PROJECT TITLE

Cleantech: Transforming Waste Management with Transfer Learning

Team Details

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Team Size: 4 Members

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Abstract

This project aims to transform traditional waste management practices using transfer learning, focusing on classifying waste into biodegradable and non-biodegradable categories with MobileNetV2. Manual segregation is inefficient and poses environmental hazards due to incorrect disposal. Leveraging AI reduces manual effort, increases sorting accuracy, and promotes sustainable waste management. The system can integrate with IoT-based smart bins for real-time sorting, providing scalable and efficient waste handling in urban environments. By reducing dependency on large datasets, the model allows faster deployment while maintaining high accuracy (~92%), contributing to clean environments and enhancing smart city initiatives.

Watch Project Demo Video

Introduction

Waste management is a growing challenge in urban areas, with manual segregation often leading to inefficiency, pollution, and increased operational costs. Recycling and effective waste management require accurate segregation, which is difficult with manual processes due to human errors and inconsistency. The integration of AI in waste classification allows for automated, fast, and precise segregation at the source. Using transfer learning enables the use of pre-trained models to achieve high accuracy with limited data, making the approach practical for real-world applications where large datasets are often unavailable.

Problem Statement

Manual waste segregation causes:

- Inefficiency and human error in waste sorting.
- Environmental pollution due to improper disposal.
- Increased operational costs in waste handling.

Need: An automated and scalable system to classify waste at the source, enabling accurate segregation for efficient recycling and disposal.

Goal: To reduce human effort and errors while promoting environmentally friendly practices in waste management through intelligent systems that can be integrated with IoT-enabled bins for seamless operation in smart environments.

Objective

- Develop an automated system to classify waste into biodegradable and non-biodegradable categories using MobileNetV2 with transfer learning.
- Minimize the dependency on large, labeled datasets while achieving high classification accuracy.
- Enable integration with smart IoT-enabled bins for real-time automated segregation.
- Improve waste management systems by reducing manual labor, minimizing environmental pollution, and promoting sustainable practices in urban waste handling.

System Architecture

1. **Image Capture:** Using a camera on a smart bin or manual upload by users.
2. **Preprocessing:** Images are resized to 224x224, normalized, and augmented for generalization.
3. **Prediction:** Using MobileNetV2, a CNN-based model, to predict the waste type.
4. **Output:** The system displays the label (biodegradable or non-biodegradable) with confidence and triggers the sorting mechanism in the smart bin for automated segregation.

This modular architecture allows easy deployment on IoT-enabled devices, ensuring scalability for smart city applications.

Dataset Used

- **Source:** Kaggle dataset combined with custom images captured for improved contextual accuracy.
- **Classes:** Biodegradable and non-biodegradable.
- **Preprocessing:** Images resized to 224x224, normalized to scale pixel values, and augmented using rotation, zoom, and flipping to enhance model generalization and reduce overfitting.
- The curated dataset ensures the model learns relevant features for accurate classification with fewer samples, aligning with the objective of resource-efficient deployment.

Model and Algorithms

Model: MobileNetV2, pre-trained on ImageNet for efficient feature extraction with minimal computational cost.

Why Transfer Learning?

- Utilizes pre-trained weights for robust feature extraction.
- Reduces data and computational resource requirements.
- Enables faster training while maintaining high accuracy.

Workflow:

- Freeze the base layers of MobileNetV2.
- Add custom dense layers for binary classification.
- Compile the model using Adam optimizer and categorical cross-entropy loss.
- Train and validate using augmented datasets for balanced learning.

This pipeline ensures the system's effectiveness in real-time applications while remaining lightweight for IoT devices.

Implementation Code

```python
import tensorflow as tf
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, Dropout, GlobalAveragePooling2D
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Data Preparation
train_datagen = ImageDataGenerator(rescale=1./255, rotation_range=20,
zoom_range=0.2, horizontal_flip=True, validation_split=0.2)
train_generator = train_datagen.flow_from_directory('dataset_path', target_size=(224,
224), batch_size=32, class_mode='categorical', subset='training')
validation_generator = train_datagen.flow_from_directory('dataset_path',
target_size=(224, 224), batch_size=32, class_mode='categorical', subset='validation')

# Model Building
base_model = MobileNetV2(weights='imagenet', include_top=False, input_shape=(224,
224, 3))
base_model.trainable = False
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dropout(0.3)(x)
x = Dense(128, activation='relu')(x)
predictions = Dense(2, activation='softmax')(x)
model = Model(inputs=base_model.input, outputs=predictions)
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Model Training
history = model.fit(train_generator, validation_data=validation_generator, epochs=10)

# Save the Model
model.save('cleantech_waste_classifier.h5')
```

Results

- **Accuracy:** Achieved ~92% validation accuracy, demonstrating effective classification with minimal errors.
- **Outputs:** Real-time display of classification results with confidence scores for user validation.
- **Confusion Matrix:** Demonstrates clear class separation, validating the effectiveness of the trained model in real-world conditions.

The results validate the model's readiness for integration with smart bins for automated waste management.

Conclusion

The Cleantech waste management system demonstrates the practical use of transfer learning to automate and enhance the efficiency of waste classification. By reducing manual effort and minimizing classification errors, it promotes environmentally friendly waste handling and scalable smart city waste management systems.

Future Scope

- **IoT Integration:** Deploy on IoT-enabled smart bins for live, automated sorting.
- **Multi-Class Expansion:** Extend to multiple waste categories for granular sorting.
- **Edge Deployment:** Optimize for low-power devices for real-time edge classification.
- **Object Detection Integration:** Expand to object detection for mixed waste scenarios, enabling further automation in recycling facilities.

Final Note

This Cleantech waste classification project uses transfer learning to automate and improve waste segregation, promoting cleaner and smarter cities. It empowers environmental sustainability while reducing manual effort, aligning technology with a cleaner tomorrow.