Enhanced CBAMWDNet: a deep learning approach for accurate dementia multiclassification using MRI scans

R Madana Mohana¹, Mohammed Affan Zuhaibuddin¹, Mohammed Faisal Hussain¹*, K Sreekar Reddy¹.
¹Department of Artificial Intelligence and Data Science, Chaitanya Bharathi Institute of Technology, Hyderabad - 500075, Telangana, INDIA.

Abstract. The rise in dementia cases emphasizes the critical need for accurate and early diagnosis. While numerous studies have focused on precise classification systems for singular dementia types, a gap exists in comprehensive classification encompassing various dementia subtypes. This research addresses this gap by curating a diverse MRI dataset containing multiple forms of dementia, aiming to develop a robust classification model. The research focuses on enhancing the CBAMWDNet, an advanced deep learning model, to precisely categorize different types of dementia like Alzheimer's, Lewy body, Frontotemporal and Vascular dementia. Originally developed for detecting tuberculosis in chest X-ray images, this model incorporates the architecture of Convolutional Block Attention Module (CBAM), Wide ResNet, and Dense blocks (WDnet). By leveraging a well-balanced and varied MRI dataset, the model's training will encompass a spectrum of dementia presentations, enhancing its capacity for nuanced classification. The proposed research aims not only to advance the capabilities of CBAMWDNet but also to contribute significantly to personalized medical diagnostics. Achieving accurate classification across diverse dementia subtypes holds the potential to revolutionize patient care, enabling tailored interventions and treatments based on precise subtype identification. This research thus underscores its relevance in the broader context of improving healthcare outcomes for individuals affected by dementia.

1 Introduction

Dementia, which ranks seventh among the leading causes of global mortality [1], is marked by a progressive decline in cognitive abilities impacting daily tasks like memory, focus, problem-solving, and perception. Despite being commonly linked with older age and sometimes seen as an inevitable part of growing older, Dementia doesn't occur as a normal part of getting older. Rather, it signifies a notable decline in cognitive abilities that significantly impacts daily life. Its primary origins lie in different brain-related illnesses and injuries rather than being an innate aspect of aging itself [2].

* Corresponding author: faisalhussain7008@gmail.com
Dementia is a diverse range of conditions, not a singular disorder. It includes various neurodegenerative disorders, each having its distinct features. Alzheimer's disease, frontotemporal dementia, vascular dementia, and Lewy body dementia stand among the most prevalent types of dementia [3]. These conditions have distinct causes and features, highlighting the importance of distinguishing between them for precise diagnosis and effective treatment. Figure 1 provides a summary of various types of dementia, accompanied by the proportionate occurrence rates of each specific type among patients.

As depicted in Figure 1, Alzheimer's disease, the most prevalent type of dementia, comprises around 60-70% of all dementia cases. It is believed to arise due to an accumulation of abnormal levels of amyloid beta (Aβ) in the brain, forming either tau proteins internally or amyloid plaques externally. This buildup disrupts neuronal function and connectivity, leading to progressive brain function decline [4].

As people age, the brain's decreased capacity to eliminate proteins is affected by brain cholesterol and is linked to a range of neurodegenerative disorders. While deterministic genetic anomalies explain a small percentage of cases (around 1-2%), the cause of Alzheimer's in most patients remains unclear.

Vascular dementia (VD) stems from brain blood flow issues, often due to minor strokes, leading to gradual cognitive decline. It involves a mix of cerebrovascular problems causing brain changes and cognitive impairments. Strokes in various brain regions, like the anterior cerebral artery area, are linked to VD [5]. Having a stroke raises dementia risk by 70%, and recent ones by almost 120%. Risk factors include age, hypertension, smoking, high cholesterol, diabetes, and prior strokes. Cerebral amyloid angiopathy, from beta-amyloid buildup, can contribute to VD occasionally [5].

Frontotemporal Dementia (FTD) is a type of dementia distinguished by the deterioration of nerve cells in the frontal and temporal lobes of the brain, resulting in the shrinkage of these regions [6]. It impacts behaviour, attitude, language, and movement and is more prevalent in individuals under 65 years old, often affecting those between 40 and 65, but it can also occur in younger adults and older individuals [7]. FTD equally affects both genders and leads to changes in behaviour, language, and emotional regulation, such as detachment from family,
excessive talking, inappropriate speech, agitation, and difficulty controlling emotions, personality, and temperament.

Lewy body dementia (LBD) is characterized by atypical accumulations of alpha-synuclein protein known as Lewy bodies in the brain, disrupting brain chemistry, and affecting thinking, behaviour, mood, and movement [8]. It ranks among the most common dementia causes and is characterized by progressive mental decline, visual hallucinations, alterations in alertness, and concentration. Physical symptoms such as muscle stiffness, slow movements, walking challenges, and tremors are evident in Lewy body dementia, mirroring those seen in Parkinson's disease [9]. Recognizing LBD can be difficult since initial symptoms often mimic those of other brain disorders or mental health conditions. It can manifest either on its own or concurrently with other brain conditions.

Although Alzheimer’s disease receives considerable attention in dementia research due to its prevalence, it’s essential to expand research efforts to encompass other subtypes like Lewy body dementia, frontotemporal dementia, vascular dementia, and others. Each of these subtypes has unique characteristics and impacts individuals differently. Therefore, a diverse approach to research can lead to a more comprehensive understanding of dementia. The main objective of this study is the careful compilation of a well-balanced dataset, encompassing five distinct classes - Alzheimer’s dementia (AD), Lewy body dementia (LBD), frontotemporal dementia (FD), vascular dementia (VD), and normal brain. This comprehensive dataset serves as the foundation for our exploration into dementia subtypes. Leveraging the advanced deep learning model, CBAMWDNet, we aim to classify these dementia subtypes effectively. This approach not only broadens the scope of dementia research but also harnesses the power of artificial intelligence to provide valuable insights into this complex field.

2 Related work

Over the past three decades, substantial progress has been made in research aimed at developing more accurate and sophisticated methods for diagnosing and classifying different types of dementia. A comprehensive survey was conducted, reviewing numerous papers focused on dementia classification and early detection, utilizing a range of techniques from machine learning to deep learning methodologies.

A new hybrid network was proposed for diagnosing Alzheimer's (AD) and predicting mild cognitive impairment (MCI) conversion using structural magnetic resonance imaging (sMRI) data [10]. In this research, a multi-scale attention convolution was introduced to capture local variations, and a pyramid non-local block was implemented to represent long-range correlations among brain features. Additionally, the network incorporated an aging transformer to incorporate information related to age for disease diagnosis. Key contributions included the adaptive aggregation of feature maps using multi-scale kernels, addressing limitations found in standard convolution methods, and the integration of age-related features to enhance both diagnosis and prediction.

Another research initiative aims to tackle the challenge of applying machine learning findings to clinical set-tings for diagnosing dementia [11]. This study focuses on employing feature selection algorithms to pinpoint valuable subsets of evaluation components related to dementia within a vast open-source dataset. It uses a cost-sensitive approach in feature selection to optimize diagnostic accuracy while considering the balance between accurately classifying dementia severity and the available time for assessment. Authors utilize a cost-
sensitive algorithm to pinpoint features that strike a balance between the accuracy of classifying the severity of dementia and the duration needed for evaluation. They also explore using RF models to predict CDR-SB (Clinical Dementia Rating - Sum of Boxes) using the chosen assessment items, excluding the data folds employed for selecting features from the training dataset. Moreover, the study extends the feature selection process by integrating a cost penalty and delves into the implications of this research for clinical integration and further evaluation.

The paper [12] explores the use of graph neural network (GNN) models for AD classification using electroencephalography (EEG) brain graphs. It compares the effectiveness of GNN models with other baseline models and investigates the impact of functional connectivity (FC) measures on the classification performance of GNN. It shows that GNN models perform better when trained using fully connected (FC) brain graphs rather than a fixed graph based on the spatial distance between EEG sensors. Furthermore, it emphasizes the significance of employing edge filtering techniques to create sparser graphs, enhancing the performance of GNNs. The paper also discusses the impact of different FC measures and frequency bands on the classification performance of GNN models.

An approach that combines cognitive tasks and EEG signal processing addresses the increasing prevalence of dementia for its early diagnosis [13]. The research included 16 individuals with dementia, 16 with early-stage dementia, and 15 healthy participants. EEG signals were captured during various resting and cognitive states. The method employed iterative filtering (IF) method for decomposition and concentrated on characteristics of EEG including variance, power spectral density, Tsallis entropy, and fractal dimension. The research performed multi-class classification using k-nearest neighbour (kNN), decision trees, support vector machine (SVM), and ensemble classifiers. The study's findings suggest that kNN exhibited superior performance compared to others in diagnosing dementia. Additionally, it highlighted cognitive tests as crucial for identifying different stages of dementia. The significance of the study lies in enhancing diagnostic accuracy, even with a limited dataset, using the IF decomposition technique.

Multi-view Separable Pyramid Network (MiSePyNet) was introduced for examining 18F-FDG PET scans [14]. This network analyzes scans from various viewpoints (axial, coronal, and sagittal) to offer additional and complementary details for early Mild Cognitive Impairment (MCI) stage identification in Alzheimer's Disease (AD). The network employs separable convolution operations to maintain spatial information while minimizing the number of training parameters. Tests carried out on the ADNI dataset show that the suggested approach surpasses both conventional and deep learning-based algorithms. It achieves an accuracy of 83.05% in forecasting the advancement of Mild Cognitive Impairment.

The study introduced a machine learning model leveraging transfer learning as its foundation to forecast dementia using magnetic resonance imaging (MRI) data [15]. Employing diverse parameter optimization techniques and k-fold cross-validation, the research aimed to boost prediction accuracy. Remarkably, the model achieved a high accuracy of 90.7%, outperforming other methods on the same dataset. The study emphasizes the importance of early dementia diagnosis for arresting neurological deterioration and highlights the potential of the suggested system in devising rehabilitation programs for patients.

The paper addresses the importance of early detection in neurodegenerative diseases for timely clinical intervention and treatment [16]. It highlights the challenge of sample imbalance in existing methods, hindering effective model training due to a scarcity of negative samples. To address this issue, the paper proposes a two-stage approach to understand the patterns of normal subjects, enabling the identification of potential negative
samples. Experimental results showcase the method's strong recognition capabilities, offering explanations aligned with physiological mechanisms. Importantly, the deep learning model doesn't necessitate retraining for different diseases, making it broadly applicable for diagnosing various brain conditions. Moreover, the research holds promise in contributing to the comprehension of regional dysfunction in diverse brain diseases, particularly Alzheimer's disease.

Medical Imaging Analysis in detecting dementia and its various forms, as it yields crucial insights for distinguishing between various types of dementia including AD, FTP, and PD [17]. The study's primary goal is to diagnose these dementia types using a singular dataset, particularly focusing on an FDG-PET brain dataset, and it employs GAN (Generative Adversarial Network) technology to address data distribution challenges within the dataset. Furthermore, the research centers on accurately diagnosing Frontotemporal Dementia (FTD), an aspect that hasn't been effectively addressed by existing methodologies. The proposed model employs deep learning techniques to analyze and diagnose multiple types of dementia, leveraging a dataset containing scans from patients sourced from ADNI, PPMI, NIFD, and Normal subjects.

Researchers extensively evaluated automated diagnostic systems based on machine learning (ML) for predicting dementia [18], examining diverse data types like images, voice data and clinical features. They discussed shortcomings in prior automated methods for dementia prediction and proposed future pathways to address these constraints. The study underscores that ML models driven by image data show promising outcomes in predicting dementia compared to voice data and clinical features. Additionally, it highlights the escalating global prevalence of dementia, its economic impact, risk factors, and characteristics. The main objective is to fulfill the demand for more such efficient automated diagnostic systems for predicting dementia.

The research investigates the connection between psychosocial factors and dementia among older adults [19]. It overcomes past study limitations by employing sophisticated data analysis techniques to pinpoint dementia-associated factors. The research utilizes cross-sectional data from a broad, nationally representative sample, exploring more than 400 variables across different domains associated with dementia. Seven different machine learning algorithms are employed to develop predictive models, followed by a method that combines models to enhance prediction accuracy. The main objective is to enhance understanding of the psychological and social factors associated with dementia, with the aim of improving its diagnosis and treatment.

The research applies deep learning technology to differentiate between Lewy body dementia (LBD) and Alzheimer's disease (AD) using Tc-99m-ECD SPECT images [20]. The main objective is to enhance the accuracy of dementia differential diagnosis, critical for tailoring patient treatment plans and strategies for follow-up care. Researchers employed a two-stage transfer learning approach and streamlined complexity of the model using ResNet-50 model, utilizing both the ADNI database and the ImageNet dataset. They transformed three-dimensional images into collections of two-dimensional images to facilitate data augmentation and ensemble learning objectives. The study assessed different deep learning models' performance in distinguishing AD/normal cognition (NC), AD/LBD, and LBD/NC using Tc-99m-ECD SPECT images. Additionally, the paper highlights the significance of precisely differentiating between AD and LBD and the challenges involved in using cerebral perfusion SPECT imaging for this purpose. It also underscores the potential of deep learning technology in neuroscience for crafting novel diagnostic and prognostic tools. Furthermore,
the study acknowledges limitations, such as the scarcity of nuclear medicine brain images for training deep learning models and the lack of pertinent research on utilizing nuclear medicine images for deep learning technology to differentiate various types of dementia.

ML techniques such as support vector machines (SVM), adaptive neuro-fuzzy inference systems (ANFIS), and artificial neural networks (ANN) were utilized to classify vascular dementia (VD) and Alzheimer’s dementia (AD) [21]. The study utilized different regional metrics obtained from resting-state functional magnetic resonance imaging (fMRI) and diffusion tensor imaging (DTI) as input features for training the algorithms, with the goal of pinpointing the most efficient feature arrangement for distinguishing between VD and AD. Furthermore, using the patients’ baseline MRI data, the determined VD-AD differentiating characteristic pattern was utilized to forecast the disease occurrence in dementia patients displaying a "mixed VD-AD dementia" (MXD) clinical profile. The paper highlights the challenges associated with accurately diagnosing AD and VD, especially when their symptoms overlap. It underscores the significance of advanced MRI techniques like rs-fMRI and DTI in characterizing dementia and distinguishing between AD and VD.

3 Comparative study

The table 1 details a comprehensive overview of twelve research studies in the domain of dementia diagnosis and prediction, each offering unique methodologies and insights. These studies span various years from 2020 to 2023 and are published across journals like IEEE, Springer, Neural Computing and Applications, among others.

The methodologies utilized in these studies cover a wide range, including machine learning approaches like graph neural networks (GNNs), convolutional neural networks (CNNs), to ensemble classifiers like random forests and support vector machines. Researchers have utilized diverse datasets, including T1-weighted sMRI scans, resting-state fMRI data, FDG-PET brain imaging, EEG datasets and cognitive assessments from sources like Open Access Series of Imaging Studies (OASIS), Alzheimer's Disease Neuroimaging Initiative (ADNI) and English Longitudinal Study of Aging (ELSA).

While these studies exhibit promising accuracies ranging from 80% to 97.7% in the diagnosis of Alzheimer's Disease (AD) or other dementia types, several limitations are highlighted. These limitations often revolve around small dataset sizes, lack of representation of various dementia types, limited generalizability, and scope for improving accuracy or model robustness. Furthermore, some studies focus solely on specific types of dementia, neglecting broader classification or early detection aspects.

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Journal</th>
<th>Year of Publication</th>
<th>Methodology (Algorithm/Tools/Libraries/Validation Measures)</th>
<th>Data Sources/Data Sets</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>[10]</td>
<td>IEEE</td>
<td>2023</td>
<td>CNN - Attention mechanism, transformer, multiscale convolution, Accuracy – 91.0%</td>
<td>T1-weighted sMRI scans from ADNI database</td>
<td>Classification of other dementia types is not done. Limited amount of training data may result in overfitting.</td>
</tr>
<tr>
<td>Year</td>
<td>Journal</td>
<td>Dataset</td>
<td>Model/Method</td>
<td>Accuracy</td>
<td>Comments</td>
</tr>
<tr>
<td>------</td>
<td>---------</td>
<td>---------</td>
<td>--------------</td>
<td>----------</td>
<td>----------</td>
</tr>
<tr>
<td>2022</td>
<td>IEEE</td>
<td>EEG</td>
<td>Graph neural network (GNN)</td>
<td>92%</td>
<td>Accuracy Cost - 86%-94%. Model is limited to EEG data.</td>
</tr>
<tr>
<td>2020</td>
<td>IEEE</td>
<td>EEG</td>
<td>Decision tree – SVM, kNN, Ensemble classifier</td>
<td>Dementia: 92% Early dementia: 91.67% Healthy subjects: 91.87%</td>
<td>Dataset is very small. Deep learning models can be adopted to improve accuracy.</td>
</tr>
<tr>
<td>2021</td>
<td>IEEE</td>
<td>F-FDG PET data from ADNI</td>
<td>Multi-view Separable Pyramid Network (MiSePyNet)</td>
<td>83.05%</td>
<td>Only considers early detection of AD. Accuracy can be improved.</td>
</tr>
<tr>
<td>2023</td>
<td>IEEE</td>
<td>MRI Scans of 150 patients from OASIS, publicly available neuroimaging dataset</td>
<td>Machine Learning – SVC, Random Forest, XGBoost, AdaBoost, MLP, Transfer learning</td>
<td>90.7%</td>
<td>Deep learning models can be adopted to improve accuracy. Dataset size can be increased for better results and generalization.</td>
</tr>
<tr>
<td>2021</td>
<td>IEEE</td>
<td>Dataset consisting of resting state fMRI data of 334 subjects' obtained from ADNI and PPMI</td>
<td>The Finer-DBN model demonstrates promising dementia recognition with an accuracy of 80% and hierarchical brain function characterization from fMRI data.</td>
<td>80%</td>
<td>Only consider Alzheimer's disease. Need to improve the model accuracy, precision, F1 score etc.</td>
</tr>
<tr>
<td>2023</td>
<td>Springer</td>
<td>The dataset has 350 patient scans, including subjects from ADNI, PPMI,</td>
<td>GAN and DCNN methods are used to analyze and diagnose multiple types of dementia using FDG-PET</td>
<td></td>
<td>Dataset is very small. Complexity in extracting relevant brain parts from PET images for diagnosis may require further refinement and validation.</td>
</tr>
<tr>
<td>Source</td>
<td>Year</td>
<td>Title</td>
<td>Details</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>------</td>
<td>-------</td>
<td>---------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>IEEE</td>
<td>2020</td>
<td>The SLR reveals that ML models driven by image data demonstrate more promising results for dementia prediction compared to clinical feature-based data and voice data.</td>
<td>The selected datasets for ML-based dementia detection are relatively small. The potential of unsupervised methods needs improvement for more accurate dementia prediction.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Springer</td>
<td>2023</td>
<td>Machine learning - Gradient Boosting Machine (GBM) algorithms, Random Forest (RF), Regularized Greedy Forests (RGF), and Logistic Regression (LR). Deep learning - a Keras-Based Convolutional Neural Network (K-CNN)</td>
<td>It used 61 datasets, including those for AD, VD, FTD, MD, and LBD. Misclassification occurred when different ML algorithms provided conflicting probability scores, affecting the model ensemble. The data set used has not consider all demographic variables.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>MDPI</td>
<td>2021</td>
<td>ResNet-50 model (with ADNI pretrain + modified) Accuracy – 84.62</td>
<td>Tc-99m-ECD SPECT images (Taiwanese Nuclear Medicine Brain Image) Researched only two subtypes of dementia, Alzheimer’s (AD) and Lewy body (LBD). Small Dataset with 308 Subjects</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### 4 Proposed methodology

#### 4.1 CBAMWDNet Model

The CBAMWDNet architecture stands as a purpose-built framework meticulously tailored for the nuanced challenge of tuberculosis classification within medical imaging [22]. Comprising a strategic amalgamation of cutting-edge components and methodologies, this neural network blueprint exemplifies a refined approach aimed at unraveling intricate patterns embedded within medical images.
At its core, the CBAMWDNet builds its feature maps employing a 7x7-sized kernel with a stride of 2. This intentional design balances the extraction of complex visual features crucial for tasks like image classification, all while mitigating computational overheads. Additionally, reduction techniques, including strategic pooling layers and a stride of 2, adeptly decrease spatial resolution, leading to parameter reduction and a more generalized model primed for versatile applications.

The hallmark of the CBAMWDNet lies in its innovative integration of the Convolutional Block Attention Module (CBAM) [22]. This sophisticated mechanism, comprising channel and spatial attention branches, empowers the network to discern pivotal elements within the input data. Through the fusion of Global Average Pooling (GAP) and Global Maximum Pooling (GMP), CBAM orchestrates a nuanced focus, enabling the model to selectively emphasize pertinent data parts while filtering out extraneous noise. This deliberate attention mechanism not only bolsters performance in tasks like image classification and object detection but also serves as a robust defense against overfitting, ensuring a more nuanced and accurate learning process.

Furthermore, drawing inspiration from the proven efficacy of Wide ResNets, the CBAMWDNet strategically amplifies growth rates while slimming down layer numbers [22]. This deliberate fusion, coupled with the intentional utilization of dense blocks fostering inter-layer connections, enhances the network's adeptness in deciphering intricate visual patterns, crucial for accurate tuberculosis classification within medical imaging.

The study seeks to leverage this model for classifying various dementia subtypes and comparing its performance against other cutting-edge models such as DenseNet, InceptionV3, AlexNet, and ResNet. Its nuanced approach to feature extraction and discernment holds immense promise in reshaping diagnostic paradigms within medical imaging analysis, opening avenues for the creation of more precise and effective diagnostic instruments.

### 4.2 Evaluation metric

#### 4.2.1 Accuracy

Accuracy represents the percentage of correctly predicted instances compared to the total instances in the dataset. While it is a straightforward metric, it may not be suitable for imbalanced classes because predicting the majority class can result in artificially high accuracy.

\[
accuracy = \frac{\text{number of correct predictions}}{\text{total number of predictions}} \tag{1}
\]

#### 4.2.2 Precision

In multiclass classification, precision is computed individually for each class. It signifies the proportion of accurately predicted instances of a specific class among all the instances predicted as that class. Precision assesses the precision of positive predictions made for each class.
4.2.3 Recall

Just like precision, recall is computed individually for each class. It evaluates the model's capability to correctly detect all instances belonging to a particular class among the total instances that truly belong to that class.

\[
\text{recall} = \frac{TP}{TP + FN} \tag{3}
\]

4.2.4 F1 score

The F1 score acts as a metric for accuracy that considers both precision and recall, evaluating the performance of the model by computing the harmonic mean between precision and recall. In multiclass classification scenarios, it's typically derived as a weighted average of the individual class F1 scores.

\[
F1 \text{ score} = \frac{2PR}{P + R} \tag{4}
\]

where P is precision and R is recall.

4.2.5 Receiver operating characteristic (ROC) curve

The ROC curve graphically depicts the performance of a binary classification model across various classification thresholds. It demonstrates the connection between the true positive rate (sensitivity) and the false positive rate (1 - specificity) across different threshold settings. The y-axis corresponds to the true positive rate (TPR), while the x-axis represents the false positive rate (FPR). Each point on the ROC curve corresponds to a specific blend of sensitivity and specificity associated with a particular threshold setting.

4.2.6 Area under curve (AUC)

The AUC curve functions as a metric for assessing the overall performance of a classifier through an analysis of its ROC curve. It computes the area under the ROC curve, providing a summary of the model's capability to differentiate between classes at various threshold settings. A higher AUC score, closer to 1 on a scale of 0 to 1, indicates superior discriminative ability of the model. Conversely, an AUC of 0.5 suggests that the model performs similarly to random guessing, indicating no discriminative ability beyond chance.

5 Conclusion

The paper presents a comprehensive exploration into the classification of dementia subtypes, elucidating the nuances and significance of identifying distinct categories like Alzheimer's dementia, vascular dementia, Lewy body dementia, and frontotemporal dementia. Emphasizing the importance of precise classification using CBAMWDNet, the paper highlighted the need for tailored approaches to diagnosis and treatment strategies. Leveraging
advancements in technologies such as deep learning, this research endeavors to refine
diagnostic accuracy and personalize care for individuals affected by these diverse cognitive
disorders.

Despite considerable strides in understanding and classifying dementia subtypes, several
critical challenges persist in this field. Addressing these gaps will be pivotal for further advancements, including the need to distinguish between overlapping symptoms among different subtypes, improving early detection methods, and developing targeted therapies for specific dementia categories. Additionally, enhancing collaboration across disciplines, advancing research into biomarkers and genetics, and harnessing emerging technologies will continue to shape our understanding and management of these complex conditions. As research progresses, the pursuit of improved diagnostic precision and effective interventions remains central, fostering a future where personalized care and innovative treatments alleviate the impact of dementia on individuals and their families.

References


