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Using Support Vector Machine to Predict the Uniaxial Compressive Strength for Lightweight Concrete

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Abstract: This study utilizes a support vector machine (SVM) supervised learning algorithm to predict the uniaxial compressive strength (UCS) of lightweight concrete (LWC). Implemented in Python 3, the model leverages a dataset of 120 samples of LWC, which was divided into training and testing sets in a 70%-30% split. Key performance indicators, including mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE), were assessed for both sets. A confusion matrix was also generated to evaluate the classification accuracy. The predictive modeling results show that the SVM algorithm achieved an accuracy of 83.63% and a precision of 85.11% in predicting the UCS of LWC samples. The calculated error metrics were promising, with MAE, MSE, and RMSE values at 0.346, 0.329, and 0.331, respectively. These findings suggest that the SVM model is capable of accurately predicting UCS for lightweight concrete, demonstrating its potential for application in concrete strength assessment. As results, the SVM model offers an efficient predictive approach for estimating UCS in lightweight concrete, providing valuable insights for material testing and construction planning. This work highlights the utility of machine learning in advancing accuracy and reliability in civil engineering materials science.

Keywords: Machine learning, SVM, Concrete, Strength prediction, Uniaxial compression, Prediction.

I. INTRODUCTION

After water, concrete is the second most widely used material on Earth (Nafees et al., 2021). It's remarkable binding properties enable it to support large structures, which has led to an ever-increasing demand. Due to its numerous advantages, the global consumption of concrete has reached an astonishing 30 billion tons per year (Alqahtani, 2021). Concrete is a composite material made up of coarse aggregates (such as crushed stone, loose rocks, gravel, asphalt, and construction waste) and fine aggregates (such as sand and gravel), which are bound together by cement and harden over time (Kumar et al., 2022). Various types of concrete are produced by these companies, including high-strength concrete (HSC), normal-strength concrete (NSC), prestressed concrete, air-entrained concrete (AEC), high-performance concrete (HPC), rapid-strength concrete (RSC), self-consolidating concrete (SCC), polymer-modified concrete (PMC), lightweight density concrete (LDC), and lightweight concrete (Bogas et al., 2013). These classifications are in line with the standards set by the American Concrete Institute, ACI (ACI PRC-213-14, 2014).

Lightweight concrete (LWC) was first used in several construction projects in the United States in the early 1900s, and its development continues to this day. Typically, the density of aggregates used for lightweight concrete ranges between 320 to 1920 kg/m^2 (Karimaei et al., 2020). The LWC is produced using lightweight aggregates, which play a crucial role in the construction industry, particularly for high-rise buildings. Currently, LWC is made using natural materials such as clay, pumice, shale, diatomite, and volcanic ash (Amiri et al., 2022; Dabbaghi et al., 2022).

The LWC is designed to be lighter than traditional concrete, making it ideal for various construction applications, especially in high-rise buildings (Lin et al., 2006). Its reduced density contributes to lower structural loads, improving energy efficiency and reducing costs in transportation and handling (Ramadoss & Nagamani, 2012). LWC maintains sufficient strength and durability for construction purposes while being easier to work with. The production process of lightweight concrete involves placing lightweight aggregates within a frame and then filling the remaining voids with cement slurry. This casting process results in the lowest density of lightweight concrete, which consequently has lower compressive strength. LWC is produced by mixing fine aluminum powder into the slurry, where it reacts with calcium hydroxide to generate hydrogen gas. This hydrogen gas, when introduced into the slurry mix, creates a cellular structure, making the concrete lighter than conventional concrete (Yuzer et al., 2011; Aslam et al., 2016). LWC can be categorized as autoclaved cellular concrete (ACC), autoclaved concrete, cellular concrete, porous concrete, Aircrete, Thermalite, Hebel Block, Aercon, Starken, Gasbeton, Airbeton, Siporex, and Ytong, each with its unique specifications (Tabsh, 2006).

Generally, LWC is a sustainable alternative for constructing energy-efficient buildings, thanks to its thermal insulation properties and cost-effective structures. The reduced dead loads ultimately lessen the design requirements for structural members, which contributes to decreased cross-sectional dimensions and reinforcing needs (Wei et al., 2020). Due to its lighter weight, the cross-sections of structural elements are also minimized, leading to reduced cement usage—a major contributor to greenhouse gas emissions—along with decreased demand for natural aggregates (Jung & Yang, 2022). Furthermore, various waste materials are repurposed as lightweight aggregates, including shredded tires, electric arc furnace slag, fly ash, and more (Faleschini et al., 2016; Kumar et al., 2017). Artificial LWC aggregates are also produced using locally sourced clays and fly ash, providing an alternative to natural aggregates and helping to reduce the consumption of natural resources (Sarabèr et al., 2012; Cahyono et al., 2019).

Unconfined compressive strength (UCS) is an essential factor for evaluating the performance and durability of LWC. It measures how much axial load the material can bear without any lateral support, giving insights into its overall structural integrity (Zhu et al., 2022). UCS is particularly important for determining whether LWC is suitable for various construction applications, especially in load-bearing components such as beams, columns, and walls (Zhang et al., 2022). Several elements influence the strength of LWC, including the type of aggregates, the water-cement ratio, and the curing conditions during the hardening process. Higher UCS values indicate a stronger material capable of supporting greater loads, resisting deformation, and maintaining stability over time (Zhang et al., 2020). As a result, UCS is a key factor in the design and construction of buildings and other infrastructures (Zhu et al., 2022). Estimating UCS accurately for LWC is crucial for several reasons. First, precise predictions ensure that the material meets strength requirements, thereby preventing potential structural failures due to underestimating its load-bearing capacity. Second, accurate UCS evaluations enable engineers to optimize the use of materials, which helps reduce waste and overall costs while still adhering to safety and performance standards (Zhang et al., 2020). Additionally, as construction projects become more complex, reliable UCS estimations assist in making better design decisions that enhance the longevity and durability of structures (Zhu et al., 2022).

One specific area where machine learning as branch of artificial intelligence is useful is in predicting the UCS of LWC, which is essential for evaluating the performance and durability of concrete structures. In the meantime, there were various algorithms that used in the prediction which are used with professional worldwide. Support Vector Machines (SVM) is a robust supervised learning algorithm used primarily for classification and regression tasks (Abdullah & Abdulazeez, 2021). It works by identifying the best hyperplane that separates different classes in the data while maximizing the margin between them. In the context of predicting UCS in lightweight concrete, SVM is particularly effective at managing non-linear relationships and high-dimensional data. This makes it well-suited to capture the complex interactions among various input parameters. By training the SVM model on historical data, it can learn patterns and relationships, enabling it to provide accurate predictions for new datasets (Gowida et al., 2021).

The use of machine learning, specifically SVM, in predicting the UCS of LWC opens up exciting possibilities for the construction industry. By employing advanced predictive modeling techniques, engineers and architects can make better-informed decisions about material selection and design, ultimately leading to safer and more efficient structures. Future research could focus on broadening the dataset to include a wider variety of LWC types and exploring the potential of ensemble methods or deep learning techniques to further enhance prediction accuracy. As the construction industry increasingly adopts innovative technologies, machine learning will be vital in optimizing construction practices and improving the performance of building materials. In this regard, this method was considered in this research to provide an accurate prediction of UCS value for LWC samples.

II. MATERIALS AND METHODS

The SVM is a supervised learning algorithm used primarily for classification and regression tasks. The core idea behind SVM is to find the best boundary, or hyperplane, that separates different classes in the dataset (Abdullah & Abdulazeez, 2021). The goal is to maximize the margin between the data points of different classes, ensuring that the classification is as accurate as possible. The hyperplane is essentially a decision boundary that helps classify new data points. In the case of non-linearly separable data, SVM uses a kernel trick to transform the data into a higher-dimensional space, making it easier to find a hyperplane that effectively separates the classes (Yue et al., 2003). The way SVM works is by focusing on the data points that are closest to the hyperplane—these are called support vectors. These support vectors are critical because they determine the position and orientation of the hyperplane (see Figure 1). By maximizing the margin, which is the distance between the hyperplane and the nearest support vectors, SVM reduces the risk of misclassifying data points, especially for unseen or future data. This approach makes SVM highly effective in achieving generalization and avoiding overfitting, even when working with complex and high-dimensional datasets (Sun et al., 2019). Another key feature of SVM is its flexibility in dealing with non-linear data. By using different types of kernel functions (such as polynomial or radial basis function kernels), SVM can map input data into higher-dimensional spaces, where a clear separation of classes becomes possible (Yue et al., 2003). This allows SVM to handle complex patterns in data that would be difficult for other linear classifiers to manage. Due to these principles, SVM is widely used in applications ranging from image recognition and bioinformatics to financial analysis, where accurate classification or regression is essential (Abdullah & Abdulazeez, 2021).

Using SVM to predict the UCS of LWC involves several steps: data collection, preprocessing, model training, and validation. First, relevant datasets that contain various factors affecting UCS such as aggregate type, water-cement ratio, and curing duration are gathered. Once the data is compiled, preprocessing steps like normalization and feature selection are critical to enhance the model's performance.

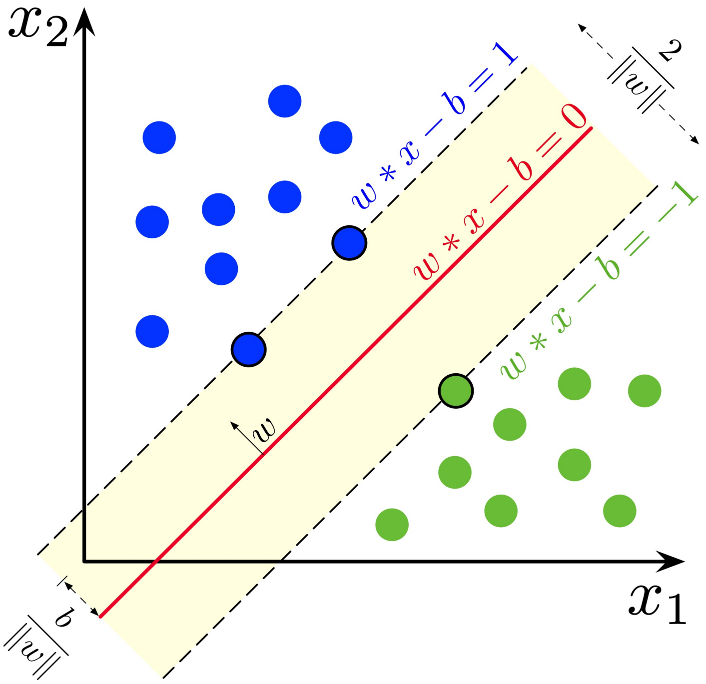

Fig. 1 A SVM classifier structure (after Yue et al., 2003)

After this, the SVM model is trained using a subset of the data, allowing it to learn the relationships between the input features and UCS. Finally, the model is validated on a different dataset to check its accuracy and reliability in predicting UCS. Figure 2, is provide the studied flowchart of process.

In this study, we utilized a dataset composed of 120 samples of LWC, specifically focusing on their UCS. Each sample in the dataset included various features that could potentially influence the UCS, such as material composition, density, and other physical properties. The diversity of these samples is critical, as it enables the model to learn a wide range of relationships between the input features and the target variable, UCS. To ensure robust model training and evaluation, the dataset was split into two distinct subsets: the training set, comprising 70% of the data (84 samples), and the testing set, consisting of the remaining 30% (36 samples). This division is essential in machine learning, as it allows us to train the model on one portion of the data while reserving another for testing its performance. This ensures that the model is not simply memorizing the training data but is capable of generalizing to new, unseen data.

The dataset consists of eight input variables and one output variable. The input variables include cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, and fine aggregate. The output variable is the UCS. The UCS was determined using the uniaxial compressive strength test, conducted in accordance with ASTM C39 standards. All cylinders were fabricated with ordinary Portland cement and cured under normal conditions. Table 1 presents the statistical values of the variables in the dataset. To analyze the interdependence of the data, correlation coefficients between the predictor variables (i.e., inputs) were calculated. This analysis is particularly important due to the significant influence of the range of the data variables. In this study, the water-to-binder ratio varied from 24% to 90%, which encompasses nearly all concrete mixes, except for those with ultra-high performance.

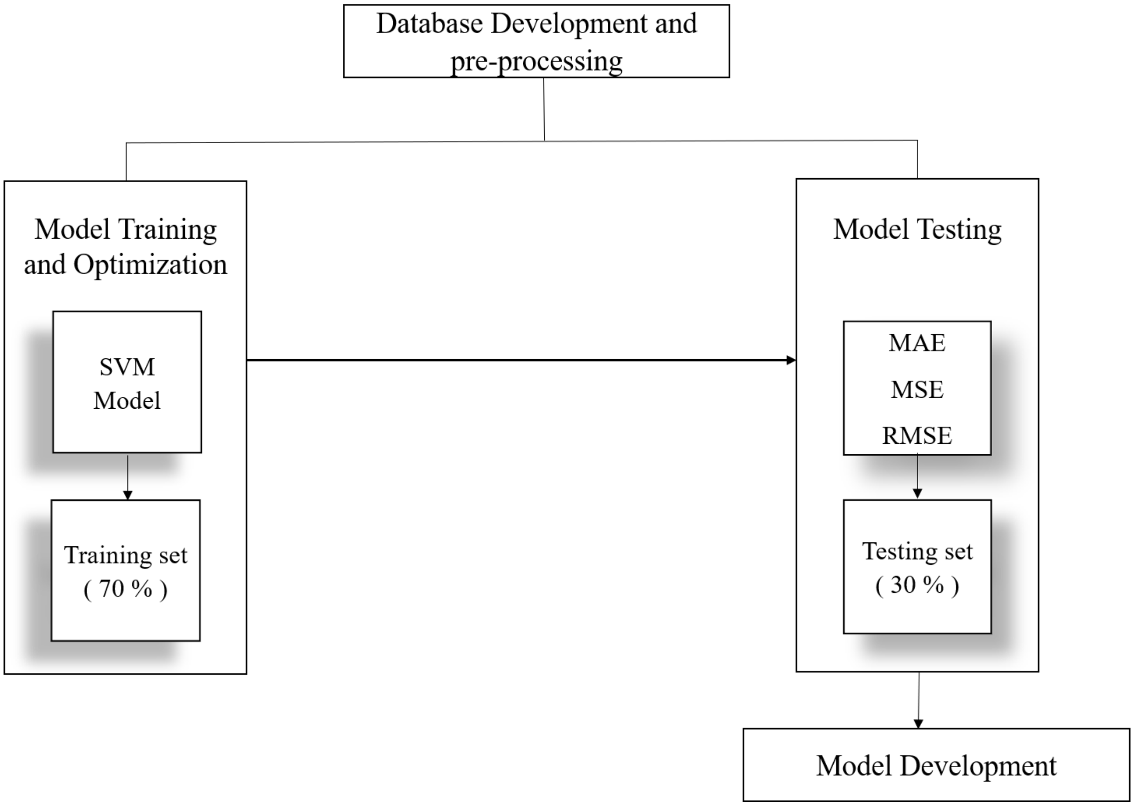

Fig. 2 Process flowchart of model implementation

Table 1 Statistical analysis for input-output variables in the dataset

Variable	Unit	Count	Max	Min	Mean	Std.
Cement	Kg/m^3	120	540	102	276.51	103.47
Blast furnace slag	Kg/m^3	120	395	0	74.27	82.25
Fly ash	Kg/m^3	120	260	0	62.81	71.58
Water	Kg/m^3	120	247	121.8	182.99	21.71
Superplasticizer	Kg/m^3	120	32.2	0	6.42	5.80
Coarse aggregate	Kg/m^3	120	1145	708	964.83	82.79
Fine aggregate	Kg/m^3	120	992	594	770.49	79.37
UCS	MPa	120	82.6	2.33	35.84	16.10

Note: Count represents the total number of samples, Max denotes the maximum value, Min indicates the minimum value, Mean is the average value, and Std. represents the standard deviation.

Before the actual model development, we conducted several preprocessing steps to enhance the quality of the dataset. This included normalization or standardization of the input features to ensure they are on a similar scale, which is particularly important for algorithms like SVM that are sensitive to the scale of the input data. Additionally, any missing or inconsistent values were addressed to prevent potential biases that could distort the model's predictions. The core of our methodology revolves around employing a SVM supervised learning algorithm for predicting the UCS of lightweight concrete. SVM is particularly well-suited for this task due to its ability to create a hyperplane that optimally separates different classes or, in our case, predicts continuous outcomes. Implementing the SVM model in Python (version 3), we leveraged its robust features for classification and regression tasks. A critical step in the model development process was selecting the appropriate kernel function. The choice of kernel whether linear, polynomial, or radial basis function (RBF); significantly impacts the model's performance. We performed initial experiments with different kernels to determine which one provided the best fit for our dataset. Additionally, hyperparameter tuning was carried out using techniques such as grid search, allowing us to identify the optimal values for parameters like the penalty parameter (C) and kernel parameters (gamma for RBF). This optimization step is crucial as it directly influences the model's predictive accuracy.

Once the optimal kernel and hyperparameters were selected, we proceeded to train the SVM model using the training set. During this phase, the SVM algorithm learned the relationship between the input features and the UCS values. By minimizing the prediction error during training, the model established a mapping from the feature space to the UCS, enabling it to make accurate predictions on unseen data. The training process is iterative and requires careful monitoring to ensure that the model is effectively learning without overfitting to the training data. After training the SVM model, we evaluated its performance using both the training and testing sets. A range of error metrics were calculated to quantify the model's predictive accuracy. The Mean Absolute Error (MAE) measures the average magnitude of errors in predictions, providing a straightforward interpretation of the average prediction error. Mean Squared Error (MSE), on the other hand, squares the differences between actual and predicted values, emphasizing larger errors, which is crucial for understanding the impact of outliers.

In addition to these metrics, we also calculated the Root Mean Squared Error (RMSE) which serves to express the error in the same units as the predicted UCS values, making it easier to interpret. The confusion matrix, though traditionally used in classification tasks, was adapted to provide insights into the model's performance in regression tasks by displaying the distribution of errors across different ranges of predicted values. This helps in understanding whether the model consistently underpredicts or overpredicts the UCS. Finally, we conducted a comparison of the performance metrics between the training and testing sets. This comparison is critical in assessing whether the model generalizes well to new data or if it suffers from overfitting, where it performs well on the training data but poorly on unseen data. By analyzing the results from the confusion matrix and the error metrics, we gained valuable insights into the model's strengths and weaknesses, allowing for further refinement and improvement in future iterations.

III. RESULTS AND DISCUSSION

This study explores the use of a SVM model to predict the 28-day UCS of LWC, focusing on how key input parameters affect strength. To assess these influences, a one-step modeling approach was chosen, implementing the SVM algorithm in Python to provide a robust prediction framework. By evaluating input parameters collectively, this study seeks to offer a simplified yet effective method for predicting UCS, contributing to advancements in concrete materials science. The research further investigates how the algorithm handles variations in data by examining both model accuracy and error metrics across training and testing phases. The data preparation phase involved organizing a dataset of 120 LWC samples. These samples were split into training and testing sets at a 70%-30% ratio, ensuring that 70% (84 samples) were used to train the model while the remaining 30% (36 samples) provided an unbiased testing ground. This split helps prevent overfitting, where the model might otherwise perform well on training data but poorly on new, unseen data. Data processing steps included removing outliers, normalizing input values, and setting up validation techniques to further refine model reliability.

The predictive capabilities of the SVM model were evaluated through various performance metrics. Key indicators such as MAE, MSE, and RMSE provided insights into the model's accuracy. Additionally, a confusion matrix was constructed to further validate classification accuracy, highlighting the model’s capacity to predict UCS values consistently. This validation process ensures that the SVM model is capable of translating raw input parameters into reliable UCS estimates for practical use in construction and materials testing. Results from the modeling show that the SVM achieved a predictive accuracy of 82.63% and a precision of 85.11% for UCS estimation. Error metrics were promising, with MAE, MSE, and RMSE values of 0.346, 0.329, and 0.331, respectively, indicating that the model can closely approximate actual UCS values. These results demonstrate the SVM's potential to act as a dependable predictive tool, especially valuable when laboratory measurements are limited or time-consuming.

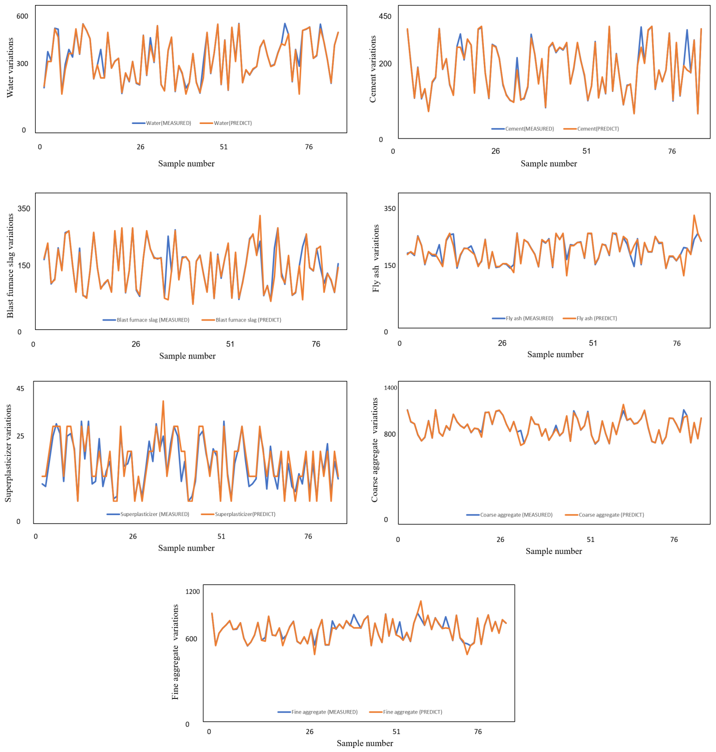

Fig. 3 Variation between predicted and measured values for input parameters in the training set, based on sample count

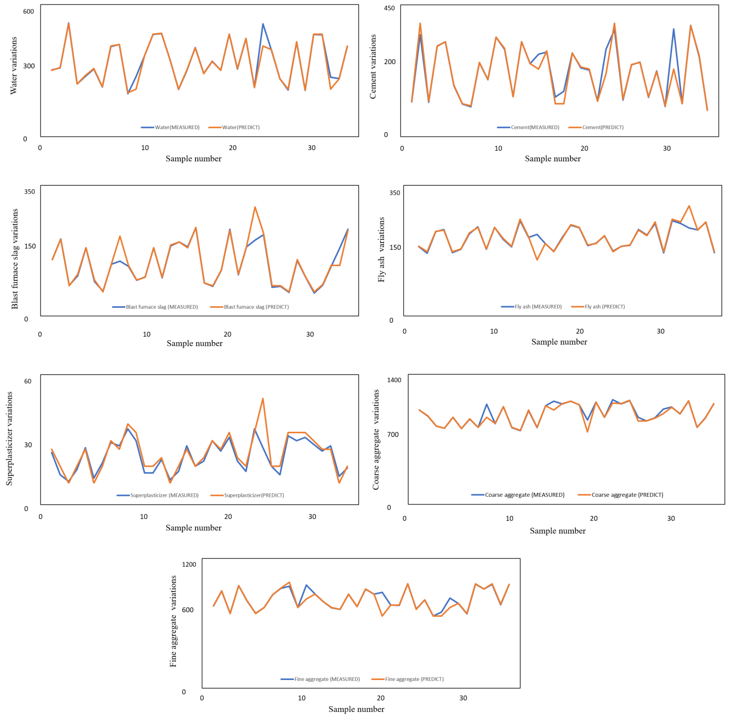

Fig. 4 Variation between predicted and measured values for input parameters in the testing set, based on sample count

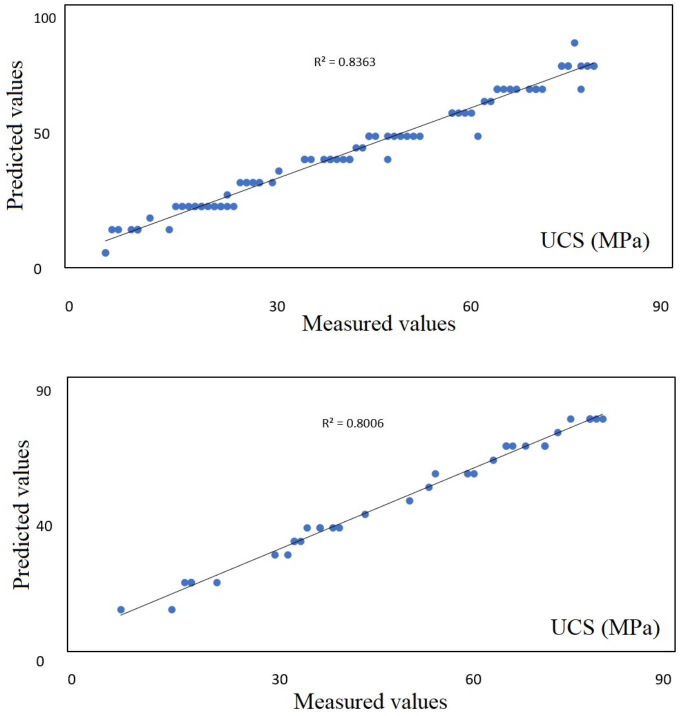

Fig. 5 Correlation between measured and predicted valued for UCS with SVM

Table 2 Calculated error metrics for LWC model

Dataset	MAE	MSE	RMSE	R^2
Training	0.346	0.329	0.331	0.83
Testing	0.351	0.338	0.345	0.80

The predictive model's effectiveness was further examined by comparing predicted UCS values to those obtained from geotechnical laboratory tests. The close alignment between predicted and observed values supports the SVM's suitability as an alternative approach for UCS estimation. Displayed results suggest that the model can effectively mimic laboratory testing conditions, offering practical insights into concrete behavior and potentially reducing the need for extensive physical testing. This could streamline materials testing protocols, saving time and resources in project planning. As results, the SVM model provides a powerful and efficient method for predicting UCS in lightweight concrete, aligning closely with actual laboratory results. The findings emphasize the applicability of machine learning models in materials science, where accurate and reliable predictions are essential for quality control and planning. By offering an alternative to traditional testing, this study contributes to broader efforts in civil engineering to incorporate machine learning into concrete performance assessment, ultimately advancing the field with innovative predictive tools.

IV. CONCLUSION

In conclusion, this study highlights the effectiveness of using a SVM model to predict the UCS of LWC. Through a one-step modeling approach and rigorous training and testing protocols, the SVM model achieved a high level of accuracy, with predictive values closely matching experimental UCS measurements. The SVM's reliability, as shown by favorable error metrics and confusion matrix analysis, demonstrates its suitability as a dependable, time-saving tool for concrete strength estimation. The approach taken in this study offers a practical alternative to traditional laboratory testing, providing accurate predictions from a limited dataset while reducing the need for resource-intensive experimentation. By efficiently handling variations in input parameters, the SVM model has shown potential to streamline the materials testing process, especially valuable in scenarios where rapid or large-scale assessments are needed. Overall, the success of the SVM model in predicting UCS supports its broader application in civil engineering and materials science. This work contributes to the growing role of machine learning in infrastructure design and construction, suggesting that similar models can be applied to other aspects of concrete and material property prediction. The study underscores the potential of machine learning as a transformative tool for advancing quality control and decision-making in the construction industry.

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Authors' contributions

Sina Aminbakhsh conducted the main data analysis, contributed to the data collection, preprocessing, and interpretation, and was responsible for drafting the initial manuscript. Ali Golsoorat Pahlaviani assisted in the development of the methodology and performed validation checks, provided supervision, conceptual guidance, and critical revision of the manuscript. All authors read and approved the final manuscript.

Conflict of interest

The authors have not disclosed any competing interests.

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References

Abdullah D.M., Abdulazeez A.M. (2021). Machine learning applications based on SVM classification a review. *Qubahan Academic Journal*, 1(2), 81-90. https://doi.org/10.48161/qaj.v1n2a50.

ACI PRC-213-14 (2014). *Guide for Structural Lightweight-Aggregate Concrete*. ACI Committee 213.

Alqahtani F.K. (2021). Sustainable green lightweight concrete containing plastic-based green lightweight aggregate. *Materials*, 14(12), 3304. https://doi.org/10.3390/ma14123304.

Amiri H., Azadi S., Karimaei M., Sadeghi H., Dabbaghi F. (2022). Multi-objective optimization of coal waste recycling in concrete using response surface methodology. *Journal of Building Engineering*, 45, 103472. https://doi.org/10.1016/j.jobe.2021.103472.

Aslam M., Shafigh P., Jumaat M.Z., Lachemi M. (2016). Benefits of using blended waste coarse lightweight aggregates in structural lightweight aggregate concrete. *Journal of Cleaner Production*, 119, 108-117. https://doi.org/10.1016/j.jclepro.2016.01.071.

Bogas J.A., Gomes M.G., Gomes A. (2013). Compressive strength evaluation of structural lightweight concrete by non-destructive ultrasonic pulse velocity method. *Ultrasonics*, 53(5), 962-972. https://doi.org/10.1016/j.ultras.2012.12.012.

Cahyono R.H., Kusuma C., Asnan M.N. (2019). Artificial Aggregate Lightweight Structural. *Annales de Chimie Science des Matériaux*, 43(4), 213-216. https://doi.org/10.18280/acsm.430403.

Dabbaghi F., Yang T.Y., Tanhadoust A., Emadi S.B., Dehestani M., Yousefpour H. (2022). Experimental and numerical investigation on post-fire seismic performance of light weight aggregate reinforced concrete beams. *Engineering Structures*, 268, 114791. https://doi.org/10.1016/j.engstruct.2022.114791.

Faleschini F., Brunelli K., Zanini M.A., Dabalà M., Pellegrino C. (2016). Electric arc furnace slag as coarse recycled aggregate for concrete production. *Journal of Sustainable Metallurgy*, 2, 44-50. https://doi.org/10.1007/s40831-015-0029-1.

Gowida A., Elkatatny S., Gamal H. (2021). Unconfined compressive strength (UCS) prediction in real-time while drilling using artificial intelligence tools. *Neural Computing and Applications*, 33(13), 8043-8054. https://doi.org/10.1007/s00521-020-05546-7.

Jung Y.B., Yang K.H. (2022). CO$_2$ emission assessment of lightweight aggregate concrete using artificial lightweight and bottom ash particles. *Journal of Material Cycles and Waste Management*, 24(6), 2172-2182. https://doi.org/10.1007/s10163-022-01469-8.

Karimaei M., Dabbaghi F., Sadeghi-Nik A., Dehestani M. (2020). Mechanical performance of green concrete produced with untreated coal waste aggregates. *Construction and Building Materials*, 233, 117264. https://doi.org/10.1016/j.conbuildmat.2019.117264.

Kumar A., Arora H.C., Kapoor N.R., Mohammed M.A., Kumar K., Majumdar A., Thinnukool O. (2022). Compressive strength prediction of lightweight concrete: Machine learning models. *Sustainability*, 14(4), 2404. https://doi.org/10.3390/su14042404.

Kumar A., Yadav S., Kumar A., Yadav S. (2017). Use of crumb rubber as fine aggregate in concrete to increase the strength of concrete block. *JETIR*, 4(JETIR1711026), 150-155.

Lin H.J., Liao C.I., Yang C. (2006). A numerical analysis of compressive strength of rectangular concrete columns confined by FRP. *Computers and Concrete*, 3(4), 235-248. https://doi.org/10.12989/cac.2006.3.4.235.

Nafees A., Amin M.N., Khan K., Nazir K., Ali M., Javed M.F., Vatin, N.I. (2021). Modeling of mechanical properties of silica fume-based green concrete using machine learning techniques. *Polymers*, 14(1), 30. https://doi.org/10.3390/polym14010030.

Ramadoss P., Nagamani K. (2012). Statistical methods of investigation on the compressive strength of high? performance steel fiber reinforced concrete. *Computers and Concrete*, 9(2), 153-169. https://doi.org/10.12989/cac.2012.9.2.153.

Sarabèr A., Overhof R., Green T., Pels J. (2012). Artificial lightweight aggregates as utilization for future ashes–A case study. *Waste Management*, 32(1), 144-152. https://doi.org/10.1016/j.wasman.2011.08.017.

Sun J., Zhang J., Gu Y., Huang Y., Sun Y., Ma, G. (2019). Prediction of permeability and unconfined compressive strength of pervious concrete using evolved support vector regression. *Construction and Building Materials*, 207, 440-449. https://doi.org/10.1016/j.conbuildmat.2019.02.117.

Tabsh S.W. (2006). Elimination of the effect of strain gradient from concrete compressive strength test results. *Computers and Concrete*, 3(6), 375-388. https://doi.org/10.12989/cac.2006.3.6.375.

Wei H., Wu T., Yang X. (2020). Properties of lightweight aggregate concrete reinforced with carbon and/or polypropylene fibers. *Materials*, 13(3), 640. https://doi.org/10.3390/ma13030640.

Yue S., Li P., Hao P. (2003). SVM classification: Its contents and challenges. *Applied Mathematics-A Journal of Chinese Universities*, 18, 332-342. https://doi.org/10.1007/s11766-003-0059-5.

Yuzer N., Akbas B., Kizilkanat A.B. (2011). Predicting the high temperature effect on mortar compressive strength by neural network. *Computers & Concrete*, 8(5), 491-510. https://doi.org/10.12989/cac.2011.8.5.491.

Zhang B., Feng Y., Xie J., He J., Yu T., Cai C., Huang, D. (2022). Compressive behaviours, splitting properties, and workability of lightweight cement concrete: the role of fibres. *Construction and Building Materials*, 320, 126237. https://doi.org/10.1016/j.conbuildmat.2021.126237.

Zhang J., Li D., Wang Y. (2020). Predicting uniaxial compressive strength of oil palm shell concrete using a hybrid artificial intelligence model. *Journal of Building Engineering*, 30, 101282. https://doi.org/10.1016/j.jobe.2020.101282.

Zhu W., Huang L., Mao L., Esmaeili-Falak M. (2022). Predicting the uniaxial compressive strength of oil palm shell lightweight aggregate concrete using artificial intelligence-based algorithms. *Structural Concrete*, 23(6), 3631-3650. https://doi.org/10.1002/suco.202100656.