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Microscopic Sand Image Classification Using Convolutional Neural Networks

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***Abstract*— This research paper reviews the use of Convolutional Neural Networks (CNNs) to categorize diverse sand type using microscopic images, with an objective of improving quality control in construction materials. The paper compares three CNN architectures—LeNet-5, Inception v3, and ResNet50—for clasiffying between specific sand categories, such as two river sands (Cipongkor and Citarum) and three types of silica sand (brown, cream, and white). Each model was trained and tested on different dataset splits, with images pre-processed to highlight specific microscopic properties. To achieve a thorough comparison, each model's performance was measured using a variety of measures such as F1-score, accuracy, recall, and precision. These measurements enabled a comprehensive evaluation of how accurately and reliably each CNN model categorized the various sand types. ResNet50 consistently delivered the highest accuracy, achieving outstanding classification in some instances, accuracy 99%, showcasing its effectiveness in capturing fine details in sand textures. These results highlight the potential of CNN-based approaches for precise and automated sand classification, which supports increased quality assurance in construction and related areas.**

***Index Terms*— Convolutional Neural Network (CNN); Inception v3; LeNet-5; sand classification; ResNet50.**

I. INTRODUCTION

In recent years, the classification of materials using image-based techniques has gained significant attention due to its potential to improve accuracy and efficiency across various industries, including construction [1]. As a fundamental component in construction, sand plays a critical role in determining the quality and longevity of concrete structures. Accurate classification of different sand types is essential, as variations in sand characteristics can directly impact structural integrity. Manual sand classification methods, which rely on visual inspection and experience, are often labor-intensive, prone to human error, and lack precision [2]. Convolutional Neural Networks (CNNs) have emerged as a powerful framework for image classification due to their ability to automatically learn and extract complex visual features, enabled by advancements in machine learning and computer vision [3]. In this paper, CNNs are used to classify sand materials from microscopic images, focusing on key features such as grain texture, color variations, and morphological patterns [4]. The classification process involves two main stages: training and testing. During the training phase, the CNN model learns to identify distinctive microscopic characteristics of pre-labeled sand images, including river sand and silica sand, by progressively adjusting its weights and parameters to optimize performance. Once training is complete, the model undergoes testing using previously unseen sand images to evaluate its generalization capabilities. Metrics such as accuracy, confusion matrices, and loss values are used to assess the model's performance and reliability in practical applications.

This paper presents an automated sand classification system that employs three architectures—LeNet-5 [5], Inception v3 [6] and, ResNet50 [7] —to classify various sand types from microscopic images. The research compares the performance of these architectures in accurately distinguishing sand types, highlighting their effectiveness in enhancing material quality control in construction.

II. RESEARCH METHOD

A. State-of-The Art

Convolutional Neural Networks (CNNs) in sand material classification systems has been explored to analyze the recommended method against current systems. CNN has been used to classify different types of soil [8]. The research implemented a CNN-based processing module, a camera for image detection, and a dataset that included Red Soil and Black Soil. Data processing techniques applied of the Keras and TensorFlow frameworks. The Results demonstrated the model's efficacy in soil classification with a 98% accuracy rate and minimal loss values.

Deep learning and machine learning have been used to classify construction materials on unbalanced datasets [9]. In order to recognize different materials, this design applied a Vision Transformer-based processing module, a camera for image identification, and a dataset that included concrete, red bricks, and

OSB boards. In this research, the Vision Transformer's performance was compared to the results of various processing modules, including Multi-Layer Perceptrons (MLPs), Support Vector Machines (SVMs), and Convolutional Neural Networks (CNNs). The results showed that, when compared to SVM and MLP, the Vision Transformer model achieved over 95% accuracy in detecting construction materials, greatly outperforming other approaches in classification accuracy.

Deep Learning: The Porosity Parameter has been applied to clasiffy soil micromorphological images [10]. Convolutional Neural Networks (CNNs) were applied to process a dataset of micromorphological soil photographs for this research. In order to increase classification accuracy of soil components based on micromorphological images, the strategy used transfer learning. The CNN model's performance was also contrasted with that of other classification techniques, including Random Forest and Support Vector Machines (SVMs). Based on measures including accuracy, precision, recall, and F1-score for each material category across three datasets, the system was able to identify soil types with 100% accuracy.

B. Block Diagram

The classification of five types of sand consist of three types of silica sand and two types of river sand. Based on their microscopic images is the focus of this research. This research comprises microscopic images of sand, including two types of river sand (Cipongkor and Citarum) and three types of silica sand (brown, cream, and white). Moreover, three CNN architectures were evaluated: ResNet50, Inception v3, and LeNet-5. The block diagram of sand classification is shown in figure 1. The block includes input, process, and output. The input is a microscopic image of sand. The process begins with detecting microscopic features of the sand using Convolutional Neural Network (CNN). The output of the system is the accuracy value of its detection and classification results of sand types. The process was simulated by using Visual Studio Code for image processing and classification.

Cipongkor and Citarum sands were specifically selected due to their prominent use in the region's construction projects. These sands are valued for their smooth texture, uniform grain size, and excellent durability, which contribute to superior performance in concrete and mortar applications. As they are frequently utilized in local construction practices, their inclusion in the dataset ensures the research relevance to real-world applications, particularly in addressing quality control challenges for commonly used materials in the area.

LeNet-5, Inception v3, and ResNet50 were selected for their various design approaches and ability to handle varying levels of image complexity and details. LeNet-5, a core CNN model, served as a baseline for evaluating the effectiveness of early CNN architectures in sand classification. Inception v3, known for its multi-scale feature extraction enabled by modified convolutions, was chosen to investigate its efficacy on textures with considerable variability. ResNet50, which incorporates residual learning and a deep architecture, was chosen to investigate its capacity to recognize complicated picture features while addressing training issues such as vanishing gradients. The integration of these models results in a full evaluation of sand classification performance across various CNN configurations.

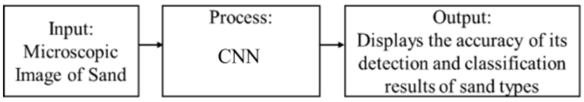

Fig. 1. Block Diagram of Sand Material Classification System

C. Digital Microscope Camera

The digital microscope camera is a camera to capture high-resolution images of specimens under magnification and display them on a computer or monitor. It enables real-time and detailed observation of microscopic samples, enhancing both viewing and analysis processes [11]. In this paper, the digital microscope camera capture microscopic images of sand particles as the input data for the Convolutional Neural Network (CNN) model. These images provide detailed representations of the sand's texture and morphology, enabling the CNN to learn and classify various sand types based on their unique microstructural properties. The digital microscope camera is illustrated in Figure 2.

Fig. 2. Digital Microscope Camera

D. Sand Materials

Sand is a common granular material in construction, composed of small rock and mineral particles with diameters ranging from 0.0625 mm to 2 mm [12]. In this paper, two types of river sand and three types of silica sand were used as the dataset. River sand, originating from riverbeds, consists of rounded particles shaped by natural erosion and transportation. Its smooth texture and high quality make it ideal for applications in concrete and mortar [13]. In contrast, silica sand, primarily composed of silicon dioxide (SiO_2), is valued for its chemical resistance and hardness. Due to its purity and durability, silica sand is widely used in industries such as hydraulic fracturing, foundry casting, and glassmaking [14]. Images of the sand material used as a dataset can be seen at Figure 3.

Fig. 3. Image Dataset: (a) Cipongkor River Sand, (b) Sand Citarum River, (c) Cream Silica Sand, (d) Brown Silica Sand, (e) White Silica Sand

E. *Convolutional Neural Network (CNN)*

A Convolutional Neural Network (CNN) is a deep learning architecture designed to process and recognize patterns in image data through hierarchical layers. CNNs are particularly effective for image classification tasks because they can automatically extract and learn features from raw pixel data without requiring manual feature selection. The structure of CNNs is inspired by the visual processing mechanisms of biological systems, specifically the hierarchical pattern recognition of the human brain [15] . The example of CNN structure is shown in Figure 4.

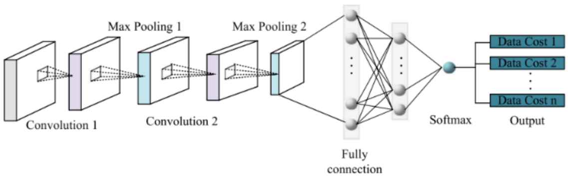

Fig. 4. Structure of a Convolutional Neural Network for Image Classification [15]

CNNs consist of several types of layers, each playing a key role in the network's ability to process image data:

- Convolutional Layer: This is the first layer where filters (kernels) are applied to the input image. Each filter slides across the image to capture low-level features like edges, textures, and colors. The result is a set of feature maps that represent different aspects of the input data. These feature maps serve as the foundation for deeper layers to learn more complex patterns.
- Activation Layer: Activation functions are applied following convolutional processes to introduce non-linearity into the network. Functions like Rectified Linear Units (ReLU) help the network capture complex, non-linear relationships within the data.
- Pooling Layer**:** The pooling layer reduces the dimensionality of feature maps while retaining key information. Max-pooling, a common technique, captures the peak value within a specific window, reducing feature map size and aiding in overfitting prevention.
- Batch Normalization Layer**:** This layer normalizes the input to each layer, helping to stabilize the learning process and speed up training. Batch normalization ensures that the network remains robust by preventing large variations in the input data.
- Dropout Layer**:** Dropout is a method for decreasing overfitting in which some neurons are randomly "ignored" during training. This forces the network to create more robust and redundant feature sets.
- Fully Connected Layer**:** The feature maps are flattened into a single vector and routed through one or more completely connected layers. This layer outputs the classification probabilities or the predicted labels for the input image, depending on the problem [16].

These CNN models are optimized to detect the minor differences in texture, coloration, and shape of grains that characterize each sand type. A comparison of sand classification performance is conducted using three prominent CNN architectures, LeNet-5 [5], Inception v3 [6] and, ResNet50 [7].

1) *LeNet-5*

LeNet-5, introduced by Yann LeCun in the late 1990s, was initially designed for image recognition tasks, specifically for classifying handwritten digits [5]. LeNet-5 is a convolutional neural network (CNN) architecture based on gradient descent, originally developed for recognizing handwritten digits. An input layer that processes 32×32 pixel pictures of digits (0–9) and an output layer with 10 nodes, each of which corresponds to a digit from 0–9, make up the conventional LeNet-5 design shown in Figure 5. Three convolutional layers, two pooling layers, and one fully connected layer make up LeNet-5's six extra layers in addition to the input and output layers. A 2×2 kernel is used by the pooling layers, and 5×5 filters are applied by the convolutional layers. Additionally, the fully linked layer lowers the number of neurons from 120 to 84, improving the model's parameter training efficiency [17]. However, its architecture is also effective at classifying patterns and textures in different images, making it useful for tasks like sand classification, where detecting microstructural details is important.

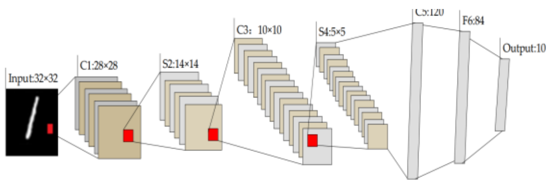

Fig. 5. LeNet-5 Architecture [18]

2) *Inception v3*

Inception v3 is a convolutional neural network (CNN) architecture developed by Google for efficient image classification tasks. The primary novelty of Inception v3 is its capacity to extract both fine and larger details from an image by employing several filter sizes (1×1, 3×3, 5×5) to collect multi-scale characteristics within the same layer [6]. This approach makes Inception v3 highly effective in handling complex images where the object size and features can vary significantly.

One of the primary improvements in Inception v3 is the use of factorized convolutions, which break down larger convolutions into smaller ones (e.g., 3×3 into two 1×3 and 3×1 convolutions). This increases computational performance and lowers the number of parameters without compromising accuracy. To stabilize the learning process and speed up and improve the reliability of training, the model also includes batch normalization [19]. The model's architecture is presented in Figure 6.

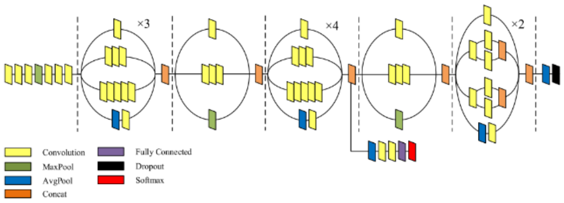

Fig. 6. Inception v3 network structure [19]

In this paper, Inception v3 is used to classify microscopic images of sand, classifying different types of sand grains based on their textures and microstructures. The architecture's ability to handle varying scales and extract detailed features makes it well-suited for this task, as the sand grains exhibit diverse shapes and patterns that require robust feature extraction for accurate classification.

3) ResNet50 (Residual Networks)

ResNet50 is a deep convolutional neural network (CNN) architecture developed to address the vanishing gradient issue that often occurs in extremely deep networks. ResNet incorporates shortcut connections that bypass certain layers, facilitating residual learning. This approach allows layers to capture the difference, or residual, between the input and the target output [7]. These connections facilitate the retention of information within the network and simplify the training process. The 50 layers of the ResNet50 model are composed of convolutional layers followed by identity shortcuts in each residual block. This architecture ensures efficient learning by allowing layers to focus on the residuals, improving accuracy and enabling deeper networks to perform better without degradation in training [20]. The structure of ResNet50 is illustrated in Figure 7.

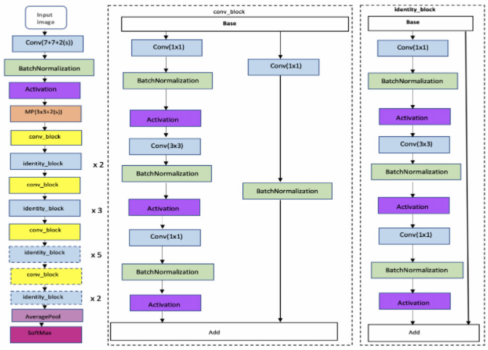

Fig. 7. Architecture of ResNet50 [20]

In this system, ResNet50 is applied to classify sand images by detecting subtle microstructural patterns in sand grains. The residual connections allow the model to capture and generalize complex features across different types of sand, improving classification accuracy.

F. Confusion Matrix

A confusion matrix is an important tool for assessing the effectiveness of a classification model [19]. It presents a clear overview of the model's predictions in comparison to the actual ground truth, classifying the outcomes into four distinct situations:

- True Positive (TP): Both the predicted and actual classes are implied to be positive since the model accurately predicts the positive class.
- The True Negative (TN): Both the predicted and actual classes are negative, demonstrating that the model effectively recognizes the negative class.
- False Positive (FP): The model makes a mistake when it predicts the positive class when the real class is negative.
- False Negative (FN): When the model wrongly assigns a positive instance to the negative class. [21].

The confusion matrix is especially useful in multi-class classification tasks, like the sand classification in this paper, as it highlights how well the model distinguishes between different classes. Key metrics including accuracy, precision, recall, and F1-score can be obtained by examining the confusion matrix; this gives information about the model's advantages and shortcomings.

In this paper, confusion matrices are constructed for LeNet-5 [5], Inception v3 [6] and, ResNet50 [7]. models to evaluate their performance in classifying different sand types. The confusion matrix supports to classify patterns of misclassification, assess the model's reliability, and guide further optimization.

Model accuracy, a standard metric obtained from the confusion matrix, is determined by calculating the proportion of correctly predicted cases (including both true positives and true negatives) relative to the total instances in the dataset. The formula to calculate accuracy is as follows.The formula for accuracy is as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

- **TP** = True Positives (correctly predicted positive cases)
- **TN** = True Negatives (correctly predicted negative cases)
- **FP** = False Positives (incorrectly predicted positive cases)
- **FN** = False Negatives (incorrectly predicted negative cases) [22]

III. Results and Discussion

A. Results

The dataset used in this paper contains 150 images for each sand type, including two river sand types (Cipongkor and Citarum) and three silica sand types (brown, cream, and white). The total amount of data is 750 images for 5 types of sand. The images were captured using a high-resolution digital microscope and were resized into 150×150 pixel as the input for CNN.

The dataset was split into five different ratios: 70:30, 75:25, 80:20, 85:15, and 90:10, with percentages allocated to training and testing sets, respectively. Exploring different training and testing data splits in this research was essential to obtain the optimum model's performance. This suggests an excellent convergence between generalization and learning, improving classification results. For each ratio, the training set contained train data and validation data. The train data consist of the majority of the images to ensure the models had sufficient data to learn and validation data were used to fine-tune the models. Test set was used to evaluate model performance. While the dataset provides a solid foundation for a preliminary research, its particular focus on specific sand samples may limit ability to generalize and cause overfitting issues. To address these issues, data augmentation methods such as random rotations, width and height shifts, zooming, brightness adjustments, and horizontal flipping were used to increase the dataset's diversity and reduce overfitting.

We compare three CNN models—LeNet-5, Inception v3, and ResNet50—optimized to distinguish fine-grained properties of sand types, including as texture, coloring, and morphology. To ensure uniform evaluation, all models were trained with the Adam optimizer, learning rate 0.00001, a batch size of 32, and up to 100 epochs. The comparison of accuracy across different dataset splits for LeNet-5 [5], Inception V3 [6], and ResNet50 [7] models is presented in Table I.

TABLE I. Accuracy Comparison Of Different Models Across Dataset Splitsable Styles

Dataset Split	CNN Architectures Accuracy		
	LeNet-5 [5]	*Inception v3* [6]	*ResNet50* [7]
70 : 30	59%	93%	93%
75 : 25	45%	96%	97%
80 : 20	72%	92%	92%
85 : 15	43%	92%	99%
90 : 10	70%	95%	95%

Table I presents a comparison of accuracy among three CNN architectures LeNet-5 [5], Inception v3 [6], and ResNet50 [7] across different dataset splits. LeNet-5 demonstrates the lowest performance among the models, with its highest accuracy recorded at 72% in the 80:20 split. Inception v3 performs considerably better, maintaining an accuracy of over 92% in the majority of splits. However, ResNet50 consistently outperforms both, achieving outstanding classification accuracy (upto 100%) at the 85:15 split. ResNet50 showed the superior performance results based on its capacity to apply residual learning in maintaining accuracy over deeper layers, which allows it to capture subtle microstructural differences in the sand images. The results exceed those reported in previous research, offering a benchmark for novelty and validating the effectiveness of the proposed approach.

Although the primary parameter to evaluate the model's classification performance was accuracy, other metrics such as F1-score, precision, recall, and confusion matrix were also employed to obtain a more comprehensive understanding of how well the model performed. Figure 8 shows the confusion matrix for the LeNet-5 model, Figure 9 illustrates the results for Inception v3, and Figure 10 displays the matrix for ResNet50. These matrices provide a detailed view of how each model classified the different sand types.To gain deeper insights into the classification performance, confusion matrices for each architecture are presented. Figure 8 shows the confusion matrix for the LeNet-5 model, Figure 9 illustrates the results for Inception v3, and Figure 10 displays the matrix for ResNet50. These matrices provide a detailed view of how each model classified the different sand types.

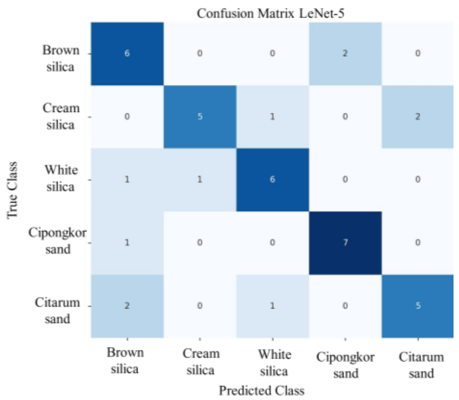

Fig. 8. Confusion Matrix for LeNet-5 Model in Sand Type Classification

From the confusion matrix, it is evident that the model achieves its best performance when classifying Cipongkor sand and Brown silica, as both sand types are correctly classified in most instances. The model shows strong accuracy in detecting these two categories, which have clear distinguishing features.

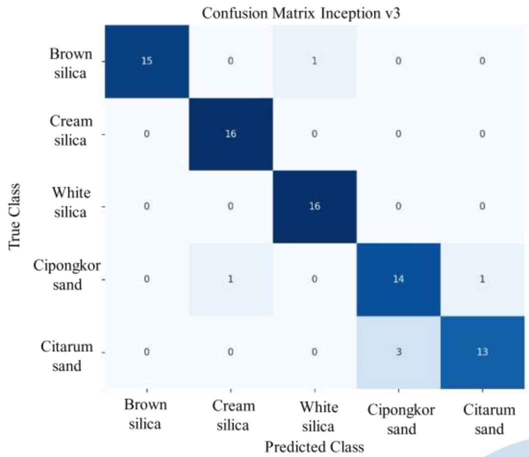

Fig. 9. Matrix for Inception v3 Model in Sand Type Classification

From the confusion matrix, the model achieves near-perfect classification for Brown silica, Cream silica, and White silica, as indicated by the diagonal dominance in the confusion matrix. The true positive rates for these sand types are impressive, showing the model's effectiveness in capturing the unique characteristics of these specific sand types.

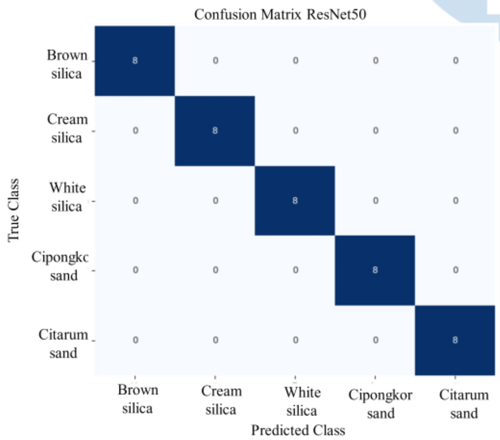

Fig. 10. Confusion Matrix for ResNet50 Model in Sand Type Classification

From the confusion matrix, we can observe that the model classifies all sand types with 100% accuracy. The matrix shows no misclassifications, indicating that the model effectively classifies each of the five sand types with complete precision, ensuring flawless performance in recognizing microscopic features.

Following the analysis of the confusion matrices, it is crucial to evaluate the models using more detailed performance metrics such as precision, recall, and F1-scores. These metrics provide a deeper understanding of how effectively each CNN architecture classifies various sand types [23]. While accuracy offers a general overview, precision, recall, and F1-scores give more specific insights into the balance between true positives, false positives, and false negatives within the classification outcomes.

Tables II, III, and IV present the precisions, recalls, and F1-scores for LeNet-5, Inception v3, and ResNet50, respectively, demonstrating each model's performance across different sand classification tasks.

TABLE II. LENET-5 RESULT

Class	Precision	Recall	F1-Score
Brown silica	0.6	0.75	0.67
Cream silica	0.83	0.62	0.71
White silica	0.75	0.75	0.75
Cipongkor sand	0.78	0.88	0.82
Citarum sand	0.71	0.62	0.67

Based on Table II, Cipongkor sand achieved the best performance with an F1-score of 0.82, while White silica also performed well with an F1-score of 0.75. Cream silica had the highest precision (0.83) but lower recall, resulting in an F1-score of 0.71. Brown silica and Citarum sand had lower F1-scores, both at 0.67, indicating areas where classification could be improved.

TABLE III. INCEPTION V3 RESULT

Class	Precision	Recall	F1-Score
Brown silica	1.0	0.94	0.97
Cream silica	0.94	1.0	0.97
White silica	0.94	1.0	0.97
Cipongkor sand	0.82	0.88	0.85
Citarum sand	0.93	0.81	0.87

Based on Table III, Inception v3 demonstrates high performance, with Brown silica, Cream silica, and White silica achieving F1-scores of 0.97. Cipongkor sand and Citarum sand, while slightly lower, still perform well with F1-scores of 0.85 and 0.87, respectively, indicating strong classification capabilities for all sand types.

TABLE IV. RESNET50 RESULT

Class	Precision	Recall	F1-Score
Brown silica	1.0	1.0	1.0
Cream silica	1.0	1.0	1.0
White silica	1.0	1.0	1.0
Cipongkor sand	1.0	1.0	1.0
Citarum sand	1.0	1.0	1.0

As shown in Table IV, ResNet50 achieves perfect results, with all sand types having precision, recall, and F1-scores of 1.0. This indicates that ResNet50 classifies all sand types flawlessly without any misclassifications.

IV. CONCLUSION

In this paper, sand type classification was performed using three Convolutional Neural Network (CNN) architectures—LeNet-5, Inception v3, and ResNet50—

on microscopic images to determine accuracy in distinguishing between sand types. Based on the results, LeNet-5 and Inception v3 both demonstrated strong performance in classifying sand types, showing their effectiveness for image processing tasks. However, ResNet50 consistently achieved the highest accuracy across all dataset splits, making it the most effective model for this research.

The results highlight the potential of CNN-based systems in real-world applications, such as material quality inspection in the construction industry. Using these models in automated systems alongside digital microscope cameras could offer a dependable solution for fast and accurate analyzing sand samples, obtaining the demands of industries such as concrete production.This approach minimizes human error, reduces inspection time, and improves the consistency of material quality, ultimately enhancing the durability and reliability of construction projects.

Nevertheless, this paper has limitations, including the use of a relatively small dataset and specific sand types, which may impact the generalizability of the models. Further research should focus on expanding the dataset to include a wider range of sand types and conditions while exploring additional CNN architectures and techniques to further improve classification accuracy. These steps will ensure the robustness and applicability of the proposed models in broader industrial contexts.

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