JURNAL INFOTEL
VOL. 17, NO. 1, FEBRUARY 2025, PP. 96–110. DOI:10.20895/INFOTEL.V17I1.1201

RESEARCH ARTICLE

Improving Concrete Mix Type Recognition Accuracy Using ANN and GLCM Features

Gasim[1,*], Rudi Heriansyah[2], Shinta Puspasari[3], Muhammad Haviz Irfani[4], Indah Permatasari[5], Evi Purnamasari[6], and Samsuryadi[7]

[1,2,3,4,5,6]Faculty of Computer and Natural Sciences, Indo Global Mandiri University, Palembang 30129, Indonesia
[7]Faculty of Computer Science, Universitas Sriwijaya, Indralaya 30662, Indonesia

*Corresponding email: gasim@uigm.ac.id

Received: July 4, 2024; Revised: December 29, 2024; Accepted: December 30, 2024.

Abstract: Concrete is an essential construction material widely used for its strength and durability. However, identifying its mix type often relies on conventional methods that are less efficient and accurate. This research evaluates the impact of image resolution on the accuracy of concrete mix type recognition using Artificial Neural Network (ANN) and Gray-Level Co-Occurrence Matrix (GLCM) features. The method involves analyzing concrete images at four resolutions: 300×300, 500×500, 700×700, and 900×900 pixels. This study emphasizes the novelty of exploring the effect of varying image resolutions on concrete mix type recognition accuracy. While ANN and GLCM are widely used in image classification, their application to investigate the resolution's role in concrete recognition remains underexplored in the literature. This focus contributes new insights to improving automated recognition systems for concrete mix types, enhancing accuracy and efficiency in the construction industry. The experimental results show a clear correlation between image resolution and recognition accuracy. Images with resolutions of 300×300 pixels yield an accuracy of 45%, which is inadequate for reliable classification. Accuracy improves with higher resolutions, reaching 62.5% and 70% for 500×500 and 700×700 pixels, respectively. Interestingly, at 900×900 pixels, the accuracy slightly decreases to 68%, suggesting that excessively high resolutions may introduce redundant details. The study identifies 700×700 pixels as the optimal resolution for accurate concrete mix classification. Future work should refine feature selection and preprocessing techniques to further optimize accuracy and computational efficiency.

Keywords: artificial neural network (ANN), concrete mix type recognition, image resolution, gray-level co-occurrence matrix (GLCM), recognition accuracy

---

1 Introduction

Concrete is a fundamental construction material valued for its strength, durability, and versatility in various structural applications [1–3]. Its composition includes Portland cement, fine and coarse aggregates, and water, making it adaptable to diverse construction needs and the most widely used material globally [1, 4, 5]. The development of different types of concrete mix is essential to ensure the quality and safety of the structures [1, 6].

Advancements in image recognition and AI have enhanced concrete mix recognition, providing more efficient and accurate solutions than traditional methods. Machine learning algorithms such as Random Forest and Decision Tree effectively forecast concrete properties by analyzing complex datasets [7–10]. They optimize mix design for strength, density, and environmental impact and predict behaviors such as durability and crack detection, reducing time and costs.

Previous research shows that increasing image resolution can significantly improve recognition accuracy in various image-based tasks, such as object recognition and texture classification. However, a higher resolution also requires greater computational resources, so it is necessary to consider the balance between accuracy and processing efficiency [11–13]. Studies show that a higher resolution is capable of capturing finer texture details, which is important for material classification [11,14]. Thus, this study aims to fill the literature gap by exploring the effect of image resolution on concrete mix type recognition.

Although Artificial Neural Network (ANN) and Gray-Level Co-Occurrence Matrix (GLCM) have been successfully applied in various image classification tasks, existing studies primarily focus on optimizing algorithms or feature extraction methods without paying much attention to image resolution as a critical factor. The role of resolution in capturing texture details for accurate classification is particularly important in domains such as concrete recognition, where surface characteristics play a vital role. This study bridges that gap by systematically investigating the impact of varying image resolutions, ranging from 300×300 to 900×900 pixels, on the recognition accuracy. By addressing this overlooked aspect, the research contributes to a deeper understanding of how image resolution affects automated recognition systems, particularly in the context of construction and material sciences.

This study evaluates how image resolution impacts the accuracy of identifying concrete mixtures using ANNs combined with GLCM features. By examining resolution variations, the research aims to improve the reliability and performance of concrete mix classification. GLCM feature extraction is expected to enhance the depiction of concrete texture and surface characteristics, boosting the model's recognition accuracy

Conventional methods of concrete mix identification often face accuracy and time efficiency constraints, with manual inspections by experts resulting in high variability [15, 16]. Therefore, an automated method is needed to speed up the identification process and improve consistency and accuracy [15, 17, 18].

Understanding how image resolution affects AI-driven concrete mix accuracy is crucial. High resolution improves detail and performance, while lower resolution boosts processing speed and efficiency. Balancing these factors is the key to optimizing systems for construction and engineering.

This research examines the impact of image resolution on concrete mix type recognition accuracy to develop an optimal model. The goal is to improve identification methods, advance concrete mix recognition, and enhance reliability in construction and engineering applications.

Numerous studies have shown that ANN excels at pattern recognition. Safar and Murshid emphasized the importance of intelligent pattern classification systems using neural network algorithms, which achieve high accuracy [19–21]. Focused on improving cognitive abilities in pattern recognition by mimicking biological neural structures, resulting in high-performance systems [22]. Analyzed the fault tolerance and generalization capabilities of ANN, showing their proficiency in recognizing patterns even with data variations. Highlighted the applications of ANN in pattern recognition, stressing their significance in knowledge processing, adaptive filtering, feature extraction, and fault diagnosis [23, 24]. In general, ANN excels in pattern recognition due to its adaptability, fault tolerance, and cognitive potential, making it a powerful tool in various fields.

ANN has advantages over other machine learning algorithms, such as decision trees or support vector machines (SVM) [25, 26]. ANNs are superior in handling complex and high-dimensional data thanks to their architecture, which is able to adapt to different types of features in the data, including complex textures and patterns [27–29]. In addition, ANNs have good generalization capabilities to data variations, making them particularly suitable for image recognition tasks such as concrete mix type identification, where texture patterns and visual details are highly divers [30,31]. These advantages make ANNs an effective tool for improving accuracy and efficiency in image-based recognition tasks.

This research aims to develop an optimal model for accurate and efficient concrete mix type identification in the construction industry. The results are expected to enhance inspection quality and reliability, providing a modern alternative to conventional methods

Automated methods with image recognition technology and AI have been developed to recognize concrete defects and predict concrete mix properties. The multi variant defect recognition technique achieved an accuracy of 98.8%, focusing on surface cracks, delamination, and spalling [7, 32, 33]. ANN to predict concrete compressive strength showed a high correlation value of 0.98, proving AI's effectiveness in forecasting concrete behavior [34–36]. Computer vision and machine learning algorithms were also explored for concrete crack detection and classification based on image processing [8, 33]. These advances demonstrate the potential of automated methods, such as image recognition technology and AI, to improve concrete mix type assessment and prediction.

Research in concrete mix type recognition often overlooks the impact of image resolution on accuracy [7, 8, 15, 37]. Most studies focus on algorithm and model development, neglecting this crucial factor [7,18,37–39]. This gap in the literature requires further investigation.

This research addresses the gap by examining the influence of image resolution on concrete mix type recognition accuracy using ANN and GLCM features. It contributes theoretically to image recognition technology and offers practical insights for the construction industry to enhance accuracy and efficiency.

This research introduces a novel method for concrete mix recognition that combines ANN and GLCM features with a focus on image resolution. This approach aims to improve accuracy and effectiveness, leveraging ANN and GLCM for their classification and texture extraction strengths. The results are expected to enhance identification accuracy and efficiency beyond traditional methods.

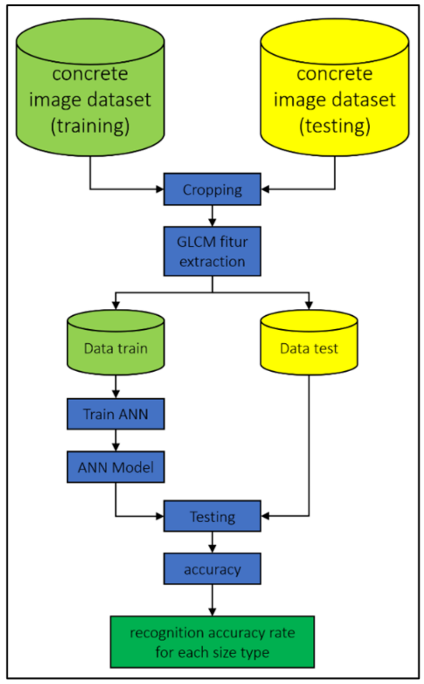


Figure 1: Research framework.

2 Research Method

The overall research flow is presented in Figure 1.

2.1 Concrete Dataset

The concrete dataset used in this study was sourced from previously conducted research, ensuring the reliability and relevance of the data [40]. This dataset includes five distinct types of concrete mixes, with each type represented by three samples designated for training purposes (concrete image dataset for training) and two samples reserved for testing purposes (concrete image dataset for testing), as detailed in Table 1 [40]. The images were taken with a 14 MP camera, ensuring high-quality visual data, and the shots were consistently made from a distance of approximately 27 cm to maintain accuracy in the imaging process [40]. This methodological approach allows a controlled environment to evaluate the performance of recognition models effectively. Table 2 presents sample images for each type of mixture.

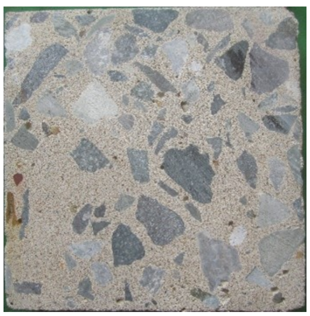
2.2 Cropping

The process of cropping or cutting images into sizes or resolutions according to experimental needs involves creating several distinct image dimensions. Specifically, the images were cropped to 300×300 pixels, 500×500 pixels, 700×700 pixels, and 900×900 pixels. This

Table 1: Composition and number of samples

Mixture type	Cement	Sand	Gravel	Number of training samples	Number of testing samples
A	1	2.5	3,5	3	2
B	1	3.5	4	3	2
C	1	3	3,5	3	2
D	1	2	3	3	2
E	1	2.25	3	3	2

Table 2: Images for each type of mix

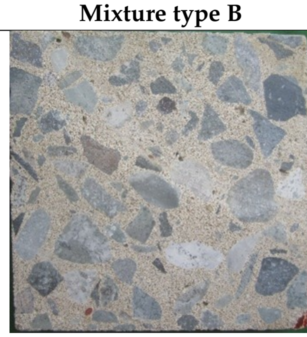


Mixture type A

Mixture type B

Mixture type C

Mixture type D



Mixture type E

method allowed for a comprehensive analysis of how varying resolutions might impact the accuracy of concrete mix type recognition. An illustration of this cropping process, which visually demonstrates the different image sizes used in the experiments, is presented in Figure 2. This approach ensured that the study could systematically investigate the effects of image resolution on the performance of the recognition model. Table 3 presents the cropped images.

Table 4 provides a comprehensive breakdown of the number of training and test images used in the study. For each type of concrete blend, there are 250 training images and 50 test images, resulting in a total of 1,250 training images and 250 test images across all blend types. This consistent composition ensures that each blend type is equally represented in the training and testing phases, which is crucial for maintaining the validity and reliability of the experimental results. The uniform distribution of image samples across different

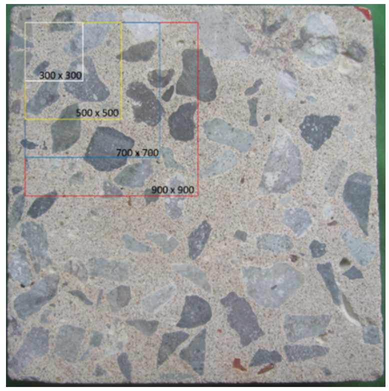
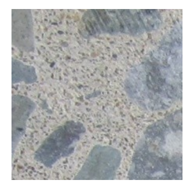


Figure 2: Cropping.

Table 3: Images for each size

			
900 × 900	700 × 700	500 × 500	300 × 300

cropping sizes, as shown in Table 4, further supports the robustness of the analysis. This methodological consistency allows for a thorough evaluation of the model's performance across varying image resolutions without introducing bias related to sample size disparities.

Table 4: Composition and number of image samples

Mixture type	**Number of training samples**	**Number of test samples**
A	250	50
B	250	50
C	250	50
D	250	50
E	250	50
Total	1,250	250

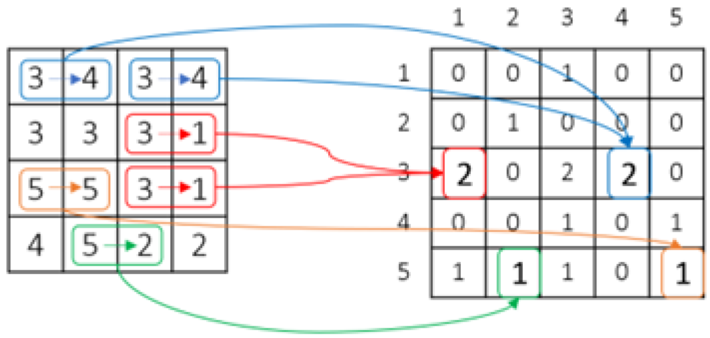


Figure 3: GLCM matrix 0°.

2.3 GLCM Feature Extraction

After the preparation and splitting of the dataset, the next step involves the extraction of texture features using the GLCM. This crucial step is essential for enhancing the machine learning model's ability to recognize and classify different concrete mix types accurately. The GLCM was introduced by Haralick et al. in 1973. This technique examines the spatial relationships between pixels within an image, offering a thorough means of quantifying textural features. By determining the frequency with which pairs of pixels with particular values occur in a defined spatial relationship, the GLCM allows the extraction of multiple statistical measures that characterize texture. This process involves calculating the occurrences of pixel pairs and analyzing these patterns to provide a detailed description of the image's texture. These measures include contrast, correlation, energy, and homogeneity, among others. The utilization of GLCM in this research aims to leverage these textural features to improve the accuracy and robustness of the concrete mix type recognition model, building on the foundational work of Haralick et al. to apply advanced techniques in modern computational contexts.

All images are converted to grey-scale images. Then, the co-occurrence matrix is calculated, which measures the frequency of pixel pairs with a certain grey value at a certain distance and orientation. Figure 3 shows the formation of the co-occurrence matrix with a distance of 1 and an orientation of 0°(zero degrees).

After the co-occurrence matrix is formed, it is continued with the extraction of contrast, homogeneity, energy, and correlation features. This stage is carried out for all training images and test images. For all training images, five training tables will be formed, namely the 300 pixels training table for 300×300 pixels image size, 500 pixels training table for 500×500 pixels image size, 700 pixels training table for 700×700 pixels image size, 900 pixels training table for 900×900 pixels image size. The training table is used to train the ANN model to recognize the test image.

2.4 Train and Test Data

Details of each training table are meticulously organised to facilitate effective data analysis and model training. Each training table consists of 1,250 columns and 4 rows corresponding to the extracted texture features: contrast, homogeneity, correlation, and energy.

Table 5: Definitions of target

Output Neuron	**Mixture Type**				
	A	**B**	**C**	**D**	**E**
Neuron 1	1	0	0	0	0
Neuron 2	0	1	0	0	0
Neuron 3	0	0	1	0	0
Neuron 4	0	0	0	1	0
Neuron 5	0	0	0	0	1

Specifically, Columns 1 to 250 contain data for mix type A, ensuring a comprehensive representation of this particular mix type. Similarly, columns 251 to 500 are dedicated to mix type B, providing a robust dataset for this category. Continuing in this structured manner, columns 501 to 750 contain data for mix type C, and Columns 751 to 1,000 encompass mix type D. Finally, columns 1,001 to 1,250 are reserved for mix type E. This systematic arrangement ensures that each mix type is distinctly categorized and easily accessible for analysis, thereby enhancing the efficiency and accuracy of the model training process.

2.5 Train ANN and ANN Model

The next stage is the establishment of an artificial neural network (ANN) model for each resolution. ANN is a computer model inspired by the operation of the human brain, which uses interconnected neurons or nodes to process information [41–43]. These neural networks learn from examples and are trained for specific tasks such as pattern recognition and data classification, similar to how biological systems adapt through changes in synaptic connections [44]. Researchers have applied ANNs in various fields, including image understanding and event analysis, especially in recognizing human-object interactions for event classification, utilizing processes such as preprocessing, feature extraction, optimization and classification to improve system effectiveness [44]. The parallel distributed processing nature of artificial neural networks enables dynamic learning and continuous performance improvement, resembling the human brain's ability to process complex patterns and make predictions. ANN is a powerful tools for pattern recognition and data classification, evolving over time without human intervention [45]. While ANNs offer the advantage of learning from feedback and solving complex problems efficiently [46].

There are single-layer and multi-layer ANN architectures. This research uses a multi-layer ANN, which has an input layer, a hidden layer, and an output layer. The output layer is compared with the target (Table 3) for each type of mixture. Table 5 is an arrangement of the values that the output layer should give for each type of mixture. For example, the input image is recognized or identified as mix type B or mix type 1:3,5:4 if the 1st output neuron is 0, the 2nd output neuron is 1, the 3rd output neuron is 0, the 4th output neuron is 0, and the 5th output neuron is 0.

The ANN model in this study can be seen in Figure 4, which consists of an input layer, hidden layer, and output layer. The input layer has 4 neurons because the features used are Contrast, homogeneity, correlation, and energy. The hidden layer has the number of neurons according to the results of the highest accuracy experiment for all image sizes, while the output layer has 5 neurons according to the number of mixture types to be rec-

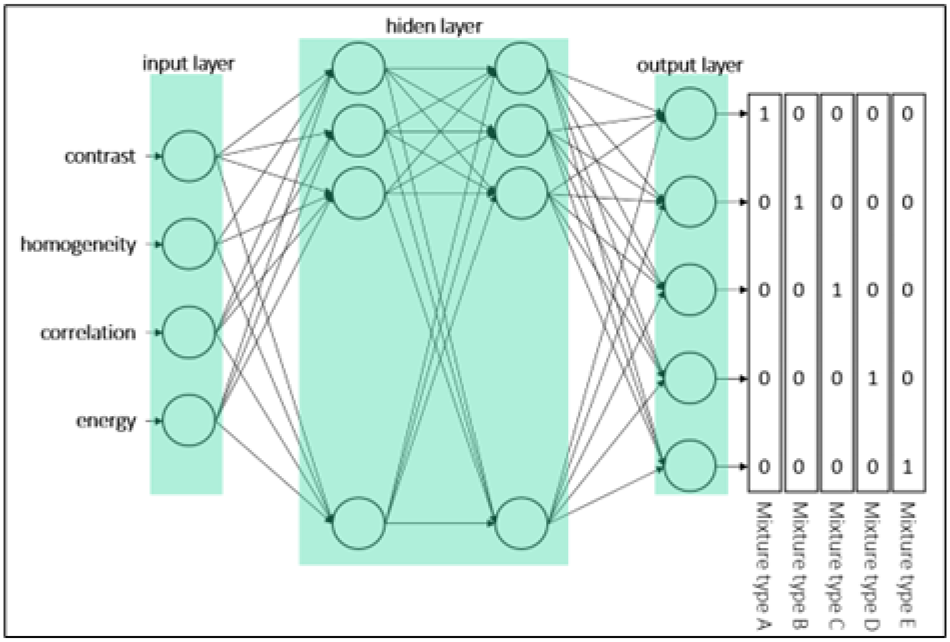


Figure 4: ANN model with input and output structure.

ognized. The parameter values in all ANN architectures are based on the results of the highest accuracy experiments during the training process.

2.6 Testing

The testing process for each image size category entails employing the corresponding Artificial Neural Network (ANN) model, previously trained using training data of identical dimensions to those of the images under test. For instance, when evaluating an image sized at 300×300 pixels, the corresponding ANN model trained on 300×300 pixel training data is utilized, consistent with the approach adopted for other image sizes.

Similar preprocessing steps applied to the training images are also implemented on the test images to ensure uniformity in feature extraction. Once the feature values, including contrast, homogeneity, correlation, and energy, are derived, they are applied to the respective ANN model for classification.

Accuracy assessment involves computing the ratio of correctly recognized images to the total number of data points across all image sizes. This standardized evaluation process enables robust comparison of recognition performance across various image resolutions, thereby providing insights into the optimal resolution for concrete mix type recognition.

3 Results

Table 6 details the specifications of the ANN models for all image sizes. They employ the back propagation algorithm, 4 input neurons (corresponding to the number of features), 5

Table 6: Specifications of ANN models for all image sizes

Component	Information
Algorithm	Back Propagation
Number of neurons in the input layer	4 Neurons
Number of neurons in the output layer	5 Neurons
Number of training data	1,250 Images
Number of test data	250 Images

Table 7: Accuracy rate for all types of image sizes

Type size	Accuracy (%)
300×300	45
500×500	62.5
700×700	70
900×900	68

output neurons (representing the number of concrete mix types), and a dataset consisting of 1,250 training images and 250 test images.

Table 7 presents the experimental findings for each image size. It is evident from the table that the 300×300-pixel size yields a low accuracy rate of 45%, suggesting that this resolution may not adequately capture the essential characteristics required for identifying concrete mix types.

The image size of 500×500 pixels show a noticeable improvement, with an accurate level of 62.5%. This indicates that as image resolution increases, the features required for identifying mix types become more discernible.

Interestingly, 700×700 pixel image size demonstrates the highest accuracy rate at 70%, emphasizing that higher resolutions provide more detailed information, which enhances recognition performance. However, at the 900×900 pixel size, the accuracy slightly drops to 68%, suggesting that beyond a certain resolution, increasing the image size may not necessarily lead to better recognition and could introduce noise or redundant details.

4 Discussion

The performance of the Artificial Neural Network (ANN) models, as detailed in Table 6, was evaluated across various image sizes to identify the optimal resolution for accurately classifying concrete mix types. The models employed the backpropagation algorithm with 4 input neurons and 5 output neurons, and the dataset consisted of 1,250 training images and 250 test images.

The experimental results presented in Table 7 show that image resolution plays a crucial role in the accuracy of the ANN models. Specifically, the 300×300 pixel images yielded an accuracy rate of 45%. This result suggests that such a resolution provides a limited representation of the essential features necessary for distinguishing between different concrete mix types.

As the resolution increased to 500×500 pixels, the accuracy improved to 62.5%, indicating that higher resolutions enhance the model's ability to extract meaningful features. Remarkably, the 700×700 pixel images demonstrated the highest accuracy rate at 70%. This underscores the importance of detailed and discernible features captured at higher resolutions, which significantly aid in the accurate recognition of concrete mix types.

Interestingly, at the 900×900 pixel resolution, the accuracy slightly dropped to 68%. This decline suggests that while higher resolutions generally improve recognition performance, excessively large images may introduce noise or redundant details, which could reduce the model's effectiveness.

In summary, the analysis highlights a clear correlation between image resolution and model accuracy. The results suggest that an optimal resolution of around 700×700 pixels is necessary to achieve satisfactory classification performance. Future work could explore refining feature selection and preprocessing techniques to enhance accuracy at lower resolutions, thereby balancing computational efficiency and performance.

5 Conclusion

This research compares the recognition accuracy levels based on various image sizes to determine the optimal size that provides the highest recognition accuracy. The image sizes used for the experiments were 300×300 pixels, 500×500 pixels, 700×700 pixels, and 900×900 pixels. After conducting experiments with these four different image sizes, it can be concluded that for concrete images consisting of cement, sand, and gravel, image sizes below 500×500 pixels are inadequate. This inadequacy is evidenced in Table 5, where the 300×300 pixel images yield an accuracy of only 45%. Consequently, image sizes below this threshold do not provide reliable results.

The best image size identified in this study is 700×700 pixels, which achieves an accuracy rate of up to 70%. This high level of accuracy demonstrates the importance of using sufficiently high-resolution images for effective concrete mix type recognition. Interestingly, at 900×900 pixels, the accuracy slightly decreases to 68%, suggesting that excessively large images may not always improve recognition performance and could introduce noise or redundant information.

These findings underscore the significance of selecting an optimal image size to enhance the performance of recognition models in the context of concrete mix analysis. Future research could explore strategies to further improve accuracy at lower resolutions to optimise computational efficiency without compromising performance.

References

[1] M. Girma and B. Asteray, "Fresh, mechanical, and microstructural properties investigation on the combined effect of biomedical waste incinerator ash and bagasse ash for high-strength concrete," *Adv. Mater. Sci. Eng.*, vol. 2022, pp. 1–15, May 2022.

[2] O. Corbu and I.-O. Toma, "Progress in sustainability and durability of concrete and mortar composites," *Coatings*, vol. 12, p. 1024, July 2022.

[3] A. K. Mishra, J. S. Sudarsan, and S. Nithiyanantham, "Feasibility study on application of ready mix concrete in construction projects in nepal," *Int. J. Environ. Sci. Technol. (Tehran)*, vol. 20, no. 7, pp. 7569–7576, 2023.

[4] A. Imam, Department of Civil Engineering, National Institute of Technology Jamshedpur, Jamshedpur, 831014, India, K. K. Sharma, V. Kumar, and N. Singh, "A review study on sustainable development of ultra high-performance concrete," *AIMS Mater. Sci.*, vol. 9, no. 1, pp. 9–35, 2021.

[5] V. A. Franco-Luján, F. Montejo-Alvaro, S. Ramírez-Arellanes, H. Cruz-Martínez, and D. I. Medina, "Nanomaterial-reinforced portland-cement-based materials: A review," *Nanomaterials (Basel)*, vol. 13, Apr. 2023.

[6] R. Muduli and B. B. Mukharjee, "Performance assessment of concrete incorporating recycled coarse aggregates and metakaolin: A systematic approach," *Constr. Build. Mater.*, vol. 233, p. 117223, Feb. 2020.

[7] Y. Gamil, "Machine learning in concrete technology: A review of current researches, trends, and applications," *Front. Built Environ.*, vol. 9, Feb. 2023.

[8] P. Ziolkowski, "Computational complexity and its influence on predictive capabilities of machine learning models for concrete mix design," *Materials (Basel)*, vol. 16, p. 5956, Aug. 2023.

[9] Y. Feng, M. Mohammadi, L. Wang, M. Rashidi, and P. Mehrabi, "Application of artificial intelligence to evaluate the fresh properties of self-consolidating concrete," *Materials (Basel)*, vol. 14, p. 4885, Aug. 2021.

[10] V. Soltangharaei, L. Ai, and P. Ziehl, "Artificial intelligence in concrete materials," in *Leveraging Artificial Intelligence in Engineering, Management, and Safety of Infrastructure*, pp. 161–183, Boca Raton: CRC Press, Sept. 2022.

[11] A. Bakhtiarnia, Q. Zhang, and A. Iosifidis, "Efficient high-resolution deep learning: A survey," *ACM Comput. Surv.*, Feb. 2024.

[12] Y. Hao, H. Pei, Y. Lyu, Z. Yuan, J.-R. Rizzo, Y. Wang, and Y. Fang, "Understanding the impact of image quality and distance of objects to object detection performance," in *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 11436–11442, IEEE, Oct. 2023.

[13] Z. Tu, P. Milanfar, and H. Talebi, "MULLER: Multilayer laplacian resizer for vision," in *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*, pp. 6854–6864, IEEE, Oct. 2023.

[14] N. Liu, M. Rogers, H. Cui, W. Liu, X. Li, and P. Delmas, "Deep convolutional neural networks for regular texture recognition," *PeerJ Comput. Sci.*, vol. 8, p. e869, Feb. 2022.

[15] L. Yu, J. Zhang, M. Bennamoun, X. Chang, V. Sirivivatnanon, and A. Nezhad, "Spatial-temporal analysis for automated concrete workability estimation," 2022.

[16] Z. Li, J. Yoon, R. Zhang, F. Rajabipour, W. V. Srubar, III, I. Dabo, and A. Radlińska, "Machine learning in concrete science: applications, challenges, and best practices," *Npj Comput. Mater.*, vol. 8, June 2022.

[17] H. Naseri, H. Jahanbakhsh, P. Hosseini, and F. Moghadas Nejad, "Designing sustainable concrete mixture by developing a new machine learning technique," *J. Clean. Prod.*, vol. 258, p. 120578, June 2020.

[18] H. Yang, S. Jiao, and P. Sun, "Bayesian-convolutional neural network model transfer learning for image detection of concrete water-binder ratio," *IEEE Access*, vol. 8, pp. 35350–35367, 2020.

[19] A. Doroshenko, "Applying artificial neural networks in construction," *E3S Web Conf.*, vol. 143, p. 01029, 2020.

[20] A. Afework and T. Sipos, "Modelling of accidents for four lane non-urban highways using artificial neural networks technique," in *2020 IEEE 14th International Symposium on Applied Computational Intelligence and Informatics (SACI)*, IEEE, May 2020.

[21] H. Elhegazy, D. Chakraborty, H. Elzarka, A. M. Ebid, I. M. Mahdi, S. Y. Aboul Haggag, and I. Abdel Rashid, "Artificial intelligence for developing accurate preliminary cost estimates for composite flooring systems of multi-storey buildings," *J. Asian Archit. Build. Eng.*, vol. 21, pp. 120–132, Jan. 2022.

[22] Y. Zeng, D. Zhao, F. Zhao, G. Shen, Y. Dong, E. Lu, Q. Zhang, Y. Sun, Q. Liang, Y. Zhao, Z. Zhao, H. Fang, Y. Wang, Y. Li, X. Liu, C. Du, Q. Kong, Z. Ruan, and W. Bi, "BrainCog: A spiking neural network based, brain-inspired cognitive intelligence engine for brain-inspired AI and brain simulation," *Patterns (N. Y.)*, vol. 4, p. 100789, Aug. 2023.

[23] H. Chen, Z. Chai, O. Dogru, B. Jiang, and B. Huang, "Data-driven designs of fault detection systems via neural network-aided learning," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, pp. 5694–5705, Oct. 2022.

[24] P. Li, Q. Liu, and Z. Liu, "Outer-synchronization criterions for asymmetric recurrent time-varying neural networks described by differential-algebraic system via data-sampling principles," *Front. Comput. Neurosci.*, vol. 16, p. 1029235, Nov. 2022.

[25] A. Hamadani and N. A. Ganai, "Artificial intelligence algorithm comparison and ranking for weight prediction in sheep," *Sci. Rep.*, vol. 13, p. 13242, Aug. 2023.

[26] J. Naskath, G. Sivakamasundari, and A. A. S. Begum, "A study on different deep learning algorithms used in deep neural nets: MLP SOM and DBN," *Wirel. Pers. Commun.*, vol. 128, no. 4, pp. 2913–2936, 2023.

[27] D. D. Giri and Assistant professor, Dentistry department, NRSMCH, "Artificial intelligence - future trend in oral diagnosis and radiology," *ijcsrr*, vol. 05, Sept. 2022.

[28] E. Karypidis, S. G. Mouslech, K. Skoulariki, and A. Gazis, "Comparison analysis of traditional machine learning and deep learning techniques for data and image classification," *WSEAS Trans. Math.*, vol. 21, pp. 122–130, Mar. 2022.

[29] R. Lippmann, "Understanding and applying deep learning," *Neural Comput.*, vol. 35, pp. 287–308, Feb. 2023.

[30] L. Scabini, K. M. Zielinski, L. C. Ribas, W. N. Gonçalves, B. De Baets, and O. M. Bruno, "RADAM: Texture recognition through randomized aggregated encoding of deep activation maps," *Pattern Recognit.*, vol. 143, p. 109802, Nov. 2023.

[31] Z. Li, J. Yoon, R. Zhang, F. Rajabipour, W. V. Srubar, III, I. Dabo, and A. Radlińska, "Machine learning in concrete science: applications, challenges, and best practices," *Npj Comput. Mater.*, vol. 8, June 2022.

[32] Y. Liu and J. K. W. Yeoh, "Automated crack pattern recognition from images for condition assessment of concrete structures," *Autom. Constr.*, vol. 128, p. 103765, Aug. 2021.

[33] T.-T. Le, V.-H. Nguyen, and M. V. Le, "Development of deep learning model for the recognition of cracks on concrete surfaces," *Appl. Comput. Intell. Soft Comput.*, vol. 2021, pp. 1–10, Mar. 2021.

[34] T. Udaya Banu, N. P. Rajamane, P. O. Awoyera, and R. Gobinath, "Strength characterisation of self cured concrete using AI tools," *Mater. Today*, vol. 39, pp. 839–848, 2021.

[35] N.-J. Wu, "Predicting the compressive strength of concrete using an RBF-ANN model," *Appl. Sci. (Basel)*, vol. 11, p. 6382, July 2021.

[36] T. T. Nguyen, H. Pham Duy, T. Pham Thanh, and H. H. Vu, "Compressive strength evaluation of fiber-reinforced high-strength self-compacting concrete with artificial intelligence," *Adv. Civ. Eng.*, vol. 2020, pp. 1–12, Jan. 2020.

[37] H.-C. Dan, G.-W. Bai, and Z.-H. Zhu, "Application of deep learning-based image recognition technology to asphalt–aggregate mixtures: Methodology," *Constr. Build. Mater.*, vol. 297, p. 123770, Aug. 2021.

[38] H. Yang, S.-J. Jiao, and F.-D. Yin, "Multilabel image classification based fresh concrete mix proportion monitoring using improved convolutional neural network," *Sensors (Basel)*, vol. 20, p. 4638, Aug. 2020.

[39] H. N. Muliauwan, D. Prayogo, G. Gaby, and K. Harsono, "Prediction of concrete compressive strength using artificial intelligence methods," *J. Phys. Conf. Ser.*, vol. 1625, p. 012018, Sept. 2020.

[40] G. Gasim, R. Rusbandi, and R. Teguh, "Identifikasi kadar campuran material pada beton keras melalui citra menggunakan jaringan saraf tiruan propagasi balik dengan fitur LBP," *JATISI (Jurnal Teknik Informatika dan Sistem Informasi)*, vol. 9, pp. 3293–3309, Dec. 2022.

[41] C. Devkar and D. S. Sharma, "A study on aspect of artificial neural networks for machine learning," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 270–274, Mar. 2023.

[42] M. D. Sadanand and D. S. Bhosale, "Basic of artificial neural network," *International Journal of Advanced Research in Science, Communication and Technology*, pp. 299–303, Jan. 2023.

[43] M. Thorat, S. Pandit, and S. Balote, "Artificial neural network: A brief study," *Asian Journal of Convergence in Technology*, vol. 8, Dec. 2022.

[44] M. Pervaiz and A. Jalal, “Artificial neural network for human object interaction system over aerial images,” in *2023 4th International Conference on Advancements in Computational Sciences (ICACS)*, IEEE, Feb. 2023.

[45] D. Florek and M. Miłosz, “Comparison of an effectiveness of artificial neural networks for various activation functions,” *J. Comput. Sci. Inst.*, vol. 26, pp. 7–12, Mar. 2023.

[46] A. Venugopal and A. K. Kapil, “Comparative analysis of convolutional and long term short memory architectures in machine learning,” in *Lecture Notes in Networks and Systems*, Lecture notes in networks and systems, pp. 43–51, Singapore: Springer Nature Singapore, 2023.