Committee Report: JCI- TC232A

Technical Committee on Construction of Literature Database and AI Application in Concrete Engineering

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Abstract

This technical committee evaluated methods for database development and utilization to foster the application of AI and machine learning technologies in concrete engineering. The committee discussed applicability through examples of regression analysis and image recognition via machine learning. Moreover, it examined publicly available experimental data and organized results reported in the Proceedings of the Japan Concrete Institute. Subsequently, these data were integrated into a comprehensive database infrastructure, and a regression model was constructed based on them. In this paper, we present results, highlight potential and challenges of AI technology, and outline future database and model development required for sustainable social infrastructure.

Keywords: Database, machine learning, deep learning, image recognition, prediction, regression analysis

1. Introduction

Social conditions, such as the transition to a low-carbon society and a declining birthrate, are driving the demand for advanced and efficient design and maintenance of concrete structures. These technologies enable efficient analysis of diverse image and numerical data to support advanced, precise prediction, recognition, and decision-making capabilities that conventional methods fail to achieve, and they offer significant potential in concrete engineering. However, challenges persist in organizing and utilizing big data because of the varied characteristics and behavior of concrete structures.

Consequently, this technical committee was established to lay the foundation for effective AI and machine learning employment and to advance their practical application in concrete engineering. Specifically, the committee intended to systematically collect and organize experimental and structural data presented at domestic and international academic conferences, including those organized by Japan Concrete Institute (JCI), and to centralize the data and develop a database platform for big data use. The committee also planned to examine methods for applying AI and machine learning using the database, to outline procedures for constructing predictive models and regression equations, and provide examples of data analysis.

Table 1: Committee Members

Chairperson	Shinichiro Okazaki	Kagawa University
Vice Chairperson	Shingo Asamoto	Saitama University
Secretary	Naoshi Ueda	Kansai University
	Takuma Kadono	Anan National College of Technology
	Mao Kuratani	Ibaraki University
	Masayuki Tsukagoshi	Fukuoka University
Members	Go Igarashi	Nagoya University
	Takasuke Saito	Hokkaido Research Organization
	Mari Kobayashi	UBE Mitsubishi Cement
	Yutaka Tanaka	Port and Airport Research Institute (PARI)
	Ji DANG	Saitama University
	Nobuhiko Nishimura	Oriental Shiraishi Corporation
	Naose Mishima	National Institute for Land and Infrastructure Management (NILIM)
Advisor	Kei-ichi Imamoto	Tokyo University of Science

For the database, the committee focused on time-dependent changes and performance parameters for designing, maintaining, and managing concrete structures, such as shrinkage, creep, carbonation depth, chloride ion diffusion coefficients, and structural performance (e.g., shear strength). The committee subsequently collected and organized data for each parameter. The committee distributed its data collection methodology to support evolving predictions and judgments, shifting from empirical approaches to data-driven ones. It introduced examples of AI-and machine-learning-based predictive and recognition models, as well as regression analyses employing these data, clarifying effectiveness and scope to provide insights into practical utility and future developments.

The data and case study presentations were organized into three working groups: the Materials Database Utilization WG, Structural Database Utilization WG, and Diagnostic Imaging Database Utilization WG. Discussions occurred at the committee level rather than within individual WGs to maximize idea exchange among members.

This report introduces analytical examples and database utilization methods explored by committee members. Moreover, it covers committee discussions, offering an overview of existing free databases, organization methods, and the status of digitized experimental databases, and analytical examples employing these resources.

2. AI Analysis Examples

2.1 Analysis of Shrinkage Experiment Databases[1)]

This section demonstrates an example employing aggregate data—such as mix proportions and rock type—combined with machine learning to build a regression model for concrete drying shrinkage.

The data were collected by the Japan Ready-Mixed Concrete Industry Association (ZENNAMA) between 2008 and 2012 (e.g., 2)). Detailed drying shrinkage data measured at six months (182 days) after demolding from 100 mm × 10 mm × 400 mm rectangular column specimens in accordance with JIS A 1129 standard were systematically collected alongside material conditions, including mix proportions, constituent materials, and other characteristics. The aggregates comprised sandstone, hard sandstone, and limestone. This study specifically covered 1,918 samples using sandstone, hard sandstone, or limestone as both fine and coarse aggregates. The results comprised 658 samples with sandstone, 254 with hard sandstone, and 815 with limestone as coarse aggregate, while 191 samples contained mixtures of two or more rock types. Notably, over 95% of fine aggregate samples consisted of sandstone. **Figure 1** depicts the frequency distribution of drying shrinkage data.

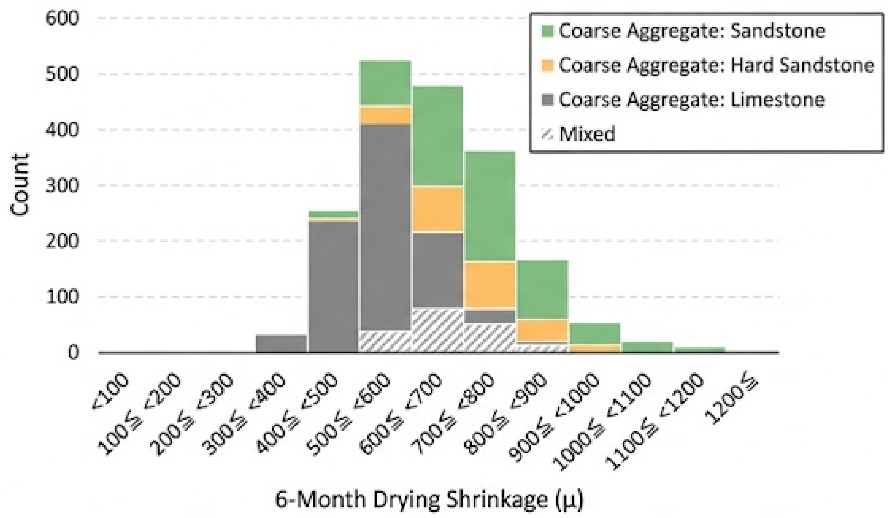

Figure 1: Frequency distribution of 6-month drying shrinkage data 1)

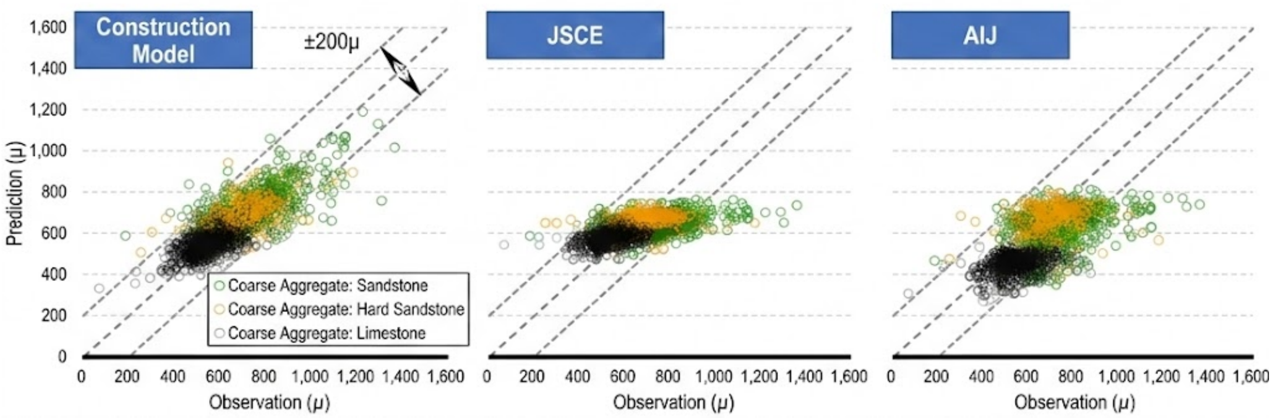

Figure 2: Comparison of measured and predicted values between the developed machine learning model and existing empirical formulas.

The analysis incorporated the unit water content W, water–cement ratio W/C, and the bone-dry densities D_s and D_g of fine and coarse aggregates, related to aggregate stiffness. Parameters associated with the aggregates' own drying shrinkage included the water content Δw and the average specific surface area S. Furthermore, a Gaussian process regression (GPR) algorithm was applied, and its performance was evaluated via five-fold cross-validation.

Figure 2 compares measured and predicted values for the developed model, the Japan Society of Civil Engineers (JSCE) Standard Specifications, and the Architectural Institute of Japan evaluation equation. The constructed model demonstrated increasing predicted values alongside rising measured values, while the error remained within ±200 μ.

2.2 Bridge Damage Recognition Using YOLO and Generative AI

For instance, image-generation technology using generative AI was incorporated into a deep learning model[3)] that automatically recognizes various damage types during bridge inspections via the YOLO11 object detection method. To enhance the damage detection model's accuracy, the committee augmented the dataset with a diffusion model that emulated real-world data distribution and generated diverse, high-quality images.

Underlying image data originated from bridge inspection reports. The dataset comprised five damage types—corrosion, cracks, free lime, water leakage, and spalling—with **Table 2** presenting the image count for each category. The resulting model, designated Case 1, served as the benchmark for damage detection accuracy.

Table 2: Number of images

Defect	*Training*	*Validation*	*Test*
Corrosion	659	82	82
Crack	803	100	100
Free Lime	492	62	62
Water Leakage	438	55	55
Spalling	612	77	77

The committee applied low-rank adaptation (LoRA) to the diffusion model[4)], introducing a low-rank auxiliary matrix while preserving the large-scale generative model's base weights to permit local parameter updates. Moreover, the committee improved controllability in the generation process by integrating caption management to characterize image shape and texture, thus ensuring content diversity. Simultaneously, the committee appended textual information to the generated images to facilitate more precise learning of the features and meanings within them. **Figure 3** presents five types of AI-generated damage images.

The committee used these images to build and test models in four cases. In Case 2, the model from Case 1 was fine-tuned with generated images to improve its generalization performance. In Case 3, a model constructed solely from generated images was subsequently fine-tuned with real images from bridge inspection reports, thus verifying whether accuracy could be maintained with generated images alone and confirming the benefit of additional training with real images.

Figure 3: Examples of generated images

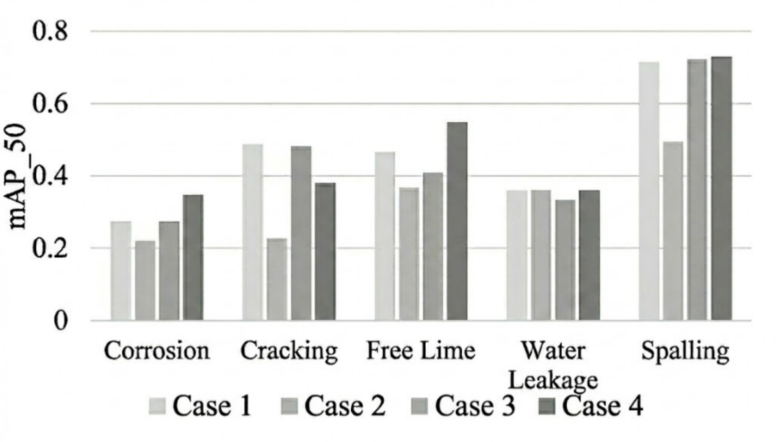

Figure 4: Comparison of mAP_50 by damage type for the test results

In Case 4, a model was built using a dataset that combined real and generated images in a 1:1 ratio to mitigate data imbalances. **Figure 4** summarizes the mean average precision at IoU = 0.50 (mAP_50) for each damage type across these cases. Compared to Case 1, which used only real images, Case 2—relying solely on generated data—demonstrated reduced damage recognition accuracy. Conversely, Cases 3 and 4, which integrated both generated and real data, produced improved detection accuracy, illustrating the efficacy of using generated images.

3. Existing Database Survey

3.1 Compressive Strength Database

The University of California Center for Machine Learning and Intelligent Systems offers free concrete compressive strength data[5]. This dataset comprises unit quantities of eight variables influencing compressive strength (cement, blast furnace slag powder, fly ash, water, fine aggregate, coarse aggregate, and high-performance air-entraining (AE) water-reducing agent) and material age, and includes 1,030 data points. The predominant strength range is 30–40 MPa, with a maximum strength of 82.6 MPa and a minimum strength of 2.3 MPa. The dataset was employed in developing a neural network–based compressive strength prediction model and remains applicable for regression analysis using a machine learning algorithm (**Figure 5**, committee review results), and the committee confirmed that this dataset can serve as basic data for material mix design and quality control.

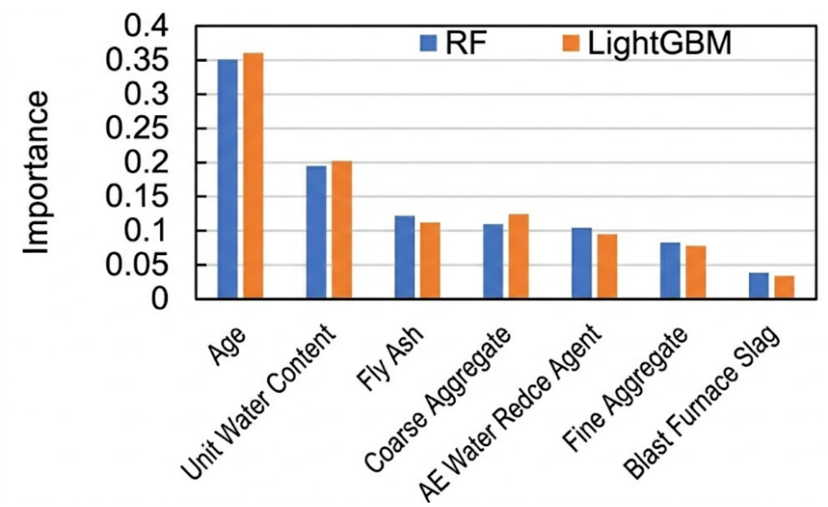

Figure 5: Feature importance analysis of various parameters for compressive strength using Random Forest and LightGBM

3.2 Shrinkage and Creep Database

Professor Bazant et al. at Northwestern University compiled data from 1,869 shrinkage experiments and 1,439 creep experiments on concrete from various regions worldwide, and made it available free of charge as a database[6]. Although long-term data or data on large-scale specimens remain limited, the experimental data typically provide the minimum information required for design prediction equations, including W/C, unit water content (or unit cement content), volumesurface area ratio, age at the start of drying (or loading), relative humidity, and temperature. Information on the countries and years in which the experiments were conducted, including Japan, is readily available, thus permitting examination of regional characteristics and the influence of material properties over time. Several studies have been published using this database, such as one comparing the JSCE Standard Specifications for Concrete prediction equations with those derived from machine learning, and another analyzing the significance of various experimental parameters[7)].

4. Database Constructed by Technical Committee

4.1 Chloride Ion Data

The committee compiled 947 data points for apparent diffusion coefficients and 470 for effective diffusion coefficients from 66 contributions in the Proceedings of the Japan Concrete Institute (JCI) between 1979 and 2023; these data derive from laboratory tests on chloride ion diffusion coefficients. The explanatory variables for quantitative analysis included the water–binder ratio (W/C), air content (%), slump value (cm), unit water content, unit total binder content, and unit binder content (cement, blast furnace slag powder, gypsum, silica fume, shirasu, limestone powder); unit total fine aggregate content and its constituents (gravel, blast furnace slag fine aggregate, waste tile fine aggregate, zinc slag, waste dissolved slag, etc.); unit total coarse aggregate content and its constituents (stone, waste tile coarse aggregate, etc.); unit admixture content (high-performance AE water-reducing agent, AE agent, AE water-reducing agent, air-content adjuster, expanding agent, rust inhibitor, thickener, etc., all in kg/m^3); compressive strength (N/mm^2); age at test initiation; and measurement period (days). Qualitative variables include cement type (normal, early-strength, moderate-heat, low-heat, blast-furnace cement, fly ash cement, silica cement, moderate-heat Portland cement, ternary system, ecocement), curing conditions (water curing, air curing, sealed curing, etc.), and measurement method (electrophoresis, immersion, immersion (wet–dry cycle)). The data concerning these variables were used to conduct various analyses supporting the findings of the committee.

4.2 Shrinkage and Carbonation Data

Experimental numerical data on drying shrinkage, autogenous shrinkage, and carbonation published in the Proceedings of the JCI were entered into a spreadsheet by the committee. The committee queried the Proceedings using the keywords “drying shrinkage,” “autogenous shrinkage," and "carbonation," then compiled each experiment's results in chronological order, prioritizing studies that provided mix proportion details. The recorded data included paper title, author, publication year, and mix proportions: water (kg/m^3), cement (kg/m^3), cement type, cement blaine (cm^2/g), fly ash (kg/m^3), fly ash blaine (cm^2/g), slag (kg/m^3), slag blaine (cm^2/g), silica fume (kg/m^3), silica fume blaine (cm^2/g), calcium carbonate powder (kg/m^3), carbon blaine (cm^2/g), fine aggregate type, fine aggregate (kg/m^3), fine aggregate density (g/cm^3), fine aggregate water absorption (%), coarse aggregate type, coarse aggregate (kg/m^3), coarse aggregate density (g/cm^3), coarse aggregate water absorption (%), and curing method. Additional data included age at drying onset, drying temperature (°C), drying humidity (%), drying duration (days), and shrinkage strain for drying shrinkage; test temperature (°C), age (days), and shrinkage strain for autogenous shrinkage; and age at carbonation onset, carbonation temperature (°C), carbonation humidity (%), CO_2 concentration (%), carbonation duration (days), and carbonation depth (mm).

The database includes 30 papers on drying shrinkage, 18 on autogenous shrinkage, and 16 on carbonation. Experimental series, differentiated by mix proportion, temperature, humidity, and CO_2 concentration, comprise 239 types for drying shrinkage, 229 for autogenous shrinkage, and 130 for carbonation. The collected time-series plots numbered 5,205 for drying shrinkage, 6,463 for autogenous shrinkage, and 4,058 for carbonation.

This database will serve as the basis for subsequent analyses and findings; the committee plans to make the digitized database publicly available.

4.3 Structural-Related Data

As part of its activities, the committee examined experimental and analytical data in structural-related papers published in the Proceedings of the JCI. Although many of these papers provided characteristic data on high-strength and fiber-reinforced concrete, few presented basic data on ordinary concrete. Consequently, the committee focused on shear fracture strength results for rod members without shear reinforcement, as reported in 8). Subsequently, the committee organized and digitized experimental results, particularly those published overseas. The digitized information included the paper title, author, publication year, as well as the maximum load during the experiment (N); width, effective height, and height of the reinforced concrete (RC) member cross section (mm); shear span and span of the RC member (mm); shear span ratio; cross-sectional area of the tensile rebar (mm^2); tensile rebar ratio; compressive strength of the concrete (N/mm^2); and yield stress of the tensile rebar (N/mm^2). The database comprised experimental data from 205 simple beam-type specimens, and the committee planned to analyze these data as part of its findings.

4.4 Image Data

Image data concerning concrete engineering primarily depicted cracks and fractures in structures, which were collected and stored independently by each committee member or their respective organization. In civil engineering, images for research purposes are publicly available on the website listed in Reference 3. In contrast, building data include residential buildings owned by individuals and corporations; privacy concerns render publication or sharing of such images challenging, thereby complicating efforts by architectural researchers to develop models for assessing building collapse. Transfer learning using images already publicly available in the civil engineering field will be necessary. Overall, these data and images provide a comprehensive resource for analyzing RC beam behavior, collapse assessment, and the development of analytical models.

5. Analysis Example Based on the Constructed Database

5.1 Analysis Based on the Chloride Ion Database

The committee utilized the database presented in Section 4.1 as training data to develop a machine learning model for regressing the chloride ion diffusion coefficient. The target variable was the apparent diffusion coefficient of chloride ions, and the explanatory variables comprised those listed in Section 4.1.

Random Forest and XGBoost were employed, with Random Forest validated by out-of-bag error (OOB) and XGBoost via five-fold cross-validation. Training data with missing values were removed, and apparent diffusion coefficients identified as outliers were similarly excluded.

Figures 6 and **7** present the top ten parameter importance analyses of the explanatory variables determined by Random Forest and XGBoost; no differences in parameter significance or ranking were observed between algorithms. Moreover, the measurement period was selected based on the influence of factors such as mixed cement type, water–binder ratio, and unit material amount, a trend that the committee confirmed as consistent with previous findings.

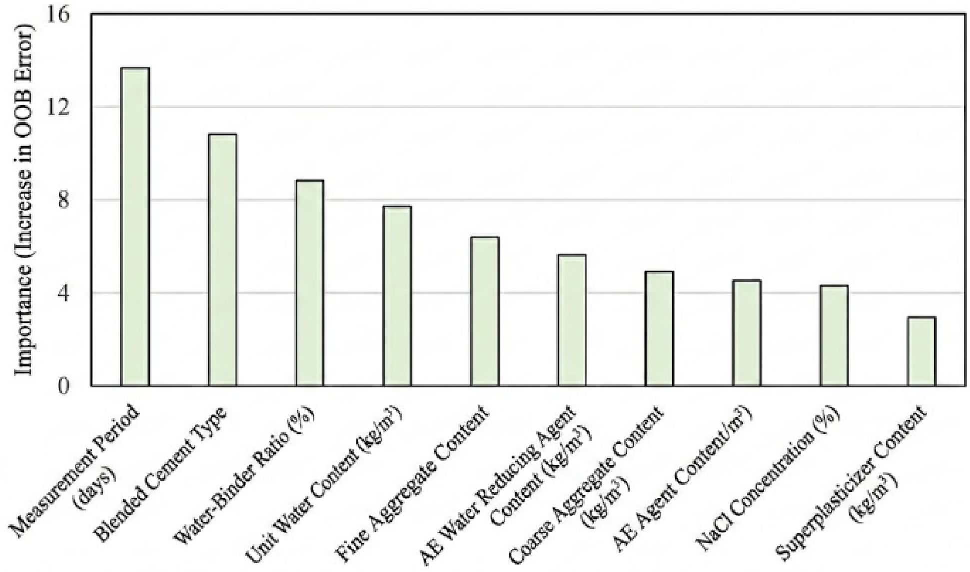

Figure 6: Feature importance analysis using Random Forest

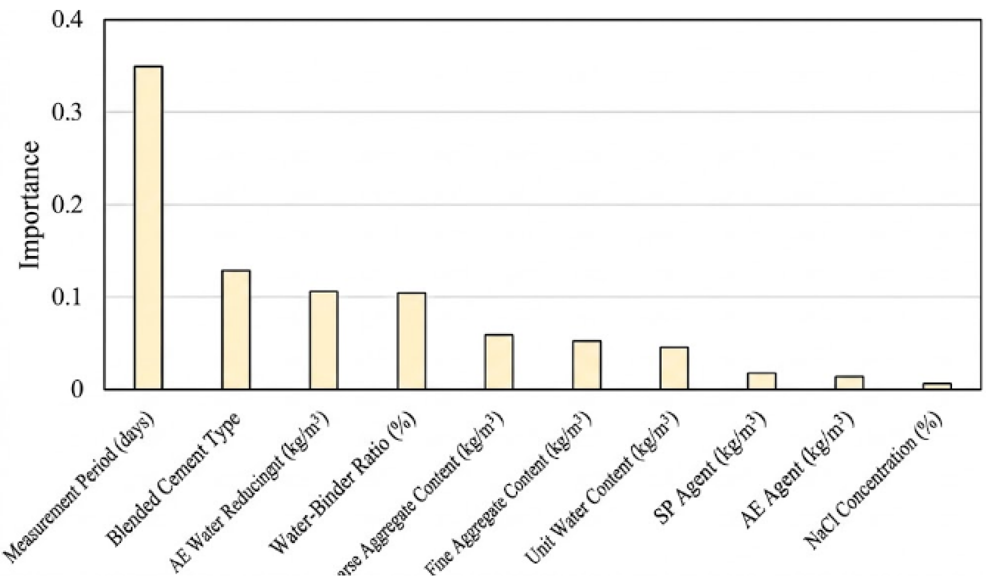

Figure 7: Feature importance analysis using XGBoost

Figures 8 and **9** depict the relationship between predicted values (calculated using the explanatory variables from the training data) and the actual measured values. Both methods exhibited robust regression performance, yet XGBoost demonstrated markedly higher accuracy than Random Forest. Notably, the training data were also used to verify the model's accuracy; this does not reflect performance on unseen data. Various validation methods suitable for the algorithm have been proposed to assess model performance, and each developed model must be verified using an appropriate method for its intended purpose.

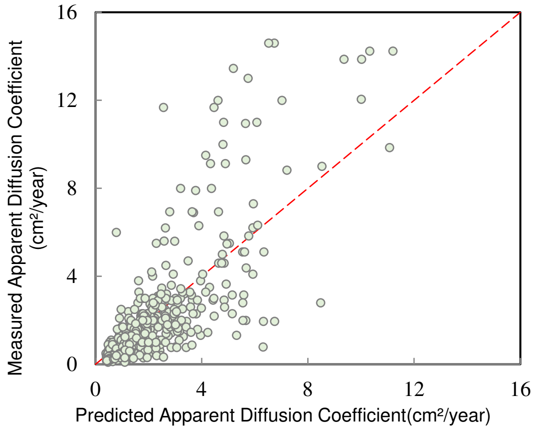

Figure 8: Prediction results by Random Forest

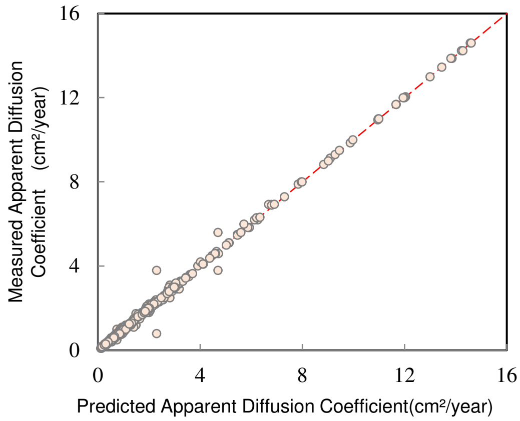

Figure 9: Prediction results by XGBoost

5.2 Analysis Based on a Database of Shear Strength

The committee employed the database organized in Section 4.3 as training data to develop a machine learning model regressing the maximum experimental load of a simple beam without shear reinforcement. In this instance, the committee examined a regression model using Random Forest, designating the maximum experimental load as the objective variable and the explanatory variables as the RC member cross-section width, the RC member effective height, the RC member shear span ratio, the cross-sectional area of the tensile rebar, the tensile rebar ratio, the compressive strength of the concrete, and the yield stress of the tensile rebar. The hyperparameters determining the performance of the regression model were optimized using three-fold cross-validation.

Figure 10 presents the results of the importance analysis of various explanatory variables. The results indicated that the shear span ratio and effective height of the RC beam exerted the greatest influence on predicting the maximum test load. **Figure 11** depicts the relationship between predicted and measured test loads derived from a Random Forest model. Predicted values, computed from training variables, were compared with measured values. The figure shows agreement between predicted and measured values at lower loads, whereas predicted values regressed below measured ones above 300 kN.

Because shear span ratio and effective height remain pivotal in the current shear strength equation, these results suggest their significance in a Random Forest–based model. These findings confirm the potential of machine learning to calculate the shear strength of rod members without shear reinforcement.

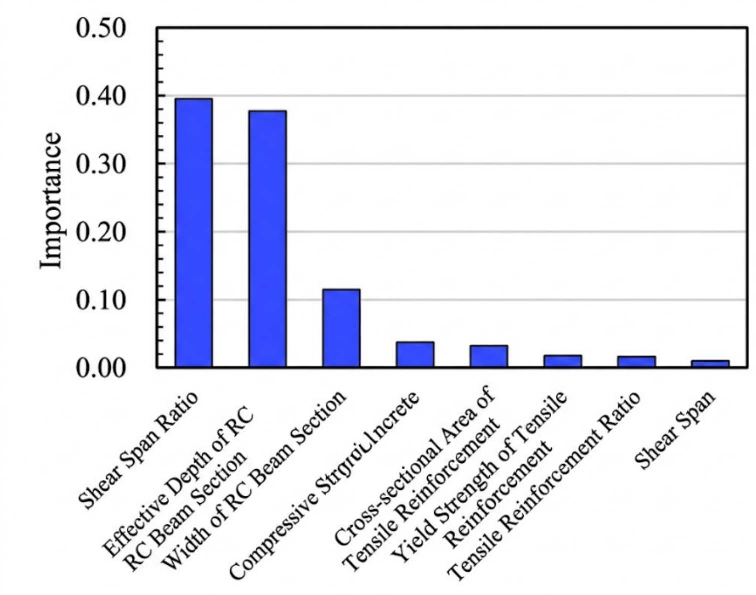

Figure 10: Feature importance analysis results at maximum load

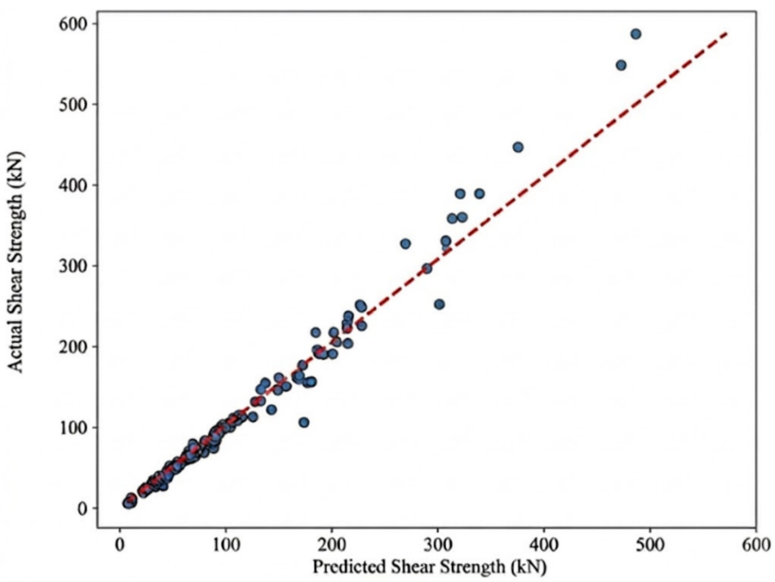

Figure 11: Relationship between experimental and predicted values of maximum load

6. Conclusions

Moreover, the technical committee evaluated big data infrastructure to facilitate AI and machine learning in concrete engineering. It also analyzed publicly available experimental data and Proceedings of the JCI data to establish a database for predictive analyses.

Recent studies have primarily focused on the mechanical properties of concrete, including conventional cementitious materials, concrete with recycled glass powder[9)], and on predicting the compressive strength of concrete containing recycled tires and recycled brick powder[10)]. The authors anticipate further publications on durability-related properties. In Japan, numerous annual reports examine concrete incorporating novel materials, and efficient advancement of new material development requires compiling experimental data into a database for dissemination among researchers.

The authors expect that the outcomes of this technical committee will promote integration of AI and machine learning technologies and contribute to more advanced design and maintenance systems for concrete structures.

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