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An Efficient Integration of Artificial Intelligence-based Mobile Robots in Critical Frames for the Internet of Medical Things (IoMTs) Using (ADP2S) and Convolutional Neural Networks (CNNs)

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Article Details

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ABSTRACT

Moving in complex environments is an essential capability of intelligent mobile robots. Decades of research and engineering have been dedicated to developing sophisticated navigation systems to move mobile robots from one point to another. Despite their overall success, a recently emerging research thrust is devoted to developing machine learning techniques to address the same problem, based in large part on the success of deep learning techniques. Real-time systems are widely used in industry, including technological process control systems, industrial automation systems, SCADA systems, testing, and measuring equipment, and robotics. Artificial intelligence-based Mobile robots have been receiving attention from researchers worldwide in recent years, especially in developing autonomous mobile robots. Artificial intelligence and Machine learning play a great role in the development of humanoid robots, they have increased humanoids efficiency and their functionality. This paper presents an optimal machine learning-assisted intelligent Convolutional Neural Network (CNN) based approach for humanoid function identification using AI and Machine learning that enable humanoid robots to evolve Human-Robot Interaction (HRI) that helps resolve crucial issues concurrently while discussing improvements in Accuracy, Precision, decision-making, and interaction skills. The paper also tests and trains the ML model using the open source dataset named direct kinematics of an IRB 120 robotic. The proposed P-CNN outperformed the other renowned algorithm designs by evaluating the performance by considering the real-time sensor data, machine learning models, and natural language processing. The proposed technique demonstrates the practical uses of humanoid robotics technologies, highlighting notable accomplishments in areas like better locomotion and human-robot interaction. Despite the encouraging progress we achieved, safety and efficiently learning the representation of non-expert strategies on large-scale real-world data using reinforcement learning remain challenging. The implementation results proved that this system operated effectively with a minimal response delay of 0.77–2.67s and a high detection accuracy (98.25%) in two experimental cases, which makes it suitable for real-time applications. This article also addresses the prospective opportunities for further research and development in humanoid robotics while suggesting further advancements in this field that could result from interdisciplinary efforts..

INTRODUCTION

Humanoid robots are designed to replicate human appearance and behavior, providing a range of applications from personal assistance to complex industrial tasks. Intro The progress in Artificial Intelligence (AI) and Machine Learning (ML) influenced the capabilities and effectiveness of humanoid robot development by a large margin. This means that AI will be able to help robots make intelligent decisions based on data, and ML to do better learning and adapting from experience [1, 2]. In this paper, the focus is on how AI & ML technology has become more accessible for developers and researchers working on humanoid robot development. The following sections review the impact of AI and ML in humanoid robotics covering its functionalities, applications, and case studies to enhance performance-centric outcomes. The advent of humanoid androids, machines engineered to resemble or act like their human counterparts, demonstrates a giant leap in the field of robotics and artificial intelligence (AI) [3, 4]. This motivated to development of robots, which could operate in human environments, naturally communicate with humans, and behave like it has human cognitive as well as physical capabilities. Humanoid Robotics has improved significantly in the last few decades from simple mechanical structures to complex artificial intelligence (AI) and machine learning (ML)--supported systems. In the first wave of humanoid robotics, robots were quite primitive, stiff devices with minimal functionality and interaction capabilities.

These early robots, like WABOT-1 [5]. Which was the first full-scale humanoid robot developed in Japan in the mid-1980s, was mainly intended to investigate the feasibility of human-like robots with little regard towards their applications. As materials, electronics, and computational power have become more advanced over the years, engineers have developed ever more sophisticated humanoid robots. Prior work in humanoid robotics has extended AI and ML technologies to improve the perception, decision-making, and interaction capabilities of robots. For example, utilizing computer vision systems with AI can allow robots to identify and process visual information, like detecting objects and interpreting human gestures. With the help of ML algorithms like (neural networks, and reinforcement learning), robots can learn from their past mistakes and experiences and adapt their behaviors to new and dynamic environments [6, 7].

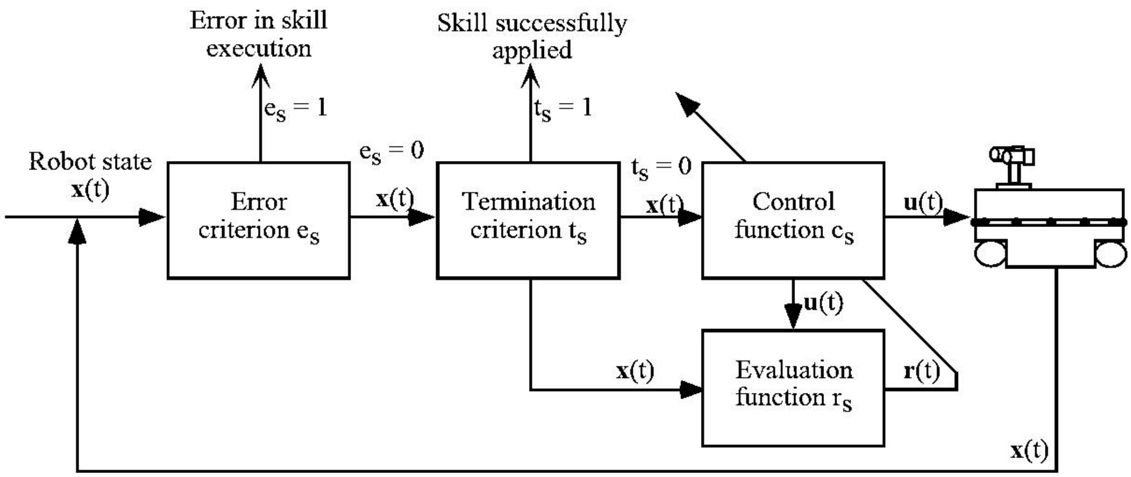

FIGURE 1: DEMONSTRATION OF ROBOT CONTROL SYSTEM [8]

MACHINE LEARNING ALGORITHMS

Humanoid robots function using Machine Learning (ML) algorithms. They provide robots with the capacity to take in large amounts of information and learn from it to then decide what to do with that data. Humanoid Robotics uses the following ML algorithms.

SUPERVISED LEARNING

This involves training algorithms on labeled data to make predictions or classify new data. Machine Learning—used for tasks such as object recognition and speech analysis, typically includes techniques like neural networks or decision trees. For example, convolutional neural networks (CNNs) have achieved well over 90% accuracy on benchmark tasks like object recognition [9, 10].

UNSUPERVISED LEARNING

This method can be thought of as a robot looking for patterns of unlabeled data For example, clustering and dimensionality reduction for anomaly detection and feature extraction are implemented using these methods. For example, k-means clustering has been successfully used for robot vision data segmentation. This method requires the training of robots by rewarding them whenever they take a good course of action. But, more interestingly, it is well suited for discovering complex behaviors and adaptive control. Traditional Q-learning and deep Q-networks (DQN) algorithms are capable of achieving state-of-the-art robot navigation and manipulation performance improvements on a subset of benchmark tasks. Mathematical representation of Q-learning algorithm [11, 12]. The Pearson correlation coefficient (r) has the following equation used for IoT based Robots as shown in Equation (1).

$$r = \frac{\sum(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum(x_i-\bar{x})^2\sum(y_i-\bar{y})^2}} \quad \text{Eq (1)}$$

$$Q(s,a) \leftarrow Q(s,a)+\alpha[r+\gamma \max a' \ Q(s' \ ,a' \ )-Q(s,a) \quad \text{Eq (2)}$$

Whereas:

- Q(s, a)Q(s, a)Q(s, a) is the value of taking action aaa in state sss,
- s' is the new state after the action,
- α is the learning rate,
- γ is the discount factor, determining the importance of future rewards.

This equation iteratively updates the action-value function Q, enabling the robot to learn the best actions to take in various states through exploration and exploitation.

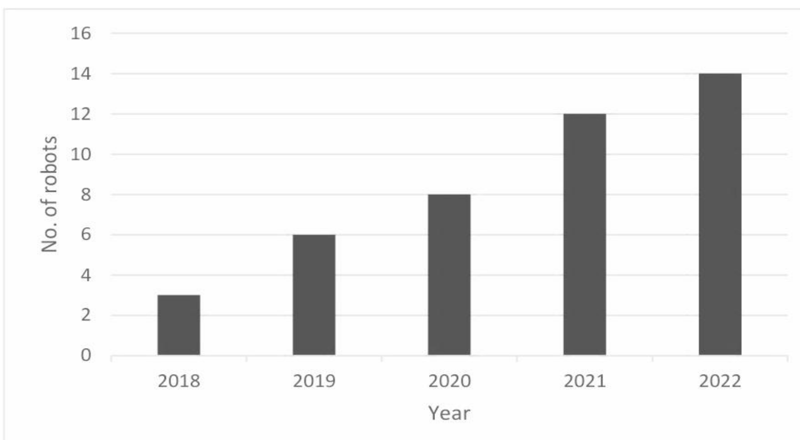

FIGURE 2: ROBOT USAGE IN COLLABORATIVE RESEARCH WORKS BETWEEN 2018 AND 2022 [13]

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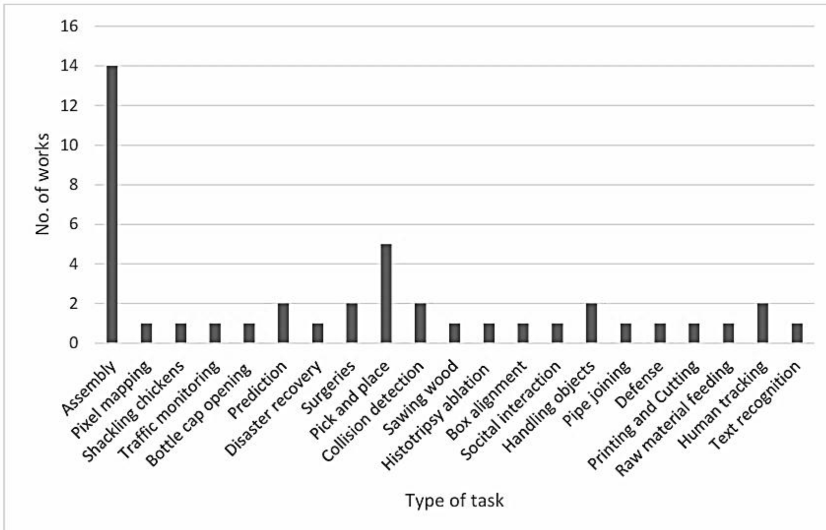

FIGURE 3: TASKS PERFORMED BY THE ROBOT IN COLLABORATIVE RESEARCH WORKS [14]

COMPUTER VISION AND PERCEPTION

Humanoid robots need computer vision to make sense of their environment and can interact with it techniques used include:

CONVOLUTIONAL NEURAL NETWORKS (CNNS)

These are responsible for image classification, and object detection tasks to help robots see, interpret and understand the visual world. CNNs have been extremely successful, with architectures like AlexNet getting a top-5 error rate of 15.3% on the ImageNet dataset. Research about mammalian visual cortex mechanisms formed the basis of Convolutional Neural Networks (CNNs). CNNs reproduce brain functionality which enables neurons to analyze various spatial patterns in visual information [15, 16]. CNN architecture refers to an essential mathematical approach that enables weight sharing along with local processing and spatial pattern retention. The LeNet-5 model created by Kate and Shukla marked the first successful implementation of CNNs for handwritten number detection during the 1980s [15, 16]. Document recognition progressed a great deal after the model introduced gradient-based learning mechanisms. CNNs demonstrate exceptional performance in data arrangements with grid-like structures such as images that equal two-dimensional pixel grids. The study reviewed the foundation of neural networks and their advanced structures alongside their primary medical diagnostic applications [17, 18].

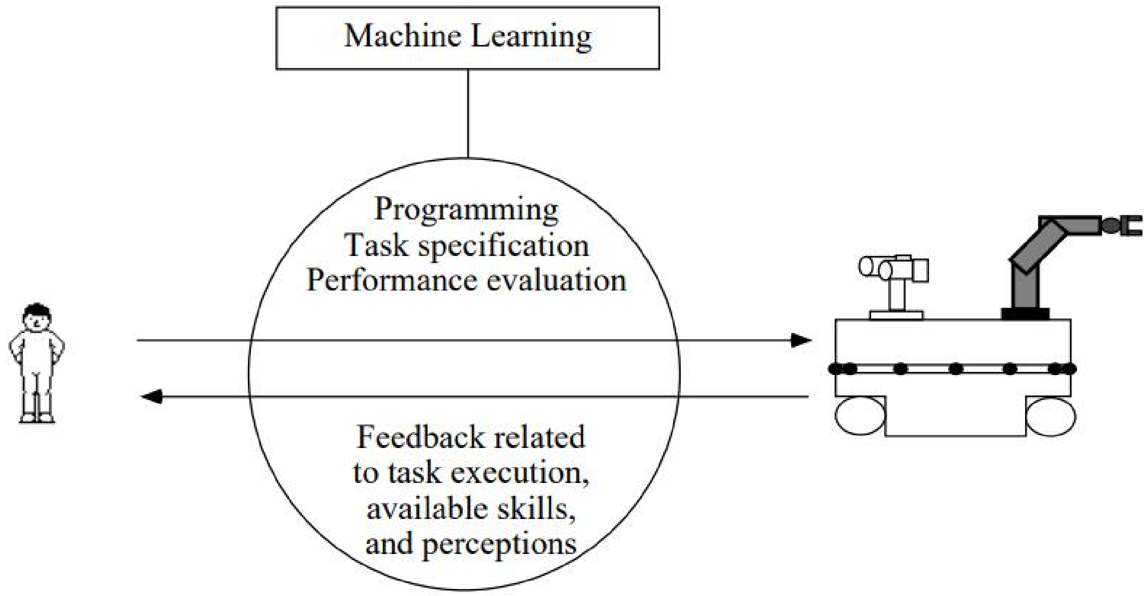

FIGURE 4: MACHINE LEARNING BASED FEEDBACK SYSTEM USED FOR IOMTS [19]

DEPTH SENSING AND IMAGE SEGMENTATION

Includes several sensors that provide 3D information to comprehend the topological knowledge of its surrounding environment used for tasks like navigation, obstacle avoidance, etc. One of the most popular sensors used in robotics to sense depth is that of the Kinect camera producing near real-time high-precision depth maps [20, 21]. This method groups image pixels into segments to make its analysis easier and help in object recognition and scene understanding. Specifically, it has achieved an excellent performance in biomedical image segmentation using the U-Net architecture with high accuracy in identifying anatomical structures [22].

RELATED WORK

The research explored the historical development of these networks starting with biological prototypes up until their modern applications where CNNs took center stage because of their transformative effects on medical image diagnostics. The review addressed major barriers that involved working with extensive labeled data collections and enhancing model comprehensibility simultaneously with showing how neural networks have substantially boosted diagnostic precision [23].

NATURAL LANGUAGE PROCESSING (NLP)

Humanoid Robots use Natural Language Processing (NLP) for Human language comprehension and generation. Key techniques include:

SENTIMENT ANALYSIS AND TRANSFORMER MODELS

This involves determining the sentiment expressed in text, which helps robots understand emotional cues. Advances in Sentiment Analysis: Progress made with accuracy >80% for different kinds of datasets. This enables the extraction of entities (names, locations) from text allowing interactions to be meaningful. There are some pre-trained systems with state-of-art performance in named entity identification, for example, the Stanford NER tool has shown good accuracy over different languages to recognize named entities [24, 25].

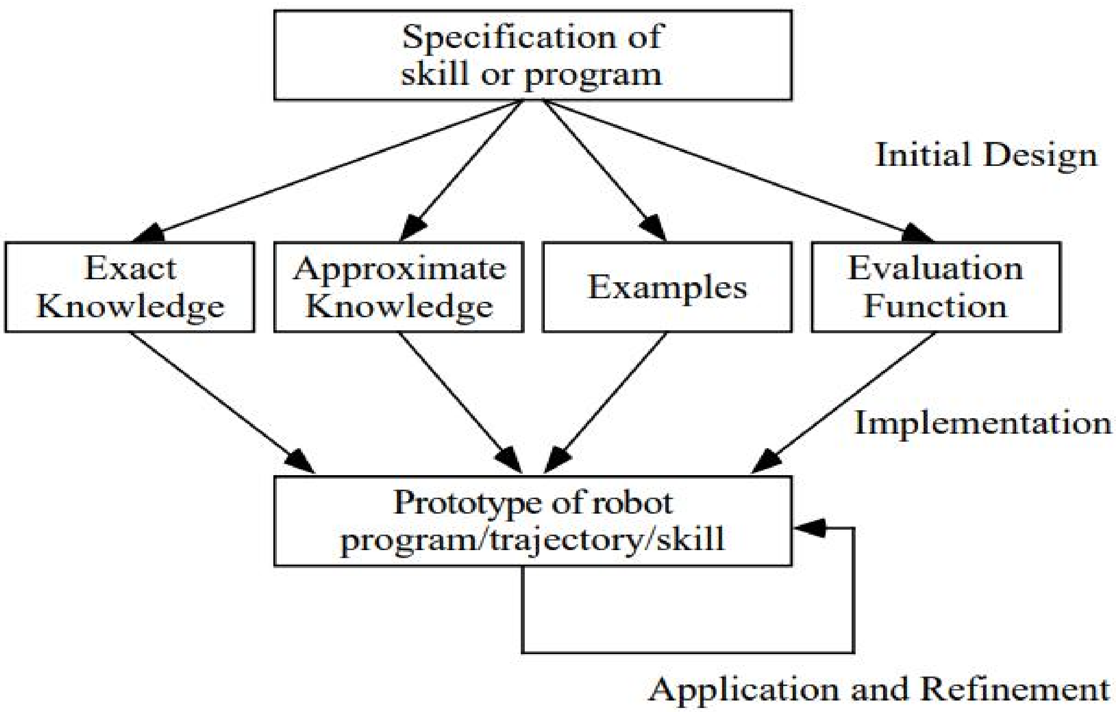

FIGURE 5: ROBOT PROGRAM TRAJECTORY USED IN IOMTS [26]

The evolution of more advanced models like BERT and GPT, has provided robots with the ability to generate text close to human-written texts. For example, BERT has set state-of-the-art results on several NLP benchmarks.

ROBOTIC CONTROL SYSTEMS

Control systems are necessary for the detailed oriented motion and coordination of humanoid robots. Proportional-integral-derivative (PID) controllers are used for basic motion control, ensuring stable and accurate movements. PID control is a classical approach, being used as a robust solution to quite an array of robotics applications. Model Predictive Control (MPC) MPC uses a model of the robot to predict future states and optimize control actions [27- 31]. Successfully implemented MPC on humanoid walking and balancing, which resulted in increased stability and robustness on exercises. Modern Deep Reinforcement Learning is a modern approach, including Deep Q-Learning and things like Model Predictive Path In, tegral that take advantage of the synergy between Reinforcement Learning and Neural Net worksabe to deal with very complex control tasks. Deep reinforcement learning algorithms, such as deep Q-networks (DQN) and proximal policy optimization (PPO), have made great progress in robotic control [31- 35]. A simple equation related to PID control is:

$$u(t)=K_p e(t)+K_i \int e(t)\,dt+K_d \frac{de(t)}{dt} \qquad \text{Eq (3)}$$

Whereas:

- $u(t)$ is the control output,
- $e(t)$ is the error (the difference between the desired and actual output),
- K_p, K_i, and K_d are the proportional, integral, and derivative gains, respectively.

This equation helps in adjusting the control inputs to minimize the error, ensuring the robot moves accurately toward its target.

MACHINE LEARNING ALGORITHMS

The ML algorithms that are required for these AI capabilities to function need integration in these humanoid robots. These algorithms help the robot to digest data on how catheters are built and then control them to effectively work to accomplish outcomes based on them. Some common ML algorithms used in humanoid robotics [36, 40].

SUPERVISED LEARNING, UNSUPERVISED LEARNING AND REINFORCEMENT LEARNING IN IOMTS

These are the algorithms that predict or classify new data according to train earlier classified data. Neural networks and decision trees, object recognition and speech signal processing, respectively are widely used techniques [41]. It helps to see the hidden pattern inside the data sets with no description. This can also work well in detecting novel occurrences or extracting useful data by engaging in some clustering or dimensional reduction. This approach trains the robot to make decisions by setting rewards for possible good choices. This also explores elastic behavioral sequences. The visual input helps humanoid robots categorize, and connect with their surroundings. These methods include: Convolutional Neural Networks (CNNs) which do image content classification and object detection (allowing robots to 'see' so that it can learn without any physical interaction [42].

METHOD & MATERIALS

The creation and improvement of effective humanoid robots *turned to AI and ML is a* complex undertaking consisting of theoretical, algorithmic, and experimental components. This part of the work describes the approach that was taken to incorporate AI and ML technologies into humanoid robotics with an emphasis on such elements as data gathering, algorithm formulation, and testing of results achieved.

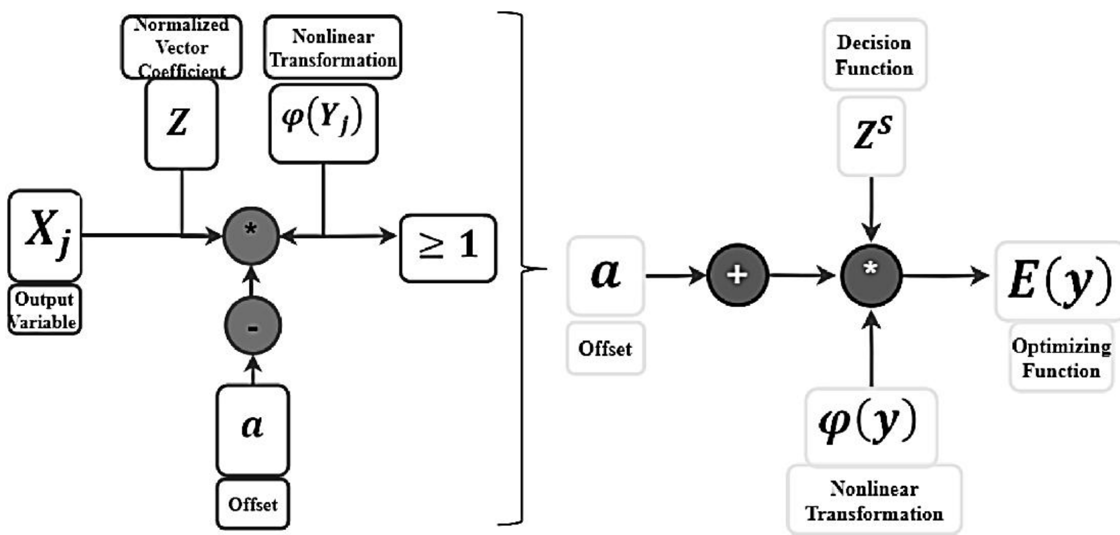

FIGURE 6: ANALYSIS OF OPTIMIZED FUNCTION FRAMEWORK FOR ROBOT

The proposed classifier contains i to represent random units of b-layer units and y to represent the total b-layer units.

$$S_i^{(b,t)} = \sum_{z=1}^{E} p_{iz}^{(b)} J_z^{(b-1,t)} + \sum_{i'}^{y} x_{ii'}^{(b)} J_{i'}^{(b,t-1)} \quad \text{Eq (4)}$$

$$J_i^{(b,t)} = \beta^{(b)}(S_i^{(b,t)})$$

Eq (5)

$$P(w) = \sqrt{\frac{t}{f(w)}} + \frac{t}{f(w)},$$

Eq (6)

$$f(w) = \frac{count_w}{totalno.oftokens},$$

Eq (7)

$$f_t = \sigma(W_f.[h_{(t-1)}, x_t] + b_f)$$

Eq (8)

DATA COLLECTION & ALGORITHM DESIGN

Humanoid robots with AI and ML features will necessarily depend on wide-ranging and high-quality data implementations for them to be effective. This starts by gathering a diverse set of datasets that captured the environments and tasks that we expected our robots to face. Humanoid robots have sensors for capturing environmental information such as cameras, LiDAR, depth sensors, etc. The sensor data also feeds the computer vision algorithms and spatial mapping necessary for navigating through space and recognizing objects.

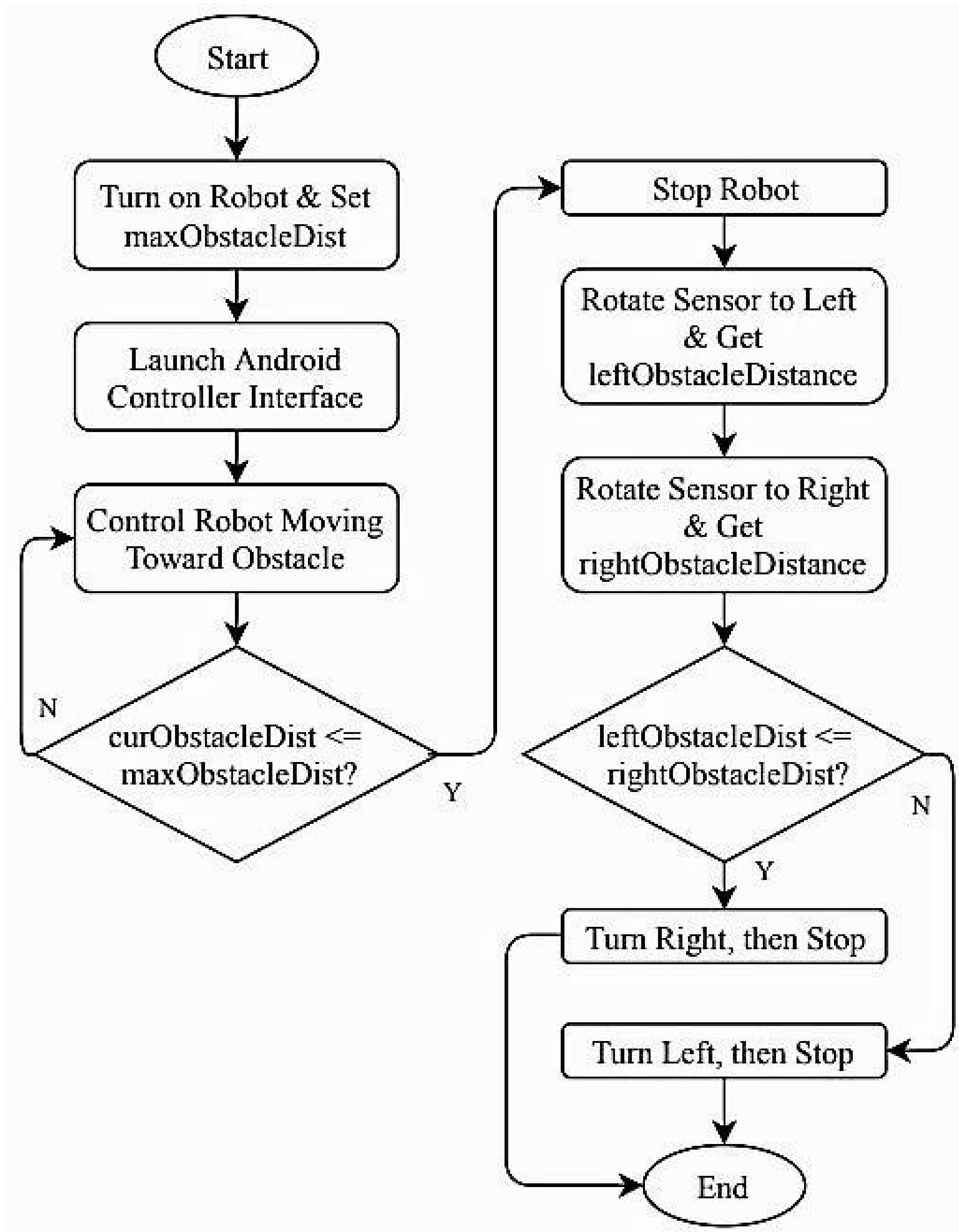

FIGURE 7: FRAMEWORK FOR HUMANOID BASED ON CONVOLUTION NEURAL NETWORK (CNN)

$$i_t = \sigma(W_i.[h_{(t-1)}, x_t] + b_i), \quad \text{Eq (9)}$$

$$\tilde{C}_t = tanh(W_c.[h_{(t-1)}, x_t] + b_c), \quad \text{Eq (10)}$$

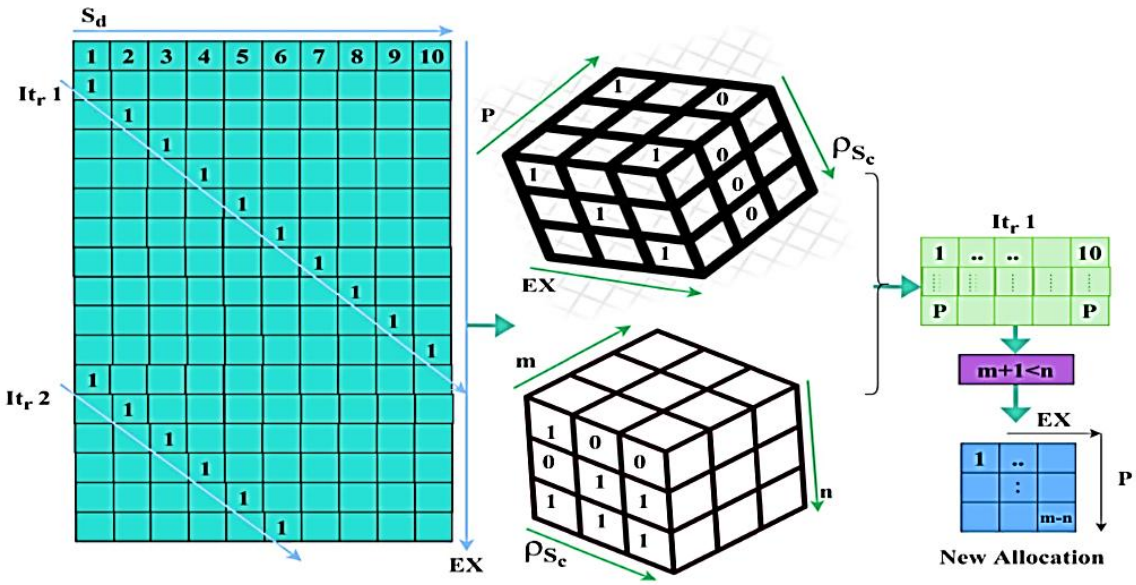

FIGURE 8: ALLOCATION AND DECISION PROCESS OF ADP2S FOR NEW TASK ALLOCATIONS

$$C_t = f_t * C_{(t-1)} + i_t * \tilde{C}_t, \quad \text{Eq (11)}$$

$$O_t = \sigma(W_O.[h_{(t-1)}, x_t] + b_o), \quad \text{Eq (12)}$$

$$B = \{B_1, B_2, \ldots, B_k, \ldots, B_l\} \quad \text{Eq (13)}$$

$$E_c = \frac{1}{K} \times \sum_{g=1}^{k} J_v^{b,t} - k_v$$

Eq (14)

$$B_{m,n}(q+1)(1 - \frac{1 - X(0,1) - X(-1,1)}{1 - c_{m,n} \times f_{mn}(q)}) = X(0,1) \times R_{s,n}$$

Eq (15)

This encompasses the advanced control algorithms used for controlling the movement and coordination of humanoid robots. Precise and stable movement of the robot is obtained by using Model Predictive Control (MPC) as well as the Proportional-Integral-Derivative (PID) controller. These algorithms are calibrated from real-world experiments.

RESULTS AND CLASSIFICATION OF PERFORMANCE

Depth Sensors such as the Microsoft Kinect have been used to capture 3D data for obstacle avoidance and gesture recognition for instance. Data gathered includes Human Interaction Data: data on human gestures, speech and emotional expressions which are used to provide more natural interactions) Such data is employed to train natural language processing EMPaThetic model and emotion recognition for more human-robot communication. Behavioral Data: The movement and, to a lesser degree, the performance of robots are tracked throughout their operation to further refine control algorithms and/or learning models. This information is key to engineering more efficient locomotion, manipulation and other behaviors for a range of robots. So, the processing of these sensed data by algorithms that we use to observe desired action is one of the main areas in AI and ML concerning humanoid robotics. Core algorithmic components: Uses Different Machine Learning Models for Various Tasks Since CNNs are a popular solution for object recognition and classification tasks, they can effectively model spatial dependency in visual data. The authors used one of them. Reinforcement Learning RL tasks are often addressed by algorithms such as DQN Deep Q-Networks which provide a means of learning the control policies that enable robots to perform complex behaviors via trial and error. Such humanoid robots must pass a strict performance evaluation to rank the efficiency of AI and ML algorithms implemented inside them. Evaluation methods include:

Simulation Testing: Algorithms are simulated before they are deployed in the real world. Simulations provide a way to evaluate robot behaviors and interactions in controlled environments and can highlight issues that might appear.

Field Trials: The robots are methodologies tested in the fields to check how they do on the actual testing ground. Tests like these give us a look at how good the algorithms are at working in non-stationary and unstructured environments.

Metrics and Benchmarking: AI and ML algorithms are assessed on performance metrics like accuracy, efficiency, reliability, etc. One of them is to be used for benchmarking, against standard datasets and tasks (to compare the performance against many other algorithms and see progression areas). As we say, it is iterative, with a feedback loop at every stage and improvement achieved. Information from the tests feeds into an algorithm which is improved to help better inform the robot. The robots are also updated for the latest AI and ML research, driving them forward technologically.

TRAINING AND VALIDATION ACCURACY OF RNN

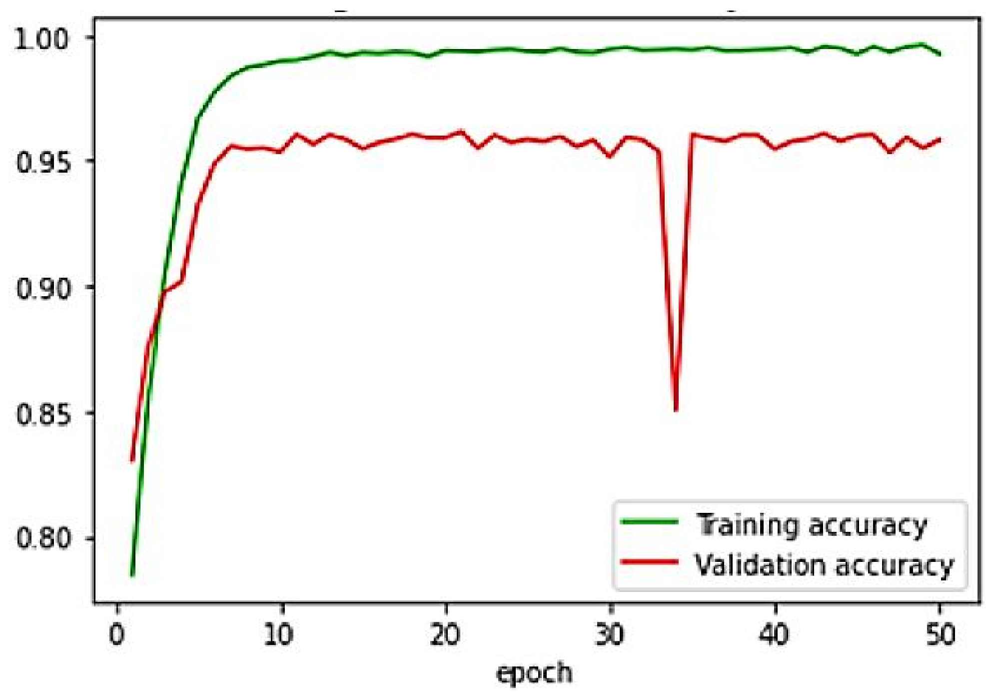

FIGURE 9: TRAINING AND VALIDATION ACCURACY OF RNN

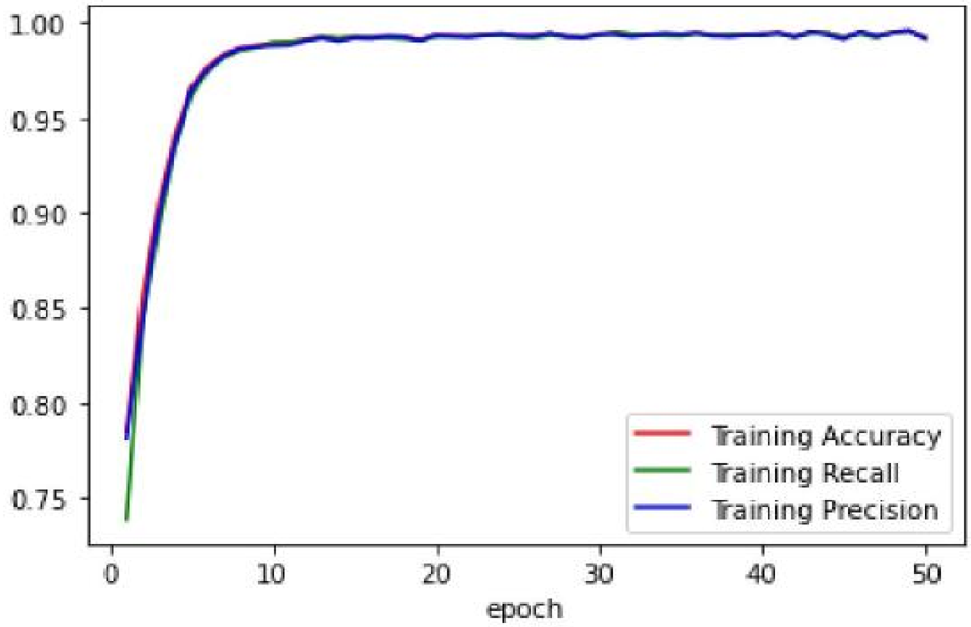

FIGURE 10: TRAINING AND VALIDATION ACCURACY, RECALL AND PRECISION OF RNN

TRAINING AND VALIDATION ACCURACY OF CNN

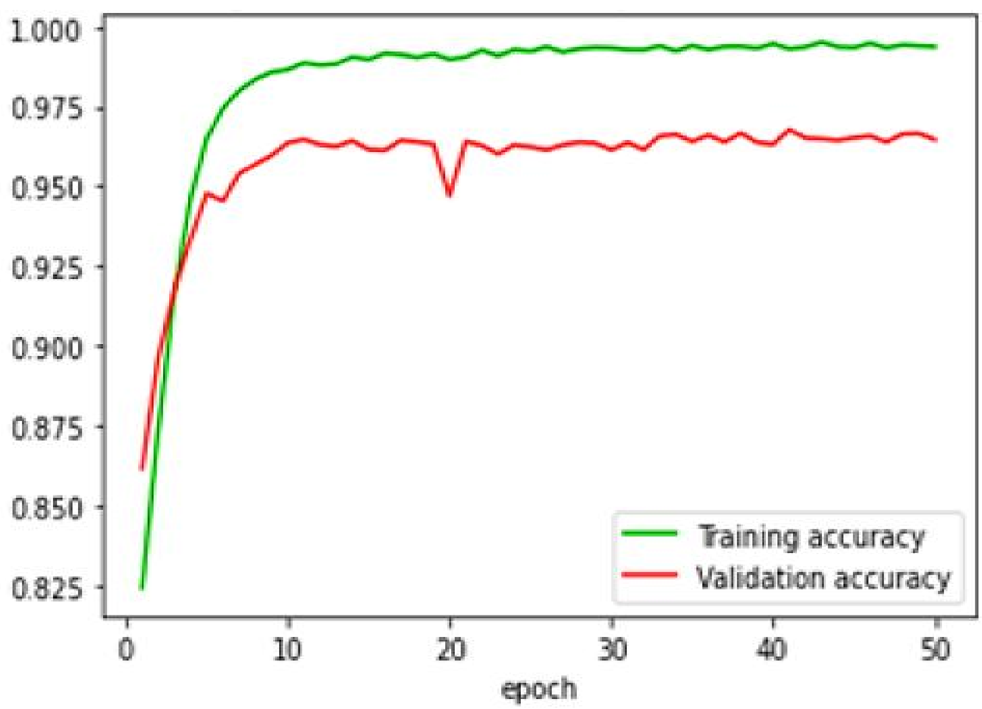

FIGURE 11: TRAINING AND VALIDATION ACCURACY OF CNN

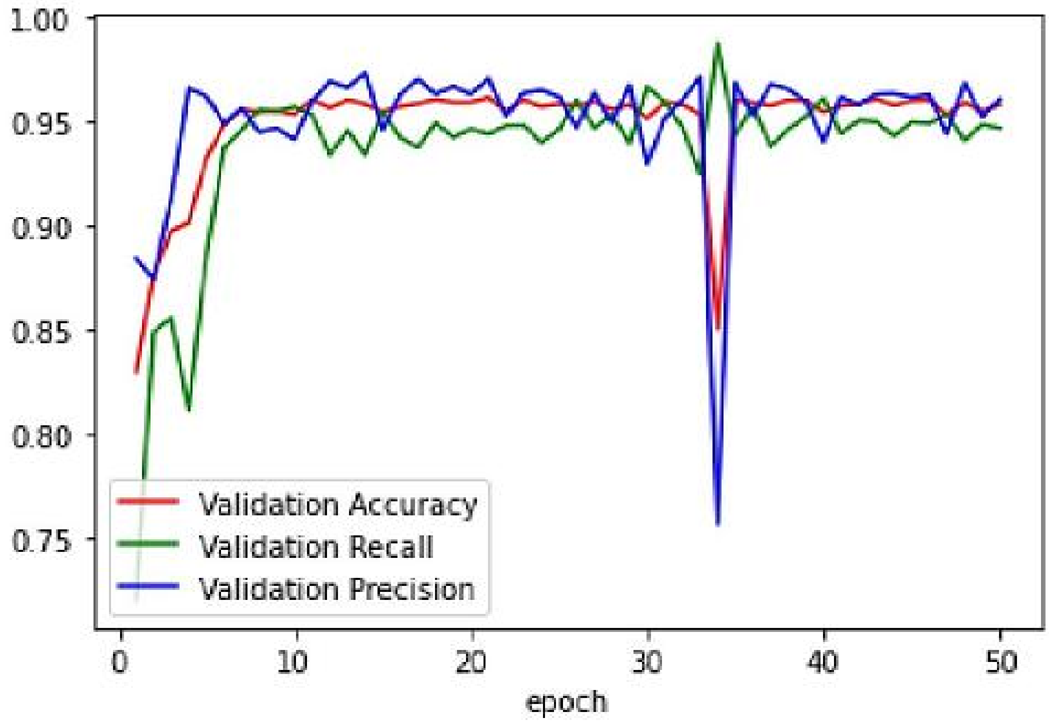

FIGURE 12: TRAINING AND VALIDATION ACCURACY, RECALL AND PRECISION OF CNN

TRAINING AND VALIDATION ACCURACY OF DT

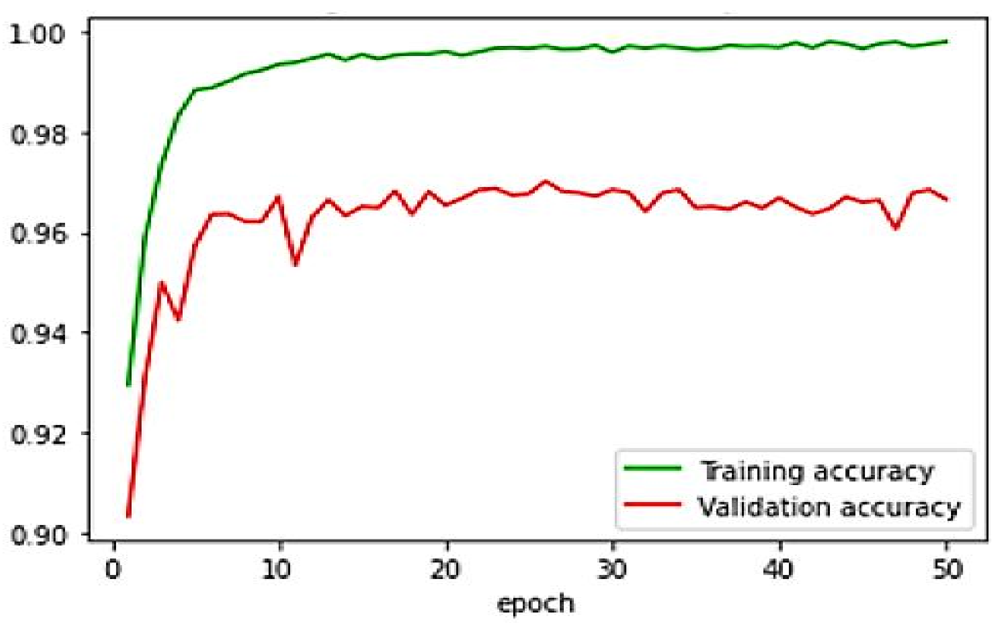

Figure 13: Training and Validation Accuracy of DT

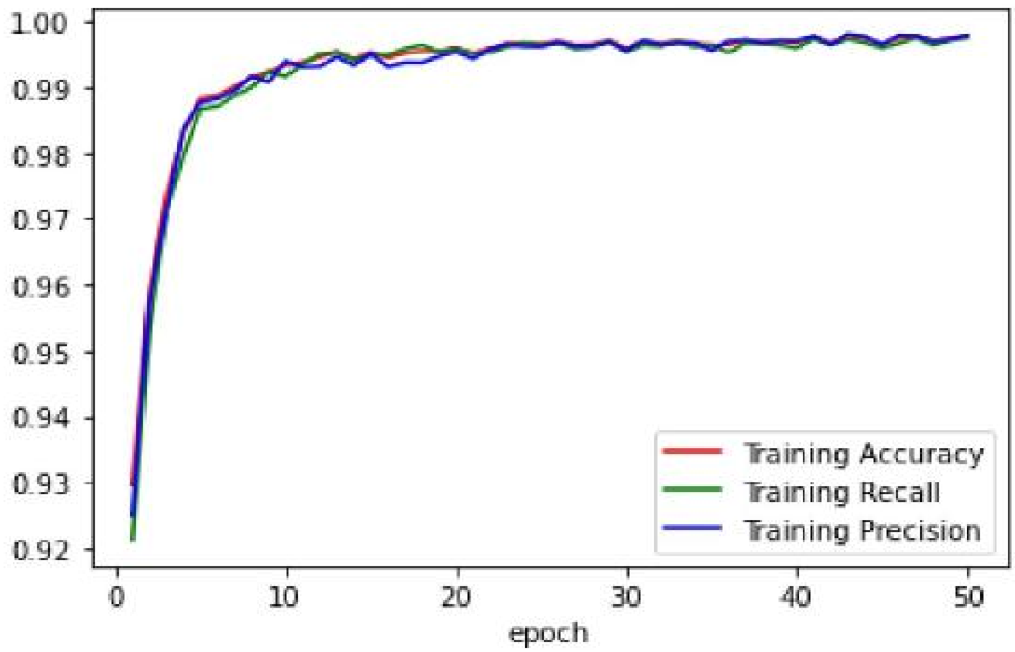

FIGURE 14: TRAINING AND VALIDATION ACCURACY, RECALL AND PRECISION OF DT

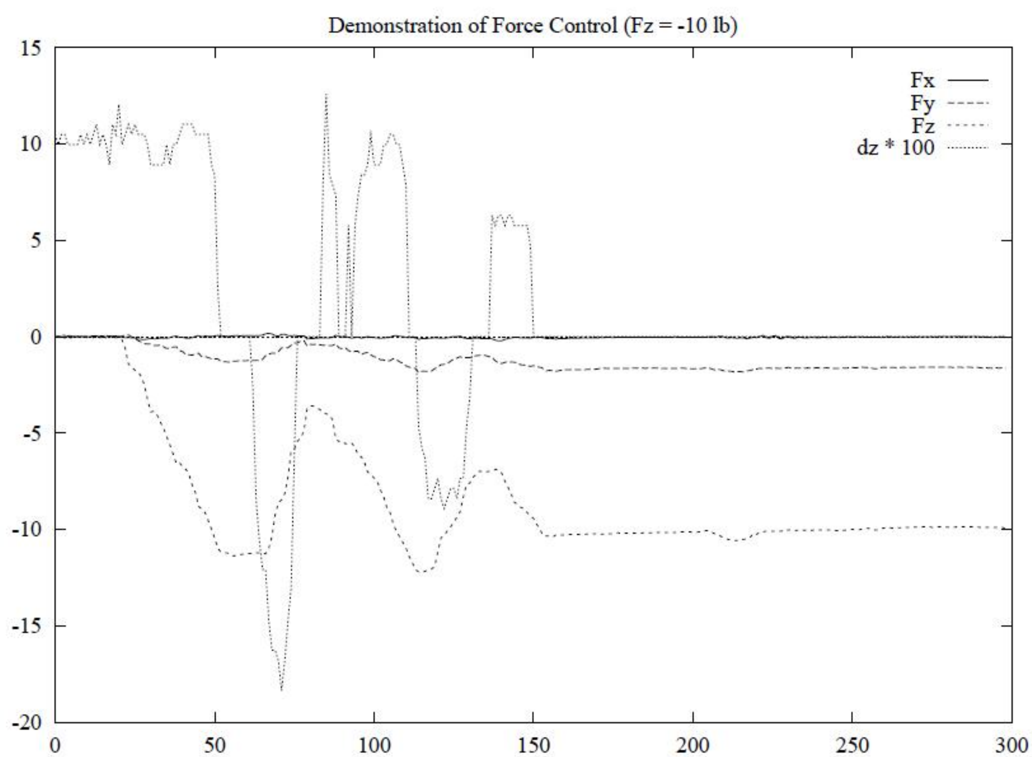

FIGURE 15: DEMONSTRATION OF ROBOTIC FORCE (FZ= -10LB)

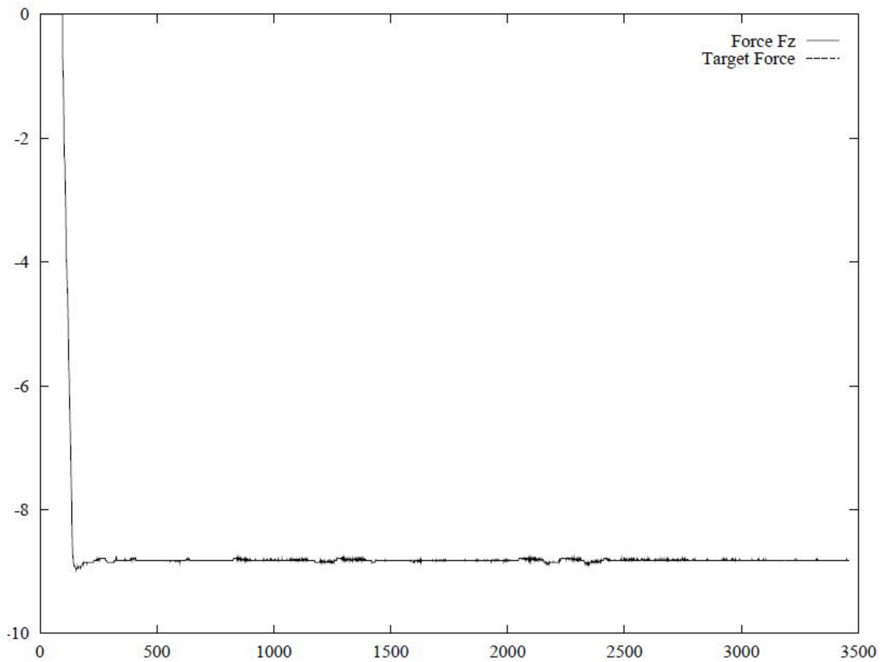

FIGURE 16: DEMONSTRATION OF ROBOTIC FORCE (FZ= -20LB)

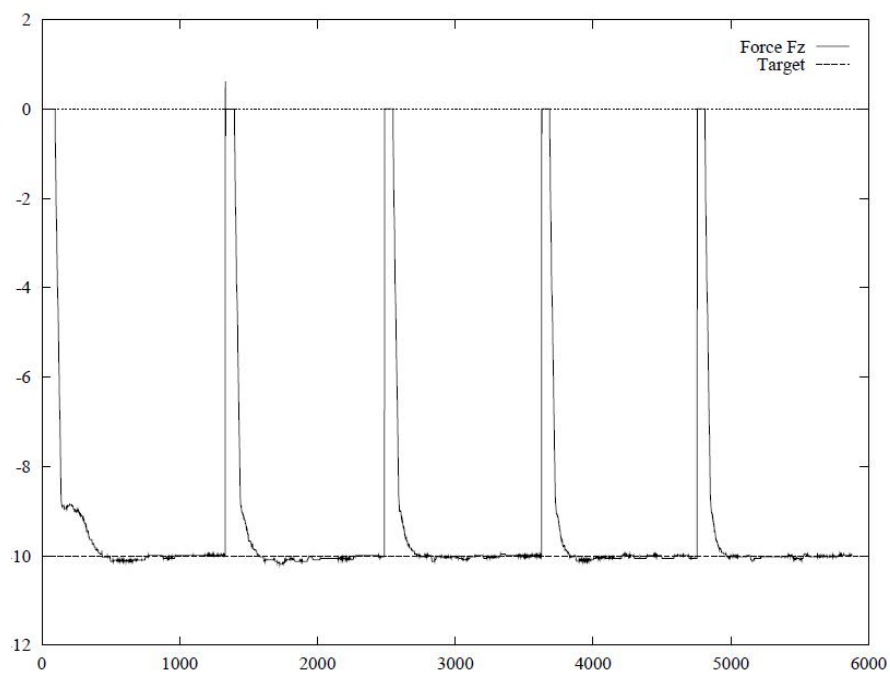

FIGURE 17: DEMONSTRATION OF ROBOTIC FORCE (FZ= -30LB)

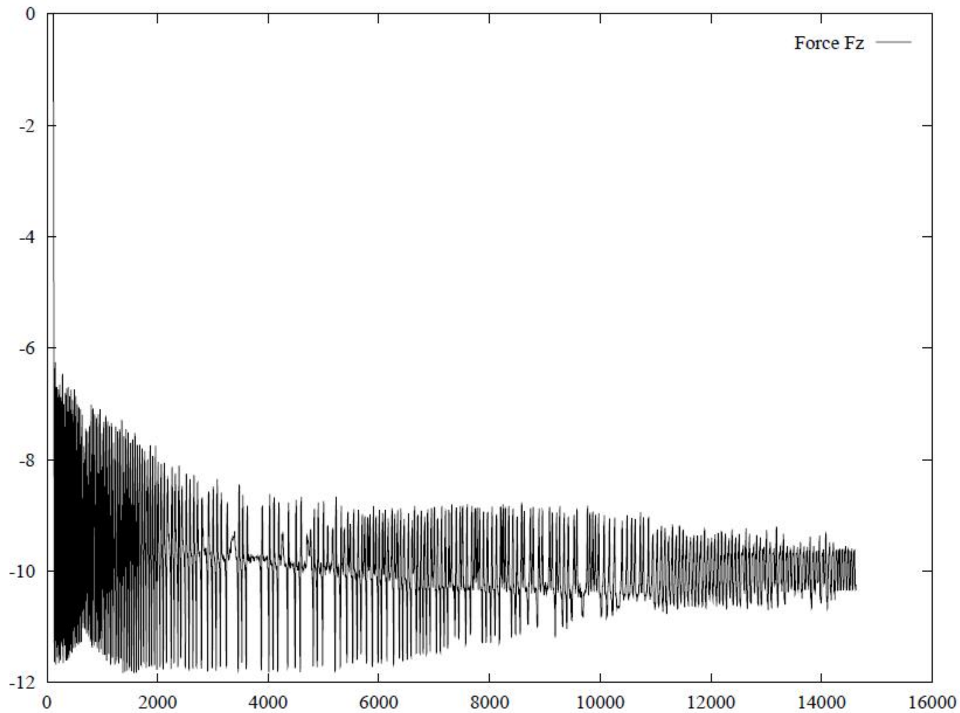

FIGURE 18: DEMONSTRATION OF ROBOTIC FORCE (FZ= 10LB)

CONCLUSION AND RECOMMENDATIONS

This research has presented the design and development mechanism and framework enhanced mobile-controlled robot using ML algorithms. Many advances in humanoid robots have been made by integrating AI and ML within them. Machine learning algorithms, computer vision, NLP and advanced control systems are the pivotal methodologies increasing humanoid robots' performance. But this kind of technology presents other challenges — such as high computational complexity, ethical considerations and safety concerns — before it can be exploited to its full potential. Addressing these issues further will depend on future studies and construction — to force the field of human robotics. Future research in humanoid robotics should be on some major areas.

Learning Algorithms with applications for task knowledge to allow performance and functioning capabilities of the humanoid robots, Learning and development algorithms for better-quality creation and versioning efficiencies. For example, research on meta-learning and transfer learning may enable robots to generalize learned skills across tasks. Higher-Level Perception Modules: Boost computer vision and sensor tech to better perceive the environment

(Depth, Segmentation, Object Detection/Categorization) Future research on neural networks focusing on multimodal perception systems with the synergy of vision, touch and auditory, etc., will also be useful for robust and adaptable robot control.

Ethical and Safety Considerations — Identifying the ethical dilemmas such as; how to make sure we are deploying robots that behave ethically, and what kind of safety mechanisms we want our humanoid robots to have for responsible deployment and use. For example.

Human-Robot Interaction: Improving NLP and emotional intelligence skills to create more natural interactions between humans and robots. The new revolution in affective computing and empathetic robotics would give the robots better recognition and response to human emotions. Addressing those things further will allow researchers to make even more progress with humanoid robotics and eventually find many new applications for them.

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