

Machine learning and IoT-based garbage detection system for smart cities

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Abstract

Today, detecting waste, collecting it, processing it, and getting rid of it are among the most significant environmental issues in developing and undeveloped counties. It has been observed that a large amount of garbage remains strewn on the roadside. This study presented a garbage detection technology such as machine learning and gadgets connected to the Internet of Things (IoT), such as an IP-enabled CCTV camera, to take pictures and send them to the city's main server. The input images are transformed into a two-dimension array of integers using Python modules and divided into the garbage and no garbage classes. There is an 80:20 split between the training and testing datasets from the input dataset. Preprocessed images are then utilised as inputs for a wide range of machine learning and neural network models for classification; these include K-Nearest Neighbour (KNN), Logistic Regression (LR), Naive Bayes (NB), and Support Vector Machine (SVM). The test data sets are applied, and a confusion matrix is formed for all models to analyse the efficiency and performance of the trained models. Results from the confusion matrix are contrasted with those from the area under the Receiver characteristics operating curve (AUC). As a result, the ConvNet model is best suited for classifying garbage or no garbage present in open space, and the LR model proposed best suits the garbage detection problem. The proposed models are best suitable for improving the efficiency of existing garbage identification systems and developing a new system for smart cities.

Subject Classification: 68T45 Machine vision and scene understanding.

Keywords: Artificial intelligence, Supervised learning, CNN, Classification, Garbage management.

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1. Introduction

Garbage has increased rapidly due to population growth and economic development. The garbage from cities around the world totals 2.01 billion tonnes every year, of which at least 33% is exceptionally not disposed of in an environmentally sound manner. Globally, daily garbage generation per person averages 0.74 kilogrammes. It is projected that by 2050, the amount of garbage generated in the world's low-income nations will have increased by a factor of three. East Asia and the Pacific generate 23% of the world's garbage, while the Middle East and North Africa only produce 6%. However, Sub-Saharan Africa, South Asia, the Middle East, and North Africa are expanding at the quickest rates. Garbage production is expected to double, triple, and even more than quadruple by 2050. Over half of the garbage is dumped in the open here; measures must be taken immediately [24]. The effects of garbage accumulation on the environment [23], human health, and prosperity will be profoundly projected by garbage generation by region (see Figure 1).

In contrast to conventional garbage management systems, the research in this paper by Masuduzzaman et. al. [1] uses an unmanned vehicle (UV) model in conjunction with a garbage collection and disposal system based on a deep learning (DL) model that collects and dispenses garbage from both land and water surfaces. The paper by Akanksha et. al. [2] presents a ground-breaking machine learning-based method for detecting, classifying, and determining whether garbage items are biodegradable. As described in the study by Paul et. al. [3], the garbage

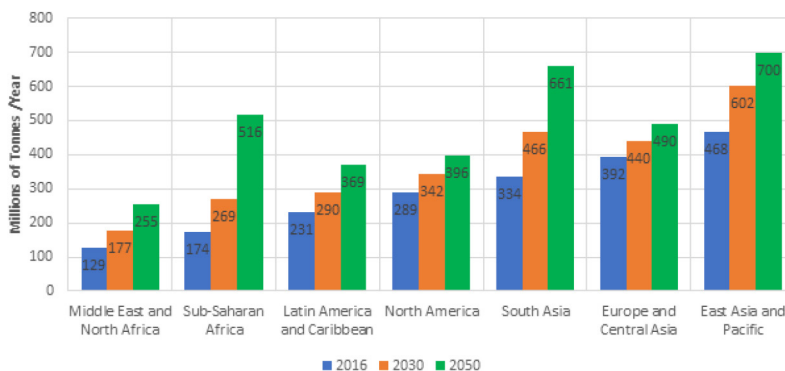


Figure 1

Expected garbage is produced in each region in metric tonnes/year.

management system will collect data from its hardware systems at crucial endpoints and then deliver it to a customer-friendly database.

Cloud-based monitoring and analysis is proposed by Lokuliyana et. al. [6] for a system of smart bins. The gathered information is fed into an algorithm, creating the best garbage truck routes. The proposed system in the study by Jajoo et. al. [7] monitors the trash can and notifies the concerned staff about the amount of trash in the can. An IoT-based solution to the garbage handling system problems is proposed in work by Bharadwaj et. al. [8]. It transmits data from the trash cans to a sensor-equipped gateway using LoRa technology and delivers it over the internet while consuming less electricity.

The management of garbage build-up is covered in work by Ghorpade-Aher et. al. [9]. The trashcan is a robot that, when given explicit instructions from a designated person, uses a Raspberry Pi and ultrasonic sensors to empty itself. Memon et. al. [5] aim to create an IoT-based ideal system that monitors garbage in real-time using smart technology. In the article, Srilatha et. al. [4] offer a framework for tracking garbage on the Internet of Things. It communicates using GPS and Ultrasonic sensors to gauge the amount of waste. Al-Masri et. al. proposed a Framework for Urban Trash Management [10]. Real-time source material breach types have to be ascertained. The research effort [11] recommends using ML and IoT to develop a smart and efficient trash collection solution. Using image processing, one may determine a disposal site's waste index.

According to the research study [12], the waste management system has a strong architecture built on deep learning and IoT. To monitor data, it suggest a microcontroller with several sensors and Bluetooth connectivity. Based on the CNN model, the proposed architecture's classification accuracy is 95.3125%, and its SUS score is 86%. The research study [15] covers cutting-edge collection techniques in Malaysia's e-waste management and recycling industry. An intelligent e-waste collection box for the home was developed with sensors to monitor the accumulation of electronic garbage [25].

The sensors used in smart city administration were studied, and estimates were made for them in the study [16]. Descriptive statistics were computed, if needed, from the finalised survey data. The research study [17] suggest that sensor is needed for which IoT application by studying various sensor applications. The research study [18] proposes a system (hardware, software, and communications) to enhance waste management and encourage public participation. Using an Internet of Things (IoT) approach, the system constantly monitors the trash collected

from the smart bin via sensors that offer real-time data on the filling level in each compartment.

This paper proposes models that use a public network of closed-circuit television (CCTV) cameras deployed for security purposes to capture images of litter on the streets. The available datasets are used to train and test the models using ConvNet [21], MLP, SVM, LT, KNN and Naive Bayes image classification algorithms. The best efficient model is proposed based on analysing the results with the test dataset.

2. Methodology

The main components of the proposed methodology are to predict the presence of garbage found in the open, which includes three major parts: (1) conversion of 2D image data set into a 2D array of numeric type, split it and providing as input for model training, validation and testing purpose, (2) developing ConvNet, MLP, SVM [22], LT, KNN and Naive Bayes models, (3) analysing the results using confusion matrix results and determining the most accurate predictive model (see **Figure 2**).

2.1 Preliminary Data Collection and Processing

The images of garbage found in open spaces have been collected from websites of the Times of India [19], the Hindustan Times [20], municipal corporations of different cities of India and the Google image repository. Collected images are categorised into two types, the image has no garbage, or it has garbage. The image with no garbage is labelled as “0”, and the image with garbage is labelled as “1”. These collected images have been used for training and testing purposes of the models. Garbage in 2D CCTV camera footage will be detected in real-time. In the first phase of the proposed methodology, the 2D image pixels will be converted into pixel values from 0 to 255 and normalised on a scale of 0 to 1, as shown in Eq. (1) [14]. According to each image category in the data set, a numeric value with the relevant labels (0: No garbage, 1: Garbage) is allocated.

$$x_{scale} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

2.2 ConvNet Model for Garbage Classification

This study suggests using a ConvNet model with an input of a 200x200x3 pixel garbage image. It has three layers (convolutional & pooling) on each, one fully connected layer and one output layer for

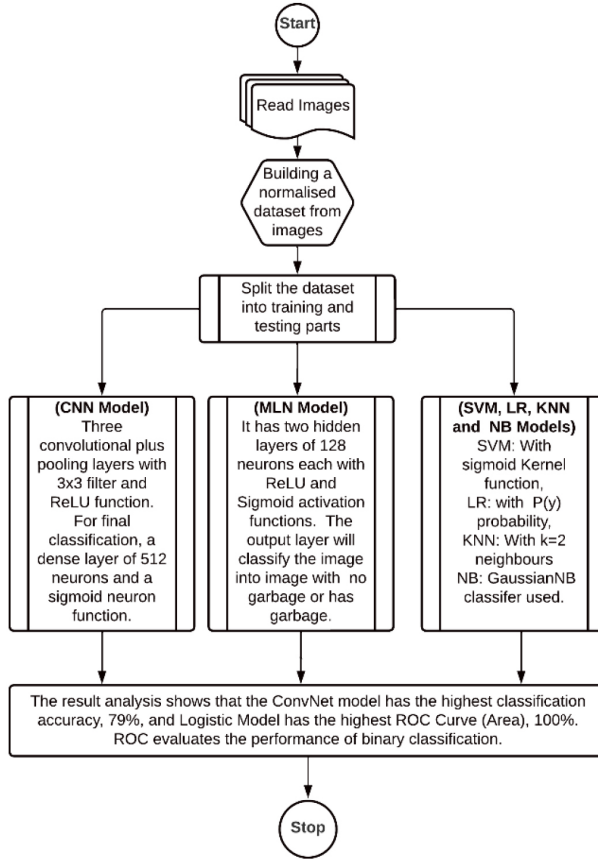


Figure 2

Flowchart of the proposed methodology

classifying if anything is garbage. The equations in Eqs. (2,3,4) show the input, filter, and output formulations.

$$Input = n_{row} * n_{col} * n_c \quad (2)$$

$$filter = f_{row} * f_{col} * n_c \quad (3)$$

$$Output = \left(\frac{n_{row} + 2p - f_{row} + 1}{s} \right) * \left(\frac{n_{col} + 2p - f_{col} + 1}{s} \right) * n'_c \quad (4)$$

Where n_{row} & n_{col} are the length and breadth of the image, and n_c is the number of channels in the input image. f_{row} & f_{col} are the length and

breadth of the filter. p, s and n'_c are padding, stride and the number of filters.

A bias term is added to the outputs after a filter is convolved over the input image. It applies a ReLU activation function, as shown in Eq. (7), to generate activations, the equation for one forward pass, as shown in Eqs. (5,6). The garbage image as an input ($200 * 200 * 3$) is a_0 and filters ($3 * 3 * 3$) are the weights w_1 . These activations from layer 1 act as the input for layer 2, and so on. In the case of convolutional neural networks, the number of parameters does not change with the size of the image. The filtration size plays a role. Let's pretend we have 16 filters.

$$z_1 = w_1 * a_0 + b_1 \quad (5)$$

$$a_1 = g(z_1) \quad (6)$$

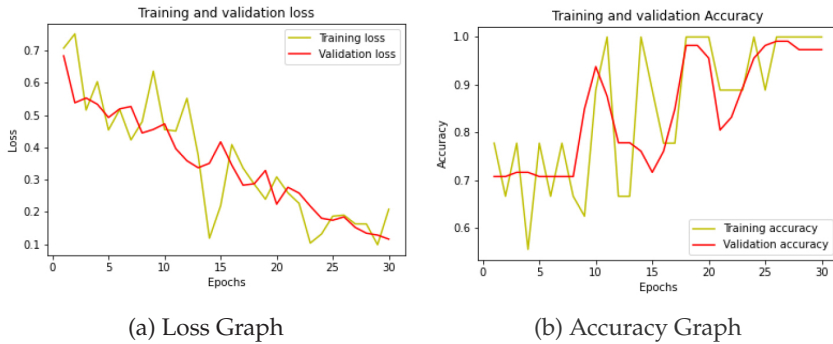
$$RELU(x) = \{ f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \quad (7)$$

$$f(x)_{sigmoid} = \frac{1}{1 + e^{-x}} \quad (8)$$

Table 1
Pseudocode of the proposed ConvNet model.

Create a convolutional neural network:
 Input shape(200,200,3); Filter size (3x3); Pool size (2x2)
 Add a Conv2D layer with 16 filter, using "ReLU" activation function
 Add a MaxPool2D layer
 Add a Conv2D layer with 32 filters, using "ReLU" activation function
 Add a MaxPool2D layer
 Add a Conv2D layer with 64 filters, using "ReLU" activation function
 Add a MaxPool2D layer
 Add a Flatten layer
 Add a Dense layer with 512 units, using "ReLU" activation function
 Add a Dense layer with 1 unit, using "Sigmoid" activation function

The pseudocode (see **Table 1**) and the proposed ConvNet model which has three layers with $2^4, 2^5$ & 2^6 filters. Each convolutional layer with the "ReLU" activation function followed by MaxPool2D (2,2) method for the pooling layer. The model employs a "Dense" layer with 512 units

**Figure 3****Graphical Representation of ConvNet Model****(a) Model loss (b) Model accuracy**

and the “ReLU” activation function after the flattening layer, and the activation function for the final “Dense” layer, a “sigmoid,” is illustrated in Eq. (8), providing the classification result, which shows the presence of garbage or no garbage. As the number of epochs grows, so does the accuracy of the outcome; in this case, it provides good results with 30 epochs, (see **Figure 3**).

2.3 MLP Model for Garbage Classification

The artificial neural network (ANN) class known as multilayer perceptrons (MLPs) is completely connected and uses a feedforward architecture. The proposed model uses a “200x200” pixel image of garbage or no garbage as an input. The input converts into the normalised matrix of 40000 independent variable x_i where i is from 1 to 40000. Each input is assigned a randomly assigned weight w_i where i is from 1 to 40000. The MLP is based on the error-correction rule. There are two passes in total: one forward and one backwards.

The forward pass involves applying the input vector x_i to the network’s sensory nodes, where i ranges from 1 to 40000, and its effects propagate layer by layer [13]. On the other hand, during the backwards pass, the synaptic weights are adjusted by an error correction rule. In the suggested model, each neuron in the network employs a nonlinear logistic function. The network can learn complex tasks due to the hidden neurons, which gradually extract from the input image vector more and more valuable characteristics. The forward pass does not change the synaptic weights of

the network, and the function signals are determined neuron by neuron. The function signal at the neuron j 's output is calculated using Eq. (9).

$$y_j(n) = \varphi \left(\sum_{i=0}^m w_{ji}(n) y_i(n) \right) \quad (9)$$

Where, $w_{ji}(n)$ is the synaptic weight tying neuron i to neuron j , $y_i(n)$ is the input signal for neuron j , the function signal seen at the output of neuron i and m the sum of all inputs, including the bias, given to neuron j . Define the error signal at the output of neuron j at interaction n using Eq. (10).

$$e_j(n) = d_{j(n)} - y_j(n) \quad (10)$$

Let N be the total amount of examples used for training, where set C represents the number of neurons in the network's output layer. By adding up all the errors and then normalising them by the set size N , as stated in Eq. (11), one may determine the average squared error energy.

$$\xi_{av} = \frac{1}{N} \sum_{n=1}^N \xi(n) \quad (11)$$

$$\delta_{j(n)} = (e_j(n))(\varphi_j(v_j(n))) \quad (12)$$

The backward pass, which begins at the output layer, carries the error signals layer by layer across the network to the left, while iteratively computing the local gradient for each neuron, as indicated in Eq. (12). It uses two hidden layers of 128 neurons each with "ReLU" and "Sigmoid" activation functions respectively. The output layer has two neurons one for image with no garbage and one for garbage on the striate.

2.4 SVM Model for Garbage Classification

The existence of garbage is also classified using the SVM classifier. We utilised the "SVC" Python library to implement SVM. The dimension of each image is 200x200 pixels. In order to categorise the class of data, In a 3:1 split, the dataset is used for training and testing purposes.

We have training sample $\{(x_i, d_i)\}$, where x_i $x_i \in R$ is the input pixels value for the i^{th} garbage image and $d_i \in \{\pm 1\}$ the class of the garbage image. The decision surface's equation, which depicts the existence of waste, is given in Eq. (13). In order to reduce the distance between hyperplanes, the distance between them is $\frac{2}{\|w\|}$. Where $\|w\| = w^T w$, with no data points are between hyperplanes.

$$w^T x + b \geq 1 \quad (13)$$

This problem can be stated as $\min_{w,b} \left(\frac{1}{2} \right) w^T w$ subject to $y_i (w \cdot x_i - b) \geq 1$, In a convex space, this is a quadratic programming problem (in w, b). We now present Lagrange multipliers $\alpha_1, \alpha_2, \dots, \alpha_n \geq 0$, as shown in Eq. (14).

$$\mathcal{L}(w, b, \alpha) = \left(\frac{1}{2} \right) w^T w - \sum_{i=1}^N \alpha_i y_i (w \cdot x_i - b) + \sum_{i=1}^N \alpha_i \quad (14)$$

Solve the Wolfe dual instead: maximize $\mathcal{L}(w, b, \alpha)$ with respect to α , subject to the constraints that the gradient of $\mathcal{L}(w, b, \alpha)$ with respect to the primal variable w & b vanish; $\frac{\partial \mathcal{L}}{\partial w} = 0$, $\frac{\partial \mathcal{L}}{\partial b} = 0$ and $\alpha \geq 0$. Now we can classify the new object x with Eq. (15).

$$f(x) = \text{sgn} \left(\sum_{i=1}^N \alpha_i y_i (x_i \cdot x) + b \right) \quad (15)$$

The training vector x_i occurs only in the form of dot product. The data points are translated into another high-dimensional space if the problem is nonlinear so that they can be linearly separated. The high dimensional space is identical to a kernel function of the input space when written as $\Phi(x_i) \cdot \Phi(x_j) = k(x_i, x_j)$, for this the Gaussian kernel function is proposed.

2.5 LR Model for Garbage Detection

Logistic regression is predictive analysis; A 2D array of normalised positive numeric values from an image serves as the model's input. To anticipate the garbage, it has 40000 independent variables; the mathematical model is shown in Eqs (16,17).

$$p = b_0 + b_1 x_1 + b_2 x_2 + \dots + b_{40000} x_{40000} \quad (16)$$

$$P(y) = \frac{1}{1 + e^{-p}} \quad (17)$$

$P(y)$ probability and $1-P(y)$ probability both fall into different classes. The model forecast $y = 1$ when $p \geq 0.5$ and $y=0$ when $p < 0.5$ for classifications.

2.6 KNN Model for Garbage Classification

The proposed KNN is used for classifying garbage or no garbage classes. Unlabeled data are categorised into the most similar tagged observation class by the KNN classifier. Observational characteristics are

collected for both the training and test datasets. We are using it in our research to find out if there is trash on the street. By default, the KNN employs Euclidean distance, which may be calculated using the Eq. (18).

$$D(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + \dots + (x_n - y_n)^2} \quad (18)$$

2.7 NB Model for Garbage Classification

The behaviour of the Naive Bayes machine learning classification approach was examined using garbage as an input. Eq. (19), in which X is the input variable and y is the output variable, contains the Bayes Theorem.

$$P(y | X) = \frac{P(X|y).P(y)}{P(X)} \quad (19)$$

2.8 Performance evaluation

This research examined the performance of models incorporating garbage recognised in open space based on the confusion matrix calculation utilising overall accuracy, recall, precision, and F1-Score as indicators.

3. Results and Discussions

It was discovered throughout the experiment that the accuracy of ConvNet and MLP performed in a particular pattern. After the fifth epoch,

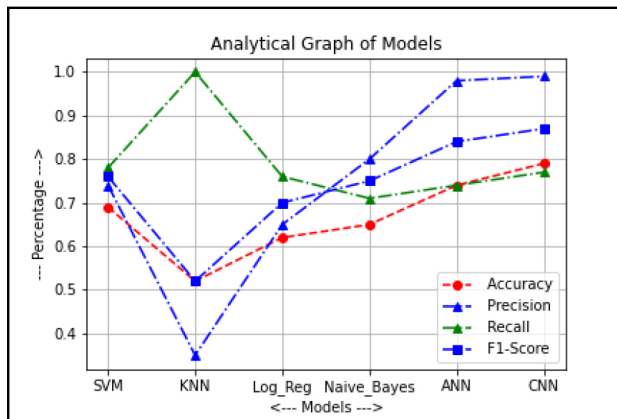


Figure 4
Comparative analysis of all models

Table 2
Analysis report of SVM, KNN, LR, NB, ANN and ConvNet Models

S. no	Model	Accuracy	Precision	Recall	F1-Score	ROC
1	SVM	0.69	0.74	0.78	0.76	0.66
2	KNN	0.52	0.35	1.00	0.52	0.91
3	LR	0.62	0.65	0.76	0.70	1.00
4	NB	0.65	0.80	0.71	0.75	0.88
5	MLP	0.74	0.98	0.74	0.84	0.75
6	ConvNet	0.79	0.99	0.77	0.87	0.87

the MLP Network's percentage accuracy result becomes constant. While the ConvNet model's performance in terms of % accuracy has changed abnormally from the fifth to the thirty-first epoch. However, the ConvNet model's accuracy is superior to the MLP's (see **Figure 4**). As shown in **Table 2**, The accuracy, precision and of F1-Score of the ConvNet model is the best, but very near to the MLP model. Whereas the KNN model has maximum recall and lowermost precision.

The accuracy of the SVM model is between 70 and 80 percent, that of the LR model is between 60 and 80 percent, while that of the MLP and ConvNet models is between 75 and 100 percent. ConvNet and MLP models outperform other classifiers in terms of accuracy with the 2D image of garbage collected by CCTV camera from the street, but LR has the best ROC curve area.

4. Conclusion

The results can be summarised as follows: the LR model with 100% of ROC (Area) is best suited for the detection of garbage, while the ConvNet model, with an accuracy of 79%, is best suited for the classification of garbage or no garbage class.

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