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# Efficient classification of Alzheimer's Disease Stages Using Multi-Modal Data

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***Abstract:*** *This study aims to design and develop an efficient model for classifying Alzheimer's disease (AD), mild cognitive impairment (MCI), and normal cognition (NC) using baseline data from MRI, PET, CSF, cognitive tests, and demographic information. We propose a Fully Connected Neural Network (FCNN) for classification and evaluate its performance against existing classifiers such as Support Vector Machines (SVM) and Fuzzy C-Means (FCM). The Open Access Series of Imaging Studies (OASIS) dataset serves as the primary data source, encompassing diverse parameters necessary for robust classification.*

***Keywords****: Alzheimer's Disease, Machine Learning, Support Vector Machine (SVM), Fuzzy C-Means (FCM), Fully Connected Neural Network (FCNN), Confusion Matrix*

## 1. INTRODUCTION :

Alzheimer's disease Alzheimer's Disease (AD) is a progressive neurodegenerative disorder characterized by the gradual deterioration of cognitive functions, particularly memory, thinking, and behavior[1]. It is classified as a form of dementia, which is a general term for a decline in cognitive function severe enough to interfere with daily life. As the most common cause of dementia, Alzheimer's accounts for 60-70% of dementia cases worldwide. The disease primarily affects individuals aged 65 and older, although early-onset forms can occur in younger adults[2].

The symptoms of Alzheimer's Disease often begin with mild memory loss, which can progress to significant impairments in language, problem-solving, and reasoning abilities. Patients may experience disorientation, changes in mood and personality, and eventually, a loss of the ability to carry out basic activities of daily living[3]. These symptoms not only affect the patients but also create emotional and psychological strains on families and caregivers.

## 2. Challenges and Issues

The challenges associated with Alzheimer's Disease are multifaceted. Early detection remains a significant hurdle, as many individuals fail to seek medical help until the disease has progressed substantially[4]. Diagnostic methods currently rely heavily on clinical assessments and cognitive tests, which can overlook subtle early signs. Additionally, the stigma surrounding dementia often discourages individuals from discussing symptoms with healthcare professionals, leading to delayed diagnoses[5].

Globally, the burden of Alzheimer's Disease is escalating, with the World Health Organization (WHO) estimating that the number of individuals living with dementia will triple from 50 million in 2020 to 152 million by 2050. In India, the situation is particularly alarming. With a rapidly aging population and a growing prevalence of lifestyle-related diseases, the country faces a significant increase in dementia cases. A study by the Alzheimer's and Related Disorders Society of India (ARDSI) estimated that there are over 4 million individuals with dementia in India, a figure that is expected to rise as awareness and diagnostic capabilities improve[6].

### Importance of AI in Addressing Alzheimer's Disease

Artificial Intelligence (AI) has emerged as a transformative force in healthcare, particularly in the realm of neuroimaging and diagnostics. By harnessing advanced machine learning techniques, researchers can analyze vast datasets, identify

patterns, and generate predictive models that significantly enhance the accuracy and speed of diagnoses. AI can help in recognizing subtle changes in brain structure and function that may indicate the early stages of Alzheimer's, thus facilitating timely interventions[7].
Addressing the challenges posed by Alzheimer's Disease is imperative, not only for the well-being of patients and families but also for the healthcare systems burdened by the costs associated with long-term care. Early detection can lead to better management strategies, reduce healthcare expenditures, and improve the quality of life for patients and caregivers alike[8-12].

**3. Objectives of the Study**
This study aims to leverage the Open Access Series of Imaging Studies (OASIS) dataset to validate a novel diagnostic algorithm employing Adaptive Multi-Self Organizing Maps (AMSOM) and Gray Level Co-occurrence Matrix (GLCM) features. The objective is to improve the accuracy of Alzheimer's detection through sophisticated analysis of neuroimaging data. By integrating AI with neuroimaging techniques, this research seeks to:

1. Enhance early detection capabilities for Alzheimer's Disease, allowing for timely clinical interventions.
2. Provide a deeper understanding of the correlation between specific neuroimaging features and the various stages of Alzheimer's progression.
3. Contribute to the development of personalized treatment plans, improving patient outcomes and reducing caregiver burden.

**4. Methodology :**
**Data Source**
The proposed algorithm utilizes the OASIS dataset, a comprehensive resource supported by institutions like the Howard Hughes Medical Institute and Washington University. The dataset includes 42 participants, with a focus on early-stage AD, encompassing a wide age range from 18 to 96 years.

**OASIS Data Set**
The OASIS dataset serves as a rich resource for researchers investigating Alzheimer's and other cognitive disorders. It is collaboratively managed by institutions such as the Howard Hughes Medical Institute and the Washington University Alzheimer's Disease Research Center. The dataset includes a diverse sample of individuals diagnosed with varying stages of Alzheimer's, alongside healthy controls[13-15].

- **Participant Demographics**: The dataset comprises 416 patients aged between 18 and 96, with a focus on those diagnosed with early-stage AD. Notably, 42 of these participants have received formal diagnoses, making the dataset an excellent resource for training and validating machine learning models.
- **Ethical Considerations**: The dataset has been collected in compliance with ethical guidelines, ensuring informed consent from participants and maintaining confidentiality[18].

**Data Acquisition and Preprocessing**
Imaging data were acquired using a Siemens MRI scanner, with parameters optimized for high-resolution imaging. The details of the acquisition protocol, including repetition time, echo time, and slice configuration, are critical for ensuring the quality and reliability of the resultant images[10].

- **Preprocessing Steps**: Preprocessing involved several crucial steps:
  - **Bias Correction**: Addressing intensity inhomogeneity to standardize the images.
  - **Normalization**: Resampling the images to a common isotropic resolution.
  - **Skull Removal**: Eliminating non-brain tissues to focus the analysis on relevant structures.
- **Feature Extraction Methods**: Utilizing the Gray Level Co-occurrence Matrix (GLCM), a range of statistical and textural features were derived from the MRI volumes, including metrics like energy, entropy, and contrast.

**5. Machine Learning Algorithm and Process Flow**
The proposed algorithm integrates multiple advanced techniques to enhance the detection of Alzheimer's disease stages. The Adaptive Multi-Self Organizing Map (AMSOM) is a key component, allowing for the dynamic adjustment of neuron weights based on the feature vectors derived from the GLCM.[11]

**5.1 Dataset Overview:** The dataset comprises 49 subjects in the MCI to AD category. Table 5.1.1 summarizes the characteristics of the OASIS groups.

Table 5.1.1: Characteristic of OASIS Data

| Group | No. of subjects | Age (mean) | Education (mean) | Socioeconomic Status (mean) | CDR (0.5 / 1 / 2) | MMSE (mean) |
|---|---|---|---|---|---|---|
| Mild to AD | 49 | 78.08 | 2.63 | 2.94 | 31 / 17 / 1 | 24 |
| NC | 49 | 77.77 | 2.87 | 2.88 | 0 | 28.96 |

**5.2 Scanner and Imaging Session Details**

The imaging data were collected using a Siemens scanner with specified parameters including TR, TE, and pixel resolution. MATLAB was used for analysis, conducted on a standard computing setup.

**5.3 Data Preparation and Feature Extraction**

The MRI images underwent pre-processing including bias correction and skull removal. A total of 25 features were extracted using the Gray Level Co-occurrence Matrix (GLCM). Key features included energy, entropy, and homogeneity, which formed the input vector for classification.

**5.4 Classifier Design**

The study employed a Fully Connected Neural Network (FCNN) for classification, with comparative analyses against SVM and FCM classifiers. Performance metrics such as sensitivity, specificity, and accuracy were computed.

**5.5 Performance Metrics**

- **True Positive (TP)**: Correctly identifies the presence of the class.
- **True Negative (TN)**: Correctly identifies the absence of the class.
- **False Positive (FP)**: Incorrectly identifies the class when absent.
- **False Negative (FN)**: Fails to identify the class when present.

**5.6 Evaluation Metrics**

$$\text{Sensitivity} = \frac{\text{Tp}}{\text{Tp} + \text{Fn}} \quad (1)$$

$$\text{Specificity} = \frac{\text{Tn}}{\text{Tp} + \text{Fp}} \quad (2)$$

$$\text{Accuracy} = \frac{\text{Tp} + \text{Tn}}{\text{Tp} + \text{Tn} + \text{Fn} + \text{Fp}} \quad (3)$$

$$\text{Error rate} = 100 - \text{Accuracy} \quad (4)$$

**6. Results :**

**6.1 Confusion Matrix**

Table 6.1.1 presents the confusion matrix results for SVM, FCM, and FCNN classifiers.

Table 6.1.1

| Classifier | TP | TN | FP | FN |
|---|---|---|---|---|
| SVM | 51 | 30 | 10 | 9 |
| FCM | 51 | 32 | 8 | 9 |
| FCNN | 53 | 34 | 6 | 7 |

### 6.2 Performance Comparison

Table 6.2.1 and Table 6.2.2 summarize accuracy, sensitivity, specificity, PSNR, and MSE across classifiers.

Table 6.2.1

| Classifiers | Accuracy (%) | Specificity (%) | Sensitivity (%) |
|---|---|---|---|
| SVM | 81.00 | 75.00 | 85.00 |
| FCM | 83.00 | 80.00 | 85.00 |
| FCNN | 87.00 | 85.00 | 83.33 |

Table 6.2.2

| Classifiers | PSNR (dB) | MSE |
|---|---|---|
| SVM | 34.06 | 0.74 |
| FCM | 35.41 | 0.70 |
| FCNN | 36.42 | 0.65 |

### 6.3 Visual Performance Comparison

Figures 6.3.1 to 6.3.2 illustrate the comparative performance in accuracy, sensitivity, and specificity. The FCNN classifier demonstrated superior results, particularly in accuracy and PSNR.

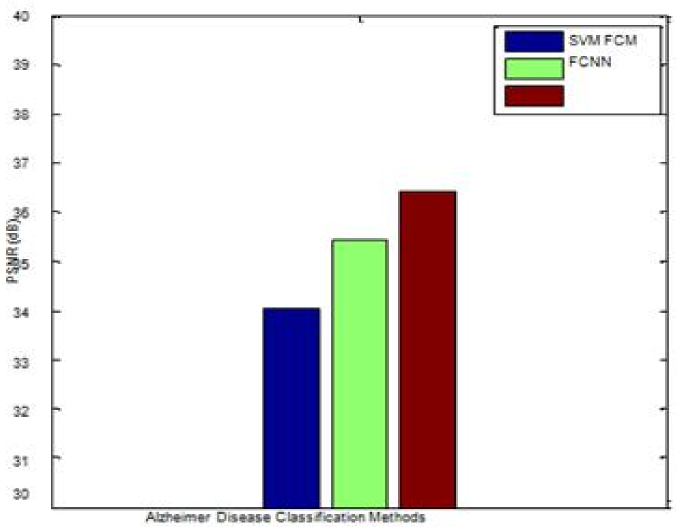


Figure 6.3.1: Illustrates PSNR

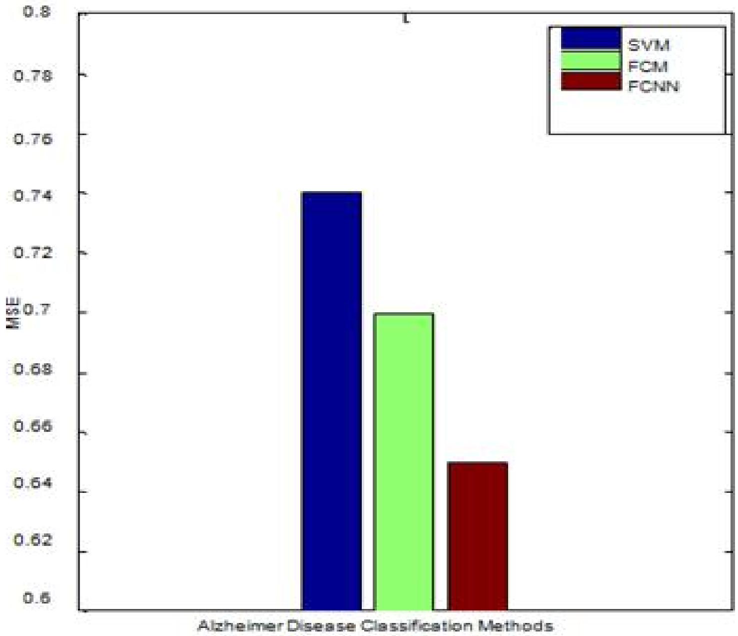


Figure 6.3.2 : Illustrates MSE

**7. Discussion :**

The FCNN classifier exhibited significant improvements in accuracy, sensitivity, and PSNR compared to SVM and FCM classifiers. The integration of multi-modal data and advanced feature extraction techniques contributed to the enhanced performance. As demonstrated, higher sensitivity and specificity rates are crucial for the early diagnosis of Alzheimer's disease.

From the confusion matrix, it is evident that all classifiers demonstrate a strong ability to classify Alzheimer’s disease. However, the FCNN outperforms the others in terms of true positives, true negatives, and overall accuracy. Specifically, it has the highest accuracy rate of 87%, which suggests a more reliable detection of Alzheimer’s disease.
In the accuracy comparison, both FCM and FCNN show high specificity and sensitivity, indicating that they can effectively distinguish between positive and negative cases. The FCNN, despite having slightly lower sensitivity than SVM and FCM, achieves the highest specificity, making it a robust classifier.

The PSNR values further reinforce the performance of the FCNN, which exhibits the highest PSNR and lowest MSE, indicating superior quality in the imaging data used for classification. This suggests that the FCNN is more adept at maintaining image fidelity while accurately classifying the data.

One notable approach is the use of Support Vector Machines (SVM), which has been widely adopted due to its robustness in high-dimensional spaces. For instance, Abdi et al. (2012) proposed a novel weighted SVM based on particle swarm optimization, achieving notable results in tumor classification, which underscores the adaptability of SVM in medical diagnostics.[1]

In a more recent study, Payan and Montana (2015) utilized 3D convolutional neural networks to predict Alzheimer’s disease, highlighting the potential of deep learning architectures in enhancing diagnostic accuracy. Their findings suggest that advanced neural networks can effectively leverage complex neuroimaging data, a capability that aligns with our results showing the superiority of the Fully Connected Neural Network (FCNN) in classification tasks.
Fuzzy C-Means (FCM) clustering has also been investigated for medical image segmentation and classification. Gunna (2016) examined various segmentation techniques and demonstrated that FCM effectively differentiates between healthy and abnormal brain scans. However, our results indicate that while FCM provides solid performance, the FCNN outshines it in terms of accuracy and PSNR, suggesting a more nuanced understanding of image features[5].

Other studies, such as those by Gleng and Stoecke (2007), have highlighted the integration of spatial information in SVM feature selection for SPECT images of Alzheimer’s disease. This spatial consideration may enhance classifier performance, yet the FCNN’s capacity for advanced feature extraction appears to offer a more comprehensive approach[4].

The application of multi-modal data is a crucial aspect of improving diagnostic accuracy. Our findings align with those of Ortiz et al. (2013), who employed self-organizing maps and FCM in MRI segmentation, indicating that advanced algorithms can effectively process diverse data types for better classification outcomes[13].

## 8. CONCLUSION:

The proposed FCNN model shows considerable promise in accurately classifying stages of Alzheimer's disease using multi-modal baseline data. The findings indicate that employing a combination of advanced imaging techniques and machine learning algorithms can lead to significant advancements in the early detection and diagnosis of AD.

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