# Mobiltiy Aware Deep Q-Reinforcement Learning Model for Building Efficient Agriculture Autonomous Robots

**Prashanth M V, Vijaya Kumar M V, Chandrashekar M Patil**

***Abstract: in recent years the research has shown that modern farms may be helpful in producing the higher amount of yields along with superior quality. Moreover, this might also help in being least dependent about the labor force. Management of digital farming and site-specific precision are few solutions, which depends on the sensor technology. Moreover, the field data collection is the best only with feasible utilization of agriculture robots (AR). For improving agriculture productivity the sensor are placed across land (geographically), these sensor sends information to multiple robots for carrying certain task such as soughing, harvesting etc. This manuscript conducted survey of various industrial robots model for agriculture environment. Using industrial robots for agricultural purpose is practically not a viable option due to complex environment. Cognitive architecture that exhibits human cognitive thinking is used for learning dynamic and complex environment with good result. In recent times, Society of Mind Cognitive Architecture (SMCA) has proposed using multi-agent and (MA) and Reinforcement learning (RL) technique. However, it is generally difficult to solve Markov decision process (MDP) problem. Thus, cannot be used under dynamic mobility and complex nature of agriculture environment. This is because MDP has many variables. For overcoming research issues, this work present mobility aware Deep Q- Reinforcement Learning (MADQRL) cognitive learning method for Society of Mind Cognitive Architecture by combining both RL and DL technique. The MADQRL are utilized for controlling mobility and communication power of robots according to dynamic environment prerequisite. Experiment outcome shows the proposed MADQRL method attain better performance than existing cognitive learning method considering memory efficiency, learning efficiency, and energy utilization.***

***Keywords: Aggriculture, Autonomous robot, Artificial inteligence, Cognitive architecture, Deep learning technique, Mobility management, Reinforcement learning, Wireless communication.***

**Revised Manuscript Received on April 30, 2020.**

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## I. INTRODUCTION

Agriculture is the backbone of major developing countries economics such as India and China where more than 50% of population depends directly or indirectly on it. Attaining higher agriculture productivity play significant factor in achieving higher GDP growth of a country [1]. However, attaining higher productivity possess number of challenges such as obtaining real-time information of water level, rainfall pattern, wind speed and so on. For collecting raw unstructured data and perform analysis, the space borne remote sensing (RM) forecasting model have deployed sensor for providing useful insight to user for various agricultural application uses [2], [3]. Modernization in farming sector is expected to generate more yields that has better quality with minimum expenses in given sustainable way and least labor force dependent. Moreover the site-specific precision and digital farming is one of the possible solution to expect the above scenario, the technology does not solely depends on the sensor but also field data gathering, this is possible only through the agriculture robots. However the growers, framers and agricultural scientist are facing the huge challenge in producing large amount of food from the restricted land, the research has been found that the food demand increase might be more. Moreover, when it comes in terms of population i.e. nearly 9.8 billion in year 2050 [4] and data indicates that it is equal to feeding a new people of 2 lakhs every single day. Moreover, the integration of control technologies, sensors and digital tools has not only given hope but also indicates that the agricultural robotics might play significant role and may leave huge impact on the modern farming. Furthermore the evolution range starts from plants digitalization, fields digitalization to the detailed information about spatial and temporal condition on timely basis, however it is not as easy it sounds the task are complicated such as achieving the complex non-linear controlling jobs for robot navigation and robot learning. In past few decades, the robot has started replacing the humans in almost every field and agriculture is one of them, meanwhile for some task the accurate navigation of mobile robots play crucial role. As the robot, popularization rises, several researcher have focused on the robot navigation and it was observed that the problem lies with the movement of robot movement i.e. moving from the starting point to the destination point. Moreover regarding the route, agricultural environment and localization is obtained from the sensor, however success in navigation depends on the main four navigation blocks motion control [5], cognition, localization and perception.

Moreover the main problem lies here is path planning, localization and mapping, the research and the demonstration has been carried out to help the problem of absolute navigation in the agro-environment. Moreover, manipulators and agriculture field robots have been integral part of digital farming [6] and precision agriculture [7]. Meanwhile the advancement in the control theory have led several interest towards the automation and change in traditional field to the industrial task, these have attracted the various companies, professional engineers and investors. Moreover, several methods is still in its prototype stage. Meanwhile the robots are capable of performing several operations such as crop investigation, P & W (Pest and weed) controller [9] and so on. AR are trained for the extreme dynamic environment and still it is expected to sense , touch or manipulate the surroundings and crop in such a precise manner that needs minimal amount and increase the efficiency [10]. Moreover, the industrial robotic with speed and precision accuracy is available; however, the application is limited due to the uncertainty task and unstructured environments make it tough. For instances the demand in off-season needs the various type of robotics and automation in the environments like greenhouses [11]. A field robot with spraying, de-leafing, and harvesting manipulator and end-effector for such tasks in a dynamic, complex, and uncertain environment should take into account the different arrangements of plant sizes and shapes, stems, branches, leaves, fruit color, texture, obstacles, and weather influences in order to operate efficiently in the real world condition.

In the case of harvesting for example, the sensing mechanism has to identify the ripeness of fruits in the presence of various disturbances in an unpredicted heterogeneous environment, while the actuation mechanism should perform motion and path planning to navigate inside the plant system or tree canopy with minimum collisions for grasping and removing the soft fruit delicately. This is by far more challenging compared to an industrial robot in charge of picking and placing a solid bolt in an assembly line.

For overcoming problems and issues in understanding agriculture environment in more efficient way cognitive architecture has been applied [12]. Cognitive architectures (CA) are a part of research in general Artificial Intelligence (AI) in building artificial minds. Artificial Intelligence (AI) is developed to understand and model artificial minds capable of behaving like human (farmer). Artificial mind can be seen as a control structure for building an independent software agent. Any computational or cognitive architecture can be seen as either a solitary agent or a multi-agent system model. When modeling behavior of human, equation or mathematical based models are not efficient or inadequate; However, in contrary, agent based system provides superior performance. In [12], [13], and [14] presented cognitive learning model namely SMCA (Society of Mind Cognitive Architecture) which composed of six layers such as reflexive, reactive, deliberative, learning, meta-control and metacognition. Further, [15] introduced rules and norms that affect metacontrol and metacognition design for SMCA. However, [16] showed building efficient learning layer play a significant part in building efficient cognitive architecture. In existing model the optimization problem of attaining efficient communication among agent/robots is modeled as Markov decision process to define the state transformation of the environment. Further, the existing cognitive architecture suffers when applied for dynamic mobility under varying antenna size (i.e. different terrain of coffee plantation). Since, it is problematic to solve the Markov decision process problem because the Markov decision process has many variables.

Further, no prior work has considered such cognitive architecture design for agriculture domain. Thus, this work present a mobility aware (MA) cognitive learning technique for agriculture domain by combining both reinforcement learning and Deep learning method namely, Deep Q-Reinforcement Learning (DQRL). In proposed model, the transmitting agent utilize MADQRL to choose the transmitting power and as well as mobility management based on the communication state, which composed of received signal strength indicator and signal-interference-to-noise-ratio of the signals (information). The receiving agent uses MADQRL to select whether to move from its location to attain better communication based on the preceding communicating performance under certain frequency channel environment model. MADQRL uses deep convolutional neural network to perform compression operation of high-dimensional state space and uses these knowledge experienced replay method to optimize the convolutional neural network parameters.

*The Contribution of research work is as follows:*

- This paper presented a Mobility aware deep Q-reinforcement learning technique for building efficient autonomous robots/agents for agriculture.
- The proposed MADQRL model attain superior performance than existing Q-learning based model [12] with minimal energy consumption, faster learning speed (efficiency), and less memory consumption considering dynamic task and terrain.

The paper organization is as follows: The proposed mobility aware deep Q-reinforcement learning model for building autonomous robots are presented in Section II. The results and experimental analysis are presented in the penultimate section. The concluding remark and future work is discussed in the last section.

## II. A MOBILITY AWARE LEARNING MODEL FOR BUILDING EFFICIENT AGRICULTURE AUTONOMOUS ROBOTS

For building efficient learning and mobility model of autonomous robots for agricultural environment. First, this work apply SMCA cognitive architecture for building agriculture autonomous robots [12], [16]. Second, present a deep Q-reinforcement learning model. Third, present an efficient mobility model using cognitive architecture.

### *a) Cognitive architecture and system model for building efficient agriculture autonomous robots:*

SMCA also known as "group of agents" [12], here the agents that are smaller and simpler are scattered in such a manner that it covers divergent layer architecture. These agents cover all the function, which are associated w.r.t mind. Moreover architecture of SMCA is implemented as the six layered architecture namely metacognition, meta-control, learning, deliberative, reactive and reflexive.

Here each layer architecture gives detail about ADS (Additive Dominating Structure) for robots, these robots can exhibit the different abilities and every behavior here is designed as the agent. Further, [16] showed improving learning layer will aid in building efficient artificial minds.

Thus, this paper presents a new cognitive architecture by improving the learning layer using deep Q-reinforcement learning model. The architecture of proposed mobility aware deep Q-reinforcement learning model is composed of 4 layers such as reactive, reflective, deliberative and learning layer as shown in Fig. 1.

**Reflexive Level:** Reflexive level is the first level and the agents exhibit the normal behaviors, moreover the given input agents produce the output. Here agent's acts as the input and behavioral approach as action is produce as output. Moreover, reflexive agents fit to the first layer of given cognitive architecture and they are designed such that it follows the environment scenario and these agents exist in the least level of CA (Cognitive Architecture).

Reflexive agents discern the environment for presence of middle and border of the environment.

In case of any progress the agents finds the adjoining location and if it is free then it moves else if it found to block then the agent changes its path.

Moreover, the agents are designed to travel in the various directions such as left, right, diagonally, forward and backward.

Later at the same level agent demonstrates the instinctive mechanism such as moving around the environment without colliding with the robots and blocks.

**Reactive Level:** Reactive Level agents exist in second layer architecture; it is a task-based agent.

Reactive level agent shows the harmonized and organized exertion and they are added into the reflexive agent behavior. BDI agent administrates the reflexive agents.

**Deliberative Level:** Third layer in architecture is deliberative layer and it contains the BDI agents, these BDI agents utilizes the flexible amount of reactive and reflexive agents to satisfy the job that are assigned to the agent in environment.

**Learning Level:** Learning level layer helps in assisting for building the foregoing incidents and the layer exert mainly based on the Meta control layer, agent learning is totally based on the RL-(Reinforcement Learning) algorithm named Q learning. Moreover, this algorithm detects the utmost reward for the given activity, also this algorithm exerts the value function policy and later the fortune reward is implemented.

**Policy:** Policy helps in recognizing the situation from environment to the agent return activity in the environment provided. Reward: It describes the job and then plans the activity pair along with situation to the one reward. Value: Value is the given revenue for attaining the reward.

**Value:** evaluate the outcome for obtaining bonus. However, very limited work is carried adopting cognitive architecture of agriculture environment and at the same time it is problematic to solve the Markov decision process problem because the Markov decision process has many variables.

For addressing this paper present a mobility aware deep Q-reinforcement learning model for attaining better learning mechanism, reduces energy consumption and reduce memory usage.

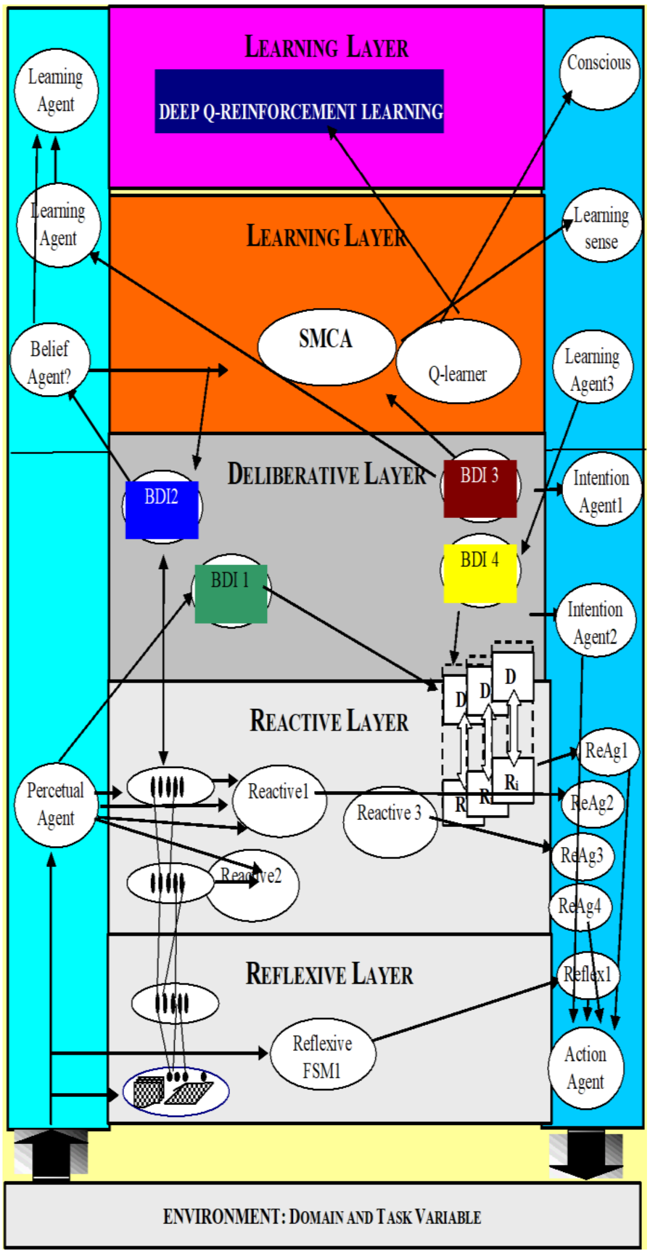


**Fig. 1. Architecture of proposed Deep-Q-Reinforcement learning model.**

Let's consider two robots/agents $\mathcal{A}$ and $\mathcal{B}$ that communicates with each other and deployed in an area of 1000*1000 meter agriculture fields. Each agent is equipped with various kinds of sensor, wireless device, machineries etc. for performing different kind of agricultural activities such as soughing, ploughing etc. The OFDM channel is considered for agents to communicate among each other. Let agent $\mathcal{A}$ sends some information to receiving agent $\mathcal{A}$ with data rate $X$ and frequency $g_0$depicted as follows

$$y^{(l)} \in Y = \{oQ_U/O\}_{1\leq o \leq O}, \qquad (1)$$

Where $O$ is the number of possible transmission power level and $Q_U$ is the maximum transmitting power. The cost for transmitting power of agent $\mathcal{A}$ is depicted by $D_U$. Then, agent $\mathcal{B}$ selects the distance to move from the present position is depicted as follows

$$a^l \in \{0,1,\ldots,N\}, \qquad (2)$$

Where $N$ is the number of possible moving directions and the cost for this is depicted as $D_S$.

Post obtaining information from agent $\mathcal{A}$, agent $\mathcal{B}$ computes the parameters such as bit error rate and radio signal strength indicator etc. from the obtained information's and then based on it computes the signal-to-noise-ratio. Agent transmits radio signal strength indicator and signal-to-noise-ratio information to agent $\mathcal{A}$ on a control or feedback channel at different time slots/sessions.

Then, there could be number of environmental factor such as Doppler effects, path loss and any physical interference because of which the signal (or communication medium) among agent $\mathcal{B}$ and agent $\mathcal{A}$ get affected. Then, the maximum utility affecting communication among $\mathcal{A}$ and $\mathcal{B}$ is computed as follows

$$v_K^{(l)} = -RSSI^{(l)} - D_{Kz^{(l)}} \quad (3)$$

Where $D_{Kz^{(l)}}$ is the maximum power of interference affecting communication among $\mathcal{A}$ and $\mathcal{B}$ under certain noise interference, bandwidth and frequency.

**b) Mobility model for building efficient autonomous robots for agricultural environment:**

This section design a deep Q-reinforcement learning based mobility model of autonomous robots for attaining efficient communication under complex terrain (i.e.. noise) of agricultural environment. In this work, the receiving agent $\mathcal{B}$ and computes the bit error rate of the collected signal. Then, computes the signal-to-noise-ratio in accordance with signal collected.

The radio signal strength indicator and signal-to-noise-ratio-indicator of the signals in the preceding timeslot is utilized by agent $\mathcal{B}$ as the state in the deep Q-reinforcement learning. This is done for establishing whether the present location is best or to move its location for better communication.

**Algorithm 1: Proposed Deep Q-Reinforcement learning based mobility model**

**Step 1: Start**

**Step 2: initialize** $\delta_s^{(0)}, \beta, E = \emptyset, t_s^{(0)}, W, M$ and $C$.

**Step 3: for** $l = 1,2,3, \dots$ **do**

**Step 4:** $t^{(l)} = [RSSI^{(l-1)}, SINR^{(l-1)}]$

**Step 5:** **if** $l \leq W$ **then**

**Step 6:** **select** $y^{(l)} \in \{1,2,\dots,N\}$ in arbitrary fashion

**Step 7:** **else**

**Step 8:** **Observe** the convolution neural network outcome as the $\mathbb{Q}$-values considering input $\mu_s^{(l)}$

**Step 9:** **Select** $y^{(l)}$using the $\epsilon$**-greedy method**

**Step 10:** **end if**

**Step 11:** **If** $y^{(l)} \neq 0$ **then**

**Step 12:** Move $y^{(l)}$ distance from present position

**Step 13:** **End if**

**Step 14:** Obtain signal information with communicating power $y^{(l)}$

**Step 15:** Compute $RSSI^{(l)}$, $BER^{(l)}$, & $SINR^{(l)}$

**Step 16:** Transmit acknowledgement information to agent $\mathcal{A}$ on feedback/control channel

**Step 17:** Compute $v_s^{(l)}$

**Step 18:** $t_s^{(l+1)} = [RSSI^{(l)}, SINR^{(l)}]$

**Step 19:** $\mu_s^{(l+1)} = \{t_s^{(l-W+1)}, y^{(l-W+1)}, \dots, y^{(l)}, t_s^{(l+1)}\}$

**Step 20:** $E \leftarrow \{\mu_s^{(l)}, y^{(l)}, v_s^{(l)}, \mu_s^{(l+1)}\} \cup E$

**Step 21:** **for** $e = 1,2,3,\dots, C$ **do**

**Step 22:** **Choose** $\{\mu^{(e)}, y^{(e)}, v^{(e)}, \mu^{(e+1)}\} \in E$ at arbitrary

**Step 23:** **End for**

**Step 21:** **Optimize/update** $\delta_s^{(l)}$ using **stochastic gradient descent**

**Step 22: End for**

**Step 23: Stop**

The Q-value for every mobility policy are computed using convolution neural network based on mobility status and communication state. Agent $\mathcal{B}$ decides whether to move from current position to another location using $\epsilon$-greedy algorithm. The proposed mobility model is described in **Algorithm 1**. Here the agent $\mathcal{B}$ computes the radio signal strength indicator and signal-interference-to-noise-ratio of the signals for estimating the state is expressed as follows

$$t_s^{(l)} = [RSSI^{(l-1)}, SINR^{(l-1)}] \quad (4)$$

Agent $\mathcal{B}$ further construct the state sequence as follows

$$\mu_s^{(l)} = \{t_s^{(l-W)}, y^{(l-W)}, \dots, y^{(l-1)}, t_s^{(l)}\} \quad (5)$$

and keeps every knowledge experienced in a memory table.

$$f_s^{(l)} = \{t_s^{(l)}, y^{(l)}, v^{(l-1)}, \mu_s^{(l)}\}. \quad (6)$$

The state sequence matrix $\mu_s^{(l)}$ is restructured into a $x * x$ matrix (i.e., in our work we restructure it to $6 * 6$) and given as input to the convolution neural network, whose parameter is depicted by $\delta_s^{(l)}$ are initialized with convolution neural network will possess $N$ outcomes.

Using signal-interference-to-noise-ratio of the received radio signal strength parameter and the mobility overhead, agent $\mathcal{B}$ computes its utility parameter at every instance $l$ using following equation

$$v_s^{(l)} = SINR^{(l)} - D_{sy^{(l)}}, \quad (7)$$

and for estimating whether to change its position based on Q-value is done using $\epsilon$-greedy algorithm is obtained as follows

$$\mathbb{Q}_s(t_s, y) = F_{t_s' \in T}\left[v_s + \beta \max_{y'} \mathbb{Q}_s(t_s', y')\right]. \quad (8)$$

where $t_s'$ is the forthcoming state obtained state $t_s$ and changing its position to certain distance $y$. The convolution neural network parameter $\delta_s^{(l)}$ is optimized using stochastic gradient descent based on loss function is obtained as follows

$$M_s\left(\delta_s^{(l)}\right) = F_{\mu_s, y, v_s, \mu_s'}\left[\left(v_s^{(l)} + \beta \max_{y'} \mathbb{Q}_s\left(\mu_s', y'; \delta_s^{(l-1)}\right) - \mathbb{Q}_s\left(\mu_s, y; \delta_s^{(l)}\right)\right)^2\right]. \quad (9)$$

where $\mu_s'$ is the forthcoming state sequence. In precise, the stochastic gradient descend operation is iterated $C$ times to optimize $\delta_s^{(l)}$ based on the arbitrarily chosen knowledge experienced $f_s^{(e)}$.

The proposed deep Q-reinforcement learning and mobility model attain superior energy efficiency, learning efficiency and memory utilization than state-of-art Q-learning based cognitive model which is experimentally proven in next section below.

## III. RESULT AND DISCUSSION

This section present performance evaluation of proposed Mobility aware DQRL (MADQRL) over existing Q-learning based model [12] in terms of learning, energy and memory efficiency.

Experiments are conducted on Windows 10 operating system, I-5 class quad core processer, with 12 GB ram, and 4 GB dedicated CUDA GPU.

The existing model SMCA [12] was implemented using Prolog and was tested using fungus world testbed. However, prolog software does not support integration of deep learning algorithm.

As a result, we implemented both proposed and existing algorithm using C# programing language. Further, we also developed a fungus world based testbed using C# programing language and Dot Net 4.5 framework. For experiment analysis we had considered an area of 1000 * 1000 agriculture field.

We had considered different kinds of robots/agent, where each agent is equipped with various equipment, sensor, and machineries.

Each agent performs task such as ploughing, leveling, manuring, and sowing of seeds. Agents communicate among each other using OFDM channel with maximum data rate of 3 mbps and time slot size of 8.

Each task performed by agents requires different time and its dependent on environmental condition (i.e., for example if soil is wet then ploughing will be faster or in other case it will be slow).

Thus, the agent has to cooperate among themselves. Since post completion of ploughing, the leveling agent will be initialized and lastly, the sowing of seed task is performed by the agents.

For attaining efficient communication among agent, efficient communication and mobility management model is required. Since communication is affected due to interference and presence of other environmental condition (i.e., noise incurred due to agents operating at different terrain height).

### a) Energy efficiency performance evaluation considering varied iteration:

This section present energy efficiency performance evaluation of proposed MADQRL-SMCA over existing Q-Learning-SMCA model under varied iteration.

Fig. 2 shows energy efficiency performance attained by both MADQRL-SMCA and Q-Learning-SMCA considering 25, 50, and 100 iteration, respectively.

From figure it can be seen MADQRL-SMCA improves energy efficiency by 40.03%, 41.25%, and 42.3% over Q-Learning-SMCA considering 25, 50, and 100 iteration, respectively.

An average energy efficiency performance improvement of 41.192% is attained by proposed MADQRL-SMCA over existing Q-Learning-SMCA model considering varied iteration.

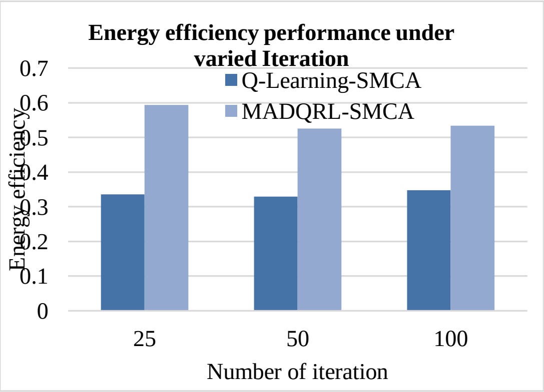


**Fig. 2. Energy efficiency performance evaluation considering varied iteration.**

### b) Memory efficiency performance considering varied iteration:

This section present memory efficiency performance evaluation of proposed MADQRL-SMCA over existing Q-Learning-SMCA model under varied iteration. Fig. 3 shows memory efficiency performance attained by both MADQRL-SMCA and Q-Learning-SMCA considering 25, 50, 75, and 100 iteration, respectively. From figure it can be seen MADQRL-SMCA improves memory efficiency by 55.88%, 52.5%, 55.93%, and 59.21% over Q-Learning-SMCA considering 25, 50, 75, and 100 iteration, respectively. An average memory efficiency performance improvement of 55.88% is attained by proposed MADQRL-SMCA over existing Q-Learning-SMCA model considering varied iteration.

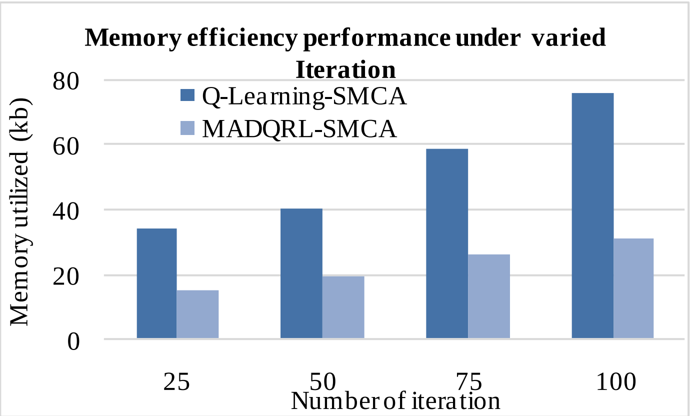


**Fig. 3. Memory efficiency performance under varied iteration**

### c) Learning efficiency performance considering varied iteration:

This section present learning efficiency (successful transmission/communication) performance evaluation of proposed MADQRL-SMCA over existing Q-Learning-SMCA model under varied iteration. Fig. 4, shows learning efficiency performance attained by both MADQRL-SMCA and Q-Learning-SMCA considering 25, 50, 75, and 100 iteration, respectively.

From figure it can be seen MADQRL-SMCA improves learning efficiency by 15.01%, 11.54%, 30.77%, and 35.42% over Q-Learning-SMCA considering 25, 50, 75, and 100 iteration, respectively. An average learning efficiency performance improvement of 23.18% is attained by proposed MADQRL-SMCA over existing Q-Learning-SMCA model considering varied iteration.

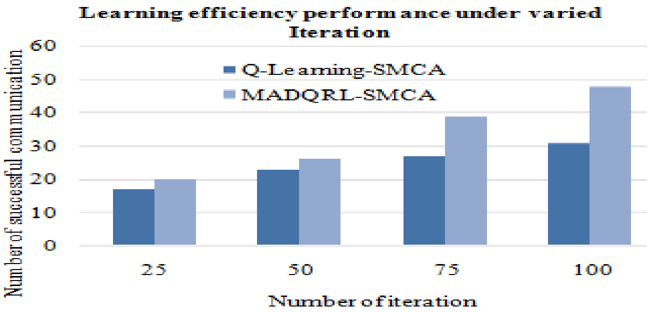


**Fig. 4. Learning efficiency performance under varied iteration.**

## IV. CONCLUSION

Firstly, this work presented a deep rooted survey in using robot for performing operation such as ploughing, soughing etc. to enhance agricultural productivity. From survey it can be seen using industrial robots for agricultural purpose is not efficient due to the complex nature of agriculture environment. For example, in coffee plantation the robots need to move and communicate considering different terrain, where the height of antenna varies affecting SINR among communicating device. For learning agriculture environment more efficiently cognitive architecture is applied for building artificial minds capable of behaving like human (farmer). However, existing model is problematic to solve the Markov decision process problem due to larger variable size. Further, no prior work has considered designing cognitive architecture for agriculture purposes. Thus, this paper presented a mobility aware learning model by combining both reinforcement leaning and deep learning model namely, Deep Q-Reinforcement Learning. The MADQRL is a multi-agent model that is used to control the communication power and mobility of agents based on dynamic environment requirement. Experiment is conducted to evaluate the performance of proposed MADQRL over existing Q-Learning model. Experiment outcome shows MADQRL improves energy efficiency by 49.192%, memory efficiency by 55.88%, and learning efficiency by 23.18% over existing Q-Learning model. Experiment outcome shows MADQRL attain superior performance than existing Q-Learning model in terms of energy efficiency, learning efficiency and memory efficiency. The overall result attained shows proposed model is robust. The future work would consider present cooperative leaning model for avoiding collision in multi-robot/agent environment with presence of obstacles.

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