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Feasible Applicability of Deep Learning for Solid Detection in Concrete Wastewater: An Evaluation

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Abstract: Concrete wastewater from mixing stations leads to environment contamination due to its high alkalinity. The wastewater can be reused if its solid content is accurately and timely detected. However, investigations into the traditional methods for wastewater reuse have demonstrated that they are time consuming and not efficient. Therefore, the exact acquirement of solid content in concrete wastewater becomes a necessity. Recent studies have shown that deep learning has been successfully applied to detect the concentration of chemical solutions and the particle content of suspending liquid. Moreover, deep learning can also be used to recognize the accurate water level, which facilitates the detection of the solid–liquid separation surface after wastewater sedimentation. Therefore, in this article the feasibility and challenges of applying deep learning to detect the solid content of concrete wastewater were comprehensively evaluated and discussed. Finally, an experimental setup was proposed for future research, and it indicated that transfer learning, data augmentation, hybrid approaches, and multi-sensor integration techniques can be selected to facilitate future experimental performances.

Keywords: solid content; mixing station; concrete wastewater; deep learning; detection

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Citation: Chen, Y.; Yao, Q. Feasible Applicability of Deep Learning for Solid Detection in Concrete Wastewater: An Evaluation. *Appl. Sci.* **2023**, *13*, 8652. https://doi.org/10.3390/app13158652

Academic Editor: H.J.H. Brouwers

Received: 26 June 2023
Revised: 24 July 2023
Accepted: 25 July 2023
Published: 27 July 2023

1. Introduction

Infrastructure construction requires a large amount of concrete. Wastewater is unavoidably produced in the concrete mixing station due to cleaning trucks and mixers [1]. Calcium oxide and calcium hydroxide in the concrete wastewater induce a high alkali content, which leads to serious soil alkalization and water pollution [2]. Therefore, determining the quantitative value of the wastewater solid content is critical for recycling what remains. The traditional and easy-to-operate exsiccation method is normally used to measure the pure mass of the solid in the wastewater [3]. But, it requires repeated steps such as weighing, drying, cooling, calculating, cleaning, etc., which are extremely time consuming. High-cost equipment and a large testing space are also essential to complete the whole exsiccation process. Moreover, it is hard to exploit real-time monitoring due to the interactive effects among the drying, cooling, and weighing processes [4]. Liu et al. [5] exploited linear analysis to calculate, correct, and predict the quantitative value of the solid content by using experimental data in addition to using the traditional exsiccation method. However, the parameters of the linear analysis cannot be universally applied to wastewater from different mixing stations. Feng et al. [6] further applied a refractometer to measure the solid content. The results show a smaller statistical dispersion, about a 0.8% deviation, compared with the standard value. More specifically, inspired by machine learning techniques, Maranhão et al. [7] applied decision tree and neural network models to fit the results of concrete-like waste geopolymer powder content and found that the amount of quartz powder is the most critical for improving the mechanical properties. Such techniques have paved the way for rapid detection and provided the quantitative reference for the mass addition of concrete materials. Nevertheless, it is hard to find relevant research on timely solid detection when handling the concrete wastewater in mixing stations. Deep learning uses cameras and image processing algorithms to extract unique information, which can timely track the solid particles in the wastewater by analyzing the images or videos during sedimentation. Hence, this research focuses on the discussion and evaluation of deep learning applications for the real-time onsite detection of solid content in concrete wastewater.

2. Deep Learning Technique

Deep learning, as a subset of machine learning, focuses on training deep neural networks with multiple layers to recognize patterns, extract features, and make predictions. Deep learning algorithms automatically extract and identify features in images for analyzing millions of images and videos, which allows them to automatically learn the features and patterns that are extremely significant for various image recognition tasks [8], as shown in Figure 1. Thus, complex tasks such as image and speech recognition, natural language processing, and autonomous driving can be successfully carried out, replacing the function of human eyes with computer algorithms and high-definition cameras that can trace and measure the targets. The Convolutional Neural Network (CNN), a classical type of deep learning model, has become the standard approach for many computer vision tasks, including image classification, object detection, and segmentation [9]. Assisted by deep learning algorithms, image data are received and transferred into the system, which the algorithm uses to learn the features and form a model to make future predictions [10]. Deep learning is widely exploited in artificial intelligence, image processing, and pattern recognition due to its high efficiency and low error rate, which can be applied in manufacturing, agriculture, transportation, etc. [11]. Notably, deep learning has been utilized for automatic product inspection, quality monitoring, and work supervision, where detection by human workers is more inconvenient [12].

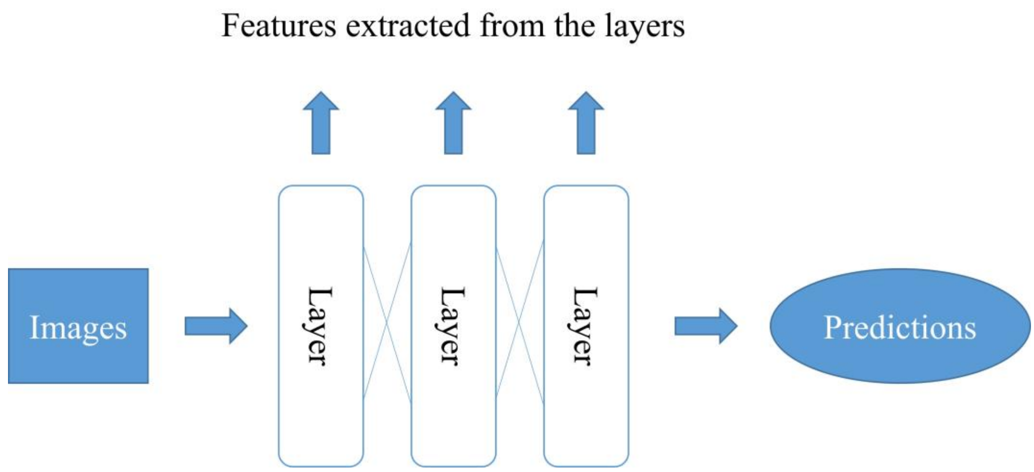


Figure 1. A structure of a deep learning neural network.

3. Discussion

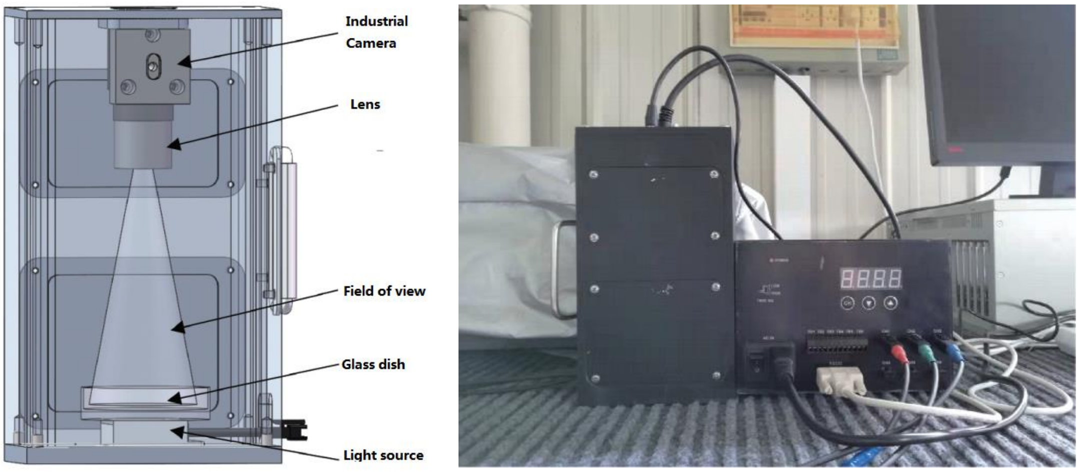
3.1. Deep Learning Applications in Tiny Object Inspections

Various investigations into industrial fault inspections have been conducted using deep learning algorithms. Cinar et al. [13] utilized image recognition to automatically inspect part faults, which largely reduced the labor cost and led to an accumulation of production data. Perng et al. [14] successfully applied image processing to efficiently detect product packaging, and Geng et al. [15] inspected the detailed dust particles in coal mines via image recognition. The accurate recognition results and rapid responding rate provide an intelligent way for detecting underground work conditions. Lakovidis et al. [16] exploited the improved Taylor sub-pixel interpolation algorithm to precisely detect product defects. Particularly, the application of deep learning in civil engineering mainly includes crack recognition, model parameter recognition, displacement measurement, vehicle load recognition, etc. [17]. Ayele et al. [18] utilized edge detection in images as a major feature to comprehensively analyze concrete cracks and dramatically enhance the results' reliability for engineering practices. Huang et al. [19] focused on the cracks in a dam and enhanced the recognition capability of crack morphology through an algorithm improvement. The system was found to accurately measure the consecutive cracks, fulfilling the requirements of onsite engineering applications. More et al. [20] used the OpenCV technique and PLC controller to design a vernier gauge for water level detection in a drainage system in mining sites, with the successful replacement of human operations. Consequently, the accurate detection of tiny product defects with image processing and recognition techniques implies the feasibility of detecting concentration and split surface levels in solutions and suspending liquids, respectively.

3.2. Deep Learning Applications in Solutions

Now that a tiny defect or difference can be accurately detected, research into solution concentration detection with image processing and recognition has been widely conducted. Liu et al. [21] carried out experiments to inspect the tungsten concentration in a solution via online image processing. Color features were extracted to train an LS-SVM model by building up a mathematical relationship between the tungsten concentration and color parameters for future predictions. The results showed that the intelligent and human-exclusive method technologically meets the industrial requirements, and replaces the traditional human-inclusive tungsten concentration analysis. Moreover, its accuracy and efficiency confirms this method's potential for future applications in other fields and in the solution concentration inspection industry. Cao et al. [22] further detected the copper ion concentration in rice-field irrigation water based on image recognition by comparing the color changes of a test paper and the targeted samples in the images. The extraction of the gray-scale eigenvalues of the test paper assisted them in establishing and comparing four detection models, and they logarithmically regressed the optimal model for the test. Furthermore, it was found that the correlation coefficients of the training set and the prediction set were 0.9438 and 0.9191, and the root mean square errors were 19.9563 mg/L and 9.7889 mg/L, with a relative error below 8%. The results were practically proved to monitor the quality of irrigation water in paddy fields. Consequently, this deep learning technique was found to thoroughly replace the manual operations and facilitated the in-time inspections for ion concentration. Moreover, Tian et al. [23] detected the concentration of a single-component dye solution using image recognition. The schematic experimental setup is shown in Figure 2a,b. Low-alkali yellow dyes were used to achieve the image samples for recognition. By comparing the maximum and average relative errors, the model with a blue light source was found to possess a brightness level of 50, which was the maximum prediction for the concentration of the solution, reaching a maximum relative error of 5.20% and an average relative error if 3.35%. Moreover, the simple structure and fast detection speed of the experimental equipment facilitated the utilization of this advanced technique of solution concentration detection.

Luo et al. [24] applied the OpenCV technique to reduce the quantity of sample images and improve the efficiency of the detection of color solutions. OpenCV exploited the gradient descent of the image brightness to precisely determine the major features of the image samples [25]. In experiments, the color features were extracted and used to predict the sample images acquired from the color solutions. The results demonstrated that the detected solution concentration extraordinarily matched the features extracted, with an allowable error of ±5% for the recognition. The research on solution detection indicates that deep learning techniques can accurately predict input images, although the research objectives are metal elements, ions, and solution colors. Therefore, deep learning applications for the concentration detection in solutions provide a methodology for the detection of solid content in suspending liquids and facilitate these extended practices in the liquid detection industry.



(a) (b)

Figure 2. (**a**) Detection structure; (**b**) image recognition system.

With its successful applications for detecting the solution concentration, Sheng et al. [26] exploited the image processing technique to detect the solid particles in mineral water. Compared with the low-efficient, time-consuming, and labor-intensive manual inspection method, the sample images from the image recognition technique were automatically acquired, analyzed, and matched with the pre-obtained images to realize target identifying, quantity counting, and size detecting for the suspending particles in the mineral water with a higher efficiency. The results showed that the deep learning technique can not only be utilized in the detection of the solution concentration, but can also be applied in the solid detection of suspending liquids. Additionally, it also carries out fast identification, accurate quantity counting, and size detection for the suspended particles in mineral water in a timely manner. Although the investigations into the detection of solid content in suspending liquids are fresh and limited, Sheng's results provide technical support and a methodological basis for the automatic detection of the concrete solid content of wastewater in mixing stations. Nevertheless, the rapid sedimentation of solids in the concrete wastewater requires an accurate recognition of the solid–liquid separation surface, which is also critical in realizing smart monitoring.

Besides the application of the deep learning technique for particle detection in mineral water, Lin et al. [27] conducted experiments of water level monitoring using image processing. A set of optical lenses were used to measure different depths of water levels, with timely image captures. Then, distortion correction, gray scaling, and binarization techniques were carried out for image recognition. The Hough transform algorithm was used to scale the horizontal line of the water level on a real-time basis. Backpropagation was repeated to compute the gradients of the objective function, which corresponded to the weights of a multi-layer module stack. Specifically, backpropagation allows the gradients to flow backward through the network, making the model learn from image data iteratively and adjust the weights accordingly to minimize the loss until the weights reach the optimum. The results showed that image processing can be used to accurately monitor the water level, which is a similar process as that for the targeted solid–liquid separation detection. Although this research focused on river water, it can be applied to the idea of detecting the slitting surface between the solid and liquid in water. Moreover, the rapid response of the recognition system facilitates its real-time application in the industry. Hence, the successful detection of solid particles in mineral water and the real-time recognition of the water level may somehow pave the way for concrete solid detection in wastewater in future experimental investigations.

More specifically, wastewater detection is executed every 20 min due to the variation in the solid content, which is caused by the continuous wastewater input from industrial practices. In such a time period, the gradually reduced speed of the solid sedimentation in the concrete wastewater leads to the different solid–liquid separation locations. To meet the time requirement, the solid–liquid separation location at a certain level needs to be recorded to determine the in-time value of the solid content. Therefore, the timely and accurate recognition of solid–liquid separation locations via deep learning is a necessity. The above research results demonstrated that the deep learning technique can be used to recognize the solid content, especially for water level markings. They encourage us to solve practical problems that occur in the concrete mixing stations, and moreover, such a technique can also save circulated labor costs and time. In summary, deep learning algorithms, such as those used for the latest research achievements in pattern recognition and object detection, have had significant success in image recognition. Compared with traditional machine learning techniques, deep learning does not require manual feature extraction to perform multilayered training. It also provides globally optimal solutions to problems, and thus displays better classification and approximation effects. Therefore, deep learning techniques can be further introduced to construct efficient and robust structural reliability assessment models, with higher accuracy and efficiency.

Nevertheless, limitations of using a deep learning model for solid-content detection in concrete wastewater also exist. Deep learning models require a large amount of annotated data for training, including concrete wastewater samples with different solid-content levels. Without sufficient data collection methods and accurate labeling, the trained model may not accurately infer the amount of solid content. Moreover, the model's accuracy and reliability under unknown circumstances may be compromised if the dataset used is limited to specific construction projects or a specific area's concrete wastewater samples, as the model may not be generalized well in regard to other construction projects or buildings of different scales. Furthermore, the generation of solid content in concrete wastewater may vary based on different construction scenarios, building scales, and construction processes, restricting the performance of the model to be less effective in various practical applications. Hence, before using a deep learning model to detect the wastewater solid content, a prerequisite regulation for exploring diverse construction scenarios is crucial to secure recognition accuracy.

3.3. The Challenges of Detecting Solid Content in Concrete Wastewater Using Deep Learning

Deep learning has the power to intelligently learn features and make accurate predictions from a large amount of image data, which is feasible and promising for offering significant improvements in accuracy and speed in the solid-content detection of concrete wastewater. However, challenges also exist:

- Data availability: The quality and quantity of data required for training deep learning models are critical to achieving a high accuracy. But, obtaining adequate datasets for solid-content detection in concrete wastewater can be challenging due to the variability in composition and particle size distribution [28]. Zhao et al. [29] investigated the particle size distribution of concrete wastewater and demonstrated that the particle size distribution of concrete wastewater is bimodal with a fine mode, which is dominated by particles less than 10 μm in diameter, and a coarse mode, which is dominated by particles greater than 100 μm in diameter. The non-uniformity of the particle size may lead to difficulty in extracting image features. Consequently, collecting an abundant amount of available data is critical to ensure the model's reliability.
- Model selection: The selection of an appropriate deep learning model for solid-content detection in concrete wastewater is critical due to the varying functions of numerous available deep learning architectures. The model should have the capability to capture the heterogeneity of the particles, the variability in particle size and density, and the interferences in the wastewater [28]. Wang et al. [30] proposed a data-driven robust adaptive control system with deep learning (DRAC-DL) for enhancing the model adaptability, which used a robust controller to construct the closed-loop control scheme. Wang et al. [31] established an event-driven model of predictive control

with deep learning (EMPC-DL), which is defined to trigger the action control to efficiently improve the running performance of wastewater treatment processes (WWTPs). Li et al. [32] applied a novel hybrid model integrated with a first-principal deep learning model to sufficiently adapt to the wastewater system and accurately predict the nitrous oxide (N_2O) emissions from wastewater treatment plants (WWTPs). To reach an optimum processing speed, the selective model and the corresponding parameters become a necessity.

- Hardware requirements: Specialized hardware and significant computational power are a solid background when applying deep learning to detect solid content in concrete wastewater because deep learning models possess multiple layers and parameters that need to be optimized during training [33]. Therefore, high-end graphic processing units (GPUs) or tensor processing units (TPUs) are key components to efficiently and timely train the models, in addition to needing to meet the hardware requirements of high-end CPUs or GPUs, and having large amounts of memory (RAM) and fast storage devices such as solid-state drives (SSDs) [34].
- Generalization: The generalization of the deep learning model assures us that the algorithm is compatible with various sources of concrete wastewater due to the heterogeneity and variation in the wastewater. An investigation into the heterogeneity of concrete and its failure behavior presented an equivalent probabilistic model for the study of concrete failure [35]. Xu et al. [36] developed several transient shock models to profile the variation in three critical water quality parameters (conductivity, temperature, and pH) in a real-time mode with flat, thin milli-electrode array (MEA) sensors, which demonstrated that the MEA sensors possess the capability of efficiently profiling the corresponding parameters from different sources of wastewater. Moreover, Varshney et al. [37] conducted comprehensive investigations into the mechanical properties and durability aspects of concrete made with wastewater to point out the similarities in the properties from different sources of wastewater. All such research work has consolidated the significance of model generalization and its applications in industrial practices.

To overcome these challenges, larger datasets are crucial for model training. Additionally, pre-trained models can be exploited via transfer learning to fine tune the parameters for a targeted image recognition task, improving the accuracy of the models. Moreover, specialized hardware and powerful computational software solutions can be further developed for improving the training efficiency. Finally, exploring new generalized imaging techniques such as hyperspectral imaging or X-ray imaging can facilitate deep learning models to comprehensively learn and recognize, leading to more accurate solid detection in concrete wastewater.

3.4. Future Research and Expectations

Our ongoing project is currently researching the solid-content detection of concrete wastewater in mixing stations. Based on the comprehensive investigations into deep learning applications for tiny object detection, solution inspection, and water surface monitoring, the experimental setup can focus on the wastewater sample extraction using test-tubes, where the distribution of the particles represents the particle situation within the wastewater source in the target mixing station. The particle sedimentation in the test tube stops at a certain time, and the solid–liquid separation surface can be marked on the tube scale. Then, images can be tracked to show the amount of solid content available for deep learning models to learn and recognize. Therefore, the specific solid content at a certain time can be monitored if the particle sedimentation, distribution, and the solid–liquid separation surface can be captured using deep learning. Some possible techniques can be selected to improve the model accuracy, speed, and efficiency:

- The data augmentation technique is a technique of artificially increasing the training set by creating modified copies of a dataset using existing data, providing the model with a more extensive data range in variations and increasing the model's accuracy [38].

- Hybrid approaches can mix different imaging techniques, which are combined with additional information and the improved accuracy from the deep learning models, such as by using hyperspectral imaging or X-ray imaging followed by deep learning algorithms [39] to improve the model performance.
- Transfer learning utilizes pre-trained models from other image recognition tasks, such as object detection or segmentation, to fine tune the target model with a small amount of image data, leading to faster and in-time model deployment [40].
- Multi-sensor integration is the process of combining data from multiple sensors, which can enhance the model generalization to improve the accuracy and reliability of the data [41]. Multi-sensor integration includes integrating different sensing technologies that capture different aspects of solid particles in concrete wastewater.

In summary, future research into the solid detection of concrete wastewater using an experimental setup with deep learning assistance can improve the accuracy, efficiency, and speed of the process, leading to better wastewater management and environmental protection. The YOLO (You Only Look Once) algorithm is a real-time object detection algorithm used in computer vision, whose basic principle is to take an image as input and divide it into a grid. Each grid cell predicts multiple bounding boxes with associated class probabilities, which are refined using regression to provide accurate object locations [42]. YOLO possesses superior features due to its real-time performance, simplicity, and reliable accuracy. Overall, YOLO is widely used in various domains, such as surveillance systems and object recognition tasks.

4. Conclusions

Based on the investigations outlined in this research, it can be seen that deep learning techniques can be widely exploited for tiny object detection in solutions, for real-time data detection and acquisition, and for production efficiency improvement. Therefore, the conclusions are:

- The investigation of the use of deep learning practices in general solution concentration detection, metal ion concentration detection, metal element concentration detection, suspended particulate matter feature recognition, and horizontal-scale line detection shows that the technique can achieve high precision and display real-time data, providing a methodological basis for the use of deep learning to detect the concrete solid content of wastewater.
- The deep learning technique can be used to accurately detect the suspending particles in mineral water and the water level of rivers. So, it is feasible to apply the deep learning technique to test the solid content of wastewater, as the sedimentation dividing line in a solid and water is similar to that in the detection of the water level. Also, the OpenCV-based edge detection technique can be used to accurately and efficiently collect the image pattern and process the features. Such algorithms may consolidate the future experimental research on the solid detection of concrete wastewater.
- To overcome the challenges of deep learning applications, such as data availability and generalization, transfer learning, and data augmentation, hybrid approaches and multi-sensor integration techniques have the potential to be utilized to provide a more accurate model performance and adaptations.
- Test tubes can be used for sampling from wastewater sources. They can also be used as the targets for image data achievement when using deep learning, as the particle distribution and solid–liquid surface separation, which are representations of the target wastewater source, can be extracted as features with this method.

Author Contributions: Y.C. participated in the literature research work and testing method discussion, and wrote the initial draft of the paper. Q.Y. proposed the methodology, analyzed the testing methods, and revised the paper. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the 9th Group of Key Discipline Projects in Henan Province Mechanical Design, Manufacturing and Mechatronics.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: We would like to thank our industrial partners Yu Li, Zhengzhou Xinyuan Mechatronic Engineering Pty. Ltd., Zhengzhou, China, and Chunyang Wu, Henan Miracle Education and Consultation Pty. Ltd., Kaifeng, China, for providing valuable technical and practical information on industrial applications.

Conflicts of Interest: The authors declare no conflict of interest.

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