

**SMART AUTOMATION SYSTEM: HUMAN OPERATOR
MONITORING AND ANOMALY DETECTION USING CAMERA
AND NODE-RED**

ONG WEI YING



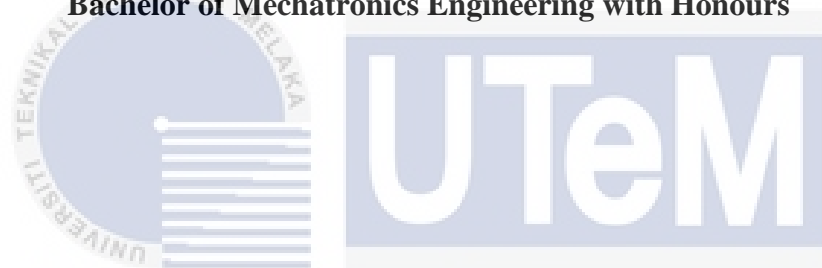
اونيورسيتي تیکنیکل ملیسيا ملاک
**BACHELOR OF MECHATRONICS ENGINEERING WITH
HONOURS**
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**SMART AUTOMATION SYSTEM: HUMAN OPERATOR MONITORING AND
ANOMALY DETECTION USING CAMERA AND NODE-RED**

ONG WEI YING

**A report submitted
in partial fulfillment of the requirements for the degree of
Bachelor of Mechatronics Engineering with Honours**



Faculty of Electrical Engineering

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UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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2021

DECLARATION

I declare that this thesis entitled “SMART AUTOMATION SYSTEM: HUMAN OPERATOR MONITORING AND ANOMALY DETECTION USING CAMERA AND NODE-RED” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

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APPROVAL

I hereby declare that I have checked this report entitled “SMART AUTOMATION SYSTEM: HUMAN OPERATOR MONITORING AND ANOMALY DETECTION USING CAMERA AND NODE-RED” and in my opinion, this thesis it complies the partial fulfillment for awarding the award of the degree of Bachelor of Mechatronics Engineering with Honours

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Date

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5/7/2021



DEDICATIONS

To my beloved mother and father



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ABSTRACT

Smart automation system is defined as the combination of automatic control of electronic devices and internet connection which allow them to be controlled remotely. It is becoming necessary in many fields and one of it is monitoring system. In the field of monitoring system, it is important to inspect and detect the action of human in order to detect and diagnose the unwanted behaviour deviation of a human operator from the pre-set sequence of actions, taking into account their possible response to the current state of the system. Security cameras such as closed-circuit television is commonly used by citizens but there is still a lot of features can be added in to the system to provide intelligence and automation. In this project, the focus is on human operator monitoring and anomaly detection with the aids of camera and Node-Red. Artificial technology is added to the monitoring system to determine the abnormal action of human. Hardware components such as laptop and laptop VGA camera are used in this project. Tensorflow.js. pre-trained model is used to perform pose estimation. Pose classifier is trained using ML5.js neural network. P5.js is used as the code editor. Node-Red is used to wire together the flows by using the nodes and make them communicate with each other. Three experiments are carried out and the results obtained will be analysed in terms of accuracy in pose classification. This system will detect the normal and abnormal poses of human.

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ABSTRAK

Sistem automasi pintar didefinisikan sebagai gabungan kawalan automatik peranti elektronik dan sambungan internet yang membolehkannya dikendalikan dari jarak jauh. Teknologi ini telah menjadi penting dalam banyak bidang dan salah satunya ialah sistem pemantauan. Bidang sistem pemantauan amat penting untuk memeriksa dan mengesan tindakan manusia untuk mengesan dan mendiagnosi penyimpangan tingkah laku yang tidak diinginkan pengendali manusia dari urutan tindakan yang telah ditetapkan, dengan mengambil kira kemungkinan tindak balas mereka terhadap arus keadaan sistem. Kamera keselamatan seperti televisyen litar tertutup biasanya digunakan oleh warga negara tetapi masih banyak fungsi yang dapat ditambahkan ke dalam sistem untuk memberikan kepintaran dan automasi. Dalam projek ini, tumpuan adalah pada pemantauan pengendali manusia dan pengesanan anomali dengan bantuan kamera dan Node-Red. Kecerdasan buatan ditambahkan ke sistem pemantauan untuk menentukan tindakan tidak normal manusia. Komponen perkakasan seperti komputer riba dan kamera VGA komputer riba digunakan dalam projek ini. Tensorflow.js. model pra-terlatih digunakan untuk melakukan anggaran pose. Pengelasan pose dilatih menggunakan rangkaian saraf ML5.js. P5.js digunakan sebagai penyunting kod. Node-Red digunakan untuk menyatukan aliran dengan menggunakan nod dan menjadikannya berkomunikasi antara satu sama lain. Tiga eksperimen dijalankan dan hasil yang diperoleh akan dianalisis dari segi ketepatan dalam klasifikasi pose. Sistem ini akan mengesan pose normal dan tidak normal manusia.

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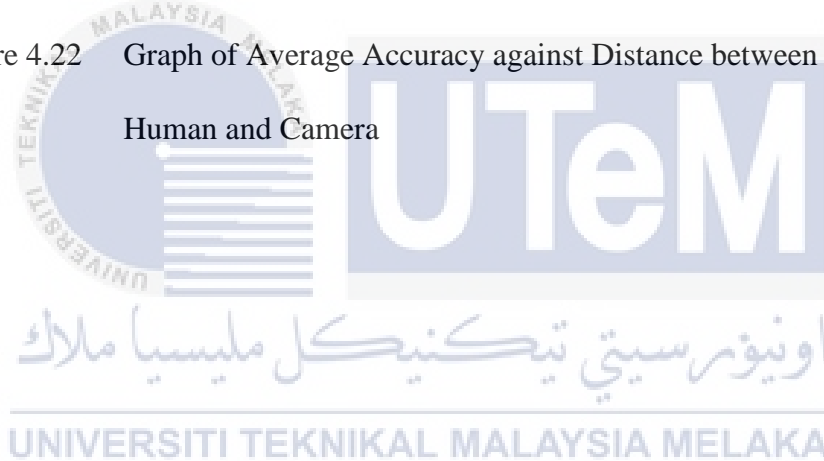
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LIST OF SYMBOLS AND ABBREVIATIONS

| | | |
|------------|---|---|
| UTeM | - | Universiti Teknikal Malaysia Melaka |
| IoT | - | Internet of Things |
| CCTV | - | Closed-circuit television |
| ILO | - | International Labour Organization |
| FOV | - | Field of View |
| NASA | - | National Aeronautics and Space Administration |
| 3D | - | 3-Dimensional |
| LBP | - | local binary pattern |
| SVM | - | Support vector machine |
| 3DConvNets | - | 3D Convolutional Neural Network |
| FC | - | Fully connected |
| MIL | - | Multiple-instance learning |
| ADC | - | Analog to Digital Converter |
| OCR | - | Optical character recognition |
| CNN | - | Convolutional neural network |
| PCI | - | Peripheral Component Interconnect |
| MIPI | - | Mobile Industry Processor Interface |
| CSI | - | Camera Serial Interface |
| FYP | - | Final Year Project |
| RGB | - | Red, green, blue |
| TP | - | True positive |
| FP | - | False positive |
| TN | - | True negative |
| FN | - | False negative |

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CHAPTER 1

INTRODUCTION

1.1 Background

Smart automation system is defined as the combination of automatic control of electronic devices and internet connection which allow them to be controlled remotely. Smart automation system works through a network of devices which are connected to the internet via different communication protocols such as Wi-Fi, Bluetooth and ZigBee (Asadullah and Raza, 2016). The devices are controlled remotely by controllers via electronic interfaces. The sensors in the IoT devices will monitor variation in motion, temperature and light to let the user gather information about the device's surrounding. To make physical changes to the IoT device, the users is required to trigger actuator which is the physical mechanisms like switches or motors which enable the devices to be controlled remotely.



Figure 1.1: Smart home automation system (Yang et al., 2018)

Smart automation system works on three levels. The first level is monitoring which is defined as user can check their devices remotely through an app. For example,

user can view the live feed of their house from a smart security camera. Next, the second level is controlling which means that user can control the devices remotely such as adjusting a security camera to view more of a living space. The third level is automation which is defined as setting up devices to trigger on another such as smart siren is alerted when an armed security camera detects an abnormal motion.



Figure 1.2: Amazon Cloud Cam (Davies, 2017)

Smart automation system is becoming necessary in many fields and one of it is the monitoring system. In the field of monitoring system, it is important to inspect and detect the action of human in order to prevent low employee productivity and industrial accident in the industry. Security cameras such as closed-circuit television (CCTV) is commonly used by industry but there is still a lot of features can be added into the system to provide intelligence and automation. Human Operator Monitoring and Anomaly Detection System using Camera and Node-Red are used to monitor the human action from the pre-set sequence of actions, taking into account their possible response to the current state of the system and will send an alert when an abnormal situation is detected.

Anomaly detection which is also called as outlier analysis that identifies data points, events, and or observations that deviate from a dataset's normal behaviour in data mining (Cohen, n.d.). For example, serious incidents such as technical malfunction, potential opportunities or a variation in consumer behaviour is indicated as anomalous data. The knowledge of machine learning is applied to automate anomaly detection.

1.2 Motivation

In this era, technology is very crucial as it is progressively involved in our daily life. Newer and advanced technology are taking the market by storm and people are getting used to it in a split second. Technology is born by accomplishing the scientific progress and breakthroughs. One of the useful technology invented is the closed-circuit television (CCTV) and alarm system. In this project, a similar technology which is Human Operator Monitoring and Anomaly Detection System using Camera and Node-Red is proposed to solve challenges.



Figure 1.3: Smart Alarm System (Ewing, 2020)

The first challenge is low employee productivity. Employee productivity means the assessment of the efficiency of worker whereas productivity means the output of an employee in a specific time duration. Based on the survey on Vouchercloud, 79% of employees admitted that they are not truly productive for the entire eight hours workday. Productivity data collected from 2000 United Kingdom workers has proven that they work less than three hours each day and the average working time is 2 hours and 53 minutes. In one hour, employees get distracted about 7 times and one distraction takes about 5 minutes. This means that in an 8 hour working duration, employee may lose up to 4 hours of valuable working time due to interruption.

Low employee productivity is affected by poor supervision. This is due to managers always being transparent or not being consistent and micromanaging or not

giving enough supervision to the employees. The second reason that causes low employee productivity is inappropriate behaviour. Actions that against the company policy or corporate integrity such as stealing, sexual harassment, stealing and arriving to work late can cause discomfort and distraction. Employees may suffer anxiety and insomnia by thinking if they should say something and risk getting caught by others. The next factor is employee frequently using smartphones. The average person in the United States checks on their phone 52 times a day. Overusing a smartphone may delay and decrease the employee efficient working time. Besides, employee always leaving their work place to go for smoking, toilet or chit-chatting. These behaviour will become worsen once there is no adequate supervision on the employee.

The first effect of low employee productivity is low profitability. Productivity and profit have a strong bond as when the resources produce a relatively low amount of goods, services or sales, the profit margin for the company is low as company also have to pay for their salary. Second, low productivity prone to downsizing when leaders want a number of workers to leave as this is the most effective way to cut labour costs. However, the leaving employee will suffer from low morale based on lost relationships and afraid losing their own jobs. The third impact is work avoidance and turnover of employee. Employee who are not concern about optimizing productivity may skip out whenever possible and lead to high rates of absenteeism and turnover in a company. Turnover happens if employees are lack of motivation and don't feel that their contributions are valued.

The second challenge is to decrease industrial accident. All this efforts are used to prevent industrial accidents such as falling from heights, injuries caused by tools and machinery, explosions, chemical burns and other cases from occurring. Industrial accident is defined as an accident happens to a person in the course of their work that results in an injury. The International Labour Organization (ILO) estimates that there are 2.3 million people around the world involve in work-related accidents or diseases annually and 6000 deaths daily. ILO estimates that there are 340 million occupational accidents and 160 million victims who suffer from work-related illnesses every year.

To solve the menace of industrial accidents, the causes of it are needed to be understood. Unsafe working conditions are one of the biggest reason and usually caused by defective plants, equipment, machines and materials. These happens by the

inappropriate guarded equipment, defective tools, faulty plant location and layout, unsafe storage and insufficient safety devices. Other than this, psychological causes such as working overtime, fatigue, tiredness and anxiety will also lead to accidents. Safety experts identify some high danger zones in an industry which are hand life trucks, wheel-barrows, electric drop lights, saw and hand rails. Unsafe acts of operator also result in industrial accidents due to lack of knowledge or skill on the worker, bodily defects and improper working attitude. Besides, climatic conditions and variations give rise to the happening of accidents. These causes include high temperature, humid condition, slippery floors and excessive noise.

The effects of industrial accidents can last for a long time or even forever. Industrial accident brings enormous consequence on the health of workers as it may cause severe injury, limbs loss, korma suffering and death. The victims will also suffer economic loss because they have to pay for the medical expenses for a long term. Some of the victims may experience mental health aftermath as they are not able to cope with their psychological shadow. Industry that happens a lot of accidents will cause loss of productivity and reputation damaging. The company will also have to compensate for the losses of the workers and products. Victims who are not able to survive will leave a psychological shadow in their parent's heart.

As a robust alternative to solve this problem, Human Operator Monitoring and Anomaly Detection System using Camera and Node-Red is proposed to improve the employee productivity and decrease the industrial accidents. The camera will capture the human movement and send alert to the user when there is an anomaly happening.



Figure 1.4: Output video of a CCTV (Park and Kim, 2015)

1.3 Problem Statement

Human operator monitoring and anomaly detection system plays an important role in ensuring industrial safety. A good diagnosis can effectively minimize the industrial accident. Nowadays security camera is getting more and more successful all over the world. There are a lot more functions for a security camera rather than just only recording the situation. The two features is added into the camera which is human operator monitoring and anomaly detection.

Image quality plays an important role in video surveillance with respect to both automated detection and human perception. In a monitored environment, the necessary features of clear image for event detection and identification and recognition of objects are good contrast, satisfactory sharpness and sufficient illumination.

Besides, correct field of view (FOV) is also crucial for video surveillance. FOV is ensured to be accurate for the monitoring of a specific site and can capture the whole body of a human from head to toe.

In addition, the noise in the raw image obtained by camera is high due to inadequate light intensity. This will caused the image to be blurred and the action of the human will be difficult to determine. Hence, the process of acquiring the image of monitored region is important in minimising the noise for better processing. To cope with the problem, a high definition and high-speed camera is needed but its cost will be more expensive. Other than this, image enhancing technique can be used to produce high quality image but it still has its limitation in noise reduction.



Figure 1.5: Security camera blurred at night (Martins, 2019)