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Artificial Intelligence Technologies and Applications Used in Unmanned Aerial Vehicle Systems

Mustafa Cosar
Hitit University

Abstract: An Unmanned Aerial Vehicle (UAV) is an autonomous airborne platform characterized by fundamental flight capabilities, including take-off and landing procedures, navigation, route tracking, and mission execution. UAVs serve civilian and military purposes across various domains, undertaking tasks that surpass human capabilities. These vehicles come in diverse hardware and software configurations, comprising essential components such as take-off and landing systems, navigation modules, emergency response mechanisms, sensory apparatus, imaging instrumentation, and energy supply systems. UAVs exhibit the capability for flight management, target identification, and mission analysis, drawing on data collected from preloaded datasets, control centers, and real-time environmental cues. Leveraging various artificial intelligence (AI) algorithms, UAVs autonomously process instantaneous data, incorporating methodologies such as artificial neural networks, image processing algorithms, learning algorithms, and optimization techniques. This paper analyses data analytics methodologies and AI technologies used by UAVs. Furthermore, an image processing application using a Convolutional Neural Network (CNN) algorithm is implemented to provide object recognition. The object recognition rate of the application developed in Python language was calculated with an accuracy of 0.7107. This finding shows that by using AI algorithms to analyze images acquired through onboard sensors, the UAV's capability to conduct critical operations such as target acquisition, obstacle avoidance and collision avoidance can be improved.

Keywords: UAV, AI, Machine learning, Image processing, Object recognition

Introduction

In recent years, a significant spotlight has been cast on the advancement of systems, underpinned by the contributions of Information Technologies (IT), engineered to provide support in endeavors exceeding human capabilities or encompassing substantial risk. These systems are predominantly identified as robotic systems or AI systems.

The term "Robot," which means "heavy and tedious labor" in Czech, was first coined by Karel Čapek in 1921. The word "Robotics" was first used in 1950 by the science fiction writer Isaac Asimov. Robotics is a software and hardware system utilized to control, disassemble, and assemble a robotic object according to its programmed instructions (Ozfırat, 2009). In the architecture of robotic systems, there are physical components encompassing mechanical, electrical, electronic, and computational modules, along with software components such as operating systems, control software, communication protocols, and task-specific software (Cosar, 2023).

The terms "Robot" and "Robotics" are often used interchangeably, but they do have some conceptual distinctions. "Robot" typically refers to a self-moving entity, whereas "Robotics" encompasses the system that constitutes such an entity. With the addition of AI, these systems become autonomous and capable of collecting data, learning, and solving problems independently. When a robotic system can emulate human behaviors, demonstrating the ability to perform these behaviors, it signifies its intelligence and learning capabilities.

The concept of AI was initially delineated by John McCarthy in 1956 as the 'science and engineering devoted to the creation of intelligent machines, especially intelligent computer programs' (McCarthy, 2007). AI systems are conceptualized to improve upon the present state, identify optimal solutions to problems, and automatically calculate and execute them. Progressing significantly beyond their initial capabilities, AI systems have currently advanced to a level where they can engage in meaningful conversations with humans and provide diverse recommendations, thus functioning at the level of a proficient assistant.

UAVs, commonly known as drones, represent autonomous aerial platforms capable of independently executing a wide spectrum of operations, including takeoff, flight, mission execution, and landing, occasionally making autonomous decisions. UAVs have gained significant traction in both military and civilian domains due to their versatility and advantages, being deployed for tasks such as observation, monitoring, transportation, search and rescue (Cosar, 2022). UAVs, commonly referred to as drones, can operate in two primary modes: remote-controlled and semi-autonomous, or fully autonomous. In the former, they are under remote human control, while in the latter, they exhibit a high degree of autonomy, often assisted by advanced AI technologies, enabling them to independently manage all aspects of their missions.

This study commences by providing an overview of the general architectures and components inherent to UAV systems. It subsequently delves into the realm of AI technologies and their current applications, which bestow upon UAVs their advanced capabilities. Finally, the study presents a practical application in image processing, specifically for object recognition. The article's structural organization unfolds as follows: The second section navigates through the conceptual framework surrounding UAVs and AI technologies, offering insights into exemplary applications and summarizing the pertinent literature. The third section meticulously elucidates the methodology of the exemplar application, expounding on the dataset employed for image processing, the AI algorithm applied, and the algorithmic underpinnings of the program developed using the Python programming language. The fourth section divulges the outcomes of running the Python program, particularly focusing on the achieved accuracy rate in object recognition and the visual outputs. In conclusion, the final section provides an exhaustive assessment that encompasses a retrospective analysis, the current state of affairs, and prospective outlook regarding the technologies under discussion. This study is positioned to make substantial contributions to forthcoming research initiatives within the realms of UAVs and AI technologies.

Conceptual Framework

UAV Systems

UAVs are autonomous aerial robotic systems capable of independently performing takeoff, flight, mission execution, and landing activities, and, in some cases, making autonomous decisions. They consist of mechanical and electronic hardware components, flight control systems, and software components designed for various purposes. In addition, they are equipped with sensors that can collect real-time data from both their own components and the external environment. Moreover, they possess communication modules that facilitate communication with other UAVs, particularly in swarm missions and with ground control centers.

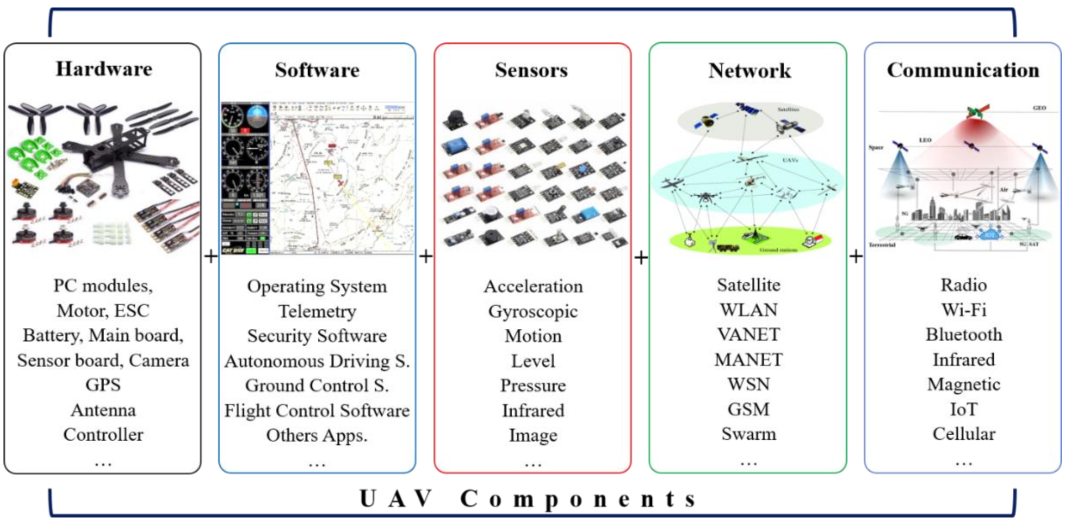

Figure 1. Components of a UAV (Cosar, 2022)

Within a UAV system, the software components encompass autonomous navigation software, image capture and processing software, mapping and route planning software, communication software, mission protocol software, and cybersecurity software. Figure 1 depicts the components of a UAV, as updated from Cosar (2022). Each heading in the figure is accompanied by sub-components. All of these components play various roles in making AI operational. Particularly noteworthy are the sensor components that have the ability to detect internal and external environmental parameters, enabling learning through data analytics and facilitating autonomous decision-making. In addition to these components, UAV systems include a fuselage and wings, which enable the UAV to stay aloft and fly. Under the fuselage, various materials are used for the chassis and connection elements. Another essential component that should not be overlooked is the power source, engine, and power transmission lines that provide energy to the mechanical and electronic components.

UAVs are classified into various categories based on their physical characteristics, wing structure, shapes, and intended applications. UAVs are categorized by their physical attributes into Fixed-Wing, Rotary-Wing, Flapping-Wing, and VTOL (Vertical Take Off and Landing). Furthermore, they undergo a separate classification based on payload capacity and whether they are designed for military or civilian purposes.

The most critical component of a UAV system is the flight control system. This component, organized as a module in terms of both software and hardware, processes data collected from the ground station, the UAV itself, and the surrounding environment during pre-flight, in-flight, and post-flight operations. The flight control system utilizes sensors to collect and process data, subsequently transmitting commands to other UAV components and relaying information to the ground station's computer system via the telemetry module.

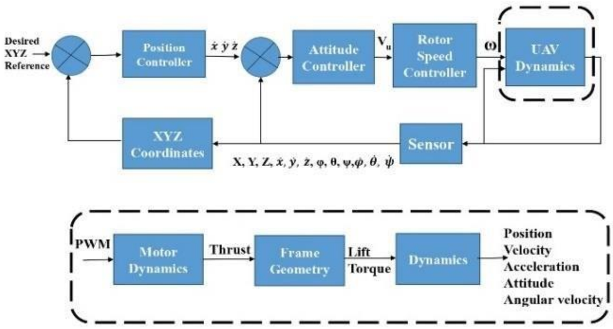

Figure 2. Block diagram of UAV flight control system (Hegde et al., 2020)

Figure 2 illustrates a block diagram of a rotary-wing UAV's flight control system, responsible for managing flight based on parameters such as altitude, distance, coordinates, wing rotation speed, and other variables. This system initially performs measurement and calculation processes to reach ideal position values based on the UAV's position during takeoff, landing, and flight. Subsequently, it calculates the disparities between the current state, as derived from data collected through sensor communication, and the desired state. Based on these calculated values, it initiates crucial processes such as mission and route optimization, triggering the autonomous decision-making process. This loop continuously operates throughout the mission.

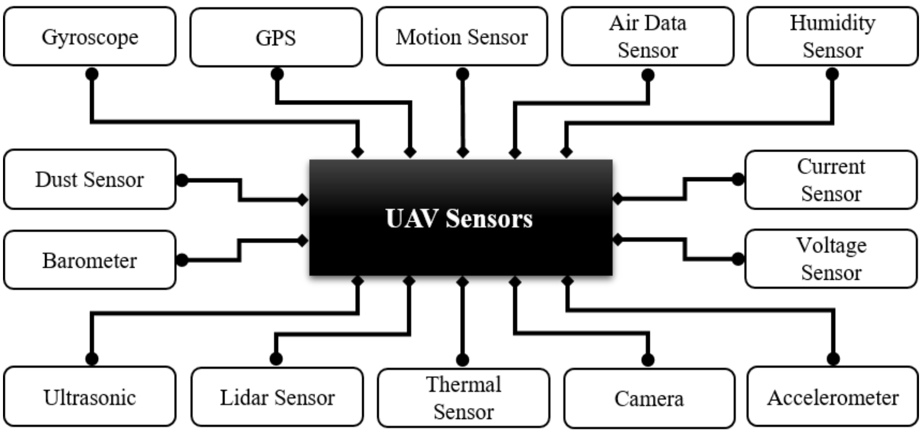

Figure 3. Some sensors found in UAV architecture

One of the most influential components in the convergence of UAVs with AI is the sensors depicted in Figure 3. This component serves as the UAV's sensory organs, providing the data that assists in situational analysis. Below, we introduce the most commonly used sensors in UAV applications.

- GPS Sensor (Global Positioning System Sensor): GPS sensors are employed to determine the UAV's geographical location on Earth, facilitating navigation and route planning. They are essential for mapping flight paths, reaching designated waypoints, and accomplishing mission objectives.
- IMU Sensor (Inertial Measurement Unit Sensor): IMU sensors measure the UAV's speed, acceleration, and angular movements. This data is crucial for maintaining flight stability, refining position calculations, and enabling precise maneuvering during flight.
- Camera Sensor: UAVs use cameras for tasks such as image and video recording, observation, mapping, and object recognition. Camera sensors are utilized to capture and analyze visual data.
- LiDAR Sensor (Light Detection and Ranging Sensor): LiDAR sensors are employed to create high-resolution 3D maps, detect objects, and measure distances accurately. They are particularly valuable for tasks like terrain mapping and environmental sensing.
- Thermal Sensor: Thermal cameras detect temperature variations and are used for operations such as search and rescue, fire monitoring, and identifying water resources.
- Gyro Sensor (Gyroscope Sensor): Gyro sensors are used to detect changes in orientation and rotation. They contribute to maintaining the UAV's stability during flight and enabling precise maneuvers.
- Radar Sensor: Radar sensors are used to monitor air traffic, avoid other aircraft, and ensure safe landings at airports.
- Ultrasonic Sensor: Ultrasonic sensors measure the distance to the ground and are crucial for automatic landings and obstacle avoidance systems.
- Pressure Sensor: UAVs employ pressure sensors to measure atmospheric pressure, providing crucial data for altitude determination and weather analysis.
- Magnetic Field Sensor: A magnetic field sensor is a vital component used for detecting changes in magnetic fields, which aids in orientation and navigation within UAV systems.
- Humidity Sensor: Humidity sensors are utilized to measure atmospheric moisture levels, offering valuable insights into environmental conditions and weather phenomena during UAV missions.
- Current Sensor: Current sensors play a fundamental role in monitoring the electrical current flowing through various components in the UAV's electrical system, ensuring both safety and operational efficiency.
- Voltage Sensor: Voltage sensors are pivotal for measuring electrical potential differences, allowing for the continuous monitoring of the electrical system's status and performance.
- Infrared Sensor (IR Sensor): Infrared sensors capture infrared radiation, enabling thermal imaging and object detection, particularly under low-light conditions, facilitating enhanced situational awareness.
- Compass Sensor: Compass sensors serve as a navigational aid, determining the UAV's orientation concerning Earth's magnetic field, thereby contributing to accurate heading control.
- Distance Sensor: Distance sensors are instrumental in gauging the range between the UAV and objects in its vicinity. They are indispensable for applications such as obstacle avoidance, terrain mapping, and precise landing procedures.

These sensors collectively bolster the sensory capabilities of UAVs, allowing them to undertake a diverse array of tasks and interact effectively with their surroundings.

Artificial Intelligence

AI is the discipline of science and engineering related to the imitation or development of thinking, learning, decision-making and problem-solving abilities that model human behavior in software and hardware systems of computer science. AI possesses a wide range of applications, including the performance of complex tasks, big data analysis, object recognition, natural language processing, autonomous decision-making, and predictive modeling. This technology enables a multitude of innovative applications spanning various domains, from industrial processes to healthcare services, automation systems to intelligent assistants.

Figure 4 depicts the systematic assessment of AI applications over a sequence of stages. The process commences with the transition from extensive repositories of big data, progressing towards meticulously curated, categorized, correlated, processed, and analyzed datasets. Subsequently, leveraging learning techniques, the dataset undergoes profound knowledge extraction. Ultimately, this acquired knowledge facilitates the generation of decisions and actions. It is imperative to acknowledge that this process imposes an additional burden in terms of hardware and software resources. Notably, the computation speed for parameter adjustments and the computational requirements for data processing introduce supplementary expenses and computational workloads for UAVs.

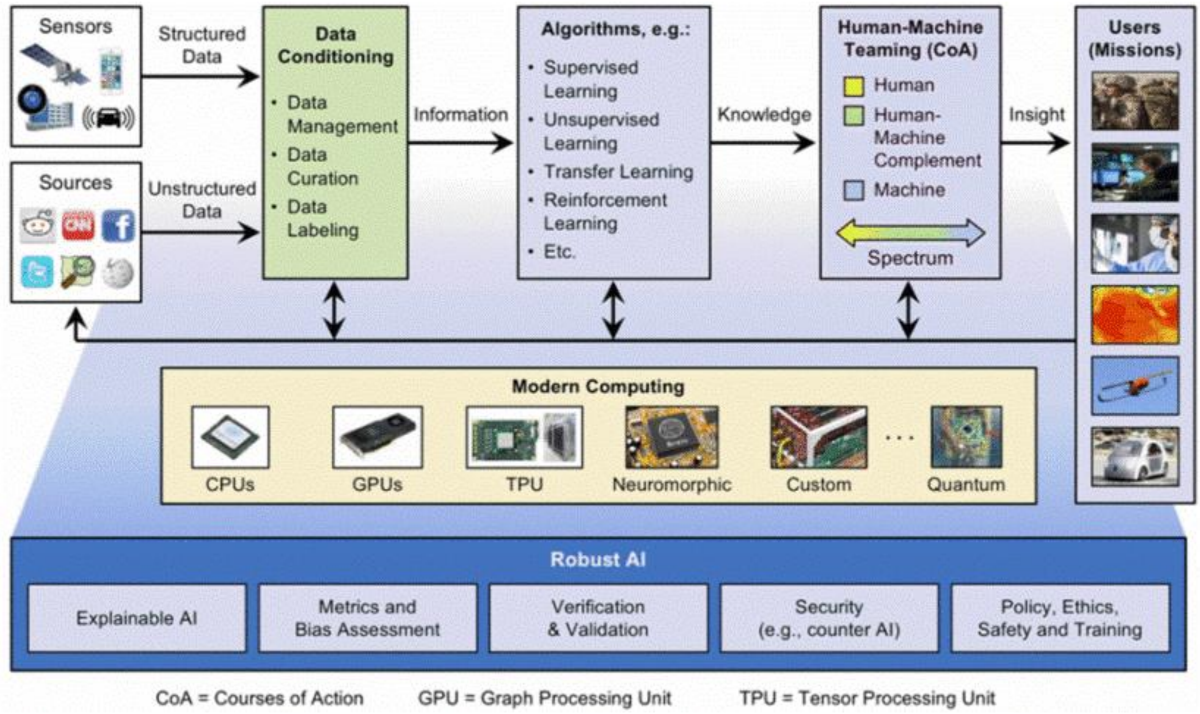

Figure 4. Architecture of a AI system (Reuter et al., 2020)

UAV and AI

AI technologies are prominently employed in processes demanding cognitive functions, such as speech recognition, image perception, autonomous navigation, and positioning. UAV systems have harnessed these AI capabilities to act autonomously and make decisions. In the early stages of UAV utilization, rudimentary challenges were addressed through human-assisted expert systems. As technology evolved, integrating human pilot behaviors to mimic analogous responses, particularly for critical decision-making, became a common practice. In recent times, the growing demand for mission diversity, speed, and energy efficiency necessitates the exploration of alternative technologies. In this context, AI technology emerges as the primary solution. This is attributed to the UAV's requirement to process dynamic environmental variables continuously and in real-time during flight.

Two distinct operational principles for UAVs and AI technologies exist, dependent on data collection and processing methods. The first, Off-board processing, hinges on data transfer and processing between the UAV and an external computer within the environment. However, this method is susceptible to external influences as the entire process occurs through a communication medium. The second approach is Onboard processing, whereby the UAV autonomously initiates data processing using its in-built hardware and software. In onboard processing, it is not possible to change pre-existing image processing rules and add new ones. Therefore, such UAVs are generally preferred in non-dynamic missions. Decision-making rules are generally straightforward, void of temporal constraints, and do not accommodate event prioritization or hierarchies' dependent on other events (Boubeta Puig et al., 2018).

The integration of AI with modules responsible for UAV flight control, encompassing image recognition, object tracking, and various information-based processes, has yielded favorable outcomes. Despite the augmented demand on software, hardware, and energy systems, the empowerment of UAVs designed for low-tolerance, sensitive tasks with robust machine and deep learning processes significantly enhances mission performance, rendering them indispensable.

UAVs face a plethora of challenges, including adverse weather conditions, energy consumption optimization, payload capacity management, mission risk mitigation, route obstacle avoidance, inherent design-related factors, cyber threats, and the dynamic nature of environmental conditions. To effectively contend with these adverse circumstances, the implementation of an autonomous system capable of independent decision-making is imperative. In this context, AI technology assumes a pivotal role in facilitating real-time situation analysis and decision-making processes.

Table 1. AI technologies used by the UAV during the mission and the application process

Task	Implementation	AI Technologies
Object recognition and tracking	It is used for autonomous UAVs that have a decision-making mechanism by real-time image processing. Noise and unwanted effects are removed from the pure image collected by the camera and other image sensors, and the simplest and clearest image is obtained. From these images, decision-making processes such as object recognition, object tracking and obstacle avoidance are initiated.	▪ Artificial Neural Networks (ANN) ▪ Nearest Neighbors (KNN) ▪ CNN ▪ Graph Neural Networks ▪ Support Vector Machine (SPV) ▪ Machine Learning (ML) ▪ Deep Learning (DL) ▪ Reinforcement Learning (RL) ▪ Markov decision process, ▪ Q-Learning (Q-L) ▪ Swarm AI Algorithms ▪ Evolutionary Computing (EC) ▪ Genetic Algorithms ▪ Gravitational Search Algorithm (GSA) ▪ Optimization Algorithms ▪ Heuristic and Meta-Heuristic Algorithms (Bee Colony, Ant Colony, Particle Swarm Opt...)
Target classification	It is used to minimize target deviations in adverse environmental conditions and areas with heavy signal traffic.	
Path planning	It is used to determine alternative routes by processing parameters such as speed, duration, path loss and target distance during the UAV's mission.	
Energy consumption	It is used to control energy consumption during landing, take-off and flight time and to prevent unnecessary consumption.	
Takeoff, landing and maneuvering	It is used to perform actions such as anomaly detection, obstacle avoidance and collision avoidance that do not comply with the functioning of the system.	
Communication	It aims to improve the quality of the signal, its transmission, and its resistance to distortion during the communication phase of the UAV with the control centre and other UAVs.	
Task optimization	It is used to increase communication, interaction and coordination in single and swarm flights of the UAV. It is generally effective in flight speed, flight duration, energy utilization and path planning.	
Flying object detection	It is used for activities such as detection, avoidance and interception by processing radar, sound, image and thermal scan data for the detection of other flying systems on the route.	
Cyber security	It is used in the detection and prevention of cyber threats and attacks against the UAV's position, swarm interaction and communication systems.	

Table 1 provides a list of AI technologies used in UAV applications. This table provides summary information about the purposes for which AI technologies are used and what kind of improvements they make. Column 3 of the Table 1 lists the most commonly used AI algorithms and optimization methods. It is possible to expand the lines of this table as the use of AI technologies becomes widespread.

Literature

Gonzales et al. (2016) conducted image processing via thermal imagery to detect, classify, and monitor wildlife in forests or open areas using drones. Zhang et al. (2018) wanted to provide cellular wireless network service by optimizing UAV positions with ML algorithms. In the Ucan base station model, they managed to reduce the energy consumption of IHs by 20-80%. Sarıbas et al. (2018) were able to real-time, accurately determine vehicle positions using the EPPC, YOLO Tiny, and YOLOv2 algorithms with a 84.49% accuracy rate based on image data collected by UAVs. Polvara (2018) successfully executed the landing of an UAV on a moving ship. The evaluation of variables was carried out for landing at a non-fixed and irregularly moving point in this application.

In the study by Line (2018), autonomous landing was performed on a moving vehicle with a QR code. Zhang et al. (2018) proposed a ANN detection algorithm using three signal features for UAV RF signals: improved slope, improved kurtosis, and improved skewness. The recognition rates of SVM, KNN, RBFNN, SOMNN, and BPNN were found to be 0.9106, 0.8828, 0.9252, 0.8459, and 0.9368, respectively.

Venturini et al. (2021) approached mission optimization in UAV swarms by using a scaled Reinforcement Learning (RL) approach in a simulation environment, achieving a success probability of approximately 0.65 to 0.7. Poudel and Moh (2021) proposed a hybrid algorithm that combines probabilistic roadmap and optimized artificial bee colony (ABC) for determining the optimal route in an environment with various obstacles through data collection over the network. The proposed algorithm was found to provide energy efficiency and packet transmission efficiency.

Tlili et al. (2022) proposed an AI-supported model for detecting errors and abnormalities during cyberattacks on UAVs. The model used the Long Short-Term Memory (LSTM) algorithm, resulting in accuracy values of 0.955 in attack detection and 0.824 in error tolerance. Boone et al. (2023) ran a ML algorithm to detect buildings in aerial images obtained from low-flying UAVs. Through image processing on maps, the model achieved a mean Average Precision (mAP) of 0.3 and an Intersection of Union (IoU) accuracy of 88%.

Method

In this study, an image processing application was developed using a classification algorithm, which is one of the AI technologies. A deep neural network model was constructed in order to classify low-resolution images available in the Keras and Tensorflow libraries through ML, and images were tested. The CIFAR-10 dataset was used as the dataset. The CNN algorithm was employed as the classification algorithm. The application's computer software was coded in the Python programming language.

Dataset

The CIFAR-10 dataset, created by the Canadian Institute for Advanced Research, was utilized. This dataset consists of 10 different object classes and contains 60,000 image sets for training and 10,000 image sets for testing, each with a size of 32x32 pixels. These images have pixel values ranging from 0 to 255. The dataset is well-suited for performing analyses as successful as those conducted by humans using AI methods (Hope et al., 2017). During the application, the value ranges were normalized to the range of 0 to 1 to process the data more effectively.

Image Classification Algorithm

In the digital environment, images are modeled as numerical three-dimensional matrices. The image processing process is carried out on this matrix using mathematical and statistical computations. CNN is a neural network based mainly on image or video type media data models. This network is an extended version of ANN used to extract features by creating a grid-like matrix structure on visual datasets.

The basic components of the architecture of the method include the 1^{st} layer convolutional layer, 2^{nd} layer pooling layer and 3^{rd} fully connected layer. How many of these layers will be used may vary depending on the type of data to be processed and the purpose of the application. Here is a mathematical model of a CNN: In this equation, X represents the input data, F represents filters, W represents the weight matrix, b represents bias, and σ represents the activation function, producing output Y. Convolution and pooling operations can be further detailed with parameters defining dimensions and indices.

Convolutional Layer

Convolutional layers perform the convolution of special filters on input data. Mathematically, in these layers, each filter conducts a dot product with the input data. The result is called feature maps. Mathematically, the convolution process can be expressed as follows. X is the input data, F represents the filters, * represents the convolution process, and Y represents the feature map. The mathematical calculation model of this process is given in Formula 1.

$$Y = X * F \tag{1}$$

Pooling Layer

Pooling layers are used to downsize feature maps and highlight important features. The most commonly used pooling operation is max-pooling. Mathematically, max-pooling can be expressed as:

$$Yi, j = max(Xi', j') \tag{2}$$

Fully Connected Layers

These layers flatten feature maps and connect them with consecutive layers. Mathematically, these layers produce an output by multiplying the input vector with a weight matrix and applying an activation function. The first fully connected layer often includes an activation function (Raitoharju, 2022).

$$Yi, j = \sigma(WX + b) \tag{3}$$

In Formula 3, Y is the output function, W is the weight matrix of the image, X is the input vector, and b is the bias. Additionally, σ represents the activation function. CNNs typically include these basic components and often consist of multiple convolution and pooling layers. When combined, these layers can extract and classify complex image features.

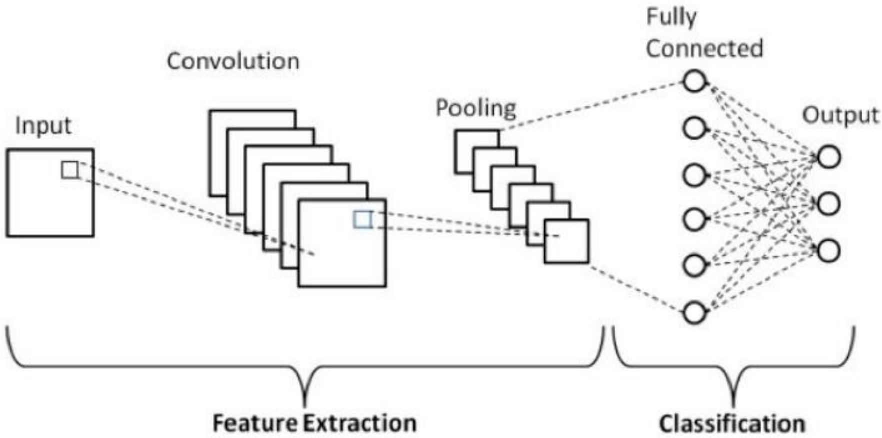

Figure 5. Schematic diagram of a basic CNN architecture (Phung & Rhee, 2019)

CNNs have distinct advantages over other pattern recognition algorithms as they integrate both feature extraction and classification processes. Figure 5 illustrates a basic schematic representation of the image processing procedure using a fundamental CNN algorithm. Figure 5, a simplified diagram of the image processing process, consists of five different layers. The number of layers varies depending on the application type and image complexity. These layers are assessed within two distinct segments. The first segment involves feature extraction and the second segment pertains to classification.

The feature extraction segment includes image resizing, weight matrix creation, and size reduction without losing the basic information of the image. At the end of this process, the feature map of the image is created. The second segment is created to classify image features. In this process, for each object category, there is an output neuron that represents the classified version of the image (Phung & Rhee, 2019).

Computer Algorithm of the Model

In calculating the accuracy of the model, the number of iterations was determined as 10. Then, coding process in Python language was started. The pseudo code of the application is presented below as Algorithm_1.

Algorithm_1. Pseudo code of the Image Processing Application

1. Import necessary libraries: TensorFlow, Keras and Matplotlib libraries
2. Load CIFAR-10 dataset
3. Define class names:
   Create a list of class names for the CIFAR-10 dataset, representing different categories like 'Airplane,' 'Automobile,' 'Bird,' etc.
4. Normalize the data:
   Scale the pixel values of the images in both training and test datasets to be between 0 and 1 by dividing by 255.
5. Create a convolutional neural network (CNN) model:
   Create the model: tf.keras.models.Sequential().
   Conv2D layers add with ReLU activation functions and MaxPooling layers to build the CNN layers.
   Flatten the data and add Dense layers for classification.
   The final Dense layer has 10 units, representing the 10 different classes.
6. Compile the model as a matric:
   optimizer, cross-entropy loss-gain, and determine 'accuracy'
7. Model's training:
   Use the training images and labels to train the model for 10 epochs with model.fit().
   The model's performance is evaluated on the test dataset during training.
8. Evaluate the test model's performance:
   The test loss and test accuracy using model.evaluate() calculate, and print the test accuracy.
9. Make predictions:
   Use the trained model to make predictions on the test images.
10. Visualize predictions and true labels:
    Create a 5x5 grid for displaying test images with their predicted and true labels.
    Loop through the test images, plot them, and label each image with its predicted and true class names.
    Use 'green' for correct predictions and 'red' for incorrect predictions.
11. Display the plot using plt.show().

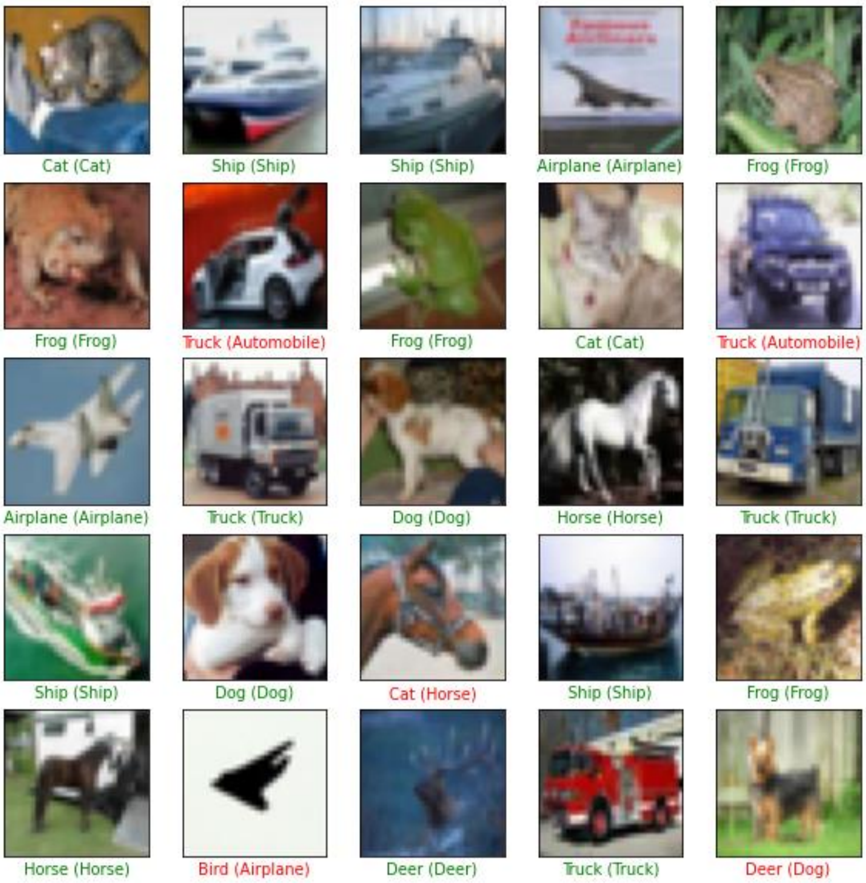

Figure 6. Object recognition matrix obtained from image processing with CNN algorithm

After training, the accuracy of the model is evaluated on test images. In such applications, where recognition is attempted with AI algorithms on the dataset of images obtained from camera images, the quality of the UAV's image capture and recording features directly affects the results. Therefore, the complexity and duration of the UAV's flight mission may change its accuracy performance.

Results and Discussion

Based on the obtained results, the application was coded using the Python programming language. When the relevant code was executed, the AI algorithm's image processing accuracy value (Test accuracy) was determined to be 0.7106999754905701. As a result of the image processing, the obtained labeled abstract matching image matrix is presented in Figure 6.

Figure 6 illustrates the results of the image predictions, with green labels indicating correct predictions and red labels indicating incorrect predictions, with the true label provided in parentheses for the red ones. A lower occurrence of red labels is desirable, signifying higher accuracy in predicting new images after the learning process. This code snippet generates a 5x5 grid presenting 25 test images alongside their predicted and true labels, highlighting correct predictions in green and incorrect ones in red. Similar structures can be employed to include additional graphs. The accuracy graphs are outlined as follows.

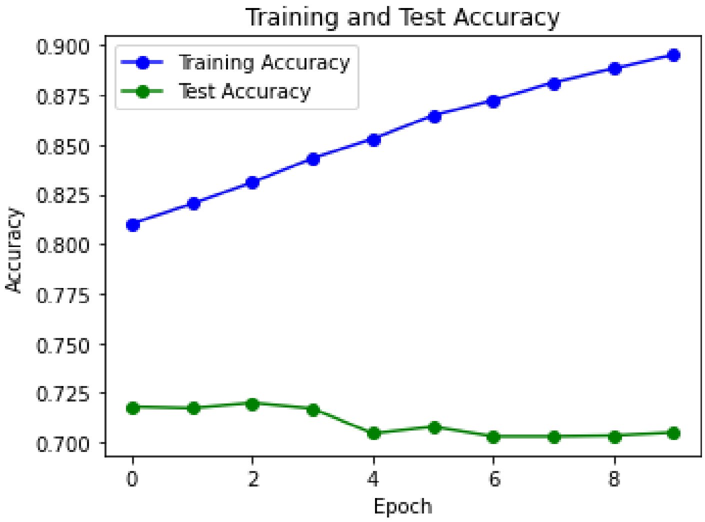

Figure 7. Image processing result accuracy values graph

When the application code is run, it creates a graph with two underlines as shown in Figure 7. This graph shows the "Training Accuracy" (in blue) and "Testing Accuracy" (in green) over trials (Epoch). These graphs show how the accuracy values change with each epoch, helping to monitor the performance of your model during training and testing.

Conclusion

In this study, an overview of AI technologies in conjunction with UAV was provided, along with contemporary applications. Subsequently, an object recognition application was implemented using AI algorithms in the image processing phase. The success rate was calculated as 0.7107.

The current structure of UAV systems imposes several constraints, including their weight, payload capacity, energy consumption, remote control limitations, and potential obstacles encountered during missions. Some of these obstacles can be overcome with pre-mission interventions, but others require real-time detection, calculation, measurement, and evaluation to make autonomous decisions. This is where AI technologies come into play, ensuring the optimal solution following a situation analysis.

AI technologies employed in UAV systems are primarily used in various stages of image processing, location accuracy computation, range and route calculation, swarm optimization, energy efficiency control, and communication system enhancements. The variable structure, quality, and parametric size of the dataset in AI applications directly impact the decision-making process of autonomous systems. In image processing procedures, the accuracy and processing time are greatly influenced by the AI algorithm used, especially when dealing with extensive data. Additionally, the technology and capacity of hardware components used in computation and data transmission stages are also crucial.

Recent developments indicate the provision of hardware solutions aimed at enhancing computational capabilities. Processors contributing to learning capabilities stand at the forefront of these solutions. New chip technologies are developed to be energy-efficient and feature high data processing capacities. Processors like AImotive aiWare3, AlphaIC Real AI Processor-Edge, Huawei HiSilicon Ascend 310, and Tesla Full Self-Driving (FSD) are specifically designed for autonomous vehicles, equipped with AI-supported computation and algorithms.

The widespread use of IT offers opportunities for remote monitoring, control, and management. As the drawbacks of these technologies are gradually eliminated, their usage expands, fostering a positive outlook. AI technologies thus present an approach that mitigates IT-related disadvantages, particularly in the context of unmanned vehicles used for remote monitoring, control, and management on land, at sea, and in the air. These AI-equipped unmanned vehicles contribute to reduced mission duration, energy consumption, and enhanced mission success rates. The future of AI is being shaped by ongoing scientific and technological research, developments, and user preferences. Notably, regulations related to legal and ethical aspects are required to maximize the benefits of AI for humanity and minimize associated risks.

Scientific Ethics Declaration

The author declares that the scientific ethical and legal responsibility of this article published in EPSTEM Journal belongs to the author.

Acknowledgements or Notes

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Author Information

Mustafa Cosar
Department of Computer Engineering, Hitit University
19030, Corum/Turkiye
Contact e-mail: *mustafacosar@gmail.com*

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