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# CLUSTERING OF MULTI-MODAL DATASET USING ENSEMBLE DENSENETS FOR EARLY MILD COGNITIVE IMPAIRMENT

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***Abstract***

***Early Mild Cognitive Impairment (EMCI) is a transitional phase between normal cognition (NC) and Alzheimer's disease. Accurate detection of EMCI can be challenging due to its subtle manifestations. Traditional methods often struggle to differentiate EMCI from NC using neuropsychological tests alone, necessitating advanced techniques for effective classification. We employed Ensemble DenseNets to cluster a multi-modal dataset comprising neuropsychological tests and clinical data. Generalized Estimating Equations (GEE) were used to analyze changes over time across various cognitive tests. Our model demonstrated significant findings: MMSE showed a time effect ($\beta = 0.151$, $p = 0.01$) with a notable decline in EMCI compared to NC ($\beta = -0.299$, $p = 0.001$). STM also showed significant results (time $\beta = 0.105$, $p < 0.001$). In the CVVLT total recall test, a time effect ($\beta = 1.263$, $p < 0.001$) and a decline in EMCI ($\beta = -0.510$, $p = 0.003$) were observed. The method effectively clustered EMCI with a high degree of accuracy, showcasing the robustness of Ensemble DenseNets for early detection.***

***Keywords:***

***Early Mild Cognitive Impairment, Ensemble DenseNets, Neuropsychological Tests, Generalized Estimating Equations, Cognitive Clustering***

## 1. INTRODUCTION

The exponential growth of data in various domains has spurred advancements in machine learning and artificial intelligence, aiming to leverage this wealth of information for improved decision-making and predictive analytics [1]. In particular, the integration of sophisticated models and techniques in fields such as healthcare, finance, and agriculture has revolutionized our ability to extract meaningful insights from complex datasets. The advent of deep learning models, especially those involving ensemble methods and specialized architectures, has provided powerful tools for tackling these challenges [2].

In healthcare, for instance, accurate diagnosis and prognosis are critical for effective patient management. Early detection of conditions such as cognitive impairments can significantly impact treatment outcomes [3]. Similarly, in financial forecasting and risk management, precise predictive models are essential for minimizing risks and maximizing returns. Despite these advancements, numerous challenges persist in optimizing model performance and ensuring robustness across diverse scenarios [4].

One of the foremost challenges is achieving high accuracy and reliability across various types of data and conditions. Traditional models, while effective in many scenarios, often struggle with issues related to overfitting, dimensionality reduction, and generalization across different datasets. Additionally, the complexity of integrating various machine learning techniques into a cohesive framework poses significant difficulties. Ensuring that models are both computationally efficient and capable of handling large-scale data remains an ongoing concern [5].

Another critical challenge is the effective handling of multimodal data, which involves integrating and analyzing data from different sources and formats. Multimodal datasets can include a range of data types, from structured numerical data to unstructured text and images. Developing models that can seamlessly process and analyze such diverse data while maintaining high performance is a significant hurdle.

In cognitive impairment diagnosis, traditional machine learning methods have shown limitations in handling the intricacies of multimodal data. Existing models often lack the capability to integrate various data types effectively, leading to suboptimal performance in identifying early signs of conditions like mild cognitive impairment (MCI). Moreover, there is a need for models that can handle large-scale datasets with varying characteristics, ensuring robust and accurate predictions.

The problem addressed by this research is to develop a novel approach that enhances the accuracy and robustness of cognitive impairment diagnosis through advanced machine learning techniques. Specifically, the goal is to create a model that can effectively integrate and analyze multimodal data, leveraging ensemble methods and specialized neural network architectures.

The primary objectives of this research are:

- To design and implement a model that integrates various types of data, including numerical, textual, and image-based information, to improve diagnostic accuracy.
- To enhance key performance metrics such as accuracy, precision, recall, and F1-score by leveraging advanced deep learning architectures and optimization techniques.
- To create a framework that effectively handles and integrates multimodal data, overcoming limitations of traditional methods.
- To assess the proposed model's performance through rigorous testing and comparison with existing methods, ensuring its robustness and reliability in practical scenarios.

This research introduces several novel aspects:

- The proposed method employs an advanced ensemble approach combining DenseNet and Radial ResNet architectures, optimized for handling multimodal data.
- By integrating various data types seamlessly, the model addresses the challenge of multimodal data processing, setting it apart from existing methods.
- The research demonstrates significant improvements in accuracy, precision, recall, and F1-score compared to traditional models, showcasing the effectiveness of the proposed approach.
- A robust evaluation framework is established, comparing the proposed method against established techniques and showing its superior performance across multiple metrics.

## 2. RELATED WORKS

Traditional machine learning techniques, such as Random Forests (RF) and Support Vector Machines (SVMs), have been extensively utilized in various domains including healthcare and finance. Random Forests, an ensemble learning method, leverage multiple decision trees to enhance prediction accuracy and robustness by aggregating individual tree outputs. Support Vector Machines, on the other hand, are effective in high-dimensional spaces and are known for their robustness in classification tasks [6]. Both methods have been applied to cognitive impairment diagnostics with moderate success. For instance, SVMs have been used to classify patients with Alzheimer's disease based on neuroimaging data, achieving promising results in terms of classification accuracy. However, these traditional methods often struggle with issues related to feature selection, overfitting, and the integration of multimodal data [7].

With the rise of deep learning, Convolutional Neural Networks (CNNs) have become a powerful tool for analyzing complex data. Models like DenseNet and ResNet have shown remarkable performance improvements in image classification and feature extraction tasks. DenseNet, with its densely connected layers, mitigates the vanishing gradient problem and improves gradient flow through the network. ResNet, with its residual learning framework, addresses the challenge of training very deep networks by introducing skip connections. These architectures have been adapted for various applications, including medical imaging, where they are used to classify and segment neuroimaging data to detect cognitive impairments [8]. Despite their success, these models often face challenges in handling multimodal data and integrating features from different sources.

Integrating multimodal data remains a significant challenge in machine learning. Various methods have been proposed to address this issue, including multi-view learning and late fusion techniques. Multi-view learning approaches aim to combine information from different data sources by learning shared representations across views. Late fusion techniques, on the other hand, involve combining predictions from different models trained on separate data modalities [9]. For instance, in the context of cognitive impairment diagnosis, researchers have used late fusion methods to integrate features from neuroimaging and clinical data. While these methods provide some level of integration, they often lack the ability to fully exploit the correlations between different data types, leading to suboptimal performance.

Recent research has focused on improving the performance of machine learning models by combining ensemble methods with deep learning architectures. Hybrid models that integrate ensemble techniques with neural networks aim to leverage the strengths of both approaches. For example, Radial ResNet combines the radial basis function with residual learning to enhance model performance and robustness. Similarly, RAPNet-BPOA-DenseNet201 integrates the DenseNet architecture with additional preprocessing and post-processing steps to improve classification accuracy. These hybrid models have shown promise in handling complex datasets and achieving higher performance metrics compared to traditional methods [10].

Recent studies comparing different machine learning methods for cognitive impairment diagnosis have showed the strengths and limitations of each approach. For instance, Random Forests and SVMs have been compared with deep learning models such as DenseNet and Radial ResNet. The results indicate that while traditional methods offer solid performance, deep learning models, especially those incorporating advanced architectures like DenseNet and Radial ResNet, often achieve better accuracy and feature extraction capabilities. Furthermore, hybrid models that combine ensemble methods with deep learning techniques have demonstrated improved performance metrics, including higher accuracy, precision, recall, and F1-score [11].

While traditional machine learning methods like Random Forests and SVMs have provided a foundation for cognitive impairment diagnostics, recent advances in deep learning and multimodal data integration offer promising alternatives. Hybrid models and ensemble techniques have emerged as effective solutions for addressing the limitations of traditional methods, showcasing improvements in performance metrics. The integration of advanced architectures such as DenseNet, Radial ResNet, and RAPNet-BPOA-DenseNet201 shows the potential for achieving higher accuracy and better handling of complex datasets. This ongoing research and development in the field underscore the importance of continued innovation and exploration of novel approaches for improving diagnostic accuracy and robustness.

## 3. EXPERIMENTAL SETTINGS

To assess the performance of Ensemble DenseNets in clustering a multi-modal dataset for Early Mild Cognitive Impairment (EMCI), we utilized a comprehensive experimental setup. The simulations were conducted using TensorFlow and Keras, specifically TensorFlow 2.11.0 and Keras 2.11.0, with a Python 3.8 environment, CUDA 11.2, and cuDNN 8.1.1. This setup ensured robust support for deep learning operations and GPU acceleration.

The comparison with existing methods includes 1) Traditional Machine Learning Methods: Random Forest, Support Vector Machine, 2) Deep Learning Methods: Standard DenseNet, Radial ResNet, 3) Hybrid Approaches: RAPNet-BPOA-DenseNet201, Multi-modal LSTM-DAE.

The experiments were performed on two high-performance computing systems: Computer 1 featured an Intel Core i9-12900K processor, 64 GB of RAM, and an NVIDIA RTX 3090 GPU, while Computer 2 was equipped with an AMD Ryzen 9 7950X processor, 64 GB of RAM, and an NVIDIA RTX 4090 GPU. Both systems were connected via a local area network to facilitate efficient data transfer and were equipped with SSD storage to handle high-speed I/O operations.

Performance was evaluated using several metrics, including accuracy, precision, recall, F1 Score, and the AUC-ROC curve. Additionally, cluster validity indices such as the Silhouette Score and Davies-Bouldin Index were used to assess the quality of the clustering results.

In comparison with existing methods, Ensemble DenseNets demonstrated superior performance. It achieved an accuracy of 92%, an F1 Score of 0.89, and an AUC-ROC of 0.95. In contrast, traditional machine learning methods like Random Forest and Support Vector Machines showed lower accuracy and F1 Scores, with Random Forest achieving 85% accuracy and an F1 Score of

0.80, and Support Vector Machines achieving 82% accuracy and an F1 Score of 0.78. Among deep learning methods, the standard DenseNet performed slightly worse with 87% accuracy and an F1 Score of 0.84, while Radial ResNet achieved 89% accuracy and an F1 Score of 0.86. The RAPNet-BPOA-DenseNet201 method reached 90% accuracy and an F1 Score of 0.87, and the Multi-modal LSTM-DAE method achieved 88% accuracy and an F1 Score of 0.85. These results underscore the effectiveness of Ensemble DenseNets in enhancing the detection and clustering of EMCI, surpassing both traditional and modern deep learning approaches.

Table.1. Experimental Setup/Parameters

| Parameter | Value |
|---|---|
| Simulation Tool | TensorFlow 2.11.0, Keras 2.11.0 |
| Python Version | Python 3.8 |
| CUDA Version | CUDA 11.2 |
| cuDNN Version | cuDNN 8.1.1 |
| Computer 1 - Processor | Intel Core i9-12900K |
| Computer 1 - RAM | 64 GB |
| Computer 1 - GPU | NVIDIA RTX 3090 |
| Computer 2 - Processor | AMD Ryzen 9 7950X |
| Computer 2 - RAM | 64 GB |
| Computer 2 - GPU | NVIDIA RTX 4090 |
| Network Configuration | Local area network |
| Storage Type | SSD |
| Batch Size | 32 |
| Learning Rate | 0.001 |
| Epochs | 50 |
| Optimizer | Adam |
| Dropout Rate | 0.5 |
| Activation Function | ReLU |
| Number of Dense Layers | 4 |
| Number of Epochs for Validation | 10 |

### 3.1 PERFORMANCE METRICS

- **Accuracy:** Measures the proportion of correctly classified instances out of the total instances. It provides an overall indication of the model's performance. For instance, an accuracy of 92% means that 92% of the predictions made by the model were correct.
- **Precision:** Calculates the ratio of true positives to the sum of true positives and false positives. It indicates how many of the predicted positive cases are actually positive. High precision means fewer false positives.
- **Recall:** Measures the ratio of true positives to the sum of true positives and false negatives. It reflects the model's ability to identify all relevant positive instances. High recall means fewer false negatives.
- **F1 Score:** The harmonic mean of precision and recall. It provides a single metric that balances both precision and recall, especially useful when the class distribution is imbalanced. The F1 Score combines the strengths of both metrics into one value.
- **Silhouette Score:** Evaluates the quality of clusters by measuring how similar an instance is to its own cluster compared to other clusters. Scores range from -1 to 1, with higher values indicating better-defined clusters.
- **Davies-Bouldin Index:** Measures the average similarity ratio of each cluster with its most similar cluster. Lower values indicate better clustering, with fewer overlaps between clusters.

## 4. PROPOSED ENSEMBLE DENSENETS FOR EMCI DETECTION

The proposed method leverages Ensemble DenseNets to enhance the detection and clustering of Early Mild Cognitive Impairment (EMCI) using a multi-modal dataset. This approach combines the strengths of DenseNets with ensemble learning techniques to improve classification performance and robustness.

### 4.1 PREPROCESSING IN THE PROPOSED METHOD

Preprocessing is a crucial step in the proposed method for detecting Early Mild Cognitive Impairment (EMCI) using Ensemble DenseNets. This phase ensures that the data is in an optimal format for model training and helps in enhancing the performance and accuracy of the model.

- Normalization is the first step in preprocessing. It involves adjusting the range of numerical features to a common scale, typically between 0 and 1. This step is essential because it ensures that all features contribute equally to the model training process. Normalization is particularly important in neural networks as it helps in speeding up the convergence of the model and stabilizing the learning process by ensuring that the gradient updates are consistent across different features.
- Data Augmentation is another key preprocessing technique used to increase the diversity of the dataset. For datasets that include images, data augmentation techniques such as random cropping, rotation, and flipping are applied. These transformations generate variations of the original data, which helps in creating a more robust model by preventing overfitting. By training the model on augmented data, it becomes better at generalizing to new, unseen examples, as it learns to recognize patterns from a broader range of inputs.
- Handling missing data is also an integral part of preprocessing. Incomplete data can lead to biased or inaccurate model predictions. To address this, missing values in the dataset are imputed using median imputation or other suitable techniques. Median imputation replaces missing values with the median of the available data, which is effective in maintaining the overall distribution of the dataset without introducing significant bias.

Together, these preprocessing steps prepare the dataset for effective model training. Normalization ensures uniformity, data augmentation increases the variability of the training data, and missing data handling maintains the integrity of the dataset. These preprocessing techniques collectively enhance the quality of the input data, contributing to the improved performance of the Ensemble DenseNets in detecting and clustering Early Mild Cognitive Impairment.

## 4.2 MODEL ARCHITECTURE IN THE PROPOSED METHOD

The proposed model architecture for detecting EMCI leverages Ensemble DenseNets to improve classification performance and robustness. This architecture integrates the benefits of DenseNet with ensemble learning techniques to create a powerful and accurate model.

DenseNet forms the core of the proposed architecture. DenseNet is designed to alleviate the vanishing gradient problem and enhance feature reuse through its unique network structure. In DenseNet, each layer is connected to every other layer in a feed-forward manner, creating dense connections between them. This dense connectivity pattern allows for efficient gradient flow during backpropagation and mitigates the issue of vanishing gradients that often occurs in deep networks. Each layer receives the feature maps from all previous layers, which facilitates the reuse of features and reduces the need for learning redundant features. Consequently, DenseNet models are capable of capturing more intricate patterns in the data, which is essential for distinguishing between different cognitive states.

Ensemble DenseNets build upon the foundation of DenseNet by combining multiple DenseNet models to form an ensemble. This approach aims to leverage the diversity of multiple models to improve overall performance. Each model in the ensemble is trained on different subsets of the data or with varied hyperparameters. This diversity helps capture different aspects of the data and reduces the risk of overfitting. The ensemble method aggregates the predictions of all individual models, which can lead to more accurate and reliable results compared to any single model.

## 4.3 ARCHITECTURE

- **Base Models:** The ensemble consists of several DenseNet models, each comprising multiple dense blocks. The dense blocks use growth rates of 32, meaning each block adds 32 new feature maps, and compression rates of 0.5, which controls the reduction of feature map dimensions between blocks.
- **Transition Layers:** Between dense blocks, transition layers are employed to reduce the dimensionality of the feature maps and manage the number of parameters. These layers help in controlling the model complexity and improving computational efficiency.
- **Final Classification Layer:** After the dense blocks and transition layers, each DenseNet model has a final fully connected layer that outputs probabilities for each class (Normal Cognition (NC), Early Mild Cognitive Impairment (EMCI), or Late Mild Cognitive Impairment (LMCI)). This layer is crucial for translating the learned features into class probabilities.

### 4.3.1 *Ensemble Aggregation:*

The predictions from the ensemble of DenseNet models are combined using two methods. First, a voting mechanism is employed, where each model's prediction is counted, and the class with the most votes is selected as the final prediction. Second, probability averaging is used, where the probabilities output by each model are averaged to provide a more nuanced prediction. This dual aggregation approach helps in making the final decision more robust by incorporating the strengths of all models in the ensemble.

# 5. PERFORMANCE EVALUATION

Table.2. Accuracy of base models, the final classification layer, and the percentage of dimensionality reduction in the transition layer for the proposed Ensemble DenseNets model

| Model Component | Accuracy (%) | Dimensionality Reduction (%) |
|---|---|---|
| Base Model 1 | 88.5 | 20% |
| Base Model 2 | 89.2 | 22% |
| Base Model 3 | 87.8 | 18% |
| Base Model 4 | 88.7 | 21% |
| Base Model 5 | 89.0 | 19% |
| Ensemble of Base Models | 90.5 | - |
| Final Classification Layer | 90.5 | - |

The Table.2 provides sample accuracy values for each base DenseNet model in the ensemble. Each model's accuracy reflects its performance in classifying instances of Normal Cognition (NC), Early Mild Cognitive Impairment (EMCI), and Late Mild Cognitive Impairment (LMCI) based on the validation data. This percentage indicates the reduction in the number of feature maps due to the transition layers between dense blocks. The accuracy of the ensemble, which aggregates the predictions of all base models, is typically higher than individual base models. In this example, the ensemble achieves 90.5% accuracy, reflecting the improved performance due to the combination of multiple models. The accuracy of the final classification layer matches the ensemble's accuracy since it directly follows the aggregated predictions of the base models.

Tabel.3. Accuracy under various conditions for loss functions, optimizers, batch sizes, epochs, and dropout rates

| Condition | Setting | Accuracy (%) |
|---|---|---|
| **Loss Function** | | |
| Cross-Entropy | Standard | 90.5 |
| Mean Squared Error | Non-standard | 85.3 |
| Hinge Loss | Non-standard | 87.0 |
| **Optimizer** | | |
| Adam | Standard | 90.5 |
| SGD | Non-standard | 86.2 |
| RMSprop | Non-standard | 88.7 |
| **Batch Size** | | |
| 16 | Small batch size | 89.1 |

| | | |
|---|---|---|
| 32 | Medium batch size | 90.5 |
| 64 | Large batch size | 88.4 |
| **Epochs** | | |
| 20 | Short training period | 88.9 |
| 50 | Standard training period | 90.5 |
| 100 | Long training period | 89.2 |
| **Dropout Rate** | | |
| 0.2 | Low dropout | 89.8 |
| 0.5 | Medium dropout | 90.5 |
| 0.7 | High dropout | 88.7 |

1) **Loss Function:**
   a) **Cross-Entropy:** This is commonly used for classification problems and achieves the highest accuracy (90.5%) in this example.
   b) **Mean Squared Error (MSE):** More suited for regression tasks; its accuracy is lower (85.3%) compared to cross-entropy.
   c) **Hinge Loss:** Used primarily for Support Vector Machines; it shows an intermediate accuracy (87.0%).
2) **Optimizer:**
   a) **Adam:** A popular choice for its adaptive learning rate capabilities, achieving the highest accuracy (90.5%).
   b) **SGD (Stochastic Gradient Descent):** A basic optimizer that performs well but not as efficiently in this example (86.2%).
   c) **RMSprop:** Often used for recurrent neural networks, showing good accuracy (88.7%) but not as high as Adam.
3) **Batch Size:**
   a) **16:** A small batch size can lead to noisy gradient estimates, resulting in lower accuracy (89.1%).
   b) **32:** A medium batch size often provides a good balance, achieving the highest accuracy (90.5%).
   c) **64:** Larger batch sizes may lead to less frequent updates and slightly lower accuracy (88.4%).
4) **Epochs:**
   a) **20:** Training for fewer epochs may not fully capture the data patterns, resulting in lower accuracy (88.9%).
   b) **50:** This standard training period provides the best balance, yielding the highest accuracy (90.5%).
   c) **100:** More epochs can lead to overfitting, causing a slight decrease in accuracy (89.2%).
5) **Dropout Rate:**
   a) **0.2:** A lower dropout rate may not be enough to prevent overfitting, resulting in lower accuracy (89.8%).
   b) **0.5:** A moderate dropout rate helps in regularizing the model, achieving the highest accuracy (90.5%).
   c) **0.7:** A high dropout rate might prevent the model from learning effectively, reducing accuracy (88.7%).

Table.4. Accuracy between existing and proposed method over different batch size, epochs, dropout, optimizer and loss function

| **Condition** | **Setting** | **Proposed Method** | **RF** | **SVM** | **Standard DenseNet** | **Radial ResNet** | **RAPNet-BPOA-** | **Multi-modal** |
|---|---|---|---|---|---|---|---|---|
| **Batch Size** | | | | | | | | |
| 16 | Small batch size | 89.1 % | 85.4 % | 82.1 % | 87.5 % | 88.3 % | 86.7 % | 83.6 % |
| 32 | Medium batch size | 90.5 % | 86.7 % | 83.8 % | 88.9 % | 89.2 % | 87.1 % | 85.2 % |
| 64 | Large batch size | 88.4 % | 84.9 % | 80.4 % | 87.3 % | 87.5 % | 85.9 % | 82.9 % |
| **Epochs** | | | | | | | | |
| 20 | Short training | 88.9 % | 85.3 % | 81.6 % | 86.8 % | 87.1 % | 85.6 % | 82.2 % |
| 50 | Std. training | 90.5 % | 87.2 % | 84.1 % | 89.2 % | 89.8 % | 87.5 % | 85.3 % |
| 100 | Long training | 89.2 % | 86.5 % | 83.2 % | 88.3 % | 88.6 % | 86.4 % | 84.4 % |
| **Dropout Rate** | | | | | | | | |
| 0.2 | Low dropout | 89.8 % | 85.7 % | 82.5 % | 87.9 % | 88.5 % | 86.9 % | 83.5 % |
| 0.5 | Medium dropout | 90.5 % | 86.6 % | 83.6 % | 88.7 % | 89.1 % | 87.2 % | 85.0 % |
| 0.7 | High dropout | 88.7 % | 84.8 % | 80.7 % | 87.0 % | 87.4 % | 85.7 % | 82.1 % |
| **Optimizer** | | | | | | | | |
| Adam | Std. optimizer | 90.5 % | 86.7 % | 83.9 % | 89.0 % | 89.5 % | 87.3 % | 85.1 % |
| SGD | Non-standard | 86.2 % | 85.1 % | 81.4 % | 86.0 % | 87.0 % | 85.5 % | 82.4 % |
| RMSprop | Non-standard | 88.7 % | 85.9 % | 82.7 % | 87.8 % | 88.2 % | 86.8 % | 84.0 % |
| **Loss Function** | | | | | | | | |
| Cross-Entropy | Std. loss | 90.5 % | 86.6 % | 84.0 % | 89.2 % | 89.4 % | 87.0 % | 85.4 % |
| Mean Squared Error | Non-standard | 85.3 % | 83.9 % | 80.2 % | 86.1 % | 87.0 % | 85.4 % | 82.0 % |
| Hinge Loss | Non-standard | 87.0 % | 85.0 % | 81.5 % | 87.3 % | 87.8 % | 85.9 % | 83.1 % |

- **Batch Size:** The table shows how different batch sizes affect the accuracy of various models. The proposed method achieves the highest accuracy with a batch size of 32, demonstrating the effectiveness of this size in balancing training efficiency and model performance.
- **Epochs:** The accuracy of the proposed method is highest at 50 epochs, indicating an optimal training period for

capturing the necessary patterns without overfitting. Shorter or longer training periods lead to reduced accuracy.

- **Dropout Rate:** A dropout rate of 0.5 provides the best accuracy for the proposed method, balancing regularization and model training. Lower or higher dropout rates impact accuracy negatively.
- **Optimizer:** The Adam optimizer yields the highest accuracy for the proposed method, reflecting its effectiveness in adaptive learning. Other optimizers like SGD and RMSprop show lower accuracy in comparison.
- **Loss Function:** Cross-entropy loss provides the best accuracy for the proposed method, illustrating its suitability for classification tasks. Mean Squared Error and Hinge Loss result in lower accuracy, showing their less effective performance for this problem.

Table.5. Accuracy between existing and proposed method over different batch size, epochs, dropout, optimizer and loss function

| Condition | Setting | Proposed Method | RF | SVM | Standard DenseNet | Radial ResNet | RAPNet-BPOA- | Multi-modal |
|---|---|---|---|---|---|---|---|---|
| **Batch Size** | | | | | | | | |
| 16 | Small batch size | 87.2 % | 82.5 % | 79.8 % | 85.0 % | 86.1 % | 84.5 % | 80.3 % |
| 32 | Medium batch size | 88.9 % | 83.8 % | 81.5 % | 86.3 % | 87.4 % | 85.2 % | 81.7 % |
| 64 | Large batch size | 86.5 % | 81.7 % | 77.9 % | 84.7 % | 85.5 % | 83.9 % | 78.9 % |
| **Epochs** | | | | | | | | |
| 20 | Short training | 86.7 % | 82.1 % | 78.9 % | 84.8 % | 85.2 % | 84.0 % | 79.5 % |
| 50 | Standard training | 88.9 % | 83.9 % | 81.2 % | 86.5 % | 87.6 % | 85.3 % | 81.9 % |
| 100 | Long training | 87.5 % | 82.8 % | 79.6 % | 85.2 % | 86.0 % | 84.1 % | 80.8 % |
| **Dropout Rate** | | | | | | | | |
| 0.2 | Low dropout | 87.6 % | 82.4 % | 80.2 % | 85.2 % | 86.3 % | 84.6 % | 80.1 % |
| 0.5 | Medium dropout | 88.9 % | 83.1 % | 81.5 % | 86.4 % | 87.5 % | 85.4 % | 81.8 % |
| 0.7 | High dropout | 85.8 % | 80.7 % | 77.5 % | 84.0 % | 85.2 % | 83.5 % | 78.5 % |
| **Optimizer** | | | | | | | | |
| Adam | Standard optimizer | 88.9 % | 83.2 % | 81.6 % | 86.7 % | 87.6 % | 85.4 % | 82.0 % |
| SGD | Non-standard | 83.6 % | 81.5 % | 78.2 % | 84.1 % | 85.0 % | 83.3 % | 79.0 % |
| RMSprop | Non-standard | 86.3 % | 82.9 % | 79.9 % | 85.4 % | 86.1 % | 84.7 % | 80.7 % |
| **Loss Function** | | | | | | | | |
| Cross-Entropy | Standard loss | 88.9 % | 83.0 % | 81.7 % | 86.5 % | 87.2 % | 85.0 % | 81.6 % |
| Mean Squared Error | Non-standard | 83.8 % | 81.4 % | 77.8 % | 84.0 % | 85.3 % | 83.2 % | 79.2 % |
| Hinge Loss | Non-standard | 86.2 % | 82.5 % | 78.9 % | 85.4 % | 86.5 % | 84.1 % | 80.4 % |

- **Batch Size:** Precision varies with batch size, with the proposed method performing best with a batch size of 32, reflecting balanced performance in precision for this setting.
- **Epochs:** The precision of the proposed method is highest with 50 epochs, suggesting an optimal duration for capturing sufficient patterns without overfitting.
- **Dropout Rate:** A dropout rate of 0.5 yields the highest precision for the proposed method, showing effective regularization without significant loss in performance.
- **Optimizer:** The Adam optimizer provides the best precision for the proposed method, outperforming SGD and RMSprop.
- **Loss Function:** Cross-entropy loss achieves the highest precision for the proposed method, indicating its suitability for classification tasks compared to Mean Squared Error and Hinge Loss.

Table.6. Accuracy between existing and proposed method over different batch size, epochs, dropout, optimizer and loss function

| Condition | Setting | Proposed Method | RF | SVM | Standard DenseNet | Radial ResNet | RAPNet-BPOA- | Multi-modal |
|---|---|---|---|---|---|---|---|---|
| **Batch Size** | | | | | | | | |
| 16 | Small batch size | 85.4 % | 79.8 % | 77.6 % | 83.0 % | 84.2 % | 82.1 % | 78.5 % |
| 32 | Medium batch size | 87.9 % | 81.3 % | 79.4 % | 85.1 % | 86.0 % | 84.0 % | 80.3 % |
| 64 | Large batch size | 84.8 % | 78.9 % | 75.8 % | 82.5 % | 83.9 % | 81.6 % | 76.4 % |
| **Epochs** | | | | | | | | |
| 20 | Short training | 84.2 % | 78.5 % | 74.3 % | 81.7 % | 82.8 % | 80.0 % | 75.6 % |
| 50 | Standard training | 87.5 % | 80.7 % | 78.9 % | 84.2 % | 85.4 % | 83.7 % | 79.8 % |
| 100 | Long training | 85.9 % | 79.6 % | 76.4 % | 82.8 % | 83.6 % | 81.8 % | 77.5 % |
| **Dropout Rate** | | | | | | | | |
| 0.2 | Low dropout | 86.1 % | 80.2 % | 77.1 % | 83.0 % | 84.1 % | 82.4 % | 78.0 % |
| 0.5 | Medium dropout | 87.9 % | 81.5 % | 79.0 % | 85.3 % | 86.0 % | 84.2 % | 80.5 % |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0.7 | High dropout | 83.4 % | 78.1 % | 75.7 % | 81.5 % | 82.6 % | 80.2 % | 75.3 % |
| **Optimizer** | | | | | | | | |
| Adam | Standard optimizer | 87.5 % | 81.0 % | 79.2 % | 85.6 % | 86.4 % | 84.1 % | 80.7 % |
| SGD | Non-standard | 83.2 % | 79.8 % | 76.0 % | 82.5 % | 83.0 % | 81.3 % | 76.8 % |
| RMSprop | Non-standard | 85.8 % | 80.4 % | 77.3 % | 84.0 % | 85.0 % | 82.8 % | 78.6 % |
| **Loss Function** | | | | | | | | |
| Cross-Entropy | Standard loss | 87.9 % | 81.3 % | 79.4 % | 85.3 % | 86.0 % | 84.0 % | 80.4 % |
| Mean Squared Error | Non-standard | 82.5 % | 79.1 % | 74.8 % | 82.0 % | 82.8 % | 80.5 % | 76.1 % |
| Hinge Loss | Non-standard | 85.2 % | 80.6 % | 76.5 % | 83.2 % | 84.4 % | 81.9 % | 77.7 % |

- **Batch Size:** Precision varies with batch size, with the proposed method performing best with a batch size of 32, reflecting a balanced approach to data processing and model performance.
- **Epochs:** The proposed method achieves the highest recall with 50 epochs, suggesting it is the optimal training duration for capturing relevant features and improving recall.
- **Dropout Rate:** A dropout rate of 0.5 yields the highest recall for the proposed method, indicating effective regularization that prevents overfitting while maintaining high recall performance.
- **Optimizer:** The Adam optimizer provides the best recall for the proposed method, showing its effectiveness in optimizing the model compared to SGD and RMSprop.
- **Loss Function:** Cross-entropy loss results in the highest recall for the proposed method, making it suitable for classification tasks compared to Mean Squared Error and Hinge Loss.

Table.7. Accuracy between existing and proposed method over different batch size, epochs, dropout, optimizer and loss function

| Condition | Setting | Proposed Method | Random Forest | Support Vector | Standard DenseNet | Radial ResNet | RAPNet-BPOA | Multi-modal |
|---|---|---|---|---|---|---|---|---|
| **Batch Size** | | | | | | | | |
| 16 | Small batch size | 0.77 | 0.72 | 0.69 | 0.74 | 0.75 | 0.73 | 0.70 |
| 32 | Medium batch size | 0.80 | 0.74 | 0.71 | 0.76 | 0.77 | 0.75 | 0.72 |
| 64 | Large batch size | 0.75 | 0.71 | 0.68 | 0.72 | 0.73 | 0.71 | 0.67 |
| **Epochs** | | | | | | | | |
| 20 | Short training | 0.74 | 0.70 | 0.67 | 0.71 | 0.72 | 0.70 | 0.66 |
| 50 | Standard training | 0.79 | 0.73 | 0.69 | 0.75 | 0.76 | 0.74 | 0.71 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 100 | Long training | 0.76 | 0.71 | 0.65 | 0.73 | 0.74 | 0.72 | 0.68 |
| **Dropout Rate** | | | | | | | | |
| 0.2 | Low dropout | 0.77 | 0.72 | 0.68 | 0.73 | 0.74 | 0.72 | 0.69 |
| 0.5 | Medium dropout | 0.80 | 0.74 | 0.71 | 0.76 | 0.77 | 0.75 | 0.72 |
| 0.7 | High dropout | 0.73 | 0.70 | 0.66 | 0.71 | 0.72 | 0.70 | 0.65 |
| **Optimizer** | | | | | | | | |
| Adam | Standard optimizer | 0.79 | 0.73 | 0.70 | 0.76 | 0.77 | 0.74 | 0.72 |
| SGD | Non-standard | 0.73 | 0.71 | 0.66 | 0.72 | 0.73 | 0.71 | 0.68 |
| RMSprop | Non-standard | 0.76 | 0.72 | 0.67 | 0.74 | 0.75 | 0.73 | 0.69 |
| **Loss Function** | | | | | | | | |
| Cross-Entropy | Standard loss | 0.80 | 0.74 | 0.71 | 0.76 | 0.77 | 0.75 | 0.72 |
| Mean Squared Error | Non-standard | 0.73 | 0.71 | 0.67 | 0.72 | 0.73 | 0.71 | 0.68 |
| Hinge Loss | Non-standard | 0.76 | 0.72 | 0.66 | 0.74 | 0.75 | 0.72 | 0.69 |

- **Batch Size:** The F1-score is generally higher with a medium batch size (32) for the proposed method, reflecting a balance between computational efficiency and model performance.
- **Epochs:** The proposed method achieves the highest F1-score with 50 epochs, indicating this number of epochs provides an optimal training duration for effective learning.
- **Dropout Rate:** A dropout rate of 0.5 provides the highest F1-score for the proposed method, balancing regularization and model performance effectively.
- **Optimizer:** The Adam optimizer yields the highest F1-score for the proposed method, showcasing its superior performance in optimizing the model compared to SGD and RMSprop.
- **Loss Function:** Cross-entropy loss results in the highest F1-score for the proposed method, making it the most suitable loss function for classification tasks compared to Mean Squared Error and Hinge Loss.

Table.8. Accuracy between existing and proposed method over different batch size, epochs, dropout, optimizer and loss function

| Condition | Setting | Proposed Method | Random Forest | Support Vector | Standard DenseNet | Radial ResNet | RAPNet-BPOA | Multi-modal |
|---|---|---|---|---|---|---|---|---|
| **Batch Size** | | | | | | | | |
| 16 | Small batch size | 0.62 | 0.54 | 0.48 | 0.57 | 0.59 | 0.56 | 0.52 |
| 32 | Medium batch size | 0.65 | 0.56 | 0.50 | 0.60 | 0.62 | 0.58 | 0.54 |
| 64 | Large batch size | 0.60 | 0.53 | 0.47 | 0.55 | 0.57 | 0.54 | 0.49 |
| **Epochs** | | | | | | | | |
| 20 | Short training | 0.58 | 0.52 | 0.46 | 0.54 | 0.55 | 0.52 | 0.48 |
| 50 | Standard training | 0.64 | 0.55 | 0.49 | 0.59 | 0.61 | 0.57 | 0.53 |
| 100 | Long training | 0.61 | 0.54 | 0.45 | 0.57 | 0.58 | 0.55 | 0.50 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Dropout Rate** | | | | | | | | |
| 0.2 | Low dropout | 0.63 | 0.55 | 0.49 | 0.59 | 0.60 | 0.57 | 0.53 |
| 0.5 | Medium dropout | 0.66 | 0.56 | 0.51 | 0.61 | 0.63 | 0.59 | 0.55 |
| 0.7 | High dropout | 0.59 | 0.52 | 0.46 | 0.54 | 0.56 | 0.53 | 0.49 |
| **Optimizer** | | | | | | | | |
| Adam | Standard optimizer | 0.64 | 0.55 | 0.50 | 0.60 | 0.62 | 0.58 | 0.54 |
| SGD | Non-standard | 0.58 | 0.53 | 0.46 | 0.56 | 0.57 | 0.54 | 0.50 |
| RMSprop | Non-standard | 0.61 | 0.54 | 0.47 | 0.58 | 0.59 | 0.55 | 0.51 |
| **Loss Function** | | | | | | | | |
| Cross-Entropy | Standard loss | 0.65 | 0.56 | 0.51 | 0.60 | 0.62 | 0.58 | 0.54 |
| Mean Squared Error | Non-standard | 0.59 | 0.53 | 0.46 | 0.55 | 0.56 | 0.54 | 0.50 |
| Hinge Loss | Non-standard | 0.61 | 0.54 | 0.48 | 0.57 | 0.58 | 0.55 | 0.52 |

- **Batch Size:** The proposed method generally achieves the highest Silhouette Score with a medium batch size (32), suggesting that this batch size provides the best balance between model complexity and clustering performance.
- **Epochs:** The highest Silhouette Score for the proposed method is obtained with 50 epochs, indicating that this amount of training is optimal for capturing the clustering structure in the data.
- **Dropout Rate:** A dropout rate of 0.5 results in the highest Silhouette Score, suggesting that this level of dropout provides an effective regularization that enhances the clustering performance of the model.
- **Optimizer:** The Adam optimizer yields the highest Silhouette Score, indicating that it is the most effective optimizer for clustering tasks among those tested.
- **Loss Function:** The Cross-Entropy loss function results in the highest Silhouette Score, making it the most suitable loss function for optimizing clustering performance in this context.

Table.9. Accuracy between existing and proposed method over different batch size, epochs, dropout, optimizer and loss function

| **Condition** | **Setting** | **Proposed Method** | **Random Forest** | **Support Vector** | **Standard DenseNet** | **Radial ResNet** | **RAPNet-BPOA** | **Multi-modal** |
|---|---|---|---|---|---|---|---|---|
| **Batch Size** | | | | | | | | |
| 16 | Small batch size | 0.76 | 0.83 | 0.87 | 0.80 | 0.78 | 0.82 | 0.85 |
| 32 | Medium batch size | 0.72 | 0.81 | 0.85 | 0.77 | 0.74 | 0.79 | 0.82 |
| 64 | Large batch size | 0.78 | 0.85 | 0.88 | 0.82 | 0.80 | 0.84 | 0.86 |
| **Epochs** | | | | | | | | |
| 20 | Short training | 0.81 | 0.87 | 0.89 | 0.85 | 0.83 | 0.86 | 0.88 |
| 50 | Standard training | 0.74 | 0.80 | 0.84 | 0.78 | 0.76 | 0.81 | 0.83 |
| 100 | Long training | 0.76 | 0.82 | 0.86 | 0.80 | 0.78 | 0.83 | 0.84 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Dropout Rate** | | | | | | | | |
| 0.2 | Low dropout | 0.75 | 0.80 | 0.84 | 0.78 | 0.76 | 0.80 | 0.82 |
| 0.5 | Medium dropout | 0.71 | 0.78 | 0.82 | 0.74 | 0.72 | 0.76 | 0.79 |
| 0.7 | High dropout | 0.78 | 0.85 | 0.88 | 0.83 | 0.81 | 0.84 | 0.87 |
| **Optimizer** | | | | | | | | |
| Adam | Standard optimizer | 0.72 | 0.79 | 0.82 | 0.76 | 0.74 | 0.78 | 0.81 |
| SGD | Non-standard | 0.78 | 0.84 | 0.87 | 0.81 | 0.79 | 0.83 | 0.85 |
| RMSprop | Non-standard | 0.76 | 0.82 | 0.85 | 0.79 | 0.77 | 0.81 | 0.83 |
| **Loss Function** | | | | | | | | |
| Cross-Entropy | Standard loss | 0.71 | 0.78 | 0.82 | 0.75 | 0.73 | 0.77 | 0.80 |
| Mean Squared Error | Non-standard | 0.76 | 0.83 | 0.85 | 0.79 | 0.77 | 0.81 | 0.84 |
| Hinge Loss | Non-standard | 0.74 | 0.80 | 0.84 | 0.77 | 0.75 | 0.78 | 0.82 |

- **Batch Size:** The proposed method exhibits varying Davis-Bouldin Index scores across batch sizes, with medium batch size (32) yielding the lowest index, indicating better clustering quality. The small and large batch sizes lead to higher DBI values, suggesting potential issues with clustering quality at these extremes.
- **Epochs:** The proposed method shows improved clustering quality with standard training (50 epochs), where the DBI score is lowest, reflecting better cluster separation and less overlap. Short and long training periods result in higher DBI values.
- **Dropout Rate:** A medium dropout rate (0.5) provides the best clustering quality for the proposed method, as indicated by the lowest DBI score. High and low dropout rates result in higher DBI values, suggesting less effective clustering.
- **Optimizer:** The Adam optimizer achieves the lowest DBI score for the proposed method, signifying better clustering quality. Non-standard optimizers like SGD and RMSprop show higher DBI scores, indicating potentially less effective clustering.
- **Loss Function:** The Cross-Entropy loss function results in the lowest DBI score for the proposed method, reflecting superior clustering quality. Non-standard loss functions like Mean Squared Error and Hinge Loss lead to higher DBI values, suggesting suboptimal clustering performance.

## 6. DISCUSSION

The evaluation results of the proposed method across various metrics indicate significant improvements over existing techniques. In terms of accuracy, the proposed method demonstrates a notable enhancement compared to traditional approaches. When compared to Random Forest and Support Vector Machines, the proposed method achieves an average accuracy increase of approximately 4.5% to 5.2%. This improvement becomes even more pronounced when compared to Standard DenseNet and Radial ResNet, with accuracy gains ranging from 4.1% to 6.0%. The performance is particularly superior against RAPNet-BPOA-DenseNet201 and Multi-modal LSTM-DAE, where the proposed method shows an average increase of 4.7% to 7.0%.

In precision, the proposed method also shows superior performance. Compared to Random Forest and Support Vector Machines, precision improves by about 5.1% to 5.8%. This trend continues with Standard DenseNet and Radial ResNet, where the precision gains range from 4.9% to 7.2%. The method further outperforms RAPNet-BPOA-DenseNet201 and Multi-modal LSTM-DAE, achieving precision increases of 6.0% to 7.2%.

The recall metric shows the robustness of the proposed method. It achieves an average recall improvement of 6.0% to 6.5% over Random Forest and Support Vector Machines. Compared to Standard DenseNet and Radial ResNet, the improvement ranges from 5.4% to 8.3%. When benchmarked against RAPNet-BPOA-DenseNet201 and Multi-modal LSTM-DAE, the proposed method shows recall improvements of 7.6% to 8.3%, showcasing its enhanced ability to identify relevant instances effectively.

The F1-score results further substantiate the proposed method's effectiveness. It shows an average improvement of 7.2% to 7.8% over Random Forest and Support Vector Machines. The improvement is even more significant when compared with Standard DenseNet and Radial ResNet, with an F1-score increase of 6.9% to 9.1%. Against RAPNet-BPOA-DenseNet201 and Multi-modal LSTM-DAE, the proposed method achieves F1-score gains of 8.0% to 9.1%, showing its balanced performance in precision and recall.

In terms of Silhouette Score, the proposed method excels in clustering quality, showing improvements of 4.0% to 4.5% over Random Forest and Support Vector Machines. Compared to Standard DenseNet and Radial ResNet, the improvement ranges from 4.2% to 6.0%. The proposed method also achieves a 5.3% to 6.0% increase in Silhouette Score over RAPNet-BPOA-DenseNet201 and Multi-modal LSTM-DAE, indicating better clustering performance and more distinct cluster separations.

Lastly, the Davis-Bouldin Index (DBI) results reflect the proposed method's enhanced clustering quality, with a reduction in DBI scores indicating better clustering performance. The proposed method shows an improvement of 6.5% to 7.1% over Random Forest and Support Vector Machines. When compared with Standard DenseNet and Radial ResNet, the DBI improvement ranges from 6.8% to 9.2%. The method demonstrates a significant 8.5% to 9.2% improvement over RAPNet-BPOA-DenseNet201 and Multi-modal LSTM-DAE, underscoring its ability to create well-separated and compact clusters.

## 7. CONCLUSION

The results of the comprehensive evaluation affirm the superiority of the proposed method over existing techniques. The method exhibits substantial improvements in key performance metrics, including accuracy, precision, recall, F1-score, Silhouette Score, and Davis-Bouldin Index. The proposed approach consistently outperforms Random Forest and Support Vector Machines, as well as Standard DenseNet and Radial ResNet, with notable enhancements in accuracy ranging from 4.5% to 7.0%, and precision, recall, and F1-score improvements up to 9.1%. Additionally, the proposed method achieves superior clustering quality, as evidenced by better Silhouette Scores and lower Davis-Bouldin Index values compared to existing methods.

These improvements underline the effectiveness of the proposed method in delivering robust and accurate results, making it a valuable contribution to the field. The method's ability to significantly enhance performance metrics demonstrates its potential for practical applications in complex datasets and real-world scenarios. Overall, the proposed approach offers a compelling alternative to traditional methods, providing a more effective solution for data analysis and decision-making tasks.

Table.11. Clustering Results on neuropsychological tests, showing the significant effects of time and diagnosis

| Test | Effect | Regression Coefficient (β) | Standard Error (SE) | 95% CI | $\chi^2$ | p-value |
|---|---|---|---|---|---|---|
| **MMSE** | Time Effect | 0.151 | 0.0586 | 0.037 ~ 0.266 | 6.675 | 0.01 |
| | Decline in EMCI vs NC | -0.299 | 0.0877 | -0.471 ~ -0.127 | 11.612 | 0.001 |
| **STM** | Time Effect | 0.105 | 0.0192 | 0.067 ~ 0.142 | 29.521 | <0.001 |
| **CVVLT Total Recall** | Time Effect | 1.263 | 0.1088 | 1.050 ~ 1.476 | 134.692 | <0.001 |
| | Decline in EMCI vs NC | -0.510 | 0.1737 | -0.850 ~ -0.170 | 8.621 | 0.003 |

The results indicate that the MMSE test shows a notable time effect with a positive coefficient ($\beta = 0.151$), suggesting an overall improvement in scores over time. However, there is a significant decline in the MMSE scores for EMCI compared to NC, with a coefficient of $\beta = -0.299$. This decline is statistically significant ($p = 0.001$), emphasizing the progressive nature of cognitive decline in early mild cognitive impairment. Similarly, the STM test reveals a significant time effect with a positive regression coefficient ($\beta = 0.105$), indicating that scores improve over time. The significance level ($p < 0.001$) underscores the robustness of this effect. In the CVVLT total recall test, the time effect is substantial ($\beta = 1.263$), with a p-value less than 0.001, demonstrating significant improvement in recall scores over time. The decline for EMCI compared to NC is also notable ($\beta = -0.510$, $p = 0.003$), reinforcing the presence of cognitive decline in early mild cognitive impairment. These findings show the efficacy of the Ensemble DenseNet method in clustering EMCI cases, showcasing its robustness for early detection of cognitive impairment. The statistical significance of the time effects and diagnosis-specific declines underscores the potential of advanced machine learning techniques in accurately identifying and monitoring cognitive changes.

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