Optimizing Object Detection in Bio-Waste Management with Improved Hyperbolic Tangent YOLOv5 and Binarization-Adapted K-Means Algorithm

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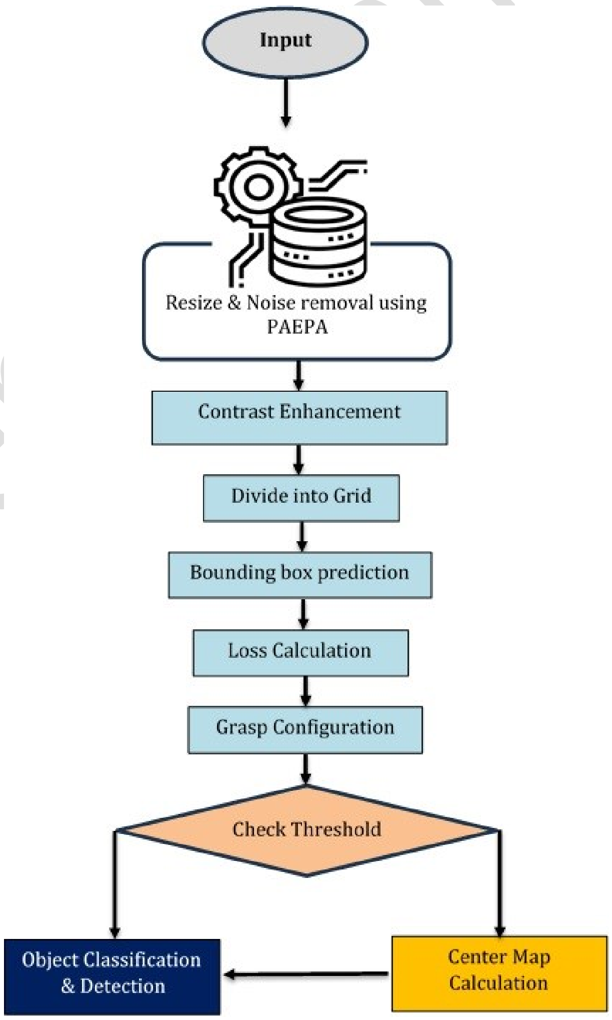
GRAPHICAL ABSTRACT



Abstract: With the increasing importance of green development, bio-waste classification has become an important element of green development. However, in garbage stacking scenarios, the task of segmenting highly overlapping objects is difficult because the bottom garbage is in an occluded state and it is usually difficult to distinguish its contours from occluded boundaries. This paper presents a rotationally invariant system for solid bio-waste container detection and bio-waste level classification. This paper proposes a rotationally invariant system for detecting solid bio-waste containers and classifying their fill levels. It employs Hough line detection to identify container orientations and positions, complemented by cross-correlation for distinguishing similar objects. Features extracted from within and outside the container area are utilized, enabling precise determination of discard levels. The system accommodates varying bio-waste amounts through transformation and rotation of container images. Object detection utilizes an Improved Hyperbolic Tangent-based YOLOv5 model with a Binarization-Adapted K-Means Algorithm (BKA) to enhance sorting accuracy. Additionally, the method efficiently calculates object motion through segmented BKA-detected objects. Experimental validation with a bio-waste image dataset demonstrates superior performance in accuracy, specificity, sensitivity, and overall precision compared to existing methodologies.

Keywords: Garbage Object Detection; Machine Learning; Deep Learning; Occlusion Recognition; Performance Measures; Bio-waste

1. Introduction

Currently, the removal of garbage from urban streets is done by hand, an approach blocked by its intrinsic drudgery and slowness [1]. In the real world, garbage frequently gathers into tangled heaps that significantly obstruct precise identification and sorting due to the "hidden-object" effect [2]. The development of reliable methods for identifying and handling obscured bio-waste is a crucial research goal given the significant challenge that incomplete information and hazy boundaries provide to efficient bio-waste management [3]. The present study examines high-precision image segmentation for occluded garbage where characteristics are challenging to extract, to optimize household garbage detection. To address this issue, we provide a unique instance segmentation technique that employs occlusion and attention perception models [4].

At the outset, the attention model enhances the quality of instance segmentation by training the neural network to prioritize informative segments of the input data based on human attentiveness. Second, the Region of Interest (RoI) is conceptualized as two overlapping layers according to the occlusion perception paradigm. The topmost layer denotes the object in the way, while the lowermost layer denotes the slightly occluded target [5]. This results in a smoother instance segmentation detection procedure by removing the boundary between them. By demonstrating a significant enhancement in garbage detection accuracy, our proposed instance segmentation approach opens the door to more efficient garbage disposal techniques [6].

Bio-waste management has become a rising challenge as the human population increases, especially in urban areas. The goal of Solid Bio-Waste Management (SBWM) systems is to control, reuse, and reduce the mountains of bio-waste that we produce daily to address this ever-increasing problem [7]. Research carried out in developed cities has shown that a strong combination of trained staff, appropriate tools, robust infrastructure, meticulous upkeep, and persistent commitment from both the public and the government may result in effective SBWM [8]. However, financial support, a more thorough engagement with bio-waste management, and a greater understanding of the environmental implications—particularly in densely populated areas—are crucial prerequisites for achieving sustainable improvement [9].

Even though SBWM research is growing rapidly, it frequently concentrates on practical issues like garbage detection and bio-waste truck routes. Researchers support the use of contemporary techniques such as RFID, GPRS, GPS, and GIS to effectively optimize SBWM and improve efficiency and accuracy [10]. Garbage disposal poses particular challenges in densely populated places including slums and apartment complexes: erroneous handling, overflowing bins, and unpleasant spills. Putting in place an online garbage level monitoring system could address these issues directly. An automated device like this would sense when a bin is full and begin to gather bio-waste before it overflows and looks chaotic, improving the public's hygiene and sanitation [11]. In contrast to the obsolete, rigid paradigm, smart bins with level sensors provide a window into a future where garbage collection adapts to real needs, saving time and money. Less operational costs, faster collection times, and a more intelligent, effective approach to maintaining clean streets are all promised by dynamic collection [12].

Over the years, one of the main areas of research has been monitoring, detecting, and detecting objects in films and their visual surroundings. These tasks in computer vision and image processing entail identifying particular objects for different reasons within digital images or movies. Previously, manual feature creation and basic trainable structures were employed for object identification and classification. Elaborate ensembles could typically increase performance by combining these features with larger context cues from object detectors and scene classifiers [13]. Before neural networks became popular, Viola-Jones and HOG detectors dominated this industry. However, generic object detection has been revolutionized by deep learning which achieves performance by directly learning feature representations from data. Similar to how the human brain can process and evaluate enormous volumes of data, deep learning is excellent at automatically identifying useful features in object classification. Its robust method outperforms existing Machine Learning (ML) algorithms in terms of accuracy, setting the standard for object recognition and comprehension [14].

With enormous networks, a wealth of millions or even billions of parameters, and an abundance of training data, deep detectors have become incredibly popular. However, the secret ingredient doesn't end there. With their enormous processing capability, GPUs have given these sophisticated models the power they require. Researchers have also used enormous datasets that reflect the chaotic reality of the world to properly train these models. These datasets contain images that are rife with internal variances within object classes and bewildering commonalities across them shown in Figure 1 [15].

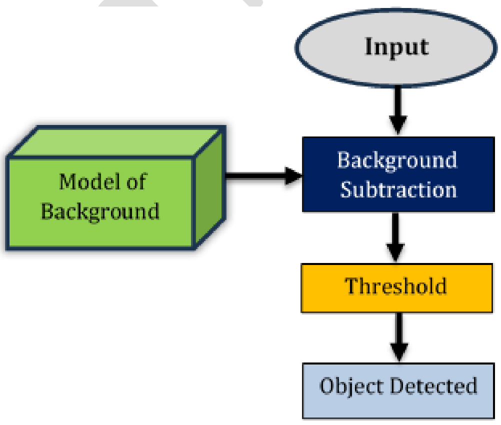


Figure 1: Generic object detection model using background modelling

A multi-scale sliding window may seem like the best option for searching the full image for items of different sizes and positions, but there are unavoidable disadvantages. Although this comprehensive method ensures item detection independent of location or size, it has drawbacks of its own. There is severe duplication and a computational overload as a result of the enormous amount of candidate windows that are produced. Furthermore, using a predetermined set of sliding window templates runs the danger of collecting unwanted areas and lowering precision [16].

Sorting construction trash could undergo a revolution by utilizing ML to increase accuracy and efficiency. Existing research demonstrating the effectiveness of Computer Vision (CV) models in recycling efforts shows that these models may learn to distinguish different bio-waste items when sufficiently fed with data. Although many CV methods have been used for bio-waste categorization, surprisingly little work has been done to solve issues like inter-occlusion and small object detection [17]. Presently, the Convolutional Neural Network (CNN), is a powerful tool for object detection and image categorization. Because of its efficacy, several CNN-based models that successfully address the challenges of sorting construction trash have been developed. Using creative methods, some researchers have taken on the problem of garbage classification [18]. The SVM-based classification was proposed after extracting features from a ResNet-50 network. In a hybrid method, combined physical data, such as weight and depth, were obtained from additional sensors with visual information retrieved by a DenseNet-169 network. Although these techniques offer higher sorting accuracy, they are not as effective at handling issues like overlapping objects and tiny item detection [19].

In certain fields, there are two types of image object detectors: one-stage, such as YOLO, and two-stage, such as Faster Recurrent CNN (FRCNN). For instance, in the first step of FRCNN, a Region Proposal Network (RPN) is used to recommend possible bounding boxes. One-stage detectors are great for speed, but two-stage detectors are the best for accurate localization and recognition. The RoI pooling layer that divides the two stages is the primary differentiator. In two-stage detectors, each candidate box in the second stage is subjected to a feature extraction process utilizing RoI Pool, which is used for subsequent classification and bounding box regression [20]. On the other hand, one-stage detectors recommend bounding boxes straight from the input image, eschewing the proposal of regions entirely. They are therefore quicker and better suited for real-time applications. These models are frequently used to discern between stiff and non-rigid things. Through the use of the self-similarity of their temporal properties, specifically their periodic evolution, we can recognize objects that move in a structured, repeating manner. This entails routinely classifying them. It has been demonstrated that optical flow analysis works well for accurately separating things that are stiff from non-rigid [21]. The Binarization-Adapted K-Means Algorithm optimizes bio-waste sorting by efficiently segmenting objects in occluded scenarios, addressing challenges of accurate classification and extraction in densely stacked waste configurations.

Although surveillance video processing has come a long way over the years, the challenge of accurately locating objects in video footage has not been overcome. There are still two main obstacles to overcome: precisely finding items and correctly categorizing them in image or video formats. Computer vision systems have traditionally approached object detection in two stages, using different identification techniques [22]. Nevertheless, the real-world difficulty of identifying and tracking moving objects in real-time video surveillance poses a significant barrier, as these techniques were primarily created for flawless image quality. Current methods frequently struggle with constraints in computational complexity and accuracy, which are exacerbated by their incapacity to consistently identify tiny objects in real-time video streams [23].

For sensors like cameras and LIDAR used in vital applications like intelligent surveillance and self-driving automobiles, bad weather can cause major problems. Critical object recognition is hampered by fog, snow, dust storms, and even gloomy weather, which severely degrades image quality. Due to poor detection caused by this visual fog of war, there are more road accidents and security breaches. We need strong image-enhancing tools to traverse these turbulent waters. Clear-eyed detection systems can be made possible by these strategies, which enhance clarity and magnify details even under the most challenging circumstances. Thus, the path is cleared for improved road safety, more focused surveillance, and eventually, a more dependable future for self-governing systems confronting the varied fury of the natural world.

Research gaps include the need for robust methods in bio-waste detection amidst occlusions and small-object challenges. Objectives are to enhance detection accuracy using IHTYOLOv5-BKA, validate with diverse datasets, and propose hardware integration for real-time application. Future work aims to expand dataset diversity and optimize mobile platform deployment for widespread environmental monitoring. This research further explores current methods for classifying and detecting objects in video surveillance, compares different object detection techniques in controlled settings, and evaluates the outcomes while investigating potential future applications of these methods.

2. Related Works

The application of computer vision techniques for "smart" garbage identification, segmentation, and classification has attracted a lot of attention. In particular, instance research segmentation for garbage detection is covered in this section. In one such work, [24] developed an algorithm suitable for street garbage recognition and detection by expanding upon the YOLACT model, which is generally utilized for generic object segmentation. Addressed the problem of high hardware requirements for garbage-focused convolutional neural networks by putting out a workable and lightweight method for object segmentation that uses SVM and RGBD data. Prior studies have focused on improving garbage identification in several ways, including speed, underwater detection, and spatial information integration. They haven't, however, sufficiently addressed the problems brought on by obscured trash because of pile-up [25].

In computer vision, identifying individual trash items has always been a difficult task, especially if it buried or overlap. This is especially true for garbage collections in the real world, where objects frequently conceal one another, thus reducing the accuracy of detection. It is imperative to address this "occlusion bottleneck" to properly sort and identify bio-waste. Scholars such as [26] have brought attention to the critical function that repetitive object recognition plays when there is occlusion. The DeepParts model was created to improve pedestrian identification performance in the presence of obscurity. To enable multi-target prediction, [27] updated the FPN network structure by adding modules such as EMD Loss. Introduced Repulsion Loss, a bounding box regression function designed to handle obscured objects, in recognition of this drawback. Still, a major obstacle is the inherent difficulty of distinguishing distinct shapes and boundaries within overlapping, crowded rubbish.

Although it works well for some garbage containers, the conventional approach is rigid. It makes use of manually created feature detectors and descriptors that are adjusted for various object transformations and backgrounds. The vast variety of bio-waste containers and how they look makes this task difficult. The method relies on manually identifying unique, observable features in an image and then characterizing those features in a way that is consistent across different transformations. However, the minimal semantic information provided by these "low-level" traits makes object detection difficult [28]. For some types of containers, a database including these attributes can yield satisfactory detection rates; however, the technique is not very flexible when applied to novel or unobserved cases.

Although there has been a significant increase in research and pilot programs for smart bio waste bin level detection over the last five years, practicality issues still exist. A study conducted in Sweden that fitted 3300 bins with infrared LED sensors and wireless communication showed promise, but the four sensors per bin created a complex setup that required specialized workers for routine maintenance and troubleshooting [29]. Similar to this, Enevo's commercial smart bins with ultrasonic technology offer an alternative, however, maintenance and cost are still obstacles. Alternative sensors, such as optical choices and capacitive moisture and point-level sensors, have been investigated by researchers [30]. Still, questions remain regarding suitability and feasibility. It is sensitive to humidity, capacitive sensors, for example, perform best during the rainy season but have limited general application. All things considered, even if remote bin-level monitoring has several advantages, its widespread acceptance depends on resolving issues with sensor limits, regular maintenance requirements, and installation costs [30].

An innovative approach to automating the detection and control of solid bio-waste bin levels was put out. Their method was based on two main components: the K-nearest neighbor (KNN) algorithm for classification and the Gray Level Aura Matrix (GLAM) for feature extraction. In essence, GLAM quantifies the frequency with which each gray level appears in the neighbors surrounding it to assess an image. The features utilized in the KNN classification are then formed from this data [31]. The system uses pre-stored reference features from training data to compare features extracted from captured images during bin monitoring. The KNN algorithm finds the K reference features that are closest to the acquired image. A majority vote based on the levels of the KNN determines the overall bin level. The system showed good accuracy, but when bins were rotated or moved, it became less effective. This emphasizes the necessity of conducting additional research on robust feature extraction and classification methods with a variety of bin designs [32].

A method for extracting lines from images and using their locations to categorize bin fullness levels was used in a study by [33]. To find lines inside each image frame, they employed a mathematical technique called the Hough transform in conjunction with gradient information. The existence of rubbish within and outside the container was then ascertained by extracting the coordinates of high-intensity edge lines. The accuracy of this method in measuring the fullness level of the bin was only 82.93%, despite its effectiveness in detecting bio-waste outside the bin [34]. This constraint resulted from the method of obtaining edge information from the complete image instead of concentrating just on the interior of the bin. Bio-waste objects do not always exhibit strong linear edge gradients, so it was not always reliable to assume that the number of lines detected in the entire image precisely related to the bio waste level because the bin opening was not marked [35]. Selecting strong descriptors is essential to building a Visual Local Area Descriptor (VLAD). Rotated BRIEF (ORB) and Oriented FAST are the methods used in this study. In contrast to competitors with patents such as SURF and SIFT, ORB provides royalty-free access. These descriptions typically require three steps [36].

Rather than depending only on the original dataset, they came up with a way to produce difficult samples that would challenge the limits of the model. With this method, feature maps were deliberately manipulated inside the model by adding spatial deformations or blocking specific ones. It was anticipated that by subjecting the model to these intentionally produced "hard examples," it would become more adept at correctly classifying more intricate and hidden items. The proposed architecture included two crucial phases and was based on FRCNN [37]. It started by creating bounding boxes for items contained in frames. Second, to produce the difficult samples, it used feature generation techniques with an emphasis on occlusion and deformation. The Pascal VOC and COCO datasets were used to train ASDN and ASTN, two adversarial networks, to deploy these techniques. With a mean Average Precision (mAP) of 69%, the results showed a notable performance improvement compared to the standard FRCNN model, a 2.6% gain [38].

FCNN is a unique object detection network that was introduced to outperform other architectures such as R-CNN, Fast R-CNN, and YOLO. Their objective was to improve object detection by using cutting-edge techniques such as RoI pooling, which extracted standardized feature maps by applying Max Pooling to all region suggestions. Furthermore, a Region Proposal Network (RPN) was utilized by FRCNN to provide property-based image proposals, which were then improved by roll pooling post-processing [39]. Bounding box coordinates and class probabilities for many objects were finally obtained by this two-step procedure, surpassing a 0.7 Intersection-over-Union (IoU) criterion. The group used distinct image sets that enhanced object recognition in images to speed up training. Remarkably, FRCNN on a single-image car dataset achieved a mAP of 60%. The authors advise utilizing a CUDA-enabled GPU with a computational capability of 3.0 or higher for the best training results [40].

There are two stages to the process of locating and describing important components in images. The first stage is to identify regions in an image that have a high probability of matching with regions of a similar nature in other images. After that, the second stage, which is called feature description, involves turning the area around each feature that has been discovered into a numerical representation that conforms to a model intended to maintain invariance properties. Every one of these stages requires important choices to be made. When it comes to feature detection, it's important to choose both the technique used and the criteria that define what makes a desired feature—that is, an ideal feature [41]. Recent surveys highlight YOLOv5's effectiveness in object detection. Challenges include accuracy in dense scenarios. Future work aims to optimize Binarization-Adapted K-Means for improved object segmentation [42].

Two primary challenges in construction trash sorting are missed small objects and inter-object occlusion due to overlapping. Addressing these issues, an IHTYOLOv5 – BKA model was developed to enhance categorization and detection accuracy. This model incorporates a shallow detection layer to focus on small bio waste objects specifically and enhances accuracy through extensive feature fusion at the fourth scale. Additionally, to bolster training data diversity and model resilience, a custom dataset and advanced data augmentation techniques were employed.

3. Proposed System

An autonomous bio waste-level detection system's design must be resilient to a wide range of difficulties. These include containers that rotate, move, or have their entrances covered by large things, and confusion brought on by outside clutter. To overcome these challenges, we suggest a laser-like focused system that locates the bin entrance, extracts important data from the bin, and feeds this information to an intelligent classifier that determines the trash level. Figure 2 shows the path taken by this novel algorithm, with each step being carefully described in the parts that follow.

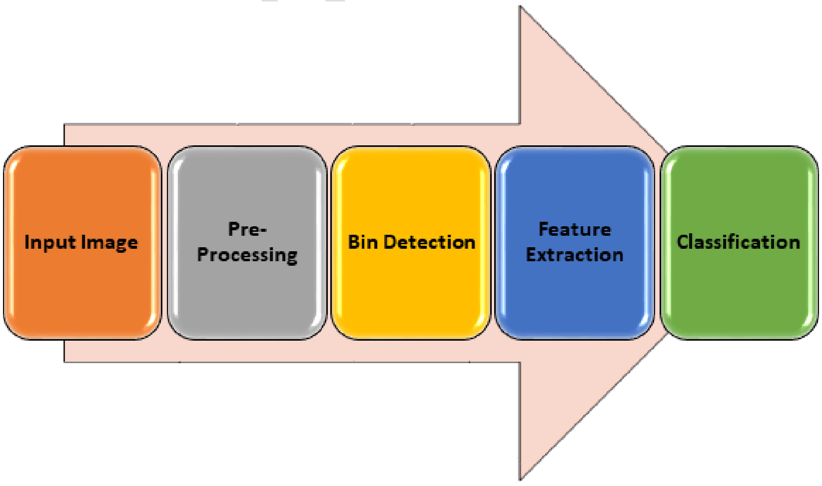


Figure 2: Steps of the proposed algorithm

3.1 Dataset

The performance of the proposed system was assessed using two datasets: a specially created building bio waste dataset and the widely used public option PASCAL VOC. The standard object-detection benchmark PASCAL VOC has four categories and twenty subcategories. The test set, which included 4952 images was taken from the test section of VOC2007. To replicate real-world garbage sorting conditions, we also used a customized dataset rich in various images of building detritus.

Although current publicly available databases such as TrashNet and Taco may facilitate garbage identification, they may not accurately represent the actualities of automated sorting. Objects that are stacked up, unclean, and oddly shaped provide a difficulty for conveyor belts. Identifying this vacuum, we created a new dataset specifically designed for robotic systems. The images that were taken on a building site are displayed in Figure 3 with a total of 3046 images of bio wastes. We used data augmentation techniques to create a reliable and broadly applicable dataset. The labelling procedure was made easier using the graphical annotation program labelling.

Figure 3: Bio waste sample dataset image

3.2 Performance Evaluation Three primary metrics were used to evaluate the model's performance: mean Average Precision (mAP), F1 score, and Average Precision (AP). Recall and precision are combined in AP to give a complete view of object detection accuracy. Precision gauges the system's capacity to accurately classify items, whereas recall indicates its capacity to recognize all pertinent items. The area under the precision-recall curve, or AP, can be found by plotting the curve. The equations

$$P = \frac{TP}{TP+FP} \quad (1)$$

$$R = \frac{TP}{TP+FN} \quad (2)$$

$$AP = \int_0^1 P.RdR \quad (3)$$

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_x \quad (4)$$

$$F1 = 2\frac{P.R}{P+R} \quad (5)$$

3.3 Image

A bio waste-level classifier was trained and tested in this study using realistic images of trash cans. The 800 x 600 pixel images were taken with a Logitech C910 camera and show 120 litter rectangular bins from a 2 m distance and 3 m height viewpoint. About 300x300 pixels make up each bin opening in the frames. Figure 4 shows instances of bins with varying fill levels. One hundred unrotated bin images with different bio waste amounts were utilized for training. These images' features were extracted, which assisted in teaching the classifier to identify four different trash levels. To make sure no bins overlapped with the training set, the classifier's performance was assessed on 60 unrotated and 60 rotated bins during testing. To evaluate the efficacy of a bio waste-level classifier, our work used a realistic data set and a strict testing regimen.

Figure.4: Samples of bin images at different bio waste levels

For all implementations, this study used a typical ASUS NJ750 PC running Ubuntu 18.04.1 LTS. A Xiaomi Pocophone F1 was used to take the images, which were then scaled to 960 by 720 pixels in the.jpg format. A set of 375 images was utilized by us. Different viewpoints, lighting situations, and distances from the containers are captured in the images. The distribution of images according to lighting is further explained in Table 1.

Table 1: Images distribution

Type	Day	Night	Total
Multiple containers (CNN)	85	61	145
Without containers (CNN)	82	64	1445
Individual containers (VLAD)	57	0	57
Multiple containers per image (CNN with VLAD)	23	10	32
Total	244	133	376

The images depict genuine garbage pickup scenes, captured from a maximum distance of ten meters, typical of a road's width. The camera angles varied between 40° and 140° assuming the front face of the container was at 90°. This study focused on four different container types with slight cosmetic changes, excluding significant variations in appearance.

Based on IHTYOLOv5 principles, a new method for object recognition and classification was developed. The first step in the procedure is to convert video data into a sequence of images. These images are carefully processed, which includes noise reduction and scaling using the Polynomial Adaptive Edge Preserving Algorithm (PAEPA). Another approach known as Contrast Limited Adaptive Edge Preserving approach (CLAHE) is used to enhance contrast in the scaled, noise-free image sequences. After this image improvement, the enhanced image sequences are used to train IHTYOLOv5 giving it the ability to recognize objects in them with accuracy. After this training phase is over, objects are recognized correctly, and each one has a bounding box that indicates its bounds. Completing the calculation of the loss caused during the detecting procedure is the last stage.

A configuration created especially to deal with this issue was put into place to enhance the system's capacity to identify items of different sizes. This setup—called Grasp—works best when combined with a threshold value to distinguish between items that are smaller and larger. The next stages of object detection and classification are subsequently handled by an IHTYOLOv5 customized algorithm. Figure 5 provides a graphic depiction of the overall system design.

3.4 Pre-processing

The first step is to separate the video data into individual frames. Thereafter, pre-processing is applied to improve these frames' clarity. This entails downsizing the images and using the PAEPA noise reduction algorithm. Resizing, however, occasionally results in the loss of pixel information and a deterioration of the image quality. A polynomial interpolation function is used to solve this. It preserves visual clarity by producing estimates of pixel intensities that nearly match the original values. Following processing, the frames are identified as follows:

$$input\ video = Q_i \rightarrow I_{f(m)} \quad (6)$$

$$I_{fi(m)} = \{I_{f1(m)}, I_{f2(m)}, I_{f3(m)}, \dots \dots \dots \dots \dots, I_{fn(m)}\} \quad (7)$$

$I_{fi(m)}$ – Frameset sequence; f_n - number of frames; and Q_i- the input video to attain the total frames.

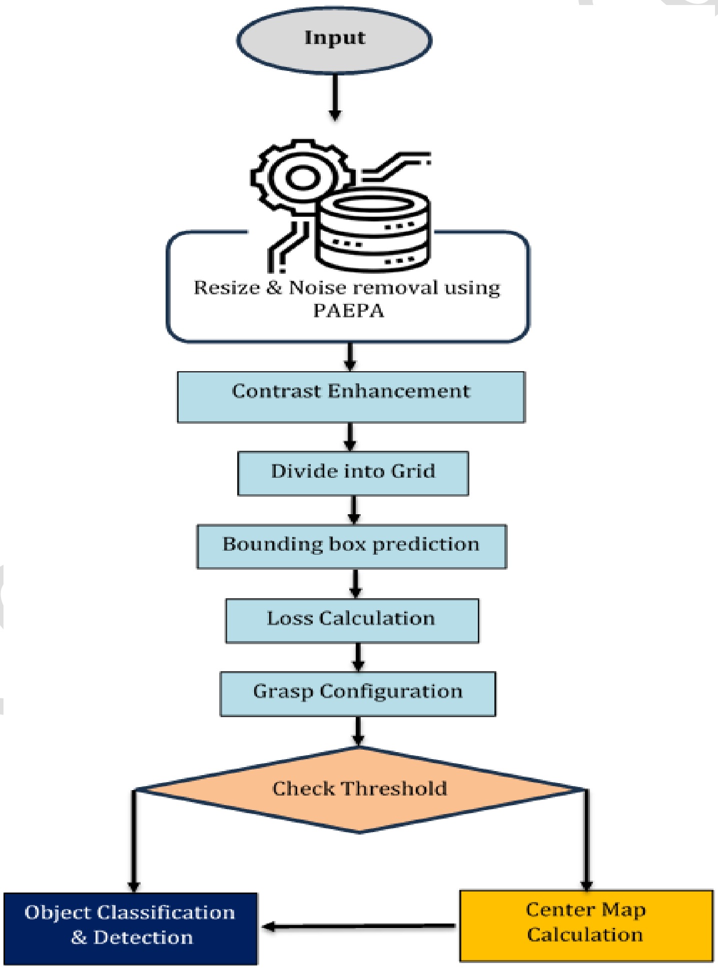


Figure 5: System architecture of proposed model for optimizing object detection in bio-waste management

Step 1: Image scaling is accomplished in the first stage using a method known as polynomial interpolation. By averaging the nearby known pixels, this approach calculates the value of unknown pixels. The interpolating polynomials for the image can be obtained as follows:

$$I_{fi(m)}^{rs}\ resizing \rightarrow I_{fi(m)}^{ipt} \quad (8)$$

Where, I_m^{rs}- resized image; and I_m^{ipt} - input image to be resized.

The interpolating polynomials $U(\varphi)$ for the image can be derived as,

$$U(\varphi) = \alpha_o + \alpha_1\varphi^1 + \alpha_2\varphi^2 + \cdots + \alpha_n\varphi^n \ (9)$$

In this case, the coefficients are denoted by$\alpha_o, \dots. \alpha_n$, while the polynomial degree is indicated by n. We use this formula to compute the values of the missing pixels by averaging their known neighbours, which leads to the creation of the interpolated image.

Step 2: Polynomial interpolation is used to create a fresh image in the second step of the noise removal procedure. Denoted as D, this "interpolated image" attempts to recreate the original image prior to noise contaminating it. The original image is first split up into several blocks, or portions, in order to accomplish this. The Discrete Wavelet Transform (DWT) method is applied to each block in order to retrieve important information about the edges of the image. These edge traits are numerically represented by the particular coefficients that DWT produces. This procedure can be stated mathematically as:

$$I_{fi(m)} = I_{fi(m)}^{ipt} + D \quad (10)$$

Wherein, $I_{fi(m)}^{ipt}$ - polynomials interpolated image; $I_{fi(m)}$ - observed image with corrupted noise D.

$$C = T\left(B_n\left(I_{fi(m)}\right)\right) \quad (11)$$

Wherein, T - DWT function, B_n – input image partitioned block of the input image; I_m, C denotes the wavelet coefficients in a,b directions.

Step 3: We concentrate on specific frequency bands within the signal in the third step. To remove background noise, a threshold is computed within each band. This threshold is established by examining the overall quantity of signal information ("total wavelet coefficients") and the diversity of the noise ("noise variance").

$$\tau_t = \frac{med|C_{ab}|}{0.6745} \times \frac{1}{\sqrt{max(\Delta_g^2 - \Delta_{noise}^2, 0)}} \qquad (12)$$

$$\Delta_g = \frac{1}{L}\sum_{a,b=1}^{L} C_{ab} \qquad (13)$$

Wherein, C_{ab}, τ_t - total wavelet coefficients; Δ_{noise} - noise variance

Step 4: An application of the "shrinking rule" is made to pinpoint an exact cutoff point, or threshold. Important features (active edges) are given smaller cut-off values according to this criterion. The following equation essentially explains how the rule applies a threshold to filter out insignificant wavelet coefficients:

$$\tau_{C_{ab}} = \beta \times \tau_t \qquad (14)$$

In this case, β indicates the chosen threshold value, and $\tau_{C_{ab}}$ indicates the particular filtering function that was applied. By following this approach, less important information is eliminated and only noteworthy aspects are kept.

Step 5: Lastly, the inverse wavelet transforms (threshold coefficients) are completed to reconstruct the noise-removed image. It is possible to express the inverse wavelet transform as

$$I_m^{\wedge} = T^{-1}\left(\tau_{C_{ab}}\right) \quad (15)$$

Wherein, , T^{-1} - inverse wavelet transform; $I_m^{\wedge}$ - denoised image

3.5 Binarization adapted K-Means Algorithm (BKA)

This new framework uses Log Energy Entropy values for pixel-to-pixel calculations instead of the standard Wiener filter, which is based on individual pixel means. Moreover, it makes use of BKM for efficient segmentation. Following segmentation, the Horn-Schunck method within the optical flow technique is used to track the movement of the objects. Object tracking is the framework's final stage, in which motion-estimated objects are used as the starting points for further processing.

The proposed methodology uses a multi-stage procedure to accurately track and recognize objects. This includes boosting contrast, reducing noise, improving visibility, and converting to the YCbCr color system. After this preliminary setup, the system carries out motion estimation, object detection, classification, and segmentation. Lastly, it keeps track of the recognized objects throughout time. Figure 6 illustrates the complex operation of this item identification and tracking system.

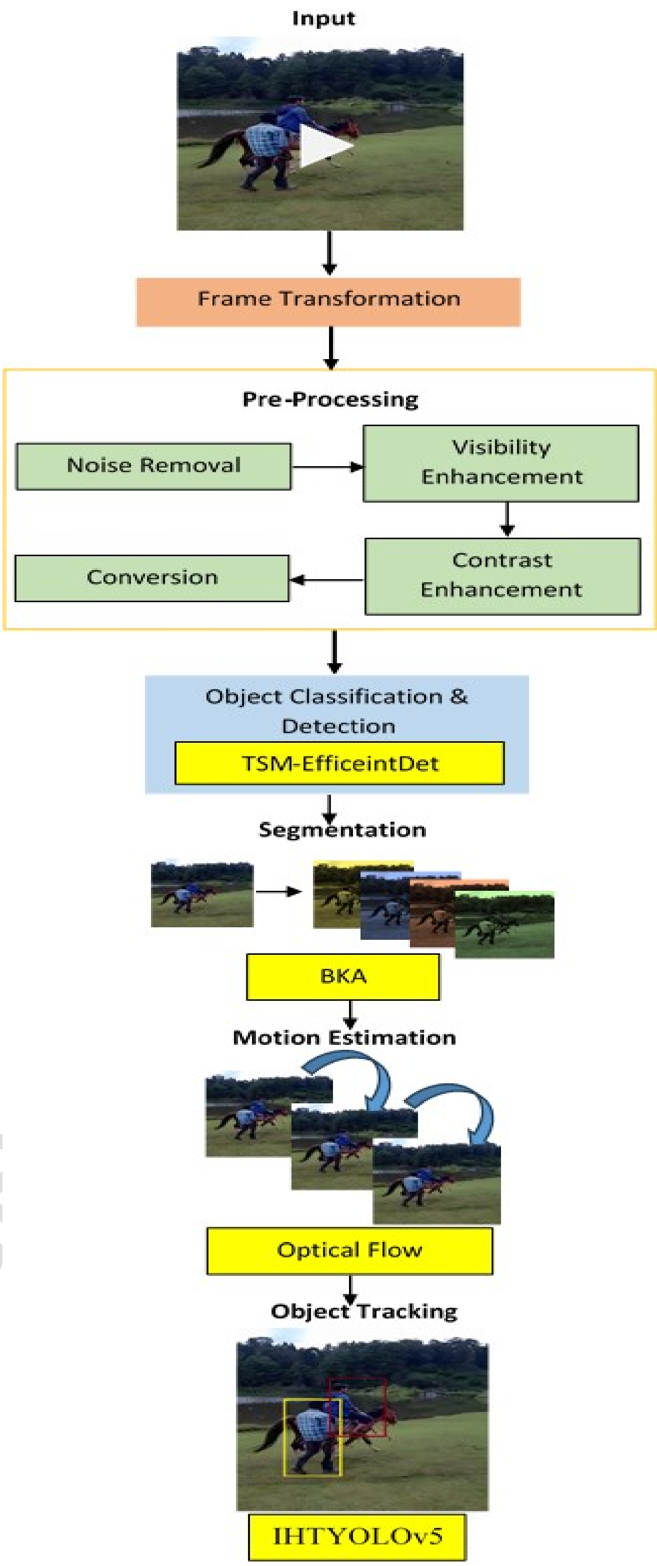


Figure 6: Object detection in bio-waste management with improved hyperbolic tangent YOLOv5 and BKA

The proposed system uses Hough line detection for container orientation, cross-correlation for object distinction, and feature extraction via Gabor filters/Sobel masks for precise solid bio-waste container detection and classification. Hough line detection in the proposed system identifies the orientation and position of solid bio-waste containers, crucial for accurate localization and classification in cluttered environments.

3.6 Noise removal by DLE-WF

Unwanted noise is frequently introduced into pixel values and intensities during image acquisition, deteriorating the information that is recorded. A digital image can be tainted by a variety of noises, however the proposed model addresses this problem by using a modified Wiener Filter (WF) called DLE-WF. Conventional WFs use pixel-mean computations to reduce noise. Nevertheless, this method may unintentionally omit important image elements. Taking into account this constraint, DLE-WF evaluates the information value of surrounding pixels using a metric known as Log Energy Entropy (LEE). DLE-WF may effectively suppress noise while maintaining important image data by focusing on the difference between minimum and maximum entropy values. Because of the improved detail retention, this refinement provides better object detection than regular WF. The subsequent section delineates the particular functions of DLE-WF's image denoising methodology.

$\sigma^2(\bullet) -$ *input image's variance*; $I(a,b)$ - Noise component; $n_i(a,b)$ – intensity; D_E - differential entropy; p(•) - probability of image pixels

- $LEE(E)$ is computed as,

$$E = -\sum_{a=1}^{N} \sum_{b=1}^{M} \{[p(x_i(a,b))]\}^2 \quad (16)$$

- D_E is computed a

$$D_E = E_{max}(a,b) - E_{min}(a,b) \quad (17)$$

  Where, $E_{max}(a,b)$ - maximum entropy image pixels; $E_{min}(a,b)$ - minimum entropy image pixels

- The image's variance is modelled as,

$$\sigma^2(x_i(a,b)) = \frac{\sum_{a=1}^{N} \sum_{b=1}^{M} (x_i(a,b)-E)^2}{(N-1)(M-1)} \quad (18)$$

$$\sigma^2(n_i(a,b)) = \frac{\sum_{a=1}^{N} \sum_{b=1}^{M} (n_i(a,b)-E)^2}{(N-1)(M-1)} \quad (19)$$

3.7 BKA Segmentation

Segmentation was used to follow the movement of the items in the images once they had been identified and classified. By dividing an image into smaller, easier-to-manage pieces, segmentation helps to simplify the image and make it easier to analyse later. BKA, a clustering-based segmentation technique chosen for this study. Specifically, this method uses the BKA clustering algorithm to separate the identified items from the rest of the input images. Using a number-based approach, this method first divides the items in the images into M different clusters. Next, to determine how close the cluster centres are to each data point, the Euclidean distance between them is computed. Nevertheless, the images' noise and unequal lighting produce intensity in homogeneities that cause the clusters of black and white fringes to be misclassified. To overcome this, a term that permits neighbouring pixel labels to affect the labelling of a specific pixel is added to the normal BKA algorithm. This updated version, known as BKA, includes the subsequent steps:

Algorithm: BKA

Input: α_f – Object detected

Output: Y_i – Object segmented

Step 1: Initialize the target objects $as\ f = 1,2, \dots, N$

{

Step 2: it segmented as $k_i = k_1, k_2, \dots, k_M$

{

Step 3: for each i we compute the centre of clusters (C_j)

{

Step 4: for j range from 1 $to\ N$

{

Step 5: **Compute** Euclidean distance as D_e

Step 6: Compute

$$E = \sum_{i=1}^{M} \sum_{\alpha_f \in k_i} \left|\alpha_f - \mu_i\right|^2 + \frac{\beta}{n_r} \sum_{i=1}^{M} \sum_{\alpha_f \in k_i} \|\alpha_f - \mu_i\|^2 \quad (20)$$

Step 7: **Evaluate** distribution intensity by Equation (20)

Step 8: **Detect** the component background as b(p,q)

Step 9: I**dentify** fringe component

Step 10: Update the function (E)

}

}

}

Step 11: Obtain the output $Y_i = Y_1, Y_2, \dots, Y_M$

}

3.8 Bin opening detection

We must first locate the perimeter of the hole and its four corners to locate this area. To accomplish this, we start by employing a method known as the Canny Edge Operator to extract edge information from the image. The Hough transform is then used to find straight lines inside the image edge. Line equation computed using Equation (21)

$ax + by = \rho$ (21)

In which b = sinh and a = cos h. After that, we examine the lengths of the 30 lines that have the most edge pixels to see if they fit within the contour of the bin. Most importantly, we look for intersections between orthogonal line pairs since these provide good candidates for bin corners. Equation (21) can be expressed as follows for each line at the intersection of two lines at a point (x,y):

$a_1x + b_1y = \rho_1$ (22)

$a_2x + b_2y = \rho_2$ (23)

To confirm that two lines are orthogonal, we multiply one by one and one by two, then add the results. The following equation is true if the lines in Equations (22) and (23) are really orthogonal:

$a_1a_2+b_1b_2=0$ (24)

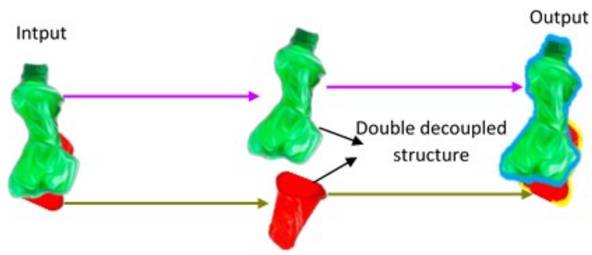


Figure 7: Invisible Occluded Region

A novel two-layer architecture for precisely segmenting overlapping items is shown in Figure 7. The top and bottom layers of this "decoupling structure" are distinct from one another and concentrate on different facets of the image. The hidden part of the "occluded" item is represented by the critical overlap between these layers, which the model addresses using a layered method. As a scout, the top Graph Convolutional Network (GCN) layer gathers vital details about the location and shape of the occluded item. The bottom layer uses this intelligence to direct its segmentation process, which allows it to map out the whole form of the occluded item precisely even while it is hidden.

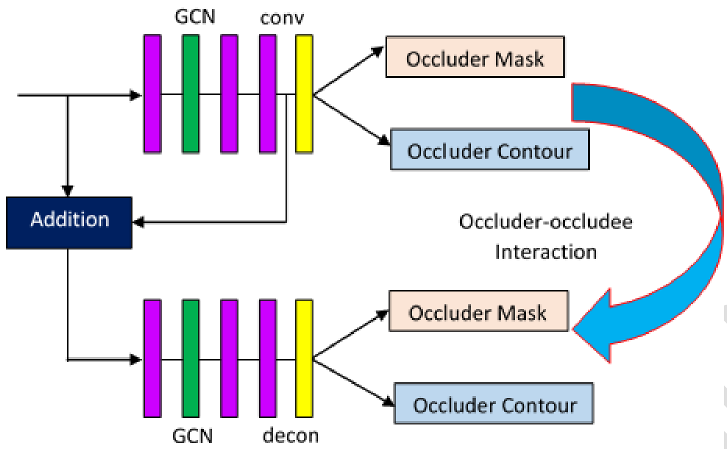


Figure 8: Occlusion Perception

The network starts with extracted RoI characteristics, represented by x. It then makes use of a Spatial Attention Module (SAM), a Fully Connected layer (FC), and a 3x3 convolutional layer (Conv). By simultaneously predicting masks and contours, the occludee branch clearly models occluded objects and extracts crucial occlusion information needed by the second layer to segment the target occludee as shown in Figure 8.

The paper addresses the challenge of segmenting highly overlapping bio-waste objects through a novel two-layer architecture. This decoupling structure uses a top Graph Convolutional Network (GCN) layer to gather crucial occlusion information, enabling precise segmentation by the bottom layer even when objects are occluded (Figure 7, 8).

4. Results and Discussions

We extracted a pre-specified set of 12 labels, and we computed percentages that were unique to each class. Table 2 demonstrates that both positive and incorrect outcomes are consistently present, which raises questions regarding the accuracy of the forecasts. The bulk of recovered labels from images containing several containers of the same class typically belonged to that class. In a similar vein, a higher concentration of labels were placed on containers nearer the camera.

Table 2: Performance metrics value

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	Total
TP	2	2	2	2	2	2	3	2	2	2	2	3	1	2	3	3	2	2	2	1	3	2	3		2	57
FP								1												1		2		2		6
F	2	2	2	2	2	2	1	1	2	2	2	1	3	2	1	1	2	2	2	2	1		1	2	2	49

Note: True Positive (TP), False Positive (FP) and Fails (F)

There is a distinct process involved in IHTYOLOv5-BKA implementation. First, each visual element is given a descriptive tag during the image labelling step of the process. This particular approach only made use of 144 pre-labelled images. Dark flow is a flexible toolset that offers an extensive tool set for training and testing stages. The distribution of object occurrences in the training dataset is shown visually in Table 3.

Figure 9: Detected the bio waste from bin using proposed system

The neural network for garbage object detection's training duration is greatly influenced by the GPU that is employed. It took nine hours to get good detection performance on a GTX 850M. As seen in Figure 9, when the IHTYOLOv5-BKA begins to over fit the dataset and eventually loses detection capability, overtraining is a cause for concern. Interestingly, Figure 10 shows that the 15,000-step checkpoint is when the iteration with mAP occurs.

Table 3: Training set class instances

	Mixed bio waste	Blue	Green	Yellow
No. of Object class	175	120	117	117

A possible bias in the model towards the mixed-bio waste class is proposed by Figures 11 and 12. This bias shows up as better mixed-bio waste container detection performance. This can be attributed to two factors: the comparable imbalance towards this class in the test set and the skewed distribution of the training data, which favours cases with mixed bio waste.

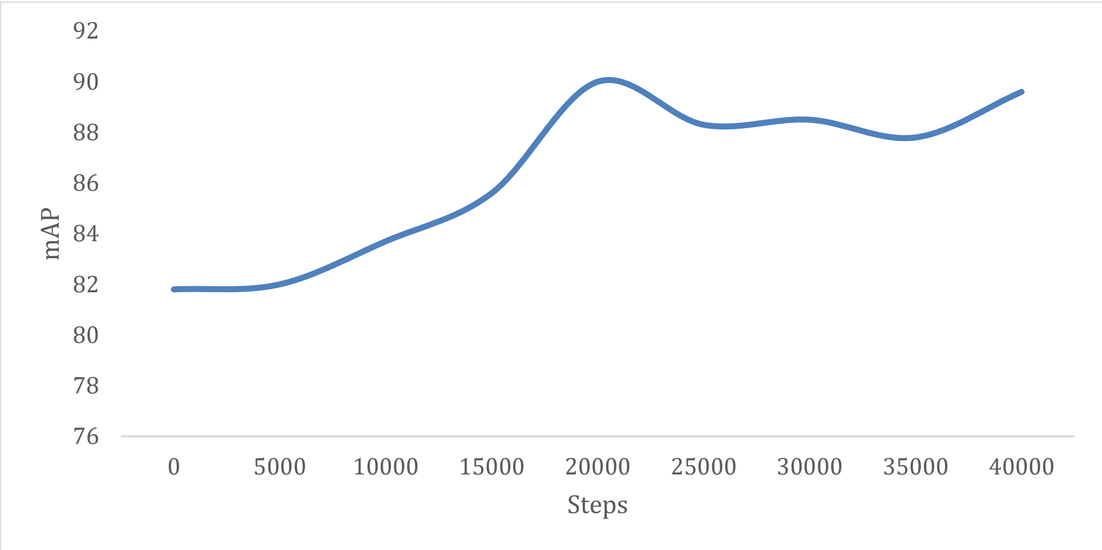


Figure 10: Training steps based on mAP

From the dataset we took rubbish images with different degrees of occlusion and examined them to perform a subjective comparison. The detections produced by several algorithms for these images were then classified. IHTYOLOv5-BKA model performed better than the others, especially when it came to human perception of trash under occlusion. This implies that it achieves a higher level of accuracy in matching the way that people would recognize these kinds of partially occluded things.

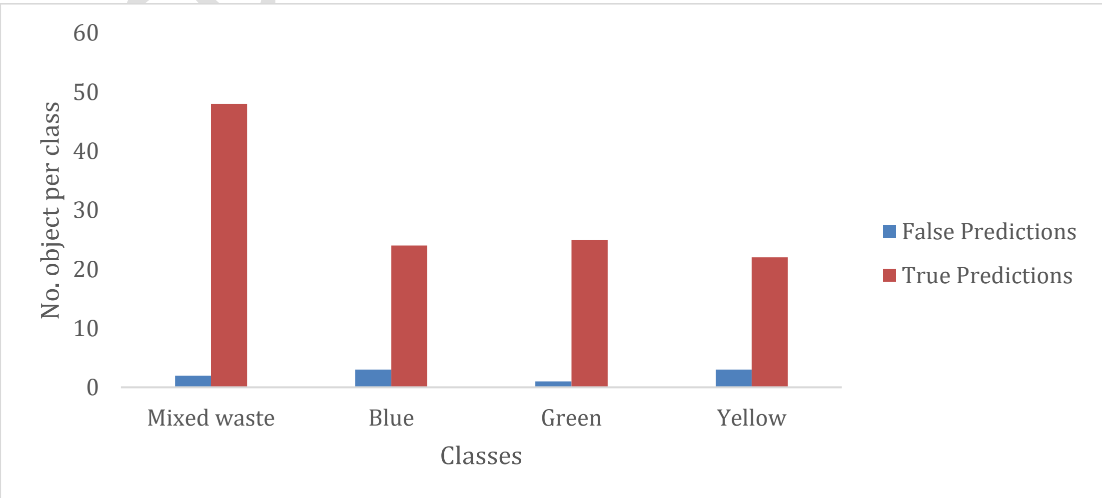


Figure 11: Object class after detection

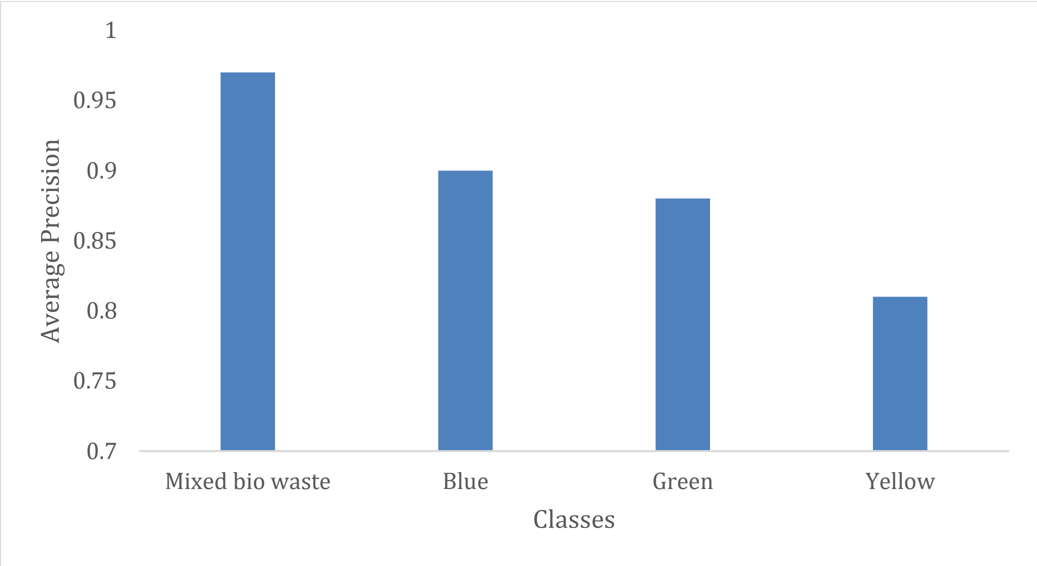


Figure 12: mAP object class after detection

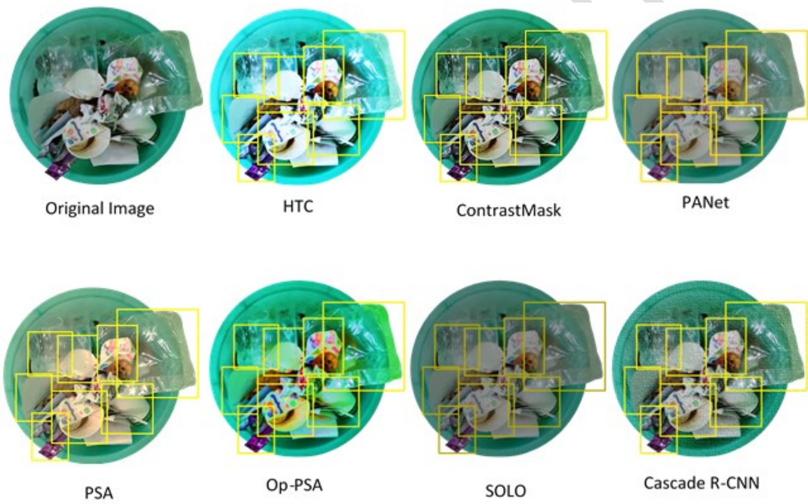


Figure 13: A large number of occluded garbage maps

The IHTYOLOv5-BKA model performs better at detection for the dataset examined in this research, especially when there is only a small occlusion. Its unique strength is that it can see the front and back layers independently, which makes it possible to model boundaries and masks with finer detail for both items that are obscured. This method improves the model's understanding of occlusion conditions and makes it easier to accurately identify even concealed garbage shown in Figure 13.

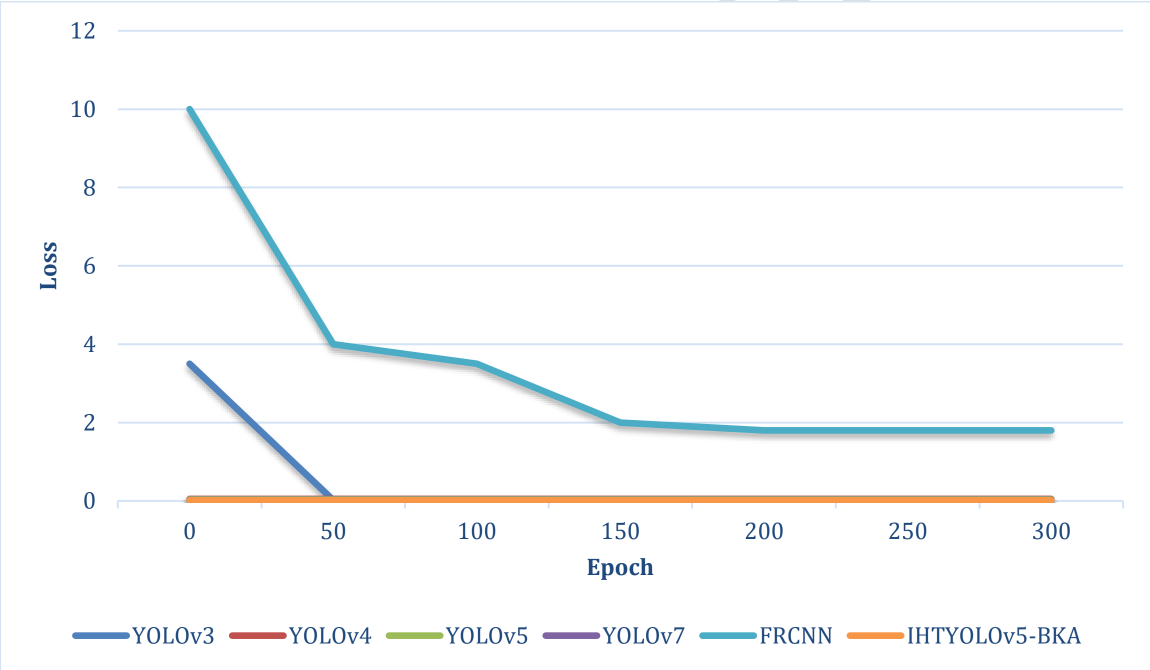
4.1 Experimental results comparison

We ran an experiment using the PASCAL VOC dataset to directly compare the performance of the IHTYOLOv5-BKA model with the existing results are shown in Table 4.

Table 4: PASCAL VOC dataset experimental results

Method	Training Dataset	Testing Dataset	mAP
IHTYOLOv5-BKA	VOC07 + 12	VOC-Test07	0.8732
YOLOv5_Y	VOC07 + 12	VOC-Test07	0.8622

Interestingly, the modified model's better object identification efficacy was demonstrated with 1.11% improvement in mAP. The IHTYOLOv5-BKA model was tested on a construction bio waste dataset with existing systems further demonstrating its advantages. The loss function and mAP metrics for each model during training and testing are displayed in Figure 14.



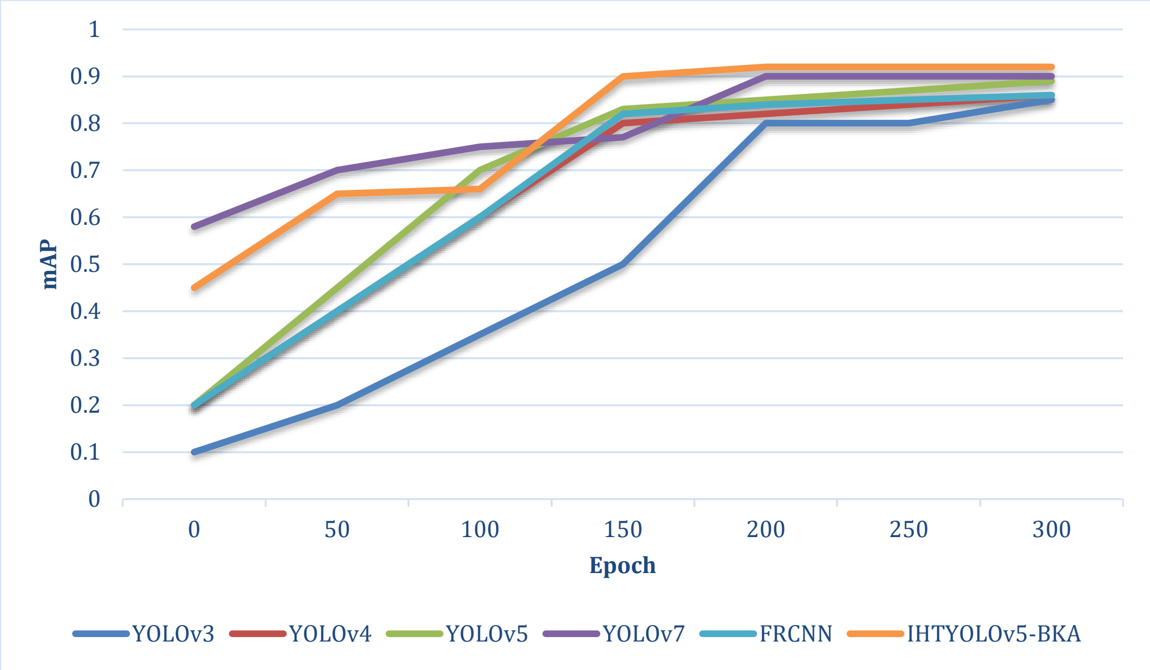


Figure 14: Loss and mAP of proposed and existing models

An instance of a false positive detection is shown in Figure 15. However, Figure 16 shows the detection system works even when there is some occlusion. This can also be observed in the video clips. Nevertheless, as shown in Figure 17, the system is not always resistant to occlusion. The capability to resist occlusion comes from the training set, which consisted of samples with occlusion. To ensure effective detection, the training set must represent what we may encounter during the detection phase. However, as shown in Figure 18, the test set is relatively small. The small size of the test set may result in minor statistical disparities shown in Figure 19.

Figure 15: Detection of objects based on false positive

Figure 16: Detection of correct bio waste from bin using occlusion during night time

Figure 17: Detection of incorrect bio waste from bin using occlusion during night time

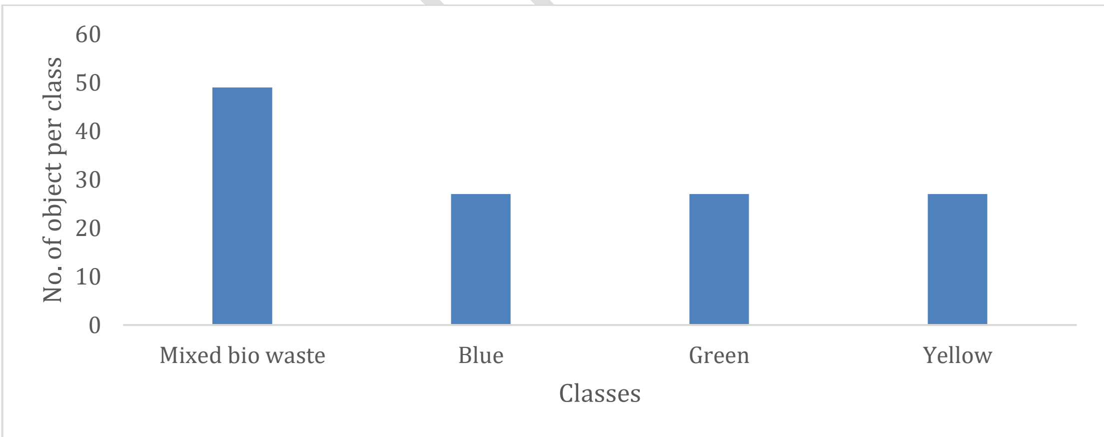


Figure 18: Test set to detect the no. of instance per class

Figure 19: (a) input; (b) bin detection by DWT (c) bin detection by proposed method

Table 5 presents a comparison between proposed and existing approaches based on performance measures. Table 6 compares the performance of the proposed and existing approaches in terms of False Positive Rate (FPR), False Negative Rate (FNR), and False Rejection Rate (FRR).

Table 5: Performance measures

Method	Specificity	Sensitivity	Accuracy	Precision	Recall	F-measure	NPV	MCC
IHTYOLOv5-BKA	94.924	98.354	98.443	95.125	99.297	97.726	98.534	94.167
DBN	92.981	94.935	94.420	93.546	94.931	94.024	92.984	91.624
RNN	88.921	92.646	91.724	89.124	92.552	90.912	92.147	89.683
CNN	87.924	93.065	91.218	88.984	93.076	90.014	91.351	88.258
DNN	83.035	88.124	86.401	84.062	88.116	85.327	86.209	82.701

Table 6: Performance analysis

Method	FPR	FRR	FNR
IHTYOLOv5-BKA	0.0324	0.0354	0.0347
DBN	0.2984	0.1084	0.1079
RNN	0.4246	0.2043	0.2062
CNN	0.5142	0.3179	0.3145
DNN	0.8264	0.7902	0.7924

5. Conclusions

The proposed system presents proposed work for rotation-invariant bin identification and bio waste level classification. This method guarantees the correct identification and categorization of bio-waste containers independent of their orientation, therefore improving system reliability under many different environmental conditions. Cross correlation and line detection let one ascertain the exact position and orientation of the compartment. Features from the bin entry area and the external of the bin area are extracted using Gabor filters or Sobel masks. Small-object detection and inter-object occlusions are the two main challenges to the effective identification of building bio waste. These problems influence the capacity of the system to detect bio waste. An enhanced IHTYOLOv5-BKA model is suggested for intelligent building waste classification to increase the accuracy of item identification. It is taught using a series of 3046 images of bio waste from building. By use of IHTYOLOv5-BKA, this work presents a successful method for object recognition and categorization. Regarding performance criteria, the suggested solution outperforms the current systems. The inter-object occlusions in tightly packed bio waste might limit the efficiency and dependability of detection, therefore making it difficult for the suggested system to correctly identify tiny items. Later studies might concentrate on the use of improved hardware configurations, the integration of sophisticated item recognition algorithms with immediate processing capabilities, and the enlargement of the dataset to cover a range of bio waste container kinds and situations.

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