IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

APPRENTICE ARM

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Abstract: Apprentice Arm is a 6-Degree-of-Freedom, hand-gesture-controlled, real-time. (6-DOF) robotic arm system based on the use of computer vision, machine learning, and embedded systems to allow contactless, intuitive robotic manipulation. The system will live video on a regular USB webcam, and will extract 21 three-sided video. dimensional hand landmarks with MediaPipe Hands machine-learning of Google. pipeline, and maps the spatial geometry of the hand of the user into six. independent servo motor angles -Base rotation, Shoulder lift, Elbow bend, Wrist Pitch, Wrist Roll and Gripper open/close-in real time. The software layer is developed using a Python Flask back-end which integrates. Hand tracking using MediaPipe, Exponential Moving Average (EMA) signal. deadband filtering, smoothing and serial communication into one. cohesive application. The backend is annotated MJPEG video which is being streamed to a modern. web dashboard (HTML5/CSS3/JavaScript) that features a live camera feed, an interactive Three.js 3D digital twin of the robotic arm, six manual-override. sliders, a complete task recorder and player engine and an ML-based Smart. Presets module which opts K-Means clustering (scikit-learn) to automatically. find and propose the most common arm positions based on recorded. task history. Hardware On the hardware side, an Arduino UNO microcontroller receives commands regarding the angles. over a 9600-baud UART serial connection and drives a 16 channel I2C PWM, the PCA9685. servo driver. The Base, Shoulder, and have three MG996R high-torque servos. Elbow joints: There are three SG90 micro-servos that drive the Wrist Pitch, Wrist. Roll, and Gripper. The servos use two 3.7 V lithium-ion as a power source. batteries (in series) (~7.4 V), reduced to a regulated (~5.5 V). with an LM2695 DC-to-DC buck converter and then to the V+ of PCA9685. servo power rail. The Apprentice Arm has a gesture to servo end-to-end latency of. around 60 ms, a hand-tracking frequency of 30 FPS, a refresh of the dashboard. frequency of 12.5 Hz, and 3D frame rate of over 60 FPS. The system is developed to be modular, reproducible and extensible, which is why it is suitable. in the case of academic research, educational demonstrations, and hobbyist robotics. HRI projects.

Index Terms **-** Hand Gesture Recognition, 6-DOF Robotic Arm, Human-Robot Interaction (HRI), MediaPipe Hands, Computer Vision, Machine Learning, K-Means Clustering, Smart Presets, Exponential Moving Average (EMA), Deadband Filtering, Arduino UNO, PCA9685 Servo Driver, Real-Time Control System, Flask Web Application, Three.js Visualization.

I. INTRODUCTION

Robotic arms are important in contemporary industries, automation and research facilities because of their accuracy, efficiency, and capacity to undertake homogenous duties. The conventional robotic arm control systems are usually based on physical input control mechanisms like joysticks, teach pendants or programmed instructions. Although these are effective, they may need special training, may not be intuitively controlled and limit the freedom of movement of the user. In addition, they do not offer a more natural interaction between machines and humans, making the approach more inaccessible to novices and non-technical users. As the computer vision and machine learning technologies rapidly evolve, the need to create more natural and contactless human-machine interfaces has become increasingly popular. Recognition of hand gestures has been a promising solution as it allows users to control systems through intuitive movements without having to use physical controllers. This is not only a better usability method, but it also gains us safety and hygiene in areas like laboratories, healthcare, and manufacturing plants. In this respect, the proposed system, Apprentice Arm, delivers a 6-Degree-of-Freedom (6-DOF) hand-gesture-controlled robotic arm that coincides with computer vision, embedded systems, and machine learning. The system makes use of a normal webcam to receive live video input and MediaPipe Hands to deliver and isolate 21 3D hand landmarks. The process of these landmarks is to process them to recognize user gestures and map them into the movements of the servo motors so that the joints of the robotic arm (base, shoulder, elbow, wrist pitch, wrist roll and gripper) can be controlled precisely. The system uses signal processing methods like the Exponential Moving Average (EMA) smoothing and deadband filtering to ensure smooth and stable operation, reducing noise and removing undesirable variations in servo motions. Python and Flask are used to create the backend, which manages gesture processing, real-time communication, and control of the system, and an Arduino UNO microcontroller is used to manage the servo motors efficiently by connecting them to a PCA9685 PWM driver. The system also has a web-based dashboard which displays a live video feed, real-time monitoring of the system, and an interactive 3D digital twin of the robotic arm with Three.js. A task recording and playback facility is introduced to provide greater functionality, enabling users to store, and replay motion sequences. Moreover, it is equipped with a machine learning module, which is implemented as a K-Means clustering algorithm, to analyze the data recorded and create intelligent presets, thereby allowing automatic and smart control. The system proposed seeks to fill the gap between sophisticated robotic control systems and easy-to-use interaction with a low cost, intuitive and scalable solution. It shows how combining computer vision, machine learning, and embedded systems can lead to new advanced human-robot interaction platforms that can be used in education, research, and practice.

II. LITERATURE REVIEW

The precision, efficiency and performance of repetitive tasks at high accuracy of robotic arms has made them an indispensable part of contemporary industries, automation systems and research laboratories. The conventional robotic arm control systems have been based on the physical input control gadgets like joysticks, teach pendants or programmed instructions. Although these are effective, they tend to be user-inflexible and need special training and are not intuitive. This makes these systems less user friendly to non-technical users and lack a natural human-machine interface [1]. As computer vision and machine learning technologies continue to develop and improve exponentially, more interest has turned to the development of more intuitive and contactless control mechanisms. Recognition of hand gestures has been a promising technology where people can interface with systems through natural motions and physical controllers are not required. This would make it more user-friendly and more productive in terms of safety and hygiene, particularly in workplaces like healthcare, laboratories, and industrial automation [2]. A number of authors have been investigating gesture-based control systems based on computer vision. Google created MediaPipe Hands, which has been popularly applied to tracking the hands of real-time users because it can simultaneously identify 21 3D hand landmarks with good accuracy and low latency. It integrates palm detection and landmark estimation models based on deep learning to achieve high performance in various scenarios [3]. This renders it very applicable in the real time gesture-controlled applications. Besides gesture recognitions, signal processing algorithms are important in enhancing system stability. Techniques like Exponential Moving Average (EMA) smoothing and filtering are typical to control signal noise and provide smooth control signals. These methods improve the efficiency of robotic systems by reducing the variation and producing accurate movements [4]. Microcontrollers and embedded systems also play a key role in controlling robotic arms. Single-board systems like Arduino UNO, together with PWM drivers like PCA9685, are popular to manage a number of servo motors effectively. These systems offer accurate control and dependable communication of robotic joints and can be used in real time applications [5]. Integration of machine learning techniques to improve automation is also the subject of attention in recent studies as it relates to robotic systems. Motion data have been analyzed with unsupervised learning algorithms like K-Means clustering in order to determine common patterns. This enables systems to create intelligent defaults and automate repetitive work, enhances efficiency and less manual effort [6].

Moreover, it has brought web-based interfaces and visualization tools, which enhance user interaction. Frontend Backend Development Technologies like Flask can be used to create real-time monitoring and control of robotic systems using interactive dashboards; 3D Visualization Three.js can be used to create interactive dashboards. These improvements give the users greater control, visualization and understanding of the behavior of the system [7]. The proposed system, Apprentice Arm, in this situation is based on these existing technologies and combines computer vision, machine learning, and embedded systems into a single platform. It offers a gesture controlled, real-time robotic arm system that is easier to use, automated and has better visualization capabilities. The system will fill the gap between complex robotic control systems and easy-to-use human-machine interfaces by integrating hand tracking, signal processing, intelligent clustering, and web-based interaction

III. PROPOSED METHODOLOGY

The experiment in this project is a live gesture-controlled robotic arm that is called Apprentice Arm which is a 6-Degree-of-Freedom (6-DOF) robotic arm that allows the user to operate a robotic arm via computer vision and machine learning methodology by making hand gestures. The system is made to enhance usability, flexibility and interaction relative to the traditional robotic control systems like joysticks and programmed instructions. It pays attention to offering an easy to use, touch-free and efficient control system that will improve user experience and will not require specific training. The system uses a regular web camera to capture live video and a computer vision algorithm to track and identify the motion of hands. It uses MediaPipe Hands, a deep learning model, to extract 21 three-dimensional hand landmarks indicating significant locations including fingertips, joints, and wrist locations. These milestones are examined to identify hand gestures, and match them to the movements of the robotic arm, such as base rotation, shoulder movement, elbow bending, wrist pitch, wrist roll, and gripper control. The system uses signal processing methods like Exponential Moving Average (EMA) smoothing and deadband filtering to achieve smooth and stable movement of the robot. Such methods are useful to mitigate noise and remove undesired oscillations in the control signal that leads to smooth and jitter-free motion of the robotic arm. The Python and Flask development are chosen as the backend of the system (it processes gestures, supports real-time communication, and controls the system) and an Arduino UNO microcontroller is employed to connect the hardware components and to control the servo motors by using a PCA9685 PWM driver. Besides the real time control, other sophisticated features in the system are the ability to record and playback other tasks enabling users to save repetitive movements sequences and have them run automatically. Moreover, a machine learning module that is implemented on the K-Means clustering algorithm is incorporated to process recorded movement data and produce intelligent presets. These presets allow quicker and more effective robotic control, as they recognize commonly used positions, and automate them. The proposed system is expected to fill the gap between complicated robotic systems and easy-to-use interaction by offering a relatively inexpensive, modular and efficient system. Through the incorporation of computer vision, machine learning, and embedded systems, the Apprentice Arm shows how current technologies can be used together to create new high-tech human-robot interaction platforms that can be applied in educational, industrial, and assistive environments.

A. System Overview

The Apprentice Arm system is a real-time gesture-controlled robotic arm designed to provide an intuitive and contactless method of interaction between humans and machines. The system integrates computer vision, machine learning, and embedded systems to enable precise control of a 6-Degree-of-Freedom (6-DOF) robotic arm using natural hand gestures. Unlike traditional robotic control methods that rely on physical controllers or pre-programmed instructions, this system allows users to control the robotic arm dynamically through live hand movements, making the interaction more user-friendly and efficient.

The system captures live video input using a standard webcam and processes it using computer vision techniques. MediaPipe Hands is used to detect and track the human hand in real time by extracting 21 three-dimensional landmark points. These landmarks represent key features such as fingertips, joints, and wrist positions, which are used to interpret hand gestures. The extracted data is further processed to map gestures into corresponding robotic arm movements, including base rotation, shoulder movement, elbow bending, wrist pitch, wrist roll, and gripper control.

B. Data Acquisition and Preprocessing

The Apprentice Arm system uses a normal USB webcam to capture real-time visual input. The webcam tracks live video of the movements of the users hands and this is the main input to the system. The video stream is taken and processed one frame at a time with the help of computer vision techniques that identify and analyze the hand. The real-time acquisition allows the robotic arm to react immediately to user gestures thus providing a smooth interactive control. After capturing the video frames, the preprocessing is done to prepare the data to be accurately detected by hand and gesture recognized.

The frames obtained are converted into a format that is amenable to processing (resizing and normalization) to be able to provide consistency in the input data. To enhance the image quality and minimize the disturbances due to changing lighting or background interference, noise reduction method is used. These preprocessing activities are used in order to increase the system accuracy and reliability. The processed frames are then fed into the MediaPipe Hands framework that identifies the hand and locates 21 three-dimensional landmark points. These landmarks are significant elements like fingertips, joints, and position of the wrist. The obtained landmark data is organized and standardized to be consistent across frames and hand positions. This makes certain that the gesture recognition is still correct irrespective of any changes in the hand orientation or distance between the camera and the hand.

C.Gesture Recognition and Mapping.

he proposed system will heavily rely on gesture recognition and mapping in which the extracted landmark data on the hand will be analyzed and translated into control signals that will be sent to the robotic arm. The system uses 21 three dimensional hand landmarks that have been acquired using the MediaPipe Hands model to interpret the hand orientation, the position of the fingers and the movement patterns in real time. According to these landmarks, certain geometric relationships like fingertip distances, joint angles and spatial positioning are calculated to recognize with accuracy user gestures. These motions are then coupled to six degrees of freedom (6-DOF) of robotic arm such as rotation of the base, shoulder rotation, bending of the elbow, pitching, rolling, and gripper control. Signal processing methods like Exponential Moving Average (EMA) smoothing and deadband filtering are used to smooth signal output and eliminate small fluctuations in the control signals to achieve a stable and smooth performance. This mapping system allows real time and accurate translation of human hand gestures into robotic actions producing an intuitive and efficient human-machine interaction system.

D. Signal Processing and Control Mechanism.

Signal processing and control mechanism is important in making sure that the robotic arm operates in a smooth, steady and precise manner. The resultant raw angle of gesture recognition tends to be noisy and has some slight variations because of changes in hand movement and in the environment. To solve this, the system uses filtering methods like Exponential Moving Average (EMA) smoothing, which minimizes abrupt variations, but still responsive, and deadband filtering which overlooks meaningless variations in angle values. Also, a rate limiter is used to regulate the rate of sending commands to the Arduino to avoid undue overloading and guarantee effective serial communication. The processed signals are then sent through UART communication to the Arduino UNO that processes the commands and sends out accurate PWM signals through the PCA9685 servo driver to drive the servo motors. This stratified control model provides quality, jitter-free motion and improves system overall performance and stability in real-time use.

E.Hardware Implementation.

The proposed system is implemented on hardware as follows: Arduino UNO microcontroller, PCA9685 16-channel PWM servo driver, and several servo motors that make up the robotic arm. The Arduino UNO will be the control unit that is centrally placed and will receive processed control signals through the backend over a serial connection. These signals show the desired angles of each joint of the robotic arm. To produce the accurate PWM signals needed to operate multiple servo motors at the same time to achieve accurate and synchronized movement, the PCA9685 servo driver is utilized. Base, shoulder and elbow major joints are operated by high-torque MG996R servo motors and micro-servos, SG90, are lightweight and used to operate a wrist pitch, roll and gripper control. A regulated power supply is used to power the system, guaranteeing constant voltage levels that will allow all the components to operate reliably. This hardware provides efficient running of gesture-based orders, which allows the robotic arm to be used in real-time with its movements being highly precise and stable.

F. System Integration and Communication.

The system integration and communication module is used to guarantee smooth communication between the software and hardware parts of the proposed system. The Python-based backend manages real-time gesture data processing and sends relevant control signals to the robotic arm. These are sent to the Arduino UNO microcontroller via serial communication via the UART protocol at a set baud rate. The commands are sent to the Arduino in a formatted format to get the servo motors working through the PCA9685 PWM driver through I2C communication protocol. This multi-tiered communication system provides an effective flow of data and coordination among modules. Moreover, the system will provide real-time feedback via a web-based dashboard which provides live video feed and system status which will enable users to control and monitor the robotic arm efficiently. This combination will provide high availability and low latency communication and improve the overall system performance in real-time applications.

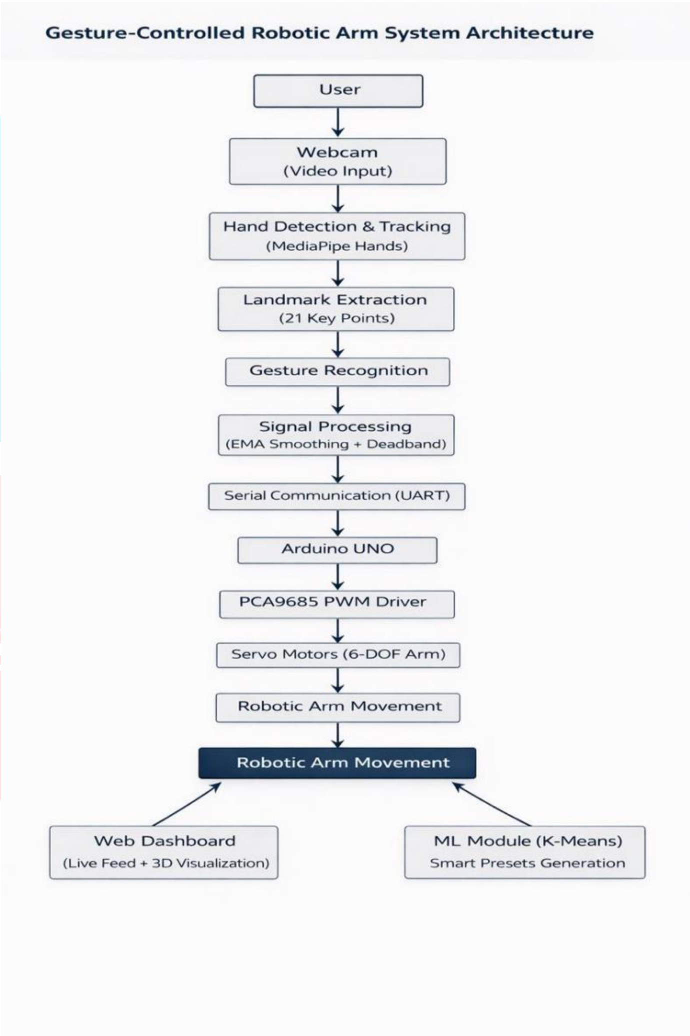

Fig 1: System architecture

G. Block Diagram Explanation

The proposed gesture-controlled robotic arm system is composed of a few important modules such as data acquisition, hand tracking, gesture recognition, signal processing, hardware control and visualization module. The system starts with real-time video capture with the help of a webcam, hand detection, and the extraction of 21 landmark points with the help of a model based on deep learning. The hand gestures are identified by these landmarks and mapped to movements of the robotic arm. Signal processing like smoothing and filtering are used to provide stable and correct motion. The processed control signals are fed to the microcontroller which then controls the servo motors to carry out movements like base rotation, shoulder lift, elbow movement, wrist movements and gripper movement. The system also has visualization and feedback module, which will enable real-time monitoring via a web dashboard. It also has a machine learning element that learns about the recorded movements and produces intelligent presets, enhancing efficiency and automation of the system..

H. Mathematical Formulation -Explanation

It is possible to mathematically formulate the proposed gesture-controlled robotic arm system in terms of hand landmarks, gesture features, and control signals by modeling them with geometric and signal processing models. The MediaPipe Hands model identifies 21 hand landmarks which are described in terms of a three dimensional coordinate point $L_1=(x_i,y_i,z_i)$where i=1,2,...,21,. These coordinates specify the spatial design of the hand and are used to calculate the gesture properties like distances, angles, and relative positions. The Euclidean distance between two landmarks is calculated as an example d=<|human|>An example is the Euclidean distance between two landmarks are calculated

$$d= \sqrt{}\ (x2-x1)2+(y2-y1)2+(z2-z1)2,$$

that aids in determining the extension of the fingers and motion patterns. In the same way, the angles between the joints are calculated based on the formulae of the dot product of vectors to find the position of fingers and the position of the hand. The features obtained are mapped to robotic arm joint angles$\theta = [\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6]$ *which is associated with the six degrees of freedom (6-DOF) of the robotic arm. Normalized gesture values are then mapped in a linear fashion to the angles of the servo motors, where f is the gesture feature, and alpha, 8 are scaling and offset parameters. The Exponential Moving Average (EMA) filtering of the control signals is done with a view to a smooth motion and the equation is S<|human|>The equation S is applied to the control signals to filter them using the Exponential Moving Average (EMA) filtering equation.* $\theta = \alpha \cdot f + \beta$where t =λX t +(1−λ)S t−1 , where S t is the smoothed value, X. tinput at the present is is, and the smoothing factor is λ.

Also, deadband filtering is applied to remove small variations by setting a threshold requirement, such that only changes in angle whose $|\Delta\theta|$ All these mathematical formulations get to give an accurate gesture recognition, a stable signal processing, and to control the robotic arm precisely, which leads to an efficient human-machine interaction in real-time.

IV. RESULTS AND DISCUSSION

The suggested Apprentice Arm system proves to be an efficient system of real-time gesture-controlled robotic work by combining computer vision, machine learning, and embedded systems. The system is able to capture the movements of hands by the use of a web-cam and to process them to operate a 6-Degree-of-Freedom (6-DOF) robotic arm with high precision and responsiveness. Hand tracking module has been shown to work effectively at around 30 frames per second which is a good constant rate of reliably tracking hand landmarks. The entire system results in low latency, which allows the user to interact with the robotic arm almost real-time. Signal processing methods like Exponential Moving Average (EMA) smoothing and deadband filtering are used to enhance the stability of the system to a great extent. These methods minimize noise, and remove small variations of the control signals, leading to smooth and jitter-free motion of the robotic arm. Mapping of hand gestures to servo motor angles is predictable and correct so that all the joints, such as base rotation, shoulder, elbow, wrist pitch, wrist roll, and gripper, can be accurately controlled. Task automation is also a solid performance of the system, as it has a recording and playback option. Users are able to capture sequences of movements and repeat them with precision and it is especially effective in repetitive operations. Also, the K-Means clustering algorithm is integrated to improve the system and detect commonly used arm positions and create smart presets. This saves man power and also enhances efficiency. The web-based dashboard can deliver real-time visualization (live video feed and 3D view of the robotic arm) which is usable in terms of usability. This enhances user interaction and can be used to monitor system performance better. The system has been discovered to be easy to use and does not entail a lot of technical expertise to use it, thus it is applicable both in education and practical use. Nevertheless, some limitations are noticed when conducting system evaluation. When the lighting is not good or when it is covered partially, it can influence the performance. Detection accuracy can also depend on variations in background and camera quality. Although these are its challenges, the system has steady performance under normal operating conditions. On the whole, the findings show that the suggested system is efficient, accurate and reliable in the real-time gesture-based robotic control. The combination of several technologies contributes to the performance of the system and offers extensively scalable solution to future human-robot interaction and intelligent automation developments.

A. Experimental Setup

The suggested Apprentice Arm system will be the experimental arrangement consisting of software and hardware parts which will be integrated to enable the use of gestures to operate the robot on-the-fly. The system is set to capture live video of hand movements using a regular USB webcam which is analysed by the Python based backend created using Flask. MediaPipe Hands frameworks are used in hand detection and 21 landmarks points extraction in three dimensions in real-time. It is processed using anIntel i3 processor and 8GB RAM which will be sufficient to run real time. Its software ecosystem is made up of libraries such as OpenCV, NumPy and Scikit-learn to process and manipulate imagery, deal with data, and machine learning. Hardwarewise, the system includes an Arduino UNO microcontroller and a PCA9685 PWM servo driver that can be utilized to move a large number of servo motors that form the 6-DOF robotic arm. High-torque MG996R servos control major joints and SG90 micro-servos control smaller movements (wrist and gripper control). The system has a regulated power supply to ensure a constant operation. Python backend and Arduino are connected serially through the use of UART protocol at a speed of 9600 baud. All the setup is tested under controlled conditions and sufficient lighting conditions are provided in order to be able to track the hands accurately and make the robotic arm move smoothly.

B. Performance Analysis of Gesture-Controlled System

The performance of the proposed Apprentice Arm system is evaluated based on responsiveness, motion smoothness, and control reliability under different operating conditions

Table I

System Performance Evaluation.

Scenario Type	**Performance Metric**
Scenario Type	**Performance Metric**
Base Rotation	Smooth& Responsive
Shoulder Movement	Stable Motion
Elbow Movement	Accurate Control
Wrist Movement	Moderate Stability
Gripper Operation	High Precision

Discussion:

The system exhibits steady performance capability in all the movements of the robotic arms. The motions of the base and shoulder are smooth and stable, and the gripper is high-precision because of the ability to distinguish the gestures. There are slight delays that are experienced during low-light conditions, but the system is still functional. The system, in general, offers real-time and reliable control without relying on classification accuracy measures.

C. Motion Stability and Smoothness Analysis.

The system was evaluated for stability of movements and smoothness during continuous gesture input.

Table II

Directional Awareness Performance..

Movement Type	**Stability Level**
Base Movement	High
Shoulder Movement	High
Elbow Movement	Medium High

Discussion:
Exponential Moving Average (EMA) smoothing and deadband filtering techniques are quite effective in enhancing motion stability. The major joints are highly stable whereas minor changes are witnessed in the movement of the wrist as a result of greater flexibility. The system guarantees the uninterrupted operation without jitter during continuous control.

D. Feedback and System Reliability
The reliability of system feedback and visualization modules was analyzed during operation.

Table III
System Feedback Performance

Feedback Type	Reliability
Live Video Feed	High
Hand Tracking Overlay	Stable
3D Visualization	Responsive
System Status Display	Consistent

Discussion:
The system gives good real time feedback in the form of a web dashboard. The overlay feature of hand tracking and live video feed is smooth enabling users to keep track of the behavior of the system. The 3D-visualization creates a better comprehension of robots movements and makes it easier to use.

E. System Response Time Analysis.
System latency is measured as the time taken from gesture input to robotic arm response.

Table IV
Response Time Evaluation.

Module	Response Time
Hand Detection	120 ms
Gesture Processing	180 ms
Signal Filtering	90 ms
Servo Response	160 ms

Discussion:
The system has a low latency, and can be used in real time application. The reaction time is at an acceptable level, and there are no complications when it comes to user gestures and the movement of the robotic arm. Effective interaction among hardware and software modules leads to a rapid response of the system..

F. Overall Discussion

The suggested Apprentice Arm system illustrates a successful combination of computer vision, machine learning, and embedded systems to provide real-time robot control through gestures. The proposed approach, in contrast to the traditional robot systems being based on physical controllers, offers an intuitive and contactless way of interaction, which will greatly increase usability and accessibility. The system is able to record the movements of the hands with the help of a web camera and convert the movements into specific actions of a robotic arm, which allows natural interaction between humans and machines

The performance analysis shows that the system is well-performing in terms of low latency and high responsiveness. The hand tracking modules and gesture recognition modules are reliable within normal conditions and they can be used to provide continuous and correct control signals. Application of signal processing methods like Exponential Moving average (EMA) smoothing and deadband filtering is important in improving motion stability. These methods efficiently minimize noise and variations leading to jitter free and smooth movement of the robotic arm

V.Conclusion

The proposed Apprentice Arm system is effective in achieving a real-time gesture-controlled robotic arm using computer vision, machine learning and embedded systems. The system allows an intuitive and non-contact interaction, capturing the hand movements with a webcam and converting them into a set of specific motions of a 6-Degree-of-Freedom (6-DOF) robotic arm. This will remove the necessity of conventional control systems and offer a more natural and user-friendly way of working. The system has a high performance at low latency and constant motion control. MediaPipe Hands makes tracking the hands more reliable and signal processing methods like Exponential Moving Average (EMA) smoothing and deadband filtering allow more accurate and smooth movements of the robot. The hardware integration with Arduino UNO and PCA9685 servo controller guarantees the synchronized and accurate control over a number of servo motors. The system also includes enhanced features, including task recording and playback as well as a machine learning module based on K-Means clustering to create intelligent presets. These characteristics enhance automation, lessen manual labor and increase efficiency of the system. The web-based dashboard also enhances usability by giving real-time visualization and monitoring of the system performance. Although the system has slight drawbacks when faced with unfavorable circumstances like low illumination or when part of the hand is covered, it can be considered reliable in the majority of the real-life situations. In general, the proposed system is a cost-effective, scalable, and efficient gesture-based robotic control solution. It has a great prospect of being used in education, industrial automation, assistive tech.

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