UNMANNED MEDICAL WASTE SEGREGATION USING DEEP LEARNING TECHNIQUES

A PROJECT REPORT

Submitted by

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submitted to the Faculty of

INFORMATION AND COMMUNICATION ENGINEERING

in partial fulfillment for the award of the degree

of

BACHELOR OF TECHNOLOGY

in

INFORMATION TECHNOLOGY

DEPARTMENT OF INFORMATION SCIENCE AND TECHNOLOGY

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JUNE 2023

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ABSTRACT

Medical waste is being produced at an accelerated rate these days due to rising healthcare needs. Medical waste contains pathogens, and dangerous bacteria that can infect patients, healthcare professionals, and the general public by spreading these drug-resistant microorganisms from healthcare facilities into the environment is a potential infectious risk.

As per the current scenario, a poor medical waste management system is followed which would lead to many dangerous situations for humans, animals, and the environment by spreading infectious diseases. It also pollutes the environment, gives off an unpleasant odour, and encourages the growth of insects and worms. If medical waste is not properly managed, the garbage collector and their family members will acquire serious illnesses. In order to save human beings from various infections, a movable system is needed which has no human intervention to dispose of medical waste. This project Unmanned Medical Waste Segregation Using Deep Learning Techniques is proposed to work to overcome the challenges mentioned above. A robotic arm can be used to separate medical wastes. The robotic arms are developed using the classification approach for the separation of medical wastes.

Deep learning techniques are employed for the classification of medical wastes. The most challenging one is the dataset which is needed for our system, where the training and classification of various types of medical waste need more accuracy. Recognition and automatic segregation of medical waste from piles of garbage are one of the tedious tasks involved in this system.

திட்டப்பணி சுருக்கம்

நாளுக்கு நாள் அதிகரித்து வரும் சுகாதாரத் தேவைகள் காரணமாக மருத்துவக் கழிவுகள் அதிக அளவில் உற்பத்தி செய்யப்படுகின்றன. மருத்துவக் கழிவுகளில் நோய்க்கிருமிகள், நோயாளிகள், சுகாதார வல்லுநர்கள் மற்றும் பொதுமக்களைப் பாதிக்கக்கூடிய ஆபத்தான பாக்டீரியாக்கள் உள்ளன, இந்த மருந்து-எதிர்ப்பு நுண்ணுயிரிகளை சுகாதார வசதிகளிலிருந்து சுற்றுச்சூழலுக்கு பரப்புவதன் மூலம் தொற்று அபாயம் உள்ளது. தற்போதைய சூழ்நிலையில், மோசமான மருத்துவ கழிவு மேலாண்மை முறை பின்பற்றப்படுகிறது, இது தொற்று நோய்களை பரப்புவதன் மூலம் மனிதர்கள், விலங்குகள் மற்றும் சுற்றுச்சூழலுக்கு பல ஆபத்தான சூழ்நிலைக்கு வழிவகுக்கும். இது சுற்றுச்சூழலை மாசுபடுத்துகிறது, துர்நாற்றம்அளிக்கிறது மற்றும் பூச்சிகள் மற்றும் புழுக்களின் வளர்ச்சியை ஊக்குவிக்கிறது. மருத்துவக் கழிவுகளை முறையாக நிர்வகிக்காவிட்டால், குப்பை அள்ளுபவர்கள் மற்றும் அவர்களது குடும்பத்தினர் கடுமையான நோய்களுக்கு ஆளாக நேரிடும். பல்வேறு தொற்றுநோய்களிலிருந்து மனிதனைக் காப்பாற்ற, மருத்துவக் கழிவுகளை அகற்ற மனித தலையீடு இல்லாத ஒரு அசையும் அமைப்பு தேவை. ஆழமான கற்றல் நுட்பங்களைப் பயன்படுத்தி ஆளில்லா மருத்துவக் கழிவுகளைப் பிரித்தெடுக்கும் இந்தத் திட்டம் மேலே குறிப்பிட்ட சவால்களைச் சமாளிக்கும் வகையில் செயல்பட முன்மொழியப்பட்டுள்ளது. மருத்துவக் கழிவுகளைப் பிரிக்க ரோபோ கைகளைப் பயன்படுத்தலாம். மருத்துவக் கழிவுகளைப் பிரிப்பதற்கான வகைப்பாடு அணுகுமுறையைப் பயன்படுத்தி ரோபோ ஆயுதங்கள் உருவாக்கப்பட்டுள்ளன. மருத்துவக் கழிவுகளை வகைப்படுத்துவதற்கு ஆழ்ந்த கற்றல் நுட்பங்கள் பயன்படுத்தப்படுகின்றன. மிகவும் சவாலான ஒன்று எங்கள் கணினிக்குத் தேவையான தரவுத்தொகுப்பு ஆகும், அங்கு பல்வேறு வகையான மருத்துவக் கழிவுகளின் பயிற்சி மற்றும் வகைப்படுத்தலுக்கு அதிக துல்லியம் தேவைப்படுகிறது. குப்பைக் குவியலில் இருந்து மருத்துவக் கழிவுகளை கண்டறிவதும், தானாகப் பிரிப்பதும் இந்த அமைப்பில் உள்ள கடினமான பணிகளில் ஒன்றாகும்.

ACKNOWLEDGEMENT

First and foremost, we would like to express our sincere gratitude to Dr. D. NARASHIMAN, Teaching Fellow, Department of Information Science and Technology, College of Engineering Guindy, Anna University, who served as our mentor and was a great source of guidance. He gave us the confidence and flexibility to successfully complete our final-year project.

We would like to thank Dr. S. SRIDHAR, Professor and Head, Department of Information Science and Technology, College of Engineering Guindy, Anna University for his gracious assistance and provision of the tools needed to complete the project.

We appreciate the reviews and helpful advice provided by the project coordinator, Dr.S.SWAMYNATHAN, and the project committee members, Dr.J.INDUMATHI, Professor, Dr.S.SENDHIL KUMAR, Associate Professor, Dr.K.VIDYA, Assistant Professor, and Dr.D.NARASHIMAN, Teaching Fellow at the Department of Information Science and Technology, College of Engineering Guindy, Anna University, Chennai.

We also thank the faculty members and non-teaching staff members of the Department of Information Science and Technology, College of Engineering Guindy Campus, Anna University, Chennai for their valuable support throughout the course of our project work.

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CAGR	Compound Annual Growth Rule
CNN	Convolution Neural Network
CPU	Central Processing Unit
CSI	Camera Serial Interface
DC	Direct current
DOF	Degree of Freedom
E2PROM	Electrically Erasable Programmable Read-only Memory
FPV	First Person View
GB	gigabyte
GPIO	General Processing Input Output
GPS	Global Positioning System
GPU	General Processing Unit
GUI	Graphical user interface
HD	high-definition
HIV	Human Immunodeficiency Virus
IMU	Inertial Measuring Unit
IOT	Internet Of Things
IR	Infrared
LiDAR	Light Direction and Ranging
$Li-Po$	Lithium Polymer
$LoRa-GPS$	Long range Global Positioning System
MB	megabyte
MHz	Megahertz
PWM	Pulse-Width Modulation
QR	Quick Response code
RAM	Random Access Memory
RCNN	Region-Based Convolutional Neural Network

ReLu	Rectified Linear Unit
RGB	Red Green Blue
SSD	Solid-State Drive
SVM	Support Vector Machine
USB	Universal Serial Bus
VGG	Visual Geometry Group

CHAPTER 1

INTRODUCTION

This chapter discusses the past and current activities that are implemented in unmanned medical waste segregation. It also clearly explains the need for a system to support sanitary workers.

1.1 BACKGROUND

As per the quote by Lailah Gifty Akita, ”When your environment is clean you feel happy motivated, and healthy”, it’s important to keep the environment clean and hygienic. As the demand for health grows, the increase in medical waste generation is gradually outstripping the load. Medical Waste contains tissues contaminated with blood and other bodily fluids, cultures and stocks of infectious agents from laboratory work, waste with infections, and sharpens such as needles, lancets, syringes, scalpels, and broken glasses. Medical Waste causes a great threat to the physical and mental health and the quality of life of Garbage Collectors in hospitals.

The major problems caused to garbage collectors by medical waste are due to the re-usability of surgery coats by doctors and nurses. It also affects the garbage collector’s family. Some facility centers may not have trained their staff correctly. Often there are smaller clinics that may not be able to invest the time or the money in the proper disposal of wastes generated. Also, waste could be placed in the wrong containers. In order to ensure that Facility centers follow proper procedures, they should be inspected on a set schedule. But it is not possible to check on a regular basis.

All individuals being exposed to hazardous healthcare waste are potentially at risk, including those within healthcare establishments that generate hazardous waste, and those outside these sources who either handle such waste are exposed to it as a consequence of careless management. By some estimates, improperly handled medical waste may have caused as much as 12% of the world's Human Immunodeficiency Virus(HIV) cases for the garbage collector and normal people. Wastes suspected to contain pathogens that pose a risk of diseases like tuberculosis, pneumonia, diarrhea, tetanus, whooping cough, etc, and other common disease transmissions through waste contaminated with blood and other body fluids, laboratory and microbiological stocks, waste including excreta and other materials that have been in contact with patients infected with highly infectious diseases in an isolation ward.

Of the total amount of waste generated by healthcare activities, about 85% is general and non-hazardous waste. The remaining 15% is considered hazardous material that may be infectious, toxic, or radioactive. India is likely to generate about 775.5 tons of medical waste per day by 2022, from the current level of 550.9 tons per day growing at a Compound Annual Growth Rate (CAGR) of about 7%. Waste generated in various states of India from June 2020 to July 2021 is shown in Table 1.1.

Table 1.1: TONS OF WASTE GENERATED IN VARIOUS STATES

S.No.	State	Waste Generated (in Tons)
1.	Maharashtra	8,317
2.	Kerala	6,442
3.	Gujarat	5,004
4.	Tamil Nadu	4,835
5.	Delhi	3,995
6.	Uttar Pradesh	3,881
7.	Karnataka	3,133

Waste that is contaminated with live parasites is frequently present in healthcare institutions that test patients for parasites. Body fluids are examined through incubation, and after the examination is over, they are discarded as waste. It makes sense that, if disposed of improperly, any waste from these kinds of procedures could be very infectious. When the skin comes into contact with any one of the pathogens in medical waste, then it can easily become infected. The importance of disposing of biomedical waste in a proper way is to decrease the dangers and risks to the communities and to decrease the incidence of HIV/AIDS, sepsis, hepatitis, and other diseases spread by infectious medical equipment by accurate waste management. So, in order to ensure the safety of health care workers, the medical waste segregation model using a Robotic arm to prevent the physical intervention of humans has been suggested.

The main objective of this project is to segregate medical waste automatically with help of a Robotic arm which helps garbage collectors avoid being affected by diseases and improve their quality of life.

1.2 PROBLEM STATEMENT

Segregation of medical waste without human intervention using deep learning techniques and robotic arms to safeguard the public health and environment.

1.3 PROJECT OVERVIEW

The proposed system uses the deep learning method CNN for image classification and Internet of things components such as sensors and actuators for automatic segregation of medical waste.

The image that is used for training the CNN model, are collected from various websources under four different classes: General, Hazardous, Infectious, and Radioactive. The images used are in the ‘RGB colour space’ and include the ‘.jpeg’ or ‘.jpg’ image formats. The file size of each image varies from 100-200 kilobytes. The total number of images used for training the convolution model is 2000 nos.

Initially, the features of images are used as the basis for classification. A convolutional neural network is used to learn more abstract features, which helps to detect and classify medical wastes more accurately. This deep learning approach using CNN not only helps in classification but can be integrated with microprocessors for making Robotic arm work. Later, the Robotic arm is used to segregate the medical waste automatically which helps Garbage collectors to take care of their well-being.

MEDICAL WASTE IMAGE DATASET

The given input images are processed based on the edges, pixel intensity, and the variance in pixel values of an image, which suits to train of the system. The smallest indivisible units that make up an image are called pixels, and each of these units has a strength that is frequently referred to as pixel intensity.

Every digital image examine typically has three colour channels, or the Red-Green-Blue channels also referred to as the ”RGB” values. Because it has been demonstrated that using all three together can create any colour palette. The colour image is constructed of several pixels, each of which contains three separate RGB channel values.

VARIOUS LAYERS IN PROCESSING AN IMAGE

The input images are processed using a deep-learning algorithm. A deep learning algorithm called Convolutional Neural Networks(CNN) is extremely effective in processing images. Three-dimensional arrays are used to store coloured images. The first two dimensions match the image's height and width (the number of pixels). The final dimension represents the red, green, and blue hues observed in each pixel.

Applications such as segmentation, object detection, and video and image recognition use CNN.

The four different layers of CNN are: 1) Convolutional Layer: This layer is the main building block of a CNN. Convolutions have been used for a very long time in image processing, mainly to sharpen and blur images, but also for other functions. CNNs establish a local connection pattern between neurons of adjacent layers using techniques like edge enhancement and embossing.

2) ReLu layer: This is the Rectified Linear unit layer. To allow for non-linearity, the output of the convolution operation is subjected to an activation function. The ReLu is the typical activation function for convolution. Every negative pixel will have its value replaced by zero. This is used to avoid vanishing gradient problems and to improve better computation performance.

3) Pooling Layer: The pooling layer is used to make the feature map less dimensional. It involves sliding a 2-Dimensional filter over each channel of the featured map and summarising features lying within the region of the filter. It is mainly used to reduce the dimensions of the feature map. Inside the CNN's hidden layer, there will be numerous activation and pooling layers. Pooling can be of the following types: max-pooling, avg-pooling and min-pooling.

4) Fully-Connected Layer: Fully Connected Layers make up the network's final few layers. The output from the last pooling or convolutional layer is flattened before being fed into the fully connected layer as the input.

After processing through all the layers of CNN, an activation function called Softmax is the final output layer in the neural network. It is a mathematical function that converts a vector number into a vector of probabilities. It is used when there exist more than two classes for classification.

INTERNET OF THINGS COMPONENTS

Creating a medical waste classification model can be integrated with a Robotic arm for automatic segregation. Robotic arms play a significant part in the segregation of components in automatic separation. The several components involved are:

(A) Two Degree of Freedom(DoF) Robotic Arm: This works over the four axis- Pick up, lift it, move it horizontally, and set it down.

(B) Motor Driver: It serves as a link between the control circuits and the motors. The controller circuit operates on low current signals whereas the motor needs a large amount of current. Therefore, the purpose of motor drivers is to convert low-current control signals into higher-current signals that can drive motors.

It consists of the servo motor, controller, power supply unit, and servo motor-specific connectors. A controller, motor driver circuit, DC motor, power supply unit, and the required direct connections are required for the dc motor. Using a tiny voltage signal from a microcontroller or control system, we employ motor drivers to supply the motor with high power.

The motor driver will rotate the motor in one direction while maintaining one pin as HIGH and one pin as LOW if the CPU sends the motor driver a HIGH input.

(C) Raspberry Pi: Raspberry Pi has a VideoCore IV GPU, 512MB ofRAM, and an ARMv6 700 MHz single-core processor. By default, Raspberry Pi supports Python 2/3, C/C++, and Scratch.

The Raspberry Pi 4 model with 8 GB RAM is used. It is a capable little device that enables people of all ages to explore computing and learn how to program in languages including Python.

(D) Raspberry Pi Cam: It is the vision of the computer. A specially created add-on module for Raspberry Pi hardware is the Raspberry Pi Camera Board. It employs a distinctive CSI interface to link to the Raspberry Pi hardware. In still capture mode, the sensor has a native resolution of 5 megapixels. It supports up to 1080p at 30 frames per second for video mode capturing.

(E) Battery: The battery suitable for working with a robotic arm is Lithium Polymer Batteries (Li-Po). These are becoming the most popular type of batteries for use in robotics because of their lightweight, high discharge rates, and relatively good capacity, except the voltage ratings are available in increments of 3.7 V.

(F) Jumper Wires: A jump wire which is normally used to interconnect the components of a breadboard or other prototype or test circuit, internally or with other equipment or components, without soldering.

The arm facilitates automatically separating the medical waste by integrating all of the hardware components and putting Raspberry Pi to work by integrating the trained model. The arm moves following the controller, and the camera module facilitates the detection of medial waste objects. The L298N 2A motor driver is utilized to operate and control the power flow for the DC motors used in the 2 DOF robotic arm. The system's integrated components are all subject to the total control of the microprocessor. The microprocessor utilizes the trained model with a controlled flow of instructions that facilitates the efficient operation of the components. Hence, a model with good accuracy supports appropriate medical waste segregation. The accuracy of the model created depends upon the format and number of images used for training the model created.

1.4 ORGANIZATION OF THE REPORT

This report is organized into 6 chapters, describing each part of the project with detailed illustrations and system design diagrams.

CHAPTER 2: It elaborates the literature survey details of the project with methodologies, pros, cons included, etc, and the advantages of this project.

CHAPTER 3: In this chapter, the automatic medical waste segregation system design of the project with the overall architecture and the modules of the architecture and the description of the modules that are used in the project.

CHAPTER 4: A detailed overview of project implementation is elaborated in this chapter.

CHAPTER 5: This chapter elaborates on the results analysis and the performance measures performed in this proposed system.

CHAPTER 6: This chapter finally concluded with the system's advantages and disadvantages and also talks about future enhancement.

The above-mentioned six chapters are followed by the References which lists all the reference documents used during various phases of the project, including journals and articles, etc.

CHAPTER 2

LITERATURE SURVEY

This chapter elaborates on the literature survey done on the existing system and the analyses of the problem statement and issues in the existing system and the proposed objectives of the new system.

2.1 AUTOMATIC WASTE SEGREGATION USING ROBOTIC ARM

Sri Suvetha C.S et al.[1] proposed a system to Automatic Bio Medical Waste Segregator. The aim of this system is to segregate biomedical waste without human intervention. This system uses FPV camera to capture images of waste and Robotic arms for automatic segregation. The hardware components used are DC Motors, Battery, Motor driver, Raspberry Pi, IMU, LiDAR, and Camera. The model is trained for 39 epochs to decrease the training loss gradually. The training loss is 1.765964 in the first epoch and subsequently decreases as the epoch size increases whereas the training and test increase. Various Machine learning models were used to distinguish the nature of medical waste and help in reducing manpower and trimming down the disposal cost. But the main drawback of this system is that it lacks real-time processing abilities due to increased processing speed and limited speed.

An Automated Robotic Arm: A Machine Learning Approach was proposed by Krishnaraj Rao N S et al.[2]. This system uses computer-based automated systems to perform industrial tasks. The system implements automated pick and place using a Robotic arm. The machine Learning approach is used for detection and traversal, which uses the Tensorflow package for better and more accurate results. A robotic arm made up of PLA Material 3D printed is used with 5 servo motors for actuation, Raspberry Pi Camera module is used as input for object detection with GPIO pins which provide the rotation of motors. A Gripper or End effector placed at end of the arm is used to grab objects. Servo motors control the slant/level position, speed, and acceleration which is coupled with sensors for input. The ultrasonic sensor is used to measure the distance of the object from the arm. The barometric pressure sensor(BMP-180) is controlled with E2PROM and Seq 12C interface and it helps in improving the accuracy of picking. The proposed system uses models to depict the object with similarity ratio, the distance of the object, and the angle inclined with the object for accurate picking of the object with an arm.

Sawant N et al.[3] proposed a system to Implementation of Faster RCNN Algorithm for Smart Robotic ARM Based on Computer Vision. This system is used to implement automatic segregation of red and blue boxes by capturing the images with an OV5674 camera and for picking and place of boxes Arm is used. ML model with Faster Region-based Convolutional Neural Networks is proposed for the system. Raspberry Pi 3B+ is used for processing and accurately classifying Red and Blue boxes. The microprocessors used are Arduino UNO and Raspberry Pi 3B+. The system makes use of 5 megapixels Raspberry Pi Camera Module with an OV5647 sensor for capturing the inputs which works better with Raspberry Pi. The Arduino UNO used is ATmega328P with 5V operating voltage and 14 Digital I/O pins. SSD MobileNet and aster RCNN are the two Machine Learning models that are proposed in this system, where the precision and recall achieved by Faster RCNN are 81.25% and 62.63%. The precision and recall achieved by SSD MobileNet are 72.86% and 56.16%.

Automatic segregate: Dry and Wet segregation using CNN(Deep Learning) with Robotic arm proposed by Guru Prasad et al.[4]. The proposed system mainly classifies TrashNet dataset into dry and wet trash using Convolutional Neural Networks(CNN) by implementing Transfer learning. This system makes use of supervised learning methods for model creation and makes use of a Raspberry Pi controller for controlling a Robotic arm to pick up and drop the waste into bins without human intervention. The image classifier of the stream captured via the Raspberry pi (RPI) camera. It classifies the input image employing a trained model on the neural network of edge impulse supported transfer learning technique for the image. A Robotic arm controlled by the microprocessor is employed for the segregation. The TrashNet dataset used contains 2390 DRY images which are under 6 classes such as Glass, Plastic, Cardboard, metal, paper, and trash, and 175 waste and 14 fruit waste images total of 2579 images. The model created is transferred to Raspberry Pi 3B+ boasting a 64-bt quad-core processor running at 1.4GHz and dual-band at 2.4GHz. The accuracy achieved with SVM is 90% and with CNN is 84.96%.

Ravi Krishna et al.[5] proposed a system Automation of Object Segregation. The main aim of the proposed system is to segregate the objects by using the conveyor system starting with the help of geared DC motor and relay, capturing and detecting the objects and using a Dexter Er2 robot that can pick a pre-specified object and place it to the specified bin in the desired location. This model uses an image processing technique is used where the captured image is compared with the pre-specified object stored in a database. The robotic arm will be controlled and placed the objects in the desired location. The Raspberry Pi 3B+ model is used to process the captured image. The image captured other than the pre-specified object involves the conveyor starting to move an object collected at the end of the conveyor system. To control the Robotic arm the python code has been formulated based on the image processing output. Tensor flow Image processing technique to classify and initialize the robotic arm by using Servo motion profile generator GUI. The model uses Raspberry Pi with Linux operating system, USB Logitech web camera, Dexter Er2 Robotics, IR

Sensor, and Relay. USB web camera is able to deliver a clear 3-megapixel resolution image or 720p HD video recording at 30 frames/sec.

Automatic segregation of waste using Robotic Arm proposed by Bhoomika P.M et al.[6]. This paper aims in developing a Robotic arm for the segregation of waste into dry and wet, using IOT devices such as IR Sensors, Moisture sensors, DC Motors, and Wi-Fi modules. IR Sensor is used to sense the presence of waste; the Moisture sensor is used to detect dry or wet waste. DC motors are used for actuating the Robotic arm. The Robotic arm performs 4 degrees of freedom. The waste level is checked by using sensors and an alert is sent through Wi-Fi Module. This paper needs to be implemented with image classification where images can be detected by the camera and automatic segregation can be performed with a Robotic arm.

2.2 SMART WASTE MANAGEMENT SYSTEM USING INTERNET OF THINGS

A CNN-Based Smart Waste Management System Using TensorFlow Lite and LoRa-GPS Shield in the Internet of Things Environment was proposed by N.C. Anak Sallang et al.[7]. This system is used to classify and categorize materials like paper, cardboard, glass, metal, and plastic. By integrating the trained model on TensorFlow Lite and Raspberry Pi 4, the camera module detects the waste and the servo motor, connected to a plastic board, categorizes the waste into the respective waste compartment. The integration of hardware, LoRa/GPS shield and ultrasonic sensors, and algorithm written in Arduino IDE sketch can send the GPS location and waste fill percentage through LoRa transceiver. The image detection scored an average precision for cardboard at 89.0%, paper at 89.6%, metal at as95.4%, plastic at 90.2%, and glass at 94.6%. From the average result of precision, it is notable that the trained model can detect the most common waste with average accuracy higher than 80%.

ShaunakVarudandi et al.[8] proposed an approach to A Smart Waste Management and Segregation System that Uses Internet of Things, Machine Learning and Android Application [8]. This study uses trash images as input to the system, based on Machine Learning techniques to detect and classify trash waste into wet and dry waste. This system consists of cloud-connected bins, to assist and track the bin. Here, Ultrasonic sensors are used to detect whether the waste is thrown into the bin or not. Humidity sensors are used to sense the moisture present in the waste and signals are sent to the servo motors for opening the flap. GPS module with cloud helps to locate the dustbins via a mobile application. Two versions of systems were elaborated, where the first version achieves an accuracy of 75% whereas the second version achieves an accuracy of 90% in classifying waste as wet and dry.

2.3 REALTIME IMAGE CAPTURING FOR CLASSIFICATION

Nagata H et al.[9] proposed the system Real-time Extraction of Objects from Any Background Using Machine Learning[9]. The main idea used is the framework for real-time object extraction using Machine Learning and real-time extraction of objects from backgrounds of similar color using infrared. The common idea used is Background subtraction to extract objects. It involves the differences between the input image and background image by using varying thresholds. The two most important steps involved are Trimap and matting processes.

Object Detection and Tracking Using Image Processing was proposed by S. Mandgi et al.[10]. This paper uses a web camera to capture live images using the OpenCV module and uses Raspberry Pi for the detection and tracking of objects. The project aims in sorting fruits into three different categories.

Many deep learning techniques for classification are listed in the survyed articles, including RCNN, Mobile Net, and CNN, which provide good accuracy but lack real-time processing capacity. Image capturing is a tedious task. Additionally, the majority of the systems described exclusively use conveyor belts with fixed arms to segregate medical waste into the two main categories of dry and wet waste. While picking an object up from different areas and classifying waste is a difficult operation, it is simple to identify things against a uniform background and in a fixed position.

Some system employs GPS to locate Bins, and they use pressure sensors to grip objects more accurately. The suggested system is movable, navigating to the location where medical waste is situated and sorting into bins by detecting QRs to ensure proper segregation.

CHAPTER 3

SYSTEM DESIGN

This chapter consists of the system design of the project with the technical architecture and the modules of the architecture and the description of the modules used in the project.

3.1 SYSTEM ARCHITECTURE OF UNMANNED MEDICAL WASTE SEGREGATOR

The technical architecture diagram of the proposed system is shown in Figure 3.1

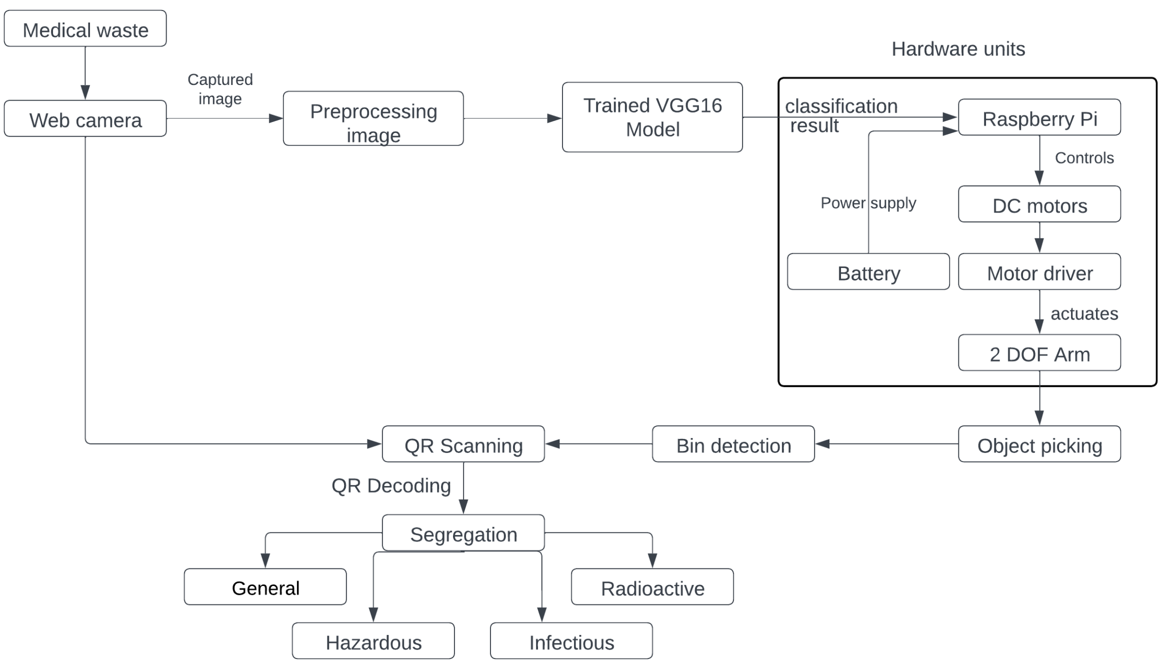

Figure 3.1: System Architecture of Unmanned Medical Waste Segregator

3.2 MEDICAL WASTE IMAGE DATA COLLECTION AND PREPROCESSING

To train a precise deep-learning model for medical waste image classification, a diverse dataset of medical waste images must be compiled and preprocessed. The following details how the data collection and preprocessing works:

1. Data Collection: A wide variety of medical waste images defining various forms of trash, including syringes, gloves, masks, sharps containers, biohazard bags, etc., were collected as data. To prevent class imbalance, the dataset must have a sufficient number of specimens for each type of waste. The medical waste images are collected from the browser using Bing downloader and manually the dataset is created with four main classes. The dataset contains 4 different classes: General waste, Infectious waste, Hazardous waste, and Radioactive waste. For effective and reliable training, the data under labels must be precise and consistent.

2. Data Preprocessing: A crucial step in preparing the dataset for training a deep learning model is preprocessing. It involves transforming and normalizing the data to improve the model's performance and facilitate effective learning. The data preprocessing is shown in Figure 3.2

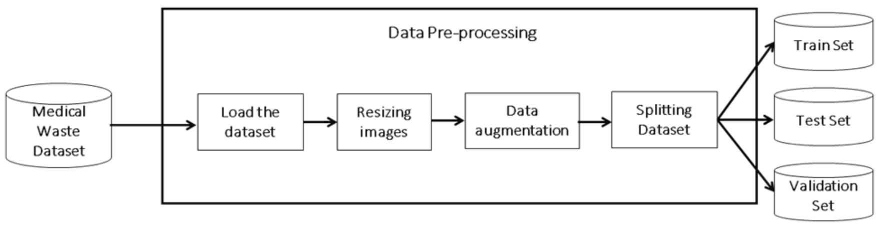

Figure 3.2: Medical waste image data preprocessing

Image resizing: Resizing each image to the same dimension that is suitable for the deep learning model. Pixel dimensions of 224x224 or 256x256 are common. Here, the medical waste images are scaled down to 224x224 pixels.

Data Augmentation: Applying data augmentation techniques to the dataset will boost its variety and generalizability. These methods include random flips, rotations, translations, and brightness/contrast modifications. In order to increase accuracy and decrease overfitting, it is applied to the input images.

Normalisation: Normalisation is the process of converting pixel values to a standard range, such as [0, 1] or [-1, 1]. Through this step, the model's training converges more quickly.

Splitting of Dataset: The dataset is then divided into a train set, test set, and validation set in order to train the model and create an accurate model. The ratio is typically 80% for training, 10% for validation, and 10% for testing.

Shuffling the dataset: Biases in training are avoided by randomly rearranging the images.

3.3 MODEL BUILDING AND TRAINING

The image from the train set is converted to an array of pixels and passed as input to Convolution layer. Features are extracted by involving various steps of pooling and convolution layer, a fine-tuned feature map is then flattened into a linear vector. The linear vector with a dense layer provides the link with the four output class labels. This CNN model is then used for model training.

Compile method is used to configure the model for training. Compiling the method takes three parameters: optimizer, loss, and metrics. The optimizer controls the learning rate. The optimizer used is 'Adam', which adjusts the learning rate throughout the training. The learning rate determines the optimal weights for the model. The loss function used is 'categorical crossentropy'. The metric used is 'Accuracy'. For training 'fit()' function is used. The CNN model built was then trained using the train set with the set of epochs (iterations on a dataset). The trained model is now tested with the images for correct classification. After completion of model training, the model is saved for further use. This saved model can be loaded again for classification. The model selected for training a medical waste image classification model is the VGG16 model.

The Visual Geometry Group (VGG) at the University of Oxford introduced the widely used deep learning model VGG16 for image classification. It is used as a standard model in the field of deep learning and has achieved good performance on a variety of image classification tasks. With a total of 16 layers, including convolutional and fully linked layers, VGG16 is known for its deep architecture.

3.4 CIRCUIT CONNECTION OF RASPBERRY PI WITH 2 DOF ARM

Both power and control connections must be made in order to link a Raspberry Pi to a 2 Degree of Freedom (DoF) robotic arm. Connect the Raspberry Pi to an appropriate power source, such as a battery or a USB power adapter. A 7.4V power supply is used here with the Raspberry Pi. Make sure the power source can deliver enough electricity to the Raspberry Pi and the robotic arm. L298N motor driver acts as the interface between the raspberry pi and DC motors along with the power supply. The L298N motor driver supports bidirectional control. The L298N motor driver is a popular and widely-used motor driver for controlling DC motors, and it has two H-bridge circuits that can be used to control the direction of the motor.

To use the L298N motor driver for bidirectional control, it is needed to connect the motor to the OUT1 and OUT2 pins (for one motor channel) or OUT3 and OUT4 pins (for the other motor channel) and set the IN1 and IN2 pins (for one motor channel) or IN3 and IN4 pins (for the other motor channel) to control the direction of the motor. The base motor in arm is connected to OUT1 and OUT2, the end effector is connected to OUT3 and OUT4. GPIO (General Purpose Input/Output) pins of the Raspberry Pi can be used to connect to external devices. The circuit connection is shown in Figure 3.3

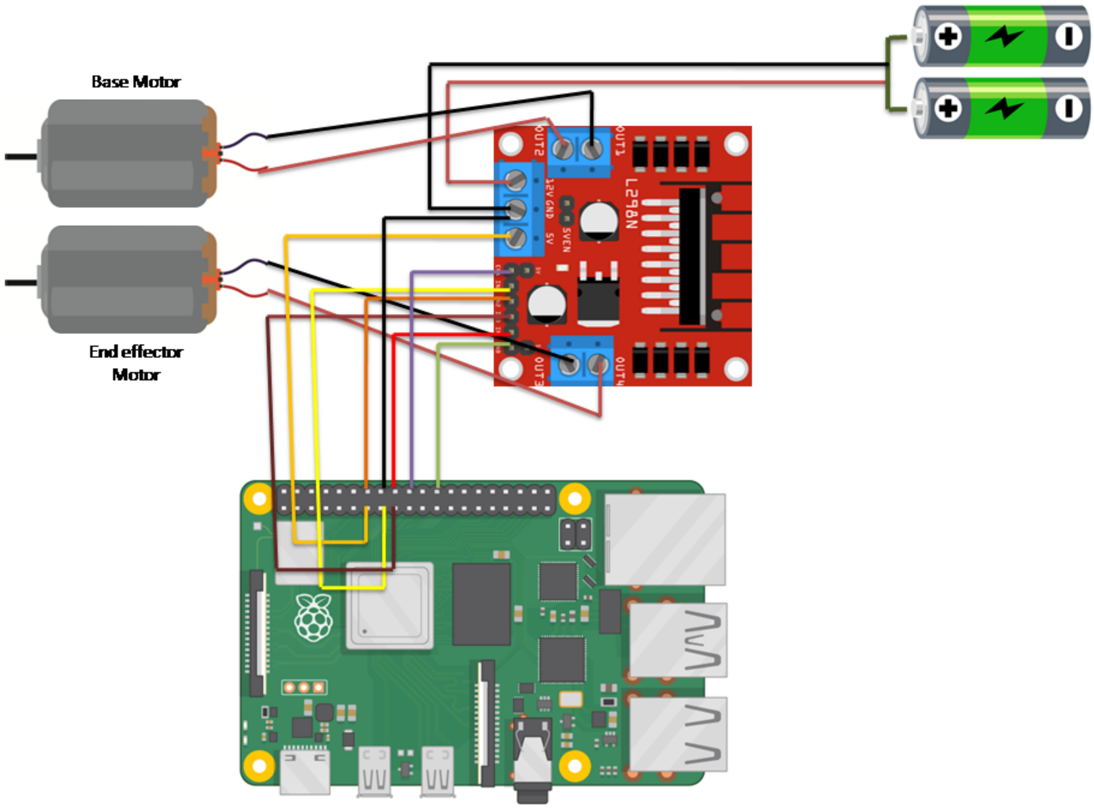

Figure 3.3: Circuit diagram of 2DoF Robotic arm

3.5 REAL TIME MEDICAL WASTE CLASSIFICATION

Real-time medical waste images are captured using a web camera. The captured images are divided into frames and classified using a machine learning model in real-time. The following section gives an overview of how the process works:

1. Capturing frames: The first step is to capture frames from the camera. This can be done using a library like OpenCV in Python, which provides functions for accessing the camera and capturing frames at a high frame rate. Python's OpenCV package is used to automatically capture images, serving as computer vision.

2. Pre-processing frames: The captured frames are then pre-processed to prepare them for classification. This may involve resizing the images to match the input size of the machine learning model, normalizing the pixel values, and applying other image processing techniques.

3. Classifying frames: The pre-processed frames are then fed into a machine-learning model, which classifies the images in real-time. The custom model has been trained on a small dataset of images where the model is created by applying transfer learning on the pre-trained model like VGG16 that has been fine-tuned for the specific task of image classification.

4. Displaying results: The results of the classification are then displayed on a screen.

This allows the user to see the results of the classification in real time. The system's effectiveness depends on how well the machine learning model performs and how quickly images are processed and classified.

The classification model built is then used with the raspberry pi camera module in real-time to detect medical waste. The raspberry pi camera module detects the position of the object that is viewed and tracked. This camera module serves as the eye for the proposed system. The images captured are transferred to the existing microprocessor, where the trained model was saved. The saved model helps in classifying medical waste. The main process involved in classifying is to detect the object by doing image segmentation by removing the background.

3.6 ROBOTIC ARM'S MOBILITY

Robotic motion is described in terms of degrees of freedom. In the concept of robotic arms, a ”Degree of Freedom” (DoF) is an independent joint that can allow the manipulator to move freely in either a rotational or translational (linear) direction. A single degree of freedom is any geometric axis that a joint can extend along or spin around.

The 2 DOF Robot experiment aims to control a four-bar linkage end effector's X-Y location. To make the process of moving objects easier and to provide the necessary motion, a pick-and-place robot arm is implemented using 2 DC motors that are connected. To make the DC motors of a robotic arm work with a Raspberry Pi, need to connect the motors to the Raspberry Pi's GPIO (general-purpose input/output) pins. Motor drivers are used to connect the motors to the Raspberry Pi. A motor driver is an electronic circuit that allows the Raspberry Pi to control the direction and speed of the motors. Connect the motor driver to the Raspberry Pi's GPIO pins. It involves connecting power and ground pins, as well as pins for controlling the direction and speed of the motors. Connect the DC motors to the motor driver, which involves connecting power and ground wires, as well as wires for controlling the direction and speed of the motors. A programming language such as Python is used to control the movement of the motors. Libraries such as RPi.GPIO or the Adafruit Motor HAT library to control the GPIO pins and send signals to the motor driver. The movement of the motors is tested by running the software and observing the movement of the robotic arm.

3.7 QR CODE DECODING AND SEGREGATION OF MEDICAL WASTE

After picking up the waste, now the Robotic arm looks for bins to segregate them into general, infectious, hazardous, and radioactive. To segregate them into respective bins, the QR code can be included. QR code detection and decoding over a bin and use it to make the robotic arm choose the correct bin. The Raspberry Pi camera captures an image of the bin and the OpenCV library helps in detecting the QR code in the image. It is done by converting the image to grayscale and then applying a threshold to binarize the image. Then use the pyzbar library to decode the information stored in the QR code. This involves extracting the encoded data from the QR code using decoding algorithms like Reed-Solomon decoding and error correction algorithms. Thus based on the decoded QR code, the robotic arm segregates the waste into the correct bin.

CHAPTER 4

IMPLEMENTATION

This chapter deals with the modules and sub-modules involved in implementing the Medical waste image classification. The tools and techniques used in the modules are detailed here.

TOOLS AND LIBRARIES USED

There are a variety of tools used to run these models efficiently. Each of the tools have contributed significantly in various technical aspects. Below is a more detailed look on the tools used:

Tool used is Pycharm IDE. PyCharm is a specialised Python Integrated Development Environment (IDE) that offers a wide range of crucial tools for Python developers. These tools are tightly integrated to produce a practical environment for effective Python, web, and data science development.Language used for this project was python 3. Libraries used were numpy, pandas, keras, tensorflow, pyzbar, cv2, opencv, matplotlib, etc. Google colab is used to train the VGG16 model.The Colab is an open-source client-server application that allows to run notebook environment entirely in the cloud.

4.1 MEDICAL WASTE IMAGE DATASET COLLECTION

Dataset contains Medical waste images, which are used for Real-time object detection and classification. The medical waste. Medical waste dataset is collected using Bing Downloader command. Initially, Google drive is mounted to the Colab. Then using the downloader command with specified sub-labels and directory, the images are downloaded and saved in the mounted google drive.

The total number of medical waste images collected using Bing Downloader is shown in Table 4.1

Table 4.1: DETAILS OF IMAGES COLLECTED FOR DATASET

Labels	Sub labels	Format of Image	Total no. of images
General Waste	Plastic Bag, Cardboard, Plastic Bottle, Aluminium Tins, Papers	.jpeg,.jpg	147
Infectious Waste	Bloody bandage, Cotton, Surgical Gloves, Surgical Apron, Mask, Oxygen tube	.jpeg,.jpg	518
Hazardous Waste	Syringe, IV bag, Tablets, Metals, Glass	.jpeg,.jpg	158
Radio-active Waste	Radioactive tins and substances	.jpeg,.jpg	105
		Total Images	928

4.2 MEDICAL WASTE CLASSIFIER MODEL

For the classification of medical waste VGG16 model is used. VGG 16 is a pre-trained convolution model with 16 deep layers. VGG is mainly designed for classification and localization. The pre-trained model is loaded using the library tensorflow which works for multi-dimensional arrays for high computations. After loading the VGG model with its trainable layer as false, the layers are flattened and fully connected to neurons in the dense layers. In the end, softmax activation is applied and VGG model is built. Even though, it is very slow to train (the original VGG model was trained on Nvidia Titan GPU for 2-3 weeks). The size of VGG-16 trained imageNet weights is 528 MB. So, it takes quite a lot of disk space and bandwidth which makes it inefficient. 138 million parameters lead to exploding gradients problem. As a result of using the manually created dataset, the accuracy tends to be lesser. The model was able to predict 90% of data under radioactive correctly and 70% of hazardous data correctly. Whereas, it could be able to find 60% of infectious data and 50% of general data.

4.3 REAL-TIME OBJECT DETECTION

Algorithm : 1 - Real-time Object Detection

```
Input: A Video
Output: Detection and classification of Medical Waste
video = Real − Time Video
for each frame of video do
    if frame is not None then
        return resize(Normalize(frame), standardized)

    else
        return None
    end if
end for
for each frame of preprocessedFrame do
    if frame is not None then
        return VGG16(frame)
    else
        return None, None
    end if
end for
```

The above algorithm-1 is used to detect and identify objects in real-time video streams. These algorithms use deep learning models to detect objects and their respective positions in a video frame. Algorithm-1 can be optimized by using techniques such as model compression, pruning, and quantization to reduce the computational complexity of the deep learning model, and by using hardware accelerators such as GPUs and TPUs to speed up the inference process.

Once the objects are detected, using the trained VGG16 model the objects can be classified into four different classes General waste, Hazardous waste, Infectious waste, and Radioactive waste. The classified result is used for the movement of the Robotic arm.

4.4 MOVEMENT OF ROBOTIC ARM

The 2 DoF robotic arm uses a Raspberry Pi and an L298N motor driver for the actuation. Setting up the Raspberry Pi and L298N motor driver by connecting the motor driver to the Raspberry Pi using jumper wires.

Connect the motors of the robotic arm to the L298N motor driver, making sure to connect the correct motor wires to the correct terminals of the motor driver. The positive and negative terminal of the motor located at the base of the arm is connected to OUT1 and OUT2. The positive and negative terminal of the motor located at the end effector of the arm is connected to OUT3 and OUT4. The Ground in the motor driver is connected to the negative of 7.4V battery. Initialize the GPIO pins by connecting with the OUT and IN pins of the motor drivers of Raspberry Pi that will be used to control the L298N motor driver.

The functions are defined to control the movement of the motors based on the text input. This function should take in the desired direction of movement (up, down and open, close) and the speed of movement. In the function, the direction of the motors is set by the IN1, IN2, IN3, and IN4 pins of the L298N motor driver. Set the speed of the motors by using Pulse-Width Modulation (PWM) to control the voltage applied to the motors. The function is called to control the movement of the motors based on user input. Making any necessary adjustments to the code or wiring to get the robotic arm working properly.

Once the robotic arm is working correctly, consider adding additional service, such as the ability to move to specific positions or follow a pre-defined path. Based on the text the arm picks up the medical waste and looks for the QR for segregation.

4.5 QR CODE DECODING

Algorithm : 2 - QR Code Decoding

```
Input: A Video
Output: Decoded QR code information
video = Real − Time Video
frame = None, QRobj = [ ], Text = None
for each frame of video do
    if frame contain QR then
        QRobj = decode(frame)
    end if
    if len(QRobj) == None  then
        Display frame
    else
        for each obj in QRobj do
            Text = obj.data.decode('utf-8')
            points = obj.polygon
            Display frame by drawing polygon and display Text
        end for
    end if
    return Text
end for
```

Algorithm-2 decodes the QR in real time and returns the text for segregation. The algorithm takes the input of live video captured by the web camera. Each input video frame is decoded with 'decode()', a pyzbar library function. This function involves the conversion of input into grayscale using cv2.cvtColor() and detects the contours with help of cv2.findContours(), where each contour is a binary image. The decoded output is provided in the list that has the following attributes:

1. Data: A byte string containing the decoded message.
2. Type: A string indicating the type of the decoded symbol (e.g., ”QRCODE”).
3. Polygon: A list of (x,y) coordinates of the corners of the QR code polygon.

If no QR codes are detected in the frame, an empty list is returned. The text is extracted from the decoded list and the polygon value are then drawn over the real-time video. The text is returned as the final decoded output which is used for the segregation into bins.

4.6 SEGREGATION OF MEDICAL WASTE INTO BINS

Algorithm : 3 - Segregation of Medical waste into Bins

```
Input: Text from Classifier and QR decoder
Output: Segregation of the medical waste into the bin
Get the CText and QRtext
if CText == QRtext then
    Drop the medical waste into the bin
else
    Search for another bin (correct QR)
end if
```

The algorithm-3 takes the input texts from the classifier and QR decoder. The medical waste is dropped into the bin that matches the information obtained from both the classifier and the QR decoder. This system uses the labeling of the bins with unique QR codes. If there is a mismatch between the two sources of information, the algorithm-3 search for the correct bin that matches the QR code with the classifier. This algorithm assumes that the classifier and QR decoder can accurately identify the type of medical waste and the corresponding bin for proper segregation of medical waste without human intervention.

CHAPTER 5

RESULTS AND PERFORMANCE ANALYSIS

This chapter is intended to highlight the importance of results reporting in the context of testing. This section gives the accuracy and the results of the classification and performance analysis. This section also provides the result of segregation by 2 DOF robotic arm.

MEDICAL WASTE IMAGE CLASSIFIER

Transfer learning is used to classify medical waste using the model VGG16, which is an object detection model that is a pre-trained model. The medical waste image dataset, which consists of 928 images of bio-medical waste that was gathered from Google images using the Bing Downloader, is used to train the medical waste classifier model. It includes general, infectious, hazardous, and radioactive medical wastes. Each image is in the size of 224x224 pixels and is RGB-colored. The dataset has been divided into three sections for model training, testing, and validation: 80%, 10%, and 10%. The dataset for medical waste is described in Table 5.1.

Table 5.1: MEDICAL WASTE DATASET DESCRIPTION

Set	General	Infectious	Hazardous	Radio-active	No. of Images
Train set	117	126	414	84	741
Test set	16	17	53	11	97
Validation set	14	15	51	10	90
Total images					928

Only 928 items are available in the dataset; hence, expanding the dataset may improve model accuracy and classification performance. For improved performance that prevents the model from being under-fitted, image files are reshaped and zoomed by performing augmentation. The model's accuracy during training and validation is 100% and 84.4%, respectively. It significantly improves real-time video classification. Here, 741 images had been utilised for training, 97 images were used for testing, and 90 images were used for validation. On evaluating with the test dataset, the model achieves a classification accuracy of around 85%. The model training is shown in the Figure 5.1.

```
[20] train = model.fit_generator(train_data_gen, steps_per_epoch = training_steps_per_epoch, validation_data=val_data_gen, validation_steps=validat
     print('Training Completed!')

Epoch 1/10
24/24 [==============================] - 609s 25s/step - loss: 20.0617 - accuracy: 0.5452 - val_loss: 5.1841 - val_accuracy: 0.6667
Epoch 2/10
24/24 [==============================] - 549s 23s/step - loss: 2.2683 - accuracy: 0.8421 - val_loss: 2.7985 - val_accuracy: 0.8556
Epoch 3/10
24/24 [==============================] - 566s 24s/step - loss: 0.3423 - accuracy: 0.9609 - val_loss: 2.7547 - val_accuracy: 0.8444
Epoch 4/10
24/24 [==============================] - 567s 23s/step - loss: 0.0546 - accuracy: 0.9879 - val_loss: 2.6417 - val_accuracy: 0.8556
Epoch 5/10
24/24 [==============================] - 565s 24s/step - loss: 5.8710e-05 - accuracy: 1.0000 - val_loss: 2.4152 - val_accuracy: 0.8333
Epoch 6/10
24/24 [==============================] - 565s 24s/step - loss: 4.7056e-05 - accuracy: 1.0000 - val_loss: 2.4041 - val_accuracy: 0.8556
Epoch 7/10
24/24 [==============================] - 566s 24s/step - loss: 3.8688e-05 - accuracy: 1.0000 - val_loss: 2.4042 - val_accuracy: 0.8556
Epoch 8/10
24/24 [==============================] - 565s 24s/step - loss: 3.4941e-05 - accuracy: 1.0000 - val_loss: 2.4051 - val_accuracy: 0.8556
Epoch 9/10
24/24 [==============================] - 563s 24s/step - loss: 3.2219e-05 - accuracy: 1.0000 - val_loss: 2.4065 - val_accuracy: 0.8444
Epoch 10/10
24/24 [==============================] - 544s 23s/step - loss: 2.9899e-05 - accuracy: 1.0000 - val_loss: 2.4074 - val_accuracy: 0.8444
Training Completed!
```

Figure 5.1: Medical Waste classifier Model Training

The model's accuracy on the training dataset that it observed through the training process is represented by the training accuracy. The validation accuracy indicates the model's performance on the validation dataset, which is comprised up of unobserved data that is utilised to evaluate its efficiency.

The model achieves good accuracy on both the training and validation sets, as can be observed from the stated accuracy values in the Figure 5.1. The training accuracy gradually increases with each epoch, reaching 100% accuracy in the later epochs, which indicates that the model is able to effectively learn from the training data. The validation accuracy, though, varies between 85-86% and does not reach the same level as the training accuracy, indicating that the model might be slightly overfitting the training set.

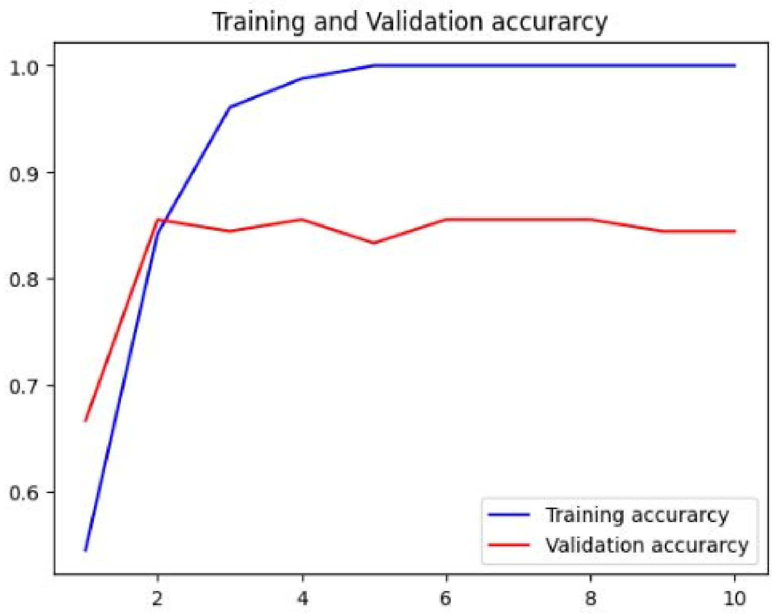

Figure 5.2: Model's performance on Train and validation accuracy

The training accuracy is represented by the blue line in the Figure 5.2. It demonstrates how the model's accuracy increases with each epoch. The training accuracy starts in the first epochs at about 55% and subsequently increases. The training accuracy eventually strikes 100% in the later epochs, indicating that the model is able to properly classify all of the training samples while it continues to learn from the training data.

The validation accuracy is represented by the red line in the Figure 5.2. It illustrates how, gradually, the accuracy of the model on the unseen validation dataset increases. The validation accuracy begins around 66–67% and varies between 85-86% during the training time. Considering the fluctuations and the observation that the validation accuracy does not increase at the same rate as the training accuracy, it is possible that the model may slightly overfit the training set of data. But through the epochs, it generally maintains a relatively high level of accuracy.

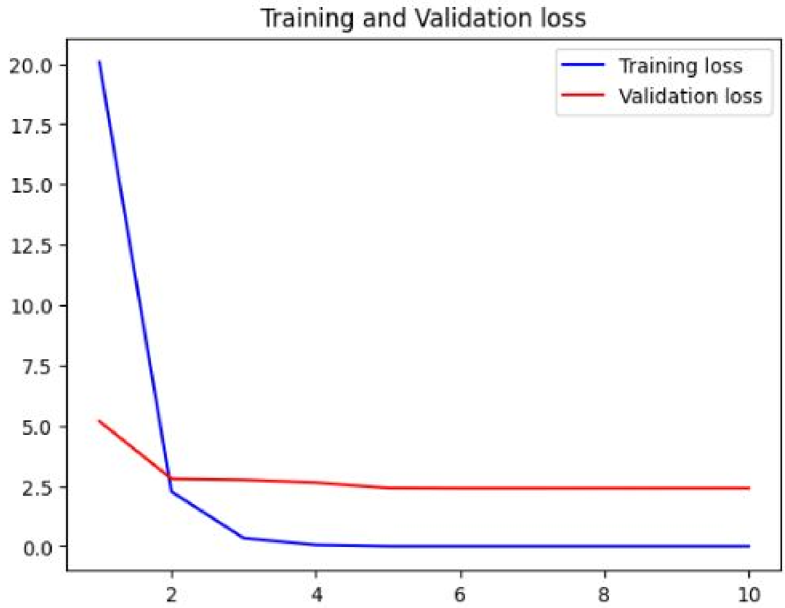

Figure 5.3: Model's performance on Train and validation loss

The training loss and validation loss values for each epoch of the training process are shown in the output that is provided in the Figure 5.3. The loss values represent the value of the loss function, specifically the categorical cross-entropy loss, which is commonly used for multi-class classification tasks.

The difference between the model's predicted results and the actual labels on the training dataset is seen in the training loss. A decreased training loss generally means that the model is learning and getting better at making accurate predictions based on the training data. Here, the training loss begins at a high value 20.0617 in the first epoch and decreases gradually with each consecutive epoch to reach low values 2.9899e-05 in the subsequent epochs. This shows that the model is effectively fitting the training data and providing highly accurate predictions.

The validation loss measures the performance of the model on a separate validation dataset that it was not used during training. It provides an estimate of how well the model generalizes to unseen data. Ideally, the validation loss should be low, indicating that the model is not overfitting the training data and can make accurate predictions on new data.

In the provided output, the validation loss values also decrease over the epochs, but they fluctuate around certain values 2.7985 to 2.7547 without showing significant improvement. This suggests that the model might be slightly overfitting the training data, as the validation loss is not decreasing as much as the training loss.

```
4/4 [==============================] - 63s 14s/step
              precision    recall  f1-score   support

           0       0.83      0.94      0.88        16
           1       0.86      0.91      0.88        53
           2       0.85      0.65      0.73        17
           3       0.90      0.82      0.86        11

    accuracy                           0.86        97
   macro avg       0.86      0.83      0.84        97
weighted avg       0.86      0.86      0.85        97
```

Figure 5.4: Classification Report

The classification report of the medial waste image classification model is depicted in the Figure 5.4. The model's performance for each class is thoroughly evaluated in the classification report, along with overall performance metrics. It provides information on the model's precision, recall, accuracy, and F1-score, providing a thorough examination of its strengths and weaknesses in classification tasks. The macro average determines the average F1 score, recall, and precision for all classes. The precision, recall, and F1-score macro averages are 0.86, 0.83, and 0.84, respectively. The weighted average calculates the average precision, recall, and F1-score weighted by the number of samples in each class. The precision, recall, and F1-score weighted averages are 0.86, 0.86, and 0.85, respectively. The overall accuracy of the model on the test dataset is 86%.

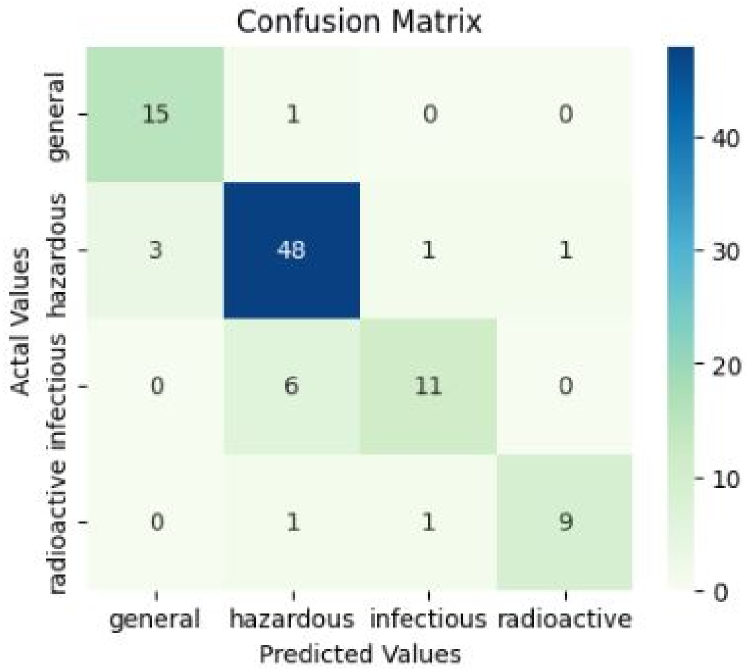

Figure 5.5: Confusion matrix for Medical Waste classifier

The confusion matrix for the Medical Waste classifier using the VGG model is depicted in Figure 5.5. It demonstrates that classes 0, 1, and 3 contain some false positives and false negatives, whereas class 2 contains false negatives. These mistakes show that the model might have problems or need to be improved. Overall, the model performs effectively and has a high accuracy rate.

REAL-TIME MEDICAL WASTE CLASSIFICATION

The Real-time classification of medical waste is performed using transfer learning of the VGG16 classifier model. The model utilises video frames in real time and classifies the object. For a more accurate classification, the frame must include a plain background and a medical object. The classifier is able to classify the medical waste into General, Hazardous, Infectious and Radio-active.

Figure 5.6 shows the output predicted as General by the classifier. Paper, Cardboard, plastics, tins, and houshold wastes are classified as General waste. About 10 objects were classified correctly in real-time by the model created using the webcamera.

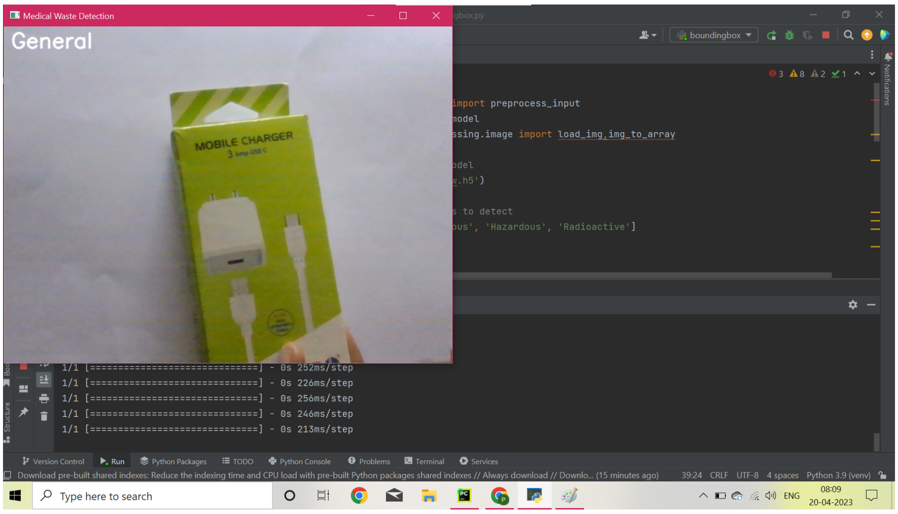

Figure 5.6: Classified result of Medical waste as - General

Figure 5.7 shows the output predicted as Hazardous by the classifier. Chemicals (medical and industrial), old drugs, and sharps (needles, scalpels, lancets, etc.). are classified as Hazardous waste.

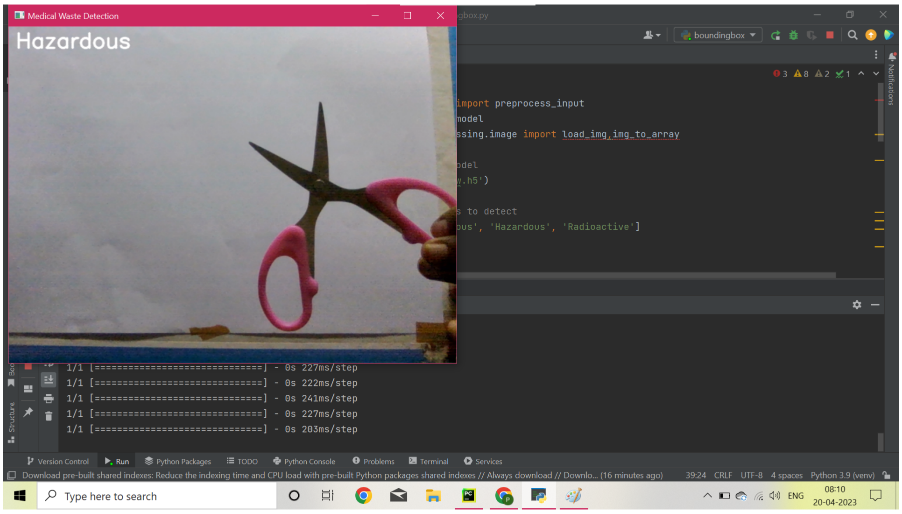

Figure 5.7: Classified result of Medical waste as - Hazardous

Figure 5.8 shows the output predicted as Infectious by the classifier. Human/animal tissue, blood-soaked bandages, surgical gloves, cultures, stocks, or swabs are classified as Infectious waste.

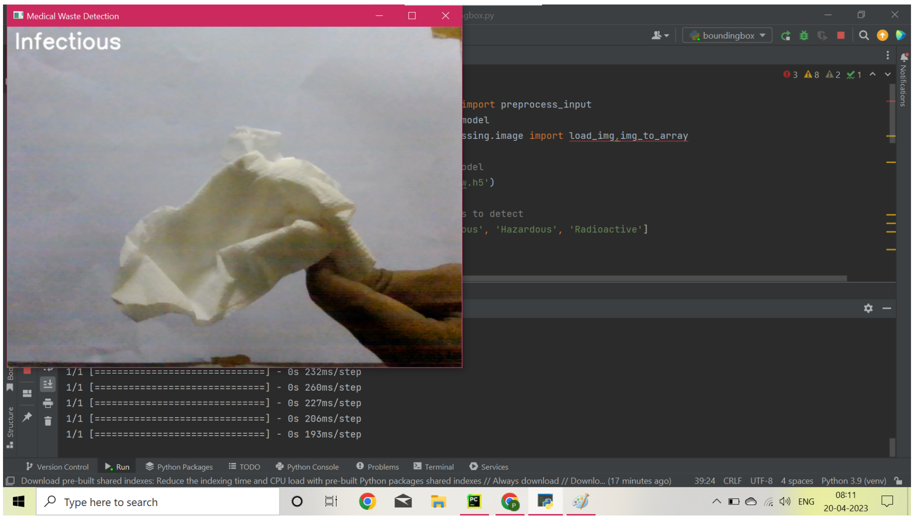

Figure 5.8: Classified result of Medical waste as - Infectious

Figure 5.9 shows the output predicted as Radioactive by the classifier. Radio-active tins and cans, and Wastes from nuclear medicine treatments, and cancer therapies are classified as Radioactive waste.

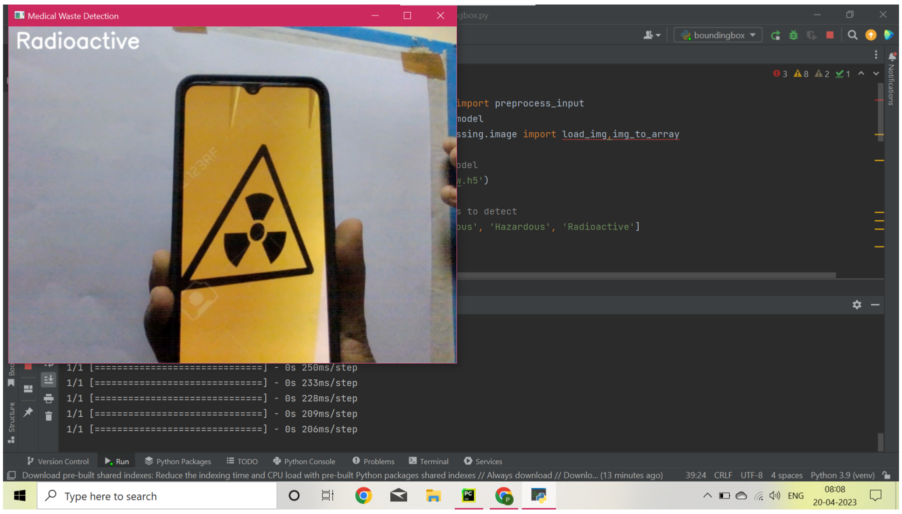

Figure 5.9: Classified result of Medical waste as - Radioactive

The model is capable of classifying the waste at greater speed and good accuracy. The text result from this module is used in QR decoding for choosing the bins to drop the medical waste picked by the arm.

QR DETECTION AND DECODING

QR (Quick Response) codes are two-dimensional barcodes that stored text information such as general, hazardous, infectious, and radioactive. The Python APIs that are capable of detecting QR are used to capture QR from the frames in real-time. Initially before integration, this module takes manual input from user as a result of classification. The output window is shown in Figure 5.10. This input text must match the QR code.

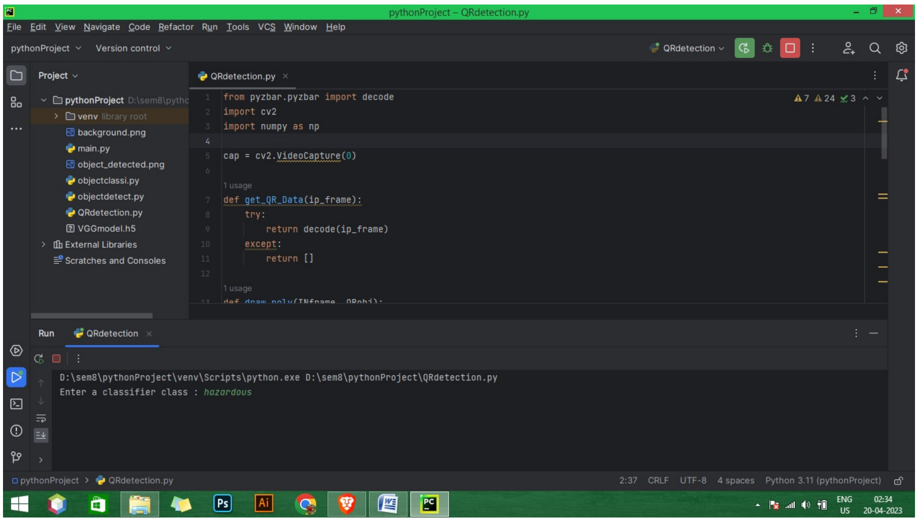

Figure 5.10: Output of user input as classifier

Figure 5.11 shows the output window that displays the decoded text output of QR code. When both text matches, the module stops searching for a QR code corresponding to the classification result and signals the arm to place the waste in a bin. The output window in Figure 5.12 displays the result of QR decoding by matching the decoded text with the corresponding classification result.

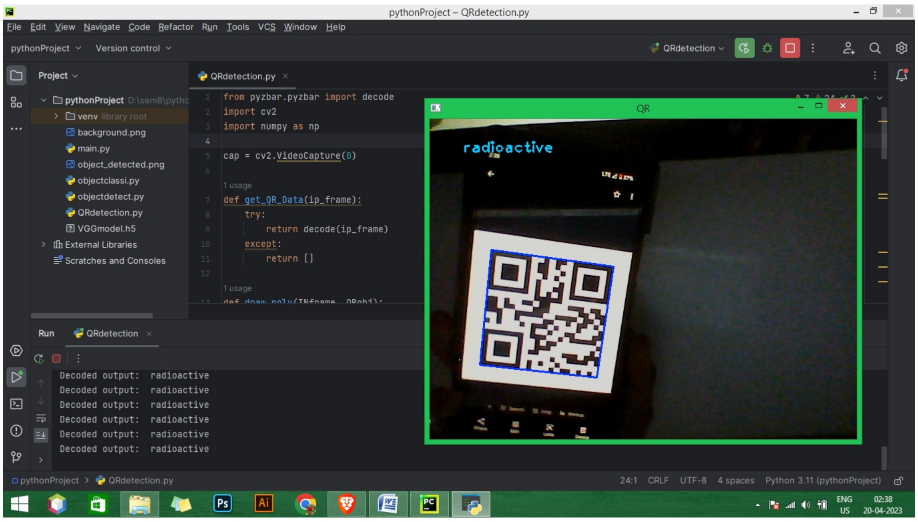

Figure 5.11: Output of QR detection and decoding

The QRs used in this system must be static in order to provide the necessary text information because it is fixed to the garbage cans. Static QR codes have fixed data inside them that never changes. Additionally, it makes it simple for the arm to locate bins. whereas if coloured bins are utilised, colour identification may be difficult due to many factors like lighting, colour variations, shadows, and image noise.

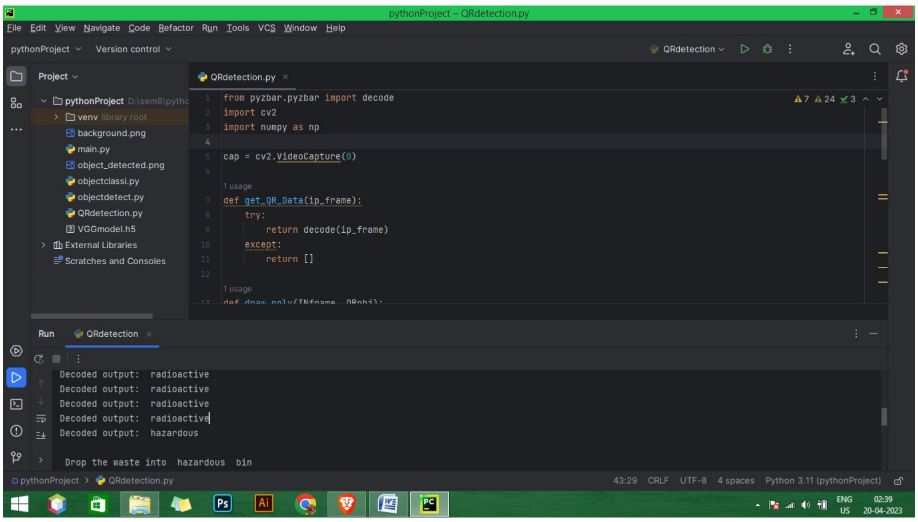

Figure 5.12: Output of QR decoding and result

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ROBOTIC ARM MOVEMENT

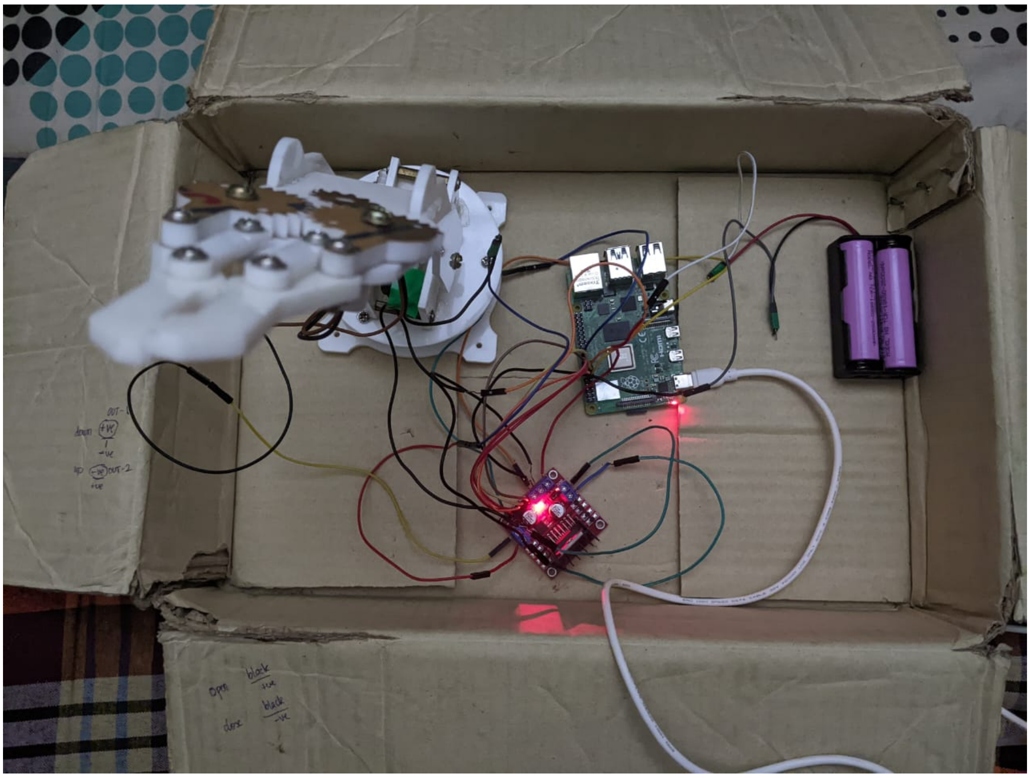

Figure 5.13: Circuit Connection of 2 DoF Robotic arm

The 2DoF arm circuit connection with raspberry pi, L298N motor driver and 7.4V Lithium-ion batteries were shown in Figures 5.13. The arm can pick up and drop objects up to 4 cm in width and can move forward and backward. The motor driver receives the signals from the raspberry pi and uses them to transmit controlled signals to power on the dc motors and operate the arm. To make the robotic arm operate autonomously, the two modules Real-time classification and QR decoding stated above need to be integrated. Now the arm is capable of picking and placing objects with respect to the instruction given in code.

CHAPTER 6

CONCLUSION AND FUTURE WORK

This chapter concludes with details of the result and discusses future improvements.

This project will demonstrate how the CNN models were used to classify medical waste. The trained model classified the medical waste data set into four categories with the help of VGG16. The four categories are general, infectious, hazardous, and radioactive. According to its category, the 2 DOF arm, which is capable of moving both forward and backward, is commanded to pick and place the object. Using a Webcam the object is identified and separated into bins and its corresponding categories based on the QR code. The QR code contains the type of category that it belongs to. Thus the arm segregated the medical waste into respective bins.

The project has completed the waste segregation effectively using the robotic arm. The trained model facilitates the robotic arm in more accurately classifying medical waste. Future research may look for techniques that improve object detection and classification while requiring less response time. By using automated waste collectors that are capable of moving, several improvisations may be made in the way waste is separated, and the collected waste can be deposited into different containers.

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