Natural Resources for Human Health
eISSN: 2583-1194

Original Research

Received 20 Aug 2026
Revised 17 Sep 2026
Accepted 05 Oct 2026

Natural Resources for Human Health 2026, Vol. 6 (23s): 1030–1038

KEYWORDS:
Disease detection, reinforcement learning, Alzheimer's disease, sMRI, Deep learning.

Alzheimer Disease Detection using Deep Deterministic Policy Gradient Algorithm and Convolution neural network (DDPG_CNN)

V. Nijana[1] And Dr.P.Selvi Rajendran[2]

[1]Research Scholar, Computer science department, Hindustan Institute of Technology and Science, India. vnijanaresearch@gmail.com
[2]Professor Department of Computer Science and Engineering Hindustan Institute of Technology and Science, India

ABSTRACT: Accurate prediction of moderate cognitive impairment (MCI), a stage between healthy aging and AD, is necessary for early detection and treatment of AD. One of the most important biomarkers for the diagnosis of AD is brain structural magnetic resonance imaging (sMRI), which has been used in various deep learning models. For longitudinal study of MCI, there are very few deep learning tools available, and the vast majority of those that do rely on the analysis of sMRI images gathered at a single time-point, neglecting the progressive character of the condition. This is due to deep learning's inherent drawbacks when dealing with longitudinal medical image data. To serve this purpose an integrated approach with Convolution neural network (CNN) and Deep Deterministic Policy Gradient Algorithm (DDPG) is introduced in this study. In this model, longitudinal sMRI images' low-level spatial characteristics are extracted and mapped to high-level feature representations using a CNN. The effectiveness of our strategy is examined using the ADNI dataset and show that it outperforms a number of cutting-edge techniques for Alzheimer's disease detection. Our findings indicate that a promising method for precisely identifying categories of Alzheimer's disease is the combination of deep learning and reinforcement learning approaches.

1. INTRODUCTION

Alzheimer disease (AD) affects thinking and memory by gradually destroying brain cells. It is a multidimensional, neurological, progressive, and irreversible brain ailment. For instance, AD has become the most significant issue for global public health and a widely prevalent neurodegenerative condition. There is no known cure for AD because there is no accurate diagnosis or treatment to halt or decrease the disease's progression. The average lifetime for Ad patients is only 3.1 years, especially when they receive an early diagnosis [1]. Amnestic is a notion that is examined as an early indicator of the clinical indications of AD and is known as mild cognitive impairment (MCI). Comparing structural imaging to a neuropsychological test, the latter is more useful for diagnosing AD. People who are 64 years of age or older and/or who are predisposed to developing AD are becoming more common [2]. According to recent estimates, more than 44 million people worldwide suffer from AD disease, and if new research discoveries are not used to the diagnosis or prevention of AD, that number would increase to more than 100 million by the year 2050 [3,4].

Magnetic resonance imaging (MRI) has been used to study the pathological alterations in the brain linked to AD. The amount of neuroimaging data has expanded over the past few decades, and using machine learning and deep learning techniques, this data is used to characterize AD. These methods were employed by a number of researchers, and they produced encouraging outcomes for the individual diagnosis and prediction of AD [4]. The predetermined features gathered from multiple studies in the process of image processing pipelines were used to analyze the AD using a variety of machine learning classifiers.

Deep learning techniques have recently gained popularity in the field of medical imaging, being employed by numerous researchers to conduct various analyses with astounding success rates for image categorization [5]. CNN, artificial neural

networks (ANN), and transfer learning are some of the techniques used most frequently in deep learning. Compared to machine learning, deep learning models allow for systematic generalization of images from low to high levels, greatly expressing the features [6].

With deep learning techniques, the input data is changed and learned from step to step, yielding a representation that is a little more abstract and composite. The program takes in an image as input in the form of a pixel matrix after abstracting and encoding the edges. The edges are ordered and encoded in order, followed by the composition of other image elements, and lastly, it depicts the image that was provided as input [4, 7]. However, according to limitations in the quantity of labeled information available in the damage detection sector, high complexity and cost of DL models, the sensitivity of the DL model for diagnosis can reach up to 5 hidden layers. In contrast, ImageNet CNN models contain thousands of layers. The shallowness of CNN models for illness diagnosis may limit the effective and ultimate prediction accuracy in fault identification.

Deep Reinforcement Learning (DRL) has gained a lot of attention in the academic world over the past few decades as a potential solution to the aforementioned dilemma. Deep reinforcement learning (DRL), which incorporates both deep learning and reinforcement learning, has been used to solve numerous complicated decision-making problems in robotics, chess, drones, and vehicle behavior. In this field, agents interact with their environments to discover the best behaviors, gradually getting better by trial and error and, generally speaking, not relying on datasets [8, 9].

The goal of the proposed method is to detect the early-stage of AD with suitable model that result in effective result with respect to accuracy, error rate and execution time. Hence a hybrid model is developed based on the deep reinforcement learning concept that combine the convolution neural network with deep deterministic gradient policy method on ADNI dataset to effectively diagnosis the AD with different stages.

2. RELATED WORKS

For a short-term longitudinal research of MCI, a VGG-TSwinformer model based on Transformer and convolutional neural network (CNN) is suggested by Zhentao Hu et al. [10]. In this model, low-level spatial features are extracted from longitudinal sMRI images and mapped to high-level feature representations using a VGG-16-based CNN. For fine-grained merging of spatially nearby feature representations, sliding-window attention is used.

Matthew Velazquez and Yugyung Lee [11] worked on constructing an ensemble model for AD detection. The goal of this study is to use a balanced random forest model and a CNN model to predict the progression of each patient's EMCI (the earliest MCI subset) to AD utilizing diffusion tensor imaging (DTI) data and electronic health records (EHR). A grid search strategy with a 98.81% success rate was utilized to determine the optimal weighting among our two models.

Deep neural networks were used by Preethi Thangavel et al [12]. to discover a mechanism to predict Alzheimer's disease sooner. The Comma Separated Value (CSV) dataset from magnetic resonance imaging (MRI) has been used. The MRI image dataset has been trained using a deep Residual Network (ResNet) and a convolutional neural network (CNN). Deep ResNet can assist this ResNet model in obtaining more data from network levels. Extensive testing reveals that the suggested procedure can produce results with an accuracy rate of 98%.

Huan Lao and Xuejun Zhang [13] introduced the intelligent deep learning network, a data-independent network built on the PCANet concept. In order to retrieve the final picture features, tensor decomposition (TD) is used to conduct data dimensionality reduction using a higher-order tensor built using the learning outcomes. Our method uses the support vector machine (SVM) to forecast clinical scores and diagnose AD using these variables as input. Analyze our method's effectiveness using the OASIS, ADNI-1, and ADNI-2 datasets.

In order to improve the accuracy in diagnosing early-stage AD disease using MRI data, Chahd M. Chabib et al. [14] present the DeepCurvMRI model, which is built on a curvelet transform (CT)-based convolutional neural network (CNN). Following initial CT preprocessing of the MRI data, a CNN model was trained with the newly created image representation. In this study, we trained DeepCurvMRI for multi- and binary-classification tasks using an Alzheimer's disease MRI scan dataset available on the Kaggle platform. DeepCurvMRI's accuracy was 98.62%.

The cognitive status of the examinee who was cognitively preserved was predicted by Tetiana Habuza [15] using a convolutional neural network-based regression model built from the brain MRI data. A model of typical aging, this one. A

significant departure from the model indicates a strong likelihood of accelerated cognitive aging. In the MCI-versus-AD classification, the current model performed commendably (AUC = 0.9793).

3. MATERIALS AND METHODS

The most difficult and important duty is identifying Alzheimer's disease (AD) in its earliest stages. Although early discovery may not cure the illness, it does slow its spread. To achieve this, we put out a hybrid model called the Deep Deterministic Policy Gradient Convolution Neural Network (DDPG_CNN) for the early diagnosis of AD. Figure 1 depicts the four-step data gathering, data pre-processing, feature extraction, classification, and performance evaluation pipeline architecture of the proposed DDPG_CNN model.

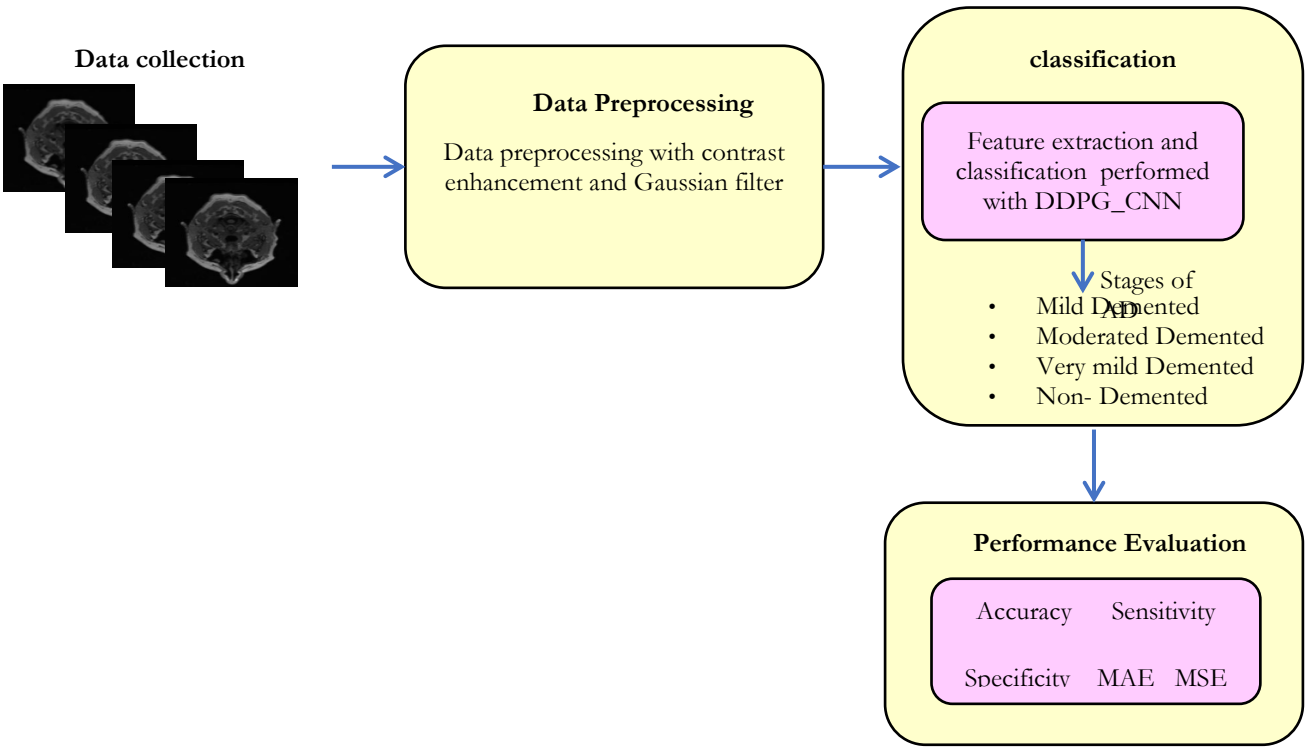


Figure 1. Proposed AD detection Framework with DDPG_CNN

Pre-processing

The preprocessing steps such as contrast enhancement and denoising on the input images for further stage is performed in this phase.

Contrast enhancement

Image quality and brightness are improved by boosting image border contrast and pixel value intervals. Techniques for enhancing contrast aid in organ distinction. The following equation is used to calculate mathematical contrast enhancement:

$$CE = \frac{pv(a,b) - I_{min}(a,b)}{I_{max}(a,b) - I_{min}(a,b)} \quad (1)$$

Where, $pv(a,b)$ represent pixel value of image, $I_{max}(a,b), I_{min}(a,b)$ represent maximum and minimum pixel intensity value.

Denoising

The image denoising method removes noise from images by employing multiple filters. In this study the Gaussian filter is applied for denoising. It removes noise by sensing mask size using the equation shown below.

$$G(a) = \frac{1}{\theta\sqrt{2\pi}} * e^{\left(\frac{-1}{2}\right).\left(\frac{a-u}{\theta}\right)^2} \quad (2)$$

Where a stands for the input value, u for the mean value, and θ for the standard deviation, which expresses the dynamics and behavior of a Gaussian distribution.

Reinforcement model:

A tuple (S, A, P, R) based Markov decision process (MDP) can be used to model RL. Where S, A, P, R denotes states, action, probability function and reward. According to its policy and the states S of the environment, the agent decides on a course of action. If the agent performs a specific action, the environment changes its state as a result to next state and the agent also receives a reward, r. The agent's goal is to discover the best course of action in order to maximize the projected cumulative rewards. Let represent the policy formally. Policies come in two varieties deterministic and stochastic defined by eqn (3) and (4)

$$\pi: S \to A \quad (3)$$

in which the state space is mapped to the action space.

$$\pi: S \times A \to [0,1] \quad (4)$$

It encompasses both the action space and the state space as a probability distribution. Let $\pi(a \mid s)$ be a representation of the conditional likelihood that the agent will act in the given states. In order to apply the aforementioned model to the diagnosis of Alzheimer's disease, a set of features to represent the illness's state, a set of actions to represent the choice, and a reward function must first be defined. Then, to determine the best policy and maximize our cumulative benefits, we should pick an acceptable algorithm.

DDPG

In this study, the DDPG method is used to solve the optimal policy π equation (Eq. (3) or (4)). Consider how DDPG produces deterministic actions in a stochastic environment to maximize cumulative rewards. It is an actor-critic and model-free approach for RL over continuous action spaces. The method combines the benefits of Deep Q NetWork (DQN) (Mnih et al., 2015) with the "deterministic policy gradient" (DPG) (Silver et al., 2014). With the same network topology and hyper-parameters, it can reliably learn sound policies for a variety of difficult physical control challenges, such as intricate multi-joint manipulations and unstable contact dynamics.

There are two NN function approximators in the algorithm. The actor network is one form of system that learns a policy function for converting a state into a deterministic action. Another alternative is the critic network, which can learn a state-action value function that accepts a state and an action as input. The actor update and critic update are included in each iteration's updates. A squared-error loss is minimized by updating the critic:

$$min_\theta xD = \frac{1}{bs}\sum_{1}^{bs} T_j - D(s_j, a_j|\theta^D)^2$$

where T_j, s_j, and a_j represents the "TD target (Lillicrap et al. 2015), state, and action respectively, and bs denotes the mini batch size. $(.|\theta^D)$ denotes a parameterized state-action value function. A "sampled policy gradient" can be used to update the actor to help maximize the cumulative reward.

$$\nabla_\theta \pi C = \frac{1}{bs}\sum_{i}^{bs} \nabla_\theta D(s, a|\theta^D)|_{s=Si, a=\pi(si)} \ \nabla_{\theta^\pi}\pi(s, a|\theta^D)|_{si,}$$

where C and $\pi(\cdot|\theta^\pi)$ denote the sum of the reward and scaled policy function, respectively.

Critic and Actor Network structure

Since the critic net and actor net are part of feature learning as well as function approximators, choosing the right structure is crucial. Through the application of deep learning, informative features drawn from a vast amount of data are discovered.

However, because its nearby elements are coupled to one another, selecting many fully-connected layers to extract the features from brain data may not be ideal. We select CNN for both the critic net and the actor net in order to handle the brain data within the input matrix. Image categorization, video identification, and "natural language processing" are just a few of the many applications available on CNN.

Three different layer types are typically seen in CNN: convolutional, pooling, and MLP. A convolutional layer follows a pooling layer structurally. Convolution is performed in the convolution layer, and the pooling layer receives the results. The "number of parameters" and "the spatial size of representation" are both decreased in the pooling layer. The data is coupled to an MLP and forms a 2D vector in the final convolutional or pooling layer. To summarize it briefly, MLP operates like a traditional classifier, whereas pooling and convolutional layers extract features implicitly. In the input matrix, which can be displayed as a 2D picture with n channels, each technical indicator corresponds to a channel.

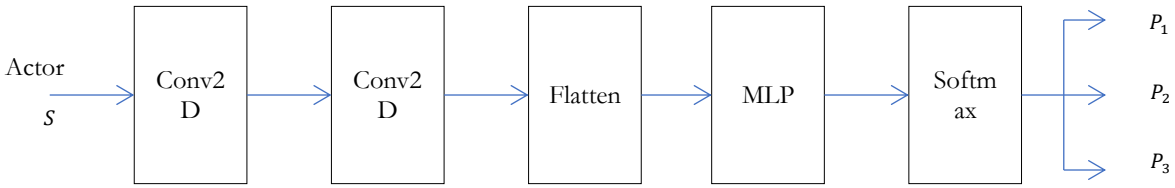
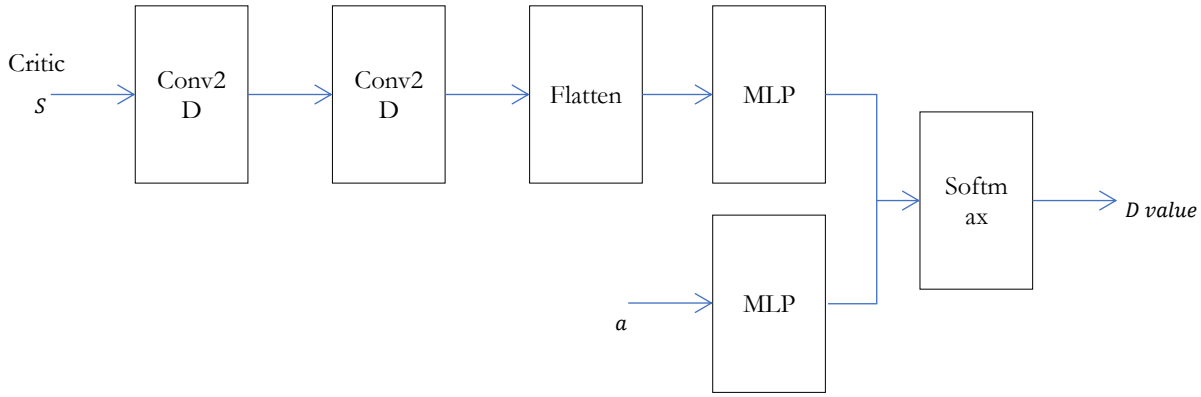


Figure 2. Network structure of actor and critic in DDPG



Our suggested CNN structures for the actor network and critic network are shown in fig. 3. The critic network's output is the D-value, and its inputs are a state s and an action a. The state s serves as the actor network's input, while its output—action probabilities$p1$, $p2$, and $p3$ for 1, 0 and 1, respectively—serve as its output. According to their probability, the choice is made between 1, 0 and 1.

4. RESULTS AND DISCUSSION

The experimental setup and the results are covered in great detail in this section. The experimental configuration includes the model and platform training knowledge used in the current investigation. The model is trained over 100 epochs (40 batches per epoch). Each trial's data is separated into 20% to 80% chunks for network testing and training. The Keras framework is employed in the implementation. Deep neural network training requires parallel processing. Thus, the open-source software python 3.0 is used for both the classifier's training and validation. The KerasRL library was utilized to build our suggested model that interacts easily with Deep Learning and uses various cutting-edge RL techniques and the run time was 690.7 s.

Natural Resources for Human Health
eISSN: 2583-1194

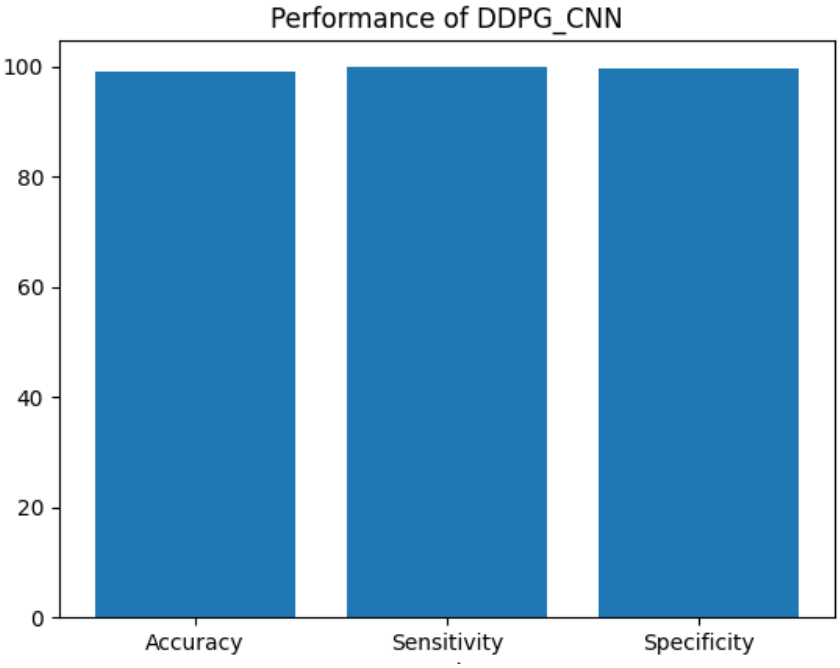


Figure 3. DDPG_CNN evaluation result with Accuracy, sensitivity and specificity values

Table 1: Performance of various RL methods on ADNI dataset

Methods	Data	Accuracy	Sensitivity	Specificity	MAE	MSE
CNN	ADNI	98.17	99.03	98.78	0.323	0.389
Q learning	ADNI	97.45	98.47	98.00	0.434	0.508
DQNN	ADNI	98.34	98.90	98.43	0.384	0.463
DDPG_CNN	ADNI	99.07	99.89	99.57	0.297	0.312

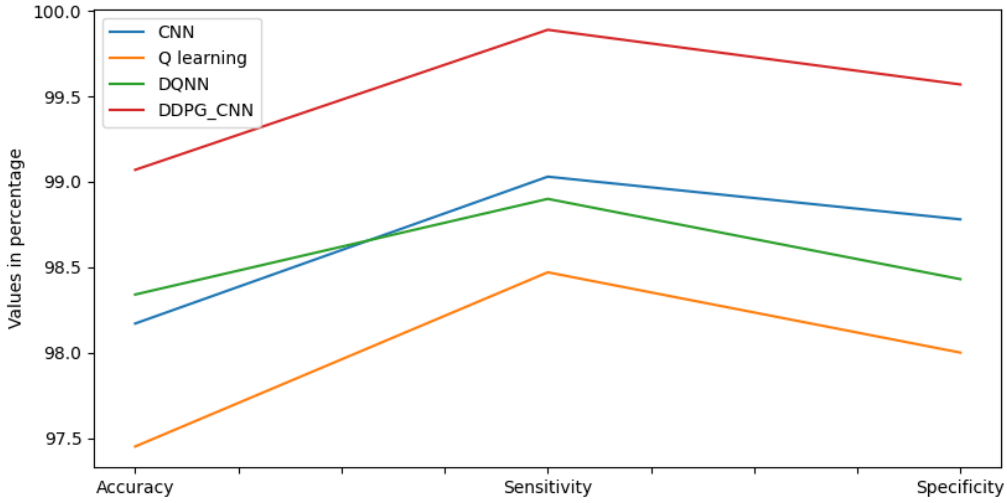


Figure 4. Performance comparison against other RL approaches

Figures 4 and 5 provide a comparison study on accuracy and loss error. The suggested DDPG_CNN model was compared to three DRL models: CNN, Q-learning, and DRNN..

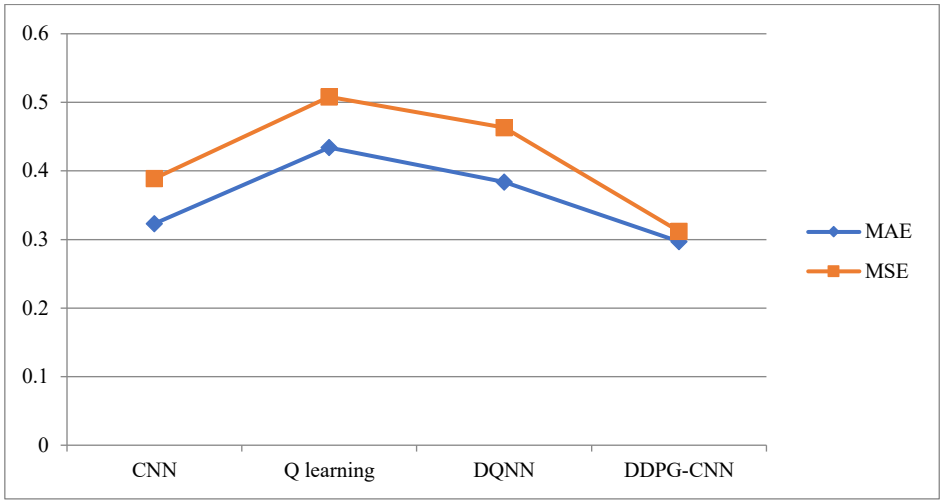


Figure 5. Error metrics evaluation of applied algorithms

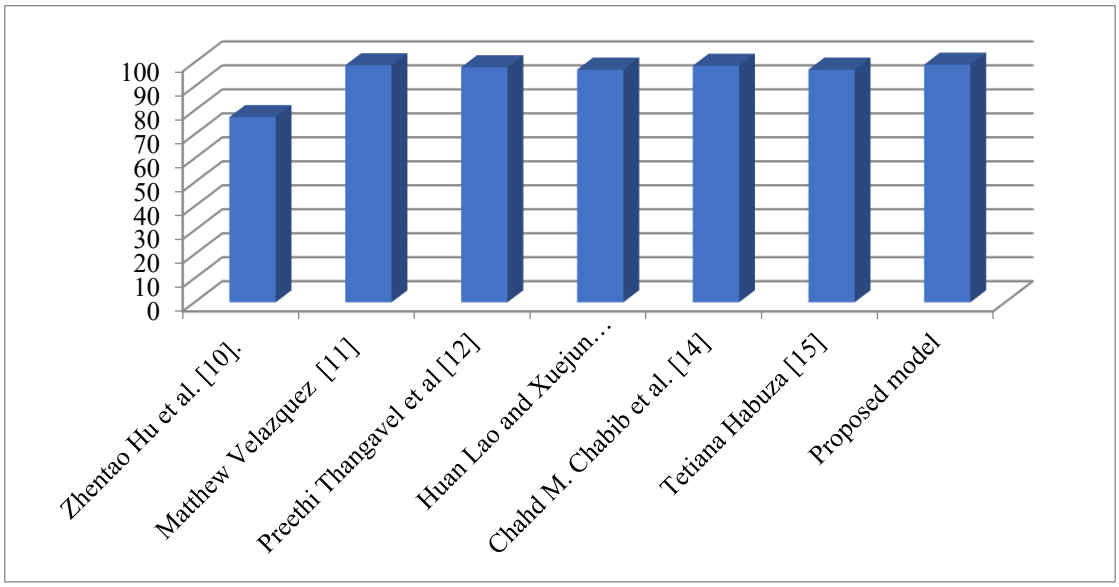


Figure 6. performance comparison against existing methods in literature

The performance achieved by the proposed method is illustrated in figures 3-6. Table 2 reveals that all the models achieved results with better than 90%, which looks to be good performance nevertheless the present DDPG_CNN model surpassed other RL with the greatest accuracy, sensitivity and specificity of 99.07%, 99.89%, 99.57%. Similarly the present model is compared with existing studies in literature and their result is shown in figure 6. The evaluation result shows that the present model is suitable for AD detection.

5. CONCLUSION

This research uses a hybrid methodology to detect and categorize different types of Alzheimer's disease. Deep Reinforcement learning techniques have recently produced effective results in the realm of medical research. In order to classify AD and detect it early, we present the deep deterministic policy gradient algorithm and convolutional neural network (DDPG_CNN) model. This study resulted in the development of a DRL-based pipeline that can accurately diagnose several types of Alzheimer's disease utilizing brain MR images. Early AD detection can aid in future disease prevention. The robustness of the method has been confirmed using several performance indicators, and higher classification performance has been confirmed by contrasting the performance of our framework with that of other well-known approaches. Our method accuracy supports its use in forecasting different phases of Alzheimer's disease for various age groups by carefully choosing the network

architecture. Furthermore, this study may merge many datasets using modern data mining algorithms to increase the effectiveness and efficacy of AD prediction at early stages.

REFERENCES

[1] L.F. Samhan, A.H. Alfarra, S.S. Abu-Naser, Classification of Alzheimer's disease using convolutional neural networks, Int. J. Acad. Inform. Syst. Res. (IJAISR) 6 (3) (2022).

[2] Culberson, J.W., Kopel, J., Sehar, U. and Reddy, P.H., 2023. aaUrgent Needs of Caregiving in Ageing Populations with Alzheimer's Disease and Other Chronic Conditions: Support Our Loved Ones. Ageing Research Reviews, p.102001.

[3] Fathi, S., Ahmadi, M. and Dehnad, A., 2022. Early diagnosis of Alzheimer's disease based on deep learning: A systematic review. Computers in biology and medicine, 146, p.105634.

[4] S.M. Nagarajan, V. Muthukumaran, R. Murugesan, R.B. Joseph, M. Meram, A. Prathik, Innovative feature selection and classification model for heart disease prediction, J. Rel. Intell. Environ. 8 (4) (2022) 333–343.

[5] S.A. Ajagbe, K.A. Amuda, M.A. Oladipupo, F.A. Oluwaseyi, K.I. Okesola, Multiclassification of Alzheimer disease on magnetic resonance images (MRI) using deep convolutional neural network (DCNN) approaches, Int. J. Adv. Comput. Res. 11(53) (2021) 51.

[6] Haque, I.R.I. and Neubert, J., 2020. Deep learning approaches to biomedical image segmentation. Informatics in Medicine Unlocked, 18, p.100297.

[7] P.R. Buvaneswari, R. Gayathri, Deep learning-based segmentation in classification of Alzheimer's disease, Arabian J. Sci. Eng. 46 (6) (2021) 5373–5383

[8] Akhloufi, M.A., Arola, S., Bonnet, A., 2019. Drones chasing drones: Reinforcement learning and deep search area proposal. Drones 3, 58.

[9] Isele, D., Rahimi, R., Cosgun, A., Subramanian, K., Fujimura, K., 2018. Navigating occluded intersections with autonomous vehicles using deep reinforcement learning, in: 2018 IEEE International Conference on Robotics and Automation (ICRA), IEEE. pp. 2034–2039.

[10] Hu, Z., Wang, Z., Jin, Y. and Hou, W., 2023. VGG-TSwinformer: Transformer-based deep learning model for early Alzheimer's disease prediction. Computer Methods and Programs in Biomedicine, 229, p.107291.

[11] Velazquez, M. and Lee, Y., 2022. Multimodal ensemble model for Alzheimer's disease conversion prediction from Early Mild Cognitive Impairment subjects. Computers in Biology and Medicine, 151, p.106201.

[12] Thangavel, P., Natarajan, Y. and Preethaa, K.S., 2023. EAD-DNN: Early Alzheimer's disease prediction using deep neural networks. Biomedical Signal Processing and Control, 86, p.105215.

[13] H. Lao and X. Zhang, "Regression and Classification of Alzheimer's Disease Diagnosis Using NMF-TDNet Features From 3D Brain MR Image," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 3, pp. 1103-1115, March 2022

[14] C. M. Chabib, L. J. Hadjileontiadis and A. A. Shehhi, "DeepCurvMRI: Deep Convolutional Curvelet Transform-Based MRI Approach for Early Detection of Alzheimer's Disease," in IEEE Access, vol. 11, pp. 44650-44659, 2023,

[15] T. Habuza, N. Zaki, E. A. Mohamed and Y. Statsenko, "Deviation From Model of Normal Aging in Alzheimer's Disease: Application of Deep Learning to Structural MRI Data and Cognitive Tests," in IEEE Access, vol. 10, pp. 53234-53249, 2022, doi: 10.1109/ACCESS.2022.

[16] Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A.A., Veness, J., Bellemare, M.G., Graves, A., Riedmiller, M., Fidjeland, A.K., Ostrovski, G., Petersen, S., Beattie, C., Sadik, A., Antonoglou, I., King, H., Kumaran, D., Wierstra, D., Legg, S., Hassabis, D., 2015. Human-level control through deep reinforcement learning. Nature 518, 529.

[17] Silver, D., Lever, G., Heess, N., Degris, T., Wierstra, D., Riedmiller, M., 2014. Deterministic policy gradient algorithms. Proceedings of the 31st International Conference on International Conference on Machine Learning-Volume 32. JMLR.org, Beijing, China pp. I-387-I-395.

[18] Lillicrap, T.P., Hunt, J.J., Pritzel, A., Heess, N., Erez, T., Tassa, Y., Silver, D., Wierstra, D., 2015. Continuous control with deep reinforcement learning. (accessed on 12. 11.18)