A NEW SMART COMMUNICATION PROTOCOL AND INTERNET OF THINGS (IOT) FOR WASTE MANAGEMENT SYSTEM

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ABSTRACT

Rapid population growth throughout the world has resulted in the improper handling of garbage in many nations, leading to several health problems and environmental contamination. Every week, the garbage vehicles collect garbage only once or twice. Due to improper wastage collection procedures, the contents of the trash can are scattered throughout the streets. This paper proposes a solution for wise and effective waste management based on deep learning (DL) and the Internet of Things (IoT) to combat this problem. The proposed method combines the ResNet-50 and Inception network models, which receive input and provide the correct solution for identifying and classifying Waste and organizing it into the appropriate waste receptacle (recyclable, organic, and hazardous wastes) without human intervention. An ultrasonic sensor is inserted in each wastage container to measure the amount of garbage filling. The integrated GPS module monitors the bin's location in real-time. Utilizing the LoRa communication protocol, the receptacle's location, real-time, and filling level are transmitted. RFID module is embedded for personnel identification in waste management. Recycled and organic residues that have been categorized can be used for greater purposes in the future. This procedure will assist the environment is becoming more valuable and ecologically secure, as well as assist us in creating a thriving verdant ecosystem and a brighter future. This method will help us establish a lush, verdant ecology and a brighter, hopeful future while making the environment more valued and environmentally secure. The proposed Res50+IncV3 network obtains 0.98 accuracy,0.97 precision, and 23% loss.

Keywords: *Waste management, Internet of Things, neural networks, ultrasonic sensor, environmental pollution*

1. INTRODUCTION

The world generates almost 4 billion pounds of garbage annually, with metropolitan areas alone accounting for a large portion of this total [1]. By 2025, this amount is expected to have increased by 70%. The garbage build-up in less affluent nations will dramatically rise over the next 25 years. The dumping of solid Waste, which includes paper, timber, plastic, metal, and glass, among other materials, is seriously developing into an issue due to the growth in the number of businesses in metropolitan areas. The primary way of garbage management is landfilling, which is wasteful, costly, and bad for the ecosystem. For instance, the health of those who live close to a waste location may be impacted [2]. Burning garbage is another popular method of waste management, but doing so can lead to air pollution and the release of potentially cancer-causing toxic chemicals into the atmosphere [3]. Therefore, recycling garbage is essential to safeguard the ecosystem and human health, and we must divide Waste into various components that can be repurposed in various ways. The developed areas are simultaneously developing and implementing some effective garbage management strategies, producing incredibly positive outcomes. The present state of affairs makes handling such a massive quantity of trash in the ensuing five years difficult. Therefore, taking all essential steps toward efficiently administrating Waste is preferable. Therefore, we must employ the finest methods and practices to handle garbage effectively and maintain a healthy ecosystem [4].

Daily garbage production has significantly increased throughout the world. A minimum of 35% of the 1.9 billion pounds of garbage produced yearly must be handled safely. According to estimates, each individual produces between 0.17

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and 4.67 kilos of garbage daily. Using an IoT and machine learning (ML) based garbage management system is the most efficient way to combat the issue of environmental contamination [5]. These technologies can offer real-time trash information and an improved route for waste pickup vehicles, cutting down on the cost and duration of the entire process. The problems with the present waste management systems originate from bad timing, which causes the waste workers to be unaware of their obligation to gather the garbage.

Additionally, they are still determining the exact position of the drop-off [6]. One major use of IoT innovation is that it is now a powerful tool for producing spectacular garbage production growth with accelerated population growth in metropolitan areas [7]. In urban areas, managing garbage may entail planning waste vehicle paths that consider societal, economic, and environmental factors. Second, the length needs to be shortened to reduce labor and keep a safe distance from excessive gasoline expenses [8].

IoT devices have been made available in a few setups to measure mailbox full levels and transmit this data online for improved choices. The sensors are linked to the microprocessor even though human intervention is equally important for collecting, conveying, and effectively dumping waste [9]. As a result, they will offer real-time data on the receptacle trash level and the waste indicator for the disposal sites. Worldwide population growth has resulted in an exponential rise in material utilization and a significant daily increase in garbage production. Ordinary garbage cans used by municipal officials are also increasingly being blamed for the ineffective gathering and handling of waste [10]. None of them can be replaced by digital receptacles, which offer real-time information and cut the price and duration of waste pickup. A lack of public knowledge is also hampering effective garbage handling. The waste management system will detect the receptacle trash level and the waste index at the disposal sites suggested in this document. The following are the contributions of this work:

- To adoptLoRa communication model for better transmission and deep learning models such as ResNet-50 and Inception V3 network model for efficient classification
- Without the assistance of a person, the built-in model receives input and provides the appropriate answer to recognize and categorize the Waste and arrange it into the appropriate waste receptacle (biodegradable, organic, and hazardous wastes).
- To improve the smartness of trash boxes using ultrasonic sensors, load measurement sensors, MOSFET switches, Analog to Digital Converter, temperature sensors, tile sensors, and microcontrollers.
- We looked at LoRaWAN transfer and retransmission by ignoring collisions and developing an effective frame structure.

In rest of the article is summarized below. Section 2 discusses the earlier IoT and neural network-based waste management systems. Section 3 details the proposed Intelligent waste management system with LoRa communication protocol. Section 4 analyzes the results by comparing them with existing methods. Finally, in section 5, the conclusion and the future direction are given.

2. RELATED WORKS

In this portion, we will discuss previous work relevant to the paradigm we have suggested. Many outstanding participants have left a substantial footprint on garbage management in deep learning and the Internet of things. Many outstanding participants have left a substantial footprint on garbage management in deep learning and the Internet of things.

A pre-existing already trained model can be utilized to classify different varieties of solid waste materials. The inception module obtained 88.6% precision in the comparative study of the Resnet and inception module's performance on the garbage net dataset. Plastic trash is a serious problem, as demonstrated by Bobulski et al. [11], and CNN-based models were crucial in identifying various plastic groups. Vgg-16, ResNet-50, and ResNet18 were among the pre-trained models that Gyawali et al. [12] concentrated on. On the dataset, the ResNet-18 obtained a confirmation accuracy of 87.8%. Automated trash pickup, various studies have been done in the past.

The authors created a garbage categorization system using image processing and convolutional neural networks in a subsequent study by Bobulski and Kubanek [13]. (CNN). In their study, they only concentrated on the identification of polyethylene. Aasim et al. [14] suggest a GSM electronic tracking system that transmits an SMS to the government when the receptacle is full, instructing them to dispatch the garbage vehicle.

In order to investigate the potential of locating the entire amount of solid refuse

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receptacles from the information taken from the pictures, Hannan et al. [15] suggested a content-based image retrieval (CBIR) system. The software calculated and analyzed the distance between the pictures using various similarity distance calculation methods. On a collection of 250 container pictures, the suggested feature extraction methods' accuracy was evaluated. The findings demonstrated that the earth movers' distance was more accurate than other distances for analyzing the resemblance of two objects.

The study described in [16] included a trash can with a microprocessor and a wireless system. It was used to display information about the amount of trash in a trash can on a mobile device with an internet link. IoT Garbage Control is suggested by Monika et al. [17] on a website page. To illustrate the volume of Waste gathered and to direct vehicles into the disposal area, the website offers a visual image of the receptacles and a colored depiction of the Waste collected.

A brilliant garbage management system has been developed by Viau et al. [18], but the problem still needs to be resolved in the suburbs or outside of urban areas. Additionally, the system needs to provide customers with information about the location of the trash receptacle or the time that the waste truck will be present. The E-waste categorization process uses the FrHHGO-based ShCNN method that Ramya et al. [19] suggested. In this case, the E-wastes pictures are classified using the ShCNN classifier, and the training procedure is carried out using the FrHHGO optimization. The FHGO and HOA were combined to create the FrHHGO.

A system to balance the workload of fog nodes that handle the requirements of intelligent real-time apps was introduced by Malik et al. [20]. A deep learning model developed by Garcia-Garin et al. [21] was created to recognize drifting marine debris in overhead photographs. The algorithm was taught using 3700 images from scans conducted with airplanes and drones. The highest precision was determined through cross-validation, and it was 0.81. This model was used in a program built with the "Shiny" software. Sheng et al. [22] created a TensorFlow Deep Learning Model for intelligent garbage management. This technique reduced operating expenses while enhancing the general appearance of the waste management system. Expanding the waste pictures already present in the dataset to give the system more freedom in identifying the wastes could have enhanced the recognition performance.

In the research of [23], a pre-trained convolutional neural network learned using ResNet-50 and Support Vector Machine was used to create a garbage categorization model. (SVM). As evaluated using public information, the suggested system's precision level was 87%. According to [24], the writers looked into how electrical Waste, or "e-waste," was classified. The proposed model was based on CNN and RCNN to classify several types of e-waste. The writers raised the suggested system's accuracy level from 90 to 97%, but the model was only intended to categorize e-waste. Glass, paper, plastic, and metal were accurately separated into their classifications within solid refuse by Costa et al. [25], who used the SVM and VGG-16 as pre-trained models to achieve their classification. Chu et al.'s [26] evaluation of the Multilayer Hybrid System (MHS) and CNN system on a single dataset. The six categories into which the data gathering was divided included paper, metal, glass, veggies, plastic, etc. The MHS system achieved an accuracy rate of more than 90%.

3. RESEARCH METHODOLOGY

The investigated system comprises intelligent waste receptacles with a real-time tracking system that incorporates multiple choices, such as ultrasonic distance and a LoRa transmission module. Energy efficiency was taken into serious consideration throughout the design process. It is assumed that multiple sources, such as solar energy or batteries, should power each node.

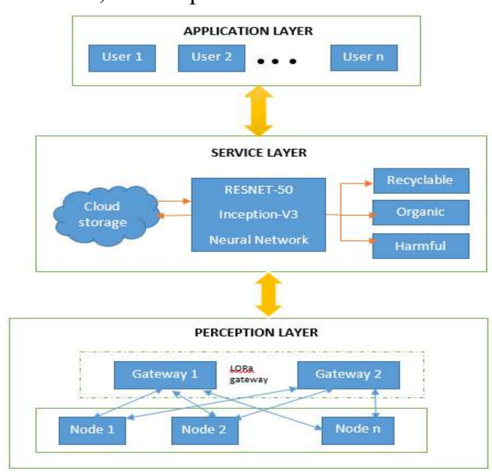

Figure 1:. Proposed neural network-based waste classification in IoT

In order to provide flexibility, a design has been created for hardware capable of using either energy source, as trash bins are often located in areas where direct sunlight is not a viable option. When utilizing the methods, the selection of the optimal electronic components for interconnection and energy efficiency was considered. The

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architecture of the suggested system is depicted in Figure 1, with the collected data being transmitted using LoRa to a cloud server, where data is stored and manipulated. The data are then classified as recyclable, organic, and harmful wastes using the RESNET-50 +Inception-V3 model.

3.1 Sensor and Gateway Module

The LoRaWAN protocol, adhering to the OSI model, offers a MAC layer protocol in addition to a link layer and network layer protocol, thus allowing sensors with a LoRa radio interface to communicate with applications with access to the Internet. The LoRa Alliance actively promotes utilizing this technology, which is available without cost. A LoRaWAN network is comprised of four constituent elements.

The sensor apparatus, typically with limited energy and computational capacity;

- A gateway a network element that facilitates the transmission and reception of data between disparate devices;
- The network server facilitates the transmission of messages between a set of gateways and the applications both ways;
- The application located somewhere on the Internet communicates with the sensors via the network server, both receiving and sending data.

Integrating an Atmel ATMega328P microcontroller and a Libelium SX1272 LoRa radio module within the system is implemented. In order to maximize energy efficiency, a power rating system, based upon the utilization of a HEF4060BP 14-stage ripple carry binary counter, is implemented to run the system, which is fueled by 4 commercially accessible 1.5 V AA batteries. This system facilitates the implementation of a strict duty-cycling policy which can lead to the complete deactivation of the sensing platform when not in use. Furthermore, because the most power-demanding elements of the platform are the ultrasonic sensor and the LoRa radio module, three MOSFETs have been utilized in the role of switches to ensure that these modules are only operational when required.

The system operates in such a manner that one of the outputs of the counter functions as a control signal for a MOSFET, which acts as the switch for the entirety of the sensing platform. Upon a high counter output, the MOSFET is transitioned to an 'on' state, and the microcontroller is consequently triggered. The ultrasonic sensor is then turned on by the microprocessor, which manages one of the two MOSFETs and measures distance in addition to the data provided by the other sensors. The sensor is then turned off, and the LoRa module is turned on using a MOSFET. The data from the sensor are then packaged into a payload and transmitted to a remote LoRa gateway. The following algorithm can be used to determine distance d by the microprocessor by measuring the Time of Flight (ToF) or the interval between the stimulus and the echo:

$$d = \frac{v_s \cdot t_{T0}F}{2} \qquad (1)$$

Where v_s. is the speed of sound, and $t_{T0}F$ is the Time of Flight. The TMP36 [28] manufactured by Analog Devices has been identified as the temperature sensor. The microcontroller samples the analog sensor using its in-built Analog Digital Converter (ADC), with a scale factor of 10 mV/°C and a linear relationship in the range between -40 °C and 125 °C, generating 750 mV when the temperature is 25 °C. The temperature T can be calculated using the equation.

$$T = \frac{V_{out} - 75}{10} + 25 \qquad (2)$$

V_{out} stands for the sensor output voltage, which is written in mV. When the container is flipped over, the inclination sensor is used to identify it. Frequently, the occurrence of vandalism necessitates vigilant observation and timely notification to an operator to allow for prompt initiation of appropriate remedial action.

3.2 LoRaWAN Class B

The LoRaWAN Class B devices serve as routers and are responsible for demodulating LoRaWAN messages and determining each receiving signal's Received Signal Strength Indicator (RSSI) and Signal-to-Noise Ratio (SNR). Data and packet information was forwarded to the cloud that contains the distant network server using the Message Queuing Telemetry Transport Protocol (MQTT) protocol. About the power supply of the gateway (GW), it is designed to be powered by the main electrical source. Nevertheless, as the data rate is amplified, the probability of message loss due to interferences and collisions also tends to augment. Additionally, there are established criteria for the portal to decipher the signal concerning sensitivity.

$$P_{RX}(dBm) = P_{TX}(dBm) + G_{system}(dB) - L_{system}(dB) - L_{channel}(dB) - M(dB) \qquad (3)$$

The transmitted power (P_{TX}), which is associated with the system gain (G_{system}) of directional antennas, is subject to certain losses (L_system), such as those incurred from feed lines and antennas, as well as losses (L_{system}) due to the

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propagation channel, with the fading margin (**M**) serving as a precautionary measure.

3.3 Data Transmission Module in LoRa

Any packet with a Received Signal Strength Indicator (RSSI) value lower than the sensitivity threshold will not be registered by the Gateway (GW) and will be seen as lost or rejected. As an exemplar, when a packet arrives at the gateway (GW) with a spreading factor (SF) of 7 and a sensitivity of -132.5 dBm, the GW will not prevent the incoming signal from being received. Yet, it is impossible for the GW to decode it.

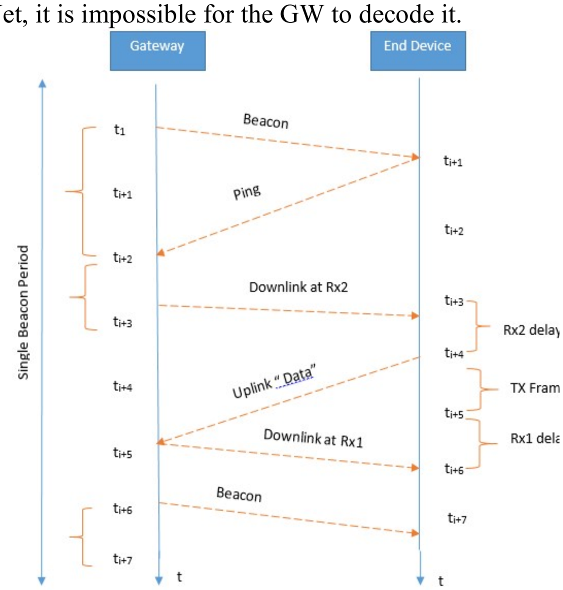

Figure 2: Transmission of messages in LoRaWAN class B

In Class B, as depicted in Figure 2, a Gateway (GW) emits a synchronization beacon. Once the device has come out of its sleep mode, it sends a "ping" to the Gateway (GW) as an indication of its readiness to receive the configurations (SF, data rate, channel) during the RX2 window. After getting the configuration, the ED sends the data to the GW in the Tx frame, opens the RX1 window after a short pause, and receives a signal from the GW to complete the exchange.

Allow data packet transmission but receive no acknowledgment. This situation might be brought on by failed data frame or ACK transmissions, or it might result from an ACK being rejected due to an inbound transmission. The mote retransmits the data packet in this situation. The mote chooses a channel at random for this and waits for a random duration between 1 and 1 + W seconds. It then transmits the data frame again. We only look at one instance where relaying might happen: (i) no impact, meaning that noise alone is to blame for the resend. The resend, in this instance, is brought on by random noise. Let ζ represent the probability that one or both ACKs or one data frame will be corrupted by noise.

It supplements the scenario in which noise does not affect the data frame or at least one ACK. The GW's chance to receive the data frame is $1 - q$. Given that the two ACK messages are separate, the mote can have $2\,(1\ - q) - (1 - q)^2$ of receiving at least one ACK. Thus, we obtain

$$\zeta = 1 - (1 - q)[2(1 - q) - (1 - q)^2 \quad (4)$$

Collisions and noise are independent. Since the first transmission attempt is successful if both the noise and collisions do not occur, the probability $p_{i,1}^{s}$ of successful transmission is the product of the absence of collisions and the probability of the absence of the noise $(1 - \zeta)$.

Noise and collisions do not interact. The chance of a successful transmission, $p_{i,1}^{s}$, is the sum of the probability of no collisions and the probability of no noise $(1 - \zeta)$, as the first transmission effort is successful if neither noise nor collisions occur. As a result, we can calculate the chance of no collisions as $\frac{p_{i,1}^{s}}{(1-\zeta)}$and the probability that the resend is only caused by noise as $\zeta\,\frac{p_{i,1}^{s}}{(1-\zeta)}$.

3.4 Classification Module in Service Layer

After data from the perceptron layer, Data calculation methodology is carried out in the service layer by classifying the data into three categories. In this section, we will demonstrate how the ResNet-50 and Inception neural networks classify images to separate digestible and indigestible garbage using our suggested approach. The ResNet-50 + Inception V3 network is a sophisticated feedforward system. It can handle a wide variety of previously unsolvable problems. The functionality of this is based on the extraction of characteristics from pictures.

The popularity of networks for image classification is largely due to their high precision. The process of image classification entails the input of an image followed by the output of the associated class to which the image belongs. In this work, we posit a system wherein Waste is divided into three main categories: recyclable, organic, and hazardous. The Inception-V3 model is an advanced version of its predecessor, the Inception-V1 model. In order to achieve better model generalization, Inception-V3 leverages various strategies to enhance the network performance [29]. Compared to the Inception-V1 and V2 models, it has a larger network. The Inception-V3 model is a deep convolutional neural network that can be trained utilizing a low-specification computing machine.

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Training is challenging, requiring up to multiple days of devoted effort. This issue is addressed through transfer learning, which conserves the last layer of the model for novel categories. The parameters of preceding layers are retained, and the Inception-V3 model is deconstructed by removing the final layer through transfer learning.

The convolutional neural network known as ResNet-50, introduced by He et al. [30], employs a network-in-network architecture composed of multiple stacked residual units, demonstrating exemplary performance in the ImageNet classification task. The composition comprises two primary components: bottleneck 1 and bottleneck 2. Using three consecutive 1x1, 3x3, and 1x1 convolutional layers in both bottleneck 1 and bottleneck 2 reduces the function of the 1x1 layer while simultaneously increasing the dimension of the input, forming a bottleneck with comparatively small input and output dimensions for the 3x3 layer. Identity mapping is an important strategy for combating the deterioration problem; the process is explained in the following: input, output, and residual vectors are represented by $x, y$and $F(x, \{w_i\})$, correspondingly, for learning. The shortcut connection and element-wise addition of $F(x, \{w_i\}) + x$ help combat the degradation problem.

$$y = F(x, \{w_i\}) + x \qquad (5)$$

In Stage 4, average pooling was integrated with the fully-connected layer based on the greatest probability of the incoming data, which can be formally expressed using the rectified linear unit (ReLU) as the activation function.

$$Pr(Y = \langle i, v\rangle, W, b = softmax(Wv) + b = \frac{e^{wiv+b_i}}{e^{wiv+b_j}} (6)$$

Where elements W and b represent the weights and bias correspondingly.

The posterior distribution was normalized utilizing Index j. The model prediction is the class that has the greatest probability of occurrence, as determined by

$$y_{prediction} = argmax_i P_r(Y =< i, v >, W, b \quad (7)$$

The weights and biases of the deep ResNet structure were enhanced by the Error Backpropagation Algorithm, which quantifies the disparity between actual and expected class labels. The Cross-entropy function (2-4) was the loss function that must be minimized for dataset V.

$$L(V, Y) = -\frac{1}{n}\sum_{i=1}^{n} y^{(1)} lna\left(v^{(i)}\right) + \left(1 - y^{(i)}\right) ln(1 - a(v^{(i)})) \qquad (8)$$

L represents the loss function. The input samples of the training dataset are represented by the set $\{v^{(1)}, v^{(2)}, \dots v^{(n)}\}$; the set $Y = \{y^{(1)}, y^{(2)}, y^{(3)}\}$ is specified to label recyclable, organic, and harmful waste items; a(v) is the output of the ResNet about the given input v.

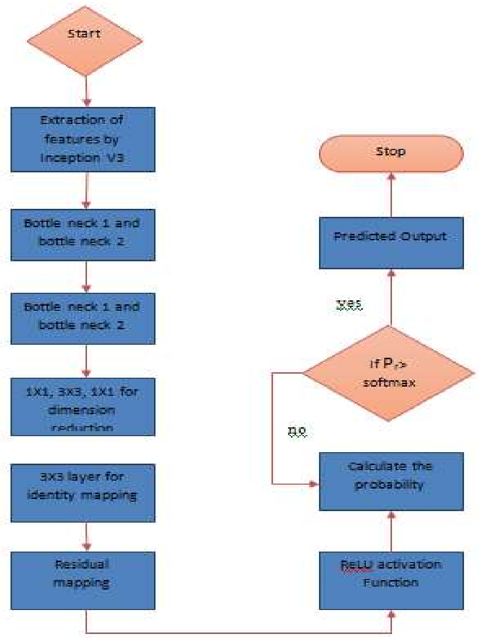

Figure 3: Flow chart for efficient waste prediction

3.5 Measuring Weight of Bin

A load measurement sensor has been installed to quantify the mass of the Waste. The microprocessor receives the calculated weight in kg, which was calculated using the load measurement sensor. The microcontroller ascertains if the weight surpasses a maximum limit. The discovery of Bluetooth contact occurs when the highest amount evoking an unfavorable reaction is exceeded. The gadget will transmit the information to the Android application if the Bluetooth connection is enabled. The device will check internet access if a Bluetooth link is impossible. If the internet link is down, the device will stop the assessment so that no data will be sent. The method allows the Android program to receive a message notifying the user to empty and restock the garbage box. The system will send the weight information gathered to the server if the internet link works properly. Real-time data tracking was made possible by an effort to obtain data effectively from a cloud service and a Bluetooth link.

The load measurement sensor determines the weight of the objects. Utilizing a formula to compute the measured weight, a conversion of the output voltage measured in $mV = V$ is typically undertaken.

Users must decide which measure they desire, such as kilograms, grams, pounds, etc. The weight

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cell has a capacity of 5 kg and a normal voltage level of 1:0–1:5 mV/V. The equivalent expression to change the outgoing voltage into weight is shown in Eq. (9).

$$\text{measured force} = A * \text{measure voltage} + B \quad (9)$$

where the measured voltage is equal to 1:0 $\mp$ 1:5Mv/V. The weight compartment B's fixed maximum number is five, which serves as the offset. The necessity of ascertaining the offset for each sensor is paramount, as the value for each device is different. The typical magnitude of the offset is typically expressed as:

$$B = 0 - 5 * \text{measured force} \quad (10)$$

4. EXPERIMENTAL ANALYSIS

Dataset description: The experiments in this article used Sekar's [31] waste categorization dataset from Kaggle, a public data source. The collection includes 25,077 pictures, of which 11,111 show reusable items and 13,966 show biological objects. The pictures are JPEG files in both horizontal and landscape orientations with color, and their size varies from 191 pixels at the lowest setting to 264 pixels at the highest setting. There were 372 pictures in the P mode and 24,705 images in the RGB color mode, which uses the three bands of Red, Green, and Blue with a pallet of three colors. (i.e., uses one channel with a palette of colors from 0 to 255). The latter was removed from the collection to avoid the color-banding issues (such as inaccurate color depiction) frequently associated with P-mode pictures when scaled. The experiments presented in this paper are based on a dataset of 24,705 images.

4.1 Results

This part demonstrates the outcomes acquired from the base model and the Res50+IncV3 structure trained with (70 * 45) and large (220 * 264) image sizes. The evaluation was performed using aggregate measures compiled from the models, including training, validation and accuracy, precision, computational speed, and loss. The expected value and an overall number of forecasts can be used to determine the precision of this effort. When analyzing the data, it is possible to express the forecast precision as a number. It can be said to be.

$$Accuracy = \frac{Correct\ Predictions}{All\ Predictions} \quad (11)$$

Table 1. Performance analysis of the proposed model

Methods	Accuracy			**Precision**		
	Training	Validation	testing	Training	Validation	**testing**
MHS + CNN (a)	0.82	0.72	0.84	0.59	0.45	0.54
SVM + VGG16 (b)	0.78	0.80	0.74	0.72	0.65	0.81
CNN+RCNN (c)	0.89	0.87	0.91	0.79	0.53	0.75
Res50 + SVM (d)	0.65	0.84	0.63	0.59	0.43	0.54
Res50+IncV3	0.97	0.91	0.98	0.96	0.89	0.97

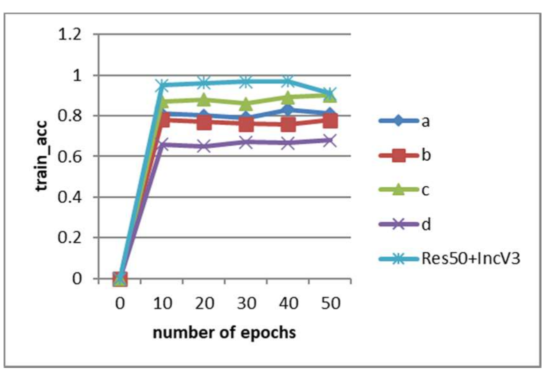

Figure 4: Evaluation of training accuracy

Fig. 4 and 5 show the number of epochs versus training /testing accuracy. As the increase of epochs, the rate of images also increases. Thus, accuracy increases.

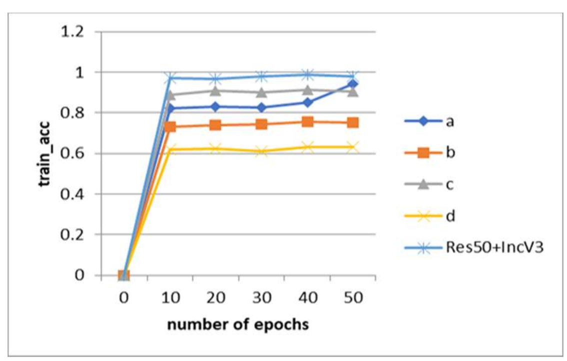

Figure 5. Evaluation of testing accuracy

Since the existing MHS + CNN, SVM + VGG16, CNN+RCNN, and Res50 + SVM not using the transfer learning process, they do not have a capacity of more training and testing accuracy. Thus, the performance of accuracy will increase

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concerning epochs. Among the methods, Res50 + SVM shows the lowest accuracy because there in a missing of activation layer. In other words, it will take more time to process and results in more delay. In the case of the proposed Res50+IncV3, it achieves 0.97 training accuracy and 0.98 testing accuracy

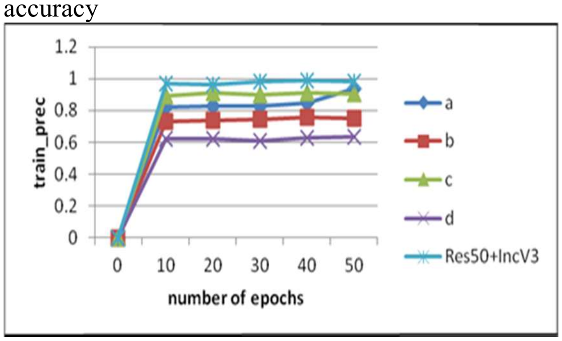

Figure 6. Evaluation of training precision

Fig. 6 and 7 describe the number of epochs versus training precision/ testing precision. As the increase of epochs, the rate of images also increases. Thus, precision increases. In the case of MHS + CNN (a), the optimizer helps in better iteration results in a moderate convergence rate, but it does not achieve better precision.

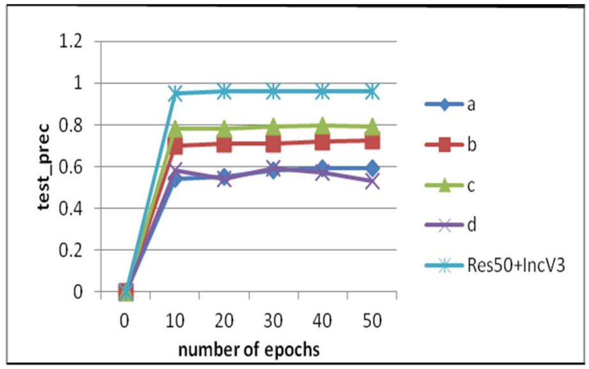

Figure 7. Evaluation of testing precision

When compared with other methods, the proposed Res50+IncV3 achieves 0.96 and 0.97 training and testing precision

Table 2: Performance analysis of the proposed model

Methods	Computational speed (%)			loss (%)		
	Training	Validation	testing	Training	Validation	testing
MHS + CNN (a)	67	74	69	78	79	77
SVM + VGG16 (b)	54	45	57	58	55	59
CNN+RCNN (c)	74	76	77	34	44	36
Res50 + SVM (d)	53	69	59	43	47	48
Res50+IncV3	94	85	91	21	23	24

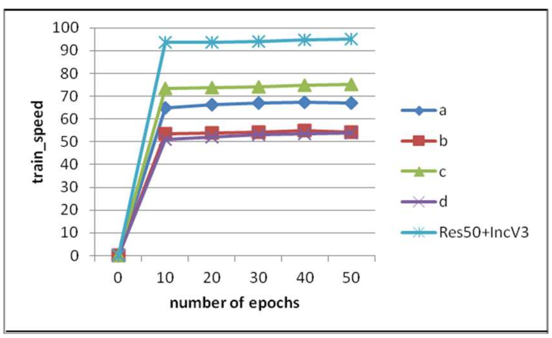

Figure 8: Evaluation of training speed

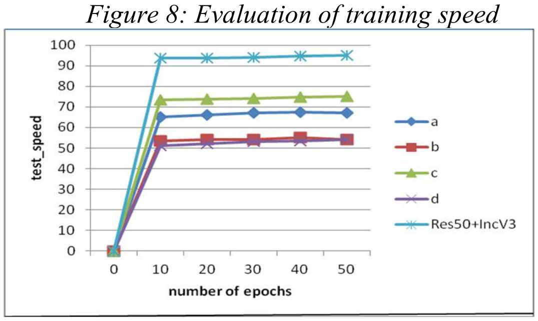

Figure 9: Evaluation of testing speed

Fig. 8 and 9 describe the number of epochs versus training/testing speed. As the number of epochs increases, the proposed method's computational speed. In the case of SVM + VGG16 (b), the storage layer cannot store more data and consumes much energy to transmit the images to the cloud. Similarly, in the case of CNN+RCNN (c), it constructs an optimal storage box to store the packets at a moderate rate. The proposed Res50+IncV3 has better computational speed as the packets are transmitted through only one optimal path according to the optimal factor. Therefore, Res50+IncV3 shows 94% of training speed and 91% of testing speed.

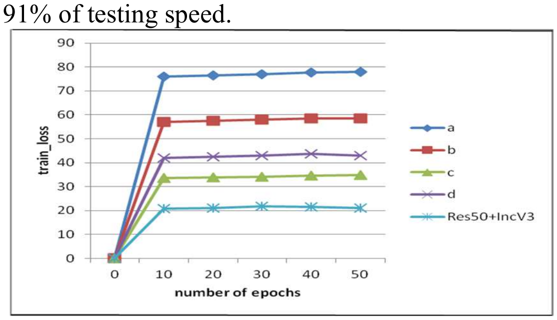

Figure 10. Evaluation of training loss

Fig. 9 and 10 describe the number of epochs versus training/testing loss. The proposed Res50+IncV3 has less loss as the images are transmitted through only one optimal path according to the optimal factor. Therefore, Res50+IncV3 shows a 21% of training loss and a 24% of the testing loss.

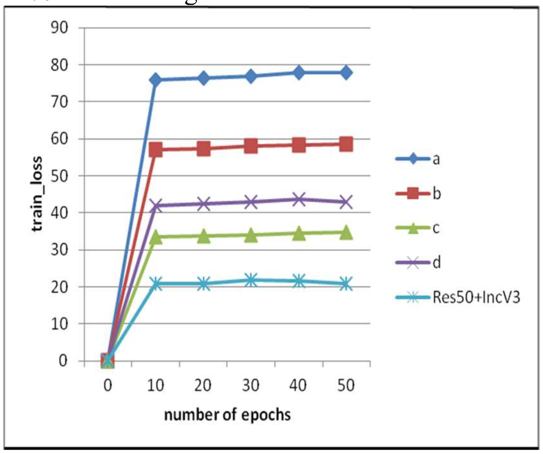

Figure 11. Evaluation of testing loss

5. CONCLUSIONS

This paper demonstrates the feasibility of incorporating the Internet of Things into a model of efficient waste management. This technique guarantees that all Waste is promptly removed when it reaches its peak. Consequently, the system will generate reliable results, increasing its effectiveness. The authors aspire to develop an intelligent waste management system predicated on the conception of sustainable, holistic waste management. Public health may be impacted by the closing of dumps due to several possible risks. The open burning of unwanted waste materials in junkyards can be a major source of environmental pollution and can spread various hazardous diseases. A system should be established to effectively oversee waste management, including disposal and collection, to ensure the appropriate regulation of unnecessary waste production. Future work includes more image processing methods with image augmentation and filtration processes to improve overall accuracy.

Contribution Statement

The authors confirm their contribution to the paper as follows: study conception and design: B. Raghuram; data collection: C.Srinivas; analysis and interpretation of results: S.Venkatramulu; draft manuscript preparation: V.Chandra Shekar Rao, K.VinayKumar, Uma N Dulhare. The author reviewed the results and approved the final version of the manuscript.

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