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### I. Introduction

Green hydrogen (GH) refers to hydrogen produced using renewable energy sources, such as hydroelectric power, solar, or wind through a process called electrolysis. In this process, water (H<sub>2</sub>O) is split into hydrogen (H<sub>2</sub>) and oxygen (O<sub>2</sub>) using electricity generated from renewable sources. Unlike conventional hydrogen production methods, which often rely on fossil fuels and emit greenhouse gases, green hydrogen production produces zero carbon emissions, making it an environmentally friendly and sustainable alternative (Squadrito, Maggio, & Nicita, 2023).

Amidst the ongoing debate within the renewables and fossil fuel sectors over the optimal production methods for green hydrogen needed for the energy transition, a new contender has emerged. This alternative presents a cost-effective approach to GH production compared to both fossil fuels and renewables: the utilization of organic and recyclable waste (Santhosh, Sarkar, & Venkata Mohan, 2021). The expense associated with manufacturing 1 kg of GH derived from organic and recyclable waste amounts to approximately \$3 per kg. In comparison, the production cost of GH from solar or wind sources ranges from \$11 to \$16 per kg. Additionally, each tonne of dry waste can yield approximately 40–50 kg of GH. Conversely, the output of GH from organic and recyclable waste may range from 30 kg to 120 kg per tonne, contingent upon the moisture content present in the waste materials (Torky, Dahy, & Hassanein, 2023).

The pursuit of sustainable energy solutions has spurred interest in harnessing GH as a clean and renewable energy carrier. A crucial step towards realizing the potential of GH lies in the efficient classification of organic and recyclable waste, which serve as key feedstocks for its production. Traditional methods of waste classification often rely on manual sorting and are labor-intensive, time-consuming, and prone to errors. In contrast, leveraging deep learning (DL) models presents a promising avenue for automating and optimizing the classification process. By harnessing the power of artificial intelligence, DL models can analyze vast amounts of waste data with remarkable speed and accuracy, enabling the identification and segregation of organic and recyclable materials with unprecedented efficiency. This paper explores the application of DL models, specifically VGG19, for the classification of organic and recyclable waste, with the ultimate goal of advancing GH production. Through experimental studies and performance evaluations, the effectiveness of the proposed model in accurately categorizing waste materials is assessed, laying the groundwork for enhanced sustainability and resource efficiency in the GH production process.

### II. Methodology

Transfer learning (TL) based VGG19 DL model was used to classify recyclable and organic waste. Figure 1 illustrates the VGG19 model used for the classification of recyclable and organic waste. Prior to performing convolution, pooling, and Fully connected (FC) operations in this model, the sizes of the waste objects are adjusted. The input size for all waste objects is taken as 224x224x3. Subsequently, these input images are fed into the VGG19 model. In the VGG19 model, 16 Conv layers with a filter size of 3x3 and 5 max pooling operations with a filter size of 2x2 are applied. Following Conv and max pooling, global average pooling (GAP) is implemented to the obtained feature maps instead of FC layers. The GAP significantly reduces the number of parameters in the network compared to FC layers. Instead of flattening the feature maps and connecting each neuron to every neuron in the next layer (as in FC layers), the GAP computes the average of each feature map, resulting in a fixed-size vector regardless of the input image size. Since the GAP involves only a simple averaging operation, it requires fewer computations, reducing both training and inference time. In addition, the GAP acts as a form of regularization by reducing the model's capacity to memorize noise or irrelevant details in the training data.

This can help prevent overfitting and improve the generalization performance of the model. After the GAP process, batch normalization (BN), FC layer with 128 neurons, another BN, dropout layer with 0.3 dropout ratio and softmax function are used as the final classifier. In VGG19 model, BN improves neural network training by stabilizing learning, accelerating convergence, and enhancing generalization performance. It does this by ensuring stable input distributions across layers, reducing sensitivity to parameter initialization, introducing regularization, enabling the use of higher learning rates, and improving gradient flow. The use of dropout layers is advantageous because they prevent overfitting by randomly disabling neurons during training, leading to more robust and generalizable models. They also facilitate ensemble learning, improve training efficiency by reducing the need for manual hyperparameter tuning, and enhance the model's ability to generalize to new data by encouraging the learning of diverse features.

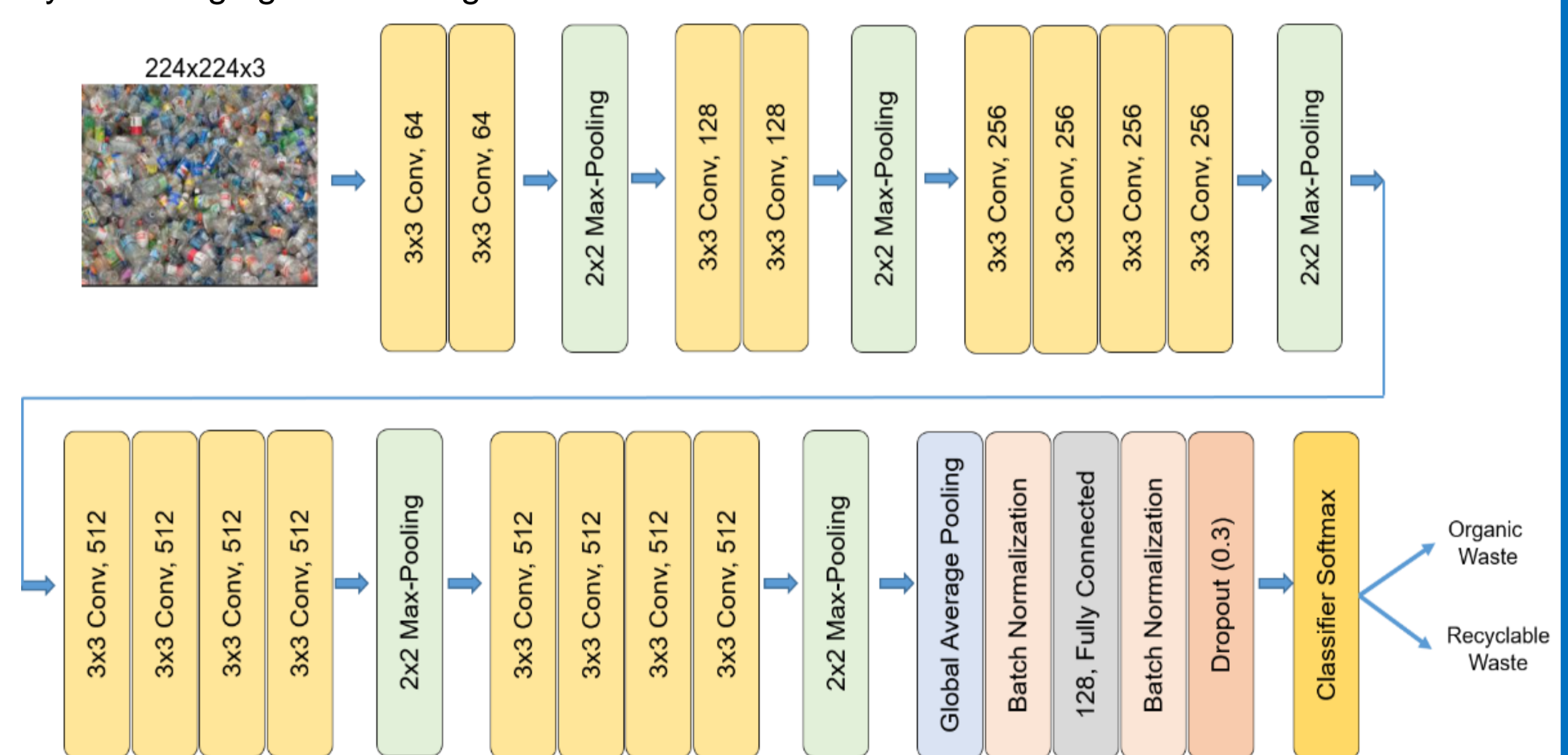


Figure 1. Proposed VGG19 model

### III. Results

Table 1 presents the classification results obtained with different models for the task of classifying organic and recyclable wastes. The models evaluated include VGG16, MobileNet, ResNet50, Xception, and the proposed VGG19. Accuracy, precision, recall, and F1-score metrics are reported for each model. The proposed VGG19 model outperforms the other models with an accuracy of 92.68%, demonstrating its effectiveness in accurately classifying waste images. Additionally, the proposed VGG19 model achieves high precision, recall, and F1-score values, indicating its ability to achieve a balance between precision and recall while maintaining high overall classification performance. These results highlight the superiority of the proposed VGG19 model for the given task compared to the other models evaluated.

Table 1. Classification results obtained with different models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
VGG16	91.96	92.41	91.4	91.8
MobileNet	91.64	92.86	90.8	91.4
ResNet50	91.08	91.63	90.5	90.9
Xception	86.39	89.82	84.7	85.5
<b>Proposed VGG19</b>	<b>92.68</b>	<b>92.93</b>	<b>92.3</b>	<b>92.5</b>

### References

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