Automated Vision-based Surveillance System to Detect Drowing Incidents In Swimming Pool

Purvang Shah
Dept. of Computer Science
University of Massachusetts Lowell
purvangvipulbhai_shah1@student.uml.edu

Anveshak Rathore
Dept. of Computer Science
University of Massachusetts Lowell
anveshak_rathore@student.uml.edu

Rakshitha Raj Kemparaju
Dept. of Computer Science
University of Massachusetts Lowell
rakshitharaj_kemparaju@student.uml.edu

***Abstract*— Swimming pools are common in homes, restaurants, and clubs these days. There will be lifeguards at each pool and many swimmers there as well, but drowning occurrences continue to occur on a regular basis. And the figures are rising steadily. We are employing machine learning system to stop drowning events in order to safeguard people from happening in swimming pools. Although there have been various regulations put into place to reduce drowning accident in some countries, communities still experience many drowning incidents. Machine learning is used to identify the drowning individual. Accordingly, a real-time system that will track swimmers in a pool using machine learning techniques and prevents drowning accidents is proposed. Using a Pi camera, machine learning is used to identify the drowning person. This system is used to monitor the swimming pool and follow swimmers; if any person is in a drowning state, the Raspberry Pi will recognize it and issue a command. The pi camera is attached to the Raspberry Pi and is taught to detect these kinds of circumstances.**

Keywords*— *Swimmers, machine learning, drowning detection, image processing, Pi camera, Raspberry Pi.

I. INTRODUCTION

Today, video surveillance can be employed as a security and monitoring tool. Observing both public and private locations has grown to be a highly delicate subject. Systems for video-based surveillance are created and placed in places like airports, train stations, and even hazardous environments. Methods based on machine learning and image processing are effective for real-time intelligent surveillance of the objects or events of interest. Real-time monitoring of locations, people, and their activities is made possible through the integration of intelligence into video surveillance systems. The tracking strategy can change depending on the target and can go from single camera to multiple camera configurations depending on the target. To address the frequent monitoring issues of occlusion and noise, the tracking must be strong.

1.1 Description

Automated vision-based surveillance for in-the-moment human behavior analysis offers an effective technique to spot any unusual occurrences in our surroundings. The technological difficulties include the necessity for accurate moving target detection and tracking in potentially dynamic backdrop environments as well as an inference module that interprets target behavior patterns into events with semantic significance.

1.2 Problem Identification

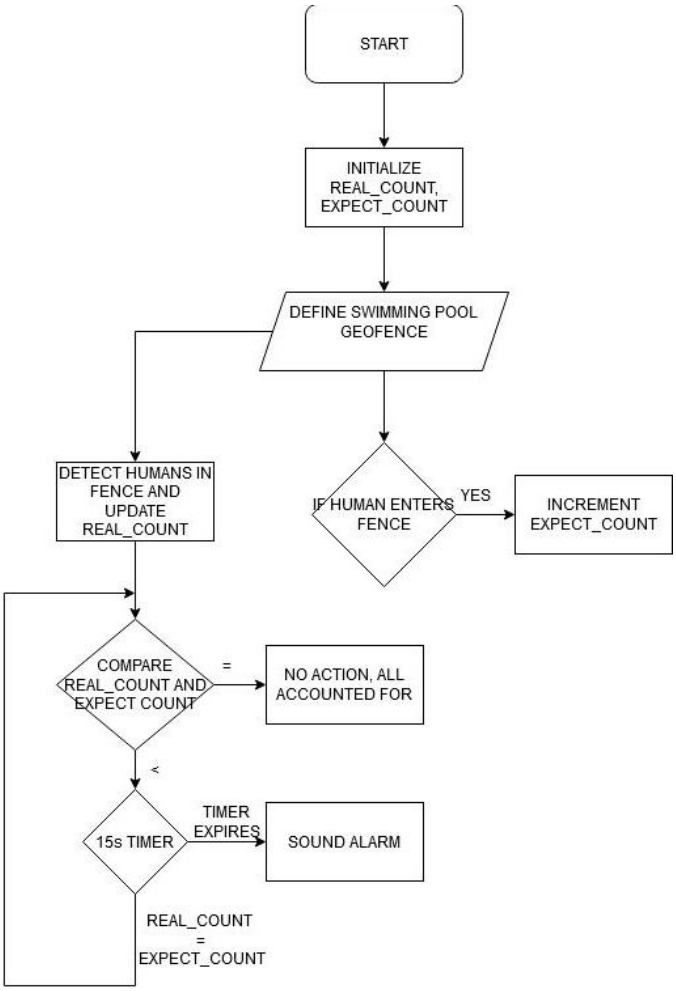
According to the WHO (World Health Organization), there are over 372,000 drowning deaths reported each year, making it the leading cause of unintentional deaths worldwide. drowning in a swimming pool kids and deaths This startling statistic Drowning is the leading cause of unintentional deaths in children aged 1 to 4 according to the CDC. The IoT surveillance strategy will assist in overcoming this issue by preventing the majority of fatalities.

The primary contribution of this research is the creation of a system for pool monitoring in order to stop drowning incidents before they start. The complete system will be controlled by the Raspberry Pi. The Pi cameras will keep an ongoing eye on the pool. The Raspberry Pi board, which is executing a Python script, will receive the data after it has been analyzed. The script will determine the positions, speeds, paths of movement, and time spent submerged for each swimmer. The computations will enable the detection of any abnormal events. If such occurrences take place, Raspberry Pi will send a command. The swimmer can be lifted out of the pool. If any impending danger arises, a warning signal will alert the lifeguard.

II. OVERALL SYSTEM ARCHITECTURE

The complete system will be controlled by the Raspberry Pi. The pool will be regularly inspected by Pi cameras. The internal camera hardware will process the 2D images that were captured. A script will be running on the Raspberry Pi board after the data has been examined there. The program will determine the positions, speeds, motion paths, and time spent submerged. The occurrence of any aberrant occurrences will be identified based on these calculations. If such occurrences take place, Raspberry Pi will instruct the lifting.

The systematic flow of the data goes by initializing the real count and expect count. Later it defines the swimming pool and detects the human enter fence, if yes, expect count will increase or else it will update the real count and compares the real and expect count. While comparison takes place the timers will be running and when it reaches the expected time limit the alarm will sound. This cycle continues to execute until it reaches the expected count.



A. Raspberry Pi 3

Model B Raspberry Pi 3 will be guided by linking the camera module on the Raspberry Pi.

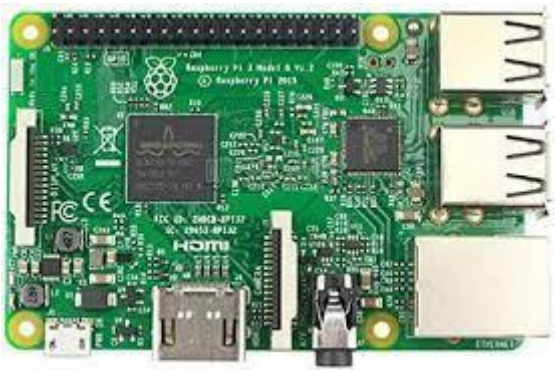


Figure 2: Raspberry Pi3 Model B

B. Pi Camera

Pi camera modules are programmed to look for drowning victims.

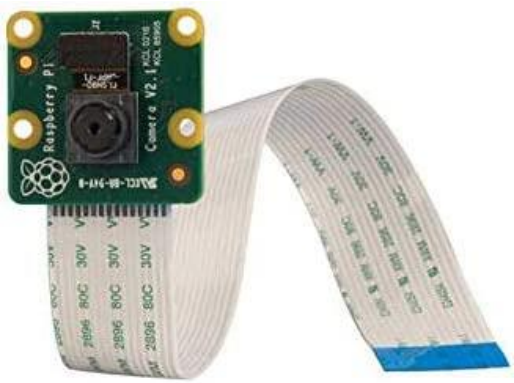


Figure 3: Pi Camera

C. MicroSD Card

Storing auto-generated incident reports with timestamps and screengrabs.

Figure 4: MicroSD card

III. EXPERIMENTAL EVALUATION

To evaluate our proposed framework, we used two videos which were obtained online. Both the videos have people walking in and out the frame. Then, we applied a pre-trained model – Efficient Net Lite0 on the video to detect the people inside the detection frame/zone (swimming pool) and, compared real and expected counter to find drowning incidents if any.

A. System Description

We used raspberry pi and a camera which was connected to the raspberry pi for our project. We used tensor flow lite library for using the efficient net lite0 model. Raspberry pi which we used had a 1 GB of RAM and quad core processor.

B. Data Collection Details and Data Summary

We used a pre-trained model, so we didn't have to collect any data for training the model. The pre-trained model was originally trained on the COCO 2017 dataset. Dataset

included images and videos. The pre-trained model can identify more than 160 different types of objects including full body detection.

C. Application Implementation and Results

We have implemented 3 different models: HAAR cascade, Convolutional Neural Network, and Efficient Net lite0

1. *Haar Cascade*

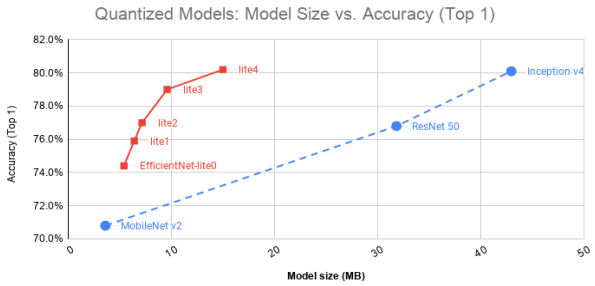
Initially, in our project, we implemented HAAR cascade on an image for the purpose of detecting people in swimming pool. HAAR cascade is a machine learning object detection tool used to discuss a variety of objects including a human being. In particular, we used full body detection from the object detection tool to detect a person. We had planned on implementing HAAR cascade on a video once we were successful with implementing on an image. But unfortunately, the results we got weren't the ones we were expecting. HAAR cascade had a very little accuracy from what we could see. As we implemented HAAR cascade on an image obtained from the internet and we didn't have any metadata, we couldn't find the exact accuracy of the model. So, then we decided to move on to Convolutional Neural Network.

2. *Convolutional Neural Network (CNN)*

Once we didn't get the expected results from HAAR cascade, we moved on to CNN. As a CNN is a complex neural structure having multiple hidden layers, initial expectations were to obtain a better accuracy than HAAR cascade. When we tried to implement CNN in Raspberry pi, the system crashed instantly. As a raspberry pi has a little RAM and a little storage, it could not handle the implementation of a big model such as CNN. So, we decided to move on to Efficient Net Lite0 for our project.

3. *Efficient Net lite0*

When we failed at implementing CNN model on raspberry pi, we decided to implement efficient net lite0 model for our project. Efficient Net lite0 is an object detection tool which is compressed version of a CNN and it is a much lighter model than a CNN. For the implementation of efficient net lite0 model, we first defined the source of the video. i.e., video saved on a local storage or an actual camera. We implemented it in such a way that while running the program, a runtime argument could be passed to change the source of the video. As we have defined a detection zone/frame which depicts a swimming pool boundary, we designed our project in such a way that if a user doesn't define any detection zone, it will automatically detect the detection zone, and if a user wants to define specific detection zone, the person could pass a runtime argument (-calibrate) which would ask user to press key 'q' or 'Q'. Once the user presses the key, it will capture the image at that particular moment in the video and user to click on 4 points to define a detection zone. Once the detection zone is defined, the system will automatically make a larger polygon and a smaller polygon around the detection zone. Those polygons are used to figure out people leaving and entering the detection zone (swimming pool). If a person is detected between the larger polygon and the detection zone, a person is entering the detection zone (swimming pool). And if a person is detected between the smaller polygon and the detection zone, a person is leaving the detection zone (swimming pool). When a person enters the detection zone (swimming pool), the expected counter is increased by 1 and if a person is leaving the detection zone (swimming pool), the expected counter is decreased by 1. And the real counter is number of people inside the detection zone (swimming pool) at that particular instance of time. Then we match expected count with real count to detect any drowning incidents. We were able to detect drowning incidents in real time with an average accuracy of 70%. As we didn't have any ground truths, the accuracy mentioned before is just an estimate from what we could see. We couldn't find any method to find the accuracy for the implemented method. However, efficient net lite0 model has around 74% accuracy for the COCO 2017 validation set as mentioned in Figure 5. The accuracy is an average for all the types of detections available in the model which includes the full body detection.



(Figure 5: Accuracy of different models)

IV. LIMITATIONS

Efficient Net lite0 model can detect up to a maximum of 25 people in the given detection frame. In real world, it is not necessary that every there will be 25 or less number of people in a swimming pool making the proposed system unreliable. Apart from this, the accuracy of the proposed model is around 70% which is not useful in the real world. Ideally, we need a system that has an accuracy of 100%. We cannot have a system that has 30% chances that drowning incidents could go unnoticed. Also, for our project, we had kept the maximum number of people detection in a frame to 10 because when we kept it at the default value (25), the frame per second(fps) was very low making the system useless in the real world. For maximum number of people detection equal to 10, the fps was at around 8. FPS as low as this doesn't work in the real world. The pre-trained model only detects a full body. And in a swimming pool, most of the time only face of a person is visible in the water. So, using full body detection in such an environment is not of much use.

V. Conclusion and Future Work

We were able to make a system which was able to detect drowning incidents using raspberry pi, a camera, and a pre-trained machine learning model (Efficient Net lite0). The proposed solution does not have a good accuracy making it difficult to use in the real world. A capable drowning detector needs a system with better processing capabilities, so that accurate real-time detection can be achieved. There is always a tradeoff between accuracy and real time detection. For the future work, a system could be made where instead of detecting only number of people in a swimming pool, each person could be identified uniquely along with the number of people in a swimming pool making the system more robust. Apart from this, instead of using full body detection, some other techniques could be deployed for identifying a person which only uses face or half body for recognizing a person.

References

[1]. International Research Journal of Engineering and Technology (IRJET) Volume: 08 Issue: 07 | July 2021

[2]An automatic drowning detection surveillance system for challenging outdoor pool environments How-Lung Eng, Kar-Ann Toh, Alvin H. Kam, Junxian Wang and Wei-Yun Yau Institute for Infocomm Research 21 Heng Mui Keng Terrace, Singapore hleng@i2r.a-star.edu.sg

[3].An Automatic Video-based Drowning Detection System for Swimming Pools Using Active Contours I.J. Image, Graphics and Signal Processing, 2016, 8, 1-8 Published Online August 2016 in MECS (http://www.mecspress.org/)DOI: 10.5815/ijigsp.2016.08.01

[4].A Novel Camera-Based Drowning Detection Algorithm Chi Zhang (Xiaoguang Li, and Fei Lei College of Electronic Information and Control Engineering, Beijing University of Technology, Beijing, China 120212zc@emails.bjut.edu.cn

[5].DESIGN OF A DROWNING RESCUE ALERT SYSTEM International Journal of Mechanical Engineering and Technology (IJMET) Volume 10, Issue 01, January 2019, pp. 1987-1995, Article ID: IJMET_10_01_194 Available online at http://www.iaeme.com/ijmet/issues.asp?JType=IJMET&VT ype=10&IType=01 ISSN Print: 0976-6340 and ISSN Online: 0976-6359

[6].METHODS AND SYSTEMS FOR DROWNING DETECTION International Publication Number (43) International Publication Date 3 August 2017 (03.08.2017)WO 2017/130187 Al

[7]. Detection of swimmer using dense optical flow motion map and intensity information Author :K. L. Chan

[8]. Thermal Imaging based off-time swimming pool surveillance System Author:Wai Kit Wong,Joe How Hui,Chu Kiong Luu,Way soong lim

[9]. Methods and Systems for Drowning Detection Author: World Intellectual Property Organization International Bureau