Journal of King Saud University – Computer and Information Sciences 34 (2022) 2072–2087

Contents lists available at ScienceDirect

Journal of King Saud University – Computer and Information Sciences

journal homepage: www.sciencedirect.com

Intelligent waste management system using deep learning with IoT

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ARTICLE INFO

Article history:
Received 18 April 2020
Revised 10 August 2020
Accepted 29 August 2020
Available online 5 September 2020

Keywords:
Deep Learning
Internet of things (IoT)
System Usability Scale (SUS)
Waste classification

ABSTRACT

Waste management leads to the demolition of waste conducted by recycling and landfilling. Deep learning and the Internet of things (IoT) confer an agile solution in classification and real-time data monitoring, respectively. This paper reflects a capable architecture of the waste management system based on deep learning and IoT. The proposed model renders an astute way to sort digestible and indigestible waste using a convolutional neural network (CNN), a popular deep learning paradigm. The scheme also introduces an architectural design of a smart trash bin that utilizes a microcontroller with multiple sensors. The proposed method employs IoT and Bluetooth connectivity for data monitoring. IoT enables control of real-time data from anywhere while Bluetooth aids short-range data monitoring through an android application. To examine the efficacy of the developed model, the accuracy of waste label classification, sensors data estimation, and system usability scale (SUS) are enumerated and interpreted. The classification accuracy of the proposed architecture based on the CNN model is 95.3125%, and the SUS score is 86%. However, this smart system will be adjustable to household activities with real-time waste monitoring.

1. Introduction

Waste management refers to those activities and actions which are required to dominate from its inceptions to demolition. Waste can be gas, liquid, or solid. Several numbers of processes are applied to deal with all types of waste, including biological, industrial, and household. Household waste can be cardboards, plastics, papers, glasses, bio waste, etc. In household activities, no trash can be recycled or classified into biological or materials. Following EUROSTAT (EUROPA, 2020), 56% or 423 million tons of waste generated domestically were recycled in 2016 in the European Union. Again, 24% or 179 million tons of waste generated locally were landfilled in 2016 in the European Union. The reports remarkably indicate how proper management of household waste is required for the recycling process. If we bind the waste management system and modern technology together, the result would be uncountable. Adequate supervision of waste results in a friendly biological environment.

Machine Learning (ML) refers to a significant function of Artificial Intelligent (AI) that allows a system the ability to learn and make the decision automatically without being explicitly instructed. Machine learning is a scientific study of some statistical models and algorithms. Due to offering the most exceptional features in computing, the popularity of ML has reached the highest peak. According to recent statistics by Tractica (CAPTERRA, 2020) shows that the market growth of ML and AI-based technology was $1.4 billion in 2016, and the growth will be increased $59.8 billion by the year 2025. These statistics clearly show the popularity of ML-based applications. Similarly, deep learning is an essential part of machine learning. The convolutional neural network (CNN) is a momentous class of deep neural networks, more specifically, deep learning. CNN presents tremendous progress in image recognition. In general, they are applied to evaluate visual imagery and often worked beside the image classification. They can be identified at the core of everything from Facebook's photo tagging to self-driving cars. They're working hard behind the scenes in everything from healthcare to security.

On the other hand, the Internet of things (IoT) refers to a system of interconnected devices, digital or often some analog machine that enriches the ability to transfer data over a network beyond demanding human to computer interactions. A statistic on IoT

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https://doi.org/10.1016/j.jksuci.2020.08.016
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(FUSON, 2020) estimated that average up to 127 new IoT devices being connected with public networks every second. Following the speedy growth, 328 million things are being connected every month. These statistics show how IoT would become significant in modern computing. As the popularity of IoT increasing day by day, the business market of IoT has also been increased. The statistics calculated that the global market of IoT will be $151.2 billion in 2023 only in smart home sectors. The whole IoT market can be classified into several branches such as heath market, banking and financial transaction, and education and training types of equipment. Researchers believe that all the digital and analog devices will be brought under the control of IoT in the following years. According to STATISTA (STATISTA, 2020), the projected market of IoT will be $1.1Trillion in the year 2023. These statistics significantly remarks on how IoT plays a vital role in the digital world.

The proposed system implements a smart system where users can take necessary precautions on the waste management system. The contributions of the paper are as follows:

- A unique way to combine two technology namely IoT and deep learning paradigms is to ensure an optimal solution in the field of garbage management.
- An intelligent way to classify bio waste and non-bio waste through image classification using deep learning.
- An architectural development process of smart trash box using ultrasonic sensor, load measurement sensor, and micro-controller.
- A smart way to monitor waste in real-time conducted by Bluetooth communication for short-range, and IoT technology for long-range using Android application.

This article is arranged into six sections. Section 2 describes the overview of related contributions; section 3 presents the overall methodology and implementation process. Section 4 depicts the data calculation process; section 5 represents the results of our proposed system along with related discussion. Finally, section 6 illustrates the conclusion of this manuscript.

2. Related Work

This section presents previous work related to our proposed model. Many great contributors had placed a significant trace in the field of machine learning and IoT on waste management. In a later work (Bobulski and Kubanek, 2019), the authors had developed a waste classification system using image processing and Convolutional Neural Network (CNN). In their work, they had only focused on the detection of polyethylene. The authors had also performed several numbers of experiments to detect terephthalate, polyethylene, high-density polyethylene, polypropylene, and polystyrene. In a study (Sreelakshmi et al., 2019), the authors had used Capsule Neural Network (Capsule-Net) for solid waste management, which was capable of detecting plastic and non-plastic materials. The authors had worked on two public data sets and found the accuracy of 96.3% and 95.7%. The complete integration was developed and tested on several hardware devices. In a study of paper (Huiyu and O, O. G., & Kim, S. H., 2019), the author had proposed a unique classification model to identify the types of waste using deep learning mechanisms. The system was also applied to recycle garbage. The paper (Adedeji and Wang, 2019) had proposed a scheme where a deep learning paradigm automatically identified garbage. The authors also claimed that the model was also applied in the classification of recycled waste. The authors of the paper (Nowakowski and Pamuła, 2020) had presented the waste classification method using a pre-trained CNN model identically known as ResNet-50 and Support Vector Machine (SVM). The accuracy of the model was 87%, which was tested on a public dataset. In paper (Misra et al., 2018), the authors had investigated a novel system of identification and classification of electronics waste, known as e-waste. The model utilized a CNN model to classify and an RCNN model to identify several types of e-waste. The authors tracked out the accuracy of detection and classification ranged from 90 to 97%. The authors of paper (Bobulski and Kubanek, 2019; Sreelakshmi et al., 2019; Huiyu and O, O. G., & Kim, S. H., 2019; Adedeji and Wang, 2019; Nowakowski and Pamuła, 2020; Misra et al., 2018) had only focused the architectural design of garbage classification systems using a deep learning system, but waste management with IoT was not proposed. In paper (Samann, 2017), the authors had introduced a significant way of the automated, robust waste management process. The authors depicted a smart trash bin designated by the ultrasonic sensor and several numbers of gas sensors. The authors had also proposed a real-time view of waste using cloud server and android application. Again, no machine learning approaches had been utilized. In a study of paper (Malapur and Pattanshetti, 2017), the author had presented a cost-effective and intelligent trash bin to ensure waste management. Due to bringing the system under the operation of IoT, the authors had added a set of devices like Arduino nano, ultrasonic sensor, and a GSM module. When the waste level crossed a minimum threshold level, the system would send an SMS to the User's mobile number using the GSM module. The system was enriched with a PIR motion sensor and a memory card that was responsible for assigning an audio message to the users. The author also claimed that the performance of the proposed system was satisfactory. The authors of paper (Singh et al., 2016), had designed a way of waste management for the smart city. The proposed model was cost-effective and time reductive. In the article (ALFoudery, A., Alkandari, A. A., & Almutairi, N. M., 2018), the authors have implemented a solution to improve waste collection and designed an IoT based model using a Raspberry pi and infrared sensor. The manager of the system was liable for scheduling and routing to improve the waste collections. In paper (Balaji, 2017), the authors have designed a smart trash bin that was capable of detecting the waste level. The proposed model was identically based on Wi-Fi and web server. The authors had used an infrared distance measurement sensor to find the empty level of the trash bin. The corresponding result and data were sent via webserver towards an android application. In a study of paper (Hong et al., 2014), the authors had also introduced a smart trash can using the mechanism of IoT and Raspberry pi. The authors of paper (Bai et al., 2018) had implemented an IoT based smart garbage system to reduce the amount of food waste. The authors had used mesh technology to bring all the components under control. The proposed model was integrated with a router and a server to collect and analyze the information for food poisoning. After successfully tested on several experiments, the amount of food waste was reduced by 33%. The contributions of the papers (Samann, 2017; Malapur and Pattanshetti, 2017; Singh et al., 2016; ALFoudery, A., Alkandari, A. A., & Almutairi, N. M., 2018; Balaji, 2017; Hong et al., 2014; Bai et al., 2018) had proposed the development of IoT based waste management system, but the authors did not provide any structural design of the garbage management scheme using the terminology of deep learning paradigm. The author of the paper (Muthugala et al., 2020) had introduced a waste pick up robot that could move on the ground. The authors had claimed that the proposed architecture detected garbage accurately using deep learning mechanisms. The accuracy of the developed prototype was 95% in waste detection. In paper (Spanhol et al., 2016), the author had proposed an innovative floor cleaning robot. The developed model had utilized a fuzzy inference system to ascertain the tradeoff between area coverage and energy usage of a tiling. The model accommodated a Weighted Sum Model (WSM) based on multiple criteria decision making (MCDM) per user preference depicted by a fuzzy inference system. In the study of paper (Muthugala et al., 2020; Spanhol et al., 2016), the authors had introduced a prototype of a waste management robot using deep learning and fuzzy inference system respectively, but contributions on IoT was not claimed.

3. Methodology

The proposed methodology is a combination of two parts, namely, waste classification through convolutional neural network and architectural design of smart trash boxes, which aids real-time data monitoring using IoT. Two structural models are merged to find excellent results in the field of waste management. Classifying wastes into proper categories helps to identify reusable waste. Identifying recyclable wastes let us utilize them without deteriorating. In the extent of image classification, deep learning algorithms acquire peerless results. The scope of minimizing the misuse of recyclable components inspires authors to add deep learning for waste classification while monitoring waste to differentiate recyclable wastes. In this article, we have divided the wastes into two broad categories named digestible and indigestible. Lack of sufficient data for waste classification, we have used finetuned models for waste classification. The waste classification using deep learning technology helps to attain categories of wastes from images. The architecture of trash boxes enables multiple sensors to take readings and data transmission for monitoring. Fig. 1 shows a block diagram of the system.

In this proposed scheme, a camera module will scan the waste materials. After successfully finishing the waste scanning and image capturing process, a pre-processing component for the captured images taken by the camera in real-time is performed. The model utilizes the only image resizing due to ensure less complexity. After that, the pre-processed images are processed by a microprocessor (Raspberry pi). The microprocessor will classify the image using a classifier and sends a command to a servo motor to put waste into the corresponding trash box. The microcontroller of the trash box will send data to an android application for real-time monitoring. This system also includes a roller which is capable of carrying the waste according to the instructions from the processing unit. Whenever the processing unit classifies waste, it sends a signal to the roller to carry that waste to the servo motor. Afterward, it stops rolling and waits for the next command from the processing unit.

3.1. Working Principle of Camera Module and Servo Motor

The camera module is attached to the microcontroller of the proposed system and responsible for capturing images of wastes. Fig. 2 shows a flow chart diagram of a camera module. Primarily, the system will be initialized and prepared for image acquisition. The camera module captures an image and sends it to the microcontroller. After receiving the image, the microcontroller will feed the image to an already trained CNN model, and the model will make a response about that image. The microcontroller uses CNN response to instruct servo motor to put the waste into the respective trash box. The microcontroller takes the decision based on the probability of individual waste belong to digestible or indigestible. Then servo motor performs its job by taking the waste and put it into the respective trash box.

3.2. Implementation and Working Principle of Trash Box

This section describes the design principle and development process of the proposed architecture of the smart trash box. Fig. 3 shows the block diagram of our developed trash box. In this figure, a micro-controller named "ESP8266" node MCU is used to program the overall methodology. An ultrasonic sensor is attached

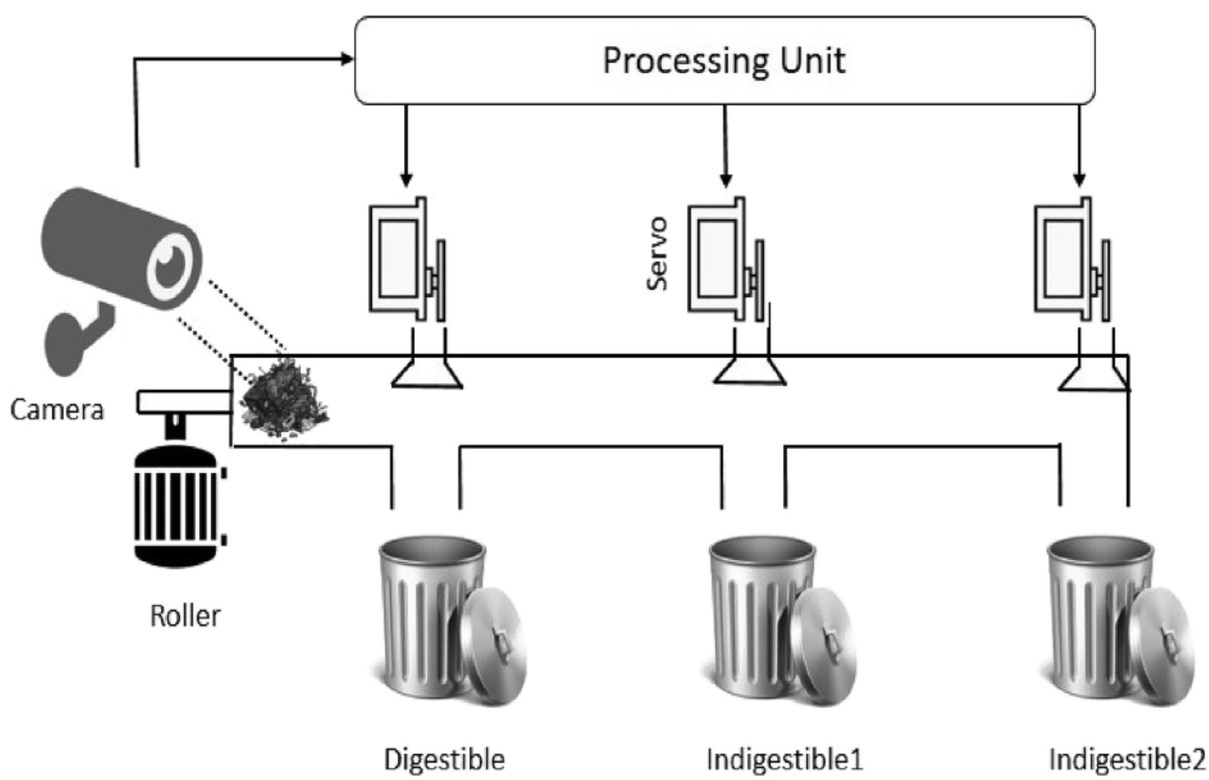


Figure 1. A block diagram of the proposed smart system

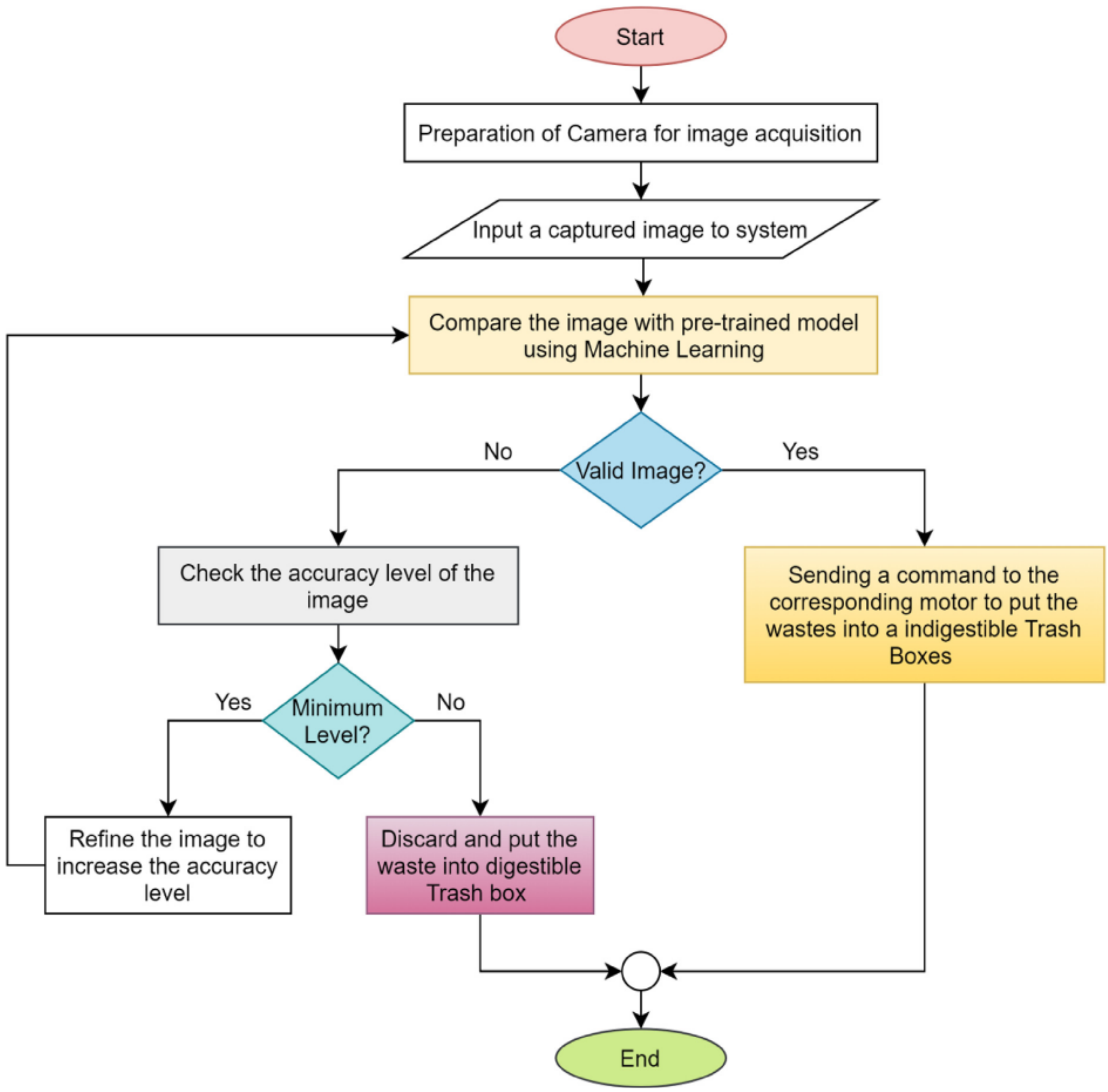


Figure 2. Camera module working principle

to the microcontroller to measure the empty level of the trash box. The ultrasonic sensor is placed at the top of our developed model. Ultrasound is transmitted and received to calculate the empty level of the trash bin. The calculated value is sent to the microcontroller. A load measurement sensor is also placed at the bottom of the surface. This sensor is responsible for calculating the weight of the waste in Kg. The load measurement sensor works on the upcoming load of waste concerning time. When a load of waste in the trash box is increasing periodically, the value of load is also increased. Then the updated value is provided to the microcontroller. The values of the ultrasonic transducer and load measurement sensor are sent to the developed android application. The users can easily observe the weight of the trash and current empty layer of the bin using an android application. If the internet connection is available, the corresponding values will send to the cloud server, and the users will be able to monitor the data in real-time through an android application.

Fig. 4 represents a flow chart of the working methodology of the ultrasonic sensor. In this figure, the system first initialized the ultrasonic sensor. The sensor sends and receives an ultrasound to measure the empty level of the trash box. Also, the ultrasound sensor sends the corresponding measured data to the microcontroller. A positive response of available Bluetooth connection results in sending the measured data to the android application. The adverse reaction of available Bluetooth connection results in checking the internet connection. If the internet connection through Wi-Fi is available, the system will send the data via a cloud server towards an android application. A fruitful attempt to receive data from both the cloud server and Bluetooth connection leads to monitor the data through the android app. To check the validity of an empty level, we have placed a threshold of the scale. If the waste crosses the threshold level, the system will stop the respective process and alert the user by sending a notification to clean and replace the trash box via an android application. In the case of an unavailable internet connection, no data will be sent.

We have placed a load measurement sensor to measure the weight of the trash. Fig. 5 presents a flow chart of the load measurement sensor working principle. In this figure, the system first initialized the sensor to read data. The load measurement sensor calculates the load in kg and sends the data back to the microcon-

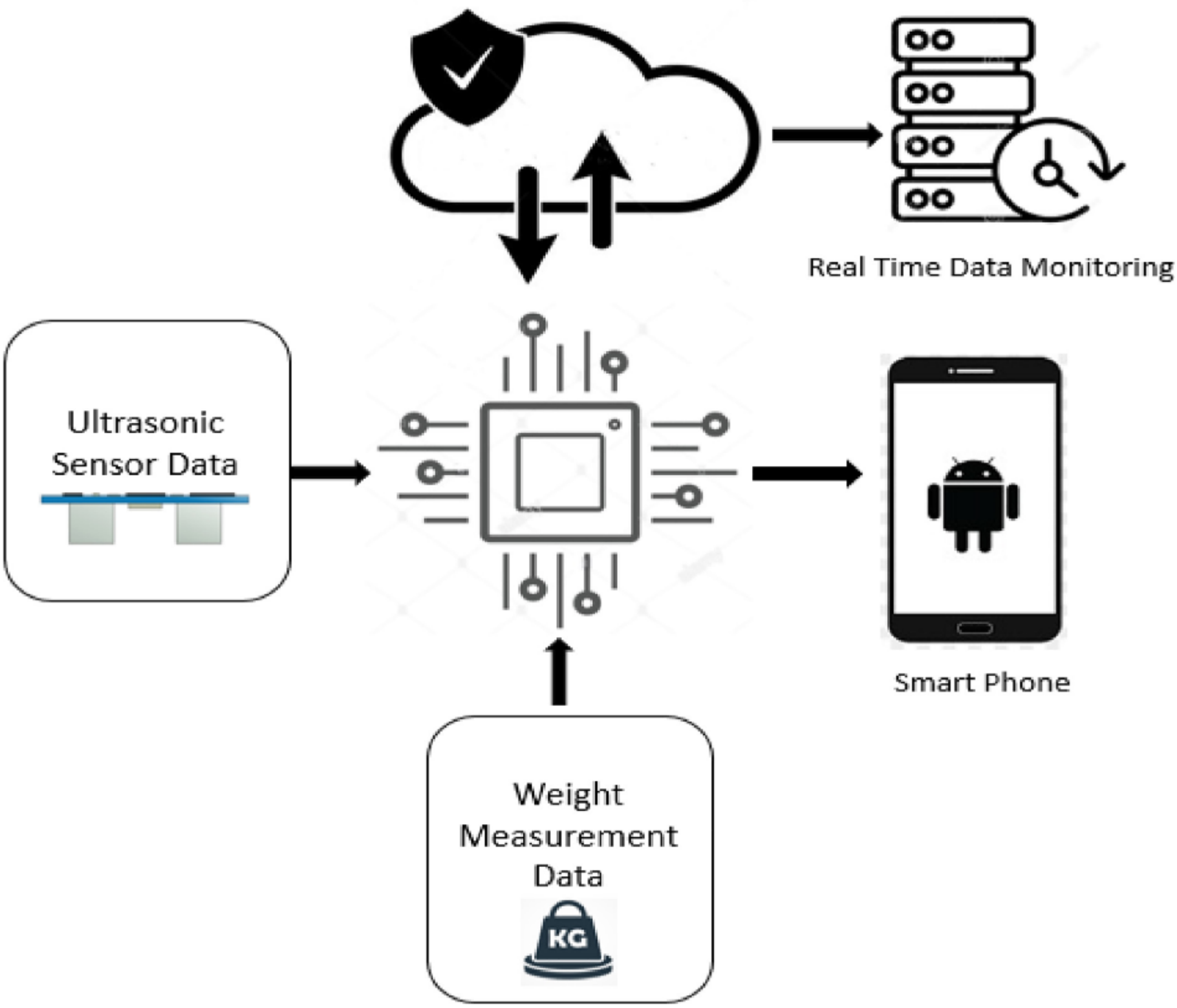


Figure 3. A block diagram and working principle of smart trash box

troller. Microcontroller checks whether the weight crosses a maximum threshold level. The negative response of over the maximum level results in finding the Bluetooth connectivity. If the Bluetooth connection is available, the system will send the data to the android application. If the Bluetooth connection is not possible, the system will move forward and check internet connectivity. If the internet connection is not in the present, the system will terminate the measurement, and no data will be sent. The system allows a notification to be transmitted to the android application that indicates the user to clean and replace the trash box. If the internet connection is in the operating, the system will send the measured weight to the cloud. A fruitful attempt to receive data from both cloud server and Bluetooth connection lead to monitor the data through an android application in real-time.

4. Data Calculation Methodology

Data calculation methodology is classified into three interconnected parts. First of all, we will present how Convolutional Neural Network (CNN) works for image classification to sort indigestible waste in our proposed solution. Secondly, we will discuss how an ultrasonic sensor works to measure the empty level of the trash box. Finally, we will provide how a load measurement sensor works to calculate the weight of the waste.

4.1. Waste Classifier (Convolutional Neural Network)

The Convolutional Neural Network (CNN) is a complex feed-forward network. It can solve a wide range of tasks that were unsolved before. CNN works by extracting features from images. CNN's are widely used for image classification because of its high accuracy. Image classification is the procedure of inputting an image and outputting the respective class that the image exists. Herein, our proposed system, we divided waste into two broad categories named digestible and indigestible waste. Indigestible waste can be cardboard, glass, metal, paper, and others.

A CNN consists of an input layer, a group of hidden layers, and an output layer (Hussain et al., 2018). The hidden layers generally include convolutional layers, Rectified Linear Unit (ReLU) layers, pooling layers, and fully connected layers. The input image is passed through the hidden layers and finally generates the output (Pan and Yang, 2009). Through the series of convolutional layers, the computer achieves a more abstract idea about an object image. Fig. 6(a) illustrates the topology of the CNN implemented for this proposed system. The network takes a 2D image as input and convolves feature learning using a 7×7 Gabor convolution filter. Different layers of CNN generate several levels of features. The existing layers perform various mathematical calculations and transmit the generated data as input to the successive layers (Kuo, 2016).

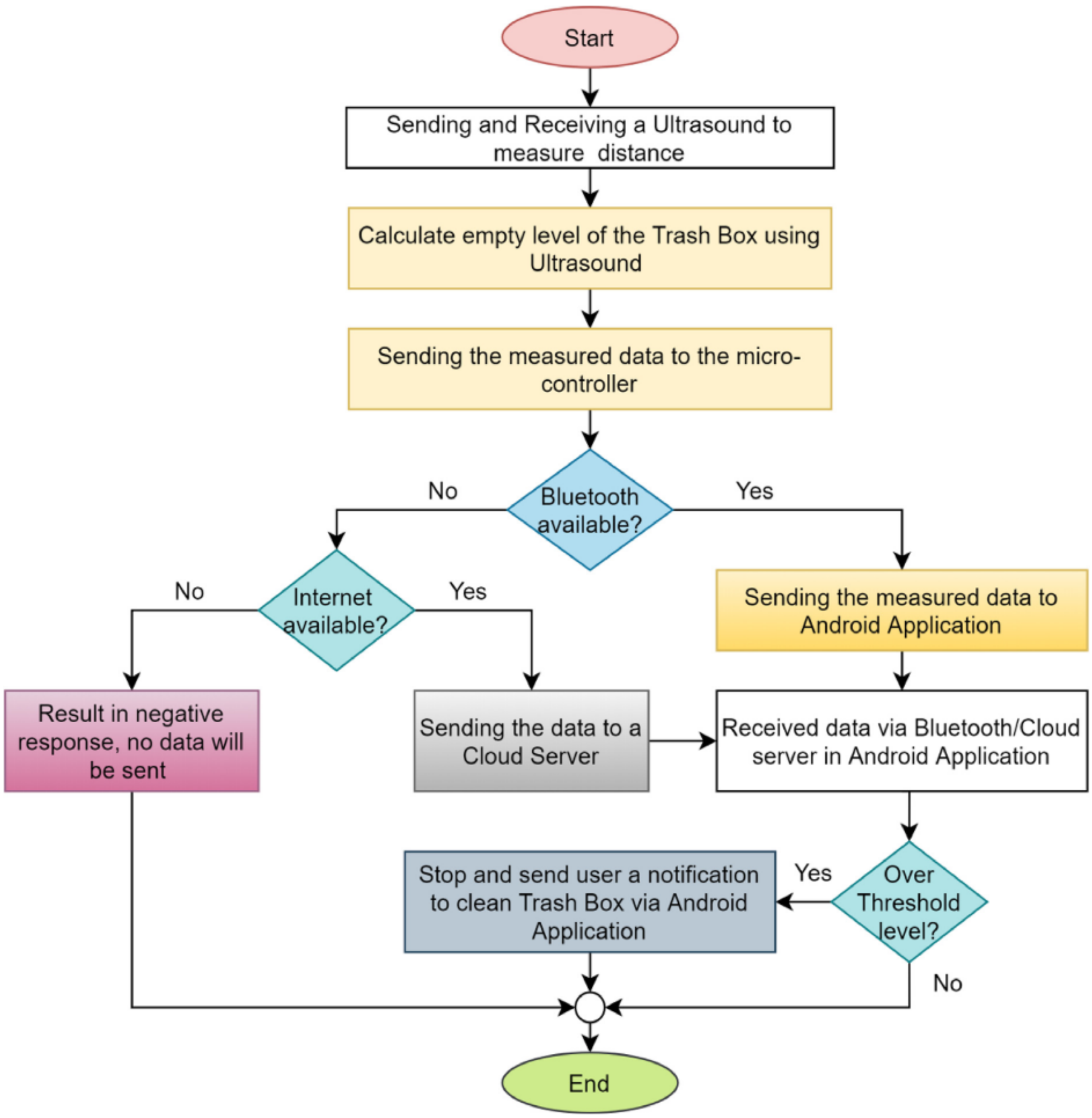


Figure 4. A flow chart of the ultrasonic sensor working principle

We have experimented with the different architecture of CNN such as AlexNet, VGG16, and ResNet34. Among that architecture, ResNet34 works significantly better than others. Fig. 6(b) illustrates the topology of the CNN implemented based on ResNet-34 for this proposed system. The network takes 224×224 size images as input and generates features using a convolution filter. Each layer performs various mathematical calculations and transmits the generated data as input to the successive layers (Phung and Bouzerdoum, 2009). A 7×7 filter with a stride of 2 is used for the first convolution layer operation over the 224×224 input image shown in Fig 6(c). The rest of the convolution layers perform 3×3 convolution with feature map size 64, 128, 256, and 512, respectively. An external bias and ReLU function are also applied in the operations. The 34 layers complete architecture of ResNet-34 is illustrated in Figure 6(a). Each convolution layer contains a feature map of three dimensions: height, width, depth. A convolution layer produces and receives a tensor of size $[W_1 \times H_1 \times D_1]$ where W_1, H_1 and D_1 express the dimensions of the tensor. The convolved output feature map is tensor of size $[W_2 \times H_2 \times D_2]$ where W_2,H_2 andD_2 are calculated by Eq. (1), (2), and (3):

$$W_2 = \frac{W_1 - F + 2 * P}{S} + 1 \tag{1}$$

$H_2 = \frac{H_1 - F + 2 * P}{S} + 1$ (2)

D_2= K (3)

Here, K refers to the number of filters,

F is the spatial extend of the filter,

and P is zero padding and S is the stride.

After the convolutional layer, the sub-sampling layer is placed to decrease the spatial resolution of the convolved feature map (LeCun et al., 1989). The image is divided into non-overlapping form. This layer deploys the max-pooling operation for downsampling (Burke, 1994). Herein, max-pooling is performed using a 3×3 pool matrix with a stride of 2, shown in Fig. 6(c). The pooling layer produces a tensor of size $[W_3 \times H_3 \times D_3]$ where W_3,H_3 andD_3 are given by applying Eq. (4), (5), and (6):

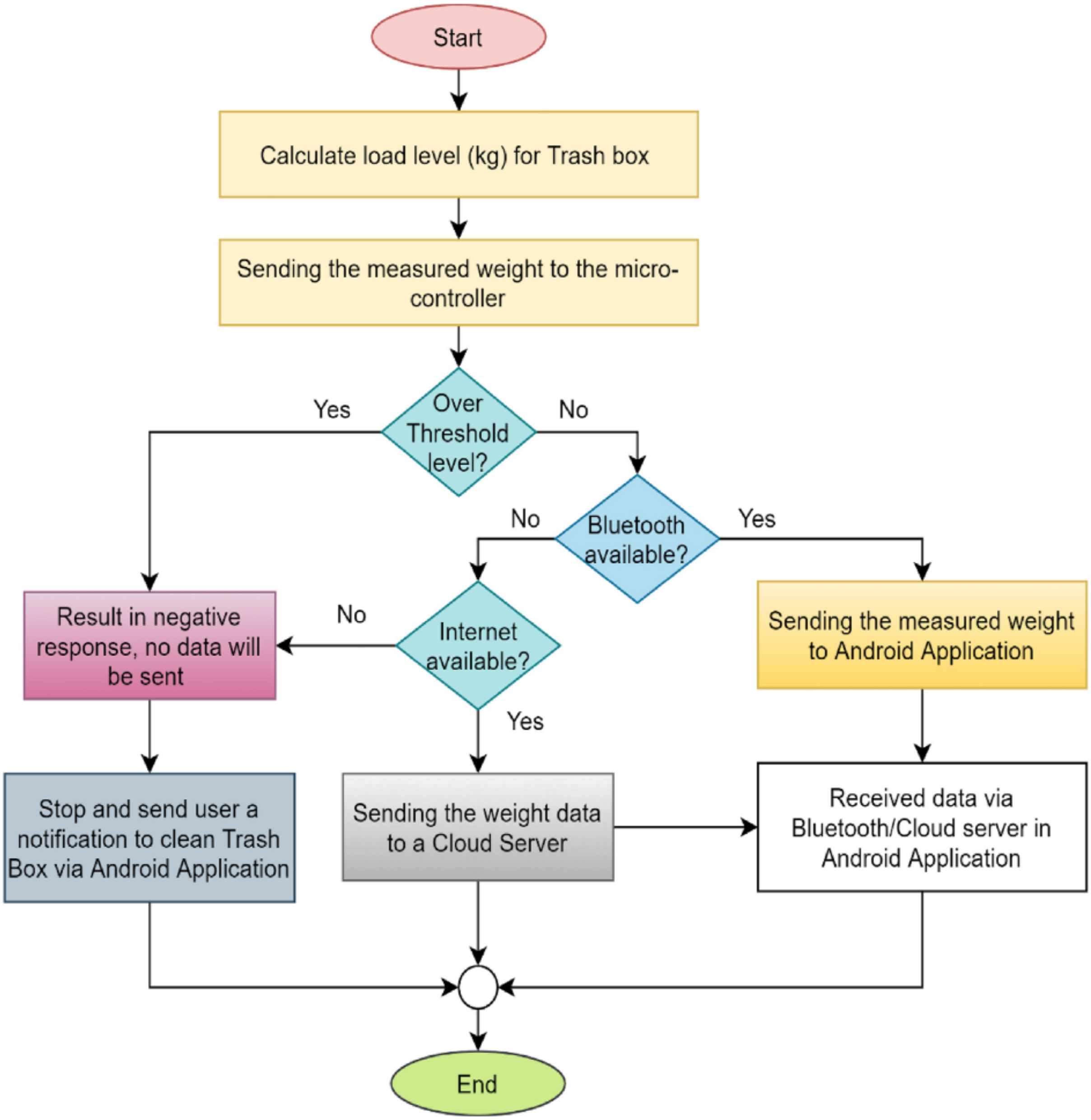


Figure 5. A flow chart of the load measurement sensor working principle

$$W_3 = \frac{W_2 - F}{S} + 1 \quad (4)$$

$$H_3 = \frac{H_2 - F}{S} + 1 \quad (5)$$

$$D_3 = D_2 D_2 \quad (6)$$

The proposed CNN network uses two fully connected layers with 1024 and 512 neurons. To eradicate the effect of overfitting, we have used Batch-Normalization and Dropout techniques on pertinent layers. Then soft-max is used as an activation function at the output layer that normalizes the input vector z of k real numbers into a probability distribution and finally classifies the image into a label (Parizeau, 2004; Ahmed et al., 2008; Lai et al., 2017). The function is given by Eq. (7).

$$\mathrm{f_j(z)} = \frac{\mathrm{e^{z_j}}}{\sum_{\mathrm{k}} \mathrm{e^{z_k}}} \mathrm{for\ j} = 1, 2, \cdots, \mathrm{k} \quad (7)$$

4.2. How an Ultrasonic Sensor works

The ultrasonic sensor emits ultrasound at 40,000 Hz that moves through the atmosphere, and if there is an obstacle on its path, the ultrasound will bounce back to the sensor, followed by laws of refection of the sound (HOWTOMECHATRONICS, 2020). To generate the ultrasound, the users need to set the Trig on a High State for ten μs. The ultrasound will send out an eight-cycle sonic blast, which will move at the acceleration sound, and it will be picked up in the Echo pin. The Echo pin will allow an output of the time in microseconds the sound wave migrated. Fig. 7 shows a block diagram of how an ultrasonic sensor works on ultrasound.

The ultrasonic sensor follows an equation of sound reflection methodology, which is depicted in the Eq. (8).

$$s = \frac{v * t}{2} \quad (8)$$

Where, v = the speed of sound = $340 m/s$

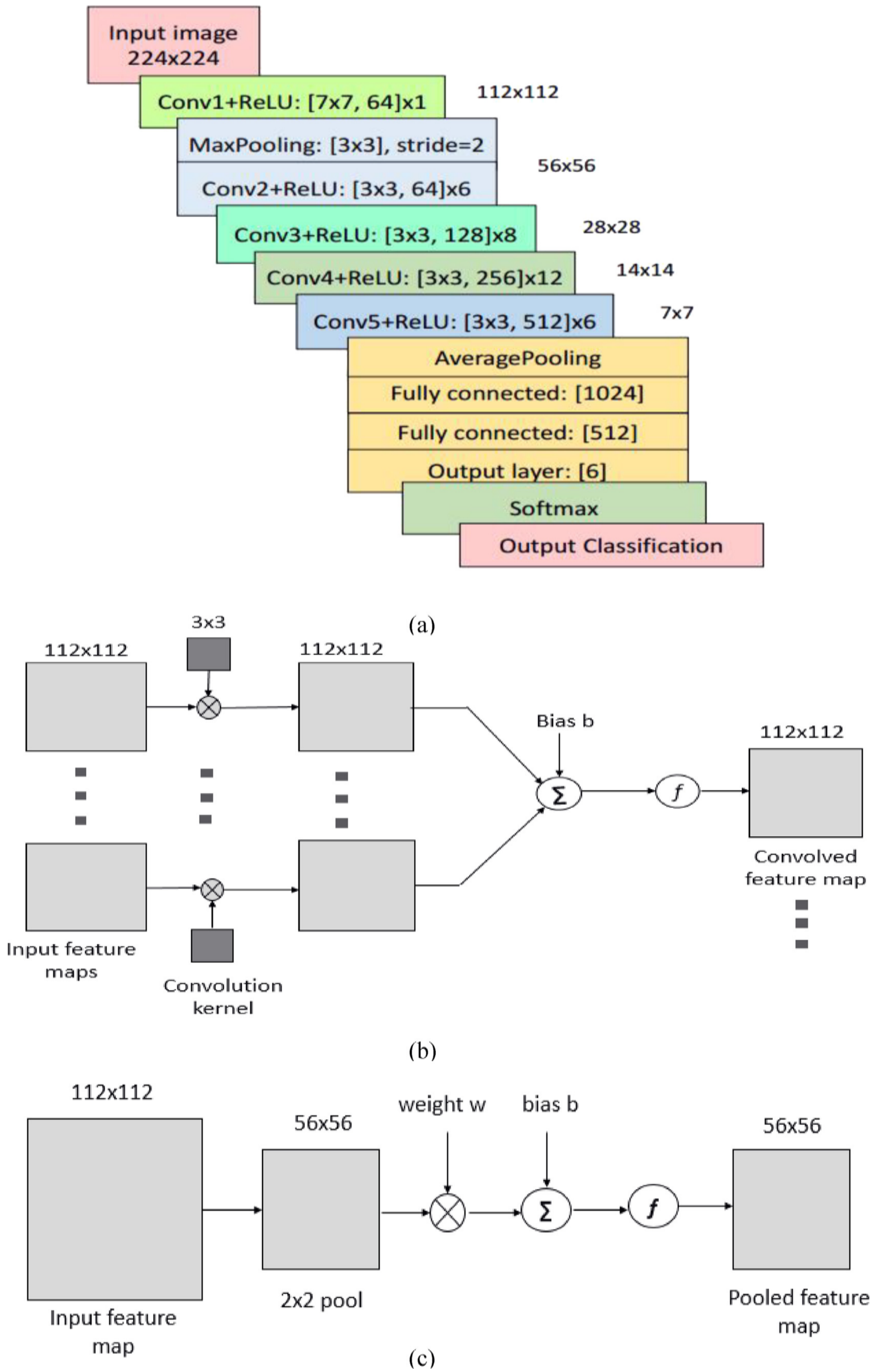


Figure 6. (a) Architecture of ResNet34 CNN model; (b) Feature map after convolution operation; (c) Max-pooling operation for down-sampling.

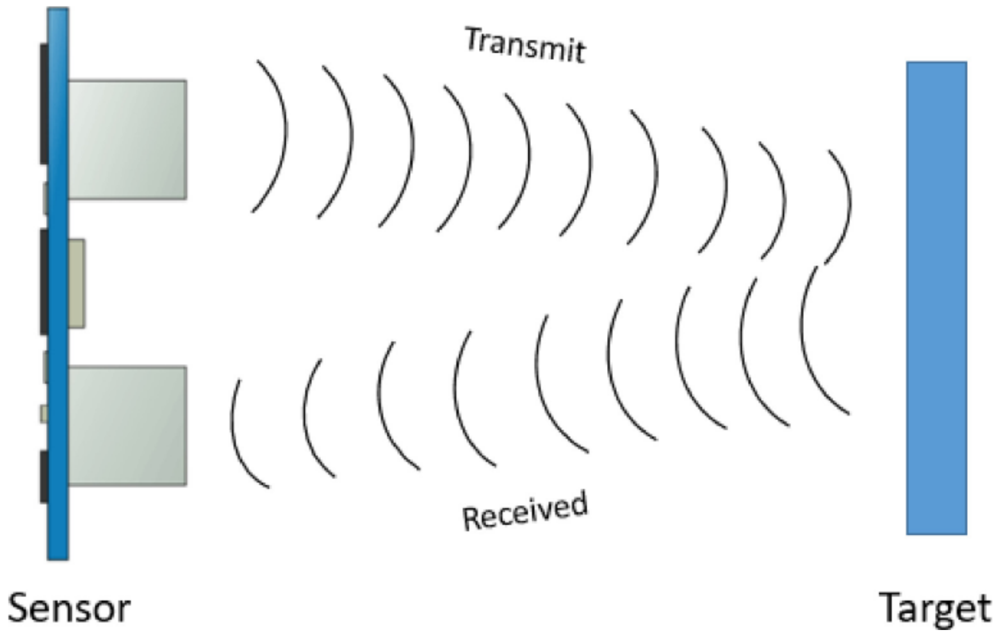


Figure 7. A block diagram of Ultrasonic sensor working principles

t = time required to transmit and receive

A. *How a Load Measurement Sensor works*

The load measurement sensor is responsible for measuring the weight of the objects. Due to calculate measured weight, a formula is usually employed to convert the output voltage level of the sensor measured in mV/V. The users need to choose which unit is preferable, like Kg, Gram, and Pounds, etc. The load cell has a standard voltage level of $1.0 \pm 1.5mV/V$, which provides a capacity of 5 Kg. The Eq. (9) shows the corresponding equation to convert the output voltage into weight (ROBOTSHOP, 2020).

$$measuredforce = A * measured\,voltage + B \tag{9}$$

Where, $measured\,voltage$ = $1.0 \pm 1.5mV/V$
So, 5, a constant highest value of the load cell
$B =$ Offset
It's essential to calculate the offset of each sensor because the specific amount varies from sensor to sensor. Typically the offset value can be:

$$B = 0 - 5 * measuredforce$$

5. Result and Discussion

In this section, we will discuss the results of our developed system along with relevant discussion. This section is furnished into four interconnected parts. Firstly, we will illustrate the effect of object detection, accuracy level, training graph, and comparison among different CNN models. Secondly, we will present experimental data of ultrasonic sensor and load measurement in response to the delay of time. Thirdly, a system usability scale (SUS) will be provided. Finally, we will present some snapshots of our developed model with a proper discussion.

A. *Waste Detection Scenario and Accuracy calculation*

This research consists of one prepared CNN network structure run with 34 different layers. In each layer of the network, the accuracy of classification is classified into varying divisions of data into training, valid, and test data. Two data division were used:

- 80% training data, 10% validation data, and 10% testing data.
- 50% training data, 25% validation data, and 25% testing data.

We have found a dataset of waste (GITHUB, 2020), including the images of glass, paper, cardboard, plastic, metal, and trash. We have used this dataset to detect indigestible waste and model training as well. The input data structure of our proposed system is shown in Fig. 8. that is required to train our model.

Initially, we have used a pre-trained CNN network, ResNet34 (PYTORCH, 2020). Training is taken place in Kaggle docker container with Intel(R) Xeon(R) CPU @ 2.00GHz, RAM 16GiB, and GPU Tesla P100-PCI-E 16GiB. The training was taken place with a pre-prepared ResNet34 network structure with an input image resolution of 224 $\times$ 224 pixels. In cyclical learning rates for training neural networks, Leslie Smith Smith, 2017 proposes a cyclical learning rate schedule that varies between two bound values. As the optimal learning rate depends on the topology of the loss landscape, it also depended on both the model architecture and the data-set. In training, we need to find a learning rate for gradient descent to make sure that our proposed neural network converges reasonably without missing the optimal error. If our learning rate is set too low, training will progress at a snail's pace as we are making minimal updates to the weights in our network. However, if our learning rate is set too high, it can cause inconvenient disparate behavior in our loss function. The learning rate finder of PyTorch, which is the implementation of Leslie Smith, suggests a learning rate of 5.13e-03 that is shown in Fig. 9 (a). Since we have utilized the pre-trained model, we have ensured tuning with different types of hyper-parameters. We have to find the learning rate at the beginning, so we have picked the optimum by plotting the learning rate from 1e-6 to 1e1. In our model, we have also tested various values for other parameters and selected the most fruitful ones.

Analyzing Table. 1, it can be seen that the trained model with 34 epochs results in the best accuracy. The more data has been fed, the more accurate the result is. We have tracked out the overall accuracy of 95.3125% with 34 epochs is a good result for such a

```
/data
     /train
         /cardboard
         /glass
         /metal
         /paper
         /plastic
         /trash
     /valid
         /cardboard
         /glass
         /metal
         /paper
         /plastic
         /trash
    /test
```

Figure 8. Input data structure to train our model

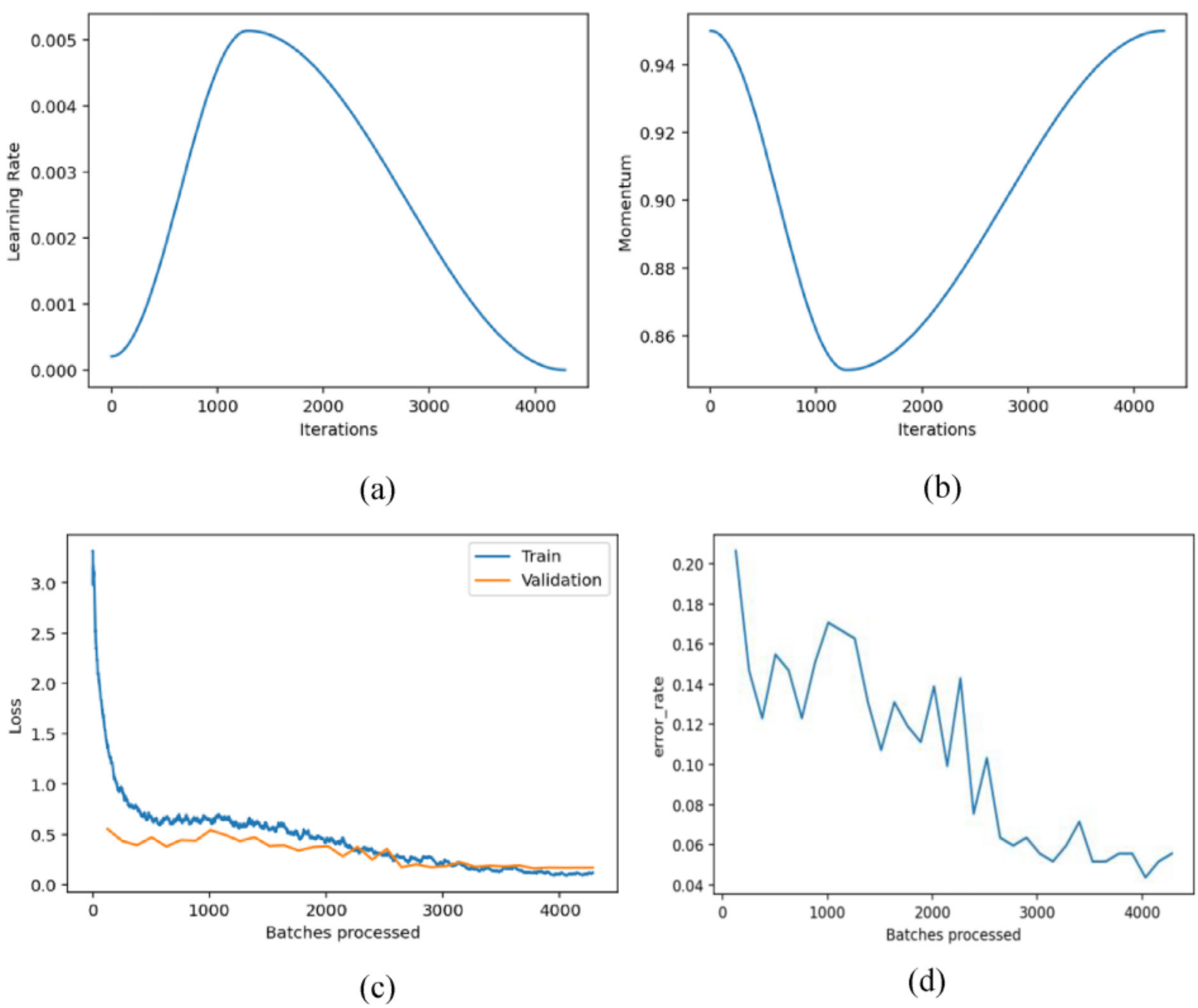


Figure 9. (a) Loss on the range of learning rate (b) Momentum and Learning rate per iteration (c) Train and validation loss (d) Error rate based on batch-processed

limited dataset. This accuracy can be even higher if the dataset is bigger. The problem with this trained model, we have faced so far, is the range of difference of various objects is enormous. A single glass can be made of diverse in color and thickness. It's very tough to even for a human to classify from such phenomena. When the trash objects are sorting by the model, the model can be

Table 1
Learning results of a 34-layer network (image resolution 224 × 224 pixels)

Number of Divisions	Type of DivisionTraining – Testing – Validation	20 epochs error rate %	27 epochs error rate %	34 epochs error rate %
1	50%-25%-25%	0.069841	0.076190	0.063492
2	80%-10%-10%	0.043651	0.051587	0.039683

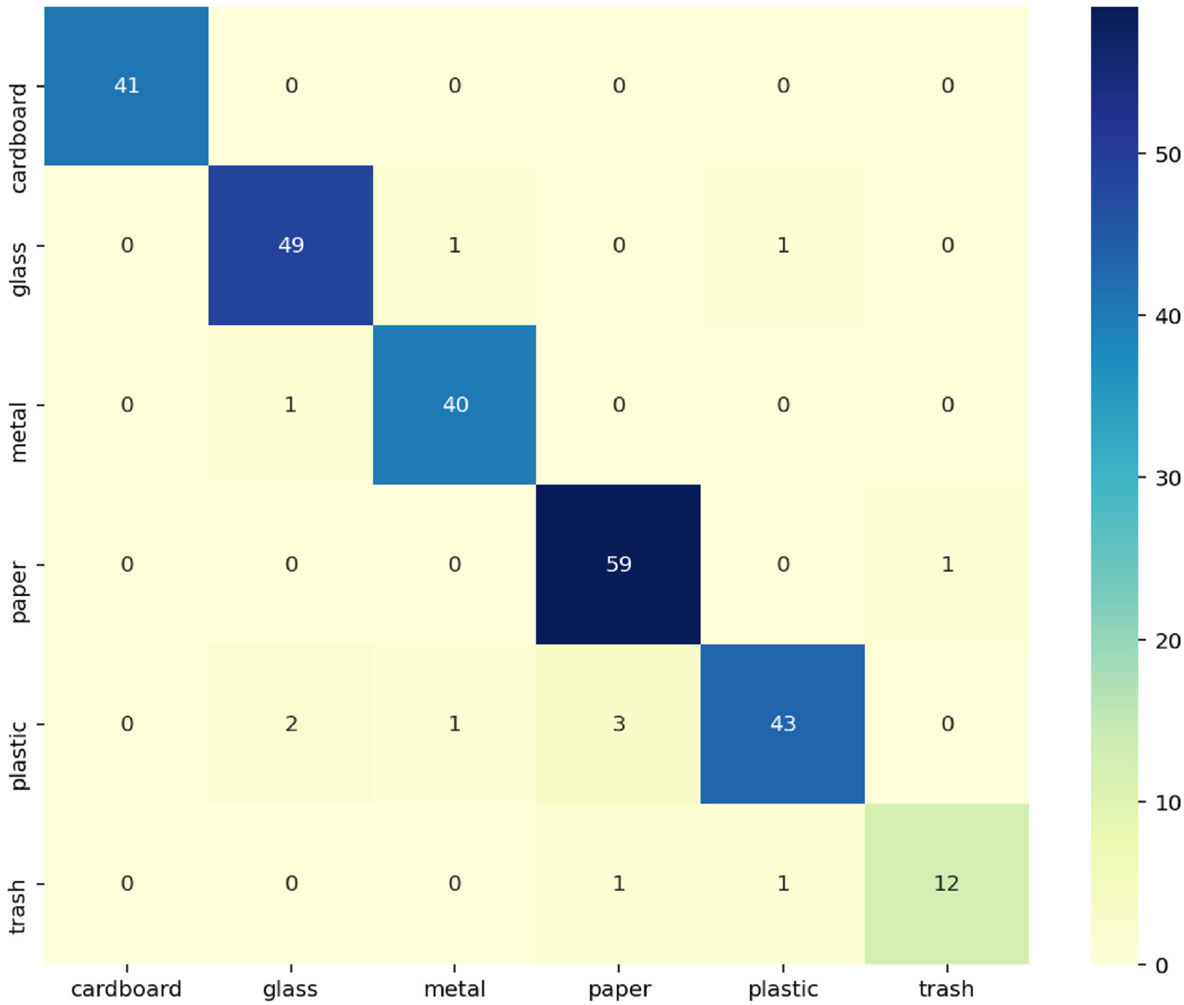


Figure 10. Confusion matrix of the test dataset

Table 2
A comparison among different CNN model

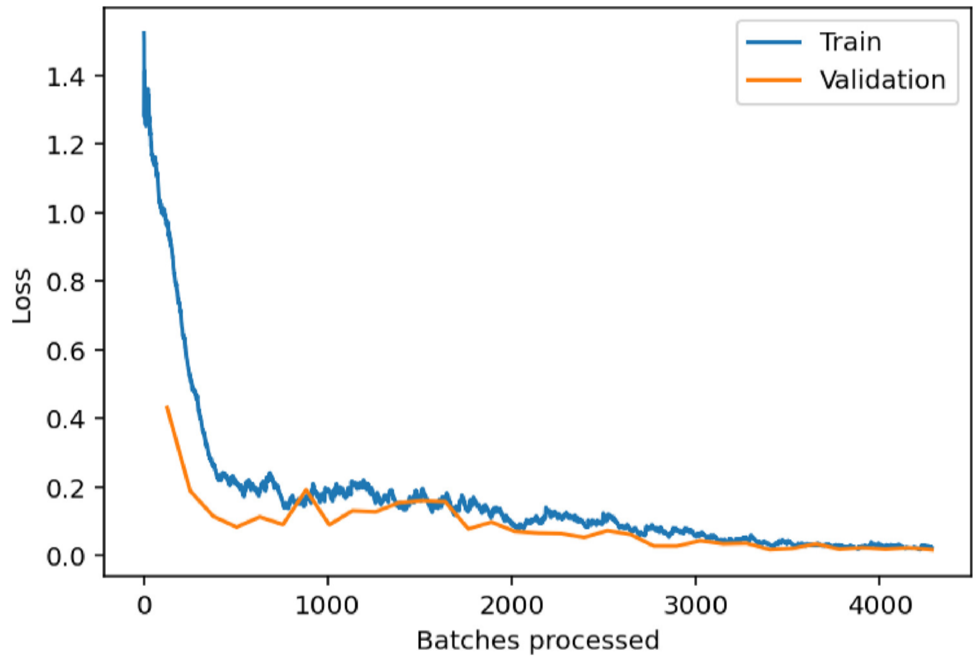
CNN Model	Number of Divisions	Type of DivisionTraining – Testing – Validation	20 epochs error rate %	Time (s)	27 epochs error rate %	Time (s)	34 epochs error rate %	Time (s)
Resnet34	1	50%–25%–25%	0.069841	637	0.076190	968	0.063492	1172
	2	80%–10%–10%	0.043651	1001	0.051587	1304	0.039683	1695
vgg16	1	80%–10%–10%	0.07422	1320	0.07812	1766	0.05859	2193
AlexNet	1	80%–10%–10%	0.21875	967	0.21094	1316	0.17188	1584
Resnet50	1	80%–10%–10%	0.04219	1237	0.05079	1558	0.0586	2093

learned more, and assure more accuracy. Fig. 9 (b), (c), (d) shows the corresponding training graph with data loss and validation as well as error rate.

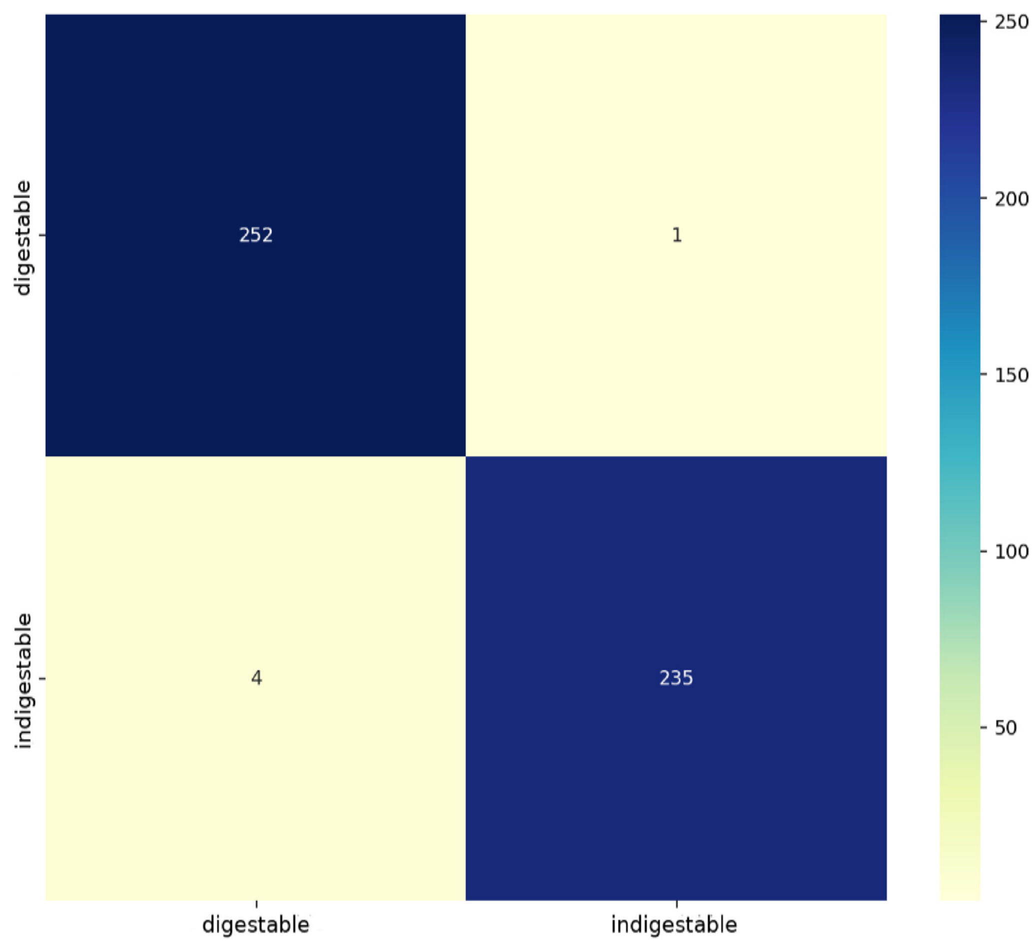
The confusion matrix of the proposed model is in Fig. 10. This matrix shows the outcomes of the ResNet-34 model on the test dataset. In this work, we have classified indigestible waste into five categories, namely cardboard, glass, metal, paper, and plastic, whereas digestible waste is combined into one as trash. Though we have an accuracy of 95%, it works much better in practice as

Table 3
The accuracy of six classes

Class	Number of Test Images	Accuracy (%)
Cardboard	41	100
Glass	52	94.231
Metal	42	95.238
Paper	63	93.651
Plastic	45	95.556
Trash	13	92.308



(a)



(b)

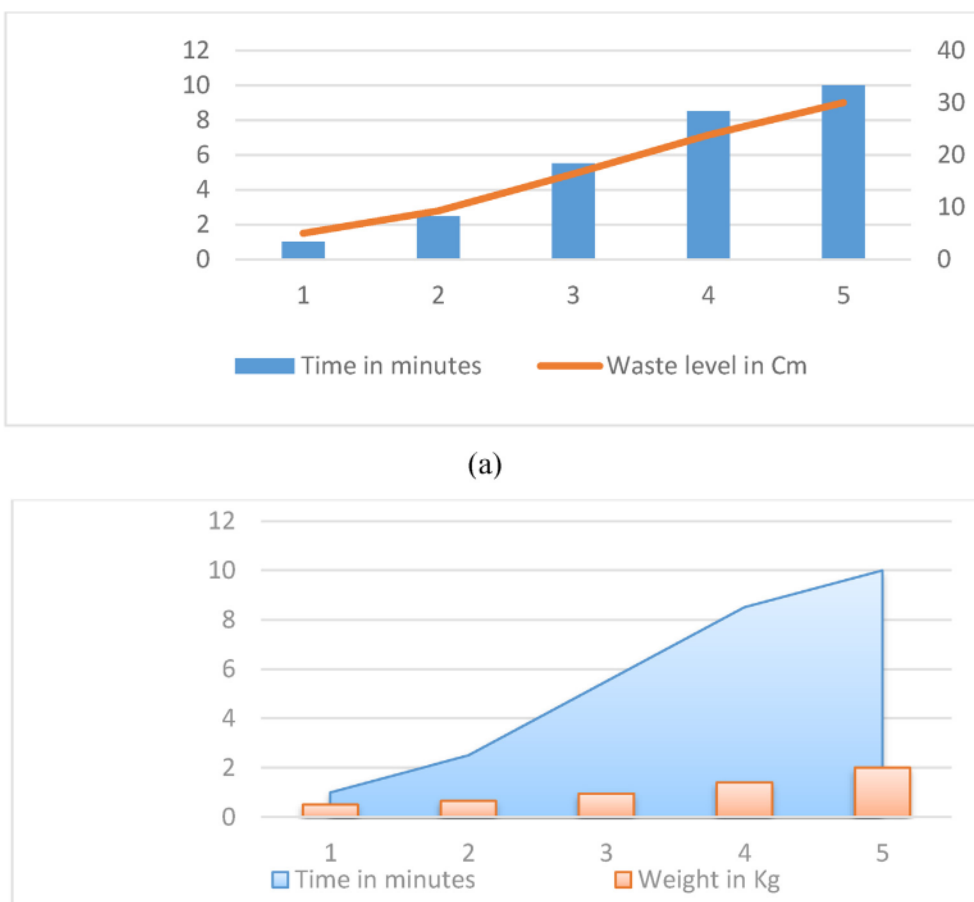
Figure 11. (a) A graph of training the whole model (b) A confusion matrix of two classes

this accuracy is for classifying wastes into six categories. The waste classifier of this proposed system trained on a dataset that contains six (6) classes. Whereas, the system consists of two types of trash boxes named indigestive and digestible. Among the six categories of the dataset, five of them are indigestive waste. The deep learning classifier identifies each captured image into one of the six categories. Then, the probability of the five indigestible categories is summed and compared with the likelihood of the remaining type. These facilities our classifier to work better in diverse situations like a mixture of waste. If waste is a mixture of waste, our system will correctly classify them and put them into the respective trash box. While we have two types of trash bin to collect wastes, thus metal classified as glass or plastic is also correct in the overall scenario. From the data of the confusion matrix, the accuracy of correct box classification is 98.01%.

We have used pre-trained AlexNet, VGG16, ResNet34, and ResNet50 model of fastai with two types of train-test-validation data division. AlexNet, with 80%–10%–10% data division, has given output of a minimum 0.17188% error rate while running at 34 epochs in 1584 seconds. VGG16 has shown some better output than AlexNet, a 0.05859% error rate with the same data division. VGG16 has taken 2193 seconds for 34 epochs. Again, we have used pre-trained ResNet50 as newer version of CNN architecture and found error rate of 0.0586% with 80%–10%–10% data division and 34 epochs. The architecture consumes 2093 seconds while running at 34 epochs. Out of the four models, ResNet34 has tracked out the utmost result. With 80%–10%–10% data division and 34 epochs, ResNet34 has provided an error rate of only 0.039683%. We have also ensured an experiment with 50%–25%–25% data division for ResNet34 that offers a good result but not optimum. Besides, AlexNet uses only five convolutional layers, and VGG16 uses 16 convolutional layers. While state-of-the-art CNN architecture ResNet34 uses 34 convolutional layers. It turns out the deeper layer of the CNN model and allows better results. Though the ResNet50 utilizes

Table 4
Experimental data of the Ultrasonic sensor and Load Measurement sensor

Number of Trails	Time delay(min)	Waste level(cm)	Empty level(%)	Weight of the waste(kg)
1	1.0	5.00	Above 90%	0.500
2	2.5	9.32	Above 80%	0.650
3	5.5	16.4	Above 45%	0.950
4	8.5	23.8	Above 20%	1.400
5	10.0	30.00	Below 10%	2.000



(a)

(b)

Figure 12. (a) A graph of Time vs. Waste level (b) A diagram of time vs. weight in Kg

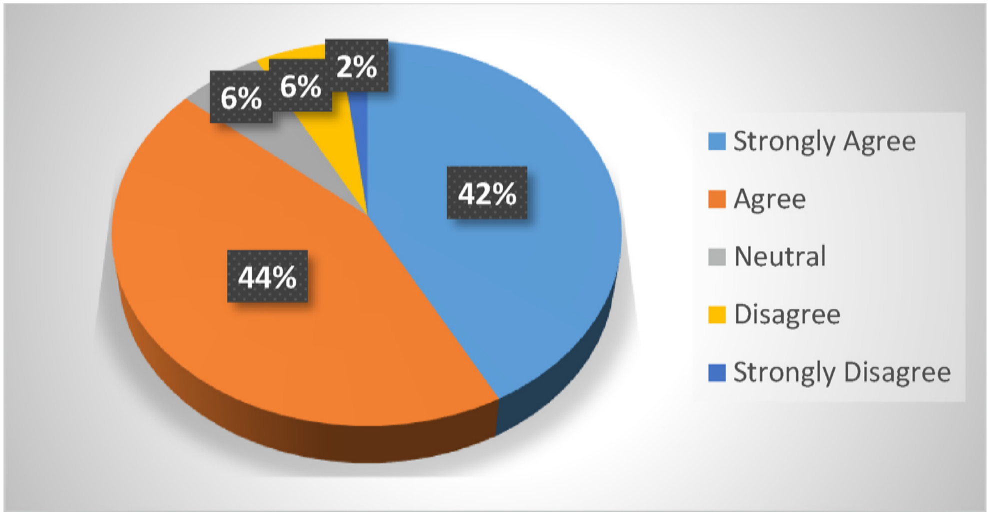


Figure 13. A Pie chart of System usability scale (SUS)

50 convolutional layers, we have tracked out that the architecture consumes more time and less accurate than ResNet34. Table. 2 shows the corresponding comparison among different CNN models and presents why ResNet34 is preferable for this research.

In our work, garbage is divided into six categories: cardboard, glass, metal, plastic, paper, and trash. We have also given different accuracy to these six classes, as mentioned in Table. 3. The experiment presents that cardboard accuracy is the best. Because cardboard images are not as illusory as plastic and glass. The accuracy of other classes is also satisfactory. Again, we have divided the whole dataset into two parts and trained our model for two classes division. Fig. 11(a) shows the corresponding train and validation graph. Herein, cardboard, glass, metal, plastic, and paper are considered as indigestible. On the contrary, the trash is considered as digestible waste. The Confusion Matrix of this training is shown in Fig. 11(b) and found the results of the model training of this division to be satisfactory. Thus, the model will be of great use in separating perishable and indigestible waste, mainly in practical terms. As biodegradable wastes can be used as decomposed organic fertilizer or other means and inorganic wastes can be sent for recycling.

5.1. Sensors data estimation

To calculate the empty level and weight of the waste, we have performed a set of experiments concerning time. Table. 4 shows the corresponding experimental data of the ultrasonic sensor and load measurement sensor. In this table, we have focused on how the system is operated in response to time. We have taken five samples, time delay in minutes, individual waste level in cm, empty level in percentage, and a load of the waste in Kg. The two output data, such as empty level and weight of the trash, will be sent to the corresponding mobile application of the users. Fig. 12 (a) shows how the waste level changes according to the change in time. Fig 12(b) shows the difference in weight of the trash concerning time.

5.2. System usability scale (SUS)

We have performed a SUS (System Usability Scale) among 14 randomly selected persons about our developed system to check whether the system is capable of our regular household activities. To accomplish this goal, we had severed them our developed application and trash bin. The users have utilized our advanced system and commented. SUS result shows that 42% of people strongly endorse in our developed system, 44% of people endorse in our solution. This result significantly indicates that a total of 86% of people recommend our refined architecture. On the contrary, 6% of people remain neutral, 6% of users give a negative response, and the rest of 2% strongly disagree with our proposed solution. The corresponding result is shown in Fig 13.

5.3. Overview of our developed model

We have ensured the development process of our proposed solution. In the development process, we have first developed IoT based smart trash box along with the android application. Then we have established a dashboard in webserver to ensure real-time data monitoring over the internet. After completing this process, we have moved forward to train our model with machine learning to classify the indigestible objects. Fig. 14 shows the developed trash box, android application, dashboard of the webserver, respectively.

6. Conclusion

This paper represents a real-time waste monitoring system utilizing deep learning paradigm and IoT. The research is conducted with a set of the development process to ensure an efficient waste management process. The proposed model has classified into two significant parts. One is the architectural model of waste classification using a raspberry pi and camera module along with the mechanism of deep learning. Another one is the embodiment of IoT based smart trash box utilizing a microcontroller with multiple sensors for real-time waste monitoring. Again, this paper represents the data calculation methodology of proposed CNN model, ultrasonic sensor and load measurement sensor. This article also presents several experimental data analysis to provide the effectiveness of the proposed method. The proposed method has found the waste classification accuracy of 95.3125%. This research is further furnished with the System Usability Scale to check the regular user's satisfaction and found the SUS score of 86%. The first limitation of this work is the model works with only five categories of indigestible waste. Another limitation is utilizing only two sensors in the developed prototype. Further, the model experiences a limitation, which is the detection of several types of holes in the trash box. The incident occurs only when bin seems full, but in fact, it's

Figure 14. (a) A snapshot of developed trash box (b) A screenshot of developed android application (c) An overview of webserver dashboard

not even half full because of the nature of the waste. If the architecture is enriched with a big data set and several types of sensors such as IR sensor, MQ Gas sensor, the solution will be more productive; the accuracy of the scheme will be broadened as well. In the future, this research will fix these three limitations to ensure more optimum results in the field of waste management. However, the proposed system will be practicable in household activities with real-time waste monitoring.

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