



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 12, December 2025

Alzheimer's Disease Prediction using Deep learning: A Review

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ABSTRACT: Alzheimer's disease is a progressive neurological disorder that affects memory and cognitive abilities. Early prediction of disease progression is essential for effective treatment planning. This project proposes an intelligent prediction system using deep learning techniques to analyze longitudinal patient data. A transformer-based model captures temporal patterns, while neural process modeling handles uncertainty in predictions. The system classifies disease stages accurately and improves reliability compared to traditional methods. The proposed approach supports early diagnosis and clinical decision-making.

KEYWORDS: Alzheimer's Disease, Disease Progression Prediction, Neural Processes, Transformer Encoder, Deep Learning.

I. INTRODUCTION

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that primarily affects memory, thinking ability, and behavioral functions. It is the most common cause of dementia among elderly populations worldwide and poses a significant public health challenge. The disease develops slowly over many years, often remaining undetected in its early stages. As neuronal damage increases, patients experience severe cognitive decline and loss of independence. The growing aging population has led to a rapid increase in Alzheimer's cases globally. This rise places a heavy burden on families, caregivers, and healthcare systems. Therefore, early detection and continuous monitoring of disease progression are critically important. Accurate prediction can significantly improve patient care and treatment planning.

Conventional diagnostic methods for Alzheimer's disease rely on clinical examinations, cognitive tests, and neuroimaging techniques. While these approaches are useful, they are often time-consuming, expensive, and dependent on expert interpretation. Additionally, traditional statistical and machine learning models face difficulties in handling high-dimensional medical data and long-term temporal dependencies. Missing values and irregular patient visits further reduce prediction accuracy. Many existing systems provide only point-based predictions without measuring uncertainty. This limitation restricts their usefulness in real-world clinical settings. As a result, there is a need for more intelligent and reliable predictive systems. Such systems must effectively model disease progression over time.

Recent advancements in deep learning have opened new possibilities for analyzing complex longitudinal healthcare data. Transformer-based models have demonstrated strong capabilities in capturing long-range temporal dependencies through attention mechanisms. At the same time, neural process models enable probabilistic learning and uncertainty estimation, which are essential for medical decision-making. Combining these techniques allows the development of robust and adaptive prediction systems. The proposed approach focuses on predicting Alzheimer's disease progression by learning patterns from longitudinal patient data. This integration improves generalization across diverse populations and enhances prediction reliability. Ultimately, such intelligent systems can support clinicians in early diagnosis and personalized treatment strategies. This work contributes toward advancing data-driven healthcare solutions for neurodegenerative diseases.

Motivation

Alzheimer's disease lacks a definitive cure, making early diagnosis and progression prediction critically important. Existing systems often fail to capture temporal relationships and uncertainty in patient data, leading to unreliable predictions. The motivation behind this work is to develop an intelligent, data-driven framework that improves prediction accuracy, handles missing or sparse data, and provides uncertainty-aware outputs. Such a system can support

clinicians in early diagnosis, personalized treatment planning, and effective monitoring of disease progression, ultimately improving patient outcomes and reducing healthcare burdens.

II. LITERATURE SURVEY

Wonsik Jung [1] - In regard to such an unfavorable situation, we define a secondary problem of estimating those missing values and tackle it in a systematic way by taking account of temporal and multivariate relations inherent in time series data. Concretely, we propose a deep recurrent network that jointly tackles the four problems of (i) missing value imputation, (ii) phenotypic measurements forecasting, (iii) trajectory estimation of a cognitive score, and (iv) clinical status prediction of a subject based on his/her longitudinal imaging biomarkers.

AlirezaSaber [2] - In this study, we propose a novel multi-scale trans former approach for pneumonia detection that integrates lung segmentation and classification into a unified framework. Our method introduces a lightweight transformer-enhanced TransUNet for precise lung segmentation, achieving a Dice score of 95.68% on the "Chest X-ray Masks and Labels" dataset with fewer parameters than traditional transformers.

SadjadRezvani [3] - Our method employs a combination of loss functions, including SSIM, IOU, and focal loss, to optimize image reconstruction quality. We created and publicly released a new dataset for lung segmentation called LungSegDB, including 1800 CT images from the LIDC-IDRI dataset (dataset version 1) and 700 images from the Chest CT Cancer Images from Kaggle dataset (dataset version 2). Our method achieved an IOU score of 98.04, outperforming existing methods and demonstrating significant improvements in segmentation accuracy.

Fatma M. Talaat [4] - This work developed a new classification model for blood microscopic pictures that distinguishes between leukemia-free and leukemia-affected images. The general proposed method in this paper consists of three main steps which are: (i) Image_Preprocessing, (ii) Feature Extraction, and (iii) Classification. An optimized CNN (OCNN) is used for classification. OCNN is utilized to detect and classify the photo as "normal" or "abnormal".

E. F. Haghish [5] - The results showed that as the classification is made at higher risk thresholds - corresponding to higher specificity levels - the severity of anxiety and depression symptoms of the FP and True Positive cases (TP) become significantly more similar. In addition, psychological distress and non-suicidal self-harm were found to be highly prevalent among the FP group, indicating that they are indeed at risk.

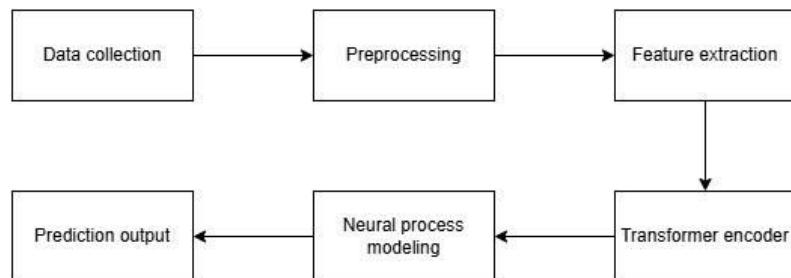
Javaria Amin [6] - The objective of this survey is to deliver a comprehensive literature on brain tumor detection through magnetic resonance imaging to help there searchers. This survey covered the anatomy of brain tumors, publicly available data sets, enhancement techniques, segmentation, feature extraction, classification, and deep learning, transfer learning and quantum machine learning for brain tumors analysis. Finally, this survey provides all important literature for the detection of brain tumors with their advantages, limitations, developments, and future trends.

FirasAbedi [7] - The reconstruction of multi-view high dynamic range images faces several challenges, including holes and artifact in the disparity map in non-linear and large baseline between the involved cameras. Furthermore, these challenges increased when a back-lighting scenario is involved, with the currently industrial growth.

Gap Analysis

- Traditional statistical models struggle with high-dimensional and longitudinal data
- Machine learning models require large labeled datasets and lack uncertainty estimation
- RNN-based approaches face vanishing gradient and long-term dependency issues
- Limited ability of existing systems to generalize across diverse patient profiles
- Inadequate integration of probabilistic modeling with temporal attention mechanisms

III. SYSTEM ARCHITECTURE



IV. PROPOSED SYSTEM

The proposed system utilizes a hybrid deep learning architecture that integrates a transformer encoder with neural process modeling. Longitudinal patient data are converted into time-series windows and embedded into high-dimensional representations. The transformer encoder captures long-range temporal dependencies through self-attention mechanisms. Neural processes introduce probabilistic modeling, allowing the system to estimate uncertainty in predictions. The decoder generates class probabilities for disease stages, enabling accurate and robust Alzheimer's disease progression prediction even in the presence of incomplete or noisy data.

V. CONCLUSION

This project presents an advanced deep learning framework for predicting Alzheimer's disease progression using longitudinal patient data. By combining transformer-based temporal modeling with neural process uncertainty estimation, the system overcomes limitations of traditional and recurrent models. Experimental results demonstrate improved accuracy, recall, and precision, highlighting the effectiveness of the proposed approach. The system provides a reliable, scalable, and clinically relevant solution that can assist healthcare professionals in early diagnosis and disease monitoring.

VI. FUTURE SCOPE

- Integration of multimodal data such as PET scans and genetic markers
- Real-time clinical decision support system development
- Incorporation of explainable AI techniques for model interpretability
- Deployment as a cloud-based healthcare analytics platform
- Extension to predict treatment response and patient survival outcomes

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