Material examination and classification using computer vision

construction robotics | international M.Sc.programme

Introduction and motivation

Material examination and classification using computer vision

Solution Strategy: In this master thesis the student should explore the newest and more important material detection CNN architectures for material detection and classification using Computer Vision.
The possibility to propose a new CNN architecture for solving the same task must be considered. Real data can be gathered on a real construction site by using a mobile platform with real RGB cameras and sensors.

Very good programming skills (Python and PyTorch) are a must.

Experience with ROS2 is a must as well.

The knowledge of the ROS2 control and navigation packages is a plus.

State of the art: The material recognition and classification by using Computer Vision is still in development. Nevertheless, there is a lot of potential behind this procedure especially in the construction sector.

Problem definition: Piles of material are often delivered on the construction site using construction machines. In the process of digitization of construction sites, the student should explore and exploit the possibility of using traditional RGB and infrared cameras for material classification in absence of digital information.

Suggested solution: Development and testing of A.I. architectures using RGB and infrared camera streams.

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Material examination and classification using computer vision

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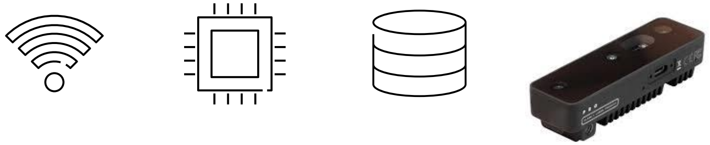
Task Description

Material examination and classification using computer vision



For Future Smart Construction Sites:
- Granular material recognition and classification
- Integration of robots with RGB-D cameras
- Unmanned intelligent construction management

Technical Implementation:
- Convolutional Neural Networks (CNN)
- Segment Anything Model (SAM)
- Machine learning and computer vision

Goals and Applications:
- Particle size and distribution prediction
- Particle shape and type recognition
- Enhancing construction efficiency and accuracy

https://www.fmdsa.org/research-network/ http://opensurfaces.cs.cornell.edu/

https://en.wikipedia.org/wiki/Convolutional_neural_network https://image-net.org/challenges/LSVRC/

Objectives & Workflow

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Automated Particle Size Detection Workflow

1. System Setup
1.1 Install ROS
1.2 Install Luxonis DepthAI SDK
1.3 Install PyTorch and Required Libraries

2. Launch RGBD Camera Node
2.1 Start Camera
2.2 Capture Depth and RGB Images

3. Develop ROS Node for Image Processing and Distance Checking
3.1 Create and Configure ROS Package
3.2 Write and Compile Image Processing Node

4. Controlling the Mobile Robot
4.1 Create Robot Control Node
4.2 Integrate Robot Control with Image Processing

5. Particle Size Detection Approaches
5.1 Segmentation-based Approach
5.2 Regression-based Approach
5.3 Classification-based Approach

6. Execution Flow
6.1 Robot Moves to Material Pile
6.2 Camera Ensures 30mm Distance
6.3 Capture RGB Image
6.4 Process Image with Pre-trained CNN Model
6.5 Predict Particle Size
6.6 Display Results

input

5.1 Segmentation-based Approach
5.1.1 Pre-process Image
5.1.2 Apply Segmentation Model
5.1.3 Identify and Measure Particles
5.1.4 Post-process and Output Results

SAM

OpenCV

5.2 Regression-based Approach
5.2.1 Pre-process Image
5.2.2 Extract Features
5.2.3 Apply Regression Model
5.2.4 Predict Particle Size
5.2.5 Post-process and Output Results

CNN regression

5.3 Classification-based Approach
5.3.1 Pre-process Image
5.3.2 Apply Classification Model
5.3.3 Classify Particles by Size Range
5.3.4 Post-process and Output Results

CNN classification

Grain Size:
μ=x.xx
σ=x.xx
Categories： x

output

Slide by Baiyi

Research methods

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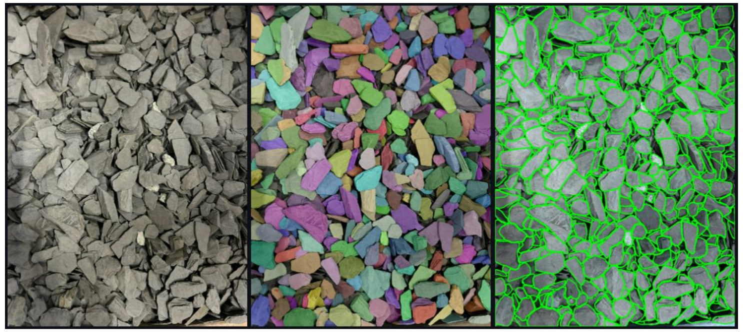
- **Segmentation-Based Method**
- Segment materials into individual particles using a segmentation model (e.g., SAM).
- Extract features from each particle.



- **Regression-Based Method**
- Use a CNN model to extract features from each image.
- Map features to numerical values.
- Training set results correlate features with specific numerical outcomes.

Grain Size:
μ=x.xx
σ=x.xx

- **Classification-Based Method**
- Train a CNN model to extract features from each image.
- Map features to corresponding labels.

Categories： x

<u>Conducted on a custom dataset to evaluate the effectiveness of each method.</u> ⇨ **<u>The dataset is crucial and plays a decisive role in the usability of the trained models.</u>**

Slide by Baiyi

Dataset

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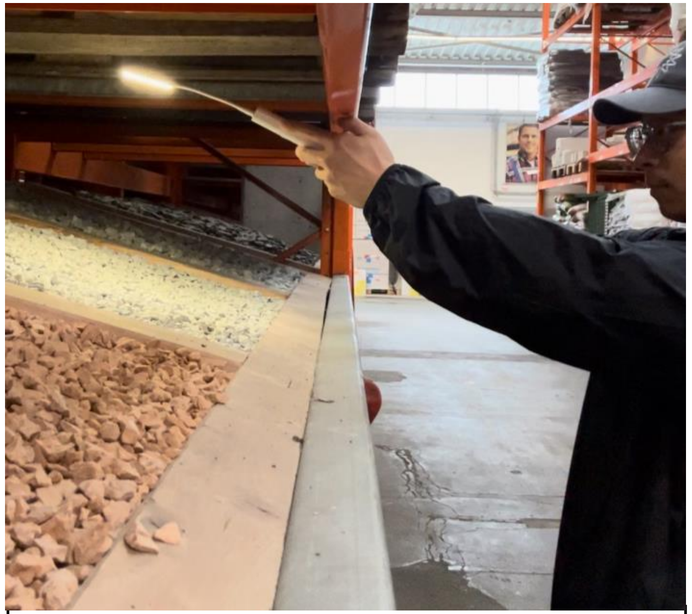
Dataset Preparation

• **Source:** Collected from Aachen Bauhaus and OBI, including 20 types of construction granular materials.
• **Diversity:** Ranges from 1-3mm gravel to 40-60mm marble chips.
• **Sampling:** Products displayed as samples, representing the construction industry with low particle size variance for easier feature extraction and learning.



• **Image Specifications:**
• Manual photography
• Consistent lighting conditions
• Fixed camera distance: 30mm
• Image resolution: 3024x4032 pixels

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Particle size detection approaches

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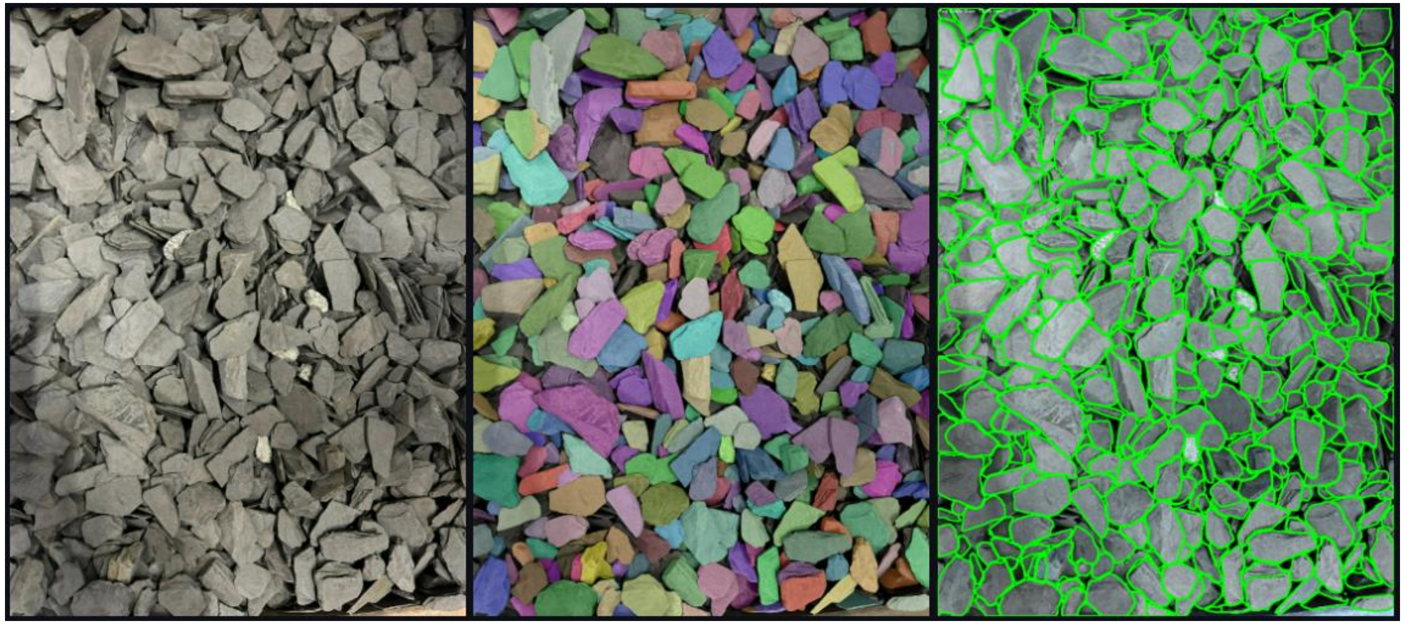
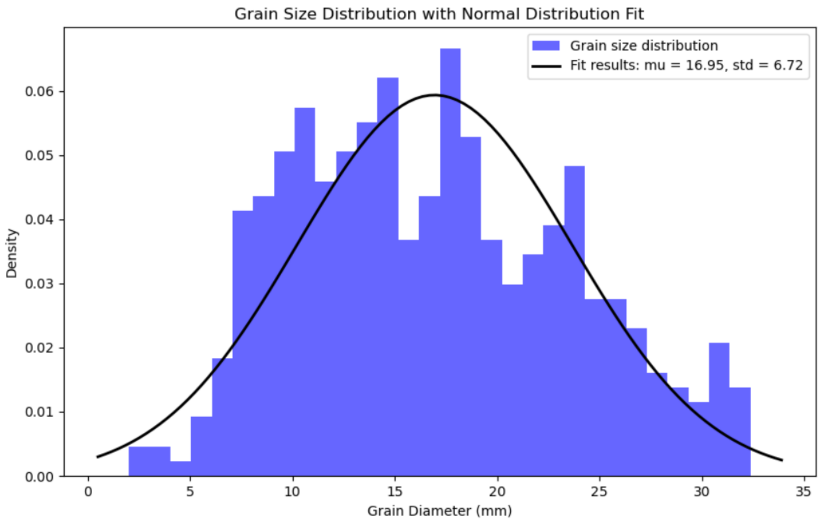
- **Segmentation-Based Method**
- Segment materials into individual particles using a segmentation model (e.g., SAM).
- Extract features from each particle using OpenCV .
- Estimate particle size distribution.





Limitations:

- Accuracy depends on segmentation quality.
- Small particles (<3mm) may appear larger due to image resolution limits.
- Large particles (>30mm) may be over-segmented due to shadows and occlusions.
- Best suited for particles sized 3-30mm.
- Segment Anything Model (SAM) is computationally intensive and time-consuming.

Particle size detection approaches

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- **Regression-Based Method**
- Use a CNN model to extract features from each image.
- Map features to numerical values.
- Training set results correlate features with specific numerical outcomes.


```
C:\Users\guoba\anaconda3\python.exe "E:\granular materials classification and particle size identification\code\CNN_predict_ResNet50_regression_with_mu_and_std.py"
Prediction for transformed image 0: mu=10.72, std=7.36
Prediction for transformed image 1: mu=9.74, std=7.45
Prediction for transformed image 2: mu=9.17, std=6.91
Prediction for transformed image 3: mu=10.39, std=6.93
Prediction for transformed image 4: mu=8.03, std=6.38
Prediction for transformed image 5: mu=9.89, std=7.76
Prediction for transformed image 6: mu=10.57, std=7.8
Prediction for transformed image 7: mu=10.43, std=7.86
Prediction for transformed image 8: mu=9.42, std=7.32
Prediction for transformed image 9: mu=9.65, std=7.04
Average Predicted Grain Size for E:\granular materials classification and particle size identification\old\input\marmorkiesel_weiss_7-15mm.jpg: mu=9.8, std=7.28

Process finished with exit code 0
```

```
C:\Users\guoba\anaconda3\python.exe "E:\granular materials classification and particle size identification\code\CNN_predict_ResNet50_regression.py"
Prediction for transformed image 0: 9.02
Prediction for transformed image 1: 8.86
Prediction for transformed image 2: 8.84
Prediction for transformed image 3: 9.42
Prediction for transformed image 4: 9.64
Prediction for transformed image 5: 9.15
Prediction for transformed image 6: 9.71
Prediction for transformed image 7: 9.32
Prediction for transformed image 8: 9.15
Prediction for transformed image 9: 13.24
Average Predicted Grain Size for E:\granular materials classification and particle size identification\old\input\marmorkiesel_weiss_7-15mm.jpg: 9.64

Process finished with exit code 0
```

input

Grain Size:
μ=x.xx
σ=x.xx

output

Particle size detection approaches

Material examination and classification using computer vision

- **Classification-Based Method**
- Train a CNN model to extract features from each image.
- Map features to corresponding labels.

Category	Characteristics	Product Names
Fine Pebbles and Gravel	Small size, rounded to semi-rounded, smooth to medium roughness	Marmorkiesel_Weiss_7-15mm, Marmorkiesel_Weiss_15-25mm, Marmorkiesel_Gruen_15-25mm, Quarzkies_Rund_Hell_8-16mm, Kies_2-8mm, Kies_8-16mm, Kies_1-3mm
Medium Pebbles and Gravel	Medium size, rounded to semi-rounded, smooth to medium roughness	Marmorkiesel_Weiss_25-40mm, Marmorkiesel_Weiss_40-60mm, Marmorkiesel_Schwarz_40-60mm, Quarzkies_Rund_Hell_16-32mm, Kies_16-32mm, Marmorsplitt_7-12mm, Splitt_2-5mm
Large Pebbles and Broken Stones	Large size, irregular shape, rough texture	Bruchsteine_Veronarot_30-60mm, Schieferplaettchen_22-40mm, Marmorsplitt_Veronarot_9-12mm, Marmorsplitt_Donaublau_8-12mm, Basaltsplitt_8-12mm, Granitsplitt_8-12mm, Marmorkiesel_Weiss_15-25mm

Categories： x

Classification Criteria:
Combines particle size, shape, and smoothness.
Three categories:
1 Small particles
2 Medium-sized particles (aesthetic, suitable for decoration and outdoor paving)
3 Large and rough particles (suitable for construction, providing higher friction)
Challenges: Overfitting issues during training.Current training paused to explore alternative methods.

Result

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Method	Key Characteristics	Advantages	Limitations
Segmentation-Based	Segments images into individual particles, extracts features (e.g., diameter, area)	Detailed particle size distribution (average size, variance)	Dependent on segmentation quality, less effective for very small (<3mm) or large (>30mm) particles
Regression-Based	Uses CNN to extract features, maps to numerical values	High accuracy with consistent conditions, faster than segmentation, adjustable labeling	Dependent on consistent testing conditions, potential overfitting issues
Classification-Based	Combines size, shape, and smoothness into categories	Broad applicability, practical for varied uses	Overfitting during training, further optimization needed

Implementation plan

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Step 1:

Deploy the robot to navigate to the material pile.

Step 2

Ensure the camera is positioned at the optimal 30mm distance.

Step 3

Capture RGB images under controlled lighting conditions.

Step 4

Utilize a pre-trained CNN model to process the images.

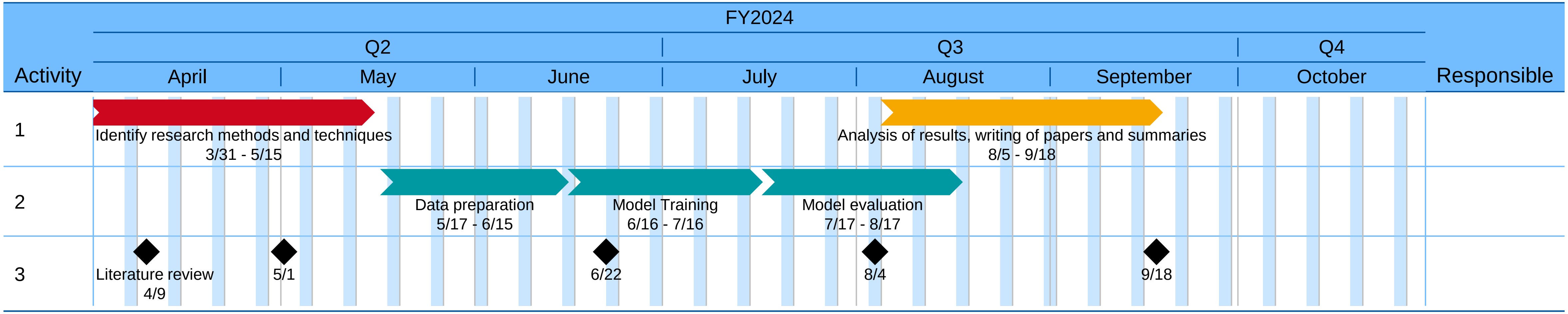
Step 5

Predict the particle size using the model.

Step 6

Display and analyze the results for construction site management.

Schedule



FY2024
Q2
Q3
Q4
Activity
April
May
June
July
August
September
October
Responsible
1
Identify research methods and techniques
3/31 - 5/15
Analysis of results, writing of papers and summaries
8/5 - 9/18
2
Data preparation
5/17 - 6/15
Model Training
6/16 - 7/16
Model evaluation
7/17 - 8/17
3
Literature review
4/9
5/1
6/22
8/4
9/18

Sources

https://paperswithcode.com/task/material-recognition/codeless
https://www.cs.columbia.edu/CAVE/software/curet/ https://www.csc.kth.se/cvap/databases/kth-tips/index.html
https://www.fmdsa.org/research-network/ http://opensurfaces.cs.cornell.edu/
https://en.wikipedia.org/wiki/Convolutional_neural_network https://image-net.org/challenges/LSVRC/
https://towardsdatascience.com/r-cnn-fast-r-cnn-faster-r-cnn-yolo-object-detection-algorithms-36d53571365e
https://arxiv.org/abs/1312.6229 https://viso.ai/deep-learning/vgg-very-deep-convolutional-networks/
http://yann.lecun.com/exdb/publis/pdf/farabet-pami-13.pdf https://arxiv.org/abs/2304.07193

Thanks for listening.
Any Question?

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