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Deep Learning-Based Methods for Inspecting Sand Quality for Ready Mixed Concrete

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Abstract:
Sand is a vital component within a concrete admixture for variety of structures and is classified as one of the crucial bulk material used. Assessing the Fineness Modulus (FM) of sand is an essential part of concrete production process because FM significantly affects the workability, cost-effectiveness, porosity, and concrete strength. Traditional sand quality inspection methods, like Sieve Analysis Test, are known to be laborious, time-consuming, and cost ineffective. Previous studies had mainly focused on measuring the physical characteristics of individual sand particles rather than real-time quality assessment of sand, particularly its FM during concrete production. This study introduces an image-based method for detecting flawed sand through deep learning techniques to evaluate the quality of sand used in concrete. The method involves categorizing sand images into three groups (Unavailable, Stable, Dangerous) and seven types based on FM. To achieve a high level of generalization ability and computational efficiency, various deep learning architectures (VGG16, ResNet-101 and MobileNetV3 small), were evaluated and chosen; with the inclusion of transfer learning to ensure model accuracy. A dataset of labeled sand images was compiled. Furthermore, image augmentation techniques were employed to effectively enlarge this dataset. The models were trained using the prepared dataset that were categorized into three discrete groups. A comparative analysis of results was performed based on classification performance metrics which identified the VGG16 model as the most effective achieving an impressive 99.87% accuracy in identifying flawed sand. This finding underscores the potential of deep learning techniques for assessing sand quality in terms of FM; positioning this research as a preliminary investigation into this topic of study.

Key words: Deep learning, CNN, sand quality assessment, Fineness Modulus, Concrete

1. INTRODUCTION

Concrete, a fundamental material in construction, is extensively used for a variety of structures, including buildings, bridges, and more [1]. As a composite material, concrete consists of water, cement, sand and other components such as crushed stone or gravel. Sand, constituting for approximately 35% of concrete's volume, is a critical component that directly influences the concrete's workability, porosity, permeability, strength, compaction, and durability [2].

In the production of concrete, various sand sizes are observed during the construction phase due to the diverse geological compositions according to regions that leads to natural variations in grain size. These differences arise from local rock types that contribute to distinct sizes and characteristics of sand particles upon weathering. The quality of concrete is closely linked to these factors, as the uniformity of sand particle distribution significantly affects the interaction strength within the materials' matrix [3, 4]. Concretes' compaction is enhanced by a well-graded distribution of sand particles which is crucial to promote effective inter-particle interactions improving its mechanical strength [5]. Conversely, inadequate particle size distribution can disrupt the formation of a stable internal framework, adversely affecting the concrete's overall performance [6].

Assessing sands' grain size primarily relies on sieve analysis tests that calculate its particle size distribution (PSD) classified according to international standard, called American Society for Testing and Materials (ASTM) C33, by which it calculates the FM describing the particle size distribution of sand [7]. However, such sieve analysis is time consuming, labor intensive and also prone to breaking of sand particles that clogs the sieve meshes during testing. This process may affect the measurement results of the PSD [8]. More importantly, this method lacks representativeness and cannot provide real-time feedback on the granular parameters during the sand-making process resulting in time lag. Given these variables, the FM of sand may vary with each batch of concrete produced and corresponds to uncertainty that can lead to lower quality of concrete [9].

As mentioned previously, in the construction industry, sand grain sizes are typically determined using sieve analysis tests. Despite its widespread use, sieve analysis has its disadvantages; it is a time consuming and laborious process that often requires manual sieving or the use of mechanical shakers [8]. This is particularly challenging when processing numerous samples or when precise measurements are essential. Additionally, sieves must be meticulously cleaned between uses to avoid cross-contamination. Moreover, samples often need specific preparation, such as drying, prior to analysis [10].

Computer vision techniques, particularly those involving deep learning, offer a revolutionary approach to automatic image analysis. Advancements in this technology, especially Convolutional Neural Networks (CNN), are notable for their high generalization ability supported by the training of billions of parameters and a substantial volume of annotated datasets. CNN excel in processing images rich in information by efficiently extracting and elevating features from low-level to high-level within their network structures [11].

In sand grain analysis, Kim et al. applied CNN to differentiate six sand grain types in two-dimensional grayscale images. In this study, accurate classification based on attributes, such as: roundness and sphericity, are challenging to discern with the naked eye. Despite the challenges, the results achieved an average classification accuracy of 98.24% [12]. Another study by Li & Iskandar devised a dynamic image analysis method which produced higher accuracy when assessing sand grain size and shape parameters compared to traditional methods [13]. Despite these advances, prior research has predominantly concentrated on quantifying the shape and size of individual sand particles. In particular, limited focus was on real-time quality assessment of sand from the perspective of FM during concrete production.

This paper introduces a deep learning-based technique for evaluating the FM of sand, designed to rapidly and precisely categorize sand quality. Such an approach could demonstrate dependable accuracy and significantly benefit the performance of concrete resulting in a sustainable and cost-effective production of construction materials.

2. MATERIAL AND METHODS

2.1. Standards for fineness modulus of sand for concrete

The calculation of FM follows the ASTM C33 standard, which involves conducting sieve analysis using ten different sizes of standard sieves (namely 9.5 mm, 4.75 mm, 2.36 mm, 1.18 mm, 0.6 mm, 0.3 mm, 0.15 mm and 0.075mm) on sand samples. The FM value of the sand samples are obtained by summing up the mass percentage retained on each sieve and then dividing by 100 according to the formula below. This method, representing the average size of sand grains, intuitively reflects the particle distribution of the sample sand [14].

$$\mathrm{FM} = \frac{\sum \text{Cumulative percent retained on each sieve}}{100} \tag{1}$$

In the production of concrete, the typical FM range for sand grains commonly used is between 2.3 and 3.1. This range is crucial for the workability, strength, and durability of concrete. FM values below 2.3 may lead to decreased workability of concrete and have a negative impact on its strength. On the other hand, FM values above 3.1 may produce overly coarse concrete particles, which can negatively influence the concretes' strength and durability [15, 16]. Various international standards and guidelines, such as the ASTM C33 standard and India's IS 383, have set forth acceptable FM ranges for concrete sand, typically between 2.3 and 3.1, to maintain aggregate quality and grading. However, the European standard BS EN 12620 does not specify an FM range [17].

This study adopts the Korean standard KS F 2527, as shown in Table 1, which explicitly defines the FM range for concrete-use sand. Based on workability and strength requirements, sand with an FM less than 2.3, between the range 2.3 to 3.1 and greater than 3.1 is defined as 'Unavailable', 'Stable' and 'Dangerous', respectively. Since this study aims to build a sand dataset based on FM for data analysis, sand samples' FM is divided into seven different types according to normal distribution. This classification assists in reducing data bias and accurately reflect the granularity distribution characteristics of sand in each image.

Table 1. FM range for concrete-use sand

Group	Type	Scope	Granularity distribution characteristics of sand
Unavailable	Type 1	FM < 1.4	Fine-Dominant
	Type 2	1.4 ≤ FM < 2.3	Mostly Fine, Some Neutral
Stable	Type 3	2.3 ≤ FM < 2.6	Partially Fine-Dominant, Normal Distribution
	Type 4	2.6 ≤ FM < 2.8	Normal Distribution
	Type 5	2.8 ≤ FM ≤ 3.1	Normal Distribution, Mostly Neutral
Dangerous	Type 6	3.1 < FM ≤4.0	Some Fine, Mostly Neutral
	Type 7	FM > 4.0	Neutral-Dominant

2.2. Construction of dataset

This study utilizes a portion of the construction sand quality management dataset provided by the Korea Institute of Geoscience and Mineral Resources [18]. It is comprised of 1,000 sand samples from 80 regions in Korea. Conducted in a laboratory setting, according to the KSF257 standard, each sand sample was subjected to sieve analysis and then captured using a high-magnification camera under a constant distance and environmental conditions to ensure the reliability of the data collected. The study collected and processed 1400 raw images with a resolution of 1000 x1000 categorizing them into three groups and seven types mentioned previously.

In CNN applications, images transformed through data augmentation processes, such as rotation and flipping, are recognized as entirely distinct. A practice widely adopted to significantly enhance CNN performance [12]. Therefore, data enhancement techniques such as horizontal flip, vertical flip, blur effect, rotation, gamma transformation and noise addition were used in this research to ensure diversity, as shown in Figure 1. Additionally, individual images were resized to 224x224 resolution to meet the input format requirements for CNN-based models.

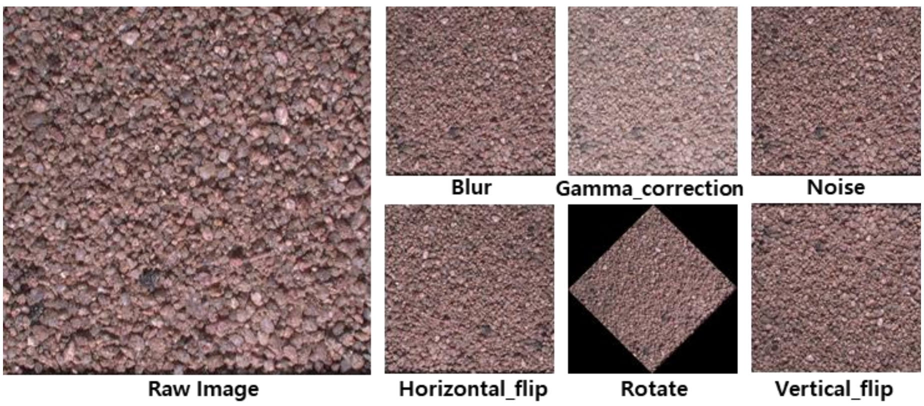

Fig 1. Data augmentation methods

As shown in Figure 3, the dataset, original and augmented datasets consisted of 9,800 images that were randomly split into training, validation and test sets in proportions of 60%, 20%, and 20%, respectively. The model performed training with the training set. From the training results, the model with the highest performance was selected using the validation dataset. Ultimately, the model's performance was gauged by its ability to predict images with the test set.

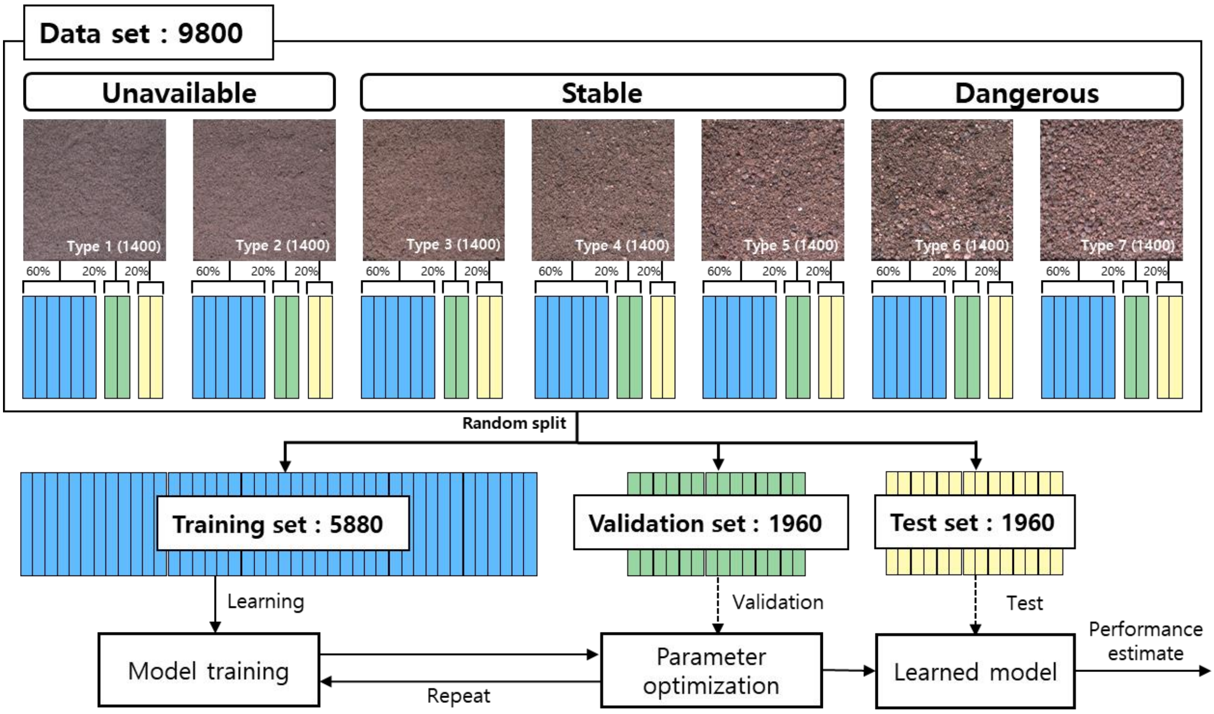

Fig 2. Development of dataset and overall workflow of CNN model

2.3. CNN-based sand classification models with transfer learning

In standard sieving methods, FM calculation is based on mass. However, relying solely on image detection methods does not permit direct measurement of particle mass or accurate calculation of their complex shapes. CNN provide a crucial solution by extracting features from images for classification. As illustrated in Figure 3, CNN mainly consists of feature extractor and classifier. Feature extractor is achieved through convolution layers followed by ReLU activation functions after maximum pooling layers. Classifier processes these features through fully connected layers ultimately outputting classification probabilities for each category to improve prediction accuracy [19]. Training CNN from without previous training requires extensive data and computational resources that makes it time-consuming and costly [12]. To overcome this, the study adopts a transfer learning approach, utilizing pre-trained models (VGG16, ResNet-101 and MobileNetV3 small) from large-scale general databases like ImageNet as backbone networks. These models have been selected for their extensive validation and superiority in performing classification tasks. Moreover, transfer learning methods accelerate the training process and generally provide better predictions [20].

Specifically, VGG16 model, with its deep and uniform architecture of repetitive 3x3 convolution layers and 2x2 maximum pooling layers stacked, achieves high accuracy in image classification and recognition tasks. Despite its size and longer training duration, VGG16 became a benchmark model in deep learning as a result of its’ exceptional performance in various computer vision objectives [12]. In order to overcome the gradient vanishing problem in deep networks, ResNet-101, with introduction of skip connections, contains 101 convolution layers that improves processing efficiency of computer vision tasks without compromising performance [20]. By contrast, MobileNetV3 small, designed for mobile or embedded systems, makes for a particularly suitable in environments with limited computing resources; as it effectively reduces computational demands through introduction of bottleneck layers [21].

In model construction process, the first step is loading three pre-trained models as feature extractors while adjusting model's last 20 layers to trainable state which allows for updates to these layers' weights during training whilst keeping the rest fixed. This method permits learning of task-specific high-level features without significantly increasing computational burden. For classifier part, a structure including batch normalization layers, flattening layer and two fully connected layers with L2 regularization is built to prevent overfitting and enhance model's generalization capability through dropout layers. Output layer is designed as softmax layer with seven units for multi-class classification. The models are compiled using Adam optimizer, with initial learning rate set at 0.00001 to facilitate stability and convergence at early stages of training.

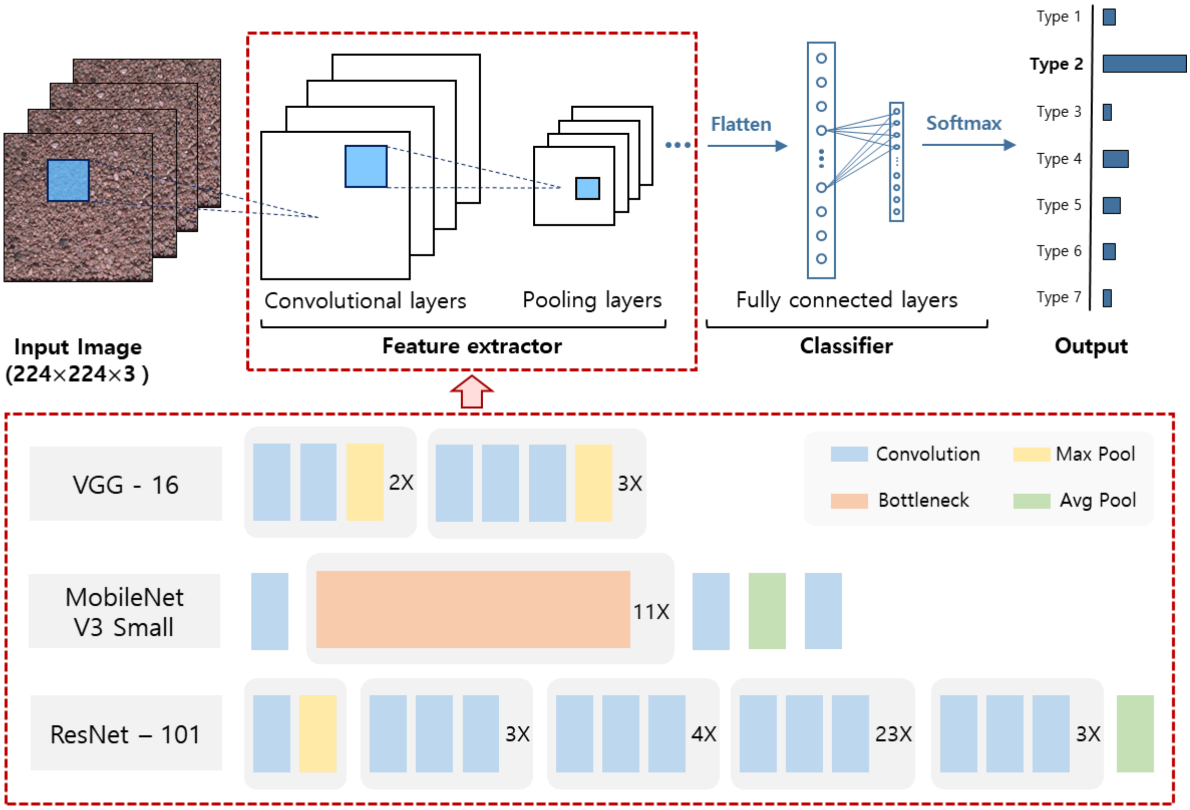

Fig 3. CNN Architecture and Transfer Learning Process

2.4. Evaluation criteria

The performance of proposed FM detection method for sand is evaluated using a set of standard performance metrics which includes: precision, recall, F1 score, accuracy and loss [20]. Precision is defined as the proportion of sand FM samples correctly classified. While recall indicates the proportion of specific FM sand samples correctly predicted out of the total samples. The F1 score, as the harmonic mean of precision and recall, provides a comprehensive assessment of the models' performance on imbalanced data. Overall accuracy directly measures the models' effectiveness across all classification tasks; becoming one of the primary evaluation metrics. The loss metric tracks changes in error throughout the training process offering a quantitative basis for assessing detection performance. These metrics are calculated based on scores from the confusion matrix, including True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). Indicators mentioned are defined below:

$$\text{Precision (P)} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall (R)} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{F1-Score} = \frac{2PR}{P+R} \tag{4}$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

3. MODEL TRAINING AND VALIDATION

This study conducted training and validation using the model constructed in Section 2.3 to prevent overfitting and underfitting, utilizing a mini batch size of 8 and 50 epochs. To ensure a consistent experimental environment for all three models, experiments were conducted on the same device equipped with a Keras -based Python 3.8 environment, an Intel(R) Core(TM) i5-12600KF @ 3.70 GHz CPU, an NVIDIA GeForce RTX 3060 Ti (8GB) GPU, and 16GB of memory, running on Windows 11 Pro. The experimental outcomes, illustrated in Figure 4, demonstrate that all three models achieved an accuracy exceeding 95%, indicating that the models effectively learned the features without overfitting or underfitting during the training and validation process.

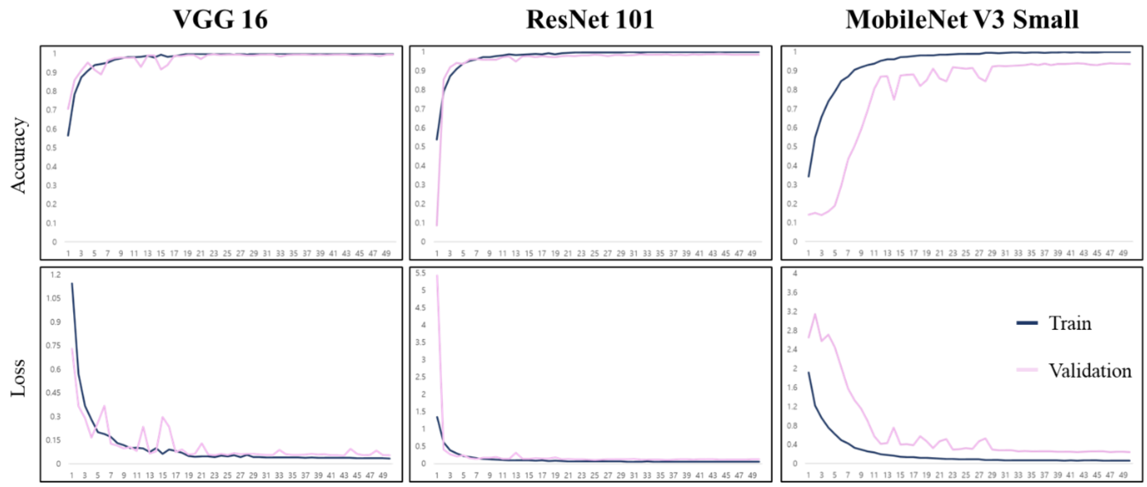

Fig 4. Model training and validation results

As Table 2 reveals, VGG16 outperformed the other models by achieving a maximum validation accuracy of 99.6% which is 6% higher than that of the lowest-performing model which was MobileNetV3 small. Also, Minimum Validation Loss was reduced by 4.8 times. Regarding training speed, ResNet-101 and MobileNetV3 small exhibited similar rates of approximately 9 seconds slower per epoch on average compared to VGG16. Consequently, in this research, for tasks of identifying the FM of concrete sand, VGG 16-based model emerges as the most suitable in terms of both accuracy and speed during the model learning process.

Table 2. Comparison of learning performance

Model	Total parameters	Average time per epoch (s)	Max Training Accuracy	Min Training Loss	Max Validation Accuracy	Min Validation Loss
VGG16	49,278,337	137	1	0.033911906	0.996428549	0.052208811
ResNet-101	26,447,425	146	0.999829948	0.053775985	0.98775512	0.110577881
MobileNet V3 small	14,375,537	144	0.998469412	0.060507882	0.939795911	0.240217581

4. PERFORMANCE EVALUATION OF THE TRAINED MODEL

The performance of models based on three distinct backbone networks was evaluated using the test data set which comprised of 1,960 input images (280 images for each of the seven sand types). The testing dataset with a variety of sand types ensured a thorough assessment of the models' generalization capabilities. Performance evaluation was primarily achieved through the final scores generated by classifiers and visualization of confusion matrices. In these matrices, true labels and prediction labels for each sand type is signified on the diagonals with corresponding values which indicates the number of images correctly classified. Conversely, values from the diagonal indicate the number of images misclassified, thus allowing for the calculation of correct classifications and misclassifications (MSC) as depicted in Figure 5. There was an increased likelihood of MSC due to the feature measurement values' similarity among adjacent sand images. Performance evaluation revealed that all models exhibited lower precision in classifying sand types 1 and 2, while the MobileNetV3 small model achieved higher accuracy solely for type 7 classification. This highlights the challenge of classifying densely arranged sand samples with high geometric similarity. In terms of detection speed, the three models demonstrated similar performance with an average processing time of 35.33 seconds. Further analysis of the models' precision, recall, F1 scores and correct classifications indicated that the MobileNetV3 Small model had the lowest average correct classification rate at 93.88%. On the other hand, VGG16 model achieved highest average correct classification rate at 99.87%. Therefore, the VGG16-based model exhibited the best performance throughout the recognition process both in terms of accuracy and speed. The findings from this study provide significant insights for the task of recognizing FM values in sand used for concrete that demonstrates the effectiveness and efficiency of models based on the VGG16 backbone network in handling such image recognition tasks.

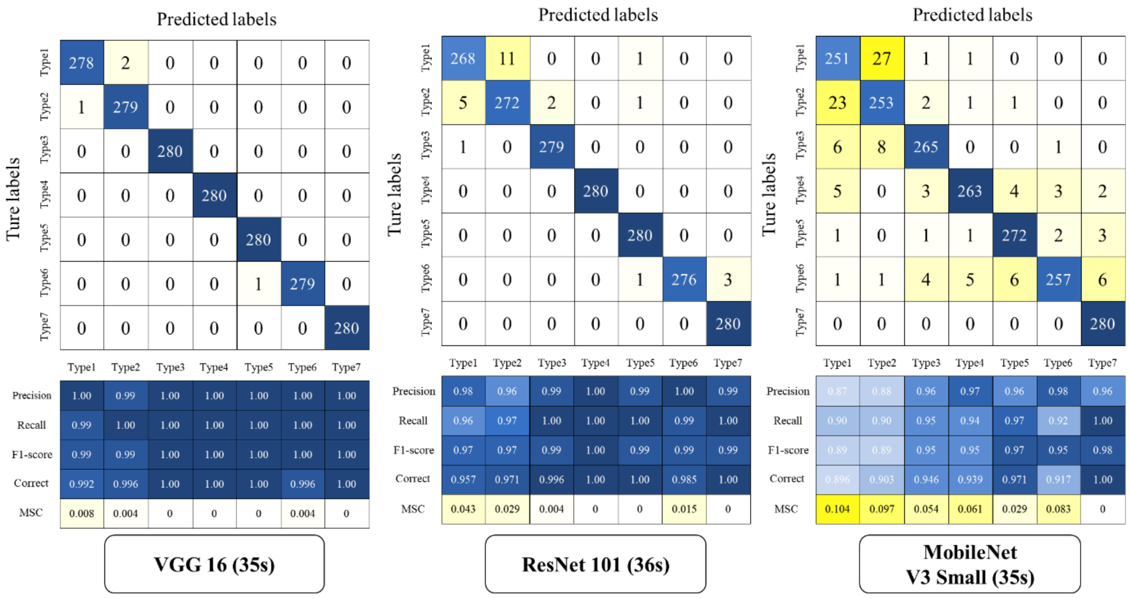

Fig 5. Confusion Matrix for Model Performance Evaluation of Classified Sand FM

4. CONCLUSIONS

In this study, we presented a sand FM evaluation method using transfer learning techniques based on VGG16, ResNet-101 and MobileNetV3 small deep learning models. The method validates the feasibility of CNN for real-time assessment of sand quality in the concrete production process by classifying the FM of dense sand grains. The experimental results show that VGG16 model leads with the highest average classification accuracy of 99.87%. Among these three models, VGG16 model achieved a speed of 56 images per second. This demonstrates the potential for deep learning to improve the accuracy and efficiency of construction materials quality inspection. This represents a significant advancement over traditional sieve analysis, providing a faster, less labor intensive and more accurate method of assessing sand quality. However, the smallest FM values for type 1 and 2 showed the lowest accuracy in all three models, such as recording of worst error rate by 8.20% using MobileNetV3 small.

Furthermore, the study faces limitations due to the geographical scope and diversity of the dataset. Moreover, the high computational resource demands of deep learning models that affect their application in resource-constrained environments. The generalization capability of CNN models in real production settings, and its ability to handle extreme samples, require further validation. Future research should focus on expanding the diversity of the dataset, optimizing models and exploring more efficient lightweight model architectures to adapt to various production conditions; with an aim to comprehensively improve the efficiency and accuracy of sand quality assessment and further advance the application of deep learning technology within the construction materials industry.

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