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Article

Intelligent Waste Sorting System: Leveraging Arduino for Automated Trash Identification and Categorization

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Abstract: As the all encompassing community evolves and urbanization accelerates, the refuse namely produce persists to rise. This dirty trash has extreme consequences to the environmental atmosphere, moving the equilibrium of the all encompassing tangible balance. Trash discovery electronics can swiftly and correctly recognize, categorize, and settle various kinds of litter to accomplish the mechanical transfer and reliable reusing of waste, and it can likewise advance the growth of a circular frugality. However, the prior trash refuse discovery science has few problems, to a degree reduced accuracy and a weak detection effect in difficult surroundings. Even YOLOv5 has realized good results in refuse discovery, the detection results cannot meet the necessities in complex sketches, so this paper uses, YOLOv5x, an enhanced YOLOv5 model. We, in this research work would like to infuse custom dataset, a comprehensive collection of images of waste categories divided into seven classes with the object detection models like YOLO towards automating trash detection and precise classification that helps in achieving better waste sorting accuracy. The research work core ambition is to exploit distinctive attributes of YOLO models combined with Arduino to give rise to a more effective trash sorting system. Traditional garbage management processes is very labour intensive work, making them time- consuming, costly, and prone to human error. To overcome these short comings, we propose the development of a deep learning-based model that can swiftly detect and classify various types of waste items in real-time. YOLO, a state-of- the-art object detection algorithm, will serve as the backbone of our model, ensuring fast and accurate identification of trash items. The integration of an Arduino microcontroller into our system adds a practical and interactive dimension. Arduino will facilitate seamless communication between the deep learning model and the physical world. This enables our system to trigger actions such as sorting, recycling, or alerting authorities, depending on the detected trash item and its classification.

Keywords: deep neural network; object detection; trash classification; waste sorting; waste detecting technology

1. Introduction

1.1. Origin of the Proposal

In our increasingly urbanized and environmentally conscious world, the management of waste has become a paramount concern. The growing volume of waste generated daily poses significant challenges for municipalities and organizations tasked with efficient and sustainable disposal and recycling. To address these pressing issues, we have embarked on a journey to harness the potential of modern technologies, specifically deep learning and IoT, to revolutionize trash detection and classification. This proposal originates from our desire to alleviate the burdens of waste management that has reached

334 million tonnes annually as shown in Figure 1 [1] below.

Figure 1. bllions of tonnes of waste produces annually.

1.2. Definition of the Problem

Our research work centres around the development of an advanced system capable of automating the detection and classification of trash items [1].The classes that we will be dealing is as shown in Figure 2 below. Traditional waste management methods are often labour intensive, error-prone, and costly. By integrating the YOLO (You Only Look Once) deep learning algorithm and Arduino- based hardware, we aim to create a solution that can effectively identify and categorize various types of trash in real-time.

The core challenge lies in seamlessly merging the capabilities of YOLO for object detection with Arduino's versatility for physical world interactions. This involves optimizing the deep learning model's performance for trash recognition, ensuring reliable communication between the model and the Arduino microcontroller, and orchestrating actions such as sorting or alerting based on the detected trash type. Furthermore, the solution should be scalable and adaptable, applicable in contexts ranging from smart bins in public spaces to advanced waste sorting facilities. Our research work aims to not only enhance the efficiency of waste management but also promote sustainable practices by encouraging proper waste disposal and recycling. By addressing these multifaceted challenges, we endeavor to demonstrate the potential of cutting- edge technology in addressing a critical global issue.

Figure 2. Different Types of Trash.

1.3. Objectives

Develop a YOLO-V5 model for Trash Detection and Classification: This objective forms the foundation of the research work by focusing on the building of a YOLO-V5 model that can proficiently detect and classify various types of trash items found in the open source dataset. The process starts with meticulous data preparation, including balancing class distributions, splitting the dataset into training and testing sets, and ensuring it's ready for model training.

The crux of this objective lies in configuring the YOLO-V5 architecture, a powerful deep learning model optimized for object detection, to suit the task of trash classification.

Develop a Waste Segregation System with Arduino: It involves the physical implementation of a garnage segregation system using Arduino technology. The foundation of this objective is establishing an Arduino setup equipped with actuators and collector bins. This hardware is engineered to seamlessly integrate with the YOLO- V5 model, effectively receiving instructions on how to sort different types of trash items.

Increase Accuracy Through Hyperparameter Tuning: It revolves around optimizing the YOLO-V5 model to achieve higher levels of accuracy in trash detection and classification. The process entails a meticulous exploration of various hyperparameter settings, encompassing aspects like learning rates, batch sizes, and even potential architectural modifications. Continuous fine-tuning and experimentation are pivotal in identifying the most effective configuration. To ensure the model's robustness and consistency, cross-validation techniques are employed.

Validate Software Algorithm with Hardware Implementation: It ensures that the software-based trash detection algorithm aligns seamlessly with the hardware- based waste segregation system. This involves extensive testing and validation, focusing on the integration of both components. Real-world testing scenarios are crucial in verifying that the hardware system effectively acts upon the classifications generated by the software algorithm.

2. Literature Survey

2.1. Applying a Deep Residual Network Coupling with Transfer Learning for Recyclable Waste Sorting [2]

The paper utilizes different ResNet architectures , namely ResNet with 18, 34, 50, 101, 152 deep layers as part of RWNet models for the classification task. These models are based on transfer learning and aim to classify various types of recyclable waste. The main evaluation metric for these models is accuracy, measuring their effectiveness in correctly categorizing waste materials. But the count of images used in the dataset(around 2,300 images) are very low in to believe the correct accuracy of the model.

2.2. MSWNet: A Visual Deep Machine Learning Method Adopting Transfer Learning Based Upon ResNet 50 for Municipal Solid Waste Sorting [3]

The paper introduces a novel deep learning network called MSWNet, designed for waste classification. The dataset used for training comprises 58,000 images categorized into four classes: hazardous, organic, residual, and recyclable waste. MSWNet leverages transfer learning with ResNet50 as its base model. Remark- ably, the model achieved an impressive accuracy rate, approaching 90 percent indicating its effectiveness in accurately classifying different types of waste materials.

2.3. Autonomous Trash Collector Based on Object Detection Using Deep Neural Network [4]

This research paper details a system for trash detection using a robot equipped with an ultrasonic sonar sensor and a camera module. The robot captures images of detected objects and sends them to a Raspberry Pi for classification as either trash or not trash using a deep learning CNN algorithm . This system enables autonomous trash identification and potential collection by the robot.

2.4. "Trash and Recycled Material Identification Using Convolutional Neural Networks (CNN)"

This research involves the development of two Convolutional Neural Networks (CNNs) inspired by the AlexNet [5] architecture. These CNNs are designed to identify trash objects in images and then further classify them into recyclable items or landfill trash objects. The system's performance is evaluated using the Trash- Net indoor image dataset, and it demonstrates excellent results, confirming the viabilityof the two- stage CNN approach for trash detection and classification.

2.5. "Domestic Trash Classification with Transfer LearningUsingVGG16"

This research paper introduces a Deep Learning model utilizing the VGG16 [6] architecture for precise classification of diverse trash objects. The model is validated on TrashNet dataset and real-world images with 92% accuracy achieved.

2.6. "Research on Recyclable Garbage Classification Algorithm Based on Attention Mechanism" [7]

This research study suggests a ResNet18 convolutional neural network model for the categorization of recyclable trash that is based on the attention mechanism. After convolution, the attention module is included so that the model can execute closer attention to the crucial data in the feature map. Glass, metal, plastic, and paper are just a few of the features of trash that the algorithm can automatically extract for classification.

2.7. "Garbage Classification and Detection for Urban Management" [8]

The goal of this research article is to employ Deep Learning and Neural Network methods to detect and classify rubbish as the world is expected to generate 3.4 billion tonnes of waste by the end of year 2050 [9]. Here, The CNN algorithm is used, put into practice, and examined. Also employed are the ROC curve and the confusion matrix. Two distinct datasets are employed in this work, one of which was created by us and the other of which was sourced from the internet. In this study, two datasets are compared using a variety of algorithms, including CNN, SVM, and faster-RCNN. This research has been carried out for ease of recycling purpose for cleaning staff [10].

2.8. "A Novel Framework for Trash Classification Using Deep Transfer Learning"[11]

This research study focuses on developing a new deep neural network [12] model called as DNN-TC which is an extension of ResNet model. The study has been carried out on VN-trash Dataset which consists of 5904 images spread across three classes that are Organic,Inorganic and Medical waste.The model has developed an accuracy of 98% on mentioned dataset

2.9. Domestic Trash Classification with Transfer Learning Using VGG [13]

Based on the VGG16 deep learning architecture, a model for classifying household trash was able to achieve over 96% accuracy on a dataset that included real-world photos and TrashNet samples. Their method makes use of transfer learning techniques to modify the pre-trained VGG16 model for precise rubbish object classification. The model has the potential to automate waste classification procedures, which would support effective waste management plans and environmental preservation initiatives.

2.10. CGBNet: A Deep Learning Framework for Compost Classification [14]

The deep learning framework CGBNet —which is intended to differentiate between green and brown compost—is presented in this research. It suggests identifying and categorizing data using superclass and subclass classification techniques. A dataset of 1,960 photos is used to train and assess six deep learning models using both label structures. Furthermore, 96% accuracy is achieved in feature extraction with a performance gain through the use of transfer learning. This approach has the potential to enhance compost categorization procedures, supporting effective waste management techniques.

2.11. A Survey on Waste Detection and Classification Using Deep Learning [15]

This review paper provides a thorough overview of classification of image and object detection models, specifically examining their use in waste detection and classification. It carefully analyzes the techniques used in these tasks, and the given benchmark trash image datasets, supplying a strong basis for grasping current approaches. It also points out difficulties faced by present methods and considers future possibilities, delivering helpful viewpoints for additional research and progress in this area. Overall, the survey offers a comprehensive examination of deep learning for trash detection and classification, summarizing key models, datasets, methods, challenges, and opportunities.

2.12. "Waste Classifications Using Convolutional Neural Network"

The paper investigates the use of three different CNN [16] architectures for automated garbage management. The top-performing model, architecture 3, uses a Kaggle dataset of 156,362 photos classified as biodegradables and non-biodegradables. With grayscale images, it achieves 81.0% accuracy with a 44% loss. Using RGB pictures, comparable results are obtained with a 49% loss and an accuracy of 82.7%. These results show that CNNs can be used for trash categorization regardless of color representation, indicating that they are a viable option for effective waste separation systems.

2.13. Garbage Detection and Classification Using a New Deep Learning-Based Machine Vision [17]

The research introduces an improved MobileNetV2 model to identify and categorize waste for sustainable recycling. It incorporates attention mechanisms in the first and last convolution layers to boost recognition performance. Transfer learning expands model adaptability by using pre-trained weight values. Also, principal component analysis decreases the dimension of the final fully connected layer, allowing real-time functioning on edge gadgets. This methodology offers enhanced productivity in waste administration through advanced garbage identification and grouping appropriate for edge computing situations.

2.14. "Deep Learning-Based Waste Detection in Natural and Urban Environments"

The paper introduces a two-stage detector for litter localization and classification in both natural and urban environments, utilizing EfficientNet [18] and its variant architectures. Litter detection is performed by EfficientDet-Det2 which locates litter and EfficientNet- Net-B2 which classifies waste into 7 categories. It is important to note that the classifier is semi-supervised and uses unlabeled images to train the classifier. The proposed method has around 70% average accuracy in waste detection and about 75% classification accuracy in the test dataset, demonstrating its potential for effective waste management in a variety of environments.

2.15. Solid Waste Classification Using Deep Learning Techniques [19]

In the field of classifying solid waste, AlexNet, DenseNet121, and SqueezeNet were assessed, with DenseNet121 proving to be the best performer, reaching an accuracy of 94.15%. This result highlights the effectiveness of deep learning networks in correctly categorizing solid waste, with DenseNet121 showing remarkable success in the classification procedure.

2.16. "Waste Classification Using EfficientNet-B0"[20]

When categorizing waste using EfficientNet B0 , transfer learning and fine-tuning were first done, and then hyperparameter search was conducted. Of the various models tested, EfficientNet-B0 turned out to be the most successful, attaining a remarkable 96% precision during training even though it was one of the smallest models looked at. This highlights the efficiency and efficacy of EfficientNet-B0 in waste classification jobs, exhibiting its capacity for precise and resource-efficient model preparation.

2.17. Convolutional Neural Network Using ResNet For Organic and Inorganic Waste Classification [21]

In the task of categorizing organic and inorganic trash, a CNN-ResNet model is improved with a capable genetic algorithm (EGA) to enhance hyperparameters. Genetic algorithms provide strength in choosing hyperparameters, while the model uses ResNet-50, a pre-trained convolutional neural network with 50 layers, to boost performance. Harnessing transfer learning methods, the EGA algorithm helps fast optimization of the CNN, guaranteeing unified precision values are reached efficiently. This combined tactic shows promise in enhancing waste classification accuracy through successful hyperparameter tuning and making use of pre-trained models for improved performance.

2.18. "IoT-Based Smart Waste Management System: Addressing COVID-19 Challenges"[22]

The system presented is an Internet of Things (IoT) enabled smart garbage bin or waste collection system intended to automate waste management processes and alert local waste authorities like municipal sanitation teams. It makes use of various parts like sensors, detectors, and actuators to build an Intelligent System (IS) and inspection system. The goal of integrating these components is to improve the efficiency of waste management by automating trash bins.

2.19. "Real-Time Waste Identification: Enhancing Waste Management in the Era of COVID-19"

This In this paper, we present detailed research that aims to enhance the accuracy and speed of the CNN object detectors used to identify municipal waste durimg COVID-19 [23]. Several types of SSD (Single Shot Detectors) and RPN (Regional Proposal Networks) were optimized for the TrashNet dataset in order to create a more accurate and faster CNN design. The best performing network was implemented on an autonomous robot system that can detect and collect trash from the ground, based on the feedback provided by the CNN.

2.20. Deep Learning Approach to Recyclable Products Classification: Towards Sustainable Waste Management [24]

The research uses DenseNet169, MobileNetV2, and ResNet50V2 convolutional neural network models and a dataset of 5,000 images of trash and waste separated into paper, plastic, glass, metal, and other categories. The study trains and tests these CNNs for garbage identification, categorization, and recognition tasks, with the goal of assisting with sustainable waste management and environmental uses.

2.21. A Deep Learning Approach-Based Hardware Solution for Garbage Categorization in the Environment [25]

The SmartBin that is being suggested makes use of deep learning image classification through CNN systems like AlexNet, ResNet, and VGG-16, integrated into a real-time embedded device. The goal is to separate trash into biodegradable and non- biodegradable types using hardware parts such as PiCam, Raspberry Pi, and infrared sensors. The research compares the performance of different pre-trained CNNs and evaluates their effectiveness together with hardware components for identifying garbage in bins.

2.22. "Advancing Garbage Classification: Insights from Convolutional Neural Networks"

This article centers on identifying individual waste items, like glass, paper, steel, and plastic, using images and videos. Several deep learning methods, including Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) [26], are used for trash categorization. These algorithms show high performance, providing fast and precise outcomes, which makes them favored options for this job.

2.23. "Intelligent Solid Waste Classification Using Deep Convolutional Neural Networks"

Images of paper, glass, plastic, and organic waste from outside surroundings are categorized using machine learning methods. Deep convolutional neural networks (DCNN) [26] with four and five layers are used for classification, with the five-layer design reaching a 70% precision level. The study shows that lowering the quantity of layers causes poorer performance in the networks.

2.24. "Advancing Trash Classification: Harnessing Convolutional Neural Networks for Automated Waste Sorting"

The paper presents AlphaTrash, a machine created to work with standard trash cans placed on curbs for automatic garbage sorting. Using a pretrained Inceptionv1 convolutional neural network [26], AlphaTrash is able to categorize trash with 94% accuracy, taking 4.2 seconds for each classification.

2.25. "Enhancing Waste Image Classification: Transfer Learning with DenseNet169"

The study proposes a DenseNet169 waste image classification model based on transfer learning [27]. To address shortcomings in existing waste datasets, the NWNU- TRASH dataset is constructed, offering balanced distribution, high diversity, and rich backgrounds to better reflect real-world scenarios.

2.26. "Improving Waste Classification: Fine-Tuning Pre-trained CNN"

Transfer learning models are proposed for automatic waste classification across six materials. Pre-trained models including ResNet50, VGG16, InceptionV3, and Xception are tested, with data augmentation performed using a Generative Adversarial Network (GAN) [28] to enhance classification accuracy.

2.27. Enhancing Waste Classification: Multilayer Hybrid Convolution Neural Network Approach [29]

The paper proposes novel classification method based on a multilayer hybrid convolution neural network (MLH-CNN), simplifying the VggNet structure with less number of parameters and higher classification accuracy. Performance is improved by adjusting the hyperparameters of the model, identifying optimal parameters for waste image classification to select the final model.

2.28. Image Recognition for Garbage Classification Based on Transfer Learning and Model Fusion [30]

The unique garbage image identification model Garbage Classification Net (GCNet) based on transfer learning and model fusion is the main topic of this research study. The neural network model of GCNet is built by combining DenseNet, EfficientNetv2, Vision Transformer respectively, after extracting garbage image features. The dataset is augmented with the resulting dataset contains 41,650 photos.

2.29. Deep Learning for Plastic Waste Classification System [31]

The research involves solving the problem of plastic of similar types and colours. Here, the authors uses deep learning and convolutional neural networks.The four classes that model classifies are Poluprylene ,PET,Polyethylene and Polystyrene type of plastic. The maximum accuracy that has been achieved is 98%.

2.30. Waste Classification System Using Image Processing and Convolutional Neural Networks [32]

The four classes are used in the article's proposed waste classification system. The results collected demonstrate that automatic waste classification by image processing and artificial intelligence techniques enables the development of practical solutions. This paper makes use of 15 convolutional layers and compares it with the 23 convolutional layer architecture.The drawback that exists is use of basic deep learning models when more powerful deep learning architectures exists.

2.31. Recyclable Waste Image Recognition Based on Deep Learning [33]

The self-monitoring module, which can combine the pertinent features of all channel graphs, compress the spatial dimension information, and have a global receptive field, is introduced to the residual network model in this waste categorization model is present in this paper However, the number of channels remains constant, allowing the model to automatically extract the characteristics of various trash image kinds and enhance the feature map's representational capabilities. In order to categorize recyclable waste and evaluate the proposed model's classification performance against alternative methods, it was tested using the TrashNet dataset. According to experimental results, this model can accurately classify images with a 95.87% accuracy rate.

2.32. Towards Lightweight Neural Networks for Garbage Object Detection [34]

This paper focused on the challenges of low accuracy and poor real-time performance in garbage classification through the development of a low-weighted garbage object detection model (YOLOG) called YOLO (YOLO stands for garbage detection). YOLOG is based on high-speed, high-performance LRF (local receptive field dilation) and works on embedded devices. Three major improvements are made by YOLOG over YOLOv4: the application of new activation functions, network structure simplification, and the construction of DCSPResNet with correct local receptive field expansion based on dilated–deformable convolution. After compiling the home rubbish picture dataset, we used it to train and evaluate the model.

2.33. ScrapNet: An Efficient Approach to Trash Classification [35]

The finding of this paper is that it uses a Deep Learning model using the EfficientNet Architecture for classifying various types of trash spread across 6 classes like cardboard, general trash etc.. The authors collected their dataset from open sources.They also introduced RWNet models, which are based on ResNet structures, for the classification of recyclable waste, focusing on accuracy as the primary performance metric.One limitation is that he dataset is imbalanced as it is a combination on 4 smaller datasets.

2.34. Smart City Solutions: Comparative Analysis of Waste Management Models in IoT-Enabled Environments Using Multiagent Simulation [36]

A major obstacle to the development of smart cities in the current period of rapid urbanization is effective waste management, as the focus shifts to sustainability and public health. Urban waste collection can be revolutionized by utilizing contemporary technology, particularly the integration of the Internet of Things (IoT) with intelligent waste containers, which will maximize efficiency and cut expenses.It involves usage of cellular networks,Wi-Fi ,Sensors for automating complete process. This study advances the area of smart city technology by offering vital information to engineers, policymakers, and urban planners who are working to create more livable, sustainable, and smart cities [37].

A comparative study of some of the papers [38] is shown in the given below Table 1:

Table 1. Comparative study of dataset of some papers of literature Survey.

S. No	Reference Paper	Datasets	Methods / Techniques / Algorithms	Accuracy
1	[2]	Recyclable Waste Sorting	Various ResNet structures (ResNet-18, ResNet-34, Transfer Learning	86.5% 88.9%
2	[3]	Municipal solid waste (MSW)	Novel Deep learning network MSWNet	93.5%
3	[4]	GINI	CNN Algorithm with arduino (ResNet)	87.69%
5	[5]	Trashnet+ Indoor Images	CNN based AlexNet Image processing based system	936% 93.4 %
6	[6]	TrashNet+ Images from wild	VGG16	96
7	[14]	Custom Dataset	CGBNet	96%
8	[16]	Kaggle	CNN with 3 different architectural designs	82.7%
9	[19]	Custom Dataset	AlexNet, DenseNet121, Squeeze Net	94.1%
10	[29]	TrashNet	MLH-CNN	92.67%
11	[34]	Domestic Garbage Image Dataset	YOLOG	AP-94.58%
12	[35]	TrashNet	Residual Network	95.67%

3. Methodology

3.1. Collecting Dataset

The research work begins by sourcing a relevant dataset, specifically the open source dataset. This dataset serves as the foundation for training and testing the YOLO (You Only Look Once) model for trash detection and classification.It includes a variety of images showcasing different types of waste, forming the essential dataset for building an effective trash detection system.

3.2. Preprocessing the Dataset for Balanced Classes (Preparing Labels for Images Accordingly)

Data preprocessing is crucial for ensuring model effectiveness. To mitigate class imbalance issues, the collected dataset undergoes preprocessing. This involves equalizing the number of images for each waste class. By achieving class balance, the YOLO model can learn from a representative and unbiased set of data, enhancing its ability to accurately detect and classify various types of trash. The total number images included are 4,745 images for training purpose. 457 for the purpose of validation, a total of 7 images are utilized, while an additional 226 images serve a different purpose of testing the model developed. The seven classes that are included are plastic, metal, glass, paper, metal, other and spyrofoam. Some sample images with their labels are shown in Figure 3 below. The labels corresponding to each image is generated with bounding boxes with help of online called as makesense.ai

Figure 3. Sample images with labels.

Each object in a picture is represented by a label in the YOLOv5 object detection framework, which consists of five parameters. The model must be trained with these parameters in order for it to correctly locate and identify items within photos. A label's five parameters are as follows:

Class ID: The object's class is indicated by this argument. An integer beginning with 0 is typically allocated as a unique identification to each class (person, car, dog, etc.). The model can differentiate between various object kinds found in the image thanks to the Class ID.

X-center: The center of the object's bounding box's x-coordinate, normalized by the image's width. The process of normalizing reduces the coordinate's actual pixel dimensions to a value between 0 and 1. This is essential to guarantee the scalability of the model's predictions across various image sizes.

Y-center: This is the y-coordinate of the object's bounding box center, normalized by the image height, just as the X-center. Additionally, it has a range of 0 to 1, which helps the model precisely locate items in an image's vertical space.

Width: The bounding box width of the item, normalized by the image width. The model can identify objects in photos with different dimensions thanks to this normalized value, The model is able to understand the size of the object in comparison to the size of the image.

Height: The bounding box height of the item, normalized by the image height. Similar to width, this normalized number aids in the model's ability to Ascertain the size of the item relative to the overall dimensions of the image which is necessary for precise object localization and detection.

3.3. Developing YOLO V5 Model for Detection

In this research work, the YOLO V5 architecture, which is a cutting-edge deep learning model for object detection, is utilized. The customization and fine-tuning of YOLO V5 are carried out using a preprocessed dataset. The main purpose of training the model is to detect trash items within images with precision, providing a robust and efficient solution for trash detection. The architecture of YOLO V5 is visually depicted in Figure 4.

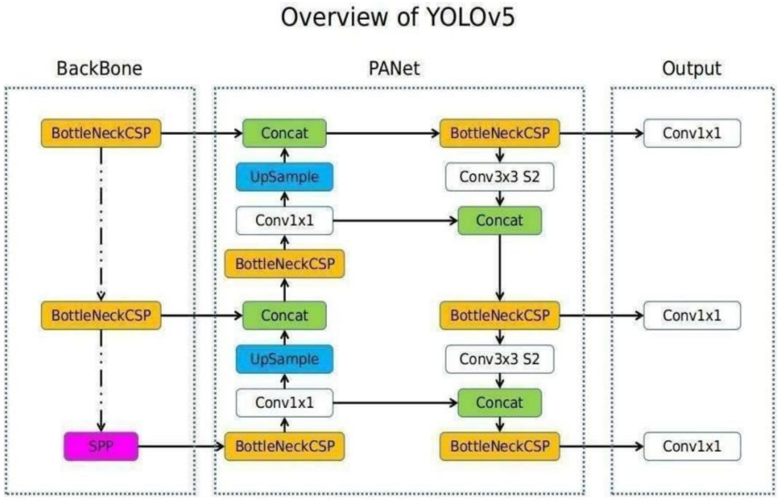

Figure 4. Overview of YOLO V5 Architecture.

3.3.1. Yolov5x Architecture

YOLov5x is a part of YOLO stands for "you only look once ", and it's One of the foremost popular deep learning models in the world. It's used to detect objects in real- time, and its speed and accuracy make it ideal for applications that need to process data in real- time. Examples include video surveillance, self-driving cars, and many more. The YOLO family is made up of several YOLO versions, each with its own set of features, improvements, and refinements. The YOLO5x variant falls into the latter category, offering a combination of speed and accuracy.

This model is based on a simple and efficient architecture. Feature extraction is carried out by the backbone, while the head is tasked with predicting the bounding box and class probabilities.

3.3.2. Model Backbone

YOLOV5 is based on the CSP (Cross Stage Partial) network strategy. CSP (Darknet53) is the same as Darknet53, the network backbone used by the authors of YOLOV3 to implement the CSP network strategy. The utilization of residual and dense blocks in CSP Network serves the purpose of mitigating the vanishing gradient problem. By incorporating these blocks, the network ensures that information can be transmitted efficiently to the deepest layers, thereby optimizing its ability to process complex data.

The CSPDarknet53 as shown in Figure 5, an advanced convolutional neural network that expands upon the ideas set out by its predecessor, Darknet53, is the central component of YOLOv5x. The initial Darknet53 was renowned for its depth and effectiveness, extracting characteristics using a series of convolutional layers. By using the Cross-Stage Partial Network (CSPNet) technique, which greatly boosts the model's efficiency by resolving the issue of duplicate computations frequently encountered in deep neural networks, CSPDarknet53 improves this. The feature map generated by the layers of the backbone is split into two sections by the CSPNet architecture. One component moves on straight to the next phase, while the other is subjected to a sequence of convolutional changes.

This strategy not only reduces computational redundancy but also encourages feature diversity, This element plays a vital role in enabling the model to generalize effectively across diverse objects and scenarios. The direct connection ensures that the gradient flow is improved throughout the network, facilitating efficient training even as the network depth increases.

The goal of CSPDarknet53's architecture is to strike a compromise between computational efficiency and depth. It makes use of a number of 3x3 and 1x1 convolutional filters, which are widely used in CNN designs due to their efficiency in processing and ability to extract features. By combining these filters with the CSPNet approach, YOLOv5x is able to extract detailed information without having to pay the large computational costs that are usually related to deep networks. Additionally, skip connections—which are similar to those in ResNet architectures—are used into CSPDarknet53 to deal with the vanishing gradient issue in deep networks. Because of these connections, gradients can flow directly through the network, facilitating the training of deeper models and enhancing the learning process.

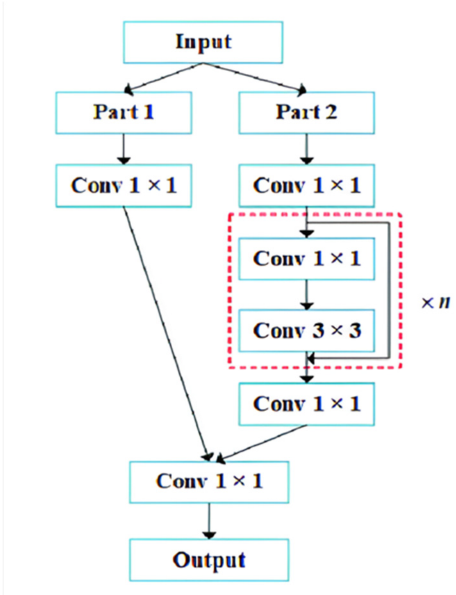

Figure 5. CSPDarkNet-53.

3.3.3. Model Neck: PANet

There has been two major changes in yolov5's neck.The first is the usage of variant of Spatial Pyramid Pooling and second has been the modification of Path Aggregation Network with the infusion of BottleNeckCSP in it's architecture.

By consolidating the data received from various inputs, the SPP block produces a result of fixed length. This characteristic allows for a substantial expansion of the receptive area and effective separation of the most crucial contextual elements, all while maintaining network performance. Previously, YOLO versions 3 and 4 utilized this block to isolate the essential features from the backbone. However, in YOLOv5, an enhanced version of the SPP block, known as SPPF, was introduced in Figure 6 to further improve the speed of the network.

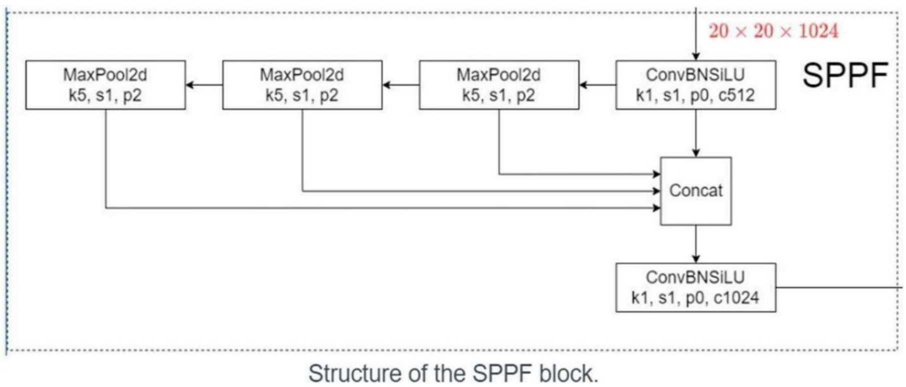

Figure 6. SPPF Block.

By connecting feature maps from various backbone depths, PANet serves as a bridge. This makes it possible for the model to use attributes that are important for differentiating between objects of diverse measurements by virtue of the fusion of top- down and bottom-up routes, PANet allows information to move from deep (low- resolution) layers to shallow (high-resolution) layers and vice versa.

Path Aggregation Network, or PANet, is a tactical improvement to the YOLOv5x architecture that greatly improves the model's recall and precision in object detection. PANet's main purpose is to make it easier for features to be fused together from various network levels so that the model may use both high-level semantic knowledge and low- level data to make predictions. In order to accomplish this, PANet implements a bottom-up path augmentation, which is an addition to the conventional top-down method used in feature pyramid networks (FPNs). This implies that lower- level features are carried up to higher resolutions (bottom-up) in addition to high-level features being transferred down to lower levels (top-down). This bidirectional flow ensures that the final feature maps used for prediction contain a rich mix of semantic and detailed information, crucial for accurately detecting objects of various sizes and complexities.

3.3.4. Role of BottleneckCSP in PANet

The BottleneckCSP as in Figure 7 module forms the core building block of various structures within PANet and other parts of the YOLOv5x architecture. Essentially, it is an improvement upon the Cross Stage Partial Connection (CSP) idea. It basically expands on the concept of dividing up the input feature maps and processing them in parallel branches to maximize performance. The 'bottleneck' layer is a crucial component of a BottleneckCSP module.

In order to greatly reduce the total count of channels within the feature map. and hence lower the computational cost of following operations, this layer commonly uses a 1x1 convolutional layer.

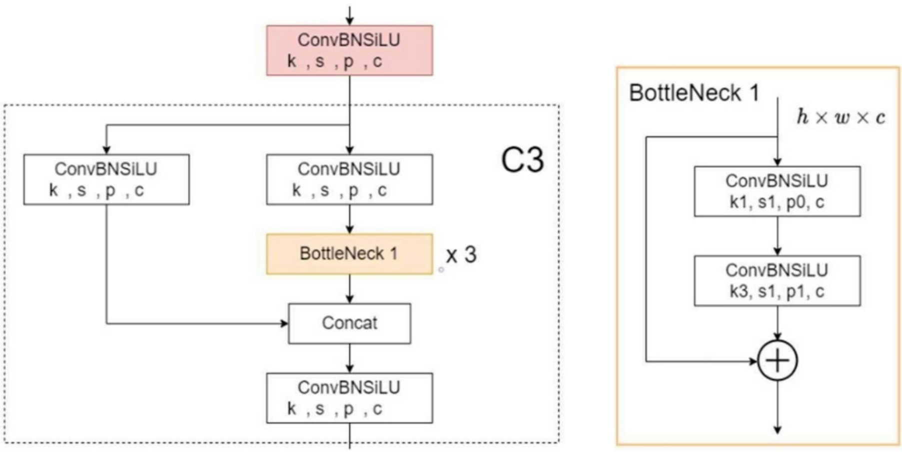

Figure 7. BottleNeck CSP Architecture.

PANet (Path Aggregation Network), the neck component of YOLOv5x, leverages BottleneckCSP modules in a strategic manner to refine the feature fusion process:

1) Processing of Feature Maps: In PANet, feature maps extracted at various backbone phases are processed independently using a series of BottleneckCSP modules.
2) The two main advantages of this technique are:
3) Computational Efficiency: The bottleneck layer in the BottleneckCSP modules efficiently lowers the feature maps' dimensionality, which facilitates quicker computations during the fusion processes that follow.
4) Feature Refinement: The BottleneckCSP module's sequence of convolutions aids in improving and refining the feature maps' representational capacity.
5) Feature Fusion: The intelligent fusion of feature maps from several backbone tiers is the primary purpose of PANet.
6) PANet uses BottleneckCSP modules in its main channels to do this: Bottom-up Pathway: Before being fused with feature maps from shallower layers, upsampled feature maps from deeper layers are frequently routed via BottleneckCSP modules. In the fusion process, this lowers computing overhead and helps align the dimensions. Top-down Pathway: In a similar vein, BottleneckCSP modules may downsample higher-resolution maps to fit the dimensions of feature maps from deeper layers for fusion in order to analyze features in a top-down pathway.

The usage of BottleneckCSP within the PANet structure of the YOLOv5x architecture exemplifies a sophisticated approach to neural network design. This combination leverages the strengths of both components to enhance feature processing and aggregation, leading to superior object detection performance without compromising on computational efficiency.

3.3.5. Head: Detection Head

The YOLOv5x detecting head is responsible for generating the final set of predictions. To accomplish this, it takes the combined feature maps from the PANet neck and utilizes them to predict bounding boxes, class probabilities, and objectness scores. These objectness scores indicate the likelihood of an object being present within a bounding box. To enhance the accuracy and effectiveness of these predictions, YOLOv5x employs predefined bounding box shapes known as anchor boxes. The detection head utilizes a series of convolutional layers to predict the modifications to the bounding boxes, objectness scores, and class probabilities for each anchor box. Both YOLOv5 and YOLOv3 and YOLOv4 share the same head structure. This head consists of three convolution layers that are responsible for predicting item classifications, scores, and the coordinates (x, y, height, and width) of the bounding boxes. The equation used to compute the target coordinates for the bounding boxes can be found in Figure 8 below.

$$
\begin{aligned}
b_x &= (2 \cdot \sigma(t_x) - 0.5) + c_x \\
b_y &= (2 \cdot \sigma(t_y) - 0.5) + c_y \\
b_w &= p_w \cdot (2 \cdot \sigma(t_w))^2 \\
b_h &= p_h \cdot (2 \cdot \sigma(t_h))^2
\end{aligned}
$$

Figure 8. Equation to calculate bounding box.

Key Points about YOLOv5x:

Multiple variants: YOLOv5 comes in various versions (s, m, l, x) offering there exists a delicate balance between precision and efficiency. YOLOv5x prioritizes higher accuracy with a larger model size compared to other variants.

High accuracy: YOLOv5x achieves state-of-the-art performance on object detection benchmarks. Faster than previous YOLO versions: It offers improved speed compared to earlier YOLO models.

Customizable: YOLOv5 is designed for easy customization and training on custom datasets.

3.4. Integrating Deep Learning Model with Camera for Real-Time Detection

To enable real-time trash detection, the YOLO V5 model is integrated with a camera system. This integration facilitates the immediate processing of video feed or images from a camera, allowing for on-the-fly detection and classification of trash items as they appear in real-world scenarios. A proposed flowchart is shown in Figure 9 as shown below.

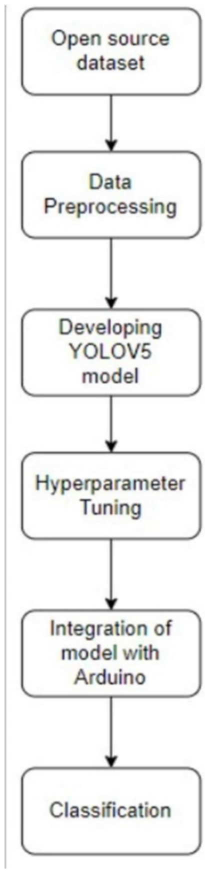

Figure 9. Flowchart of the Proposed System for classification.

3.5. Classifying Real-time Trash into Collector Pits with Arduino

The research work extends beyond detection to practical waste management. Using an Arduino-based system, the detected trash items are classified into different collector pits or bins. This classification enables automated waste segregation, ensuring that each type of trash ends up in the appropriate container. This integration of hardware and software forms a holistic solution for efficient and automated waste disposal.

4. Conclusions

A notable breakthrough in the realm of waste management is exemplified by our research work, which centers on the development of an automated trash detection and classification system. By harnessing the power of YOLO and Arduino, coupled with the capabilities of deep learning and IoT technology, we have taken a significant step towards enhancing efficiency and sustainability in waste management practices we have demonstrated the potential to transform how society deals with its waste. The integration of YOLO for object detection and classification ensures the accurate and real- time identification of trash items, reducing the reliance on manual sorting. The incorporation of Arduino adds a practical dimension, enabling seamless communication between the deep learning model and physical actions, such as sorting or alerting authorities. This versatility makes our solution adaptable for various waste management scenarios, from smart bins to larger-scale sorting facilities. Our research work aligns with the global drive towards environmentally conscious practices, promoting proper waste disposal and recycling . By automating the process, we aim to streamline waste management operations, reduce human error, and ultimately taking steps to promote cleanliness and sustainability is essential for creating an environment that is both cleaner and more sustainable in the long run Finally, our automated trash detection and classification system exemplify the transformative power of technology in addressing pressing global challenges. By offering a scalable and adaptable solution, we take a step forward in reshaping waste management for the betterment of society and the planet as a whole.

Our YOLO and Arduino-powered automatic garbage identification and classification system has the potential to go in a number of exciting new areas that might completely transform waste management procedures. A significant opportunity is presented by the system's scalability and adaptability to various operational scales, ranging from small- scale urban settings to large-scale industrial environments. A greater range of communities and companies may be able to access sustainable waste management if the system is customized for certain circumstances, maximizing its usefulness and efficacy. Another critical area of development is the integration of cutting edge IoT technology to enable better, more connected waste management ecosystems. In addition to facilitating waste sorting, this has the potential to facilitate the acquisition of essential data pertaining to the creation and elimination of waste.which could help to optimize waste processing and recycling initiatives. Moreover, pursuing collaborations with government bodies, environmental organizations, and the private sector could accelerate the adoption of this technology, demonstrating its value in practical applications and encouraging broader societal engagement in sustainable waste practices.

Author Contributions

The conceptualization of the project was done by B.V.J. and L.S.K. The dataset was collected by H.C. and G.S.T. Followed by preparation of software, that is developing of YOLOV5 model was done by M.M.A. and B.V.J. Analysis of the project was carried out by L.S.K. Preparation of the original draft was done by M.M.A. and H.C. Finally, B.V.J. helped in reviewing and editing the draft. All authors have read and agreed to the published version of the manuscript.

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Conflict of Interest Statement

The authors declare no conflicts of interest.

Data Availability Statement

Data is unavailable due to privacy or ethical restrictions.

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