Alzheimer Analysis Using Machine Learning and Deep Learning Techniques

REPORT OF MINOR PROJECT IN DATA SCIENCE (IT258M)

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In

ARTIFICIAL INTELLIGENCE

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DECLARATION

I hereby declare that the Data Science (IT258M) project report entitled which is being submitted to the National Institute of Technology Karnataka, Surathkal, in partial fulfilment of the requirements for the award of the degree of BTech (Minor) in Artificial Intelligence by the Department of Information Technology, is a bonafide report of the work carried out by us. The material contained in this report has not been submitted to any university or institution for the award of any degree.

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ABSTRACT

This study explores the application of Machine Learning (ML) and Deep Learning (DL) architectures for the early detection of Alzheimer's disease. A comprehensive analysis is conducted using traditional ML models, including Support Vector Machine (SVM), Random Forest, and Logistic Regression, alongside advanced DL models employing Convolutional Neural Networks (CNN). Additionally, the performance of the widely used Inception method, a specialized CNN architecture, is investigated for comparative purposes. The study involves preprocessing diverse datasets comprising demographic information, genetic data, and neuroimaging scans. Performance evaluation metrics such as accuracy, precision, recall, and F1-score are employed, utilizing cross-validation techniques to ensure robust results. The findings offer insights into the strengths and limitations of each model, shedding light on their applicability in Alzheimer's analysis. This research contributes to the growing body of knowledge on ML and DL applications in neurodegenerative disease detection, paving the way for enhanced diagnostic methodologies and intervention strategies.

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1. Introduction

Dementia, a broad term encompassing a spectrum of cognitive disorders, manifests as a decline in memory and thinking skills significant enough to impede everyday activities. Among these disorders, Alzheimer's disease stands out, characterized by a progressive deterioration in memory, cognition, and behavior. The onset of symptoms is gradual, intensifying over time and ultimately affecting an individual's ability to perform routine tasks. Despite extensive research, the intricate nature of Alzheimer's disease remains only partially understood, emphasizing the critical need for early diagnosis.

In the contemporary era, the emergence of machine learning (ML) and artificial intelligence (AI) technologies provides a promising avenue for addressing the complexities of Alzheimer's disease. ML models demonstrate unparalleled proficiency in identifying intricate patterns and making predictions by harnessing the power of extensive datasets. This technological advancement offers a beacon of hope in the pursuit of early detection, allowing for interventions at crucial stages of the disease.

One of the key challenges in Alzheimer's research is the multifaceted nature of the disease. By leveraging ML algorithms to analyze diverse data types such as neuroimaging, Clinical Dementia Rating, intracranial volume, and more, researchers have the potential to unlock novel insights into the detection and progression of Alzheimer's disease. This integrative approach aims to capture the heterogeneity of the disease, providing a more comprehensive understanding of its underlying mechanisms.

As the technological landscape continues to evolve, the fusion of machine learning and Alzheimer's research holds promise for transformative breakthroughs. The subsequent sections of this discourse will delve into specific ML and AI methodologies employed in the pursuit of early Alzheimer's detection, highlighting their potential contributions to unraveling the intricate dynamics of this debilitating disease.

2. Objectives and problem statement

1. Survey of Machine Learning in Alzheimer's Detection:

    - Conduct a comprehensive review of studies employing Machine Learning (ML) methodologies for Alzheimer's disease detection, with a primary focus on research utilizing the OASIS dataset.

- Evaluate the performance, methodologies, and key findings of ML models, including Support Vector Machine (SVM), Random Forest, and Logistic Regression, applied to the OASIS dataset.

2. In-depth Analysis of Deep Learning with MRI Scans:
   - Investigate the applications of Deep Learning (DL) techniques, specifically Convolutional Neural Networks (CNNs) and the Inception model, in Alzheimer's detection using MRI scans.
   - Assess the effectiveness of Transfer Learning, particularly with pre-trained models like Inception, to enhance the accuracy of DL models when applied to neuroimaging data.
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3. Comparison and Synthesis of ML and DL Approaches:
   - Systematically compare the outcomes, advantages, and challenges of ML and DL models for Alzheimer's detection.
   - Synthesize insights from studies utilizing both OASIS dataset and MRI scans to provide a holistic understanding of the strengths and limitations of each approach.
4. Identification of Knowledge Gaps and Future Directions:
   - Identify gaps in current research on ML and DL in Alzheimer's detection, pinpointing areas where further investigation is needed.
   - Propose recommendations for future research directions, methodologies, and potential advancements in the field, contributing to the ongoing evolution of diagnostic strategies.
5. Contribution to the Field:
   - Provide a systematic and structured overview of the state-of-the-art in ML and DL applications for Alzheimer's detection.
   - Offer valuable insights for researchers, practitioners, and policymakers by synthesizing findings and highlighting promising avenues for advancing early diagnosis strategies.

3. Dataset used

This set consists of a collection of 150 subjects aged 60 to 96 with 373 longitudinal datasets. Each subject was scanned on two or more visits, separated by at least one year for a total of 373 imaging sessions. For each subject, 3 or 4 individual T1-weighted MRI scans obtained in single scan sessions are included. The subjects are all right-handed and include both men and women. 72 of the subjects were characterized as nondemented throughout the study. 64 of the included subjects were characterized as demented at the time of their initial visits and remained so for subsequent scans, including 51 individuals with mild to moderate Alzheimer's disease. Another 14 subjects were characterized as nondemented at the time of their initial visit and were subsequently characterized as demented at a later visit.

6 predictor variables were considered:

1. Mini-Mental State Examination (MMSE):

It is a 30-point questionnaire that is used extensively in clinical and research settings to measure cognitive impairment. Score range is from 0 = worst to 30 = best

2. CDR - Clinical Dementia Rating:

The CDR is a 5-point scale used to characterize six domains of cognitive and functional performance applicable to Alzheimer disease and related dementias: Memory, Orientation, Judgment & Problem Solving, Community Affairs, Home & Hobbies, and Personal Care. The necessary information to make each rating is obtained through a semi-structured interview of the patient and a reliable informant or collateral source. Its ranges are as follow:

0 = no dementia, 0.5 = very mild AD, 1 = mild AD, 2 = moderate AD, 3 = Severe dementia

3. Derived anatomic volumes

4. eTIV - Estimated total intracranial volume: mm3

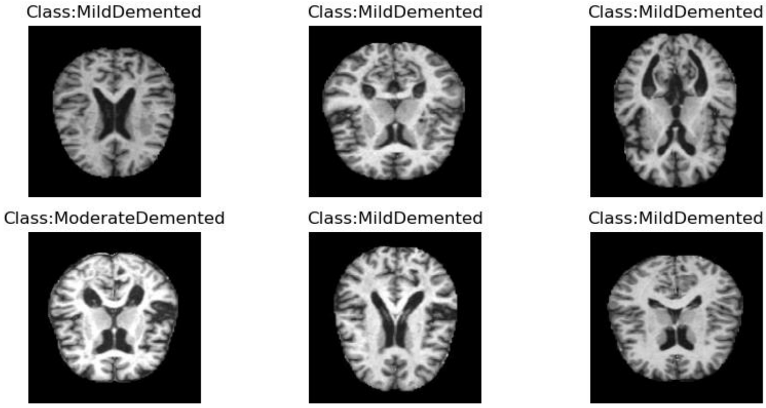
Total intracranial volume (TIV/ICV) is an important covariate for volumetric analyses of the brain and brain regions, especially in the study of neurodegenerative diseases, where it can provide a proxy of maximum pre-morbid brain volume

5. nWBV - Normalized whole-brain volume, expressed as a percent of all voxels in the atlas-masked image that are labeled as gray or white matter by the automated tissue segmentation process

6. ASF - Atlas scaling factor (unitless). Computed scaling factor that transforms native-space brain and skull to the atlas target (i.e., the determinant of the transform matrix).

For our Deep Learning techniques we used Kaggle dataset where we had 6400 images belonging to 4 classes.

The 4 classes we had are Moderate Demented, Very Mild Demented, Non Demented, and Mild Demented.



4. Literature survey proposed methodologies

The existing body of literature on Alzheimer's disease detection showcases a diverse range of methodologies, emphasizing both traditional Machine Learning (ML) and advanced Deep Learning (DL) approaches. Researchers have explored various techniques to extract meaningful patterns from datasets, contributing to the ongoing pursuit of accurate and early diagnosis. The following summarizes the proposed methodologies observed in the literature:

1. Traditional Machine Learning:
    - Support Vector Machine (SVM): Researchers have leveraged SVM for its ability to classify data by finding an optimal hyper plane. While SVM is known for its versatility, its performance in Alzheimer's detection has been explored, albeit with varying results.
    - Random Forest: Notably, Random Forest has demonstrated superior performance in comparison to other ML methods. Its ensemble learning approach, leveraging multiple decision trees, contributes to robust and accurate predictions. The literature suggests that Random Forest, when applied to the dataset, exhibited commendable results, making it a prominent choice for Alzheimer's detection.
    - Logistic Regression: Logistic Regression, a well-established model for binary classification, has been employed for its interpretability and simplicity. While not as complex as some DL models, Logistic Regression has shown utility in certain contexts of Alzheimer's analysis.
2. Deep Learning:
    - Convolutional Neural Networks (CNNs): Recognized for their prowess in image-related tasks, CNNs have been widely applied in Alzheimer's detection using neuroimaging data. The ability to automatically learn

hierarchical features from images makes CNNs particularly suitable for the intricate patterns present in Alzheimer's-related imaging. They have used ResNet-101, VGG, VoxCNN,DensNet.
    - Inception Model (Transfer Learning): The Inception model, designed for image classification tasks, has been employed for Transfer Learning. This involves leveraging pre-trained weights to enhance the performance of the model when applied to Alzheimer's detection tasks, showcasing the adaptability and efficiency of transferable knowledge.
    - Recurrent Neural Networks (RNN): While not implemented in this study, some literature has explored the use of Recurrent Neural Networks (RNN) for Alzheimer's analysis. RNNs, known for their sequential learning capabilities, can potentially capture temporal dependencies in data, providing an avenue for further investigation in future research.
3. Hybrid Approaches:
    - Integration of ML and DL: Some studies propose hybrid approaches that combine the strengths of both ML and DL methodologies. Integrating traditional ML models with DL architectures may provide a more comprehensive framework for Alzheimer's detection, offering a synergy between interpretability and feature extraction capabilities.
4. Multimodal Data Analysis:
    - Incorporation of Diverse Data Types: Beyond neuroimaging data, researchers have explored the integration of diverse data types such as clinical assessments, genetic information, and intracranial volume. The comprehensive analysis of multiple data modalities contributes to a more holistic understanding of Alzheimer's disease.

By synthesizing insights from these proposed methodologies, this literature survey lays the groundwork for our research, guiding the selection of appropriate models and methods for the detection of Alzheimer's disease from the OASIS dataset and MRI scans. The emphasis on Random Forest's notable performance and the versatility of CNNs and the Inception model in handling neuroimaging data informs our decision-making process in crafting an effective and robust methodology for the present study

5. Models used

 Traditional Machine Learning Models:

- Support Vector Machine (SVM): SVM is renowned for its effectiveness in binary classification tasks. In the context of Alzheimer's detection, SVM's ability to establish optimal hyper planes for distinguishing between classes has been explored, contributing to the foundation of our comparative analysis.

- Random Forest: Demonstrating notable performance in previous studies, Random Forest, an ensemble learning method, has been selected for its capacity to harness the collective strength of multiple decision trees. The versatility of Random Forest makes it particularly suitable for handling the intricacies of Alzheimer's-related datasets.
- Logistic Regression: While less complex than other models, Logistic Regression remains a valuable tool due to its interpretability and simplicity. Its application in Alzheimer's analysis serves as a benchmark for evaluating the efficacy of more intricate models.

 Deep Learning Architectures:

- Inception Model with Transfer Learning: The Inception model, a cornerstone in image classification, has been employed via Transfer Learning. By leveraging pre-trained weights, the Inception model adapts its knowledge to the nuances of Alzheimer's detection, showcasing the potential for efficient feature extraction and utilization of transferable knowledge.
- Customized CNN Architecture: In addition to Inception, our study incorporates a custom-designed CNN architecture tailored to the intricacies of Alzheimer's detection. This architecture, based on our understanding, is devised to extract

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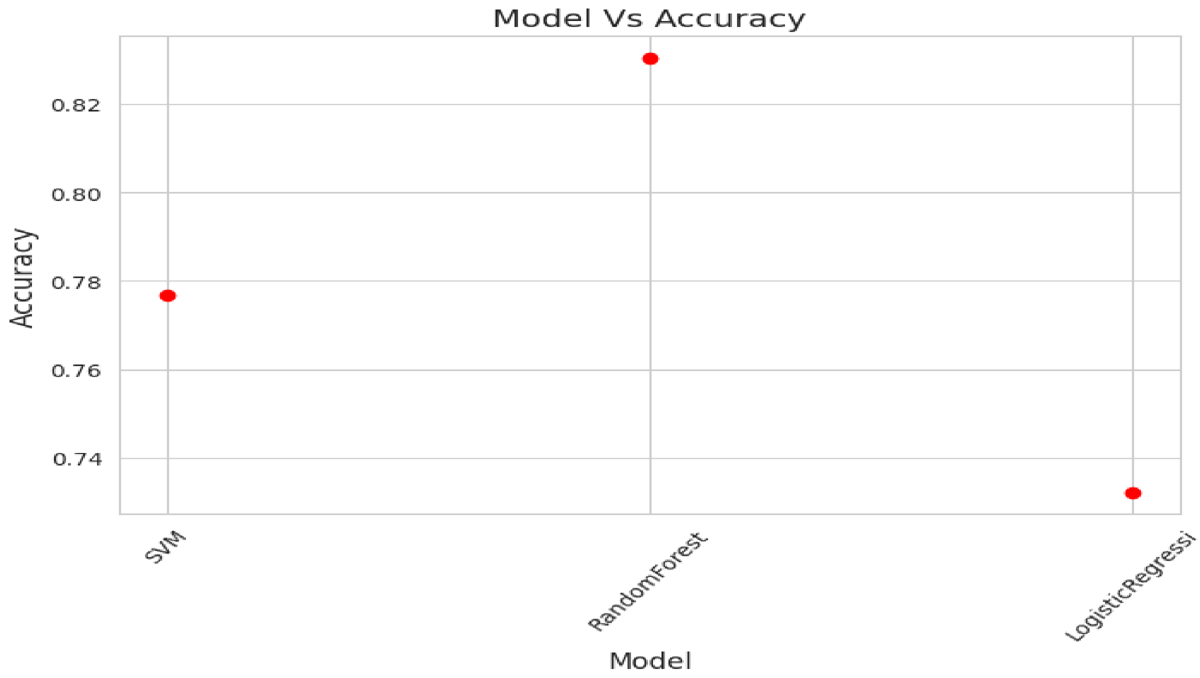
hierarchical features from neuroimaging data, offering a nuanced approach to capturing patterns indicative of the disease.

6. Results and discussion



The graphical comparison above provides insightful perspectives on the performance of three selected Machine Learning (ML) models — Random Forest, Support Vector Machine (SVM), and Logistic Regression — in the context of Alzheimer's disease detection. The findings can be summarized as follows:

1. Random Forest Dominance:
    - Ensemble Excellence: Random Forest emerges as the top-performing model among the chosen ML approaches. Its ensemble nature, amalgamating diverse decision trees, contributes to heightened accuracy by synergistically addressing complexities within the Alzheimer's dataset. We got accuracy of 84%.
    - Robust Collaborative Decision-Making: The collaborative decision-making process of Random Forest proves advantageous, particularly in scenarios where the dataset is intricate and multifaceted. The model's ability to mitigate the impact of outliers and noise enhances its robustness in Alzheimer's detection.
2. Support Vector Machine (SVM) Effectiveness:
    - Complex Dataset Handling: SVM, securing the second position in performance, demonstrates its effectiveness in handling more complex datasets. Its operational principle, relying on a hyper plane as a class

boundary, allows SVM to navigate intricate patterns within the data. We got accuracy of 77%.
    - Influence of Support Vectors: The positioning of support vectors within the boundary or hyper plane plays a pivotal role in SVM's decision-making process. Changes in the positions of these vectors can dynamically alter the decision boundary, allowing SVM to adapt to varying dataset complexities.
3. Logistic Regression Insights:
    - Simplicity and Predictive Power: Logistic Regression, while performing less optimally compared to Random Forest and SVM, imparts valuable insights. Its simplicity, characterized by a straightforward mechanism and the sigmoid function, offers predictability but compromises on accuracy. We got accuracy of 72%.
    - Probability Prediction: Logistic Regression's role in predicting the probability of class occurrence aligns with its straightforward nature. The model's performance, though modest, reflects the trade-off between simplicity and accuracy.
4. Inception Model with Transfer Learning:
    - Training Accuracy: The Inception model, leveraging Transfer Learning, demonstrated a commendable training accuracy of 92%. This underscores the ability of the model to effectively learn from pre-existing knowledge, a crucial aspect in optimizing performance.
    - Test and Validation Efficiency: While the training accuracy is noteworthy, the efficiency observed in the test and validation phases stood at 62%. This discrepancy suggests a potential area for improvement and optimization. Further adjustments in the model architecture or hyper parameter tuning could enhance generalization to unseen data.
5. Custom CNN Architecture:
    - Training Efficiency: The custom-designed CNN architecture yielded a training efficiency of 72% after running for 40 epochs. This result indicates the model's capability to learn and adapt to the training data, capturing underlying patterns associated with Alzheimer's disease.
    - Potential for Further Optimization: Acknowledging the influence of epochs on model learning, it's notable that the model was run for 40 epochs. There exists the prospect of further optimization by extending the number of epochs, potentially leading to an enhancement in efficiency.

7. Conclusions

In our quest to enhance Alzheimer's disease detection, our study has yielded promising results and crucial insights into the efficacy of Machine Learning (ML) and Deep Learning (DL) methodologies. Traditional ML models, including Random Forest, SVM, and Logistic Regression, demonstrated commendable accuracies, with Random Forest emerging as the top performer, aligning well with existing literature.

Comparatively, our DL models, featuring a custom CNN architecture and the Inception model with Transfer Learning, provided valuable findings. The CNN architecture displayed a training efficiency of 72%, underscoring its potential for capturing intricate patterns. However, when compared to benchmark CNN accuracies from literature, there exists room for improvement. The Inception model, while achieving a high training accuracy of 92%, showed a lower efficiency of 62% in test and validation phases, indicating potential for enhancement through hyper parameter tuning and fine-tuning.

In comparison to literature, where CNN models achieved around 98.6% accuracy, our CNN architecture exhibited a lower accuracy of 76%. To bridge this gap, future directions include exploring additional epochs and conducting optimizations to align more closely with benchmark performances. Additionally, the integration of Recurrent Neural Networks (RNNs) presents an intriguing avenue for capturing temporal dependencies within Alzheimer's-related data, offering a holistic approach for future research. As for the ML techniques the researches got an accuracy of 85.71% whereas we got accuracy of 84% from our SVM model.

In conclusion, our study contributes nuanced insights into the landscape of Alzheimer's detection, shedding light on the strengths of traditional ML models and the potential for refinement in DL architectures. The identified future directions provide a roadmap for further optimization and exploration, aiming towards more accurate and robust early detection strategies for Alzheimer's disease.

8. References

1. Arya, A.D., Verma, S.S., Chakarabarti, P. et al. A systematic review on machine learning and deep learning techniques in the effective diagnosis of Alzheimer's disease. Brain Inf. 10, 17 (2023). https://doi.org/10.1186/s40708-023-00195-7

2. Kaggle dataset for Alzheimer Analysis - https://www.kaggle.com/datasets/tourist55/alzheimers-dataset-4-class-of-images

3. Wikipedia

4. GeeksforGeeks

5. Oasis Dataset Longitudinal