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Power Supply Technologies for Drones and Machine Vision Applications: A Comparative Analysis and Future Trends

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Abstract: The field of Unmanned Aerial Vehicles (UAVs), or drones, is encountering quick development in the areas of air transportation and computerization. Progress in innovation has prompted more noteworthy capacities and highlights in UAVs, which are currently broadly involved by the military and flying industry for an assortment of high-end generally safe errands. Highly advanced UAVs that can be controlled remotely via a controller, mobile phone, or ground station cockpit have been developed through the integration of automation technology and machine vision, which includes thermal imaging, cameras, sensors, and other sensors. The three primary characteristics of UAVs will be investigated in this study, namely power-source technology, deep-learning neural networks for computer vision, and some of the applications that are used the most. The goal is to thoroughly examine these characteristics and offer suggestions for addressing some of the difficulties of optimizing UAV performance and also exploring potential future trends.

Keywords: UAVs; drones; machine learning; computer vision; power sources

Citation: Pekias, A.; Maraslidis, G.S.; Tsipouras, M.G.; Koumboulis, F.N.; Fragulis, G.F. Power Supply Technologies for Drones and Machine Vision Applications: A Comparative Analysis and Future Trends. *Telecom* **2023**, *4*, 459–476. https://doi.org/10.3390/telecom4030024

Academic Editor: Carlos Marques

Received: 3 June 2023
Revised: 12 July 2023
Accepted: 21 July 2023
Published: 1 August 2023

1. Introduction

UAVs, or drones, are aircraft that do not have human pilots on board. They can be controlled from a ground station remotely or independently, using sensors and actuators [1]. The historical backdrop of UAVs can be traced back to the Second World War; however, it was only after the 1980s that their innovation progressed fundamentally, basically for military applications. Aeronautics, mechanical engineering, computer science, mechatronics, robotics, and power electronics are just a few of the engineering fields that have been combined to create advanced UAVs with a wide range of capabilities and applications. Depending on the application, modern UAVs are outfitted with sophisticated surveillance systems, digital and infrared cameras, thermal sensors, radar, and GPS. They have acquired ubiquity in late years because of their different non-military personnel applications, for example, payload conveyance, traffic checking, aiding risky regions, catastrophic event reaction, and salvage activities. UAVs are also used for more private, hobby-like activities, like photography [2,3]. In this paper, we will break down a cutting-edge sort of robot and its condition of the cutting-edge circumstance. We will discuss future UAV industry trends and compare the most recent sources on the subject. From their early emergence in the 20th century to the present, unmanned air vehicles have introduced novel engineering technologies to a vast field of study. Three criteria were used to select the references used in this paper: the significance of content, its popularity, and chronological release.

The key contribution of our research paper endeavors to undertake a comparative analysis of power supply technologies for drones and machine vision applications to identify and forecast future trends in the UAV technology sphere.

The seamless incorporation of automation technology and machine vision, including cameras, sensors, and thermal imaging, has led to the development of highly sophisticated UAVs that can be remotely controlled via various mediums such as a controller, mobile phone, or ground station cockpit. As it directly affects the UAV's flight time and payload capacity—both of which are crucial elements for both military and commercial applications—power source technology continues to be a key component of UAVs. To further improve UAV capabilities, particularly in high-risk missions, machine vision applications, such as cameras and sensors, are being used increasingly. This analysis is indispensable in making informed decisions regarding the selection of power sources and machine vision technologies for specific UAV applications. Additionally, our research endeavors to identify future trends in UAV technology, which is crucial considering the rapidly evolving nature of the UAV industry. By identifying these trends, we can obtain valuable insights into the direction of UAV technology and make informed decisions regarding investments in research and development. Consequently, our research paper offers valuable insights into the intricate interplay between power supply technologies and machine vision applications, two fundamental components of UAV technology. UAVs have been exhaustively studied with the help of machine vision applications. The utilization of machine vision in UAVs enables cutting-edge technologies such as visual navigation algorithms, obstacle detection and avoidance, and aerial decision-making [4]. Vision-based algorithms have been devised for a myriad of applications, encompassing visual surveillance, aim systems, recognition systems, collision-avoidance systems, and navigation [5]. Recent research endeavors have primarily concentrated on applying machine vision to control unmanned underwater vehicles (UUVs) [6]. These applications have undergone progressive evolution, with distinct projects categorizing and evaluating the performance of strategies [7]. The integration of computer vision technologies in UAVs has precipitated advancements in autonomous positioning, aerial collision avoidance, and other intelligent applications [8]. This undertaking [9] presents an in-depth examination of the deployment of computer vision systems by UAVs, with a particular emphasis on its myriad applications, facilitated through data search, information storage, and chiefly, data processing and analysis. A machine vision system tailored for aerial surveillance [10] is capable of interpreting and processing data acquired by a UAV's on-board infrared camera, which is configured for automatic fire detection applications, wherein an alarm is triggered upon fire identification. The implementation of an open-loop control algorithm is demonstrated to precisely position the TVS laser ray within the UAV's Field of View (FOV), leveraging the theoretical concept of a continuous FOV [11]. In [12] the attitude, altitude, and motion of a UAV can be estimated using a camera mounted on the UAV, employing either catadioptric or fish-eye sensors. The machine vision component of a system devised to enable Unmanned Aerial Systems (UAS) to autonomously maneuver around civil aerodromes, relying solely on a monocular camera, is expounded upon [13].

The paper's organizational structure follows this outline: Section 2 provides an overview of UAV classification, followed by Section 3 which delves into the applications of AI, Deep Learning, and Computer Vision in UAV sensing. Section 4 comprehensively covers UAV power sources, including batteries, fuel combustion engines, solar power, hydrogen fuel cells, methanol fuel cells, supercapacitors, and laser charging technologies. Section 5 focuses on the energy management system, while Section 6 highlights various UAV applications. Lastly, Section 7 addresses current challenges and future trends.

2. UAV Classification

Understanding the drone's technical characteristics is essential. UAVs are identified by their physical components, such as the aircraft configuration and propulsion system, just like conventional aircraft. However, unlike conventional aircraft, UAVs do not have windows or a cockpit. However, some UAVs are built with the option of pilot or unmanned working modes. Because there is no human pilot, there is more room for experimentation and design, especially with the airframe and engine configurations, which has led to a wide range of UAVs. Weight, wing configuration, and rotor configuration have all been used to classify UAVs in the past. Chaurasia et al. [1] categorized UAVs according to their weight as micro (less than 2 kg), mini (more than 2 kg and less than 20 kg), small (more than 20 kg and less than 150 kg), and large (more than 150 kg). UAVs are also categorized by wing configuration, with fixed-wing, rotary, and flapping wings being the most common. Flapping wings are extremely rare. Furthermore, rotor classification [14] is another method of categorizing UAVs, in which they are classified by the number of rotors and their configuration [1], such as quadcopter, hexacopter, single-rotor, and so on, as shown in Figure 1.

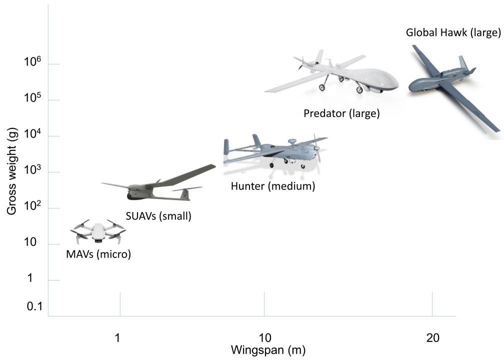

Figure 1. Drone chart distribution based on UAVs' weight and wingspan size (Reprint with permission from Ref. [15]. Copyright 2022 IEEE).

Helicopters are not just designed for human-occupied, large aircraft purposes. They can also be produced in the form of small, unmanned drones. These drones come in various sizes, ranging from toys for children to larger drones equipped with cameras. The price of a drone increases as its size grows. Some single-rotor drones can be purchased in stores for as little as 20$, while others cost thousands online. A characteristic of single-rotor commercial drones is that they run on fuel instead of electricity, depending on their size. Although they are more efficient than multi-rotor drones, they are not as efficient as fixed-wing drones. Both single-rotor drones and fixed-wing drones are challenging to fly and require proper balance. Single-rotor drones are not as versatile as multi-rotor drones, but they can carry heavier payloads. They are commonly purchased by individuals seeking a new hobby [14]. In addition to fixed-wing and multi-rotor drones, several other types of UAVs cannot be classified as one or the other. Some UAVs possess characteristics of both multi-rotor and fixed-wing systems, and these are referred to as hybrid systems. An example of such a drone is a hybrid quadcopter, which utilizes multiple rotors for vertical takeoff and landing, while also incorporating wings to allow for longer-range flight. Less commonly seen are UAVs that cannot be classified as either fixed-wing or multi-rotor systems. One example of this type of drone is the ornithopter, which flies by mimicking the wing movements of birds and insects. These drones are still largely in the developmental stage and are not widely used in practical applications. Some well-known ornithopters include the Delfly Explorer, which mimics the flight of a dragonfly, and the Micromechanical Flying Insect, a drone in development designed to resemble a fly in both size and movement. Another type of UAV that falls outside of the fixed-wing or multi-rotor classification is the jet-engine drone. The T-Hawk drone is a well-known example, utilizing a turbofan to give the appearance of an unmanned jetpack rather than a fixed-wing or multi-rotor drone. Additionally, it is important to note that unmanned balloons, such as hot air, helium, or hydrogen-filled balloons, can also fly by heating the air inside; however, they are generally not considered drones. This also applies to rockets and jetpacks [16–18].

3. AI, DL and Computer Vision in UAV Sensing

3.1. Artificial Intelligence

The goal of artificial intelligence, a rapidly developing field, is to enable machines to carry out tasks that would typically require human intelligence, like those made possible by new information and technological communication systems like the Internet of Things (IoT). Teaching machines to mimic human behavior is the field's main goal. Key ideas in AI include machine learning and deep learning, which entail the construction of multiple artificial neural network layers. Numerous industries have advanced significantly as a result of these methods [19–21].

3.2. Deep Learning and Computer Vision

Computer vision is the field of artificial intelligence that enables computer systems to extract important information from visual inputs such as images and videos and respond accordingly. Machine vision uses AI to allow computers to perceive, observe, and understand their surroundings. Image processing is used to automate tasks that the human visual system can perform. To work properly, computer vision requires a large amount of data, as it analyzes these data to identify and recognize specific inputs, such as frames or images. To instruct a computer on identifying automobiles, it requires a substantial amount of car illustrations to enable it to acquire the ability to distinguish and discern cars, including those that are free from any physical impairment or blemish [22]. Neural networks (NNs) are machine learning techniques that are influenced by biological neural networks. NNs use nodes (also known as neurons) to transmit information in the same way as human bodies do. The most frequent type of NN in UAV technology is the convolutional neural network (CNN). CNNs are a particular kind of NN that is designed for the exclusive purpose of identifying images. Convolution, as the title suggests, is the technique through which the initial image at the input of a machine vision application is altered with filters that identify significant image features like boundaries (Figure 2). The system shall acquire knowledge about the screened data it identifies independently and correspond it with the anticipated result. A distinguishable instance is identifying the label of an entity in a specific picture that serves as an input. Typically, filters consisting of 3×3 or 5×5 squares are employed to detect the orientation of the boundary or characteristic: leftward, rightward, upward, or downward.

Deep artificial neural networks frequently acquire more efficient data representations than shallow ones. Nevertheless, incorporating many layers in a CNN can lead to the problem of vanishing or exploding gradients, which can make optimization challenging [23]. In reality, the back-propagation technique is utilized to comprehend the significance of the filter parameters' weights utilized in the convolution process.

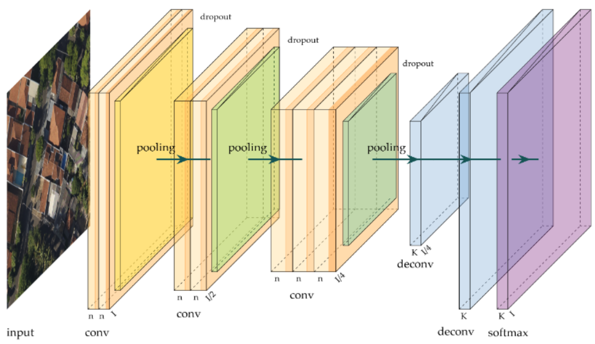

Figure 2. Training process of a CNN [24].

The utilization of an activation function is a crucial step in the convolution procedure. Within a neural network, activation functions determine how the input's weighted sum is transformed into an output from a node or group of nodes in a specific layer of the network.

Although there are diverse options for activation functions, the non-linear function ReLU (Rectified Linear Unit) is the most commonly employed [23,25]:

$$\sigma(x) = max(0, x) \tag{1}$$

Tanh:

$$\sigma(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

and *Sigmoid*:

$$\sigma(x) = \frac{1}{1 + e^x} \tag{3}$$

Non-linear activation functions are especially suitable for constructing multi-layer artificial neural networks as they can consistently approximate all functions, as demonstrated by the universal approximation theorem. The ReLU function is particularly favored in unmanned aerial vehicle applications owing to its uncomplicated mathematical expression and derivative:

$$f(x) = \begin{cases} x, & \text{if } x > 0 \\ 0, & \text{if } x \leq 0 \end{cases} \tag{4}$$

$$f'(x) = \begin{cases} 1, & \text{if } x > 0 \\ 0, & \text{if } x < 0 \\ \text{undefined}, & \text{at } x = 0 \end{cases} \tag{5}$$

The ReLU activation function is effective in preventing the vanishing gradient problem that can occur during the training of a neural network. In this process, the weight of each layer receives an update based on the error function. Pooling layers, such as max-pooling layers, are frequently placed between two convolutional layers to minimize the spatial volume of the input image. The max-pooling layer has no parameters; however, it does have two hyper-parameters: the filter (F) and the stride (S).

Generally, if we have the following dimensions:

$W_1 \times H_1 \times D_1$, then
$W_2 = \frac{(W_1 - F)}{S+1}$
$H_2 = \frac{(H_1 - F)}{S+1}$
$D_2 = D_1$

Where W_2, H_2 and D_2 are the width, height and depth of output. The final stages of a CNN structure for computer vision contain fully connected layers that respond to the input activation function [26]. These layers are made up of weights, biases, and neurons that are linked together and used to categorize images into numerous categories through training. The SoftMax activation function is often used for multi-class classification and is situated at the end of the fully connected layer in a CNN, whereas the Logistic activation function is used for binary classification. The final output layer displays labels that have been one-hot encoded.

Two well-known types of CNNs commonly used on UAVs are VGG-16 and AlexNet:

- VGG-16 is a highly accurate object identification and classification system, identifying 1000 photos from 1000 different categories with 92.7% accuracy. It is a popular picture classification technique that may be simply applied to transfer learning [27].
- In contrast, AlexNet is proficient in identifying objects that are not centered, as demonstrated by the fact that most of its top 5 classifications are appropriate for each frame. In 2012, AlexNet emerged as the winner of the ImageNet contest, boasting a top 5 error rate of only 15.33%, which was significantly lower than the 26.2% achieved by the runner-up. Additionally, AlexNet is acknowledged for pioneering deep learning in fields like medical image analysis and natural language processing [28].

Now, let us explore some examples and real-world applications of computer vision in tasks involving UAVs Various object detection benchmarks have been used to evaluate object detection algorithms. These benchmarks include datasets like the Daimler dataset [29], captured by a vehicle in an urban environment, with thousands of annotated pedestrians for training and testing. The Caltech dataset [30] consists of hours of videos recorded from a vehicle in regular urban traffic, with annotated bounding boxes representing pedestrians. The KITTI-D dataset focuses on evaluating detection algorithms for cars, pedestrians, and cyclists in autonomous driving scenarios. Mundhenk et al. [31] created a dataset with diverse car images from different locations, while the UA-DETRAC benchmark [32] provides a large dataset for vehicle detection. PASCAL VOC is a pioneering dataset [33] that standardized object detection, image classification, object segmentation, person layout, and action classification tasks. ImageNet [34] expanded on this work, significantly increasing the number of object classes and images available for training and evaluation. The MS COCO dataset, introduced by Lin et al. [35], includes a vast number of images with manually segmented objects across various categories, offering more detailed annotations compared to ImageNet. Single-object tracking is a foundational challenge in computer vision, involving the estimation of a target's trajectory in a video sequence, given its initial state. Over the years, numerous datasets have been curated for evaluating single-object tracking algorithms. Wu et al. [36] have developed a standardized platform to assess these algorithms, significantly increasing the dataset size from 50 to 100 sequences. Multi-object tracking, on the other hand, is a crucial research problem with diverse applications in surveillance, behavior analysis, and autonomous driving. Prominent multi-object tracking evaluation datasets include PETS09, PETS16, and KITTI-T [35]. Crop health monitoring is a crucial task performed by farmers daily to identify potential threats such as diseases, pests, and slow growth rates. Traditional methods involved visual inspection and manual collection of ground samples from random locations. For more than 50 years, color and infrared photography captured by various platforms have been employed to monitor crop growth. Advanced image data analysis tools enable drones equipped with mounted cameras to identify crops with diseases or deficiencies. Drones are extensively utilized in the agricultural sector for field mapping and crop monitoring. By utilizing images captured by drone-mounted cameras, a vegetation indices map can be generated. These indices provide valuable information about crop conditions, including disease presence, nutrient requirements, and water stress levels [37]. Drones in agriculture facilitate various activities that contribute to crop health monitoring, allowing for timely corrective actions to prevent crop spoilage. Here are a few examples of drone applications in crop health monitoring [38].

3.3. Deep Reinforced Learning

Deep reinforcement learning (DRL) is a field of machine learning that merges the principles of deep learning (DL) and reinforced learning (RL) to generate an optimal solution through experience. Through multiple iterations, this experience evaluates a reward system to determine the most suitable actions for an agent. The interaction occurs at each discrete time step t in the series. The agent receives a state S_t from the state space S and chooses an action A_t from a collection of feasible actions in the action space $A(S_t)$ at each time step. As a result of the previous action, the agent receives a numerical reward $R_{t+1} \subset R$ from the environment one time step later. The agent has now entered a new state S_{t+1} [39]. The incorporation of DRL into UAV management was implemented to tackle particular challenges encountered in that field (see Figure 3). DRL supports the undertaking of UAV control by enabling it to operate with algorithms that do not require a model when the UAV model is excessively intricate to determine, to accommodate non-linearities in the system, to learn how to attain the objective without explicit training, and to operate in unfamiliar environments [40].

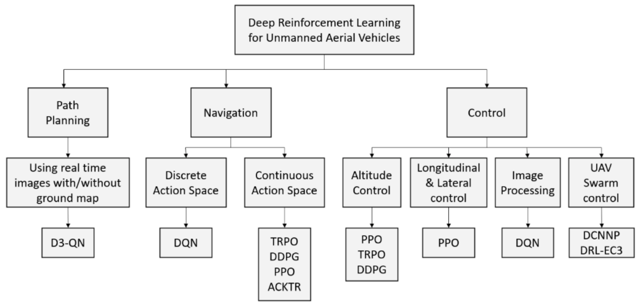

Figure 3. Taxonomy graph of DRL Algorithms for UAV Tasks [40].

4. UAV Power Sources

UAVs can be classified based on their power source [15]. Different types of UAVs are used for different applications, and there is a suitable power source for each application. Some options include fuel cells, combustion engines, batteries of various technologies, and more. These power sources are crucial for the operation of UAVs and must meet certain requirements such as size, weight, cost, and power density. Power density is the amount of energy contained in a power source, measured as energy per unit weight, typically in Joules per cubic meter (J/m^3) or watts per cubic meter (W/m^3, W = J/s). One way to evaluate power sources is through the Ragone diagram of a supercapacitor [41], which can have high specific power but low specific energy (Wh/kg), which limits its ability to operate for extended periods.

4.1. Batteries

There are various types of batteries suitable for different UAVs based on their size and application. Some of the commonly used battery types for UAVs include lead-acid, lithium-polymer (Li-Po), alkaline, nickel-metal hydride, and lithium-ion (Li-Ion). Among these, Li-Po and Li-Ion batteries are the most popular for drones due to their high energy density and lightweight, which enables them to be manufactured in different sizes and shapes, and have high discharge rates. However, these batteries are also relatively expensive and may have safety hazards such as overheating and explosions. Additionally, they require special chargers and are not always readily available on the market. To determine the best battery for a specific UAV application, it is crucial to compare the specifications of different power supplies. For example, power density is important for aircraft acceleration, energy density is crucial for range, and cycle life is critical for battery life. Additionally, factors such as size, weight, and cost also play a role in determining the suitability of a battery for a specific UAV application [42–44].

4.2. Fuel Combustion Engines

The drones that run on gasoline-powered fuels produce amazing results because they can operate for almost a day on a single tank. Due to its many benefits, two-stroke piston engines are typically seen in UAVs. It is affordable, sturdy, user-friendly, and extensively available as it is a recognized technology. Diesel engines are superior to petrol engines in several ways, including being more durable, efficient, and fuel-flexible. The weight of these engines is a huge plus. The UAV's fuel amount lowers as it operates, making the aircraft lighter and giving it more speed and range [45]. The most efficient turbo engines are those that are more state-of-the-art, such as turbofans, turbojets, or turboprops. However, their use is ruled out due to their weight, price, and numerous intricate systems that demand pompous upkeep. Some UAVs with military uses do, however, use turboprop engines.

4.3. Solar Power

Solar electricity is a well-established technology that utilizes photovoltaic panels, as shown in Figure 4, to convert sunlight into electrical energy [46]. Specifically, the panels use the Maximum Power Point Tracker (MPPT) method to efficiently capture the maximum amount of power possible from the photovoltaic cells. The MPPT algorithm continuously monitors the voltage and current of the panel and adjusts the duty cycle of the DC-DC converter to maintain the optimal operating point for the cells. This process is controlled by a microcontroller or more advanced computer system. Solar panels are frequently utilized in stationary unmanned aerial vehicles and are significantly impacted by environmental factors like sunlight and temperature.

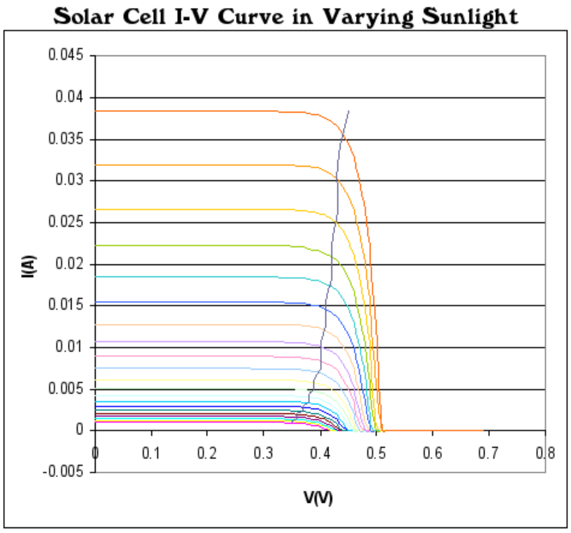

Figure 4. The I-V curve of a photovoltaic solar cell is where the line intersects the knee of the curve with the point of maximum power transfer.

4.4. Hydrogen Fuel Cells

A hydrogen fuel cell is an electrochemical cell that turns hydrogen's chemical energy into electricity via two redox processes. As a byproduct of combining hydrogen and oxygen, the process generates power, heat, and water [47]. Fuel cells that utilize proton exchange membranes (PEMFCs) are highly appropriate for transportation purposes owing to their lower pressure and temperature ranges, as well as their reliance on specialized electrolyte membranes that conduct protons. They are considered the upcoming major innovation in power technology and have the potential to replace the Space Shuttle's alkaline fuel cells. Jiao et al.'s recent study [48], a new PEMFC technology was proposed that increases power density by reducing the film thickness of commercial membranes and incorporating a cerium salt to improve the thin film's stability (see Figure 5). However, PEMFCs also have some disadvantages, such as a short lifespan, a high cost, and the requirement for large or heavy fuel storage.

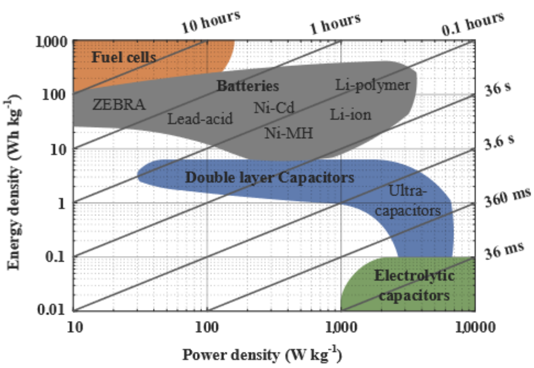

Figure 5. Diagrams for energy and power density of various energy storage devices [49].

4.5. Hybrid Energy Sources

A hybrid system combines two or more power sources, each of which has its advantages depending on the circumstances. The strength and energy efficiency of the system is enhanced by this strategy [45]. One common example is the integration of fuel cells and batteries. The functioning of fuel cells necessitates the utilization of apparatus like fuel and air pumps, valves, and compression systems, which can cause delayed responses and probable fuel insufficiency leading to decreased efficiency, reliability, and durability. However, the combination with batteries can overcome these drawbacks and offer advantages to the hybrid system, as noted in [42,50].

4.6. Methanol Fuel Cells

The typical method for producing hydrogen involves splitting water and natural gas, which results in a high production cost. The methods for storing hydrogen by compression and liquefaction, however, are considerably more expensive. To increase the amount of hydrogen for the compression process, the storing pressure rises from 200 bar to 700 bar. It is required to use more durable tanks, whose weight is meant to be high, under such high pressure. When hydrogen is controlled by a cryogenic system at 20.4 K, it is in liquid condition and ready for the liquefaction process. As a result, liquid fuel-feeding Direct Methanol Fuel Cells (DMFCs), which provide higher specific energy and possibly longer endurance, have been utilized by UAVs. Additionally, because of its liquid phase, methanol is considerably simpler to transport, store, and handle. As a result, elaborate and expensive auxiliary facilities are avoided, which in turn lowers the cost. Because of the resources from biomass, methanol is also more accessible than hydrogen, which further reduces the cost. The use of DMFCs in UAVs is being hampered by two problems, though. One is the poorer energy efficiency compared to hydrogen fuel cells, which is caused by the slow kinetics of the methanol oxidation process (MOR), and the other is the issue of CO species poisoning the catalyst during MOR, which leads to performance degradation over time [51].

Proton exchange membrane fuel cells (PEMFCs), which have an anode DL, an anode CL, a PEM, a cathode CL, and a cathode DL, can simply be used as a model for how DMFCs should be constructed. Liquid methanol is given to the DL and diffuses to the CL, where it is oxidized in the presence of water to produce carbon dioxide, protons, and electrons:

$$CH_3OH + H_2O \rightarrow CO_2 + 6H^+ + 6e^- \tag{6}$$

$$E_a^0 = 0.02\text{V} \tag{7}$$

Following that, the produced protons are delivered by PEM to the cathode, where they participate in the ORR process:

$$3/2O_2 + 6H^+ + 6e^- \rightarrow 3H_2O \tag{8}$$

$$E_c^0 = 1.23\text{V} \tag{9}$$

When the previous two equations on the anode and cathode are combined, the overall reaction can be represented as follows:

$$CH_3OH + 3/2O_2 \rightarrow CO_2 + 2H_2O \tag{10}$$

$$E^0 = 1.21\text{V} \tag{11}$$

DMFCs have a theoretical voltage that is lower than that of hydrogen fuel cells. Similarly, activation, Ohmic, and concentration losses lead a DMFC's real voltage to be significantly lower than its theoretical value. Furthermore, the practical operating voltage of DMFC is substantially lower than that of hydrogen fuel cells due to the methanol crossover phenomenon. The oxygen on the cathode reacting with the methanol delivered from the anode to the cathode resulting in low voltage and mixed potential .

4.7. Hydrogen Fuel Cell and Super Capacitor Combination

Previous studies and experimental combinations that employed supercapacitors (SC) and hydrogen fuel cells (HFC) had several limitations. These constraints will be crucial in this experiment. Bauman and colleagues create an HFC car by combining an SC bank and a 35 kW HFC. The HFC employs a boost DC-DC converter to achieve the required voltage for the motor (250–400 V). As a result, a smaller HFC can be employed, resulting in less vehicle mass and lower total expenses. The SC bank contains 27, A. Townsend et al. [45], where two SC-packs with a capacity of 405 V, 2 F are made up of six 2.5 V, 350 F cells connected in series.

Because it makes the system lighter, cheaper, and more efficient, the SCs do not utilize a DC-DC converter. The SCs store the energy produced by regenerative braking and supply additional power only when necessary (during accelerations). The best fuel economy is achieved when the kinetic energy of the vehicle and the potential energy of the SCs remains constant. This study reveals that the HFC and SC combination cannot compete with the HFC and battery combination because the SC bank lacks adequate energy storage to meet peak power demand. Combining a few SC banks in parallel is recommended to boost energy storage capacity; however, this greatly increases system weight and reduces fuel consumption to an infeasible level below that of the HFC and battery combination [52].

Thoungthong and colleagues hypothesized that an SC bank of 292 F, 500 A, 30 V, and a proton exchange membrane fuel cell of 500 W, 40 A, 13 V might power an HFC car. The HFC will use a single-direction boost converter to meet power requirements and store regenerative braking energy, while the SCs will use a two-direction boost converter. The HFC will provide most of the power for this configuration, with the SC bank being used when peak power needs are noted, or regeneration breaking energy exceeds zero. The HFC will also be utilized to recharge the SCs throughout the operation.

This configuration allows for a reduction in the amount of HFC utilized, increased efficiency over only using HFC, and energy recovery via regenerative braking. Because the HFC requires 5–10 min of steady power, the system may fail at startup if just SCs are used as an auxiliary power source. Future improvements to either of these case studies would be to improve the energy characteristics of the SCs or to investigate the possibility of a hybrid system that uses a battery to absorb the majority of these constant power requirements [53,54].

4.8. Supercapacitors

The polarization of the electrolyte solution can be used to store supercapacitor energy [55]. The ions are separated in a supercapacitor using the dielectric interface, as shown in Figure 6:

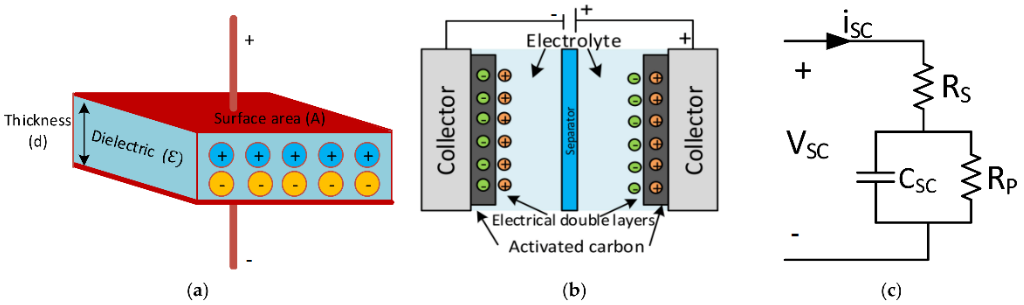

Figure 6. (**a**) Structure of electrostatic capacitor, (**b**) structure of SC, (**c**) equivalent circuit model of SC [56].

Electrochemical double-layer capacitors, or supercapacitors, offer numerous benefits compared to conventional capacitors. One of these advantages is their ability to store a lot of energy in a small volume due to their high capacitance and large surface area. Another advantage is that they can release energy faster due to their high-power rating. In addition, their capacitance value is higher than that of conventional capacitors.

4.9. Laser Charging Technology

Laser beaming is a technique used frequently in military intelligence and surveillance operations to extend missions [57]. The laser receives energy from an external source and generates a narrow, focused beam of light with a specific frequency and wavelength. This is aimed at the photovoltaic cell that was made just for a UAV. The laser beam is converted back into usable energy by this photovoltaic cell, which is used to recharge the drone's battery. On a UAV, a maximum power point tracking device can be installed to improve energy transfer efficiency. The experiment was carried out using laser beaming technology on a quadrotor UAV with a modified solar cell array that could receive energy from an infrared laser as shown in [48]. The experiment, which was carried out at the Future of Flight Museum in Everett, Washington, ultimately revealed that the given quadcopter, which had a total mass of one kilogram, was able to remain in the air for more than 12 h in a row. This technology works with both fixed-wing and multi-rotor UAVs of different sizes and does not care what the environment is like. However, the most significant drawback of this method is that a source of energy must always be mobile and close to the UAV, making it unsuitable for some long-range applications. Another issue is safety in the workplace. In general, lasers are thought to pose a risk to human health, and working with high-intensity lasers can only be done with protective gear on. Also, lasers are not allowed in all places, especially in urban areas where they can be very disruptive to people's lives [58,59].

Battery-powered commercial UAVs are widely used for a variety of applications, including aerial photography, surveying, inspection, and delivery. There are several types of battery-powered commercial UAVs, including fixed-wing UAVs, multi-rotor UAVs, etc. The most popular examples which are widely on the market are depicted in the first row of Table 1.

Table 1. Categorized Commercial UAVs by Energy Source.

Battery Powered UAVs	• **DJI Phantom 4 Pro**: The most popular quadcopter out there. Mainly used for photography and videography. • **Parrot Anafi**: A fixed-wing UAV that is used for surveying and mapping. • **Matternet M2**: This is a quadcopter UAV that is used for medical delivery.
Fuel Powered UAVs	• **Yamaha RMAX**: A multi-rotor UAV that is used for agricultural purposes. • **Aeryon SkyRanger**: A quadcopter UAV that is used for aerial inspection and monitoring.
Solar-Powered UAVs	• **Sunbird Solar-Powered UAV**: A fixed-wing UAV by BAE Systems. • **Airbus Solar UAV**: A fixed-wing UAV powered by solar cells and lithium-ion batteries. • **Zephyr Solar-Powered UAV**: also an Airbus Product.
Hybrid source UAVs	• **Boeing Insitu Integrator**: A fixed-wing UAV that is powered by a combination of a gasoline engine and electric motors. • **Honeywell T-Hawk**: This is a vertical takeoff and landing (VTOL) UAV. • **MMC HyDrone 1800**: A multi-rotor UAV that is powered by a combination of batteries and a hydrogen fuel cell.

Drones with traditional motorization, typically powered by diesel or gasoline are presented in the second row of the above table. On the other hand, the advantages of commercial solar-powered UAVs include long flight times and low operational costs since they do not require any fuel. The following examples of commercial solar-powered UAVs are depicted in the third row above, which are in development or an experimental phase. Finally, the main advantage of hybrid-powered UAVs is that they have the benefits of both the power sources that are being used. Some suitable examples are shown in the last row of the table.

5. Energy Management System

UAVs require a reliable and efficient energy management system to operate effectively. UAV energy management systems typically consist of a battery or a combination of batteries, a power converter, and a control system. One important aspect of UAV energy management is maximizing the energy efficiency of the system. This can be done through several techniques, such as optimizing the flight path, adjusting the power output of the motor, and using regenerative braking to recover energy during descent [60].

The estimation of the battery's remaining capacity and the monitoring of its health are two important aspects of UAV energy management. Algorithms are used to predict the state of charge and remaining capacity of the battery by analyzing the temperature, voltage, and current data. Overall, the efficient and dependable operation of UAVs depends on a well-designed and effective energy management system. It has the potential to shorten flight times, improve safety, and lower operational costs [50].

6. UAV Applications

Automated unmanned airplanes are not generally restricted to military use, as the market and innovation keep on advancing. Even for tasks that could be risky for humans to perform, they are increasingly being used for everyday tasks. For instance, the fully autonomous UA known as the General Atomics MQ-9 Reaper was initially developed solely for the use of the United States Air Force. Because it is equipped with neutralization systems, its primary function is air defense. The IAI Eitan, an unmanned reconnaissance aircraft primarily tasked with collecting and providing intelligence imagery, signals, measurement, and signature information, is another example of a similar aircraft. In their respective nations, these aircraft represent cutting-edge technology. Precision Agriculture (PA) is a significant use of UAVs, which is a harvest efficiency board framework in light of cutting-edge aviation, data, and correspondence innovations. Crop production can now be managed more precisely and effectively thanks to these technologies [61–65]. Experts in the field of archaeology have the option to employ UAVs to survey a particular region of importance and establish three-dimensional representations of historical landmarks, as opposed to depending on traditional two-dimensional maps. This is an exciting utilization of drone capabilities in this industry. As an illustration, in 2014, drone technology was utilized to renovate the aged remains of Aphrodisias, a diminutive Hellenistic Greek municipality situated in Turkey.

Additionally, drones can also be used to enhance cultural tourism by providing guided tours of historical sites, a feature that has been utilized during the COVID-19 pandemic and can be beneficial for remote students. The potential of Unmanned Aerial Vehicles (UAVs) extends beyond just tourism and archaeology, encompassing a variety of uses including photography, freight transportation, scientific exploration, monitoring, and civic defense. The emergence of Swarm Unmanned Air Vehicles (SUAVs), a fleet of UAVs that collaborate to achieve a shared objective, is broadening the horizon of UAV applications even further. SUAVs rely on autonomous decision-making rather than human operation [66,67]. Despite the continued use of military applications, there is an increasing fascination with civilian uses of drones. Inexpensive drones and their groups have the potential to become an encouraging foundation for groundbreaking research initiatives and forthcoming commercial applications that can aid in a variety of tasks. The advancements in sensor technology installed on UAVs are creating new opportunities for unmanned operations, resulting in entirely novel kinds of applications and services.

A suitable accurate application of the swarm formation is around rescue operations. In certain emergencies, such as floods, using multiple UAVs can be more helpful than just one. Floods are becoming more common due to environmental changes, and a swarm of UAVs can be used to search for people more efficiently during high water flow [68]. If one UAV carries a life jacket for someone affected by the flood, a group of UAVs can make a significant impact on search and rescue efforts. The swarm can also share location and photo data to make better use of resources. By assigning different roles to different UAVs, such as one collecting data and others dropping supplies, a swarm can work together effectively. Overall, a swarm of UAVs can be highly effective in emergencies when searching for and rescuing people [69]. The are multiple techniques of UAV swarm formation and most of them are based on triangle shape figures.

7. Current Challenges—Future Trends

A challenge the industry faces is the production of hydrogen fuel cell-powered UAVS for commercial usage. Commercial UAVs driven by hydrogen fuel cells are still in the experimental and development stages and are not yet widely available. However, several businesses are striving to create fuel cell-powered UAVs for a range of uses, including surveillance, inspection, and mapping. One illustration is the "Alpha 800" UAV created by UAVOS Inc., (https://www.uavos.com/, Redwood City, CA, USA) which uses a hydrogen fuel cell and has a maximum flight time of 2.5 h [70]. Another example is Horizon Unmanned Systems' (HUS) "Hycopter", a multi-rotor UAV with ultra-light fuel cells that convert hydrogen in the aircraft frame into electricity to power the rotors. According to citehorizon, the technology will transform existing 20–30 min multi-rotor operations into flights lasting several hours, allowing for cheaper/faster aerial surveys and making drone delivery more realistic [71].

The aerospace industry has shifted its focus towards UAVs, as they strive to improve their operational efficiency, power management, and application versatility in the future. This way, air vehicles can become more effective and adaptable to various use cases.

The aerospace industry is exploring new power-source solutions, one of which is the integration of lithium-sulfur batteries (Li-S). These batteries offer several advantages, including cost-effectiveness due to the use of low-cost materials such as sulfur as opposed to nickel or cobalt. Additionally, Li-S batteries have a higher power density with a theoretical energy of 2700 Wh/kg [72]. This has been demonstrated by the successful use of Li-S batteries in a UAV by the chemical department of LG in South Korea, which completed a stable high-altitude flight test. Furthermore, Li-S batteries have been integrated with a solar cell-powered drone and have proven to be effective in a broad-wing UAV [73]. Dalhousie University and Tesla's battery partner conducted research on advanced battery technologies with a focus on cells with higher energy density (Figure 7). They highlighted that such cells hold promise for not just electric cars but also drones and electric planes. The stability of their cycles remains a significant hurdle for these cells. Although the target was to attain 50 rotations in the past year, the utilization of a refined electrolyte has the potential to prolong longevity up to 200 rotations. Nevertheless, this advancement might not meet the commercialization standards, as the present industry demands 800 to 1000 rotations [74]. The cell has a gravimetric energy density of 360 Wh/kg and a volumetric energy density of 1000 Wh/kg [74].

When utilizing drones to enhance network connectivity and IoT applications, safeguarding security and privacy is of utmost importance. Hostile user attacks on drones can compromise the confidentiality, privacy, and integrity of data. To ensure the protection of drones, advanced technologies such as distributed ledger and wireless physical layer security must be thoroughly examined and evaluated. Along with security, forthcoming research must also strive to strike a balance between the level of security offered by these technologies and the necessity to sustain top-notch service and reliability. Energy consumption is a critical challenge faced by swarm UAVs. A swarm of UAVs may impede the successful completion of missions due to their size, which increases with battery capacity. Therefore, for the successful deployment of swarm UAVs, it is essential to find means of reducing the size and improving energy efficiency. The battery capacity of a swarm of UAVs is crucial to the successful completion of their missions. The size of the UAVs also increases with the battery capacity. A review by Yongkun Zhou et al. [75], discusses the use of autonomous battery maintenance mechatronics systems as a potential solution to this problem. With this method, a dead drone battery can be replaced quickly with a fully charged replacement while multiple other batteries are being charged simultaneously. Additionally, this system can be set up to provide optional uptime expansion and a compact footprint, allowing for battery maintenance with minimal drone downtime. One more huge test confronting UAVs is the issue of network safety. Security remains a major issue that must be addressed, as a growing number of UAV-related cyberattacks are being reported.

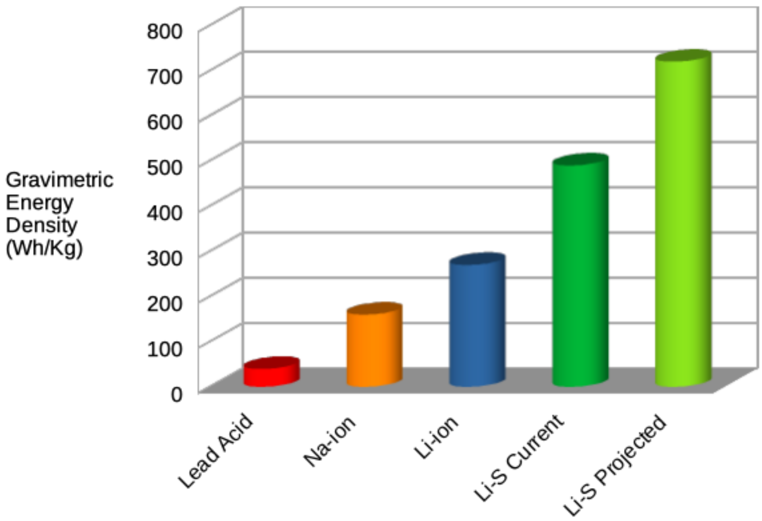

Figure 7. Gravimetric energy density of Li-S batteries compared to the state-of-the-art alternative battery technology (Reprint with permission from Ref. [15]. Copyright 2022 IEEE).

The danger is especially significant in military scenarios like combat missions, where falsification and Sybil attacks on UAVs present a considerable hazard. The matter of location privacy is also closely connected to localization and should be taken seriously. To avoid revealing their exact location to unintended parties, users can use various techniques, such as obfuscation. These issues are particularly pertinent when dealing with Cyber-Physical Systems (CPS) and the IoT. Another viable option is to utilize identity and site validation protocols that incorporate public-key-based authentication mechanisms and motion validation to confirm the authenticity of a group of UAVs.

8. Conclusions

This research investigates the three essential aspects of UAV technology that present the most technical challenges: energy sources, computational vision utilizing NNs, and applications. The classification of UAVs can be a complex endeavor due to various factors such as dimensions, weight, power supply, and intended use. It is crucial to take a systematic approach when determining the appropriate power source for a specific application. The amalgamation of computer vision, artificial intelligence, and neural networks are crucial advancements in the advancement of smart processes, therefore rendering unmanned aerial vehicles (UAVs) a valuable resource in military as well as civilian domains.

Our work examined thoroughly different power supply technologies for drones and machine vision applications. We have gained valuable insights into the technical challenges by studying energy sources, computational vision with neural networks, and their practical uses in UAVs. Classifying UAVs is complex due to various factors like size, weight, power requirements, and intended purposes. Therefore, it is crucial to approach power-source selection systematically, considering the specific needs of each application. Our comparative analysis deepened our understanding of the strengths and limitations of different power supply technologies. Moreover, the integration of computer vision, artificial intelligence, and neural networks has greatly advanced intelligence processes. This combination has made UAVs highly valuable in both military and civilian uses. The use of computational vision and neural networks has enhanced UAV capabilities in surveillance, object detection, and autonomous navigation, among other applications. Looking ahead, ongoing advancements in power supply technologies will continue driving innovation in the field of drones and machine vision. Exploring new power sources like fuel cells and solar panels is crucial to improve the endurance and efficiency of UAVs. In summary, this comparative analysis has contributed to our understanding of power supply technologies for drones and machine vision applications. It emphasizes carefully considering specific requirements when selecting a power source. The integration of computational vision and neural networks has created new possibilities, making UAVs indispensable tools in various industries. With continued research and development, the future of drone power supply technologies looks promising, shaping the potential and capabilities of these autonomous systems.

Author Contributions: Conceptualization, A.P. and G.F.F.; methodology, A.P.; validation, F.N.K. and M.G.T.; writing—original draft preparation, A.P.; writing—review and editing, A.P., G.S.M., M.G.T., F.N.K. and G.F.F.; supervision, M.G.T., F.N.K. and G.F.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data sharing not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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