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DEVELOPING AN AUTONOMOUS DRONE FOR EARLY DETECTION OF FOREST FIRES

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Abstract: This research aims to develop an autonomous drone system for early detection of forest fires. By integrating specialized sensors with AI algorithms, the drone can quickly identify fire outbreaks in remote areas, enabling prompt responses to potential threats. The study provides a detailed analysis of sensor capabilities and data collection methods to optimize detection accuracy. Advanced AI algorithms, such as machine learning and computer vision techniques, are utilized to enhance real-time data processing and decision-making. The system architecture is robust and scalable, allowing deployment in diverse forest environments. The focus is on ensuring the drone's autonomy for navigating challenging terrains and performing continuous monitoring without human intervention. Regulatory compliance is addressed by thoroughly examining current aviation and environmental laws, ensuring the drone operates within legal frameworks while maximizing efficacy. Field trials in various forest regions demonstrate the system's effectiveness in early fire detection, with case studies showing its success in preventing fire escalation. The research highlights the potential for integrating this technology into existing forest management practices, offering a cost-effective and sustainable solution for fire prevention.

Key words: AI, sensors, autonomy, machine learning, environmental monitoring.

1. INTRODUCTION AND LITERATURE REVIEW

Forest fires are among the greatest natural hazards we face, with devastating consequences for the environment, including the destruction of vast forest areas, natural habitats, and various species of plants and animals. These disasters also pose a direct threat to human life and well-being. Consequently, early detection of these fires is essential for the effective prevention and management of such emergencies, enabling rapid intervention and limiting the spread of flames. Traditional detection methods, such as human observations and reports from residents, are often inefficient and can lead to significant delays in reporting fires. Therefore, a technological and innovative approach is necessary to improve the efficiency of the detection process and reduce response time.

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Protecting human life is a critical reason for the early detection of forest fires. These fires can endanger the lives of people, both those directly involved in firefighting and residents of affected areas. Early detection allows for the rapid initiation of intervention operations and the preventive evacuation of people from threatened areas, thereby reducing the risk of loss of human life. Furthermore, early detection is vital for saving natural habitats and biodiversity. Forests are invaluable ecosystems that house a wide variety of plant and animal species. Forest fires can irreversibly destroy these habitats and cause a loss of biodiversity. Detecting fires in their early stages allows for swift and effective intervention to limit the spread of the fire and protect the forest's flora and fauna.

In addition to protecting life and biodiversity, early detection helps in conserving natural resources. Forests play an essential role in conserving soil, water, and air. Forest fires can lead to soil erosion, pollution of water sources, and degradation of air quality. Early detection enables the implementation of preventive and intervention measures to minimize the impact on natural resources and facilitate ecosystem regeneration. Moreover, reducing material losses is another significant benefit of early detection. Forest fires can cause substantial damage to private properties, infrastructure, and the local economy. Quick detection allows for the rapid intervention of firefighting teams and the implementation of adequate protection measures, thereby reducing material losses and the costs associated with reconstruction and recovery.

Efficiency in emergency management is also greatly enhanced by early detection of forest fires. It provides the opportunity to efficiently coordinate intervention operations by directing human and material resources to affected areas. The use of autonomous drones for fire detection can cover large areas in a short time, providing real-time information and images to intervention teams, facilitating appropriate decision-making and actions. In conclusion, early detection of forest fires is crucial for protecting human life, saving natural habitats and biodiversity, conserving natural resources, reducing material losses, and improving efficiency in emergency management.

The paper by Chahil Choudhary, Anurag, and Pranjal Shukla [1], aims to develop a robust ML model for detecting forest fires using drone imagery. The primary objective is to leverage the capabilities of machine learning to process and analyse the vast amounts of data generated by drones, thereby identifying patterns and anomalies indicative of forest fires. The proposed model is intended to improve the speed and accuracy of forest fire detection, thus enabling quicker response and mitigation efforts.

The primary objective of the FireFly Project [2] is to develop an automated system that addresses the limitations of existing UAV technologies, which often struggle with early fire detection due to the limited resolution and sensitivity of thermal cameras. By combining UAVs with ground-based IoT sensors, the project aims to detect forest fires at their inception, even when obscured by dense tree canopies. This hybrid approach leverages the strengths of both aerial and ground-based systems to provide a more comprehensive and effective solution for forest fire monitoring and prevention. Another important paper is [3] by Sergey Filist et al., which demonstrates how a methodology and algorithm for autonomous UAV flight trajectory planning can improve the early detection of ignition sources. The proposed method involves three distinct flight plans covering area surveillance, navigation to the fire source, and return to the departure point. The mathematical modelling of the UAV flight control algorithm, executed using MATLAB® R2019b, demonstrated control stability and accelerated identification of the ignition source coordinates, exceeding the set goals by 1.5 to 2 times. The paper [4] by Rodrigo De la Fuente, Maichel M. Aguayo and Carlos Contreras-Bolton, demonstrates how an integrated forest fire monitoring system can be optimized using a combination of surveillance towers, monitoring balloons, and drones. The authors develop a mixed-integer linear programming (MILP) model that optimizes the location of these monitoring technologies and the routing of drones to ensure extensive terrain coverage while minimizing costs. The proposed algorithm includes six components: a solution procedure, perturbation procedures, local search procedures, a call to a general-purpose solver for the MILP model, a global reset strategy, a local reset strategy, and an acceptance criterion.

The research tests the model and algorithm on both random instances and a real-life case study in Chile, showing that while the MILP model can solve small instances, the algorithm can find good-quality solutions for all instances. This study provides valuable insights for the government and private sector in designing an integrated fire monitoring system that leverages the strengths of watchtowers, monitoring balloons, and drones, aiming to enhance early detection and response to forest fires.

2. PROBLEM CONTEXT

Forests face threats from various factors, both abiotic and biotic. Non-living factors include fires, drought, storms, and air pollution, while living factors encompass animals, insects, and diseases. Fires, a common abiotic threat in the Mediterranean region, have been increasing alongside major storms, averaging two per year over the last six decades. Air pollution, primarily from vehicles and factories, also endangers forests. Additionally, the expansion of transportation infrastructure fragments forests, posing a significant threat to biodiversity. Overall, approximately 6% of forested areas are impacted by at least one of these factors [5, 6].

European forests are significantly affected by climate change, which varies across different regions, influencing forest growth rates, forested areas, and species diversity. These changes also affect the spread of living organisms, such as parasites, and the frequency and intensity of extreme weather events. Key challenges include the forests' ability to adapt to these changes and their role in mitigating them, such as using wood instead of non-renewable resources for energy and materials [7].

Historically, forest fire detection relied on human observations and reports from residents or observation towers, which had several drawbacks: delays in reporting, difficulty accessing remote areas, and reliance on weather conditions for visibility.

Recently, unprecedented and devastating fires have occurred globally, affecting areas from the United States to Australia, Indonesia, Africa, the Amazon, and even the Arctic. In Europe alone, over 400,000 hectares of land are burned annually by vegetation fires, causing severe damage to protected areas. In 2023, over 48% of forest fires occurred in designated conservation zones. Variations in rainfall, frequency of lightning strikes, and temperature fluctuations contribute to the frequent and severe wildfires in various ecosystems, from boreal peatlands to tropical forests. Climate models predict worsening weather conditions in most European regions under high-emission scenarios, leading to an increase in fire-prone areas and an extended fire season [5], [7].

3. PROPOSED SOLUTION

The current trend across all sectors is towards automating systems and providing autonomous tools to ease human labour. For the efficient early detection of forest fires, the proposed solution is an autonomous drone equipped with artificial intelligence for image processing.

Designing the architecture of an autonomous drone for forest fire detection must consider the specific environmental requirements and the tasks the drone needs to perform. This involves careful planning and evaluation of available hardware and software components, as well as integration and communication with other systems and teams [8], [9]. A well-designed architecture ensures the efficient and reliable functionality of the autonomous drone, enabling early detection and effective management of forest fires.

Key characteristics in drone design include:

- Flight platform: selecting a suitable drone capable of carrying necessary equipment and sensors, with enough autonomy to cover large areas.
- Specialized sensors: integrating appropriate sensors, such as thermal cameras, smoke sensors, gas sensors, and localization systems, to provide essential data for fire detection and monitoring.
- Power system: ensuring a reliable power system, which may include batteries, additional power sources, or energy management systems to maximize the drone's autonomy during missions.
- Automatic control system: developing an automatic control system that enables the drone to perform necessary tasks autonomously. This involves navigation and route planning algorithms, allowing the drone to follow predefined routes and avoid obstacles.
- Fire detection algorithms: designing and implementing specialized algorithms for forest fire detection. These algorithms may use image analysis techniques, artificial intelligence, or other methods to identify specific signs and patterns of forest fires in collected images and data.

To detect fires, the drone uses an OV7675 camera for continuous image capture, and artificial intelligence analyses the smoke's movements and path. Future enhancements include a module with a thermal camera and a visual spectrum camera to transmit images to a fire monitoring center and analyse the damage. The thermal imaging device measures the thermal radiation emitted by objects, identifying temperature changes specific to forest fires. Autonomous drones can use thermal cameras to detect and pinpoint heat sources related to fires, producing thermal images to highlight the affected regions. The self-flying drone also comes with communication and navigation equipment. It can send data and information immediately to the intervention team or a command centre using communication equipment, allowing for effective organization and a quick response to the wildfire. GPS technology enables the drone to track its location in real-time, making it easier to plan routes and closely observe the fire-stricken region. To manage and control the drone, the H743 WING V3 with an ARM Cortex-M7 processor is used, providing the computational power necessary for executing complex flight control algorithms. This ensures improved stability and accuracy while flying and offers advanced features like GPS navigation, waypoints, and automatic stabilization. The controller includes a gyroscope, a barometric altimeter, a MicroSD card slot as a black box, along with a current regulator and a voltmeter. To incorporate all features, two additional companion computers are used: an Arduino Nano 33 BLE and an Arduino Nano. The Nano model controller is a compact microcontroller, ideal for fitting into a drone without taking up too much space. Its small size allows for flexible positioning and installation within the drone's layout, and it can be programmed using the Arduino language, which is simple and user-friendly.

4. MATHEMATICAL MODEL OF THE AUTONOMOUS DRONE

In this chapter, we will detail the mathematical model of an autonomous drone, covering the equations of motion, the forces and moments generated by the rotors, as well as the control model. These components are essential for understanding and simulating the behaviour of an autonomous drone.

4.1 The equations of motion

The equations of motion describe the translational and rotational dynamics of the drone. These are fundamental to understanding how the drone responds to various control inputs.

The translational motion of the drone is governed by Newton's second law (1):

$$m\frac{d^2\vec{x}}{dt^2} = \vec{F} - m\vec{g} \tag{1}$$

where:

- m is the mass of the drone.
- $\vec{x} = [x, y, z]^T$ represents the drone's position in Cartesian coordinates.
- $\vec{F}$ is the total force generated by the rotors.
- $\vec{g} = [0,0,-g]^T$ is the gravitational acceleration, with g being the gravitational acceleration.

This equation shows how the drone's acceleration depends on applied forces and gravitational force.

The rotational motion is described by the moment equation:

$$I\frac{d\vec{\omega}}{dt} = \vec{\tau} - \vec{\omega} \times (I\vec{\omega}) \tag{2}$$

where:

- I is the inertia tensor of the drone.
- $\vec{\omega} = [p, q, r]^T$ is the angular velocity.
- $\vec{\tau}$ is the total moment generated by the rotors.

These equations (1), (2) describes how angular velocity changes over time based on applied moments and drone inertia properties.

4.2 Forces and moments generated by rotors

Forces and moments generated by rotors are essential for controlling drone motion. Each rotor contributes to lift force generation and control moments.
The force generated by a rotor can be modelled as:

$$F_i = k_f \omega_i^2 \tag{3}$$

where:
- F_i is the force generated by rotor i.
- k_f is a thrust coefficient.
- ω_i is the angular velocity of rotor i.

The moment generated by a rotor is given by:

$$\tau_i = k_m \omega_i^2 \tag{4}$$

where:
- τ_i is the moment generated by rotor i.
- k_m is a moment coefficient.

Typically, a quadcopter has four rotors arranged in a square. Opposite rotors spin in opposite directions to stabilize the drone and allow control over yaw movements (rotation around the vertical axis).

4.3 Control model

Drone control involves adjusting rotor speeds to achieve desired position and orientation. A PID (Proportional-Integral-Derivative) controller is often used for this purpose.
The PID controller is defined by:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{de(t)}{dt} \tag{5}$$

where:
- $u(t)$ is the control signal.
- $e(t)$ is the error, the difference between desired and current position.
- K_p, K_i, K_d are the PID constants that adjust the proportional, integral, and derivative response.

The PID control minimizes position and orientation errors, ensuring a stable and precise trajectory for the drone.
The graphs (Figure 1) illustrate the dynamic behaviour of the drone as it attempts to reach and stabilize at a target position using a PID controller. The position graph indicates that the drone achieves significant vertical movement while maintaining relatively stable horizontal positions [10]. The velocity graph shows an initial acceleration followed by a deceleration, aligning with the position control strategy. The angular velocity graph reveals active rotational control, with oscillations in the x and y directions and a steady increase in the z direction, demonstrating the effect of applied moments for stability and orientation control.

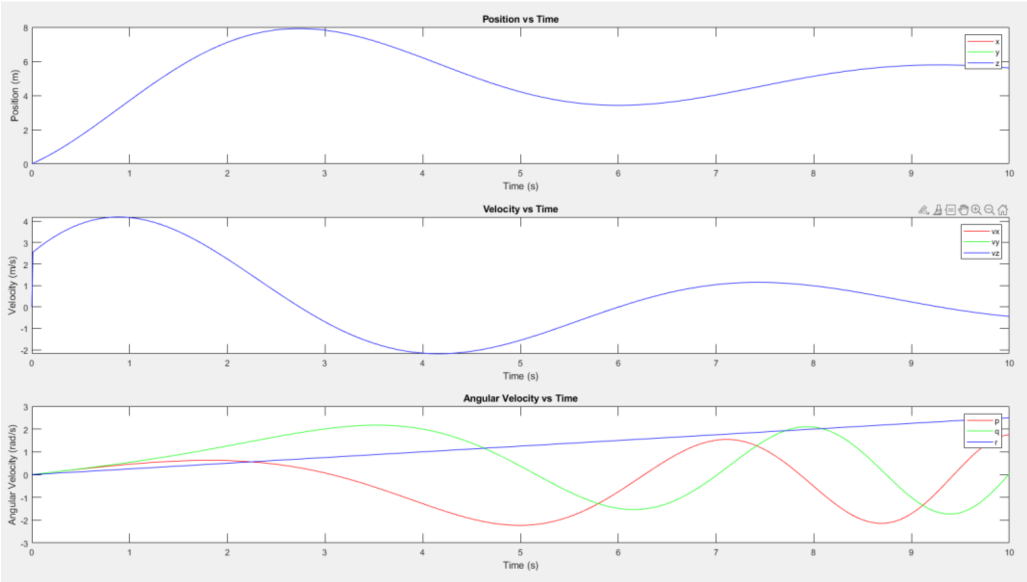

Fig.1. Simulation of drone motion: position, velocity, and angular velocity over time

Overall, the simulation results indicate effective control of the drone's position and orientation, achieved through the combined use of PID control for translation and constant moments for rotation.

5. NAVIGATION AND TRAJECTORY PLANNING

Navigation and trajectory planning are essential components in developing the software system of an autonomous drone, enabling it to move through a complex environment and perform specific tasks without human intervention. The navigation of an autonomous drone involves determining its position and orientation in space and calculating an optimal trajectory to reach a destination.

Navigation algorithms rely on various techniques and sensors to ensure accuracy and reliability. The basic navigation system is satellite-based (GPS), which is frequently used for locating the drone in space. GPS provides precise coordinates of the drone's position, allowing it to move along predefined trajectories. For cases when the GPS signal is lost, I have created a Lua script for an inertial navigation system (INS), which uses accelerometers and gyroscopes to measure the drone's accelerations and angular velocities. These measurements are integrated to estimate position and orientation in real-time. I have also implemented a GSM module, allowing access to and viewing of the drone's telemetry at any time with Ardupilot software (Figure 2).

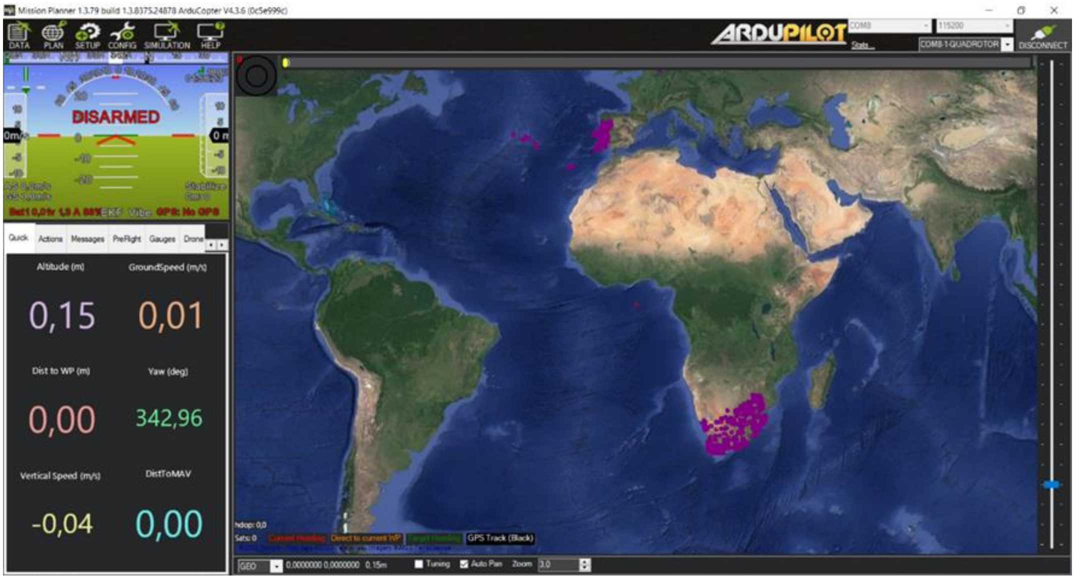

Fig.2. Ardupilot GUI

6. AI SYSTEM FOR FIRE DETECTION

To develop a robust AI system for fire detection [11], the Edge Impulse platform was utilized. This section outlines the comprehensive process of training the AI, from data collection to configuring the neural network structure.

The first step in training the AI system involves collecting relevant data. For this purpose, the camera on a smartphone was used to capture images.

These images were taken in various conditions to ensure a diverse dataset, which is crucial for the model to learn to recognize fires in different scenarios and environments. Using the smartphone camera, a substantial amount of image data was acquired. This step is critical as the quality and diversity of the data directly impact the performance of the AI model. Images were captured in different lighting conditions, from various angles, and in multiple settings to cover a wide range of potential fire appearances.

Once a sufficient number of images were collected, the next step was to label the data. This involved identifying and marking the presence of fire in each image. Accurate labelling is essential as it teaches the model what to look for when detecting fires. Each image was carefully reviewed and annotated to ensure high-quality labelled data.

After labelling the data, the next step was configuring the training blocks on the Edge Impulse platform.

The image size was standardized to 96x96 pixels (Figure 3). This size was chosen to balance the need for detail with the computational efficiency required for training the model. Smaller images are quicker to process, but they must still be large enough to capture the necessary features for fire detection.

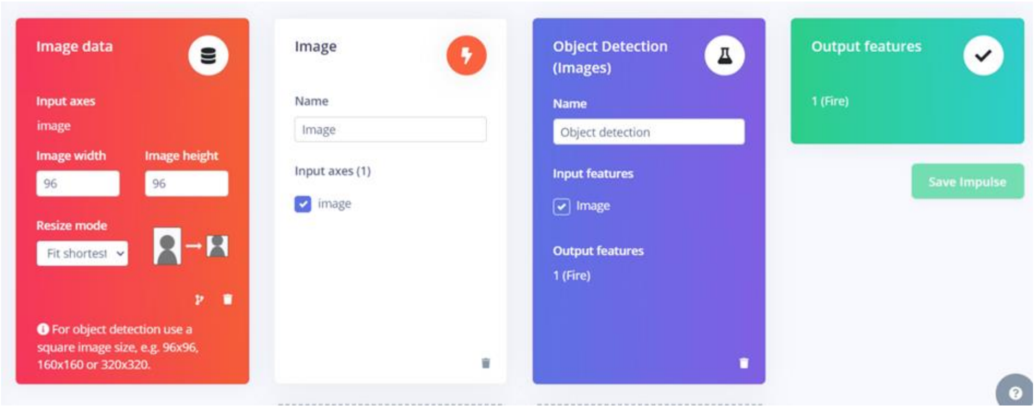

Fig.3. Configuring image data and object detection settings on Edge Impulse platform

The next step was to define the labels that would be used during training. In this case, the primary label was "fire," indicating the presence of fire in the image. This label is crucial for the supervised learning process, where the model learns to associate specific features in the images with the labelled categories.

With the image size and labels set, the neural network structure was configured. The Edge Impulse platform provides various options for building and customizing neural networks. For fire detection, a Convolutional Neural Network (CNN) was chosen due to its effectiveness in image recognition tasks [12]. The CNN architecture was designed to include multiple convolutional layers, pooling layers, and fully connected layers to extract and learn features from the images efficiently (Figure 4).

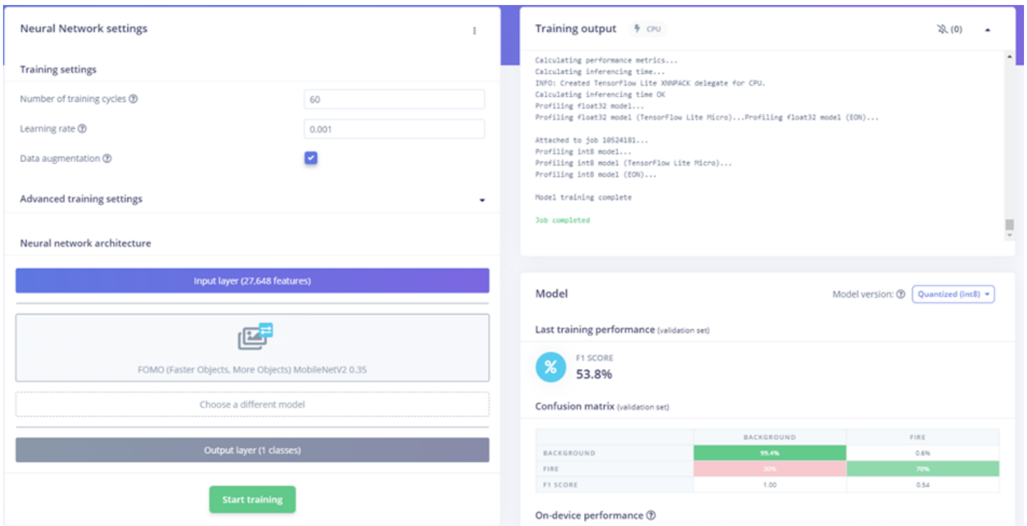

Fig.4. Neural network training and performance metrics for fire detection on Edge Impulse platform

After completing the rigorous training process using the Edge Impulse platform, the AI model for fire detection was successfully developed. The model underwent extensive training, as detailed in the previous steps, which included collecting a diverse dataset of images, accurately labeling them, and configuring the neural network structure. The training settings were meticulously chosen, with 60 training cycles, a learning rate of 0.001, and data augmentation to enhance the model's robustness.

The neural network architecture was carefully designed, incorporating multiple layers to effectively learn and extract features necessary for accurate fire detection. The model's performance was evaluated, showing an F1 score of 53.8%, indicating a balanced precision and recall rate. The confusion matrix provided insights into the model's accuracy, with a high rate of correct classifications for both fire and non-fire images.

Upon completion of the training, the AI model was deployed and tested on new data. The accompanying image illustrates the successful identification of a fire, with the model confidently detecting a flame with a high confidence score of 1.00 (Figure 5).

Fig.5. Fire detection AI model identifying a flame with high confidence

This result showcases the model's effectiveness in recognizing fire, even in varying conditions and settings, as captured in the diverse training dataset.
This successful detection is a testament to the robustness of the AI model developed through a comprehensive training process. The precise identification of the fire in the image highlights the potential applications of this model in real-world scenarios, offering a reliable tool for early fire detection and prevention. The deployment of such an AI system can significantly enhance safety measures, providing timely alerts and enabling prompt responses to fire incidents.

7. CONCLUSION

The research into developing an autonomous drone for early detection of forest fires has yielded promising and impactful results, showcasing a significant step forward in the realm of environmental monitoring and disaster prevention. The meticulous design process and integration of advanced technologies have demonstrated the feasibility and effectiveness of employing drones equipped with artificial intelligence for fire detection.

The core of this study lies in enhancing early detection capabilities, a crucial factor in initiating timely responses and preventing the devastating spread of forest fires. By leveraging specialized sensors and state-of-the-art AI algorithms, the autonomous drone system is able to promptly identify fire outbreaks. This not only helps in safeguarding vast forest ecosystems but also plays a vital role in protecting human lives and property in adjacent communities. The ability of the drone to detect fires early significantly mitigates the risks and potential damage, highlighting the system's importance in contemporary forest management strategies.

The integration of artificial intelligence into the drone's functionality, particularly through the use of the Edge Impulse platform, has been a pivotal aspect of this research. The AI model was rigorously trained using a diverse dataset, ensuring its robustness and reliability. The use of Convolutional Neural Networks (CNN) and meticulous data labelling has allowed the model to accurately recognize fires under various conditions, including different lighting and environmental scenarios. The successful detection of fires in real-world tests underscores the model's efficacy, providing a reliable tool for early fire detection and prevention.

Furthermore, the comprehensive system design of the autonomous drone was crafted with precision to meet specific environmental requirements. This included the integration of thermal cameras, GPS navigation, and real-time communication capabilities, which together ensure that the drone can operate autonomously in challenging terrains and provide continuous monitoring without human intervention.

The robustness of the system architecture allows for effective and reliable performance, even in diverse and complex forest environments.

In conclusion, the successful development and deployment of the autonomous drone system for early detection of forest fires represent a milestone in environmental technology. This research not only highlights the potential applications of such systems in real-world scenarios but also underscores the importance of integrating advanced AI and drone technologies in safeguarding our natural resources. The precise identification and rapid response capabilities of the system promise to enhance safety measures, offering a reliable and innovative tool for protecting forests and communities from the threat of wildfires.

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