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DEVELOPMENT OF A MACHINE LEARNING-BASED WASTE CLASSIFICATION SYSTEM USING VGG-16 CNN FOR ENHANCED BIODEGRADABLE AND NON-BIODEGRADABLE SEGREGATION

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Abstract:

Waste management struggles with the segregation of biodegradable and non-biodegradable waste due to improper disposal, leading to contamination and reduced recyclable material quality. This study addresses these challenges by developing a machine learning-based waste classification system. Utilizing image classification techniques, specifically the VGG-16 Convolutional Neural Network (CNN) model, the system categorizes waste into biodegradable and non-biodegradable using a dataset from an open-source website. The methodology includes eight phases: preliminary study, knowledge and data acquisition, data pre-processing, model design, development, testing, and evaluation. A prototype using Maker Uno and a servo motor physically demonstrates waste classification. Despite challenges like limited high-quality components, this study aims to enhance recycling efficiency and sustainability by using VGG-16 with different epochs and shows the prototype's effective functionality, offering a promising solution for improving waste segregation and management.

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Keywords:

Biodegradable, Classification, Machine Learning, Recycling, Waste

Introduction

Waste management refers to the systematic transformation of waste materials into new goods or materials, with the aim of conserving resources and minimizing waste (Vollmer et al., 2020). The process involves the collection, categorization, treatment, and reutilization of discarded materials, including plastic, paper, glass, metal, and other similar substances. Various public locations, such as universities, city centres, underground transportation systems, and commercial complexes, provide dedicated containers for different categories of waste.

However, a considerable amount of waste often starts out in a mixed state, making disposal efforts less effective. Many people disregard waste separation practices and simply toss everything into one bin. This habit of combining various types of waste in a single container creates significant challenges for waste management facilities, hindering their ability to properly sort and process the materials. This results to the need for a costly and time-consuming separation process and adds complexity to the recycling of the waste (Azis, F. A., Suhaimi, H., & Abas, E., 2020). This factor also will have an impact on the overall quality of the materials (Abdel-Shafy & Mansour, 2018). Improper waste sorting significantly prolongs the time and necessitates increased human effort to separate the various categories of waste (Nandhini et al., 2019). The mixed state of waste also diminishes the quality and value of non-biodegradable commodities. Recyclables that are contaminated may have to be thrown away as waste, resulting in more landfill disposal and wasted resources.

While it is true that not all waste can be treated and will need to be disposed of in an engineered landfill, it is important to ensure effective segregation at the source for the waste that can be handled. The waste classification system is a very effective and cost-efficient management tool that may greatly benefit the public in the present day (Gondal et al., 2021). By segregating biodegradable and non-biodegradable waste at the source, the biodegradable waste may be directed to compost plants where it can be converted into organic compost. This compost can then be utilized in agriculture and other relevant fields.

Currently, the approach of sorting solid waste relies heavily on manual labour, which is hindered by various challenges such as low productivity, expensive labour costs, and an unfavourable working environment that increases the risk of human contamination. One of the primary challenges faced by this approach is the incorrect segregation of waste by the public (Knickmeyer, 2020). The lacking capability in planning, developing, constructing, and managing solid waste management, coupled with a shortage of technical and human resources, has resulted in the illegal dumping of waste in various locations (Salwa Khamis et al., 2019). Furthermore, the combination of biodegradable and non-biodegradable waste restricts the possibility of achieving efficient waste reduction, reuse, and recycling. Inadequate waste segregation hinders recycling initiatives and sustainability objectives.

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An initiative must be undertaken to ensure the preservation of sustainability objectives. To address these issues, this study proposes using image classification in waste management by using machine learning to solve the problem of incorrect waste segregation, thereby enhancing the effectiveness and sustainability of the recycling process.

The structure of this paper is as follows: Literature review that discusses on waste management, machine learning and Convolutional Neural Network. Then methodology used is described that involved 8 phases followed by findings and results. Finally, conclusion and future work to conclude this paper and offers recommendations for future studies.

Literature Review

There are 3 points that will be discussed in LR which are waste management, machine learning and Convolutional Neural Network (CNN).

Waste Management

Waste management involves the collection, transportation, processing, management, and monitoring of waste generated by human activities, aiming to minimize its negative impact on the environment, human health, and aesthetics (Talukdar et al., 2018). Solid waste, particularly plastics, presents a significant threat to environmental conservation due to its rapid production rate and the low reuse rate of these polymers (Gothai et al., 2022). Plastic waste refers to the collection of used plastic items, which are made from a chemical compound known as polymer (Okunola A, Kehinde I, Oluwaseun, & Olufiropo E, 2019). Additionally, biodegradable waste management poses a major challenge, as it naturally pollutes the environment during degradation. When large amounts of biodegradable waste decompose, they can harm the ecosystem and nearby residents.

The residue left after industrial waste treatment is hazardous and detrimental to both the environment and human health (Sabir et al., 2020). This can negatively impact the surrounding environment. In Malaysia, landfilling is a widely supported and low-cost method of solid waste disposal, with 85% of waste ending up in landfills. Other disposal methods, such as incineration, have been adopted only on a small scale. The current incinerator is considered inefficient due to factors like improper waste segregation and high moisture content. The land available for development in Malaysia is gradually decreasing due to the ongoing reliance on landfilling (Salwa Khamis et al., 2019). Effective waste management is essential to ensuring that recycled waste is handled properly and to prevent environmental pollution.

Machine Learning

Machine learning is a branch of artificial intelligence that enables computers to learn and evolve without explicit programming (Durgadevi et al., 2020). It encompasses a wide range of algorithms that make intelligent predictions based on data sets, which often contain millions of data points. Recent advancements in machine learning have reached a level of human-like semantic understanding and information extraction, as well as the ability to identify abstract patterns with greater accuracy than human experts (Nichols et al., 2019). Machine learning includes various types such as supervised learning, where models learn from labelled data to make predictions or classifications.

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In supervised learning, the model is provided with a dataset and knows what the expected output should look like, based on the assumption that there is a relationship between the input and the outcome. Then there is unsupervised learning, which identifies patterns in unlabelled data using methods like clustering or dimensionality reduction. This approach allows us to address problems even with little to no knowledge of what the solutions might be, helping us uncover structures by combining data-supported correlations between variables. Another type is reinforcement learning, where agents learn by interacting with an environment and receiving rewards or penalties. This method is often used in software and equipment to discover the most efficient behaviour (Kumar et al., 2022). Semi-supervised learning is another approach, which combines labelled and unlabelled data to improve understanding. Lastly, deep learning utilizes multi-layered neural networks to detect complex patterns.

In waste management, several machine learning techniques are applicable, such as CNN, Decision Trees (DT), and Extreme Learning Machines (ELM). These techniques are among the most used methods in the field to address challenges in waste management.

Convolutional Neural Network (CNN)

A CNN is a deep neural network widely used in AI, machine learning, and computer vision to handle image data and solve instance segmentation problems. CNNs can identify objects within images or videos by providing object bounding boxes, classes, and masks. They work similarly to the human brain's visual system by directly interacting with image pixels to extract features, making the process efficient. The weight-sharing feature and pooling layers in CNNs reduce the number of parameters required, simplifying the network and enhancing the training process (Kusumawati et al., 2023; Gothai et al., 2022; Yin et al., 2022). Figure 1 shows the architecture of CNN.

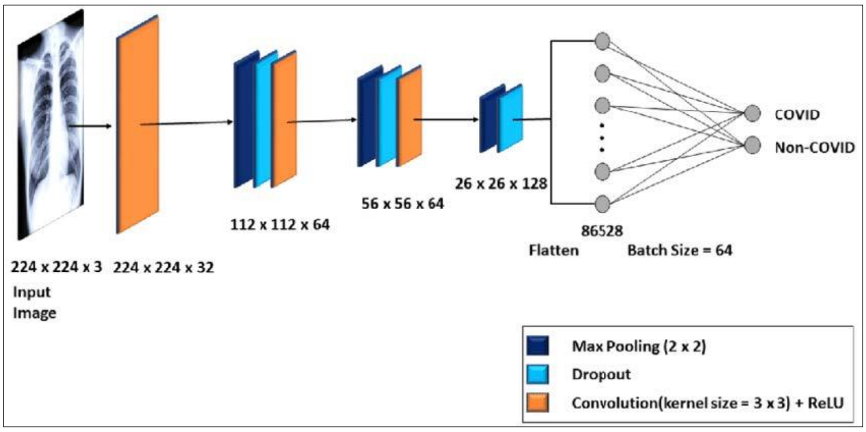

Figure 1: Convolutional Neural Network Architecture

Source: (Madaan et al., 2021)

In waste management, CNN techniques are frequently employed for tasks such as waste classification, detection, and segmentation. Notable CNN architectures include VGG-16, known for its deep layers and strong performance; Fastnet-34, which is optimized for quick processing; ResNet50, a 50-layer network that effectively extracts features and addresses the vanishing gradient issue; and ResNet18, a lighter version of ResNet50 that offers good results with lower computational demands. These CNN approaches have been crucial in advancing solutions to waste management challenges (Pandey et al., 2023; Gyawali et al., 2020).

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Methodology

There are 8 phases involved in conducting this research - preliminary study, knowledge acquisition, data pre-processing, model design, model development, model testing and evaluation, prototype design and prototype development. Figure 2 depict these 8 phases.

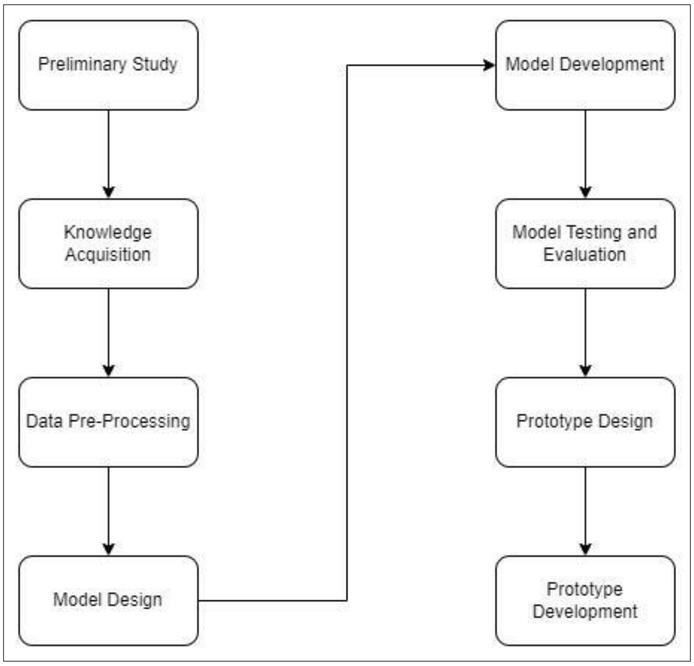

Figure 2. Methodology Phases

The first phase of the research methodology, known as the preliminary study, involves a systematic investigation conducted at the start of a research project to determine its feasibility, and gather crucial information before moving forward. This phase focuses on understanding the background of waste detection in bins and the techniques used. It includes reviewing academic articles, consulting with experts, and exploring reliable sources like research papers and online databases to gain a thorough understanding of the problem and develop effective solutions.

In the knowledge acquisition phase, a variety of articles are gathered to provide foundational reading for research on image classification in waste management. Based on insights from existing studies, the most appropriate machine learning algorithm for waste classification is identified. Convolutional Neural Networks (CNNs) emerge as the best choice due to their superior ability to accurately extract and classify features from images. The research also delves into the classification of biodegradable and non-biodegradable waste, with a strong emphasis on image-based techniques. The initial step involves locating relevant open-source datasets, such as those on Kaggle.com, a popular platform for similar research endeavours. The chosen dataset comprises images of various materials, including paper, cardboard, glass, metal, and plastic. The primary outcome of this phase is a comprehensive literature review on machine learning techniques for image classification, which will provide valuable insights and guide the development of an effective waste detection system.

In the data pre-processing phase, it was necessary to decrease the number of images in the dataset. This ensured consistency in the trained models when selecting appropriate images

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related to the objective of the study. The objective was to focus on paper and cardboard materials for biodegradable waste, and glass, metal, and plastic for non-biodegradable waste. The situation arose due to an imbalance in the number of images within the dataset, leading to overfitting during the training process and resulting in unstable outcomes. A compilation of images was then created, consisting of a total of 1200 images. Specifically, 600 images were selected for the biodegradable category and another 600 images for the non-biodegradable category. These images were used to train the model. The data were categorized into two distinct groups: biodegradable and non-biodegradable waste elements. This approach guaranteed the efficient processing of data to properly address the problem. Figure 3 and Figure 4 show the compilation of biodegradable and non-biodegradable images.

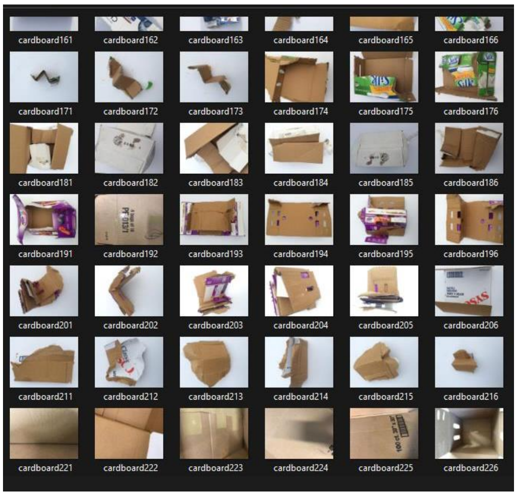

Figure 3. Biodegradable Dataset for cupboard

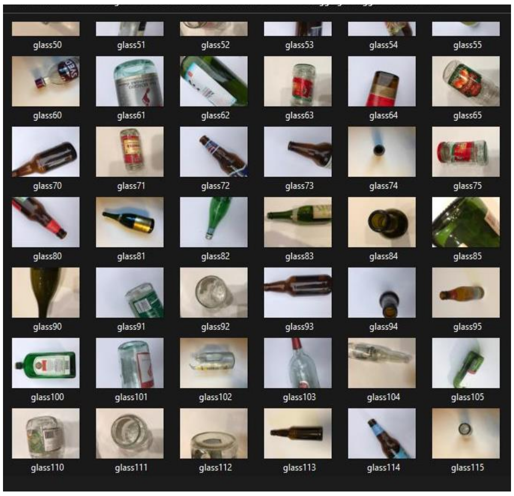

Figure 4. Nonbiodegradable Dataset for Glass

In the model design phase, the goal is to develop an efficient model architecture for waste classification using machine learning or deep learning techniques. This involves creating a model that accurately classifies waste items into predefined categories using Python. Various factors were considered, including the complexity of waste types, variability in waste composition, and data availability. This study explores machine learning techniques, particularly CNN VGG-16. Python's extensive libraries, like TensorFlow, Keras, and Scikit-learn, are used to implement and experiment with model architectures, adjust hyperparameters, and optimize performance to create a waste classification prototype.

In the model development phase, the model system code was developed for waste classification in the bin by using Phyton. The source of the code was obtained from the open-source database website which is GitHub that was then modified to adapt with the performance of the classification system.

In the model testing and evaluation, the focus is to test and evaluate the Phyton-based model by testing the model's functionality and performance. This is to ensure that the model meets the requirements and produces accurate results. Then, evaluation was carried out to assess the model's overall performance.

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Next is the prototype design that focus on producing the physical prototype that embodies the model's functionality for waste classification in the waste bin. This phase includes designing the tangible and functional representations of the model by integrating the Python programming language with Arduino hardware platform. This integration allows the prototype to interact with waste items, capture their characteristics, and initiate the waste classification process based on the embedded machine learning model. Figure 5 and Figure 6 shows the early prototype design and system interface.

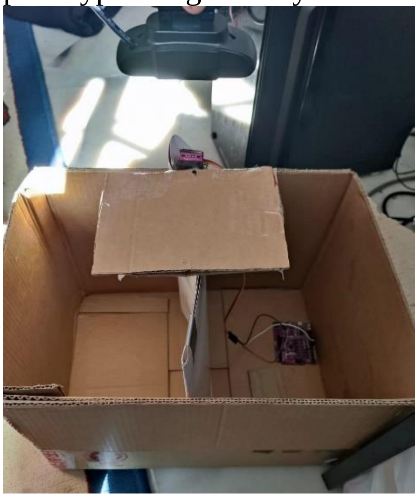

Figure 5. Early Prototype Design

Figure 6. System Interface

The last phase is prototype development, which is developing the fully functioning prototype system. The fully functioning prototype proves the model's feasibility, efficiency, and applicability. The prototype system shows how the model can accurately classify waste and simplify waste classification. The prototype consists of two biodegradable and non-biodegradable boxes, equipped with an external camera that attached at a standing bottle and the camera is pointed at the platform of the prototype.

Figure 7. External Camera

The camera shown in Figure 7 can capture image with a quality of 720p, making it captured the image of the waste efficiently in HD. Then, it will capture the image of the material on the platform as shown in Figure 8 to detect the waste materials and the trained model will respond

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to the captured image, classify it whether it is a biodegradable or non-biodegradable materials and making the servo motor connected to the Arduino to rotate to the correct waste materials compartment. The deliverable is a working physical prototype system that demonstrates the functionalities of the model shown in Figure 9.

Figure 8. Prototype Platform

Figure 9. System Prototype

Findings and Results

This section explains the experiments that were conducted, the conclusions, and results based on hyperparameters. To attain the best level of accuracy in the shortest period of training time, certain hyperparameters are adjusted.

Experiment Setting

Three experiments were conducted using the VGG-16 model to ensure the reliability of the trained CNN architecture. By running parameter tuning on the model, specifically the epoch of the model, the model shows the performance of the model, and it can be improved and evaluate more precisely by training the model using the obtained and processed dataset that consists of biodegradable and non-biodegradable materials images which are paper, cardboard, glass, metal and plastic images. The epoch used for these experiments are epoch 10, epoch 20 and epoch 30. These experiments examine the performance of an image classification model and investigated the impact of varying the number of epochs during training. The primary objective is to identify the optimal epoch setting that would lead to effective generalization to new and unseen data. To conduct the experiment, a dataset comprising 1200 images was utilized for both training and testing.

Comparison Result Between Epoch 10, Epoch 20 and Epoch 30 on VGG-16

Throughout the experiment, the validation accuracy and validation loss were recorded for each epoch. The validation accuracy represents the proportion of accurate predictions on a distinct validation dataset.

Journal of Information System and Technology Management JISTM
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Table 1: Comparison between Model Epoch in VGG-16 Model

Epoch	Validation Accuracy	Validation Loss
10	94%	17%
20	95%	15%
30	95%	15%

Based on the results shown in Table 1, it is evident that the model attains a 94% accuracy at epoch 10, which increases to 95% at epoch 20 and remains constant at epoch 30. Conversely, the validation loss, which measures the discrepancy between the model's predictions and actual targets, initiates at 17% during epoch 10, decreases to 15% during epoch 20, and remains consistent throughout epoch 30. The model's persistent high validation accuracy and stable validation loss indicate that it is effectively learning and generalizing to unseen data. For VGG-16, 20 epochs seem to be the ideal choice, resulting in the highest accuracy and low validation loss.

Training Process

The VGG-16 architecture is used in this Python code to create an image classification model utilizing transfer learning. The goal is to classify images into two waste categories which are biodegradable and non-biodegradable. The code loads and preprocesses the images before splitting them into training and testing as displayed in Figure 10.

```
# scale the raw pixel intensities to the range [0, 1]
data = np.array(data, dtype="float") / 255.0
labels = np.array(labels)

# partition the data into training and testing splits using 75% of the data for training and the remaining 25% for testing
(trainX, testX, trainY, testY) = train_test_split(data, labels, test_size=0.25, random_state=42)
```

Figure 10. Splitting Training and Testing Data

The Adam optimizer is used to compile the model, and during training, a learning rate reduction callback helps in fine-tuning the model which is at 0.001 then the model is saved after training. This method enables the model to utilize ImageNet to achieve successful waste classification even with insufficient data, resulting in a robust and accurate solution for waste classification system.

Upload Sketch into Arduino

This Arduino code is designed to control a servo motor to perform waste segregation based on commands received from an external source which is a Python script running on VS Code and it was uploaded to Maker UNO. Then, a Servo Motor is connected to pin 8 and it receives commands such as 'a' or 'b' through serial communication from an external source. When 'a' is received which is biodegradable waste, the servo rotates to position 30 degrees and after performing the tasks, the motor will rotate into default position, resetting its movement. When 'b' is received, the servo rotates to position 150 degrees, and the code is shown in Figure 11.

Journal of Information System and Technology Management
JISTM
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```
if(d[0] == 'a'){

  s.write(30);
  delay(500);
}
else if(d[0] == 'b') {
  s.write(150);
  delay(500);
```

Figure 11. Servo Command

Real-Time Waste Classification

This code uses a pre-trained deep learning model to perform real-time waste classification on webcam images. It connects to an Arduino device through serial communication and sends commands based on the waste type prediction. The captured frame is displayed with the waste type label, and the code will stop when a key is press thus, closing the window. This setup enables waste segregation by controlling the Arduino device to sort waste into each category. Figure 12 displays a paper tissue, while Figure 13 showcases a plastic bag. These figures illustrate the window output that indicates the sort of waste for each item.

Figure 12. Biodegradable Waste

Figure 13. Non-Biodegradable Waste

System Prototype

Figure 14 shows the physical prototype develop with Maker UNO and Servo Motor. This prototype is integrated with the classification system that allows the prototype to do the tasks given from the system.

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Figure 14. Final Prototype Development

Initially, in order to start the prototype, it is necessary to provide the Maker UNO with a power supply, which should be connected to the laptop to establish a connection between the system and the webcam. This is because, in order for the system to operate well, it necessitates computer vision capabilities, which are provided by the hardware in the form of a personal laptop. Subsequently, the code for computer vision, which will capture an image, will be executed in the VS Code Integrated Development Environment (IDE). An interface for the user will pop up, requesting the user to click the "Capture Image" button. The captured image will then be displayed in a separate window, labelled with its corresponding waste type: either biodegradable or non-biodegradable materials. Upon detecting a substance, the motor will shift the platform towards its corresponding category, with biodegradable waste being directed to the right side and non-biodegradable waste to the left side.

Conclusion and Future Work

This study has determined that VGG-16 with 30 Epochs tuning demonstrates better performance compared to other epochs. This model demonstrated a remarkably effective capability for categorization. Therefore, VGG-16 was selected as the framework to develop the physical prototype, which utilizes Maker UNO as a waste sorting prototype employing machine learning. Empirical evidence confirms that the prototype performed effectively during the testing phase. During the operation of the prototype, the code including OpenCV was executed to identify waste materials using the camera. Subsequently, the system captured an image of the material and categorized it as either biodegradable or non-biodegradable in a separate window, clearly indicating the waste category. Simultaneously with the classification process, the servo motor shifted, transferring waste into the appropriate bins.

For future work, it is advisable to employ Flask for deploying the model and integrate it with a user-friendly graphical interface that mimics a system website, instead of executing the code repeatedly through the VS Code IDE. Furthermore, it is also advisable to employ a more extensive dataset and broaden the range of waste categories when training the upcoming model. This strategy has the potential to result in increased accuracy, decreased loss, and a reduction in overfitting.

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References

Abdel-Shafy, H. I., & Mansour, M. S. (2018, December). Solid waste issue: Sources, composition, disposal, recycling, and valorization. Egyptian Journal of Petroleum, 27(4), 1275–1290. https://doi.org/10.1016/j.ejpe.2018.07.003

Azis, F. A., Suhaimi, H., & Abas, E. (2020, August 12). Waste Classification using Convolutional Neural Network. Proceedings of the 2020 2nd International Conference on Information Technology and Computer Communications. https://doi.org/10.1145/3417473.3417474

Durgadevi, S., Thirupurasundari, K., Komathi, C., & Balaji, S. (2020, December 10). Smart Machine Learning System for Blind Assistance. 2020 International Conference on Power, Energy, Control and Transmission Systems (ICPECTS). https://doi.org/10.1109/icpects49113.2020.9337031

Gondal, A. U., Sadiq, M. I., Ali, T., Irfan, M., Shaf, A., Aamir, M., Shoaib, M., Glowacz, A., Tadeusiewicz, R., & Kantoch, E. (2021, July 19). Real Time Multipurpose Smart Waste Classification Model for Efficient Recycling in Smart Cities Using Multilayer Convolutional Neural Network and Perceptron. Sensors, 21(14), 4916. https://doi.org/10.3390/s21144916

Gyawali, D., Regmi, A., Shakya, A., Gautam, A., & Shrestha, S. (2020). Comparative Analysis of Multiple Deep CNN Models for Waste Classification. ArXiv, 10.48550/arXiv.2004.02168

Knickmeyer, D. (2020, February). Social factors influencing household waste separation: A literature review on good practices to improve the recycling performance of urban areas. Journal of Cleaner Production, 245, 118605. https://doi.org/10.1016/j.jclepro.2019.118605

Kumar, R., Thakur, P., & Chauhan, S. (2022, May 26). Special Disease Prediction System Using Machine Learning. 2022 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COM-IT-CON). https://doi.org/10.1109/com-it-con54601.2022.9850843

Kusumawati, D., Ilham, A. A., Achmad, A., & Nurtanio, I. (2022, December 13). Vgg-16 And Vgg-19 Architecture Models In Lie Detection Using Image Processing. 2022 6th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE). https://doi.org/10.1109/icitisee57756.2022.10057748

Nandhini, S., Mrinal, S. S., Balachandran, N., Suryanarayana, K., & Ram, D. S. H. (2019, April). Electronically assisted automatic waste segregation. 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI). https://doi.org/10.1109/icoei.2019.8862666

Nichols, J. A., Herbert Chan, H. W., & Baker, M. A. B. (2018, September 4). Machine learning: applications of artificial intelligence to imaging and diagnosis. Biophysical Reviews, 11(1), 111–118. https://doi.org/10.1007/s12551-018-0449-9

Journal of Information System and Technology Management JISTM
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Okunola A, A., Kehinde I, O., Oluwaseun, A., & Olufiropo E, A. (2019). Public and Environmental Health Effects of Plastic Wastes Disposal: A Review. Journal of Toxicology and Risk Assessment, 5(2). https://doi.org/10.23937/2572-4061.1510021

Pandey, A., Jain, H., Raj, H., & Gupta, P. P. (2023, April 7). Identification and Classification of Waste using CNN in Waste Management. 2023 IEEE 8th International Conference for Convergence in Technology (I2CT). https://doi.org/10.1109/i2ct57861.2023.10126312

Salwa Khamis, S., Purwanto, H., Naili Rozhan, A., Abd. Rahman, M., & Mohd Salleh, H. (2019, April 18). Characterization of Municipal Solid Waste in Malaysia for Energy Recovery. IOP Conference Series: Earth and Environmental Science, 264, 012003. https://doi.org/10.1088/1755-1315/264/1/012003

Sabir, M. O., Verma, P., Maduri, P. K., & Kushagra, K. (2020, December 18). Electrically controlled artificial system for organic waste management using Black Soldier Flies with IOT monitoring. 2020 2nd International Conference on Advances in Computing, Communication Control and Networking (ICACCCN). https://doi.org/10.1109/icacccn51052.2020.9362816

Talukdar, P., Baruah, M., & Saikia, P. (2018). Waste management for sustainable agricultural production: A brief review. Asian Journal of Home Science, 13(2), 657-659. http://researchjournal.co.in/online/AJHS/AJHS%2013(2)/13_657-659_A.pdf

Vollmer, I., Jenks, M. J. F., Roelands, M. C. P., White, R. J., Harmelen, T., Wild, P., Laan, G. P., Meirer, F., Keurentjes, J. T. F., & Weckhuysen, B. M. (2020, June 25). Beyond Mechanical Recycling: Giving New Life to Plastic Waste. Angewandte Chemie International Edition, 59(36), 15402–15423. https://doi.org/10.1002/anie.201915651

Yin, X., Lu, J., & Liu, Y. (2022, July). Garbage Detection on The Water Surface Based on Deep Learning. 2022 International Conference on Computer Engineering and Artificial Intelligence (ICCEAI). https://doi.org/10.1109/icceai55464.2022.00145