Fırat Üniversitesi Deneysel ve Hesaplamalı Mühendislik Dergisi

Kritik Görevler İçin Akıllı İnsansız Hava Aracı: Gerçek Zamanlı Görsel Zekâya Sahip Bir VTOL İHA'nın Geliştirilmesi

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Öz

Bu çalışma, arama-kurtarma, gözetleme ve hassas tarım gibi kritik görevler için optimize edilmiş, yerleşik gerçek zamanlı görsel zekâ sistemine sahip sabit kanatlı bir Dikey Kalkış ve İniş (VTOL) insansız hava aracının (İHA) tasarımını, üretimini ve değerlendirmesini sunmaktadır. İHA, hafif ve düşük maliyetli malzemeler ile 3B baskı bileşenleri kullanılarak üretilmiş, bu sayede geliştirme maliyetleri önemli ölçüde azaltılmış ve sistemin hem akademik araştırmalarda hem de saha uygulamalarında erişilebilirliği artırılmıştır. Bu çalışmanın temel katkısı, tamamen açık kaynaklı bir mimari içerisinde VTOL işlevselliğinin, gömülü donanım üzerinde gerçek zamanlı derin öğrenme çıkarımıyla bütünleştirilmesidir. Mevcut İHA'ların çoğu hacimli veya pahalı donanımlara bağımlı iken, önerilen sistem nesne tespitini (YOLOv5s) doğrudan Raspberry Pi 4B üzerinde gerçekleştirerek harici hesaplamaya gerek duymadan verimli yerleşik işlem yapabilmektedir. Üç farklı algılama modeli- YOLOv5s, Tiny-YOLOv4 ve MobileNet-SSD-özel olarak oluşturulmuş bir hava veri kümesi üzerinde eğitilmiş ve gerçek zamanlı performans açısından değerlendirilmiştir. YOLOv5s modeli, %82,4 ortalama hassasiyet (mAP@0.5) ve 4,2 FPS değerleriyle en yüksek doğruluğu elde etmiştir. Modüler ve ölçeklenebilir tasarımı sayesinde, önerilen İHA platformu, gerçek dünya koşullarında akıllı hava sistemlerinin uygulanması için pratik ve ekonomik bir çözüm sunmaktadır.

Anahtar kelimeler: Sabit kanatlı insansız hava aracı, Döner kanatlı hava aracı, Gerçek zamanlı hava gözetimi, Gömülü yapay zekâ, VTOL İHA

*Yazışılan yazar

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Smart Drone for Critical Missions: Development of a VTOL UAV with Real-Time Visual Intelligence

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Abstract
This study presents the design, construction, and evaluation of a fixed-wing Vertical Take-Off and Landing (VTOL) unmanned aerial vehicle (UAV) equipped with an onboard real-time visual-intelligence system optimized for critical missions such as search and rescue, surveillance, and precision agriculture. The UAV was built using lightweight, cost-effective materials and 3D-printed components, which considerably reduced development costs and improved accessibility for both academic research and field applications. A central contribution of this work is the integration of VTOL functionality with real-time deep-learning inference on embedded hardware within a fully open-source architecture. Unlike most existing UAVs that depend on bulky or expensive hardware, the proposed system performs efficient object detection (YOLOv5s) directly on a Raspberry Pi 4B, enabling onboard processing without external computation. Three detection models-YOLOv5s, Tiny-YOLOv4, and MobileNet-SSD—were trained on a custom aerial dataset and evaluated for real-time performance. YOLOv5s achieved the highest accuracy, with a mean Average Precision (mAP@0.5) of 82.4 % at 4.2 FPS. Owing to its modular and scalable design, the proposed UAV platform offers a practical and affordable solution for implementing intelligent aerial systems in real-world critical-mission environments.

Keywords: Fixed-wing drone, Rotating-wing aircraft, Real-time aerial surveillance, Embedded AI, VTOL UAV

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1. Introduction

Drone technologies are rapidly advancing and have been increasingly adopted across sectors such as defense, healthcare, and agriculture in Turkey. This study focuses on the practical development of unmanned aerial vehicles (UAVs), addressing key aspects of their design, construction, and application. UAVs can be categorized into four main types according to their structural configuration: fixed-wing, rotorcraft, flapping-wing, and unconventional designs [1]. The chronological evolution of fixed-wing UAVs has progressed through nine main stages, as shown in Figure 1.

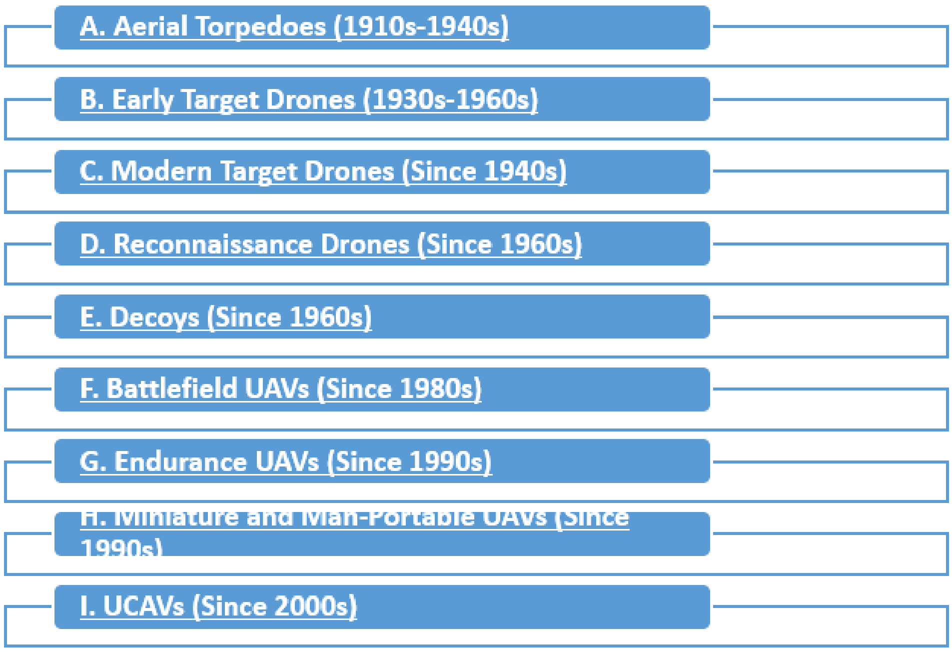


Figure 1. History of fixed-wing UAV

Figure 2 shows the commercial UAV market growth from 2010 to 2025. A substantial increase occurred between 2012 and 2017 for communication-related applications. UAV-based inspections have also expanded rapidly since 2010, particularly in assessing infrastructure such as power lines, solar panels, bridges, and wind turbines [2, 3].

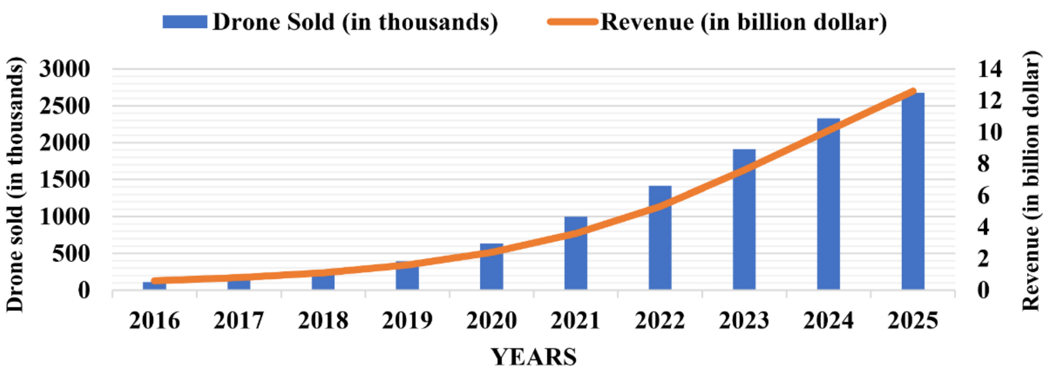


Figure 2. The forecasted global market growth for commercial drones (Buchholz, 2019)

For visual inspection tasks, UAVs are generally classified as rotary-wing or fixed-wing. Fixed-wing UAVs provide longer flight ranges and are suitable for wide-area surveillance and monitoring. Their ability to capture images over large distances is advantageous, although they require more space to change direction and have slower response times. Rotary-wing UAVs, by contrast, are better suited for confined environments such as cities or construction sites. They can take off and land vertically and maintain stable hovering, making them effective for short-distance missions and aerial imaging [4, 5]. However, vibrations caused by rotor movement may reduce image stability in some cases.

Compared with fixed-wing aircraft, rotary-wing UAVs provide greater maneuverability and are well-suited for capturing horizontal imagery over medium-sized areas [6]. The main advantages and disadvantages of both types are summarized in Figure 3 [7].

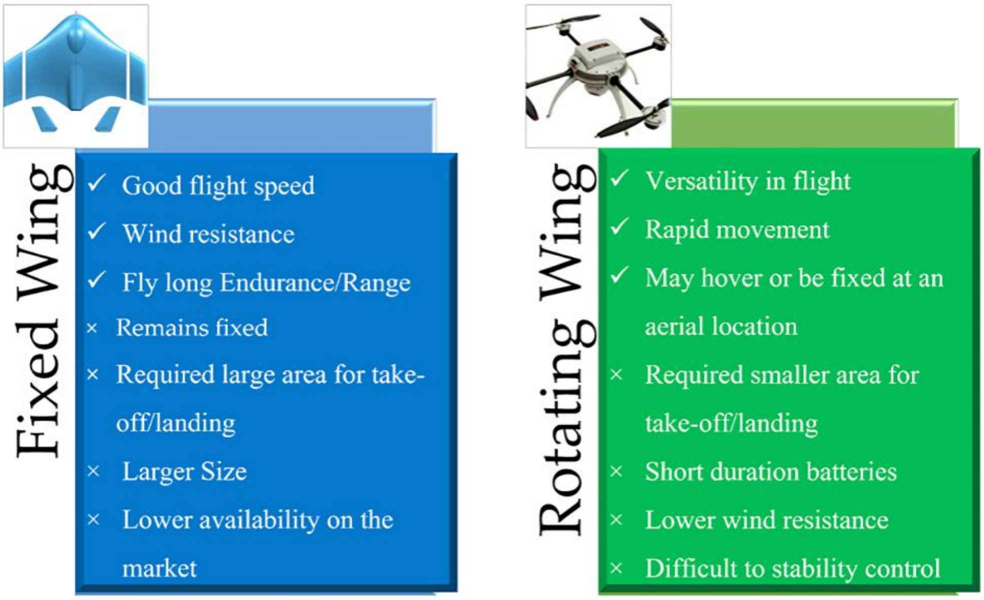


Figure 3. Main Different Between Fixed and Rotating Wing Airplane (Advantages '✓' and disadvantages '×')

UAVs are now used widely in defense, disaster management, environmental monitoring, and logistics. Their autonomous operation across different terrains makes them valuable for missions such as search and rescue, aerial surveillance, and payload transport. Fixed-wing VTOL drones combine long-range efficiency with vertical take-off and landing capability, removing the need for runways while retaining the endurance benefits of fixed-wing designs [5, 8]. Despite these strengths, research on cost-effective UAVs equipped with onboard artificial intelligence remains limited. Many commercial systems depend only on basic sensors, highlighting the need for affordable UAVs that can perform real-time inference to support situational awareness and autonomous control [9, 10].

This study adopts a dual focus: (1) the design and construction of a low-cost fixed-wing VTOL UAV and (2) the integration of real-time object detection using deep-learning models on embedded hardware. The UAV was developed around the FY-41AP flight controller and inspired by the Titan Cobra VT airframe, a 2 m-wingspan quad-plane known for efficient VTOL performance. The onboard vision system employed a YOLOv5s model on a Raspberry Pi 4B, trained on the COCO dataset and an additional custom aerial dataset to enhance detection accuracy. The system achieved a 5.5-kg payload capacity and supported surveillance operations at altitudes between 30 and 60 m. Comparative evaluation of YOLOv5s, MobileNet-SSD, and Tiny-YOLOv4 demonstrated the feasibility of real-time, low-power AI detection. Future enhancements will include thermal imaging, autonomous mission planning, and multi-UAV coordination. By combining practical UAV fabrication with onboard intelligence, this work provides a scalable and adaptable platform for security, search-and-rescue, environmental monitoring, and precision agriculture.

Unlike prior works that focused separately on UAV flight performance or AI model development, this study contributes a systems-level innovation. It demonstrates the integration of real-time object detection on a low-cost, fixed-wing VTOL UAV using only open-source hardware and software. The novelty lies not in proposing a new theoretical model but in the applied deployment, optimization, and real-world validation of

AI-powered UAV systems under resource constraints. This approach lowers barriers for research and humanitarian applications by providing a replicable, scalable, and affordable platform.

1.1. Literature Review

Numerous studies have investigated UAV applications across specific domains. For example, one study developed and tested a UAV for the 2022 AIAA Design/Build/Fly competition, targeting vaccine delivery and humanitarian operations during the COVID-19 period [11]. Another experimental work verified the feasibility of UAV-based building inspections in areas that are difficult to access [12].

Studies on UAV noise perception have identified gaps in psychoacoustic evaluation and regulation, highlighting the importance of systems that balance technical efficiency with public acceptance [4]. In robotics, UAVs have been applied to autonomous wall-building tasks using RGB-D sensing and cooperative path planning. Research on tilt-rotor platforms such as TURAC has advanced understanding of low-cost prototyping and flight validation but mainly addressed mechanical performance rather than onboard AI integration. Overall, few investigations have examined affordable, AI-enabled fixed-wing UAVs that perform real-time inference in flight using open-source hardware and modular design [13].

The integration of YOLO algorithms with UAVs has recently gained momentum, enabling real-time object detection across many fields. A comprehensive review describes the evolution of YOLO-based UAV technology (YBUT) and its applications in engineering, agriculture, automation, and transportation. The review also suggests future directions for interdisciplinary development [14].

Another important research area in UAV systems is Simultaneous Localization and Mapping (SLAM), which supports autonomous navigation. Recent studies have examined SLAM and data-fusion techniques such as Kalman filters and visual odometry, emphasizing sensor fusion for accurate perception and object detection. These findings highlight continuing challenges and research opportunities in SLAM-based UAV navigation [15].

Mobile object-detection systems face similar performance constraints when UAVs operate in limited environments. A comparative study evaluated 22 lightweight CNN models from the MobileNet and EfficientDet families on seven mobile devices, showing trade-offs between detection accuracy and latency. The results underline the need for further optimization of CNNs in embedded applications [16].

Within Intelligent Transportation Systems (ITS), UAVs serve as valuable mobile data-collection platforms. Recent surveys group existing contributions into Functionality, Application, and Planning categories, highlighting UAV roles as aerial base stations and emergency responders. The studies also summarize common simulation environments and datasets used for testing and identify key challenges for integrating UAVs into ITS infrastructure [17].

The deployment of advanced object-detection models such as YOLOv4-Tiny on edge devices has become a major focus area. Recent research demonstrated that a quantized YOLOv4-Tiny model on Raspberry Pi 5 achieves fast inference and low power consumption for aerial emergency detection, confirming the feasibility of energy-efficient AI systems for real-time safety-critical applications [18].

UAVs have also shown strong potential in early forest-fire detection through multisensor fusion. A recent study introduced the FFDM-F model, which combines visible and infrared imagery to improve fire-detection precision by over 10 % and reduce false alarms. This approach demonstrates the benefits of multisource image fusion for environmental monitoring using UAVs [19].

Unlike earlier studies that addressed either flight performance or AI model development separately, the present research combines both aspects in a practical methodology. It integrates real-time onboard object detection with a VTOL-capable fixed-wing UAV using open-source components. This approach targets cost-sensitive and mission-critical applications that require both endurance and edge-intelligence capabilities.

2. Materials and Methods

2.1. Main components

2.1.1. Airplane 3D printed model

The fuselage forms the central structure of a fixed-wing aircraft, providing balance and ensuring aerodynamic stability during flight. To meet these design requirements, a commercially available 3D model was obtained from an online vendor. The selected airframe, Titan Cobra VT (Figure 4), is a quad-plane with a 2-m wingspan designed for smooth takeoff and landing, even under challenging conditions. The A-tail configuration enhances roll and pitch control during forward flight. The design files and assembly instructions are publicly available on the Titan Dynamics website [10].

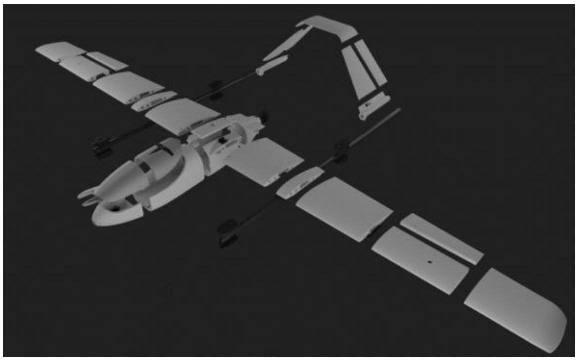


Figure 4. Titan cobra design from titan dynamics

2.1.2. 3D printer

Utilizing a 3D printer involves the transformation of digital designs into tangible objects through the sequential addition, fusion, and solidification of multiple layers of material. For this study, the Creality Ender 3 Pro printer was employed.

2.1.3. Flight ontroller

As shown in Figure 5, the FY-41AP flight controller was utilized in this study. Designed for FPV flight on both fixed-wing and multi-rotor aircraft, the FY-41AP serves as an inertial attitude measurement instrument. Equipped with an integrated OSD video overlay system, it offers crucial flight data such as power management, airspeed, altitude, and flight direction through an electronic compass, ensuring clear visual guidance while keeping essential information readily visible. The latest iteration of the FY-41AP features enhanced altitude control and a GPS module, enabling improved pinpoint inertial navigation and automated piloting capabilities. Flight stabilization is achieved through a combination of integrated sensors including a 3-axis gyro, 3-axis accelerometer, 3-axis magnetometer, and a barometric pressure sensor. For seamless installation, detailed instructions are provided on the manufacturer's official website [20].

Figure 5. FY-41AP Autopilot module

2.1.4. ESC (Electronic speed controller)

The Electronic Speed Controller (ESC) regulates motor speed and ensures reliable propulsion performance [21]. In this study, an 80-A Skywalker ESC was used to control motor operation, as shown in Figure 6.

Figure 6. ESC circuit used in project

2.1.5. Brushless motor

A brushless DC motor operates using three-phase AC input and replaces the mechanical commutator of brushed motors with an electronic controller [22]. The Sunnysky X3520-KV520 motor (Figure 7) was selected based on its performance specifications and suitability for UAV propulsion.

Figure 7. Sunnysky x3520 kv520 motor

2.1.6. Electric propeller

The chosen electric propeller is a two-bladed fan tailored for specific applications within our field. Each fan is identified by a four-digit code, with the first two digits denoting its length and the latter two indicating the blade inclination. Our selection, the APC12*6 fan, was made following careful consideration and consultation of the engine efficiency table (Figure 8).

Figure 8. APC 12 x 6 electric propeller

2.1.7. Servo motors

Servo motors are precision electric motors renowned for their ability to rotate machine parts with exceptional accuracy. Equipped with a control circuit providing real-time feedback on the motor shaft's position, these motors ensure precise rotational movements. In our project, we require four units of the Emax ES08MAII servo motor (Figure 9) to facilitate controlled movements over various distances and angles.

Figure 9. Emax ES08MAII servo motor

2.1.8. RC 2.4Ghz transmitter

The RC transmitter, operating wirelessly on the 2.4GHz spectrum and depicted in Figure 10, serves as a pivotal device through which the aircraft pilot transmits control commands directly to the receiver. This communication mechanism enables manual control over the aircraft, allowing for seamless maneuvering during flight operations.

Figure 10. Flysky FS-i6 FS I6 2.4G 6ch RC transmitter controller

2.1.9. Receiver

The receiver plays a critical role in establishing wireless communication between the controller and other aircraft components. Utilizing a 2.4GHz WiFi connection, the receiver (such as the Flysky RC FS-iA6B

Receiver shown in Figure 11) ensures efficient data transmission, directly interfacing with the controller to facilitate precise control over the aircraft.

Figure 11. Flysky RC FS-iA6B receiver

2.1.10. Li-po battery

Rechargeable lithium-polymer (Li-Po) batteries are widely used in electric aircraft due to their high energy density. As shown in Figure 12, this project used eighteen 18650-type cells (3.7 V, 2200 mAh, 20 C discharge rate) to supply consistent power for flight operations [23, 24].

Figure 12. 18650 Battery

2.1.11. MS battery management system

The definition of BMS varies from application to application. In general, BMS refers to a management scheme that monitors, controls, and optimizes an individual's performance or multiple battery modules in an energy storage system. The BMS, depicted in Figure 13, or Battery Management System, plays a crucial role in optimizing the performance and safety of the battery system. This intelligent management scheme monitors, controls, and safeguards individual or multiple battery modules within the energy storage system. In our application, the BMS ensures optimal battery performance while implementing safety protocols to mitigate risks during operation [25].

Figure 13. The 6s bms circuit capable of charging 6 cells in series

2.1.12. Carbon fiber rods

Carbon fiber rods were selected for their high strength-to-weight ratio and flexibility. Each rod consists of carbon fibers embedded in a resin matrix to provide stiffness and durability. In this project, the rods were installed within the wing structure to increase rigidity and resistance to stress during flight, as illustrated in Figure 14 [26].

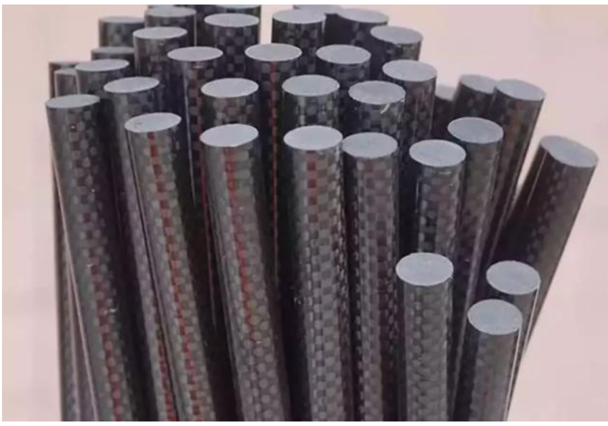


Figure 14. Carbon fiber rods

2.1.13. Raspberry Pi 4B as the edge ai processor

The Raspberry Pi 4B was used as the onboard computing unit for real-time object detection. It features a quad-core Cortex-A72 (1.5 GHz) processor, 4 GB RAM, integrated Wi-Fi/Bluetooth, and dual-display outputs (Figure 15). The board processed aerial images during flight and executed deep-learning inference tasks. It also interfaced with the camera module for image capture and data transfer [27].

Figure 15. Raspberry Pi 4B used for onboard AI processing

2.1.14. Camera module-raspberry pi camera V2

For aerial image acquisition, the UAV utilizes the Raspberry Pi Camera Module V2, a lightweight and high-definition imaging unit capable of recording 1080p video and capturing 8-megapixel still images. It connects to the Raspberry Pi via the Camera Serial Interface (CSI) port and enables low-latency, high-resolution video capture in real time (Figure 16). This module was selected based on its compact size, proven compatibility with the Raspberry Pi ecosystem, and minimal power consumption, making it well-suited for embedded UAV applications [28].

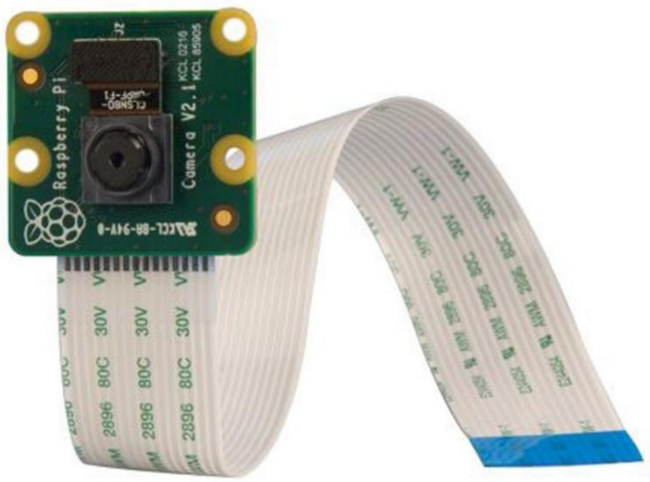


Figure 16. Raspberry Pi Camera V2 module used for capturing real-time video feed

2.1.15. Object detection model and deployment framework

The YOLOv5s (You Only Look Once v5 – small variant) model was adopted for onboard object detection due to its optimal balance between inference speed and detection accuracy. Initially pre-trained on the COCO dataset, the model was subsequently fine-tuned using a custom aerial dataset comprising 300 images collected during UAV test flights. For deployment on the Raspberry Pi, the trained YOLOv5s model was converted to the ONNX format and executed using PyTorch Mobile, ensuring compatibility with resource-constrained edge environments [29].

2.1.16. Custom Dataset and Annotation Workflow

To tailor the detection model for aerial perspectives, a domain-specific dataset was developed using imagery captured at altitudes of 30 to 60 meters during UAV missions. The collected images were manually annotated using the Roboflow platform, with bounding boxes applied to key object classes such as person, car, and truck [30]. This annotated dataset was then used for transfer learning, allowing the YOLOv5s model to adapt to the specific visual characteristics and viewpoints encountered in UAV-based surveillance tasks [31].

2.2 Design and development

2.2.1 UAV body design

The pinnacle of any product's journey lies in its design phase. In the case of this UAV body, meticulous attention was given to crafting its form and function using Ultimaker Cura software, showcased in Figure 17. The printing and assembly instructions, pivotal for bringing this design to life, were sourced from the Titan Dynamics website. The final assembly stage resulted in a functional UAV that integrates all structural and electronic components into a ready-to-fly platform.

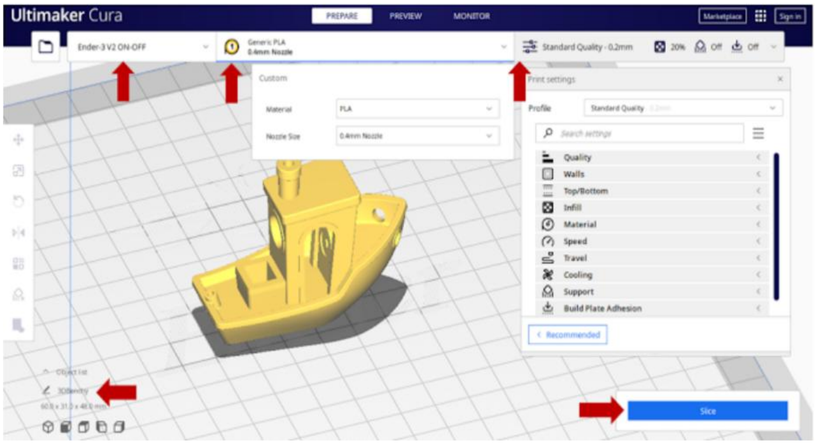


Figure 17. Ultimaker cura main interface

To execute the printing process, the Creality Ender 3 Pro Printer was selected for its precision and reliability. It served as the cornerstone in materializing the various components of the airplane body, as illustrated in Figure 18.

Upon completion of the printing and assembly stages, our UAV reached its final state, exemplified in Figure 19. This culmination represents the culmination of meticulous planning, precise execution, and unwavering dedication to crafting a functional and formidable aerial vehicle.

Figure 18. The creality ender 3 pro printer used in making parts of fixed-wing aircraft

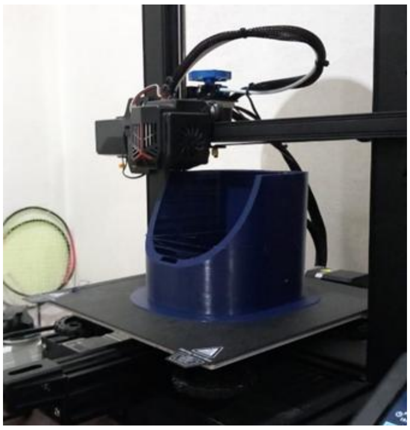


Figure 19. AUV parts assembly process

2.2.2. Electrical connection

The electrical system comprises key components including the FY-41AP flight controller circuit, LiPo battery, GPS module, ESCs (Electronic Speed Controllers), brushless motors, receiver, and four servo motors. Power from the battery is efficiently distributed to both the FY-41AP controller board and ESCs. Each ESC is individually linked to its respective brushless DC motor, ensuring precise control over propulsion. The GPS module and receiver interface directly with the FY-41AP controller board. Upon receiving signals from the transmitter, the receiver relays this information to the FY-41AP controller, which acts as the central hub for processing commands. This control board then disseminates control signals to all interconnected components, orchestrating seamless operation.

The GPS module serves a critical role in navigation, facilitating path-finding capabilities for the UAV. ESCs, on the other hand, regulate the speed of brushless motors, optimizing performance and maneuverability. The comprehensive electrical connection setup is depicted in Figure 20, showcasing the culmination of meticulous wiring and integration efforts

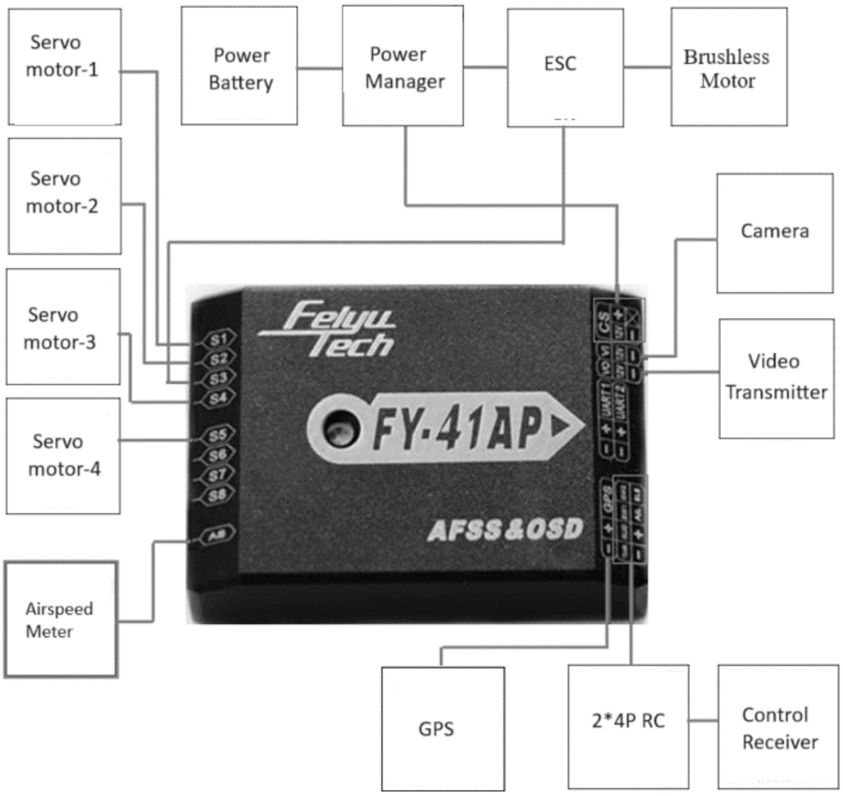


Figure 20. Electrical connection for AUV

2.2.3. Flight controller configuration

The configuration process for the flight controller involved the utilization of the FYGCS 5.11 application, illustrated in Figure 21. This specialized application is tailored specifically for the FY-41AP flight controller, offering unparalleled efficiency and user-friendly adjustment capabilities. Renowned for its intuitive interface and streamlined functionality, the FYGCS 5.11 application simplifies the configuration process, distinguishing it from other controllers in terms of ease of use and efficiency.

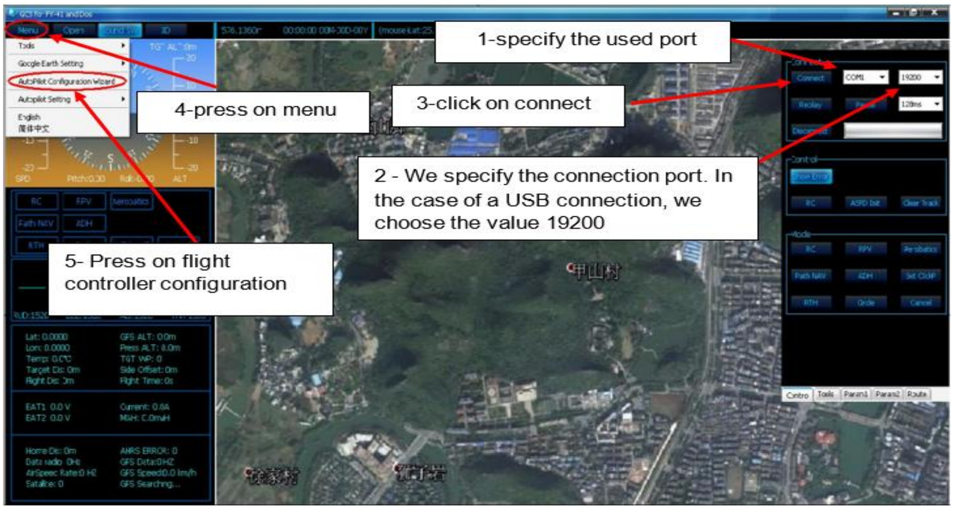


Figure 21. Fygcs 5.11 main interface

To finalize the configuration process, we must follow the six steps outlined in Figure 22:

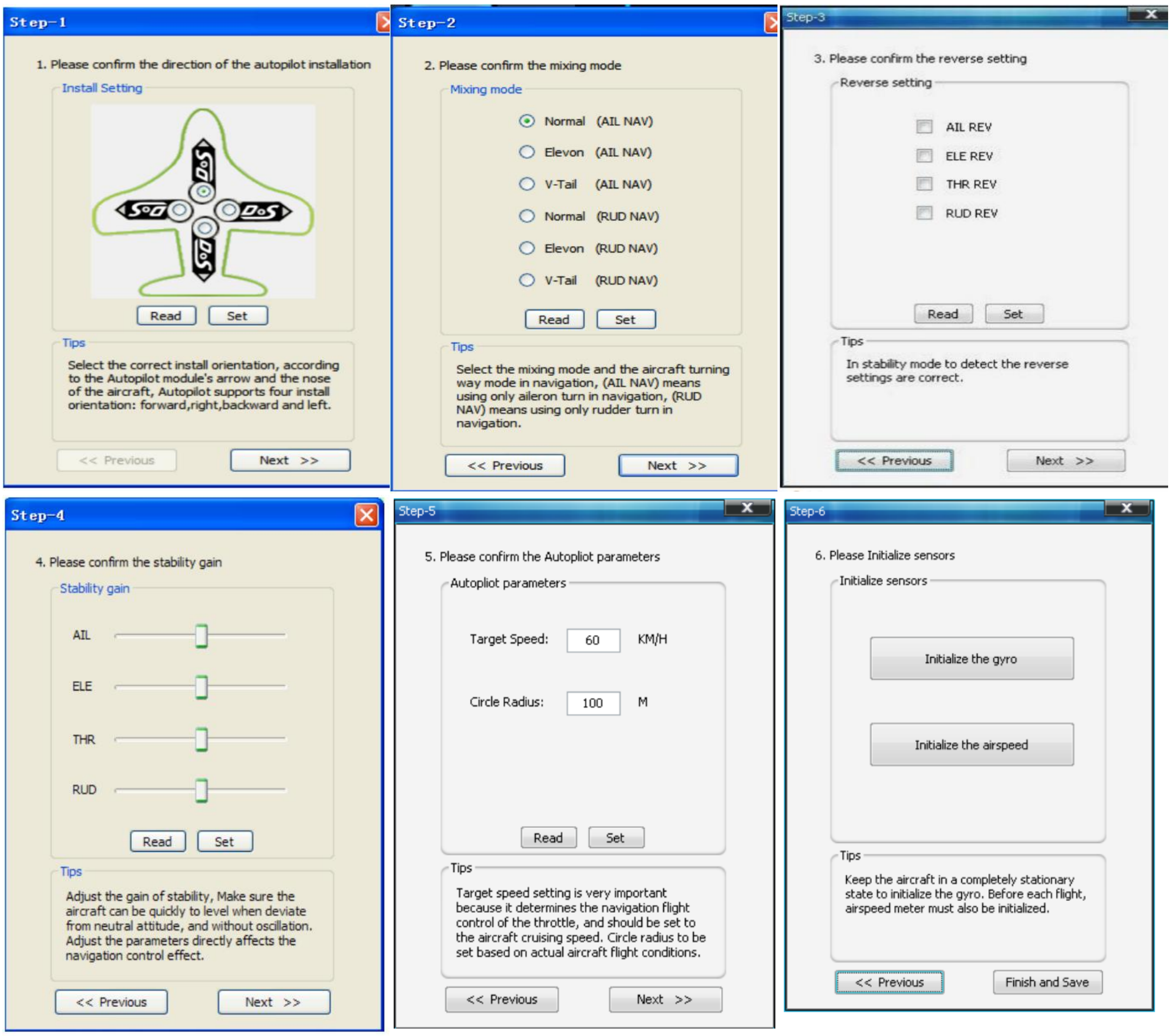


Figure 22. The main flight controller configuration steps

Following meticulous adjustments within the application, the stabilizer settings of the fixed-wing drone were finely tuned, ensuring optimal performance and stability during flight operations. This comprehensive configuration process represents a critical step in the preparation of the UAV for successful deployment and mission execution.

2.2.4. Selecting batteries

To ensure our ESCs and brushless motors receive the optimal voltage of 26V for peak performance, we've selected Samsung INR18650 LiPo batteries for our study. These batteries boast a nominal voltage of 3.7V and a maximum voltage of 4.2V when fully charged.

To achieve the required 26 V output, six 4.2 V batteries were connected in series, resulting in a total maximum voltage of 25.2 V. In series configurations, voltage adds while capacity remains constant; in parallel configurations, capacity adds while voltage remains the same (Figure 23). This setup ensured stable and efficient power delivery to the propulsion system [32].

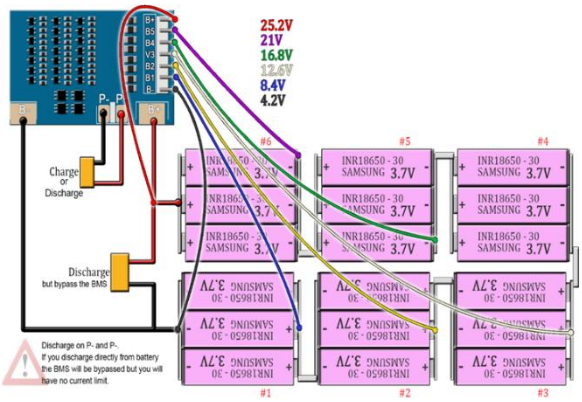
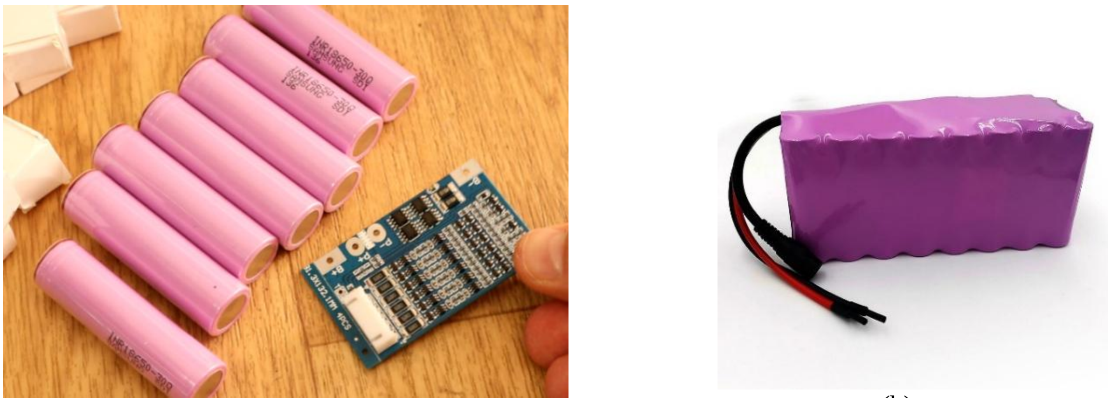


Figure 23. 6S BMS connection

As depicted in Figure 24, during the battery assembly process, it's crucial to consider the utilization of connectors capable of effectively transmitting high currents. This ensures that the battery operates with the requisite efficiency needed to power the engine optimally. Additionally, it's imperative to verify the circuit output values using a multimeter to validate the accuracy of the connections. By adhering to these procedures, we guarantee a reliable and robust electrical system, essential for the smooth operation of our UAV.



(a) (b)

Figure 24. BMS circuit and batteries (a) before assembly (b) after assembly

2.2.5. Movement mechanism and function of the moving parts in the fuselage

Before flight, it is essential to perform automatic movement checks on the aileron, elevator, and rudder servos to verify proper functionality, following the manufacturer's instructions [33]. For the aileron servo, when rolling the plane to the right, the right aileron should move downward while the left moves upward; the opposite occurs when rolling left. If movement is incorrect, adjust using the AIL dial (Figure 25).

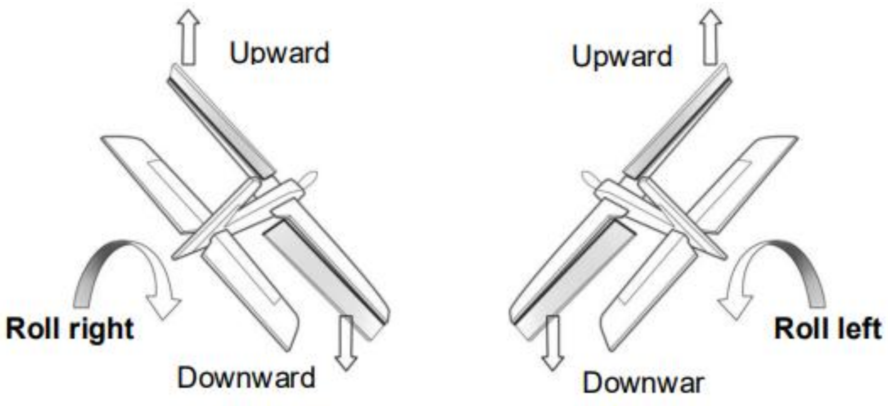


Figure 25. Aileron servo auto movement configuration

For the elevator servo, tilting the nose upward should cause the elevator to move downward, and vice versa when tilting the nose downward; incorrect movement can be corrected via the ELE dial (Figure 26).

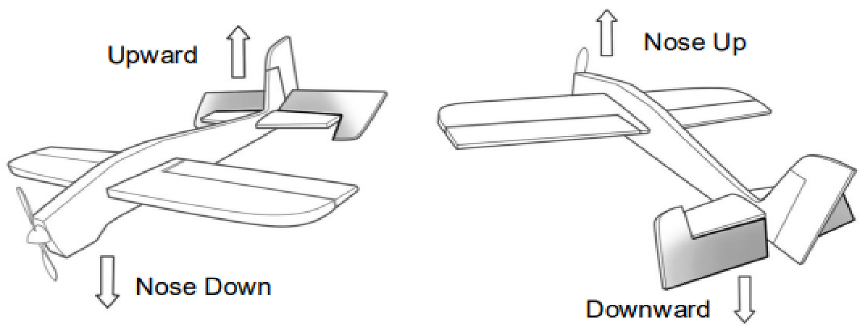


Figure 26. Elevator servo auto movement configuration

For the rudder servo, rotating the plane clockwise should result in the rudder moving left, while a counterclockwise rotation should cause it to move right; use the RUD dial if adjustments are needed (Figure 27). Correct servo response to control inputs is required to maintain flight stability and maneuverability.

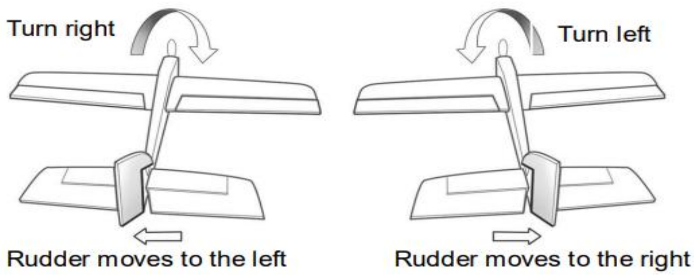


Figure 27. Rudder Servo Auto Movement Configuration

2.2.6. Integration of AI-Based object detection for surveillance

A lightweight object-detection module was integrated to enable real-time aerial surveillance. The onboard Raspberry Pi 4B processed image data captured by a 5 MP camera using a pre-trained YOLOv5s model optimized for edge devices. The model detected objects such as people and vehicles directly during flight. Three detection models-YOLOv5s, MobileNet-SSD, and Tiny-YOLOv4-were compared, with YOLOv5s showing the best balance between accuracy and efficiency.

The model achieved a mean Average Precision (mAP@0.5) of 82.4 % on the test set and an average frame rate of 3–5 FPS, which was sufficient for low-altitude UAV missions. Figures 28–30 illustrate the system architecture and example detections.

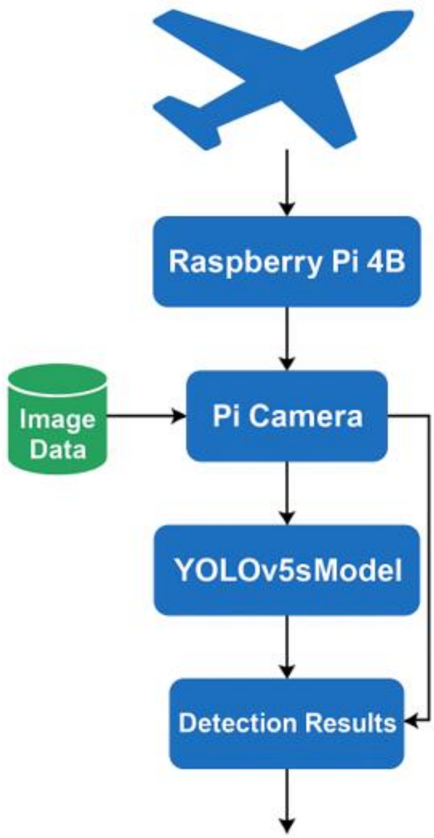


Figure 28. System architecture showing AI-powered object detection integration onboard the UAV

2.2.7. Dataset used for object detection

The COCO (Common Objects in Context) dataset was used to train and fine-tune the object detection model employed onboard the UAV. COCO is a large-scale object detection, segmentation, and captioning dataset containing over 330,000 images, more than 1.5 million object instances, and 80 object categories, including humans, vehicles, animals, and everyday objects [27].

For this work, a subset of the COCO dataset relevant to aerial surveillance was utilized, focusing on object classes such as "person", "car", "truck", and "bicycle". The dataset includes diverse contexts and labeling, which supports training models for outdoor and aerial surveillance tasks. The use of COCO allowed for effective transfer learning, where the pre-trained weights from COCO were fine-tuned with 300 aerial images collected using the UAV itself to improve domain-specific accuracy. This hybrid training strategy helped achieve a balance between general object detection performance and specific optimization for aerial views captured at altitudes between 30 and 40 meters.

3. Results and Discussions

3.1. Testing the aircraft functionality

During installation, all electronic components were positioned to maintain the aircraft's balance. The flight controller was aligned with the center of gravity, and the battery was secured for stability. The aircraft was then suspended under the wings to verify the center-of-mass alignment, which confirmed acceptable balance for stable flight. Ground tests (Figures 29 and 30) verified onboard system functionality and airworthiness.

Figure 29. The fuselage after final assembly and painting

Figure 30. Balance test showing the aircraft suspended from a single wing point

The development process also involved two failed experiments, which led to structural damage:

- In the first trial, the original engine was underpowered and was replaced with a larger motor (Figure 31, left). However, this introduced excess torque, causing uncontrollable rotation and a crash.
- The second failure resulted from a malfunction in the right aileron's servo motor (Figure 31, right), causing the aircraft to spin and crash.

Figure 31. Failed prototypes during pre-takeoff tests

3.2. Successful flight test and payload evaluation

After two unsuccessful trials, the third prototype achieved a stable and controlled flight (Figure 32). Following calibration of all systems, the UAV successfully carried a payload of 5.5 kg, comparable to that of commercial-class platforms. This capacity allows integration of additional mission modules such as sensors, delivery containers, or onboard AI units.

Figure 32. Aircraft used in successful test prior to takeoff

In addition to descriptive observations, the flight performance results were systematically documented to provide clearer insight into endurance, payload capacity, and environmental conditions during testing. Table 1 summarizes the outcomes of all flight trials, including failed attempts and successful missions, along with relevant contextual factors such as wind conditions and payload weights. This structured overview highlights both the challenges encountered during early tests and the stability achieved in the final prototype.

Table 1. Summary of flight test results

Test No.	Flight Duration (min)	Distance Covered (km)	Payload (kg)	Weather/Wind Conditions	Notes
1	0 (failed takeoff)	-	-	Calm	Underpowered motor
2	<1 (crash)	-	-	Light wind (~5 km/h)	Servo malfunction
3	18	12.5	3.0	Calm	Stable flight
4	22	15.2	5.5	Moderate wind (~10 km/h)	Successful, max payload

3.3. Cost analysis

As shown in Table 2, the total component cost was 29.637 TL (≈ 985 USD), which is considerably lower than comparable commercial VTOL UAVs priced between 3.000 and 35.000 USD on online marketplaces [35]. This demonstrates the cost-effectiveness of the developed platform.

Table 2. Component Costs in Turkish Lira

Part	Qty	Unit Price (TL)	Total (TL)
Emax ES08MAII servos	4	400.00	1.600.00
Sunnysky X3520-520KV motor	1	2.031.00	2.031.00
Propeller 12×8	1	100.00	100.00
ESC 60A Skywalker	1	1.800.00	1.800.00
Remote Control (Skydroid T12)	1	6.897.00	6.897.00
18650 Battery	20	120.00	2.400.00
SpeedyBee F405	1	1.400.00	1.400.00
BMS 6S	1	350.00	350.00
Matek M8Q-5883 GPS	1	1.280.00	1.280.00
Polymaker PolyLite LW-PLA (spools)	2	1.800.00	3.600.00
Carbon Fiber Rods	1	3.000.00	3.000.00
Raspberry Pi Compute Module CM5, 4GB RAM	1	3.482.87	3.482.87
Raspberry Pi Kamera Modül V2	1	1.669.42	1.669.42
Total Cost			29.637.29

3.4. Real time performance metrics

A flight mission was conducted to evaluate real-world detection performance. The onboard system identified vehicles and people from aerial video streams. During live operation, the detection model achieved an average rate of 4.2 frames per second (FPS) and a latency of 230 ms on the Raspberry Pi 4B. The AI module consumed less than 4 W of power, producing minimal impact on flight endurance.

A custom aerial dataset was created from images captured during test flights and annotated with Roboflow and LabelImg for object classes (person, car, motorbike). The dataset, combined with COCO images, was used for fine-tuning.

To assess real-time behavior under realistic conditions, test flights were carried out in campus and urban environments containing dynamic objects.

Each scenario included at least 10 test flights, during which the UAV flew at altitudes ranging from 30 to 60 meters. The onboard system was tasked with detecting three target classes: person, car, and motorcycle. The UAV successfully identified all categories across scenarios, demonstrating robustness in diverse conditions.

3.5. Model Selection and comparison

YOLOv5s was selected for its balance of computational efficiency and detection accuracy. The model was compared against MobileNet-SSD and TinyYOLOv4 on the aerial test dataset. In addition to the commonly used mAP@0.5 metric, precision, recall, and F1-score were calculated to provide a more comprehensive evaluation of detection reliability. As shown in Table 3, YOLOv5s not only achieved the highest mAP but also outperformed the other models in terms of accuracy metrics, including mAP@0.5, precision, recall, and F1-score, confirming its suitability for real-time UAV-based surveillance. While MobileNet-SSD exhibited faster inference speed, it lagged in accuracy and overall detection balance.

The evaluation of object detection models was conducted using a curated aerial dataset collected during UAV test flights. As shown in Table 3, YOLOv5s achieved superior performance across all key metrics, including mean Average Precision (mAP@0.5), precision, recall, and F1-score. Specifically, YOLOv5s obtained an mAP@0.5 of 82.4%, outperforming MobileNet-SSD (72.1%) and TinyYOLOv4 (74.6%). In terms of detection reliability, YOLOv5s reached 83.1% precision and 81.6% recall, resulting in an overall F1-score of 82.3%. These results highlight YOLOv5s as the most balanced model, capable of maintaining both accuracy and consistency in real-time aerial surveillance.

Although MobileNet-SSD had the fastest inference speed (≈ 5 FPS), its lower precision (70.4 %) and recall (71.2 %) reduced its suitability for safety-critical missions. Tiny-YOLOv4 offered moderate accuracy but performed below YOLOv5s in all metrics. Overall, YOLOv5s provided the best balance between computational demand and accuracy, confirming its suitability for resource-constrained embedded platforms. This evaluation validates the feasibility of deploying deep-learning-based detection within low-cost UAV systems for real-world applications.

Table 3. Object detection model accuracy metrics on UAV aerial dataset

Model	mAP@0.5	Precision (%)	Recall (%)	F1-Score (%)	Inference Speed (FPS)	Power Draw (W)
YOLOv5s	82.4%	83.1	81.6	82.3	~4.2	<4W
MobileNet-SSD	72.1%	70.4	71.2	70.8	~5.0	<3.5W
TinyYOLOv4	74.6%	73.0	72.1	72.5	~3.8	~4W

3.6. Evaluation and comparative model performance

The object detection module was tested during real-time, low-altitude flight missions (30–40 meters). The YOLOv5s model achieved 4.2 FPS with a latency of 230 ms on a Raspberry Pi 4B, confirming the feasibility of embedded edge-AI for lightweight surveillance tasks in small UAV platforms. Table 4 summarizes runtime metrics such as inference speed, latency, power draw, and edge suitability.

Table 4. Object Detection Model Runtime and Deployment Performance on UAV Aerial Dataset

Model	mAP@0.5	Avg FPS	Latency	Power Draw (W)	Edge Suitability
YOLOv5s	82.4%	4.2	230 ms	<4W	Excellent
MobileNet-SSD	72.1%	5.0	190 ms	<3.5W	Good
TinyYOLOv4	74.6%	3.8	260 ms	~4W	Moderate

While MobileNet-SSD offered marginally better speed, YOLOv5s provided superior accuracy and robustness, making it the optimal choice for this UAV system.

To put the contributions of this work in context, Table 5 compares the developed UAV system against recently related works. In contrast to prior works that adopted multirotor-based platforms or performed offline object recognition, the presented approach makes use of a complete open-source fixed-wing VTOL UAV system with onboard real-time inference. In addition, the developed system supports higher payload capacity and improved energy efficiency while relying on accessible and low-cost hardware components.

Table 5. Comparison of the Proposed UAV with Related Studies

Study	UAV Type	AI Model	Hardware	Real-Time?	Payload Capacity	Open Source	Novelty
Wu et al. [1]	Multirotor	YOLOv3	Jetson TX2	✓	Not specified	✗	Precision agriculture use case
Zhou et al. [5]	Multirotor	YOLOv4-tiny	Jetson Nano	✓	Low	✗	Aerial surveillance, no VTOL
Guerra et al. [4]	VTOL Fixed-wing	–	PX4	✗	4 kg	✗	Terrain mapping only
This Study	VTOL Fixed-wing	YOLOv5s	Raspberry Pi 4B	✓	5.5 kg	✓	Real-time AI on low-cost, modular platform

Note: Reported values represent averages across 10 test runs. Standard deviations for detection accuracy metrics were within ±1.2%, and latency variations were within ±15 ms.

4. Limitations and Future Work

Despite the satisfactory performance of the UAV during testing, several limitations were identified:

- **Altitude constraint:** Detection accuracy decreased at higher altitudes because smaller image scales made objects harder to identify.
- **Lighting sensitivity:** Detection performance declined under low-light or high-glare conditions, limiting operation in certain environments.
- **Computational limits:** The current onboard hardware restricted the deployment of larger models or multi-camera configurations, reducing the potential for complex detection tasks.

Although this study did not propose a new detection algorithm, it demonstrated the practical feasibility of deploying existing deep-learning models on a modular, low-cost UAV platform. The emphasis remained on applied deployment and system-level integration for real-time intelligence in the field.

To overcome these limitations, future research will focus on the following improvements:

- **AI-functionality expansion:** Adding object-tracking capability, thermal-imaging support for night operations, and anomaly-detection features to widen application areas.
- **Flight-autonomy enhancement:** Incorporating AI-based path-planning and obstacle-avoidance algorithms to increase operational safety and independence in dynamic environments.
- **Extended endurance:** Investigating higher-capacity or solar-assisted batteries to lengthen flight time and range.

These developments are expected to improve the UAV system's adaptability and efficiency for use in diverse fields such as security, environmental monitoring, disaster response, precision agriculture, and humanitarian logistics. While initial flight tests confirmed technical feasibility, the sample size was limited. Additional experiments under varied environmental conditions—including wind, temperature, and longer missions—will be required to verify long-term endurance and reliability.

5. Conclusion

This study presents a practical and systematic approach to the design, construction, and testing of a cost-effective VTOL (Vertical Take-Off and Landing) fixed-wing UAV platform. The results demonstrate that advanced aerial systems can be developed with affordable, commercially available components and 3D-printed structures, making the technology accessible to small research groups and institutions with limited resources.

A major contribution of this work is the successful integration of an onboard AI-based object-detection system using the YOLOv5s model on a Raspberry Pi 4B. The UAV performed real-time inference during flight, achieving a mean Average Precision (mAP@0.5) of 82.4 % and an average processing speed of 4.2 FPS at altitudes between 30 and 60 m. These findings demonstrate the feasibility of deploying deep-learning models on low-power edge devices for aerial-surveillance tasks.

The developed UAV also exhibited stable flight behavior, efficient energy consumption (≈ 2.1 Wh per km), and the ability to carry payloads of up to 5.5 kg. With a 4S4P 16800 mAh battery configuration, it achieved an estimated range of 120 km and more than 2 hours of continuous flight, making it suitable for extended missions such as monitoring, inspection, and logistics.

From an economic perspective, the total system cost (≈ 985 USD) is considerably lower than that of comparable commercial UAVs, positioning the platform as a scalable solution for applications in disaster response, security surveillance, environmental monitoring, agriculture, and humanitarian operations. Although performance decreased under low-light or high-altitude conditions, these limitations suggest directions for future work, including the integration of thermal imaging, advanced sensors, and coordinated multi-UAV systems.

In summary, this research indicates that low-cost, AI-enabled UAV systems can be effectively designed for mission-critical applications. The findings provide a foundation for future advancements in autonomous navigation, enhanced sensing, and multi-agent coordination in aerial robotics.

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7. Author Contribution Statement

In the study, Author 1 contributed to conceptualization, data curation, formal analysis, investigation, methodology, validation, visualization, writing – original draft, writing - review and editing.

8. Ethics Committee Approval and Conflict of Interest Statement

Ethics committee approval is not needed for preparing the article. There is no conflict of interest for this article.

9. Ethical Statement Regarding the Use of Artificial Intelligence

During the preparation of this manuscript, the artificial intelligence tool ChatGPT (developed by OpenAI) was used solely for limited purposes such as language editing and translation. All scientific content, analyses, interpretations, and results are the sole responsibility of the authors.

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