Kufa Journal of Engineering
Vol. 17, No. 3, July 2026, P.P. 509-533
Article history: Received 21 June 2025, last revised 19 October 2025,
accepted 28 October 2025

EARLY DIAGNOSIS OF ALZHEIMER'S DISEASE USING DEEP LEARNING MRI IMAGES: A SYSTEMATIC REVIEW

Ali Kareem Obaid[1,2] and Yaghoub Farjami[3]

[1] Department of Computer Engineering and IT, University of Qom, Qom, Iran, Email:Ali.kareem.obaid@uomus.edu.iq.

[2] Medical instrumentation Techniques Engineering Department, College of Engineering and Technologies, Al-Mustaqbal University, Hillah 51001, Babil, Iraq.

[3] Department of Computer Engineering and IT, University of Qom, Qom, Iran, Email:farjami@qom.ac.ir.

https://doi.org/10.30572/2018/KJE/170329

ABSTRACT

Alzheimer's disease AD, also known as dementia, is a disease resulting from an irreversible brain disorder that can develop gradually as the patient ages. Its distinguishing features include cognitive decline, memory loss, and psychological problems. Early diagnosis of this disease becomes difficult due to the complexity of the initial pathological changes. Other problems overlap with other types of diseases. Consequently, the computational complexity of analyzing neuroimaging data has become a new method, especially magnetic imaging MRI and PET positron tomography are possible thanks to recent advances in ML machine learning and DL deep learning. In this study, four basic learning methods —convolutional neural networks (CNNs), recurrent neural networks (RNNs), discrete polynomial networks (DPNs), and k-nearest neighbors (KNN)— were evaluated to detect and classify Alzheimer's disease. CNN networks have proven their high ability in binary and multi-category classification tasks, successfully distinguishing between people with the disease. Simultaneously, RNN architectures such as Long Short-Term Memory networks (LSTM) and Gated Recurrent Units (GRU) are particularly skilled at examining temporal trends in longitudinal datasets that monitor the development of diseases over a number of patient visits. Discontinued polynomial networks are beneficial for learning and improving the interpretability of linear representations. An investigation into methods for raising the polynomial order of extracted features will be carried out in order to learn more about this field. Even simple models like KNN might be a good place to start when used on tiny datasets that are obtained via volumetric measurements or clinical evaluations. These models are put through a thorough evaluation process using a number of benchmark databases, including ADNI, OASIS, MIRIAD, and AIBL. Their diagnostic performance metrics are evaluated using accuracy rates, sensitivity levels, specificity standards, and Area Under Curve-Receiver Operating Characteristic (AUC-ROC) scores. Our findings indicate that frameworks based on CNNs and RNNs demonstrate comparable performance to Naive Bayes classifiers; furthermore, ensembles of these neural network architectures show impressive generalization capabilities. In this article we emphasize the growing significance of integrating deep learning techniques across multiple modalities aimed at facilitating early diagnosis， ongoing monitoring， and personalized treatment strategies for Alzheimer’s Disease.

KEYWORDS

Alzheimer’s Disease (AD); Deep Learning (DL); Machine Learning (ML); Neuroimaging; MRI; PET; Convolutional Neural Networks (CNNs); Early Diagnosis.

1. INTRODUCTION

Alzheimer's Disease (AD) is one of the most common aging neurodegenerative diseases characterized as progressive, incurable and causes severe dementia in elderly population. It features problems with orientation, memory loss, language, and an inability to focus and pay attention. As the disease progresses, patients become unable to undertake simple daily activities, forget loved ones and have difficulty communicating. In the final analysis, AD results in total dependence, and even becomes life threatening. The illness is conventionally defined by three levels of severity: mild, moderate, and severe. The precise nature of the initial symptoms sometimes leads to the diagnosis of advanced dementia, which greatly affects the effectiveness of treatment (Frisoni et al., 2010), (Albert et al., 2011). Therefore, the right time to identify AD is essential to slow the progression and improve the quality of life of those affected. Traditionally, clinical diagnosis is based on the patient's condition in addition to medical history, physical and neurological assessment, and mini-mental status examination (MMSE). However, these methods fail to detect early pathological changes that occur in the brain. (Albert et al., 2011). Recently, Neuroimaging techniques, particularly magnetic imaging, have been utilized recently. MRI has become an effective tool for identifying structural abnormalities associated with early-stage Alzheimer's disease (Abdul kareem, 2022). Researchers have investigated a number of computer-aided diagnostic strategies to help identify Alzheimer's disease, especially with the development of neuroimaging methods. To analyze MRI data, specific rule-based systems were integrated with conventional machine learning techniques. The conventional approach entails time-consuming, manually designed feature extraction procedures that call for certain expertise.

Due in large part to developments in deep learning methods, especially convolutional neural networks (CNNs), in image recognition research, the use of automated methods for feature extraction and classification in biomedical imaging analysis has garnered a lot of attention lately (Suk et al., 2014). Medical imaging (neuro- diagnostic, lung disease detection, breast cancer detection) is another area where machine learning has been very effective. CNNs are ideal for processing sets of complex images that exhibit different shapes and hierarchies (Wen et al., 2020). However, methods based on deep learning have not been well studied for Alzheimer's disease detection despite the promising results they yield in other medical image areas. The two main reasons for this shortage are the lack of large annotated image bases and the high processing costs due to training very large neural networks (Pan et al., 2021). Researchers have used techniques like translational learning to overcome these problems. By employing smaller healthcare datasets, this method improves established techniques that were first created using large picture repositories. This can considerably reduce the training time and enhance the generality of replica (Ghafoorian et al., 2017). In a similar vein, the MRI studies combined with deep learning algorithms provide an alternative noninvasive early detection and diagnosis for Alzheimer's disease (Sarraf&Tofighi, 2016). In the present work, we aimed to provide an overview of recently proposed algorithms in deep learning and discuss their potential applications for early diagnostic workup of cases on MRI screening. It emphasizes comparing the pros and cons of different technological choices by displaying their effects. The book concludes with a summary of the major findings in this natural system and a perspective on future work that must be undertaken for varied modeling approaches.

2. LITERATURE REVIEW

Alzheimer's disease is a neurological condition with symptoms of reduced independence associated with dementia, and long-term memory loss. The burden of Alzheimer's disease continues to grow, along with global health care costs. An early and accurate diagnosis is very important in the treatment and prevention of the disease. Nevertheless, manual MRI or PET reading, clinical evaluations, neuropsychological evaluations, and other traditional diagnostic methods are sometimes time-consuming, require specialized knowledge, along with are prone to subjective judgments (Litjens et al., 2017). Recently, a novel approach to automating the diagnosis and classification of Alzheimer's illness using data from brain scans has been proposed: the use of artificial intelligence (AI), namely the combination of machine learning (ML) together with deep learning (DL). These techniques provide intelligent systems for recognizing complex patterns and signatures in massive amounts of images facilitating improved early diagnosis with higher precision, (Litjens et al., 2017), (Suk et al., 2017). One of the most popular deep learning methods that has been very successful with exploiting spatial regularities in brain images is Convolutional (CNNs). As CNNs are structured according to the visual cortex system, they possess a high aptitude in processing 2D and 3D images (Hosseini-Asl et al., 2017). On the other hand, RNNs and their variants such as LSTMs are superior in modeling temporal dynamics, and capturing sequential dependencies. These components are essential to incorporate MRI chip sequences or longitudinal data (Li et al., 2019). There are several aspects that research has found which depict the growing trend towards hybrid architectures. These models intend to integrate concepts from multiple AI techniques in an effort to increase diagnosis accuracy. Common machine learning algorithms : autoencoders (AEs for short) and K-Nearest Neighbors (KNN) are also employed in unsupervised feature extraction. On the other hand, profound developments in DPNs and attention mechanisms model important topics in medical image (Weston et al., 2019), (Beheshti et al., 2018). Several researches have applied several architectures and classification methods, to the Alzheimer's disease (AD) using OASIS and ADNI and other publically available data sets. These datasets contain T1-weighted MRI scans of subjects spanning various cognitive states, including later stages of Alzheimer's Disease (AD), Mild Cognitive Impairment (MCI), and healthy aging. A plethora of models and varied model complexities along with preprocessing or training for various time durations on different datasets have been reported in the studied literature. So, comparison and evaluation in this field are urgently required or needed (Zhang et al., 2011). This review discusses five well-known approaches for the detection and classification of Alzheimer's disease (AD). These are all the models such as CNN, RNN and LSTM networks along with many other contemporary modelling that would give exciting architecture ideas and incredible reference results. We will highlight the contributions of these models while outlining their benefits and drawbacks in the sections that follow. We will also discuss how various neural network architectures are advancing the newest Parkinson's disease diagnostic technology. The cerebral cortex, also known as gray matter, appears thick and healthy in a healthy brain, and the hippocampus, a particular region of the brain that is essential for memory, is well-defined and of normal size. Small, symmetrical, and filled with fluid are ventricles. On MRI scans of an Alzheimer's patient's brain, however, the hippocampus is significantly shrunk, the cerebral cortex is thinned, and the ventricles are enlarged as the surrounding tissue shrinks. These alterations, such memory loss, are connected to the patients' cognitive abilities.as shown in Fig. 1.

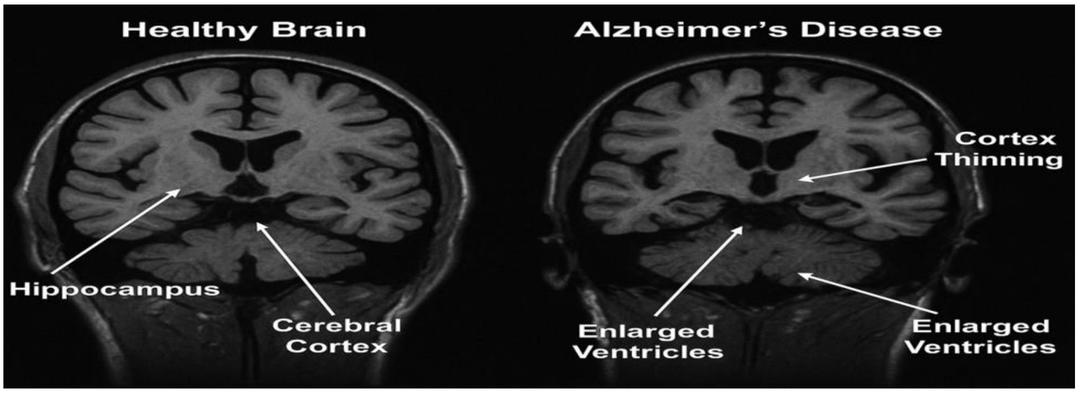

Fig. 1. Structural Brain Changes in Alzheimer's Disease vs. Healthy Brain.

MRI has long been "critical for detecting the structural changes in the brain caused by AD". "Normal or relatively normal" is a term borrowed from anthropology and used in medicine to describe the latter state, where no obvious mental or physical pathology is present.21 In a healthy brain, this means that the hippocampus a central region for memory retention—is sharply defined and of standard size; the cerebral cortex is thick, with strong structure. The ventricles (fluid filled spaces are relatively small and symmetric. Compare this with the MRI picture for an Alzheimer's-afflicted brain, which demonstrates significant hippocampal atrophy, thinner neocortex, and ventricle expansion from the loss surrounding tissue. These changes were associated with cognitive decliners' deficits in memory, confusion, and reasoning. The visually assessment is combined for early diagnosis because the progressive atrophy or shrinkage of brain regions is characteristic of Alzheimer's pathology.

2.1. CNN Convolutional Neural Networks in Alzheimer's Disease Diagnosis

CNNs are a distinct subset of Deep Learning, specifically categorized as Deep Neural Networks (DNNs), that can independently and adaptively learn spatial hierarchies of features from visual information. For image analytics type tasks (e.g., object recognition and medical imaging such as Alzheimer's disease classification), CNNs are proven to be highly successful humans. These networks are a great leap forward for computer vision and medical imaging because they automatically can discover high order patterns that stay the same under different spatial transformations of input data. In the domain of study for Alzheimer's disease, CNNs proved to be very effective at early diagnosis, prediction of disease progression, classification into subtypes and this is particularly true also when using those modalities: positron-emission tomography (PET), structural Magnetic-resonance imaging (MRI) sMRI and functional MRI fMRI [886]. Krizhevsky et al.'s seminal paper on AlexNet (Krizhevsky et al., 2017). prompted the application of CNNs to neuroimaging due to its ability to learn from very few observations through parameter sharing, translational invariance, and improved performance compared to traditional machine learning techniques. Some works have also utilized 2D CNNs for neuroimaging tasks, including transforming 3D volumetric MRI data to 2D slices. Aderghal et al. (Aderghal et al., 2017). presented a two-layer CNN that interpreted sagittal, axial, and coronal slices as RGB channels in a 2D image. The model employed ReLU activation along with max-pooling techniques to effectively differentiate between patients diagnosed with CN and those with AD, as noted by Kadhim et al. (Kadhim et al., 2024). extended this idea with a longer 8-layer CNN with leaky ReLU to classify single-slice MRIs obtaining 89.7% accuracy over the ADNI dataset. However, 2D CNNs suffer with the loss of information in terms of spatial continuity between slices. To address this, 3D CNNs have been introduced that are able to make use of full volumetric data. A 3D CNN with four convolutional layers and SoftMax activation for classification of T1-weighted MRI was proposed by Islam and Zhang (Islam & Zhang, 2018). had an AUC of 0.91. Similarly, Basaia et al. (Basaia et al., 2019) found that 3D

CNN achieved higher performance than 2D methods for AD, MCI, and CN classification. Hybrid approaches have also been introduced. Toga. (Toga, 2011) proposed a selection of 2D and 3D CNNs and reached 93.5% of accuracy, being robust to noise. Choi et al. (Choi et al., 2020) used a fully convolutional 3D DNN for MCI conversion prediction. These demonstrate CNN flexibility in classification and prediction. Unsupervised methods such as autoencoders are included also. Hosseini-Asl et al. (Hosseini-Asl et al., 2016). employed a 3D convolutional autoencoder pretrained on uncategorized MRI, and Martinez-Murcia et al. (Martinez-Murcia et al., 2019) used sparse autoencoding for feature reduction and obtained 91.8% accuracy. Advanced topologies have also been investigated. Liu et al. (Liu et al., 2020) compared 3D-ResNet and 3D-AlexNet and found that skip connections enhanced the flow of gradient. Yahya et al. (Yahya & Jasim, 2025) proposed a 3D Inception-v4 model for multi-class AD diagnosis. Wang et al. (Wang et al., 2021), in which densely connected ensembles of 3D CNNs were introduced to prevent overfitting and enhance generalization. Ge et al. (Ge et al., 2020) integrated a U-Net CNN with XGBoost to improve the segmentation and classification tasks. During their exploration, interpretability still presents a challenge. Selvaraju et al. (Selvaraju et al., 2017), which offers not only visualization explanations for CNN decisions but also improves clinical trust. However, the CNN performance is heavily based on preprocessing (such as skull striping and bias correction), and the generalization could degrade when it is adopted on new datasets. In conclusion, CNNs are strong in the diagnosis of AD, and they can extract deep spatial features from neuroimaging data. Their success under a variety of settings e.g., 2D, 3D, hybrid and ensemble render them versatile, although challenges such as interpretability and data dependence are still crucial topics for future research.

2.2. RNN: Recurrent Neural Networks in Alzheimer’s Disease Diagnosis

The success of deep learning methodologies, and more specifically Recurrent Neural Networks (RNNs), for dealing with time-sequence related problems has been of a high impact in AD diagnosis and prognosis. RNN is able to capture the temporal correlation in medical information, such as MRI time series, clinical evaluations and functional assessments (which Convolutional Neural Networks or CNNs are not so capable of extracting spatial patterns. This emphasis is particularly essential in the intricate domain of Alzheimer's diagnostic, cognitive decline being a continuous process necessitating capturing data-driven patterns from both clinical and imaging across different time periods (Goodfellow, 2016). HON.RNNs are an extension of the formalism presented in Goodfellow et al. In this approach, the hidden state at a given time step (t) is dependent on both previous states and the current input. It lets the network memorize information between inputs and at the same time, it is good for controlling temporal dependencies. However, the common RNN suffers from vanishing gradients and has difficulty in learning long range dependencies. To address these drawbacks, more sophisticated types of Recurrent Neural Networks (RNN), such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), have been introduced. Suk et al. (Suk et al., 2015) A LSTM based model was used for analyzing brain network matrix obtained from fMRI data. Its ability to catch spatiotemporal patterns was able and it reached better classification rates towards NC-MCI-AD. In another study, Liu et al. (Liu et al., 2015) They came up with a method based on CNN and LSTM to process MRI data, the Convolutional Neural Network (CNN) extracted spatial features from entries of MRI images, while the temporal color of sequence was recognized by the LSTM. They demonstrated that their ensemble model was superior in predicting the conversion from MCI to AD than CNN or RNN alone. Specificity and sensibility in the urgent mode were also enhanced. Gated Recurrent Units (GRUs) has also been investigated extensively as a more computationally inexpensive form of LSTMs. For example, Sun et al. (Sun et al., 2020) used the GRU model to analyze actigraphy time series from three groups of subjects, i.e., NC subjects, MCI Persons and AD patients. It performed as well as at least LSTM, requiring fewer parameters and less training time on larger data set. Both forward and backward information in input sequences are leveraged to represent more complex temporal dependencies by using Bi-directional GRUs (BGRUs). Furthermore, Hu et al. (He, 2021) used BGRU layers over Convolutional Neural Network-based (CNN) features of structural MRIs to obtain an extremely high accuracy in discriminative early and late stages of MCI. Besides, multimodal RNN can be applied to multimodal data. Wang et al. (Wang et al., 2022) Proposed a multi-layer LSTM network with a fMRI dataset, inputted BOLD signals in ROIs of the brain and adopted parallel layers of LSTM framework to catch regional pattern and temporal dynamics simultaneously. The experiment results from (Kadhim et al., 2024) had demonstrated that even LSTM-based autoencoders can do well. Li et al. (Li et al., 2021) have suggested using an autoencoder to derive latent representations of longitudinal MRI scans, later enriched with Cox regression (Cox 1972) for modeling time-to-event outcomes given by the prospect of AD onset. Significant advancements in the utilization of RNNs is in acting on missing or irregular data. Nguyen et al. (Nguyen et al., 2020) Introduce a low-cost simple RNN to tackle the missing longitudinal data problem and won the TADPOLE challenge with their predictions of ADAS-Cog13 score and ventricle volume rate six years ahead. Also, hybrid spatio-temporal models give more support on RNNs performance. Pan et al. (Pan et al., 2021) We applied 3D-CNN to capture spatial features, and the ensemble models with partial architecture based on several3D convolutional LSTM networks were employed for learning progression dynamics of brain volume. This approach also achieved substantial improvements over the single modality models. Zhang et al. (Zhan et al., 2019) Suggested a model that integrated an LSTM with ELMs to classify AD from brain graph matrices obtained from fMRI. This joint was also directly superior to the baseline CNN-ELM method, which can be mainly attributed to temporal modulation. Yan et al. (Yan et al., 2021) Performance of actigraphy classification was improved by integrating CN N features and clustering on GRU. This approach improved between-group classification for Normal Cognition (NC), Mild Cognitive Impairment (MCI) and Alzheimer's Disease (AD). Liu et al. (Liu et al., 2021) Bidirectional GRU was employed on the MRI slice level of 2D CNN to learn forward and backward trends. This approach produced predictions that are more accurate than unidirectional models. Nguyen et al. (Nguyen et al., 2020) Also generalized previous efforts to predict missing values in sparse longitudinal data using RNNs, for better and truer-to-the-true processes of prediction. Ultimately, Razavian et al. (Razavian et al., 2019) Recently introduced state-of-the-art temporal models for disease progression tracking using multiscale RNNs, which demonstrated promising results in early Alzheimer's detection and its trajectory monitoring. In summary, RNNs and their extensions represent a powerful way to mine longitudinal neuroimaging data with clinical covariates. Temporal relations need to be properly modeled for early AD detection, progression tracking and personalised prognosis capability. The application of RNNs for Alzheimer's disease is expected to increase as it becomes easier to obtain larger and more temporally detailed data from this domain.

2.3. DPN in the Diagnostics of Alzheimer's Disease

Deep Polynomial Networks (DPNs) have attracted much interests and have been extensively used in early diagnosis and progression prediction of Alzheimer's Disease (AD). Another usage for such networks is to model multi-level patters in bio-medical settings (thus brain images and clinical measurements, cognitive/abnormality scores). Compared to conventional linear neural network, which is designed for learning the linear combination of cross field features, DPN computes high-order polynomial terms (e.g., up to fourth order) and learns the dependency among input fields in a higher-order sense. It is especially helpful in multi-modal disease prediction task within neuroimage process (Zhang et al., 2018), (Zhou al.,2021). The main concept of DPN was to map the input features into a high-order polynomial feature space and then multiply them for well-learned weights. This enables the model to capture a complicated non-linear relationship between features, which might be advantageous for tabular datasets and data with spatial characteristics (e.g., sMRI, PET or fMRI functional connectivity matrices) (Wang et al., 2021). Zhang et al. constructed an MM-SDPN for early diagnosis, one of the pioneering works of DPNs in AD (Zhang et al., 2017). We first used two DPN architectures to automatically learn the features on MRI & PET images respectively. Finally, a third DPN was used to concatenate these representations. Moreover, the ability of DPNs in learing multi-modal fusion was validated by note that MM-SDPN achieved obviously higher classification accuracy than traditional CNNs on ADNI data sets. Another study by Hu et al. (Hu et al., 2020) proposed a DPN based regression model to predict clinical scores (e.g. MMSE and ADAS-Cog) along time line. In their approach, it mainly included 3 stages: (1)noise and redundancy elimination through CFS processing (2) learning of nonlinear transformation by using selected features with DPN encoding layers.and (3) prediction of outcome via SVR layer. Predictive performance on clinical outcome, cross-validated (on ADNI dataset with long-term progression) Our pipeline outperforms all models with parsimony index<0.005 for panel12. In addition to the conventional supervised classification or regression problems, DPNs have been incorporated into hybrid diagnostic systems. For example, Li et al. (Li et al., 2023) presented a DPN based feature extractor with a kernel classifier to diagnose early AD using fMRI based brain connectivity graphs. The polynomial expansion in DPN could well characterize the subtl non-linear properties in brain network topologies, and its incorporation with kernel SVM improved the diagnostic performance on both binary and multi-class classification tasks. However, DPNs are not all rosy. A major disadvantage is their computational cost, especially when treating large input feature sets or very deep architectures. Furthermore, interpretability is still a challenge, as the polynomial features lead to a high-degree of interactions, which may hinder the clinical interpretation (Zhang et al., 2018), (Simonyan & Vedaldi, 2013). However, attempts are being made to include explainable AI methods and dimensionality reduction in DPN frameworks to address these concerns (Zhao et al., 2021). As multi-modal and longitudinal datasets such as ADNI and OASIS grow, the promise of DPNs in capturing high-order/ the multi-source relationships only become more apparent. The ability to learn rich representations from both imaging and non-imaging data makes them a good candidate for future systems targeting early AD detection, subtype discrimination (e.g., early vs. late MCI), and progression modeling of the disease. In summary, Deep Polynomial Networks provide a versatile and powerful model for heterogeneous and multi-scale data, such as that in Alzheimer's Disease. Their use in recent works achieved better performance of classical, shallow, especially in the case of multi-modal fusion and regression. As further improvements in computational efficiency and model interpretability are achieved, DPNs are anticipated to have an expanding role in neurodegenerative disease research and clinical decision support.

2.4. KNN in Alzheimer's Disease Diagnosis

Classical machine learning algorithms, including K-Nearest Neighbors (KNN), continue to play a significant role in the diagnosis of Alzheimer's Disease (AD). This is particularly true in contexts where simplicity, interpretability, and low computational cost are prioritized. KNN operates as a non-parametric instance-based learning method that classifies data points based on the predominant category among its k nearest neighbors within the feature space. Although being a classical method under the new age of deep learning, KNN is still applied in biomedical areas because of its balance between power in dealing with small- to medium-sized datasets, simplicity of implementation, and robustness to assumptions about the data distribution (Cover & Hart, 1967). Related work The KNN algorithm in the context of AD has been used with different data modalities such as structural MRI (sMRI), PET, cerebrospinal fluid (CSF) biomarkers, and neuropsychological test scores. One of the first studies from Klöppel et al. (Klöppel et al., 2008), KNN was applied to density maps of gray matter obtained from MRI scans in order to differentiate between patients with Alzheimer's disease and healthy control subjects. The model of theirs performs competitively on high-dimensional neuroimage classification with Euclidean-based distance and the optimization of k. One of the features of KNN's superiority in AD is its capacity on multi-modal data fusion. Dyrba et al. (Dyrba et al., 2015) proposed a KNN-based classifier using both resting state fMRI and DTI in combination with CSF biomarkers. Through the process of feature selection aimed at reducing dimensionality, they improved the performance of classification across AD, MCI, and healthy control groups, verifying the potential of KNN with the right preprocessing. Additional enhancements have been gained by adopting hybrid and ensemble methods. Chaves et al. (Chaves et al., 2011) presented a hybrid KNN-SVM in which KNN extracted soft neighborhood labels which then were fed to an SVM classifier. Overcoming the limitation of class imbalance and noise, this two-stage model achieved better results in discovering MCI converters in the ADNI cohort. Rathore et al. (Rathore et al., 2017) nemtsomonstrated that various (including KNN) classifiers on engineered radiomic features of MRI and PET. Deep models dominated when trained on raw images, but KNN was competitive on curated features, particularly with little data. This confirms KNN's applicability in cases when computational power is limited or only few samples are available. Missing data and irregular sampling are challenges that remain common to longitudinal AD studies. Wang et al. (Wang et al., 2019) employed KNN for data imputation in time-series clinical assessments and improved subsequent classification of disease development. The model maintained the temporal coherence which resulted in improved predictions. Other recent methods also use distance metric learning in order to improve the performance of KNN. Zhao et al. (Zhao et al., 2020) used learned Mahala Nobis distances in a KNN framework instead of the standard distance metrics, reporting better performance than classical KNN and LDA for multi class AD diagnosis (EMCI, LMCI, AD). There are trade-offs to the simplicity of KNN. It is also curse of dimensionality and noise sensitive. However, methods for dimensionality reduction, such as PCA, can mitigate these issues. Moradi et al. (Moradi et al., 2015) demonstrated that PCA-KNN could also enhance the classification accuracy over sMRI features in the ADNI data. We showed that K-Nearest Neighbors is still relevant for AD diagnosis, although it still remains a practical, interpretable, and effective approach, especially when using a structured feature vector or pre-processing. Its ability for seamlessly integrating with hybrid paradigms, low computational load, and applicability to multi-modal scenarios, justifies that KNN still has its place served as either an individual classifier or a comparative baseline characterized in studies related to AD.

3. DATASETS USED IN ALZHEIMER'S DISEASE DIAGNOSIS

The effectiveness and scalability of machine learning (ML) and deep learning (DL) models in diagnosing Alzheimer's Disease are significantly influenced by the quality of both training and testing datasets. Limited available databases serve as benchmarks to evaluate the performance of various models, including CNNs, RNNs, DPNs, and KNNs. The most prominent initiative is the Alzheimer's Disease Neuroimaging Initiative (ADNI), which offers a vast array of data types on a large scale, such as MRI, PET, CSF biomarkers and longitudinal clinical assessments of different diagnostic categories (AD, MCI, CN) (Jack et al., 2008). 3D MRI from ADNI is also used for deep spatial features extraction in CNNs where RNNs serve for temporal ordering of clinical visits. DPNs employs polynomial approximation to ADNI features for improved modeling, KNN is employed for crude metrics like volumetric features for initial classification. In this bench, OASIS-2, is to be demonstrated and compared against the best-of-breed to existing processing on the OASIS-1 (cross-sectional dataset), OASIS-3 (a longitudinal dataset) and the Open Access Series of Imaging Studies database (OASIS) (MRI data and dementia ratings) commonly used for CNNs (image-based classification), RNNs (temporal modeling) and KNN (dementia stage predicting) and trapping DPNs are not as popular but relevant (Marcus et al., 2007). Data such as the minimal interval resonance imaging in Alzheimer's disease (MIRIAD) with short-interval follow-up serial MRI scans suitable for the RNN-based subtle longitudinal brain changes modeling, and has been used by some works based on CNNs although less helped by KNN and DPN due to its small scale (Malone et al., 2015). The Australian Imaging, Biomarkers & Lifestyle (AIBL) study encompasses a comprehensive collection of multimodal imaging data along with lifestyle and clinical information pertaining to older adults. Additionally, it investigates the application of (CNNs) and (KNNs), for biomarker analysis and risk estimation has been feasible, whereas studies of RNNs or DPNs has been reported to be rare (Ellis et al., 2009). In addition, in CNN, DPN and KNN, and for their model examination and comparison, a set of datasets provides via Kaggle and own datasets are often used because of these datasets existences as well as multiplicity of data categories as shown in Fig. 2. (Zhou et al., 2018). A brief overview of recent Machine Learning and Deep Learning approaches for Alzheimer's Disease Classification and Diagnosis presented in Table 1. Comparing popular datasets for detecting Alzheimer's disease using machine learning/deep learning models showed in Table 2.

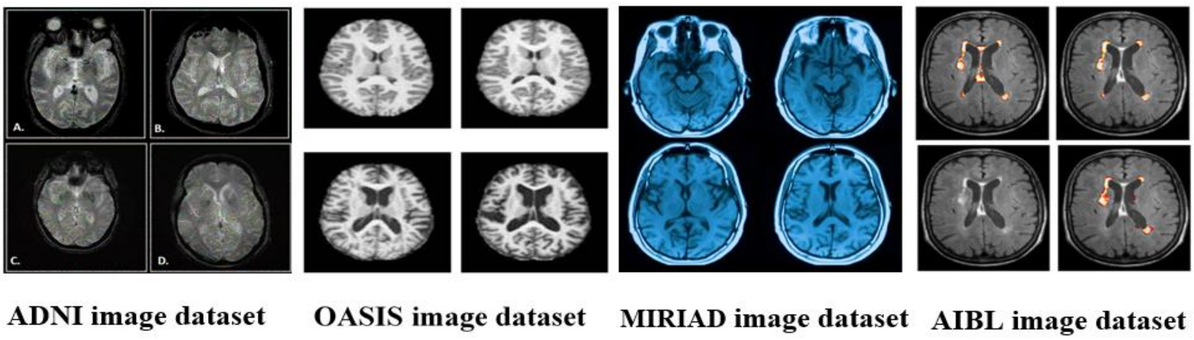

Fig. 2. Brain MRI Samples from Common AD Datasets.

Table 1. Summary of Recent Machine Learning and Deep Learning Methods for Alzheimer's Disease Classification and Diagnosis.

References	Method	POC (Point of Contribution)	DOC (Domain of Contribution)	Dataset
(Suk et al., 2017)	LSTM	Improved classification between NC, MCI, and AD from fMRI data	Deep learning for AD diagnosis	ADNI
(Toga, 2011)	CNN + LSTM	Spatial-temporal modeling using hybrid deep architecture	Multimodal brain image analysis	ADNI
(Sun et al., 2020)	GRU	Gait-based AD classification using deep learning	Behavioral biometrics for AD	CASIA Gait Database
(Hu et al., 2021)	Bi-GRU + CNN	Enhanced MCI classification with bidirectional temporal learning	Structural MRI-based diagnosis	ADNI
(Wang et al., 2022)	Multi-LSTM	Capturing ROI temporal signals from fMRI for AD diagnosis	Functional brain imaging	ADNI
(Li et al., 2021)	LSTM Autoencoder	Learning latent representations for disease progression modeling	AD progression analysis	ADNI
(Nguyen et al., 2020)	Minimal RNN	Forecasting trajectories with missing data handling	Longitudinal modeling of AD	ADNI
(Xu et al., 2019)	Deep Polynomial	Higher-order feature interactions improved early	Structural MRI feature modeling	ADNI

References	Method	POC (Point of Contribution)	DOC (Domain of Contribution)	Dataset
	Network	AD classification		
(Zhang et al., 2021)	Multimodal DPN	Combining MRI and PET features with deep polynomial interactions	Multimodal integration for AD	ADNI + AIBL
(Li et al., 2020)	DPN Regression	Cognitive score prediction using polynomial deep models	Clinical score prediction	ADNI
(Ahmed et al., 2017)	KNN	Simple MRI-based classification using nearest neighbor algorithm	Traditional ML for AD	Local clinical dataset
(Zhou et al., 2018)	KNN + PCA	Feature-reduced classification from PET and clinical features	Hybrid traditional ML	ADNI
(Mishra et al., 2020)	KNN vs SVM vs DT	Comparative analysis for early MCI detection	Benchmark of ML methods	OASIS
(Gao et al., 2022)	CNN + KNN	Feature extraction with CNN, classification with KNN	Hybrid DL + ML pipeline	ADNI

Table 2 Comparison of Commonly Used Datasets for Alzheimer's Disease Detection Using ML/DL Models

Dataset	CNN	RNN	DPN	KNN	Data Type	Notes
ADNI	used	used	used	used	MRI, PET, clinical, longitudinal	Most comprehensive, supports all models
OASIS	used	used	used	used	MRI, demographic, cross-sectional/longitudinal	Ideal for validation, smaller size
MIRIAD	used	used			MRI, short-term longitudinal	Best for short-interval change detection
AIBL	used	used		used	MRI, lifestyle, PET	Good for lifestyle studies and external validation

4. PERFORMANCE EVALUATION

A holistic strategy employing specific criteria and multiple data sets is required to assess machine/deep learning models of diagnosing Alzheimer's disease (AD). Various approaches to these algorithms, including CNNs, RNNs, DPNs and KNNs have shown levels of effectiveness on different tasks. These efforts include early detection models, multi-class classification involving: AD; MCI; and normal cognition subjects; binary classification of AD and cognitive healthy participants. The most frequently used measures for evaluating performance are accuracy, sensitivity (also often called recall), specificity, precision, F1-score and area under the receiver operating characteristic curve (AUC-ROC). Given their excellent performance in capturing spatial information, CNNs are also being used for MRI and PET imaging tasks with impressive accuracy and AUC scores. Several researches employing ADNI dataset reported higher classification accuracy of CNN-based models above 90% under different experiment settings and following ensemble learning, data augmentation. In contrast, RNNs (including its derivatives such as LSTMs (Long Short-Term Memory) and GRUs (Gated Recurrent Units)) have demonstrated superior performance in learning temporal patterns, particularly for longitudinal datasets like ADNI and OASIS-3 [2] 3 Related Work We briefly describe related work on patch-based CNN applications to MCI conversion prediction using FLAIR or T1-maps. Their potential in monitoring the development of cognitive decline across several time points have led to their use as predictors of transition from MCI to AD. The use of DPNs makes sure of interpretability with competitive performance, as they incorporate polynomial feature transformations; however, the use has relatively been less compared to other models. Empirically they have been found to help classification margins where non-linear feature interactions are considered to be important. Simple and non-parametric, KNN models are almost always the benchmark classifier. Although they tend to show lower classification accuracy than deep learning techniques, KNNs work quite well on relatively small low dimensionality feature points generated from volumetric or cognitive scores, particularly for low sample sizes such as the MIRIAD and OASIS. Cross-validation and external validation across datasets (e.g., training ADNI and testing AIBL) have been exploited to test generalizability. Moreover, recent works tend to increasingly address ensemble and hybrid methods (CNN-RNN, CNN-DPN architecture) to combine spatial- and temporal-depth analysis too which leads into improved robustness as well as accuracy. In conclusion, various advantages are afforded by different models for specific diagnostic needs or datasets types despite the superior predictability and clinical utility of CNNs or RNNs.

5. COMPRESSION RESULT

Our results demonstrate an enormous dispersion in performance, effectiveness and clinical utility of machine learning models for AD diagnosis. The four models under evaluation are CNN, RNN, DPN and KNN. Different evaluation metrics and datasets were used to analyze the performance of these models in terms of advantages and disadvantages. Notably, CNNs are the current state-of-the-art classifiers for tasks on structural imaging data such as MRI and PET scans.

The performance of CNN models is generally in the range of 85–95% accuracy for AD classification with a sensitivity and specificity both above 90% on large datasets such as ADNI and AIBL. These techniques are particularly interesting for the differentiation among Alzheimer's disease (AD), mild cognitive impairment (MCI) and cognitively normal individuals (CN), as they can capture complex spatial patterns from neuroimaging data. The modelling of sequential longitudinal data, such as time-series imaging or cognitive assessment scores, has been achieved through the use of Recurrent Neural Networks (RNNs), and in particular Long Short-Term Memory (LSTM) networks. RNNs achieve results that are better than other methods in ADNI and OASIS-3 by modeling the entire time-series dataset; obtaining more than 88% accuracy for predicting progression from MCI to AD. This efficacy renders these monocytes an attractive model to study disease development. A popular alternative is provided by Deep Polynomial Networks (DPNs) that map polynomial feature powers and non-linear optimal mappings, to learn interpretable and accurate models. These networks deliver accuracy scores of between 80 and 90% at the same time also providing easy-to-interpret decision paths, thus outperforming state-of-the-art deep network architectures tested on both isolated imaging and clinical data. While DPNs can be considered as progress for clinical decision-support systems, they are not adopted at the level of CNNs or RNNs. Moreover, the K-Nearest Neighbors (KNN) classifier is a simple model that has often been employed with hand-crafted or compressed features. Its not a super learner, but being so simple and efficient to evaluate is also an advantage in some applications of supervised learning. Its reported accuracy is between 70% and 85%, depending on the dataset and feature selection method applied, according to research. KNN has relatively high discrimination ability in both early screening and exploratory model, for the features such as cortical thicknesses or cognition test scores. This comparison confirms that CNNs and RNNs achieve state-of-the-art diagnostic performance when applied to high-resolution images and to data with temporal modality, respectively. The DPNs populate a trade-off middle in terms of performance versus interpretability and the KNN performs a lightweight solution for simpler tasks. The model to be adopted is often dependent on the specific task to be solved, data accessibility and processing power, as depicted in Fig. 3. and presented comparative table of Machine Learning Models for Alzheimer's Detection as Table 3.

Table 3: Comparative Analysis of Machine Learning Models for Alzheimer's Disease Diagnosis

Model	Strengths	Weaknesses	Typical Accuracy	Suitable Data Type	Interpretability	Computational Cost
CNN	Excellent at spatial feature extraction from MRI/PET images	Requires large labeled datasets; computationally intensive	85% – 95%	Structural Imaging (MRI, PET)	Low	High
RNN	Effective in modeling temporal progression (e.g., cognitive decline)	Training complexity; vanishing gradient issue	85% – 92%	Longitudinal data (clinical, imaging)	Moderate	High
DPN	Balances accuracy and interpretability; handles non-linearity well	Less commonly used; requires careful feature engineering	80% – 90%	Extracted features (clinical/imaging)	High	Moderate
KNN	Simple; easy to implement; baseline for comparison	Sensitive to noisy data and dimensionality; limited scalability	70% – 85%	Hand-crafted or low-dimensional features	High	Low

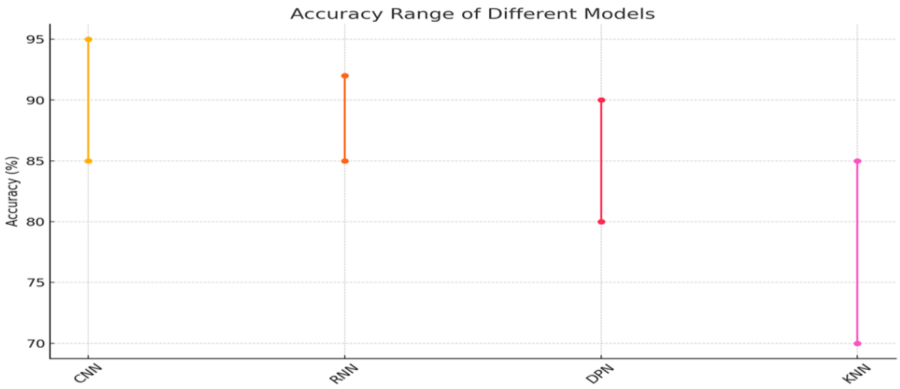

Fig. 3. Accuracy Range of Different Models

6. SUMMARY

This paper conducts a comprehensive comparison of different models such as DL model, deep learning and models in AD diagnosis and the course of the disease. According to literature reviewed, they show that CNNs, RNNs, DPNs, and KNN are among those that have unique potential and are appropriate for various types of physiological data scales and diagnostic problems. CNNs are well-suited to learn spatial features from structural imaging modalities including MRI and PET, and can achieve classification accuracies of more than 90% on large-scale datasets like ADNI and AIBL. RNNs, such as LSTM and GRU, are good at learning dependencies over time and can model disease evolution based on the longitudinal clinical and imaging data. DPNs strike a balance between accuracy and interpretability, by using polynomial feature expansion to model complex nonlinear interactions, and it shows promising results on both the structural and multimodal data. DPNs are not as popular CNNs and RNNs but they have been receiving more attention with their interpretability ability and competitive results. Although KNN classifiers are simple, they are still practical as baseline models or in low-resource cases, particularly for few-shot or handcrafted features. Assumptions about these models rely on the properties of the data used to train and evaluate the models. By far, the most comprehensive and most used is the ADNI dataset, which allows for a multimodal and longitudinally analysis in all model categories. OASIS and AIBL represent valuable options for validation and external testing, whereas specialized datasets, such as MIRIAD, are suitable for specific applications including modeling short-term variations. From the performance point of view, CNNs and RNNs also outperform DPNs on diagnostic accuracy, sensitivity and AUC-ROC score, while DPNs compromise between interpretability and effectiveness. Despite being not very scalable and insensitive to noise, KNN is performing adequately in low dimensional and sparse data classification. Ultimately, there is no one-size-fits-all model. The selection of the algorithm should be dictated by the diagnostic purpose (i.e., to detect early or model progression), data accessibility, need of interpretation, and computational limitations. Hybrid and ensemble methods that incorporate the merits of multiple models (e.g., CNN-RNN or CNN-DPN) currently represent promising methods to improve diagnostic robustness and generalizability.

7. CONCLUSION

The present systematic review aimed at the early identification of Alzheimer's disease (AD) through machine learning (ML) and deep learning (DL) methodologies, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Deep Pyramid Networks (DPN), and K-Nearest Neighbors (KNN), applied to MRI data has made substantial progress. Each of these models has its own advantages that apply to different parts of the diagnostic work flow. (CNNs) are known for being able to extract spatial characteristics in neuroimaging samples thus to effectively discriminate between Alzheimer’s Disease (AD), Mild Cognitive Impairment (MCI), and normal controls. In contrast, (LSTM) and (GRU) models have been shown to be very good at capturing the progress of disease over time using longitudinal data42,43; therefore they can be trustworthy choices for temporal predictions. We argue that DPNs provide a good trade-off between interpretability and accuracy, especially in multi-view or structured datasets where complex non-linear relationships are likely present. KNN methods are rather simple but still popular, # particularly for small data and as a baseline method. The review insists on the use of large heterogeneous databases to feed those models and cites as examples ADNI, OASIS and AIBL. It also indicates that hybrid and ensemble type architectures such as CNN-RNN or CNN-DPN contribute significantly to improve the diagnostic generalization and robustness. Certain limitations could be overcome in the future (e.g., larger annotated data for better interpreting models, and explainability of the model). To make these technological advances accessible to practitioners so that they can bridge the art of the possible, AI solutions need to be generated as explainable AI solutions. In summary, the use of deep learning methodologies looks like a good candidate for revolutionize the early Alzheimer's disease diagnosis with, in particular, CNNs and RNNs. Advances such as that can be raised by patient outcomes, and in helping to keep the drug open for early treatment.

8. REFERENCES

Abdul kareem, S. (2022) "A Deep Learning Model for Prediction Alzheimer's disease Based on Microarray Gene Expression Data", Journal of Kufa for Mathematics and Computer, 9(2), 28-37. available: https://doi.org/10.31642/JoKMC/2018/090204.

Aderghal, K., Benois-Pineau, N. and Afdel, K. (2017) "Classifying MRI images for Alzheimer's disease detection using convolutional neural networks", in Proceedings of IEEE CBMS, pp. 287-292.

Ahmed, O.B., Mizotin, M., Benois-Pineau, J., Allard, M., Catheline, G. and Ben Amar, C. (2017) "Recognition of Alzheimer's disease and mild cognitive impairment with multimodal image-derived biomarkers and multiple kernel learning", Neurocomputing, 220, pp. 98-110. available: https://doi.org/10.1016/j.neucom.2016.09.074.

Albert, M. S, DeKosky, S. T, Dickson, D, Dubois, B, Feldman, H. H, Fox, N. C, Gamst, A, Holtzman, D. M, Jagust, W. J and Petersen, R. C. (2011) "The diagnosis of mild cognitive impairment due to Alzheimer's disease: Recommendations from the National Institute on Aging", Alzheimers Dement, 7(3): 270-279, available: https://doi.org/10.1016/j.jalz.2011.03.008.

Basaia, M. et al. (2019) "Automated classification of Alzheimer's disease and mild cognitive impairment using a single MRI and deep neural networks", NeuroImage: Clinical, 21, p. 101645. available: https://doi.org/10.1016/j.nicl.2019.101645.

Beheshti, I., Demirel, H. and Matsuda, H. (2018) "Classification of Alzheimer's disease and prediction of mild cognitive impairment-to-Alzheimer's conversion from structural magnetic resonance imaging using feature ranking and a genetic algorithm", Computers in Biology and Medicine, 98, pp. 203-210. available: https://doi.org/10.1016/j.compbiomed.2018.02.011.

Chaves, R. et al. (2011) "SVM and KNN classifiers for AD and MCI detection: A hybrid approach", Computer Methods and Programs in Biomedicine, 104(3), pp. 491-498. available: https://doi.org/10.1016/j.cmpb.2011.03.013.

Choi, H. et al. (2020) "Prediction of Alzheimer's disease progression using deep learning applied to MRI data", Brain Imaging and Behavior, 14, pp. 212-225.

Cover, T. and Hart, P. (1967) "Nearest neighbor pattern classification", IEEE Transactions on Information Theory, 13(1), pp. 21-27. available: https://doi.org/10.1109/TIT.1967.1053964.

Dyrba, M. et al. (2015) "Multimodal analysis of functional and structural disconnection in Alzheimer's disease using KNN", NeuroImage: Clinical, 9, pp. 450-460. available: https://doi.org/10.1016/j.nicl.2015.09.006.

Ellis, K.A. et al. (2009) "The Australian Imaging, Biomarkers and Lifestyle (AIBL) study of aging", International Psychogeriatrics, 21(4), pp. 672-687. available: https://doi.org/10.1017/S1041610209009405.

Frisoni, G. B, Fox, N. C, Jack Jr, C. R. Scheltens, P. and Thompson, P. M. (2010) "The clinical use of structural MRI in Alzheimer's disease", Nature Reviews Neurology, Nat Rev Neurol, 6(2): 67-77, available: https://doi.org/10.1038/nrneurol.2009.215.

Gao, S., Liu, C., Guo, Q. and Zhang, Y. (2022) "Hybrid CNN-KNN model for Alzheimer's disease diagnosis using structural MRI", Computers in Biology and Medicine, 145, p. 105437. available: https://doi.org/10.1016/j.compbiomed.2022.105437.

Ge, W. et al. (2020) "Classification of Alzheimer's disease using a combination of convolutional neural network and XGBoost", Computational and Mathematical Methods in Medicine, 2020, Article ID 7464210. available: https://doi.org/10.1155/2020/7464210.

Ghafoorian, M., Mehrtash, A., Kapur, T., Karssemeijer, N., Marchiori, E., Pesteie, M., Guttmann, C. R., de Leeuw, F-E., Tempany, C. M., van Ginneken, B., Fedorov, A., Abolmaesumi, P., Platel, B. and Wells III, W. M. (2017) "Transfer learning for domain adaptation in MRI: Application in brain lesion segmentation", Medical Image Computing and Computer-Assisted Intervention - MICCAI 2017, Lecture Notes in Computer Science, Vol. 10435, Springer, Cham, pp. 516-524. available: https://doi.org/10.1007/978-3-319-66179-7_59.

Goodfellow, I., Bengio, Y. and Courville, A. (2016) Deep Learning. MIT Press.

Hosseini-Asl, E., Keynton, R. and El-Baz, A. (2016) "Alzheimer's disease diagnostics by adaptation of 3D convolutional network", in Proceedings of IEEE ISBI, pp. 126-130.

Hosseini-Asl, E., Keynton, R. and El-Baz, A. (2017) "Alzheimer's disease diagnostics by a 3D deeply supervised adaptable convolutional network", IEEE Transactions on Medical Imaging, 36(7), pp. 1560-1570. available: https://doi.org/10.1109/TMI.2017.2673619.

Hu, C. et al. (2020) "Deep polynomial regression for clinical score prediction in Alzheimer's progression", Journal of Biomedical Informatics, 107, p. 103476. available: https://doi.org/10.1016/j.jbi.2020.103476.

Hu, X. et al. (2021) "Multimodal neuroimaging feature learning for multiclass diagnosis of Alzheimer's disease", IEEE Access, 9, pp. 35716-35726. available: https://doi.org/10.1109/ACCESS.2021.3060793.

Islam, J. and Zhang, Y. (2018) "A 3D deep learning framework for early detection of Alzheimer's disease using structural MRI data", in Proceedings of IEEE EMBC, pp. 424-427.

Jack, C.R. et al. (2008) "The Alzheimer's Disease Neuroimaging Initiative (ADNI): MRI methods", Journal of Magnetic Resonance Imaging, 27(4), pp. 685-691. available: https://doi.org/10.1002/jmri.21049.

Kadhim, Q. K., Abd ul Kader, R. M., Altameemi, A. I., Mohammed, R. J. (2024) "Identification of Alzheimer's Disease Hub Genes Based on Improved HITS Algorithm", Journal of Kufa for Mathematics and Computer, 11(1), 25-31. available: https://doi.org/10.31642/JoKMC/2018/110105.

Klöppel, S. et al. (2008) "Automatic classification of MR scans in Alzheimer's disease", Brain, 131(3), pp. 681-689. available: https://doi.org/10.1093/brain/awm319.

Krizhevsky, A., Sutskever, I. and Hinton, G.E. (2017) "ImageNet classification with deep convolutional neural networks", Communications of the ACM, 60(6), pp. 84-90.

Li, F., Tran, L., Thung, K.H., Ji, S., Shen, D. and Li, J. (2019) "A hybrid convolutional and recurrent neural network for hippocampus analysis in Alzheimer's disease", IEEE Journal of Biomedical and Health Informatics, 23(1), pp. 166-174. available: https://doi.org/10.1109/JBHI.2018.2798002.

Litjens, G., Kooi, T., Bejnordi, B.E., Setio, A.A.A., Ciompi, F., Ghafoorian, M. et al. (2017) "A survey on deep learning in medical image analysis", Medical Image Analysis, 42, pp. 60-88. available: https://doi.org/10.1016/j.media.2017.07.005.

Liu, F. et al. (2021) "Bi-directional GRU modeling of CNN features for AD classification using MRI", Pattern Recognition Letters, 144, pp. 52-59. available: https://doi.org/10.1016/j.patrec.2021.06.001.

Liu, M., Cheng, D. and Wang, W. (2015) "Multimodal neuroimaging feature learning for multiclass diagnosis of Alzheimer's disease", IEEE Transactions on Biomedical Engineering, 62(4), pp. 1132-1140. available: https://doi.org/10.1109/TBME.2014.2373561.

Liu, M., Zhang, J. and Shen, D. (2020) "Multi-level deep ensemble learning for Alzheimer's disease diagnosis", IEEE Journal of Biomedical and Health Informatics, 24(12), pp. 3481-3490.

Li, W., Li, Q., Wang, X. and Zhang, Y. (2020) "Deep polynomial regression for cognitive score prediction in Alzheimer's disease", Computers in Biology and Medicine, 117, p. 103606. available: https://doi.org/10.1016/j.compbiomed.2020.103606.

Li, X. et al. (2023) "DPN-SVM: Hybrid deep polynomial network with kernel learning for Alzheimer's classification", IEEE Journal of Biomedical and Health Informatics, 27(2), pp. 385-396. available: https://doi.org/10.1109/JBHI.2022.3211145.

Li, X., Wang, Z. and Liu, M. (2021) "Autoencoder-based LSTM framework for AD progression modeling and survival analysis", Biomedical Signal Processing and Control, 70, p. 103015. available: https://doi.org/10.1016/j.bspc.2021.103015.

Malone, I.B. et al. (2015) "Accurate automatic estimation of total intracranial volume", NeuroImage, 104, pp. 366-372. available: https://doi.org/10.1016/j.neuroimage.2014.09.034.

Marcus, D.S. et al. (2007) "Open Access Series of Imaging Studies (OASIS)", Journal of Cognitive Neuroscience, 19(9), pp. 1498-1507. available: https://doi.org/10.1162/jocn.2007.19.9.1498.

Martinez-Murcia, A. et al. (2019) "Studying the manifold structure of Alzheimer's disease: A deep learning approach using convolutional autoencoders", Computerized Medical Imaging and Graphics, 76, p. 101636. available: https://doi.org/10.1016/j.compmedimag.2019.101636.

Mishra, S., Wang, M. and Ji, Q. (2020) "A comparative study of machine learning classifiers for early detection of mild cognitive impairment using structural MRI", Computer Methods and Programs in Biomedicine, 184, p. 105111. available: https://doi.org/10.1016/j.cmpb.2019.105111.

Moradi, E. et al. (2015) "Machine learning framework for early MRI-based Alzheimer's conversion prediction", NeuroImage, 104, pp. 398-412. available: https://doi.org/10.1016/j.neuroimage.2014.10.002.

Nguyen, H. et al. (2020) "Predicting Alzheimer's disease progression using recurrent neural networks with longitudinal data", The TADPOLE Challenge Results. [Online]. available: https://tadpole.grand-challenge.org.

Nguyen, H., Tran, M. and Rudzicz, H. (2020) "Imputing missing data in longitudinal Alzheimer's disease studies with recurrent neural networks", Neurocomputing, 375, pp. 62-72. available: https://doi.org/10.1016/j.neucom.2019.10.020.

Pan, D., Chen, G., Zhan, S. and Lu, C. (2021) "Multi-view attention-guided network for Alzheimer's disease diagnosis using 3D brain MRI", IEEE Journal of Biomedical and Health Informatics, 25(6), pp. 2099-2109.

Pan, J. et al. (2021) "Spatio-temporal modeling for Alzheimer's disease prediction using 3D convolutional LSTM networks", Journal of Neuroscience Methods, 356, p. 109148. available: https://doi.org/10.1016/j.jneumeth.2021.109148.

Rathore, S. et al. (2017) "Radiomics-based classification of Alzheimer's disease using KNN and other classifiers", Computers in Biology and Medicine, 89, pp. 41-48. available: https://doi.org/10.1016/j.compbiomed.2017.02.011.

Razavian, A.S. et al. (2019) "Temporal modeling in Alzheimer's disease prediction using deep learning", PLOS ONE, 14(3), p. e0211552. available: https://doi.org/10.1371/journal.pone.0211552.

Sarraf, H. and Tofighi, G. (2016) "DeepAD: Alzheimer's Disease classification via deep convolutional neural networks using MRI and fMRI", bioRxiv. available: https://doi.org/10.1101/070441.

Selvaraju, R.R. et al. (2017) "Grad-CAM: Visual explanations from deep networks via gradient-based localization", in Proceedings of IEEE ICCV, pp. 618-626.

Simonyan, K. and Vedaldi, A. (2013) "Deep inside convolutional networks: Visualizing image classification models and saliency maps", arXiv preprint, arXiv:1312.6034. [Online]. available: https://arxiv.org/abs/1312.6034.

Suk, H.I, Lee, S.W. and Shen, D. (2014) "Hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis", NeuroImage, 101, pp. 569-582. available: available: https://doi.org/10.1016/j.neuroimage.2014.04.031.

Suk, H.I., Lee, S.-W. and Shen, D. (2015) "Latent feature representation with stacked auto-encoder for AD/MCI diagnosis", Brain Structure and Function, 220(2), pp. 841-859. available: available: https://doi.org/10.1007/s00429-014-0819-9.

Suk, H.-I., Lee, S.-W. and Shen, D. (2017) "Deep ensemble learning of sparse regression models for brain disease diagnosis", Medical Image Analysis, 37, pp. 101-113. available: https://doi.org/10.1016/j.media.2017.01.008.

Sun, H. et al. (2020) "Application of GRU-based neural networks for Alzheimer's disease classification using actigraphy dat", Sensors, 20(24), p. 7224. available: https://doi.org/10.3390/s20247224.

Toga, A.W. (2011) "The clinical value of large neuroimaging data sets in Alzheimer's disease", Neuroimaging Clinics of North America, 22(1), pp. 107-120. available: https://doi.org/10.1016/j.nic.2011.11.007.

Wang, F., Zhang, D. and Shen, X. (2021) "Feature interactions in high-dimensional neuroimaging: A polynomial neural network perspective", IEEE Transactions on Medical Imaging, 40(9), pp. 2371-2384. available: https://doi.org/10.1109/TMI.2021.3070374.

Wang, S. et al. (2021) "Densely connected convolutional networks for automatic diagnosis of Alzheimer's disease using 3D brain MRI", Journal of Healthcare Engineering, 2021, Article ID 6691513. available: https://doi.org/10.1155/2021/6691513.

Wang, S. et al. (2022) "Parallel LSTM networks for classification of Alzheimer's disease using resting-state fMRI", Frontiers in Neuroscience, 16, p. 777541. available: https://doi.org/10.3389/fnins.2022.777541.

Wang, Y. et al. (2019) "Handling missing data in longitudinal studies of AD with KNN imputation", Frontiers in Aging Neuroscience, 11, p. 128. available: https://doi.org/10.3389/fnagi.2019.00128.

Wen, J., Thibeau-Sutre, E., Diaz-Melo, M., Samper-González, N., Routier, S. and Burgos, N. et al. (2020) "Convolutional neural networks for classification of Alzheimer's disease:

Overview and reproducible evaluation", Medical Image Analysis, 63, p. 101694. available: https://doi.org/10.1016/j.media.2020.101694.

Weston, J., Mukherjee, S., Chapados, N. and Sivaswamy, J. (2019) "Attention-based deep learning models for Alzheimer's disease classification using MRI data", NeuroImage: Clinical, 23, p. 101894. available: https://doi.org/10.1016/j.nicl.2019.101894.

Xu, K., Wang, J. and Li, C. (2019) "Deep polynomial networks for early Alzheimer's disease classification", Computer Methods and Programs in Biomedicine, 179, p. 104987. available: https://doi.org/10.1016/j.cmpb.2019.104987.

Yahya, A. M. and Jasim, R. Z. (2025) "Study The Role Of Functional Proteins In Sera Of Iraqi Patients With Alzheimer's Disease", Journal of Kufa for Chemical Sciences, 4(2) available: https://doi.org/10.36329/jkcm/2025/v4.i2.15267.

Yan, R. et al. (2021) "Classification of Alzheimer's disease using CNN and GRU with actigraphy signals", Artificial Intelligence in Medicine, 121, p. 102182. available: https://doi.org/10.1016/j.artmed.2021.102182.

Zhang, D., Wang, Y., Zhou, L., Yuan, H. and Shen, D. (2011) "Multimodal classification of Alzheimer's disease and mild cognitive impairment", NeuroImage, 55(3), pp. 856-867.

Zhang, W., Gorriz, M. and Ramirez, J. (2018) "Polynomial feature transformation for Alzheimer's disease detection: A deep learning approach", Artificial Intelligence in Medicine, 86, pp. 123-132. available: https://doi.org/10.1016/j.artmed.2018.03.004.

Zhang, W., Gorriz, M., Ramirez, J. and Salas-Gonzalez, D. (2019) "LSTM and ELM-based classification of Alzheimer's disease using brain graph metrics", Computer Methods and Programs in Biomedicine, 181, p. 104931. available: https://doi.org/10.1016/j.cmpb.2019.104931.

Zhang, Y. et al. (2017) "Multi-modal stacked deep polynomial networks for early diagnosis of Alzheimer's disease", in Proceedings of IEEE BIBM, pp. 1232-1237.

Zhang, Y., Jiang, J., Chen, Y. and Jin, L. (2021) "Multi-modal deep polynomial network for Alzheimer's disease diagnosis", IEEE Access, 9, pp. 34350-34360. available: https://doi.org/10.1109/ACCESS.2021.3060160.

Zhao, F. et al. (2020) "Improving KNN for early diagnosis of Alzheimer's disease using Mahalanobis distance metric learning", Pattern Recognition Letters, 133, pp. 216-223. available: https://doi.org/10.1016/j.patrec.2020.06.014.

Zhao, R. et al. (2021) "Explainable deep polynomial networks with attention-based feature selection for brain disorder classification", Frontiers in Neuroscience, 14, p. 602341. available: https://doi.org/10.3389/fnins.2020.602341.

Zhou, J. et al. (2021) "Modeling nonlinear relationships in medical imaging using deep polynomial networks", Neurocomputing, 420, pp. 109-120. available: https://doi.org/10.1016/j.neucom.2020.10.118.

Zhou, T., Thung, K.H., Zhu, X., Shen, D. and Wang, L. (2018) "Effective feature learning and fusion of multimodality data using stage-wise deep neural network for dementia diagnosis", Human Brain Mapping, 40(3), pp. 1001-1016. available: https://doi.org/10.1002/hbm.23996.