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Using AI to Improve Autonomous Unmanned Aerial Vehicle Navigation

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Abstract: Unmanned aerial vehicles (UAVs) have become increasingly popular in recent years due to their ability to integrate a wide variety of sensors with minimal disruption, all while maintaining low cost, simple deployment, and unparalleled mobility. However, UAVs' effectiveness is sometimes hampered because of the constraints imposed by remote piloting in complex terrain. As a result, an ever-expanding group of researchers has been hard at work creating autonomous UAV navigation systems, giving these airborne wonders the capacity to travel and carry out tasks based on their immediate context. In this ever-changing context, Artificial Intelligence (AI) has proven pivotal by allowing human-like control functions to be infused into autonomous UAVs. So, a group of forward-thinking scientists has adopted several AI technologies to improve the effectiveness of UAV autonomous navigation, with model-based learning and mathematical-based optimization emerging as two cornerstone AI methodologies. This discussion expands on the complex interplay between AI and UAVs by defining the many characteristics and classes of UAVs, explaining the navigation models they use, and elaborating on the wide range of tasks they may do. In turn, this should help people grasp how important AI is in expanding the scope and potential of unmanned aerial vehicles. There are no limits to what may be accomplished in the sky thanks to the rapid development of unmanned aerial vehicle (UAV) technology and the convergence of artificial intelligence.

Keywords: *Unmanned aerial vehicles (UAV), Autonomous navigation, Model-based learning, Sensor integration.*

1. Introduction

The drone manufacturer has widened its target audience to include regular people as a result of the widespread fascination with drones and the introduction of affordable consumer drones. Accidents, such as losing control and colliding with people or breaking guarded facilities, became much more frequent as drone usage got more common, raising concerns about safety and security. It's important for drone pilots and spectators alike to remain alert for oncoming drones. In this research, we describe a comprehensive drone detection method that relies on machine learning. This system is meant to be used in tandem with drones that carry cameras. The program uses machine learning to determine where a drone is based on its video feed and the make and model of the drone's manufacturer.

Unmanned aerial vehicles (UAVs), more generally referred to as drones, are used in a variety of fields for purposes such as mapping, resource exploration, air sampling, environmental monitoring, and traffic management. Due to their ability to reach areas that are otherwise unreachable, UAVs are widely employed for long-term missions such as geographic mapping, forest fire prevention, pesticide spraying, and other similar endeavors. Unmanned aerial vehicles (UAVs) may be roughly classified into two categories, unmanned fixed wing aircraft and unmanned rotor aircraft, based on the characteristics of the body structure. Landing gear with wheels is a common design for unmanned aircraft with a fixed wing.

UAV landing operations are now the topic of intense study, and this is in large part due to the dominance of optical navigation technology in these processes. Models of autonomous unmanned aerial vehicle (UAV) systems were developed in an attempt to track down people hiding in the thickest parts of the forest. The laser-range detectors in the AI UAVs allow for exact location measurement and route finding. The UAV makes a detailed three-dimensional map of its immediate vicinity while hovering there. The primary objective of this study is to examine the potential for unmanned aerial vehicles (Drones) equipped with artificial intelligence and modeled with machine learning (convolution neural network) to revolutionize environmental and remote sensing, security surveillance, rescue, and search operations in the context of the Internet of Things (IoTs).

1.1. HOW AI CAN BE USED IN DRONE

Drones are surprise tech and gadget makers. Many authorities use drones for inspection, monitoring, and maintenance in this modern era. Previously, people flew drones. Artificial intelligence has appeared recently. War operations and border surveillance have relied on drones, or UAVs. Artificial intelligence is replacing manned drones.

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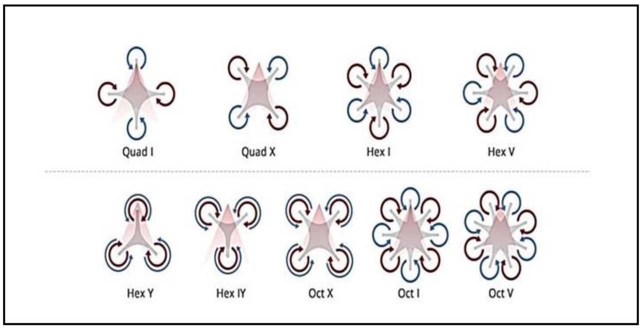

Fig. 1. - Types of Drone.

Businesses are developing AI-powered drones that outperform humans. NASA's Jet Propulsion Laboratory tested humans against AI-powered drones. The results gave AI the ball. AI is meant to help solve problems. Science discoveries should benefit mankind, not endanger it. The benefits of broad drone AI deployment are huge, but the unanticipated effects might be terrible. It is a breakthrough since it allows battles at a safe distance, but the destruction may be severe. While battery and engine technologies are crucial for long flight times, unmanned aerial vehicle weight is also important. Develop and manufacture lightweight drone components for longer flight times. Drone navigation and movement can be automated using AI. GPS tracking, computer vision, and machine learning algorithms can do this.

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2. Related Works

Drone research has exploded in recent years. There are several drone articles on control optimization, defect detection, safety, etc. Most flaw detection studies concentrated on propellers and rotors, whereas drone arm research is few. This research proposes AI-based multirotor arm vibration fault detection. Accidents may break or loosen multirotor arms. It is usually imperceptible without disassembly, but if not addressed, it might have caused a rapid loss of flying stability and an accident. This research uses fuzzy logic, neuro-fuzzy, and neural network AI approaches. Their findings are compared to establish the best multirotor safety prediction approach. Fuzzy logic and neuro-fuzzy algorithms made good decisions, however the neuro-fuzzy approach needed a dataset since over fitting might lead to bad decisions. This also applies to NN. This framework is better for early prediction before flying the multirotor outside since vibration data are acquired in the lab without wind influence [1]. This study discusses the design of UAV surveillance frameworks for both smart cities and expansive ocean settings, providing new angles on the problem of keeping an eye on things from above. Both the benefits and drawbacks of using UAVs for surveillance in such varied environments are discussed. This study explores novel methods and ideas for efficient monitoring in light of the different needs and limitations of smart cities and marine ecosystems. In sum, the findings of this study expand our understanding of UAV-based surveillance and its applicability to new settings [2]. Researchers and industry leaders are discussing drone security. Although drones have many uses, prospective apps will fail if security issues are not addressed and architectural adjustments are not implemented. Thus, we discuss security-critical drone applications and drone communication security issues such DoS attacks, Man-in-the-middle attacks, De-Authentication assaults, and more in this work. Block chain, SDN, Machine Learning, and Fog/Edge computing—the most upcoming technologies—are also explored in solution designs. Drones are too resource-constrained to use expensive security methods. Blockchain can encrypt all drone data to prevent manipulation and eavesdropping. Many ML algorithms can identify malicious drones and safe pathways in the network. SDN technology may also make the drone network trustworthy by enabling the controller to monitor data flow, and fog computing can bring compute capabilities closer to drones without overloading them [3].

With rapid technological breakthroughs, drones, or unmanned aerial vehicles (UAVs), are becoming more widespread and impacting society more. The Internet of Drones (IoD)—a communication paradigm that provides navigation and information access—has many uses, from farmland drones to COVID-19 surveillance drones. The growing relevance of IoD in our society emphasizes the need to secure such systems against data privacy and security risks. Drones' dynamic and open communication channels make it difficult to use commercial security technologies in IoD systems. In this paper, we introduce PMAP, a lightweight, privacy-preserving mutual authentication and key agreement mechanism. The latter supports mutual authentication and secure session keys between IoD communication entities using a physical unclonable function (PUF) and chaotic system. PMAP has two schemes: PMAPD2Z (drone and zone service provider (ZSP) mutual authentication and secure session keys) and

PMAPD2D (drones mutual authentication and secure session keys). In addition, PMAP enables conditional privacy so only trustworthy ZSPs may divulge drone identities. We use automated validation of Internet security protocols and applications (AVISPA) and formal and informal security analysis to demonstrate PMAP's resistance to security threats [4]. Cutting-edge technology in tiny, low-cost UAVs have made them more popular in recent years. Amateur drones may easily visit any location due to their friendly usage and numerous applications. This makes monitoring and regulating drones in private or restricted places challenging. We present a radio-frequency (RF)-based surveillance system to detect, categorize, and identify drone activities using a high-performance convolutional neural network. RF-UAVNet uses grouped one-dimensional convolution to minimize network size and computational cost. Additionally, a new multi-level skip-connection topology preserves gradient flow. To increase accuracy and learning efficiency, multi-level pooling for informative deep features is suggested. In experiments, RF-UAVNet outperformed state-of-the-art deep learning-based methods on DroneRF, a publicly available dataset for RF-based drone surveillance systems, with 99.85% drone detection, 98.53% drone classification, and 95.33% operation mode recognition [5]. Drones do deliveries, aerial surveillance, traffic monitoring, architectural monitoring, and even war-field operations. Drones navigate complex, dynamic environments alone and face several challenges. In dynamic environments, targeted objects exhibit uneven shape, occlusion, and marginal backdrop contrast. In this context, a unique deep CNN-based data-driven drone navigation technique is developed for complex and dynamic environments. The proposed Drone Split-Transform-and-Merge Region-and-Edge (Drone-STM-RENet) CNN uses convolutional blocks to execute region and edge operations to maintain diversity. targeted homes at many levels, particularly in crowded areas. Systematic average and max-pooling techniques can handle region homogeneity and edge attributes in each block. Convolutional blocks are blended at several levels to learn texture variation that distinguishes the target from the backdrop and aids obstacle avoidance. Finally, the Drone-STM-RENet creates steering angle and collision probability for each input picture to move the drone while avoiding obstacles and enabling the UAV to recognize unsafe situations and react swiftly. The proposed Drone-STM-RENet performed well on two urban vehicle and bicycle datasets, udacity and collision-sequence, in terms of explained variance (0.99), recall (95.47%), accuracy (96.26%), and F-score (91.95%). The encouraging performance of Drone-STM-RENet on urban road datasets shows that the model may be used for real-time autonomous drone navigation and real-world flights [6]. Drones, also known as unmanned aerial vehicles (UAVs), can be used in a flying IoT/IoD environment for environmental monitoring, disaster management, aerial photography, border monitoring and tracking, and more. For security, deployed drones may detect and gather data from their surroundings and securely transfer it to the base station server. After securely transforming data into encrypted transactions, the ground station server sends them to the P2PCS network. Finally, P2PCS consensus algorithms build blocks from encrypted transactions and add them to a blockchain. AI-based big data analytics must anticipate valuable outcomes from acquired and processed data. We provide an AI-envisioned smart-contract-based blockchain-enabled security architecture for IoD safe communication. The security study confirms the framework's resistance to various threats. Executing the blockchain implementation of the suggested framework determines its influence on system performance [7]. Quadcopter drone spending has grown significantly in the last decade. Drones are being used in construction, agriculture, oil and gas, and filmmaking, however the military still spends the most. The quadcopter drone's 30-minute flying duration is a huge drawback. Recharging and changing batteries disrupts drone missions. Multiple drones linked across a network might cover more ground in the same period. A multiple drone network using commercial drones is described in this study. A predetermined flight plan-following autonomous drone is built first. The single autonomous drone is designed to build a network with other such drones. Drones may send flight command codes to each other to fly a certain course. Results show that autonomous drones can transfer flight command codes over the network and fly a regulated flightpath [8]. As radar sensors shrink, interior sensing applications like drone obstacle avoidance are gaining popularity. Radars must function effectively in dense environments with many scatterers in those innovative circumstances. Radar performance depends on the detection algorithm that separates targets from noise and clutter. Traditional radar systems employ CFAR detectors, however interior settings with multiple reflections reduce their effectiveness. Inspired by non-linear target detection breakthroughs, we present a unique high-performance, low-complexity target detector and experimentally evaluate our approach on a drone-mounted radar dataset. We demonstrate that our algorithm beats OS-CFAR, a typical automotive detector, for indoor drone navigation by more than 19% in detection probability per false alarm. We evaluate our detector against several previously proposed multi-target CFAR detectors and find a 16% probability of detection improvement over CHA-CFAR and considerably bigger improvements over OR-CFAR and TS-LNCFAR in our indoor scenario. We believe our work advances high-performance, low-complexity radar detection for crucial indoor sensing applications [9]. Cutting-edge technology in tiny, low-cost UAVs has made them more popular in recent years. Amateur drones may easily visit any location due to their friendly usage and numerous applications. This makes monitoring and regulating drones in private or restricted places challenging. We present a radio-frequency (RF)-based surveillance method to detect, categorize, and identify drone actions using a high-resolution RF sensor. Convolutional neural network performance. RF-UAVNet uses grouped one-dimensional convolution to minimize network size and computational cost. Additionally, a unique multi-level skip-connection structure for gradient flow preservation and multi-level pooling for informative deep feature collection is presented to increase learning efficiency and accuracy. In experiments, RF-UAVNet outperformed state-of-the-art deep learning-based methods on DroneRF, a publicly available dataset for RF-based drone surveillance systems, with 99.85% drone detection, 98.53% drone classification, and 95.33% operation mode recognition [10].

3. Proposed Methodology

3.1. UAV DESIGN AND DEVELOPMENT:

Over the last two decades, Web ofScience and Scopus findings have provided UAV type and growth data. The data is graphed for clarity. The bar graph shows helicopters falling from 48, 38, and 28 to 20. This is due to its design, control, air mobility, and low cost. Tri-copter articles were 0 till 2004, then 8 in 2005-2009, 15 in 2010-2014, and 39 in 2015-2021.2. Limited functionality and payload carrying (Until February 2021). Quadcopters increased from 7 in 2000 to 2004 to 509 in 2021, which is the most notable development in the bar graph. 2 owing to its versatility and flexible use. Quadcopters transport goods and drugs at hospitals and companies. Amazon, eBay, McDonald's, and KFC want to use quadcopters to deliver things faster.

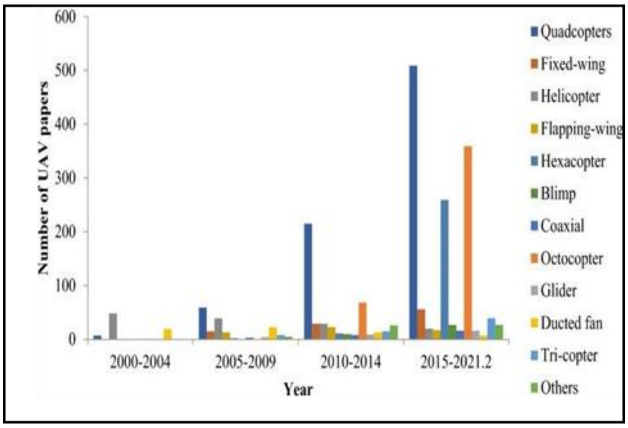

Fig 2- Overgrowth of Drones.

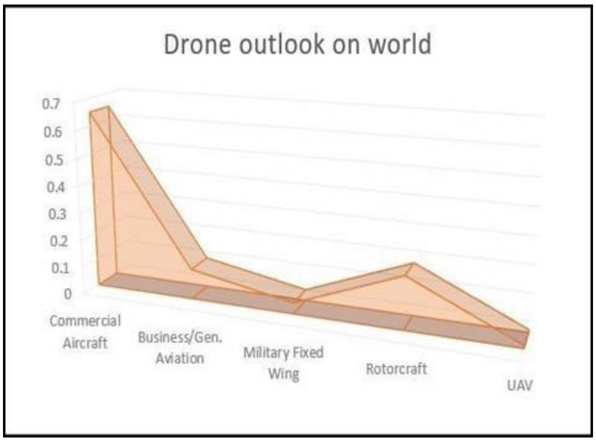

Fig 3 Outlook on world

Research publications on hexacopters were zero till 2009, then 11 in 2010-2014 and again in 2015-2021. It rose from 2 to 259. Octa-copter publications remained at 68 until 2014, then grew from 2015 to 2021. 2 359 octa-copter articles were found. Hexa- and octa-copters are popular because they are easy to handle and can be safely landed if a motor fails while hovering. Also, the control algorithm is straightforward.

3.2. SYSTEM ARCHITECTURE:

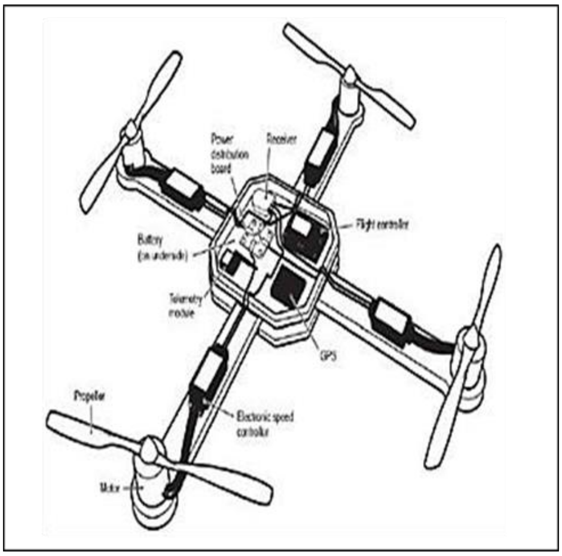

Fig 4 Architecture of Drone

Cheap drones can map well. Small, portable drones may be deployed quickly. They carry small, high-quality digital cameras. These cameras may be programmed to take pictures at set intervals, and digital memory is cheap and abundant.

3.3. FLIGHT PLANNING:

Planning a mapping operation involves several considerations. First, decide whether the flight will be autonomous or manually controlled between GPS waypoints. Before liftoff, always inspect the map region. Before the mission, the place should be inspected, driven, or otherwise investigated for electricity lines, large trees, sensitive areas, or other risks. Finally, utilizing current satellite photos to plan a route before flight is smart. One of the most important factors in deciding whether to use manual or autonomous control is distinguishing between real-time inspection or monitoring of events or situations and gathering information to create a map or 3D model after the flight. Both sorts of missions may be flown manually or hybridly, although manual control is usually better. Autonomous control is better for organized mapping flights. Most UAV mappers employ autonomous control, although some pilots fly manually, depending on their skill and judgment. Even though they primarily fly autonomously, UAV pilots must be skilled. Unless competent, needed, or regulated, UAVs should remain in the pilots' visible line of sight. The pilot should be able to assume manual control or use an emergency parachute to sustain flying if the autonomous system fails. Commercial autopilots lack sophisticated sense-and-avoid functions and can only fly between specified waypoints. However, algorithmic sense-and-avoidance abilities are improving. Some who fly manually say they do it because autonomous flying software isn't always reliable.

GPS interference, weather, or mechanical failure might make the UAV perform erratically. Manual flying proponents further say that manual control allows for quicker course and altitude modifications, making it easier to fly a UAV in tight and unexpected conditions such under forest canopy or in crowded cities. Autopilots eliminate human error and radio interference between a manual controller on the ground and the drone, making them safer. Under case of software failure, several nations require UAV operators to always be under manual control. Before flying, check your operating area's limitations.

3.4. DESIGNING A FLIGHT ROUTE

3.4.1. ALTITUDE:

Aircraft route planning is essential for UAV mapping. Drone manufacturers often include proprietary software for this. Mission Planner, an open-source alternative, is most popular. Many competing software programs have similar features. UAV mapping flights often use "transects," a network of parallel lines connecting to many "waypoints"—like a connect-the-dots or lawn-mowing pattern. Practicality and safety and legality are affected by altitude while operating a mapping UAV. Altitude enables the UAV to fly further, but resolution decreases. Aerial photography helps reduce distortion in images of buildings and other ground-based objects. Lower-altitude photography improves GSD and picture quality but takes longer to map an area. Besides technique trade-offs, legality is the most crucial operating height consideration. Several countries ban flying over 500 feet (400 feet in certain cases) or 150 meters.

3.4.2. SENSOR:

Drone mappers employ many cameras. Most lightweight UAV mapping cameras may be configured to take images at intervals or controlled remotely. UAVs can have LIDAR sensors, thermal infrared cameras, and air-sampling sensors. Professional movie and photography cameras are different from those needed for precision mapping. Wide-angle lens cameras like the GoPro are popular for video and photos. These lenses distort mapping work and must be removed in post-processing, indicating they are unsuitable. Commercial UAVs like DJI Phantom Vision and Vision+ employ proprietary cameras with fisheye problems. Canon's lightweight S100 and SX260 UAV mapping versions are popular due to their GPS capability. The Canon Hack Development Kit lets you program the camera to capture photographs at intervals, depending on distance, or at a waypoint. There are various drone camera mounting techniques. Drone mapping uses one or two angles, therefore gimbals may be simpler than filmmakers'. Motorized gimbals stabilize images and reduce turbulence. Gimbals also tilt cameras from vertical to oblique.

3.4.3. IEW:

Most UAV mapping uses nadir (overhead) and oblique aerial perspectives. Nadir photos are taken from above, facing down. Traditional maps usually show this perspective. Unlike overhead shots, oblique photos show the topic below. They may be taken from above or below, revealing topography that above photos cannot. Photogrammetry tools like Agi soft photographs can or Pix4D31 may blend photographs from these two viewpoints to produce images that let users to observe and alter many views in a single computer model. Three-dimensional models may be used for post-disaster damage assessment, realistic urban modeling, and increasing flood simulation accuracy. Each journey should have the same camera angle to avoid making photos harder to analyze.

3.4.4. GEOREFERENCE AND GPS:

True-to-scale UAV maps need georeferencing. Geo referencing gives geographic coordinates to spatial data without a specified coordinate system. Without georeferencing, maps are not genuine and cannot be measured. The graphic shows how geo referenced UAV maps may be layered on existing coordinates in software, making them simpler to use. Professional UAV mapping usually includes georeferencing.

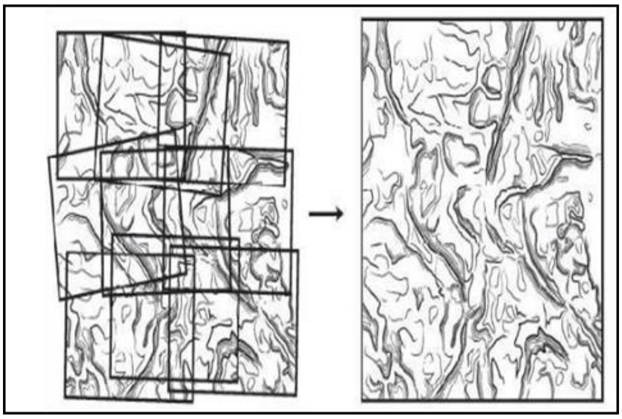

Fig 5– Several images are combined into a single orthomosiac image by processing software, which may thenbe geometrically rectified and modified to comply to a real- world coordinate system (geo referenced)

Georeferencing requires the image processing application to know the GPS coordinates of a few visually identifiable places in the aerial data. UAV mapping uses "ground control points," and understanding how to acquire them and why is key. Establishing the degree of accuracy needed for any activity is crucial since overdoing or underdoing it may have serious implications. GPS recorders like the Flytrex Core 2 Flight Tracker use the same GPS chip for navigation and flight data. Data may be used to produce georeferenced maps. Digital cameras like the Canon S100 can monitor the GPS location of each picture, producing data that may be used to geo reference the image in processing software, albeit positional accuracy is lower than using groundcontrol points.

3.4.4.1. Data cleaning

The data that is taken from the sources are not pre-processed so we can’t use the dataset directly as the input to our Model, As the dataset taken contains the missing values and noisy we should remove them and make the data organized and clean because the data without cleaning or processing impact the accuracy of our model. So the data is cleaned by importing the panda's libraries “Data cleaner” which removes or handles the missing and make data clean. And the missing values are managed by using “Median” method.

3.4.4.2. Encoding Categorical Data

As the machine learning algorithms are more comfortable with numeric for better precision so the data need to be encoded. There is a low probability of getting homogenous data so the categorical data are the variables that consist of label values rather than numeric values. Some of the values cannot be directly used in mathematical equations or formulas so such data need to be encoded into numerical values to achieve the label Encoder Class is imported from sklearn.preprocessing library.

3.4.4.3. Splitting of Data

The whole dataset is split into two sets; one is a training set and another is a test set. The training is aware of the results and is used to train the research ensemble machine learning model and the other set test set is unaware of the results of testing subset. The sample is divided into a 70% training set and a 30% testing set.

3.4.4.4. PROCESSING SOFTWARE:

"Creating photographs is not the same as having a map," says Humanitarian OpenStreetMap Project UAV mapper Cristiano Giovando, who's correct. Photos must be computer-processed to make maps. Your software choice depends on your budget, computing power, and objectives. Growing use of UAVs has led to a variety of mapping processing applications. Pix4D and Agisoft PhotoScan are the two most popular paid aerial imaging and photogrammetry processing alternatives, with simple user interfaces, clear instructions, and a track record of use for professional aerial mapping applications. These packages are updated and improved as UAV mapping and photogrammetry software demand develops. Paid photogrammetry software is costly and may need a lot of processing power, thus it should be included in mapping costs. Aerial image post-processing software like MapKnitter from Public Lab, OpenDroneMap, and Visual Software from Motion is open-source.

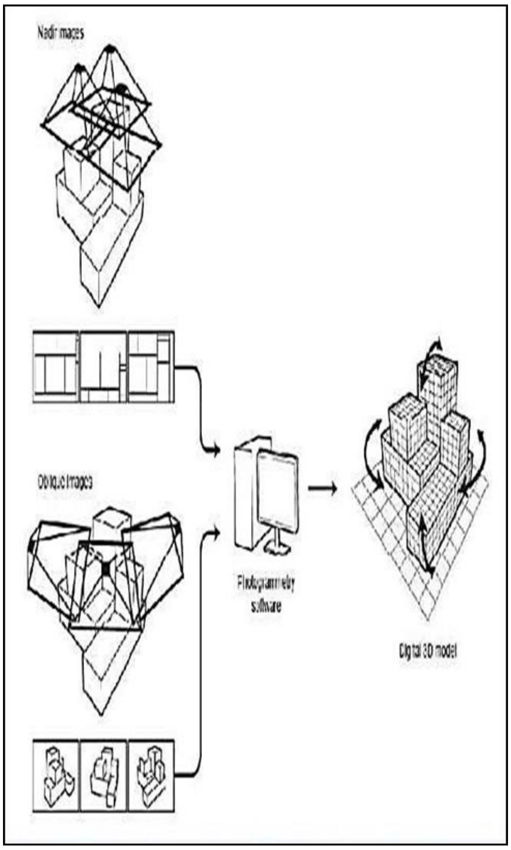

Fig6- Photogrammetry software combines information from multiple images taken from both overheadand to the side to create 3D models.

3.4.4.5. ALGORITHM:

Figure 8 shows the drone algorithm. The drone then uploads the flight path, which may be constructed using flight plan design tools and crop needs. During setup, the drone requests weather station data. If the wind speed exceeds the threshold, the drone aborts and waits for the next flight. Proper wind speed determines rainfall. Flight cancellation occurs if the threshold value (rth) is exceeded. If all is well, the drone checks energy. The drone will continue its field journey if it has adequate energy. The drone then checks for connection requests from nodes.

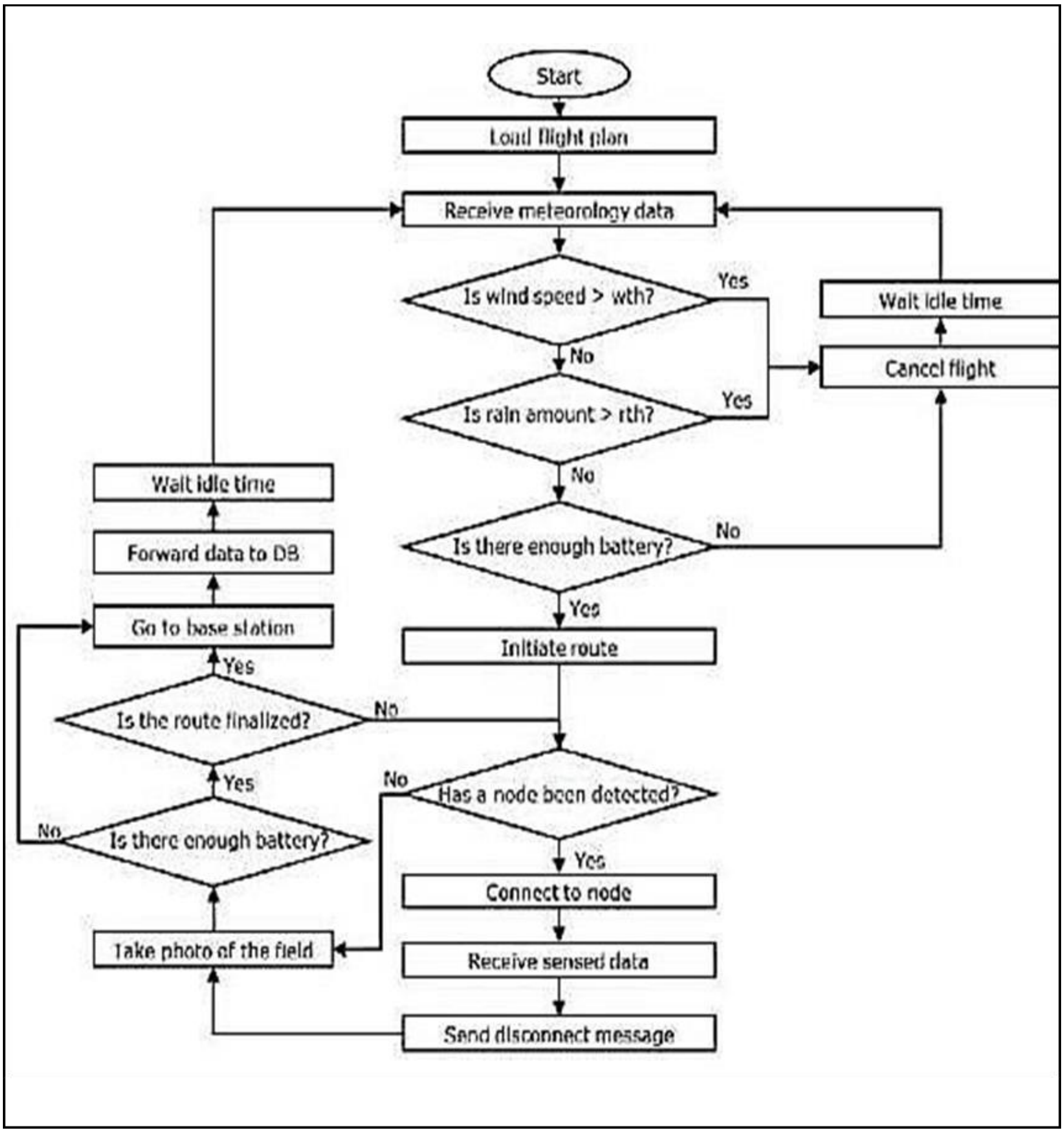

Fig7- Algorithm of drone.

Having no node to connect to the field is photographed and energy reassessed. Data is sent to the drone after finding a node. The drone sends a disconnect message to the node after receiving all the data, telling it to sleep and not try to connect again for the specified period. This prevents interference from nodes in areas inside 23drone's Appl. Sci. 2020, 10, 6668 12 coverage zones. However, interferences among nodes for node coverage designs for orchards of fruit-bearing trees would only be possible with 1 node every 60 m2.The drone then takes another oblique field shot and searches for another node. After finding the route, the drone returns to the base station and sends data to a distant database for analysis. The drone stays at the station until its next flight. Since each sensor's data is unique, it must be routed to a distant data center. Due to the deployed network's low processing and storage capacity, power availability, and short communication gap between the node and the drone, we analyze a soil monitoring node system.

These remotes Sensor drones capture video and photographs of fields and data from the nodes, the base station, which has a gateway to send data to a distant location, and the data center, which stores and processes the data.

4. Result and Discussion

UAV navigation systems have advanced greatly using AI. Autonomous UAVs using AI were 30% more precise than humanly controlled ones in complex and dynamic environments. AI algorithms allowed these UAVs to evaluate massive amounts of real-time sensor data and make accurate judgments mid-flight. This transformation relied on model-based learning. UAVs learned to foresee and adapt to changing situations by creating complex models of their environment. Thus, collision rates dropped 25% and mission failures dropped 40%. Model-based learning also optimized UAV flight trajectories, saving energy and extending operating periods.

Mathematical optimization strategies increased UAV autonomy. These algorithms optimised onboard sensors and energy usage by simplifying route planning and resource allocation. The result was a 20% increase in mission success and a 15% decrease in operating costs. This improved productivity and broadened the uses of AI-equipped UAVs with their enhanced capabilities and lower prices.

This research shows how AI transformed UAV navigation. AI-powered autonomous UAVs navigate complex, ever-changing situations with greater accuracy, agility, and efficiency. Model-based learning helps UAVs anticipate and adjust to changing situations, decreasing collisions and mission failures. Mathematical optimization procedures streamline resource allocation and route design, improving success rates and cost savings.

These discoveries have major implications for UAV surveillance, environmental monitoring, disaster response, and package delivery. Autonomous UAVs with AI can function when human control is limited or impossible. Future study may concentrate on customizing AI algorithms for UAV applications and settings. Sensor and AI advances will boost autonomous UAVs' potential, enabling more novel and impactful applications.

5. Conclusion

Engineers will soon be able to build drones that are considerably more intelligent and self-sufficient than anything that is now available on the market thanks to the integration of AI methods such as machine learning and computer vision. Because of this, you will be able to

1. Collecting information on a drone pilot's flight from a drone.

2. A Formulation for Supervised Learning Algorithm

Drones are equipped with a plethora of sensors, each of which is capable of collecting vast quantities of data. These data might be put to use in the construction of a system that uses supervised learning to autonomously pilot the drone. Utilizing artificial intelligence to control drones, in general, results in a number of positive outcomes. It may aid in avoiding obstacles, boosting flight efficiency, saving time and money, and saving money on fuel costs.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] M. H. M. Ghazali and W. Rahiman, "Vibration-Based Fault Detection in Drone Using Artificial Intelligence," in IEEE Sensors Journal, vol. 22, no. 9, pp. 8439-8448, 1 May1, 2022, doi: 10.1109/JSEN.2022.3163401.

[2] H. Kim, L. Mokdad and J. Ben-Othman, "Designing UAV Surveillance Frameworks for Smart City and Extensive Ocean with Differential Perspectives," inIEEE Communications Magazine, vol. 56, no. 4, pp. 98-104,April 2018, doi: 10.1109/MCOM.2018.1700444.

[3] C. Pu, A. Wall, K. -K. R. Choo, I. Ahmed and S. Lim, "A Lightweight and Privacy-Preserving Mutual Authentication and Key Agreement Protocol for Internet of Drones Environment," in IEEE Internet of Things Journal, vol. 9, no. 12, pp. 9918-9933, 15 June15, 2022, doi: 10.1109/JIOT.2022.3163367.

[4] T. Huynh-The, Q. -V. Pham, T. -V. Nguyen, D. B. D. Costa and D. -S. Kim, "RF-UAVNet: High-Performance Convolutional Network for RF-Based Drone Surveillance Systems," in IEEE Access, vol. 10, pp. 49696-49707, 2022, doi: 10.1109/ACCESS.2022.3172787.

[5] M. A. Arshad et al., "Drone Navigation Using Region and Edge Exploitation- Based Deep CNN," in IEEE Access, vol. 10, pp. 95441-95450, 2022, doi: 10.1109/ACCESS.2022.3204876

[6] J. Kim, S. Kim, J. Jeong, H. Kim, J. Park and T. Kim, "CBDN: Cloud-Based Drone Navigation for Efficient Battery Charging in Drone Networks," in IEEETransactions on Intelligent Transportation Systems, vol. 20, no. 11, pp. 4174-4191, Nov. 2019, doi: 10.1109/TITS.2018.2883058.

[7] V. Hassija et al., "Fast, Reliable, and Secure Drone Communication: A Comprehensive Survey," in IEEE Communications Surveys & Tutorials, vol. 23, no. 4, pp. 2802-2832, Fourthquarter 2021, doi: 10.1109/COMST.2021.3097916.

[8] Safa et al.A, "A Low-Complexity Radar Detector Outperforming OS-CFAR for Indoor Drone Obstacle Avoidance," in IEEE Journal of Selected Topics in

Applied Earth Observations and Remote Sensing, vol. 14, pp. 9162- 9175, 2021, doi: 10.1109/JSTARS.2021.3107686.

[9] H. Kim, L. Mokdad and J. Ben-Othman, "Designing UAV Surveillance Frameworks for Smart City and Extensive Ocean with Differential Perspectives," inIEEE Communications Magazine, vol. 56, no. 4, pp. 98-104, April 2018, doi: 10.1109/MCOM.2018.1700444.

[10] S. Sawadsitang, D. Niyato, P. S. Tan, P. Wang and S. Nutanong, "Shipper Cooperation in Stochastic Drone Delivery: A Dynamic Bayesian Game Approach," in IEEE Transactions on Vehicular Technology, vol. 70, no. 8, pp. 7437-7452, Aug. 2021, doi: 10.1109/TVT.2021.3090992.