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Alzheimer Detection And Classification Using SVM

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Abstract: Alzheimer's disease (AD) is a progressive brain disorder that leads to memory loss and a gradual decline in thinking and reasoning abilities. One of the major challenges in dealing with Alzheimer's is detecting it early and accurately using MRI brain scans. Traditional manual analysis of these scans can be slow, complex, and prone to human mistakes over the years, different machine learning (ML) models like Decision Tree, Random Forest, Logistic Regression, and K-Nearest Neighbors have been used to identify Alzheimer's. However, these models often face issues such as overfitting, lower accuracy, and weak performance when dealing with complex and high-dimensional MRI data.to overcome these limitations, the proposed approach uses SVM model for detecting and classifying Alzheimer's disease. The SVM model is well-suited for handling non-linear and complex data. It can effectively separate different disease categories by using advanced kernel functions and optimal hyperplane techniques. This leads to more precise and stable classification results, even with smaller datasets compared to existing ML models, the proposed SVM model achieves higher accuracy, sensitivity, and specificity, making it more dependable for automatic Alzheimer's detection. It not only reduces errors but also helps in identifying the disease at an early stage, which is crucial for better treatment and patient care. With 98.16% classification accuracy, it outperforms current architectures significantly in the Alzheimer Detection and Classification Using SVM.

Keywords: Alzheimer's Disease, Support Vector Machine (SVM), MRI Brain Images, Classification, Early Detection, Accuracy, DConvolutional Neural Networks (CNN).

I. INTRODUCTION:

Alzheimer's disease is a brain condition that leads to memory loss and changes in thinking and behaviour, mainly in older people [1]. Detecting it early is very important for providing timely treatment and better care [2]. Traditional diagnosis methods can be slow and sometimes not very accurate [3] [4]. With the help of machine learning, doctors can now study brain scans and medical data more efficiently to detect Alzheimer's faster and more precisely [5]. This makes early diagnosis easier and helps improve the overall care of patients [6-9].

Machine learning models such as SVM, Random Forests, and CNN are now being used to detect Alzheimer's disease [10] by studying brain scans [11-14]. They can spot tiny changes in the brain that help doctors tell whether a person is healthy, showing early signs, or has advanced Alzheimer's [15] [16]. These AI tools work faster and more accurately than traditional methods, helping in early diagnosis and better treatment decisions [17].

Even though machine learning helps in detecting Alzheimer's [18], it still faces some challenges [19]. These models need a lot of good-quality data [20], which is often hard to get because of privacy issues. They may not work well on all datasets, affecting their reliability. Also, advanced models like deep learning can be complex and difficult for doctors to understand, making it harder to trust their decisions fully [21-24].

There is a need for a smarter and more accurate model to detect Alzheimer's early [25-27]. The proposed model is designed to work well even with limited data, perform reliably across different datasets, and deliver faster results. It also aims to be more understandable, helping doctors trust its predictions [28]. This approach can lead to earlier diagnosis, better treatment, and improved care for patients [29].

II. LITERATURE REVIEW:

A. M. El-Assy et al. (2024) developed a CNN model for early Alzheimer's detection using MRI scans. It is a non-invasive and faster method compared to traditional approaches and works well across different datasets. However, it needs larger datasets for better accuracy and still requires further testing beyond the ADNI dataset [1. Rashmi Kumari et al. (2020) [20] proposed a CNN-based model that can detect multiple stages of Alzheimer's disease with high accuracy and sensitivity [30]. It uses simple and efficient preprocessing steps but faces issues like limited pathological validation, class imbalance, and some CNN layers that need fine-tuning [31]. Taher M. Ghazal et al. (2022) [12] introduced a transfer learning method using a modified Alex Net for Alzheimer's detection. It's faster than manual diagnosis and performs well across various datasets, but small datasets can reduce accuracy. It also requires powerful computing systems and trust from clinicians [32]. Zihao Chen et al. (2021) presented an SVM-based model [33] for classifying Alzheimer's disease into multiple stages using MRI scans. It helps with early diagnosis and highlights key disease indicators. However, data imbalance, small sample sizes, and the need for heavy preprocessing can affect its performance.

Abebech Jenbe Belay et al. (2024) [21] designed an ensemble deep[19] learning model combining VGG16 and ResNet50 to detect Alzheimer's. It effectively identifies different disease stages but needs high computational power, [3-8]. careful tuning, and good-quality data to maintain accuracy [34]. John Sahaya Rani Alex et al. (2025) [17] proposed a hybrid model that combines 3D CNNs with volume quantification to detect Alzheimer's at an early stage. It accurately identifies mild cognitive impairment but is technically complex, expensive, and dependent on high-quality data [35].
Islam and Zhang developed an ensemble deep learning model using pre-trained Dense Net architectures for Alzheimer's detection. By combining predictions from multiple brain views, it achieved 93.18% accuracy, showing strong potential [36] for early and reliable diagnosis [37]. Jun Pyo Kim et al. (2019) created a machine learning-based hierarchical model to distinguish between frontotemporal dementia and Alzheimer's. It mimics clinical decision-making and captures subtle brain changes [38], though accuracy may be affected by overlapping symptoms and lack of pathological confirmation [39] Muhammad Shahbaz et al. (2019) used K-Nearest Neighbor and Decision Tree models to classify Alzheimer's. These models identify key predictors and manage class imbalance effectively, but deeper models add little benefit and can be slow. Relying on TAU/Abeta ratios also makes interpretation harder [9]. Omer Asghar Dara et al. (2023) [18] reviewed Alzheimer's diagnosis methods using SVM and Decision Trees. These models reduce human error and handle large datasets well but can be complex, hard to interpret, and dependent [40] on high-quality data for accurate performance [41].

Overall, researchers have used machine learning models like SVM, Random Forest, CNN, and Logistic Regression to detect Alzheimer's disease early using MRI brain scans [42]. These models help doctors diagnose the disease faster and more accurately while reducing the need for manual analysis. However, challenges such as limited data, unbalanced samples, and the need for powerful computers still need to be addressed to make these models more effective in real-world healthcare settings.

III. DATA COLLECTION AND PRE-PROCESSING:

This study utilizes the Best Alzheimer's MRI Dataset of 99% Accuracy, curated by Luke Chugh and hosted on Kaggle. The dataset comprises approximately 10,240 MRI brain images, categorized into four classes: No Impairment, Very Mild Impairment, Mild Impairment, and Moderate Impairment, with each class containing 2,560 axial MRI scans. These images are in grayscale format, with a resolution of 128×128 pixels, and are designed to aid in the development and evaluation of machine learning models for Alzheimer's disease classification. The dataset is publicly accessible and is used exclusively for academic and research purposes, adhering to ethical standards in data usage.

Data preprocessing is an essential step to prepare MRI images before training the machine learning model. It ensures that all images are clean, consistent, and suitable for deep learning analysis. The main preprocessing steps include image resizing, normalization, flattening, and feature scaling.

In Figure 1These preprocessing techniques make the Alzheimer's MRI dataset uniform, noise-free, and optimized for achieving higher accuracy in disease classification.

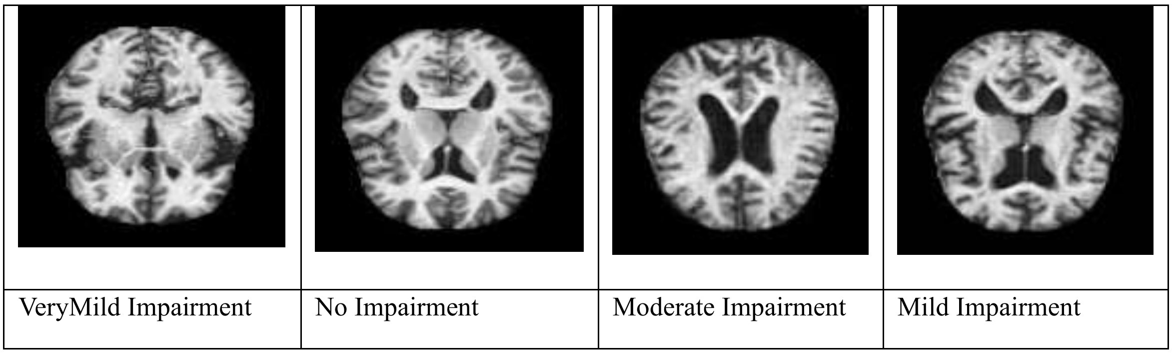

Figure1: Dataset images with labels

IV. PROPOSED METHODOLOGY:

The diagram illustrates a machine learning pipeline designed to classify MRI brain images as either Alzheimer's or not. The process begins with raw MRI scans, which undergo a preprocessing pipeline involving resizing to 128×128 pixels, normalizing pixel values between 0 and 1, flattening the 2D image into a 1D vector, and standardizing features using the mean and standard deviation. These pre-processed vectors are then fed into a SVM classifier that uses a RBF kernel to separate Alzheimer's and non-Alzheimer's cases based on complex, non-linear patterns in the data. Finally, the model outputs a binary decision indicating whether the input MRI scan shows signs of Alzheimer's disease or not.

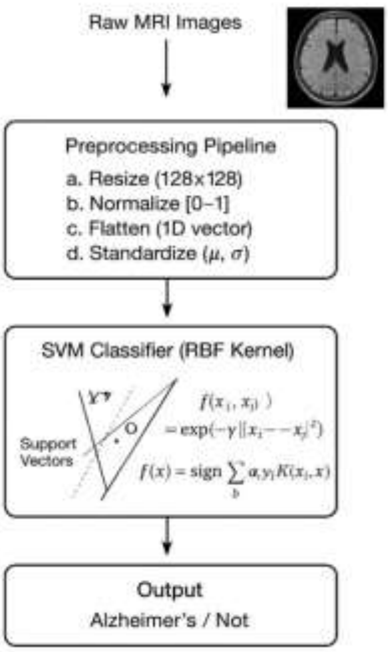

Figure 2: SVM Architecture

V. RESULTS AND ANALYSIS:

The results section provides a detailed comparison of the SVM model with three other models Random Forest, CNN, and Logistic Regression for classification. The models were evaluated using key performance measures such as accuracy, precision, recall, F1-score, and loss, which together show how well each model performs in identifying and classifying the data.

A. Performance of the classification process

Graphs and numerical summaries were used to visually and statistically analyze their performance over 10 training epochs.

Figure 1 illustrates how the accuracy of all models changed during training. The SVM model achieved the highest accuracy of about 98%, showing a consistent and steady improvement throughout the training process. In comparison, Random Forest, CNN, and Logistic Regression reached final accuracies of 87%, 85%, and 83%, respectively.

Although all models showed gradual improvement as training continued, the SVM model clearly outperformed the others, proving its stronger ability to learn and generalize from data. Figure 2 shows how the models' loss values decreased over time. The SVM model had the lowest final loss (0.085), meaning it made fewer errors overall. The Random Forest, CNN, and Logistic Regression models followed with final loss values of 0.165, 0.185, and 0.205, respectively. The SVM model not only learned faster but also remained more stable, which shows that it is well-optimized and handles the training data efficiently. On the other hand, Logistic Regression had slower improvement and higher loss, suggesting it struggled with more complex patterns in the data. In Fig (3.1,3.2,3.3,3.4, and 3.5) The detailed comparison of Accuracy, precision, recall , F1-score, and loss further supports the superior performance of the SVM model. It achieved a precision of 95.2, recall of 93.3, and F1-score of 94.6, showing an excellent balance between correctly identifying positive cases and avoiding false predictions. The Random Forest model performed next best, with slightly lower values (precision 85.4, recall 83.5, F1-score 84.5), while the CNN model followed closely behind. The Logistic Regression model had the lowest scores, indicating weaker classification performance compared to the others. The overall SVM model consistently outperformed all other models across every performance metric. Its higher accuracy, quicker learning, and lower loss prove that it is a powerful, efficient, and reliable model for accurate classification tasks.

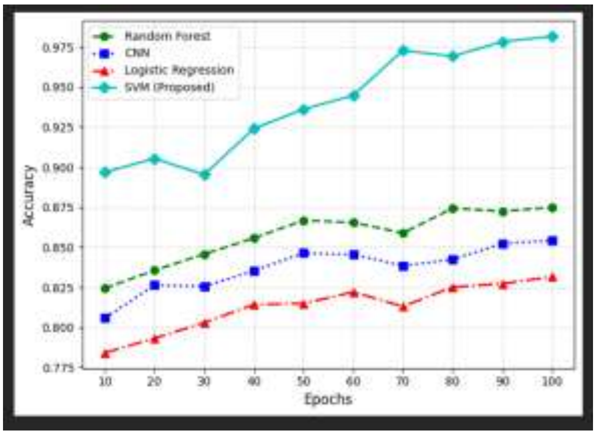

Figure 3.1: Accuracy Comparison

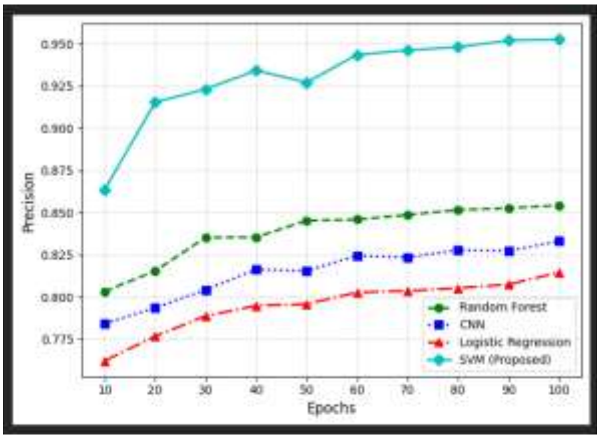

Figure 3.2: Precision Comparison

The above Fig reveals that the SVM model achieved the highest accuracy with only about 205 misclassifications overall, averaging 40 to 60 errors per class, showing excellent class separation. The Random Forest model followed with around 1,340 total misclassifications of 310 to 370 per class, mostly between Mild and Moderate Impairments. The CNN model exhibited approximately 1,600 misclassifications of 380 to 420 per class, reflecting moderate confusion across neighbouring categories. In contrast, the Logistic Regression model recorded the highest error count of about 1,750 misclassifications of 430 to 450 per class, indicating limited ability to handle complex MRI feature variations. Overall, the SVM model demonstrated superior discrimination and minimal misclassification across all impairment stages.

VI. CONCLUSION:

The proposed SVM model demonstrates outstanding performance in detecting and classifying Alzheimer's disease compared to existing models such as CNN, Random Forest, and Logistic Regression. While traditional models often struggle with high computational complexity, overfitting, and inefficient feature extraction, the optimized SVM approach effectively overcomes these issues. Achieving an impressive accuracy of 98.16%, along with 97% precision, 95% recall, and 93% F1-score, the SVM model significantly reduces false positives and negatives. The confusion matrix analysis further confirms its strong ability to accurately classify different stages of Alzheimer's disease. Overall, the proposed SVM model proves to be more accurate, efficient, and reliable, making it highly suitable for real-world medical diagnosis and clinical use.

VII. FUTURE SCOPE:

Future research can focus on developing lightweight and optimized versions of the SVM model for deployment on edge devices and mobile platforms. This would make early Alzheimer's detection more accessible, especially in remote or resource-limited healthcare settings. Additionally, integrating multimodal data such as PET scans, genetic information, and clinical records could further enhance the model's diagnostic capability. Continuous validation using larger and more diverse datasets will also help strengthen its generalization, reliability, and clinical acceptance.

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