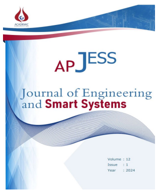

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AI-Embedded UAV System for Detecting and Pursuing Unwanted UAVs

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Abstract

In recent years, the use of unmanned aerial vehicle (UAV) platforms in civil and military applications has surged, highlighting the critical role of artificial intelligence (AI) embedded UAV systems in the future. This study introduces the Autonomous Drone (Vechür-SIHA), a novel AI-embedded UAV system designed for real-time detection and tracking of other UAVs during flight sequences. Leveraging advanced object detection algorithms and an LSTM-based tracking mechanism, our system achieves an impressive 80% accuracy in drone detection, even in challenging conditions like varying backgrounds and adverse weather.

Our system boasts the capability to simultaneously track multiple drones within its field of view, maintaining flight for up to 35 minutes, making it ideal for extended missions that require continuous UAV tracking. Moreover, it can lock onto and track other UAVs in mid-air for durations of 4-10 seconds without losing contact, a feature with significant potential for security applications.

This research marks a substantial contribution to the development of AI-embedded UAV systems, with broad implications across diverse domains such as search and rescue operations, border security, and forest fire prevention. These results provide a solid foundation for future research, fostering the creation of similar systems tailored to different applications, ultimately enhancing the efficiency and safety of UAV operations. The novel approach to real-time UAV detection and tracking presented here holds promise for driving innovations in UAV technology and its diverse applications.

Keywords: Deep Learning; Object Detection; ROS; Aerial Vehicle; LSTM; UAV

1. INTRODUCTION

In recent years, unmanned aerial vehicle (UAV) platforms in civil and military fields have increased daily and become a critical technology. The artificial intelligence (AI) embedded UAV system has great importance and potential in the future [1-3]. Research and development, search and rescue operations, aerial photography, videography, border security, traffic control, forest fire prevention, working in toxic chemical gas environments, preventing poaching, natural resource exploration, agriculture, extraction, and UAV detection while in the air are all applications for AI embedded UAVs. UAV usage is becoming more common due to the nature of aircraft. The increased usage has given resulted in unwanted UAVs in restricted areas. Tracking trespassing UAVs is also important and detecting the UAVs is an emerging field [4-6]. Especially drone detection in the air is challenging due to the fast-changing background. Therefore drones can be detected using AI with other vehicles.

Specialized systems must be created for tracker UAVs. Rotary wing UAVs(drones) can contain hardware units such as brushless DC motors, electronic speed controllers, various sensors (pressure, gyro, compass, GPS, ultrasonic), propellers, power systems, cameras, and communication systems. The rotary-wing unmanned aerial vehicle takes off with the lift force obtained by rotating the rotors of the propellers. Rotation of the rotor at different speeds, the rotation movements performed on the fuselage axis set in the center of the aircraft enable it to move in the horizontal or vertical axis. When the rotors' angular velocity changes, a signal is sent to them to allow the flight controller to compile the directives and provide the rotors with the correct orientation [1].

UAVs are aircraft that can move in a predetermined trajectory utilizing the sensors on board or can be controlled by the user using a remote control. Advances in sensor technology and embedded electronic device manufacturing have allowed these tools to increase in capabilities and reduce size. In line with these developments, the UAV has become widely used in defense and civil applications. UAV border security is ensured in the defense industry and at crime scenes. In addition to being employed for applications like research, surveillance, adversary, and target identification, it may also be used in civil applications for things like locating fire zones, search and rescue, and assessing geographic changes brought on by natural catastrophes [4-6]. With the aid of cameras, Drones can detect UAVs with embedded deep-learning algorithms.

With object tracking, the aim is to keep the information of the relevant object from entering the scene to its exit by matching the detected objects between consecutive video frames. As a result of the object tracking, activities given as input to the optimization phase of the video synopsis are created [3]. The tracking algorithm and deep learning embedded system can detect and track other UAVs [7-9]. LSTM (long short-term memory) can be tracked with a deep learning algorithm [10-12].

In this project, Autonomous Drone (Vechür-SIHA) was developed for detecting and tracking other UAVs while in flight sequence. The system was simulated in Robot Operating System (ROS). Inside the simulated environment drone model was used for tracking UAV. After simulations and calculations, a Fighter drone was developed and built. The real-time UAV detection was made with object detection algorithms inside the simulation and in real-time. The system was embedded with a tracking algorithm based on LSTM (Long-short term memory). The system achieves high-accuracy drone detection in changing backgrounds and weather conditions (%80 accuracy), LSTM drone tracking can be accomplished even with multiple drones inside the field of view, and the system is capable of flying for 35 minutes. The system also can be locked other UAVs and track them while flying. The system can track other UAV's 4-10 seconds without losing contact.

In recent years, the usage of unmanned aerial vehicle (UAV) platforms has increased dramatically in both civil and military fields, leading to the development of critical new technologies. One area that holds particular promise for the future is the use of artificial intelligence (AI) embedded UAV systems, which have the potential to revolutionize a wide range of applications [1-3]. These applications include research and development, search and rescue operations, aerial photography and videography, border security, traffic control, forest fire prevention, working in toxic chemical gas environments, preventing poaching, natural resource exploration, agriculture and extraction, and UAV detection while in the air. UAV usage is becoming increasingly common, thanks to its unique capabilities and versatility, but this has also led to the emergence of unwanted UAVs in restricted areas. Tracking and detecting these trespassing UAVs has become an urgent need in many contexts, making UAV detection and tracking an emerging field of research [4-6]. One of the main challenges in this area is detecting UAVs in the air, which is made difficult by the fast-changing background. However, AI can be used to detect drones in combination with other vehicles, and specialized systems can be developed for tracking UAVs.

Rotary wing UAVs (also known as drones) are equipped with hardware units such as brushless DC motors, electronic speed controllers, various sensors (including pressure, gyro, compass, GPS, and ultrasonic sensors), propellers, power systems, cameras, and communication systems [1]. The rotary-wing unmanned aerial vehicle takes off with the lift force obtained by rotating the rotors of the propellers. Rotation of the rotor at different speeds, and the rotation movements performed on the fuselage axis set in the center of the aircraft, enable it to move in the horizontal or vertical axis. When the rotors' angular velocity changes, a signal is sent to them to allow the flight controller to compile the directives and provide the rotors with the correct orientation. Advances in sensor technology and embedded electronic device manufacturing have allowed UAVs to increase in capabilities and reduce in size, making them widely used in defense and civil applications.

In the defense industry and at crime scenes, UAV border security is ensured by deploying UAVs for applications like research, surveillance, adversary, and target identification. UAVs may also be used in civil applications, such as locating fire zones, search and rescue operations, and assessing geographic changes brought on by natural catastrophes [4-6]. With the aid of cameras, drones can detect other UAVs using embedded deep-learning algorithms.

Object tracking aims to keep the information of the relevant object from entering the scene to its exit by matching the detected objects between consecutive video frames. As a result of object tracking, activities given as input to the optimization phase of the video synopsis are created [3]. The tracking algorithm and deep learning embedded system can detect and track other UAVs with high accuracy [7-9]. One popular method of doing this is to use a long short-term memory (LSTM) algorithm, which has shown promising results in previous research [10-12].

The developed autonomous drone system, called Vechür-SIHA, was able to detect and track other UAVs in real time during flight sequences. The system was first simulated in the Robot Operating System (ROS) environment using a drone model to track the UAVs. Based on the simulation results and calculations, a small fighter drone was then designed and built. The system was equipped with an object detection algorithm that allowed for real-time UAV detection, even in changing backgrounds and weather conditions, achieving an accuracy of up to 80%. Furthermore, the system utilized a tracking algorithm based on long-short-term memory (LSTM) to track multiple drones simultaneously within its field of view, with a tracking duration of 4-10 seconds before losing contact. The developed system was also capable of flying for up to 35 minutes and locking onto and tracking other UAVs while in flight. These results demonstrate the feasibility of using AI-embedded UAVs for detecting and tracking other UAVs, which could be useful in a wide range of applications such as border security, surveillance, and search and rescue operations.

2. MATERIALS AND METHODS

In this section, the system development from simulation to real-life application. The study was organized: ROS simulation, Deep learning-based drone detection algorithm development, mechanical and electronic system design, and real-time flight application.

Vechür-SIHA is designed for fighter UAV competitions in Teknofest/Turkey. The competition goal is to detect other UAVs with vision systems and track them without breaking visual contact for 10 seconds. In every flight, more than 12 UAVs were flying in simultaneously. Our Autonomous System (Vechür-SIHA) is designed as a hexacopter with a rotating wing structure. The system can be controlled fully autonomously or manually. Vechür-SIHA can engage in dogfights through blocking or evasive maneuvers by detecting other nearby unmanned vehicles with the artificial intelligence-assisted visual detection system. In addition, the UAV will transmit the images and flight data received during the flight to the ground station in real-time using antennas that receive and transmit radio frequency signals. While our system position data is shared with the competition server connected via ethernet, other UAV data is received. The server also sends information about other UAVs to track and make evasive maneuvers. With the 2.4 GHz radio control, manual control can be encrypted and carried out at a sufficient distance. The system was simulated in a Robot operating system (ROS), and object detection algorithms were used for UAV detection for simulations and real-life applications.

Drones, also known as small, remotely-controlled unmanned aerial vehicles (UAVs), are used in a variety of societal roles such as law enforcement, medical, construction, search and rescue, parcel delivery, remote area exploration, topographic mapping, forest/water management, and inspection of large infrastructures such as power grids [1]. Their low cost and ease of operation have made drones accessible for recreational and entertainment purposes [2]. However, drones can be intentionally or unintentionally misused, posing a threat to the safety of others. For instance, an aircraft can be severely damaged if it collides with a consumer-sized drone, even at moderate speeds [3]. Additionally, an ingested drone can quickly disable an aircraft engine. The increasing occurrence of drone sightings in restricted airport areas is also a significant risk, leading to the total closure of airports and the cancellation of hundreds of flights [4]. Some hobbyist drone operators violate aviation safety regulations, sometimes without knowledge, leading to several near-misses and verified collisions with UAVs. Thus, research on drone detection has increased significantly [5,6] to counteract potential risks due to intrusion in restricted areas, either intentional or unintentional.

This paper addresses the design and evaluation of an automatic multi-sensor drone detection and tracking system using state-of-the-art machine-learning techniques. We extend the methods from conclusions and related literature recommendations [5,7] to enhance our development. In addition to effective detection, classification, and tracking methods, sensor fusion is also considered a critical open area to achieve greater accuracy and robustness compared to a single sensor. However, research in sensor fusion for drone detection is limited [7-10]. This work includes collecting and annotating a public dataset to train and evaluate the system. A lack of public reference databases serves as a benchmark for researchers [5]. Thus, we include three different consumer-grade drones in the dataset together with birds, airplanes, and helicopters, which constitutes the published dataset with the largest number of target classes (drone, bird, airplane, and helicopter). In building the classes, we consider other flying objects that are likely to be mistaken for a drone [11,12]. Additionally, we address the system's classification performance as a function of the distance to the target, with annotations of the database including such information.

A preliminary version of this article appeared at a conference [13]. In this contribution, we substantially increase the number of reported results. For instance, we extensively analyze the effect of the internal parameters of different detectors on their performance for various sensors. We also report results with a radar module and provide comments about the fish-eye camera motion detector, all of which were missing in the previous publication. Additional results on the fusion of sensors are also provided, including an Appendix with complementary observations and visual examples. Furthermore, we provide new detailed information about the system architecture, hardware, and software employed, including details about implementation and design choices not included in the previous publication. We describe the related work in more detail.

The remainder of the paper is organized as follows. Section 2 describes the related work. Section 3 extensively describes the proposed system, including the architecture, hardware components, involved software, Graphical User Interface, and dataset. The experimental results are presented and discussed in Section 4. Finally, the conclusions are presented in Section 5.

Several sensors can be used for drone detection, such as radar (on several different frequency bands, both active and passive), cameras in the visible spectrum, cameras detecting thermal infrared emission (IR), microphones to detect acoustic vibrations, sensors to detect radio frequency signals to and from the drone and the controller (RF), and scanning lasers (Lidar) [8]. As explored in [14], even humans can be employed for the task, and animals can be trained for

2.1. Autonomous Drone Specifications

Vechur-UAV can be used at an altitude of 2 km, 35 minutes of flight time was calculated considering the power consumption of the motor and the 22000 mAh value of the battery. The selected motors are enough to accelerate the Vechür-SIHA, which weighs around 4 kg to 15 m/s.

A 2 MP wide-angle camera was used. The captured images are processed by the artificial intelligence algorithm working on the embedded system computer (Jeton Nx-Nvidia, USA), capable of 21 trillion operations per second using 48 tensor cores. Thus, a Vechür-SIHA is developed with the infrastructure capable of performing tasks that require high computing power, such as target detection, target maneuver estimation, and target locking and tracking. A deep learning object detection algorithm (Yolov4-Tiny) was used, and TensorRT optimization was performed to improve the processed frame per second. The system was capable of image processing at 22 FPS (frame per second), which is suitable for detecting UAVs through the wide-angle camera. Due to our data and specifications, the estimated minimum detection range was 5 meters, and the maximum was 50 meters. It is planned to transmit end-to-end encrypted flight telemetry data at a range of 40 km and transmit it to the ground station in near real-time. In addition, the video transmission system is designed to transmit images at a range of about 4 km with delays of less than 30 milliseconds.

Vechür-SIHA constantly receives GPS data from the competition server and moves through to the other UAV's location. Suppose the UAVs detect the system and start analyzing trajectory, the number of elements with LSTM (Long-short term memory), and data received from the ground station. In that case, the system is also embedded with sub-systems that can follow the course using SLAM algorithms to control its route. SLAM is used for the shortest route calculation for following other UAVs.

2.2. Autonomous Drone Mechanical and Electronic System Design

In the mechanical design phase, the chassis diameter was determined as 600 mm, taking into account the dimensions of the electronic materials and the minimum distance between the propellers due to drone weight. The system consists of an embedded computer, flight controller, and battery pack. The chassis is designed in two layers to position the Electronic system, which has a developer kit, control card, and communication modules and is given in Figure 1.

Carbon fiber will be used in the drone's top-bottom plate, arms, and engine holder apparatus to provide durability and lightness. A modular flight computer holder has been designed on the bottom plate for easier removal and installation of the Jetson Xavier NX, which will be positioned in the center of the drone. The current breaker used as part of the security measures is shown in Figure 2 and is placed such that it may be rapidly intervened in case of a bad circumstance.

The system was designed with an appropriate deep-learning platform (Jettson Xaiver NX). The electronic flight controller system was embedded with a 32-bit high-performance STM32F427 ARM Cortex M7 processor that compiles real-time information collected from sensors and other flight units into the NuttX RTOS operating system, providing safe autonomous/manual flight. Inside the cube, isolated from vibration and external factors, 3 IMUs and two barometric sensors communicating with SPI protocol provide highly accurate real-time information. In addition to 8 main and six auxiliary output pins, and also supports communication protocols such as UART, CAN, I2C, USB, DSM, and S-BUS. The Pixhawk Cube, Flight Control Board, includes a dedicated processor, an independent power supply, and an integrated backup system that includes protocols such as fail-safe and manual in-flight override (Figure 1).

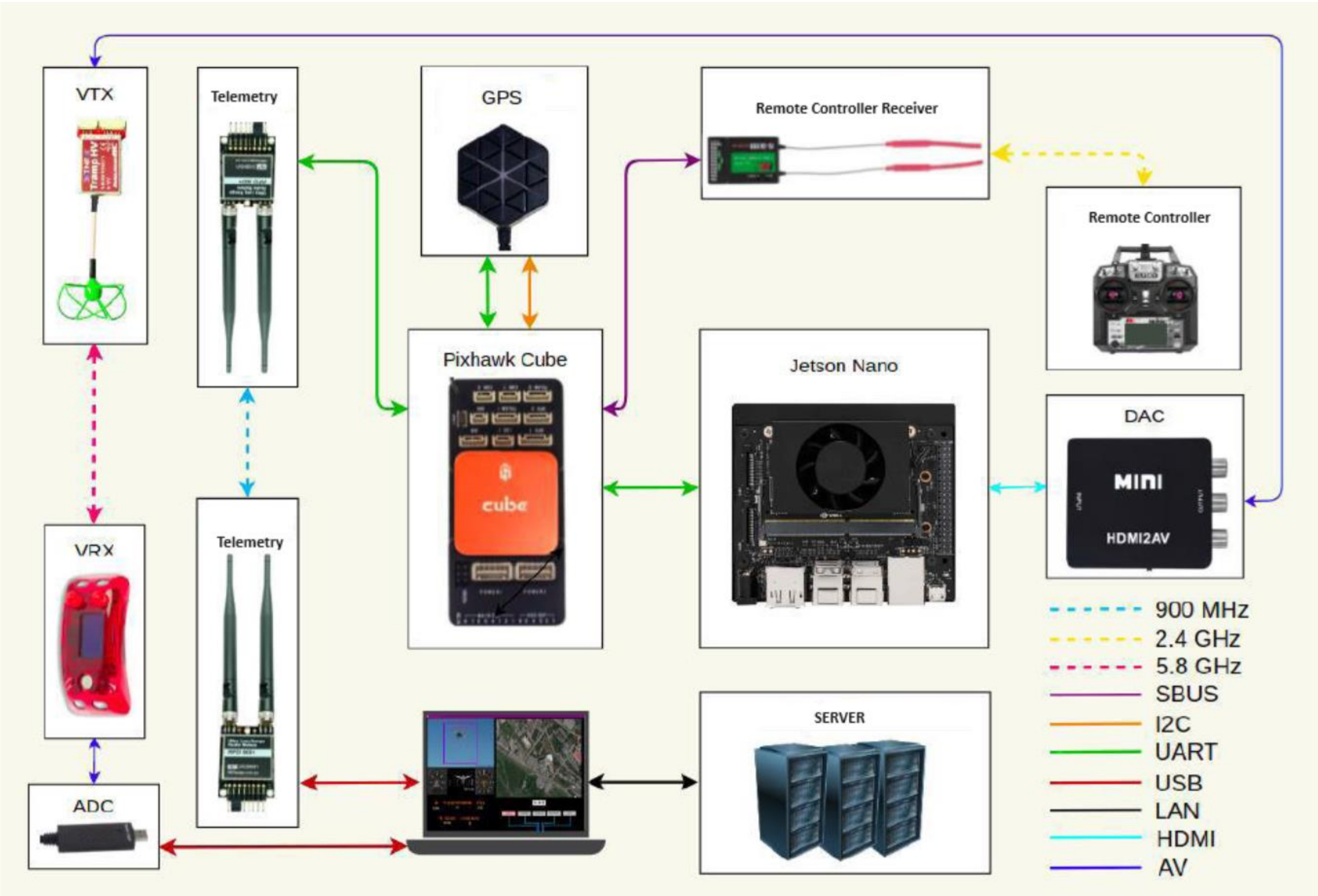

Figure 1. System and communication diagram

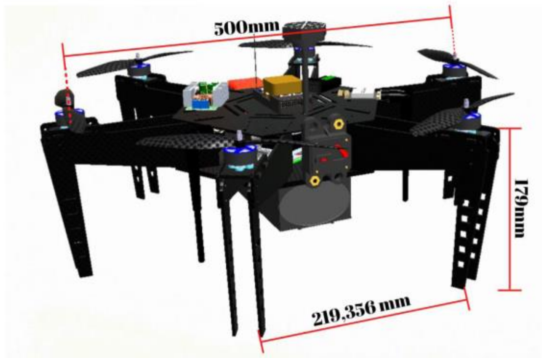

Figure 2. Autonomous drone mechanical design

Considering the weight of the 6-blade Vechür-SIHA system, as demonstrated in Figure 2, there are approximately 669 grams of thrust per hover engine. Thrust power was measured with a thrustmeter for more accurate system balancing and power management.

Static and flow analyses of Vechür-SIHA were carried out using the 3D analysis program. The average density and weight of carbon fiber used in Vechür-SIHA are 1.76 g/cm3 and 0.198 g/m2, respectively. The tensile strength of the carbon fiber is 3,530 MPa, the modulus of elasticity is 230 GPA, and the end stress is 1.5%, according to the manufacturer. According to the information in Figure 3, carbon fiber with Young's modulus of 230 GPA was selected. The maximum force at takeoff and during flight (assumed at full throttle) was derived from the bottom of the engine as a function of the engine's thrust in the static analysis of the Vechür-SIHA arms. Figure 3. shows that when the maximum force is applied, a maximum force of 8.46 MPa is generated on the arms. As a result of the analysis, it can be seen that the arms exceed the tensile strength of carbon fiber.

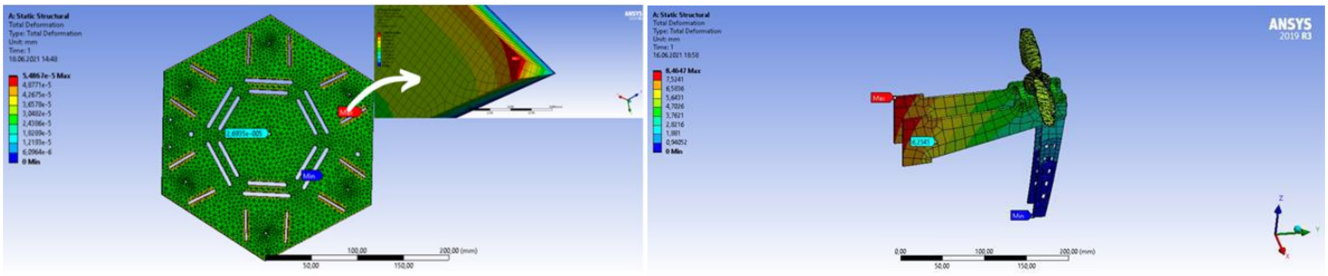

Figure 3. Static analysis of Vechür-SIHA brushless DC motor holder and landing gear

Figure 4. ROS simulated environment for drone detection

2.3. Robot Operating System(ROS) Simulation

The ROS Melodic, a well-established version, was used. A gazebo was used for environment simulation. Firstly, the necessary infrastructure was prepared for more than three rotary-wing UAVs to be able to fly (Figure 4) simultaneously. The SDF files of the UAV model, which are available in the hector_quadrotor packages used in the ROS environment, are designed according to demand and the capabilities of dogfighting competition. SITL software was used for establishing the Ardupilot-ROS connection, and the UAVs can perform autonomous flight according to the coordinates entered in the simulation environment. Autonomous detection of targets is ensured by integrating OpenCV libraries and darknet_ros structure into the Gazebo environment. Afterward, developed algorithms in the ROS environment were tested under real-world conditions.

2.4. Data Collection, Data Augmentation, and Object Detection-Tracking Algorithm

Artificial intelligence algorithm was used in both ROS and Real-world applications. Deep learning models like R-CNN, YOLO, and SSD that can generate real-time predictions are widely used [12]. In our system, FPS and optimization are very crucial. In a real-life environment, only prediction is not enough; simultaneously, the drone needs to be detected without losing contact. Jetson Nano (Nvidia, USA) is embedded inside the drone for real-time application. Jetson nano can be used in deep learning algorithms due to tensor cores, small size, and inference optimization. Because of the FPS needs, a small object problem Yolo Tinyv4 was selected. TenorRT and Onnx optimization can be used with the YOLO algorithm family. Also, Yolo Tiny models can detect smaller objects at a higher speed [12].

YOLOv4 Tiny Algorithm

✓ **Input image:**

- YoloV4 Tiny takes an input image as its initial input.

✓ **Network architecture:**

- YoloV4 Tiny uses a modified neural network architecture, which is typically a smaller and shallower version of the YoloV4 architecture to reduce computational complexity.
- It consists of a series of convolutional layers, followed by downsampling and upsampling layers to extract features and reduce the spatial dimensions of the image.

✓ **Anchor boxes:**

- YoloV4 Tiny uses anchor boxes to predict the bounding boxes for objects. These anchor boxes are predefined in terms of width and height to match the expected object sizes in the dataset.

✓ **Object detection:**

- The network predicts bounding boxes for objects and class probabilities at multiple scales (usually 13x13 and 26x26 grids).
- Each grid cell predicts a fixed number of bounding boxes (usually 3 or 6, depending on the configuration).
- For each bounding box, the network predicts the (x, y) coordinates of the bounding box's center relative to the grid cell, width, height, and class probabilities.
- The class probabilities represent the likelihood of the object belonging to a specific class (e.g., person, car, dog).

✓ **Non-maximum suppression (NMS):**

- After predictions are made at multiple scales, a post-processing step called non-maximum suppression is applied to remove duplicate and low-confidence detections.
- NMS selects the bounding box with the highest confidence for each object and removes overlapping boxes that have a high intersection-over-union (IoU) with the selected box.

✓ **Output:**

- The final output of YoloV4 Tiny is a list of bounding boxes, each associated with a class label and a confidence score.

✓ **Object classification:**

- YoloV4 Tiny can classify objects into predefined classes based on the highest class probability associated with each bounding box.

✓ **Bounding box refinement:**

- Optionally, the bounding box coordinates can be refined to improve the accuracy of object localization.

✓ **Post-processing:**

- The final detected objects can be drawn on the input image, and their class labels and confidence scores can be displayed.

✓ **Evaluation and optimization:**

- YOLOv4 Tiny's performance is evaluated using metrics like mean average precision (mAP).
- Model training and hyperparameter optimization are performed to improve detection accuracy.

YoloV4 tiny algorithm explained briefly. Implementing YoloV4 Tiny typically requires expertise in deep learning frameworks like TensorFlow or PyTorch, along with access to labeled training data for specific object detection tasks.

The system deep learning models were prepared according to the changing environment and fast movements [13-15]. Therefore, the data was augmented using several techniques to simulate different movements and angles (Figure 5). Data augmentation techniques included flipping, mirroring, adjusting brightness, blurring, gamma, and adding Gaussian noise. The resemblance of the movement effect in our real-time flying sequence led to the augmentation. Fast movements, shutter speeds, frames per second (FPS), weather conditions, and sun positions can impact real-time images. Our data consist of four thousand images. The augmentation was made limitedly to prevent overfitting of our model. In the competition, every team has a different drone design, which affects the model accuracy in real life.

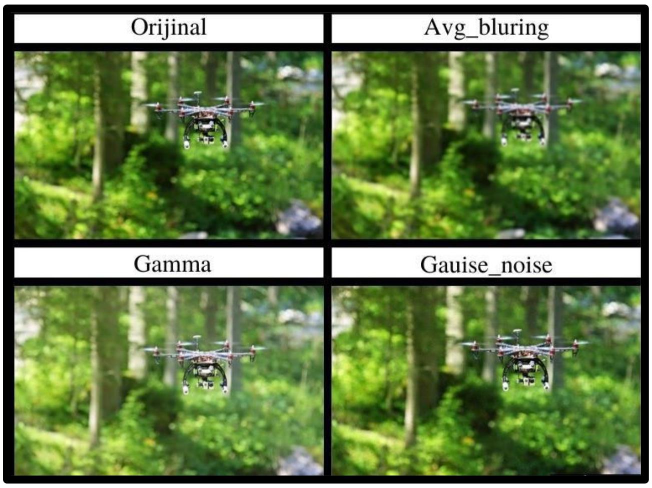

Figure 5. Data augmentations examples

Algorithm for Drone Detection and Tracking with YOLOv4 Tiny is explained briefly in the followint sequence:

✓ **Image acquisition and preprocessing:**

- Real-time imagery is captured using the drone's onboard camera.
- Captured images are preprocessed, resized, and normalized for input compatibility with the YOLOv4 Tiny model.

✓ **Model deployment and inference:**

- A pre-trained YOLOv4 Tiny model, optimized for real-time inference, is deployed.
- The model analyzes the preprocessed images for drone detection.

✓ **Object detection:**

- Detected drones are identified in the images, taking into account their presence and spatial coordinates.

✓ **Non-maximum suppression (NMS):**

- Non-maximum suppression is applied to refine drone detections, eliminating redundancy and preserving confidence.

✓ **Tracking initialization:**

- A tracking algorithm (e.g., SORT) is initialized, associating unique IDs with each detected drone for tracking continuity.

✓ **Drone tracking and prediction:**

- Continuous monitoring updates the drone's position and movement over time.
- Predictive capabilities estimate future drone positions based on historical trajectories.

✓ **Real-time ground station communication:**

- The tracking system transmits real-time information on detected drones, including their positions and IDs, to a ground station.

✓ **Visualization and alert mechanisms:**

- The tracked drones are visualized on the ground station's interface, while alert mechanisms promptly notify operators of any unauthorized or suspicious drone activity.

✓ **Collision avoidance (optional):**

- As needed, a collision avoidance system is integrated to maintain safe distances between the tracking drone and others, implementing avoidance actions when necessary.

✓ **Continuous operation and system resilience:**

- The system is designed for continuous operation throughout the drone's mission.
- It is equipped to handle system failures and ensure robust performance.

✓ **Mission completion and termination:**

- The algorithm concludes when the drone mission is successfully completed.

The drone detection and tracking algorithm with YOLOv4 Tiny involves capturing real-time imagery from a drone's camera, preprocessing the images, and running them through a pre-trained YOLOv4 Tiny model for object detection to identify other drones in flight. Non-maximum suppression is applied to refine the drone detections. Then, a tracking algorithm is initialized to continuously monitor and predict the movements of detected drones, assigning unique IDs to each. The tracked drone information is communicated to a ground station in real-time for visualization and alerts, ensuring the operators are aware of drone activity. Optionally, collision avoidance measures can be implemented. This system operates throughout the drone's flight mission and terminates upon mission completion. The algorithm's specific implementation will depend on the hardware, software, and application requirements.

2.4.1. LSTM (Long Short-Term Memory) tracking algorithm

The tracking of the detected object is a critical task. The control algorithm is dependent on the detection signal. Also, to perform the tracking, it is necessary to use an iterative neural network to establish a relationship between the object's previous steps and its current position. In the system, LSTM (Long Short-Term Memory) was preferred. LSTM has four gates: Forget, Input, Cell State, and Output. Gate of Forgetting: It is the gate that decides which information will be forgotten or kept. Information from the current input (Xt) and the previous hidden state (ht-1) is subjected to the sigmoid activation function. Entrance Gate: It consists of two parts; First, the previous hidden state (ht-1) and the current input (Xt) are passed through a sigmoid process to decide which values to update.

Then, the same two inputs are "tanh” activated to regulate the mesh and multiplied by the sigmoid output (it) to update the cell state (C't). Cell state: Input from the previous cell state (Ct-1), multiplied pointwise by the output of the gate. If the forget output is 0, it discards the previous cell output (Ct-1). This output is punctually added with the input gate output to update the new cell state (Ct). The current cell state will be the entry for the next LSTM unit. Exit port: The hidden state contains information about previous entries and is used for prediction. The exit port regulates the current hidden state (ht). The previous hidden state (ht-1) and the current input (tx) are passed to the sigmoid process. This output is multiplied by the output of the "tank" function to get the current hidden state. The current state (Ct) and the current latent state (ht) are the final outputs of a conventional LSTM unit.

The primary usage of LSTM in the project;

An algorithm has been developed using the LSTM model to produce solutions against scenarios that may prevent our UAV from being locked during the competition.

ROS and LSTM were used to simulate the drone's detection during flight. Algorithms were designed to create and develop the Vechür-SIHA software to perform air combat maneuvers and to ensure that the system performs accurately. Drone detection was simulated in the ROS gazebo environment. The ROS communication diagram is demonstrated in Figure 6.

3. RESULTS AND DISCUSSION

The designed system can perform duties at an altitude of 2 km within 17 minutes of flight time. The selected engines are strong enough to accelerate the UAV, which weighs approximately 4 kg to 15 m/s. A camera with a minimum resolution of 2 MP and a wide angle of up to 170 degrees can detect other UAVs. The captured images will be processed with the artificial intelligence algorithm working on the embedded computer, which can perform 21 trillion operations per second with 48 tensor cores on it. Thus, a UAV with the infrastructure that can perform tasks that require high processing power, such as target detection, maneuver estimation, and tracking, was made without any error. The Vechür-SIHA can transmit flight telemetry data to the ground station at a range of 40 km, in an end-to-end encrypted manner and with very low delay. In addition, the video transmission system is designed to transmit images at a range of approximately 4 km with delays of less than 30 milliseconds. In addition to directing to the surrounding UAVs with the data received from the ground station, it will contain sub-systems that can follow the course with SLAM algorithms to control its route and prevent crashing. Tests were carried out during flight; By recording parameters such as flight time, delay, and the internal temperatures of the engines during a mission when the aircraft is fully loaded.

Today, it is undeniable that UAVs provide a significant advantage to countries in terms of reconnaissance, surveillance, and usage as a weapon system, asymmetrical effect, and cost-effectiveness. The primary evidence for the dimensions and sizes of these vehicles vary according to the desired performance and uses. The vehicle family has been expanded according to the variety of weapons and ammunition they carry. The study focused on UAV technologies and subfields [1,2].

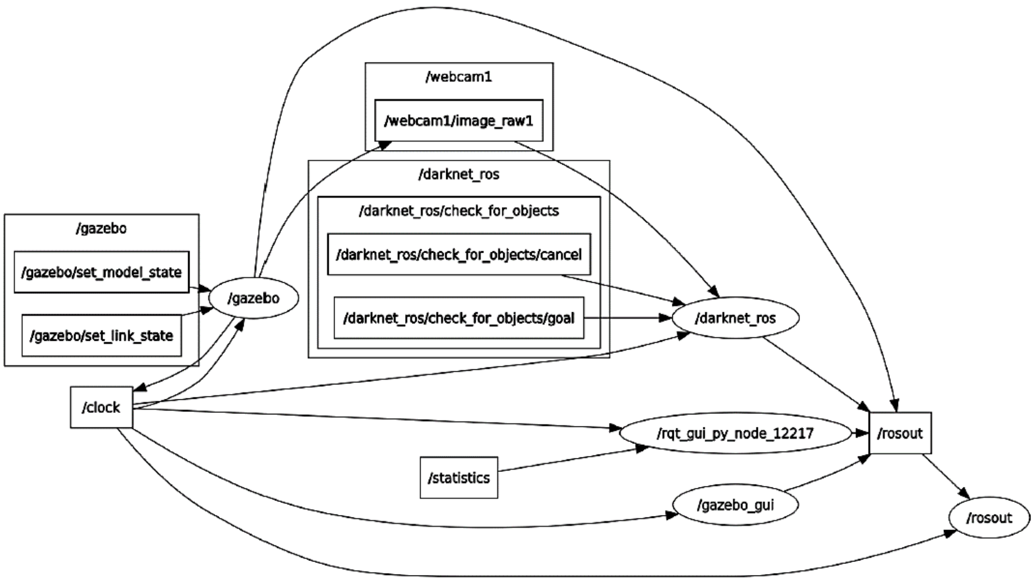

Figure 6. ROS communication diagram

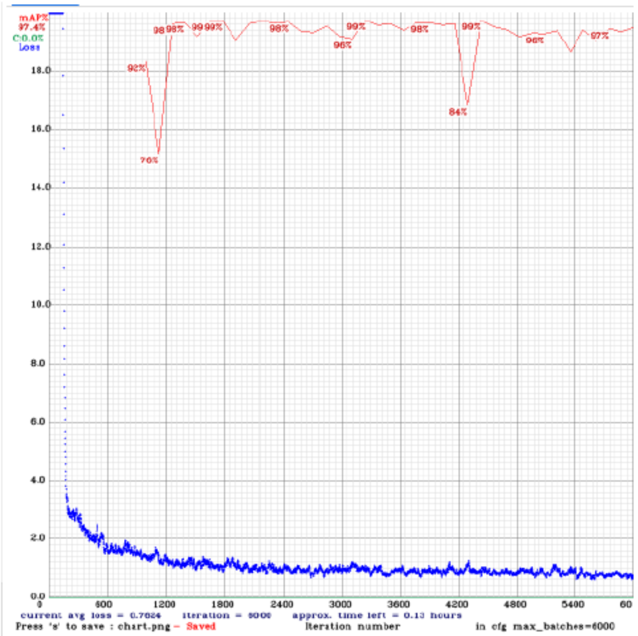

Figure 7. Yolov4-tiny model training results.

Designed system ROS simulation results, Deep learning model prediction results, and system integration was demonstrated in this section. The real-time performance and accuracy comparison shows that the performance of the YOLO structure is better than the other models compared to the FPS and AP (Accuracy Points) [1-3].

Table 1. YoloV4 and YoloV4-Tiny model training results.

Model	Accuracy	Loss	FPS
YoloV4-Tiny	%97	%0.323	10.10
YoloV4	%98.5	%0.124	7
YoloV4-Tiny			TensorRT 24.99 FPS

Table 2. Hyperparameter optimization for YoloV4-tiny

Hyperparameter	Range or Options
Learning Rate	[0.001]
Batch Size	[16]
Number of Epochs	[120]
Backbone Architecture	[CSPDarknet53]
Anchor Box Scales	[[2, 4], [1, 3], [3, 5]]
Anchor Box Ratios	[[0.5, 1.0], [0.75, 1.0], [0.5, 1.5]]
Input Image Size	[416x416]
Data Augmentation	[Yes]
Weight Decay	[0.0001]
Dropout Probability	[0.2]
Optimizer	[Adam]
Learning Rate Scheduler	[StepLR]

The Darknet-53 architecture, consisting of 53 layers of convolution, is used to deepen the YOLOv3 network structure, and residual blocks have been added to this network. Instead of using the softmax function in YOLOv3, the logistic function is used for multi-label predictions. Another critical feature of YOLOv3 is its multiscale prediction, which improves the algorithm's ability to predict small objects. In 2020 the YOLOv4 algorithm was introduced, which is a further development of YOLOv3 [20]. Some new technologies, such as weighted residual links, cross-stepped partial links, and cross-mini-batch normalization, are built into this algorithm to improve the speed and accuracy of object detection. In this context, the YOLOv4-Tiny (416 x 416) architecture is used (Figure 7), which offers the highest real-time performance and prediction accuracy among the current models for small-sized objects suitable for our system.

This dataset was relatively complicated. The background in flight constantly changes. In our dataset, there are several different backgrounds with different drones. After model training, and hyperparameter optimization as shown in Table 2, TensorRT optimization was performed, and the fps was improved from 10 to 25 FPS (Table 1 and Figure 8).

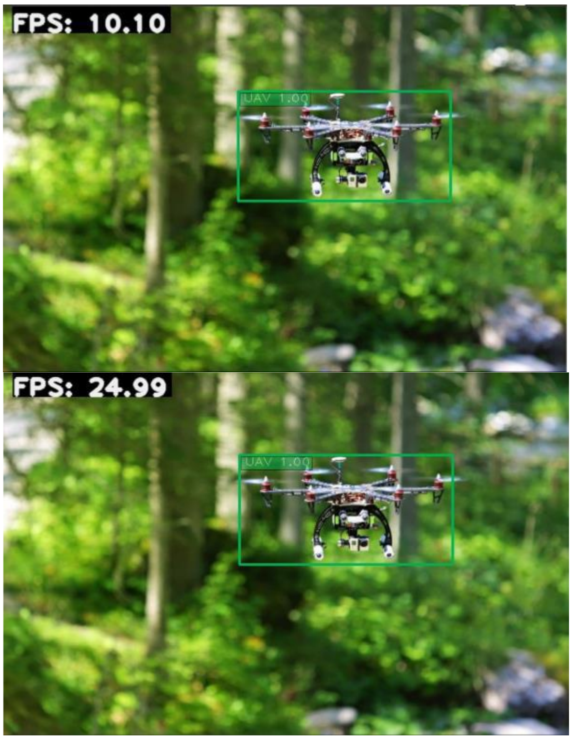

Figure 8. Model training results and TensorRT optimization real-time results

Using the LSTM model, an algorithm was developed to solve scenarios that could prevent the Vechür-SIHA from being locked during the competition.

Some sample scenarios;

- Image distortions,
- Errors in target detection,
- Confrontation with more than one target at a time, algorithm steps for preventing the tracking faults.

The simulations were carried out in ROS and then implemented in the system.

1. The location data of the objects obtained from the YOLOv4 Tiny neural network are obtained on the images.

2. When the target indicated by the target UAV determination algorithm is reached according to the location data shared by the server

a. Comparing GPS orientations of UAVs requested to be tracked even with the presence of more than one UAV in the field of view and the movements of the UAVs detected by the camera,

b. Single target is tracked without restrictions, as in Figure 9 a.

3. Positions detected on the second video frame are estimated by LSTM, as shown in Figure 9 b.

4. In Figure 9 c, the positions of the UAVs from the third video frame are compared to the positions estimated by the LSTM in the second frame, and the UAV with the highest percentage of agreement (IoU) is tracked.

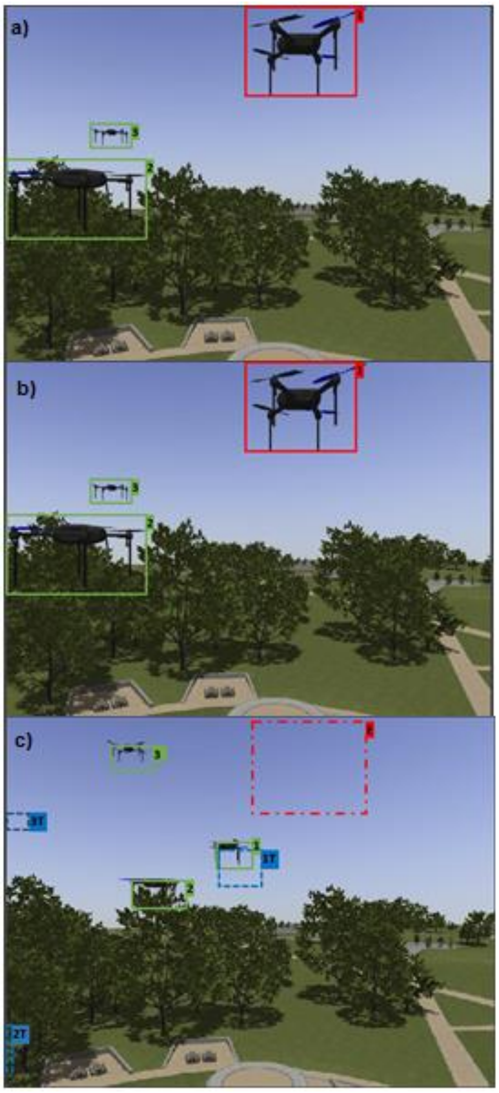

Figure 9. LSTM Location estimation with the red bounding box

Figure 10. Real-time application of Yolov4-tiny Drone detection algorithm.

Escape algorithm; According to the competition terms, Vechür-SIHA is obligated to avoid the ban operation of other UAVs during the competition. In this direction, the movements of the Vechür-SIHA are stored with the LSTM structure, and the outputs of the target tracking system of other UAVs are simulated (Figure 10). The stages of this process;

1) UAV GPS movement is similar to Vechür-SIHA for 5 seconds and is considered a threat, and escape maneuvers were made.

2) By calculating the estimated orientation of the Vechür-SIHA with the LSTM structure, the orientation of the locking quadrant of the other UAVs is estimated.

3) The escape operation is performed when Vechür-SIHA escapes in the opposite direction of the orientation predicted by LSTM.

4) However, when the Vechür-SIHA tries to detect competitor UAVs, the system decides on locking priority within other UAVs.

Real-time UAV detection was made with our developed Drone system. Deep learning and LSTM algorithm were used while Vechür-SIHA was flying. The real-time application of the UAV system example is shown in Figure 11.

LSTM Real-Time Locking Test: In this direction, the LSTM model has been trained, and solutions have been produced for scenarios that may occur simultaneously with more than one target. The trained LSTM model was tested on a YOLOv4-Tiny model with blue caps detected for convenience. Some of the steps performed in the tests;

- Identifying the closest target while in the field of view of more than one UAV at the same time,
- Compensating for frame losses in the target detection model,
- It can be listed as maintaining the visual-locking on the initially determined UAV and completing the tracking without interfering with other UAVs.

Figure 11. Vechür-SIHA system

Target detection and tracking tasks, which are the primary mission of the UAV system, were carried out at the Sakarya University of Applied Sciences football field and Bursa Yunuseli Airport, and the study's final results were obtained. The detection rate of the UAVs displayed in the trials reached 80%, and the follow-up process was carried out. However, the detection rate at Bursa Airport was recorded as 45%. The reasons for achieving such a low detection accuracy were determined as follows.

- Since remote UAVs are difficult to detect and are shown in very-low resolution by the camera and lens technology that is being used,
- Distortions in the images due to the vibrations and shifting of the field of view,
- Detection algorithms for such technical problems of the UAV system need to be implemented with suitable hardware systems,

The relatively low accuracy due to the detection's changing backgrounds made tracking targets challenging.

Therefore, the system was developed with object tracking algorithms to prevent these and improve accuracy. As a result of the trials, 4-10 second locking and tracking of other UAVs was accomplished and was shown in Figure 12.

The intersection of drone technology and deep learning has ignited a transformative era in aerial imagery analysis. This concise summary encapsulates key insights from two seminal papers [21, 22], highlighting the diverse and impactful applications of this fusion.

Figure 12. Real-life application and competition environment.

Resarchers unveil the realm of real-time human action recognition in drone imagery, leveraging deep learning to monitor and identify human activities from aerial perspectives [23]. Another system pioneer the integration of deep learning with RGB and thermal imaging on drones, enhancing monitoring operations with improved situational awareness and precision [24,25].

These groundbreaking studies underscore the potential of deep learning in drone-based imagery analysis, with applications spanning security, infrastructure monitoring, and urban planning. Moreover, they emphasize the need for interdisciplinary collaboration, bridging computer vision, remote sensing, and robotics to advance drone systems.

4. CONCLUSION

The increasing use of commercial drones presents a pressing need for efficient tracking during flight, a complex task due to diverse embedded algorithms and dynamic backgrounds [1-2]. The developed UAV system successfully detects, tracks, and provides information about UAVs in flight, offering the potential to protect against unauthorized UAVs and enhance various applications. However, further improvements are required for more precise tracking and enhanced image acquisition systems [9].

Tracking UAVs in restricted areas holds paramount importance for several reasons. Firstly, it safeguards airspace safety by swiftly identifying and addressing potential hazards, benefiting air traffic and ground safety [15-16]. Secondly, it combats illicit activities such as terrorism and espionage involving drones [17-18]. Lastly, monitoring UAVs aids in managing the increasing congestion of airspace and preventing collisions, a critical concern given the rising number of UAVs [17-18].

Achieving UAV tracking relies on a suite of technologies, including radar, GPS, and computer vision. Radar provides essential data on UAV location, speed, and altitude, while GPS precisely pinpoints UAVs and predicts their trajectories. Computer vision, including object detection and identification, aids in UAV recognition [19].

Real-time data analysis through advanced algorithms and machine learning further enhances UAV tracking, helping identify unusual or hazardous activity [20]. Integration with security and air traffic control systems offers a comprehensive airspace overview, aiding authorities in informed decision-making and ensuring airspace safety and efficiency[22-24].

In summary, effective UAV tracking in restricted areas demands a multifaceted approach, combining diverse technologies and cutting-edge data analysis methods. This comprehensive system is indispensable for upholding airspace safety, security, and efficient management.

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