Early Alzheimer's Disease Detection Through Targeting the Feature Extraction Using CNNs

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***Abstract*—Alzheimer's Disease (AD) is a persistent, irreversible, and degenerative neurological disorder of the brain that currently has no effective therapy. This condition is identified by pathological abnormalities in the hippocampal area, which may develop up to 10 years prior to the onset of clinical symptoms. Timely detection of pathogenic abnormalities is essential to impede the worsening of AD. Recent studies on neuroimaging have shown that the use of Deep Learning techniques to analyze multimodal brain scans may effectively and correctly detect AD. The main goal of this work is to design and develop an Artificial Intelligence (AI) based diagnostic framework that can accurately and promptly detect AD by analyzing Structural Magnetic Resonance Imaging (SMRI) data. This study presents a novel approach that combines a Directed Acyclic Graph 3D-CNN with an SVM classifier for timely detection and identification of AD by analyzing the Regions of Interest (RoI) like cerebral spinal fluid, white and gray matter, and the hippocampus in SMRI images. The proposed hybrid model combines Deep Learning for feature extraction and Machine Learning techniques for classification. The obtained results demonstrate its superior performance compared to earlier methods in accurately identifying individuals with early mild cognitive impairment (EMCI) from those with normal cognition (NC) using the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset. The model attains a classification accuracy of 97.67%, with precision at 94.12%, and sensitivity at 98.60%.**

Keywords—Alzheimer's Disease (AD); convolutional neural networks (CNN); Support Vector Machine (SVM); Directed Acyclic Graph (DAG); Late Mild Cognitive Impairment (LMCI); Alzheimer's Disease Neuroimaging Initiative (ADNI)

I. Introduction

Dementia is a broad word that encompasses many cognitive impairments that hinder daily functioning, impacting memory, thinking, language, and problem-solving skills. AD is the main source of dementia with distinct pathological features in the brain, responsible for around 80% of cases [1]. AD is defined by permanent neurodegeneration and currently lacks the potential for treatment. Neurodegenerative illnesses provide significant challenges in countries with a mostly aging population. It is the sixth primary cause of mortality and has a substantial global impact, mostly affecting the older demographic [2]. MR imaging is a diagnostic modality that uses T1-weighted images to identify and examine the morphological and structural irregularities associated with brain atrophy [3]. Therefore, MR imaging plays a crucial part in screening and diagnosing of AD [4, 5]. The incidence of the ailment has surpassed original forecasts due to the increasing older population and the simultaneous commencement of their diagnosis [6]. This necessitates due attention to effectively handle Alzheimer's diagnosis and treatment.

While the exact process behind the progression of Alzheimer's is still not fully understood, existing knowledge indicates that the illness may be broadly categorized into three separate stages i.e. Preclinical, MCI, and AD [7, 8]. There are no noticeable symptoms of AD in the preclinical stage. However, subtle changes begin to occur in the brain. These pathological changes can start many years, even decades, before any cognitive symptoms appear [9]. The second stage is characterized by MCI, where individuals start to notice slight but measurable changes in their cognitive abilities, particularly memory. These changes are more significant than what is expected from normal aging, although they do not reach a level of severity that hinders one's ability to carry out everyday activities [10]. In the last stage of AD, the cognitive decline becomes sufficiently pronounced to disrupt everyday activities. Individuals may encounter memory impairment, disorientation, and challenges with tasks that require planning or decision-making, may struggle with recognizing familiar people or places, and may experience a decline in physical abilities such as walking, swallowing, and bladder and bowel control [11].

The field of Machine Learning (ML) and Deep Learning (DL) has gathered considerable attention in over the past few years for its ability to accurately detect and isolate possible features of dementia illness, by accurately identifying the minute morphological changes in brain structure by analyzing MRI data [12, 13]. DL methodologies have proven that the area of AD detection has seen notable advancements via the use of CNNs [4, 14]. CNNs shall effectively extract structural characteristics from T1 MRI data with a large number of dimensions, leading to more precise tailored diagnoses. Furthermore, the implementation of an ensemble approach is gaining more significance in the field of medical image evaluation [15, 16]. AD has a quick and profound impact on the hippocampus, making it one of the most damaged brain areas and making it vital for the prompt detection of AD. The hippocampus is composed of several subdomains, each exhibiting distinct characteristics. A comprehensive evaluation of neurodegenerative disorders in medical applications heavily relies on the subfields of the hippocampus [17]. Scholars have proposed that the analysis of form and volume characteristics of hippocampal subfields in many MRI scans provides advantages in the prompt identification and assessment of AD [18, 19].

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The process of classifying hippocampus characteristics entails extracting them from either 2D or 3D MRI images using 2D and 3D CNNs [20,21]. When doing a comparison between 3D convolutions performed on a whole MRI and 2D convolutions performed on slices, it is evident that the former can capture crucial 3D structural information that is vital for distinction [22]. The brain MRI data has a lot of dimensions, thus, three-dimensional CNNs [23] are computationally difficult and need a longer training time compared to two-dimensional CNNs. The above-said facts served as the motivation for this work. The goal of this research is to facilitate the timely detection of AD using the popular SVM classifier with more emphasis on the input features fed to it. This is accomplished by employing a new DAG CNN approach to perform feature extraction. In this study, both 2D and 3D DAG-CNN is used. In summary, a hybrid of CNN combined with SVM classifier is employed to perform early detection of AD. The next section gives a detailed comment on the literature work done in this direction.

II. Literature Review

Hongbo Xu et al. [24] proposed a CNN that utilizes multi-scale attention to diagnose AD by analyzing hippocampal subfields. This study employs two datasets, procured from Peking University of China and ADNI. These datasets consist of a combined sample of 283 NC patients and 241 AD cases. The network can easily extract 3D data characteristics from three different planes of hippocampus subfields as input. This improves computational efficiency and reduces network complexity. Experimental methods have shown notable classification performance in identifying AD, eliminating the need for manual feature extraction. Bo Liu et al. [25] employ MRI scans of the hippocampus and an attention mechanism (DenseNet-AM) to improve classification accuracy. The empirical findings illustrate that the DenseNet-AM is 92.8% accurate, the sensitivity is 97.1%, and the specificity is 89.6% when distinguishing between instances of cognitive normalcy and AD. Malik et al. [26] presented a novel methodology known as the intuitionistic fuzzy random vector functional link network (IFRVFL), which utilizes brain imaging data to diagnose AD. This study aims to improve existing approaches by incorporating a fuzzy weighted approach into the IFRVFL model to improve its capability to withstand challenges. This methodology considers the importance of individual data samples while minimizing the influence of outliers and noise. Experimental studies indicate that in comparison to cases of Alzheimer's dementia (AD), the IFRVFL model has a higher level of efficacy in identifying both MCI and early identification of AD in clinical settings. Shuqiang Wang et al. [27] conducted a research where they introduced a new approach that combines 3D-DenseNets to automatically diagnose Alzheimer’s (AD) and moderate cognitive impairment by analyzing 3D brain magnetic resonance images. A comprehensive assessment was conducted for evaluating the performance of the suggested model using the ADNI dataset with 833 patients, and it was determined to be superior. The suggested approach enhances the transmission of information across layers by integrating several connections and a weighted-based combining approach is employed to integrate diverse topologies. A promising result was seen in the automation of dementia illness identification by employing an ensemble strategy that incorporates dense connections and a weighted-based fusion method. Reddy et al. [28] provide a deep hybrid framework in their research, which employs boosting approaches to classify 3D MRI images of Alzheimer's. The research primarily focuses on early diagnosis and utilizes the categorization of subcategories of MCI. The system uses ResNet 50 and VGG16 to extract structural information from MRI volumes followed by using Extreme Gradient Boosting (XGBoost) for classification. Pallawi et al. [29] employed a Transfer Learning approach to distinguish between various phases of Alzheimer's with an enhanced EfficientNetB0 model via MRI images obtained from the Kaggle dataset. To tackle the issue of inadequate data, data augmentation techniques were used. Consequently, the model effectively categorized several classes with a precision rate of 95.78%, exceeding the efficacy of existing methodologies. Rui Guo et al. [30] provide a novel approach known as graph-based fusion (GBF) in their research. This technique utilizes imaging, genomic, and clinical data to effectively identify degenerative illnesses. By combining a multi-graph fusion module with an imaging-genetic combining module to efficiently extract unique information from many data modalities. The effectiveness of the GBF approach is shown by trials done on benchmarks about the identification of degenerative illnesses, in contrast to known graph-based methods. In their study, Xiaowei Yu et al. [31] has focused on developing a supervised deep tree model (SDTree) to forecast the advancement of AD at an individual level. The proposed SDTree methodology employs a nonlinear reversed graph embedding method inside a hierarchical tree framework within a latent space for enhanced prediction. This technique encompasses the whole spectrum of Alzheimer's progression and enables the generation of predictions for future instances. Furthermore, the attainment of a resilient depiction of the tree is accomplished by using node clustering in locations with high population density. Moreover, a novel methodology is suggested for multi-class classification by using a supervised deep tree architecture that integrates class labels to guide the acquisition of tree structure.

The reviewed works focus on several facets of AD diagnosis, using novel methodologies such as multi-scale attention (Hongbo Xu et al.) and attention processes (Bo Liu et al.) to improve efficiency and precision. Innovative approaches like IFRVFL (Malik et al.) proficiently manage noise and outliers, while 3D-DenseNets (Shuqiang Wang et al.) and hybrid frameworks integrating ResNet and XGBoost (Reddy et al.) emphasize early identification of MCI categorization. Transfer Learning (Pallawi et al.) attains high precision by data augmentation, whereas graph-based fusion (Rui Guo et al.) amalgamates multi-modal data to enhance accuracy. The SDTree model (Xiaowei Yu et al.) provides a comprehensive framework for predicting AD development.

The research highlights many constraints in the categorization systems used for AD in the literature. Hongbo Xu et al. [24] and Pallawi et al. [29] demonstrate how dataset variety limits model generalizability to larger populations. In approaches like Malik et al. [26], Shuqiang Wang et al. [27], and Rui Guo et al. [30], computational complexity is a major issue. Dense networks, fuzzy logic systems, and graph-based solutions need plenty of resources, limiting scalability. Many researches, such as Bo Liu et al. [25] and Pallawi et al. [29], focus on specific brain areas or use single-modal data, missing the opportunity to increase accuracy via multi-modal integration. The techniques of Reddy et al. [28] and Xiaowei Yu et al. [31] enhance architectural complexity, which reduces interpretability and hinders clinical applicability. Finally, research like Bo Liu et al. [25] and Malik et al. [26] lack rigorous evaluations compared to state-of-the-art methodologies or real-world clinical datasets, leaving practical robustness untested.

Conventional methods often need the extraction of features by hand, a process that may time-consuming and potentially overlook crucial attributes. In addition, current models may have difficulties in dealing with noise, resulting in a decrease in classification accuracy. Additionally, there are difficulties in accurately detecting the initial phases of AD and differentiating them between various phases of cognitive decline. The issue of inadequate data might ultimately restrict the capacity to train resilient models, hence affecting their overall effectiveness.

To overcome these limitations, the researchers in this study have developed methods like DAG CNNs for automatically extract features from the SMRI images, by avoiding the need for manual feature extraction and capturing more relevant characteristics. Advanced architectures like DAG CNNs enhance accuracy by better analyzing complex data, such as brain MRI scans. This research also used data augmentation methods to overcome the problem of inadequate data by artificially expanding the amount and variety of the dataset. This results in improved training and more efficient models. The hybrid models used in this study combine the strengths of multiple methods like DL for extracting the significant features and ML techniques for performing classification to further improve classification performance.

A. Novelty

The proposed methodology is innovative in integrating DAG 3D-CNN with SVM to facilitate the prompt detection of AD, utilizing the advantages of both methodologies." Although CNNs are proficient in feature extraction, SVM classifiers are recognized for their resilience in managing small sample data and high-dimensional feature spaces, which are typical issues in medical imaging datasets. This hybrid method offers a distinctive means to enhance classification efficacy in AD diagnosis.

The DAG architecture for CNNs facilitates a versatile route for feature propagation and allows for more profound feature investigation, circumventing the vanishing gradient issue. Our method provides a customized solution to the unique problems of volumetric medical data by building the architecture specifically for these issues, distinguishing it from conventional CNN architectures used in analogous applications.

The researchers have chosen DAG-CNN architecture because to its capacity for parallel processing of features across several scales, enhancing the network's proficiency in capturing the spatial hierarchies present in 3D medical pictures. This structure enhances generalization by mitigating overfitting, since the modular architecture allows for selective feature aggregation.

III. METHODOLOGY

Fig. 1 demonstrates a system specifically developed for the prompt identification and categorization of AD. This approach uses CNN and SVM. The method starts by obtaining the brain's SMRI data from ADNI, and KAGGLE datasets. These images are essential for discerning structural alterations corresponding to AD since they record intricate details about the brain's composition. Following that, the SMRI images go through pre-processing, a crucial stage that employs methods including skull stripping, normalization, shrinking, and noise reduction. Pre-processing ensures that the pictures are normalized, strengthening key characteristics while decreasing noise and unnecessary details, thereby improving the accuracy of further investigations. Once the data has been pre-processed, it is then split into two distinct training and validation sets. These two datasets are then used for training and assessing efficacy of the model, during the training process, therefore mitigating overfitting and ensuring the model's ability to effectively generalize to novel data.

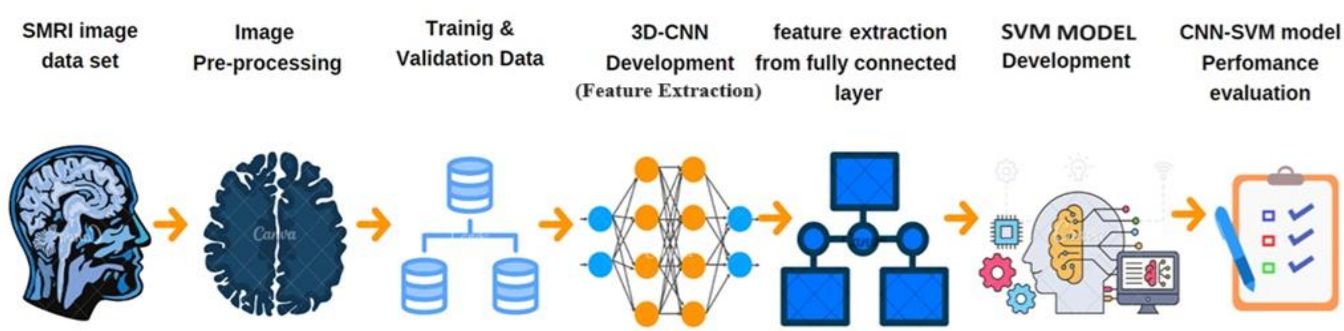


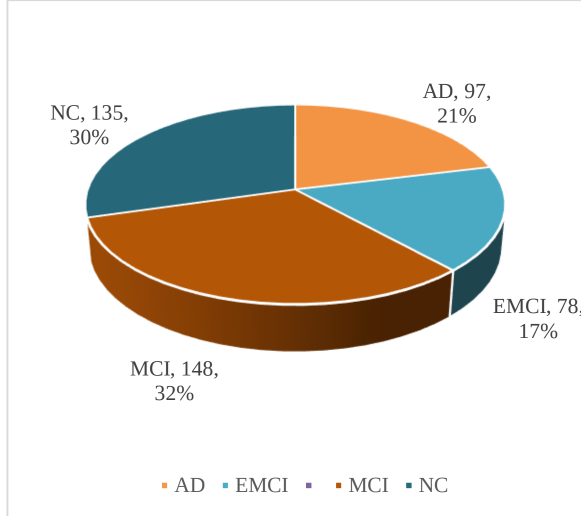
Fig. 1. Block diagram for the methodology.

The crux of this method is in the development of a CNN network, which excels at processing volumetric structural MRI data with great efficiency. The CNN automatically acquires the ability to extract spatial characteristics from brain images that are symptomatic of AD. At first, a 2D-CNN was developed to analyze the 2D slices of the MRI images. The 2D-CNN model has many advantages, namely its simplicity and decreased computational expenses. This is due to its ability to evaluate images on a per-slice basis, resulting in faster training and lower resource requirements. The implementation of the 2D-CNN model is straightforward, and the training periods are quicker because of the reduced complexity in processing 2D images. However, the 2D-CNN approach does have significant drawbacks. 2D CNNs evaluate each slice independently, which might result in the loss of crucial spatial connections between slices and the omission of significant characteristics necessary for precise Alzheimer's diagnosis. Due to the constraints of 2D-CNNs in accurately representing the whole 3D architecture of the brain, it became imperative to switch to a 3D-CNN. The 3D-CNN model enables the analysis of the whole volumetric SMRI data while maintaining the spatial connections between various brain areas. This comprehensive approach allows the model to better detect minor alterations in structure that are linked to the early stages of AD, resulting in enhanced accuracy in categorization. The use of a 3D model aligns with the objective of achieving improved accuracy and reliability in the early detection of AD, making it a vital step in our research. Once the network completes the image processing, it proceeds to extract the significant features from the fully connected layers of the CNN. These layers function as classifiers inside the network and integrates the features collected into a condensed representation. Subsequently, this representation is used to train an SVM model, which categorizes the data into distinct classes, such as AD or normal cognitive. The SVM classifier is used because of its resilience in distinguishing classes in spaces with a large number of dimensions, hence enhancing its effectiveness as a classifier when paired with the characteristics retrieved by the CNN.

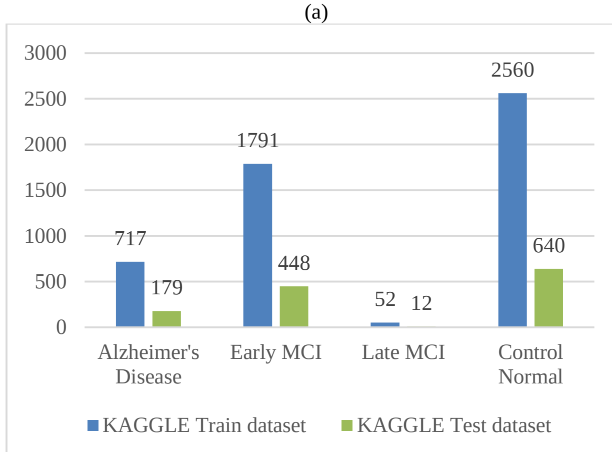
Finally, the efficacy of the integrated CNN with SVM model is assessed by measuring parameters such as accuracy, precision, recall, and F1 score. This assessment is vital in guaranteeing that the suggested model is not just accurate but also reliable and has the ability to extrapolate well to new, unfamiliar data. In summary, our technique successfully integrates DL for automated extraction of features using traditional ML for classifiers, resulting in an efficient method for the prompt identification of dementia. Such detection is essential for immediate attention and treatment.

A. SMRI Datasets

This research used structural MRI images received from the ADNI and KAGGLE databases. The ADNI consists of four distinct phases, including ADNI 1, ADNI GO, ADNI2, and ADNI4. Each phase has its specific aims and cognitive stages. This study used structural MRI images. Fig. 2(a) depicts the AD dataset utilized in this study. Among the 455 participants in the ADNI study, there were 97 AD subjects, 78 early MCI subjects, 148 LMCI subjects, and 135 subjects with normal cognition (NC).



(a)



(b)

Fig. 2. (a) ADNI data set, (b) KAGGLE data set.

The dataset obtained from Kaggle shown in Fig. 2(b) and has four different classes: NC, Early EMCI, Late MCI, and AD. The dataset is divided into separate training and test sets. The training dataset composed of 5120 photos, whereas the test dataset has 1279 images. The NC class contains the largest quantity of photos, consisting of 2560 for training and 640 for assessment. The EMCI dataset consists of 1791 pictures for training and 448 images for testing, whereas the AD dataset comprises 717 training images and 179 test images. The LMCI class has the lowest number of pictures, with a total of 52 for training and 12 for assessment.

B. Preprocessing and Segmentation of SMRI Images

Fig. 3 depicts the methodological steps employed for the early identification of AD using the data samples acquired from the ADNI and KAGGLE. The collected images are in NifTi (.nii) format. The N4ITK bias correction is first performed to eliminate low-frequency noise and the resulted image are shown in Fig. 3(a). Subsequently, the raw volumes are subjected to pre-processing through the Statistical Parametric Mapping [45] toolbox in MATLAB. During the pre-processing stage of SPM, the images were co-registered with the ICBM-152 template to align them to the Montreal Neurological Institute coordinate system (MNI) and additionally, the images are normalized, skull stripped (Fig. 3b) and categorized into white, gray matter, and cerebral spinal fluid as shown in Fig. 3(c). Hippodeep [44] tool is used for segmenting left and right hippocampal and shown in Fig. 3(d). Subsequently, the images were resized to dimensions of 256*256*128. The pre-processed data is separated into two distinct sets: training and validation. The proposed 3D-CNN is the trained and validated via these two datasets. The trained CNN is utilized to extract important characteristics from the input SMRI data. These characteristics obtained from the flattening layer of CNN are further partitioned into validation and training features, which are then utilized for both training and testing of the suggested DAG based 3D-CNN with SVM model.

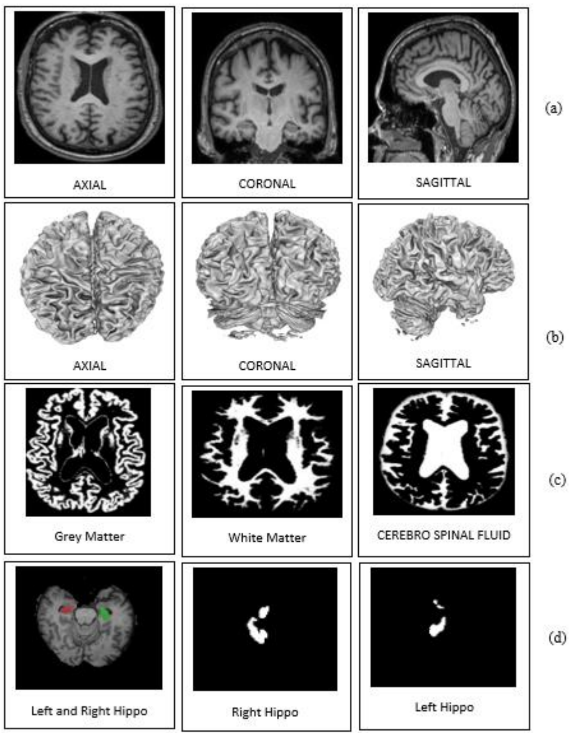


Fig. 3. (a) N4 bias correction, (b) Skull stripping, (c) Segmented WM, GM, & CSF, (d) Segmented Hippo.

C. Design and Development of DAG Based 2D/3D-CNN

The CNN and ML classifiers are often used AI tools for the identification and categorization of Alzheimer's, and their performance largely relies on the features extracted and analysed. Traditionally, researchers manually extract certain characteristics, which are then incorporated into ML classifiers for categorization. This research study employs a DAG based 2D/3D layered CNN model as shown in Fig. 4 for automatically extracting characteristics from SMRI data, leveraging their strength in handling substantial volumes of visual information. The architecture remains the same for both 2D and 3D except that the layers are made to handle 2D and 3D data respectively. This variant is brought in to observe the magnitude of change in the classifier performance metrics, which 3D layers offers compared to the 2D layers in the suggested CNN framework. The proposed CNN framework uses multiple paths and concatenation layers to learn, extract, and combine diverse feature representations, improving the model's proficiency in appropriately classifying AD. The core structure of the proposed CNN framework comprises of four distinct layers: convolutional, normalization, pooling, and activation. The proposed model employs a total of six convolutional blocks, each composed of four layers, namely convolutional layer (CL), batch normalization (BN), max pooling (MP), and leakyRelu (LR) activation layer. The convolutional layer applies 3*3*3 kernel filtering to extract various characteristics from the input SMRI images, subsequently accompanied by a LeakyReLU activation, batch normalization, and max pooling to extract and condense the significant features from SMRI images effectively. These extracted features by pooling layer are fed to ML classifier. The pooling layer decreases the spatial dimensions of the feature maps, effectively decreasing the trainable variables and controlling overfitting. The BN layer helps to stabilize and speed up training by normalizing the inputs to the next layer. After passing through the series of convolutional blocks, the feature maps are transformed into a one-dimensional vector before being inputted into fully connected layers for final classification. Prior to feeding the data into the CNN, MRI images are pre-processed, resized to dimensions of 256x256x128, and normalized. The DAG based 3D-CNN was trained for 10 epochs with a learning rate of 0.001, using the Adam optimizer with categorical cross-entropy loss, employing a batch size of 8. The dataset's class imbalance was addressed by the use of class weights.

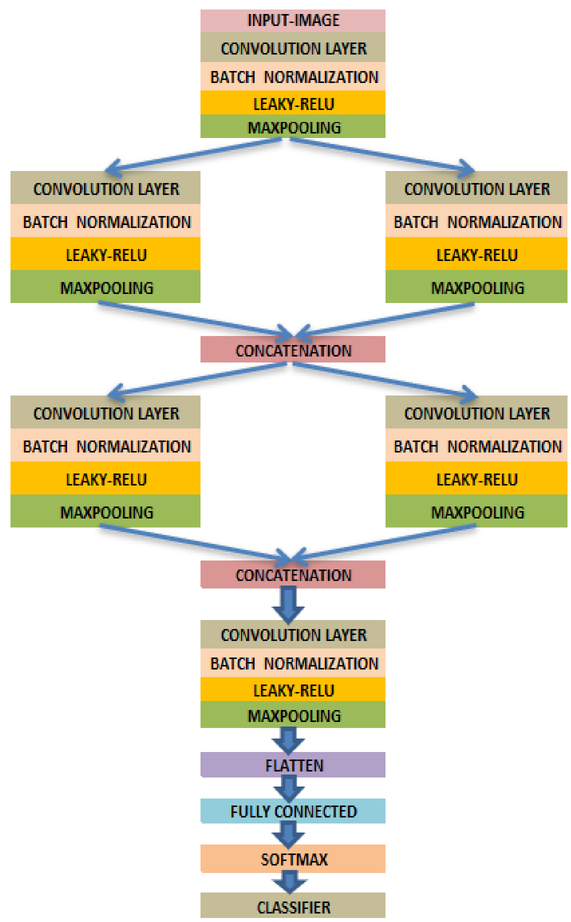


Fig. 4. Proposed DAG-CNN architecture.

1) Advantages of DAG-CNN over other architectures: The DAG structure enhances computational performance and minimizes redundancy in feature extraction compared to conventional CNN systems. In contrast to ResNets or DenseNets, which depend on unique skip connections, the DAG architecture offers a more universal approach for adaptive feature flow, especially advantageous for 3D data where spatial information is essential.

The integration of CNN and SVM arises from the use of their complementing advantages: CNNs excel at extracting deep, hierarchical features, whilst SVMs are particularly proficient in classification problems involving tiny or unbalanced datasets. This is especially pertinent in the early identification of AD where the quantity of the information often poses a constraint.

The CNN-SVM combination offers superior feature separation compared to end-to-end CNN classifiers, since SVM emphasizes optimizing the separation among classes in a high-dimensional space. This hybrid method guarantees that the retrieved characteristics are both deep and properly distinguished for classification, resulting in enhanced sensitivity and specificity.

D. Framework of the Proposed DAG Based 3D-CNN with SVM Classifier

The primary aim of this investigation is to improve upon existing approaches by modifying the architectures of CNNs to extract critical features and ML classifiers for accurate AD categorization. The proposed architecture shown in Fig. 5 has high capacity to produce innovative solutions that can efficiently detect Alzheimer's in its initial stages.

The use of hybrid DAG 3D-CNN with an SVM classifier has been demonstrated to be a very efficient methodology for a diverse array of classification jobs. The superiority of the DAG 3D-CNN with SVM lies in its hybrid nature. The proposed model by combining a CNN for characteristics extraction with an SVM for classification leverages the strengths of both techniques. The enhancement of classification performance, interpretability, and generalization ability is accomplished with the resilience of SVMs and the feature extraction capabilities of CNNs. Support Vector Machines (SVMs) use non-linear mechanisms and flexibility to enhance decision boundaries and accuracy, CNNs have a remarkable ability to obtain hierarchical and discriminative features from raw input data, which are crucial for identifying pathological changes associated with AD. Furthermore, the classifier incorporates the regularization properties of Support Vector Machines (SVMs), ensuring robustness against overfitting. The method shown in Fig. 5 depicts the flow of data through a hybrid DL and ML model for Alzheimer’s classification.

The SVM is a popularly used ML methodology utilized for categorization tasks. The methodology is specifically formulated to ascertain the hyperplane that optimizes the degree of differentiation between observations that correspond to different classifications. The mathematical formulation of the decision function for Support Vector Machines (SVM) is:

$$f(x) = sign(w.x + b) \quad (1)$$

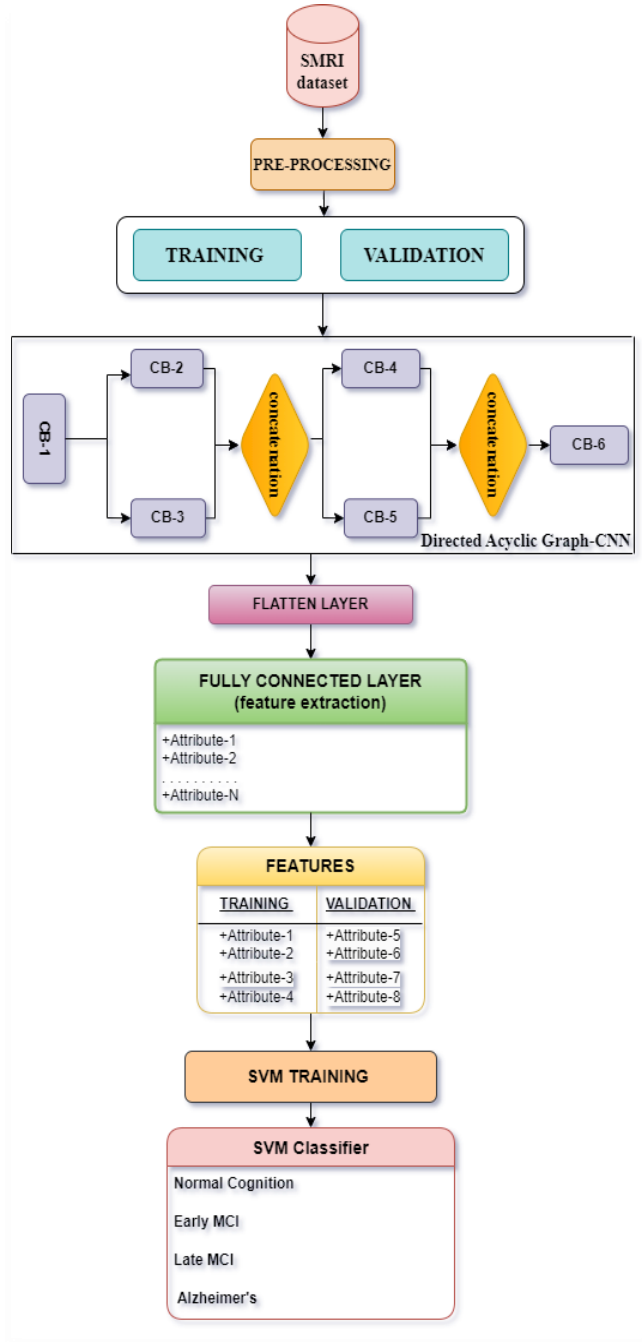


Fig. 5. Proposed DAG-CNN with SVM classifier.

where b is the bias factor, the weight vector is w, an input feature vector is x, and the sign function is denoted by sign(.). The distance between the nearest data point xi and the hyperplane known as support vectors is derived using the below Eq. (2).

$$distance(xi, hyperplane) = \frac{|w.xi+b|}{\|w} \| \quad (2)$$

$$\| \text{ w } \| = (\text{w}1^2 + \text{ w}2^2 \pm \ldots\ldots\ldots + \text{wn}\hat{}2)\hat{}1/2 (3)$$

where b is the bias factor, the weight vector is w, and ‖w‖ is the magnitude or Euclidean norm of weight vector and calculated as shown in Eq. (3), an input feature vector in n-dimensional space is xi. The margin is inversely proportional to the size of w. The main objective of SVM is to ascertain the ideal values of w and b coefficients that enable the attainment of the largest margin. The ideal values for the weight vector w and bias b are obtained by addressing an optimization problem that tries to increase the margin between classes while decreasing misclassification errors. In case of data that is not linearly separable, Support Vector Machines (SVM) include a slack variable xi for each data point. This variable allows for a certain degree of misclassification, striking a balance between maximizing the margin and minimizing errors. This results in an optimization problem in which the goal is to minimize the expression as shown in Eq. (3).

$$distance(xi, hyperplane) = \frac{1}{2} \parallel \mathrm{w} \parallel^2 + C.\Sigma\, \mathrm{xi} \tag{4}$$

where C determines the balance between the size of the margin and the penalty for misclassification.

IV. Results and Discussion

Timely identification is crucial in effectively controlling and perhaps slowing down the progression of Alzheimer's dementia, making it an essential area of investigation. Hence the primary objective of this current study is to develop a highly efficient hybrid AI model with the combination of DAG-CNN and SVM classifier that can identify AD by analyzing SMRI data.

Both Classification and early detection of AD are accomplished by using the proposed DAG CNN and SVM framework, developed using MATLAB 2022b. 80% of pre-processed images were utilized for training and 20% for validation.

AD may be classified as four different phases: Preclinical (Normal Cognitive), Early MCI, Late MCI, and AD. This research study attempted on three distinct binary classifications under three case studies.

- Case 1: EMCI Vs subjects with Normal Cognition (NC). This distinction is of utmost importance in detection of subjects in the initial stages of AD.
- Case 2: EMCI with LMCI
- Case 3: LMCI with AD

Initially, this study involved in extracting the volumetric features manually using the ITK-SNAP[43] cloud-based application, specifically focused on SMRI images. Around 22 volumetric characteristics were extracted from specific regions inside the hippocampus. These manually extracted features were fed as input for a SVM classifier, which yeilded an accuracy of 88.4% for discriminating EMCI with Normal Cognitive (case 1 scenario), which triggered the use of CNN-based automated feature extraction to achieve improved accuracy. Table I depicts the performance of an SVM model achieved for 22 manually extracted volumetric features shown in Table II from hippocampal subfields. The performance metrics are listed for SVM classifier.

Next, a 2D-CNN was designed and used to analyze 2D slices of the SMRI images available in the ADNI and KAGGLE repository. On the Kaggle dataset, the 2D-CNN module without an SVM classifier demonstrated a classification accuracy of 90.17% in differentiating between NC and EMCI, 98.98% in differentiating between NC and AD, and 90.43% in differentiating between EMCI and LMCI. The accuracy in distinguishing between NC and EMCI, AD and NC, and EMCI and LMCI using the 2D-CNN architecture without an SVM classifier were 94.20%, 89.97%, and 82.17% respectively, for the ADNI dataset. The suggested DAG 2D-CNN without the SVM classifier model's efficacy metrics for the Kaggle and ADNI datas+ets are presented in Table III.

However, since the accuracy was not optimal for all cases, the proposed CNN architecture with 2D layers was converted into 3D layers which is capable of processing the complete volumetric SMRI data and capturing the spatial connections inside the brain's structure to enhance the model's capability to accurately diagnose the Alzheimer's in early-stage. The suggested DAG 3D-CNN without the SVM classifier model's efficacy metrics for the ADNI dataset are presented in Table IV. The accuracy in distinguishing between NC and EMCI, AD and NC, and EMCI and LMCI using the 3D-CNN architecture without an SVM classifier were 96.86%, 90.45%, and 96.67% respectively, for the ADNI dataset.

The proposed DAG 3D-CNN with SVM classifier outperforms the 2D and 3D-CNN modules. With the ADNI dataset, the hybrid DAG 3D-CNN with the SVM model is 97.67 per cent accurate. Tables V and VI provide the performance outcomes of the hybrid DAG 3D-CNN with SVM classifier and the comparison of SVM model, 2D-CNN for ADNI and KAGGLE datasets & 3D-CNN with and without SVM models, respectively, to identify the Alzheimer's at an initial stage. The comparative analysis of different models and their performance for the ADNI and KAGGLE dataset is shown in Table VI. This evaluation considered five regions of interest (ROIs).

TABLE I. PERFORMANCE EVALUATION OF THE SVM CLASSIFIER FOR MANUALLY EXTRACTED VOLUMETRIC FEATURES OF HIPPOCAMPAL SUBFIELDS USING ITK-SNAP FOR ADNI DATASET

Classification	Accuracy	Precision	Sensitivity	F1 Score
NC with EMCI	**88.40**	86.60	94.00	0.90
EMCI with LMCI	80.40	80.70	80.40	0.80
LMCI with AD	86.00	94.00	78.00	0.85

Table I and Fig. 6 displays the efficacy metrics of an SVM classifier used for categorizing various phases of AD. The classification is determined by analysing 22 volumetric characteristics extracted from hippocampus subfields using the ITK-SNAP[43] tool, which are depicted in Table II. The classifier achieved 88.40% accuracy in differentiating EMCI from NC. The classification model achieved a precision of 86.60%, a sensitivity of 94.00%, and an F1 score of 0.90. These findings demonstrate that the classification method is very successful in identifying Alzheimer's in its first stages. Nevertheless, although achieving satisfactory outcomes, the accuracy remains inferior to the findings reported in the research literature. Thus, to improve the precision and efficacy of prompt identification, our research study has shifted to

CNN-based automated feature extraction, yielding superior outcomes.

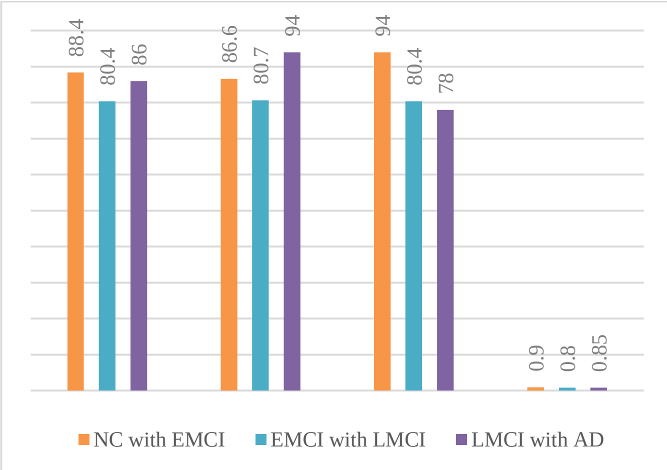


Fig. 6. Performance metrics of SVM classifier.

TABLE II. VOLUMETRIC FEATURES EXTRACTED FROM THE HIPPOCAMPUS SUBFIELDS FOR EARLY DETECTION AND CLASSIFICATION FROM ADNI DATASET

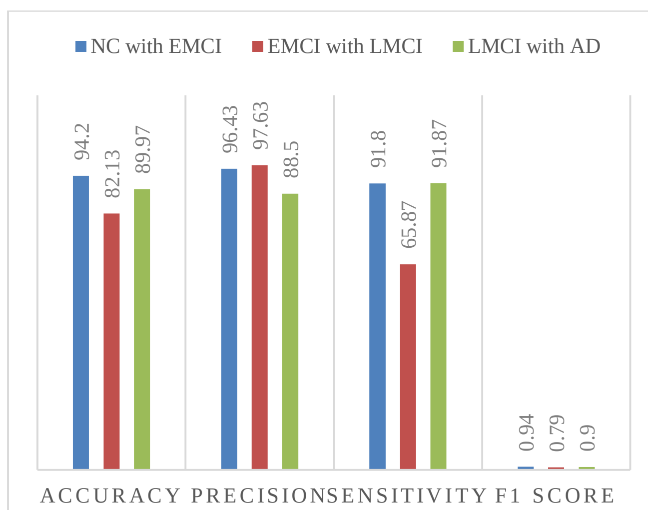
22 Volumetric Features extracted from the hippocampus subfields			
Sl. No.	Left Hippo	Sl. No.	Right Hippo
1	Left CA1 (Corno Ammonis 1)	12	Right CA1 (Corno Ammonis 1)
2	Left CA2	13	Right CA2
3	Left CA3	14	Right CA3
4	Left DG (Dentate Gyrus)	15	Right DG (Dentate Gyrus)
5	Left Tail	16	Right Tail
6	Left Sub (Subiculum)	17	Right Sub (Subiculum)
7	Left Erc (Entorhinal Cortex)	18	Right Erc (Entorhinal Cortex)
8	Left A35	19	Right A35
9	Left A36	20	Right A36
10	Left Phc (Parahippocampal Cortex)	21	Right Phc (Parahippocampal Cortex)
11	Left Cysts	22	Right Cysts

The hippocampus has morphologically and functionally diverse subfields that differ in AD susceptibility. Early AD begins with tau buildup and neuronal loss in CA1.Though seldom studied, recent findings suggest CA2 role in social memory and pathological changes in AD. CA3 and Dentate Gyrus (DG) are Essential for pattern separation. structural changes may cause early cognitive impairment. The entorhinal cortex (ERC) and perirhinal cortex (PHC), which are crucial for hippocampal input and output, are among the first areas to atrophy in AD. Object recognition and memory encoding depend on the perirhinal cortex near the hippocampus. Since A35 and A36 allow hippocampus-cortical memory network connection, neurodegeneration in these regions corresponds with cognitive difficulties in early AD. Recent studies show that volumetric abnormalities in these regions suggest pathogenic processes like tau accumulation, and include them in the feature set improves sensitivity to early AD changes. Fluid-filled hippocampal cysts may suggest neurodegenerative processes including gliosis or vascular changes. Cystic changes, seldom seen in AD, may be linked to structural atrophy in nearby hippocampus subfields, improving hippocampal health assessment.

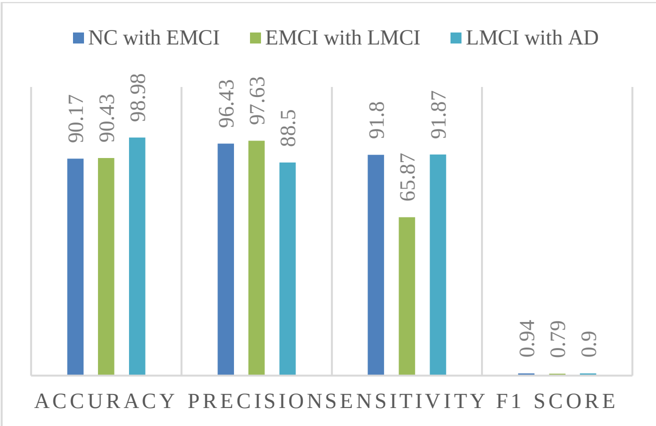
TABLE III. COMPARISON OF THE EFFICACY OF THE PROPOSED DAG 2D-CNN CLASSIFIER ON THE ADNI AND KAGGLE DATASETS

Classification	**dataset**	**Accuracy**	**Precision**	**Sensitivity**	**F1 Score**
NC with EMCI	adni	**94.20**	96.43	91.80	0.94
EMCI with LMCI		82.13	97.63	65.87	0.79
LMCI with AD		89.97	88.50	91.87	0.90
NC with EMCI	kaggle	**90.17**	86.86	87.05	0.87
EMCI with LMCI		90.43	89.82	97.54	0.94
LMCI with AD		98.98	98.97	100.00	0.99

Table III presents a comparison of the efficiency of the proposed framework on two datasets, namely ADNI and Kaggle. The results are shown in Fig. 7(a) and 7(b). The model is evaluated by measuring its performance metrics across three classification tasks: distinguishing EMCI from NC, LMCI from AD, and EMCI from LMCI. The model achieves high accuracy on both datasets for distinguishing EMCI from NC, with the ADNI dataset slightly outperforming the Kaggle dataset. The model shows very high accuracy and F1 score, especially on the Kaggle dataset, indicating excellent efficacy in differentiating LMCI from AD. The model performs the lowest on this classification for distinguishing EMCI from LMCI, particularly on the ADNI dataset, where sensitivity is much lower compared to the Kaggle dataset. Overall, the model demonstrates strong performance in distinguishing NC from AD, with somewhat lower performance for differentiating EMCI from LMCI



(a)



(b)

Fig. 7. (a) Performance metrics of 2D-CNN for ADNI data (b) Performance metrics of 2D-CNN for Kaggle.

TABLE IV. PERFORMANCE OF PROPOSED HYBRID DIRECTED ACYCLIC GRAPH 3D-CNN CLASSIFIER FOR ADNI DATASET

Classification	Accuracy	Precision	Sensitivity	F1 Score
NC with EMCI	**96.86**	100	95.04	0.97
EMCI with LMCI	90.45	94.42	90.50	0.92
LMCI with AD	96.66	96.87	96.66	0.96

Table IV shows the efficiency metrics of the suggested DAG 3D-CNN model for the ADNI dataset. The model demonstrates strong performance in distinguishing EMCI from NC and has achieved an accuracy of 96.86%. The model has remarkable performance, achieving perfect precision, a sensitivity of 95.04%, and an F1 Score of 0.97%. The model efficacy metrics are plotted and shown in Fig. 8.

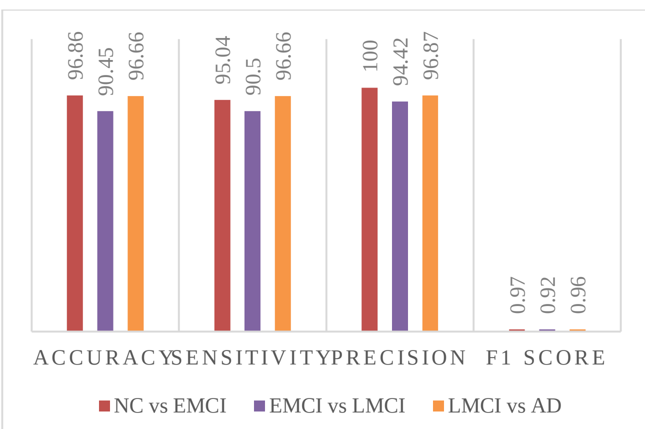


Fig. 8. Performance metrics of 3D-CNN.

TABLE V. PERFORMANCE OF PROPOSED HYBRID DIRECTED ACYCLIC GRAPH 3D-CNN WITH SVM CLASSIFIER FOR ADNI DATASET

Classification	Accuracy	Precision	Sensitivity	F1 Score
NC with EMCI	**97.67**	94.12	98.60	0.96
EMCI with LMCI	98.33	96.86	96.86	0.96
LMCI with AD	100	100	96.67	0.98

Table V shows the efficiency metrics of the suggested DAG 3D-CNN with the SVM classifier model for the ADNI dataset. The model demonstrates strong performance in distinguishing EMCI from NC and has achieved an accuracy of 97.67%. The model has remarkable performance, achieving perfect precision, a sensitivity of 98.60%, and an F1 Score of 0.96%. The model efficacy metrics are plotted and shown in Fig. 9.

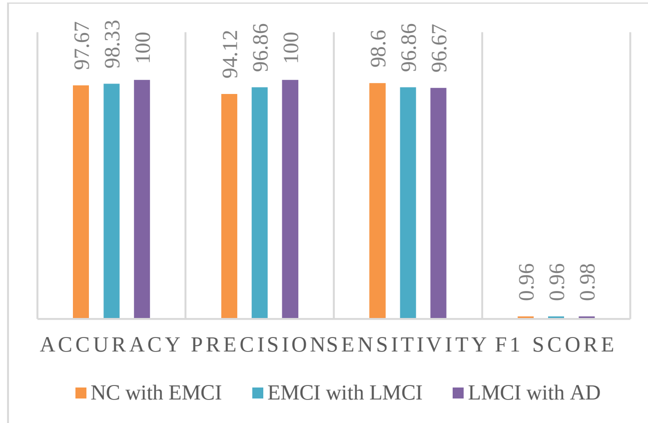


Fig. 9. Performance metrics of 3D-CNN with SVM.

TABLE VI. COMPARATIVE ANALYSIS OF THE PROPOSED MODELS FOR EARLY DETECTION OF AD

Method	Accuracy	Precision	Sensitivity	F1 Score
SVM with manually extracted features (ADNI)	**88.40**	86.60	94.00	0.90
2D-CNN (Kaggle)	**90.17**	86.86	87.05	86.96
2D-CNN (ADNI)	**94.20**	96.43	91.80	94.06
DAG 3D-CNN (ADNI)	**96.86**	100	95.04	0.97
DAG 3D-CNN with SVM (ADNI)	**97.67**	94.12	98.60	0.96

Table VI displays the performance measures for five distinct models employed in the early identification and categorization of AD. An SVM classifier with manually extracted features achieved 88.40% accuracy in discriminating early MCI with normal cognitive. The 2D-CNN model achieved a 90.17% accuracy when trained on Kaggle data. However, when trained on ADNI data, the same model performed better, with an accuracy of 94.20%. The DAG 3D-CNN model achieved a 96.86% accuracy when trained on ADNI data. The DAG 3D-CNN with SVM classifier surpassed all other models, with an accuracy of 97.67%. The five distinct model's Accuracy values are plotted and shown in Fig. 10.

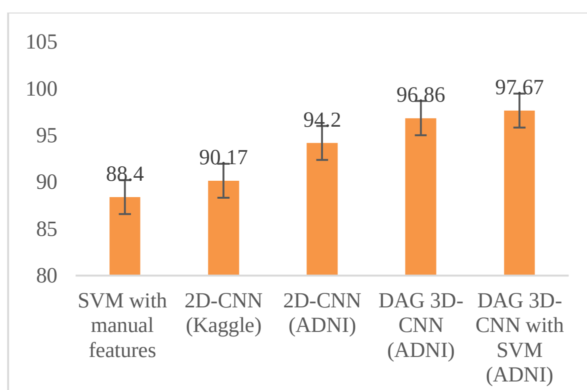


Fig. 10. Performance metrics of the proposed models.

TABLE VII. THE ACCURACY COMPARISON OF PROPOSED MODEL WITH VARIOUS ALGORITHMS FOR EARLY ALZHEIMER'S DISEASE DETECTION

Ref. No.	Dataset used	Algorithms used	Accuracy
B. K. Choi et al. [32]	Adni	2D-CNN	78.1%
M. Ghazal et al. [33]		3D deeply supervised adaptable CNN	93.2%
S. Basaia et al. [34]		DL and CNN	87.1%
C. Feng et al. [35]		3D-CNN & FSBi-LSTM.	86.36%
Archana B et al. [36]		CNN	95.82%
R. Joshi et al. [37]		Densenet-169	91.80%
C. Kaur et al. [38]		Random Forest	86.24%
S. Samanta et al. [39]		CNN	85.73%
B. Kumar Yadav et al. [40]		CNN	94.57%
A. J. Nair et al. [41]		VGG	90.34%
F. Hajamohideen et al. [42]		Siamese CNN	91.83%
Proposed model		SVM with manually extracted features	88.40%
Proposed model	Kaggle	2D-CNN	90.17%
Proposed model	Adni	2D-CNN	94.20%
Proposed model		3D-CNN with DAG	96.86%
Proposed model		3D-CNN with DAG and SVM classifier	97.67%

Table VII presents a comparison of the efficiency of several methods for the ADNI and Kaggle datasets. The suggested model, which used a 3D-CNN combined with an SVM classifier, produced an impressive accuracy of 97.67%, Additional models, such as 3D-CNN without SVM attained 96.86% and those using 2D-CNNs, achieved high performance as well, with accuracies of 94.2% for ADNI and 90.17% for the Kaggle dataset respectively. The comparison clearly illustrates the better efficacy of the suggested approach, especially the DAG 3D-CNN with the SVM classifier, which attains the best accuracy of 97.67%. The performance metrics of various algorithms are plotted and shown in Fig. 10.

A. *Discussion*

This research aimed to create and assess sophisticated DL methodologies for the early identification of AD via SMRI datasets, employing both 2D and 3D CNN architectures in conjunction with an innovative integration of SVM classifiers. The suggested strategies shown substantial improvements in classification accuracy relative to current approaches in the literature.

Numerous recent researches have used DL methodologies for the categorization of AD, resulting in differing degrees of efficacy. B. K. Choi et al. [32] used a 2D-CNN, attaining an accuracy of 78.1%, hence underscoring the constraints of conventional 2D convolutional techniques. Advanced models, such as the 3D deeply supervised adaptive CNN by M. Ghazal et al. [33], demonstrated an accuracy of 93.2%, while frameworks like FSBi-LSTM integrated with 3D-CNN by C. Feng et al. [35] attained 86.36% accuracy.

The suggested 3D-CNN using a DAG architecture attained an accuracy of 96.86%, surpassing the majority of documented research. The integration with an SVM classifier enhanced performance to 97.67%, establishing a new standard in AD classification accuracy, exceeding prior benchmarks established by models such as Densenet-169 (91.80%) by R. Joshi et al. [37] and Siamese CNN (91.83%) by F. Hajamohideen et al. [42]. This notable improvement is due to the DAG architecture's capacity to capture complex spatial information in SMRI data and the SVM's effective decision boundary optimization. The results indicate the capability of automated systems to offer dependable assistance in clinical decision-making for the early identification of AD.

B. *Clinical Significance of the Findings*

1) Early diagnosis: Our approach, integrating 3D-CNN with SVM for the early identification of AD, facilitates diagnosis in its first stages, perhaps prior to the onset of clinically observable cognitive impairment. Early identification is essential for prompt interventions, such cognitive therapy or pharmaceutical treatments, which may decelerate illness development.

2) Customized therapy: By pinpointing certain parts of the hippocampus afflicted in initial phases of AD, our approach may facilitate the development of individualized therapy techniques, focusing on the brain areas most severely impacted by the condition.

3) Monitoring illness progression: The volumetric alterations in the hippocampus subfields may function as biomarkers for assessing illness progression over time, providing a non-invasive instrument for doctors to evaluate treatment effectiveness and disease trajectory. The methodology may be applicable.

V. CONCLUSION

This research work introduces a novel method for the timely identification of AD via Structural MRI images. The proposed strategy utilizes deep neural networks i.e. DAG 3D-CNN for significant characteristic features extraction followed by SVM as a classifier. The model is trained and assessed by employing the Kaggle and ADNI datasets. For the Kaggle and ADNI datasets, the 2D-CNN module being evaluated offered an accuracy of 90.17% and 94.20%, 3D-CNN without SVM offered an accuracy of 96.86% and the hybrid 3D-CNN module with SVM classifier presented a superior accuracy of 97.67% in detecting EMCI subjects, respectively. This proves that the hybrid framework is relatively good and suitable for early detection and classification for all three case studies dealt in this research work. The efficacy of the suggested DAG 3D-CNN with SVM classifier technique in early Alzheimer's (AD) diagnosis shall be improved by training the network with additional clinical information, and by enhancing the number of ROIs used in the study.

A. *Limitations and Future Work*

This study, like other studies, has certain limitations that must be acknowledged. The sample size and insufficient demographic diversity may restrict the model's generalizability to wider groups. Subsequent research should use bigger and more heterogeneous datasets to corroborate the model's resilience across other demographics. Secondly, while this work used a 3D-CNN for SMRI data, the integration of other imaging modalities like PET and fMRI might significantly improve classification accuracy and diagnostic capabilities. Despite these constraints, this work establishes a significant basis for enhancing automated detection techniques for AD and highlights critical avenues for further research.

Future research areas include investigating multimodal fusion by integrating SMRI with other imaging techniques like PET and fMRI, so offering a more holistic perspective on AD pathology and enhancing model efficacy. Furthermore, using longitudinal research to observe temporal changes may facilitate the building of prediction models capable of both early detection of AD and monitoring its advancement. Incorporating clinical data, including cognitive scores and genetic information, might significantly improve the model's accuracy and personalization, allowing more customized treatment strategies for AD patients. Ultimately, exploring other DL methodologies, such attention processes or reinforcement learning, might enhance model efficacy in intricate neuroimaging tasks.

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