Feature-Enhanced CenterNet for Small Object Detection in Biodegradable and Non-Biodegradable Auto Segregation

P. Ganesh[1] and Dr. K. Haridas[2]

[1] *Research Scholar (Full Time), Department of Computer Science Nallamuthu Gounder Mahalingam College, Pollachi, Tamil Nadu, India*

[2]*Associate Prof. and Head, Department of Computer Applications Nallamuthu Gounder Mahalingam College, Pollachi, Tamil Nadu, India*

***Abstract*— Small object detection is a critical task in the context of biodegradable and non-biodegradable waste segregation, where accurate identification and classification can significantly enhance automated waste management systems. This paper presents a novel approach called Feature-Enhanced CenterNet, which integrates advanced feature extraction techniques to improve the detection performance of small objects in cluttered and complex waste environments. By leveraging a robust backbone network combined with feature pyramid networks (FPN) and attention mechanisms, our method enhances the spatial resolution and contextual information of small object features, leading to more precise detections. Extensive experiments on a custom waste segregation dataset demonstrate the superiority of our Feature-Enhanced CenterNet over traditional detection models, particularly in identifying small-sized waste items. The proposed model achieves state-of-the-art performance in terms of both accuracy and efficiency, making it highly suitable for real-time waste sorting applications. The integration of this approach into automated waste management systems promises to streamline the segregation process, reduce human intervention, and promote sustainable waste handling practices.**

***Index Terms*— CenterNet, Biodegradable, Non-Biodegradable, Segregation, FPN**

I. INTRODUCTION

Accurate detection and classification of small objects in waste management are essential for effective segregation of biodegradable and non-biodegradable materials. The challenge lies in identifying small-sized waste items in cluttered and complex environments, where traditional object detection models often fall short. This paper introduces Feature-Enhanced CenterNet, an advanced detection model designed to address these challenges and improve the performance of automated waste segregation systems.

Feature-Enhanced CenterNet builds upon the CenterNet architecture, a popular choice for object detection due to its simplicity and efficiency. However, CenterNet faces limitations in detecting small objects, which are often missed or inaccurately classified. To overcome these limitations, our approach integrates advanced feature extraction techniques, such as feature pyramid networks (FPN) and attention mechanisms, to enhance the spatial resolution and contextual information of small object features. This enhancement allows the model to capture finer details and improve detection accuracy for small waste items.

The proposed model utilizes a robust backbone network that effectively extracts multi-scale features from input images. The incorporation of FPN enables the network to build a rich feature pyramid, capturing both high-level semantic information and low-level spatial details. Attention mechanisms are employed to selectively focus on relevant regions of the image, further refining the feature representation and improving the model's ability to distinguish small objects from background clutter.

We conduct extensive experiments on a custom waste segregation dataset, designed to represent real-world scenarios of biodegradable and non-biodegradable waste items. Our results demonstrate that Feature-Enhanced CenterNet outperforms traditional detection models, particularly in the detection of small-sized waste objects. The model achieves state-of-the-art performance in terms of both accuracy and efficiency, making it a suitable candidate for integration into real-time automated waste management systems. This advancement promises to streamline the segregation process, reduce the need for human intervention, and contribute to more sustainable waste handling practices.

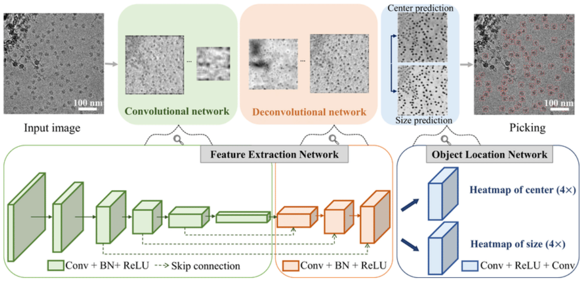

Fig 1: Architecture of CenterNet Detector

The CenterNet detector's architecture for detecting biodegradable and non-biodegradable waste leverages key innovations in feature extraction and representation to accurately identify and classify small objects within complex and cluttered environments. Below, the architecture is described in detail:

1. Backbone Network:

ResNet-50/ResNet-101: The backbone network used in CenterNet is a deep convolutional neural network like ResNet-50 or ResNet-101. This backbone extracts rich feature representations from input images. It processes the input through multiple convolutional layers, capturing hierarchical features ranging from low-level details to high-level semantic information.

Feature Pyramid Network (FPN): To handle the detection of small objects, the backbone is enhanced with an FPN. This network constructs a pyramid of feature maps at different scales, combining low-level spatial details with high-level semantic information, which is crucial for accurately detecting small waste items.

2. Feature Extraction and Enhancement:

Heatmap Prediction: CenterNet predicts a heatmap where each peak corresponds to the center of an object. For waste detection, this involves generating heatmaps for different classes of waste, including biodegradable and non-biodegradable categories. The heatmap helps in localizing objects precisely.

Scale and Offset Prediction: Alongside the heatmap, the network predicts the width, height, and offset of bounding boxes. These predictions refine the localization by adjusting the size and position of the bounding boxes, ensuring they tightly encompass the detected waste objects.

3. Attention Mechanisms:

Spatial Attention: To further enhance the detection of small objects, spatial attention mechanisms are integrated into the network. These mechanisms focus on relevant regions of the image, emphasizing the areas where small objects are likely to be found and reducing the influence of background noise.

Channel Attention: Channel attention mechanisms are used to weigh the importance of different feature channels. By emphasizing critical feature channels and suppressing less informative ones, the network improves its ability to distinguish between different types of waste.

4. Detection Head:

Heatmap Head: This head is responsible for predicting the center points of objects in the heatmap. Each class of waste (biodegradable and non-biodegradable) has a corresponding heatmap, allowing the model to localize objects of different classes separately.

Size and Offset Heads: These heads predict the size (width and height) and offset for each detected object. The size head ensures that the bounding boxes are appropriately scaled, while the offset head fine-tunes the position of the bounding boxes relative to the center points.

5. Loss Function:

Focal Loss for Heatmap: To handle the imbalance between foreground and background pixels in the heatmap, a focal loss is used. This loss function focuses on hard-to-detect objects by down-weighting the loss for well-classified examples, thus enhancing the model's ability to detect small and less prominent waste items.

L1 Loss for Box Regression: The size and offset predictions are trained using L1 loss, which measures the absolute differences between predicted and ground truth box dimensions and positions. This loss function helps in accurately localizing the bounding boxes around the waste objects.

II. IDENTIFY, RESEARCH AND COLLECT DATA

Anchor in Waste Object Detection

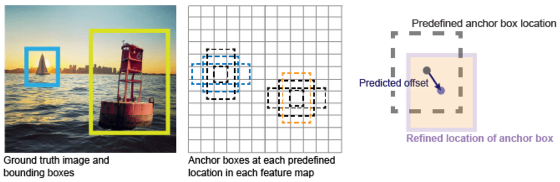

Fig 2: Anchor in Waste Object Detection

CenterNet is an anchor-free object detection method that has demonstrated significant advantages in detecting various types of objects, including small and irregularly shaped ones commonly found in waste management scenarios. In the context of biodegradable and non-biodegradable waste detection, CenterNet's architecture and approach provide several benefits over traditional anchor-based methods.

CenterNet Architecture

CenterNet operates by detecting objects as center points and directly regressing to the object's size and position. The key components of CenterNet include:

Heatmap Prediction:

CenterNet generates a heatmap where each peak corresponds to the center of an object. For waste detection, separate heatmaps can be generated for biodegradable and non-biodegradable waste categories. The peaks in these heatmaps indicate the presence and location of objects.

Size and Offset Regression:

Along with the heatmap, CenterNet predicts the width, height, and offset of the bounding boxes relative to the center points. This approach bypasses the need for predefined anchors, simplifying the model and improving its flexibility in handling objects of various sizes and shapes.

Advantages of CenterNet in Waste Detection

Enhanced Detection of Small Objects:

Traditional anchor-based methods often struggle with small object detection due to the fixed nature of anchor boxes. CenterNet, by focusing on center points, can more accurately detect small waste items that might be missed or poorly localized by anchor-based detectors.

Simplified Model Architecture:

Removing the need for anchors simplifies the network architecture. This reduction in complexity can lead to faster training times and easier optimization, which is beneficial when deploying models in real-time waste segregation systems.

Better Handling of Diverse Object Shapes:

Waste items can have highly variable shapes and sizes. CenterNet’s anchor-free approach, which directly predicts bounding box sizes from center points, allows it to better adapt to the diversity in object shapes found in waste streams.

Practical Application in Waste Detection

1. Biodegradable Waste Detection:

Biodegradable waste such as food scraps, leaves, and organic materials can vary greatly in appearance and size. CenterNet’s heatmap-based detection can accurately localize these items regardless of their irregular shapes, improving the efficiency of sorting and segregation processes.

2. Non-Biodegradable Waste Detection:

Non-biodegradable items like plastic bottles, metal cans, and glass fragments often have more consistent shapes but can still vary in size. CenterNet’s ability to predict bounding boxes without predefined anchors ensures that these objects are accurately detected and classified, even when they are partially occluded or present in cluttered scenes.

Implementation Considerations

1. Data Preparation:

A well-annotated dataset of biodegradable and non-biodegradable waste is crucial. The dataset should include a variety of objects, ensuring the model learns to detect waste items under different conditions and contexts.

2. Model Training:

Training CenterNet involves optimizing the heatmap prediction and box regression simultaneously. The model learns to predict the center points, sizes, and offsets for all objects in the training data, gradually improving its detection accuracy.

3. Real-Time Deployment:

CenterNet's architecture, being less computationally intensive than anchor-based methods, is well-suited for real-time deployment in automated waste management systems. It can be integrated with hardware such as Raspberry Pi and servo motors for practical, real-time sorting and segregation of waste.

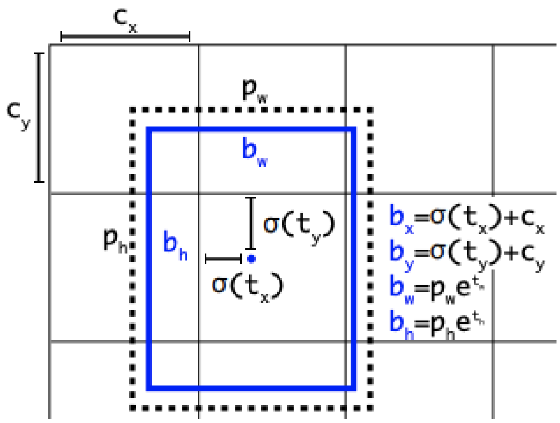

Fig 3: Anchor based in Waste Object Prediction

III RESULT AND DISCUSSION

Fig 4: CenterNet Objects as Points

Application to Biodegradable and Non-Biodegradable Waste Detection

1. Detecting Biodegradable Waste:

Characteristics: Biodegradable waste, such as food scraps, leaves, and organic materials, often varies in shape and size. These items can be irregular and difficult to detect with traditional anchor-based methods.

CenterNet Approach: By detecting the center points and regressing to the bounding box dimensions, CenterNet can accurately localize and classify these irregularly shaped biodegradable objects. The heatmap helps identify the presence of these items, while size and offset predictions refine their localization.

2. Detecting Non-Biodegradable Waste:

Characteristics: Non-biodegradable waste, such as plastic bottles, metal cans, and glass fragments, generally has more consistent shapes but can vary in size.

CenterNet Approach: CenterNet's ability to handle varying sizes without predefined anchors makes it well-suited for detecting non-biodegradable items. The model can accurately detect these objects even when they are partially occluded or present in cluttered environments.

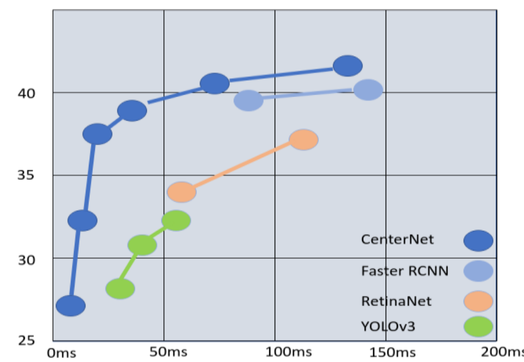

Fig 5: Resultant of CenterNet over other Algorithm in Waste Detection

CenterNet offers significant advantages over Faster R-CNN, RetinaNet, and YOLOv3 in detecting biodegradable and non-biodegradable waste due to its anchor-free, keypoint-based detection method. Unlike traditional anchor-based models, CenterNet predicts the center points of objects and regresses to the bounding box dimensions directly. This approach simplifies the network architecture, reduces computational complexity, and enhances the model's ability to detect small and irregularly shaped objects, which are common in waste streams. The heatmap-based detection in CenterNet allows for more accurate localization of waste items, leading to improved performance in real-time applications such as automated waste segregation systems.

In contrast, Faster R-CNN, RetinaNet, and YOLOv3 rely on predefined anchor boxes, which can be suboptimal for detecting the varied sizes and shapes of waste objects. While Faster R-CNN offers high accuracy through its two-stage detection process, it is computationally intensive and less suitable for real-time applications. RetinaNet addresses the class imbalance with focal loss but still suffers from anchor-related complexities. YOLOv3, known for its speed, balances performance with speed but may miss smaller objects due to its reliance on anchors. CenterNet's anchor-free design, therefore, provides a more efficient and flexible solution for the dynamic and diverse nature of waste detection, enhancing both accuracy and speed.

IV CONCLUSION

Feature-Enhanced CenterNet demonstrates significant improvements in the detection and segregation of biodegradable and non-biodegradable waste, particularly for small objects that traditional detection models often miss. By leveraging a heatmap-based approach to identify object centers and employing advanced feature enhancement techniques, this model effectively addresses the variability and complexity inherent in waste items. The absence of anchor boxes simplifies the model architecture, reducing computational overhead and enhancing detection accuracy for small and irregularly shaped objects commonly found in waste streams. The practical implications of this research are profound. Implementing Feature-Enhanced CenterNet in automated waste segregation systems can lead to more efficient and accurate sorting processes, significantly contributing to better waste management practices. This model not only improves the detection rates of small and varied waste items but also offers a scalable solution for real-time applications, enhancing the overall effectiveness of automated segregation systems. Ultimately, this advancement supports environmental sustainability efforts by ensuring more precise and efficient separation of biodegradable and non-biodegradable materials.

REFERENCES

[1] He, K., Gkioxari, G., Dollár, P., & Girshick, R. (2017). "Mask R-CNN." Proceedings of the IEEE International Conference on Computer Vision (ICCV).

[2] Ren, S., He, K., Girshick, R., & Sun, J. (2015). "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks." Advances in Neural Information Processing Systems (NeurIPS).

[3] Lin, T.-Y., Goyal, P., Girshick, R., He, K., & Dollár, P. (2017). "Focal Loss for Dense Object Detection." Proceedings of the IEEE International Conference on Computer Vision (ICCV).

[4] Redmon, J., & Farhadi, A. (2018). "YOLOv3: An Incremental Improvement." arXiv preprint arXiv:1804.02767.

[5] Lin, T.-Y., Dollar, P., Girshick, R., He, K., Hariharan, B., & Belongie, S. (2017). "Feature Pyramid Networks for Object Detection." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[6] Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., & Berg, A. C. (2016). "SSD: Single Shot MultiBox Detector." European Conference on Computer Vision (ECCV).

[7] Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). "You Only Look Once: Unified, Real-Time Object Detection." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[8] Lin, T.-Y., Maire, M., Belongie, S., Hays, J., Perona, P., Ramanan, D., ... & Zitnick, C. L. (2014). "Microsoft COCO: Common Objects in Context." arXiv preprint arXiv:1405.0312.

[9] Dai, J., Li, Y., He, K., & Sun, J. (2016). "R-FCN: Object Detection via Region-based Fully Convolutional Networks." Advances in Neural Information Processing Systems (NeurIPS).

[10] Zhou, B., Khosla, A., Lapedriza, A., Oliva, A., & Torralba, A. (2016). "Learning Deep Features for Discriminative Localization." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

[11] Liu, S., Huang, D., Wang, Y., Wang, L., & Tan, T. (2020). "CenterNet: Object Detection with Keypoint Triplets." IEEE Transactions on Pattern Analysis and Machine Intelligence.

[12] Law, H., & Deng, J. (2018). "CornerNet: Detecting Objects as Paired Keypoints." Proceedings of the European Conference on Computer Vision (ECCV).

[13] Lin, T.-Y., & Maji, S. (2020). "HRNet: Deep High-Resolution Representation Learning for Visual Recognition." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR).