International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-6, April 2020

Post Disaster Rescue Assist using Machine Learning

K. Gangadaran, R. Dhinesh, S. Sam Peter

Abstract: ***During any disaster, the first step is to formulate a disaster rescue team to help those in distress. When the team goes into action, it is important to analyse the survivors withstood on the rooftops. It is hard to search for rooftop survivors by entering and searching every house. So, there are many Machine Learning techniques and algorithms such as image recognition and classification and these can be quite helpful in assessing the survivors as the algorithms can analyse and observe images from the sources. They can also identify the rooftop survivors and make a mark over them. Machine Learning can quite effectively identify humans apart from environmental objects, flooding, blocked roads from the disaster occurred locations.***

Keywords: Drone Assist, Flood Rescue, Machine Learning, SIFT

I. INTRODUCTION

The flood is one of the natural disasters that affects the cities, towns and residential areas which makes people suffer and lose their normal living. This makes people immobilize from moving to safer areas. So, they were forced to move up to their roofs to stay safe. They were termed as the Rooftop Survivors (RS). Hence, they cannot travel themselves to the safer places due to the flood running through the streets. In this situation, the government will send their rescue teams to rescue the people who were affected and sheltered over them roofs (RS) to a safer place. The rescue teams usually use the rescue boats and begin their search for the survivors and rooftop sheltered people. They search each and every rooftop and rescue the survivors.

II. SEARCH AND RESCUE PROBLEMS

Normally, the rescue team begins the search for survivors without any gears. It is known as the initial search method for flood victims. They enter the house to reach the rooftop and search for the victims. The next step is they bring in the rescue helicopters to start searching for the Rooftop Survivors (RT). These two methods are the only search techniques that have been carried out to search for the RT. Though it faces several problems and circumstances, the major issue is it takes so much time for the rescue team to get in the house and reach the rooftop. Some rooftops were unmanned and empty. It results in much waste of time and delays the rescue operation. It also involves more man-power. Also, in the case of searching from rescue helicopters, it cannot be lowered more than a certain altitude.

Even the cost involved in carrying out the search operation from a helicopter is much higher. It also includes the fuel cost and other expenses. For the fact, the cost involved in a rescue search operation in a Canadian village is nearly 6.8 million USD. In considering the whole picture, this traditional method includes more man-power and financial expenses and more time consuming.

III. WHY AUTOMATED SEARCH?

Researchers and social activists were actively working on this problem mainly to reduce both the man-power and financial cost involved in the rescue search process of the RT's. Also, the most needed improvement is to reduce the time involved in this rescue process. After a long period and with enough technological development researchers have built many IOT devices to help the rescuers reduce their effort involved in searching. Some of the devices like flood rovers, water resistant robots, signal enhancers for communication devices in the affected areas. Though it still needs many improvements. One of the best contributions is applying the concept of drones in the rescue search process. The unmanned devices fly through the flooded areas to find the survivors. These drones are controlled by an operator from the base station or any safe zones. With the help of cameras in the drones the operator is able to carry on the search process from base station and communicate with the rescue personals in the flood areas. Due to the advancements in the communication field the drones can be controlled from a long distance. The temporary signal towers were deployed in the areas for signal enhancement. But even with this advancement it has not been so easy to find people clearly with the drone cameras. This makes all those developments one step behind the success line.

IV. CONTRIBUTION

In our study, we propose a method which uses the Convolutional Neural Networks (CNN),

Scale Invariant Feature Transformation (SIFT) combined with the usage of deep learning algorithms which includes the two parameters, one is the pixel breakdown and other checks for the value is TRUE or FALSE. When TRUE the algorithm clusters the pixels together and makes a readable cluster group which then cross checks with the datasets that were used to train the model.

Revised Manuscript Received on April 30, 2020.

***** Correspondence Author

K. Gangadaran*, CSE, Sri Krishna College of Technology, Coimbatore, Tamil Nadu, India.

R. Dhinesh, CSESri Krishna College of Technology, Coimbatore, Tamil Nadu, India.

S. Sam Peter , assistant professor at Sri Krishna College of Technology, Coimbatore.

This algorithm is faster than it sounds and can be used with livestream videos.

A. Dataset

Fig.1 Pixel from a frame

This is a sample image [**Fig.1**] that is used to explain about the algorithm used in the model. From the image you can see a small green coloured rectangle at the top left corner of the image. That is scaled to actual 8x8 pixel size. Consider this pixel as a sample to understand the working of this algorithm. Mainly it works with the colour intensity comparison with the nearby pixels. For example, if the right pixel has high contrast value and the left pixel has nearly equal contrast of the middle pixel it clusters with the left pixel.

Fig.2 Histogram version of the pixel

The above picture shows the contrast comparison with each pixel in a frame. The matrix like values are the contrast values of the nearby pixels of the selected pixel.

V. IMPLEMENTATION AND RESULT

The same technique is applied in the proposed example picture. The pixel chosen from the image is made to compare with the nearby pixels.

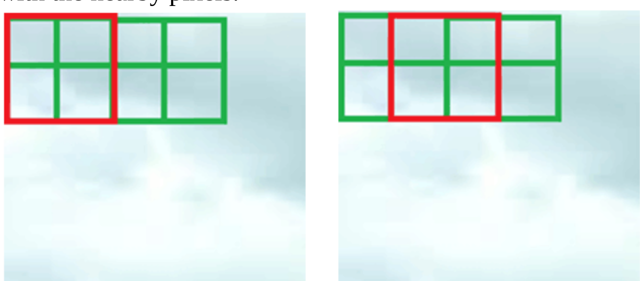

Fig.3 Pixel variation

The above picture [**Fig.3**] shows how the pixel clustering happens with the help of the used algorithms. With the help of this algorithms the relay video is classified into frames and the broke down into pixels which then used to make a cross check with the contrast.

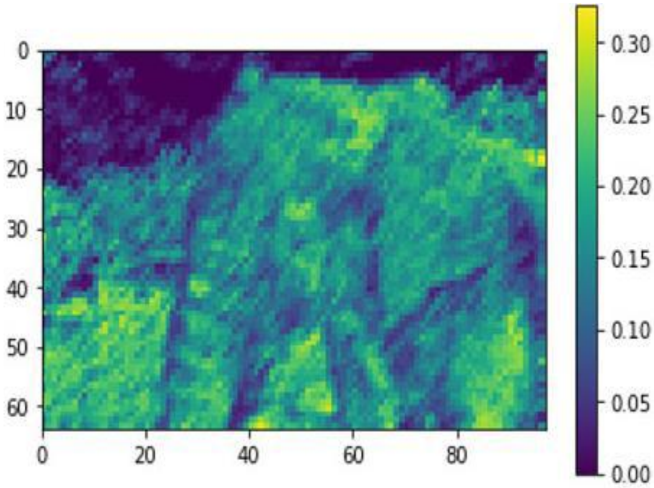

Fig.4 Histogram sample

The above image [**Fig.4**] is a histogram version of an elephant picture. By converting it into contrast-based pixels it is easier for the system to check for the similarity between each pixel.

The pre trained model can recognise each pixel from the image and groups them until a valuable cluster is formed and checks the matrix skeleton with the plenty datasets that have been trained before.

Fig.5 Real-time outcome

Above image [**Fig.5**] is the real-time output of the proposed model.

VI. CONCLUSION

The paper introduces a different approach towards the traditional rescue methods which will effectively decrease the man-power, financial costs, searching time, and danger involved in the rescue operations. It will make a well-versed knowledge for the opportunity involved in inter departmental researches towards a common social cause.

REFERENCES

1. J. Hosang, R. Beneson, B. Schiele,"How good are detection proposals really?", Proc. Brit. Mach. Vis. Conf., pp. 1-12, Sep. 2014.
2. S. Ren, K. He, R. Girshick, J. Sun, "Faster R-CNN: Towards real-timeobject detection with region proposal networks", IEEE Trans. Pattern Anal.

3. Mach. Intell., vol. 39, no. 6, pp. 1137-1149, Jun. 2017.
4. J. Redmon, S. Divvala, R. Girshick, A. Farhadi, "You only look once:
5. Unified real-time object detection", Proc. IEEE Conf. Comput. Vis. Pattern
6. Recognit., pp. 779-788, Jun. 2016.
7. J. Redmon, A. Farhadi, "YOLO9000: Better faster stronger", Proc. IEEE Conf. Comput. Vis. Pattern Recognit., pp. 6517-6525, Jul. 2017.
8. F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, K. Keutzer, SqueezeNet: AlexNet-level accuracy with 50x fewer parameters
9. A. G. Howard et al., MobileNets:Efficient convolutional neural networks
for mobile vision applications, 2017
10. X. Zhang, X. Zhou, M. Lin, J. Sun,"ShuffleNet: An extremely efficient convolutional neural network for mobiledevices", Proc. IEEE Int. Conf. Comput.Vis. Pattern Recognit., pp. 6848-6856,Jun. 2018.
11. A. Wong, M. J. Shafiee, F. Li, B.Chwyl, Tiny SSD: A tiny single-shotdetection deep convolutional neuralnetwork for real-time embedded objectdetection, 2018
12. G. Bae, S. Kwak, H. Byun, D. Park,"Method to improve efficiency of humandetection using scale map", Electron.Lett., vol. 50, no. 4, pp. 265-267, Feb.2014.
13. H. Hattori, V. N. Boddeti, K. Kitani,T. Kanade, "Learning scene-specific
14. pedestrian detectors without real data",Proc. IEEE Int. Conf. Comput. Vis.Pattern Recognit., pp. 3819-3827, Jun.2015.
15. Z. Cai, Q. Fan, R. S. Feris, N.Vasconcelos, "A unified multi-scale deep
16. convolutional neural network for fastobject detection", Proc. 14th Eur. Conf.
17. Comput. Vis., pp. 354-370, Oct. 2016.

AUTHORS PROFILE

Gangadaran kaameswaan, IV CSE
Sri Krishna College of Technology,
Coimbatore, Tamil Nadu, India.
Email: k.gangadaran10@gmail.com

Dhinesh Ravichandar, IV CSE
Sri Krishna College of Technology,
Coimbatore, Tamil Nadu, India.
Email: 16tucs032@skct.edu.in

Sam Peter. S, Working as an assistant professor at Sri Krishna College of Technology, Coimbatore. He received his B.E. in Computer Science and Engineering from CSI College of Engineering, Ooty. Tamil Nadu in the year 2011 and M.E. in Computer Science and Engineering from Sri Krishna College of Technology, Coimbatore, Tamil Nadu in the year 2014. His area of specialization is image mining. Email: S. Sam Peter@skct.edu.in