Early Prediction of Neurodegenerative Disease Progression using Quantum Twin Learning for Multimodal Patient Digital Twins: A Survey

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Abstract: Rapidly rising neurodegenerative diseases around the globe are caused by the ageing population including Amyotrophic lateral Sclerosis (ALS), Parkinson's Disease (PD), Huntingdon's Disease (HD) and Alzheimer's Disease (AD). The bimodal clinical manifestations and multimodal medical information, coupled with the lack of certainty in long-term courses still pose significant challenges of early forecast of disease progression. Artificial Intelligence (AI), Digital Twin and Quantum Machine Learning (QML) have brought about significant transformation in healthcare.Artificial Intelligence (AI), Digital Twin, and Quantum Machine Learning (QML) represent game-changers within the healthcare sector, having had a profound impact on the field in recent years. To this end, this survey provides a comprehensive introduction to the concept of a multimodal patient digital twin and hybrid multiclass/multilabel quantum–classical learning methods for prediction of neurodegenerative diseases. This paper will discuss an overview of the existing AI diagnostic envelopes, multimodal data integration, Quantum Computing applications, and Digital Twin architectures for the healthcare sector. In addition, existing challenges, datasets, applications, and research directions into the future are discussed. The survey highlights the advantages of QTL for improved predictions, and the potential to model more complex temporal patterns and precision medicine for neurodegenerative diseases.
Keywords: Neurodegenerative Diseases, Digital Twins, Quantum Machine Learning, Multimodal Learning, Predictive Healthcare, Artificial Intelligence, Precision Medicine.

Introduction

Neurodegenerative diseases are conditions that are chronic and progressive, and include the slow loss of cells in the brain and nervous system [1]. Alzheimer's disease, Parkinson's disease, and Huntington's disease are just a few of the diseases which impair memory, thinking, mobility, and life quality [2]. Effective planning of treatment and preventive healthcare interventions relies on early diagnosis and prognosis [3].

Traditionally, clinical diagnosis has been based on imaging studies, cognitive assessment, biomarkers and physician expertise [4]. Disease progression patterns, however, are not the same for each patient making the prediction of early disease progress difficult. Moreover, health-care data are extremely heterogeneous and range from magnetic resonance imaging (MRI), positron emission tomography (PET), wearable sensor signals, genomic data, to electronic health records (EHRs) [5].

In medical diagnosis and predictive healthcare applications Artificial Intelligence (AI) and Deep Learning (DL) techniques have proven to be quite promising in terms of their performance [6]. However, traditional AI models struggle to handle the high dimensionality of multimodal data and deal with the uncertainty and variability of disease progression pathways [7]. In recent years, Digital Twin has emerged as a novel paradigm to provide virtual replicas of patients for continuous monitoring, simulation, and prediction within healthcare systems [8].

At the same time, Quantum Computing and Quantum Machine Learning (QML) gives a more powerful computing to solve complex optimization and pattern recognition problems [9]. Hybrid quantum–classical learning models have the potential to improve feature representation, multimodal learning, and predictive accuracy in healthcare applications [10].

This survey explores the integration of multimodal patient digital twins with Quantum Twin Learning approaches to support early prediction of the progression and development of neurodegenerative diseases, ways to build personalised predictive healthcare systems.

2. Related Work

The prediction of neurodegenerative diseases has made remarkable progress with recent developments in Artificial Intelligence (AI), multimodal healthcare analytics, Digital Twin technology, and Quantum Machine Learning (QML) [11]. Medical imaging, data provided by wearable sensors, electronic health records (EHRs), and deep learning architectures have been used to early diagnosis and analysis of disease progression by various researchers [12]. While these approaches had a certain success on prediction accuracy, they had limited ability to cope with heterogeneous multi-modal data in healthcare and were heavily dependent on manual feature engineering [14].Since the emergence of Deep Learning, a CNN demonstrates its efficacy in medical image analysis and was widely used [15]. CNN-based methods demonstrated good performance for identifying spatial features from MRI brain images to detect AD at an early stage [16]. Likewise, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs) networks were designed to capture temporal disease progression patterns in the longitudinal patient records [17]. The transformer-based architectures further enhanced the sequential learning and multimodal feature representation aspects [18].Several studies were conducted on the multimodal learning frameworks that the imaging data can be combined with clinical, genomic, and wearable sensor data [19]. The multi-modality fusion solutions showed that they achieved notably better prediction performance than single modality systems [20]. But still, there are some obstacles concerning the processing of high dimensional data, handling missing values and data imbalance and complexity of calculation in the existing methods [21].The Digital Twin technology has recently become a promising approach in healthcare [22]. Patient Digital Twin is a virtual patient created continually through the use of physiological, clinical and behavioural data [23]. Digital twins have been investigated with respect to personalized treatment planning, chronic disease monitoring, rehabilitation systems and even predicted healthcare applications [24]. For neurodegenerative diseases, a digital twin can be used to simulate disease progression and effectiveness of treatment [25]. However, most of the currently available digital twin systems are based mainly on the traditional AI models and lack of efficient mechanism to deal with uncertainty and complex multimodal interactions [26].Recently, a new computational paradigm, called Quantum Machine Learning (QML) has been noted as a promising approach which aims to tackle some of the drawbacks of classical AI [27]. Variational Quantum Circuits (VQCs), Quantum Neural Networks (QNNs) and Quantum Support Vector Machines (QSVMs) have been proved to be effective in optimization, classification and pattern recognition applications [28]. Hybrid quantum–classical learning models can combine classical learning feature extractors with quantum layers for enhancing the efficiency of learning [29]. Quantum learning has been recently studied in the field of healthcare for medical image classification, genomic, drug discovery and disease prediction [30](Gargashi, 2021).

However, at this early stage, the use of quantum learning to model the progression of neurodegenerative diseases is still limited by the hardware used and scalability problems [31].Some recent studies have tried to merge Digital Twin technology with AI based prediction systems [32]. To date, however, only a few studies have investigated the capability of multimodal patient digital twins together with hybrid quantum-classical learning models to predict neurodegenerative diseases in the early stages [33].

Table 1. Comparative Analysis of Existing Approaches for Neurodegenerative Disease Prediction

Ref.	Existing Work	Technique Used	Data Modalities	Advantages	Limitations
[13]	Traditional ML-based Disease Prediction	SVM, Random Forest, Logistic Regression	Clinical and MRI Data	Simple implementation and low computational cost	Limited feature learning capability and lower prediction accuracy
[15]	CNN-based Neurodegenerative Disease Detection	Convolutional Neural Networks (CNNs)	MRI/PET Images	Automatic feature extraction and improved image classification	Requires large labeled datasets and high training cost
[17]	RNN/LSTM-based Disease Progression Models	RNN, LSTM	Longitudinal Clinical Data	Captures temporal disease progression patterns	Vanishing gradient issues and limited multimodal fusion
[18]	Transformer-based Multimodal Learning	Attention Mechanisms and Transformers	Imaging + Clinical + Sensor Data	Better sequence modeling and multimodal representation	High computational complexity
[19]	Multimodal Deep Learning Frameworks	CNN + LSTM Hybrid Models	MRI, PET, EEG, Clinical Data	Improved prediction accuracy through multimodal fusion	Sensitive to missing and noisy data
[22]	Healthcare Digital Twin Systems	AI-enabled Patient Digital Twins	Clinical and Wearable Data	Real-time monitoring and personalized healthcare	Limited predictive intelligence and scalability
[27]	Quantum Machine Learning for Healthcare	QNN, QSVM, VQC	Medical Imaging and Genomic Data	Efficient optimization and high-dimensional representation	Quantum hardware limitations and noise sensitivity
[29]	Hybrid Quantum–Classical Learning Models	CNN + Variational Quantum Circuits (VQC)	Medical Imaging Data	Enhanced feature learning and reduced parameter complexity	Limited real-world deployment and benchmarking
Proposed Work	Quantum Twin Learning for Multimodal Patient Digital Twins	Hybrid Quantum–Classical Learning with Digital Twin Integration	MRI, PET, Clinical, Wearable Sensor, and Behavioral Data	Personalized disease modeling, multimodal fusion, temporal prediction,	Scalability challenges and dependency on evolving quantum hardware

Ref.	Existing Work	Technique Used	Data Modalities	Advantages	Limitations
				and early progression analysis	

The proposed Quantum Twin Learning framework aims to address these limitations by combining multimodal patient digital twins with hybrid quantum–classical learning models for accurate and personalized neurodegenerative disease progression prediction.

Research Gap Identification: It can be seen from the comparative analysis that current machine learning and deep learning methods mainly deal with only a single modality of healthcare data, like MRI images or medical records. While multimodal deep learning frameworks are more accurate in predictions, they still face computational challenges, lack interpretability and struggle when attempting to model uncertain long-term disease trajectories.

Most existing digital twin-based healthcare systems offer personalized patient monitoring and simulation tools, but are built on traditional AI methods and do not include advanced predictive intelligence. Analogously, Quantum Machine Learning models with high computation potential to operate on high dimensional healthcare data are also not very good in predicting progression of neurodegenerative illnesses.

Thus, intelligent framework is required that can do the following:

- Integrating heterogeneous multimodal healthcare data,
- Dynamically modeling patient-specific disease progression,
- Capturing temporal and uncertain disease trajectories,
- Supporting personalized and preventive healthcare decisions,
- Leveraging the computational advantages of quantum learning.

The proposed Quantum Twin Learning framework addresses these research gaps by combining:

1. Multimodal Patient Digital Twins,
2. Hybrid Quantum–Classical Learning,
3. Temporal Disease Progression Modeling,
4. Personalized Predictive Healthcare Analytics.

This integrative platform could have a profound impact on the early predictive accuracy and clinical decision support in the field of neurodegenerative diseases.

Survey Methodology and Analysis

This survey aims to explore current research on predicting neurodegenerative diseases with Artificial Intelligence (AI), Digital Twin technology, multimodal healthcare analytics, and Quantum Machine Learning (QML). Major scientific databases, such as IEEE Xplore, SpringerLink, ScienceDirect, PubMed, ACM Digital Library and Google Scholar, were used to gather relevant studies. Based on the literature reviewed, four categories of machine learning models, deep learning models, Digital Twin-based healthcare systems, and quantum learning techniques can be distinguished. The traditional machine learning models were weaker in their ability to work with complex multimodal healthcare data, whereas deep learning models were better at improving prediction accuracy by extracting features automatically with the help of temporal learning. Digital Twin technology also facilitated customised patient monitoring and predictive healthcare, while Quantum Machine Learning showed the potential to process high-dimensional healthcare data, and to complete complex optimization tasks. The existing studies, however, have been mostly limited to the study of these technologies separately, and very few studies have investigated the use of integration of these technologies for predicting the progression of neurodegenerative diseases. In summary, the survey highlights the promise of combining multimodal patient 'digital twins' and the hybrid system of quantum–classical learning in the field of future early cancer prediction, personalized treatment planning and intelligent clinical decision support systems.

Conclusion

The fact that neuro-degenerative diseases, like other diseases, are complex in nature and develop over time make it important to have reliable techniques that make early detection of such possible. Existing methods on Artificial Intelligence, Digital Twins, Multimodal Health Analytics and Quantum Machine Learning for disease progression prediction have been included in the survey. Predictive healthcare based on deep learning and DSs DTs is beneficial but is also faced with some problems such as multimodal data, individualization/computational complexity etc. The future of Quantum Machine Learning in medical applications is exciting and promising, with several potential applications and possibilities emerging for the future.The future of Quantum Machine Learning in medicine holds great promise and exciting possibilities as the field advances. The survey revealed that not much research was done on the synergy of multimodal patient digital twins and hybrid quantum–classical learning models. In summary, Quantum Twin Learning is a potential solution for the early prediction of diseases, personalized healthcare and providing intelligent clinical decision support.

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