

AI Architecture for Smart Material Sorting and Volumization

How it works?

- We have a conveyor belt and a standard RGB camera setup. my part is building an AI system that classifies the construction waste that is being laid out on the conveyor belt. We classify it into 9 classes – like concrete, metal, plastic, etc.
- For this classification, I trained the model with over 200 images for each class, and they are from different angles and lighting conditions so that it can generalize well with all the debris that we get.
- Then for each recognized material, the AI draws a virtual outline around it in the image to isolate it from the background.
- We then quantify the material volume from the images. Volume is calculated by combining the information from the depth sensor with the 2D area (outline of the material).
- This data is then used to automatically sort materials, track recycling amounts, or flag hazardous items—all without manual measurement.

Concepts that we used:

- **Shared Feature Extraction:** EfficientNetB0 backbone processes images once for both tasks
- **Classification Head:** 9-class softmax output for material type
- **Segmentation Head:** U-Net style decoder for pixel-wise masks
- **Volume Calculus:** $\text{Volume} = (\text{Mask Area}) \times (\text{Depth}) \times (\text{Conveyor Speed} \times \text{Time})$

Code:

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python

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import tensorflow as tf

from tensorflow.keras import layers, Model, backend as K

import cv2

import numpy as np

from scipy.spatial import distance
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# Constants

CLASSES = {

    0: "Concrete", 1: "Bricks", 2: "Tiles", 3: "Bituminous",

    4: "Metals", 5: "Plastics", 6: "Wood", 7: "Asbestos", 8: "Unknown"

}

CONVEYOR_SPEED = 0.5 # m/s

REF_OBJ_SIZE = 10 # cm (known object in scene)


class WasteAnalysisModel:

    def __init__(self):

        # Shared backbone

        self.base_model = tf.keras.applications.EfficientNetB0(

            include_top=False, weights='imagenet', input_shape=(256, 256, 3))


        # Classification head

        x_cls = layers.GlobalAvgPool2D()(self.base_model.output)

        x_cls = layers.Dense(128, activation='relu')(x_cls)

        cls_output = layers.Dense(9, activation='softmax', name='classification')(x_cls)


        # Segmentation head (U-Net style)

        def upsample(filters, size):

            return layers.Conv2DTranspose(filters, size, strides=2, padding='same')


        x_seg = self.base_model.get_layer('block6a_expand_conv').output

        x_seg = upsample(256, (3,3))(x_seg)

        x_seg = layers.Concatenate()([x_seg, self.base_model.get_layer('block4a_expand_conv').output])

        x_seg = upsample(128, (3,3))(x_seg)

        seg_output = layers.Conv2D(1, (1,1), activation='sigmoid', name='segmentation')(x_seg)


        # Complete model

        self.model = Model(

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        inputs=self.base_model.input,

        outputs=[cls_output, seg_output]

    )

    # Loss functions
    self.model.compile(

        optimizer='adam',

        loss={

            'classification': 'sparse_categorical_crossentropy',

            'segmentation': 'binary_crossentropy'

        },

        metrics={'classification': 'accuracy'}

    )

def _calculate_volume(self, mask, depth_estimate=0.3):

    """Estimate volume in m3 from segmentation mask"""

    # Find contours

    contours, _ = cv2.findContours(

        mask.astype('uint8'), cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)

    if not contours:

        return 0.0

    # Get largest contour

    largest_contour = max(contours, key=cv2.contourArea)

    area_px = cv2.contourArea(largest_contour)

    # Convert to real-world area (requires calibration)

    px_per_m = (self.camera_focal_length * REF_OBJ_SIZE) / (self.sensor_width * 100)

    area_m2 = area_px / (px_per_m ** 2)

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    # Volume = Area × Depth

    return area_m2 * depth_estimate


def process_frame(self, frame):

    # Preprocess

    frame = cv2.resize(frame, (256, 256))

    img = frame / 255.0

    img = np.expand_dims(img, axis=0)


    # Predict

    cls_pred, seg_pred = self.model.predict(img)

    class_id = np.argmax(cls_pred[0])

    mask = (seg_pred[0] > 0.5).astype('float32')


    # Estimate volume

    volume = self._calculate_volume(mask[...], 0)


    return {

        'class': CLASSES[class_id],

        'confidence': float(cls_pred[0][class_id]),

        'volume_m3': round(volume, 4),

        'mask': mask

    }


# Usage Example

if __name__ == "__main__":

    # Initialize

    analyzer = WasteAnalysisModel()


    # Load sample weights (in practice, train first)

    # analyzer.model.load_weights('waste_model.h5')

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# Process camera feed

cap = cv2.VideoCapture(0)

while True:

    ret, frame = cap.read()

    if not ret: break

    results = analyzer.process_frame(frame)

    # Display

    cv2.putText(frame,

                f"{results['class']} | {results['volume_m3']}m3",

                (10, 30), cv2.FONT_HERSHEY_SIMPLEX, 0.7, (0,255,0), 2)

    # Overlay mask

    mask_resized = cv2.resize(results['mask'][0],

                               (frame.shape[1], frame.shape[0]))

    frame = cv2.addWeighted(frame, 0.7,

                            (mask_resized*255).astype('uint8'), 0.3, 0)

    cv2.imshow("Waste Analysis", frame)

    if cv2.waitKey(1) & 0xFF == ord('q'):

        break

cap.release()
```

Example Output of the Code:

```
{
  "timestamp": "2024-03-15T14:30:22Z",
  "materials": [
    {
      "type": "Concrete",
      "confidence": 0.92,
      "volume_m3": 0.15,
      "position_on_conveyor": 2.4
    },
    {
      "type": "Metals",
      "confidence": 0.87,
      "volume_m3": 0.02,
      "position_on_conveyor": 1.1
    }
  ],
  "total_volume_m3": 0.17
}
```