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RESEARCH ARTICLE

# Autonomous Strike UAVs in Support of Homeland Security Missions: Challenges and Preliminary Solutions

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**ABSTRACT** Unmanned Aerial Vehicles (UAVs) are becoming crucial tools in modern homeland security applications, primarily because of their cost-effectiveness, risk reduction, and ability to perform a wider range of activities. This study focuses on the use of autonomous UAVs to conduct, as part of homeland security applications, strike missions against high-value terrorist targets. Owing to developments in ledger technology, smart contracts, and machine learning, activities formerly carried out by professionals or remotely flown UAVs are now feasible. Our study provides the first in-depth analysis of the challenges and preliminary solutions for the successful implementation of an autonomous UAV mission. Specifically, we identify the challenges that must be overcome and propose possible technical solutions for them. We also derive analytical expressions for the success probability of an autonomous UAV mission and describe a machine-learning model to train the UAV.

**INDEX TERMS** Homeland security, blockchain, machine learning technology, on-board black box, smart contracts, UAV.

## I. INTRODUCTION

For several decades, the United States has employed remotely piloted Unmanned Aircraft Vehicles (UAV) for both military and Homeland Security (HS) services [1], [2]. Several HS analysts have pointed out that UAVs are attractive from both strategic and tactical standpoints because they are cheaper to deploy than crewed (i.e., manned) aircraft and can carry out dangerous missions without risking human lives [3].

In addition, with the gradual introduction of increasingly sophisticated UAVs, supported by advances in machine learning (ML), several new types of missions are now within reach. These include cargo and resupply, air-to-air combat, close air support, communication relays, aerial refueling, search-and-rescue, and counter-terrorism missions [4]. It is becoming evident that, due to their increased technological sophistication and reduced size, UAVs are well-suited to carry out many types of HS missions that, until very recently, could only be performed successfully by crewed aircraft. Such considerations could enable friendly forces to station UAVs closer to the front lines than crewed aircraft, potentially reducing the time required to carry out time-sensitive HS missions.

As the US is withdrawing from conflicts around the world, our HS applications will have to increasingly rely on UAVs for various missions, including intelligence, surveillance, and the acquisition of ground targets in counter-terrorism missions [2], [5], [6].

It is widely known that the U.S. Department of Defense (DoD), in conjunction with the US Department of Homeland Security (DHS), is developing several experimental concepts such as aircraft system-of-systems, swarming, and lethal autonomous weapons that explore new ways of employing future generation UAVs [4], [7], [8], [9]. Aligned with this effort, the main objective of this study is to bring UAVs to the next level of sophistication by enabling autonomous UAVs to conduct strike missions against entrenched high-value terrorists.

In the past, such missions were carried out by Special Operations personnel and/or remotely piloted UAVs, and

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recent advances in blockchain technologies, smart contracts (SC), and ML have made it possible for these missions to be carried out successfully by autonomous UAVs. Our first main contribution is to identify the main challenges that must be overcome to implement our vision; our second main contribution is to propose preliminary solutions to these challenges. To the best of our knowledge, this is the first paper in the open literature available to us that discusses the challenges inherent in making such high-priority HS missions feasible and how these challenges can be successfully overcome.

The remainder of this paper is structured as follows: Section II reviews related work. Section III provides the necessary background information. Section IV introduces our working scenario and basic assumptions. Section V identifies the main challenges involved in enabling autonomous strike UAVs. Next, Section VI provides preliminary solutions to the challenges identified in Section V. Section VII introduces the concept of blockchain-based SCs. Section VIII identifies some of the on-board sensors to support HS missions. Section IX presents the UAV simulation model. Section X offers details of our ML framework in support of autonomous strike UAVs as well as a host of empirical evaluations. Section XI delves into a discussion of advanced ML techniques and their relevance to our research. Finally, Section XII offers concluding remarks and map out directions for future work.

## II. RELATED WORK

The rapid growth of UAV technology, particularly in HS and military operations, has attracted considerable attention and development in recent years. This section examines the latest literature and research that has contributed to the increasing use of UAVs in modern military and HS operations.

The authors of [10] conducted a comprehensive survey on the use of ML in the context of UAVs. It begins by addressing the growth of UAVs and how ML can help them perform better. The survey then organized the use of ML into four categories: perception and feature extraction, feature interpretation and regeneration, trajectory and mission planning, and aerodynamic control and operations. The survey describes several ML algorithms and strategies for each category, demonstrating how they are used to improve UAV operations such as image processing, object detection, autonomous navigation, and data transmission. It emphasizes the role of ML in improving UAV intelligence for activities such as environmental monitoring, surveillance, and communication. The paper also discusses the challenges involved in integrating ML with UAVs, such as processing restrictions, data management, and energy efficiency. The paper concludes with suggestions for future research initiatives, including the creation of more advanced ML models for UAVs operating in diverse and complicated situations.

The authors of [11] comprehensively reviewed the relationship between mobile edge computing (MEC), ML, and UAVs in the context of the Internet of Things (IoT). The paper presents a thorough assessment of the most recent advances in the use of MEC and ML in UAV networks. It addresses the advantages and disadvantages of combining various technologies and focuses on their potential to improve performance, efficiency, and capacity of UAV systems. The survey also examines several scenarios and use cases, emphasizing MEC and ML's impact on UAV operations in a variety of settings and applications. The paper concludes by discussing future research issues and expected advances in this growing field.

The authors of [12] present a detailed review of the use of Reinforcement Learning (RL) in Multi-UAV Wireless Networks (MUWN). It investigates numerous elements of RL to improve UAV operations, including data access, sensing, collection, resource allocation, edge computing, localization, trajectory planning, and network security. This study examines the particular issues of implementing RL in UAV networks, including the computing limits and changeable environmental variables. The paper concludes with suggestions for future research and the creation of sophisticated RL models to increase the efficiency and effectiveness of MUWNs.

The authors of [13] provide a detailed examination of the construction of a UAV system designed for anti-terrorist activities. It offers a thorough examination of numerous components, such as electrical systems, sensor systems, vision systems, ground control stations, propulsion systems, and structural systems. This study examined various UAV models and evaluated their capabilities using variables, such as payload endurance, cost, and system components. It also recommends changes to the chosen UAV platform to improve its performance in anti-terrorist missions. The report concludes with a thorough evaluation of the effects of these adjustments on the UAV's performance, emphasizing the need for an adapted architecture in UAV development for specialized missions.

The authors of [14] investigate the application of AI-powered UAVs for security and surveillance, particularly in challenging environments, such as dense forested areas. It concentrates on the development of UAV systems that use cutting-edge technology, such as laser-range detectors for exact location evaluation and path finding, as well as 3-D mapping capabilities for comprehensive environmental awareness. This study highlights the potential of using AI-powered UAVs to improve security measures. The use of convolutional neural networks and IoT frameworks is also discussed, demonstrating how these technologies can transform environmental sensing, security monitoring, and search-and-rescue operations.

In their discussion on the employment of AI-powered UAVs for military purposes, the authors [15] categorize various UAV types according to various factors, including weight and flying characteristics. This suggests identifying vital military assets such as trucks and artillery from UAV surveillance imagery in real-time using the YOLOv5 deep learning algorithm. The model was trained using a dataset of more than 10,000 tagged photos from military

hardware and demonstrated good accuracy. AI-powered UAVs offer improved battlefield awareness and intelligence when connected to military command-and-control networks. Important benefits, including force multiplication and less risk to human life, are highlighted in this research, but problems such as false positives require further development. Overall, it shows how automated detection and autonomous capabilities can be added to UAVs through deep learning and computer vision, thereby eliminating the need for human operators in numerous dangerous military operations. This study highlights the system interoperability and offers a technique for YOLOv5-based real-time important item recognition from UAV footage.

The authors of [16] present a distributed blockchain-based platform for UAVs. Its main goal is to improve security and operating autonomy in an IoT setting. The proposed solution includes a special, secure, and light blockchain structure for UAV communication. This reduces the need to compute power and storage space, while still providing privacy and security benefits. A reputation-based consensus system is created to ensure the reliability of the autonomous network. Different types of transactions are set up for different types of data accesses. The platform protects UAV-based apps from possible vulnerabilities by using simple cryptography, new transaction and block structures, and a consensus method similar to Delegated Proof of Stake (DPoS) along with a reputation rating system. Performance reviews of the system show that it is effective at lowering latency, speeding up data flow, and strengthening security against various threats.

## III. BACKGROUND

UAVs represent a significant step forward in technology that can be used in a growing number of different areas [13], [14]. SCs and blockchain technology can be used to manage UAVs. This is a new concept, especially for HS and military missions where safety, autonomy, and reliability are essential. Using a private blockchain for this purpose has many benefits, such as better protection, more limited access, and faster transaction times compared to public blockchains. The main characteristics of private blockchains are their high transaction processing rate and limited access, which permits only a small number of approved users to interact with the network. Public blockchains have slower transaction rates because they require network-wide consensus, frequently via proof-of-work processes, which results in faster consensus times and more transactions completed per second. Compared to public blockchains, where data is immutable and modifications need agreement across all subsequent blocks, private blockchains offer increased data privacy because changes may be made quickly after consensus is reached across all nodes [17].

### A. SMART CONTRACTS

SC technology is directly related to blockchain, which is the underlying platform that allows these contracts to function with the highest level of security and transparency. SCs or self-executing programs embedded in blockchain, are transforming digital interactions. The blockchain acts as a decentralized ledger, recording all transactions across a computer network. This architecture not only ensures SCs' immutability and traceability but also eliminates the need for a central authority or middleman, resulting in a more direct and transparent form of engagement and transaction execution [18]. The combination of SCs and blockchain technology enables a new era of automated, safe, and effective digital transactions, offering a wide range of opportunities across different sectors [19], [20].

## IV. WORKING SCENARIO – A HIGH-LEVEL DESCRIPTION

Recently, it was suggested that UAVs have tremendous potential for air-to-ground strike missions [13]. A strike UAV can launch weapons such as *precision-guided missiles* against a ground target. While the state-of-the-art in air-to-ground strike missions is that there is always a man in the loop, in the sense that the UAV is piloted remotely, the vision of our work is to leverage the latest technology to enable fully autonomous strike UAVs.

With this in mind, throughout this paper, we assume that a UAV is deployed in support of a HS strike mission involving a high-value terrorist target in a foreign country. Such missions may well operate in "contested territory" in which terrorist forces are active. By their nature, these missions are top secrets and do not rely on the intelligence collected from foreign state actors. In fact, the mission may well be deployed without the approval of foreign state actors.

Given the context of the mission we are contemplating, we assume that the targeted terrorist organization does not have the wherewithal to take out or jam US communication satellites and, consequently, we rely on satellite-to-UAV communications for the duration of the mission.

We assume that the UAV carries, as part of its payload, standard on-board sensory equipment, including a gyroscope (or inertial navigation system), electro-optical cameras, infrared (IR) cameras for use at night, and synthetic aperture radar (SAR). SAR is a form of radar that is used to create two- or three-dimensional reconstructions of objects, such as landscapes. SAR uses the motion of the radar antenna over a target region to provide a spatial resolution finer than that of conventional radars. Such missions must avoid civilian casualties. We assume that the mission will be aborted if civilians are close to the intended target. In this regard, night missions are safer to execute because civilians (especially children) are unlikely to be present; however, they require much more sophistication in terms of localization and image processing.

Figure 1 provides a comprehensive overview of the working scenarios. Here, we see a network of systems working together to achieve a targeted mission. The system consists of a base station, referred to as a Mission Control Center (MC2), equipped with blockchain systems and SCs, alongside a satellite communication system. Additionally, each UAV is equipped with an onboard Black-box (BBX) an integrated blockchain system, and a SC within the UAV

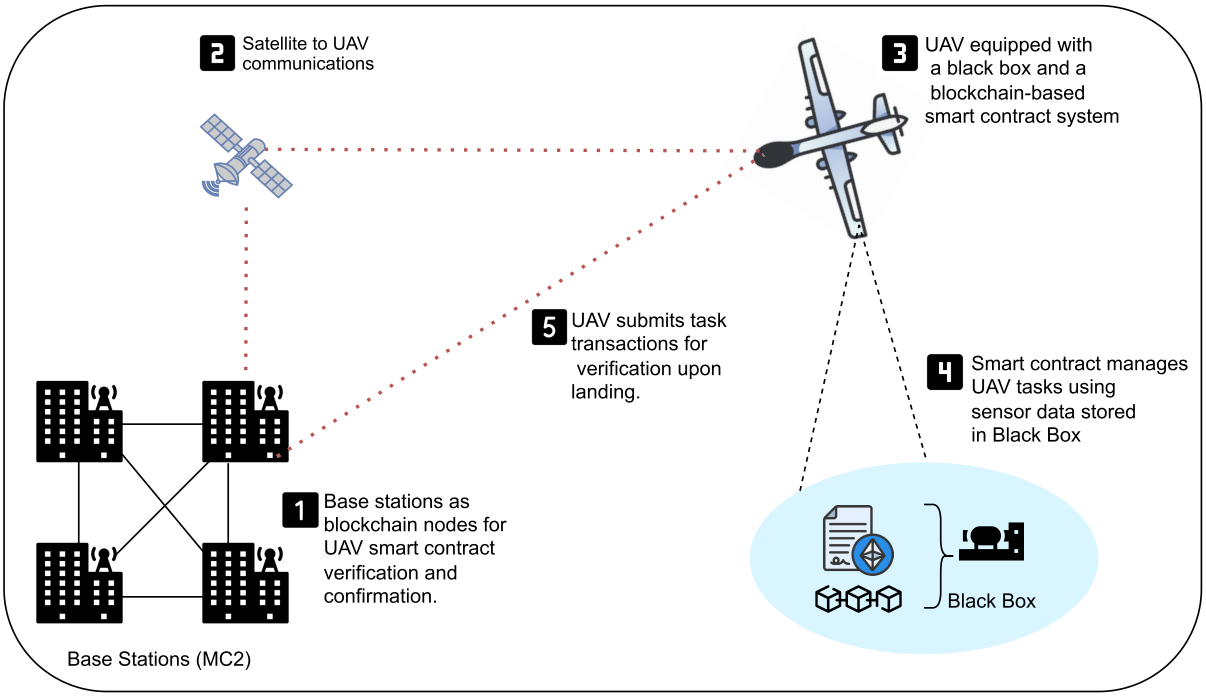


**FIGURE 1.** A comprehensive overview of our working scenario.

network to improve data integrity, operational autonomy, and security [16], [21]. Although this paper assumes a single UAV, the proposed system is equally applicable to multiple coordinated UAVs.

Preparing a mission of the type we have in mind involves conducting several experimental missions, referred to as *training runs*, that involve more hands-on real-world conditions, by the *human experts* both daytime and nighttime, each intended to evaluate the sequence of tasks that collectively make up the mission. The data collected in each training run is carefully analyzed by human experts back at MC2 to establish the conditional success probability of a future task given the status of the current task. The data from successive runs is aggregated by human experts at the MC2 and used to train the ML model. Specifically, human experts analyze the flight information stored in the tamper-proof on-board BBX, for example, collected UAV imagery, along with maneuvers performed by the UAV in response to sensory information. Consequently, human experts can assign conditional probabilities to individual tasks based on the successful or partly failed status of the previous task in the sequence. Strict conditions for avoiding civilian casualties are stipulated and encoded as part of the SC to oversee the mission. In our vision, once the ML model is effectively trained through these experimental mission data, it is ready to carry out the mission autonomously, without the need for continuous communication with MC2. This absence of communication is crucial for security purposes because it prevents unauthorized access and tampering with the data or UAV operations. We note that the on-board BBX serves as a reliable and secure storage system for the gathered information, protecting it from potential breach or corruption.

### A. ENHANCEMENTS WITH RESPECT TO EXISTING UAV SYSTEMS

Due to the unique combination of blockchain and ML in a UAV scenario, it is difficult to make direct comparisons. However, we can identify possible enhancements by considering acknowledged constraints in current systems in the following manner:

- Enhanced efficiency:
  - Autonomous Decision Making: Our system differs from traditional UAV systems by minimizing supervision by humans and increasing operational efficiency through the use of ML.
  - Optimized Mission Execution: By using SCs, UAVs can function automatically, adjusting to mission-specific needs without requiring manual reconfiguration.
- Enhanced security:
  - Data Integrity and Confidentiality: Utilization of a private, single-node blockchain architecture in the UAV guarantees that all recorded data is immutable and protected against unauthorized access. This represents a notable improvement compared to systems that rely on less secure, centralized data storage methods.
  - Robust Against External Attacks: The decentralized structure of blockchain and the autonomous capabilities of SCs offer inherent security advantages that decrease the system's vulnerability to hacking and identity attacks frequently seen by traditional systems.
- Enhanced autonomy:

– Adaptive Mission Planning: The system can be adapted to different operating conditions on the fly, thanks to SCs and ML. This makes UAV operations much more autonomous than they could be with previous models.

## V. CHALLENGES

To make the vision of autonomous striking UAVs a reality, several technical challenges must be overcome. The aforementioned challenges are discussed in this section. Preliminary solutions to these challenges are presented in Section VI.

The challenges include, but are not limited to the following:

- Accurate UAV localization in space and time. As discussed in Section VI, accurate 3-D UAV localization under all weather conditions is an ongoing effort of great interest to both the research and the user community. The challenge of locating UAVs in time contains, as a sub-challenge, the time synchronization of the UAV and the MC2. Initially, the UAV and MC2 are assumed to be synchronized, synchronization may be lost, owing to clock drift, and periodic re-synchronization becomes necessary [22], [23]. This re-synchronization may not be performed directly with the MC2 in case of Non-Line-of-Sight (NLoS) operations and must be performed using the UAV-satellite link. Because we assume unimpeded UAV-satellite Communication and time synchronization are possible as long as the UAV is linked to one of the satellites. It is worth noting that time synchronization involves passive listening and does not require active UAV communication with satellites;
- Enabling secure communication between MC2 and the UAV. In our philosophy, such communication occurs sporadically to minimize the likelihood of the UAVs are being detected. However, these types of communications are vital when, for example, MC2 wants to inform the UAV about the mission being aborted. Similarly, under specific conditions, when it becomes clear that the mission cannot be successful (e.g. children play near the target), the UAV seeks permission to abort the mission. In a Line-of-Sight (LoS) scenario, these communications occur directly between the UAV and MC2. Otherwise, communication will occur between the UAV and one of the satellites in the supporting satellite constellation. In either case, such communications may involve time-dependent frequency hopping and, as such, require tight time synchronization between the two parties [24];
- Tamper-proof collection and storage of accurate in-flight sensory data and various maneuvers performed by the UAV in response to received sensory input. Reliable, untampered sensor data and the corresponding UAV responses collected during *training* missions are necessary to train the ML model. Such data is also essential for auditability, particularly if the mission is aborted. Finally, the provenance of each piece of sensory data and the UAV response must be recorded and ascertained;
- Identifying the target and confirming that the target is clear of civilians. A fundamental requirement for a successful mission is to prevent civilian casualties;
- Allowing dynamic changes in the mission parameters. This suggests that some form of reliable communication, either direct or indirect via a satellite, has been established between MC2 and the UAV;
- BBX tamper-resistance: The UAV must blank/destroy its BBX if it is captured.

## VI. TECHNICAL DETAILS: ADDRESSING THE CHALLENGES

The main goal of this section is to outline our preliminary solutions to the challenges identified in Section V. Our solutions are, necessarily, sketchy but should give the reader a sense of what the technical solutions involve.

### A. ACCURATE UAV LOCALIZATION AND NAVIGATION

UAV localization is a fundamental challenge in autonomous navigation and has received extensive attention in scholarly literature [25], [26], [27], [28], [29]. As already mentioned, satellite (e.g. GPS) communications are available to the mission, and we contemplate using GPS for both synchronization (to within 100 nano-seconds) with the MC2 and UAV localization [3], [30].

As it turns out, UAVs can navigate without GPS. GPS-denied UAVs rely on a mix of high-tech sensors to operate. They can use:

- On-board optical sensors that act as UAV's eyes and stabilize it throughout the flight. Each of these on-board sensors provides the UAV with reference points and data points regarding its altitude, attitude, and location;
- Similarly, UAVs can use a wide range of technologies to navigate in a GPS-denied environment. They can use GNSS receivers, inertial navigation systems (INS), LiDAR scanners, ultrasonic sensors, and visual cameras to navigate autonomously [31];
- One of the stated goals of the training runs is to acquire situational awareness, recognizing landmarks in the terrain, rivers, lakes, etc. Night navigation may use well-known elements of celestial navigation [32];
- Finally, GP-denied UAVs may also use a navigation technique known as SLAM (Simultaneous Location and Mapping) to create, during training, a map of their surroundings and understand their position within it [33].

### B. ENABLING SECURE COMMUNICATION BETWEEN THE MC2 AND THE UAV

One of the fundamental tasks that must be performed as part of a successful mission is communication with MC2. Depending on the mission, two types of communication are required. For missions deployed within approximately 50 miles of MC2, LoS communication may be used. For

missions beyond 50 miles from the home base, NLoS communication is required. In this paper, we assume that NLoS controls communications between MC2 and the UAV, forwarded through one of several satellite support constellations [4]. Recall that we assume that the targeted terrorist organization can not take out or jam US communication satellites, and consequently, we rely on satellite-to-UAV communications for the duration of the mission. However, the communication link to MC2 is lost, the UAV is programmed to return to its base, and the mission is aborted.

### C. TAMPER-PROOF COLLECTION AND STORAGE OF FLIGHT DATA

In our vision, the workhorse of the mission is an on-board tamper-proof BBX.

- The BBX implements the functionality of an *append-only ledger* for the duration of the current flight.
- The BBX records and stores every piece of sensory data collected by the UAV sensors, along with a time stamp and provenance information.
- For ML training and auditing purposes, BBX also records action(s) taken by the UAV in response to each sensory input. This will allow human experts at MC2to evaluate the successful completion of various intermediate tasks that constitute the mission.

In light of the above, it is clear that the BBX serves as an *on-board command and control center*. Before a flight, the BBX is loaded with the individual tasks that constitute the mission, confirmed by human experts at MC2. The integration of an advanced BBX and append-only ledger (i.e., blockchain) technology creates a powerful and secure system for data collection and mission management. In our system, the BBX functions as an essential safeguard for the information collected by the UAV, while simultaneously ensuring integrity, traceability, transparency, security, and auditability. Each data entry or transaction can be traced back to its origin, making it easier to verify its authenticity and identify potential issues.

### D. IDENTIFYING AND CONFIRMING THE TARGET

As previously mentioned, the missions we contemplate involve several training runs whose stated goal, among others, is to locate and identify the target (which, to fix ideas, we assume the target to be an isolated building). The location of the building was acquired through day-time training missions and confirmed by a human expert at the MC2. The same procedure was repeated during subsequent night-time training runs, where the target was confirmed using IR and SAR imagery. As previously mentioned, the mission is aborted if civilians are identified as being close to the target. However, since we envision a night-time execution of the strike, the presence of civilians close to the target is a very unlikely event.

### E. ALLOWING DYNAMIC MISSION CHANGES

It is essential for MC2 to order a mission in progress. This is accomplished by sending a specific encoded message to the UAV using the satellite communication channel, as discussed above. Such an order must be confirmed by the UAV using a different communication channel, such as a different satellite in the constellation.

### F. ERASING BBX CONTENT UPON CAPTURE

The main idea is to prevent the adversary from identifying mission parameters and flight data. Several techniques can be used to address this challenge [23]. The standard procedure is to eliminate the BBX contents. Another more sophisticated approach is to automatically generate fake data. Fake data can be generated beforehand and would replace the actual content of the BBX, with the intention of misleading the adversary.

### G. SCALABILITY AND OPERATIONAL INDEPENDENCE

It is, indeed, very tempting to scale up the number of participating UAVs. However, these missions are top secret, and proceeding undetected is of paramount importance. The fact remains that the more UAVs participating, the better the success chances but the larger the detection probability by the adversary. Along this line of thought, our philosophy, expressed several times in the paper, is that during the mission, communications need to be kept to a minimum. In effect, this implies that each UAV must act independently. While, at this point, the ideal number of UAVs in the mission is unknown, striking a balance between mission success and detection probability remains a nagging open problem. We expect that the answer is technology-dependent. The more sophisticated the UAVs and the smaller their footprints, the lesser the likelihood of detection by the enemy. As far as blockchain is concerned, scaling does not pose a problem since, as discussed above, each UAV is independent. Similarly, ML does not have a scaling problem. On the contrary, the more data available from BBXs, the easier it is for the ML engine to learn.

## VII. PROPOSED BLOCKCHAIN-BASED SCS

A novel approach to improve data integrity and security in autonomous attack missions is to include blockchain technology in the BBX of UAVs. These HS operations have sensitive and high-security requirements, so a single-node, private blockchain architecture is used. This section describes our blockchain architecture.

### A. BLOCKCHAIN ARCHITECTURE CHOICE

The requirement for complete control over the data access and validation procedures as well as security motivates the choice of a private, single-node blockchain architecture during active mission stages. A private blockchain limits access to predefined entities, in this case, the UAV's BBX itself, as compared to public blockchains, where the ledger is maintained by several nodes and is available to everyone. This

design ensures that classified mission data stays inaccessible to other entities, thus minimizing the risk of data breaches or unauthorized access. The blockchain architecture is intended to expand and sync with more MC2 nodes after the mission is completed. This adaptability makes it a scalable and safe platform for post-mission analysis and data preservation by enabling improved data validation and incorporation into larger military databases.

Let $\mathcal{B}$ denote the blockchain employed on the BBX UAV. A series of blocks will define the status of $\mathcal{B}$ at any time $t$ during the mission as follows: blocks $\mathcal{B}(t) = [b_1, b_2, \ldots, b_n]$, where a set of transactions $T_i$ containing data records from the tasks of the UAV, like sensor data, navigation routes, and mission-critical decisions, are stored in each block $b_i$.

### B. SCS DESIGN FOR UAV MISSION TASKS

We provide a conceptual framework for SCs in our UAV system, which is an automated and responsive approach designed to handle important mission tasks. Each contract, denoted as $\mathcal{C}$ and deployed on the blockchain $\mathcal{B}$ is created with a certain function to be fulfilled to ensure a seamless transfer from take-off to mission execution to post-mission analysis.

For example, the TakeoffManager SC oversees pre-flight checks and clearances, to ensure all systems are operational before takeoff. Once the UAV takes off, the Navigation-Manager SC guides the UAV, dynamically adjusting its path based on real-time environmental and geographical data. The SurveillanceManager SC takes over when the UAV approaches its target, examining data to verify the target's identity and status. The EngagementDecisionManager SC makes strategic decisions about whether to strike during engagements by weighing several criteria. The StrikeManager SC makes sure that the payload is deployed precisely if a strike is approved. The DamageAssessmentManager SC evaluates the result and reports the data to the MC2. The following description illustrates how these SCs manage the tasks of the UAV. So, each of these SCs performs actions $A_k$ automatically based on conditions $\Phi_k$ obtained from the UAV operational data.

action $A_k$ mission abort is triggered by the SC.

#### 1) TAKEOFF SC (TAKEOFFMANAGER)

**Trigger:** It begins when the UAV is ready to take off.

**Function:** Checks weather, system checks, and permissions from MC2 before a flight. Based on sensor data and pre-set safety checks, it makes sure that all systems are ready for take-off.

#### 2) NAVIGATION SC (NAVIGATIONMANAGER)

**Trigger:** Activated after takeoff.

**Function:** Tracks GPS and inertial navigation data to help guide the UAV within the path that was planned ahead of time. It changes the flight path in real-time based on data about the surroundings, threats, and geography to make sure the best route is taken.

#### 3) SURVEILLANCE SC (SURVEILLANCEMANAGER)

**Trigger:** Starts the attack as soon as the UAV gets close to the target.

**Function:** In order to receive information, it controls the sensors. Analyze the data to confirm target presence and status to provide real-time updates to MC2.

#### 4) ENGAGEMENT DECISION SC (ENGAGEMENTDECISIONMANAGER)

**Trigger:** Once target validation is complete.

**Function:** Choose an engagement method based on the engagement rules, the state of the target, and factors in the local environment. This SC evaluates the risk and possible security and decides whether to strike or not.

#### 5) STRIKE EXECUTION SC (STRIKEMANAGER)

**Trigger:** After the engagement decision.

**Function:** Manages the use of weapons directed with accuracy. Controls weapon systems and flight dynamics to guarantee accurate target striking with real-time modifications based on environmental changes and sensor data.

#### 6) DAMAGE ASSESSMENT SC (DAMAGEASSESSMENTMANAGER)

**Trigger:** After strike execution.

**Function:** Determines the damage using SAR data and high-resolution imagery. gathers a complete damage report and forwards it to MC2.

### C. PARTICIPANTS AND THEIR ROLES IN THE UAV BLOCKCHAIN SYSTEM

The blockchain system deployed within a UAV, particularly in the context of autonomous military operations, involves various participants. Each plays a crucial role in the ecosystem to ensure the integrity, security, and functionality of the system.

#### 1) UAV

Primary participant and actor in the blockchain system. The responsibility is as follows:

- Gathers operational data, including mission specifics, sensor outputs such as images, radar data, and environmental conditions, and stores them in BBX.
- Carries out actions defined by SCs based on the conditions met during the mission.
- Acts as a single-node blockchain during missions, ensuring data immutability and security by recording all mission-related data to its local blockchain.

#### 2) MC2

Command and supervision center. It has the following responsibilities:

- Deploys and updates SCs onto the UAV's blockchain-based on mission requirements and objectives.

- Post-mission, it synchronizes with the UAV's blockchain to retrieve and analyze mission data, integrating insights into broader military strategies.
- Monitors mission progress and makes high-level decisions, including mission abort or rerouting based on real-time data.

### D. INTEGRATION OF THE BBX WITH SCS

The BBX, which utilizes blockchain technology, is crucial to ensure data security and manage operations with the help of SCs. In the following sections, we describe how the BBX is incorporated into UAV system operations.

#### 1) SYSTEM INITIALIZATION

Before the mission begins, the BBX is configured to act as a single node of the blockchain, ensuring that all data related to the mission is securely recorded. SCs are then implemented on the BBX to allow for mission control based on real-time data.

#### 2) ROLE OF THE BBX

- The BBX has two roles. Firstly, it records all of the data as a set of immutable blocks while serving as a single node of a private blockchain for the duration of the mission. Secondly, it uses real-time data inputs from the UAV's sensors to carry out SCs.
- The SCs embedded within the BBX can be configured to decide independently whether to change the UAV's trajectory or terminate the operation in response to particular circumstances, such as detecting individuals in the target area.

#### 3) MISSION EXECUTION SCENARIO

- **Pre-Mission:** The MC2 deploys the latest version of SCs to the BBX based on the mission objectives and rules. These SCs are designed to work with the data collected by the UAV sensors.
- **During-Mission:** During the UAV operation, it gathers information such as sensor data, pictures, and navigation paths that are saved in the BBX. This data is then compared to the conditions set by the SCs in the BBX. If any of these conditions are met, the specific actions outlined in the SCs are activated, ensuring adherence to mission guidelines and facilitating reactions.
- **Post-Mission** After the mission is completed, the BBX synchronizes the blockchain data with MC2, enabling secure data storage, therefore establishing the system for future missions and historical data integrity audits.

### E. SECURITY CONSIDERATIONS AND RISK MITIGATION

Many possible weaknesses surface when blockchain technology and SCs are used in UAV systems. Risks are discussed in this part, along with the measures taken to guarantee data integrity and reliable system operation.

Blockchain is, by its very nature, a very secure technology. It is immutable in the sense that once recorded in the blockchain, the information cannot be changed. We also assume that the on-board BBX, a standard feature of all commercial and military aircraft, acts as a tamper-free device that contains all information collected or generated during the flight. This information has great value, especially the data collected during training runs. Once back at the base (i.e., in a presumably safe environment), the contents of the BBX will be added, as a new block, to the on-the-ground blockchain and will be used as input to the ML engine.

In a more mundane setting, the content of the BBX can be used, in a Bayesian fashion, to update our beliefs about the various conditional task success probabilities. Similarly, should an SC fail, the alternative would be a more traditional control module cognizant of the tasks to be performed as part of the mission.

#### 1) ENSURING DATA INTEGRITY IN BLOCKCHAIN

The integrity of the data kept on the blockchain is very important for the successful operation of UAV missions. To overcome the risk of data loss and tampering, the following are possible solutions:

- **Immutable Record-storage** Using blockchain will inherit immutability to ensure that data cannot be changed once recorded. Therefore, it protects the integrity of mission data, especially when all information syncs with MC2.
- **Cryptographic Hash Functions:** Every block on the blockchain includes a secure link made possible by a cryptographic hash of the one before it. Any attempt to change transaction data inside a block would show tampering by violating the hash links.
- **Regular Audits and Consensus:** During missions, the blockchain works primarily as a single-node system, but upon returning to the MC2, consensus algorithms verify the data to ensure that it is accurate and free of corruption.
- **Secure Communication Channels:** Transmit data between UAVs and control stations using end-to-end encrypted channels to prevent interception.

#### 2) FALLBACK MECHANISMS FOR SC FAILURES

The purpose of SCs is to automate crucial mission tasks according to predefined rules. However, unexpected operational circumstances or coding errors may be the cause of failures. The following are possible solutions to overcome these issues:

- **Code Auditing and Testing:** To find weaknesses, SCs are carefully audited and tested before implementation.
- **Upgradable Contracts via Proxy Patterns:** While SCs are immutable, the proxy architecture enables the underlying logic to be updated in response to problems found or changing requirements without compromising the status or part of the original SC [34].

- **Redundancy Measures:** Implement backups for important SCs, like duplicate contracts, that can be used if the main SC operation fails.

## VIII. SENSORS UTILIZED IN AUTONOMOUS UAV MISSIONS

This section discusses several types of sensors used in UAVs and their role in ensuring mission success. UAVs are equipped with various sensors that enable a wide range of tasks under various circumstances. These sensors not only improve navigation and targeting accuracy but also allow the UAV to adapt to different environmental and operational conditions. An appropriate sensor configuration enhances mission success through precise navigation, target identification, engagement accuracy, and damage assessment [35]. Additionally, UAVs offer the advantage of enhancing border surveillance, especially in covering remote border regions that are currently under-monitored. Equipped with Electro-Optical (EO) sensors, or cameras, they can detect objects as small as a milk carton from an altitude of 60,000 feet [36]. The authors of [37] provided a comprehensive evaluation of relevant sensors, whereas [38] discussed more advanced sensors used specifically in UAVs in military applications.

### A. NAVIGATION AND STABILITY SENSORS

- **GPS Sensor**: Provides precise location data crucial for navigation and spatial orientation throughout the mission.
- **Accelerometer**: Measures the UAV's acceleration, aiding in flight dynamics analysis and stability during various phases of the mission.
- **Gyroscope**: Ensures stability in flight by maintaining angular velocity and orientation, which are critical for accurate targeting.
- **Anemometer**: Assesses wind speed and direction and feeds data to navigation systems for flight adjustments.

### B. ENERGY MONITORING SENSORS

- **Battery sensor**: Monitors battery health and charge level, ensuring sufficient power for mission completion.

### C. ADVANCED SURVEILLANCE SENSORS

- **Electro Optical sensors**: High-resolution cameras and infrared sensors. During daylight, high-resolution cameras provide detailed visual data, whereas infrared sensors provide thermal imaging for nighttime operations.
- **Synthetic Aperture Radar (SAR)**: Enables terrain analysis and change detection, is effective in various weather conditions, and has light availability.
- **Multispectral and Hyperspectral Sensors**: Capture data across multiple light wavelengths, providing comprehensive environmental information.
- **Laser Range Finders and Laser Illuminators**: Enhance the accuracy of distance measurements and target illumination.
- **Gyro-Stabilized Systems**: Ensure stable imaging, which is crucial for surveillance and reconnaissance.

### D. SPECIALIZED SENSOR SYSTEMS

- **Specialized imaging systems**: such as the AN/DVS-1 COBRA system, are designed for specific military tasks such as mine detection in beach surf zones.

### E. SENSOR NETWORKING AND DATA INTEGRATION

- The integration of these sensors into a networked system, such as the Mini-Micro Data Link System (M2DLS), allows for the aggregation and efficient processing of data from various sources, thereby enhancing the operational capabilities of UAVs.

The integration of these sensors into the UAV platform not only assists in target neutralization but also ensures the safety and efficiency of the UAV throughout the mission. An advanced sensor suite significantly enhances the operational capabilities of UAVs, enabling them to perform crucial tasks with high precision and minimal collateral damage [22], [35], [37].

## IX. UAV SIMULATION MODEL

This section describes the simulation model that we used to generate the synthetic dataset of this study. We built the simulation model to effectively mimic the sensor outputs and operational dynamics of a UAV during military missions. The model provides reliability, variability, and alignment with the real-world conditions of the dataset.

### A. NUMBER OF SIMULATED MISSIONS AND TASKS

To reflect the complete lifecycle of a typical HS operation, we generate data for 20,000 missions, each mission includes six key operational tasks: takeoff, navigation to the target, surveillance, engagement decision, strike execution, and damage assessment.

### B. TIME OF THE MISSION

The model randomly sets a time of day for each mission to simulate different environmental lighting conditions, which is critical for sensors like infrared visibility. Overall success of each mission: A mission is initially considered successful if the total number of successful missions is less than half of the total missions. This threshold ensures that approximately 50% of all missions in the simulation are marked as successful, aiming to maintain a balanced dataset. Success ratio of each task: Within each mission, the success of each task is determined by two different criteria. First, a task is considered successful if the mission is already assumed to be successful. Alternatively, success for each task can happen independently in a random way if a generated random number is greater than 0.2, which means that the task has an 80% chance of being successful.

### C. GPS AND SENSOR DATA

GPS coordinates for each task simulate progressive movement, reflecting realistic navigation patterns. The coordinates change smoothly from start to end positions based on the task's sequential order and success status. To cover global geographical extents, the GPS readings are distributed as: (latitude between -90 and 90 degrees, longitude between -180 and 180 degrees, altitude 0 for takeoff start and 3000 meters for the last task).

Figure 2 shows instances of a UAV trajectory generated by our simulation: Each figure shows the trajectory of the UAV in an individual mission (from mission 1 to mission 3). The figure shows the GPS coordinates (Latitude in the x-axis, Longitude in the y-axis, and Altitude in the z-axis). The values of each coordinate for each mission are annotated in red text near the data point. Each data point in the plot represents the starting point of each task.

The accelerometer measures the UAV's motion dynamics, directly linked to the GPS data that tracks the UAV's trajectory. As the UAV progresses through its mission, changes in GPS coordinates are complemented by corresponding accelerometer readings that reflect the intensity of movement. This relationship is more obvious during takeoff and navigation tasks, where acceleration and altitude changes are significant. Simulated anemometer to measure wind speeds are higher in unsuccessful tasks (8-30 m/s) compared to successful tasks (0-10 m/s), indicating adverse conditions can affect UAV operations.

### D. GYROSCOPE STABILITY

shows lower values in unsuccessful tasks, generally ranging from 0.7 to 1.0 in successful tasks and 0 to 0.69 in unsuccessful tasks.

### E. ELECTRO-OPTICAL VISIBILITY

For this sensor, we generate values between 0.5 and 1 to indicate clear visibility, which leads to a successful task. Similarly, we generate values from 0 to 0.6 to simulate compromised visibility due to environmental obstacles or sensor faults. We assume that UAVs are equipped with infrared cameras for nighttime visibility. Its values are between 0.5 and 1 for successful night tasks. Similarly, values between 0 and 0.6 are generated to simulate low visibility in some cases such as daylight tasks.

### F. HIGH-RESOLUTION CAMERA

we here simulate an assessment of the camera quality. If the camera captures high-quality images that are part of successful tasks, the data ranges from 0.5 to 1. For unsuccessful tasks, the quality deteriorates, with values between 0 and 0.7, affected by adverse weather, poor lighting, or technical glitches.

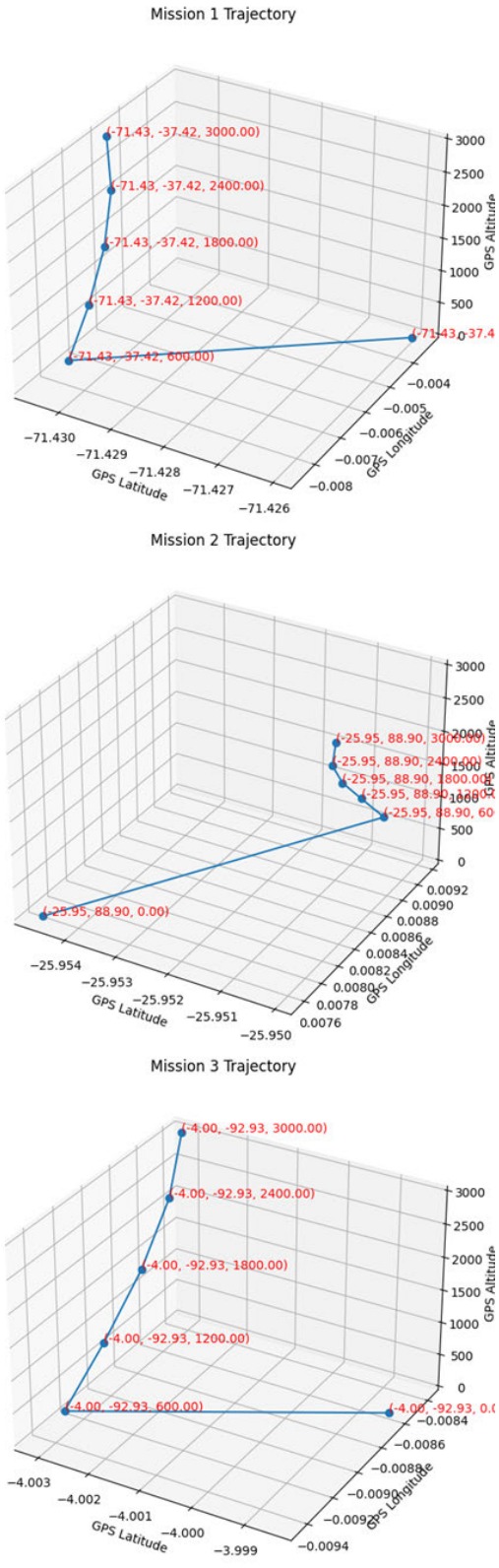


**FIGURE 2.** Simulated trajectory of a UAV during three missions.

### G. SAR TERRAIN ANALYSIS

We simulate the case where a UAV utilizes SAR for precise terrain mapping. The output of this analysis ranges between

0.5 and 1 for successful terrain analysis during the task, whereas a range of 0 to 0.7 in unsuccessful tasks when the mapping is not accurate.

### H. BATTERY LEVELS

The battery level simulation varies significantly based on the task number and success. For successful tasks, battery levels start high (90-100% for the takeoff task) and decrease progressively in each subsequent task. Battery levels decrease more rapidly in unsuccessful tasks, starting between 60-70% in the takeoff task and reaching as low as 0-20% by the final task. AI Decision: the values of AI decision show lower values in unsuccessful tasks, generally ranging from 0.4 to 1.0 in successful tasks and 0 to 0.60 in unsuccessful tasks.

## X. ML METHODOLOGY

Autonomous UAVs for HS tasks exhibit increased potential when ML algorithms are used. Although AI has not been widely used in HS settings, the consensus among analysts is that AI technologies (including ML) can have a significant impact [4], [39]. Indeed, advanced ML algorithms can learn from past experiences, adapt to novel conditions, and make autonomously correct decisions. This enhances the ability of UAVs to execute complex tasks and navigate challenging environments. Furthermore, the capacity of ML to process and interpret vast amounts of data in real-time can enhance the situational awareness of autonomous UAVs, thereby improving their precision and efficiency [40].

In the previous section, we used analytical expressions to determine the likelihood it is that a UAV mission will succeed. In this section, we use a ML model [4], [39] that can be trained on data from previous training runs, and used to make decisions in real-time regarding the final mission. The situational awareness, accuracy, and efficiency of UAVs are improved because of ML's ability to manage and analyze enormous volumes of data in real-time [40]. In this study, we use a Random Forest (RF) model to identify successful UAV missions based on the features provided by the mission tasks.

### A. THE RF MODEL

For the analysis of our UAV mission dataset, we chose the RF model, a powerful ML classifier introduced by [41]. This model uses a majority-vote approach to assign a class based on the predictions of several decision trees. We selected the RF model because of its better capability to handle high-dimensional data and resistance to overfitting, which is critical given the multidimensional nature of our synthetic dataset. As indicated, the dataset includes a wide range of features from multiple sensors, each of which contributes complex data regarding the UAV performance across various mission tasks.

Our RF model implementation relies on the Scikit-learn package [42], which is well known for its efficiency and applicability in ML tasks. The number of decision trees in the model was set to n $\bar{5}$00. This value provides an appropriate balance between computing efficiency and model accuracy. To prevent over-fitting, the maximum depth for each tree was limited to five levels.

The dataset was randomly divided into two parts for training and validation, 80% for training and 20% for testing. The strength of RF lies in its ability to utilize the data discrimination capabilities of individual trees to create an effective classification model. This feature is very useful for our dataset, which consists of $P$ data points and $Q$ characteristics and covers a wide range of mission-specific parameters and sensor readings [43]. By combining the decisions from several trees, the RF model can handle complicated and possibly non-linear relationships in our dataset. This dataset includes mission-specific parameters (such as the probability of success of each task) and multiple sensor readings (such as GPS coordinates, battery levels, and data collected by environmental sensors).

### B. DATA DESCRIPTION

UAV training is critical for preparing UAVs for real-world applications. During these training sessions, UAVs are deployed to carry out simulated missions that closely match actual conditions in the field. A critical component of this process is the thorough collection and analysis of the data by experts. From takeoff to return to the base, these experts carefully monitor and assess a wide range of parameters linked to each mission task. They meticulously calculate the success ratio for each mission, capturing the effectiveness and precision of UAV performance in various environments. The cumulative assessment of these task-specific success rates, together with a thorough review of the mission's overall execution, help human experts assess whether the operation may be classified as successful or unsuccessful. This detailed expert-driven analysis is critical for improving UAV capabilities and ensuring their ability to prepare for real deployment.

Because we did not have access to actual HS or military UAV sensor data (which are, understandably, not in the public domain), a synthetic dataset was created to simulate these sensor readings closely. Figure 3 shows a detailed overview of the simulated dataset of the UAV training missions. This study addresses the lack of real-world operational data in UAV missions, particularly in sensitive operations such as high-value target neutralization.

The synthetic dataset aims to capture realistic mission situations using feature patterns and relationships based on the actual UAV mission characteristics. It includes a variety of characteristics of UAV functioning, including task-related variables, environmental conditions, and performance metrics. For example, ''GPS_Latitude, GPS_Longitude, and GPS_Altitude'' offer geographical positioning, while ''Battery_Level and AI_Decision'' indicate the UAV's operating state and autonomous decision-making ability, respectively. It also shows the task success ratio, offering insights into the performance and operational efficacy of the UAV throughout the simulated flight.

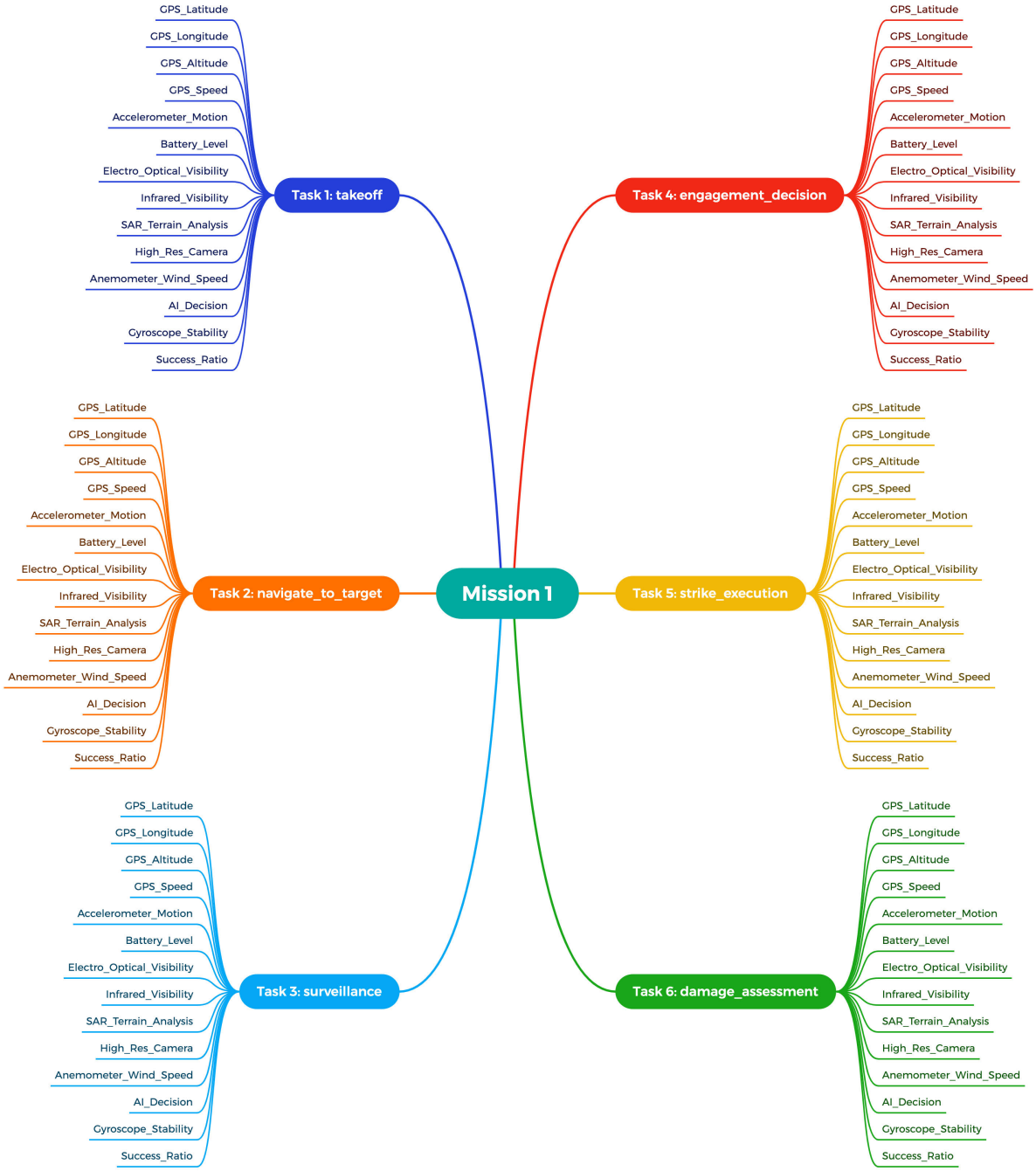


**FIGURE 3.** Comprehensive overview of UAV training mission data.

Each mission phase, from "takeoff" to "return_to_base," is characterized by relevant features. These include environmental sensors like "Electro_Optical_Visibility" and "Infrared_Visibility," essential for understanding the conditions under which the UAV operates. The dataset also includes decision points, such as target identification and engagement, based on fused sensor data and predefined rules.

Synthetic data is used as a training dataset for ML algorithms, which are designed to predict mission success and uncover important variables that influence the results. The UAV system can learn to forecast mission outcomes and optimize its decision-making process in various settings by training the ML model on this synthetic dataset.

Dataset,[1] which is created to reflect the complexity of real-world UAV operations, serves as an excellent base for specifically seeking mission outcomes and measuring success indicators. This provides information on the dataset and model availability. This approach allows for risk-free,

[1]The dataset and the model are provided in the following: [44].

complete training and evaluation of UAV systems, ensuring capability for a wide range of operational scenarios and improving overall mission efficacy.

Although the creation of synthetic data has several advantages, it also has some drawbacks. The lack of reality and accuracy of synthetic datasets is a major cause of concern. Synthetic data can identify patterns and connections, but they often cannot represent complicated changes that exist in real-world data. Working with complex data types, such as natural language text or photos, in which syntactic accuracy, grammar, and visual elements are crucial, worsens this issue. Evaluating the veracity of the AI data poses an additional challenge. Synthetic datasets may not accurately or consistently represent the complexity and anomalies present in real data, rendering them unreliable as a basis for training models. Complicating matters further is the fact that synthetic data synthesis relies on real-world data. Synthetic data may become less helpful over time if the underlying data is incorrect or changes, leading to constant updates and monitoring [45].

Some strategies mitigate the drawbacks of synthetic data, regardless of these challenges. It is important to diversify the generated data to make the synthetic dataset more realistic for real-world events by ensuring that the data covers a wide range of characteristics. The use of solid data metrics is important. Metrics, such as recall, accuracy, and precision, are useful for assessing and improving the quality of synthetic datasets. It is necessary to conduct routine testing of the generated data against the features and biases of the real-world data. Therefore, it is possible to detect and address biases or inaccuracies in a synthetic dataset using statistical tests and metrics. Furthermore, to keep synthetic datasets current and reflective of real-world events, it is important to monitor the changes in real-world data and update them accordingly. By implementing these strategies, one can increase the reliability and accuracy of synthetic data and convert them into stronger tools for data-driven tasks [45].

#### 1) UAV OPERATIONAL DATA ANALYSIS

In addition to the previously defined parameters and success ratios, the operation of a UAV is closely linked to its response to sensory input. When the UAV performs its mission, each task executed in response to the sensor data is fully reported. This methodology can be likened to a BBX approach, in which each maneuver is recorded, including course corrections, altitude changes, and responses to environmental factors, such as wind.

Following the completion of the mission, this detailed record allows human experts to assess the behavior of the UAV in the context of the input parameters at each instant. For example, if the UAV effectively adjusts its altitude under difficult wind conditions, the expert would consider the task successful based on the UAV's adept flexibility with environmental input. However, a failure to adapt or an inaccurate reaction would be recorded as unsuccessful, providing valuable insight into potential areas for the development of UAV programming and decision-making algorithms.

Furthermore, our approach considers the future employment of smart missiles to provide rapid and clear evidence of mission success, particularly in activities such as strike execution. Smart missiles with onboard computers can transmit real-time data and pictures as they approach and strike their targets. This advanced equipment provides a more direct and reliable technique for confirming target impact than traditional methods such as post-mission reports or external sources such as spy satellites, or ground operations.

However, it is important to note that the use of smart missiles for mission success confirmation is only a component of a larger scheme. Alternative verification methods, such as from-the-ground reports and satellite imaging, are considered valid in scenarios in which smart missiles are not employed or are unavailable.

This enhanced approach to data analysis and mission evaluation corresponds to the growing nature of UAV technology and military methods. We aim to provide an integrated view of UAV mission success and its drivers by combining traditional data analysis methods and new smart weapons capabilities.

### C. MODEL EVALUATION AND RESULTS

The evaluation of the classification models includes a wide range of metrics [46], each providing distinct perspectives on the performance of the model. These metrics are of utmost significance in determining the efficacy of the model, especially in situations involving particular demands, such as class imbalance or varying costs linked to various types of classification errors.

#### 1) EVALUATION METRICS

In the following section, we explain the metrics used to evaluate classification models [47].

Accuracy is the most straightforward metric. The metric shows the ratio of accurate projections (including true positives and true negatives) to the overall number of cases analyzed.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{1}$$

Precision is crucial when the cost of false positives is high. In such cases, it is critical to reduce the rate of false positives to avoid potentially negative implications of incorrect positive classifications. As a result, in situations where the implications of mistaking a negative instance for a positive instance are severe, precision becomes a more essential measure than simply improving total accuracy.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{2}$$

Recall (sensitivity) is particularly important when missing a positive instance (false negative) incurs a high cost. In such

cases, identifying as many true positives as possible is critical, even if it results in a higher number of false positives. A strong recall is critical in situations where the consequences of missing a positive case are severe, and exceed the disadvantages of false-positive errors.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{3}$$

F1-score is especially useful when precision and recall must be balanced. For example, in a classification task where both false positives and false negatives are costly, the F1-score provides a single statistic that balances these two characteristics. This is the harmonic mean of precision and recall, which ensures that both metrics equally contribute to the overall score.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

The area under the ROC Curve (AUC) is a common ML statistic for binary classification. A higher AUC value generally implies a better model because it demonstrates that the model can distinguish between positive and negative classes across all feasible thresholds. This is particularly useful for analyzing models in cases where the ideal classification threshold is unknown and must be altered based on the specific costs or benefits associated with true positives, false positives, true negatives, and false negatives.

### 2) EVALUATION AND RESULTS

We assessed the performance of our RF model using the previously described measures. Its overall efficacy can be observed in a large number of correctly predicted outcomes, with an accuracy of 0.87. Its precision of 0.79 and perfect recall of 1.00, in particular, show that it can effectively detect positive outcomes while reducing false positives. An F1 score of 0.88 further illustrates this performance balance.

We also compared our RF model to other classifiers; SVM (LibSVM), AdaBoost, Naive Bayes, and Bagging all showed a similar pattern of accuracy, with each model obtaining an accuracy of 0.87. Table 1 presents the models results. RF, SVM (LibSVM), Naive Bayes, and Bagging with Decision Trees had similar precision values of 0.79; however, AdaBoost had a slightly higher precision of 0.80. RF, SVM (LibSVM), Naive Bayes, and Bagging with Decision Trees maintained a perfect recall score of 1.0, whereas AdaBoost had a slightly lower recall of 0.96. All the models had similar F1 scores, indicating a fair trade-off between recall and precision. AdaBoost trails slightly behind with an F1 score of 0.87, while the RF model, SVM (LibSVM), Naive Bayes, and Bagging with Decision Trees also had an F1 score of 0.88. These results show that all classifiers function well, with only a slight difference in metrics; however, the RF model shows a slight edge, especially in terms of precision and recall.

We evaluated the effectiveness of the models for predicting the outcome of UAV missions and observed significant differences in their confusion matrices. RF, SVM (LibSVM), Naive Bayes, and Bagging with Decision Trees models show exceptional accuracy in correctly identifying successful missions, as indicated by the absence of any false negatives in their confusion matrices. The RF algorithm produces a confusion matrix of [[1452, 529], [0, 2019]], the SVM (LibSVM) algorithm shows a confusion matrix of [[1457, 524], [0, 2019]], the Naive Bayes algorithm provides a confusion matrix of [[1445, 536], [0, 2019]], and the Bagging with Decision Trees algorithm produces a confusion matrix of [[1451, 530], [0, 2019]]. This indicated an increased ability to identify successful missions. Nevertheless, these models demonstrated a significant number of false positives, suggesting their ability to frequently predict success.

**TABLE 1. Performance metrics of classification models.**

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Random Forest | 0.87 | 0.79 | 1.00 | 0.88 |
| SVM (LibSVM) | 0.87 | 0.79 | 1.00 | 0.89 |
| AdaBoost | 0.86 | 0.80 | 0.96 | 0.87 |
| Naive Bayes | 0.87 | 0.79 | 1.00 | 0.88 |
| Bagging | 0.87 | 0.79 | 1.00 | 0.88 |

However, the AdaBoost model exhibits equal performance in detecting both successful and unsuccessful missions, as evidenced by its confusion matrix [[1487, 494], [74, 1945]]. Although there were many cases of false negatives, this model had a reduced rate of false positives compared with the other models. This balance indicates the more precise ability of the mission parameters. Figure 4 shows the confusion matrices of the five classification models.

We also evaluated our models using the Receiver Operating Characteristic (ROC) curve, which is an essential element in the evaluation of classification models as it shows how well the model can differentiate between classes. Figure 5 shows the ROC curves for RF, SVM (LibSVM), AdaBoost, and Bagging with Decision Trees models. RF, SVM (LibSVM), AdaBoost, and Bagging with Decision Trees all showed ROC Area Under the Curve (AUC) values of 0.87, which is a clear indication of their high degree of classification effectiveness and ability to distinguish between positive and negative classifications. The Naive Bayes model was excluded from the ROC AUC analysis because our implementation did not provide the probability estimates required for ROC curve creation.

We performed a thorough cross-validation evaluation to assess the efficacy of five distinct classification models: RF, SVM (LibSVM), AdaBoost, Naive Bayes, and Bagging with Decision Trees. To provide accurate and reliable assessments, a cross-validation procedure was performed for five different runs. We created a box plot 6 by combining the data from each of the five runs to compare the performances of these models. This box plot clearly illustrates the distribution of accuracy ratings for each model while also illuminating the robustness and variability of the various models.

The box plot illustrates the cross-validation results, which are as follows: The RF model demonstrated consistently high performance across the runs, as shown by

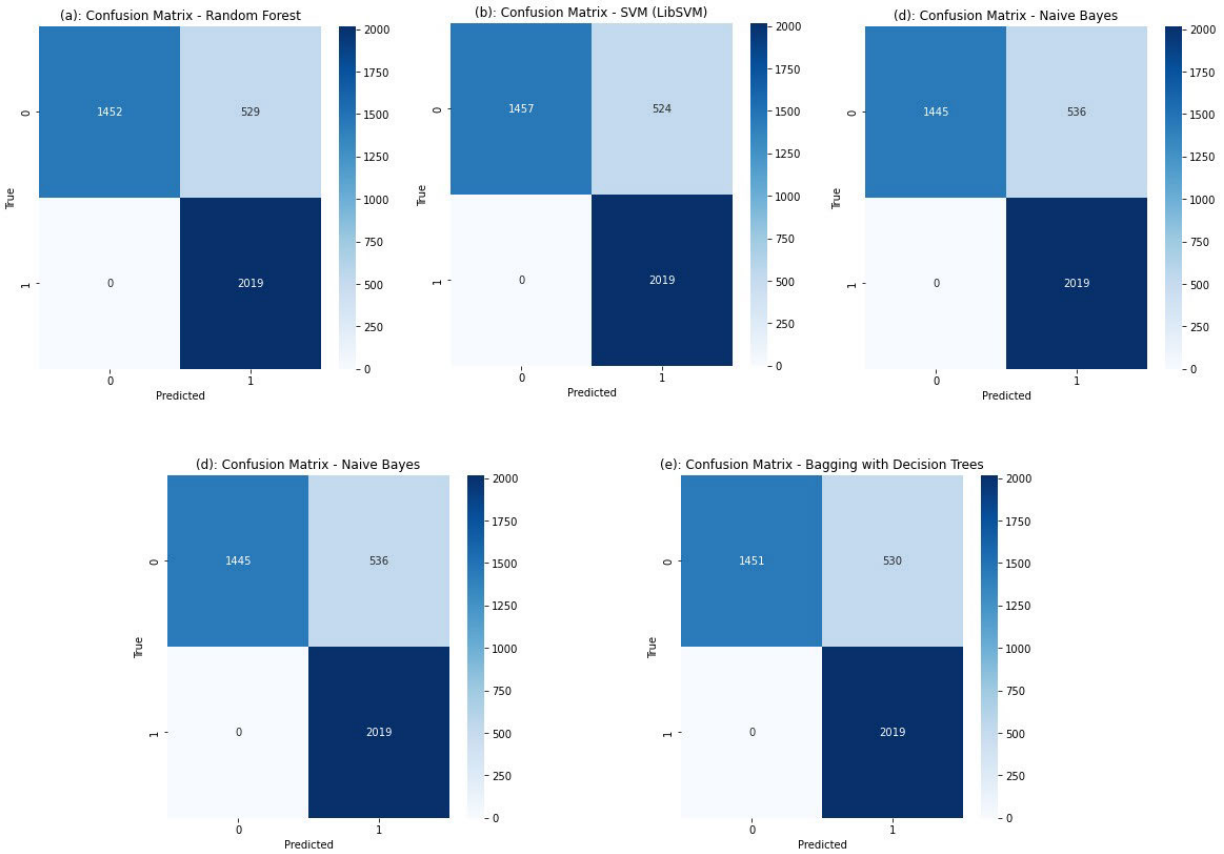


**FIGURE 4.** Confusion matrices for five different classification models. (a) RF model. (b) SVM (LibSVM) model. (c) AdaBoost model. (d) Naive Bayes model. (e) Bagging with Decision Trees model.

its mean accuracy scores, which varied from 0.8555 to 0.8695. The accuracy ratings of the SVM (LibSVM) model ranged from 0.8538 to 0.8635, suggesting a consistent and similar level of performance. The scores for the AdaBoost model ranged from 0.8538 to 0.8708, demonstrating its efficacy in multiple iterations. The Naive Bayes model demonstrates a competitive prediction skill, with scores ranging from 0.8588 to 0.8712. Finally, the Bagging with Decision Trees model produced scores ranging from 0.8658 to 0.8510, indicating that it was a reliable classifier.

## XI. DISCUSSION

This section discusses several related aspects of the proposed system.

The MC2 can update the terms and conditions defined in SCs, deploy new versions due to new changes in the mission, or update the rules of engagement.

In the field, ML models can be easily updated or re-trained with little loss of time, especially for applications at the network edge. Since the program is containerized, several local copies of the model are kept, and the model can be replaced in response to changes in configuration or the introduction of a new context, ensuring a seamless transition without losing any data [48]. To preserve forecast accuracy over time despite concept drifts or modifications to data patterns, cloud management systems must retrain their ML models. Determining if and how to successfully retrain models is crucial, as studies show that retraining existing models may achieve accuracy similar to that of newly trained models at a lower cost [48], [49]. To ensure effective dynamic resource management in cloud systems, the problem is figuring out when retraining is necessary and when and how much data to retrain using [49], [50].

Despite the existing use of RF models for mission success prediction, integrating advanced ML techniques, particularly Deep Q-Networks, and specialized ML algorithms for UAV communications has the potential to further transform HS UAV applications. Deep Q-Networks, as described in [51], provides a comprehensive approach to real-time on-board decision-making. This technology has the potential to significantly improve the efficiency of UAVs in power management and data collection, which are critical for long-term complex HS operations. Furthermore, the authors of [52] emphasized the potential of ML to optimize UAV communication systems. The improved communication protocols allowed by ML would not only provide better data transfer and processing but would also improve situational awareness and coordination of the UAV fleet. These advanced ML applications meet these adaptability and efficiency requirements in HS scenarios, implying that AI will play an important role in the future.

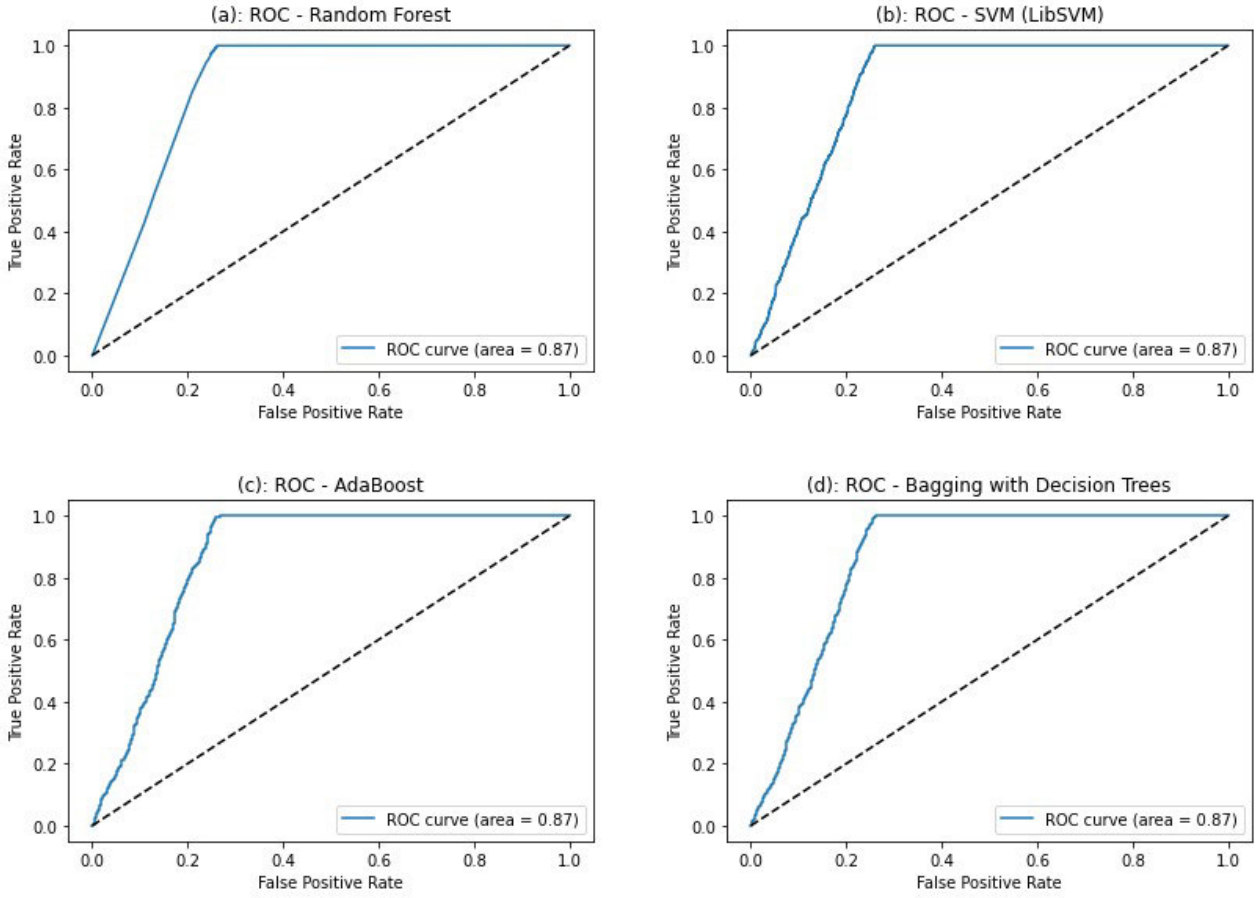


**FIGURE 5.** Receiver operating characteristic (ROC) curves for four different classification models.

Furthermore, the integration of multiple and advanced ML models, such as Convolutional Neural Networks (CNNs) for image analysis, Recurrent Neural Networks (RNNs), and transformers for sequential data interpretation for structured mission data, provides a variety of techniques for further improving UAV capabilities. In particular, CNNs can revolutionize target identification and surveillance through advanced image processing [53]. RNNs and transformers offer unparalleled advantages in analyzing temporal data, which is essential for real-time decision-making and strategy formulation [10]. An integrated application that utilizes multiple ML models not only enhances the particular capabilities of each technique but also addresses the various issues encountered in modern HS and military applications. The incorporation of advanced ML algorithms represents a significant advancement in UAV operation [54], resulting in increased operational effectiveness, adaptability, and strategic superiority in both complex and dynamic scenarios.

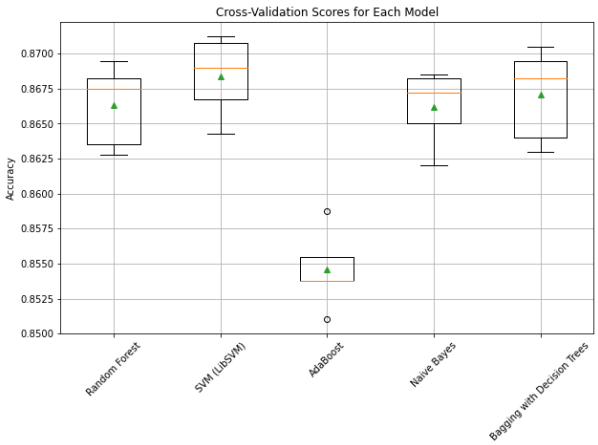


**FIGURE 6.** Box plot of classification model cross-validation results. The distribution of accuracy scores from five-fold cross-validation for five different classification models is shown in this figure: AdaBoost, Random Forest, SVM (LibSVM), Naive Bayes, and Decision Tree-Based Bagging.

## XII. CONCLUDING REMARKS AND DIRECTION FOR FUTURE INVESTIGATIONS

In this paper, we identified the challenges related to enabling autonomous UAVs, deployed in support of HS applications, to carry out strike missions against high-value terrorists. We suggest that recent developments in ledger technology, SCs, and ML will enable autonomous UAVs to successfully complete these missions. We derived analytical expressions for the success of a mission depending on the interdependence of the tasks within the mission. Finally, we demonstrated an ML framework for autonomous UAVs.

### A. DIRECTIONS FOR FUTURE INVESTIGATIONS

In spite of many technological advances, several issues remain unresolved and are receiving attention. Graph Machine Learning (GML) is a recently proposed ML technology in which the power of graph representation is harnessed [55], [56] and used to advantage [57]. In this context, graph decomposition techniques [58] are useful tools to enhance the scalability of GML techniques.

Under current technology, there are several limitations to deploying UAVs. For example, it is infeasible to deploy a UAV in inclement weather or under conditions where the on-board sensors are unable to provide reasonable input data to guide the mission. It is equally infeasible to strike targets that are out of reach for the UAV itself. Indeed, the most common NATO type UAVs can fly at 10,000 ft (3,000 m) altitude and up to 50 km in range [36]. Tactical UAVs can fly up to 18,000 ft (5,500 m) altitude and about 160 km in range [37]. Yet another limitation is the payload that UAVs can carry. It is well known that the heavier the load the UAV carries, the noisier it is and hence easier detectable. These physical limitations must be taken into account when planning any UAV mission, including the type of strike mission we have in mind [37].

Many other avenues are open for future investigation. One of these is mission security. Although we have developed our mission with minimal communication requirements, in the future communications may play an important role [30], [59], and ensuring a high level of security will become essential. Another open problem is the type of communication and local processing that the UAV must perform [4] while in flight.

## REFERENCES


[1] (2017). *DOD Dictionary of Military and Associated Terms as of March 2017*. [Online]. Available: https://www.tradoc.army.mil/wp-content/uploads/2020/10/AD1029823-DOD-Dictionary-of-Military-and-Associated-Terms-2017.pdf

[2] (2024). *U.S. Department of Homeland Security*. Accessed: Mar. 8, 2024. [Online]. Available: https://www.dhs.gov

[3] F. Ahmed, J. C. Mohanta, A. Keshari, and P. S. Yadav, "Recent advances in unmanned aerial vehicles: A review," *Arabian J. Sci. Eng.*, vol. 47, no. 7, pp. 7963–7984, Jul. 2022, doi: 10.1007/s13369-022-06738-0.

[4] J. R. Hoehn and K. P. Kerr, "Unmanned aircraft systems: Current and potential programs," Congressional Res. Service (CRS), Tech. Rep. CRS R47067, Feb. 2022. [Online]. Available: https://crsreports.congress.gov/

[5] J. R. Hoehn, "Precision-guided munitions: Background and issues for congress," Congressional Res. Service (CRS), Tech. Rep. CRS R45996, Oct. 2020. [Online]. Available: https://crsreports.congress.gov/

[6] J. R. Hoehn, M. F. DeVine, and K. M. Sayler, "Unmanned aircraft systems: Roles, missions, and future concepts," Congressional Res. Service (CRS), Tech. Rep. CRS R47188, Jul. 2022. [Online]. Available: https://crsreports.congress.gov/

[7] J. Schneider and J. MacDonald. (2017). *Why Trrops Don't Trust Drones: The 'Warm Fuzzy' Problem*. Foreign Affairs. [Online]. Available: https://www.foreignaffairs.com/articles/united-states/2017-12-20/why-troops-dont-trust-drones

[8] C. Andersen, D. Balir, and M. Byrnes. (2018). *Trust, Troops and Reapers: Getting 'Drone' Research Right*. [Online]. Available: https://warontherocks.com/2018/04/trust-troops-and-reapers-getting-drone-research-right/

[9] D. Harrison. (Mar. 2021). *Rethinking the Role of Remotely Crewed Systems in the Future Force*. Center Strategic Int. Stud. [Online]. Available: https://www.csis.org/analysis/rethinking-role-remotely-crewed-systems-future-force

[10] H. Kurunathan, H. Huang, K. Li, W. Ni, and E. Hossain, "Machine learning-aided operations and communications of unmanned aerial vehicles: A contemporary survey," *IEEE Commun. Surveys Tuts.*, vol. 26, no. 1, pp. 496–533, 1st Quart., 2024.

[11] Z. Ning, H. Hu, X. Wang, L. Guo, S. Guo, G. Wang, and X. Gao, "Mobile edge computing and machine learning in the Internet of unmanned aerial vehicles: A survey," *ACM Comput. Surv.*, vol. 56, no. 1, pp. 1–31, Jan. 2024.

[12] Y. Bai, H. Zhao, X. Zhang, Z. Chang, R. Jäntti, and K. Yang, "Toward autonomous multi-UAV wireless network: A survey of reinforcement learning-based approaches," *IEEE Commun. Surveys Tuts.*, vol. 25, no. 4, pp. 3038–3067, 2023.

[13] M. Tahir, S. I. Ali Shah, and Q. Zaheer, "Aircraft system design for an anti-terrorist unmanned aerial vehicle," in *Proc. Int. Conf. Eng. Emerg. Technol. (ICEET)*, Feb. 2019, pp. 1–8.

[14] U. O. Matthew, J. S. Kazaure, A. Onyebuchi, O. O. Daniel, I. H. Muhammed, and N. U. Okafor, "Artificial intelligence autonomous unmanned aerial vehicle (UAV) system for remote sensing in security surveillance," in *Proc. IEEE 2nd Int. Conf. Cyberspac (CYBER NIGERIA)*, Feb. 2021, pp. 1–10.

[15] A. Petrovski, M. Radovanović, and A. Behlić, "Application of drones with artificial intelligence for military purposes," in *Proc. 10th Int. Sci. Conf. Defensive Technol. (OTEH)*, 2022, pp. 92–100.

[16] T. Ahamed Ahanger, A. Aldaej, M. Atiquzzaman, I. Ullah, and M. Yousufudin, "Distributed blockchain-based platform for unmanned aerial vehicles," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–16, Aug. 2022.

[17] R. Yang, R. Wakefield, S. Lyu, S. Jayasuriya, F. Han, X. Yi, X. Yang, G. Amarasinghe, and S. Chen, "Public and private blockchain in construction business process and information integration," *Autom. Construct.*, vol. 118, Oct. 2020, Art. no. 103276.

[18] M. Aljohani, R. Mukkamala, and S. Olariu, "A smart contract-based decentralized marketplace system to promote reviewer anonymity," in *Proc. IEEE Int. Conf. Blockchain Cryptocurrency (ICBC)*, May 2023, pp. 524–532.

[19] *Smart Contracts*. Accessed: Jan. 29, 2024. [Online]. Available: https://ethereum.org/smart-contracts

[20] IBM. *What Are Smart Contracts on Blockchain?*. Accessed: Jan. 29, 2024. [Online]. Available: https://www.ibm.com/topics/smart-contracts

[21] M. G. Santos De Campos, C. P. C. Chanel, C. Chauffaut, and J. Lacan, "Towards a blockchain-based multi-UAV surveillance system," *Frontiers Robot. AI*, vol. 8, Jun. 2021, Art. no. 557692.

[22] S. Olariu, A. Wada, L. Wilson, and M. Eltoweissy, "Wireless sensor networks: Leveraging the virtual infrastructure," *IEEE Netw.*, vol. 18, no. 4, pp. 51–56, Jul. 2004.

[23] A. Wadaa, S. Olariu, L. Wilson, M. El-Toweissy, and K. Jones, "Training a wireless sensor network," *Mobile Netw. Appl.*, vol. 10, pp. 151–168, Feb. 2005.

[24] S. Olariu, Q. Xu, and A. Y. Zomaya, "An energy-efficient self-organization protocol for wireless sensor networks," in *Proc. Intell. Sensors, Sensor Netw. Inf. Process. Conf.*, 2004, pp. 55–60.

[25] H. S. AbdelSalam and S. Olariu, "BEES: Bioinspired backbone selection in wireless sensor networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 23, no. 1, pp. 44–51, Jan. 2012.

[26] D. Fox, W. Burgard, and S. Thrun, "Markov localization for mobile robots in dynamic environments," *J. Artif. Intell. Res.*, vol. 11, pp. 391–427, Nov. 1999.

[27] S. K. Pandey, M. A. Zaveri, M. Choksi, and J. S. Kumar, "UAV-based localization for layered framework of the Internet of Things," *Proc. Comput. Sci.*, vol. 143, pp. 728–735, Jan. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1877050918321409

[28] B. Zhao, X. Chen, X. Zhao, J. Jiang, and J. Wei, "Real-time UAV autonomous localization based on smartphone sensors," *Sensors*, vol. 18, no. 12, p. 4161, Nov. 2018, doi: 10.3390/s18124161.

[29] Y. Li, R. Yu, and B. Zhu, "2D-key-points-localization-driven 3D aircraft pose estimation," *IEEE Access*, vol. 8, pp. 181293–181301, 2020.

[30] J. Yousaf, H. Zia, M. Alhalabi, M. Yaghi, T. Basmaji, E. A. Shehhi, A. Gad, M. Alkhedher, and M. Ghazal, "Drone and controller detection and localization: Trends and challenges," *Appl. Sci.*, vol. 12, no. 24, p. 12612, Dec. 2022, doi: 10.3390/app122412612.

[31] S. M. Shithil, A. A. M. Faudzi, A. Abdullah, N. Islam, and S. M. Saad, "Robust sensor fusion for autonomous UAV navigation in GPS denied forest environment," in *Proc. IEEE 5th Int. Symp. Robot. Manuf. Autom. (ROMA)*, Aug. 2022, pp. 1–6.

[32] S. Yue-Hua and C. Yuan-Li, "Image feature extraction for vision-based UAV navigation," in *Proc. Chin. Autom. Congr. (CAC)*, Nov. 2018, pp. 1130–1134.
[33] E. A. R. Martínez, G. Caron, C. Pégard, and D. L. Alabazares, "Photometric path planning for vision-based navigation," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2020, pp. 9007–9013.
[34] S. Meisami and W. E. Bodell III, "A comprehensive survey of upgradeable smart contract patterns," 2023, *arXiv:2304.03405*.
[35] J. Chen, K. H. Johansson, S. Olariu, I. Ch. Paschalidis, and I. Stojmenovic, "Guest editorial special issue on wireless sensor and actuator networks," *IEEE Trans. Autom. Control*, vol. 56, no. 10, pp. 2244–2246, Oct. 2011.
[36] C. C. Haddal and J. Gertler, "Homeland security: Unmanned aerial vehicles and border surveillance," Congressional Res. Service (CRS), Res. Service Rep. CRS RS21698, 2010. [Online]. Available: https://crsreports.congress.gov/
[37] M. Javaid, A. Haleem, S. Rab, R. P. Singh, and R. Suman, "Sensors for daily life: A review," *Sensors Int.*, vol. 2, Feb. 2021, Art. no. 100121.
[38] Mil. Aerosp. *Sensor Payloads for Unmanned Vehicles*. Accessed: Jan. 28, 2024. [Online]. Available: https://www.militaryaerospace.com/uncrewed/article/16707400/sensor-payloads-for-unmanned-vehicles
[39] A. Konert and T. Balcerzak, "Military autonomous drones (UAVs)—From fantasy to reality. Legal and ethical implications," *Transp. Res. Proc.*, vol. 59, pp. 292–299, Jan. 2021.
[40] A. Suresh. *Machine Learning—IEEE PES Dayananda Sagar College of Engineering, Bangalore*. Accessed: May 8, 2023. [Online]. Available: https://edu.ieee.org/in-dscepes/2019/12/11/machine-learning/
[41] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, pp. 5–32, Oct. 2001.
[42] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and É. Duchesnay, "Scikit-learn: Machine learning in Python," *J. Mach. Learn. Res.*, vol. 12, pp. 2825–2830, Nov. 2011.
[43] V. Jain and A. Phophalia, "M-ary random forest—A new multidimensional partitioning approach to random forest," *Multimedia Tools Appl.*, vol. 80, nos. 28–29, pp. 35217–35238, Nov. 2021.
[44] M. Aljohani. (May 2023). *UVAs*. Accessed: May 20, 2023. [Online]. Available: https://github.com/meshari-aljohani/UAVs
[45] *The Benefits and Limitations of Generating Synthetic Data*. Accessed: Jan. 27, 2024. [Online]. Available: https://syntheticus.ai/blog/the-benefits-and-limitations-of-generating-synthetic-data
[46] P. Sujatha and K. Mahalakshmi, "Performance evaluation of supervised machine learning algorithms in prediction of heart disease," in *Proc. IEEE Int. Conf. for Innov. Technol. (INOCON)*, Nov. 2020, pp. 1–7.
[47] *Classification | Machine Learning | Google for Developers*. Accessed: Nov. 22, 2023. [Online]. Available: https://developers.google.com/machine-learning/crash-course/classification/video-lecture
[48] J. Gómez-Luna, Y. Guo, S. Brocard, J. Legriel, R. Cimadomo, G. F. Oliveira, G. Singh, and O. Mutlu, "Machine learning training on a real processing-in-memory system," in *Proc. IEEE Comput. Soc. Annu. Symp. VLSI (ISVLSI)*, Jul. 2022, pp. 292–295.
[49] L. Kidane, P. Townend, T. Metsch, and E. Elmroth, "When and how to retrain machine learning-based cloud management systems," in *Proc. IEEE Int. Parallel Distrib. Process. Symp. Workshops (IPDPSW)*, May 2022, pp. 688–698.
[50] P. J. Rogers, B. Pisupati, T. Khinvasara, R. Chopra, and K. Purandare, "Live updating of machine learning models," uS Patent 17 015 318, Apr. 22, 2021.
[51] K. Li, W. Ni, E. Tovar, and A. Jamalipour, "On-board deep Q-network for UAV-assisted online power transfer and data collection," *IEEE Trans. Veh. Technol.*, vol. 68, no. 12, pp. 12215–12226, Dec. 2019.
[52] S. B. Aissa and A. B. Letaifa, "UAV communications with machine learning: Challenges, applications and open issues," *Arabian J. Sci. Eng.*, vol. 47, no. 2, pp. 1559–1579, Feb. 2022.
[53] S. Egli and M. Höpke, "CNN-based tree species classification using high resolution RGB image data from automated UAV observations," *Remote Sens.*, vol. 12, no. 23, p. 3892, Nov. 2020.
[54] Mil. Aerosp. *Artificial Intelligence and Machine Learning for Unmanned Vehicles*. Accessed: Jan. 26, 2023. [Online]. Available: https://www.militaryaerospace.com/uncrewed/article/14202040/artificial-intelligence-and-machine-learning-for-unmanned-vehicles
[55] K. Nakano, S. Olariu, and J. L. Schwing, "Broadcast-efficient protocols for mobile radio networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 10, no. 12, pp. 1276–1289, Dec. 1999.
[56] S. Olariu, J. L. Schwing, and J. Zhang, "Optimal parallel algorithms for problems modeled by a family of intervals," *IEEE Trans. Parallel Distrib. Syst.*, vol. 3, no. 3, pp. 364–374, May 1992.
[57] S. Wei, Y. Zhao, X. Chen, Q. Li, F. Zhuang, J. Liu, F. Ren, and G. Kou, "Graph learning and its advancements on large language models: A holistic survey," 2023, *arXiv:2212.08966*.
[58] B. Jamison and S. Olariu, "P-components and the homogeneous decomposition of graphs," *SIAM J. Discrete Math.*, vol. 8, no. 3, pp. 448–463, Aug. 1995.
[59] P. E. Peralta, M. A. Luna, P. de la Puente, P. Campoy, H. Bavle, A. Carrio, and C. C.Ulloa, "Performance analysis of localization algorithms for inspections in 2D and 3D unstructured environments using 3D laser sensors and UAVs," *Sensors*, vol. 22, no. 14, p. 5122, Jul. 2022.

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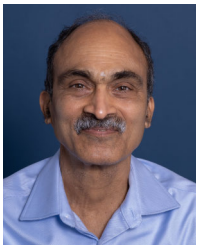

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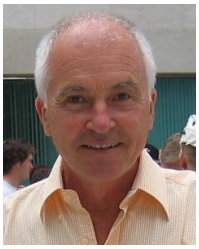

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