Dry waste segregation using seamless integration of deep learning and industrial machine vision

1st Prof. Harsh Kapadia
Instrumentation and Control Engineering Department
Institute of Technology, Nirma University
Ahmedabad, India
harsh.kapadia@nirmauni.ac.in

2nd Prof. Alpesh Patel
Instrumentation and Control Engineering Department
Institute of Technology, Nirma University
Ahmedabad, India
alpesh.patel@nirmauni.ac.in

3rd Dr. Jignesh Patel
Instrumentation and Control Engineering Department
Institute of Technology, Nirma University
Ahmedabad, India
jbpatel@nirmauni.ac.in

4th Shivam Patidar
Instrumentation and Control Engineering Department
Institute of Technology, Nirma University
Ahmedabad, India
15bic065@nirmauni.ac.in

5th Yash Richhriya
Instrumentation and Control Engineering Department
Institute of Technology, Nirma University
Ahmedabad, India
15bic059@nirmauni.ac.in

6th Darpan Trivedi
Instrumentation and Control Engineering Department
Institute of Technology, Nirma University
Ahmedabad, India
16bic160@nirmauni.ac.in

7th Priyank Patel
Instrumentation and Control Engineering Department
Institute of Technology, Nirma University
Ahmedabad, India
16bic158@nirmauni.ac.in

8th Meet Mehta
Instrumentation and Control Engineering Department
Institute of Technology, Nirma University
Ahmedabad, India
15bic164@nirmauni.ac.in

Abstract**—** Municipal solid waste management has been one of the most critical issues of urban cities today. Increasing population, constructions, industries, etc. are the major factors creating a large amount of waste that is dumped onto the landfill sites. Various systems have been proposed and are under the utilization for the management of municipal waste which includes mechanical vibration-based size-based sorters, eddy current sensor-based sorting of metallic waste, automatic optical waste sorters, etc. This paper focuses on a novel solution for solid waste segregation using the concepts of machine vision and deep learning. The proposed concept is tested for the segregation of solid dry waste particularly plastic bottles, aluminum cans, and tetra packs. The prototype system developed for the segregations works at high speed and accuracy. The prototype system sorts 250 objects per minute with an average accuracy of 96%. The proposed novel idea be extended and implemented for other types of waste segregation and can include more categories of solid dry waste. The system provides a solution for the ever-challenging municipal waste management problem.

Keywords—Deep learning, machine vision, automation, convolutional neural network

I. Introduction

Municipal waste management is one of the major aspects which has to be considered in terms of making our city environment healthier and better for living. Due to the progress in information technology, the use of computing technology has taken place in many applications including waste management. The problem of urban waste has reached a point of concern. Unscientific disposal can cause very harmful effects on the environment as well as human health [1]. An increase in solid waste is inevitable due to an increase in population and economic growth. The major issue is the unmatched capacity of waste handling compare to waste generation. The increase in the production of waste is not balanced with the increase in its management capacity. The paradigm shift requires some level of involvement by the people in regulating waste [2]. Lack of official historical data and inconsistency in existing data is a major hurdle while studying the solid waste management of developing nations like India [21]. The complexity of the waste problem is not only related to the technical solution but also involves social behavior. Waste is expected not to be a burden anymore but can also be utilized economically to increase community income.

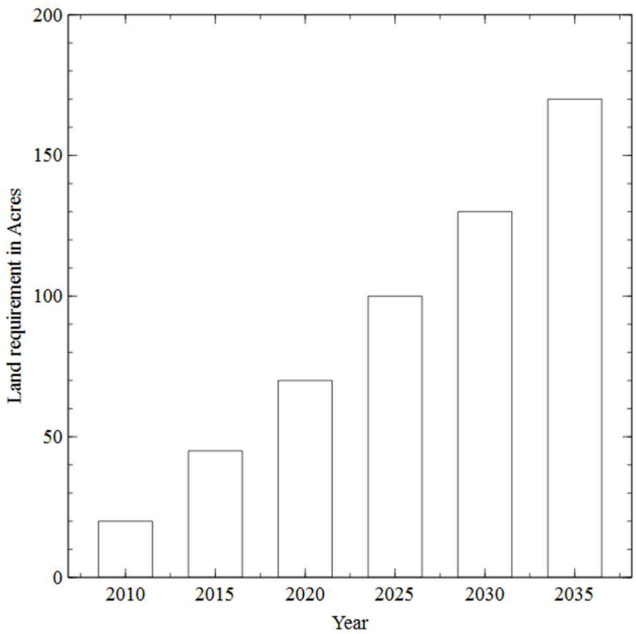

Fig. 1. Year wise data of land requirement for waste dumping in India

According to report on “Task Force on Waste to Energy” by planning commission, it is estimated that urban India will generate 2,76,342, tonnes per day (TPD) of waste by 2021. The generation will rise to 4,50,132 TPD by 2031; and 11,95,000 TPD by 2050 [22]. Out of the total waste generated, more than 80% is dumped into the open yards in unhygienic manner leading to health and environmental degradation. The untapped waste has a potential of generating 439 MW of power from 32,890 TPD of combustible wastes including Refused Derived Fuel (RDF), 1.3 million cubic metre of biogas per day or 72 MW of electricity from biogas and 5.4 million metric tonnes of compost annually to support agriculture [23]. Figure 1 shows the landfill requirement in acres over the years, which suggests a significant rise in the number of landfill sites required for dumping municipal waste [18]. Segregation of waste is a very key aspect of waste management. Unfortunately, in India, the present major practice is to use manual segregation of waste. There is a great need for an effective, high speed, economical, and automated waste handling and segregation system.

Researchers have proposed many techniques for the separation of different materials or types of waste. Tribostatic separation is used for sorting plastic using contact electrification [3]. Hydrocyclone is used to separate objects according to their density using centrifugal force. Jigging is another separation technique based on density [4]. It utilizes the interaction of buoyancy, gravity, and acceleration. Disc screen is a separation technique that helps in size-based sorting. Eddy current based separators are used to separate non-ferrous metals for non-conducting materials [5]. Magnetic density separation is used to sort different polymeric materials [6]. This technique varies the density of a magnetic flid which causes the polymeric materials of different densities to float at different levels. Froth floatation technique is used to separate plastic from the waste stream using the hydrophobicity of plastic [7]. Various vision-based techniques are also used to separate various types of waste using feature matching, X-ray-based sorting, etc. Hence, it can be concluded that various techniques are available but they can be applied to only specific classes of waste. Therefore, deep learning-based classifiers should be used as they can classify any kind of waste provided its dataset is trained. DNN based classifiers have high accuracy and provide fast results as a result they are more efficient. Researchers around the globe well addressed the problem of municipal waste management systems using techniques like the use of eddy current for segregation of ferrous and non-ferrous metallic waste, trommel (size based mechanical rotary sorter), dry and wet waste separator, use of robots for sorting waste, vision-based and inductive sensors array-based waste sorting. The systems have been proposed and tested for waste materials like recyclable paper, plastic, glass bottles, non-ferrous metals, metallic waste, in general, municipal waste, etc. The strong contribution of the research community in the area of municipal waste management has been discussed below in detail.

Ernst Schloemann et. al. presented his work on eddy-current techniques for segregating nonferrous metals from waste [5]. The author suggested in the paper that using eddy-current techniques many types of waste can be segregated. This method can be applied to municipal solid waste, automobile scrap, glass cullet, polyester bottle scrap, and electric-cable scrap. All applications mentioned above have been elaborated on in detail. The author has emphasized the benefits of using eddy current based separators over other conventional methods for these applications and also summarised test data for the same.

S. Sudha et. al. presented their work on an automatic classification method for environment-friendly waste segregation using deep learning [8]. The paper highlights the shortcomings of manual segregation of solid waste i.e., hazardous, less efficient, etc. The authors have proposed a deep learning algorithm using Caffe to classify objects as biodegradable and non-biodegradable.

Narendra Sivakumar et. al. presented their work on the design and development of an automatic clustered, assorted trash segregation system [9]. The author proposes a spot segregation unit that effectively separates various categories of refuses generated by municipalities. The sweeping mechanism of the system is controlled using a wireless interface using Xbee and a GUI is developed to provide easy control of the system. For detection of metals and their separation an electromagnet. To separate dry waste, a squirrel cage blower is used.

Mohammad Osiur Rahman et. al. presented their work on an intelligent computer vision system for segregating recyclable waste papers [10]. The author discussed various advantages of automated sorting systems over human inspection regarding worker fatigue, throughput, speed, and accuracy. The author proposes a smart vision system that segregates paper into different grades using first-order features. The database is constructed using a statistical approach with intra-class and inter-class variation techniques. Finally, the K-nearest neighbor (KNN) algorithm is applied to achieve the required identification.

Dr. Tuomas J. Lukka et. al. presented their work on robotic sorting using machine learning [11]. The authors propose a sorting system for construction and demolition (CND) waste by picking valuable objects from the conveyor using robotic hands. The authors also describe the solution to some of the key problems like recognizing materials and grasping irregular objects from the conveyer without resorting to human sorters.

Fitzwater G. Ang. et. al. presented their work on automated waste sorter with mobile robot delivery waste system [12]. The authors propose a solution to automate the sorting process of steel cans, aluminum cans, glass bottles, and plastic bottles. A sensor array is used for each material to be sorted, along with a conveyer belt as the Automated Waste Sorter (AWS). The Mobile Robot Waste Deliver System (MRWDS) is composed of a line following robot that can collect waste and dump it at the receiving end of the AWS.

Affan Shaukat et. al. presented their work on the visual classification of waste material for nuclear decommissioning [13]. The authors propose a solution incorporating a machine vision system for the identification of waste from decommissioned nuclear plants. A random forest learning algorithm is used for object classification whereas rotation and scale-invariant moments are used to describe object shapes in the scene.

George E. Sakr et. al. presented their work on comparing dep learning and support vector machines for autonomous waste sorting [14]. The paper discusses these two machine learning techniques and compares them on grounds of accuracy and speed of classification. As a result, the SVM model tends to be more accurate and faster and is then implemented on a Raspberry pi 3.

Sathish Gundupalli Paulraj et. al. presented their work on automated municipal solid waste sorting for recycling using a mobile manipulator [15]. The authors propose the development of a robotic manipulator for the autonomous sorting of useful recyclables from municipal solid waste. The developed manipulator has a thermal imaging camera, proximity sensor, and a 5-DOF robotic arm. The algorithm extracts key point features from the thermographic image and feeds them into a clustering model to map them. Finally, a Support Vector Machine (SVM) classifier is used for identifying recyclable material.

Matti Kutila et. al. presented their work on scrap metal sorting with color vision and inductive sensor array [16]. The authors propose an automatic scrap metal sorting system that employs a color vision-based optical sensing system and an inductive sensor array. The system can only separate reddish and bright metals. The use of sensor provides sensor fusion provides good performance despite the diversity of the scrap metals.

From the literature review, it is observed that there is still scope for improvement and research for solid waste management systems as a whole. Most of the researchers have proposed concepts for waste management with constraints like limited/specific category of waste, amount of waste managed, practical applicability for implementation, computation resources requirement in case AI/ML based methods, etc. These constraints provide research to find or develop an improved solution to the ever-challenging problem of municipal solid waste management. The appropriate implications of the potential solutions for MSW at the centralized and decentralized level need to be emphasized through various available of scientific treatment processes. Hence municipalities, along with the involvement of informal sectors, private agencies required to focus on creating potential opportunities and achieves the long-term goal of the MSWM sustainability for Indian cities [24].

In the paper, a convolution neural network (CNN) based solid waste classifier is proposed which can classify waste objects like plastic bottles, tetra packs, and metallic cans. These three types of objects have been chosen to prove the concept and prototype development. Other criteria for the object selections are its recycled value and the higher percentage of their presence in the overall solid waste collected. A prototype system is developed comprising of mechanical structure, automation systems, sensors, industrial camera, illumination, embedded systems, and computation system. All these components have been seamlessly integrated into the system to enable robust and steady solid waste sorting. The novel idea of the work proposed in the paper is the CNN-based classifier and machine vision implemented online and integrated with the physical system.

II. SYSTEM OVERVIEW

Municipal waste management is one of the biggest challenges of most of the urban cities around the globe and is one of the important factors under consideration along with water and electricity management for smart cities development. With increasing population, urbanization, the problem of waste management will get worse than ever. The situation demands a robust, accurate, and cost-effective solution for waste management. Various methodologies have gained popularity for waste management. One of the popular and widely used methods is the segregation of ferrous and non-ferrous materials using the concept of eddy current based sorter. But it does not solve the much bigger problem of waste management other than ferrous materials.

Major constituents of waste are sand, plastic (bottles, polythene, etc.), cloths, metals, paper, stones, building material waste, etc. [5]. Cost-effective handling of waste and segregation into various usable categories like bio-degradable and non-bio-degradable, combustible and non-combustible, etc. is the need. Collected waste can be first separated into bio-degradable and non-bio-degradable categories. Out of which, bio-degradable waste can be turned into organic manure while non-bio-degradable can be further separated into combustible and non-combustible waste. Sorted combustible waste can be further shredded and can be turned into Refused derived fuel (RDF) [6].

The proposed system utilizes the concepts of machine vision and deep learning for high-speed segregation of solid waste mainly plastic bottles, metal can, and tetra-packs. The segregation is achieved by the integration of mechanical assembly, automation system, and vision system. A major part of the mechanical assembly contains parts fabricated using mild steel (MS) channels, angles, and nets, both powder, and redox coatings were used for vibrating feeder, conveyor belt and collector bin covering, induction motor stand, control panel, and the human machine interface (HMI) panel. Conveyor belt fender and legs were built using industrial aluminum sections. Other important components were collector bins fabricated using medium-density fiberboard (MDF), white-colored polyvinyl chloride (PVC) conveyor belt, and nut bolts, etc. were used to give strength to the structure.

Figure 2 shows the block diagram of the developed solid waste segregation system. The diagram depicts information flow between different components of the system.

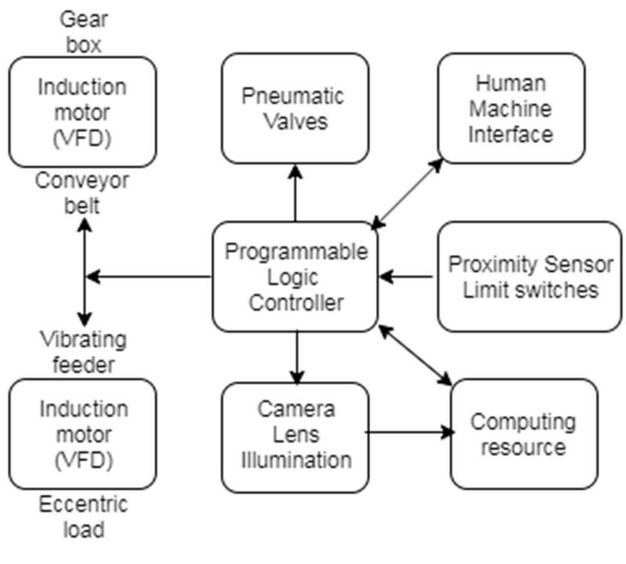

Fig. 2. Overall system block diagram

The automation system comprises the proximity sensors for object presence detection, limit switches, system control (start, stop, and emergency stop), two variable frequency drive (one for conveyor belt induction motor and another one for the vibration feeder motor), pneumatic system (solenoid valves for pneumatic blast used for sorting), web server and SCADA. Mechanical assembly is made up of a vibrating feeder running on an induction motor with eccentric load, a conveyor belt running on an induction motor with gearbox, vision box (industrial camera and illumination), four collector bins (one each for collecting plastic bottles, metal cans, tetra-packs, and other materials), control panel (PLC, VFDs, etc. and wiring), pneumatic control panel (three solenoid valves and pneumatic supply) and cover of moving parts for safety. The vision system comprises an industrial camera, lens, white color illumination, and a personal laptop with high-end configuration is used as the central computing resource.

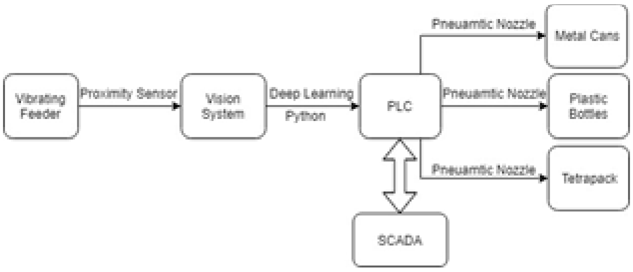

Fig. 3. Operational flow chart

The proposed system is designed to handle the only dry municipal waste. The assumption made here is that the collected municipal solid waste is separated by a system into dry and wet waste. Later the dry waste is again segregated into 2D and 3D waste where 2D means flat objects or objects with less thickness or height for example paper sheet, plastic wrapper, polythene bags, etc. whereas 3D object means objects with a certain height for example plastic bottle, metal can or tetra pack etc. The motive behind the selection of 3D waste objects namely plastic bottles, metal cans, and tetra packs is to prove the functionality of a convolution neural network centric approach to waste classification and further segregation. Also, the selected waste objects are recyclable and have certain monetary benefits and value. The flow of operation is shown in figure 3 and it is discussed further.

The 3D waste namely containing only plastic bottles, metal cans, and tetra packs is dumped into a vibrating feeder. The vibrating feeder is a mechanical structure fitted with an induction motor with an eccentric load to produce vibration. The vibrations produced would in turn transfer one object at a time from the feeder to the conveyor belt. The mechanical design of the feeder is such that the output way of the feeder has obstructions such that only one object can pass through it at a time. The design of the vibrating feeder is a very crucial factor in the overall system operation as its output speed would affect the overall segregation speed of the system. Waste objects with random size, as well as shape variations would be handled by the vibrating feeder. Hence the design should be such that it can operate with different sizes and shapes of the waste objects. The conveyor belt was operated by 3 phase 1400 RPM induction motor with a gearbox ratio of 1:7 for speed reduction. The motor was operated by a variable frequency drive.

At the start of the conveyor belt, a vision system box is placed which contains multiple proximity sensors, an industrial camera (Matrix Vision GmbH, model no. - mvBlueFOX MLC-205 GC, 5 MP, CMOS color MT9P031 sensor from Aptina Semiconductor, global shutter, USB 2.0, 5.8 fps, board-level industrial camera) and lens (Matrix Vision, M12, 8mm focal length) assembly, white color illumination all enclosed into a box such that outside illumination does not affect the performance of the camera. The reason for using an industrial camera, lens, and illumination is to acquire real-time blur and distortion-free images for classification. The industrial camera is used in the hardware trigger mode to capture the image of the object when it is detected by one of the multiple proximity sensors. The proximity sensors are mounted at different heights from the surface of the conveyor belt covering the random height variations of the waste objects. The software for object classification is written in python software.

Fig. 4. Sample of image dataset

Python software along with supportive libraries like OpenCV, NumPy, Matplotlib, SciPy, scikit-learn, TensorFlow, object detection, etc. was installed on a laptop (7th gen Intel i5 processor, 8GB DDR4 RAM,2GB NVIDIA GeForce 940MX graphics) which was used as a computing machine. The convolution neural network model was trained with more than 10,000 images per class. Figure 4 shows few samples of the waste objects dataset. The dataset indicates that objects have random shapes, sizes, and colors. The main motive behind the selection of the CNN-based approach is the random variations in the images of the objects. These random variations are difficult to program by conventional image processing-based approach or even machine learning-based approach which required accurate feature extraction. Hence the waste classifier was developed with a convolution neural network model named "Inception version3".

Inception v3, a convolution neural network model which is faster, is widely used and has attained 78.1% accuracy on the very popular ImageNet dataset. The model has a total of 42 layers optimized to achieve lower error rates. For application to activation inputs batch norm is used and for computation of losses, softmax layer is used [17]. The model was originally trained for 10,000 classes including over a million images. The main concept of the model is factorizing convolutions which reduce the number of hyper-parameters without decreasing the efficiency of the network. The proposed solution approach utilizes the concept of transfer learning, wherein we retrain the final layer of an existing model i.e., a model developed for a task is used again as the starting point for a model on another task or application. As a result, the knowledge gained during the first training is retained and the model can train it on a smaller dataset without extensive training and get highly accurate classifications.

The model was retrained for three major classes i.e., metal cans, plastic bottles, and tetra packs. These objects were chosen as they have the highest recyclable value out of the overall municipal solid waste generated and collected. The model was trained on over 10,000 images per class with 5,000 training steps and a 0.01 learning rate. Developed mechanical structure and image acquisition hardware were used to capture images for data set preparation. Data augmentation methods like flip, rotate, crop, and brightness, etc. were used to increase the dataset size. The model was trained using the TensorFlow library and tailored using python. The resolution of the images in the dataset was kept 640 x 480 in order to improve the overall computation time. A classification model is not successful until almost all variations are taken into account while making the dataset. Hence, the dataset was prepared to account for all kinds of images ranging from various angles and positions of the objects to crushed, twisted, or broken objects to make the model more accurate and efficient. The model was trained with the augmented dataset which took around 4-5 hours of training time on the system described earlier. Quite a few iterations of dataset preparation, data augmentation and model training had to be performed in order to improve the overall accuracy of the system. The performance of the model is discussed in the results and analysis section.

The prediction score computed by the model in python software is communicated to a programmable logic controller (PLC) via non-isolated RS485 communication. Mitsubishi FX5U PLC, GS2107 HMI, VFD and other required products were used in the system for automation. The PLC is the heart of the automation system which provides reliable and robust control of the machine operations. Three pneumatic nozzles and four collector bins were placed at a fixed distance after the vision box on the conveyor belt. With the use of a compressor, solenoid valves, and pneumatic nozzles, sorting of the waste objects was carried out by PLC digital outputs. Each class of the object was thrown and collected into its respective collector bin by the pneumatic blast. A proximity sensor was placed before each pneumatic nozzle to detect the presence of the object and trigger the pneumatic nozzle. The separated waste objects can be further used for recycling and further processing. The fill level of each bin was measured using low-cost ultrasonic distance sensors. For ensuring the safe and stable operation of the system, limit switches were mounted, for example, each collector bin was placed with a limit switch such that, if the collector bin is not in its proper place the system will give an error. For machine local control, monitoring purposes and parameter configuration, a human machine interface (HMI) was used. A SCADA (Mitsubishi MCworks64) was developed to visualize the system operation, performance, diagnosis, historical trends, and remote monitoring, reports, alarms history etc. PLC, SCADA and HMI were connected through a local network ethernet switch via Modbus TCP/TP. Figure 5 shows the mechanical design of the system along with notations.

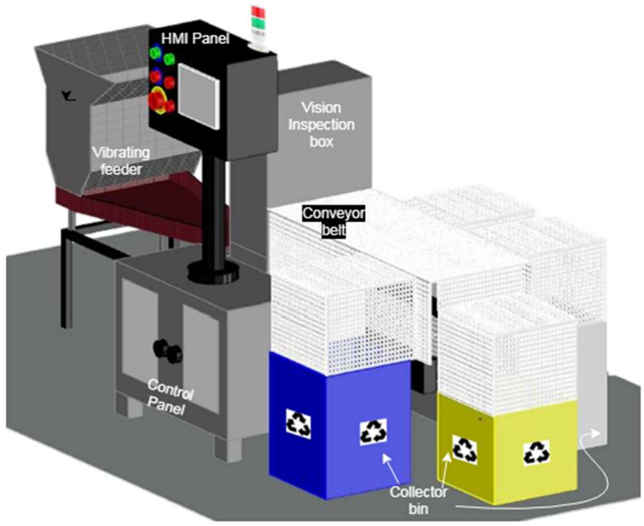

Fig. 5. Mechanical design view

III. RESULTS AND ANALYSIS

Robust and accurate performance of machine vision-based systems heavily relies on the coherent system integration with automation components, robust mechanical assembly, and precise vision system. Figure 6 shows the image of the developed solid waste segregation system. The developed system works at a rate of 200-250 objects per minute and consumed about 1.4kWH of energy. Overall computation time was varying between 240 to 300 milliseconds.

Fig. 6. Actual model photograph

The total computation time comprised of image acquisition time, image processing time and result communication time.

Image acquisition time varied between 20-30 milliseconds depending on the hardware trigger, processing time varied in range of 170 milliseconds to 200 milliseconds and result communication time varied between 10-20 milliseconds. With the use of a dedicated high configuration computing source, the speed can be increased for high-speed segregation.

Evaluation of the CNN model for dry waste classification was carried out. Characteristics like model training accuracy, validation accuracy, confusion matrix, precision-recall, accuracy, etc. were computed for the model. The model was validated using different types of objects (plastic bottles, metal cans, and tetra packs) which were not used in the training. The model was found to be performing accurate classification for the test objects considered. Figure 7 shows the model training accuracy and validation accuracy plotted versus the number of steps. Both accuracies were found to be nearly 99% as visible from the graphs which state that the model has learned the classes and variations present in the dataset of each class. The model testing was carried out on 300 (100 of each class) waste objects. A multi-class confusion matrix was developed after testing the model in the system. Actual class and predicted class information are shown in table 1 which signifies the classification ability of the model. The data presented in the table justifies the ability of model to accurately classify the class of object. The model achieved an average accuracy of the 96% which is shown in table 2. Reported high precision and recall values of the models shows that the model is able repeatedly perform the classification with utmost precision.

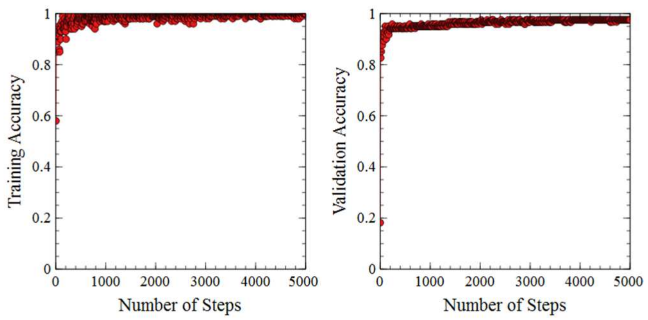

Fig. 7. Model training accuracy and validation accuracy graphs

TABLE I. MODEL CONFUSION MATRIX

		Predicted		
		Plastic bottle	Metal can	Tetra pack
Actual	Plastic bottle	97	2	1
	Metal can	5	92	3
	Tetra pack	1	1	98

TABLE II. MODEL ACCURACY, PRECISION AND RECALL

	Precision	Recall	Accuracy
Plastic bottle	94.2	98	96
Metal can	96.8	92	
Tetra pack	97	98	

A simple graphical user interface was developed in the python software to show the current image, identified class of object and statistical data. Figures 8, 9, and 10 show the display window showing the classification results of metal can, plastic bottles, and tetra packs respectively. The classifier is robust enough to accurately classify crushed objects, plastic bottles with/without wrappers, plastic bottles with/without caps, broken or torn objects, etc. The re-trained model is invariant to these variations in the input images. Images were acquired using an industrial camera and inconsistent illumination and background conditions, which enabled the model to learn the features. However, in few cases like the plastic bottle is of the same brand as that of metal can or metal can brand is same as that of the tetra pack, the model gave incorrect results. The issue can be addressed by updating the training and testing dataset. Images of objects with same brand and cover the variations as much as possible should be added in the dataset and the model should be retrained.

Fig. 8. Result image correctly identifies metal can

Fig. 9. Result image correctly identifies plastic bottle

Fig. 10. Result image correctly identifies tetra pack

IV. CONCLUSION

Waste classification is a trivial problem faced by developing and underdeveloped countries around the globe due to increased usage of plastic, and improper waste handling and management systems. Researchers and industries have addressed the problem and significant contributions were made. Vision-based dry waste classification and segregation system are discussed in the paper. Specifically, the use of deep learning integrated with machine vision is a novel contribution to the work discussed in the paper. An automatic dry waste segregation system has been developed using the concepts of deep learning and machine vision technology seamlessly integrated into an automation system. The developed prototype system is capable of handling dry waste namely plastic bottles, metal cans, and tetra packs, and sorting them at a rate of around 200-250 objects per minute which can be increased up to around 500 objects or more per minute with a higher frame rate camera and high configuration computing resource. The classification was performed using a re-trained CNN model called inception v3. The CNN model has trained 9000 images per class and validated over 1000 images per class. Classification accuracy of 96% was obtained for the model testing. The obtained accuracy proved the applicability of deep learning in the classification of dry waste. To prove the concept, three objects were chosen which can be increased to more than 100 different objects after studying the collected dry waste.

REFERENCES

[1] M. Sharholy, K. Ahmad, G. Mahmood and R. C. Trivedi, "Municipal solid waste management in Indian cities–A review," *Waste management,* vol. 28, no. 2, pp. 459-467, 2008.

[2] T. Narayana, "Municipal solid waste management in India: From waste disposal to recovery of resources," *Waste management ,* vol. 29, no. 3, pp. 1163-1166, 2009.

[3] M. Lungu, "Electrical separation of plastic materials using the triboelectric effect," *Minerals Engineering,* vol. 17, no. 1, pp. 69-75, 2004.

[4] C. Hendrics and X. Weihong, "Suitable separation treatment of stony components in construction and demolition waste (CDW)," *International RILEM Conference on the Use of Recycled Materials in Building and Structures. Bagneux, France,* 2004.

[5] E. Schloemann, "Eddy-current techniques for segregating nonferrous metals from waste," *Conservation & recycling,* vol. 5, no. 2-3, pp. 149-162, 1982.

[6] E. Bakker, P. C. Rem and N. Fraunholcz, "Upgrading mixed polyolefin waste with magnetic density separation," *Waste Management,* vol. 29, no. 5, pp. 1712-1717, 2009.

[7] M. S. Reddy, T. Okuda, K. Kurose, T. Tsai, S. Nakai, W. Nishijima and M. Okada, "Surface ozonation of polyvinyl chloride for its separation from waste plastic mixture by froth floatation," *Journal of Material Cycles and Waste Management,* vol. 12, no. 4, pp. 326-331, 2010.

[8] S. Sudha, M. Vidhyalaskhmi, K. Pavithra, K. Sangeehta and V. Swaathi, "An automatic classification method for environment: Friendly waste segregation using deep learning," *IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR),* pp. 65-70, 2016.

[9] N. Sivakumar, A. R. Kunwar, S. Patel, S. Kumar and S. P. Mala, "Design and development of an automatic clustered, assorted trash segregation system," *IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT),* pp. 409-413, 2016.

[10] M. O. Rahman, A. Hussain, E. Scavino, H. Basri and M. A. Hannan, "Intelligent computer vision system for segregating recyclable waste papers," *Expert Systems with Applications,* vol. 38, no. 8, pp. 10398-10407, 2011.

[11] T. J. Lukk, T. Tossavainen, J. V. Kujala and T. Raiko, "ZenRobotics Recycler-Robotic sorting using machine learning," *Proceedings of the International Conference on Sensor-Based Sorting (SBS),* 2014.

[12] F. Ang, M. K. A. R. Gabriel, Jameson Sy., Jenny Jane O. Tan and C. A. Alexander, "Automated waste sorter with mobile robot delivery waste system," *De La Salle University Research Congress,* pp. 7-9, 2013.

[13] A. Shaukat, Y. Gao, J. A. Kuo, B. A. Bowen and P. E. Mort, "Visual classification of waste material for nuclear decommissioning," *Robotics and Autonomous Systems,* vol. 75, pp. 365-378, 2016.

[14] G. E. Sakr, M. Maria, D. Ahmad, N. K. Mia and A. Hadi, "Comparing deep learning and support vector machines for autonomous waste sorting," *IEEE International Multidisciplinary Conference on Engineering Technology (IMCET),* pp. 207-212, 2016.

[15] S. G. Paulraj, H. Subrata and A. Thakur, "Automated municipal solid waste sorting for recycling using a mobile manipulator," *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference,* pp. V05AT07A045-V05AT07A045, 2016.

[16] M. V. Kutila and A. Vattulainen, "Scrap metal sorting with colour vision and inductive sensor array," *International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce,* vol. 2, pp. 725-729, 2005.

[17] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shelns and Z. Wojna, "Rethinking the inception architecture for computer vision," Proceedings of the IEEE conference on computer vision and pattern recognition, vol. 2826, p. 2818, 2016.

[18] R. J. a. S. Ahmed, "Status and challenges of municipal solid waste management in India: A review," *Cogent Environmental Science,* vol. 2, no. 1, p. 1139434, 2016.

[19] T. Narayana, "Municipal solid waste management in India: From waste disposal to recovery of resources," *Waste management ,* vol. 29, no. 3, pp. 1163-1166, 2009.

[20] M. Lungu, "Electrical separation of plastic materials using the triboelectric effect," *Minerals Engineering,* vol. 17, no. 1, pp. 69-75, 2004.

[21] K. T. Renu Hujare, "Solid Waste Generation Data Variability in India—An Unnoticed Hurdle," in *Recent Developments in Waste Management. Lecture Notes in Civil Engineering*, vol. 57, Springer, 2020, pp. 435-459.

[22] "Report of the Task Force on Waste to Energy," Planning Commision, Government of India, 2014.

[23] S. SINGH, "Solid Waste Management in Urban India: Imperatives for Improvement," *Observer Research Foundation Occational Paper No. 283,* November 2020.

[24] A. A. Akhilesh Kumar, "Recent trends in solid waste management status, challenges, and potential for the future Indian cities – A review," *Current Research in Environmental Sustainability,* vol. 2, 2020.