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A Framework Combining YOLOv2 and Motion-Adaptive Inference with Multiple Data Splits for Waste Management in Smart Sustainable City

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Abstract**—** Sustainability is a key goal of the United Nations Sustainable Development Goals. Smart sustainable cities are futuristic urban centers expected to dominate the world in the future. Effective waste management is one of the critical indicators of a smart sustainable city. Previous studies have developed waste management models using AI algorithms, particularly convolutional neural networks. However, these studies often struggled with balancing detection speed and accuracy. This article proposes a framework that combines an optimized YOLOv2 model with motion-adaptive inference to achieve a balance between speed and accuracy in detecting organic and recycle materials. The proposed framework has been applied to detect organic and recycle materials alongside baseline algorithms, and it demonstrates improved performance in balancing speed and accuracy compared to the baselines. Making it suitable for adoption in smart sustainable cities. The proposed framework can be integrated into real-time systems to enhance waste disposal management in smart sustainable cities.

Keywords**—** Convolutional Neural Network; Sustainability; Waste Materials; Fast YOLO.

I. Introduction

The intersection of smart city and sustainability produces smart sustainable city with the aim developing a city without toxic impact on the environment and optimize the utilization of resources in the city [1-2]. One of the key indicators of environmental sustainability in achieving a smart sustainable city is effective waste disposal and material recycling, which should be integrated into the city planning for short, mid, and long-term urban projects [3]. Increase in population is increasing the challenges of waste management in smart cities [4]. Thus, effective waste management model or systems is required to solve the challenges. Studies were adopting algorithm requiring manual feature engineering for solving machine learning problem [5] including developing waste disposal management system [6] before finding effective solution with convolutional neural network (CNN) [7]. It was demonstrated that large-scale backpropagation networks, can processed images directly without the need for manual feature engineering (Figure 1). The network can learn from raw image data, paving the way for tackling problems involving large-scale, low-level information [8].

Since its inception, the CNN has received tremendous attention and has significantly evolved in the field of visual recognition [10]. It continues to be a leading approach for object detection, as evidenced by recent studies [11-16]. A combination of CNN with LSTM and transfer learning for the separation of organic and recycle waste images for sustainable environment was conducted in [17].

Fig. 1 Typical convolutional neural network with three filters [9].

The CNN has been intensively adopted for the identification of waste and recycle materials as evident in the survey covered by [18]. A CNN extract visual features for waste brand identification before feeding to KNN for prediction [19]. However, it is found that the CNN suffered from localization problem when solving problem regarding object detection. Girshick et al. [20] introduce region into CNN referred to as region with CNN (R-CNN) to solve the challenge of localization in the CNN. Ghadekar et al. [21] adopted R-CNN for the classification of waste from images having nine distinct categories such as plastic, glasses, metal objects, trash, cardboard, papers and more. A mask R-CNN and YOLOv8 were adopted for plastic waste sorting for the purposes of recycling [22]. Jain et al. [23] adopted Mask R-CNN for the detection of underwater waste in order to clean the water body.

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However, the bottleneck in fast R-CNN is the issue of convergence time associated with the region computation. To mitigate this challenge, region proposal network (Faster R– CNN) with capability of sharing full convolutional image features together with the network for detecting the object [24]. Nie et al. [25] uses fast R-CNN to detect garbage during sorting. Similarly, Jose & Sasipraba, [26] propose the use of dual faster RCNN to predict waste for effective waste management in cities. However, Despite the high accurate level recorded by Fast R-CNN, it still suffer from computational complexity especially when it is meant for integration into embedded system [27]. The computational complexity in R-CNN motivated the introduction of "*You only look once*" (YOLO) to reduce the computational complexity where computation of bounding box coordinates and probability of class are performed simultaneously [28]. Arulmozhi et al. [29] applied YOLO for the detection of garbage for waste management. The Single shot multibox detecton (SSD) is introduce to improve the computational speed of the single shot detectors (YOLO) including Faster R-CNN) and accuracy [27]. The SSD has been applied to waste disposal and management [30-33].

The issues with previous studies on waste management are that they primarily focus on either accuracy or computational complexity, with limited effort to explore the interplay between accuracy and computational complexity. To close this gap, the paper propose the adoption of fast YOLO combining optimized YOLOv2 with motion-adaptive inference that accelerate YOLOv2 object detection [34].

The other sections of the article include Section 2, which provides a detailed discussion of the methodology; Section 3, which presents the results and discussion; and finally, the article concludes with Section 4.

II. Waste Management in Smart Sustainable City

Typical waste management begins with the generation of waste from households, industries, streets, public facilities, retail businesses, and other sectors. The waste is then collected and transported by private, government, or informal waste collectors before undergoing sorting, dismantling, and processing. Subsequently, the waste is either recycled and reused in domestic markets, exported, converted into energy, or disposed of in landfills. The overview of the waste management lifecycle is shown in Fig. 2 [35].

The production of products and consumption has changed in the current "circular economy" regarded as environmentally friendly. The circular economy is built on the assumption that materials used will be recycled and reused. The recycling of materials have been typically conducted by humans to recover valuable materials. The manual approach is ineffective because of low productivity and increasing health risk [36]. The increasing amount of generated waste globally is triggering pollution, management of waste and recycling. Therefore, requires advance strategies such as AI to enhance waste management ecosystem [37]. One of the key functions of waste management is monitoring in view of the fact that it is required to ease waste management issues such as generation of the waste, collection, transporting, treatment and disposal processes. In achieving zero waste management, waste characterization is an effective step towards achieving the zero waste management [38].

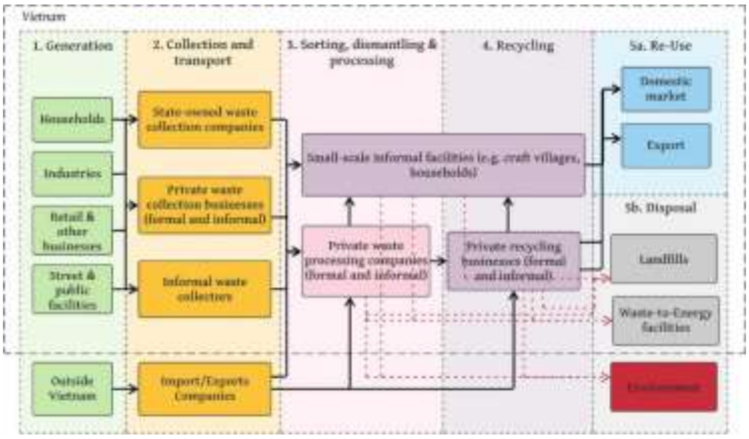

Fig. 2 The lifecycle of waste management value in Vietnam [35].

The future cities are expected to be shaped by the intersection of smart technologies and waste management because of urban landscape transformation. As such, produce a comprehensive approach to sustainable urban environments [39]. Waste management functionality in smart city is beyond its conventional role of disposing rubbish. The integration of state-of-the-art technologies and data driven models is paving a path to sustainable development and improving quality of life [40].

The adoption of AI in municipal waste management have the potential to enhance the effectiveness of collecting waste, processing and classification of the waste [37]. The classification of garbage is recommended strongly for use in solid waste management in municipal [36]. There are AI based technologies that enhance waste management such as smart garbage bins, robots and prediction models. The monitoring of garbage wirelessly enable the detection of waste bins, predict the collection of waste and optimize the waste processing facilities performance [37].

III. Methodology

This section provided the study detailed procedure of the methodology for easy understanding by the readers. The major component in the section is the datasets and the adopted framework.

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A. *Datasets*

The data used in this study contained images of waste involving organic and recycle materials, the sample of the data is presented in Fig. 3 The data is publicly available online through Kaggle as waste classification. The data has 25077 organic and recycle images [41].

Fig. 3 Sample of the waste comprising of organic and recycle materials

B. *Propose framework*

The Fast YOLO comprised of the optimized YOLOv2 and the motion-adaptive inference. Each of the frame is fed to 1D convolutional layer. The convolutional layer produces the motion probability map (see Figure 4). Subsequently, transmit it to motion-adaptive inference to find out if computation to updated class probability map requires deep inference. The deep inference is perform only when required to fasten the rate of object detection [34].

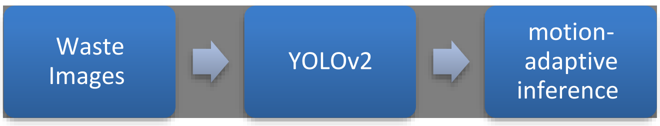

Fig. 4 Procedure for the Fast YOLO classification of organic and recycle materials

The platform used to run the experiment is Google Colab with free access to cloud-based CPUs and GPUs. The datasets described in Section A is splits multiple times: 50:50%; 70:30% and 60:40%. There is no universally accepted data partition ratio; most researchers rely on a single partition ratio, such as 80%-20%. However, such partitioning is often biased toward the pre-training data. To ensure fairness and robustness, this paper employs a multiple data splits technique. The datasets were divided into multiple splits to evaluate the robustness and consistency of the Fast YOLO in identifying organic and recyclable materials across different data splits. For the purpose of evaluation, similar algorithms like the CNN, R-CNN, Fast R-CNN, YOLO and SSD were applied to identify organic and recyclable materials across the different data splits. The performance metrics: Precision, Recall, F1 –score and accuracy were adopted for the study, those metrics are commonly adopted in the literature (e.g., [42-43]).

IV. Results and Discussion

The Tables I – III present the results obtained after running the algorithms to identify organic and recyclable materials from images of waste datasets described in Section III. Tables I–III present the results for multiple data partition ratios, including a 50:50 split, which creates a balance between the training and test datasets without bias.

TABLE I
ALGORITHMS FOR DETECTING ORGANIC AND RECYCLABLE MATERIALS WITH A 70:30 DATA PARTITION RATIO

Algorithm	**Precision**	**Recall**	**Accuracy**	**F1 -score**
CNN	85.67	84.34	84.79	84.87
R-CNN	86.56	88.45	87.11	90.34
Faster R-CNN	87.78	87.56	89.52	90.52
YOLO	92.43	92.38	92.91	92.29
SSD	91.68	92.96	91.24	92.34
Fast YOLO	**93.89**	**94.94**	**93.45**	**94.96**

TABLE II
ALGORITHMS FOR DETECTING ORGANIC AND RECYCLABLE MATERIALS WITH A 50:50 DATA PARTITION RATIO

Algorithm	**Precision**	**Recall**	**Accuracy**	**F1 -score**
CNN	70.51	71.61	74.81	74.83
R-CNN	72.06	73.39	77.57	77.74
Faster R-CNN	73.90	77.51	79.58	80.72
YOLO	80.85	82.93	83.88	85.94
SSD	79.51	82.04	85.72	86.19
Fast YOLO	**82.72**	**83.74**	**86.99**	**87.88**

TABLE III
ALGORITHMS FOR DETECTING ORGANIC AND RECYCLABLE MATERIALS WITH A 60:40 DATA PARTITION RATIO

Algorithm	**Precision**	**Recall**	**Accuracy**	**F1 -score**
CNN	81.49	81.99	82.79	82.85
R-CNN	83.34	83.91	85.61	85.91
Faster R-CNN	85.09	86.73	86.09	87.48
YOLO	88.43	**91.38**	90.31	90.31
SSD	87.84	89.23	89.41	90.09
Fast YOLO	**89.27**	90.94	**91.95**	**92.48**

Table I indicate that Fast YOLO outperforms the baseline algorithms with the best accuracy, followed by the YOLO and SSD. The CNN has recorded the lowest accuracy.

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Table II indicates that Fast YOLO maintains its position leading the accuracy measure, followed closely by SSD and YOLO. Table III, shows that Fast YOLO again leads the accuracy measure, while YOLO and SSD achieve second and third places, respectively.

Tables I – III clearly show that results demonstrate superiority of Fast YOLO consistently offering superior accuracy in varying data partition ratios. In terms of precision, its indicate that the Fast YOLO recorded the highest precision, meaning that it has the most reliable ability in minimizing false positives followed by YOLO and SSD with a strong precision. The CNN recorded the lowest precision, lagging behind. This suggest that the CNN misclassifies more non-target materials as organic or recyclable. Fast YOLO perform well in recall except in the case of 60:40 splits where YOLO standout, suggesting capacity to identify almost all organic and recycle materials. Again, Fast YOLO leads with the highest F1-score, indicating its exceptional balance between the precision and the recall. The possible reasons why the Fast YOLO outperform the other algorithms is likely because of its single step approach to detect object, simplified architecture that reduces computational complexity and ability to process images at high frame rates. Further observation on Tables I – III indicates that the baseline CNN is lagging behind on all the performance indicators. This is not surprising as the other algorithms were improvement over the baseline CNN.

The results in the tables reveal that accuracy reduces as the amount of training data decreases and vice versa, indicating that the accuracy of the algorithms is directly proportional to the size of the training data. This trend highlights the sensitivity of the algorithms to the size of training data available. As such, the lowest accuracy for all the algorithms is recorded at the 50:50 data partition, while the highest accuracy is achieved at the 70:30 data partition for all the algorithms. The Fast YOLO is more resilient to this changes compared to the other algorithms making it a reliable option in the situation where data is limited.

TABLE IV
COMPUTATIONAL SPEED OF THE ALGORITHMS IN IDENTIFYING ORGANIC AND RECYCLE MATERIALS

Algorithm	**70:30**		**50:50**		**60:40**	
	FPS	Time(m)	FPS	Time(m)	FPS	Time(m)
CNN	7	14.22	5	9.00	7.51	12.19
R-CNN	10	19.45	8	13.51	10.06	17.13
Faster R-CNN	15	28.17	13	23.00	13.00	22.53
YOLO	23	34.32	19	30.12	22.00	31.32
SSD	32	43.00	28	37.14	31.18	39.11
Fast YOLO	**48**	52.22	**45**	43.45	**48.23**	50.23

Table IV present frames identified per second (FPS) for the algorithms, it is found that the Fast YOLO achieved the best FPS across the data partition ratios among the compared algorithms suggesting fast processing times in detecting organic and recycle materials from the waste. It is established from Tables I – IV that Fast YOLO has better balance between computational speed and accuracy compared to the baseline algorithms.

The Fast YOLO is robust as suggested by the findings across multiple data partition ratios because of the consistent performance. The adaptability of the Fast YOLO makes it less sensitive to varying training data compared to the other algorithms. The high precision recoded by the Fast YOLO makes it an idle candidate algorithm for waste management systems in smart sustainable city requiring high precision in the identification of waste. The high accuracy archived by the Fast YOLO position it suitably for deployment in large-scale smart sustainable city where real-time waste identification and management is required. For example, the monitoring and optimization of waste collection routes. The quick and fast ability of the identification of organic and recycle waste is in line with the goal of sustainability in smart sustainable city by improving the process of recycling waste, reduction of dependence on landfill and ultimately reduces carbon dioxide footprint. The Fast YOLO outstanding performance with limited training data (50:50) makes it fit for smart sustainable cities in early stages of digitization process aiming at developing waste management systems.

The high precision and computational speed achieved by Fast YOLO is advantageous in practical applications because it has the ability to minimize misidentification of waste ensuring fast accurate sorting and recycling in the smart sustainable cities. The Fast YOLO with highest recall is valuable in waste management systems where ensuring maximum detection of recyclable materials is critical for sustainability goals. However, YOLO is the idle candidate algorithm ahead of Fast YOLO if the slits is 60:40 because the YOLO has a better recall in this case, it is the only case where Fast YOLO lag behind. The Fast YOLO F1-score demonstrates the Fast YOLO reliability and robustness to achieve high detection accuracy across almost all relevant metrics, making the Fast YOLO suitable for integration into real-time smart sustainable city waste management systems. The findings in the study emphasize the critical role of advanced waste detection algorithms in triumphing the objectives of a smart sustainable city.

V. CONCLUSIONS

The study proposes the adoption of optimized YOLOv2 with motion-adaptive inference for waste management systems to contribute in achieving environmental

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sustainability goal in smart sustainable city. Comparison with baseline algorithms suggest the robustness, effectiveness and efficiency of the Fast YOLO, making it an ideal candidate algorithm for developing effective waste disposal and material recycling management system in smart sustainable city. As this is initial work, the project intend to integrate Fast YOLO with vision transformer combining Internet of Things sensors and urban analytics for broader smart sustainable city platforms to develop holistic waste disposal and recycling materials management system.

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Conflict of Interest

The authors declare that there is no conflict of interest

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