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# Classification of waste sludge dry matter content through texture analysis for estimating failures

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## Abstract
Wastewater treatment plants produce sludges that are characterized by a high-water content, requiring a dewatering process prior to their disposal or reuse. The conventional thermogravimetric method for dry matter content analysis is time consuming, limiting real-time decision making. This study investigates the application of texture analysis as an efficient and timely approach to classify sludge dry matter content and identify potential process failures. The proposed approach achieved a successful classification rate of 85.7%, with the samples falling into two distinct categories: those with dry matter content levels of "≤17%" and those exceeding ">22%". These findings demonstrate the potential of texture analysis as a valuable tool in waste management and treatment processes, offering a precise method for differentiating between varying dry matter content in waste sludges.

**Keywords**: sludge dry matter content; classification; texture analysis; failure prediction

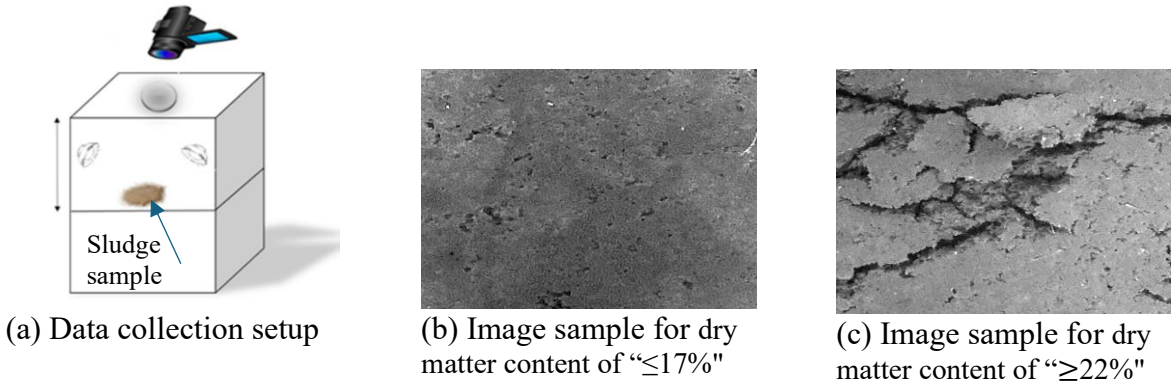
## Introduction
Wastewater treatment plants generate significant amounts of waste sludge with high water content, requiring further treatment before disposal or reuse (Wang et al., 2017). Sludge treatment involves dewatering, which can reduce water content to between 70% and 88%, thereby minimizing environmental impact, reducing volume, odour, and improving stability (Kamizela & Kowalczyk, 2019; Cao et al. 2021). Traditionally, sludge dry matter content is determined manually by weighing the wet and dry samples, making these methods labor-intensive and time-consuming, which hinders real-time operational decisions. This approach is even more challenging, particularly in smaller plants with restricted laboratory infrastructure, thus necessitating the transportation of the sludge to an external laboratory for the analysis.

Advancements in digital image processing provide powerful tools for extracting quantitative data across various fields and have prompted consideration of their potential applications in wastewater treatment plants. Image analysis aids medical diagnostics through CT scans and MRIs, tracks deforestation and pollution via satellite imagery, ensures product quality in industries, and supports agriculture by optimizing irrigation and monitoring crop health (Soille, 2000). Image analysis focuses on extracting numerical data from images through fully or semi-automated techniques, including texture analysis, image characterization, brightness assessment, and pattern recognition. This technology utilizes standard cameras or smartphones to simplify the process and support real-time parameter identification (Satoh et al., 2021). Texture is one of the image features used to analyse images (Dhabliya et al., 2024). Texture features quantify the apparent texture of an image (Juwono et al., 2023). In the context of sludge management, texture analysis involves quantifying smoothness or coarseness as the water content of sludge affects its appearance, texture, and granularity. High-water sludge tends to be smooth and homogeneous, while low-water sludge may

appear coarse or clumpy. This study demonstrates the effectiveness of texture analysis in categorizing sludge by dry matter levels and predicting dewatering process failures, offering a practical solution for enhancing wastewater treatment operations.

**Method**

In order to estimate the dry matter content of the sludge, sludge samples were collected from the centrifuge effluent of an urban wastewater treatment plant. Prior to the acquisition of the images, three distinct methods were employed on the sludge samples. These included direct imaging of the sludge surface, creation of a cut surface using a knife, and generation of a flat surface by compressing the material between two lamellae. Images were captured under controlled laboratory conditions using a standardized camera setup in a dark room with consistent lighting (see Figure 1.1.a). Two typical lamellae compressed captured images of "dry" and "wet" sludge samples are shown in Figure 1.1 (b) and (c), respectively. As it is clearly apparent from these images, although the dryer sludge samples exhibit "cracks", the sludge samples with high water content have significantly smooth surface. Our approach is based on this observation. We quantify the textures resulting from these cracks in order to estimate the dry matter content of sludge.




(a) Data collection setup

(b) Image sample for dry matter content of "≤17%"

(c) Image sample for dry matter content of "≥22%"

**Figure 1.1** Data collection system and sludge samples

Classification of waste sludge dry matter content is comprised of pre-processing the image, extracting texture features and evaluating the features to estimate the water content. The flow diagram of the algorithm is given in Figure 1.2. Detecting the cracks is the main component of this algorithm. Before detecting the cracks, the image is smoothed to improve the performance of the detector. Both high-water sludge and low-water sludge exhibit small dark spots while the latter exhibits also large dark spots appear as cracks. We apply morphological bottom-hat transform to detect dark spots on light background (Dougherty, 1992). This transform removes the background. As a result of this, the smooth regions are filtered and the dark objects in the image are highlighted. This process is instrumental in differentiating moist and dry soil. The bottom-hat filtered image is thresholded for further analysis of the cracks. The number of white pixels in the thresholded image is expressed as a ratio of the total number of pixels in the image. This ratio is utilized in the decision-making stage of the analysis.

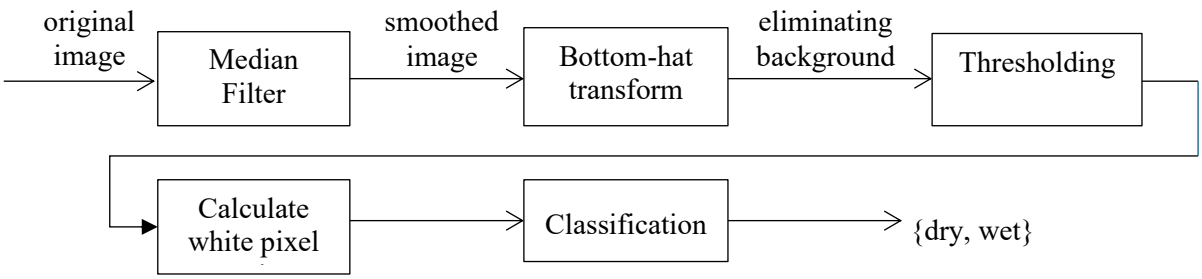
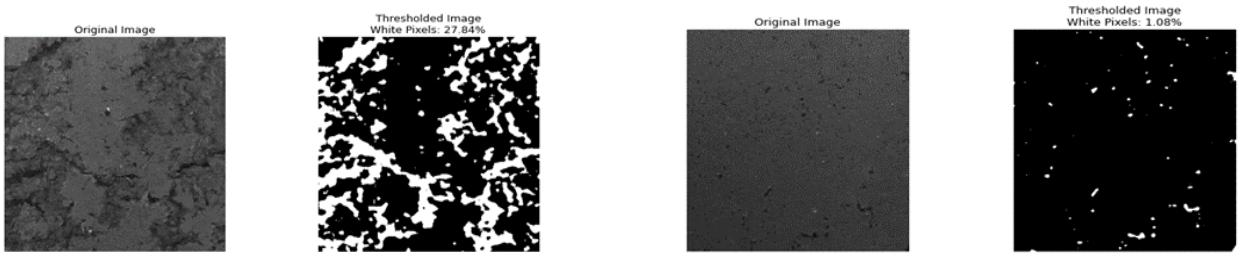



**Figure 1.2** Block diagram of the implemented algorithm

Figure 1.3 (a) and (b) show two sludge samples and the corresponding thresholded images for low-water and high-water content. The resulting thresholded image for the low-water sludge has much more white pixels compared to those of the other sludge sample. For these two sample images, the ratios of the white pixels are 27.8% and 1.1%, respectively. A smaller ratio is an indication of *dryness* of the sludge.




(a) (b)

**Figure 1.3** Sludge samples and the thresholded images a) Sample 17, 22.1% dry matter content, b) Sample 5, 15.8% dry matter content.

**Results and discussion**

A total of twenty samples of waste sludge were subjected to analysis. The selected sludges exhibited a range of dry water contents, with nine samples having a dry matter content of "≤17%" and eleven exceeding ">22%". The classification of the dry matter content was carried out dependent on the percentage of white pixels in images. Based on the analysis of the available image samples given in Table 1.1, a value below 8% of white pixels is considered as an indicative of a dry matter content classification of "≤17", whereas a value above 8% is indicative of a dry matter content classification of "≥22". The analysis yielded a success rate of 85.7% for the proposed algorithm as the cracks are denser in dryer sludge. The analysis demonstrated that the cracks, specifically their edged structure and area, is a crucial factor in estimating the dry matter content of the sludge. This was also observed in the sludges where the algorithm incorrectly identified them as having a higher moisture content than was actually present.

**Table 1.1** Analysis of the algorithm in the sludge samples

| Image Name | % Dry matter | White Pixel Percentage | Predicted Status | Actual Status |
|---|---|---|---|---|
| Sample 1 | 14.6 | 0.93 | ≤17 | ≤17 |
| Sample 2 | 13.7 | 6.17 | ≤17 | ≤17 |
| Sample 3 | 15.0 | 6.01 | ≤17 | ≤17 |
| Sample 4 | 14.1 | 4.29 | ≤17 | ≤17 |
| Sample 5 | 15.8 | 1.08 | ≤17 | ≤17 |
| Sample 6 | 16.7 | 7.76 | ≤17 | ≤17 |
| Sample 7 | 14.0 | 6.00 | ≤17 | ≤17 |
| Sample 8 | 14.4 | 6.37 | ≤17 | ≤17 |
| Sample 9 | 14.7 | 6.74 | ≤17 | ≤17 |
| Sample 10 | 22.3 | 4.65 | ≤17 | ≥22 |
| Sample 11 | 22.3 | 14.28 | ≥22 | ≥22 |
| Sample 12 | 22.1 | 17.74 | ≥22 | ≥22 |
| Sample 13 | 22.9 | 9.91 | ≥22 | ≥22 |
| Sample 14 | 22.6 | 6.33 | ≤17 | ≥22 |
| Sample 15 | 22.7 | 8.45 | ≥22 | ≥22 |
| Sample 16 | 22.1 | 4.46 | ≤17 | ≥22 |
| Sample 17 | 22.1 | 8.08 | ≥22 | ≥22 |
| Sample 18 | 22.0 | 22.84 | ≥22 | ≥22 |
| Sample 19 | 22.3 | 18.58 | ≥22 | ≥22 |
| Sample 20 | 22.1 | 27.84 | ≥22 | ≥22 |

**Conclusion**

Dewatering process prior to disposal or reuse of sludge resulting from sewage-treatment process requires dry matter content analysis. The conventional methods are time consuming, limiting real-time decision making. This study investigates the application of texture analysis as an efficient and timely approach to classify sludge dry matter content and identify potential process failures. The proposed approach is able to distinguish wet sludge, "≤17%", from dry sludge, "≥22", with a success rate of over 85%. These findings demonstrate a potential use of texture analysis as a valuable tool in waste management and treatment processes.

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