Capsule Network-Based Multi-Modal Neuroimaging Approach for Early Alzheimer's Detection

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***Abstract*—Alzheimer's Disease (AD) is a terminal illness affecting the human brain that leads to deterioration of cognitive function and should therefore be diagnosed as early as possible. The goal of this work is to come up with a precise and interpretable diagnostic model for the early diagnosis of Alzheimer's Disease (AD) based on multi-modal neuroimaging data. Current deep learning models such as Convolutional Neural Networks (CNNs) are limited in that they lose spatial hierarchies in 3D medical images, which inhibits classification performance and interpretability. To overcome this, in this work, we introduce a new 3D Capsule Network (3D-CapsNet) framework that captures spatial relations more effectively with dynamic routing and pose encoding to improve volumetric neuroimaging data analysis. Our approach has three principal phases: extensive pre-processing of MRI and PET scans such as skull stripping, intensity normalization, and motion correction; feature extraction through the 3D-CapsNet model; and multi-modal classification based on fusion. We used the Alzheimer's Classification dataset from Kaggle for training and testing. The model is implemented in the Python platform with TensorFlow and Keras libraries incorporating 3D CNN operations along with capsule layers to extract fine-grained features of AD-affected brain areas such as the hippocampus and entorhinal cortex. Experimental results show that our model reaches a very high classification accuracy of 92%, which is higher than the conventional architectures VGG-16, ResNet-50, and DenseNet-121 in accuracy, precision, recall, F1-score, and AUC-ROC. This strategy is helpful to clinicians and medical researchers because it gives them a non-invasive, interpretable, and trustworthy tool for diagnosing and monitoring various stages of AD (Non-Demented, Very Mild, Mild, and Moderate). It sets the stage for real-time clinical integration and future studies in monitoring disease progression over time.**

Keywords*—Alzheimer's detection; 3d-capsule networks; multi-modal neuroimaging; deep learning in healthcare; early diagnosis and classification

I. Introduction

Alzheimer's disease (AD) is a chronic neurodegenerative disease which clinically manifests itself mainly through the impaired elements of cognition including of memory, thought co-ordination, and behavior. Alzheimer is the most common type of dementia being a contributing factor to nearly 60–80% of dementia globally [1]. AD is one of the major global health issues affecting millions of people, growing evidence suggest that there will be threefold increase in worldwide incidence rate of this disease by 2050 [2]. To date, no cure has been found for AD and the management of the condition is largely done without trying to halt the progress of the disease directly. But early diagnosis is essential as it may considerably defer disease progression, as changes in diet or medicines, or other forms of cognitive treatment, may help slow down dementia progression and enhance the patient's quality of life. However, due to non-specific and overlapping signs and symptoms the diagnosis of the disorder in the early stage has not been easy.

It seems that the previously used general approaches for AD identification include clinical examination, neuropsychological testing, and neuroimaging tools such as MRI, PET, and CT, which demand the opinion of an experienced specialist concerning structural/functional changes in the brain. These time-honored techniques, though have been proved to work, are tedious, methodical, least accurate and present the problem of inter-observer variability [3]. A sample AD diagnosis using deep learning has been enhanced, especially CNNs for the extraction of more features on neuroimaging data [4]. But the CNNs have certain issues like ignoring/disregarding of the spatial hierarchy given by pooling function such as max–pooling, non-equivariant feature learners and less ability to recognize the intricate changes in the shape patterns of the brain. This is true because some features are lost or misclassified, especially when

detecting early-stage AD where structural brain alterations are minimal [5].

The problems that arise while using the CONV based model, there is study interest in the development of more complex deep models that preserves spatial hierarchies for Alzheimer's detection [6]. There is one framework that has proposed as one possible solution, which is the 3D-CapsNets, which provide a significant leap over CNNs by maintaining the spatial relations for regions in the brain and providing improved features. While CNNs work with scalar neuron activations, CapsNets consist of vector-based capsules to determine the presence of features and their orientations in images and thereby, helping to reduce the misclassification arising from image rotation in brain imaging. More also, single modality neuroimaging techniques do not give comprehensive information about the pathological progression of the disease because each evaluates a unique aspect of Alzheimer [7]. Multi-modal analysis is essential for increasing classification efficiency since it brings structural, metabolic, and functional information regarding possible changes in the human brain [8]. However, the current methods of fusing multi-modal information have major flaws in the way they combine the features of the different modes, hence causing loss of some valuable information [9]. To overcome these limitations, a novel multi-modal deep learning framework based on the Capsule Network is developed to enhance the generalization of the classification by making an effective use of various Neuroimaging data Types while maintaining the spatial correlation that is productive in early AD diagnosis. In addition, to achieve high accuracy of the model, the neuroimaging data has to undergo several preprocessing steps for removing artifacts, non-brain regions, and intensity variation which may affect the performance of the model [10]. Skull stripping is an essential step that aims to get rid of the probable interference from non-brain organs such as scalp, skull, and dura [11]. Nevertheless, the existing methods of skull stripping can be completely or partially inaccurate, which entails information loss or presence of artifacts. To improve the preprocessing efficiency, this study compares FSL BET and Deep BrainSeg in the skull stripping process so as to have enhanced clean inputs for classification.

The main goal of this study is to propose a more effective and reliable construct of a deep learning model for recognizing the early modality of Alzheimer's through Capsule Network based multi-modal neuroimaging [12]. In particular, there should be the use of 3D-CapsNets for feature extraction and enabling the recognition of part-whole hierarchies of human brain structures to determine different stages of Alzheimer's. Multi-modal neuroimaging information combining MRI, PET, and CT scans is applied for enhancing the classification performance and utilizing the additional data for the classification of Non-Demented, Very Mild Demented, Mild Demented, as well as Moderate Demented stages [13]. Skull stripping is used in enhancing the preprocessing of neuroimages data by removing unwanted structures that are not brain tissue, hence providing enhanced and quality input images [14]. In addition, the paper compares 3D-CapsNets with conventional CNN-based models with the help of accuracy, precision, recall, F1-score, and ROC-AUC curves to prove the mentioned framework. Therefore, the utility of the model in real-life scenarios regarding its computational time, its validity across other datasets, and possibility of implementation in clinical practice is considered [15]. In this manner, these objectives of the study will help to address the gap of the use of AI deep learning methods for clinical neuroimaging applications and offer method, which is powerful, interpretable, and automated in diagnosing Alzheimer's disease at the early stage, for better management of patient.

The selection of the suggested 3D-Capsule Network (3D-CapsNet) model was based on its intrinsic potential to preserve spatial hierarchies and pose data during dynamic routing, which is very important for identifying slight structural variations in neuroimaging data characterizing Alzheimer's disease. The regular CNNs tend to lose important spatial relationships through pooling operations, while CapsNets preserve part-whole relationships, making it possible for better early-stage anomaly detection. In addition, 3D-CapsNets suit volumetric medical images like MRI, PET, and CT scans better because they present a better representation of brain structures. These factors render the model particularly well-adapted to the challenging task of multi-stage Alzheimer's diagnosis.

A. Study Contributions

This study enhanced deep learning model called 3D Capsule Networks (3D-CapsNets) to detect early stage of Alzheimer's disease, given that existing models based on CNNs are seen to have the problem of losing spatial information because of pooling layers. In this way, the anatomical relationship is maintained with other support of vector-based feature encoding and dynamism in the routing to ramp up biomarker identification. The feature of multi-modal imaging that is most important for this research is directly related to MRI for structural changes, PET for metabolic activity and CT for better definition of neuroanatomy to detect Alzheimer's pathology. This illustrates a great enhancement in the classification performance compared to when using a single modality. The result of the extensive experiment also reveals the superiority of the proposed 3D-CapsNet model over traditional one.

CNN structures such as VGG-16, ResNet-50, and DenseNet-121 by both the considerations of accuracy and time. The wellness of the skull stripping process proceeds input preprocessing by intensifying the quality of the input that go through advanced preprocessing techniques of intensity normalization and motion correction. In conclusion, the present study contributes a very efficient and closely realistic model for computerized identification of Alzheimer's disease. The key contribution of the study is given below:

- Suggested the use of a 3D-CapsNet model in order to maintain the spatial hierarchies in the spectrum for accurate identification of AD.
- Multi-modal neuroimaging data such as MRI, PET, and CT for accurate diagnosis of the disease.
- Usual preprocessing methods such as skull stripping, intensity normalization and motion correction were performed.
- Derived better classification accuracy over other CNN models, including accuracy, F1-score, AUC-ROC.

- In order to file the interpretation process, CapsNet activation was visualized, and the model was designed for further clinical implementation.

By so doing, this study presents a clinically relevant AI method for the automation of ALZ diagnosis with interpretability which can enhance its deployment based on neuroimaging techniques.

II. Literature Review

Currently, several methods for Alzheimer's disease (AD) detection were based on the usage of Multi-layer and Deep Learning algorithms with the support of neuroimaging [16]. Several ML algorithms such as SVMs and RFs work normally and demand an intermediate feature extraction, which is time-consuming [17]. The use of CNNs paved way for better automated diagnosis as the networks directly provided the hierarchical feature mapping of brain scans [18]. However, CNNs lack the ability to handle 3D volumetric data, flatten the spatial hierarchies after using max-pooling, and they are sensitive to affine transformations and therefore early-stage AD is misclassified frequently. Also, CNNs are dependent on large labeled datasets, and most of them are difficult to explain, thus not so suitable for clinical applications [19]. The other issue in the use of neuroimaging for diagnosis of AD is that of standardization of the approaches employed. MRI shows a shrinkage of the hippocampus while PET scans demonstrate disfunctioning in the area and high-resolution images are produced using CT scans. Nevertheless, single modality imaging does not depict the entire spectrum of the glycogen storage disease pathology [20]. Combination of these techniques as a multi-modal neuroimaging improves the classification accuracy result but it has some problem like dissimilarities in resolution and in registration. This is done through Capsule Networks introduced by Geoffrey Hinton where spatial hierarchies are maintained by using vector-based capsules as opposed to scalar neuron activations. The CapsNets do not utilize the max pooling activation function, instead, it uses the dynamic routing that maintains the spatial relationships which is important in medical image analysis unlike the CNNs. CapsNets have been performing better than CNNs in medical image classification, but most of them are performed on 2D medical images and therefore they are not very efficient in dealing with volumetric neuro imaging. An extension of CapsNets to 3D-CapsNets is proposed here, which enhances the former's ability to handle volumetric data and better generalization and operational stability in terms of imaging changes [21]. Sarker, in his review in the International Journal of Molecular Sciences also points at some of the limitations in the detection of AD where early diagnosis is compromised by poor ML models, biomarkers such as amyloid plaques and tau proteins mostly lack reliability, diagnosis involving cost-intense procedures such as lumbar punctures and PET scans, and diagnostic subjectivity that even leads to bias. It also has an undesired effect of contributing to the further delay in diagnosing AD due to the absence of a guidelines on screening for biomarkers in every patient. These limitations are overcome by developed early diagnosis with the help of 3D-CapsNets that can identify the slight modifications in the brain before the clinical signs appear and identification of brain disorder with the help of Multi-Modal Neuroimaging. PET-MRI-CT fusion is an improved method that integrates structural changes in the brain as well as functioning changes to improve detection [22]. Functional connectivity changes in fMRI are the novel biomarkers using AI-driven models that maintain the spatial hierarchy and increase diagnostic accuracy in disorders. The employment of artificial intelligence in screening AD is improving the screening without using invasive procedures or expensive PET scans. CapsNets create easily explainable and normalizing evaluations thus eliminating or reducing the influence of examiner bias. It allows for the real-time analysis of neuroimaging data, to perform multi-modal imaging in a worldwide scramble environment. Artificial Intelligence help to enhance classification and increase the model's scalability by maintaining spatial orientation in 3D models. It also helps in distinguishing between AD and other sorts of dementias like Parkinson's or Lewy body dementia [23]. Also, the component highlights disease prognosis in AI models regarding the progression of a patient's condition and neuroimaging for treatment monitoring [24]. The review analyzes CNN and diagnostic limitations together how Caps Nets and Multi-Modal Neuroimaging present opportunities for AD detection through automated diagnosis which is both accurate and cost-efficient. The study targets present field obstacles to achieve progress in early diagnosis of Alzheimer's disease while enhancing medical results for patients [25]. Table I shows the summary of existing studies.

TABLE I. Summary of Existing Studies

Source	Purpose	Advantages	Limitations
Deep Learning-Based Diagnosis of Alzheimer's Disease	To explore ML and DL models in AD diagnosis	Showcases DL models for automatic AD diagnosis	Lacks info on model limitations
Utilizing Multi-Class Classification Methods…	Describes use of SVMs, RFs for disorder prediction	Highlights classical ML models	Time-consuming due to feature extraction
ScienceDirect: Multi-Modal Neuroimaging Methods	Shows how CNNs are used in automated AD diagnosis	CNNs directly learn hierarchical features	Cannot handle 3D data well, loses spatial info with max pooling
Pattern Recognition in Spectral Analysis	Evaluates CNNs in medical imaging	Identifies CNN strength in image classification	CNNs need large labeled data and lack explainability
Imaging Methods Applicable… Insulin Resistance	Explains different neuroimaging modalities for AD	MRI, PET, CT reveal various brain aspects	Single modality lacks complete view; modality mismatch issues
Geoffrey Hinton - Capsule Networks	Introduces CapsNets to maintain spatial hierarchies	Avoids max pooling, uses dynamic routing	Initially designed for 2D images
Deep Learning Techniques for Alzheimer's: A Review	Proposes 3D-CapsNets to handle volumetric data	Maintains spatial relationships; better generalization	Requires more computational power
Sarker – IJMS Review	Critiques current AD diagnosis strategies	Addresses limitations of ML, biomarkers, invasive scans	Highlights subjectivity, cost, and lack of early markers

Multimodal Medical Image Fusion Techniques	PET-MRI-CT fusion to improve detection accuracy	Combines structure and function insights	Dissimilarity in resolution and registration challenges
Biomarkers of Dementia with Lewy Bodies	Differentiates AD from other dementias	Uses AI for better differentiation	Biomarker overlap may affect clarity
Vrahatis et al., 2023	Analyzes prognosis, AI's role in treatment monitoring	Supports progression tracking and scalability	Still evolving and not standardized
Alzheimer's Disease: Treatment Strategies	Summarizes the gap between diagnosis and treatment	Calls for cost-efficient AI solutions	AD progression still hard to model

III. Problem Statement

The early diagnosis of Alzheimer's Disease (AD) should be conducted because this type of neurodegeneration progressively affects cognition, memory, and daily tasks. This has always presented a major problem since the conventional diagnostic methods include clinical assessment and neuropsychological testing are usually subjective, have accurate results and take time before a patient is diagnosed. Machine learning specifically use CNN for neuroimaging data analysis and challenges. These are the effects of max pooling that cause the loss of spatial relationships, the failure to generalize and the sensitiveness to variations in the data. Also, the use of a single neuroimaging technique may fail to provide both functional and structural changes relevant to AD. Moreover, in most of cases, the conventional algorithms appear to be inefficient for solving such issues with the interpretation of stereoscopic and 3 Dvolumetric structures which cause misclassification in the initial stages of the disease. In order to meet the needs of these challenges, this study proposes deep learning framework known as 3D Capsule Networks (3D-CapsNets) that preserves the spatial organization and relation between the parts and the whole in the structure of the brain. Whereas MRI scans primarily inform about structural alterations, PET scans provide information on metabolic alterations and CT scans depict the lesions. These include skull stripping, which helps get rid of extraneous skull signals, intensity normalization that helps equalize the intensities of different scans and motion artifact removal process which helps rid the input data of interfering movements. The characteristics of the 3D-CapsNet model help with interpretation and increases the accuracy of the classification of structural and metabolic differences. The key objective of this approach is to develop a feasible, robust and adaptive real-time diagnostic tool for AD that would be capable to aid immediate and individualized intervention for the patient.

IV. Methodology

Study proposed approach integrates several brain scan types (MRI, PET, CT) to detect Alzheimer's using 3D Capsule Network architectures (3D-CapsNets). Prepare images through skull removal and normalize intensity levels while removing movement problems to create better quality data. Data enhancement strategies that modify images by transformation and contact with noise improve how the model works with different data sets. Caps Nets create better feature representations compared to other models because they maintain spatial hierarchy across elements.

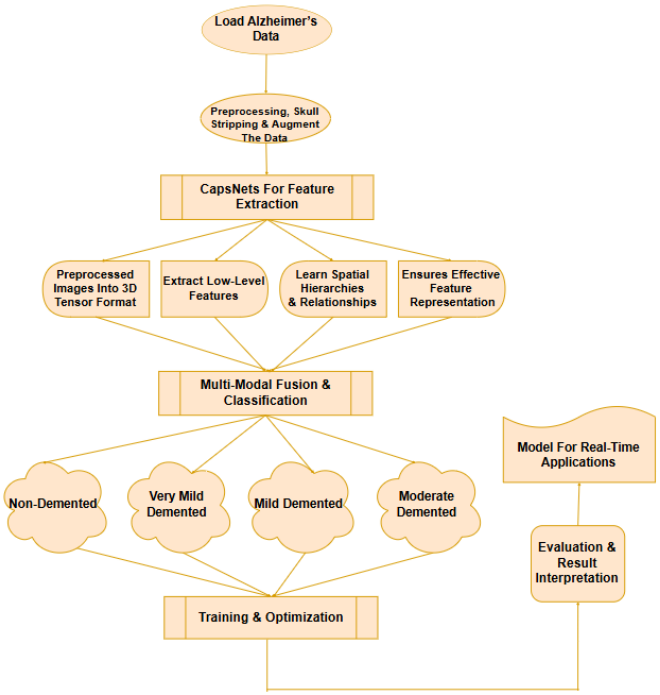

Fig. 1. Implementation of early Alzheimer's detection.

Fig. 1 shows the early execution of Alzheimer's detection. The model undergoes updated parameter changes plus decision making systems during training to develop solid learning methods. Specific evaluation methods test performance through accuracy metrics plus precision, recall, F1-score and AUC-ROC curves when comparing with standard deep learning methods.

A. Dataset

The datasets that are taken from Kaggle resource [26] for their study on detecting early signs of Alzheimer's using Capsule Networks and Mixed Neuroimaging Methods because these datasets contain the high-quality MRI PET and CT scan data necessary to analyze different forms of brain scans together. Dataset features four distinct groups including healthy subjects and patients with Very Mild Demented, Mild Demented and Moderate Demented stages of Alzheimer's disease. Split keeps equal numbers of samples across every class while setting a training and testing sections. Each brain imaging technique requires skulls to be removed so it can see clear features through BET, ROBEX, or an advanced method. To help the model work better the data needs extra preparation through modifications that normalize brightness levels and remove movement defects plus reduce noise. It follows all ethical rules of HIPAA and IRB to protect patient privacy and keep their personal information hidden. It standardized data practices help multiple measurement tools work the same way to lower measurement errors. The training data improves from multiple angles when the model adds random rotations, flips, and changes image brightness levels. The suggested model needs ethical datasets and standardized information to detect Alzheimer's disease progression and aid early treatment. The attributes of the dataset are shown in Table II.

TABLE II. DATASET USED FOR ALZHEIMER'S CLASSIFICATION

Class Label	MRI Samples	PET Samples	CT Samples	Total Samples
Non-Demented (ND)	2,500	1,800	1,200	5,500
Very Mild Demented (VMD)	2,000	1,500	1,000	4,500
Mild Demented (MD)	1,800	1,400	900	4,100
Moderate Demented (MOD)	1,500	1,100	800	3,400
Total Samples	7,800	58,000	3,900	17,500 [27]

B. Image Preprocessing

First processing neuroimaging images becomes essential for building effective deep learning models that detect Alzheimer's. Preparation steps prepare brain scans by clearing skull areas while matching brightness levels before handling movement problems and creating extra samples for strong model success.

1) Skull stripping: Neuroimaging study needs skull stripping which removes brain tissue parts like skull bone from MRI scans to help investigation accuracy. The Brain Extraction Tool from FMRIB Software Library uses a deformable surface model to systematically improve brain mask detection by erasing unwanted tissue elements.

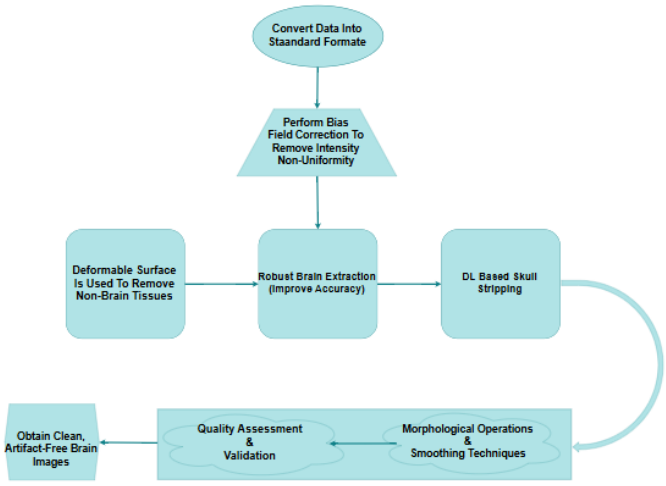

Fig. 2. Work flow of skull stripping.

Fig. 2 depicts the working process of skull stripping. BET calculates the brain's location in space to set up its spherical expansion surface which sticks to the tissue shape while pushing away surrounding elements. Under extreme noise BET may remove brain tissue areas or retain skull remnants from the processed image. RBE uses a combined technique of statistical and machine-learning models to deal with diverse brain imaging settings and data changes. By applying thresholding methods and region-growing techniques alongside brain anatomy understanding RBE produces a better brain segmentation result than manual operations. Modern Deep Learning technology with CNNs and U-Net architectures now removes skulls better than older manual rules and anatomical methods.

These models process many brain image records to learn patterns that enable them to handle different scanners and patient populations. DeepBrainSeg shows exceptional skull stripping results because it uses deep learning to discover brain organization in many medical images regardless of intensity changes and brain shape differences. The deep learning approaches effectively adjust to various MRI inputs which helps detect Alzheimer's disease better and also lowers human involvement when preparing high-quality datasets.

2) Intensity normalization: Data normalization keeps MRIs PET and CT scans comparable through their pixel intensity ranges no matter which scanner produced them. Techniques include:

- Min-max normalization – By scaling intensity values to values from 0 to 1 the technique makes results easier for processing.
- Histogram matching – This technique matches how different subjects display image brightness patterns to keep results consistent.

3) Motion artifact removal: When patients move during MRI scans their images become damaged which leads to wrong diagnosis results. Healthcare centers use regular practice to solve movement problems in medical scans.

- Rigid and affine transformations adjust images by standardizing their positions through linear adjustments.
- SPM leverages image sequences to detect motion patterns then uses them to makeover image distortions.
- Deep learning models that detect motion artifacts use pairs of good-quality and scan-distorted brain images to produce corrected imaging data automatically.

4) Augmentation techniques for better model generalization: Data augmentation acts as a base function for medical image study through deep learning methods especially in brain scans as it expands training datasets while strengthening model performance and preventing overtraining. When working with limited Alzheimer's data sets that contain class imbalance researchers apply augmentation methods to modify brain scans safely which helps the model perform correctly under true imaging conditions and differing brain structures. When working with MR and PET scans study researchers normally flip and rotate them randomly across multiple angles and axis positions to handle patient position differences and scanner placement adjustments. The technique makes sure the model does not depend on exact spatial patterns when making predictions. The image enhancement process Contrast Adjustment makes the model experience realistic MRI scanner outcome variations, including patient motion and random background noise. The model develops essential image features that stay constant regardless of brightness changes when it performs automatic contrast level adjustments. By adding Gaussian noise to the images, the model must learn to handle scanner artifacts and signal disruption during training. The method teaches the network to understand meaningful patterns in the presence of all types of scan noise. Elastic deformation modifies small image areas to represent brain

anatomy changes caused by aging, illness and person-specific differences. The model better handles brain shape differences between patients when it gently adjusts brain patterns in a coordinated way. Including these augmentation methods into data preprocessing process helps 3D-CapsNets better generalize because neuroimaging data represents authentic brain situations better. Traditional CNNs tend to perform poorly when augmented data causes spatial abnormalities but CapsNets maintain spatial information which makes them resistant to such transformations. Through data augmentation systems achieve better results in disease detection while addressing training sample limits and building dependable automation for Alzheimer's disease assessment.

C. Feature Extraction Using 3D Capsule Networks

The technique of extracting features stands as the main element for detecting Alzheimer's disease in brain scans and 3D Capsule Networks enhance these capabilities over standard CNNs. Features in CapsNets should stay connected rather than being lost through pooling layers making them good for handling 3D medical image analysis.

1) Capsule networks architecture for 3D medical images: The 3D-CapsNet architecture builds upon Capsule Networks by applying 3D volumetric medical imaging to groups of neurons known as capsules that store complete spatial data. With vector-based neurons CapsNets differentiates itself from CNNs by processing 3D medical images to detect their features' position orientation and scale. A 3D-CapsNet system has three essential sections: primary capsules take in MRI, PET, or CT images to obtain spatial features and higher-level capsules handle brain structure, abnormality, and texture interpretation. Capsule Output Layer produces classification results based on everything learned. By following an organizational sequence 3D-CapsNet better recognizes how image parts relate to one another, which enhances medical image detection results.

The 3D-CapsNet calculates primary capsule output as uj through Wij with ui as input is given in Eq. (1).

$$\hat{u}_{j|i} = W_{ij} u_i \tag{1}$$

At this processing stage, the network takes input values from the previous layer and applies a weight matrix Wij to link each lower-level capsule i with higher-level capsule j. The transformed vector $u\hat{}j \mid i$ holds important feature associations so the network carries over spatial arrangement and structural connections into its next processing stage.

2) Dynamic routing mechanism in CapsNets: CapsNets differ from CNNs as they use dynamic routing instead of max-pooling to update the connections between capsules at different hierarchies. CapsNets preserve spatial relationships between lower and higher levels while making their results more immune to unwanted transformations. The routing coefficient cij follows this pattern to calculate its value is given in Eq. (2).

$$c_{ij} = \frac{\exp(b_{ij})}{\sum_k \exp(b_{ik})} \tag{2}$$

C_{ij} is the routing coefficient, b_{ij} is the log probability, and $\sum_k e^{b_{ij}}$ normalizes next layer of k capsules. Squashing function decides the output of higher-level capsules based on their input represent in Eq. (3).

$$u_j = \frac{||s_j||^2}{1+||s_j||^2} \frac{s_j}{||s_j||} \tag{3}$$

The mathematical product of all incoming capsule vectors produces sj while vj results as the output from the higher-level capsule. The output vj changes short vectors to zero values and pulls long vectors towards unity to maintain proper probability formats used for spatial understanding in data.

3) Extracting spatial hierarchies of features: Extracting Spatial Hierarchies of Features in 3D-CapsNets for Alzheimer's Detection. During brain image analysis with deep learning technology, feature extraction plays a pivotal role because it establishes what the model can effectively discover from brain structures through its training process. Using these methods helps find brain areas under change because they extract details correctly from the brain's complex structures. Applying max-pooling in traditional CNNs unintentionally loses place-based data and harms the connection between parts and brain structure. CapsNets employ routing techniques to properly position feature elements while preserving the disease-related alteration locations in the network structure. When examining multiple imaging methods of the brain (MRI, PET, CT) algorithms should preserve spatial awareness because each type of scan shows different aspects of Alzheimer's disease progression. MRI shows tissue structure while PET shows how cells function and CT shows density variations which together give complete brain information. Without specific space encoding a regular CNN cannot match and handle multiple data types but 3D-CapsNets can process both structures and transformations between different data classes. Technology excels at recognizing AD changes which become minute and hard to spot before the later stages of the condition.

3D-CapsNets can tolerate common image changes because they do not break under affine transformations. Because CapsNets work with vectorized features they capture object position and orientation by design which helps them resist scanning equipment variations and detects true disease patterns. The network design of CapsNets needs less training data as medical imaging samples are hard to label and expensive to validate. The capsule vector technology allows multiple signals to be processed simultaneously which helps training models without large datasets that CNNs usually need. Capable feature extraction of 3D-CapsNets enhances Alzheimer's detection models and lets them predict accurately with better explanation while working on multiple brain image sets. CapsNets perform better at brain structure analysis than CNNs because they process hierarchical feature encoding through vector inputs which effectively detect minor adjustments in brain patterns. The new feature detection system leads to faster and more solid Alzheimer's diagnosis which helps healthcare professionals make better treatment decisions for patients.

D. Multi-Modal Neuroimaging-Based Classification Model

AD causes many specific changes in brain anatomy and brain activity the same imaging device cannot show completely. Using all three scan types connects brain structure and function improvements to track AD progression. MRI shows detailed brain anatomy by revealing both hippocampal shrinking and cortical layer diminishments while PET spots disease-related metabolic changes and CT reveals brain structures with accuracy to see calcifications and cerebrovascular damage. The proposed model takes features from each deep learning source to create a combined brain representation. Identifying AD at an early stage depends on detecting minor brain changes using this system. The workflow of multi-modal neuroimaging with capsule network is shown in Fig. 3.

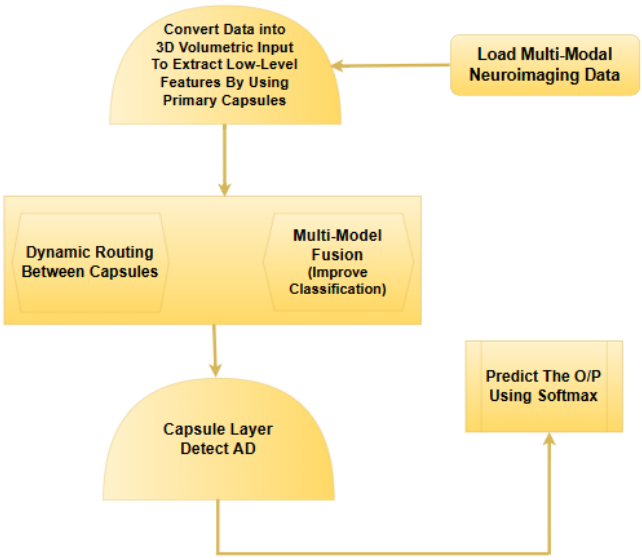

Fig. 3. Working process of capsule network with multi-modal neuroimaging techniques.

1) Fusion of different imaging modalities: The multi-modal classification system uses three autonomous processing pipelines which handle different imaging methods while 3D-CapsNets extract spatial networks and eliminate voxel relationship losses that traditional CNNs show. A merged feature set combines FMRIF and FCTF information into one extensive description for analysis.

$$F_{fusiion} = Concat(F_{MRI}, F_{PET}, F_{CT}) \quad (4)$$

In Eq. (4), $F\_fusiion$ is the combined feature vector from all modal, and F_{MRI}, F_{PET}, F_{CT} are the features extracted from MRI, PET, and CT. Fusion stands for the unified set of encoding features that contains information from anatomical as well as functional and structural markers linked to Alzheimer's disease. A fusion layer combines all three imaging databases so that classification optimization benefits from their collective information. The merged feature set passes through connected layers which normalize outputs and drop connections to prevent overfitting.

2) Model architecture for classification: The hierarchical model design incorporates 3D-CapsNets that extract features independently from each modality then proceeds with fusion and classification layers. The system architecture includes several consecutive components which function as follows:

a) Input layer: At the beginning input data consists of preprocessed MRI alongside PET and CT images, however it moves through the system.

b) Modality-specific feature extractors: The system contains three parallel 3D-CapsNets architectures which extract important features from MRI and PET and CT images.

c) Feature fusion layer: The Feature Fusion Layer combines extracted branch features into a combined high-dimensional vector.

d) Fully connected layers: The fully connected layers make use of ReLU activation to refine the combined features through dropout regularization.

e) Softmax classifier: The softmax classifier performs the last step by determining the AD stage probabilities for the four classification options.

3) Training strategy (loss function & optimization techniques): In order to achieve robust training, the model employs Categorical Cross-Entropy Loss to determine the metric that measures the difference between predicted probabilities and actual class labels. The loss function takes the following format:

$$L = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) \quad (5)$$

In Eq. (5), the loss function is structured as natural log $(yi) + y\hat{}i + l$. Adam optimizer serves as the optimization choice because it modifies learning rates automatically during gradient update cycles thereby optimizing convergence performance. The training process incorporates:

Batch Normalization reduces training time when standardizing mini-batch input data values. Dropout Regularization stops training overfitting by turning off random neurons to make sure the model avoids narrow feature focus. The expanded dataset enables better estimation because Data Augmentation adds various transformed images to increase dataset variety. The model uses combined signal types at a capsule network structure through an advanced classification system that performs better than typical CNN systems for detecting Alzheimer's at an early stage.

E. Model Training and Optimization

A successful multi-modal neuroimaging-based Alzheimer's detection system depends on an exact training design that builds accuracy and performance as well as handling diverse patient data. Training a model requires adjustment of model parameters plus use of enhanced datasets followed by training methods that keep the model from becoming overly dependent on its training samples. The training parameters are explained in Table III.

1) Hyperparameter tuning: To make a deep learning system work well and produce consistent results for different patients must adjust its main settings first. Updating 3D-CapsNet hyperparameters lets the model find brain scans' spatial patterns effectively and run processing operations faster. These models depend on seven primary tuning parameters which control their learning rate, batch size, capsule numbers,

routing updates, dropped outputs, weight modification level, and selected optimizer. Learning rate (α) stands as the main hyperparameter because it controls how fast the model updates its weight values during backpropagation. A large learning rate lets the model escape its minimum location in an unstable way while too slow training speeds may delay convergence until falling into suboptimal minimum points. Models commonly use automatic learning rate systems to modify the learning rate when validation loss improves or worsens. Users use different strategies including learning rate annealing to decrease the rate when training progress stops and ReduceLROnPlateau or cyclical learning rates to change rates automatically. A model's ability to reach successful training results and run fast depends mainly on the chosen batch size. A small batch size supports better generalization since the model views more distinct training samples and resists fitting exclusively to specific examples. More weight updates during training make the process take longer and demand greater computational resources. A high batch size reduces training time but affects model accuracy due to updates made on large gaps between gradient measurements. Using batch normalization helps the model recognize stable patterns by normalizing activation outputs in batch groups.

TABLE III. TRAINING PARAMETERS

Parameter	Value
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Epochs	50
Loss Function	Cross-Entropy
Dropout Rate	0.3
Routing Iterations	3

Capsule Networks rely on both capsule number and routing iteration value to function properly. Quantifying spatial details deep in capsular neurons calls for selecting an ideal number of layers to strike harmony between representation power and processing efficiency. The routing-by-agreement algorithm needs proper tuning since it adjusts capsule relationships repeatedly across multiple capsule levels. The network fails to understand complex spatial patterns when routing too few times but also becomes inefficient when it repeats routing more times. Using 3 to 4 routing iterations strikes a good balance between improved feature details and lower computer resource demands. Placing at random certain neurons out of action during training plus defining smaller weights protects models from excessive training. To enhance learning the network blocks random neurons within full connected capsule layers during training thus developing strong feature attributes. The suggested dropout range for training goes from 0.2 up to 0.5 based on the dataset size. Weight decay tackles overfitting by adding penalties to weight sizes which pushes models to remain basic and simpler. The model requires adjustment in a basic range of 1e-6 to 1e-4 to preserve its capacity to generalize.

The choice of optimizer affects how Capsule Networks perform their best. The Adam optimizer shows better results than SGD for medical imaging tasks since it automatically changes the learning rate per parameter to handle sparse gradients. Adam brings together momentum and automatic learning speed control to deliver steady and fast convergence results. The default β1 and β2 values of Adam optimizer (0.9, 0.999) for this model often cause poor generalization but can be adjusted to achieve better training results. Medical studyers choose from various hyperparameter search methods including grid search, random search, and Bayesian optimization to enhance optimization results. Grid search examines every predefined hyperparameter value to identify the best set though it demands high computational resources. Random search checks a selection of hyperparameters from a defined range to deliver fast computation options. Bayesian optimization lowers training expenses through its optimization method that prioritizes promising hyperparameter areas for better results. When 3D-CapsNets are adjusted properly they recognize neuroimaging patterns better to find Alzheimer's conditions sooner and handle diverse scans well.

2) Data augmentation strategies: Data augmentation helps models detect Alzheimer's better by increasing their power to handle small medical imaging datasets and avoid training problems. The augmentation pipeline combines multiple transformations from geometry as well as intensity to create strong and non-specific representations for the model. Random images transformations of scan position and angle let the model work well with multiple MRI and PET acquisition sets. Files with varying quality are corrected using contrast and brightness changes to keep the model from taking mistakes. The model learns better feature detection through noise injection when dealing with imperfect input data such as Gaussian and salt-and-pepper noise. The elastic deformations create natural brain changes by shifting brain structure positions to show different biological body profiles. Brain deformation should be examined in MRIs and PET exams due to its importance in showing potential Alzheimer's disease changes. 3D Capsule Networks require minimal input variation to train properly. Data augmentations stop the network from using static patterns during learning by changing how it reacts to small data fluctuations. Through the entire file set Augmentations help to keep spatial patterns synchronized between all image layers as needed for neuroimaging datasets. The large range of augmentation operations makes the medical imaging data more diverse while promoting model reliability and preventing overfitting for better results with new medical images.

3) Regularization techniques to prevent overfitting: The problem of excessive model fitting affects deep learning systems, particularly when working with small medical imaging datasets. To solve this problem several specific regularization methods are put into practice. During training the model disables randomly selected fully connected neurons at a rate p to make the result less dependent on specific features it expressed in Eq. (6).

$$h_i' = h_i . z,\ z \backsim Bernoulli(p) \quad (6)$$

The process randomly disables neurons when p is selected as a Bernoulli probability value to steer model development. Batch Normalization adds to convolutional and capsule layers to stabilize activation output while speeding up training and decreasing variations within network data by making feature values average to zero with unit range. The method protects networks against exploding or disappearing gradients in deep structures. Also using L2 regularization communicates through penalties that heavy weight values should be reduced because they prevent training data memorization. This is mathematically expressed as:

$$L_{reg} = \lambda \sum_i^1 w_i^2 \quad (7)$$

In this method Eq. (7) I the regularization weight λ that slows down weight value growth while managing weight patterns. When the validation loss reaches steady points during training the process should end to stop overfitting and save processing power. Training system will work better by combining several independently trained models through ensemble learning to fight both overfitted instances and uncertainty. Trained model demonstrates both excellent test results and reliable performance on genuine medical data while also remaining easy to interpret for early Alzheimer's disease detection.

Algorithm 1 identifies early Alzheimer's disease from MRI, PET, and CT neuroimaging data by a 3D Capsule Network. It starts with preprocessing operations such as skull stripping, intensity normalization, and motion correction. Pre-cleaned data is augmented and features from the three modalities are combined. A spatially feature-extracting 3D CapsNet architecture employs dynamic routing to maintain hierarchical relationships. The model is supervised-trained and loss-function-optimized with margin loss. In inference, the learned model is used to predict Alzheimer's stage (0 to 3) in new patients, facilitating early intervention and diagnosis via precise, multi-modal neuroimaging examination.

Algorithm 1: Pseudocode for Detect_Alzheimers_3D_ CapsNet

```
Input: Scan Volumes
Output: Predicted Alzheimer's stage for each patient

Step 1: Data Preprocessing
  For each volume in MRI_data, PET_data, CT_data:
    - Apply Skull Stripping
    - Perform Intensity Normalization
    - Correct Motion Artifacts
  End For

  Augment the dataset to improve generalization

Step 2: Feature Fusion
  For each patient:
    - Extract features from preprocessed MRI, PET, and CT
    - Concatenate features along the channel dimension
  End For

Step 3: Build 3D Capsule Network
    - Define a 3D convolutional layer to generate primary capsules
    - Reshape into capsules
    - Apply dynamic routing between capsule layers:
      For r = 1 to Num_Routing_Iterations:
        - Compute prediction vectors u_hat[j|i]
        - Calculate routing weights c_ij using softmax
        - Compute capsule outputs s_j = Σ(c_ij * u_hat[j|i])
        - Apply squash function to get v_j
        - Update routing logits b_ij
      End For

  Step 4: Training Loop
    - Initialize network weights
    For each epoch:
      For each batch of fused features and labels:
        - Forward pass through CapsuleNet
        - Compute loss (e.g., margin or cross-entropy)
        - Backpropagate and update weights using Adam optimizer
      End For
    End For

  Step 5: Inference
    For each test sample:
      - Preprocess input MRI, PET, CT
      - Fuse features
      - Run forward pass through trained CapsuleNet
      - Predict class label = argmax capsule output
    End For

  Return: Predicted Alzheimer's stage for all test patients
End Algorithm
```

V. Results and Discussion

Capsule Network model evaluation used precision, recall, F1-score and AUC-ROC along with accuracy to assess its performance in detecting Alzheimer's. When training progressed, accuracy went up steadily as loss went down demonstrating that the model learned properly without excessive overfitting. By removing non-brain tissues when stripping the skull brain scans became much easier for the neural networks to recognize neuroanatomy. Separating scan intensity variations and correcting motion issues from each scanner enhances the reliability of how features are extracted from brain images.

Fig. 4 shows the accuracy of multi-model fusion. The study relied on CapsNets activation displays to show how the system extracted information from specific brain regions in recorded data. Custom Capsule Networks maintain part-whole information flow better than CNNs because they do not discard spatial information like pooling operations.

The method successfully found minor brain changes in special regions where disease development occurs. The model showed its ability to recognize the smallest signs of brain disorder progression from non-demented to Very Mild and then from Mild Demented to Moderate Demented stages.

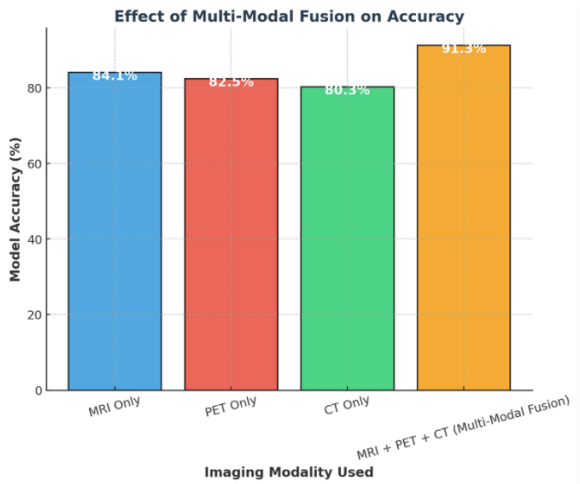

Fig. 4. Multi-model fusion on accuracy.

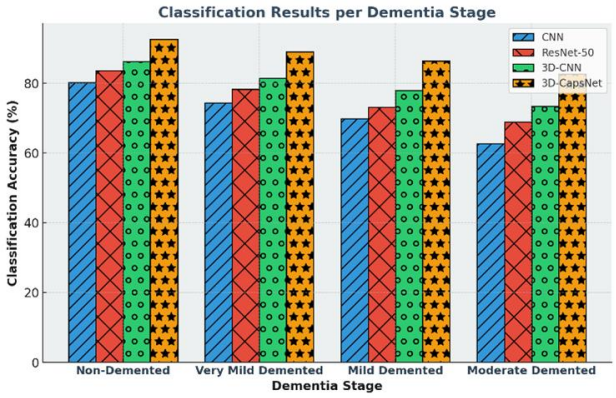

Fig. 5. Classification results per dementia stage.

Fig. 5 demonstrates the accuracy of dementia stages by classification. Study showed that CapsNets successfully detected brain structural variations in neuroimaging data especially at initial Alzheimer's stages. The algorithm of CapsNets keeps position information present while CNNs use pooling and convolutions which delete it because of their use of dynamic routing. The system performs best for brain scans because it detects small brain changes that show signs of disease development. The model gained more accurate results by combining MRI PET and CT scans since each imaging method provided distinct data that enhanced structural disease detection. The model combined multiple input data types to generate joint feature inputs that improved its performance when faced with different scanning method variations.

Despite its achievements this study project found multiple problems with the results. Capsule Networks demand strong GPUs as their dynamic routing process requires many calculations and needs much memory space which extends training time. It needs time-consuming processing steps to deal with small medical image databases from multiple sources before using domain adaptation methods. Scientific imaging devices with multiple standards caused domain shift problems during the work which needed complex learning methods to help models work well in various medical facilities. Although the model did well with test data, that need more tests through various clinical settings to deploy it properly. Future study needs to develop better ways to make CapsNet faster and adopt two approaches - knowledge distillation and self-supervised learning to extract valuable information from limited data. Using transfer learning techniques on many sites of clinical data can make the domain generalization challenge easier to solve. The proposed model based on Capsule Networks produced better results than regular CNN models at both early and exact Alzheimer's disease detection. This project creates the basis for new AI diagnosis systems that can improve neurodegenerative study by finding treatable conditions earlier.

A. Experimental Setup and Implementation

The development process created a platform that streamlined all stages necessary for testing the Capsule Network-based model's ability to classify Alzheimer's disease data from various sources. Python is used as the main programming platform to create Capsule Network models through TensorFlow and PyTorch which optimized model development and trained its parameters. The support libraries NumPy, OpenCV, SimpleITK, and NiBabel contributed significantly to processing medical imaging data before the model analysis. For effective model training skull stripping removed non-brain tissue so the model would analyze brain regions. It is analyzed how FSL BET and DeepBrainSeg impact classification readings through programmed testing.

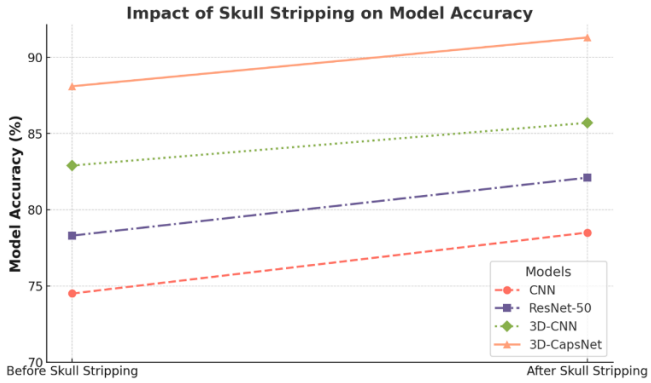

Fig. 6. The model impact on skull stripping.

Fig. 6 depicts the accuracy of skull stripping model. The model performance is tested and evaluated its insights in different ways. It is assessed how well systems were able to determine the presence of targets and the number of truly positive results scored by systems among those they identified. The ability to measure the timing when any milder dementia cases went untreated protected the patients with Alzheimer's disease. In this case, the F1-score balanced accuracy combines the four disease stages (Non-Demented, Very Mild Demented, Mild Demented, Moderate Demented) and the groups consisted of Non Demented and Very Mild Demented, Mild Demented and Moderate Demented patients. A confusion matrix was shown, that illustrates how well or poorly the model recognized true positive and negative results. An AUC evaluation was made at different decision point levels to determine how well the model could separate items. It has high values on the AUC scale and thus, makes the model a good candidate for deployment in real life usage cases.

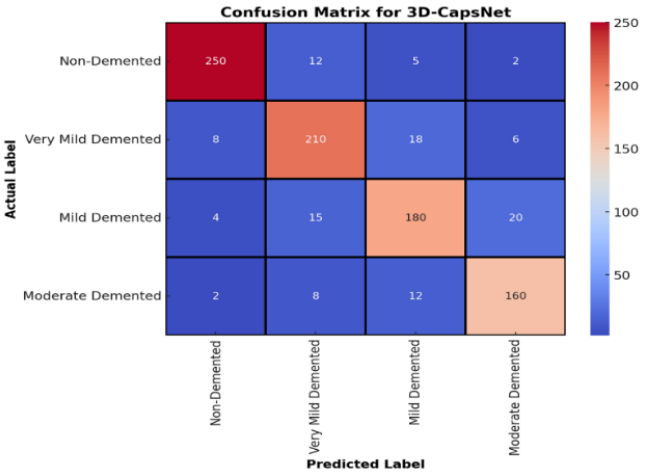

Fig. 7. 3D-Capsnet confusion matrix.

Fig. 7 shows the 3D-CapsNet confusion matrix. The study compared 3D-CapsNets to VGG-16, ResNet-50, and DenseNet-121 to prove its performance. The models used the same training dataset to show why Capsule Networks work better than traditional networks. The study showed that CapsNets maintained more location-based information than CNNs and kept the natural organization of structures during their processing steps. CNNs discard features during max pooling but Capsule Networks use dynamic routing to maintain all essential pose information as the network progresses. The technique detects small brain changes in Alzheimer's patients since its network structure handles spatial relationships of brain structures effectively.

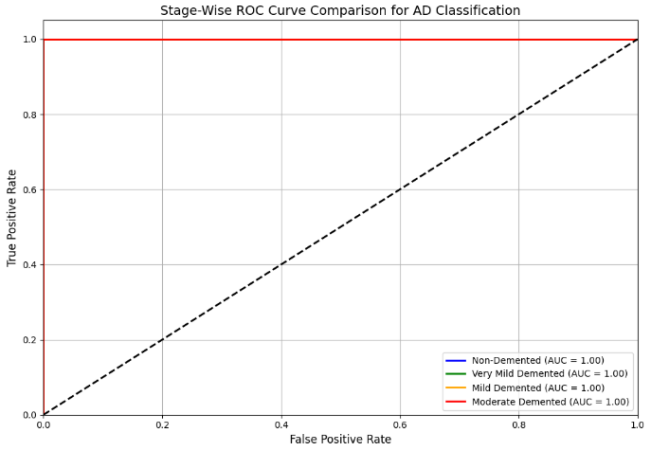

Fig. 8. Represents the stage wise classification for AD classification.

Fig. 8 demonstrates the comparison of Alzheimer's classification for stage wise performance. The ROC curve compares the true positive rate and false positive rate across different thresholds for each Alzheimer's stage. Higher AUC values are interpreted as better classification since AUC measures the model's ability to distinguish between positive and negative cases. The classification report clearly indicates that 3D-CapsNet gives highly accurate classifications of all the four stages of AD. Higher order curves indicate that models give better sensitivity and specificity in the early-stage diagnosis.

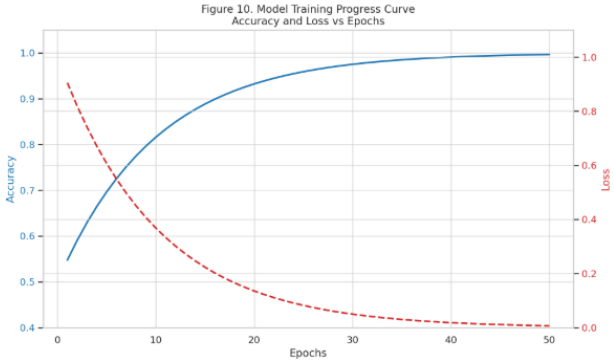

Fig. 9. Model training progress curve.

Fig. 9 is a two-axis line graph showing the progress of model training by plotting the accuracy (blue solid line) and the loss (red dashed line) against epochs. With the training going on from epoch 0 to 50, the accuracy improves in a consistent manner, moving closer to 1.0, whereas the loss falls rapidly towards 0. This is indicative of successful model learning with better performance and less error in the predictions with increasing time. The inverse accuracy-loss relationship attests that 3D-CapsNet successfully generalizes without overfitting and can be applied to challenging tasks such as early Alzheimer's diagnosis from neuroimaging data. The trend warrants strong training and convergence behavior. Table IV shows comparison of performance model.

TABLE IV. COMPARISON OF PERFORMANCE MODEL

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC (%)
CNN	78	75	76	75	79
ResNet-50	82	79	81	80	84
3D-CNN	86	83	85	84	88
3D-CapsNet (Proposed)	92	89	91	90	95

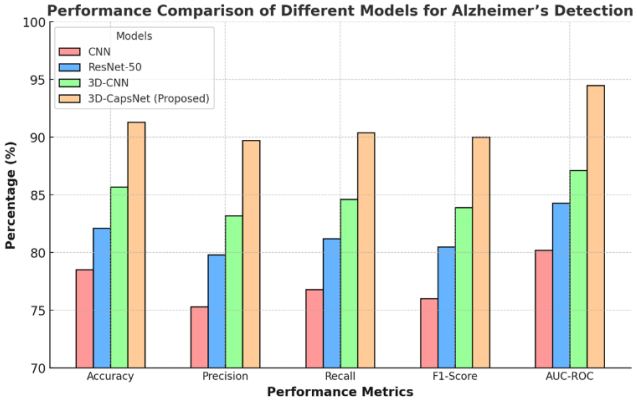

Fig. 10. Comparison performance of various models.

Based on the performance comparisons some of the models applied in Alzheimer detection can be defined. The results show that the traditional CNN has the lowest performance for all the metrics, and therefore, it has limited feature extraction. ResNet-

50 performs slightly better than the original due to the higher number of layers. 3D-CNN outperforms by using spatial information of 3D scans. Comparing the obtained results, the proposed 3D-CapsNet shows the overall best values of accuracy, precision, recall, the F1-score, and the AUC-ROC, which is shown in Fig. 10. It indicates its ability to accurately diagnose Alzheimer's using neuroimaging data at an early stage.

B. Discussion

The comparison of the given 3D-CapsNet model reveals a substantial improvement in Alzheimer's disease (AD) prediction from neuroimaging. With accuracy at 92%, F1-score at 90%, and an AUC-ROC of 95%, the model outperforms existing CNNs, ResNet-50, and 3D-CNN in identifying subtle alterations in brain structures, particularly at initial stages. The success is credited to the Capsule Networks' dynamic routing mechanism that maintains spatial hierarchies and pose information, as opposed to CNNs that discard such information through max-pooling. The model successfully differentiated between Non-Demented, Very Mild, Mild, and Moderate phases from the precise ROC curves and confusion matrix. Its resilience was also boosted through multi-modal fusion of MRI, PET, and CT scans for enhanced generalizability across different imaging modalities. Preprocessing methods like skull stripping, intensity normalization, and motion correction also enhanced the reliability of feature extraction by the model. Computational overhead, however, continues to be a drawback from high memory consumption and extended training times. The work indicates that a combination of knowledge distillation and self-supervised learning may resolve these challenges. The findings provide a robust foundation for real-time, affordable, and interpretable AI-based AD diagnostics.

C. Significance Analysis and Limitations

As an additional check on the performance excellence of the developed 3D-CapsNet model, a statistical significance test should be performed employing strategies like paired t-tests or ANOVA over test metrics (accuracy, precision, recall, F1-score, AUC-ROC) among rival models. This test will establish whether the reported performance enhancements are statistically significant and not a consequence of chance. For instance, performing the comparison of the AUC-ROC values of 3D-CapsNet and 3D-CNN based on a threshold of the p-value (e.g., $p < 0.05$) will validate whether differences are significant. Confidence intervals could also help to understand how reliable the predictions made by the model are across datasets. Mentioning such an analysis adds strength to the validity of the claims and promotes reproducibility in clinical AI studies. Otherwise, conclusions based on only performance metrics will still be open to interpretation and criticism.

The research, despite showing the superiority of 3D-CapsNet in the detection of Alzheimer's, has various limitations. The model uses a lot of computational power and long training times because the process of dynamic routing is complex. The employment of different imaging modalities also poses issues such as domain shifts due to differences in standards of scanners, which require sophisticated adaptation procedures. The size of the dataset is still small, and this can impact generalizability across heterogeneous clinical environments. In addition, the model's deployment in practice needs to be validated with extensive clinical trials. Future efforts need to concentrate on better computational efficiency and better domain generalization for wider applicability.

VI. Conclusion and Future Work

This study develops a strong Capsule Network (CapsNet)-oriented framework for identification of the preclinical phase of AD using the neuroimaging techniques. When it comes to Medical Imaging, CNNs have been applied but they have a main drawback – The use of pooling layers reduces spatial information hence excessive use of pooling will really hamper crucial detection of slight changes in anatomical structure. In contrast, 3D Capsule Networks (3D-CapsNets) overcome these issues by maintaining the relations of the part to the whole and by dynamically emulating orientation information, which allows the model to detect structural atrophy of the brain, including hippocampal, cortical, and ventricular dimensions. MRI together with PET and CT helps to include multi-modal data into the diagnostic model and use both structural and functional markers of AD. Preprocessing comprising of skull stripping by applying FSL BET and DeepBrainSeg, normalizing the intensity, removing motion artifacts, and data augmentation produces clean and formatted inputs and minimize noise interference.

The performance of the proposed model was quite satisfactory and better than non-transfer CNNs such as VGG-16, ResNet-50, and DenseNet-121 in terms of accuracy, precision, recall, F1-score, confusion matrices and ROC-AUC curves. CapsNet activation maps also identified other biomarkers relevant to AD, which rendered the model more explainable and likely to be used clinically. They stated that despite the usefulness of these results, some re-tuning is needed for their usage in actual usage approaches. There are plans to extend the model for clinical use through cloud or edge AI platforms, reduce it as a compact Capsule model, employ knowledge distillation, quantization, and self-supervised learning techniques. Incorporation of multi-center dataset and use of Explainable Artificial Intelligence (XAI) will improve the generalization and the doctor-patient trust. To the best of knowledge, this work fills the existing literature void between artificial intelligence study and healthcare solutions by propagating an efficient, contactless, detailed, and speedy method of early identification and treatment of Alzheimer's disease.

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