Int. Jrl. of **Human Computations & Intelligence**
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

RESEARCH ARTICLE

Enhancing the Capabilities of Remotely PilotedAerial Systems Through Object Detection, FaceTracking, Digital Mapping and Gesture Control

Lavanya N L . Anish Bhat . Bhanuranjan S B . K G Lakshmi Narayan . Manjunath Bharadwaj V

Department of Computer Science
Sapthagiri College of Engineering, Bangalore, Karnataka, India.

Received: 23 April 2023 / Revised: 30 April 2023 / Accepted: 11 May 2023

DOI: 10.5281/zenodo.7937975

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; Gesture control; Digital mapping

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.

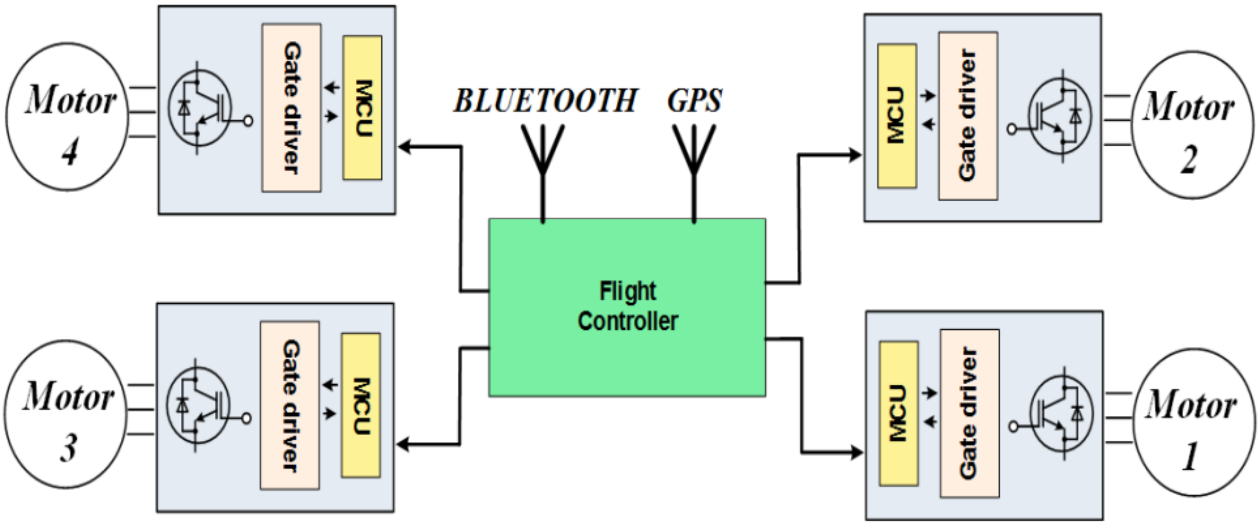


Fig 1: Architecture of a Remotely Piloted Aerial System.

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,

Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

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.

III. PROBLEM STATEMENT

In this paper, 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.

IV. 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.

MILESTONE RESEARCH FOUNDATION
Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

V. SYSTEM DESIGN

A quadcopter has to be able to move in three separate directions—vertically, laterally, and rotateally—in order to be able to fly. Each of them may be accomplished utilising the quadcopter's four propellers in accordance with Newton's third law. The spinning propellers force air down. Newton's third rule of motion involves pushing the air downward, just like a helicopter does. The quadcopter is propelled upward by the response, which is a force known as lift. Each propeller will provide lift, and the quadcopter's overall lift will be equal to the sum of the lifts produced by each of the four propellers. For the quadcopter to take off, the overall force of the lift must be greater than the force of gravity. When the forces of lift and gravity are equal, the quadcopter may hover in the air without moving vertically.

The quadcopter travels vertically when the lift force acts straight up. But a lift can also move laterally if it operates at an angle. This is due to the lift's uneven distribution of forces, which causes lateral movement that can be both forward and backward as well as side to side. By changing the propellers' speed, lateral movement is achieved. Uneven levels of lift are produced on the two sides of the quadcopter by altering the speed of the quadcopter's two propellers on one side and/or the other.

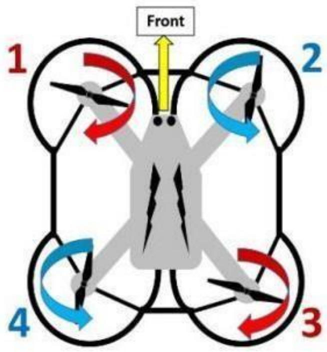


Fig 2 :Direction Of Propellor Rotation.

In comparison to the lift produced on the opposite side, the lift produced on the side with the faster spinning propellers is greater. As a result, the quadcopter moves towards the side where less lift is produced. A quadcopter's propellers also experience torque when they revolve since each propeller generates torque on its own. As a result, two propellers produce torque that operates in a clockwise direction, while two produce torque that acts in an anticlockwise direction. The forces thus cancel one another out. The quadcopter may also be made to rotate by using this torque. The anticlockwise force operating on the quadcopter will be stronger than the clockwise torque acting on it if these propellers revolve more quickly than propellers 2 and 4.

The quadcopter turns anticlockwise as a consequence. Naturally, the quadcopter will rotate in a clockwise direction if propellers 2 and 4 spin more quickly than propellers 1 and 3. Two propellers push air upward while two push air downward as they rotate in opposing directions. When these pressures are combined, the overall lift is zero, preventing the quadcopter from taking off. Engineers employ two distinct propeller blades to get around this. Figure shows that the propeller on the left has a higher front left edge than the other, which has a higher front right edge. Due to this design, even though the two propellers rotate in different directions, the air is really propelled in the same direction by both of them.

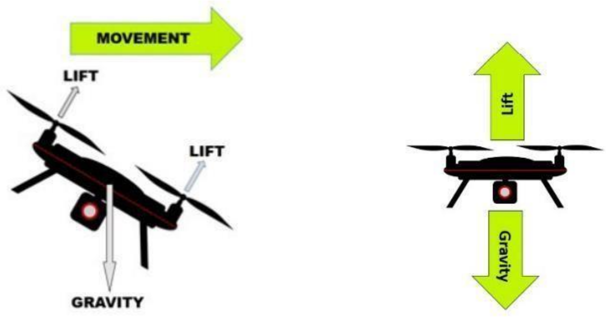


Fig 3: Movement of RPAS.

VI. SYSTEM IMPLEMENTATION

Surveillance Module

We can perform surveillance on a given area by controlling the movement of the RPAS by using either a joystick or a keyboard. The live feed from the RGB-D sensors can be viewed on a screen which is connected to the same network as the drone. Still images can be captured at any moment using a pre-programmed key on the controller device. One of the benefits of using drones for surveillance is their ability to cover large areas quickly and efficiently. Drones can be equipped with high-resolution cameras, thermal sensors, and other advanced technologies that provide real-time data and imagery. This information can be used to monitor borders, search for missing persons, monitor wildlife, and track criminal activities. This has many uses in home security, search and rescue, military operations, exploration, videography.

Object Detection Module

Object detection for RPAS is implemented using the YOLO algorithm. YOLO stands for "You Only Look Once" which recognizes and detects several objects in a picture. The class probabilities of the discovered photos are provided by the object identification process in YOLO, which is carried out as a regression problem. Convolutional neural networks (CNN) are used by the YOLO method to recognize items instantly. The approach just needs one forward propagation through a neural network to identify objects, as the name would imply. This indicates that a single algorithm run is used to do prediction throughout the full picture. Multiple class probabilities and bounding boxes are simultaneously predicted using the CNN. The YOLO algorithm works by dividing the image into N grids, each having an equal dimensional region of SxS. Each of these N grids takes part in the detection and localization of the object it contains. Correspondingly, these grids predict bounding box B coordinates relative to their cell

Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

coordinates, along with the object label along with confidence value of the object being present in the cell. The following reasons make YOLO Algorithm significant: Speed, High Accuracy, Learning capabilities.

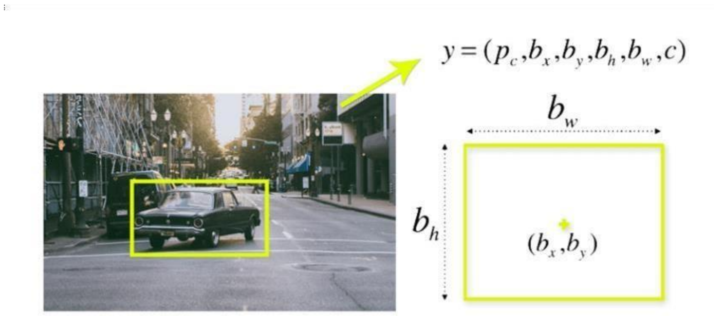


Fig 4: Object Detection

Face Tracking Module

The implementation for face tracking is done by first setting up a frame and identifying a face. The identification of a face is done using the Viola-Jones method. Upon finding a face, the RPAS follows the person or the closest person among a group of people based on distance from starting point. Developed in 2001 by Paul Viola and Michael Jones, the Viola-Jones algorithm is an object-recognition framework that allows the detection of image features in real-time. Before detecting a face, the image is converted into grayscale, since it is easier to work with and there's lesser data to process.

The Viola-Jones algorithm first detects the face on the grayscale image and then finds the location on the coloured image. Viola-Jones outlines a box (as you can see on the right) and searches for a face within the box. It is essentially searching for these haar-like features. The features below show a box with a light side and a dark side, which is how the machine determines what the feature is. Sometimes one side will be lighter than the other, as in an edge of an eyebrow. Sometimes the middle portion may be shinier than the surrounding boxes, which can be interpreted as a nose. The speed of tracking depends upon the distance between the person and the RPAS.

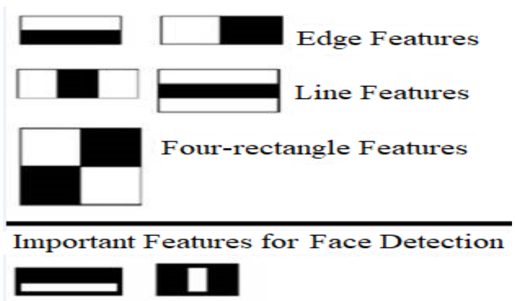


Fig 5: Face detection using Haar-like features

Digital Mapping

Digital Mapping is performed using visual odometry. The use of digital mapping in remotely piloted aerial systems (RPAS) has brought about significant advancements in various fields such as urban planning, environmental management, and agriculture. 2-D digital mapping, in particular, has proven to be a valuable tool for capturing and analyzing geographic information in real-time. 2-D digital mapping involves the creation of two-dimensional maps that provide a bird's eye view of the earth's surface. This mapping technology allows for the identification and visualization of objects, terrain features, and geographic information such as streets, buildings, and land cover. RPAS equipped with high-resolution cameras and sensors can capture detailed imagery and data, which can then be processed into 2-D maps. The velocity of the drone and its location from the bounding boxes is used to determine the current location of the drone relative to the image which is used as the reference. This is used to create a digital map of the path of the drone. This map is visible on a display device and the location is outputted as relative coordinates. Used for topographic surveys, photogrammetric solutions, progress monitoring, disaster management, and agriculture and forestry.

Gesture Control

Gesture control involves recognizing hand gestures in real time using machine learning techniques and computer vision and utilizing them to control the movement of the RPAS. A machine learning-based software library called MediaPipe Gesture Recognizer has been developed by Google that can be used with a webcam or other camera to recognize different hand gestures in real-time. The MediaPipe Gesture Recognizer analyses video data using a neural network to recognize various hand gestures based on the user's finger and palm movements. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used in combination by MediaPipe Gesture Recognizer to analyze video data and identify hand motions.

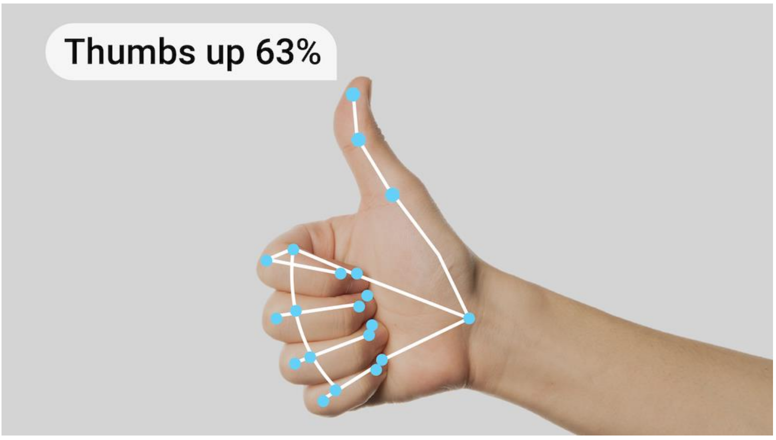


Fig 6: Recognition of hand gesture and display of hand landmarks

MILESTONE RESEARCH FOUNDATION
Int. Jrl. of Human Computations & Intelligence
Vol. 02, Issue 03, 2023
ISSN: 2583-5696

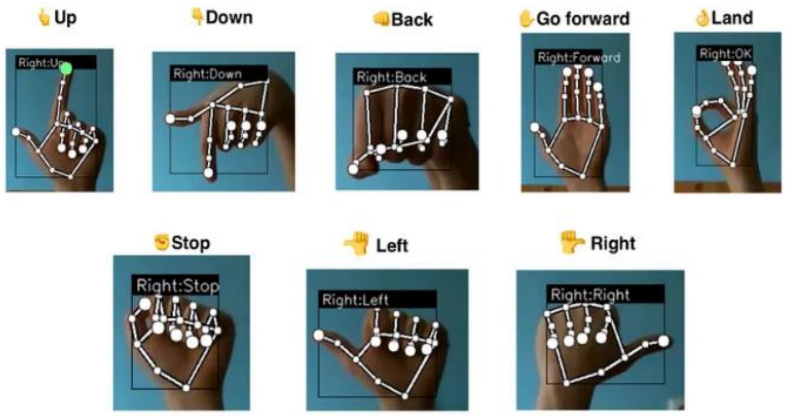
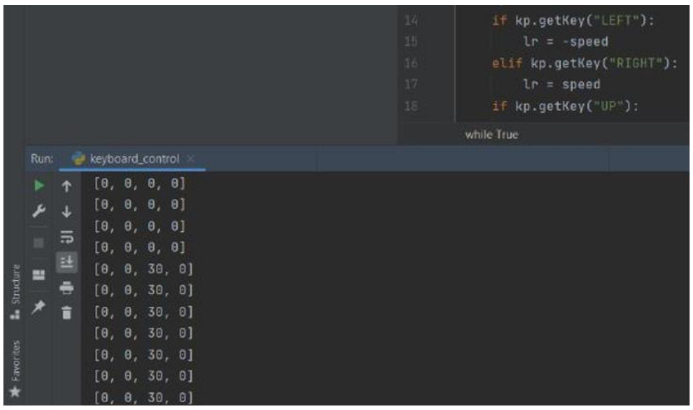


Fig 7: Various hand gestures for RPAS control

The RNN is used to recognize a particular hand gesture by looking at the temporal sequence of the hand motions, while the CNN is used to extract information from the video frames and locate the hand. Real-time hand gesture recognition is possible with the MediaPipe Gesture Recognizer task, which also displays the results of the recognition as well as the hand landmarks of the hands that were found. This task receives either static data or a continuous stream and uses an ML model to act on image data. The task yields hand landmarks in world coordinates, hand landmarks in picture coordinates, and types of hand gestures. After recognizing a hand gesture, it can be used to control the movements of the RPAS. For instance, pointing up with index finger to increase altitude, pointing down to decrease altitude, closed fist to stop movement, pointing right or left to move right or left respectively and "OK" hand gesture to land the RPAS. It has several use cases. Robotics is one area where the MediaPipe library is put to use for gesture control of drones. Building hand gesture recognition models for real-time drone control, researchers and developers employ MediaPipe. Applications for this technology include surveillance, inspection, and search and rescue operations.

VII. RESULTS



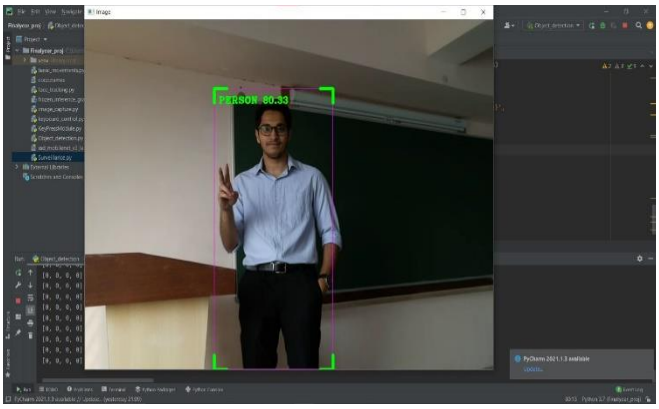


Fig 8: Surveillance (with movement parameters)

Fig 9: Object detection(person)

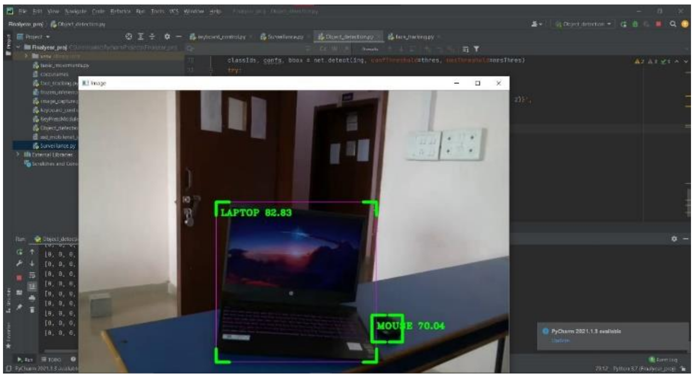


Fig 10: Object detection(Laptop and mouse)

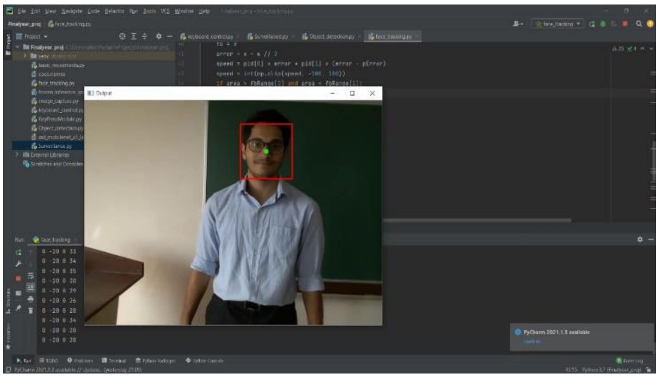


Fig 11: Face tracking

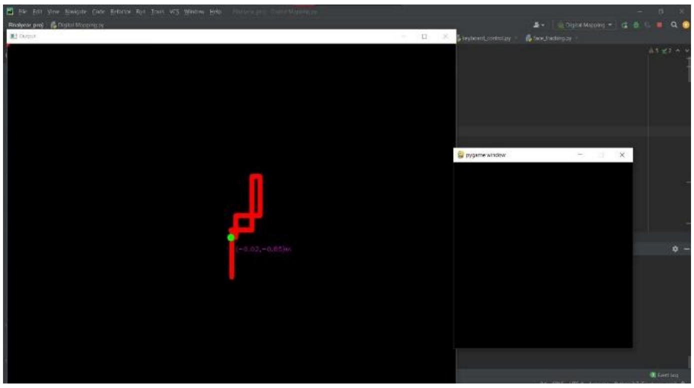


Fig 12: Digital mapping

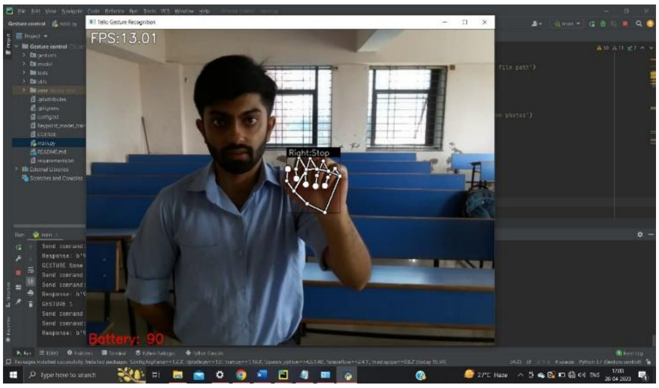


Fig 13: Gesture control(Stop)

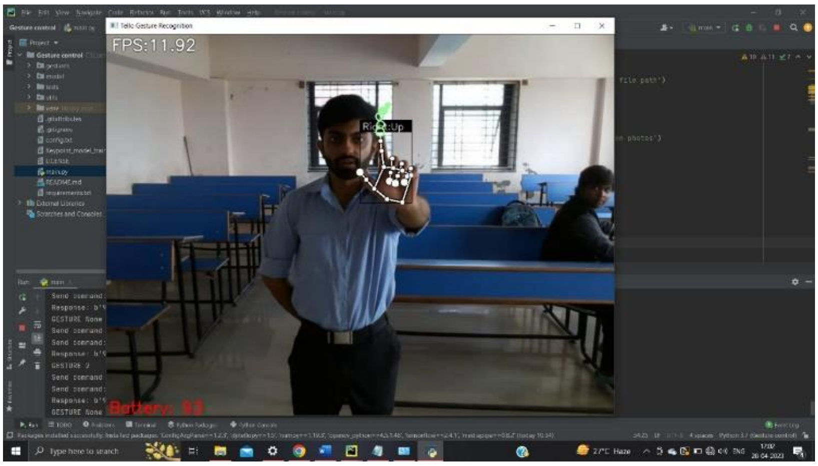


Fig 14: Gesture control(up)

VIII. DISCUSSION

RPAS can cover a large area in a short span of time, making them more efficient than traditional methods of data collection. This can be particularly useful for tasks such as crop monitoring, land surveying, and infrastructure inspections. By using RPAS, data can be collected more quickly and accurately, allowing for faster decision-making and better resource allocation. RPAS can provide highly accurate and precise data, making them useful for tasks that require a high degree of accuracy, such as surveying and mapping. The data collected by RPAS can be used to create detailed 3D models, which can be used for planning and analysis purposes. Additionally, RPAS can be equipped with high-resolution cameras and sensors, allowing for detailed data collection and analysis. RPAS can be used to perform tasks in hazardous or hard-to- reach areas, such as inspecting power lines or pipelines, without putting human operators at risk.

This can reduce the risk of accidents and injuries, while also increasing the safety and efficiency of operations. RPAS can be a cost-effective alternative to traditional methods of data collection, such as manned aircraft or ground-based surveys. RPAS are generally less expensive to operate than manned aircraft, and they can be used for a wider range of tasks. Additionally, they require less manpower to operate, reducing the overall cost of operations. The use of RPAS is subject to regulations and restrictions that vary by country and can be complex and time-consuming to navigate. Operators must obtain appropriate licenses and permits, and adhere to strict guidelines on where and how RPAS can be flown. Failure to comply with these regulations can result in fines and legal consequences. RPAS can be used to collect data on individuals without their knowledge or consent, raising privacy concerns. For example, RPAS equipped with cameras could be used for surveillance purposes, raising questions about the appropriate use of the technology.

To address these concerns, regulations have been introduced in many countries to restrict the use of RPAS for privacy-invasive purposes. RPAS operations can be impacted by weather conditions, such as high winds or precipitation, which can limit their usefulness. For instance, high winds can cause RPAS to lose control, while precipitation can damage sensitive electronics. This means that RPAS may not be suitable for certain tasks in certain weather conditions. RPAS technology is still evolving and can have technical limitations, such as limited battery life, which can limit their capabilities and potential applications.

IX. CONCLUSION

In this paper, we try 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.

REFERENCES

1. Anish Bhat, Bhanuranjan S B, K G Lakshmi Narayan, Manjunath Bharadwaj V, & Lavanya N L. (2023). Survey On Object Detection, Face Tracking, Digital Mapping and Lane Following For Remotely Piloted Aerial Systems (RPAS) . International Journal of Human Computations & Intelligence, 2(2), 94–105. https://doi.org/10.5281/zenodo.7900522
2. Kim, T. Y., & Kim, J. N. (2020). Implementation of unmanned aerial system for surveillance mode. International Conference on Information and Communication Technology Convergence. https://doi.org/10.1109/ictc49870.2020.9289181
3. Tayara, H., Soo, K. G., & Lu, N. (2018). Vehicle Detection and Counting in High-Resolution Aerial Images Using Convolutional Regression Neural Network. IEEE Access, 6, 2220–2230. https://doi.org/10.1109/access.2017.2782260
4. Sambolek, S., & Ivašić-Kos, M. (2021). Automatic Person Detection in Search and Rescue Operations Using Deep CNN Detectors. IEEE Access, 9, 37905–37922. https://doi.org/10.1109/access.2021.3063681
5. Saetchnikov, I., Tcherniavskaia, E. A., & Skakun, V. S. (2021b). Object Detection for Unmanned Aerial Vehicle Camera via Convolutional Neural Networks. IEEE Journal on Miniaturization for Air and Space Systems, 2(2), 98–103. https://doi.org/10.1109/jmass.2020.3040976
6. Karahan, M., Kurt, H., & Kasnakoglu, C. (2020). Autonomous Face Detection and Tracking Using Quadrotor UAV. 2020 4th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT). https://doi.org/10.1109/ismsit50672.2020.9254469
7. Çetinkaya, O., Sandal, S., Bostanci, E., Güzel, M. S., Osmanoglu, M., & Kanwal, N. (2019). A Fuzzy Rule Based Visual Human Tracking System for Drones. 2019 4th International Conference on Computer Science and Engineering (UBMK). https://doi.org/10.1109/ubmk.2019.8907104
8. Surinta, O., & Khruahong, S. (2019). Tracking People and Objects with an Autonomous Unmanned Aerial Vehicle using Face and Color Detection. ECTI DAMT-NCON. https://doi.org/10.1109/ecti-ncon.2019.8692269
9. Rabah, M., Rohan, A., Mohamed, S. a. M., & Kim, S. (2019). Autonomous Moving Target-Tracking for a UAV Quadcopter Based on Fuzzy-PI. IEEE Access, 7, 38407–38419. https://doi.org/10.1109/access.2019.2906345
10. Morbale, Naregalkar, Singh, A., Dwivedi, P., & Mathur, R. (2022). “Quadcopter Drone with Face Recognition.” IJSERM.
11. Kumar, S. S., Ahmed, S. T., Vigneshwaran, P., Sandeep, H., & Singh, H. M. (2021). Two phase cluster validation approach towards measuring cluster quality in unstructured and structured numerical datasets. *Journal of Ambient Intelligence and Humanized Computing*, *12*, 7581-7594.
12. Ahmed, S. T., Kumar, V. V., Singh, K. K., Singh, A., Muthukumaran, V., & Gupta, D. (2022). 6G enabled federated learning for secure IoMT resource recommendation and propagation analysis. *Computers and Electrical Engineering*, *102*, 108210.
13. Shen, Q., Jiang, L., & Xiong, H. (2018). Person Tracking and Frontal Face Capture with UAV. International Conference on Communication Technology. https://doi.org/10.1109/icct.2018.8600068
14. Feng, Y., Yu, S., Peng, H., Li, Y., & Zhang, J. (2021). Detect Faces Efficiently: A Survey and Evaluations. IEEE Transactions on Biometrics, Behavior, and Identity Science, 4(1), 1–18. https://doi.org/10.1109/tbiom.2021.3120412
15. Nguyen, T. T., Mann, G. K. I., & Gosine, R. G. (2014). Vision-based qualitative path-following control of quadrotor aerial vehicle. International Conference on Unmanned Aircraft Systems. https://doi.org/10.1109/icuas.2014.6842281
16. Zhou, H., Kong, H., Wei, L., Creighton, D., & Nahavandi, S. (2015). Efficient Road Detection and Tracking for Unmanned Aerial Vehicle. IEEE Transactions on Intelligent Transportation Systems, 16(1), 297–309. https://doi.org/10.1109/tits.2014.2331353

17. Oliveira, T., Aguiar, A. P., & Encarnação, P. (2016). Moving Path Following for Unmanned Aerial Vehicles With Applications to Single and Multiple Target Tracking Problems. IEEE Transactions on Robotics, 32(5), 1062–1078. https://doi.org/10.1109/tro.2016.2593044
18. Ahmed, S., Guptha, N., Fathima, A., & Ashwini, S. (2021, January). Multi-View Feature Clustering Technique for Detection and Classification of Human Actions. In *Proceedings of the First International Conference on Advanced Scientific Innovation in Science, Engineering and Technology, ICASISET 2020, 16-17 May 2020, Chennai, India*.
19. Ahmed, S. T., Guptha, N. S., Lavanya, N. L., Basha, S. M., & Fathima, A. S. (2022). IMPROVING MEDICAL IMAGE PIXEL QUALITY USING MICQ UNSUPERVISED MACHINE LEARNING TECHNIQUE. *Malaysian Journal of Computer Science*, 53-64.
20. Muthukumaran, V., Vasudevan, S., & Siddiqha, S. A. (2023). Secure Public Key Cryptosystem for in Smart City using Algebraic Structure. *International Journal of Human Computations & Intelligence*, *2*(1), 20-25.