Deep Recurrent Q Reinforcement Learning model to Predict the Alzheimer Disease using Smart Home Sensor Data

Dhanusha.C1, A.V.Senthil Kumar2
1Research Scholar, Hindusthan College of Arts and Science, Coimbatore.
2Professor, Department of MCA, Hindusthan College of Arts and Science, Coimbatore.
E-Mail: kunjukannan020817@gmail.com

Abstract. Early detection of alzheimer disease is an essential process of the elderly persons when they are with the mild cognitive impairments. This work adapts the smart home based alzheimer disease detection by recording the daily activities of the resident’s equipped with the sensor devices in their appliances as smart home. Using sensor data based clinical assessment of alzheimer patient is very complex as it is uncertain to predict such vague monitoring and understanding its deep characteristics. To acquire the deep characteristics of sensor dataset unlike the existing conventional supervised learning paradigm, this paper constructs an optimized self-learning model known as reinforcement learning process. This proposed model Deep Recurrent Q Learning based Reinforcement Model (DRQLRM) Process comprised of two stages they are pretraining using recurrent neural network to overcome the overfitting and fine tuning of the parameters involved in deep neural network and Deep Q learning process is used as reinforcement approach which uses the agents rewards and penalties to determine the optimal agents and their experience to predict the unknown pattern in the uncertain condition in effective way. The proposed model produced better result in CASA smart home test bed for investigating the presence of alzheimer

Keywords: Alzheimer, Smart home, Sensor data, Deep Q learning, Reinforcement, Recurrent Neural Network

1. Introduction

Activity Learning (AL) has the ability to define about the models which can identify human actions and the role of smart environments with the objective of helping [1]. In recent research development usage of smart home-based health care applications are started increasing to provide high quality of caring services especially for elderly persons [2]. This paper focuses on using smart home sensor systems to collect the daily activities of the elderly persons by sensing with the help of sensors appliances and it is recorded. The collected sensor data is used to predict the presence of alzheimer by monitoring the resident’s daily behavior in terms of Activity of Daily Living (ADL), without disturbing them and if any changes in their order of activities it can be effectively identified at the early stage of alzheimer’s by developing deep learning models.

In this paper the advantage of using Deep reinforcement learning model is adapted as it has the capability to handle voluminous data and enhanced evaluation measure to discover, appraise and acknowledge widespread data procedures for Alzheimer Disease Detection.

Few important aspects to be considered for constructing deep reinforcement learning are

- With restricted sample data, understanding the patterns and its underlying basic structure
Objective functions have to be reviewed with the persistent illustration of events.

The proposed framework needs the ability to consistently achieve better results even in dynamic environment as the alzheimer disease prediction is done daily activities of aged peoples using sensor data collected from smart home.

2 Related Work

Prafulla et al [3] in their work stated that it is feasible to conduct alzheimer prediction process using smart home sensor data and activity behavior of resident’s. The model relies only on the statistical features of the collect information and it is less reliable in uncertain environment. Tanveer et al [4] reviewed numerous works of alzheimer detection by extracting the features, selecting potential ones and classification. Most of the works are related to the supervised learning models. Geert Litjens et al [5] in their work reported that using statistical and deep learning method can be used to handle the uncertainty very effectively. Novak et al [6] developed an abnormality based self-organizing map which investigates regular activities of elderly adults to detect cognitive impairments. Gray et al [7] constructed the random forest classifier for multimodal classification to detect the Alzheimer disease by analyzing MRI and PET data. Ane Alberdi et al [8] designed a smote boost algorithm to handle the misbalancing during feature selection to detect changes in their activities due to cognitive impairments and advise them to meet medical experts at the earliest.

3 Problem Statement

The existing supervised learning models developed for alzheimer disease detection performs the process of prediction by utilizing the labels defined for each instance used as input during the training time. But in this proposed work reinforcement learning solves the problem on its own instead of receiving explicit instruct to perform its task. But while using Q learning model [10] as reinforcement it is very difficult to distinguish and investigate the alzheimer disease detection. The Deep Q learning is empowered by Recurrent Neural Network which performs pre-training to gain historical expirence and apply for new patients disease detection. Thus, the objective of this proposed framework is to construct an effective self-reinforcing model which deeply analyse the daily activities of elderly person’s and discover their cognitive

4 Reinforcement Learning

Reinforcement is a type of artificial intelligence which have the behaviour of dynamic programming characteristics which constructs and offers training to the algorithm by exploiting a policy of reward and penalty [9]. Unlike machine learning models, reinforcement learning solves the problem on its own instead of receiving explicit instruct to perform its task. Markov Choice Procedure is considered for learning process which embrace the performance of RL. By collaborating and interacting with the atmosphere, RL functions as an agent during its learning process. This agent will either rewarded or penalized based on their correct or wrong actions. RL as an agent itself learns without the assistance of humans by increasing its rewards and restraining its penalties.
Figure 1. Workflow of the Reinforcement Learning (RL) Process.

The workflow of the reinforcement learning process is depicted in the figure 1. Consider an agent who is in the state ‘st’ and decides to conduct an action ‘ac’. The agent receives a reward $RW(st, ac)$ and transfers to another new state $st'$ when an action is completed. To accomplish mapping function between state and action is done based on a policy, it is used in each state to discover specific action to be done by an agent. Discovering an optimal policy $\pi^*$ is the main objective of an agent in its lifetime. It amplifies the whole reduced reward as formulated below as

$$\pi^*(st) = \arg\max_{ac\in\text{Agent}} \gamma \sum_{st'\in\text{state}} pl_{stac}(st', ac)V^*(st', ac)$$

where $V^*(st', ac)$ is a value function that is used for estimating state–action for evaluating the expected reward based on $\pi$. The utmost optimized function is accomplished by applying greedy optimal policy, evaluated by finding an agent which obtains highest reward of all other states. The function for optimality is denoted in the equation

$$V^*(st', ac) = RW(st, ac) + \max_{ac\in\text{Agent}} \gamma \sum_{st'\in\text{state}} pl_{stac}(st', ac)V^*(st', ac)$$

Henceforth, reinforcement learning agent detects the presence of alzheimer through the interactions. It maximizes value of rewards by defining policy of best bellman and adopting and dynamic programming is used for value function.

5 Q-LEARNING Model
The Q learning model is one of the most important progress in RL, it evaluates which action the agent have to take next related to function of action value. It determines the existing value in a definite state after that it creates specification in the concern state. It assesses single state action value by developing temporal variance control algorithm as a policy[1]. The Deep Q function considers present state ‘st’ as well as action ‘ac’ as input and generates needed reward for the action of concern state. Before initializing the environment, Q function arbitrarily fixes a value. In later stages, after analyzing the environment it updates the value by providing optimal value for the action ac at the state ‘st’. Meanwhile, agent iteratively perform sequence of action until it reaches its maximum reward.

6. Methodology: Deep Recursive influenced Q Reinforcement Learning Model for Prediction of Alzheimer Disease
The proposed Deep Recursive influenced Q Reinforcement Learning which considers forecasting of alzheimer disease as regression problem which can be fixed with supervised learning paradigm. This work used smart home-based behavior data to predict the presence of alzheimer by considering aged people’s activities of daily living with the help of smart home test bests and its corresponding activity performance feature is treated as input parameters. While using RL the efficnecy of attaining knowledge about alzheimer detecting agents is identified by their obtained rewards so far. This consequence in unbalanced response related to agents while acclimatize their efficacy together with classificaion using supervised learning. Because the agents won’t identified from available instances or records which are considered as input values are not competently known in the process of learning. Those factors impose that agent needs to be more effective in recognizing alzheimer patient’s characteristics in deep. Thus, this work adapts the deep Q learning model which designs a predicting environment related to the input parameters which translates
conventional learning process to reinforcement model.

Let us consider the environment as an alzheimer prediction process, it includes specific feature combinations as parametric and constraint value that helps to predict alzheimer disease and individual combination comprised of instance set along with labels. While an agent begins its play it discovers Activities of Daily Learning (ADL) datasets value of parameters involved in the actions to achieve its rewards. Each near by or more approximate predicted value of the target (presence/ absence) of alzheimer, the agent attains either positive or negative reward based on its action related to its state at a specific time. The agent recieves an aggregate score when it ends its entire process.

To handle the huge information of Activities of Daily Learning collected from smart homes sensor devices, this work used the Recursive Neural Network (RNN) as stack of layers for Deep Q network (DQN) agent by utilizing the parameters of RNN and mapping function is applied between RNN output to Deep Q values. Let xt represents input of training dataset at time t, the hidden state is signified as Ht at time t. Present xt input and hidden layer state Ht-1 which is a previous one fixes Ht and Ot denotes present layer’s output at time t. The expected output Yt of training data and observed output Ot discover the error rate at time t is denoted as L. The weight distributed by RNN are signified as u, v and w. The Activation function of hidden layers is represented by F and b1 and b2. are the threshold across RNN.

The state value of hidden layer at time t (i.e) Ht is formulated as

\[ H_t = f(u \times x_t + w \times H_{t-1} + b_1) \]

The output Ot predicted at time ‘t’ is formulated as

\[ O_t = f(v \times H_t + b_2) \]

The error (L) occurred in RNN during time ‘t’ is equated as

\[ L_t = O_t - H_t \]

Figure 2. Recurrent Neural Network.

The RNN vital characteristics is that it can efficiently identifies the alzheimer presence is achieved by actual features representation as self-learning process among layer to layer and the constrain of sparse size which resolves problem of overfitting. In this work RNN is designed with a single input layer followed by three hidden layers and finally with one output Q layer. All the RNN layer is comprised of activation function
known as ReLU and regularization L1 is utilized. This consequence absolute values of the data parameters
to be penalized in the network while the data volume is high. Prior to training the model, an enormous
state-action pairs space which consequenses to instability among correlation of data. During training phase to
ensure non-divergence experience replay is used from the agents experience and it is stored in replay memory which holds the information of the concern state its action and reward obtained for that
environment of the current time stamp along with next time stamp’s state.
Primarily, at time ‘t’, replay of experience ‘rp’ will save experience of agent and consequence to a group of
particular experience set. An experience of individual Et at a time ‘t’ is expressed as
\[ Et = (s_{t}, a_{t}, r_{t}, s_{t+1}) \]
And the memory at time t is defined as
\[ Memt = \{E1, \ldots, Et\} \]
To eliminate the divergence among parameters replay experience is an prominent idea which enables the
agents to identify their experience during process of learning. The DRQN’s training process comprised of
two stages, in the first stage RNN is used for pre-training and in the second step DQN agent training is done.
Based on \( \varepsilon \) Greedy policy [12] the agents choose and execute an action with arbitrary probability \( \varepsilon \). Here,
the chance of occurrence (probability) \( 1-\varepsilon \) selects concern action denoting q value which is maximum. Deep
Q learning is optimized by adapting stochastic gradient learning. The weights assigned to the network is
done by data involved in training process.
The algorithm of Deep Recursive influenced Q Reinforcement Learning Model for alzheimer prediction is shown as follows.
Input: CASA dataset
Output: Alzheimer prediction
Procedure
Begin

Stage 1: RNN for pre-training the network model

- Assign the memory capacity of replay as N
- Assign the RNN with arbitrary weights \( wti \)
- For \( i = 1 \) to \( n \)
- Train ith Hidden layer \( Hi \)
- Parameters of \( Hi \) is saved
- End for
- Set Q action value with hidden layer’s parameters such as weight and bias
- Set parameter of \( Q' \) (target action value) same as the parameters involved in \( Q \).

Stage 2: DQN agent Training process

- For event 1 to \( m \)
- Set the observation series by genearting predicted patient arbitrarily
- For \( t = 1 \) to \( M \)
- Choose a arbitrary action ‘act’ with chance of possibility \( \varepsilon \)
- Do action ‘act’ to recieve reward ‘rwt’
- Arbitrarily produce next state \( s(t+1) \)
- Memory (Mem) is saved as \( (s_{t}, a_{t}, r_{t}, s_{t+1}) \)
Owing to network parameter $\theta$ gradient descend is applied $(\nabla w_t, -Q(s_t; a_t; \theta)^2)$

Assign $Q' = Q$

End for

End for

7 Results and Discussions

The Effectiveness of Deep Recurrent Q Learning based Reinforcement Model (DRQLRM) model for alzheimer disease detection using smart home-based behavior data is analyzed by evaluation the model using various evaluation metric. The DRQLRM is implemented using python code and it is compared with three supervised learning models they are Random forest Tree (RF), Conventional Artificial Neural Network (ANN) and Deep Neural Network (DNN). The dataset used for predicting alzheimer is collected from CASA [13] composed of Activities of Daily living (ADL) of 400 elder peoples using smart home testbeds. It holds the information of 1BHK single resident apartments fortified with sensors in door, light, temperature, water and motion. The evaluation metrics used for determining the efficiency of four different prediction models are shown in the table 1 and they are RMSE, MSE and Accuracy.

| Prediction Models | RMSE | MSE | Accuracy |
|-------------------|------|-----|----------|
| DRQLRM            | 0.02 | 0.12| 0.98     |
| DNN               | 0.08 | 0.27| 0.91     |
| ANN               | 0.10 | 0.38| 0.86     |
| Random forest     | 0.71 | 0.8 | 0.79     |

The figure 3 shows the performance of the proposed DRQLRM produce less RMSE value compared to DNN, ANN and RF. This is because the reinforcement model learns through its experience of agents and its action to forecast the symptoms of the alzheimer based on activities of daily learning of the older peoples. The other algorithms worked as a conventional supervised learning model which uses the labels during training phase.

Figure 3. Comparative analysis based on RMSE.
The MSE value obtained by DRQLRM, DNN, ANN and RF is depicted in the figure 4. The results proved the efficiency of the reinforced model of Deep Q learning which enhances the learning process of the agents by applying greedy algorithm-based policy for providing rewards and penalties for their right actions and wrong actions respectively for alzheimer disease detection.

![Figure 4.](image)

The figure 5 illustrates accuracy value obtained by four prediction models in alzheimer using smart home testbeds. The results revealed that by understanding the depth characteristic of activities of daily learning by the elderly peoples, the earlier stage of alzheimer can be more accurately predicted by the proposed DRQLRM by applying Recursive neural network during pre-training phase and applying the Q values to evaluate the expected output and controlling the overfitting of the parameters. Thus, the existing models provide less accuracy because of the vagueness in determining the presence of alzheimer using smart home datasets.

![Figure 5.](image)
8 Conclusion

This paper constructs the reinforcement model by adapting deep Q learning for predicting the presence of alzheimer among elderly persons by examining the activities of their daily learning process. The sensor data are collected and used for investigation, this reinforcement model empowers its learning process by adapting the recurrent neural network and Q learning model is used to overcome the problem of overfitting and parameter fine tuning. It predicts the presence of alzheimer based on the irregularities of their daily activities. It self learns with the agents reward and penalty obtained during its training phase without using the class labels and recurrent neural network is used to gain the previous experience during pre-training phase. The simulation results provides detailed evaluation of the DRQLRM for alzheimer disease detection compared to the other deep learning and conventional supervised models.

References

1. Bravo J, Fuentes L, de Ipina, D.L. Theme issue: Ubiquitous computing and ambient intelligence. Pers. Ubiquitous Comput. 2011, 15, 315–316.
2. Rashidi, P.; Mihailidis, A. A Survey on Ambient Assisted Living Tools for Older Adults. IEEE J. Biomed. Health Inform. 2013, 17, 579–590.
3. Prafulla Nath Dawadi, Diane Joyce Cook, Maureen Schmitter-Edgecombe, Automated Clinical Assessment from Smart home-based Behavior Data, IEEE J Biomed Health Inform. 2016 July, 20(4): 1188–1194.
4. Tanveer M. Richhariya, Bharat, Khan, Riyaj Rashid, A.H. Prasad, Mukesh Khanna, Pritee Lin, Chint-Teng, (2020). Machine Learning Techniques for the Diagnosis of Alzheimer’s Disease: A Review. ACM Transactions on Multimedia Computing, Communications and Applications.
5. 16. 35. 10.1145/3344998.
6. Geert Litjens, Thijs Kooi, Babak Ehteshami Bejnordi, Arnaud Arindra Adiyoso Setio, Francesco Ciompi, Moheen Ghafoorian, Jeroen Awn Van Der Laak, Bram Van Ginneken, and Clara I Sánchez. 2017. A survey on deep learning in medical image analysis. Medical image analysis 42 (2017), 60–88.
7. Novak, M.; Binas, M.; and Jakab, F. 2012. Unobtrusive anomaly detection in presence of elderly in a smart-home environment. In ELEKTRO, 2012, 341–344. IEEE
8. Gray, K.R.: Machine learning for image-based classification of Alzheimer’s disease, Ph.D. thesis, Imperial College London (2012)
9. Ane Alberdi, Alyssa Weakley, Maureen Schmitter-Edgecombe, Diane J. Cook, AsierAztiria, Adrian Basarab, Maitane Barrenechea, Smart home-based prediction of multi-domain symptoms related to Alzheimer’s Disease, IEEE Journal of Biomedical and Health Informatics PP(99):1-1, 2018
10. M. L. Littman, “Value-function reinforcement learning in Markov games,” Cognit. Syst. Res., vol. 2, no. 1, pp. 55_66, Apr. 2001.
11. T. Mannucci, E.-J. van Kampen, C. de Visser, and Q. Chu, “Safe exploration algorithms for reinforcement learning controllers,” IEEE transactions on neural networks and learning systems, vol. 29, no. 4, pp. 1069–1081, 2018.
12. C. A. Merck and S. Kleinberg, “Causal explanation under indeterminism: A sampling approach.” in AAAI, 2016, pp. 1037–1043
13. T. Mannucci, E.-J. van Kampen, C. de Visser, and Q. Chu, “Safe exploration algorithms for reinforcement learning controllers,” IEEE transactions on neural networks and learning systems, vol. 29, no. 4, pp. 1069–1081, 2018. [325] C. A. Merck and S. Kleinberg, “Causal explanation under
indeterminism: A sampling approach.” in AAAI, 2016, pp. 1037–1043
14 D. Cook. Learning setting-generalized activity models for smart spaces. IEEE Intelligent Systems, 2011
15 Dhanusha C, A.V Senthil Kumar. “Intelligent Intuitionistic Fuzzy with Elephant Swarm Behaviour Based Rule Pruning for Early Detection of Alzheimer in Heterogeneous Multidomain Datasets” ‘International Journal of Recent Technology and Engineering (IJRTE)’, ISSN: 2277-3878, Volume-8 Issue-4, November 2019. Page No.: 9291-9298.Scopus Indexed
16 Dhanusha.c,Dr.A.V Senthilkumar, Enriched Neutrosophic Clustering with Knowledge of chaotic Crow Search Algorithm for Alzheimer Detection in Diverse Multidomain Environment “International Journal of Scientific & Technology Research(IJSTR)”,ISSN:2277-8616,Volume-9 Issue-4,April 2020 Edition. Page No:474-481,Scopus Indexed.
17 Dhanusha,c,Dr.A.V Senthilkumar,Dr.Ismail Bin Musirin, Boosted Model of LSTM-RNN for Alzheimer Disease Prediction at their Early Stages” International Journal of Advanced Science and Technology(IJAST) Vol. 29, No. 3, (2020), pp. 14097 – 14108”.