and quantum-inspired models while keeping its computational performance efficient during any inference task. Its timely delivery of solutions makes it suitable to be embedded into web interfaces with no significant computational delays.

In contrast to traditional models that only target a single disease, Neuro-Q-Net allows simultaneous multi-disease classification. Deep learning, ensemble learning, and quantum machine learning are further integrated to guarantee robustness, stability, and consistent predictions. Neuro-Q-Net provides a helpful assistant for physicians in the diagnosis of neurodegenerative diseases.

8 . RESULT AND DISCUSSION

The experiments on performance analysis evidence the good optimization of the precision, reliability, and interpretation capabilities of Neuro-Q-Net. The additional integration of GradCAM views further improves the application properties of NEURO-Q- NET. These views help better understand the decision-making procedure followed by the software solution. Minor differences regarding closely related disorders exist. These issues are ascribed to the pathophysiological properties of the diverse neurodegenerative disorders. In any case, the results confirm the NEURO-Q-NET solution as an ac- curate, interpretable, and applicable solution for the differential diagnosis of neuro-degenerative disorders applying the FDG-PET molecular imaging technique. Disease classification results of the proposed Neuro-Q-Net model are illustrated in Fig. 2.

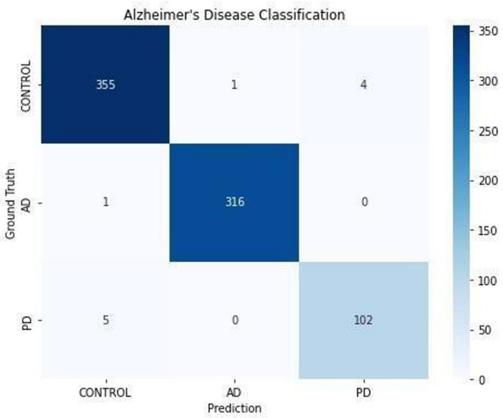

Fig. 2. Disease Classification of Neuro-Q-Net

9. CONCLUSION

The Neuro-Q-Net has been developed as a strong and intelligent diagnostic platform that can not only detect and classify several neurodegenerative diseases together but also through the power of FDG-PET imaging in the human brain. The challenges faced in machine learning, such as unavailability of data, imbalance in classes, and overlap- ping properties, have been countered by using Generative Adversarial Networks, Deep Convolutional Neural Networks, and Quantum Machine Learning techniques.

The experimental outcome proves the hypothesis that Neuro-Q-Net is indeed more efficient than the conventional single model and single disease strategy on all critical parameters, such as accuracy, sensitivity, and specificity. Additionally, the fact that the proposed method is capable of carrying out proper discrimination in the case of critical neurological disorders, such as Alzheimer's disease and Parkinson's disease, increases its potential in healthcare applications. Lastly, the ensemble quantum layer adds to the robustness and confidence of each prediction to be sufficiently accurate and suitable for use in the decision-support system in healthcare.

10. FUTURE WORK

Despite the effectiveness of the proposed Neuro-Q-Net framework in multi-class diag- nosis, some promising avenues of research still exist. A prominent one includes con- sidering multimodal source information. A compilation of information from structural MRI, functional MRI, electroencephalography, and biomarkers might help in creating a more encompassing feature set that portrays the development of neurodegenerative disorders more effectively. Multimodal fusion can help in detecting neurodegenerative disorders at an earlier stage by exploiting distinct development patterns in structure, function, and metabolism [13].

A further critical area of development is to extend the framework to more cases of neu- rodegenerative and neurological disorders [12] such as vascular dementia, Lewy body de- mentia, Huntington’s disease, and multiple system atrophy. Improving the classifica- tion power of the Neuro-Q-Net can surely help in making it a more useful diagnostic tool. Moreover, development of a more precise system to measure the level of diseases as well as the progression of diseases can certainly aid in personalized treatment and surveillance of patients.

Future work will be on combining methods of explainable artificial intelligence (XAI) to improve the transparency and interpretability of our model. Visualizing the key areas of the brain and metabolic patterns involved in the classification process may help to build trust among clinicians to validate our model. Even now, it is very important to apply explainability to our medical model to understand the reasoning behind it.

In addition to that, the quantum machine learning piece of Neuro-Q-Net can also be developed further. This is because access to quantum computing hardware is getting more common by the day, meaning that in the future, actual quantum computers can be used to make training more efficient in terms of computation and to explore more com- plex models using quantum circuits.

Future studies will require extensive validation on a variety of datasets. Optimization of the model for real-time processing, as well as integration with the healthcare information system, will be needed for it to be useful in the clinic. Learning more about the specifics of the radiological and pathological changes associated with COVID-19 will also be crucial for deeper analysis and future research. Regulatory approval and a clinical trial will be needed for it to be implemented.

In conclusion, the future work outlined below targets the improvement of the robustness, interpretability, and relevance of Neuro-Q-Net, making it a next generation intelligent diagnostic tool for the assessment of neurodegenerative diseases.

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