Flame Perception APP：

Enabling Fire Engineers and Researchers to Understand and Analyze Flame Data

By

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Abstract

Existing research on flame detection mainly focuses on the improvement of algorithms, from traditional image processing methods to the combination of image processing and machine learning methods. However, people from fire engineering field who analyze fire information in their daily work have limited access to these algorithmic improvements, meaning they can not readily apply emerging novel techniques to practical work.

In this project, we aim to bridge this gap by exploring and applying the recent computer vision and deep learning techniques along with interface design to help fire engineers and researchers access and analyze flame data without previous knowledge in computer science. To achieve this aim, we participate in weekly lab meetings in the fire protection department in Worcester Polytechnic Institute to observe their fire research behavior and understand user needs. We conduct experiments in both traditional computer vision methods and a combination of computer vision and deep learning models to find the appropriate techniques that satisfy user needs from fire experts. We then build a software pipeline integrated with those algorithms to help fire experts calculate, visualize, and analyze flame data, deploying this application on the cloud. Finally, we evaluate the application by inviting both fire researchers and students from other majors to test the application in a semi-structured user study. The results of the evaluation suggest that the web application prototype is a useful tool for understanding flame data, but also the software pipeline has room for improvement. We discuss implications of the feedback gathered during our testing process and propose how we could improve the application in future work.

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Acknowledgments

I would like to thank Prof. Lane Harrison for this guidance, patience, enlightenment, and encouragement. I would like to thank Prof. Ali S. Rangwala, Hamed Farahani from Fire Protection Department for their support and communication during the user study, prototype design, application development, and user testing process.

Their mentorship helps us always follow our schedule and make everything goes right.

Since my major is Interactive Media and Game Development, I have very few previous knowledge in fire protection engineering. During 2019 summer, with the invitation from Prof. Ali, I visited the Combustion Lab of the Fire Protection Department two times a week and participated in their weekly group meeting. Engaged in the research activities in the lab, I got to understand their research behavior and what they need for the application.

I would like to thank everyone who took part in the user study. With your feedback, I continued polishing the application to provide better user experiences, and finally, we made it. The user study is significant for our project, and you all contributed your efforts. It cannot be successful without your help.

I would like to thank my parents from the bottom of our hearts. They supported us spiritually throughout our life.

Chapter 1 Introduction

Fire is one of the most common natural hazards, and detection at an early stage of fire is extremely important to minimize loss of lives and property damage.

According to the Annual Disaster Statistical Review [1], across the world, in the year 2015, wildfire disasters caused 494,000 victims with damage worth USD 3.1 billion, and the devastating wildfires continued from 2017 into 2018 (Figure 1-1). In 2018, the Attica Fires in Greece becomes the deadliest wildfire in Europe in this century and has killed nearly 126 people. In the United States, the California Camp Fire killed 88 people and caused damage worth nearly 16.5 billion USD.

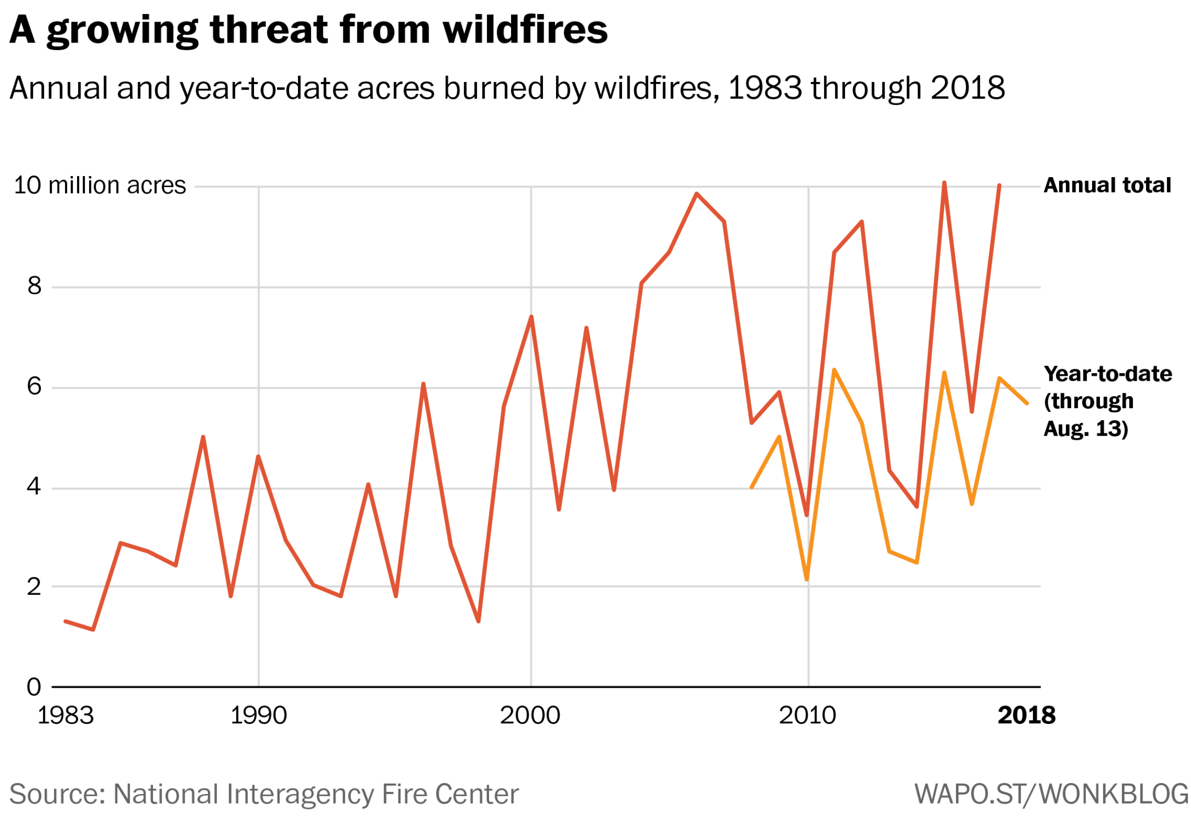


Figure 1-1 Annual and year-to-date acres burned by wildfires, 1983 through 2018.

Fire engineering applies science and engineering principles to protect people, property, and the environment from harmful fire hazards. Fire protection district is widely distributed across the world and provides firefighting, fire protection, fire investigation, and technical rescue services [2].

In addition to fire protection departments in the industry, some universities also have fire engineering majors and laboratories. Worcester Polytechnic Institute's fire engineering department promotes fire research, developing practical solutions through an extensive fire laboratory programs.

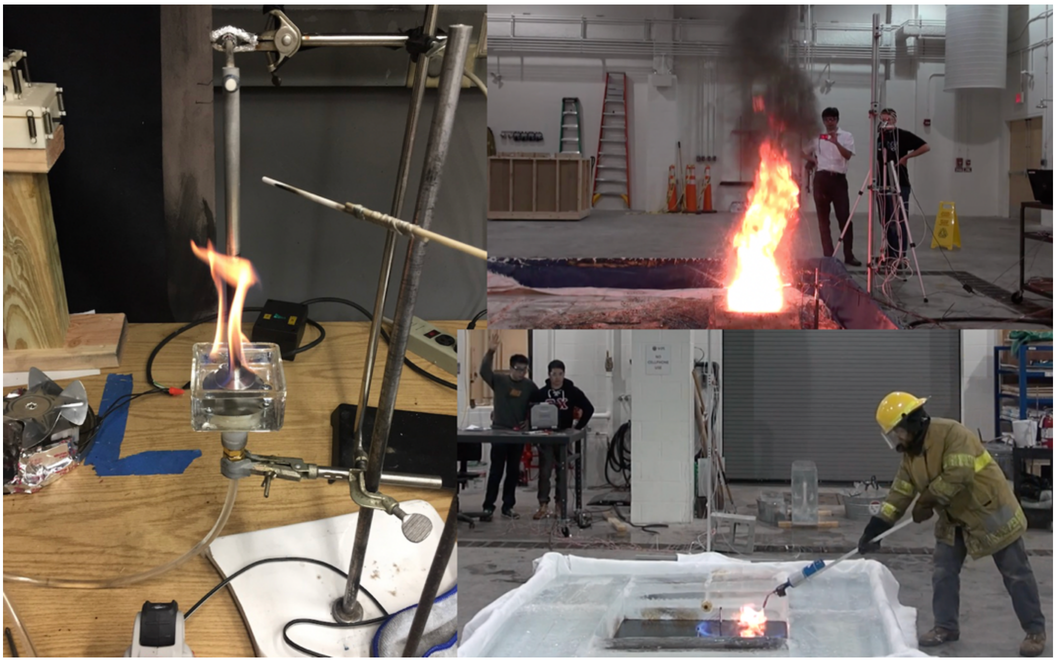


Figure 1-2 How fire researchers in the Combustion Lab in WPI conducted in lab studies of fire.

This project is a cooperative work with the Combustion Lab of the Fire Protection Department in Worcester Polytechnic Institute. The Combustion Lab conducts research which enables fire safety professionals to predict fire hazards through developing novel techniques to measure fire-induced flows and help fire protection engineers understand complex fire problem[3] (Figure 1-2).

In recent years, the convolutional neural network (CNN) in deep learning has become a widely adopted technique because of its high accuracy recognition rate in industry applications.

There are some researchers from computer science field exploring flame detection using deep learning in both flame images [4] and video sequence [5]. Researchers who write these papers are trying to explore flame detection with reliable and effective techniques to help solve problems in practice.

Although the academic exploration of fire detection indeed improves algorithm performance, those most advanced techniques have rarely been reached by researchers and engineers in Fire Protection field to put into practice. This project aims to bridge the gap between those techniques and real user needs of fire protection experts and help people access flame data without previous knowledge in computer science or programming.

We first conducted behavior observation and user study with fire researchers in the Combustion Lab at WPI. We defined the functions of our application based on their research behavior. Then we experimented with current techniques to help satisfy user needs from fire experts. We conducted experiments in both traditional computer vision methods and a combination of computer vision and deep learning models. Specifically, we implemented image segmentation and image enhancement methods to extract flame shape. We also experimented with Convolutional Neural Network to detect flame motion.

As for the software pipeline, we consulted with experts in the Combustion Lab on building a web application to implement the flame detection algorithms. To better assist the fire experts to analyze flame data, we utilized flask [6] as a backend framework and the D3.js [7] library to help visualize the flame data on the front end. The user could upload the fire video on a phone or a laptop via the website link, and the back end host on the cloud will process the video with the flame detection algorithms. The extracted flame data will then be sent back to the front end and displayed as visualization.

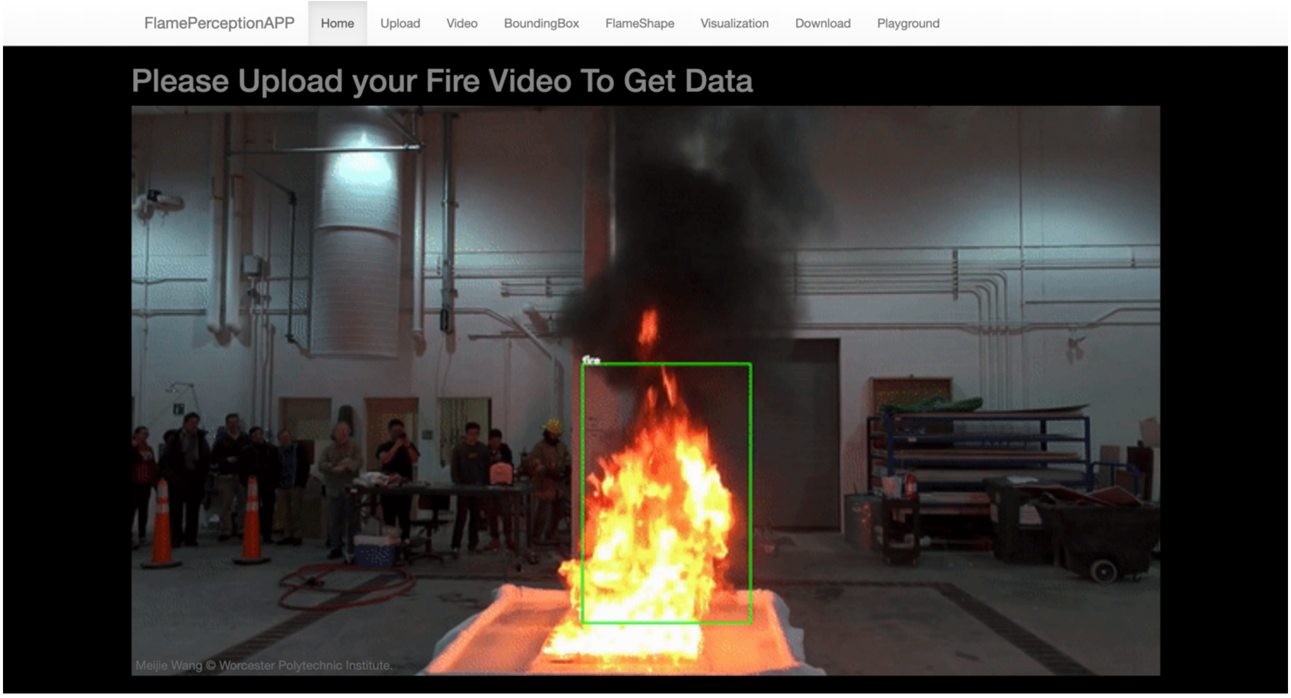


Figure 1-3 Homepage interface of the application.

The application (Figure 1-3) is the first attempt to apply the most recent computer vision and deep learning techniques for flame detection into user needs from the fire protection engineering field. We deployed the Flame Perception Application on cloud and invited both fire experts and students from other majors to test the application. We designed a survey and evaluated the system prototype based on testing feedback. The web application turned out to be a useful tool to help both fire experts and non-professionals to understand flame data. However, there's still some work to improve around the software pipeline to bring a better user experience.

Chapter 2 Related Work

Our work is inspired by previous work focused on fire detection algorithms and applications. We first collected previous works of exploration in fire detection algorithms.

2.1 Computer Vision Enabled Fire Detection

The features of fire play an important role in the development of fire detection systems. Visual features like color-based model, shape-based model, motion-based model, fuzzy-based model could be used for flame detection. Among them, color-based model alone performs well [8]. The color usually ranges from red to yelloe and may turn white when the temperature is very hgh.

Multiple feature models have been applied to increase the accuracy of fire detection because the size, area, shape, and number of fire regions in an image vary from frame to frame, sometimes making the surfaces of fire region too rough for detection. A method was proposed in 2012 using multi-stage pattern recognition techniques [9]. The proposed algorithm consists of four stages, first moving region detection using an adaptive mixture Gaussian model, and then fire color segmentation using FCM clustering. After that, parameter extraction is used from the tempo-spatial characteristics of fire regions, and support vector machines are used for fire identification. This multi-stage technique inspired our later work to detect different fire features.

2.2 Machine Learning Optimized Fire Detection

2.2.1 Shallow Learning and Deep Learning

Shallow learning and deep learning are both methods to detect flame from images. Deep learning has been used in object detection, recognition, and tracking [11] and turned out to be an efficient way to resolve visual problems [12]. In a paper published in 2018, researchers experimented with the YOLO model for flame detection. They concluded that compared with shallow learning, the performance of deep learning is not affected by using flame colors or not when training with a large dataset [4].

2.2.2 Computer Vision and Deep Learning

In a previous paper using motion and color features to detect video fire smoke, one method is put forward which not only uses color model or motion model but also analyzes temporal variations of flames intensity [13]. The novel method used color features and back-propagation neural network to classify the features of smoking. Motion features by using optical flow are adopted in this method. Support vector machine (SVM) can classify fire pixels in an image, which makes the output of this classification more robust against noise.

A color fire feature detection and recognition scheme based on convolutional neural network method was proposed in 2018 [14]. In this method, an RGB-based model is first used to extract the color feature of fire image and obtain the candidate area. The neural network classifies the normalized feature maps after that. Finally, the fire signal is obtained by the classification result of CNN and evaluate the performance of the proposed neural network. This algorithm is shown to achieve superior performance in improving the fire color feature recognition based on RGB model accuracy.

2.3 Fire Detection Applications

Although there has been some research working on fire detection algorithms with different techniques, there’s not too much work about the application with these advanced fire detection algorithms. A few researchers explore early flame detection in surveillance videos using deep CNN. The application system is put forward because sending all the streaming data of multiple cameras during surveillance is impractical due to network constraints. The deep learning-enabled fire detection disaster management system creates an autonomous and reliable communication medium for transmission an alert of fire. In the paper of CNNs based fire detection in surveillance videos, a cost-effective fire detection CNN architecture for surveillance videos is proposed [10]. The model is inspired by GoogleNet architecture and is fine-tuned with a special focus on computational complexity and detection accuracy. The proposed architecture dominates the visual features based fire detection methods and the AlexNet architecture based fire detection methods. The number of false alarms is still high and further research is required in this direction to put CNN based fire detection disaster management system into practice.

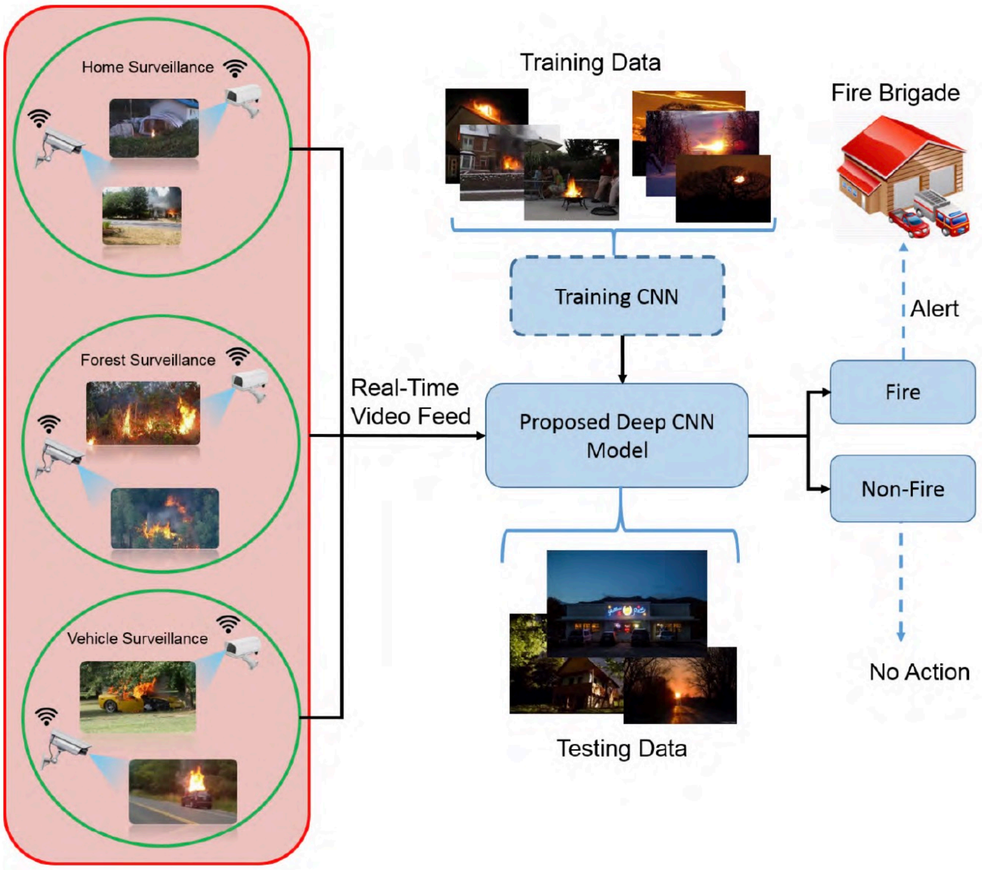


Figure 2-1 Early flame detection in surveillance videos using deep CNN.

Souce: K. Muhammad et al.: CNNs Based Fire Detection in Surveillance Videos[10].

Chapter 3 User Study

3.1 Overview

In order to understand the research methods and processes of fire engineers, and to mine user needs, we established multiple visits with the Combustion lab of Fire Protection Department in Worcester Polytechnic Institute. In the summer of 2019, we participated in the weekly meeting of the Combustion Lab and listened to the presentations made by the lab researchers.

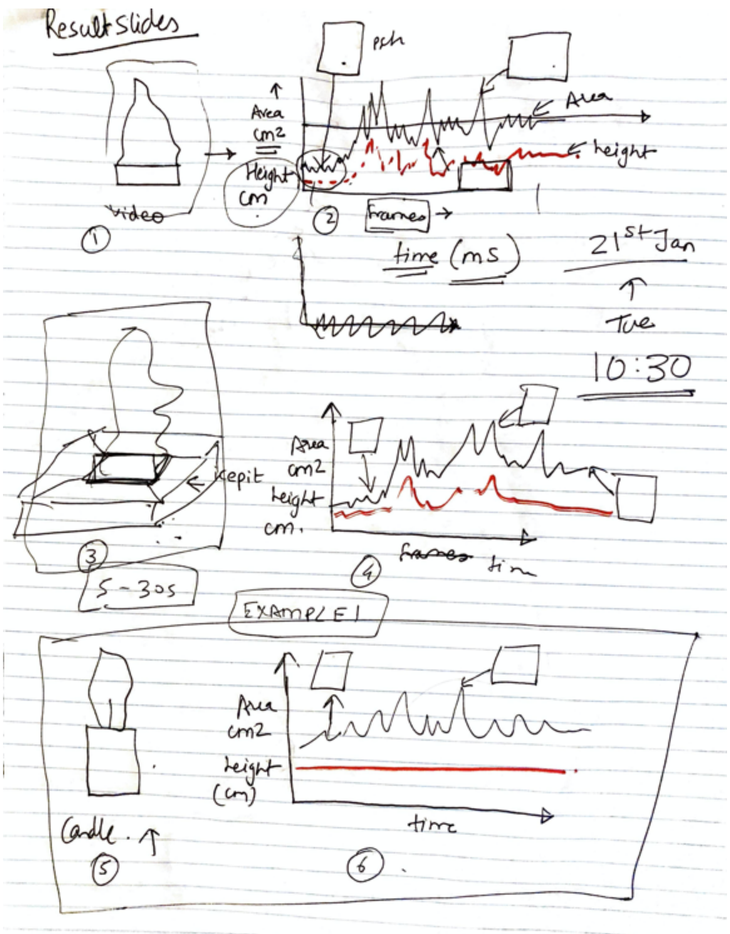


Figure 3-1 Discussion draft about visualization of flame data with reserachers from fire protection department. We agreed to build line charts for different types of fire, with time frame as x-axis, flame area(cm^2), flame height(cm) as y-axis.

3.2 Application Task Analysis

3.2.1 User Group

There were a total of 10 researchers in the combustion lab in the summer. Their research topics were quite different, some were to study the airflow with flame, some focused on studying the bubbles, some were to study the factors affecting the flame propagation rate, and some focused on the relationship between the flame and the air. The types of flames they studied were also very different, from explosive flames as large as a dozen meters high to small candle flames. But these studies will help them better understand flames and apply flame control research results to fire protection practice.

3.2.2 Identify Users' Research Method

Although their research directions and types of flames are diverse, a common method they all use is to control and simulate different types of flame environments in-lab study and record flame videos with cameras. The Fire researchers observe their recorded flame videos, compare the effects, and draw experimental conclusions based on video data analysis.

We found that the method fire researchers used to analyze flame video is very manual, mainly by observing and comparing video images and using Matlab for image processing. Through interviews and communications, we found that fire researchers do not make full use of the principles and functions of these Matlab codes, nor do they process and analyze the data after image processing.

The interview showed that the advanced flame detection algorithms proposed in the field of computer vision are not fully used by fire engineers and researchers who need flame detection and flame data acquisition in practice.

3.2.3 Identify Users' Target

In order to better help fire researchers obtain flame information in research experiments, we went through and summarized their fire research presentations. We found that they paid particular attention to the height of the flame, the shape of the flame, the area of the flame, and the frequency of the flame. These factors are important features that they always used in fire experiments in different research topics and experiment environments.

3.2.4 Identify Data Visualization Form

As fire researchers are also not familiar with data representation forms, to better help flame researchers understand flame data, we also discussed with them about the visual form of flame data. We tested with line chart, bar chart and pie chart draft to visualize the flame information, and line chart turned out to be a more convincing visual chart for fire researchers (Figure 3-1). The line charts visualization system will be addressed in the design and development of the application to help fire researchers understand flame data more intuitively.

3.3 Summarization

In the summer of 2019, we participated in a weekly lab meeting in the combustion lab at WPI, listened to their presentations, and visited their lab studies. Through the engaged research activities with fire researchers from the fire protection department at WPI, we identified users' research methods, discovered fire experts' concerns when conducting in-lab studies, and figured out better ways to communicate fire information.

These user studies helped us set up clear application tasks when building the application and find appropriate techniques to build the software pipeline. The user testing result showed that our user study process lays a good foundation for the success of the application.

Chapter 4 Flame Perception Methods Experiments

Based on our previous user study, the main function of the application is to detect the height of the flame, the shape of the flame, the area of the flame, and the frequency of the flame of frames in fire video. According to our previous search of related works, visual features like the color-based model, shape-based model, motion-based model, fuzzy-based model are generally used for flame detection. Our this section of work focused on experiments of different flame detection algorithms to target fire researchers' real needs and pick up the algorithms with the best performance for the detection of different fire features.

4.1 Computer Vision

Our first implementation is to use computer vision library. OpenCV[15] is the leading open-source library for computer vision, image processing, and machine learning. OpenCV is being used for a very wide range of applications which include: street view image stitching, automated inspection and surveillance, robot and driver-less car navigation and control, medical image analysis, video/image search and retrieval, movies - 3D structure from motion, Interactive art installations. Here we tried both Image Segmentation technique and Image Enhancement technique and did a comparison of the results.

4.1.1 Image Segmentation

First, we used Image Segmentation with Distance Transform and Watershed Algorithm in OpenCV to segment flame shape in frames. In this algorithm, we use the OpenCV function cv::filter2D to perform some laplacian filtering for image sharpening, the OpenCV function cv::distanceTransform to obtain the derived representation of a binary image, where the value of each pixel is replaced by its distance to the nearest background pixel, and the OpenCV function cv::watershed to isolate objects in the image from the background (see Figure 4-2). As we can see from the comparison figures, the flame shape is nearly accurately segmented from background objects. However, due to the reflected light, it's hard to segment the flame shape from the desk with this segmentation algorithm.

Figure 4-1 Original flame image (comparison with Figure 4-2 and Figure 4-3).

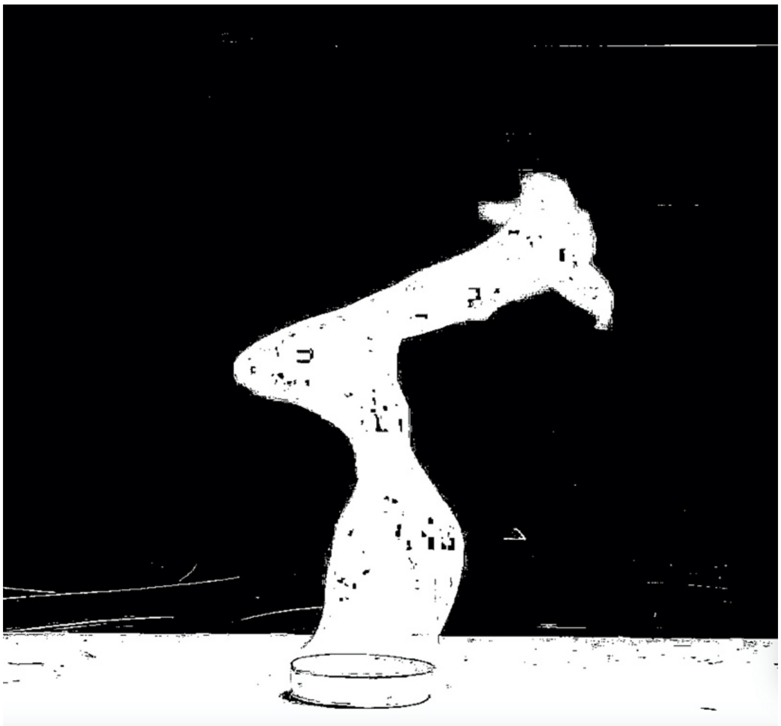


Figure 4-2 Effects of image segmentation with distance transform and watershed algorithm based on Figure 4-1.

Figure 4-3 Effects of iimage enhancement alrorithm based on Figure 4-1.

4.1.2 Image Enhancement

Then we tried basic image enhancement using basic operator for brightness, contrast, and grayscale. The objective of image enhancement is to restore the image that is distorted during the transmission from one form to another form. The whole techniques centered upon the detailed formations and characteristics norms of image and according to the desire of applications and tools, the algorithm can be changed at any stage of the process. Adaption of all the algorithms in the image enhancement is easy. But with all the key features of the flame image, we need to care that flame features with lightness, brightness, and the color is hard to be simultaneously incorporated into the algorithm (see Figure 4-3).

4.2 Motion Detection

Deepgaze [16] is a library for human-computer interaction, people detection and tracking which uses Convolutional Neural Networks (CNNs).

Deepgaze is based on OpenCV and Tensorflow, some of the popular libraries in computer vision and machine learning. We tried Deepgaze library and implemented Color detection using the histogram back projection algorithm and compared it with our previous computer vision implementations of image segmentation and image enhancement algorithms. Because the flame feature is combined with lightness, brightness, and the color of flame, color detection implementation here is far less effective than our previous computer vision method. Then we tested Motion detection and tracking using frame differencing on a video streaming. This algorithm is effective in tracking flame motion.

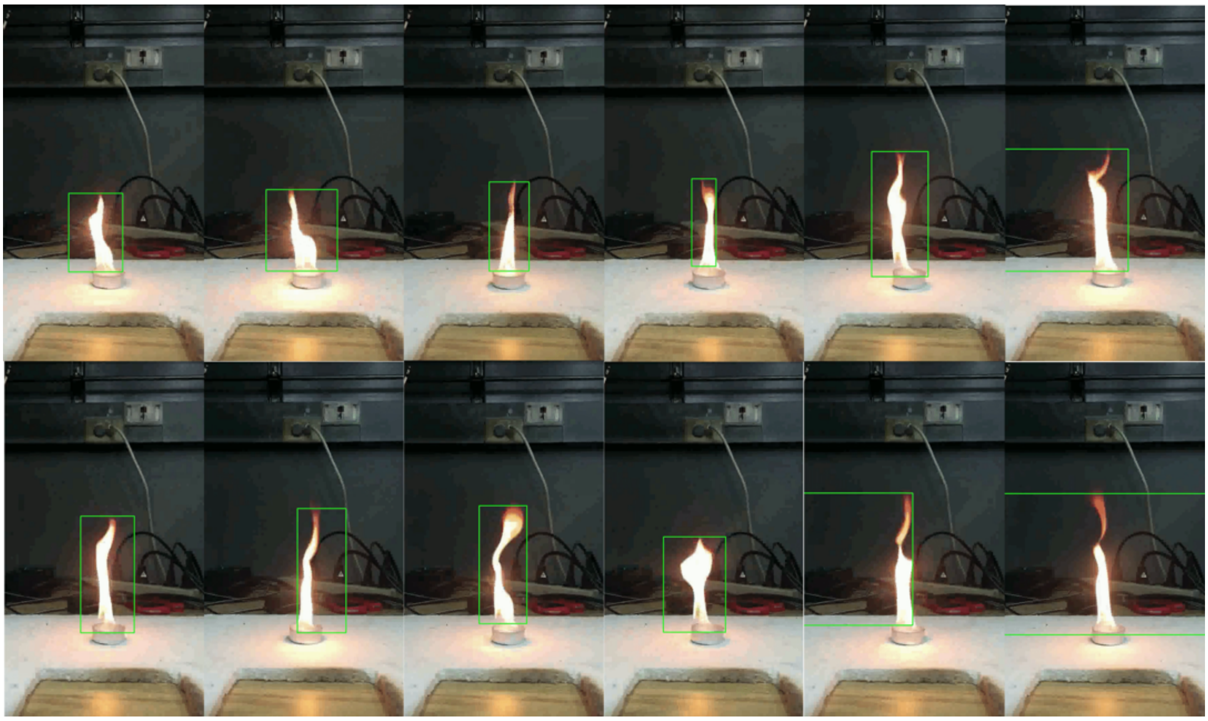


Figure 4-4 Flame motion detection with Deepgaze library performs well to detect flame hight.

However, this algorithm could only detect flame height and the frequency of the flame's motion, the important flame area data could not be calculated with this algorithm and flame height information is not accurate because of possible scene object motion disturbance (see

Figure 4-4). Thus we decided to establish our flame dataset and train deep learning model for flame detection.

4.3 Mask RCNN

In deep learning areas, YOLO [17] and RCNN are generally used models for object detection. In this project, We tested a model called Mask R-CNN which could efficiently detect objects in an image while simultaneously generating a high-quality segmentation mask for each instance. The method extends Faster R-CNN by adding a branch for predicting an object mask in parallel with the existing branch for bounding box recognition. In this project, we tried to use the MaskRCNN model as the deep Neural Network to train a flame detection model (see Figure 4-5) , so we could output flame area with mask, flame height with bounding box.

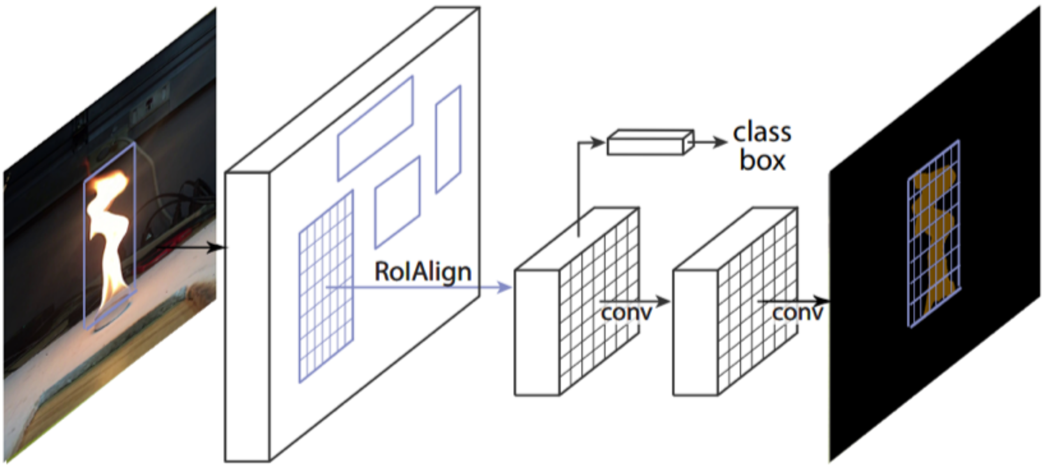


Figure 4-5 Implementation of Mask RCNN framework for instance segmentation on flame image.

4.3.1 Flame Dataset

To build the dataset for training the model, we extracted 1000 images(per image every 5 frames) from a previously recorded in lab study fire video. We labeled the images with PixelAnnotationTool (https://github.com/abreheret/PixelAnnotationTool). We devided the labelled images into two parts: 900 images as training dataset and 100 images as test dataset (see Figure 4-6 and Figure 4-7). We used Tensorflow API to convert the image data to Tensorflow record format for training.

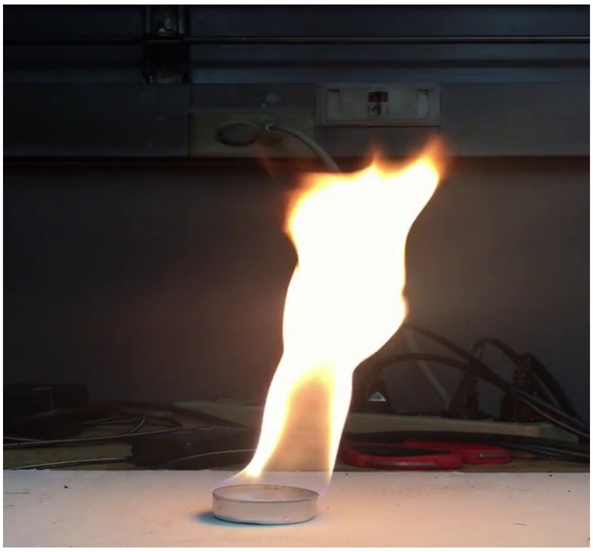


Figure 4-6 Original flame image extracted from the fire video for building the dataset and training.

Figure 4-7 Labeled flame image created by the Pixel Annotation Tool as training dataset.

4.3.2 Prediction Result

Mask R-CNN is a fairly large model. Especially that our implementation uses ResNet101 and FPN. Our first training ran 2000 steps at a rate of 2.396 sec/step, and the lost arrived at 0.0004. Then we tried more steps which is nearly 20000 steps, at a rate of 4.049 sec/step, and the loss arrived 0.0000. But our testing dataset proved that this training caused model overfitting (see Figure 4-8). After that, we put forward many methods to improve the model, like

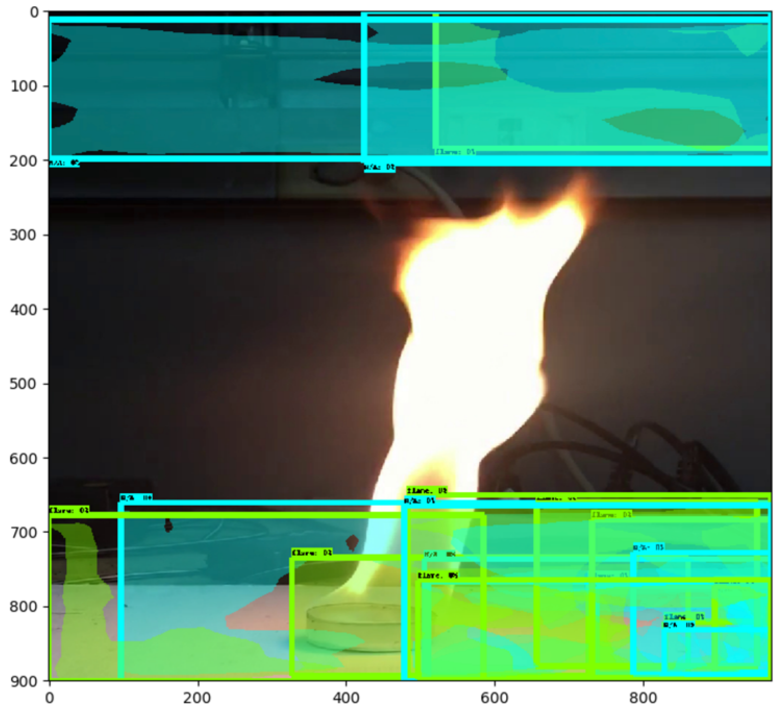


Figure 4-8 Generated flame mask after first round of training.

enlarging the dataset, pre-processing the images before training and so on. We tried the possible methods we could do but the performance is always not good. We consulted deep learning experts about the model performance, then we came to the conclusion that flame shape changed too fast and is very hard to predict well without a very huge dataset for training. Considering our limited labor and the uncertain result produced by this method, we decided to switch back to our previous computer vision method of image segmentation and image enhancement algorithms.

4.4 Infrastructure

Since the purpose of this project is to design and develop software for fire engineers and researchers and help them easily get access to flame data, the design of the application and infrastructure will be based on our previous application tasks analysis during user study. As for the infrastructure of the software, we need to decide about building a web application or mobile application. With a mobile application, the fire researchers could easily record the in lab fire experiments on the phone and get the flame data output. However, considering that in most cases, researchers in Fire Protection Department use professional cameras like Canon instead of phones to record fire videos, we finally decide to build a web application. With web applications, researchers could upload the video they recorded whether by phone camera or by a professional camera. The application will be designed to be responsive on both computer and mobile, in this way, users could simply open the website on mobile phone and upload the video to get immediate in lab study result, or they could access the website via computer and upload fire videos recorded with a professional camera.

4.4.1 Software System

To satisfy the application tasks we defined during previous user study, we proposed the software system as Figure 4-9 indicates. First, there will be pre-trained models of flame data put in the back end. According to our previous flame detection algorithms experiments, we need to implement different algorithms to detect different aspects of flame features to ensure accuracy. Those flame detection algorithms and models will be incorporated into the flask framework as the back end system. The user records the fire video and uploads it whether on phone or on laptop via the website, the back end will store the uploaded video and the flame detection model and algorithms will be called to process the flame video data, output prediction result and give the data back to the front end, the front end user interface will give the data file for downloading and also visualize the data for analyzing.

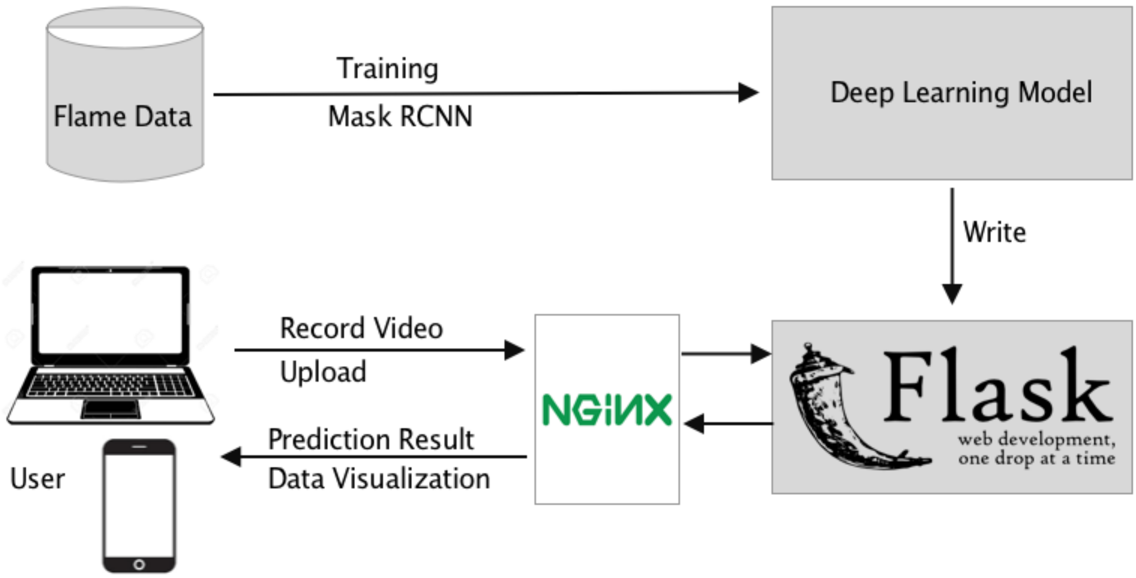


Figure 4-9 Diagram of the software system model.

4.4.2 Application Framework

We chose Flask [6] as a back end framework to build the application. Flask is a micro web framework written in Python. It is classified as a micro framework because it does not require particular tools or libraries. It has no database abstraction layer, form validation, or any other components where pre-existing third-party libraries provide common functions. However, Flask supports extensions that can add application features as if they were implemented in Flask itself. Extensions exist for object-relational mappers, form validation, upload handling, various open authentication technologies and several common framework related tools. Flask is very flexible and lightweight, great for smaller projects and would be a perfect choice for building this type of light application. The front end of the web application would mainly consisted of two parts. One part is the uploading page where the user uploads the fire video. The other part is the data output page, where the user could download the processed flame data of the video and interact with the data visualization.

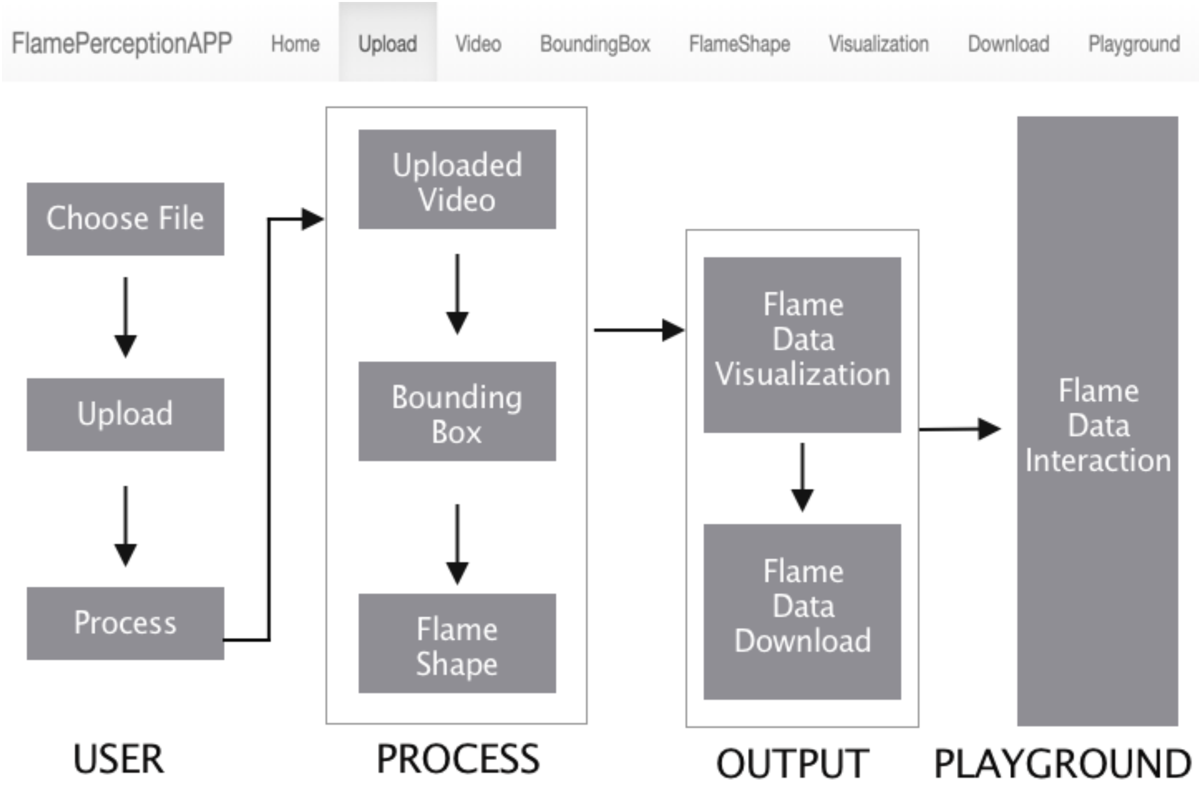


Figure 4-10 Diagram of User flow and interaction model with the system.

4.4.3 User Flow

The user interface of the web application will consist of four parts (see Figure 4-10). The first part is upload page where users choose their own fire video and click upload to process. The second part is for processing, to give users a direct understanding of what and how their fire video is processed by the application system, they could switch to Video section to watch the video they uploaded, and they could also switch to BoungdingBox or FlameShape session to watch the processing image with bounding box or enhanced flame shape parsed by the system back end. To directly get access to the processed data, the user could use the Download section or the Visualization section to explore the interactive flame data in the third part of the app. And we also add a PLAYGROUND section with pre-processed fire videos and interactive flame data to help people understand different flame patterns.

4.4.4 Visualization

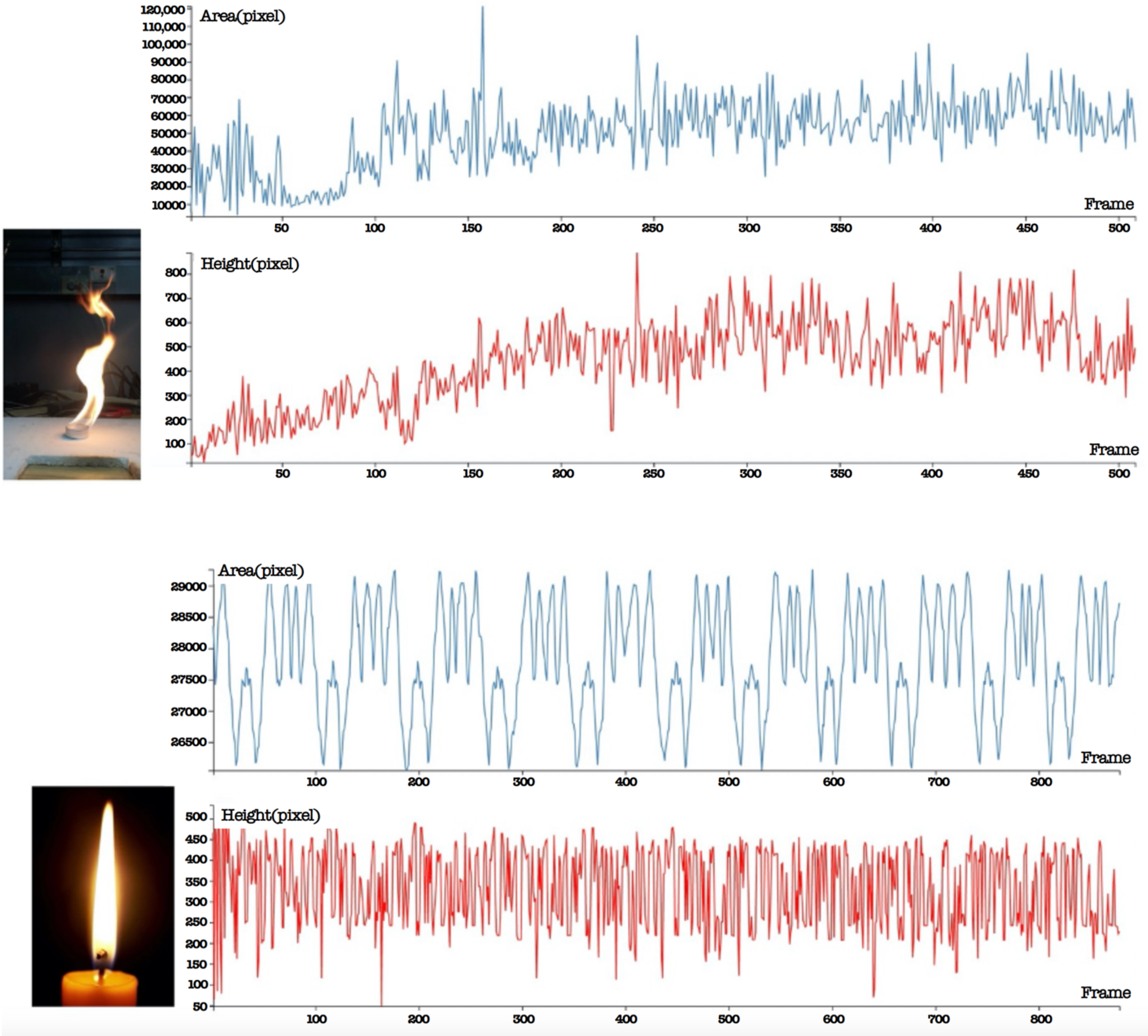


Figure 4-11 Visualization of flame data pattern of different types of flames. Comparing the two figures of different types of flame data visualization, we could conclude that candle flame is more periodic in both flame height and flame area. Comparing the flame height and flame area charts, we could see that the changing trend of flame height is related to changing trend of flame shape.

Since this is a web application, there is a need for us to satisfy the application tasks we defined during previous user study and build data visualization on the web front end to help users understand data festures. So we used D3.js [7] library on the front end. D3.js is a JavaScript library for producing dynamic, interactive data visualizations in web browsers. It makes use of Scalable Vector Graphics (SVG), HTML5, and Cascading Style Sheets (CSS) standards. As we've talked about visualization form of the flame data in our previous user study, line chart with time sequence as x-axis and flame height/ flame area value as y-axis is a suitable chart type to visualize the data (see Figure 4-11).

4.4.5 Playground

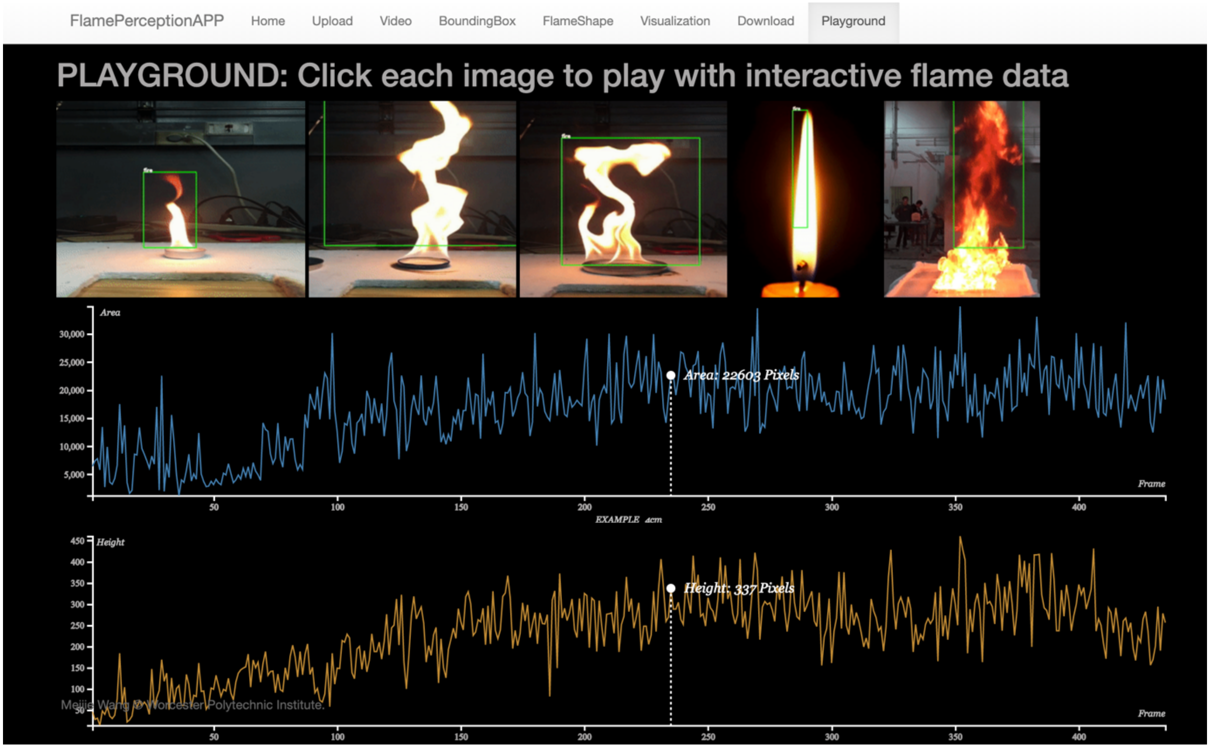


Figure 4-12 PLAYGROUND section of the web application.

PLAYGROUND section is added during our application development process (see Figure 4-12).

At first, some of our internal testers complained that they didn't have enough fire videos in hand but they want to see if the visualization pattern really make difference for different fire video. To solve this question, we pre-processed some fire videos by our system and visualized the flame pattern. Users could click each fire image to access the visualization patterns, and after they compare different flame patterns, they will directly understand different types of flame. This will also give people from fields other than fire engineering a general sense about flame data patterns.

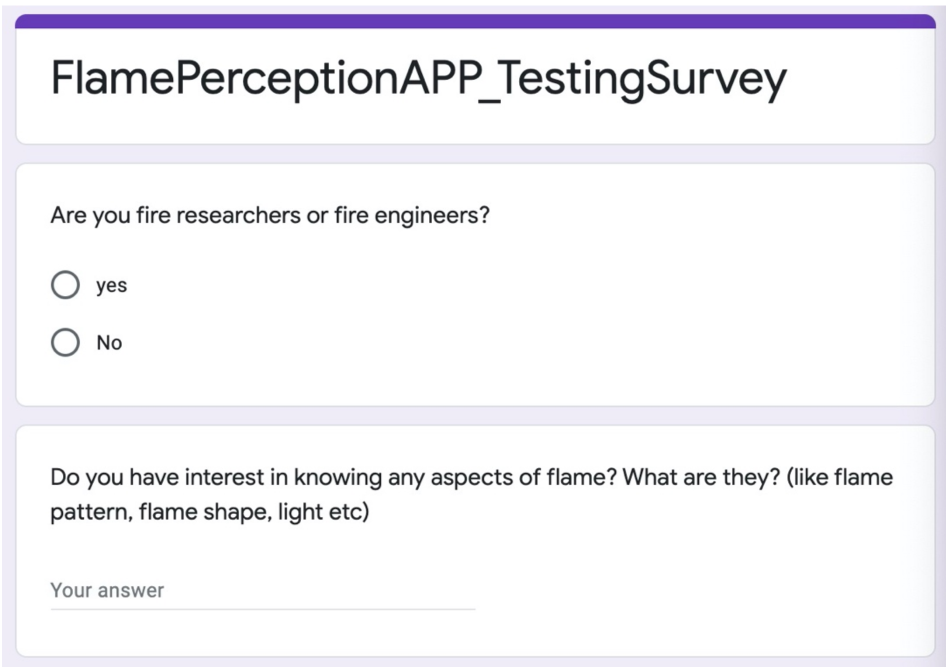
Chapter 5 User Testing And Evaluation

After we deployed the app to the cloud, we invited some people to test the Flame Perception APP. In our app testing round, we not only invited fire engineers to test but also invited people from fields other than fire engineering to participate in the test.

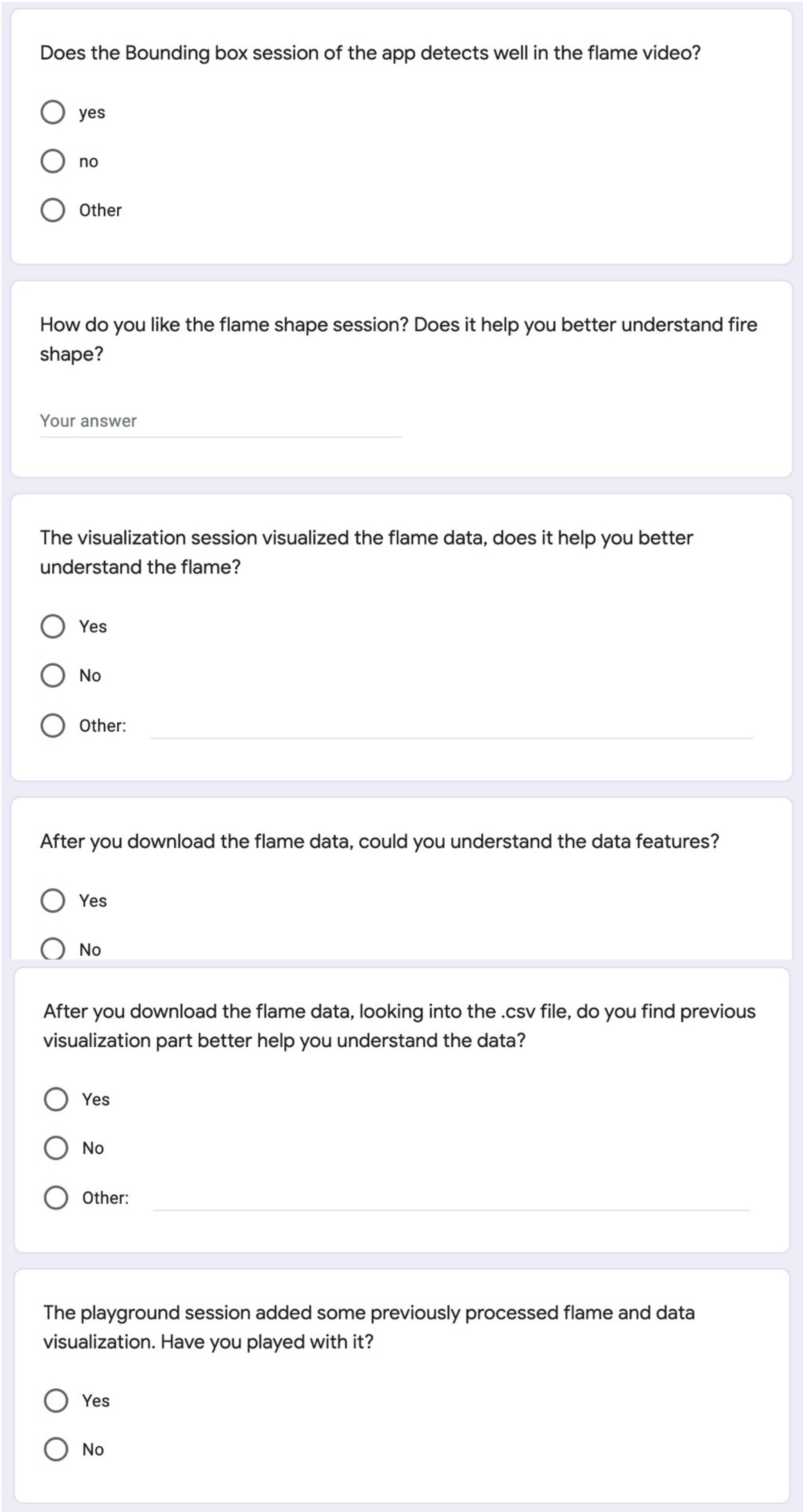
The entire test session is divided into two parts, first is to use this web app for flame detection, and then to complete the user experience questionnaire. We designed a survey to help us understand users' feedback after testing. At the time we write this paper, we in total gathered 10 testing results, among which 5 are from fire engineers or researchers, 5 are from data science students.

5.1 Survey Design

In the design of the questionnaire, in order to keep testers engaged, we limited the number of questions to 11 (see Figure 5-1). The questionnaire is divided into three parts. The first part is the collection of the background status of the testers, whether they are related to the fire engineer, and what specific questions are interested in fire. The second part is about whether the fire bounding box, fire shape segmentation, fire data download, fire data visualization, and playground functions provided by the app are fully used and understood by



users, and can meet the research needs of professionals. The third part is a general understanding of whether this app helps users better understand flames and collect more


Does the Bounding box session of the app detects well in the flame video?

- yes
- no
- Other

How do you like the flame shape session? Does it help you better understand fire shape?

Your answer

The visualization session visualized the flame data, does it help you better understand the flame?

- Yes
- No
- Other:

After you download the flame data, could you understand the data features?

- Yes
- No

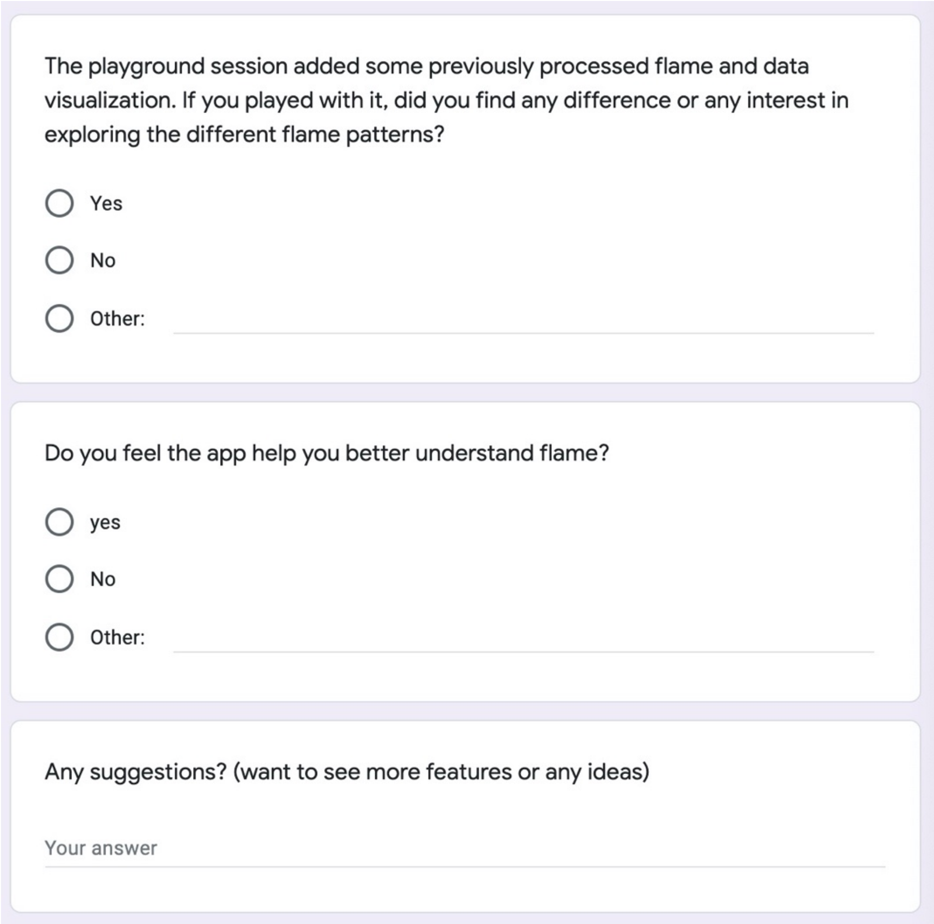
After you download the flame data, looking into the .csv file, do you find previous visualization part better help you understand the data?

- Yes
- No
- Other:

The playground session added some previously processed flame and data visualization. Have you played with it?

- Yes
- No

suggestions from users.


The playground session added some previously processed flame and data visualization. If you played with it, did you find any difference or any interest in exploring the different flame patterns?

Yes

No

Other:

Do you feel the app help you better understand flame?

yes

No

Other:

Any suggestions? (want to see more features or any ideas)

Your answer

Figure 5-1 Questionare:

https://docs.google.com/forms/d/e/1FAIpQLSecOBEYeZ42Gbufo7Ti0X33x0gg2H5GnZHyIKEFhBcl9IvikQ/viewform?usp=sf_link

5.2 Testing Result

We finally tested the application with 5 fire related professionals and 5 non-related professionals, a total of 10 people (see Figure 5-2). In addition to the flame area, height, frequency that we already calculated in the software system, some users are interested in flame pulsation frequency, flame angle and temperature.

80% of the testers believed that the bounding box part had a relatively correct detection of the flame video they uploaded. All testers said that the flame shape session helped them understand the flame shape, but some testers said that due to the processing speed of the system, the fire shape appeared very slowly and was slightly inaccurate. 77.8% of testers indicated that

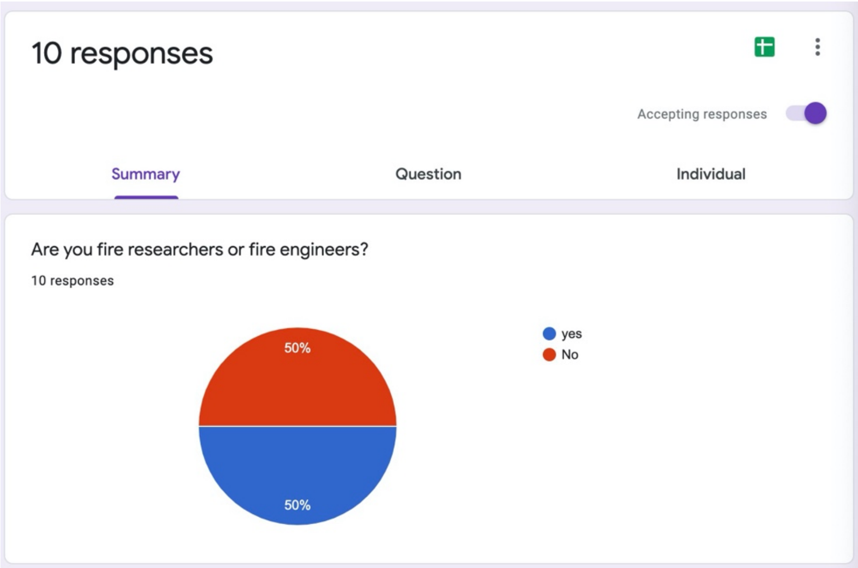


Figure 5-2 Are you fire researchers or fire engineers?

Figure 5-3 Do you have interest in knowing any aspects of flame? What are they? (like flame pattern, flame shape, light etc)

visualization of flame data helped them better understand the characteristics of flame data, but 11.1% of testers indicated that the system did not show visualization during the test. This will happen when testers move too quick to see the visualization component but it should take sometime for the backend system to process the data and send back to front end for visualoization. 50% of the testers said that after downloading the flame data, they did not understand the characteristics of the data. All the testers have tried the PLAYGROUND session, and 90% of the testers said that this part of the content helped them discover and understand the differences in the data patterns of different types of flames. In the end 80% of the testers said that using this app helped them understand flame data more conveniently, but 20% still suggested that this app is still not user friendly enough for people who do not have data expertise.

During this round of testing, we received some very valuable suggestions. Some fire professionals think that the flame recognition algorithm needs to be improved. As fire experts, they put forward that low contrast, high soot generation sometimes happened during their reserach. We need to figure out some methods to reduce smoke interference to flame area identification. And they think that specific phenomena like puffing flame, needs to be carefully treated. These requirements from fire reserachers are very specific, we will try to improve flame detection algorithms considering these special situations in our future work, but computer vision method has limitation in dealing with special details.

There are suggestions about the software system. For example, the server needs to be improved, to allow a rapid processing of large-size videos. They complained that curr

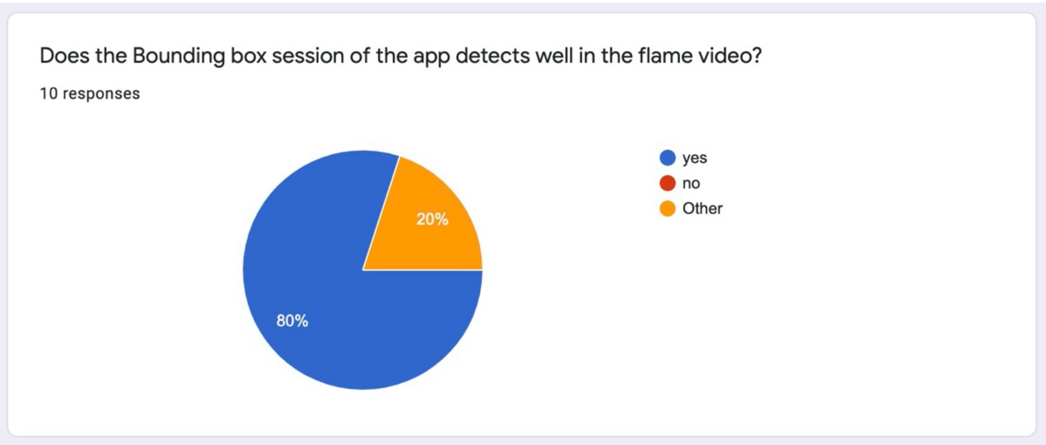


Figure 5-4 Does the Bounding box section of the app detects well in the flame video?

ent processing speed needs to be improved. Some testers put forward that brief instructions are expected for the output file and they also suggest that the output data show the flame size should embed a connection between the real size and pixel instead of directly using pixel values.

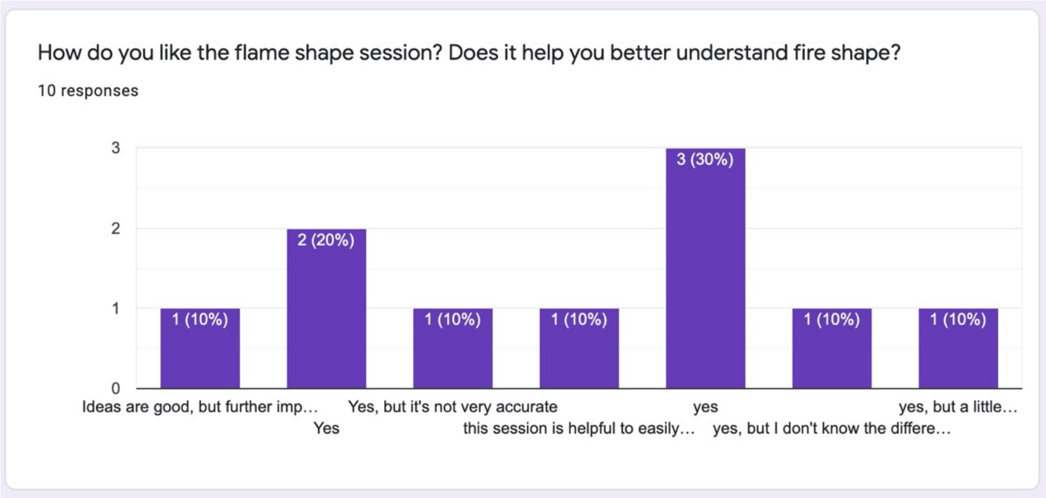


Figure 5-5 How do you like the flame shape section?

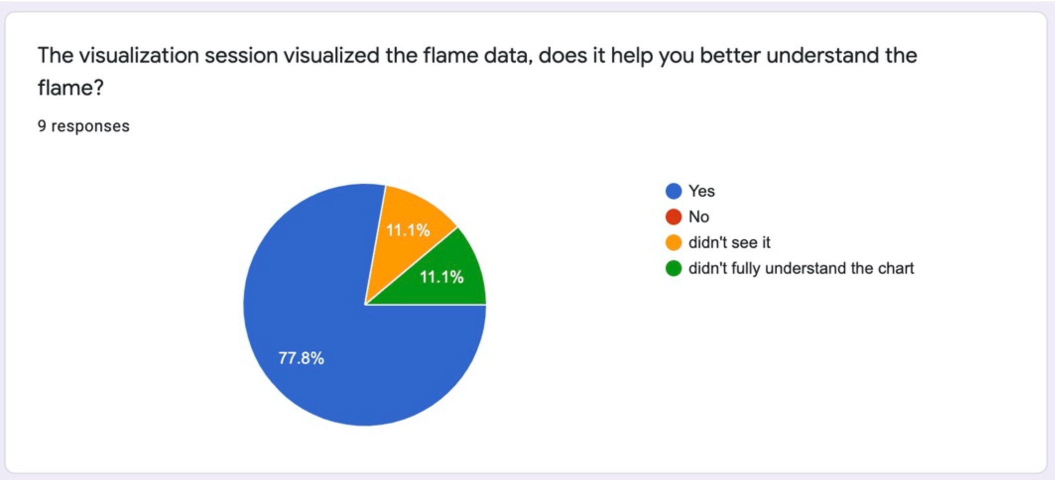


Figure 5-6 The visualization section visualized the flame data, does it help you better understand the flame?

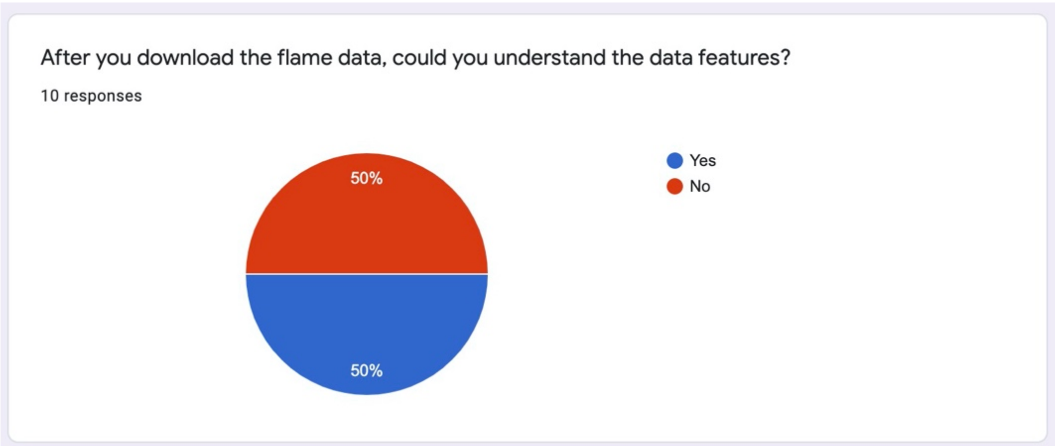


Figure 5-7 After you download the flame data, could you understand the data features?

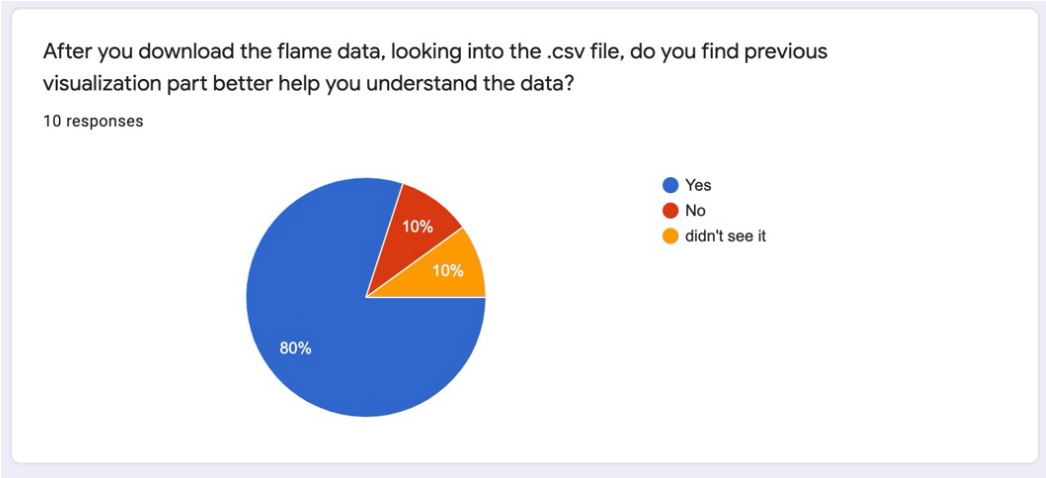


Figure 5-8 After you download the flame data, looking into the .csv file, do you find previous visualization part better help you understand the data?

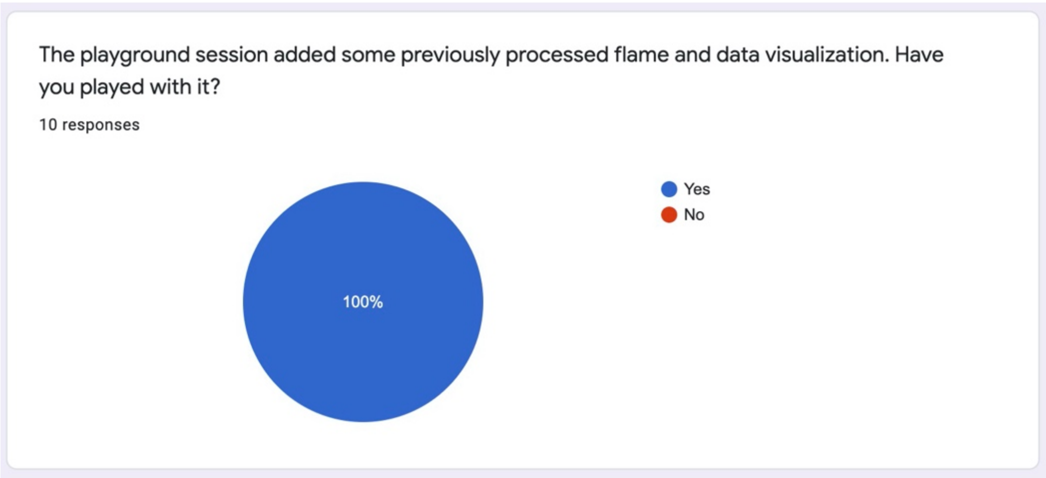


Figure 5-9 The playground section added some previously processed flame and data visualization. Have you played with it?

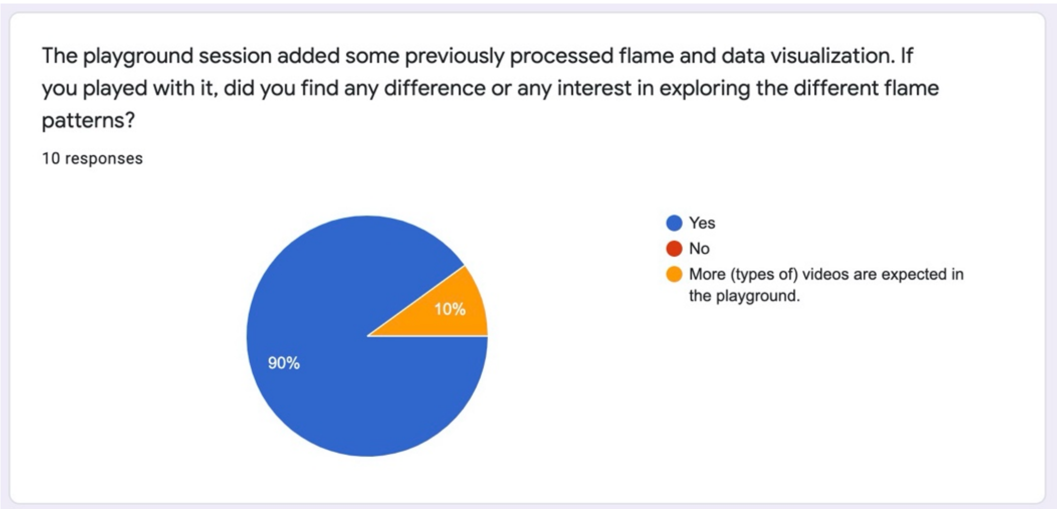


Figure 5-10 The playground section added some previously processed flame and data visualization. If you played with it, did you find any difference or any interest in exploring the different flame patterns?

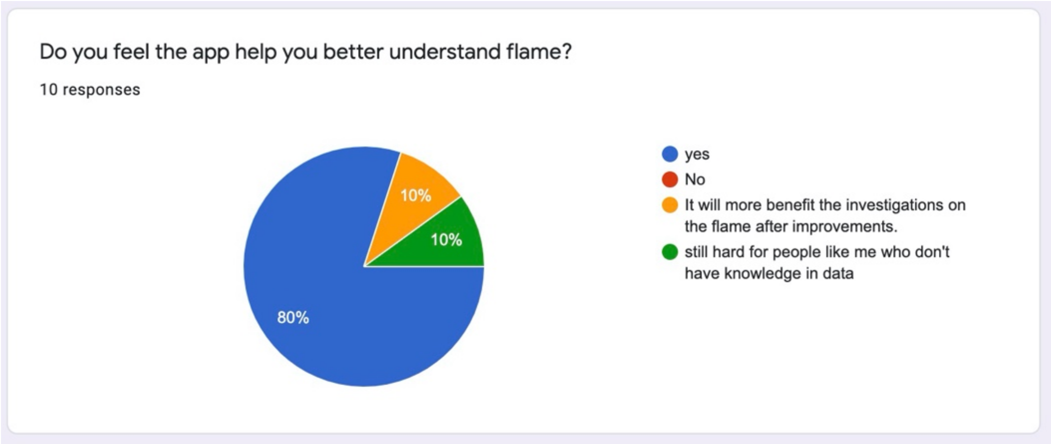


Figure 5-11 Do you feel the app help you better understand flame?

5.3 Discussion

Computer vision enabled flame perception and analysis is a topic that is rarely mentioned, on the one hand because of the specificity and particularity of the profession, and on the other hand because of the high accuracy requirements for flame detection.

5.3.1 Satisfaction of User Needs

We built the application based on our application tasks analysis during the user study in the combustion lab in WPI. The flame features we detected in the application like flame area, flame shape, flame height and flame frequency proved to be the most important factors engineers and researchers care about during our prototype testing. According to fire experts, the visualized flame data patterns reflect some flame features they found from previous research and academic papers, which verifies the significance and effectiveness of this project.

5.3.2 Algorithm Improvement

During our user study and prototype testing, we find that fire reserachers always care about the accuracy of flame perception data as the most important task. Although our current techniques perform well on most fire videos, in some special situations, the fire may be accompanied by smoke, the interference of these blocking smoke cannot be ruled out simply by computer vision techniques, which will affect the accuracy of flame perception algorithm.

5.3.3 Software Pipeline Optimization

By building this software, we connected the research needs of flame researchers with flame recognition tasks using computer vision and deep learning techniques. Researchers can download the data processed by the cloud system by opening the web page and uploading the video to the cloud, and they can play with the visualized data on the web front end. However, as some testers complained that they have to wait for the processed data for a long time, we have to optimize the backend system to make it process at a faster speed. To solve the processing speed problem, we could also deploy the application on the cloud with a better GPU, which will be a little bit more expensive.

Chapter 6 Conclusion and Future Work

6.1 Conclusion

We presented the Flame Perception App, a web application that enables fire engineers and researchers to understand and analyze flame information like flame area, flame height and flame change frequency data. To extract application tasks, we participate in the weekly lab meeting in the fire protection department in WPI, observe fire research process, and interview with fire researchers. To achieve the application tasks we defined during the user study, we conduct experiments in both traditional computer vision methods and a combination of computer vision and deep learning models and find the appropriate techniques that meet the tasks. To make the application accessible to fire engineers and researchers, we build a software pipeline integrated with those algorithms and deploy the application on the cloud. To evaluate the application we built, we invited both fire researchers and students in data science to test the application.

6.2 Future Improvements

Although our current work was well received by both fire researchers and people from other fields, there is still something we need to do to improve the system.

6.2.1 Computer Vision Techniques

Our current algorithm calculates flame shape as pixels in the image instead of the centimeter, it will be hard for fire researchers to compare the flame data in different videos. To solve this problem, we will need to add input of reference substance size to help scale flame shape data.

6.2.2 Special Situations

In our future work, we also need to consider some special situations. For example, the fire may be accompanied by smoke, our current computer vision techniques could not rule out the interference of these blocking smoke and the accuracy of flame perception algorithm is still a big challenge.

6.2.3 Raw Data Pre-processing

During testings, we found that Some of the flames in recording videos are out of camera range and its height/area information in the recorded videos is not correct. As a result, we need to write a program to filter the raw data in the data processing part.

6.2.4 Software Infrastructure Optimization

Besides, our current application pipeline is relatively basic and we haven't put much effort into its optimization. In future promotion applications, we need to optimize software systems and deploy cloud with a better GPU at a higher cost to help increase computing speed and guarantee better user experience.

We hope that our flame perception app can finally enter the fire engineering departments and be used by more people interested in fire information.

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Appendix

Appendix A: Survey

1. Are you fire researchers or fire engineers?

Mark only one oval.

yes No

2. Do you have interest in knowing any aspects of flame? What are they? (like flame pattern, flame shape, light etc)

3. Does the Bounding box session of the app detects well in the flame video?

Mark only one oval.

yes no

Other

4. How do you like the flame shape session? Does it help you better understand fire shape?

5. The visualization session visualized the flame data, does it help you better understand the flame?

Mark only one oval.

Yes

No

Other:

6. After you download the flame data, could you understand the data features?

Mark only one oval.

Yes

No

7. After you download the flame data, looking into the .csv file, do you find previous visualization part better help you understand the data?

Mark only one oval.

Yes

No

Other:

8. The playground session added some previously processed flame and data visualization. Have you played with it?

Mark only one oval.

Yes

No

9. The playground session added some previously processed flame and data visualization. If you played with it, did you find any difference or any interest in exploring the different flame patterns?

Mark only one oval.

- Yes
- No
- Other:

10. Do you feel the app help you better understand flame?

Mark only one oval.

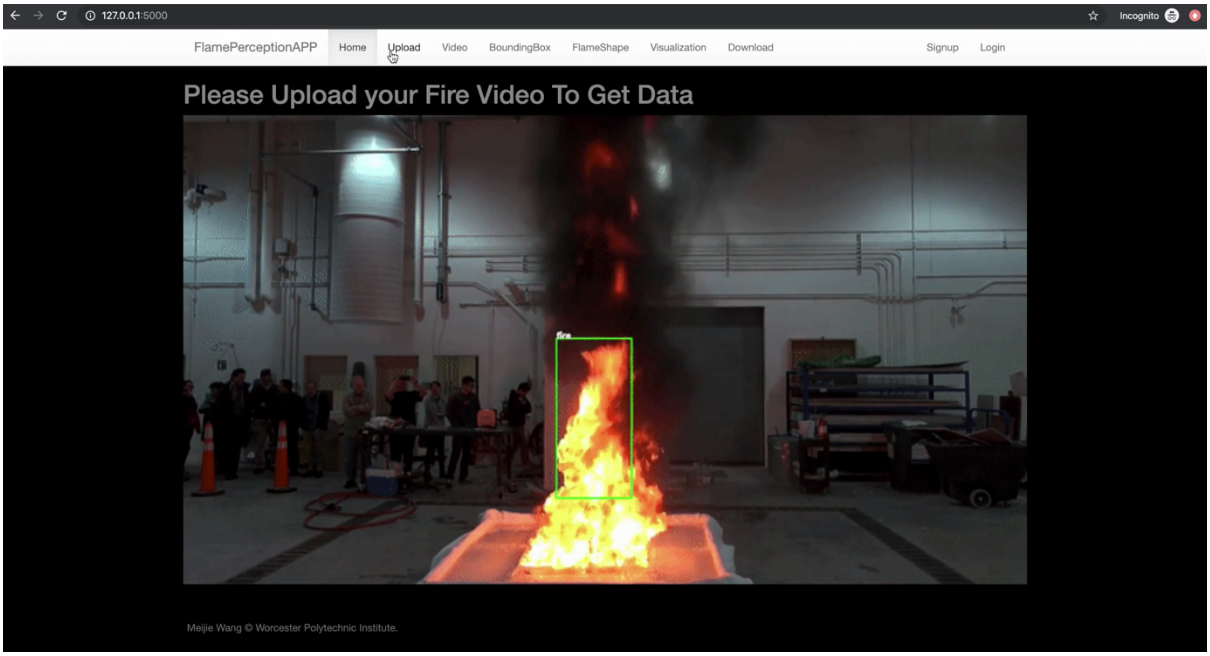
- yes
- No
- Other:

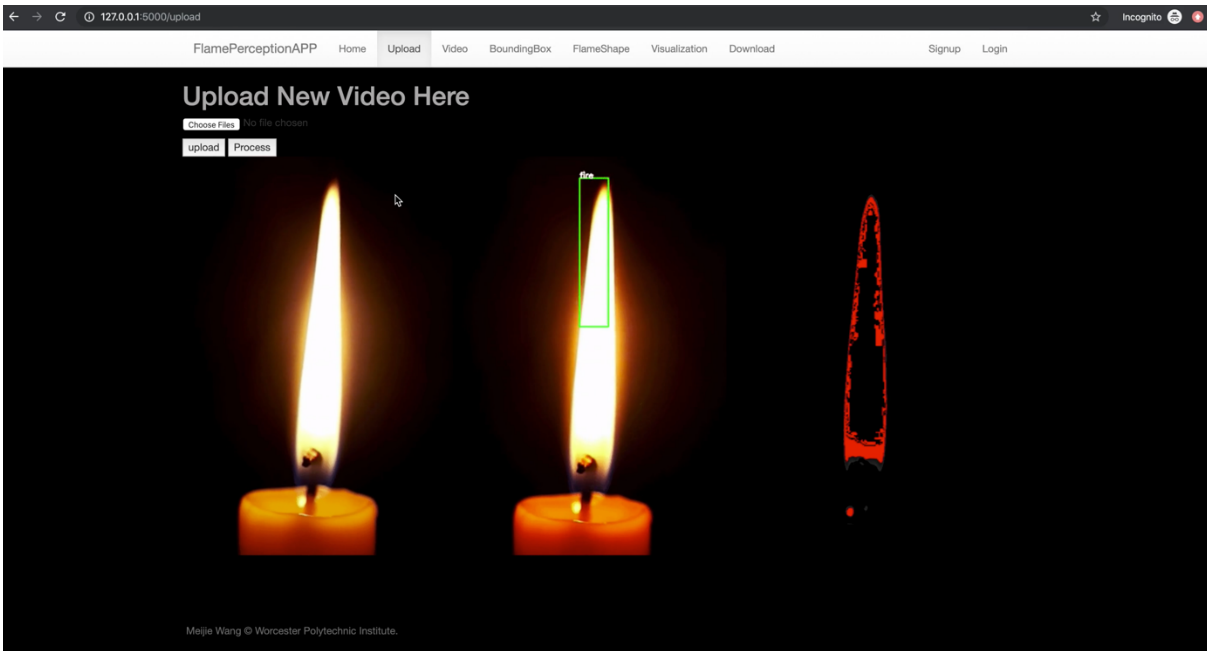
11. Any suggestions? (want to see more features or any ideas)

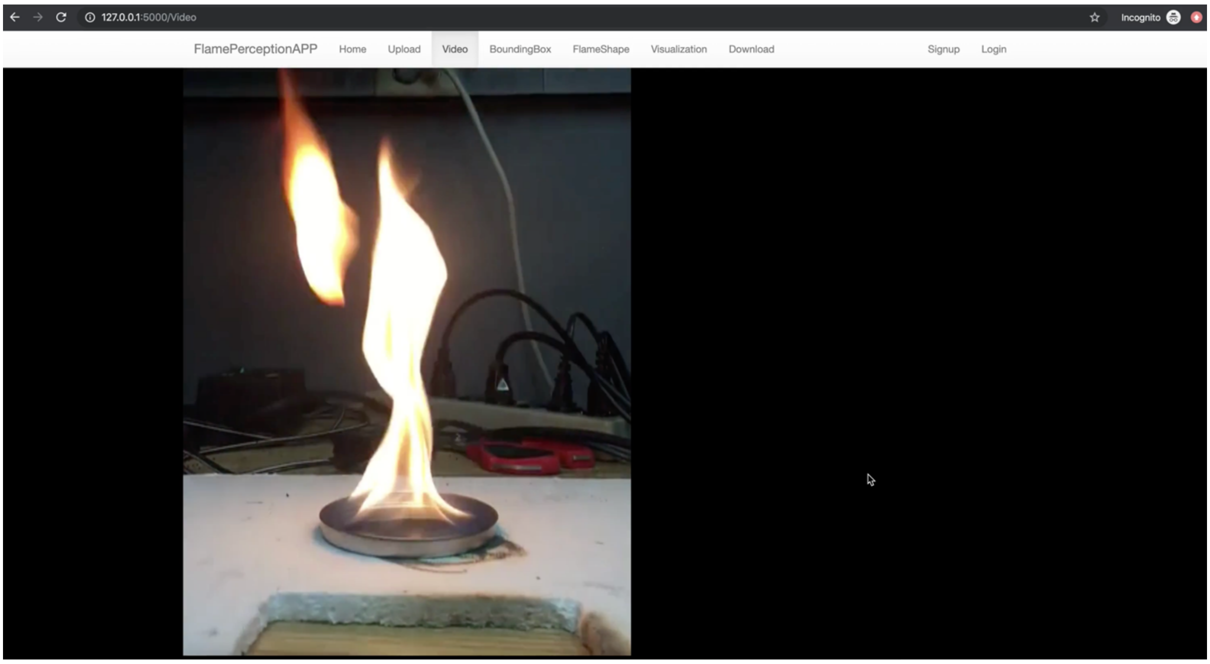
This is the link of the survey:

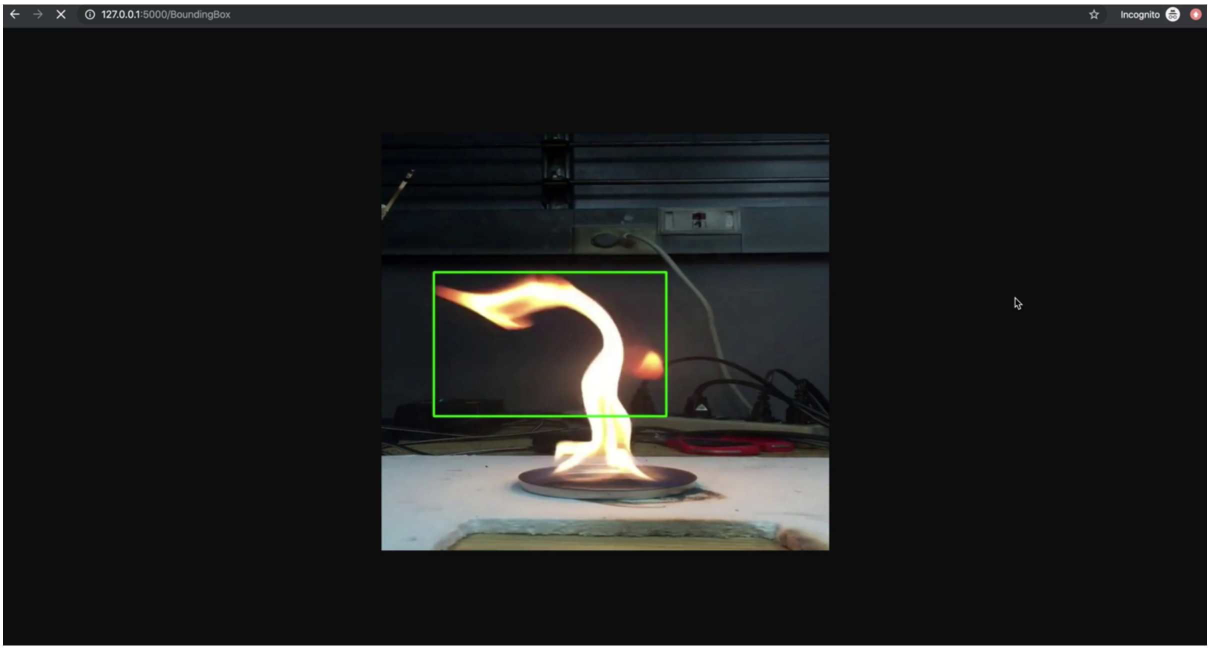
https://docs.google.com/forms/d/e/1FAIpQLSecOBEYeZ42Gbufo7Ti0X33x0gg2H5GnZHyIKEFhBcl9Ivi
kQ/viewform?usp=sf_link

Appendix B: Application User Interface

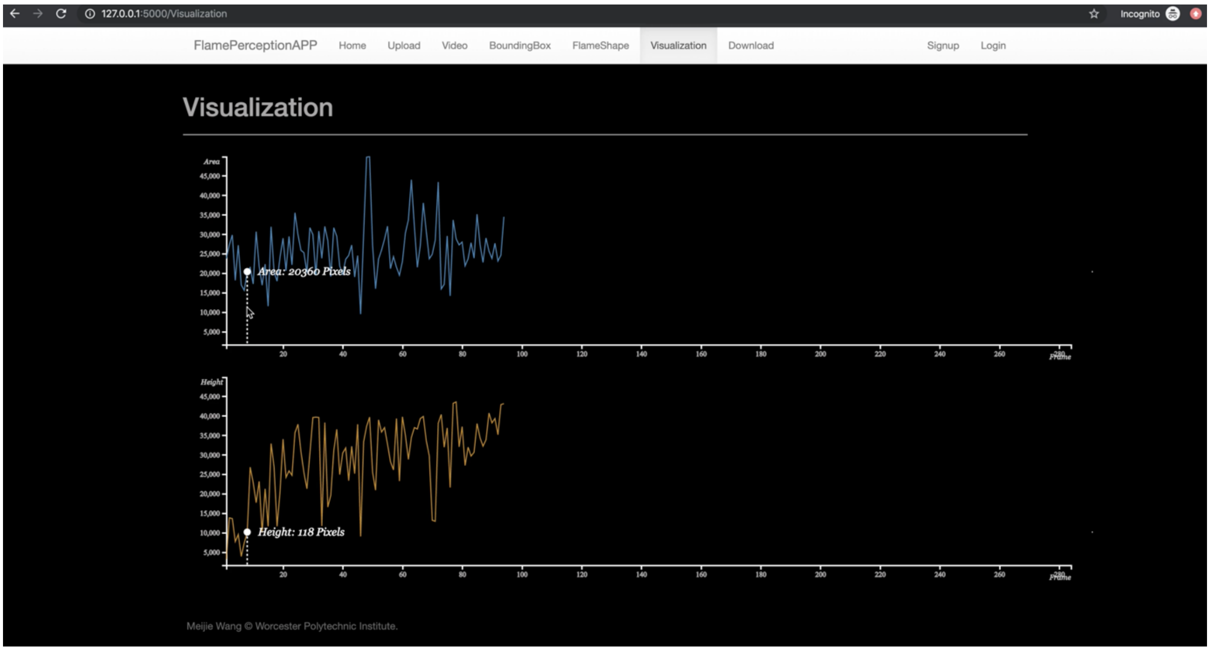


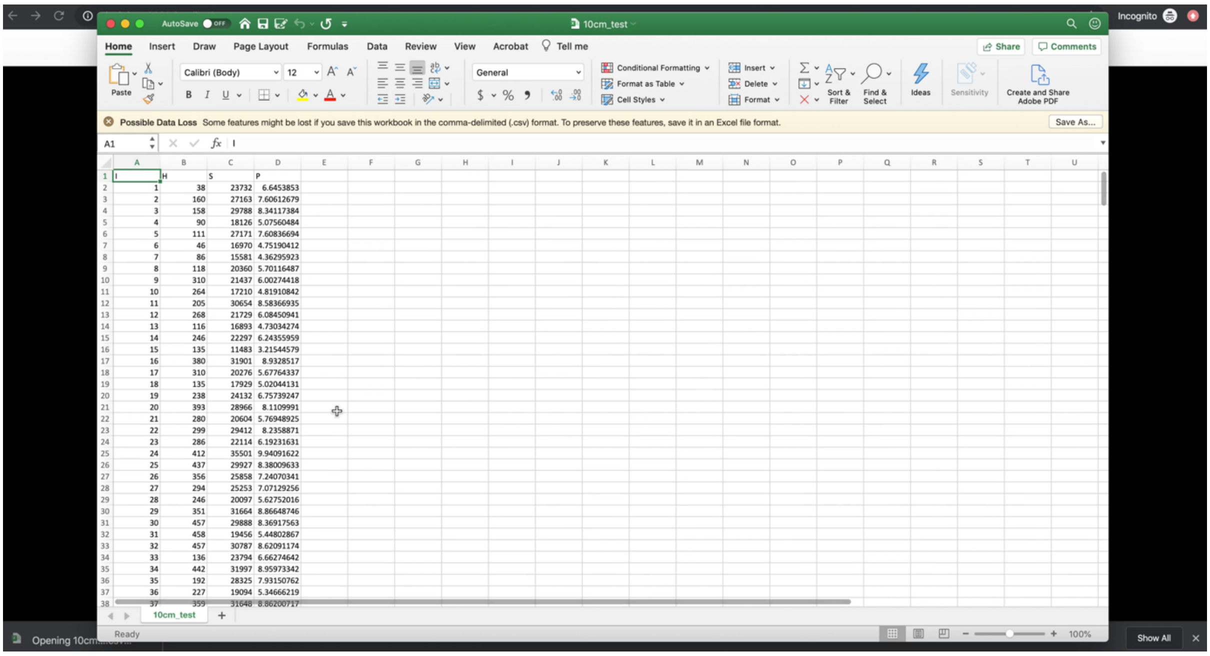



127.0.0.1:5000/Video
Incognito
FlamePerceptionAPP
Home
Upload
Video
BoundingBox
FlameShape
Visualization
Download
Signup
Login


127.0.0.1:5000/BoundingBox
Incognito


127.0.0.1:5000/FlameShape
Incognito


127.0.0.1:5000/Visualization
Incognito
FlamePerceptionAPP
Home
Upload
Video
BoundingBox
FlameShape
Visualization
Download
Signup
Login
Visualization
Area
Area: 20360 Pixels
Height
Height: 118 Pixels
Meijie Wang © Worcester Polytechnic Institute.



I	H	S	P
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2	160	27163	7.60612679
3	158	29788	8.34117384
4	90	18126	5.07560484
5	111	27171	7.60836694
6	46	16970	4.75190412
7	86	15581	4.36295923
8	118	20360	5.70116487
9	310	21437	6.00274418
10	264	17210	4.81910842
11	205	30654	8.58366935
12	268	21729	6.08450941
13	116	16893	4.73034274
14	246	22297	6.24355959
15	135	11483	3.21544579
16	380	31901	8.9328517
17	310	20276	5.67764337
18	135	17929	5.02044131
19	238	24132	6.75739247
20	393	28966	8.1109991
21	280	20604	5.76948925
22	299	29412	8.2358871
23	286	22114	6.19231631
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25	437	29927	8.38009633
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