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SURVEY / LITERATURE REVIEWS

Survey On Object Detection, Face Tracking, Digital Mapping and Lane Following For Remotely Piloted Aerial Systems (RPAS)

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Abstract – Remotely Piloted Aerial Systems (RPAS) for remote sensing, a significant way of obtaining geographic data, has benefits like real-time, adaptability, high-resolution, cost-effectiveness, etc., and it can acquire data in risky environments without jeopardizing flight crews. It has great potential and a promising future since RPAS remote sensing is a powerful companion to airborne and spaceborne remote sensing. This work provides a comprehensive view of recent advancements in the field of Remotely Piloted Aerial Systems (RPAS) with machine learning features. The focus is on some specific areas: Face tracking, Object Detection, Surveillance. The paper describes the methods and algorithms used for these applications, discusses their performance and accuracy, and highlights the challenges faced in the implementation of such systems. The paper also provides an overview of the various platforms and tools used for the development of these systems, including hardware and software components. The review concludes by highlighting the future directions for research and development in this field.

Index Terms – Remotely Piloted Aerial Systems; remote sensing application; Object detection; Face tracking;

I. INTRODUCTION

A remotely piloted aerial system (RPAS) is a type of aerial vehicle which requires minimum human control for its operation. We propose a RPAS which is capable of video-based surveillance, object detection, face tracking, lane following and a digitally mapped system which takes coordinates from the user instantaneously and follows the path given out by the user on a screen. The RPAS is usually called an Unmanned Aerial Vehicle (UAV) which employs aerodynamic forces to lift the vehicle, is scalable or recoverable, can fly autonomously, and can carry a lethal or nonlethal payload. Its usage is currently limited by difficulties such as satellite communication and cost, but the advent of programmable drones has enabled engineers to implement various technologies in an unmanned aerial vehicle which has applications in numerous fields. RPAS were originally developed for the aerospace and defence sectors, but they have now been made available to the civilian population due to the higher levels of effectiveness as well as the security they provide.

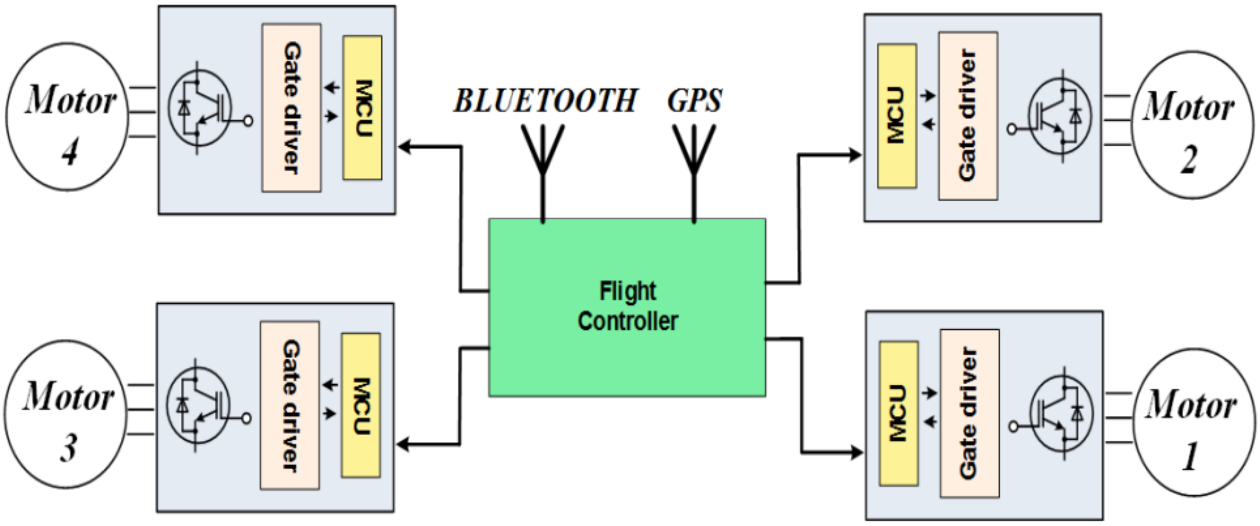

Fig. 1: Architecture of a Remotely Piloted Aerial System.

These autonomous robotic drones have variable degrees of autonomy as they fly. An RPAS's autonomy can range from remotely piloted, wherein an individual commands its movements, to advanced autonomy, where it makes decisions about its movement using a collection of sensors and LiDAR detectors. Drones are ideal for some of the world's most difficult undertakings since they can be flown at different altitudes and distances while being controlled remotely. They can be found assisting in the hunt for survivors after a hurricane, supporting the military and law enforcement with an aerial surveillance capability during terrorist incidents, and promoting scientific study in some of the world's most hostile climates. Even in our homes, drones provide amusement for enthusiasts and are an indispensable tool for photographers.

II. BACKGROUND

The popularity of unmanned aerial vehicles (UAVs), also known as drones or remotely piloted aircraft systems (RPAS), has increased recently as a result of their capacity to fly independently and collect detailed aerial data and pictures. The use of RPAS for surveillance, object detection, face tracking, lane following, and digital mapping has an array of range of applications, from military and law enforcement to commercial and recreational use. RPAS can be equipped with cameras, sensors, and other technologies that enable them to capture detailed images and data from the air. This data can be used for a variety of purposes, such as monitoring traffic, detecting objects and people, tracking movements, and creating detailed maps of terrain and structures. For example, in the military and law enforcement sectors, RPAS are used for reconnaissance, surveillance, and intelligence gathering. They can be used to monitor and track potential threats, survey areas that are difficult to access, and provide real-time situational awareness to ground troops.

Agricultural operations, infrastructural inspection, search and rescue missions, and environmental monitoring are just a few of the business uses for RPAS. For example, drones equipped with thermal imaging cameras can be used to detect heat signatures and identify individuals who may be lost or injured in a wilderness area. In the field of transportation, RPAS are being used for lane following and object detection in autonomous vehicles. They can help vehicles navigate complex road networks and avoid obstacles in real-time. Digital mapping is another important application of RPAS. RPAS can produce incredibly accurate maps of the landscape and built environments through the collection of aerial photography and data. These maps may be utilized for a range of tasks, including urban planning, disaster response, and environmental preservation. The usage of RPAS for monitoring, recognizing objects, face tracking methods lane following, and mapping purposes has a wide range of applications in many different industries, and it is anticipated that their use will increase over the next several years as technology develops and new uses are found.

In this survey, we attempt to find out whether we can integrate multiple functionalities like surveillance, object detection, face tracking, lane following and digital mapping into a single remotely piloted aerial system therefore making it a versatile agent for use in various sectors like security, scientific research, defense, urban planning, law enforcement etc. We try to integrate all these features so that they can work seamlessly and complement each other's functionalities to form a complete product of high value using minimal computing resources and having less power requirements. Furthermore, we make use of a wide variety of learning algorithms to implement the aforementioned features. This makes the RPAS more intelligent, and its working can improve over time.

III. OBJECTIVES

The objectives for a project titled RPAS (Remotely Piloted Aircraft System) with the following features could include - Surveillance: Develop a system that enables the RPAS to conduct surveillance activities such as monitoring borders, traffic, wildlife, and other activities. Face Tracking: Design a system that enables the RPAS to track human faces and recognize them using machine learning algorithms. Object Detection: Develop a system that allows the RPAS to detect objects and identify them with high accuracy, using computer vision techniques and deep learning models. Lane Following: Create a system that enables the RPAS to follow designated lanes autonomously, using advanced navigation systems and sensors. Digital Mapping: Develop a system that enables the RPAS to create accurate and detailed digital maps of the surrounding environment, using LiDAR or other mapping technologies. Overall, the objective of the project is to create an RPAS that can perform a range of tasks with high precision and reliability, by integrating advanced technologies such as machine learning, computer vision, navigation systems, and mapping technologies.

IV. LITERATURE SURVEY

First and foremost, we look at the control mechanisms for the RPAS. In [1] we look at the fundamentals of remote-controlled airplane systems (RPAS) and independent control, in addition to RPAS physical facilities, various degrees of autonomy, and the benefits and drawbacks of using artificial

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intelligence now on the market. However, current RPAS still need a manual pilot operator to provide double-layer security and safety, despite research showing that RPAS with a fully autonomous vehicle at its core would significantly boost decision-making and total mission accuracy and precision, security, and effective. We assess the different levels of autonomy for the control of the RPAS ranging from level 0 (no automation) to level 5 (full automation). A human pilot controls Level 0 RPAS manually, remotely, or both.

The pilot is still in charge of the vehicle's general functioning and safety in Level 1. A level 1 RPAS can guide the vehicle using navigational sensors and algorithms. The pilot is still in charge of the operation's safety and is prepared to assume command over the directions, elevation, and velocity of the event that a response to a issue fails. Level 2 RPAS can regulate both attitude and acceleration/deceleration. At level 3, the vehicle can detect its environment, manage safety-critical operations, and make informed decisions in ambiguous situations. A level 4 RPA may often carry out the flying mission and monitor the surroundings since RPAS, which have a set of defined rules that regulate their activity. Level 5 vehicles are capable of controlling and monitoring the environment under all conditions without the need for human involvement. They also meet or exceed all lower autonomy levels. The levels 3 and 4 of the aforementioned autonomy levels correspond to our suggested approach.

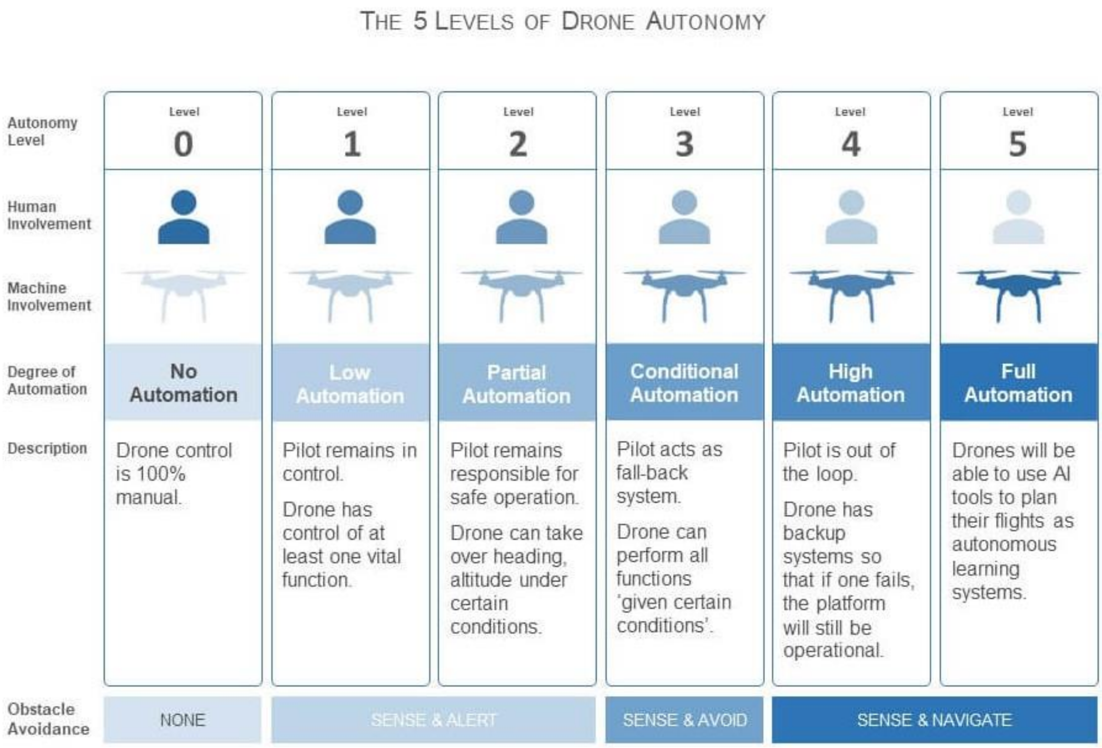

Fig. 2: Levels of Autonomy

[2] presents a design for an unmanned aerial system that can transmit monitoring video from an RPAS to the ground control system in a surveillance area. We focus on a relay technique in particular to avoid deteriorating communication performance. We compare the performance of a relay network and a

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single path system as a result of the experiment. The authors suggest a relay system that consists of an interconnected RPAS, ground control station, and relay drone. The RPAS gathers video data of a certain area. Two drones are operated by the GCS, which can also gather video data from drones as needed. The GCS receives video data from the RPAS through the Relay drone. With the aid of socket programming, video frames are transmitted. The relay drone receives the frames from the RPAS, which acts as the server, and transmits them to the ground control center. The usage of TCP for connection can lead to retransmission and caching on the side of the ground control station, which is one of the system's limitations.

The research done in [3] focuses on exploiting aerial photos to detect automobiles and introduce a counting mechanism. In order to extrapolate a vehicle spatial density map all across aerial image, convolutional neural networks are used. It has been tested using the Two readily available data sets are the Munich and Overhead Imagery Research Data Sets. The recommended vehicle algorithms for recognition in the scientific literature fall into two categories: shallow learning-based techniques and deep learning-based methods. Hand-crafted features are developed and followed by a classifier or cascade of classifiers in shallow learning-based methods. Nevertheless, deep learning designs like convolution neural networks have beat shallow learning methods, which do not provide the requisite accuracy in the vehicle recognition job (CNN). Nonetheless, deep learning-based approaches have been employed for vehicle recognition tasks due to their exceptional performance across a variety of domains, including images and sounds. More precisely, approaches using region-based convolutional neural networks (RCNN) excelled in detecting objects.

A completely convolutional regression network is suggested by the authors (FCRN). An input picture and its corresponding ground truth are provided to the FCRN in order to reduce the discrepancy between the output expected and the actual ground truth during training. A straightforward connected component approach is then utilised to return the count and location of the observed cars after the results of the trained model is empirically thresholded during inference. In [4], we acknowledge the necessity of setting up a search and rescue operation to aid the injured and give medical care during natural disasters. Finding a lost or injured person is the main objective of a SAR operation, which aims to cover the most ground in the quickest amount of time. As they can quickly and easily capture a vast, controlled area, drones (also known as UAVs or drones) are becoming more and more common in search operations. A comprehensive analysis of a substantial body of recorded material is still difficult. Even for an expert, it might be difficult to locate persons who are small for the region they are in since they are frequently hidden by foliage or blended into the ground and in peculiar positions as a result of falls, injuries, or tiredness.

Thus, it is crucial that people and objects can be automatically identified in photos and videos captured by drones during these operations. Utilizing a VisDrone standard and a specifically built dataset SARD produced to replicate rescue scenarios, this study investigated the reliability of existing state-of-the-art detectors. These detectors included Faster R-CNN, YOLOv4, RetinaNet, and Cascade R-CNN. Object tracking and picture segmentation have lately gained significant importance in satellite and aerial imaging, according to [5]. Convolutional neural networks along with other deep learning techniques are heavily correlated with current advancements in this field. When supplemented with an adequate amount of training data, CNNs perform better than traditional approaches based on Viola-Jones and Support Vector machines. Unfortunately, there are a number of widespread problems that result in classification inaccuracy when CNNs are used for object recognition on aerial photos. The first one has to do with the camera's restricted spatial resolution and shooting angle. The second one results from the limited dataset for particular object types that hardly ever exist in the collected data.

The efficiency of various deep neural networks for detecting items with resemblant patterns on photographs within a constrained set of pre-trained datasets is compared in this paper. The YOLO ver. 3 network has been shown to offer faster analysis and better accuracy than SSD, R-CNN, Fast R-CNN, and Faster R-CNN designs. This paper [6] uses the camera of a quadrotor UAV to suggest a system for tracking and detecting human faces. Using a wireless link, the quadrotor captures images and video of the human face while in flight and uploads them to a computer. The Viola Jones algorithm is used by face identification algorithms to identify human faces. Several faces can be detected simultaneously by a face detection algorithm. The Quadrotor UAV's camera records a video, [16] [17] and In the initial frame, a face tracking methodology detects the face's feature points and tracks them in following frames. The effectiveness of face identification and face tracking algorithms is assessed using images and video footage of human faces. It might be inferred that face tracking algorithms are capable of monitoring human faces and that face detection algorithms successfully detect single and numerous faces. An actual time face monitor is one of among the most well-liked innovations in the world of image processing [7].

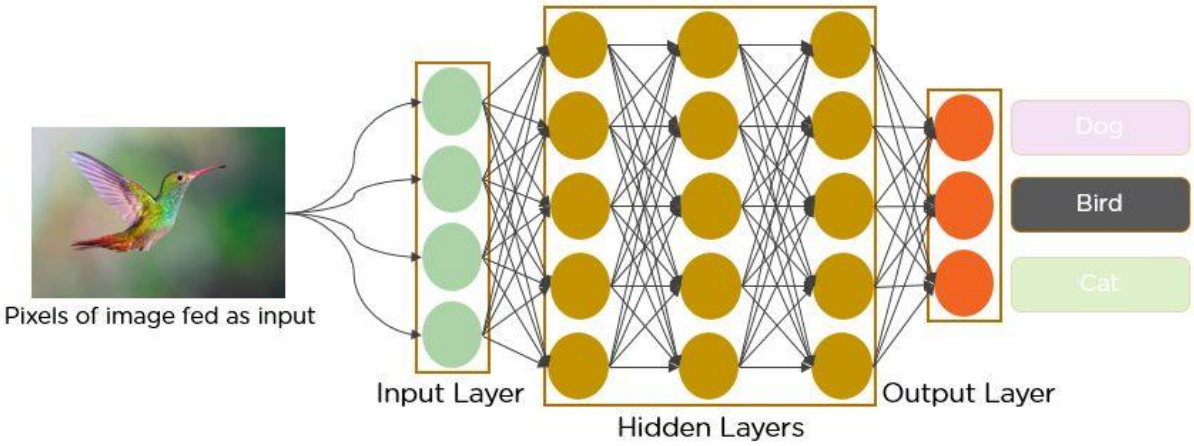

Fig. 3: YOLO algorithm

Systems are created specifically to serve this purpose. Despite extensive study and significant recent advances in the field of face recognition, existing approaches confront significant challenges when it comes to implementing face identification and producing the recognition swiftly. These systems track wandering faces of individuals in the field of view of the camera. Two processes, sampling and testing, are used in face recognition tasks. Some of the requested human face photographs were imported into the identification software, which will eventually be incorporated into the primary computer application. The drone then finds the right person in a location. It then recognises all of the physical characteristics of humans and never loses them. [8] suggests an remotely piloted aerial system tracking method for persons and objects (UAV). It can go anywhere and is used as a surveillance camera.

The UAV's video is not set up as a closed-circuit television permanently. To support our recommendations, we make use of the face recognition and objection detection. The AR-Drone 2.0 was the UAV type employed in this investigation. The front camera is restricted because the view is fixed and cannot be changed while the aircraft is in flight. Two experiments were created. First, a Because they offer a high level of analytical precision, the Haar-cascade predictor and max-margin recognition along with convolutional neural network based attributes are employed for face detection utilising photos. The second is a colour detection system that can be used as an obstacle detection system that simply focuses on the colour of things. The experiment's findings can be applied to tracking individuals and items in smart cities. [9] Moving targets-tracking is a tempting usage for quadcopters and a very challenging, demanding area of research because of the intricate quadcopter mechanics and the fluctuating speed of the target's movement over time.

Numerous control methods have been developed as a result to use a video camera to monitor a moving object. This work creates a fuzzy-PI controller that modifies the PI controller's settings using positioning and change-of-position information as input. Instead of being compared to a standard PID controller, the suggested controller is contrasted with a gain-scheduled PID controller. Many experiments with a quadcopter following a moving target are undertaken in both indoor and outdoor settings, during the day and at night, to assess the designed system's performance and figure out which one works better. According to the data, the recommended controller performs admirably for keeping an eye on a moving target under various conditions, especially at night. [10] Those who are unwilling to cooperate with other biometric identification methods like fingerprint, iris, or hand scans will find a facial recognition system to be more suited and friendly. Most of the time, there is no system in place to follow the accused, and they escape with their loot.

The introduction of a system that can recognise a criminal and at the same time instantaneously warn the relevant authorities to take precautions in order to catch him is made feasible with the aid of image processing software, such as facial recognition. Audio-visual analysis and safety precautions are two more facial recognition softwares. It is a biometric identification technique, however a face is needed rather than a hand or finger. Instead of fingerprint or hand scan technology, military organisations prefer facial recognition technology. A pre-trained facial recognition classifier called Local Binary Patterns Histogram (LBPH) is one sort of facial recognizer that can identify faces if there is enough facial recognition data available for it to do so. Most real-time applications make use of facial recognition technologies that are already in use by international security firms or armed forces.

In [11], the authors describe a technique for automatically taking an image of the target's front while tracking a designated walking person using an unmanned aerial vehicle (UAV). The suggested approach consists of three components: Vision-based UAV control, face detection and localization, person detection and identification, and feature point localization. In the person tracking phase, they match the specified target person using the Locality-constrained Linear Coding (LLC) method with a deep neural network called YOLOv3 for person detection. In frontal face perception, we use Multi-task Cascaded neural networks with convolution (MTCNN) for face detection. On the basis of the visual information acquired from the two modules, the unmanned aerial vehicle may fly above the target person and take a picture of their frontal face. [12] Researchers have recently created a number of well-liked and efficient face detectors, ranging starting with the Viola-Jones face sensor to the contemporary CNN-based ones. Traditional face detectors, on the other hand, find it difficult to identify different faces that are present "in the wild" because to the massive growth in photos and videos that contain faces with varying scales, appearances, expressions, occlusions, and poses. With the advent of deep learning techniques, face identification experienced notable advancements at the cost of a sizable rise in computation. This study gives a detailed and comprehensive examination in terms of accuracy and efficiency of representative deep learning-based algorithms.

They also compare and discuss the evaluation measures for the widely used and difficult datasets. Two metrics—FLOPs and latency—are used in a thorough analysis of a number of successful deep learning-based face detectors to determine how effective they are. [13] This study provides a vision-based subjective 3D navigation technique and presents first results from the path-following control of quadrotor aerial vehicles using the Funnel Lane theory. The Kanade-Lucas-Tomasi (KLT) corner characteristic in the picture is detected along the reference path to provide a funnel lane for navigation. Following that, a funnel-lane navigation calculation is used to predict the proper yaw angle and altitude for the next movement. The quadrotor Ar.Drone's front RGB-D sensor, direction determination, and altimeter are all utilised in the navigation process of the suggested algorithm. The suggested method's outstanding benefit is that it operates autonomously in surroundings without GPS without the assistance of an external tracking device and is computationally efficient.

When compared to other methods, path following requires at least one matched feature. Applications for the suggested navigation approach include visual-homing, visual-servoing, and visual-teach-and-repeat (VT&R). The suggested solution is first tested in real time using the quadrotor Ar.Drone in the ROS and Gazebo simulators. [14] The suggested method's unique benefit is its ability to operate autonomously in circumstances where GPS is unavailable, without the aid of an external tracking system, and it is also computationally efficient. When compared to other methods, path following requires at least one matched feature. The suggested navigation method has applications in visual homing, visual servoing, and visual teach-and-repeat (VT&R). Using the quadrotor-equipped Ar.Drone in the ROS and Gazebo simulators, the suggested method is initially evaluated in real time. In UAV footage, a framework for effective road detection and tracking is suggested.

In particular, a quick homography-based road-tracking technique is developed to track road segments automatically, and an accurate graph-cut-based road area extraction method is offered to be used both during initialization and during tracking. The framework's excellent efficiency can be ascribed to two factors: road detection only takes place when it is necessary, and highly quick homography-based tracking is used to locate the road most of the time. Experiments are conducted using drone videos of real road scenarios that we downloaded from the web and filmed. With a precision of 98.4% and an average processing speed of 34 frames per second for 1046 595 videos, the encouraging findings demonstrate the usefulness of our approach. [15] introduces the moving path following (MPF) issue, which broadens the scope of the conventional path following problem, which is only applicable to stationary pathways [18].

This problem calls for an automobile to converge to and follow a predetermined geometric moving path without an exact time requirement. Tracking land/air vehicles and monitoring gas clouds are examples of jobs that can be phrased as MPF problems, where the desired path's motion is determined by the velocity of the intended vehicle or cloud. The challenge of tracking single and numerous ground targets utilizing operating at constant height is described, and the authors develop an error environment for MPF for the general case of time-varying paths in a two-dimensional environment. In order to achieve this, a path-generation algorithm and a Lyapunov-based MPF control rule are proposed, together with results for convergence and performance metrics.

REFERENCE	YEAR	EXPLAINATION	DRAWBACKS
[1]	2021	• Levels of autonomous control for RPAS • Level 0 indicates full pilot control and Level 5 indicates full autonomy	• Full autonomy requires huge computation capability • The requirements of full autonomy is not yet met
[2]	2021	• Unmanned RPAS using a relay drone • The relay drone acts as both server and client to maintain communication between RPAS and GCS	• There is a dependency on the relay drone • Communication lag may arise
[3]	2018	• Vehicle detection and counting using CNN • Uses two groups of algorithms, shallow learning as well as deep learning methods	• The results from shallow learning methods are sometimes inconclusive. • Deep learning techiniques involve multiple iterations and are more time consuming.
[4]	2021	• Comparing the reliability of R-CNN, YOLOv4, RetinaNet and Cascade R-CNN. • These detectors are employed in search and rescue operations	• The availibility of multiple options leads to confusion • High time complexity can cause problems during emergency situations
[5]	2020	• Comparative analysis of the abilities of several deep neural networks to identify items with patterns similar to those on photographs	• Overlearning of the neural network can take place unwarranted strain on the related devices
[6]	2020	• Human face detection and tracking with a camera of Quadmotor UAV. • Can detect multiple faces in a single video frame	• Face detection and tracking is carried out using different modules which increases the overall risk factor of the system.
[7]	2019	• Kalman filter is used to improve tracking accuracy in outdoor environments. • In order to move the drone towards the person in real time, fuzzy logic is applied.	• Adjusting for differences in altitude of the target face is challenging.
[8]	2019	• Face detection using Haar-cascade classifiers • Max-margin object detection with CNN based features.	• The varying contrast of image colours can bring out errors in detection

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[9]	2019	• Fuzzy-PI controller is used to change the paramenters of PI controller to facilitate Target Tracking	• This method cannot be used to track unstable target in low light conditions
[10]	2018	• Presents a dataset intended to facilitate research for drone-based face recognition. • Provides videos with annotated face regions to a high-resolution gallery image.	• This is a dataset based approach • No learning capabilites are provided to the device • Device Incompatibilty might also occur
[11]	2020	• Person detection and recognition • face detection and feature points localization • vision based UAV control	• Camera quality and drone speed can affect the performance of this system.
[12]	2021	• Two metrics—FLOPs and latency—are used in a thorough analysis of a number of successful deep learning-based face detectors to determine how effective they are.	• Face detection is based on the shape of the face which can sometimes produce erronous output.
[13]	2019	• Proposes a path following quadrotor using a vision based KLT corner features. • Works independently in a GPS denied environment	• This system requires a ground based relaying robot for correct working in an outdoor environment.
[14]	2019	• In UAV footage, a framework for effective road recognition and tracking is suggested. • A graph-cut-based detection method is presented to precisely extract a designated road section at both the initialization and tracking stages.	• In UAVs, drift inaccuracy and zigzag contour issues are more common at low altitudes at fast speeds.
[15]	2019	• Introduces the moving track following (MPF) issue, in which a vehicle must reach and adhere to a predefined geometric moving route without regard to a predetermined time frame.	• Poor system performance and cannot work without an external agency controlling it.

V. CONCLUSION

In this paper, we have proposed to zero in on an effective way to integrate multiple features into an aerial system which is either remotely controlled or partially automated. The features are namely surveillance, face tracking, object detection, lane following and digital mapping. We first look at multiple methods to perform surveillance using RPAS. Then we explore the various algorithms to perform object detection and their dependencies. This is an ambitious and challenging endeavour that requires a multidisciplinary approach. By integrating advanced technologies such as machine learning, computer vision, navigation systems, and mapping technologies, the RPAS can perform a range of tasks with high precision and reliability.

The developed system can provide valuable support to various fields, such as security, transportation, wildlife conservation, and urban planning, by enhancing the efficiency and accuracy of data collection and analysis. Overall, the project has the potential to contribute to the development of innovative RPAS systems that can meet the increasing demands for advanced aerial platforms in various applications.

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