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Intelligent Drone Medical Assistive Device for Accidental Support Individuals

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Serving the needs of human beings is much more important to us. So, considering how to service the product or provide medicinal support is also very important to reach the destination. While supported by the local field-side forces, it is going through delays and getting affected by the delays in medical treatment. Why this failure in medical support? To avoid this delay, I have come up with a trend in technology in real life to send things like oxygen to the nearby hospital and make it emergency support on an urgent basis. At the same time, we can look for college and industry, food, and grocery items that we can utilize for the same methods. We can make it using AI technology used in the drone system and so by using different scales of sensors and cameras for recognition for bill service for auto-detection and bill payment as well. Nowadays, most people try to use their outside food purchases quickly, so we can get it via air drone easily without delay. This process is unintentionally free and GPS-based, with an advantage system to track the location. And confirmation of customer detection can help to unlock the lock-unlock the drone's locked body, get material, and lock the door once service is received. If there is any unwanted attack, it will be updated with the tracking system. There is an anti-drone system used here. This activity can be avoided.
Keywords: Artificial intelligence, Drone, UAV, GPS, Anti attack detection sensor.

1. Introduction

Unmanned systems are used in many applications today. Unmanned aerial vehicles (UAVs), also known as drones, are considered to be extremely powerful. Drones have many uses to support different sectors. Drones are used in aerial photography, surveillance, transportation and delivery, military applications, and many other applications. Most drones have two flight modes. The first mode is that the drone can fly completely autonomously without human intervention[17]. This can be achieved by setting up a flight plan and connecting to a drone computer before launch. In the second type of flight, the pilot sits in a sort of operating room, where he has full control of the drone. Drones usually require a high-precision GPS to pinpoint the exact location [1]. In addition, drones have different designs and specifications. Based on the application, the engineer can determine the type of drone needed to meet the mission requirements. A drone is supported by a payload that performs a specific mission. With a large number of scaled detectors, sensors, cameras, etc., you can load different payloads into an artificial intelligence system [18]. One of the uses of drones is to avoid unwanted attacks while delivering packages. Traditional inspections tend to be unsafe for personnel. With the help of a drone, the test can be performed autonomously without human intervention. Imagine a scenario where a drone detects a receiver of a product like medicine in a hospital, confirms with image technology, and locks the handover of the product. It gives the operator accurate results. In this study, machine learning-based algorithms are implemented for the proposed system. The performance of various machine learning (ML) algorithms was tested and compared. These algorithms are decision trees (DT), support vector machines (SVM), random forests (RF), and artificial intelligence systems (AI). The metrics used in the performance comparison were accuracy, precision, recall, and F1 score. The data from the algorithm was performed with the correct detected location in this study. The exact location of each spot was noted using a GPS, and the product was dropped off at the service location [19].

2. Related research work:

We've recently seen a lot of drone technology around the world that uses drones to do airline support systems in the medical and party delivery fields. They use drones for a variety of applications, such as security, inaccessible equipment monitoring, pipeline inspection, surveying, and mapping. They use different types of drones, such as fixed-wing and multi-rotor drones. Fixed-wing aircraft are used to cover long distances, and multi- rotor aircraft are used for structural inspections [11]. These drones are imagers capable of capturing images in the RGB spectral range, digital elevation models (DSM), and thermal images. The image has a ground resolution of about 2.3 cm and a maximum height of 100 m. We use drones to perform regular visual inspections of their daily routine work due to their low cost and time efficiency. Visually, the inspection is done using a regular RBG image captured by a drone camera. These images are stored and analyzed by the Geographic Information Systems (GIS) team. When a problem is detected, an operator is dispatched to the site to investigate the problem, and delivery detection is done once the product is delivered to its place.

If a problem occurs in the underground place, the anti-drone system will be applied via the control room server using AI [13]. Consistent vegetation lines appear in the captured image around the place as a sign of theft. Meanwhile, the maintenance department also uses drones. an infrared camera for inspecting power lines in remote areas. The site operator then inspects a complete map showing the faulty area or recognizes the area as the destination. This system is useful for monitoring and security [15]. There are some restrictions. These limits are as follows: This system is implemented to detect irregularities in the pipeline service for multipurpose basically, different types of devices need to be attached to the drone, including a spectrometer detector. The action of an anti-theft detector camera Also, this system is a real-time system that takes quick action to run the image analysis. The purpose of this study is to leverage an existing drone system with an infrared camera and add unmanned technology for a fast AI service process. This system is a real-time detection process without human intervention. We can increase the distance from the current scenario of 12 km to 50 km. We have to use a high-frequency range transmitter and receiver. A high-powered load system and a power backup system are combined with a solar system to avoid battery discharge over longer distances.

3. Skyline Inspection Challenges in Sender to Receiver & Receiver to Sender:

As part of this investigation into the new approach to technology, I got the idea to detect the issue via an online process with skyways. The size and material of the box depend on the type and quantity of gas or food it contains. They also have plumbing for heating and cooling and an anti-theft system. The distance of the receiver varies because the payload and efficiency of the battery backup have a small system and because of the capacity that connects the platform and destination area. Regarding the inspection process, we will allow workers to perform routine visual inspections of GPS platforms at the beginning of their work shifts [7] [8] [9]. Otherwise, the backup battery will be fully charged and the solar system will be switched on for recycling. The charging battery is attached to the load, which is monitored from the control zone. If anomalous measurements are found, a visual inspection is performed, and if it is found that it is not switched on, we can control it via the control room to make it switch on if needed. In the event of a delivery line process, the inspector carries a detector that can detect the image of the item if it matches and determine if they delivered it. Therefore, the detection process is very important for surveillance platforms [16]. In addition, to measure longer distances, GPS will be turned on to detect the distance. The AI Drone system uses intelligent pig inspection, in-line inspection (ILI), and outline inspection (OLI). ILI was performed by driving an inspection probe into a battery backup, and outline inspection (OLI) was done by the GPS.

The data obtained from ILI helps determine the accuracy of the backup charge and the location to perform the task. There is also a predictive model that uses this data to estimate the life of the backup energy. Depending on the estimation of the predictive model, such tests will be carried out in 5 to 10 years. If the battery or GPS model needs maintenance or replacement, the components will be thoroughly inspected [20]. This is a process that costs hundreds of thousands of dollars. In addition, we use a variety of well-known inspection methods, including non- destructive inspection and wireless-based devices and detectors. We already have robust and accurate multi- pipeline inspection procedures, but they require training, funding, and human resources. To work on this new technology, we need more support from the industry and government. In addition, workers must follow intensive safety procedures. In addition, some inspection methods are considered to be relatively expensive. But more accuracy is more in demand in the market now than ever, so it is wonderful research work.

4. Proposed System

Accordingly, this system is proposed to help monitor real-time emergency and industrial situations for human needs. It will be achieved by automating the inspection process, GPS location, and picture confirmation for goods delivery and payment techniques, as well as reducing human interaction. Visual inspection can be easily replaced with a live video streaming camera carried by a drone. On the other hand, the manual process of hospital-side confirmation can be done, and, forest side, any accidental case can be covered with medical support. The detection process will be replaced by the proposed payload mounted on the drone.

(a) (b) (c)

Figure-1 a, b, c Proposed AI Medical Drone System Test in Salem Area on Highway

I. System Block Diagram

The diagram of the system blocks of the suggested system is displayed in Figure 1 and block diagram shown in Figure 2 and in detail points explain here with point I, II, III, IV, V and VI. The payload and the drone make up the system. The drone's payload is a mechanism that it uses to complete particular mission objectives. The flight controller known as the onboard computer is responsible for connecting to and managing the payload (OBC). The OBC is the system's core, directing all other subsystems by gathering input from sensors and managing actuators. A command received from the pilot via radio frequency signals received by the transceiver is used to control the motion sensors and a few actuators connected to the OBC in the drone system.

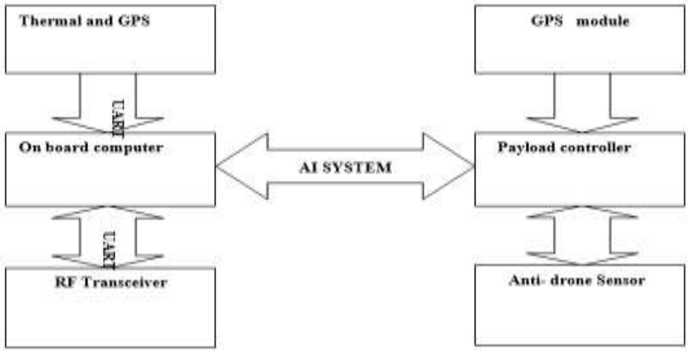

Figure-2 Block diagram of system components

II. Drone system

The drone carries a location-detecting system is taken by the drone. Multi-rotor drones are appropriate for this kind of inspection task. Pipeline inspections are limited in scope, but this type of drone has a limited lifespan of roughly 38 minutes. An RF signal can be used to remotely control the drone.

III. Thermal Camera

The radioactive thermal imaging gadget is the primary cargo connected to the drone's air traffic controller. The strength of the infrared (IR) signal that the camera's detector was able to detect to determine the surface temperature. To work with this system, the thermal imager must have a spectral band between 7.5 and 13.5 m. As usual, infrared cameras have a poorer resolution than RGB visible-light cameras. To capture more light, infrared cameras feature bigger pixels (approximately 17 Meters in size).

IV. Payload Controller

The Raspberry Pi 3 is used as the payload controller in this system due to its inexpensive cost, small weight, and interoperability with a variety of data buses. Also crucial for this kind of device is that uses less power than other microcontrollers [10]. Additionally, it is generally used to develop machine learning algorithms because it is based on the Python language. Due to its superior CPU performance when compared to other Raspberry Pi modules, the Raspberry Pi 3 was selected. To implement machine learning in real-time processing, a powerful CPU is required.

V. GPS module

The Raspberry Pi was selected to establish a UART connection with a GPS module. The patch antennas used by GPS are suitable for outdoor use. Furthermore, it features a per-sample pulse (PPS) output that permits the flight controller and the payload controller to synchronize their timing.

VI. Anti-drone Detector

A small sensor is known as an anti- drone detector. It is utilized to determine the precise amount of any leakage or fire and to support the thermal camera's detection results. A sudden attack of work performance time will then be returned for safety, and the next task will be processed. Even if an unknown result can be found with only a thermal camera, using a conventional gas detector with GPS return action will speed up the processing of thermal images. In such devices, the flight controller's CPU performance is constrained by power consumption [12]. As a result, compared to the time required for image processing, examining the detector's raw data only takes a few milliseconds. The suggested approach will provide a prompt, real-time alarm in the event of a leak. It will keep all the information gathered for GIS analysis. Direct streaming of this data to a base station is an option. The thermal camera attached to the OBC allows for the offline collection of this data. The gas detection system will then be notified by the OBC in one of three scenarios. First, a directive will be received, and second, a difference in control room pressure will be the cause. The third situation is when the temperature readings are outside of range. The main OBC will receive the data from the payload system and store it there before communicating with the ground base station. The primary OBC will use UART to connect to the payload controller, as depicted [14]. The payload controller will interface with the location detector sensor via the I2C data bus and with the GPS module via UART.

VII. Flow chart

The flow charts for the detection process in the flight controller software and the payload controller software are shown in this section. A flowchart of the on-board flight controller detection procedure is shown in Fig.3.

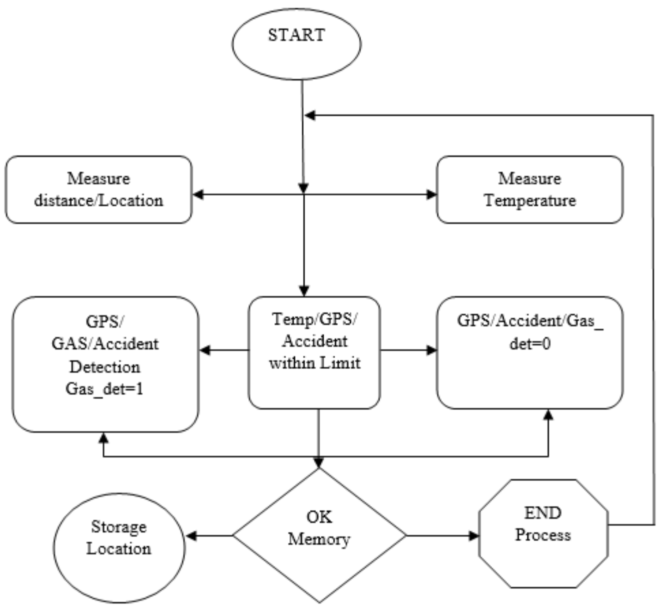

Figure-3 Flow chart of GPS location detection

As depicted, Flow charts Figure 3, the drone system will fly to verify the pipeline's thermal integrity. When the operation has begun and an image has been taken, the image will be examined for temperature differences. The payload would start the detection procedure by setting the flag GPS-detector to "1" if any difference was found. The flag will be set to the default value of "0" if no variation in location or temperature is found. If there is enough storage, the image will then be stored. Otherwise, the process will halt if the memory is full. On the flight controller software, all other control operations will be running concurrently. The payload controller will receive the detection flag regularly.

Figure of Flow chart:

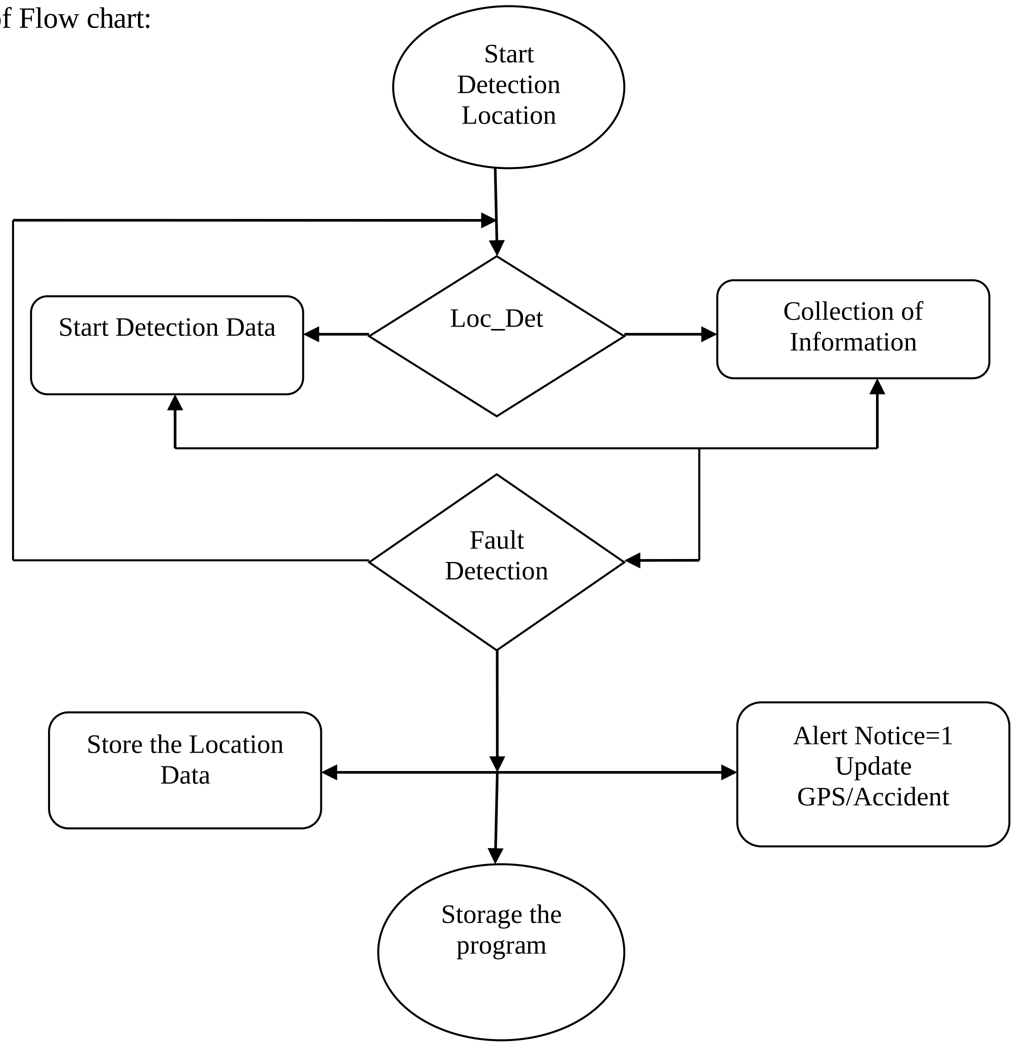

Figure-4 Flow chart for GPS and fault gas detection

The process flow diagram for the payload controller's detecting step is shown in Figure 4. The operation will begin as it is depicted and look for the detection flag; if it is set to 1, it will turn on the detector and begin gathering data. The constructed classification model will be used to classify the collected data. If a leak is found, the GPS coordinates of the leak will be recorded. Additionally, a real-time alarm flag will appear in the control room. Furthermore, a live leakage map of pipes will be conducted in the field using GPS coordinates. The drone camera is pointed at the leakage site to be photographed using the warning flag as well.

5. System Implementation

To categorize pipeline leakage detection data, many popular machine-learning classification methods were developed on a Raspberry Pi 3. The dataset utilized is an actual dataset for detecting methane pipeline leaks. The data is divided into two classes: "0" for no leakage and "1" for leakage. The classification process takes less time than multi-class classification because it is binary. These algorithms were used to evaluate each other's performance in terms of accuracy, evaluation matrix, and overall classification time. Decision Tree (DT), Support Vector Machine (SVM), and Random Forest are these algorithms (RF). The ML methods that will be used in the comparison as well as the evaluation matrices will be introduced in this part.

A. Machine Learning Algorithms

a. Decision Tree (DT):

Each node in the tree-like structure branches out to form further nodes. A single node with a weight and cost probability is regarded as a testing node. Till the tree's maximum depth, nodes branch from a single testing node. The leaves, the deepest level node, stand in for the class label. [5]

b. Support Vector Machine (SVM):

It is a model for supervised classification. Despite being utilized for both linear and nonlinear non-linear classification, it outperforms other models in this area. In N-dimensional space, where N is the number of characteristics that can best categorize data points, the hyper-plane is calculated. [3]

c. Random Forest (RF):

It creates the forest by combining various decision trees. The classification is based on the category that received the most votes from all involved decision trees. It is a supervised classification technique that outperforms a single decision tree in terms of accuracy and robustness. [2]

B. Evaluation Criteria

Using a confusion matrix, the effectiveness of the machine learning approaches was evaluated. The ML performance of the tested data based on the real data class is described by a two-dimensional matrix [6]. It assesses each class's True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) rates in order to determine accuracy, precision, recall, and F1 Result. The definitions for each measurement provided by the confusion matrix are as follows.

1) Accuracy:

It is one of the assessment matrices used to assess the effectiveness of ML models, and it was calculated using equation 1.

$$\text{Accuracy} = (TP + TN)/ (TP + TN + FP+ FN) \quad \ldots\ldots (1)$$

2) Precision:

It measures the expected positive values that really happened. It determines the ratio of the true positive values to the reported positive values. The calculation makes use of Equation 2.

Precision =TP/ (TP + FP)……………. (2)

3) Recall:

The percentage of actual true positive values that were correctly predicted is measured. Equation 3 illustrates the computation of recall for a single class.

Recall =TP/ (TP + FN)...(3)

4) F1 result:

It computes the classification model's average precision and recall. Equation 4 shows the calculation of the F1 Score value for a single class using the recall formula.

Recall=2*(precision*recall)/(precision+recall) …… (4)

6. Result and Discussion

The pipeline has a cylindrical shape, making it possible that the leak is not exactly in the middle of the pipe perpendicular to the detector, even though it appears to be simple to identify leaks using a gas detector. As a result, the detector will rotate to obtain readings from various angles. It is also challenging to determine whether this reading qualifies as leaking because gases diffuse quickly in the air. In this study, a machine learning system was trained on a sizable real dataset of methane pipeline inspection using a gas detector to categorize the signals as leakage or not. The dataset was divided into training-to-testing ratios of 80% to 20%.

The evaluation measures for each classifier are shown in Tables I, II, and III. It demonstrates that among all classifiers, RF provides the greatest accuracy of 97.25 percent. It demonstrates that SVM offers the lowest accuracy at 71%. The precision of the RF and DT classification models is nearly equal when the other variables in the confusion matrices are taken into account. However, SVM has the lowest precision, recall, and f1-score values, while RF is marginally superior. In general, RF and DT produced superior outcomes to the SVM.

RF RESULT			
Class	precision	recall	F1-result
0	0.96	0.98	0.97
1	0.98	0.97	0.97
Accuracy	97.25%		
Time (ms) 75			

TABLE I RF PERVERSITY MODEL

SVM RESULT			
Class	precision	recall	F1- result

0	0.70	0.71	0.70
1	0.72	0.71	0.72
Accuracy	71%		
Time (ms)	2630		

TABLE II SVM PERVERSITY MODEL

DT RESULT			
Class	precision	recall	F1- result
0	0.94	0.96	0.95
1	0.96	0.94	0.95
Accuracy	94.95%		
Time (ms)	78		

TABLE III DT PERVERSITY MODEL

The classifier's effectiveness is evaluated by the total amount of training time needed because this system runs in real-time. As a result, the RF classifier classifies the data in 75 milliseconds, DT in 78 milliseconds, and SVM in 2630 milliseconds. It demonstrates that, when compared to the other classifiers in this investigation, SVM performs the least well. Results from RF and DT differ slightly, although RF has higher accuracy and requires less processing time.

Although faster processing requires more power, with this system the power consumption between DT and RF is very low. Thus, this system incorporates the RF classifier. As a result, a detection process that previously completed manually in minutes or hours is completed with this technology in milliseconds. Additionally, this technology doesn't require any human interaction, protecting workers from explosive and poisonous gases. The length and expense of the inspection procedure are somewhat reduced by this technique.

7. Conclusions

The inspection of pipelines is a difficult task. This study demonstrated that pipeline inspections may eventually pose a hazard to people's lives. A similar procedure is frequently costly and time-consuming. The proposed approach, however, can assist the oil, GPS, Road side accident in congested area and GAS industries in conducting such inspections with the least amount of losses in terms of staff safety, time, and expense. Nevertheless, this study only utilized one dataset. Multiple datasets will be tested in order to achieve better results and outcomes. Additionally, image processing would help ensure the quality of the inspection in a more redundant system.

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Data and code availability:-

The data and code used in this work can be accessed for reader by approaching the author who wrote it. As per the concern of the study of this article, reader can contact the main author Chandrashekhar Kumar Gmail id-chandrashekharbandhu@gmail.com.

Declarations:-

Conflicts of Interest- Each writer agrees with the content and is given the authorization to submit it. The authors declare that they have no competing interests.

Additional information-The main body contains no missing material.

Ethical clearance-There had been no experiments involving human tissue.

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