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Waste Segregation System

Roshan Khadka[1, *], Priyanshu Joshi[2], Nandan Kumar Kanth[3], Sujin Gwachha[4]

[1]Computer and Electronics Department, Kantipur Engineering College, Lalitpur, Nepal, khadkaroshan009@gmail.com
[2]Computer and Electronics Department, Kantipur Engineering College, Lalitpur, Nepal, priyanshu1.joshi@gmail.com
[3]Computer and Electronics Department, Kantipur Engineering College, Lalitpur, Nepal, nrkanth01@gmail.com
[4]Computer and Electronics Department, Kantipur Engineering College, Lalitpur, sujingwachha@kec.edu.np.com

Abstract

Effective waste management is crucial for environmental sustainability and automated waste classification systems plays a vital role in this process. The project focuses on developing a waste segregation system utilizing a Raspberry Pi microcontroller along with the VGG-16 Convolutional Neural Network (CNN) model for accurately categorizing waste into paper, plastic, and metal classes. The system utilizes the VGG-16 model for its high accuracy in distinguishing between different waste materials. The system begins by IR sensor detecting the presence of waste and capturing the image of waste item using a Pi Camera. The image is then sent to the trained VGG-16 model which categorizes the waste into one of three classes. The highest prediction category is selected and microcontroller sends a signal to the servo motor which rotates the bin according to the provided signal eliminating the need for manual sorting. For the validation dataset, the model achieved an accuracy of 85.76%, and for the test dataset, the accuracy was 85.44%. The precision, recall, and F1-score metrics demonstrate strong performance across all three waste categories, with paper showing the highest recall at 0.93 in validation and 0.94 in testing. The system successfully segregated waste materials based on their classification into the appropriate bins.

Keywords: Convolutional Neural Network, Image Processing, Raspberry Pi, VGG-16 Model, Waste Classification

1. Introduction

Automatic waste segregation is an advanced technology that significantly enhances waste management by efficiently categorizing and separating various types of waste for proper disposal. The system combines hardware, software, machine learning algorithms, and sensors to improve sorting accuracy. By automating the segregation process, it offers a cost-effective and environmentally friendly solution to the growing challenges of waste disposal. With global waste production reaching 1.9 billion tons annually and projected to exceed 45 billion tons by 2055, traditional manual segregation methods are becoming impractical (Sharma & Jain, 2019). While sensor-based systems, including infrared, metal, and moisture sensors, have been developed, they often require continuous monitoring due to their limited accuracy. However, integrating artificial intelligence, deep learning, and real time monitoring has significantly improved waste classification, making the process more precise and efficient. AI-driven image processing further enhances accuracy, reducing reliance on manual labor and streamlining modern waste management systems, which promotes better sustainability.

2. Objectives

The main objective of the project is to develop an AI- Based waste Classification system using VGG-16 to categorize waste into plastic, paper and metal.
The other sub objectives of the project are as follows:

- Real time waste detection using Infrared sensor
- Automatic segregation process using servo motors
- Waste level detection syst

3. Literature Review

(Swaminathan et al., 2019) proposed an IoT-based smart bin. It comes with three compartments, each with its functionality. The first compartment consists of an infrared IR sensor and metal detector. The second

**Corresponding Author*

compartment consists of an IR sensor to detect dry waste and moisture sensors to detect wet waste. The last compartment is subdivided into three bins for the collection of segregated waste respectively. The system connects to Wi-Fi for data transmission to a specific server. The storage compartment consists of a rotating table with three bins, namely dry, wet, and metal. It rotates according to the type of waste detected in the previous compartment.

(Wang et al., 2015) proposed an automated approach to segregate recyclable material. The recycling bin is equipped with four types of sensors, namely inductive sensors to detect plastic, a capacitive sensor to detect metal, a photoelectric sensor to detect paper, and a proximity sensor to detect motor position. When waste is inserted into the recycle bin, three types of sensors connected to Arduino Uno operate to detect the type of material. Once the detection is completed, the circular plate holding the waste will be rotated by the direct current motor to the respective material's compartment. A pusher then pushes the recyclable material to the separation bin. The proposed system relies on several sensors that can add up to the maintenance and manufacturing cost of the recycling bin.

(Costa, 2018) proposed an automated waste separation system using a combination of deep learning and traditional techniques to minimize the impact of incorrect garbage disposal. The experiment utilizes pre-trained models such as VGG-16, Alex Net, Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF). The system targets four waste categories: glass, metal, paper, and plastic. The VGG-16 deep learning method demonstrated efficiency with a 93% accuracy in its best scenario. However, it's noted that CNN approaches are computationally expensive, requiring significant resources. The paper suggests improving CNN accuracy through techniques like augmentation and fine-tuning, emphasizing that more data enhances CNN results.

(Yang & Thung, 2016) proposed an approach to classifying garbage into six different recycling categories (i.e., metal, paper, glass, plastic, trash, and cardboard) by using a support vector machine (SVM) with scale-invariant feature transform (SIFT) features, and a convolutional neural network (CNN). Their approaches achieved an accuracy rate of 63% and 22% for the trained SVM and the CNN respectively.

(Faria, R., et al.) proposed a system proposed a system that can classify organic and solid waste using deep convolutional neural network. They prepared dataset contains around 5600 images with four classes including one organic waste class and three solid waste classes (glass, metal, and plastic). On this dataset, several CNN architectures including 3-layer CNN, VGG-16, VGG-19, Inception-V3, and ResNet50 have been implemented for training. Among them, VGG-16 outperforms other models with 88.42 % accuracy.
In the past, numerous systems for the appropriate handling and separation of wastes were implemented. While each system has its unique qualities, none of them has every feature that the current situation requires. The previous system's reliance on difficult-to-use GSM or Wi-Fi caused connectivity problems. The system also used inaccurate sensors, which limited the device's performance and required regular repair. As a result, the system we are working on combines machine learning and image processing with a compact and straightforward architecture to produce optimal results.

4. Methodology

4.1. Algorithm Description

4.1.1. Convolution Neural Network (CNN)

The CNN algorithm typically follows these steps:

a. CNN takes an image as input and processes it using multiple layers to extract features and classify it.
b. A kernel (filter) slides over the image to detect patterns.
c. Convolution Operation:

$$(I * K)(x,y) = \sum_{m}\sum_{n} I(m,n).K(x-m, y-n) \qquad \text{(Equation 1)}$$

Where I is the input image, K is the kernel (filter) and x, y are pixel positions.

d. ReLU Activation Function:

$$f(x) = \max(0, x) \quad \text{(Equation 2)}$$

Replaces negative value with zero, introducing non-linearity.

e. Pooling Layer (Max Pooling):

$$P = \sum_{i=1}^{n} max(X_i) \quad \text{(Equation 3)}$$

Reduces dimensionality by selecting the highest value in a region.

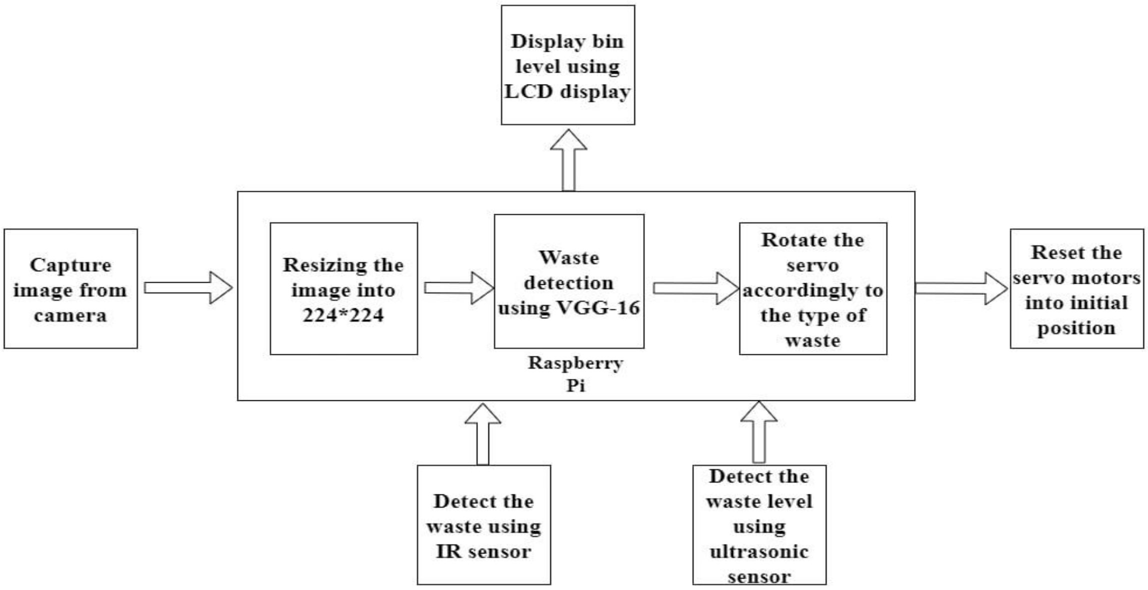

Figure 1. System Block Diagram

f. Flattening: Converts 2D feature maps into a 1D vector for the fully connected layer.

g. Fully Connected Layer (Dense Layer):

$$y = W \, . \, X + b \quad \text{(Equation 4)}$$

Where w is weight matrix, X is input vector and b is bias term.

h. SoftMax Activation Function (Classification):

$$S(x_i) = \frac{e^{xi}}{\sum_j e^{xj}} \quad \text{(Equation 5)}$$

Converts raw outputs into probability scores for classification.

4.1.2 VGG-16 (Visual Geometry Group 16)

VGG-16 algorithm follows the following steps:

1. Input Image Processing: The input image is represented as a 3D matrix of size 224×224×3 (Height × Width × Channels).
2. Convolution Operation: A kernel (filter) K of size f × f × d slides over the input, computing dot products to extract features. The convolution operation is given by:

$$Z = (X * K) + b \quad \text{(Equation 6)}$$

Where X is the input, K is filter weights, $*$ denotes convolution, b is the bias and Z is the feature map.

3. ReLU Activation: The activation function applies a non-linearity to introduce complex representations. It is defined as:

$$f(x) = ma\,x(0, x) \quad \text{(Equation 7)}$$

Ensuring only positive values are passed to the next layer.

4. Pooling (Max Pooling): Reduces spatial dimensions while retaining essential features. The max pooling operation with a stride s and filter size f is given by:

$$P_{i,j} = max\left(X_{i:i+f,j:j+f}\right) \quad \text{(Equation 8)}$$

   Where P is the pooled output.

5. Dimensionality Reduction: The layer-wise breakdown of pooling is shown below:

Table 1. Pooling Layers

Layer	Input Size	Output Size
Pool 1	224*224* 64	112*112*64
Pool 2	112*112*128	56*56*128
Pool 3	56*56*256	28*28*256
Pool 4	28*28*512	14*14*512
Pool 5	14*14*512	7*7*512

6. Flattening: The final feature map of size 7×7×512 is reshaped into a 1D vector:

$$F = Flatten(Z) \quad \text{(Equation 9)}$$

Where F is a 1×4096 vector.

7. Fully Connected Layer (FC Layer): The flattened vector is passed through dense layers:

$$Y = W\,.\,X + b \quad \text{(Equation 10)}$$

Where W is the weight matrix, X is the input vector, and b is the bias.

8. SoftMax Activation: The final layer converts logits (outputs) into probabilities for classification:

$$\sigma(z_i) = \frac{e^{zi}}{\sum_j e^{zj}} \quad \text{(Equation 11)}$$

Ensuring the sum of all probabilities equals 1.

9. Output Prediction: The class with the highest probability is selected as the final output.

4.1. Data Collection Procedures

We used the image database created by (Yang & Thung, 2016) containing images of recycled objects across six classes with about 400 images each, totaling about 2,400 images. According to the authors, the data acquisition process involved using a white poster board as a background. The lighting and pose for each photo are different, which introduces variation in the database. The dataset was then modified and augmented with the help of Roboflow where it was later split into training, validation and testing sets with approximately 5000 images. This dataset is classified into three classes: ’metal’, ‘paper’ and ’plastic’ with a split ratio that’s around 81% for training, 11% for validation and 8% for testing. The total images for paper and plastic were around 1750 and the metal 1500.

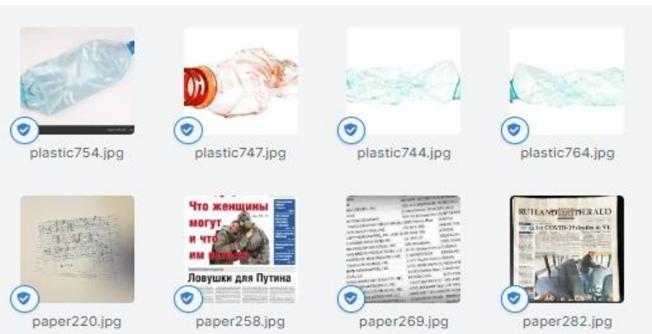

Figure 2. Dataset

4.2. Tools and Techniques

1. Classification Using VGG-16: The classification of waste using VGG-16 involves training the VGG-16 model on a dataset of waste images. The model learns to recognise and classify different types of waste based on features extracted from the images. Once trained, the model can accurately classify new waste images in real time, enhancing the efficiency of the waste segregation system.
2. Performance Metrics: The model's performance was evaluated using metrics derived from the confusion matrix, including precision, recall, and F1score. These metrics provide a comprehensive understanding of the model's accuracy and reliability.

4.3. System Workflow

The detailed workflow of the system is as follows:

- Initialization: The system starts and initializes all components.
- Image Capture: Cameras captures image when the IR sensor value is high.
- Image Classification: The Captured image is then processed in real time using the trained VGG-16 to classify the waste.
- Bin Rotation: According to the predicted output of the model the signal is given to the servo motor which rotates accordingly.
- Bin level: The ultrasonic sensor is used to measure the distance between the sensor and the waste to give the bin level and show the bin level status using Led.

4.4. Implementation Details

Initially, the system is idle. Once the controller detects the presence of waste using an IR sensor. A picture of the waste object which needs to be categorized is taken. Before passing the image through the VGG-16 model for classification, the image must go through preprocessing, which typically involves resizing the image to a specific size that fits the input size expected by the model architecture. This is done to ensure consistency in the dimensions of the input images across the entire dataset. The preprocessed result is then sent to a CNN network that uses the VGG-16 algorithm to categorize the input image into one of three classes. The category with the highest prediction is then selected as the predicted category of the input image. Based on this prediction, an appropriate signal is sent to the central processing unit, which is the Raspberry Pi. The processing unit then sends a signal to the servo motor which rotates according to the signal given by the processor. In our model we have two bins in which one of the bins is divided into three compartments which is responsible to categorize three different types of wastes and the second bin is marked as excess bin in which the user throws the waste in case the first bin is full. If the first bin is full, then the LCD displays a 'Bin Full' message. In this case, the user must throw the waste in the excess bin.

5. Result and Analysis

To evaluate the performance of our classification model, different CNN architectures were considered, including a 3-layer CNN, VGG-16, VGG-19, ResNet50, and Inception-V3. Due to hardware constraints, VGG-16, VGG-19, and ResNet50 were the most feasible options. Among these, VGG-16 was selected as the optimal architecture as it balanced execution time and classification accuracy. According to prior research, VGG-16 achieved an accuracy of 88.42%, making it a suitable choice for our dataset.

The dataset was trained using the VGG-16 model, and training and validation accuracy were monitored using the model accuracy chart. To mitigate underfitting and overfitting, multiple epochs were experimented with, ultimately setting the epoch count to 25 as no significant improvement was observed beyond this point. Data augmentation techniques were employed to enhance model robustness, leading to some fluctuations in the validation curve due to the presence of noisy data.

The dataset, consisting of 3000 images, was used for training and evaluation, producing the following results for validation and test sets regarding accuracy, precision, recall and F1 score. For single classification tasks, the processing time on the Raspberry Pi was approximately 32 seconds. The total processing time for Raspberry pi for categorizing 3 classes took around 95 seconds.

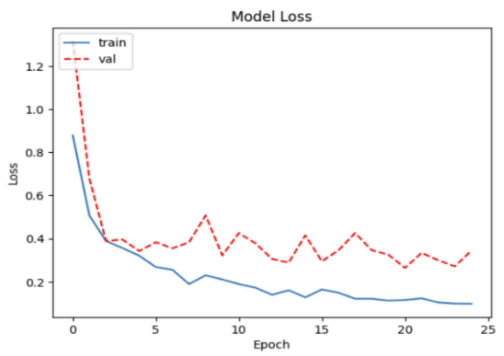

Figure 3. Model Loss

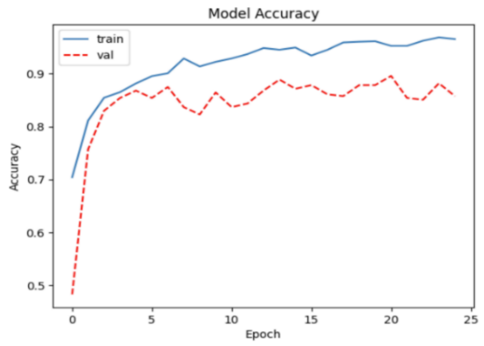

Figure 4. Model Accuracy

The classification reports for validation and test sets (Figures 3 and 4) provide detailed performance metrics. For the validation dataset, the model achieved an accuracy of 85.76%, while for the test dataset, the accuracy was 85.44%. The precision, recall, and F1-score values indicate strong performance across all three waste categories, with paper exhibiting the highest recall of 0.93 in validation and 0.94 in testing.

```
Confusion Matrix for valid:
[[ 88  11   2]
 [  8 128   1]
 [ 19   4  55]]

Validation Accuracy: 85.76%

Validation Classification Report:
              precision    recall  f1-score   support

       metal       0.95      0.71      0.81        78
       paper       0.90      0.93      0.91       137
     plastic       0.77      0.87      0.81       101

    accuracy                           0.86       316
   macro avg       0.87      0.84      0.85       316
weighted avg       0.87      0.86      0.86       316
```

Figure 5. Validation Report

```
Confusion Matrix for test:
[[52  8  1]
 [ 2 46  1]
 [ 7  4 37]]

Test Accuracy: 85.44%

Test Classification Report:
              precision    recall  f1-score   support

       metal       0.95      0.77      0.85        48
       paper       0.79      0.94      0.86        49
     plastic       0.85      0.85      0.85        61

    accuracy                           0.85       158
   macro avg       0.86      0.85      0.85       158
weighted avg       0.86      0.85      0.85       158
```

Figure 6. Test Report

Figures 1 and 2 illustrate the confusion matrices for the validation and test datasets. The matrices demonstrate the model's ability to classify plastic, paper, and metal efficiently. However, certain misclassifications were observed, particularly in cases where, aluminum foil containers visually resembled plastic containers. This led to instances where aluminum foil was incorrectly categorized as plastic. This suggests that additional features, such as texture and spectral properties, could enhance classification accuracy.

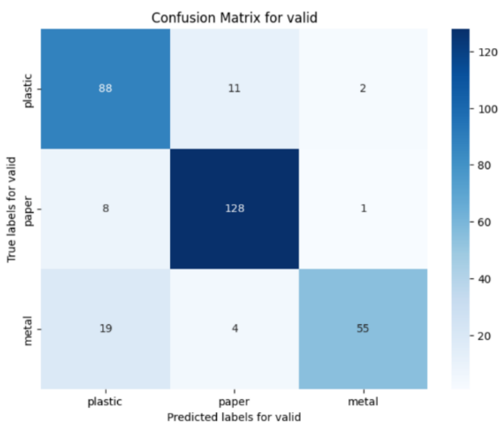

Figure 7. Confusion Matrix for Valid

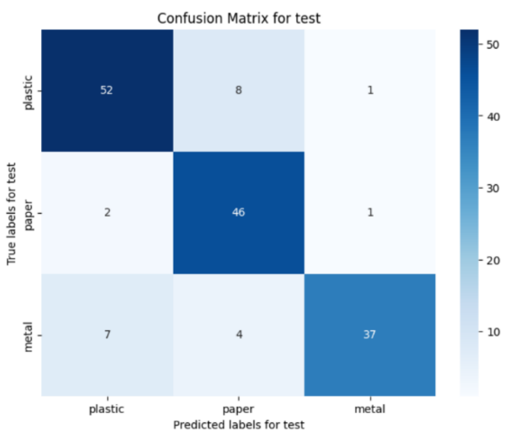

Figure 8. Confusion Matrix for Test

Figures 7 and 8 illustrate the confusion matrices for the validation and test datasets. The matrices demonstrate the model's ability to classify plastic, paper, and metal efficiently. However, certain misclassifications were observed, particularly in cases where aluminum foil containers visually resembled plastic containers. This led to instances where aluminum foil was incorrectly categorized as plastic. This suggests that additional features, such as texture and spectral properties, could enhance classification accuracy.

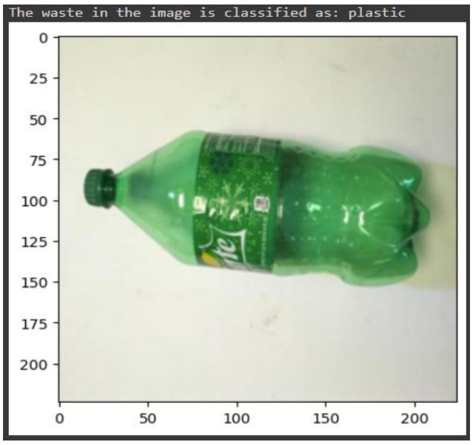

Figure 9. Paper Classification Result

Figure 10. Hardware Implementation

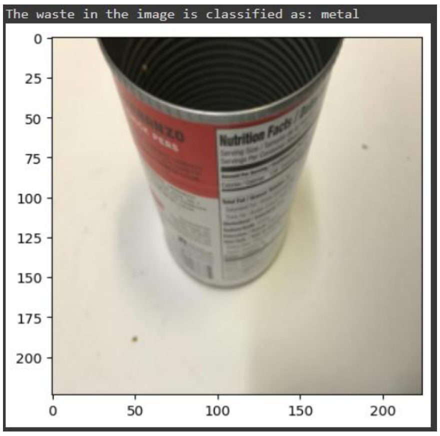

Figure 11. Metal Classification Result

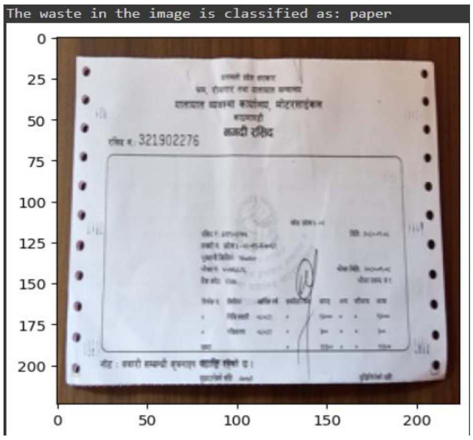

Figure 12. Paper Classification Result

Additionally, hardware implementation challenges were encountered. The rotating mechanism in the physical system posed issues due to the weight of the component and fluctuations in power supply from the lithium battery, leading to occasional malfunctions. Future work should focus on optimizing hardware design and integrating additional sensor-based validation techniques to improve real world performance.

6. Conclusion

The project was implemented successfully including advanced technology to improve waste categorization and disposal efficiency. By using an infrared sensor for waste detection, along with image preprocessing and classification using the VGG-16 model, the system accurately categorizes waste into three distinct classes. While some misclassifications occurred due to visual similarities, the results indicate that the model is well-suited for real world waste classification applications.

7. Limitations and Future Enhancement

7.1. Limitations:

- **Dependency on Sensor Accuracy:** The system's performance is dependent on the accuracy of sensors, which may be affected by environmental conditions such as light, dust, humidity and temperature fluctuations.
- **Limited Material Recognition:** The system may struggle to differentiate between certain materials with similar physical properties, leading to potential misclassification.

- **Scalability Challenges:** Expanding the system to handle large-scale waste management require additional computational resources and hardware modifications.
- **Maintenance Requirements:** Regular calibration and maintenance of sensors and mechanical components are necessary to ensure consistent performance.

7.1 Future Enhancement:

- **Enhanced Sensor Integration:** Future iterations of the system should incorporate more advanced sensors, such as weight sensors, to provide more comprehensive data about the waste bins. Weight data can help estimate the volume of waste in each bin and provide a more accurate indication of when a bin is nearing capacity.
- **Dynamic Model Training**: Implement a mechanism for dynamic model training. This involves continuously up- dating the machine learning model with new data to adapt to changing waste compositions and patterns. This ensures that the model remains accurate and relevant over time.
- **Energy-Efficient Hardware**: Optimize the system for energy efficiency by exploring low-power hardware components and energy-saving algorithms. This can extend the operational life of the system, especially in locations where a continuous power supply may be challenging.

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