A Dual-Model Framework for Stage-wise Detection and Treatment Simulation of Alzheimer's Disease using CNN and Reinforcement Learning

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Abstract— **This research proposes a hybrid artificial intelligence approach for early detection and treatment simulation of Alzheimer's disease. A convolutional neural network model is used to classify brain MRI images into four progressive stages: Cognitively Normal, Early Mild Cognitive Impairment, Late Mild Cognitive Impairment, and Alzheimer's Disease. To support personalized treatment planning, a *reinforcement* learning agent based on Q-learning is implemented to simulate various treatment strategies. The agent learns optimal actions for each disease stage with the goal of slowing progression. The integrated model demonstrates effective performance in both stage classification and treatment recommendation, providing a foundation for clinical decision support systems.**

Keywords— **Alzheimer's Disease, MRI Classification, Convolutional Neural Network, Reinforcement Learning, Q-learning, Early Detection, Treatment Simulation**

1. INTRODUCTION

Alzheimer's Disease (AD) is a chronic neurodegenerative condition that increasingly damages memory, cognitive functions, and behavior. Early diagnosis of the disease and timely treatment are critical to enhancing patients' quality of life. Conventional diagnostic tests, such as cognitive tests and neurological exams, are usually ineffective and sometimes incapable of correctly identifying early symptoms of the disease. As there is an increase in artificial intelligence, especially with respect to the arena of deep learning, Convolutional Neural Networks (CNNs) have come to act as effective tools to scan brain MRI images while finding early signs of Alzheimer's. At the same time, Reinforcement Learning (RL) presents a framework of optimizing and modeling treatment protocols based on experience through learning by doing. This paper proposes a hybrid method that combines CNN-based stage classification with a Q-learning-based treatment simulator to assist in the early diagnosis and personalized therapeutic planning of Alzheimer's Disease.

2. LITERATURE SURVEY

Artificial intelligence methods, especially deep learning and reinforcement learning, have emerged with very good potential in the early diagnosis and treatment planning for Alzheimer's Disease (AD). Sharma et al. [1] suggested a CNN architecture for precise early detection of AD based on MRI data, which produced high classification performance at different stages. Likewise, Wen et al. [2] suggested a CNN model based on T1-weighted MRI scans that successfully extracted brain structure abnormalities for AD detection.To assist with treatment planning, Tang et al. [3] proposed a reinforcement learning model that simulated disease progression and learned stage-dependent treatment policies. Following this, Xiao et al. [4] developed dynamic treatment regimes based on reinforcement learning to tailor care across the disease trajectory.Litjens et al. [5] discussed an exhaustive overview of deep learning in medical imaging, further emphasizing the importance of AI-based diagnostic systems. ADNI dataset [6] is crucial in such research by offering standardized neuroimaging data. With the use of this dataset, Tauseef [7] obtained 98% accuracy using an EfficientNet-B4 model, showing the capabilities of advanced CNNs for the diagnosis of AD.These pieces of work combined provide the foundation for the suggested hybrid model, linking CNN- stage detection with treatment simulation by reinforcement learning.

3. SCOPE OF RESEARCH

This project presents the development of a comprehensive, intelligent system aimed at the early Identification and treatment simulation of Alzheimer's Disease by integrating Convolutional Neural Networks (CNNs) with Reinforcement Learning (RL). It involves classifying brain MRI scans into four progressive stages—Cognitively Normal, Early Mild Cognitive Impairment, Late Mild Cognitive Impairment, and Alzheimer's Disease—using a customized CNN model trained on preprocessed neuroimaging data. In parallel, a Q-learning-based reinforcement learning agent is employed to model treatment strategies, enabling the simulation of disease progression under various intervention scenarios. The scope of the work includes the use of publicly available datasets and synthetic inputs;

real clinical data is not used in the treatment simulations at this stage. However, the system has been designed with flexibility and scalability in mind, allowing for future integration of real-time patient information, clinical input, and more advanced decision-making techniques. Overall, the project contributes to the advancement of AI-driven healthcare systems, laying the groundwork for automated diagnosis and smart treatment planning in neurodegenerative disease management.

4. METHODOLOGY

This paper introduces a hybrid model for Alzheimer's Disease detection and simulation of treatment using Deep Learning and Reinforcement Learning. The process includes four principal stages, as shown in Figure 1.

4.1 Dataset Preparation and CNN Classification

MRI scans were retrieved from public datasets such as ADNI and a Kaggle implementation [6][7], covering four stages: CN, EMCI, LMCI, and AD. Scans were preprocessed through grayscale conversion, resizing to 128×128 pixels, and augmentation(figure 7). A custom CNN model developed using TensorFlow/Keras was employed for multi-class prediction, consisting of convolutional, pooling, dropout, and dense layers. Performance was measured using accuracy, confusion matrix, and standard evaluation metrics.

4.2 Reinforcement Learning Simulation

An AlzheimerEnv custom environment was created in which disease stages are defined as states, and the agent selects from no, mild, or aggressive treatment options. In Q-learning, the 4×3 Q-table was iteratively updated using rewards that reflect disease progression, allowing the agent to learn optimal treatment policies. The stage predicted by the CNN is passed to the RL agent, which then chooses an effective treatment action from the Q-table. This integration enables automated diagnosis and treatment planning with visual feedback in the form of Q-tables and reward trends.

4.3 Frontend Deployment

An intuitive Streamlit frontend allows users to upload MRI scans, receive stage predictions, obtain treatment suggestions, and view the model's decision-making process. This interface enhances usability for clinical and educational purposes.

5. MODELING AND ANALYSIS

The framework combines two AI approaches—Convolutional Neural Networks (CNNs) for MRI-based classification and Reinforcement Learning (RL) for treatment simulation—to create an integrated platform for early diagnosis and personalized planning for Alzheimer's Disease.

5.1 CNN Architecture and Training

A CNN model was engineered to categorize Alzheimer's stages from grayscale MRI scans. Its structure consists of convolutional and pooling layers for feature extraction, dropout to avoid overfitting, and dense layers with softmax output for multi-class classification into CN, EMCI, LMCI, and AD. Trained with three multi-class loss functions and an adaptive optimizer, the model was tested with accuracy, precision, recall, and F1-score. Confusion matrix assured its capability to discriminate between closely related phases such as EMCI and LMCI. Figure 2 depicts an MRI labeled as EMCI with 94.66% confidence.

5.2 Q-Learning Setting and Policy Learning

Simulation of treatment was done in a special RL setting, AlzheimerEnv, where a state corresponds to each stage of the disease and the agent chooses between no, mild, or severe treatment. Rewards are based on the effect of actions on the progression of the disease. By using Q-learning and the Bellman equation, an optimal policy is extracted by having the agent update a Q-table, which eventually supports early aggressive treatment and subsequent conservative approaches, in agreement with clinical wisdom. The agent's total reward over time is represented in Figure 3, and the last Q-table and reward patterns are indicated in Figure 4. A close examination of the Q-values and how they are clinically meaningful is demonstrated in Figure 5.

5.3 Integrated Pipeline and User Interface

The CNN and RL models are combined into one single pipeline, with the CNN-predicted stage input into the RL agent that chooses the best treatment from the Q-table. The system is implemented using an interactive Streamlit interface, where users can upload MRI scans, get classification and treatment recommendations, and see the decision-making process visualized. A snapshot of the frontend interface built upon Streamlit is shown in Figure 6, demonstrating real-time stage prediction and treatment output. This configuration fills the gap between diagnosis and decision support, enabling it to be made clinically and research usable.

6. RESULTS AND DISCUSSION

The system was evaluated on two significant dimensions: the CNN-based classification model and the Q-learning-based treatment simulator. Outcomes confirmed the functionality of the system in accurate staging of Alzheimer's and suggesting appropriate treatment actions according to learned policies. Accompanying graphs and figures further vindicate these results.

6.1 Classification and Policy Performance

The CNN model was highly accurate on stage prediction, particularly on stages of CN and AD. There was some minor ambiguity between EMCI and LMCI due to them being clinically identical. Confusion matrix (Figure 1) verified the model's ability to discriminate structural MRI patterns between stages. Figure 2 is an example MRI identified as EMCI with 94.66% confidence. Meanwhile, Q-learning agent learned optimum treatment policies successfully. As training continued, cumulative rewards grew (Figure 3), and the final Q-table (Figure 4) reflected rational mappings—favoring intensive treatment at early stages and minimal intervention at late stages. This demonstrated the agent's ability to emulate realistic treatment behavior.

6.2 Usability and Interface Insights

A Streamlit user interface was used to make the system interactive and simple to use. Users can upload MRI scans, receive stage predictions, and view treatment suggestions. Q-tables and reward curves (Figure 5) assist users in understanding how the model learned its decision logic, making it beneficial to researchers and clinicians alike.

6.3 Streamlit Interface and Usability

A frontend built with Streamlit was developed to make the system interactive and user-friendly. The system permits users to upload MRI images and receive an immediate classification result and treatment suggestion. The training process can be understood better using visualizations like Q-tables, reward plots, and interface components (Figure 6), making it helpful for clinicians as well as researchers.

7. CONCLUSION

This paper describes a hybrid AI system using a combination of deep learning and reinforcement learning to facilitate early diagnosis and simulation of treatments for Alzheimer's Disease. A CNN model was designed to identify MRI scans as four stages of disease, facilitating correct automatic diagnosis. A Q-learning agent, in conjunction, simulated treatment policies by acting within a disease progression environment. Collectively, these models constitute an integrated system that can both detect the stage of the disease and suggest appropriate treatment actions according to learned policies.
The CNN demonstrated steady classification accuracy, and the RL agent appropriately learned stage-specific treatment policies. Integration with a Streamlit-based frontend provides the capability to upload scans, see predictions, and understand treatment advice through Q-tables and reward plots.
This framework helps in the development of smart, explainable decision-support tools for neurodegenerative disease management and has potential for future clinical application through further optimization and incorporation with real-world data.

8. REFERENCES

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FIGURES

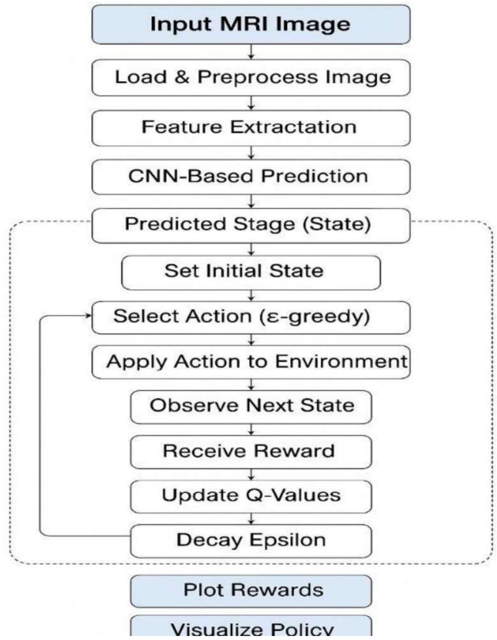

Fig. 1. A Dual-Model Framework for Stage-wise Detection and Treatment SimAlzheimer's Disease using CNN and Reinforcement Learning Workflow Diagram

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Predicted Stage: EMCI (94.66% confidence)
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Fig. 2. CNN model prediction for an EMCI-stage MRI scan with 94.66% confidence, correctly classifying the input image as Early Mild Cognitive Impairmen

Fig. 3. *Episode reward trend during Q-learning, showing the agent's progression toward an optimal treatment policy.*

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Episode 50: Total Reward = -1, Epsilon = 0.778
Episode 100: Total Reward = -6, Epsilon = 0.606
Episode 150: Total Reward = -9, Epsilon = 0.471
Episode 200: Total Reward = -9, Epsilon = 0.367
Episode 250: Total Reward = -10, Epsilon = 0.286
Episode 300: Total Reward = -6, Epsilon = 0.222
Episode 350: Total Reward = 6, Epsilon = 0.173
Episode 400: Total Reward = -9, Epsilon = 0.135
Episode 450: Total Reward = -10, Epsilon = 0.105
Episode 500: Total Reward = -6, Epsilon = 0.082
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Fig. 4. *Q-learning reward trend and final Q-table showing stage-wise treatment preferences learned by the agent.*

Q-Table Interpretation:

Stage	No Treatment	Mild Treatment	Strong Treatment	Best Action
CN	0.90	1.52	3.78	Strong
EMCI	-5.11	-5.65	-6.02	No Treat
LMCI	-9.85	-9.86	-9.74	Strong
AD	0.0	0.0	0.0	Any

Fig. 5. *Q-table interpretation showing strong treatment favored in CN, limited action value in EMCI/LMCI, And neutral outcomes in AD stage.*

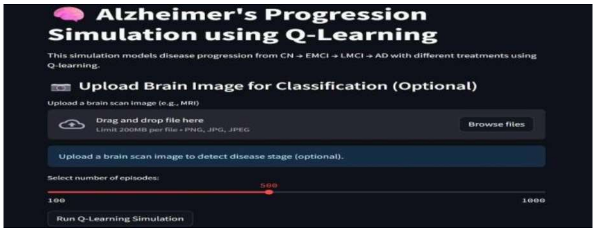

Fig 6: *Main interface of the Streamlit application allowing the user to upload an MRI image for Alzheimer' Stag classification and treatment simulation.*

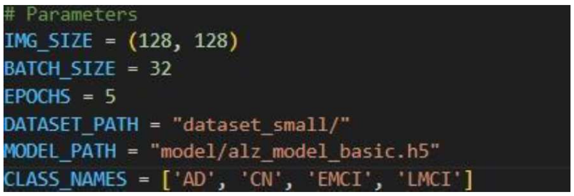

Fig 7: *Images were resized to 128×128 and labeled as AD, CN, EMCI, or LMCI*