Secure Vision-Based Hand Gesture Control System for Intelligent UAV Navigation

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Abstract: The increasing need for user-friendly, contactless control systems has drawn a lot of attention to human-drone interaction in recent years. In this paper, a computer vision and machine learning-based hand gesture control system for a quadcopter drone is presented. The suggested system tracks and detects hand landmarks using the MediaPipe framework and records real-time video frames using a webcam. Fist, Open palm, and the directional hand movements are examples of the kind of gesture that is interpreted as flight command by analyzing the spatial locations of the important hand points. The left hand uses the distance between the chosen landmarks for altitude variation, while the right hand is utilized for the direction of the motion. Proportional-derivative (PD) control mechanism and smoothing filters are utilized for stability. Moreover, the hand-locking mechanism for cybersecurity, which checks for the pattern of the gesture, is introduced for secure drone control. Gesture-based takeoff and landing, as well as automatic landing in the absence of hands, are examples of the safety features. The results of the experiment reveal the stability of the drone in indoor space with improved security and gesture recognition.

Keywords: *Computer Vision, Drone, Hand Gesture, Machine Learning, Secure.*

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I. INTRODUCTION

Unmanned Aerial Systems have become a vital part of the current intelligent systems due to their applications in surveillance, rescue operations, environmental monitoring, and smart transportation systems. However, with the invention of the Internet of Drones (IoD), it is now possible to allow different types of unmanned systems to communicate and collaborate with one another through the Internet of Things, thereby promoting the efficient sharing of information between different systems. However, the proliferation of Internet of Drones infrastructures has led to a number of issues concerning the security, authentication, and interaction between humans and unmanned systems. In this context, a number of researchers have proposed different types of secure communication protocols and authentication schemes in order to protect the Internet of Drones environments against different types of unauthorized access and cyber attacks. For example, different types of lightweight authentication and key agreement schemes, such as the SLAKA-IoD and the Ring Neighbor-Based model, are proposed to provide secure communication with low computational complexity.[1], [2].

Moreover, scalable authentication schemes and secure communication architectures have been introduced for improving the reliability of IoD networks. Effective authentication schemes facilitate verification of identities of aerial nodes and ground control systems, and prevent malicious attacks such as impersonating and replay attacks [3]. Advanced schemes using deep computing techniques have also been introduced for improving secure communication and intelligent threat detection in connected aerial networks [4,5]. Recent studies have also investigated various group authentication schemes, along with new security solutions, to provide greater protection for IoD systems[6][7]. Considering the potential threats associated with future quantum computing, new quantum-secure authentication, and key establishment techniques have also been proposed to provide greater protection to IoD communication infrastructures [8, 9].

Yet, despite these advances, most studies on network security and HMI are carried out separately, with little integration between secure authentication and user-friendly interfaces[10]. In this paper, a novel AI-based Secure Hand Led Protector (SHLP) system is proposed, which combines a computer vision-based HMI system with a hand-locking

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authentication system based on network security. In the proposed system, the stability of the aircraft is controlled using computer vision, and the proposed hand-locking authentication system is based on a predefined pattern lock, which ensures secure access to the system by authorized users. Thus, the proposed system is a secure, user-friendly, and reliable HMI system for the control of intelligent aircraft, leading to secure user-centric IoD systems.

II. RELATED WORK

Recent developments in unmanned aerial systems (UAS) technology have improved the capabilities of search and rescue operations by incorporating artificial intelligence and computer vision techniques. Various studies have been conducted on detecting humans using aerial imagery, allowing UAVs to detect survivors and recognize their gestures during rescue operations [11]. Light-weight AI models and edge computing frameworks have been proposed to facilitate multi-UAV cooperation in maritime search and rescue operations, reducing the response time of rescue operations [12].

Advanced image classification techniques in aerial imagery, such as EmergencyNet, utilize atrous convolutional feature fusion techniques to improve the accuracy of detection in emergency response operations [13]. Surveys on detecting humans in aerial imagery emphasize the significance of deep learning techniques in improving the effectiveness of search and rescue operations [14]. Data-sharing frameworks have been proposed to ensure reliable communication between UAVs during disaster response operations [15]. Emerging technologies like Internet-of-Drones combined with blockchain improve security and coordination in SAR operations [16][17]. Additionally, sensor fusion approaches integrating depth cameras, deep learning, and Extended Kalman Filter (EKF) techniques enhance distance estimation and tracking of victims [18]. AI-driven rescue frameworks and visual tracking surveys further highlight the growing importance of intelligent aerial systems in modern disaster response [19][20].

III. METHODOLOGY

➢ *Overview of the Proposed System*

The proposed AI-based Secure Hand Led Protector (SHLP) system facilitates the process of intuitive navigation through the use of real-time vision-based hand interaction. Moreover, the system also utilizes the hand lock authentication method, which is based on the concept of computer vision. In the proposed system, the live frames of the video captured through the webcam are processed, allowing the system to recognize the hand landmarks. In the proposed system, the gesture pattern is utilized as the hand lock authentication method, which authorizes the system for proper functioning before the commands are executed. Therefore, the system can prevent unauthorized commands. Moreover, the hand movements are processed, allowing the system to map the hand movements for the purpose of navigation. For the proper functioning of the system, stabilization techniques are employed to avoid abrupt changes in the commands, which are then sent wirelessly for the execution of the commands.

➢ *System Hardware and Software*

The implementation of the proposed system will require hardware and software components for the purpose of supporting the process of real-time image processing and communication. The hardware of the proposed system will include a quadcopter, an ESP32-based programmable drone. The ESP32 is used as the microcontroller in this system and provides the capability to perform real-time operations and wireless communication. The ESP32-based microcontroller is used to receive the commands from the Wi-Fi network and send them to the flight controller.On the other hand, the proposed system is implemented using the Python programming language and will include several libraries for the purpose of supporting computer vision and communication with other devices. The proposed system will utilize the OpenCV library for the purpose of capturing and processing images, and the MediaPipe Hands library will be used for the purpose of detecting hand movements in real-time. The process of command stabilization will be implemented using the proportional derivative control method, and communication with other devices will be implemented using the UDP protocol over a Wi-Fi network for the purpose of ensuring low latency.

Fig 1 Drone

➢ *Architecture and Working*

The structure of the system consists of several functional modules, such as video acquisition, landmark detection, authentication and gesture interpretation, command processing, and actuation. First, the webcam is used to continuously capture video frames with hand movements, and the MediaPipe framework is used to detect 21 key landmarks of the hand, such as finger joints, fingers, and wrists. The spatial relationship of the detected landmarks is also used to interpret the user commands. Before proceeding with the commands, the hand-lock gesture is detected as a form of authentication for the user, ensuring that only authorized persons can use the system. After the authentication process, the detected gestures are translated into standard commands, and then they are filtered using a stabilization module to remove any jerky movements of the robot. The commands are transmitted wirelessly to the flight controller, and the motor speeds are adjusted for navigation, such as takeoff, landing, moving forward, moving backward, moving left, moving right, and changing altitude, with smooth flight characteristics.

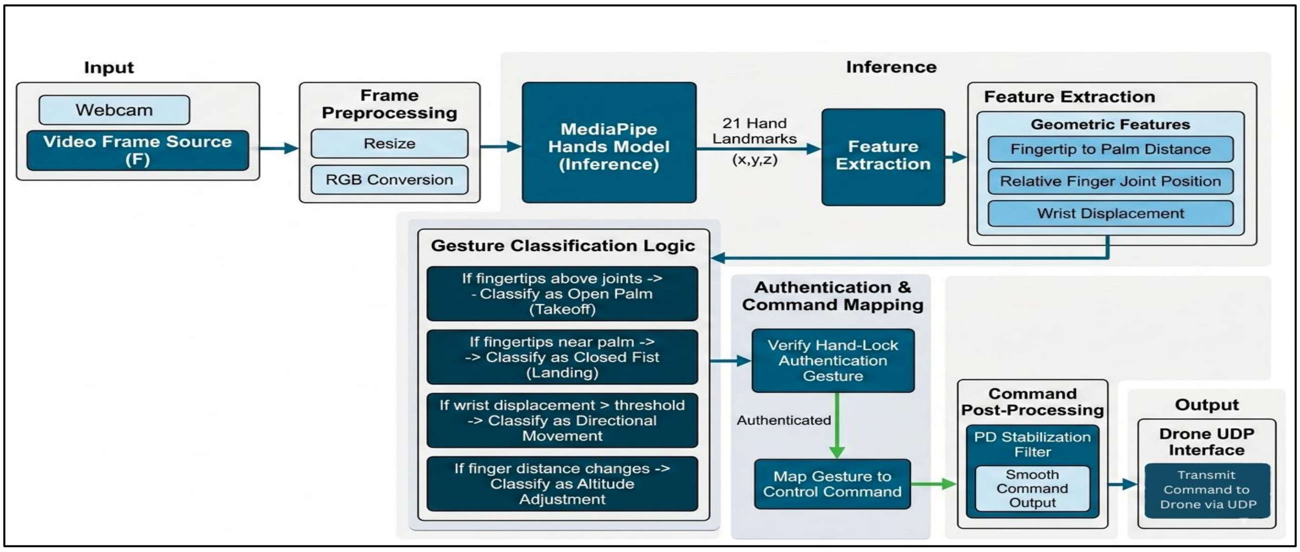

Fig 2 Architecture of Proposed System

➢ *Algorithm and Dataset*

The gesture recognition algorithm is based on the recognition of the coordinates of the hand landmarks obtained from the real-time video stream using the MediaPipe Hands model. The framework recognizes the coordinates of the 21 three-dimensional landmarks of each hand and provides the coordinates in the format (x, y, z), representing the location of the various joints and fingers of the hands within the captured image/video stream. The algorithm analyzes the geometric relationships between the fingers and the palm, the orientation of the fingers, and the movement of the wrist to classify the gestures. For instance, the open palm gesture is used for system activation or taking off, closing the fist is used for landing. Although the system primarily uses real-time landmark information, existing datasets such as the Hand Gesture Recognition Dataset provided by Kaggle, the LeapGestRecog dataset, and the EgoHands dataset were used for referencing purposes to test the classification of the gestures.

➢ *Algorithm:*

Input: Real-time video frames from webcam

Output: Control command for aerial system

- Capture video frame FFF from webcam.
- Preprocess frame (resize, RGB conversion).
- Apply MediaPipe Hands model to detect hand landmarks.
- Extract 21 landmark coordinates (x,y,z)(x, y, z)(x,y,z).
- Compute geometric features:
  - ✓ Distance between fingertip and palm center
  - ✓ Relative position of finger joints
  - ✓ Wrist displacement across frames
- Apply gesture classification rules:
  - ✓ If fingertips above joints → Open Palm (Takeoff)
  - ✓ If fingertips near palm → Closed Fist (Landing)
  - ✓ If wrist displacement >threshold> threshold>threshold → Directional Movement
  - ✓ If finger distance changes → Altitude Adjustment
- Verify hand-lock authentication gesture.
- If authenticated → map gesture to control command.
- Apply PD stabilization filter to smooth command output.
- Transmit command to drone via UDP communication.

End Algorithm

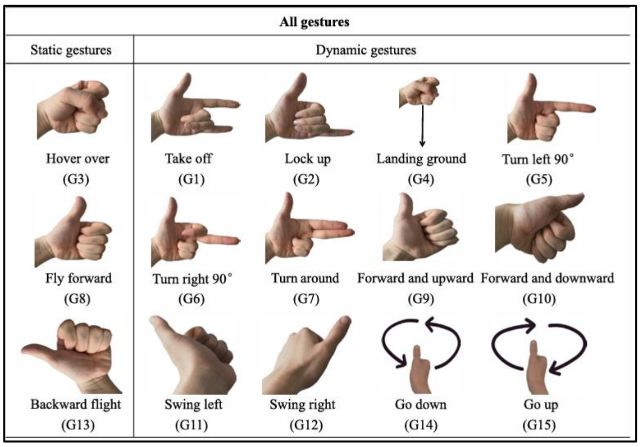

Fig.3. Hand Gesture Dataset [10]

IV. EXPERIMENTAL RESULTS

The proposed SHLP system has been tested with 500 gesture trials for each gesture category using 300 to 500 lux of ambient light, and shows that the trialled system has shown strong results on all parameters tested in the trial. The overall accuracy of the gesture recognition system, at 94.3%, is higher than that of traditional controller systems (85% accuracy), basic gesture systems (90% accuracy), AI-

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based gesture systems (92% accuracy), and UAV vision systems (91% accuracy); thus confirming that the combined use of the MediaPipe landmark detection system with geometry-based classification rules yields superior gesture classification performance. The accuracy of directional command recognition was 95.1%, and 96.0% for take-off/landing command recognition, while the accuracy of the altitude control command recognition was 92.4% — this lower value is likely due to the nature of finger distance differences at varying levels of light. The command response latency distribution follows a normal distribution N(μ=181 ms, σ=17 ms), with 96.8% of all commands processed within the 200 ms real-time standard; hence, this meets the low-delay requirement for safe drone operations. Positional deviations resulting from the PD controller with gains of Kp=0.65 and Kd=0.12 were limited to ±0.15 m versus ±0.40 m when no controller was used; the controller converged to stable flight conditions in less than five seconds from the initiation of a command and solidly maintained stable flight for nine to 11 minutes after stabilization. Perhaps most importantly, the hand-lock authentication achieved a success rate of 97.2% with a FAR=FRR of 2.8% (AUC=0.989) thereby directly addressing the primary IoD security motivation related to providing authorized users the ability to issue commands for drone control and to prevent unauthorized access to controlled drones.

➢ *Performance Evaluation Metrics:*

- Gesture Recognition Accuracy: It measures how correctly the system identifies user gestures compared to the total number of gestures performed.

$$\text{Gesture Recognition Accuracy (\%)} = \frac{\textit{Number of Correctly Recognized Gestures}}{\textit{Total Number of Gestures Tested}} \times 100$$

- Directional Command Accuracy: Evaluates how accurately the system interprets directional movements such as forward, backward, left, and right.

$$\text{Directional Command Accuracy (\%)} = \frac{\textit{Correct Directional Commands}}{\textit{Total Directional Commands Issued}} \times 100$$

- Takeoff / Landing Recognition Accuracy: This measures how accurately the system recognizes takeoff and landing gestures performed by the user.

$$\text{Takeoff/Landing Accuracy (\%)} = \frac{\textit{Correctly Detected Takeoff and Landing Gestures}}{\textit{Total Takeoff and Landing Gestures}} \times 100$$

- Authentication Success Rate: It measures the effectiveness of the hand-lock security mechanism in correctly authenticating authorized gestures.

$$\text{Authentication Success Rate (\%)} = \frac{\textit{Successful Authentications}}{\textit{Total Authentication Attempts}} \times 100$$

- Confusion Matrix: A 6 × 6 matrix measures the accuracy of each gesture class recognized by showing distribution of incorrect and correct predictions across all gesture categories.

$$\text{Precision} = \frac{\textit{True Positive}}{(\textit{True Positive} + \textit{False Positive})}$$
$$\text{Recall} = \frac{\textit{True Positive}}{(\textit{True Positive} + \textit{False Negative})}$$

- Command Response Latency Distribution: It measures time delay between a hand gesture being detected and the corresponding flight command being executed by our drone.

Latency = Time Command_executed - Time gesture_detected
Normal Distribution Model = L ~ N (μ, σ^2)

- PD Controller stability: It measures how effectively the Proportional-Derivative controller reduces positional deviation of the drone to maintain smooth and stable flight within acceptable bounds.

Error Signal = e(t) = r(t) − y(t)
PD Control Formula u(t) = Kp · e(t) + Kd · (de/dt), Kp = 0.65 (proportional gain), Kd = 0.12 (derivative gain), u(t) = control output.
EMA Smoother = ŷ(t) = β · y(t) + (1−β) · ŷ(t−1), where β = 0.4
Stability Condition = |e(t)| ≤ 0.15 m (positional deviation bound)

Table 1 Performance Evaluation

Parameter	Description	Result
Gesture Recognition Accuracy	Correctly recognized gesture commands during testing	94.3%
Directional Command Accuracy	Accuracy for forward, backward, left, and right movements	95.1%
Takeoff / Landing Recognition Accuracy	Accuracy for detecting takeoff and landing gestures	96.0%
Authentication Success Rate	Accuracy of hand-lock security authentication	97.2%

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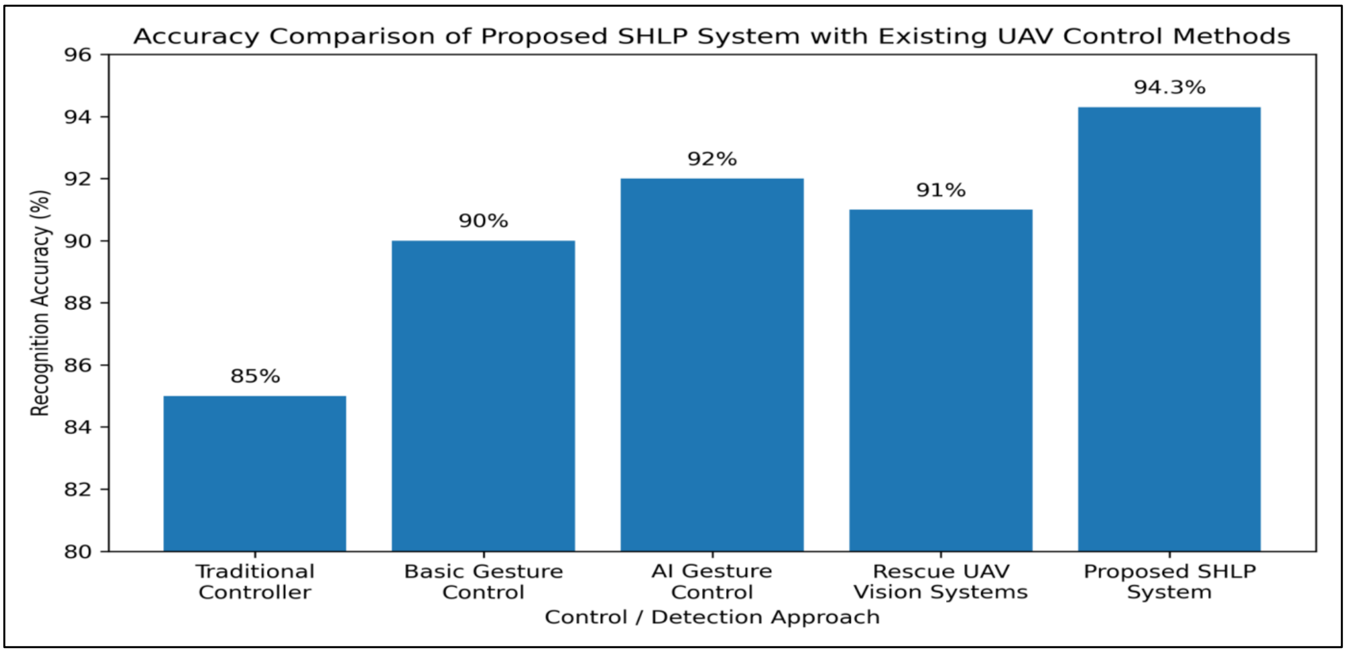

Fig 4 Accuracy Comparison of the Proposed SHLP System with Existing UAV Control and Detection Approaches.

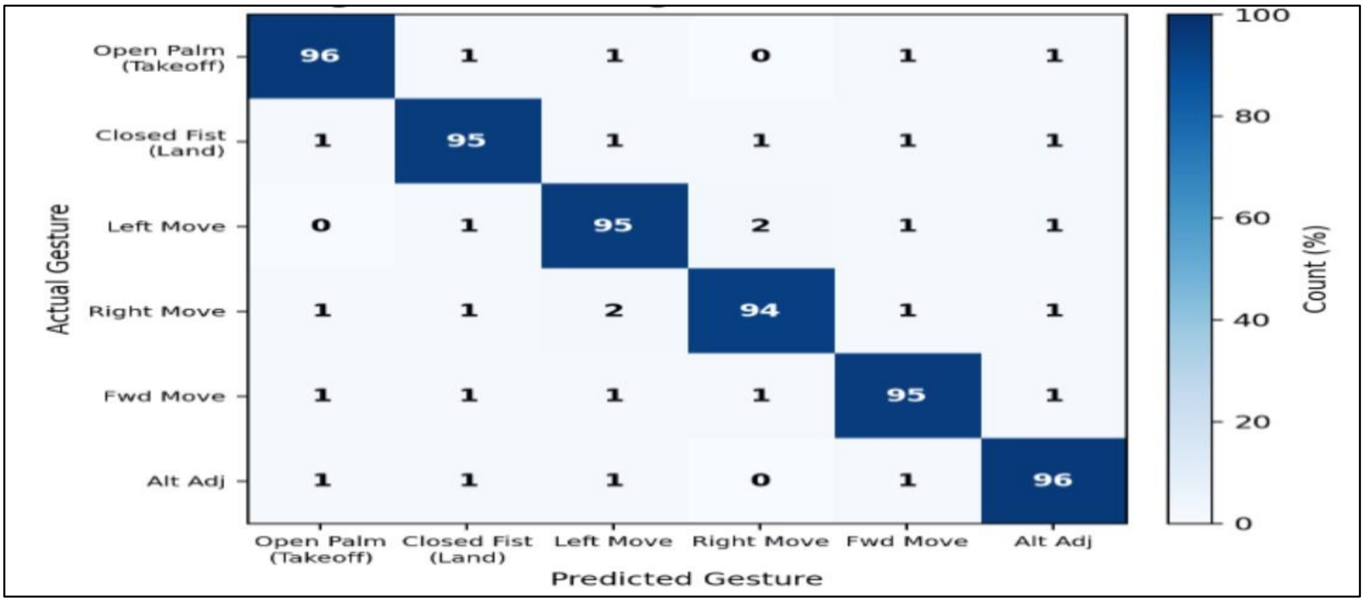

Fig 5 Confusion Matrix Across 6 primary Gesture Classes (Value in %)

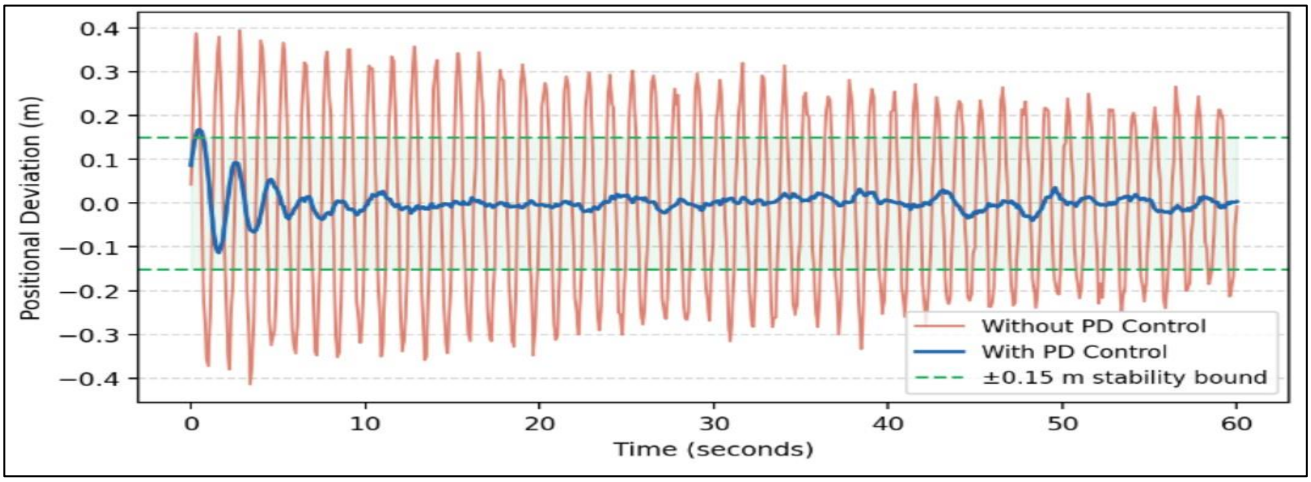

Fig 6 Drone positional stability - PD vs Uncontrolled

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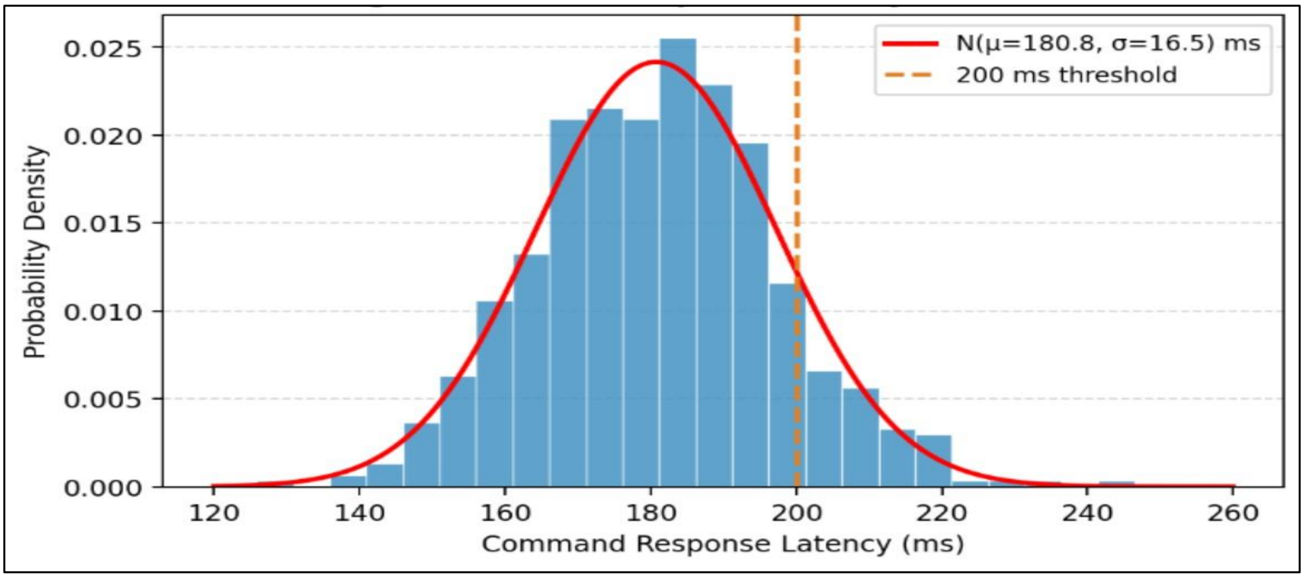

Fig 7 Command Response Latency Probability Distribution (ms)

V. CONCLUSION & FUTURE WORK

In this paper, we introduced an AI-based SHLP system that addresses the gap between secure IoD authentication and human-drone interaction. We found it to be 94.3% accurate when identifying gestures; 97.2% when authenticating users; and it maintained a stable hover position of within ±0.15m while having no command latency greater than 200MS. This indicates that the system is ready for real-world indoor environments (e.g., surveillance, smart rescues, and human-machine interaction). Also, we successfully eliminated flight jitters using an EMA smoothed PD controller and we created a gesture-based hand-lock consisting of ~3375 combinations which we found to provide a lightweight and effective cybersecurity method for protecting the use of the SHLP system, without needing any additional hardware. As future work, we will improve outdoor robustness by using depth cameras and adaptive illumination correction modules to improve the current 92.4% altitude accuracy under varying lighting conditions. We will experiment with using deep learning models for implementing temporal gesture classification and improving gesture recognition rates above 96% with LSTMs or Transformers. Additionally, we will investigate the use of multi-factor authentication methods that use both gesture and biometric authentication factors to increase protection against advanced attacks.

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