Energy Efficient Path Planning For Aerial Photography Based Disaster Response

B. Tech. Final year project Report

By

Mangu Singh	**(Roll No. B190641EE)**
Aayush Patidar	**(Roll No. B190458EE)**
Akshay Nirmal	**(Roll No. B190939EE)**
Piyush Agarwal	**(Roll No. B190889EE)**

Under the guidance of

Rakesh R Warier

Department of Electrical Engineering

NATIONAL INSTITUTE OF TECHNOLOGY CALICUT

NIT Campus P.O., Calicut - 673601, India

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CERTIFICATE

This is to certify that the Project entitled "Energy Efficient Path Planning For Deep Learning Based Aerial Surveying" is a bonafide record of the work done by Piyush Agarwal, Mangu Singh, Aayush Patidar, Akshay Nirmal, under my supervision and guidance, in partial fulfilment of the requirements for the award of Degree of Bachelor of Technology in Electrical and Electronics Engineering from National Institute of Technology Calicut for the academic year 2023.

Dr. RAKESH R WARIER
Assistant Professor
Dept. of Electrical Engineering

Dr. PREETHA P
Associate Professor & Head
Dept. of Electrical Engineering

Place: NITC
Date: 09.12.2022

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Piyush Agarwal
B190889EE

Mangu Singh
B190641EE

Aayush Patidar
B190458EE

Akshay Nirmal
B190939EE

ABSTRACT

In this project deep learning based aerial surveying of an area has been performed.For aerial inspection a UAV is needed. The primary goal is to manage the UAV flight path in such a way that the energy consumed by the UAV should be as minimal as possible. After the efficient path planning the data can be collected and then the data can be processed. With the help of processed data it can be concluded that if the area is affected by a calamity.

Coverage path planning is the operation of finding a path that covers all the points of a specific area. Thanks to the recent advances of hardware technology, Unmanned Aerial Vehicles (UAVs) are starting to be used for photogrammetric sensing of large areas in several application domains, such as agriculture, rescuing, and surveillance. However, most of the research focused on finding the optimal path taking only geometrical constraints into account, without considering the peculiar features of the UAVs, like available energy, weight, maximum speed, sensor resolution, etc. This paper proposes an energy-aware path planning algorithm that minimises energy consumption while satisfying a set of other requirements, such as coverage and resolution. The algorithm is based on an energy model derived from real measurements. Finally, the proposed approach is validated through a set of experiments.Unmanned aerial vehicles (UAVs) are frequently adopted in disaster management. The vision they provide is extremely valuable for rescuers. However, they face severe problems in their stability in actual disaster scenarios, as the images captured by the on-board sensors cannot consistently give enough information for deep learning models to make accurate decisions. In many cases, UAVs have to capture multiple images from different views to output final recognition results. In this paper, we desire to formulate the fly path task for UAVs, considering the actual perception needs. A convolutional neural networks (CNNs) model is proposed to detect and localise the objects, such as the buildings, as well as an optimization method to find the optimal flying path to accurately recognize as many objects as possible with energy awareness. The simulation results demonstrate that the proposed method is effective and efficient, and can address the actual scene understanding and path planning problems for UAVs in the real world well.

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CNN– Convolutional Neural Networks
UAV– Unmanned Aerial Vehicle
DL– Deep Learning

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CHAPTER 1

INTRODUCTION

The unmanned aerial vehicle (UAV) is often used in disaster management. For example, after a disaster, people can use the UAV to detect the disaster area to find the damaged buildings and residents; and in the disaster recovery stage, the UAV can be used to assess the severity of the disaster, the feasibility, and cost of the reconstruction. They are utilised to assist people in disaster reconstruction planning. However, a serious problem with UAV is that their battery is limited and cannot be used for long-term or large-scale survey tasks. Therefore, how to develop a feasible flight path for efficient and accurate target detection has become a very important issue. This task mainly consists of an important aspect of energy aware path planning.

1.1 OBJECTIVES

1. Search and Rescue Operation
2. To Design energy efficient UAV trajectory for covering area of interest:
   Here we will design an energy efficient trajectory for covering areas of interest by using several techniques. For example taking path where the turns ratio is minimum.
3. To Use trained CNN for processing UAV collected images:
   Now our task is to use a trained CNN algorithm to process UAV collected images.We explore the use of different CNN architectures and using different hyperparameters.

1.2 UAV Remote Sensing and CNN

To begin with UAVs. Unmanned Aerial Vehicle – UAV popularly known as drone, is an airborne system or an aircraft operated remotely by a human operator or autonomously by an onboard computer. There are two broad classes of UAVs – Fixed wing and Rotary based.

For surveying purposes we are combining both UAV and remote sensing technology.*Remote sensing* is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft). Special cameras collect remotely sensed images, which help researchers "sense" things about the Earth. Cameras on satellites and aeroplanes take images of large areas on the Earth's surface, allowing us to see much more than we can see when standing on the ground.And sonar systems on ships can be used to create images of the ocean floor without needing to travel to the bottom of the ocean are some example UAV remote sensing.

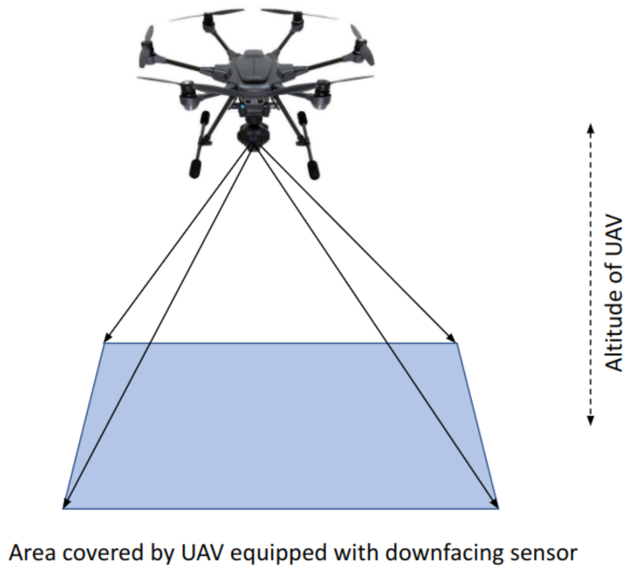


Fig. 1.1: UAV remote sensing

UAV combined with remote sensing technology have been creating new vistas in global scenarios to acquire the geospatial data on land resources and environment. The imagery obtained from UAVs can immensely support many applications ranging from large-scale mapping, urban modelling to vegetation structure mapping. Specifically in the NE region of our country with limited connectivity and difficult terrain conditions, the local planning and developmental activities can be greatly improved by the UAV survey.

The remote-sensing community is always committed to developing remote-sensing methods for improving the performance of aspects, such as preprocessing, segmentation, and classification. Neural networks, the basis of deep learning (DL) algorithms, have been used in the remote sensing community for many years.The main advantage of CNN compared to its predecessors is that it automatically detects the important features without any human supervision. For example, given many pictures of cats and dogs, it can learn the key features for each class by itself.convolutional neural networks can extract informative features from images, eliminating the need of traditional manual image processing methods.

1.3 NEED of ENERGY EFFICIENCY

Battery-powered UAVs are the most convenient and inexpensive. However, the energy of battery-powered UAV is limited and can only provide a short flight time. Therefore, for a large monitored area where the nodes to be visited are distributed, we hope that the UAV can finish as many tasks as possible in the duration of flight. How to reduce the energy consumption of the UAV and make it collect data from as many sensor nodes as possible in the duration of flight?

That has become an important challenge which UAV-assisted data collection methods have to confront in practical applications.

If the energy efficiency of the UAV can be improved, more tasks will be completed and more sensor nodes will be visited in the duration of flight. This can also reduce the number of UAVs and the cost of input in an application scene where multiple UAVs alternately or collaboratively collect data. Conversely, if the energy efficiency of the UAV is not high, the recharge cycles of the UAV will increase and data collection will be delayed, which results in not only collecting data not in time but also losing data (e.g., for a sensor node, the new sensed data can erase the old data that has not been collected).

Improving the energy efficiency of a UAV has important practical significance in other aspects. For example, when the UAV is used to search and rescue the trapped people in an earthquake and other disaster sites, it can make the UAV visit as many search-and-rescue points as possible in the duration of flight and save the search-and-rescue time and more lives.

CHAPTER 2

METHODOLOGY

2.1 ENERGY MODEL:

Given the large variety of drones, each with specific physical characteristics, like weight, type of power supply, propellers, etc., deriving a general parametric energy model that can be used to predict the energy consumption in different operating conditions is a hard task. In this work, we propose a method that can be used to model and analyse the energy consumption of a specific drone as a function of its speed and operating conditions.

In this section, we present the drone energy-consumption model for a UAV that needs to traverse a set of waypoints in a surveyed area to perform data collection tasks. The UAV is a quadrotor with quad-core 64-bit, 2.56 GHz processor and 3300 mAH Li-Po battery. We used the energy model proposed by Lige Ding to formulate the energy consumption problem. As the energy consumption of a drone depends on the drone speed, the energy consumption model needs to consider the different flight stages including acceleration, deceleration, hovering, and turning. The consumed power is calculated by multiplying the supply voltage and the current, which is measured by an energy measurement module. The experiments conducted by Lige Ding provided a better understanding of the energy performance of a drone.

2.1.1 Effect of velocity:

The UAV was commanded to fly in a straight line at different constant speeds. The power consumption measured at 2 m/s, 4 m/s, 6 m/s and 8 m/s were 242W, 245W, 246W and 268W, respectively.

Power consumption during acceleration and deceleration was recorded and can be used to calculate energy consumption when UAV accelerates and decelerates. Similar readings of power consumption were observed during the acceleration and deceleration phases as observed in effect of velocity. As velocity increases, power consumption during acceleration increases and vice versa.

Energy consumption model for flying straight When a UAV flies from a starting point to a target point, it goes through three phases: acceleration, uniform speed, and deceleration. We can calculate energy consumption at different speeds and distances E(v,d)

$$E(v,d) = \int_0^{t_1} P_{acc}dt + \int_{t_1}^{t_2} P(v)dt + \int_{t_2}^{t_3} P_{dec}dt \quad (1)$$

2.1.2 Effect of Turning:

In this experiment, the power consumption of the UAV was recorded when it rotated at four different angles 45, 90, 135, 180. It was assumed that an angular speed of ω_{turn} (2.07 rad/sec) would require P_{turn} (260 W) for the turn. The energy consumption at turning angle $\Delta\theta$ can be calculated by

$$E_{turn} = P_{turn}\frac{\Delta\theta}{\omega_{turn}} \quad (2)$$

where E_{turn} denotes Energy consumption during turn, Pturn denotes Power consumption during turn, $\Delta\theta$ denotes turning angle, !turn denotes angular velocity during turn.

When a UAV travels for a short distance, it is not able to achieve a uniform speed because it directly goes from the accelerating phase to decelerating phase. The 1st equation can be used to evaluate the optimal drone speed. When the distance is too short, the drone will take its whole time accelerating and decelerating, and when the distance between two-way points is large enough, drones can go through all flight phases and reach an optimal speed. Once the path length is ideal, the drone can remain at the optimal speed.

2.2 CNN:

CNNs are most frequently used for image classification, such as detecting highways in satellite photos or categorising handwritten characters and numbers. In addition to these more commonplace tasks, CNNs also excel at signal processing and image segmentation.

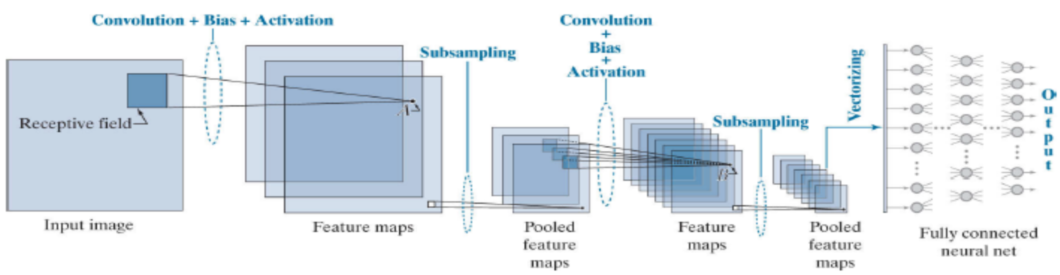


Fig. 2.1: CNN architecture

Receptive field selects a region of pixels in the input image. The receptive field is moved over the image and, at each location, forming a sum of products of a set of weights and the pixels contained in the receptive field.The number of spatial increments by which a receptive field is moved is called the stride. Our spatial convolutions in previous chapters had a stride of one, but that is not a requirement of the equations themselves.When repeated for all locations in the input image, this results in a 2D set of values that we store in the next layer as a 2-D array, called a feature map.

Max pooling operation calculates the maximum value for patches of a feature map, and uses it to create a downsampled (pooled) feature map. Translating the image by a small amount would not significantly affect the values of most pooled outputs (Translational Invariance). Could result in loss of accurate spatial information

The nature of the learned features is determined by the kernel coefficients. Note that the contents of the feature maps are specific features detected by convolution. For example, some of the features emphasise edges in the character. The pooled features are lower-resolution versions of this effect. If you look at each map carefully, you will notice that it highlights a different characteristic of the input. For example, the map on the top of the first column highlights the two principal edges on the top of the character. The second map highlights the edges of the entire inner region, and the third highlights a “blob-like” nature of the digit, almost as if it had been blurred by a low pass kernel. The other three images show other features. Although the pooled feature maps are lower-resolution versions of the original feature maps, they still retained the key characteristics of the features.

2.3 PATH PLANNING:

When we talk about the energy efficient path planning algorithm, the first thing we can consider for the path planning is that the distance travelled by the UAV should be minimum and second thing we can consider is to minimise the number of turns as the figures given below figure a has more number of turns as compared to figure b. So the second path planning would be better.

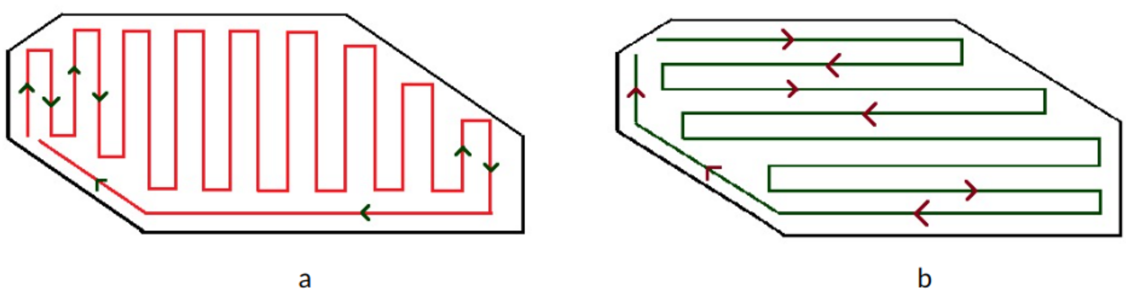


Fig. 2.2: Two ways of path planning for an area

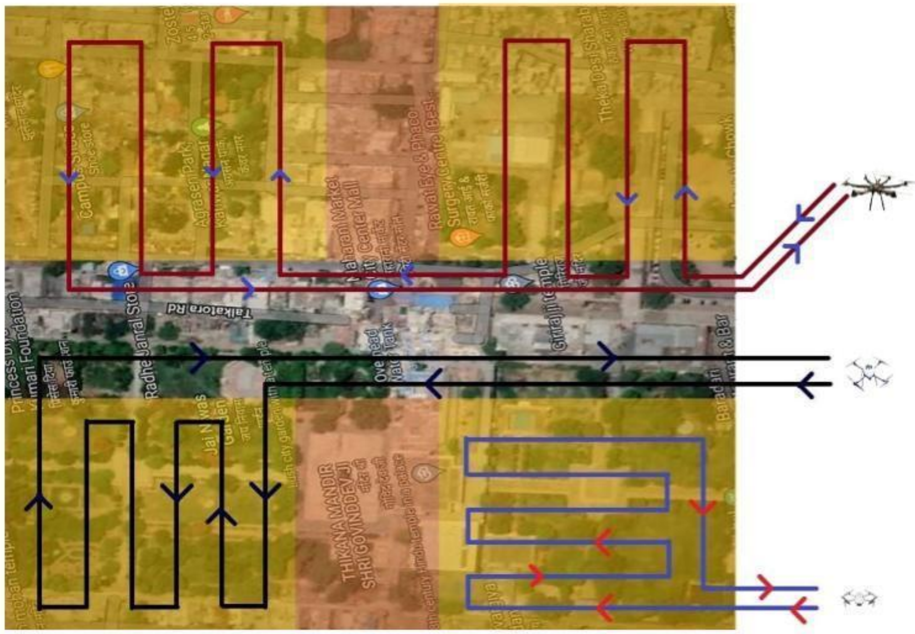


Fig. 2.3: Collective data collection by different types of UAVs

For an example we want to do a survey of the above given area.We only need to monitor the area which is in yellow. We are not allowed to enter into the red part so we can say that the red part is a restricted area. For collecting image data from the yellow part we have three UAVs in total. So our task is to combine UAVs in such a way so that the energy consumed by them is minimal.

Hexacopter UAV, DJI inspire 1 UAV, DJI F450 UAV all of them have different power capabilities, different number of sensors along with different load batteries. The Hexacopter UAV is larger in size and has more flight time so it monitors more area as compared to the others, as we can see from the figure also. Similar kinds of behaviours are followed by the DJI inspire1 and the DJI F450 also. In comparison to DJI F450, DJI inspire1 has more flight time so it is monitoring farther areas.

CHAPTER 3

Simulations and Discussions

3.1 Search and Rescue:

The real power that drones provide to rescue operators is the easy access to aerial data of a large area, which gives the rescue team the ability to expedite the process of finding a missing person, where every second count.Drones can carry different types of payloads that can be used in different situations. Two of the popular payloads are the 4K wide-angle camera and the thermal camera that are extensively used during search and rescue missions.HD video from a drone is not that useful in a search and rescue mission, since the resolution is lost when looking at a still image. On the other hand, a high resolution still image can provide valuable information to the people on the ground looking for the missing person. This is why cameras that can capture high resolution still images are preferred.Thermal cameras are also used in search and rescue missions, especially during night time missions.

3.2 Image Data Collection:

AIDER (**A**erial **I**mage **D**ataset for **E**mergency **R**esponse applications): The dataset construction involved manually collecting all images for four disaster events, namely Fire/Smoke, Flood, Collapsed Building/Rubble, and Traffic Accidents, as well as one class for the Normal case.

The aerial images for the disaster events were collected through various online sources (e.g. google images, bing images, youtube, news agencies websites, etc.) using the keywords ”Aerial View” or ”UAV” or”Drone” and an event such as Fire”,”Earthquake”,”Highway accident”, etc. Images are initially of different sizes but are standardised prior to training. All images were manually inspected to first contain the event that was of interest and then to have the event centred at the image so that any geometric transformations during augmentation would not remove it from the image view. During the data collection process the various disaster events were captured with different resolutions and under various conditions with regards to illumination and viewpoint. Finally, to replicate real world scenarios the dataset is imbalanced in the sense that it contains more images from the Normal class. This subset includes around 500 images for each disaster class and over 4000 images for the normal class. This makes it an imbalanced classification problem.

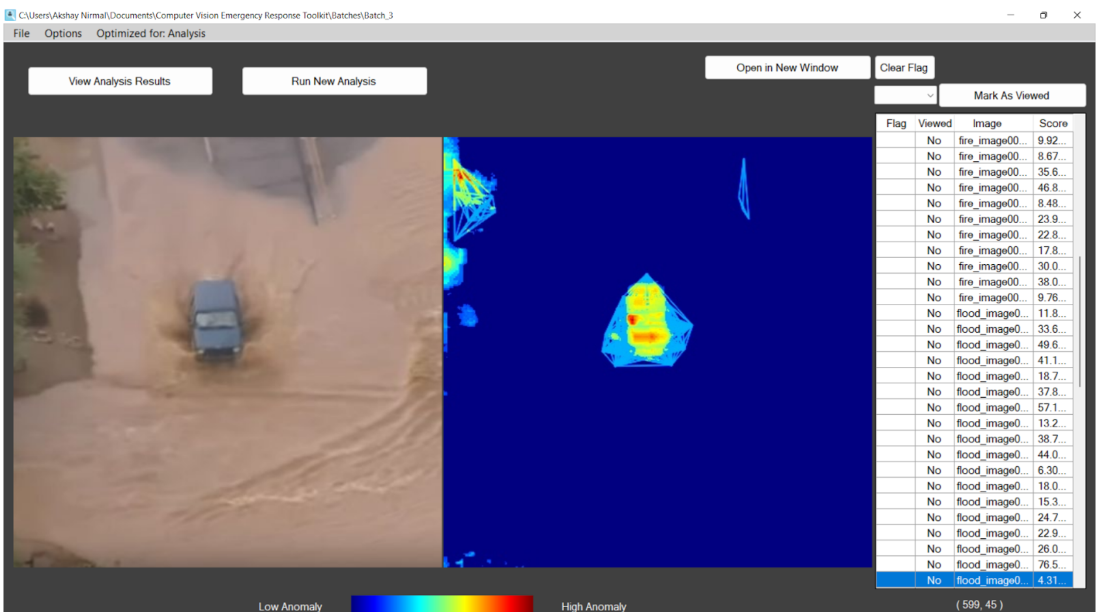
It is advised to further enhance the dataset that random augmentations are probabilistically applied to each image prior to adding it to the batch for training. Specifically there are a number of possible transformations such as geometric (rotations, translations, horizontal axis mirroring, cropping and zooming), as well as image manipulations (illumination changes, colour shifting, blurring, sharpening, and shadowing).

This dataset is associated with the following publications: C. Kyrkou and T. Theocharides, "EmergencyNet: Efficient Aerial Image Classification for Drone-Based Emergency Monitoring Using Atrous Convolutional Feature Fusion," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 1687-1699, 2020, doi: 10.1109/JSTARS.2020.2969809. C. Kyrkou and T. Theocharides, "Deep-Learning-Based Aerial Image Classification for Emergency Response Applications Using Unmanned Aerial Vehicles," 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW), Long Beach, CA, USA, 2019, pp. 517-525, doi: 10.1109/CVPRW.2019.00077.

Fig. 3.1: Sample images of disasters such as fire, flood, building collapse and road accidents

3.3 Image Analysis

For image analysis software named as Computer Vision Emergency Response Toolkit is used.The Computer Vision Emergency Response Toolkit is an application that allows users to detect features of interest in high-resolution photos obtained from UAV fly-overs. Users can run an analysis job by selecting a single image, a set of images, or a folder of images through the interface provided. Upon completion of the analysis of the image(s) provided, users can view the features of interest side-by-side with the original image, also through the interface provided. The ability to view jobs and their respective image heat map pairs is available anytime, even while a job is running. In addition, there is a checkbox feature provided that enables users to keep track of the images they have reviewed and what is left to be done.



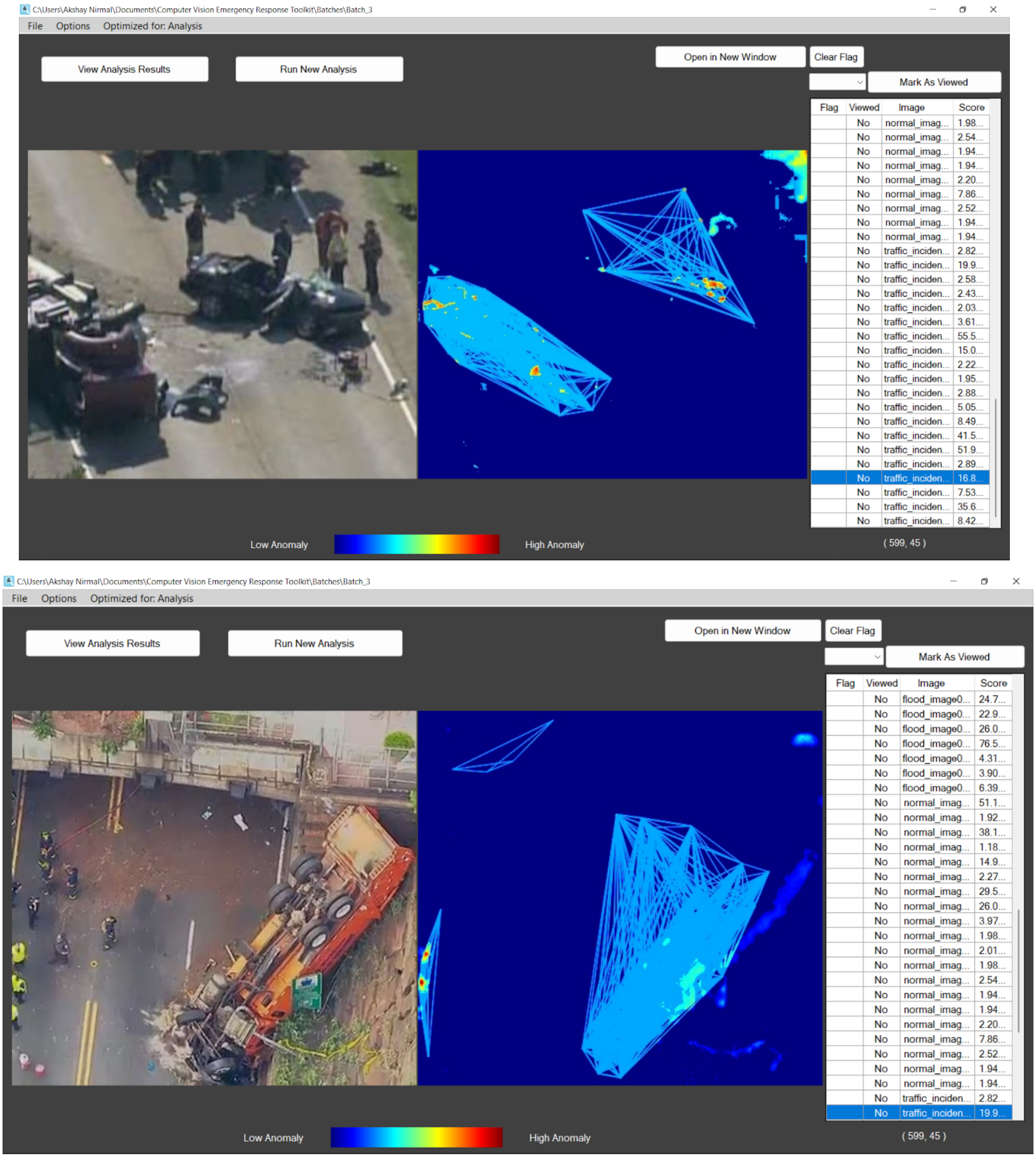


Fig 3.2: Sample images obtained after the analysis

This algorithm uses the colour of each pixel to find areas of interest in an image. It takes an average colour value across the image and compares this value to every pixel's colour value. The algorithm highlights pixels with colour values that are significantly different from the average colour value of the image. These pixels are considered to be anomalous and they usually indicate areas of debris or signs of a missing person.

CONCLUSION

In this project we have discussed a broad idea of doing energy efficient path planning for aerial photography based disaster response.A drone path planning model that takes into account the overall amount of energy used to complete a task should be minimum is proposed. The drone's acceleration, deceleration, hovering, and turning are the foundation of the energy model.From the data gathered from UAV surveying, The data can be used for the multiple objectives using CNN and deep learning algorithms as mentioned in the report.The AIDER data set has been used for simulation purpose.By using Computer Vision Emergency Response Toolkit images have been analysed successfully. The algorithm highlights pixels with colour values that are significantly different from the average colour value of the image. These pixels are considered to be anomalous and they usually indicate areas of debris or signs of a missing person.Hence,the project can be concluded with various completed tasks and learnings like energy efficient path planning of a UAV,proposing an energy model,collecting images and after analysis promulgated results.

REFERENCES

1. Sindhuja Sankaran. A Path Planning Method with Perception Based on Sky Scanning for UAVs. Article on mdpi. 24 January 2022.
2. Lucas Prado Osko, Jose Marketo Junior. A Review on Deep Learning in UAV Remote Sensing. ScienceDirect. October 2021.
3. Carmelo di Franco, Giorgio Buttezzo. Energy Aware Coverage Path Planning of UAVs. IEEE. 2015
4. C. Kyrkou and T. Theocharides, "EmergencyNet: Efficient Aerial Image Classification for Drone-Based Emergency Monitoring Using Atrous Convolutional Feature Fusion," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 13, pp. 1687-1699, 2020, doi: 1109/JSTARS.2020.2969809.