

Automated Cow Dung Detection and Collection Robot Using YOLOv8 and Robotics

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Abstract. The improper disposal of cow dung poses severe environmental and health challenges, including the spread of vector-borne diseases and respiratory issues. Conventional methods for dung collection, reliant on manual labor and traditional tools, are inefficient, labor-intensive, and expose individuals to significant health risks. This study addresses these concerns by developing an automated cow dung detection and collection robot that combines advanced AI, machine learning, and robotics to provide an efficient, safe, and cost-effective solution. The proposed system utilizes the YOLOv8 deep learning model for real-time detection of cow dung with an accuracy of 85%. A dataset of 200 images, covering various natural environments, was meticulously preprocessed, annotated, and used for training the model. The robot's mechanical framework employs a forklift mechanism and a lead screw for efficient dung collection, guided by a Raspberry Pi and Arduino Nano, which coordinate the detection and collection processes. The system is capable of collecting up to 150 kg of dung per day at an operational cost of 1 rupee per kilogram, demonstrating its practicality and scalability for real-world applications. This research highlights the robot's superiority over conventional systems in terms of health safety, cost-efficiency, and environmental impact. The design and performance validation indicates that the robot is a sustainable solution for rural and urban waste management.

Keywords: Automated waste collection, Cow dung detection, YOLOv8 deep learning, Sustainable agriculture, Robotics in waste management.

1. Introduction

Cow dung remains a relevant agricultural product scale of obsession in livestock farming, especially in remote places where such cattle rear. However, poor disposal of cow dung is also a serious health hazard as it leads to environmental degradation and an increase in vector-borne pathogens. The presence of pathogenic *E. coli* and *Mycobacterium paratuberculosis*-containing pathogens causes damaging health conditions amongst individuals such as developing gastrointestinal tract and respiratory diseases [1][2]. Moreover, the prevalence of using cow dung for usual purposes during the COVID-19 pandemic has aroused the fear of promoting health risk perspectives such as Cutaneous Mucormycosis which is a sore affecting the nose region caused by

a deadly fungal infection. With these lowlights in cow dung use, it still provides an opportunity to be harnessed for various eco-friendly practices that can include biogas and organic farming that increases soil nutrients without the use of chemical fertilizers [3].

The current systems don't employ any advanced technology and involve a lot of manual labor and usage of traditional tools for dung collection, which are not effective and require lots of drudgery. People have also used alternatives, for instance, fuel made from dung cakes. However, this has caused a lot of indoor pollution because harmful gases are released when they are burned [4]. In addition, these ways do not solve the challenge of appropriate disposal or use and sanitation of cow dung. In this case study, the method applied focuses on the creation of an autonomous robot incorporating a YOLO (You Only Look Once) model, capable of real-time identification of cow dung. The robotic device has a camera and the images were processed by a Raspberry Pi computer embedded within the robot. Anytime cow dung is observed, a signal is sent to an Arduino Nano capable of working engine drivers; this is performed to steer a mechanical part called a scoop. The scoop allows the robot to collect the dung and place it in a storage compartment within the robot. This new method helps to not only make the process of collection more convenient but also reduce the health risks to humans that may arise from this collection.

The importance of this research goes beyond mere ease of operations but instead focuses on critical problems faced within the agricultural sector about waste management. This project aims to automate the disposal of cow dung to improve the efficiency of farming operations and reduce exposure to health hazards associated with conventional techniques. Moreover, by helping convert cow dung into useful products i.e., biogas, organic fertilizers, etc., this technology helps in environmental conservation and development of the rural economy as well.

2. LITERATURE REVIEW

2.1 Machine Learning

Mitra et. al[5] used deep learning models for image processing. During the research, SVMs were found to be more accurate than CNNs. The model was divided into 4 parts for image recognition i.e. plastic, paper, tin, and glass. They used Google's TensorFlow AI for object detection. The most important necessary libraries used in this project are NumPy, Matplotlib, OS, TensorFlow, Utils, and OpenCV. In the online GitHub Repository, the training data was obtainable which was mainly used in the classification of garbage for recyclability status. Faster R-CNN is prepared for 6 mother classes dependent on cardboard, glass, metal, paper, plastic, and trash, so if the mother is paper the child cannot be tinned. The number of epochs for the neural network was 200000 steps. Testing the trained model is the last part of the process. After the training is completed, the frozen inference graph is exported. This is used for identifying and classifying the objects in a real-time feed utilizing webcam, images, and videos. Hence, the model was 91% accurate.

In[6], authors have proposed an architecture for the litter classification into the specified categories as per the benchmark approaches. EfficientNet-B0 architecture was used for classification. Further to this, a two-stage detector deep learning framework was proposed to identify and classify garbage into seven categories with up to 75% accuracy. In [7] a model is implemented using The TrashNet dataset which is analyzed for classification of waste images. Additionally, CNNs & a DRL scheme, and

a Dense-Net model were used by authors with The TrashNet dataset for detecting objects followed by deep reinforcement. For segregation and classification of MSW, a method is proposed based on the K nearest Neighbour algorithm. An image dataset was obtained from the Kaggle with as many as 34 categories of solid waste.

In[7], an architectural design of a smart trash bin is introduced which utilizes multiple sensors with microcontrollers. It is deployed with IoT and Bluetooth communication for data monitoring. Additionally, a camera module scans the waste materials. After the scanning and image capturing process, a pre-processing component for the captured images taken by the camera in real-time is performed. Apart from the camera, an ultrasonic sensor is used to measure the empty level of the trash box. Ultrasound is transmitted and received to calculate the empty level of the trash bin. For classification different architectures of CNN such as AlexNet, VGG16, and ResNet34 were used. To improve the performance of architecture a big data set and several types of sensors such as IR sensor, and MQ Gas sensor can be integrated in the system.

Authors in[8], have proposed a waste classification system for polyethylene terephthalate, high-density polyethylene, polypropylene, and polystyrene. From results it can be seen that using image processing and artificial intelligence methods, allows deployment of effective automatic waste classification systems that operate in the real world. The hydrocyclone uses centrifugal force to separate materials of different densities, they used the froth flotation technique for the hydrophobicity of the plastic to separate it from the rest of the waste. They used 3d colored sensors and a conveyor belt for detection and separation.

Razak et al[9] proposed using a Deep Learning algorithm to classify the waste as Metal, Paper, Plastic, and nonrecyclable waste. The classification was performed using AlexNet Convolutional Neural Network (CNN) architecture in real-time so that the waste can be dropped into the appropriate chambers as soon as it is thrown into dustbins through this computer vision approach. Caffe is a type of algorithm, used for vision acknowledgment. Around 80% accuracy was achieved.

Aishwarya et al.[10] proposed application is a method to detect non biodegradable waste from the bins so that the nonbiodegradable waste can easily be separated from the bins. Data was divided into three major categories of non-biodegradable waste that were glass, metal, and plastic. They used Analog & Digital Image processing. A raspberry Pi camera was designed which was used to detect three categories of non-biodegradable waste. The model failed to differentiate between plastic & glass yet it achieved an accuracy of 75%.

Mohammad et al.[11] have employed a deep learning-based framework to localize and classify different types of wastes. There exist approaches that classify garbage into recycling categories similar to Google's OverFeat.

Nandhini et al.[12] The robot can sense whether there is waste present or not before moving towards it, this has been achieved using ultrasonic radiations and calculating the distance between the object and the robot. A convolutional network of 5 layers was employed for differentiating between wastes. The Arduino is programmed such that, if the ultrasonic sensor senses the presence of waste in the predefined location, then the robotic arm links are moved at fixed angles so that it can pick up the object and place it on the classifier platform. If the object isn't present, then it moves to the next location within the workspace until it finds a waste. An electronically assisted waste segregation system was designed and tested.

A waste segregation system was created and validated. Zhang et al.[13] seek to enhance the accuracy of waste sorting using deep learning and to present a possibility for

intelligent waste classification based on computer vision/mobile phone terminals. A better waste classification model based on the residual network is proposed. Their model is capable of classifying various types of waste while enhancing the accuracy of waste classification. The proposed model was validated on the TrashNet dataset to sort recyclable waste and contrast its sorting performance with other models. Experimental results indicate that the classification accuracy of this model for images is 95.87%. This paper suggests a waste image classification model (CTR) using ResNet18, which can use deep learning techniques to sort various types of waste.

Etinkaya et al [14] Recycling waste sorting with high accuracy has become a significant area of research in recent years due to its direct effect on the environment and economy. Computer-aided approaches are able to provide effective performances in recycling processes which consist of big data sizes. In this work, a deep learning (DL) based image analysis approach has been improved by using Python programming language and the YOLOv8x DL algorithm to optimize the recycling processes. From the simulation results, it can be concluded that DL-based approaches can provide high accuracy in image recognition and can successfully be used in the processing of big data sets.

Miguel et al [15] conduct a component of an ongoing study to replace the identification of waste containers through radio-frequency identification. The aim of this paper is to introduce a computer vision-based method of identification that carries out detection through images, video, or real-time video capture to recognize various types of waste containers. This method is more flexible compared to the existing method of identification and does demand as many resources. There are two methods used, one based on feature detectors/descriptors and the second based on convolutional neural networks. Two approaches are employed, one using feature detectors/descriptors and the other using convolutional neural networks. They used the YOLOv2 and YOLOv3 for good results. The problems addressed in the paper are the aging population in the workforce, the high costs that are hindering sustainability, and the labor shortages that are hindering agricultural productivity.

Yuan et. al [16] explores various methodologies related to the use of robots and autonomous machines in agriculture. It emphasizes the application of advanced technologies such as deep learning and machine learning, which are increasingly integrated into agricultural practices. The focus is on modeling, detection, and control technologies that enhance precision farming, crop protection, and harvesting. The research aims to improve the efficiency of agricultural production through innovative robotic and autonomous solutions, thereby addressing the identified challenges. They did an extensive review of 26 papers leading to better understanding and productivity. The methodologies discussed are expected to lead to more resource-efficient agricultural practices, ultimately enhancing the quality and sustainability of agricultural outputs. While the paper discusses various advancements, it may not fully address the integration of these technologies across all agricultural sectors or the long-term impacts of automation on rural employment. There is a need for further exploration into the economic implications of adopting these technologies, particularly for small-scale farmers who may face barriers to entry. The paper could benefit from more empirical studies that assess the real-world effectiveness of the proposed robotic solutions in diverse agricultural settings.

Winfield et. al [17] focused on developing biodegradable microbial fuel cells (MFCs) for powering robots, specifically the EcoBoost series. The results indicated that various alternative materials, such as paper, gelatin, alginate, and even natural rubber from

condoms, were tested as replacements for conventional components in MFCs. However, initial experiments with condom membranes did not produce any electrical current, highlighting challenges in material selection. The EcoBots demonstrated the potential for autonomy, as they could move towards food sources and expel waste, showcasing the practical application of MFCs in robotics. The team ensured that all materials tested were both biodegradable and non-toxic through microbiological techniques and composting studies. The methodology involved identifying and testing a range of biodegradable materials to replace traditional components in MFCs. This included exploring porous materials that could facilitate proton transfer while being biodegradable.

A significant research gap identified was the lack of biodegradable alternatives to proton exchange membranes (PEMs), which are typically expensive and inhibit microbial metabolism. The study aimed to fill this gap by developing porous materials that could serve as effective replacements. The environmental impact of conventional plastics used in MFCs and robotics. The need for sustainable energy sources in robotics, particularly through the use of biodegradable materials. The challenge of creating a fully autonomous robot that can sustain itself by consuming organic matter, including its parts, thus contributing to a circular ecosystem.

3. Methodology

3.1. Cow dung detection system

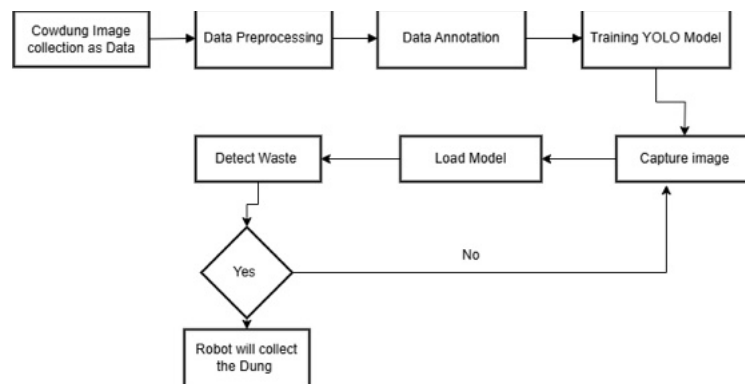


Fig. 1. Workflow for Cow Dung Detection

Figure 1 shows the flow chart of the cow dung detection system, further, each component of the process is explained below:-

3.1.1. Dataset Collection

Data was gathered through real-world data acquisition by taking pictures of cow dung from different roads. The present dataset consists of 200 images describing different natural environments and their influence on the shape, size, and surface characteristics of cow dung. These images are important to build an automatic system to identify cow dung for health monitoring purposes. The provided dataset collects a broad spectrum of environmental factors, which makes it possible to work with the data as close as possible to the actual conditions. This makes the overall approach to enable the

automated detection system to be more reliable and accurate and to be implemented in various contexts for real-time health monitoring purposes.

3.1.2. Data Preprocessing

Data preprocessing is a crucial step when it comes to the enhancement of the performance of the machine learning model. The value of a clean source of images could not be overemphasized and as a result, the images in the datasets that were used in this study underwent a rigorous data cleansing and enhancement pipeline. The images of cow dung were cropped such that the region of interest that contains the cow dung was highlighted. After that, all the images were resized to a standard format so that the dimension is standardized and reduces the loading time during the training of the model. Subsequently, the preprocessed dataset guarantees a good input to the model to accurately detect cow dung under different environmental conditions.

3.1.3. Data Annotation

Data annotation therefore greatly helped in training the machine learning model in the identification of cow dung in practical real scenarios. All the images in the given dataset were evenly labeled by drawing a box as shown in figure 2, around the cow dung in the particular frame. These regions were manually annotated into samples training the model to learn to accurately identify these areas of interest. The coordinates of the annotated bounding boxes with the corresponding labels were then stored in a text file in YOLO 1.1 format. This format contains such data as the class tag, as well as normalized coordinates of the box (center x, center y, width, height) to make object detection seamless during the training phase of the model. With the help of the new format for the localization annotations, the dataset was aligned to the YOLO format that helped to advance state-of-the-art object detection models enabling faster predictions as well as greater accuracy.



Fig. 2. Annotated Images of Cow Dung for different resolution

3.1.4. Training Yolo Model

For the model training phase, YOLOv8 (You Only Look Once version 8) was used since it has high accuracy and efficiency for real-time object detection. Figure 3 shows images recognized by the trained model. The annotated dataset included the cow dung images with the bounding box labels written in YOLO 1.1 format on which the YOLOv8 model was trained with images shown in figure 3. Given the images with

their annotations, the model was able to learn the spatial patterns needed for the detection. The training was done over 200 iterations so that the model receives enough exposure to learn the identification of cow dung and Pitbulls in any possible circumstance. The model was trained for a long time to capture the smaller details of cow dung shapes, textures, and multiple sizes of cow dung thus making the model quite robust. Thus the trained model has the capability of accurately detecting cow dung in different environments in practical fields.



Fig. 3. Training image of cow dung using the Yolo model



Fig. 4. Validation image of cow dung using Yolo model

Figure 4 shows the validation results of the Yolo model for the detection of cow dung. However, a further electronics system to pick up the dung and put it in the bucket is explained in the next section of the research.

3.2 Electronics system of the robot

Figure 5 shows the electronic system of the automatic cow dung collection robot. First, the camera detects the cow dung on the road using the input codes and with the help of the microcomputer. Then it sends the captured image to the Raspberry PI which decodes it and sends it to the Arduino. The Arduino sends messages to the motors which help to lift the cow dung using the forklift mechanism and store it inside the bucket.

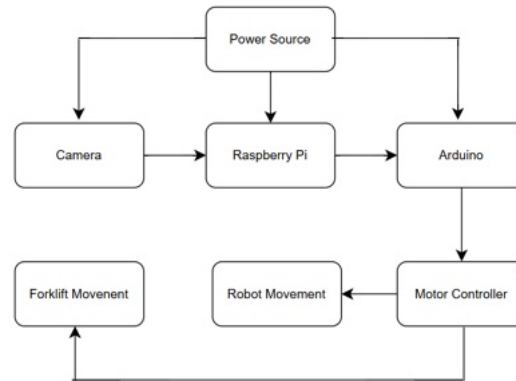


Fig. 5. Automatic System for Cow Dung Collection Robot

Hence the above project saves manual power and uses AI and robotics for efficient collection of stale cow dung on streets which is an impending threat to humans and animals as well. Further, the mechanical design and the construction are explained in the next section of the research.

3.2. Mechanical design

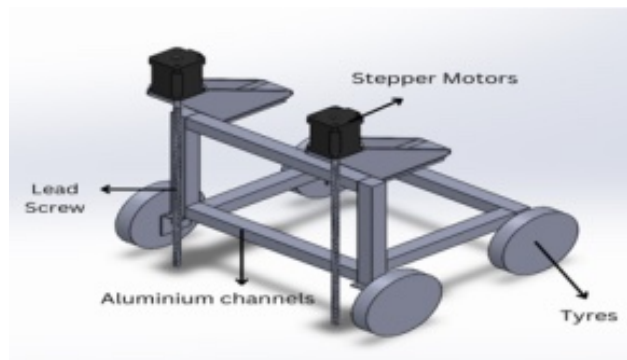


Fig. 6. Complete 3D design of the Cow dung collection bot

Figure 6 shows the complete design of the automatic cow dung collection robot. The design was started by considering the bot as the simply supported beam. Considering the bot as the simply supported beam helped us in this research to identify the load on the wheel.

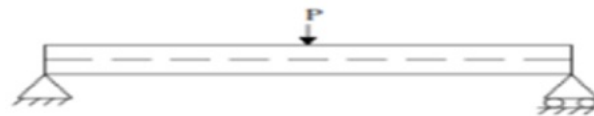


Fig. 7. Bot as the simply supported beam

Figure 7 shows the representation of the simply supported beam, in this both the wheels represent the support of the beam. However, the point load represents the weight of the

bot. This is efficient for collecting the cow dung using the forklift mechanism.

Based on this load calculation, the next step was to identify the value of the torque on the motor, which resulted in the selection of the motor and the battery power needed to operate. Looking at the amount of the load the type of steel channel needed to be used was decided. Further to pick up the cow dung from the road a forklift mechanism was decided as it was simple to make and assemble. Further based on the weight of the cow dung the motor size for picking up the cow dung was decided which was connected to the lead screw for linear motion of the prototype.

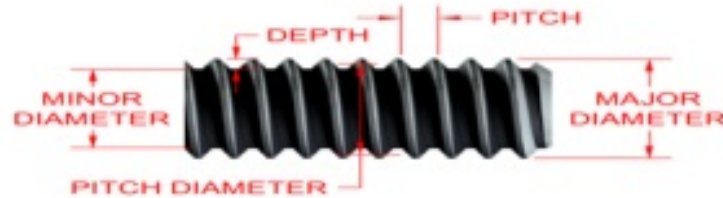


Fig. 8. Terminology of the lead screw

Figure 8 shows the terminology of lead screw and the specifications of the Leadscrew written below:-

- The pitch of our screw is 4mm which is 200 steps,
- The pitch is 0.02mm.
- No. of steps = Distance required to be moved / 0.02.

To test the efficiency of the design, a complete 3D model shown in Figure 6 was manufactured and tested. The results of the same were discussed in the next section of the research paper.

4. RESULTS AND DISCUSSION

Through the robot mechanism and image recognition system, research achieved an accuracy of 85%. Using the Jupyter Notebook, the researcher developed the code and used Roboflow for image processing, recognition system, and augmentation to efficiently and enhanced identify cow dung on the streets. The system is highly environment friendly and cost-effective, targeting cow dung with fueling efficiency, and does not require manual power.



Fig. 9. Actual Cow Dung Collection Bot

As shown in figure 9 the prototype was made using environment-friendly material such as renewable tyres, carbon free plates and aluminium body. Compared to manual labor and conventional tools, this robot can cause minimum health risks and has a low cost and high efficiency. It costs around 1 rupee per kg for dung collection and can lift around 150 kg of dung every day. This model currently has achieved an accuracy of 85% but the aim is to achieve an accuracy of more than 90% which would boost the capabilities of our prototype and would serve as a better version of itself.

Table 1: comparative result of the bot with other working systems

Parameters	Labour	Labour + Conventional Tools	Automated Dung Collection Robot
Health	Very Risky	Low Risk	No Risk
Maintenance	Need Holidays	Yes	Yes
Capital & Operational Cost	Very High	High	Medium

Table 1 shows the comparative result of the automated cow dung collection bot with other working systems based on various parameters like health, maintenance, Capital and operational cost, and the Life span. Considering human health as the primary consideration our bot is best compared to labour and manual machines. Whereas maintenance is higher than other systems the operational cost is medium compared to the other systems. Overall the life span of the system is high relative to the other system.

5. CONCLUSION

This research demonstrates the successful development of an automated cow dung detection and collection robot, addressing a critical environmental and health issue through the integration of advanced AI and robotics. The YOLOv9 model achieved an 85% accuracy rate in detecting cow dung in various environments, utilizing a dataset of 200 images with rigorous preprocessing and annotation techniques. The robotic system, equipped with a camera, Raspberry Pi, and Arduino Nano, effectively captures, collects, and stores up to 150 kg of cow dung daily at an operational cost of 1 rupee per kilogram. Compared to traditional labor-intensive methods, the proposed solution significantly reduces health risks, improves waste management efficiency, and supports eco-friendly practices like biogas production and organic farming. Furthermore, the design considerations, including the simply supported beam model and lead screw specifications, optimized the robot's structural and mechanical performance. The comparative analysis revealed that the robot outperforms conventional methods in health safety, lifespan, and operational cost, despite higher maintenance requirements. Future enhancements aim to improve detection accuracy beyond 90% and expand the robot's adaptability to various terrains, advancing the scope of its application in sustainable agriculture and urban waste management.

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