
Thermal vision camera equipped drone for predictive maintenance of grid sub-stations

Capstone II Report

Adilet Baktykerey and Askar Zhanaliyev

Nazarbayev University
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For the document preparation \LaTeX online text editor was used. For simulations open-source general-purpose programming language Python was used.



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Participant(s):

Adilet Baktykerey
Askar Zhanaliyev

Supervisor(s):

Professor Prashant Jamwal

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Abstract:

In the modern era, a constant supply of electrical energy is an essential part of society. Any cause that may result in power outage should not only be eliminated but detected in advance and prevented. Power system protection techniques and planned maintenance and inspections were intended to prevent those faults, however despite these measures faults still occur and result in equipment malfunction. This capstone project is intended to design a system that processes infrared images and detects overheating in the power substation units, preventing equipment from damage and ensuring constant operation of the power system. This project introduces a system that analyzes images captured on thermal cameras, uses image processing algorithms to detect hot-spots and make a decision upon equipment's condition. By building a web application, a general system has been implemented that is open for any power company, which establishes a service of maintenance and reduces manual inspection.

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Preface

This work is done by Nazarbayev University students for the Capstone II project.

Nazarbayev University, May 15, 2020



Adilet Baktykerey
<adilet.baktykerey@nu.edu.kz>



Askar Zhanaliyev
<askar.zhanaliyev@nu.edu.kz>

Chapter 1

Introduction

1.1 Background

An electrical power system is an extremely complex interconnected network, where the occurrence of faults is inevitable. Although faults can be caused by lightning strikes or environmental disasters, the vast majority is triggered by equipment failures, such as physical damage of transmission lines, malfunctioning of protective relays or transformer overheating. Equipment failure may lead to loss of synchronism, which drastically deteriorates the performance of the system and can result in power outages. Regular inspections and maintenance in power sub-stations would minimize the risks of failure and can eliminate the possibility of outages, which will, in turn, save a huge amount of expenditures [9]. A lot of countries practice foot patrol maintenance, where small crews personally inspect transmission lines, pylons, insulators and other substation equipment for visible damages. Infrared or corona detection cameras are used to observe failures not visible by a naked eye. However, this type of maintenance is time-consuming, tedious, inefficient, labour-intensive and major faults may be overlooked because of human factor [5]. The use of manned aerial vehicles (MAV), like helicopters, is also outdated technology that is ineffective and resource-intensive since it requires humans resources, a pilot, inspectors and recorders [19]. This approach has better performance in terms of speed and accessibility to remote areas. However, demands huge investment, that is not justified and not beneficial for the company.

In the last decade, more emphasis has been made to decrease the human involvement in the inspections, in order to increase the efficiency of operation and do not danger the lives of workers. In [2], [3], a new innovative pulling robot that moves along transmission lines avoiding obstacles is used, which detects single phase to ground faults. The limitation is that it is not fully automated and requires a human to control it and cannot detect phase-to-phase or triple-phase faults. The

design of an automatic lifting robot has been introduced in [15], where a system that adjusts to the unique landscape of the environment for both indoor and outdoor substations. The design significantly increased the efficiency of inspections, but also increased the initial investments as well as the operational cost of the robot. For some of smaller companies and developing countries, such technology may not be beneficial. In [16], researchers propose a fully automated acquisition system for inspection robot that operates in real-time. The robot distinguishes between the equipment and can detect only physical damages, like broken cables. Authors have not considered thermography method and did not equip the robot with thermal cameras, and only the binocular system was used. There are also works that do not focus on either MAV or robots, rather utilizes simple sensors to detect overheating. A. Kadechkar et al. [8] designed a real-time, wireless and contactless system using Hall effect sensors to inspect conductors. Such a system is extremely cheap, very light and has a high accuracy of maintenance, however, is only suitable for transmission line inspections and not mobile, meaning that cannot be simultaneously used for numerous equipment. Climbing robots are also occasionally used in power sub-station maintenance [10]. Such robots can freely move along the conductors and avoid obstacles through sensors. Advantage of this type of inspection is its accuracy. However, building such robots is expensive and its sensors can be damaged by the electromagnetic field of the power lines.

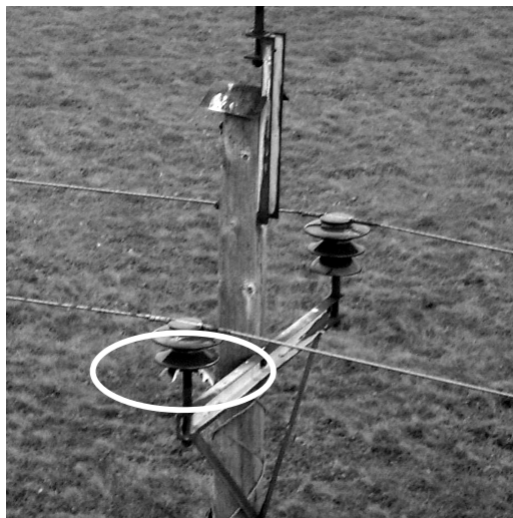


Figure 1.1: Image of a damaged insulator taken from UAV

Another newly developing and emerging approach is to use an unmanned aerial vehicle (UAV) for power system inspections, which is the focus of this capstone project. Since the establishment of unmanned aerial vehicles, a lot of indus-

tries have been using the technology. It is also becoming popular in power system field, because of its versatility and wide range of functionality. One of the advantages of UAV is that it can be equipped with extra components to fill the needs of the user. For instance, placing cameras, sensors and other components to enhance the features of the vehicle [14]. Another advantage is that speed of the vehicle can be chosen and regulated. Use of fast-speed quadcopter is anticipated to achieve a fast inspection rate. Additionally, UAVs are very useful to operate in remote areas and places that are dangerous to human, ensuring the safety of the crew. Images from UAV can be sent in a real-time with a minimum delay to the server, which in turn can conduct all analysis. The exemplary image is shown in Fig. 1.1. Few studies are already concentrating on implementing the idea of using UAV for substation maintenance. In [20] fully automated system to detect line faults, including their exact location has been introduced. However, the work is just on the first levels of progress, and proposed model's inspection efficiency is poor and not optimized. In [11], [7] the use of UAV to inspect transmission lines have been used, with better efficiency compared to [20].

However, to the best of our knowledge, none of the works has been made to use thermal vision equipped UAVs to detect not only line faults but internal damages of all types of equipment, including oil-filled transformers, switching gears, circuit breakers etc.

1.2 Problem Statement

Overheating at various power system components like transformers, circuit breakers, insulators or others causes a fault at the power systems and may potentially lead to a failure of the system. Such faults are costly and repairment actions will take a lot of time, effort and budget of the company. Therefore, it is preferable for power companies not just to eliminate faults, but to detect in advance [14]. Furthermore, early identification of the overheating process can prevent problems of overvoltage and prevent fire or explosion. The main emphasis of this capstone project will be made towards detecting overheating, as opposed to state-of-art studies mentioned before that focuses on the analysis of overhead lines only. For every successful detection of overheated components, the company will not suffer extra costs for repairing, which results in a normal operating condition of the power system without any faults. This leads to customer benefits, where customers do not suffer from blackouts and do not experience any issues with the lack of electricity provided. Thus, they will be provided by a constant electricity supply.

1.3 Objectives

Due to the current global and local situation happening because of COVID-19 pandemic, our research team were ought to adapt for current circumstances and slightly shift the vector of initial plans. For these reasons, with the approval of the supervisor, it was decided to build a more autonomous and more service-based system, which assumes that thermal images have been captured by UAV. With such intents, online web-application has been build, where our system processes requested images and make overheating analysis, finally offering an image with hot-spots that indicates vulnerable areas of the equipment. The main idea has not been altered, except that it is not practical to construct a mechanical model of UAV with a mounted thermal camera on it, thus the focus is made towards hotspot detection under the scope of capstone II project.

Chapter 2

System Design

2.1 Operation principles

As mentioned in the previous section, the initial design has been changed, but still, customers (power companies and substations) are required to take pictures with UAVs. The system design is based on the thermography testing of the equipment. Thermographic testing is an advanced method of detecting faults in electrical equipment, which enables to tackle overloading, overheating, misbalancing and connection issues. Such method allows to determine whether temperatures of electrical components are healthy, deteriorating or at the dangerous level. It is an extremely useful method to identify potential failures by minimizing risks of severe equipment failure, including explosion. The rise in temperature can be caused by several reasons. One of them is the increase in contact resistance [6].



Figure 2.1: Thermography technology applied on transformer

According to Joule's law, where an increase in resistance will lead to an increase in power dissipation. If such an increase in resistance of the equipment can be detected early, significant damages can be prevented. In normal conditions, an increase in temperature will indicate a "hot spot", which can be captured by infrared cameras [4]. Moreover, the fault of the cooling system causes the temperature to

rise. For instance, if generated heat in the transformers does not exit through the cooling system due to blockage of tubes in a heat exchanger, the transformer will be heated excessively and may lead to severe damages. Alternatively, the reason for temperature rise could be leakage currents in insulator systems. This is caused by dirt or contaminants and it leads to the heating of the equipment [4].

For three-phase power transmission lines, the system analyzes and compares the joints of the lines. The increase in resistivity is directly proportional to temperature rise as has been described above. Thus, detecting a difference in temperature at three joints will indicate that there is a possibility of failure. Depending on the magnitude of that difference, the severity of the failure can be estimated [13].

2.2 System Model

The initial design of the proposed system is illustrated below:

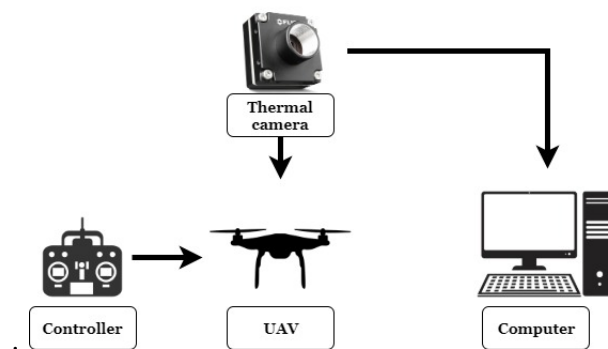


Figure 2.2: Initial architecture of the proposed system

The thermal camera is mounted onto UAV, while UAV itself receives commands from the controller. Images are captured in real-time onto the camera, while UAV is completing its predefined routes over the substation. Taken images are sent to a local computer at the station, which analyzes them for hotspots using image processing algorithms. However, objectives have been changed and a new system model design is proposed.

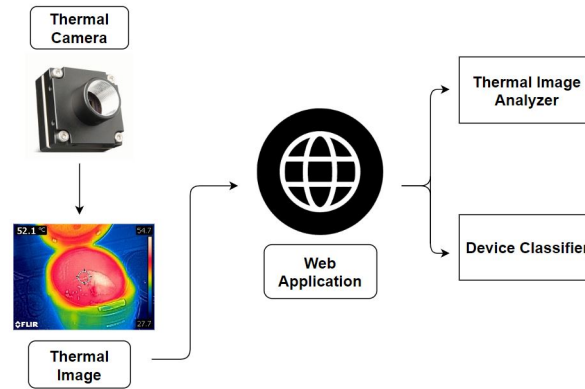


Figure 2.3: Novel architecture of the system

In the new approach, images are assumed to be already taken via UAV and thermal images of the required equipment are available for analysis. Web application takes thermal images as inputs and processes them to detect potential areas of failure. Also, it processes images and identifies what type of equipment is given, successfully distinguishing between transformers, transmission lines, motors, substations and power plants. Thus, a unique service for power companies has been built, where a customer will directly upload images onto web application and get equipment's condition information in an instance.

The image processing is a main and integral part of this project. Correct identification of objects as well as effective elimination of unnecessary data from the input, such as trees, mountains, rivers, grass houses or roads, is critical in getting accurate results. These elements can create interference of necessary video with background video [12]. Thus, a certain algorithm of unit detection that distinguishes between various substation units like transformer or motor has been implemented. For equipment analysis, edge enhancement, thresholding and target extraction are key elements in detecting the features of the observed unit. Mentioned algorithms are successfully implemented using software tools. The most famous of them are MATLAB Image Processing Toolbox and OpenCV library for Python and the latter has been chosen for this project [1].

However, before a customer that has access to UAV and the thermal camera could be found, for the appropriate testing of the system, a compact thermal camera that can be mounted onto UAV has been used to detect overheating. For both initial and new design of the system, FLIR C3 thermal camera has been used. The above mentioned camera can be seen in Fig. 2.4:



Figure 2.4: Thermal camera FLIR C3

The camera has a decent operating temperature range from -10C to +150C and acceptable accuracy of 2%. Also, this model of camera is cheap and has 2 hours of battery operating time, which is enough for an average substation inspection. However, the quality of the images is not high, which is the main drawback of FLIR C3.

Chapter 3

Results

3.1 Code Structure

As it was mentioned before, for image processing part Python language was used. MATLAB has huge functionality, however, it was inferior due to the fact that Python is more viable for hardware interaction. Furthermore, Python is open-source, while MATLAB for proper usage has an additional activation fee [17].

Mainly, the following Python libraries were used to accomplish the objectives:

- OpenCV
- Numpy
- Matplotlib

OpenCV was implemented to use basic image processing algorithms such as image conversion from BGR to HSV, image blurring, image dilation etc.

Meanwhile, **Numpy** library was helpful for creating and manipulating arrays, because analytically any image is an array of numbers with various values.

Finally, **Matplotlib** library was used for showing results in a presentable manner as it can be seen in Fig. 3.7

3.2 IR image

"IR" in IR image stands for *infrared*. As human eyes are not capable of seeing infrared radiation, extra devices that detect them are necessary such as PIR (Passive Infrared) detector. Then, those images are mapped into visible light using certain

colour map making them IR image. The example of such colour map and IR image is shown below:



Figure 3.1: Colour map



Figure 3.2: IR image

In Fig. 3.7 , an infrared image of the mounted 3-phase transformer with one of the wires faulted is illustrated. It is trivial that through a faulted line higher amount of current flows. Thus, it results in a greater copper loss, which consequently transforms into heat energy. Hence, in figure below, one line is heated more, resulting in brighter colours.

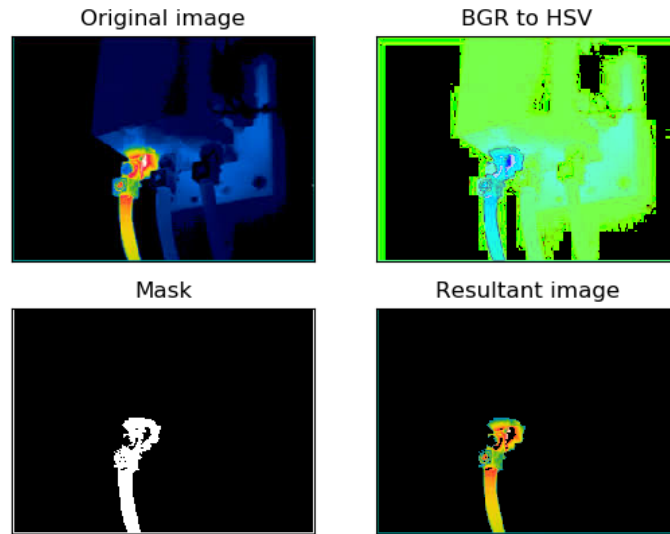


Figure 3.3: Process of analyzing transformer

In the figure above, IR image is first converted to HSV domain. The HSV scale stands for Hue, Saturation, Value. It does a better job at visually explaining the concept of light [18].

Then, the HSV image was used to create a mask that filters out a red colour as it is a region where the highest temperature peak occurs. It was done by setting upper and lower boundaries of red colour in the code.

Finally, mentioned mask was used for the original image to show the faulted section. A bitwise *AND* operation was done to multiply the original image and mask. The code for the above operations was included in Appendix A.

The same principle was applied to the following image of faulted line:

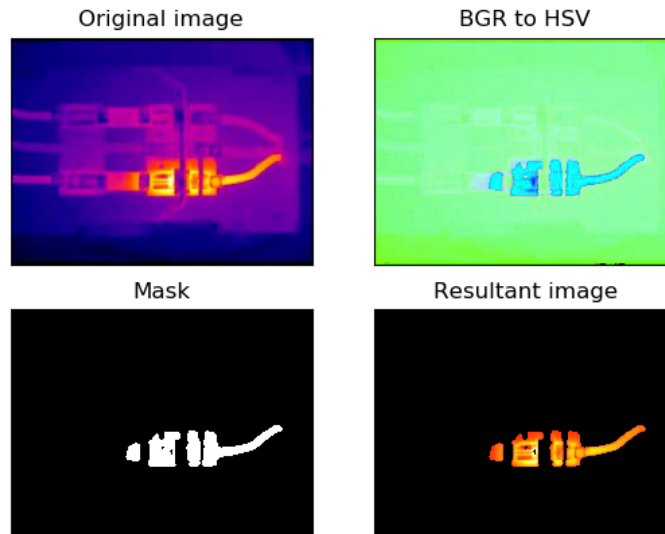


Figure 3.4: Faulted line IR image

3.3 Hotspot detection

To identify the hotspot in an image captured by the camera, there is a need for proper colour mapping. For this purpose, in hotspot detection part pre-built package for FLIR cameras, *flirimageextractor* was imported, which is based on ExifTool (It is a free and open-source software program for reading, writing, and manipulating the image, audio, video, and PDF metadata). To test the algorithms none of the Internet databases were used, all of the images have been captured by purchased FLIR C3 thermal camera. In particular, infrared images of chandelier, cooker, iron, kettle, laptop and laptop charger, phone charger, cup, radiator, refrigerator and sink has been used. Such sample choice has been made due to the unavailability of laboratory facility and equipment.

In this *flirimageextractor* package, there is a method called *get_thermal_np()* which returns numpy array containing temperature values for each pixel. After applying this function, the maximum temperature point was plotted and shown on the image itself. After getting the maximum temperature of the equipment, it is up to the customer to decide how to interpret the data, because depending on the mechanical structure and age of the equipment, for every substation nominal ratings differ. For these reasons, it was decided just to illustrate the hotspots. The code is available in Appendix B.

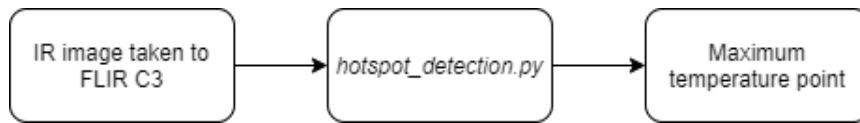


Figure 3.5: hotspot_detection.py input and output

Also, from the below figure the resultant image and maximum temperature point can be observed. It is clear that it is 67.51 degrees. The algorithm detects temperatures with a high accuracy of 98%, which is suitable for the ranges of electric equipment. However, current circumstances did not allow to test real substation equipment nor laboratory equipment. Thus, it was decided to use images taken by our thermal camera of electronic equipment like refrigerators, cooker, radiator for the analysis.

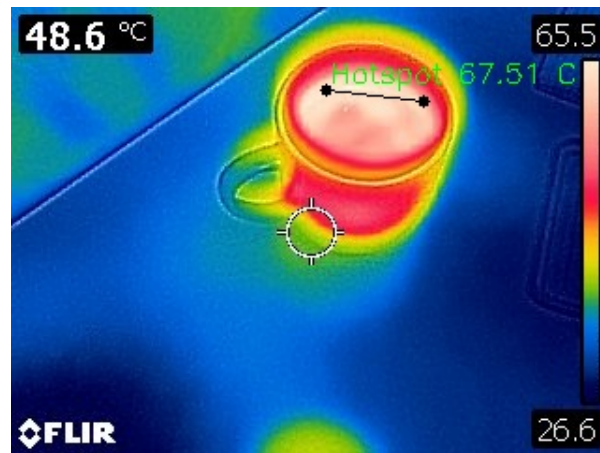


Figure 3.6: Resultant Image

3.4 Image Classification

In this project, also image classification was done, using IBM Watson. It is a paid service for visual recognition based on deep neural network. However, as the capacity of our image is not huge, Lite version was used, which provides services for free.

In this platform, custom model called Device Classifier was created. The model classifies between 5 distinct classes:

- Transformer

- Motor
- Transmission line
- Substation
- Power plant

For training of each class approximately 140-150 images were used. The communication between IBM Watson and our PC was established through the Application Programming Interface (API). The code is available in Appendix C.

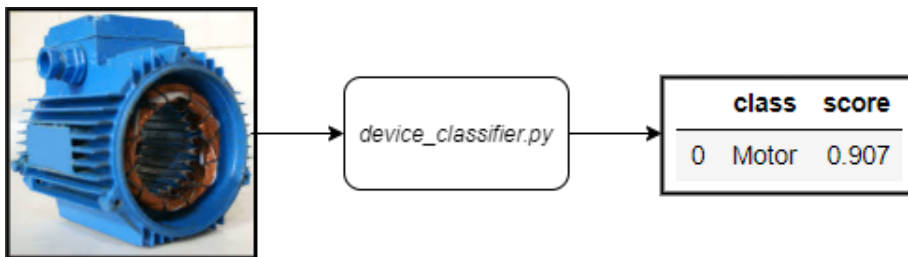


Figure 3.7: `device_classifier.py` input and output

This module has been implemented in order to automate the process of image analysis. Such functionality allows the system to distinguish between power substation units, with an accuracy of 90.7%. Such feature is necessary because of the varying nominal operating temperature ratings of different equipment. The accuracy of the device classifier is acceptable, because there are not many units in the power substations, however it can be easily increased with larger training size.

3.5 Web Application

With intent of providing easy to use service for power substations to utilize, web application has been built. Web application consists of two parts.

- Front-end
- Back-end

Frontend is made using Angular (open-source web application framework). In order to run front-end application NGINX HTTP server is used.

Back-end is made using Flask Framework, because it is written in Python. This is a core point, in which hotspot detection and image classification is implemented.

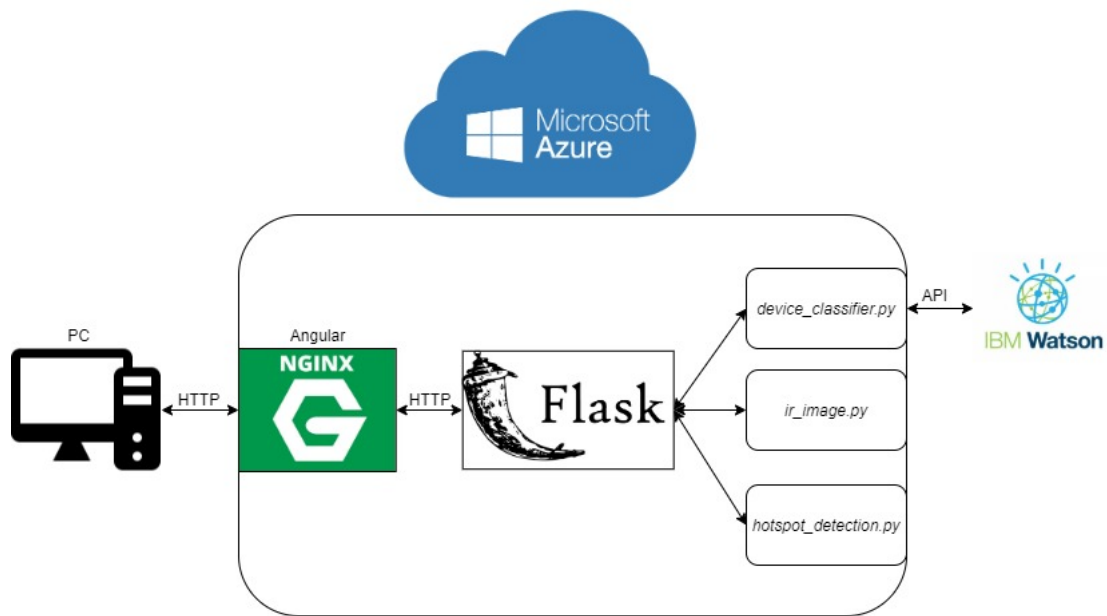


Figure 3.8: Web application structure

Deployment of the web application was done by Microsoft Azure Cloud Services on Linux Ubuntu virtual machine. Whole application structure can be concluded by Fig. 3.9.

The web application can be accessed through web-site *http://capstone.orda.group/* and its interface is illustrated in the Fig. 3.9

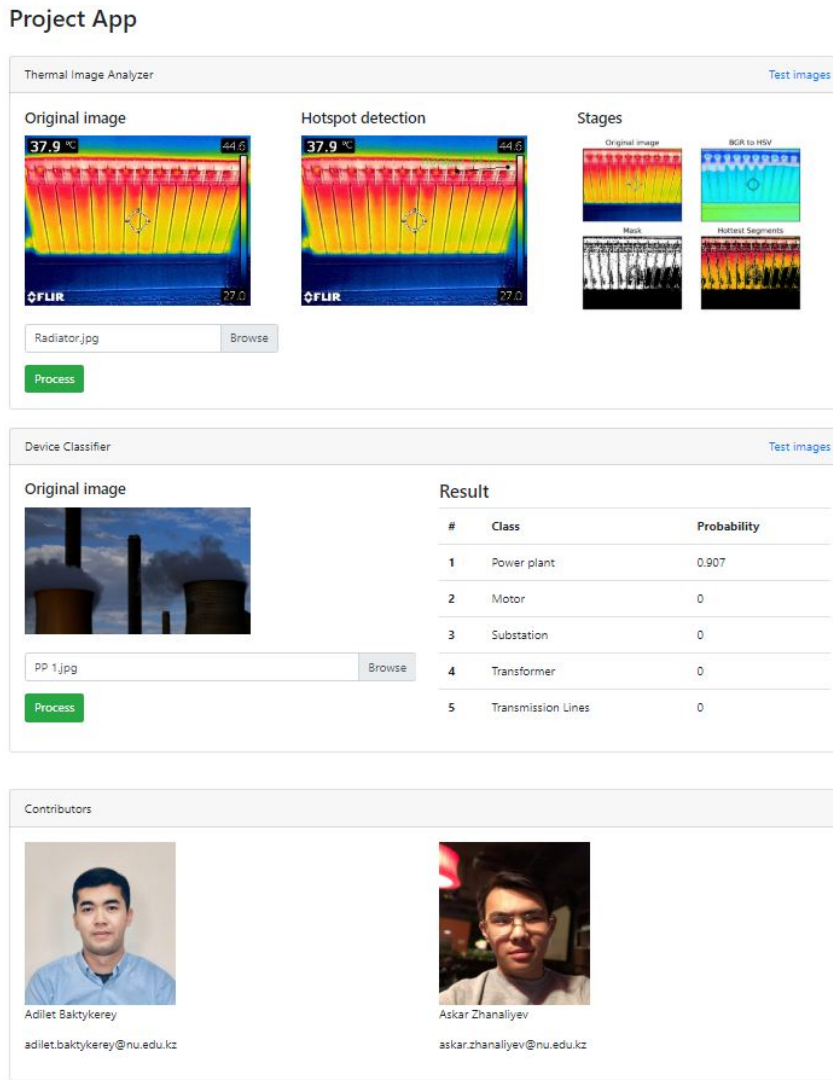


Figure 3.9: Web application interface

Test images can be found by link https://github.com/adilet-b11/capstone_project/tree/master/Test%20images or there is a hyperlink in an upper-right corner of each section in web application called "Test images".

Chapter 4

Conclusion

The objectives of the capstone project may have changed, but despite that successfully achieved. The service-based online web application has been created that can be utilized by any power company or private sectors to analyze power equipment's condition. Two modules, namely thermal image analyzer and device classifier, have been implemented into the web-application. Thermal image analyzer that processes the input data and detects hotspots of the equipment, showing good accuracy of 98%. Device classifier distinguishes between different power substation units with an accuracy of 90.7%. Such a system enables to switch scheduled based maintenance to the predictive maintenance, where faults can be identified and eliminated before they take place.

However, future work is expected to be properly executed with better thermal camera resolution and quality, which will increase the accuracy of hotspot detection to 99%. With better working conditions and access to laboratory and power substation, a system can be tested for real equipment. Also, the construction of a mountable structure that connects the thermal camera with UAV will be done. So that the entire system can be fully automated and an end product, which both takes images from the UAV and sends it to the web-application for the analysis is achieved. To conclude, future work should be done towards full automation of the process and total elimination of human interaction for measurements and analysis. Better thermal camera with higher resolution and better UAV with long operating time would further improve the performance and reliability of the system.

Bibliography

- [1] Ying-Chieh Chou and Leehter Yao. "Automatic diagnostic system of electrical equipment using infrared thermography". In: *2009 international conference of soft computing and pattern recognition*. IEEE. 2009, pp. 155–160.
- [2] T Disyadej et al. "Application in O&M Practices of Overhead Power Line Robotics". In: *2019 IEEE PES GTD Grand International Conference and Exposition Asia (GTD Asia)*. IEEE. 2019, pp. 347–351.
- [3] Thongchai Disyadej et al. "High Voltage Power Line Maintenance & Inspection by Using Smart Robotics". In: *2019 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*. IEEE. 2019, pp. 1–4.
- [4] Henri Eisenbeiss et al. "A mini unmanned aerial vehicle (UAV): system overview and image acquisition". In: *International Archives of Photogrammetry. Remote Sensing and Spatial Information Sciences* 36.5/W1 (2004), pp. 1–7.
- [5] Chenguang Feng and Ruiming Qian. "Mechanism Design and Crawling Process Force Analysis of Inspection Robot for Power Transmission Lines". In: *2019 IEEE International Conference on Unmanned Systems (ICUS)*. IEEE. 2019, pp. 221–225.
- [6] Ian Golightly and Dewi Jones. "Visual control of an unmanned aerial vehicle for power line inspection". In: *ICAR'05. Proceedings., 12th International Conference on Advanced Robotics, 2005*. IEEE. 2005, pp. 288–295.
- [7] Daxin Hui et al. "Research on Details Enhancement Method of UAV Inspection Image for Overhead Transmission Line". In: *2019 International Conference on Smart Grid and Electrical Automation (ICSGEA)*. IEEE. 2019, pp. 27–31.
- [8] Akash Kadechkar et al. "Real-Time Wireless, Contactless, and Coreless Monitoring of the Current Distribution in Substation Conductors for Fault Diagnosis". In: *IEEE Sensors Journal* 19.5 (2018), pp. 1693–1700.
- [9] R Levi and M Rivers. "Substation maintenance testing using an expert system for on-site equipment evaluation". In: *IEEE transactions on power delivery* 7.1 (1992), pp. 269–275.

- [10] Luis F Luque-Vega et al. "Power line inspection via an unmanned aerial system based on the quadrotor helicopter". In: *MELECON 2014-2014 17th IEEE Mediterranean electrotechnical conference*. IEEE. 2014, pp. 393–397.
- [11] Tianqi Mao et al. "Development of Power Transmission Line Defects Diagnosis System for UAV Inspection based on Binocular Depth Imaging Technology". In: *2019 2nd International Conference on Electrical Materials and Power Equipment (ICEMPE)*. IEEE. 2019, pp. 478–481.
- [12] Oswaldo A Menendez, Marcelo Perez, and Fernando A Auat Cheein. "Vision based inspection of transmission lines using unmanned aerial vehicles". In: *2016 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*. IEEE. 2016, pp. 412–417.
- [13] Serge Montambault et al. "On the application of VTOL UAVs to the inspection of power utility assets". In: *2010 1st International Conference on Applied Robotics for the Power Industry*. IEEE. 2010, pp. 1–7.
- [14] René Pfitzner, Konstantin Turitsyn, and Michael Chertkov. "Controlled tripping of overheated lines mitigates power outages". In: *arXiv preprint arXiv:1104.4558* (2011).
- [15] Haipeng Wang et al. "Research on the Technology of Indoor and Outdoor Integration Robot Inspection in Substation". In: *2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC)*. IEEE. 2019, pp. 2366–2369.
- [16] Zhenli Wang et al. "Autonomous Collection System of Substation Patrol Robot". In: *2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*. Vol. 1. IEEE. 2019, pp. 1563–1566.
- [17] "Welcome to Python". In: *Python.org* (2019). URL: <https://www.python.org/>.
- [18] "Welcome to the Learn site". In: *Learn.leighcotnoir.com* (2019). URL: <http://learn.leighcotnoir.com/artspeak/elements-color/hue-value-saturation/>.
- [19] Guangjian Yan et al. "An airborne multi-angle power line inspection system". In: *2007 IEEE International Geoscience and Remote Sensing Symposium*. IEEE. 2007, pp. 2913–2915.
- [20] Alexandros Zormpas et al. "Power transmission lines inspection using properly equipped unmanned aerial vehicle (UAV)". In: *2018 IEEE International Conference on Imaging Systems and Techniques (IST)*. IEEE. 2018, pp. 1–5.

Appendix A

Python code *ir_image.py*

```
1 import cv2 as cv #importing libraries
2 import numpy as np
3 from matplotlib import pyplot as plt
4
5 img = cv.imread('fault.jpg', 1) #uploading an image
6 img = cv.cvtColor(img,cv.COLOR_BGR2RGB) #converting to RGB as MATLAB
   ↪ recognizes only RGB
7
8 img_hsv=cv.cvtColor(img, cv.COLOR_RGB2HSV) #converting to HSV
9
10 lower_red = np.array([0,50,50]) #setting boundaries of red colour
11 upper_red = np.array([100,255,255])
12 mask = cv.inRange(img_hsv, lower_red, upper_red) #creating mask
13
14 img_result = cv.bitwise_and(img, img, mask=mask) #bitwise AND Operation
15
16 titles = ['Original image', 'BGR to HSV', 'Mask', 'Resultant image']
   ↪ #plotting the results
17 images = [img, img_hsv, mask, img_result]
18
19 for i in range(4):
20     plt.subplot(2, 2, i + 1), plt.imshow(images[i], 'gray')
21     plt.title(titles[i])
22     plt.xticks([]), plt.yticks([])
23 plt.show()
```

Appendix B

Python code *hotspot_detection.py*

```
1 import flirimageextractor
2 import cv2
3 import numpy as np
4
5 img_path = 'Adilet.jpg'
6 img = cv2.imread(img_path)
7
8 def hotspotFinder(img_path):
9     ir_image = flirimageextractor.FlirImageExtractor()
10    ir_image.process_image(img_path)
11    temps = ir_image.get_thermal_np()
12    max_temp = np.max(temps)
13    #4 is the ratio between temperature array and image
14    coord = np.where(temps==max_temp)*np.array(4)
15    return coord, max_temp
16
17 hotspot = hotspotFinder(img_path)
18 #Take reversively
19 x = hotspot[0][1]
20 y = hotspot[0][0]
21 z = round(hotspot[1],2)
22 #biasing points
23 w = 220
24 h = 50
25 cv2.circle(img, (x,y), 3, (0,0,0), -1)
26 cv2.line(img,(x,y),(w,h),1)
27 cv2.circle(img, (w,h), 3, (0,0,0), -1)
28 cv2.putText(img, "Hotspot " + str(z) + ' C', (w-50,h-10),
29             ↪ cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 255, 0), 1)
30 cv2.imshow('Resultant image', img)
```

```
31 cv2.waitKey(0)
32 cv2.destroyAllWindows()
```

Appendix C

Python code *device_classifier.py*

```
1 my_apikey = 'B5b3G2VOKRLtUDxgk0GenbY_qv59-OdotwhdWK29x8gJ'
2 import time
3
4 from ibm_watson import VisualRecognitionV3
5 from ibm_cloud_sdk_core.authenticators import IAMAuthenticator
6 authenticator = IAMAuthenticator(my_apikey)
7
8 visrec = VisualRecognitionV3('2020-04-13',
9                               authenticator=authenticator)
10 import json
11 with open('Motor.zip', 'rb') as Motor, \
12     open('PP.zip', 'rb') as PowerPlant, \
13     open('SS.zip', 'rb') as Substation, \
14     open('Transformer.zip', 'rb') as Transformer, \
15     open('Transmission Lines.zip', 'rb') as TransmissionLine:
16     response = visrec.create_classifier(name="Device Classifier",
17                                       ↪ positive_examples={'Motor': Motor, 'Power plant':
18                                       ↪ PowerPlant, 'Substation': Substation, 'Transformer':
19                                       ↪ Transformer, 'Transmission line': TransmissionLine})
17 print(json.dumps(response.get_result(), indent=2))
18
19 classifier_id = 'DeviceClassifier_1744264373'
20
21 from pandas.io.json import json_normalize
22
23
24 def getdf_visrec(images_file, apikey=my_apikey):
25     json_result = visrec.classify(images_file=images_file,
26                                  ↪ threshold='0.6', classifier_ids=classifier_id).get_result()
26
```

```
27 json_classes =  
    ↪ json_result['images'][0]['classifiers'][0]['classes']  
28  
29 df = json_normalize(json_classes).sort_values('score',  
    ↪ ascending=False).reset_index(drop=True)  
30  
31 return df  
32  
33 getdf_visrec(images_file = open('./Motor 1.jpg', 'rb'))
```