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Development of an Intelligent Waste Classification System Using Deep Learning-Based Image Classification

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ABSTRACT: This study aims to develop an automated waste classification and separation system for plastic and metal materials using deep learning models based on image data. Three models of convolutional neural network (CNN) architectures were evaluated and compared: a custom-built Simple CNN, the pre-trained YOLOv8 classifier, and ResNet50 implemented with transfer learning. The dataset consisted of 5,068 images (2,422 metal and 2,646 plastic), which were divided into training, validation, and test sets to ensure comprehensive performance evaluation. Accuracy, precision, recall, and F1-score metrics were used to ensure the performance of each model. The results indicate that the YOLOv8 model achieved the highest accuracy of 94.86%, followed by ResNet50 with 94.37%, and the Simple CNN model with 81.32%. Furthermore, this study discusses the advantages and limitations of each model in terms of computational requirements, training time, and accuracy, and identifies the most suitable model for practical waste separation applications.

KEYWORDS: Deep Learning, Image Classification, Waste Sorting, Smart Recycling, CNN, YOLOv8, ResNet50, Transfer Learning**.**

I.INTRODUCTION

Rapid urbanization, migration, and industrialization are key factors that have turned efficient waste management into a critical social and environmental challenge. According to the *UNEP Global Waste Management Outlook 2023*, global municipal solid waste is projected to reach 3.8 billion tons annually by 2050, creating significant environmental and logistical challenges [1]. Improper waste handling also contributes to greenhouse gas emissions and severe health issues. Deep learning-based intelligent solutions can enhance sorting efficiency and support a circular economy [2].
Traditional waste segregation methods are predominantly manual, time-consuming, inaccurate, and inefficient [3]. Plastics constitute a large proportion of recyclable waste, yet their separation is particularly challenging due to contamination and the diversity of plastic types. Therefore, intelligent deep learning approaches are essential for effective sorting [4]. Nahiduzzaman et al. (2025) aimed to improve classification accuracy, reduce human involvement, and increase recycling efficiency in their study [5].

CNN-based approaches have demonstrated remarkable success in image classification, especially when trained on well-prepared datasets [6,7]. CNNs can identify plastics, metals, paper, and glass; however, real-world performance declines when objects are broken, occluded, or poorly illuminated. Object detectors such as YOLO, particularly YOLOv8, enable highly accurate and fast real-time sorting [8–10]. Models like ResNet50, when applied with transfer learning, have been shown to reduce training time while achieving high accuracy [11]. Hybrid models combining ResNet and YOLO have demonstrated superior detection capabilities [12].

In this study, we propose an intelligent waste segregation system focusing on metal and plastic classification. Three models were employed: ResNet50 with transfer learning, a pre-trained YOLOv8 classifier, and a custom-designed Simple CNN. A dataset of 5,068 images was used to evaluate comparative performance based on accuracy, precision, recall, F1-score, and confusion matrices.

II. MATERIALS AND METHODS

The objective of this research is to develop an intelligent waste segregation system capable of distinguishing between metal and plastic waste using deep learning techniques. The research process consists of three main stages: dataset preparation, preprocessing, and model selection, training, and testing (Figure 1).

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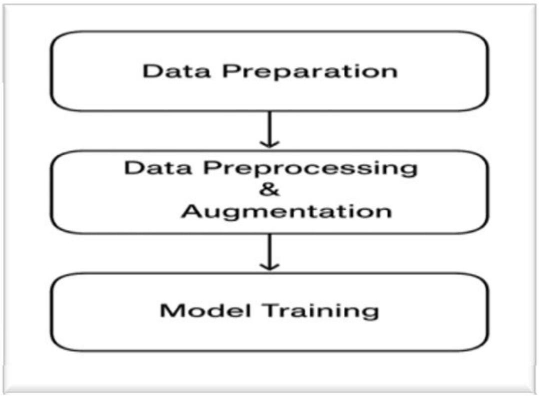

Figure 1: Research Process

2.1 Dataset Preparation

The dataset consists of a total of 5,068 images, including 2,422 samples of metal and 2,646 samples of plastic, downloaded from an open-source repository. To ensure accurate model performance evaluation, the quality of the data was carefully verified. The dataset was divided into three subsets: 70% for training, 15% for validation, and 15% for testing.

2.2 Data Preprocessing

Data preprocessing is essential to ensure that different deep learning models behave consistently and optimally. All images used in this study were preprocessed prior to model training. For both the Simple CNN and ResNet50 models, a standard input size of **224 × 224 pixels** was adopted. Resizing ensures that all images have uniform dimensions, allowing the models to efficiently extract and learn relevant features.

To improve training stability and model robustness, pixel intensity values were normalized using the ImageNet mean $[0.485, 0.456, 0.406]$ and standard deviation $[0.229, 0.224, 0.225]$. Training data were augmented to enhance generalization and reduce overfitting. Augmentation techniques included random brightness adjustment, random rotation, and horizontal flipping, enabling the models to recognize objects under varying lighting and orientation conditions.

For the YOLOv8 classifier, images were resized to **640 × 640 pixels** to comply with the model's default input settings. No additional data augmentation was applied to YOLOv8 in this study. These preprocessing steps were necessary to ensure that each model could effectively learn to distinguish between metal and plastic waste while handling variations in image quality, orientation, and illumination.

2.3 Model Architecture

In this study, three deep learning models were employed for the classification of metal and plastic waste: the YOLOv8 classifier, a pre-trained ResNet50 model utilizing transfer learning and a custom-designed Simple CNN model. These models were selected to compare their performance in intelligent waste segregation tasks and to explore different approaches to image classification.

2.3.1 Simple Convolutional Neural Network (CNN)

To establish a baseline for image classification, a Simple CNN model was designed. The block diagram of the proposed Simple CNN architecture is presented in **Figure 2**.

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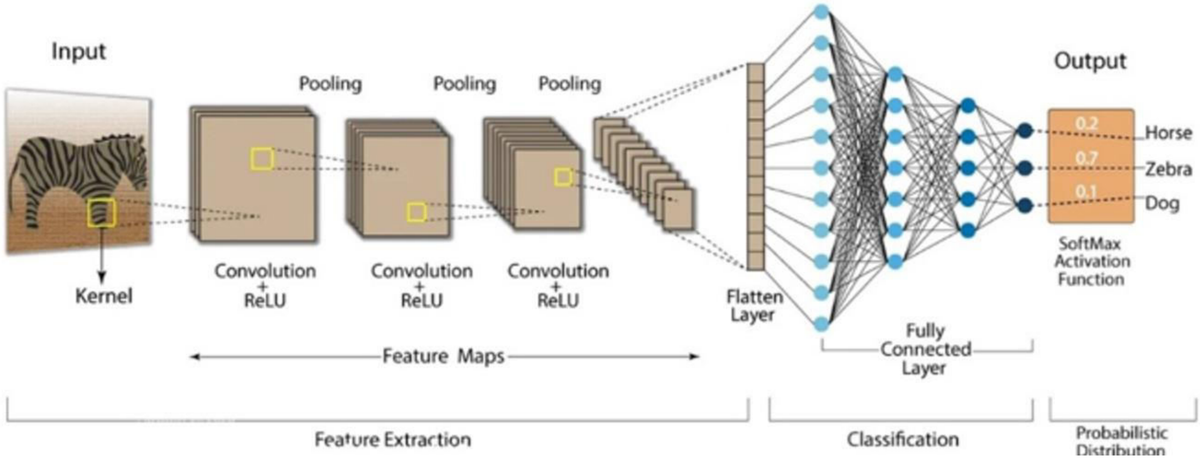

Figure 2. Convolutional Neural Network (CNN)

The network consists of the following layers:
Input Layer: Accepts images of size **224 × 224 × 3**.
Convolutional Layers: Three convolutional layers with **32, 64, and 128 filters**, respectively. Each convolutional layer is followed by a **ReLU activation function** to introduce non-linearity.
Pooling Layers: After each convolutional layer, a **Max-Pooling layer** is applied to reduce spatial dimensions and computational complexity.
Fully Connected Layers: Two dense layers with **128 and 64 neurons**, respectively, using **ReLU activation**.
Output Layer: A **Softmax layer** with two neurons representing the classes: *metal* and *plastic*.
The network was trained using the **Adam optimizer** with a learning rate of **0.001** and **categorical cross-entropy loss**. Despite its simplicity, this CNN model effectively learned discriminative features and served as a baseline for comparison with more advanced architectures.

2.3.2 ResNet50 (Transfer Learning)

ResNet50 is a deep convolutional neural network pre-trained on the ImageNet dataset, designed to address the vanishing gradient problem in very deep networks through the use of residual connections. In this study, transfer learning was implemented as follows:
Pre-trained Layers: The original ResNet50 convolutional base was utilized to leverage previously learned image features.
Custom Classifier: The original output layer was replaced with a fully connected layer consisting of **two neurons** for metal and plastic classification.
Fine-Tuning: The last few layers of ResNet50 were unfrozen to adapt to the fine-grained features of the waste dataset.
Training: The model was trained using the **Adam optimizer** with a learning rate of **0.0001**, and **early stopping** was applied to prevent overfitting.
The pre-trained features of ResNet50 enabled faster convergence and superior performance compared to the Simple CNN model.

2.3.3 YOLOv8 Classifier

YOLOv8 (*You Only Look Once, version 8*) is a state-of-the-art object detection and classification model known for its efficient feature extraction and high-speed inference capabilities:
Model Setup: The YOLOv8 classifier was used in its pre-trained form, with the final classification layer adjusted for two classes: *metal* and *plastic*.
Input Size: Images were resized to **640 × 640 pixels** to match the model's input requirements. Transfer learning was applied using weights previously trained on the COCO dataset.
Inference: YOLOv8 typically provides both class predictions and bounding boxes; however, for the purposes of this study, only classification outputs were considered. The model was employed to evaluate whether an advanced object detection framework could deliver superior performance in waste classification without real-time detection requirements.

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2.3.4 Training Setup

To ensure fair performance comparison under equivalent conditions, all three models were trained using **Google Colab Pro** with an **NVIDIA A100 GPU**. The same dataset structure and preprocessing techniques (resizing, normalization, and augmentation) were applied across all models for both training and validation.

The Table 1 below summarizes the key hyperparameters used for each model.

Table 1. Hyperparameter Configuration

Model	Epoches	Batch Size	Learning Rate	Optimizer	Loss Function	Image Size
Simple CNN	25	32	0.001	Adam	Cross Entropy Loss	224*224
ResNet50	25	32	0.001	Adam	NLL Loss (Log Softmax output)	224*224
YOLOv8 Classifier	25	16	SGD	Adam	Cross Entropy Loss (Internal)	640*640

2.3.5 Evaluation Metrics

The models were evaluated using the following metrics:
Accuracy: The percentage of samples correctly classified.
F1-Score, Precision, and Recall: Used to measure the balance of performance across classes.
Confusion Matrix: Applied to visualize the accuracy of each class and identify misclassifications. This provides a clear overview of how well each model performs on the same dataset.

III. MODEL PERFORMANCE COMPARISON AND ANALYSIS

This section presents the results of training and evaluating three classification models—Simple CNN, ResNet50, and YOLOv8 on two waste categories: *plastic* and *metal*. The models were assessed using standard metrics such as accuracy, precision, recall, F1-score, and confusion matrix.
A comparative analysis was conducted using the performance metrics obtained from YOLOv8, Simple CNN, and ResNet50 for the metal and plastic waste classification task. Among the three models, YOLOv8 demonstrated superior generalization and achieved the highest accuracy, as illustrated in Figure 3. This was followed by ResNet50, which exhibited slightly lower accuracy (Figure 4). The Simple CNN model produced the lowest accuracy, primarily because it could not capture all the fine details present in the dataset (Figure 5).

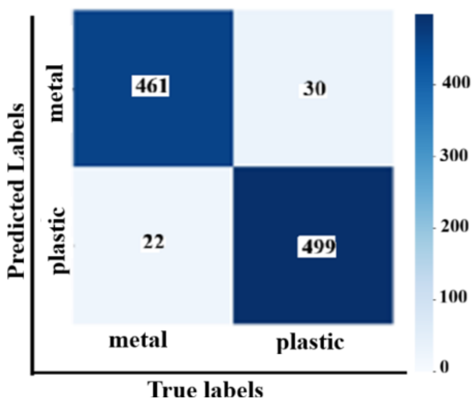

Figure 3. YOLOv8 confusion matrix results

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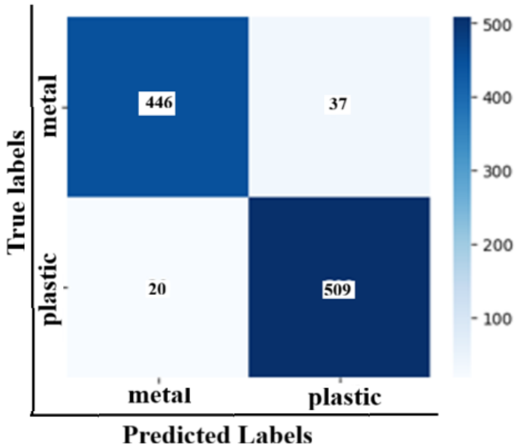

Figure 4. ResNet50 confusion matrix results

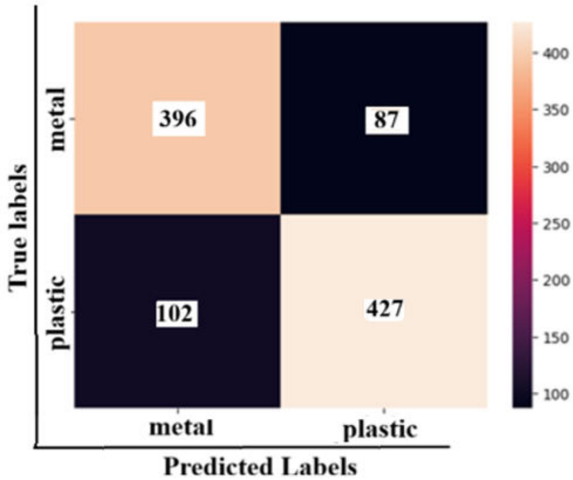

Figure 5. Simple CNN confusion matrix results

The comparative performance results of all three models on the same dataset are presented in Table 1. As shown in Table 2, the YOLOv8 model achieved the highest classification accuracy, followed by the ResNet50 model, while the Simple CNN model produced the lowest accuracy.

Table 2. Comparison of Model Performance

Model	Validation Accuracy
YOLOv8	94.9%
ResNet50 (Transfer Learning)	94.37%
Simple CNN	81.32%

The classification performance of all models was comprehensively analyzed using metrics such as accuracy, precision, recall, F1-score, and confusion matrices for both plastic and metal classes. The results obtained are presented in Table 3.

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Table 3. Detailed Class-Specific Performance

Model	Class	Precision	Recall	F1-Score
YOLOv8	Metal	0,9389	0,9545	0,9466
	Plastic	0,9578	0,9433	0,9505
ResNet50	Metal	0,96	0,92	0,94
	Plastic	0,93	0,96	0,95
Simple CNN	Metal	0,80	0,82	0,81
	Plastic	0,83	0,81	0,82

IV. CONCLUSION AND FUTURE WORK

All three models demonstrated strong performance in classifying plastic and metal waste; however, notable differences in accuracy were observed. The Simple CNN model, which exhibited the lowest performance, was unable to capture the complexity of the dataset. The ResNet50 model delivered promising results across both categories, while YOLOv8 achieved the highest performance with an average F1-score of 0.9466. Therefore, YOLOv8 can be considered the most suitable model for this binary classification task in terms of precision, efficiency, and consistency. ResNet50, on the other hand, may be the best option for minimizing specific error types, such as avoiding false positives for metal or false negatives for plastic.

In conclusion, both YOLOv8 and ResNet50 can serve as reliable architectures for practical intelligent waste classification systems, significantly outperforming the Simple CNN model. The results demonstrate the effectiveness of deep learning models in segregating waste composed of metal and plastic. ResNet50's deeper architecture and pre-trained feature extraction enabled it to capture complex visual patterns, while YOLOv8 produced competitive results, proving that object detection models can be easily adapted for image classification tasks. Conversely, the lower accuracy of the Simple CNN model indicates that shallow architectures struggle with complex variations in waste images. Overall, the findings highlight that transfer learning and advanced architectures substantially improve waste classification accuracy and support their potential for practical smart waste management applications.

This study addressed the development of an intelligent waste classification system designed to automatically segregate metal and plastic waste using image data. Three models were employed: a custom-built Simple Convolutional Neural Network (CNN), a pre-trained YOLOv8 classifier, and ResNet50 utilizing transfer learning. The dataset used for training and testing consisted of 5,068 images (2,422 metal and 2,646 plastic samples), divided into training, validation, and test sets to ensure robust evaluation. The models were assessed using metrics such as accuracy, precision, recall, F1-score, and confusion matrices. As shown in Table 1, YOLOv8 achieved the highest accuracy, followed by ResNet50 and Simple CNN.

Additionally, the strengths and weaknesses of each model were analyzed in terms of computational complexity, training time, and classification accuracy. These findings provide practical insights for developing intelligent recycling systems and highlight the potential of deep learning-based approaches for smart waste segregation.
Overall, all three models successfully classified metal and plastic waste, but their performance varied significantly. The Simple CNN provided a baseline but struggled to capture the visual complexity of the dataset. ResNet50 achieved high precision and recall through transfer learning, while YOLOv8 delivered the most balanced and overall best results, including the highest average F1-score.

To advance toward real-world smart waste management applications, the following improvements are suggested:

- Expand the dataset to include additional waste categories (e.g., glass, paper, organic materials) for multi-class classification.
- Deploy lightweight models on edge devices or smart bins for real-time waste segregation.
- Enhance robustness to lighting variations using advanced data augmentation or synthetic image generation techniques.

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- Develop a functional prototype integrating automated sorting systems, conveyor belts, and cameras to validate real-world applicability.

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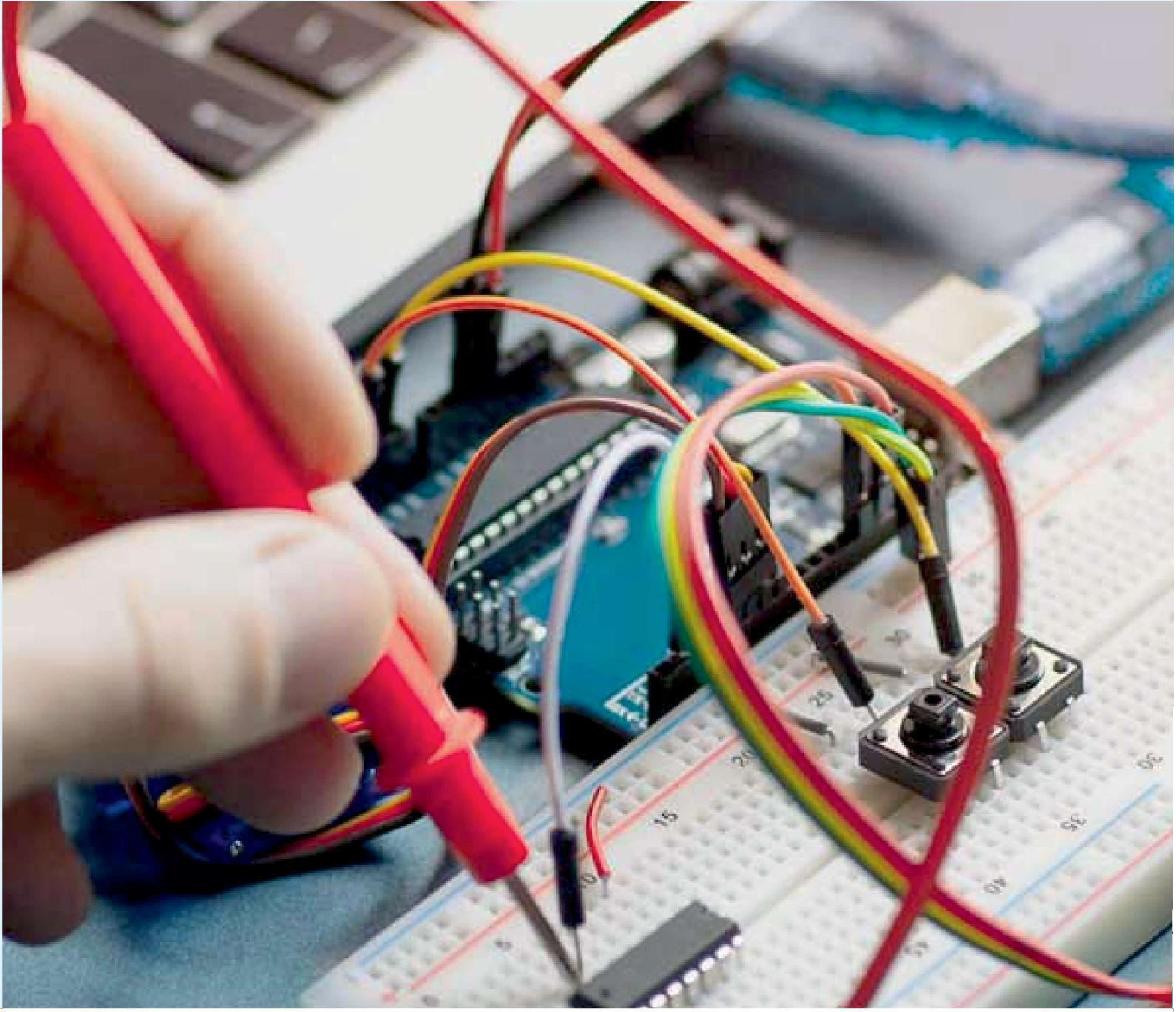

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