



Self-Organizing Adaptive Recurrent Neural Network for Lifelong Learning

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Abstract

Life-long learning can learn consistently over a long period of time by updating new knowledge while retraining from previous learning experiences. Imitation is the capacity to understand the behaviors of others and reproduce them. Imitation learning is a way to learn and acquire new skills through another agent's observation of these skills. The First achievement through imitation is other's actions by vision using different development theories. This paper presents a developmental model of imitation learning based on the hypothesis that humanoid robot acquires imitative abilities as induced by sensorimotor associative learning through self-exploration. Our proposed method "SOARIN" network that connected hierarchically. The efficient and effective method SOARIN consists of three stages namely neuron activation, neuron matching, neuron learning. We



learn to incorporate and update upper body behavior according to the joint angles visualized by the robot sensor by using all these steps. The temporal connections represent the series of neurons activated during the learning process. Through vision, sensors understand and learn action automatically and store data in episodic memory.

Keywords: Incremental learning, Episodic memory, Robot upper body actions learning.

Introduction

Imitation learning, also known as Programming by Demonstration (PbD), is a basic method of training that defines more efficient interaction between people. Imitation is an efficient behavior in social learning whereby a person observes and copies the behavior of another. At a very early- age, by watching others perform these tasks, babies acquire knowledge of how to manage their bodies and perform activities. Imitation learning is the part of machine learning in which autonomous robots interact with the environment without human interference. Imitation learning is a way of learning and acquiring new skills through other agents' observation of these skills. In the field of robotics, imitation learning plays a very important role. Several researches show that imitation ability develops early in life [1]. For example; first-year babies communicate with newborn babies, learn how to execute acts by watching other actions. Babies can mimic hand movements and motions of the body, during experience with their surroundings, they eventually gain more complex imitative capabilities.

Robots can walk and behave in a hominid- centered world, enabling them to engage in our everyday routine, as a result of recent advancements in robotics. That has generated a need to develop automatons configured with behavioral learning abilities. Unlike humans, whereas robots need to be designed according to particular applications, robots have specific capacities to learn from their surroundings. It is not possible to specifically pre-program a robot with such capabilities because of the variety of behavior



to be performed and the variety of potential interactions with objects and people. A human being will explain the task, while the robot, imitating the humans, observes and executes these equivalent tasks. The key feature of imitation learning is the development of a simplified model of a gesture task from the trainer's observation.

Memory is important for processing, learning, the experiences of robots in complex environments, just like humans seem to adapt faster and memorize previous events and execute tasks simultaneously. Our Imitation learning system is based on incremental learning; system learn behavior automatically links with episodic memory. Episodic memory is a type of recollection that specifically and continually maintains experiences. In episodic memory, the learning process is completely unsupervised [22].

Our purposed algorithm is "Self-organized adaptive recurrent incremental network" (SOARIN). SOARIN is formed by several "adaptive recurrent growth networks when required" (ar-GWR). Our method is long-life learning that can learn continually around a long period while retrained already exist data. Our represented algorithm contains three principle processes of neurons, activation, learning, matching. Our system uses imitation learning to perform upper body actions linked with episodic memory. The ar-GWR rapidly learns from the series of previous experiences in episodic memory.

A new action is formed by the combination of different joint angles. The learning process is triggered and the robot learns the new action. When the current input action has no already exist then added this action in episodic memory. A new action is formed by the combination of different joint angles. The learning process is triggered and the robot learns the new action. When the current input action has no already exist then added this action in episodic memory. In life-long learning, neuron learning is carried out to remove the issue of catastrophic forgetting [23].

We have discussed the following fundamental problems when constructing



an incremental imitation learning system: How a system can independently episode and determine the beginning and end of the movement using onboard vision sensors during a continuous interaction without depending on the details a priori. How the robot can maintain for quick and accurate retrieval, use a self-organizing method to incrementally create new knowledge without corrupting previously learned data. What does the system store in episodic memory all actions that are performed and how we update already existing data in episodic memory [24].

The paper is organized as follows. Section III introduces the computational models of the proposed method. The experimental setup and results are showed and discussed in Section IV and Section V. Finally, we conclude the paper and highlight some future work.

Related Work

Fritzik [2] "Growing Cell Structure (GCS) first unsupervised neural network. GCS is based on SOM [3] The system consists of k-dimensional simplices (A simplex is a generalization of the concept of a triangle or tetrahedron to arbitrary dimensions in geometry, like 2-simplex is equal to triangle, 3 simplex means tetrahedron, etc). The value of k is predefined it is typically k equal to 2; in other words, the simplicity is triangles. At each λ iteration, where λ is a fixed, is inserted into a new node, the node located to allow the node that in previous steps created the greatest error. If any stopping criteria are met, the network continues to evolve and expand. This might also consist of a given network size with an appropriate size. The default number for a recorded network error. One of a series of perfectly interconnected networks is the GCS. But this network creates a problem when we delete any node which causes upheaval. To resolved this problem, we used the Hierarchy of GCS's arrangement in a tree.

Fritzik [4,16] suggests Growing Neural Gas (GNG), In GNG, the network interface is not limited, with connections for each input is generated between the two highest performance nodes. The two best-matching nodes,



i.e. the two nodes whose weights in the Euclidean term are nearest to the input, are chosen for each given data provided to the network. If it does not already exist, a neighborhood relation is created between the two nodes and along with the neighbors of the winning node, the locations of these nodes are moved such that their weight regulates the feedback better. The value of unused edges increases, while the edges are used to reset their age to 0. The edge is eliminated until the age of an edge is greater than the threshold, but this network has a problem, the growing process carried out new nodes added at any time. For the next hundred iterations, several nodes will be added one after another, and then no more added nodes. The new node's location is based on the input node and the existing winning node.

Parisi, G.I., Tani [5,25], propose a self-regulating neural system to learn to evaluated human activity progressively from video stream. His proposed model is based on ordered, self-organized neural networks to learn from pose-emotional depictions of action. Each architectural layer comprises a new Growing When Required (GWR) variant. The model is based on three mechanisms that are consistent with the neuronal data from the animal visual preceptive. Detailed movement is observed in two separate coexistence paths, then merged to get a common sense. Both mechanisms have class divisions for generalizing model and image analysis behavior with increasing growth, ranging from low to high visual stimulus descriptions. The input-driven self-organization of the nervous system is important for tuning the neurons according to the input distribution. KTH used as a backbencher dataset. Further results demonstrate that our learning can adapt non-steady inputs, avoiding catastrophic interference and handling in which labels are damage. But in some cases, the result of GWR not satisfied for complex environments.

Kemker.R [6] suggests purposed MLP-based catastrophic forgetting. Neural networks are equipped incrementally for classification tasks. He solved the previous work. "MNIST" problem with more challenging dataset.



He establishes five common mechanisms for disaster-forgetting prevention: Regularization., Ensemble, Rehearsal, Dual-Memory model, Sparse-coding. The combination of rehearsal pseudo-rehearsal and dual- memory systems is ideal for increasingly learning new classes. Regularization and assembly are best at separating multiple sessions differing in a common DNN (Deep neural network) framework. While this rehearsal program was working fairly well, all training data needed to be preserved for replay. But this type of system not applicable for real- world lifelong incremental. Our research proves this catastrophic forgetting is not solved by considering the process.

Lopez Paz Ranzoto [7] The Gradient Episodic memory (GEM) model has been proposed to allow data to be transmitted efficiently to previous steps. An episodic memory used to store a collection of examples encountered from a given task to avoid catastrophic forgetting is the fundamental feature of GEM. GEM recognizes the losses as input variables on tasks' $k < t$ episodic memories, therefore limiting the failure on the new task 't', avoiding their growth while enabling them to shrink. This strategy takes considerably more memory than other methods to Regularizing, such as EWC (Extend Memory lifetime for Recommend Pattern) at training.

Itauma Isong Itauma [8] suggests Gesture Imitation using Machine learning Techniques in which a robot that uses various machine learning approaches to imitate simple upper torso moves. He proposed Decision based Rule (DBR). Compared to linear regression models, the learning methodology has greater accuracy in gesture estimation. In a system that recognizes gestures, it was proposed to use 3D trajectories formed of a reduced couple of policies. The position product of the directional vectors (top right elbow and shoulder elbow) between the shoulder and elbow and the elbow to hand is estimated to calculate the angles for Right Elbow Roll and LeftElbowRoll. For implementation of imitation learning use RGBD camera. In a 3D Cartesian coordination system, the measurement was based on points. Decision-based learning (DBL) process of online learning gets.



Methodology

Our purposed methodology is SOARIN. Self- Organizing Adaptive Recurrent Neural Network is generated by various numbers of (ar-GWR). SOARIN model has an episodic memory that is working for lifelong learning. In lifelong learning networks process new incoming data as well as update already existing data. The ar-GWR rapidly learns the series of past experiments in episodic memory the ar-GWR learns and replicates input information in the episodic memory layer by adding neurons to the layer.

Soarin Architecture

SOARIN model has an episodic memory that is working for lifelong learning. Lifelong learning networks process new incoming data as well as update already existing data. To find the spatiotemporal relationship of the incoming data, the episodic memory contains the adaptive recurrent, (ar-GWR) network that incrementally produced neurons and topological connections in the layer. By measuring the activation value of neurons, the ar-GWR determines the winning neuron based on an actual input and temporal connection. jTemporal connection is the sequence of previously activated neurons that are connected with time delay. The ar-GWR rapidly learns the sequences of past observation in episodic memory the ar-GWR learns and reproduces input data examples in the episodic memory layer. Each neuron in the layer is composed of a weight vector and several temporal attributes. The time data in the real world is a temporal attribute.

There are three stages of ar-GWR, activation of neuron, matching of neuron, learning of neuron. To determine the best matching neuron(BMN), apply the Neuron Activation. The ar-GWR has the activation function to determined the best neuron matching (BMN) ωb based on the input $x(t)$. The activation function used in ar-GWR is

$$b = \operatorname{argmin}(Tj) \quad (1)$$

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input from created pose streams (position, orientation) the joint of a human hand. In DBL

$$T_j = \alpha_1 \|x(t) - \omega_j\|^2 + \sum^k \alpha_k \|E_k(t) - e_{k,j}(t)\|^2 \quad (2)$$

system visualize human action using RGBD camera and the compute joint angle node, joint angle pass to prediction system where predicts the gestures of human-robot imitate the human action. But this system is expensive for computation cost.

$$E_k = \beta \cdot \omega_{j-1} + (1 - \beta) \cdot e_{k-1,j-1} \quad (3)$$

When we have input $x(t)$ then the activation value of BMN is calculated as

$$a_b(t) = \exp(T_b) \text{ where } T_b$$

calculated by using the equations (1) to (3). Where α_i and β both are contributing factors that control the effects of the current input according to established a temporal connection between neurons.

$$q^{new} = q^{old} + 1$$

previously activated neuron, ω_{j-1}

Previously

$$\begin{aligned} &(b, j-1) \\ &(b, j-1) \end{aligned}$$

activated neuron's weight at $t - 1$ and E_k is a global element of the network. According to the model mentioned throughout [9,11], each neuron has a regularity counter $r_j \in [0,1]$ that shows the strength of its firing over time. The regularity counter is found as

$$\Delta r_j = \tau_j \cdot \lambda \cdot (1 - r_j) - \tau_j \quad (4)$$

Where τ_j and λ both are decay elements that regulate the regularity counter's [10,14,15] decaying form. The value of the regularity counter for each newly formed neuron is $r_j = 1$ and iteratively decays to 0.

In neuron matching, if the best matching neuron activation value $a_b(t)$ is less than the threshold a new neuron is connected to the network [12,13]. This indicates that a new neuron, N is generated if we have: $a_b(t) < \rho_a$ and $r_b < \rho_r$ with new weight vectors that are computed as



$$\omega_N = 0.5 \cdot (x(t) + \omega b) \quad (5)$$

$$e_{k,N} = 0.5 \cdot (E_k(t) + e_{k,b}) \quad (6)$$

In neuron learning, the best matching neurons have an activation value greater than the threshold $a_b(t) > \rho a$. In neuron learning BMN b and its topological neighbors n updated, neuron learning is carried out. The topological neighbor points to the connection between the neurons and is an important aspect in the learning of the network. Neuron learning is done in life-long learning to remove the problem of Catastrophic forgetting. In which a neural network begins to forget the data learned in the previously trained tasks while training on new tasks or groups.

Episodic Memory

A sequence of events creates an episode in the episodic memory, store experienced, and episodes that connect one another. We introduce temporal links that identify patterns of activation of recurrent neurons in the network. The temporal connections (previous winner node and current winner node) encode the sequence of neurons that have been triggered during the process of learning.

A temporal link will be increased by 1 for each learning iteration, which is sequentially stimulated between two neurons. When we get new input at time t that is connected with previously activated neuron $j-1$ at time $t-1$ in every learning process and $g = \text{argmax } Q(m,n)$

Where g is the next neuron can be obtained from the encoded temporal series by selecting the largest value of Q for each recurrent neuron m , n is the neighbor of m . Without requiring any input data, the activation sequence of recurrent neurons may be restored. If there is a node that no longer has neighbors or existing edges, delete them in that case. The deletion process is completed.

Experimental Setup

In this chapter, we will discuss the experimental settings and analysis of the proposed architecture. In this section, the proposed architecture for real



time robot deployment is tested. The dataset contains several different actions regarding the upper part of the body. As we discussed in the methodology chapter that the performance of the robot depending on the selection of the neurons for the threshold value.

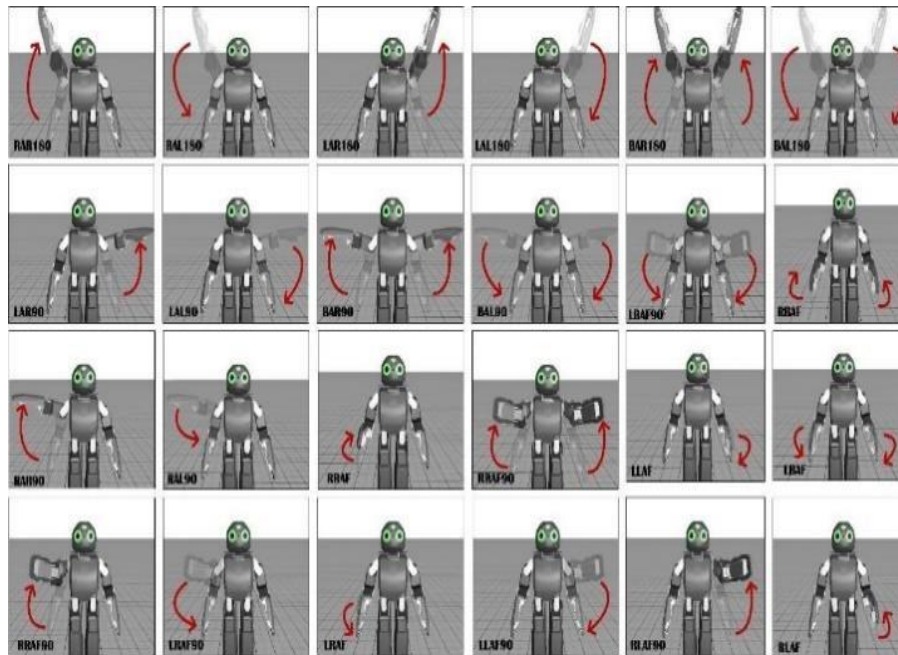


Fig 2: During experimentation, the robot performs various actions

The conduct variations include raising and lowering the left and right arm by 180deg one at a time, concurrently raising and lowering both arms by 180 deg, raising and lowering left and right arm by 90deg one at a time, raising and lowering left and right arm by 90deg one at a time. The types of actions completed for testing are summarized in Table 4.1. Trying to access the efficacy of the proposed algorithm. These actions are performed out by the robot at different repeating times, i.e. the series of these actions is not fixed and performed randomly. Any of these acts are done with a delay, while others are performed fluidly to confirm the architecture's efficiency.

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For example, the punch action created by the combination of RLAF90 and RLA, two motion labels that have already been learned.

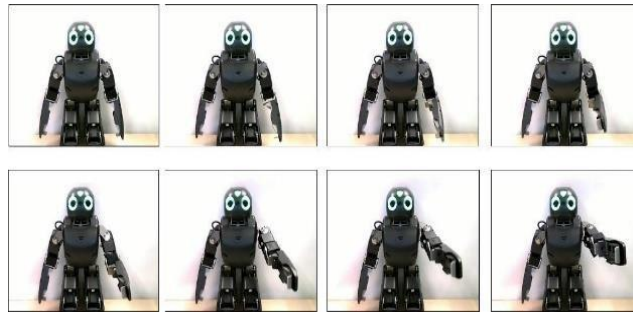


Fig 3: Punch" action

The composite action of 'Hi' is similarly developed in the same manner. Initially, the learning process starts with the definition of simple motion. Later, by combining two or more movements, more complex behavior are produced. Whenever the learner can memorize an already observed action then the observer recalls this action from episodic memory to produced complex behavior.

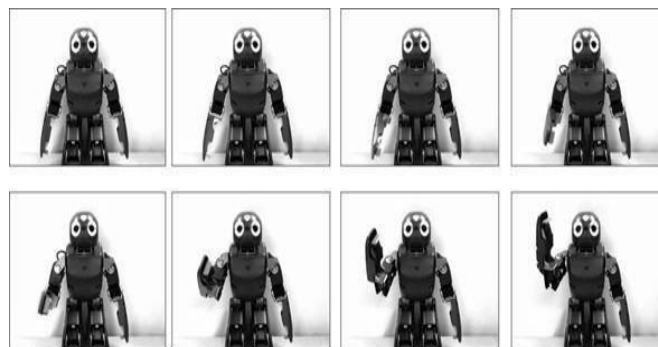


Fig 4. "Hi" action.

To measure the performance by quantization error, we repeated experiments. The connection between sensory input and episodic neuron weights is computed by TQE(total Quantization error). The temporal representation of input data is used to learn and activate each episodic neuron.

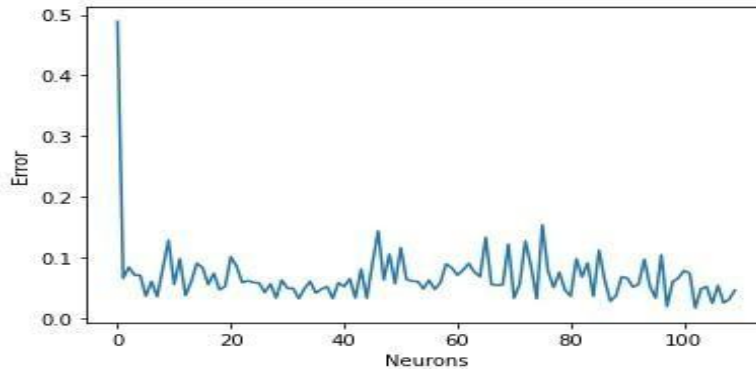


Fig 5: Total number of generated neurons for each traverse.

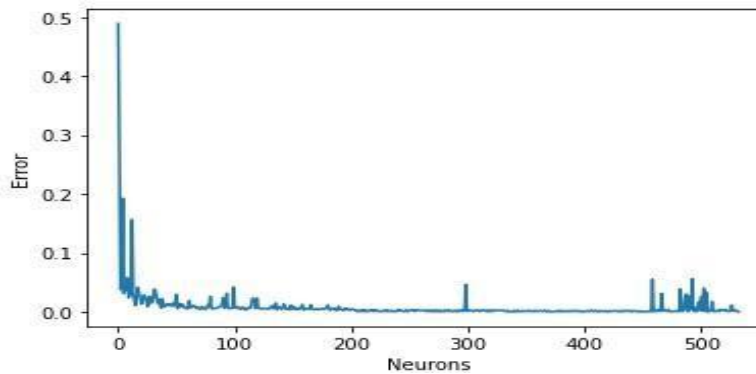


Fig 6. Total number of generated neurons for each traverse when we changed threshold value

Figure 5 show that Numbers of neurons added in episodic memory by computing the activation value with threshold, according to our purposed algorithm SOARIN.

The ar-GWR quickly learns the sequence of past experiences in episodic memory. The learning mechanism is triggered and the robot learns the new action. When the observed action’s activation value $a_b(t) < \rho_a$ less than the give threshold value, where we have a threshold value $\rho_a = 0.85 - 0.80$ it means this action is no already exist then added this action in episodic memory. On the other hand, the newly observed action’s activation $a_b(t) > \rho_a$ value greater than the given threshold value $\rho_a = 0.85 - 0.80$, where we have a threshold value it means this action is already present in episodic memory then update this action according to our purposed method.



In figure 6 number of neuron increased because we changed threshold value $0.99 - 0.5$, addition of neuron in episodic memory is processed as in figure 5.

Conclusion

On behalf of the latest autonomously behave of robot's eruption, Self-organizing recurrent neural network (SOARIN) extensively used for autonomous robot who explore environment without the human interaction, SOARIN also used for indoor spaces, stimulus location, and mapping without any human interference. SOARIN has three steps, to decide the best-matching neuron. The activation feature is related to every neuron in the network and whether it can be triggered ('fired') or not. The second step in neuron matching, a new neuron is having a connection to the network at every learning point. Neuron learning third step of SOARIN in which updates already exist data. In life-long learning, neuron learning is carried out to remove the issue of catastrophic forgetting. We learn to incorporate and update upper body behavior according to the joint angles visualized by the robot sensor by using all these steps. In the future, there is also potential for progress, we can work on the other massive datasets of benchmarks to obtain higher consistency. We will be introduced semantic memory connected with episodic memory using another approach.

References

- [1] G. Aschersleben, Early development of action control, *Psychol. Sci.* 48 (2006) 405–418.
- [2] Fritzke, B. (1994). Growing cell structures—A self-organizing network for unsupervised and supervised learning. *Neural Networks*, 7(9), 1441–1460 .
- [3] " Cox, L. H., Johnson, M. M., & Kafadar, K. . Exposition of statistical graphics technology. *ASA Proceedings of the Statistical Computation Section* (pp. 55–56).



- [4] [Fritzke, B. A growing neural gas network learns topologies. In G. Tesauro, D. S. Touretzky, & T. K. Leen (Eds.), (pp. 625–632). *Advances in Neural Information Processing Systems 7 (NIPS'94)*, Cambridge: MIT Press..
- [5] Parisi, G.I., Tani, J., Weber, C. and Wermter, S., 2017. Lifelong learning of human actions with deep neural network self-organization. *Neural Networks*, 96, pp.137-149
- [6] Kemker, R., McClure, M., Abitino, A., Hayes, T.L. and Kanan, C., 2018, April. Measuring catastrophic forgetting in neural networks. In *Thirty-second AAAI conference on artificial intelligence*.
- [7] Lopez-Paz, D. and Ranzato, M.A., 2017. Gradient episodic memory for continual learning. In *Advances in Neural Information Processing Systems* (pp. 6467-6476).
- [8] Itauma, Itauma Isong, Hasan Kivrak, and Hatice Kose. "Gesture imitation using machine learning techniques." *2012 20th Signal Processing and Communications Applications Conference (SIU)*. IEEE, 2012.
- [9] J. C. STANLEY, "Computer simulation of a model of habituation," *Nature*, vol. 261, pp. 146– 8, 06 1976.
- [10] S. Marsland, J. Shapiro, and U. Nehmzow, "A self-organising network that grows when required," *Neural Networks*, vol. 15, no. 8, pp.1041–1058, 2002.[Online].Available:<http://www.sciencedirect.com/science/article/pii/S0893608002000783>
- [11] N. Anjum and M. R. Chowdhury, "International Journal of Advanced Research in Computer and Communication Engineering," *SSRN Electron. J.*, 2024, doi: 10.2139/ssrn.4847308.
- [12] Anjum, N., & Alam, S. (2019). A comparative analysis on widely used web frameworks to choose the requirement based development technology. *Int. Adv. Res. J. Sci. Eng. Technol*, 6(9).
- [13] Dhal, K., Kashyap, A., & Chakravarthy, A. (2023, December). Robust



collision avoidance of quadric and polygonal surfaces moving in planar environments. In *2023 62nd IEEE Conference on Decision and Control (CDC)* (pp. 7117-7124). IEEE.

[14] Dhal, K., Kashyap, A., & Chakravarthy, A. (2021, December). Collision avoidance and rendezvous of quadric surfaces moving on planar environments. In *2021 60th IEEE Conference on Decision and Control (CDC)* (pp. 3569-3575). IEEE.

[15] Ahmad, S. (2025). Entrepreneurship and Sustainable Leadership Practices: Examine how entrepreneurial leaders incorporate sustainability into their business models and the leadership traits facilitating this integration. *Journal of Entrepreneurship and Business Venturing*, 5(1).

[16] Easwaran, V., Orayj, K., Goruntla, N., Mekala, J. S., Bommireddy, B. R., Mopuri, B., ... & Bandaru, V. (2025). Depression, anxiety, and stress among HIV-positive pregnant women during the COVID-19 pandemic: a hospital-based cross-sectional study in India. *BMC Pregnancy and Childbirth*, 25(1), 134.

[17] Easwaran, V., Alshahrani, S., Mantargi, M. J. S., Bommireddy, B., Khan, N. A., Alavudeen, S. S., ... & Awais, M. (2024). Examining factors influencing public knowledge and practice of proper face mask usage during the COVID-19 pandemic: a cross-sectional study. *PeerJ*, 12, e16889.

[18] Nguyen, L., Trinh, X. T., Trinh, H., Tran, D. H., & Nguyen, C. (2018). BWTaligner: a genome short-read aligner. *Vietnam Journal of Science, Technology and Engineering*, 60(2), 73-77.

[19] Nguyen, H. U., Trinh, T. X., Duong, K. H., & Tran, V. H. (2018). Effectiveness of green muscardine fungus *Metarhizium anisopliae* and some insecticides on lesser coconut weevil *Diocalandra frumenti* Fabricius (Coleoptera: Curculionidae). *CTU Journal of Innovation and Sustainable Development*, (10), 1-7.

[20] Bailey, D. W., Tabini, R. A., Horton, H., Libbin, J., Al-Khalidi, K., Alqadi,



A., ... & Waldron, B. (2009). CS-Potential For Use Of Kochia Prostrata And Perennial Grasses For Use In Rangeland Rehabilitation In Jordan.

[21] Hood, K., & Al-Oun, M. (2014). Changing performance traditions and Bedouin identity in the North Badiya, Jordan. *Nomadic Peoples*, 18(2), 78-99.

[22] Butt, S., & Yazdani, N. (2023). Relationship Between Execution of Quality Management Practices and Firm's Innovation Performance: A Review of Literature. *Journal of Asian Development Studies*, 12(3), 432-451.

[23] Butt, S., Umair, T., & Tajammal, R. (2024). Nexus between Key Determinants of Service Quality and Students' Satisfaction in Higher Education Institutions (HEIs). *Annals of Human and Social Sciences*, 5(2), 659-671.

[24] Zaurez Afshar, M., & Hussain Shah, M. (2025). Performance Evaluation Using Balanced Scorecard Framework: Insights from A Public Sector Case Study. *INTERNATIONAL JOURNAL OF HUMAN AND SOCIETY*, 5(01), 40-47.

[25] Afshar, M. Z. (2023). Exploring Factors Impacting Organizational Adaptation Capacity of Punjab Agriculture & Meat Company (PAMCO). *International Journal of Emerging Issues in Social Science, Arts and Humanities (IJEISSAH)*, 2(1), 1-10.