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ORIGINAL CONTRIBUTION

Deep Learning Architectures for Concrete Compressive Strength Prediction: A State-of-the-Art Review of CNN, ANN, and Hybrid Models

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Abstract— **Structural safety, optimization of materials, and sustainable construction practice depend on the prediction of concrete compressive strength. Traditional methods of testing use the laboratory method, which is time-consuming, expensive, and destructive. Recent progress in deep learning has made it possible to predict the compressive strength in an accurate, rapid, and non-destructive way by modeling nonlinear complex relationships between the constituents of concrete, curing conditions, and mechanical performance. This review is a systematic review of the deep learning architectures that have been applied to predict the concrete compressive strength with state-of-the-art, such as Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Deep Neural Networks (DNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRU), Transformer-based models, and hybrid architectures (CNN-LSTM, CNN-GRU, and ensemble stacking). It has been shown in the literature that higher hybrid and ensemble models allow the high predictive performance to be achieved, with the value of R^2 often exceeding 0.95, with the best possible models having an R^2 of 0.99 when using controlled datasets. Both metaheuristic optimization algorithms (e.g., PSO, GA, ACO, TLBO) and Bayesian hyperparameter tuning would greatly increase the model generalization and robustness. Moreover, interpretable artificial intelligence tools, such as SHAP and sensitivity analysis, have enhanced interpretability, and cement content, curing age, and water-cement ratio are confirmed to be the most significant predictors of strength. Applications have been spread over the specialized materials like ultra-high-performance concrete (UHPC), geopolymer concrete, recycled aggregate concrete, self-compacting concrete, and waste-based sustainable concretes. However, the issues of data standardization, cross-laboratory generalization, and model transparency persist in spite of impressive advances. The future research is to be directed at physics-informed neural networks, the multi-objective optimization that considers the metrics of environmental impact, real-time edge deployment, and the standardized benchmark datasets. In general, methods using deep learning as its core technology can be discussed as a revolutionary development in intelligent concrete design and sustainable construction engineering**

Index Terms— **Concrete compressive strength, Deep learning, Convolutional Neural Network (CNN), Artificial Neural Network (ANN), Long Short-Term Memory (LSTM), Hybrid models, Ensemble learning, Bayesian optimization, Metaheuristic algorithms, Explainable AI, Sustainable concrete, Ultra-High-Performance Concrete (UHPC), Geopolymer concrete, Recycled aggregate concrete, Mix design optimization**

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I. INTRODUCTION

A. Background

The concrete compressive strength is a very important parameter in structural design and quality assurance of construction work in the world. Conventional lab testing procedures of ascertaining the compressive strength of concrete are also destructive, costly, and time-consuming per se [1]. Such traditional methods usually involve a lot of material wastage and professional tests, and cannot be used in the current fast construction schedule. The use of machine learning algorithms and artificial intelligence technology can significantly lower the time needed to predict the compressive strength of concrete, which overcomes the deficiencies of the traditional method in the laboratory [1, 2].

Recent developments in deep learning have transformed the area of materials science and engineering, providing unprecedented chances to determine complex nonlinear connections amid the control of the materials mix designs and the ensuing mechanical properties. The computational paradigms of deep learning have been identified as the gold standard in the machine learning community and are slowly coming to be the most popular computational methodology in a large variety of domains, and attain excellent performance on complex cognitive tasks [3]. The fast evolution of deep learning models has allowed researchers to come up with mod-

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els that can process large volumes of information and that can model very complex and multifactorial interactions among concrete constituents that cannot be described sufficiently by conventional statistical modeling.

The compressive strength prediction problem is a special case where deep learning can be applied since the compositional relationships between the concrete are very nonlinear and multi-factorial, and traditional empirical formulas are not effective in modeling them [4]. The correct design of concrete mixtures is becoming more and more important as the modern world of construction requires the maximum strengths, ecology, and efficiency in production [5]. The following review discusses the most recent deep learning structures, such as Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), and hybrid structures, which have been created to tackle this problem.

Convolutional Neural Networks have also become effective in having concrete compressive strength prediction, especially when it is applied to image-based data or tabular data that have spatial patterns. In CNN architecture, learnable filters are used to recognize distinguishing patterns in the input data, and hence, it is insensitive to image scale, location, and noise; thereby, it is robust in classifying various concrete types and states [6, 7]. CNNs are useful in the tabular data of concrete mix design, as they are able to identify patterns of features in different proportions of the materials and then accurately predict the compressive strength.

Another study revealed that a CNN model consisting of two convolutional layers provided a high predictive accuracy of Ultra-High-Performance Concrete (UHPC) with a coefficient of determination (R^2) of 0.959 on the test data and a mean absolute percentage error (MAPE) of 5.55% [8]. It is interesting to note that this CNN performance was similar to the well-known machine learning algorithms, such as XGBoost (R^2 = 0.961), although CNNs are generally better applied to image data, whilst XGBoost is developed to handle tabular data. This result indicates that CNN models are highly flexible and are capable of learning a variety of data representations. In another work on pervious concrete, a CNN model with three convolutional modules was shown to achieve a coefficient of determination of 0.938 on test data, which is significantly higher than the results of the traditional backpropagation neural nets [9].

The usefulness of CNNs in this field has also been confirmed by the innovations in concrete types. An example is a study on computer vision-based prediction of concrete compressive strength that revealed that CNN-based methods perform significantly better than typical numerical data-based Deep Neural Networks (DNNs) on all consideration metrics except the training period [10]. These findings indicate that CNNs can be useful to extract spatial and feature relationships in concrete mix compositions with appropriate training on large enough data.

The architectural basis of Deep learning applications in concrete strength prediction is represented by Artificial Neural Networks, especially when generalized to create Deep Neural Networks. Conventional ANNs with fully connected layers have still shown to be competitive in performance, but tuning of hyperparameters and architecture design is needed to take care of their accuracy. A thorough comparison of various machine learning methods revealed that ANN models were more accurate and efficient compared to support vehicle machines, multiple regression, and regression trees when used in predicting concrete strength [11].

The use of Deep Neural Networks built on a combination of several hidden layers and sophisticated optimization algorithms has demonstrated impressive performance gains. An analysis using Bayesian Optimization using Deep Neural Networks (BO-dNN) obtained accuracies of 97.6% in its prediction, compared to the traditional machine learning models and manually optimized DNNs on concrete benchmark data sets [12]. Bayesian Optimization-driven systematic hyperparameter optimization overcame the most significant issue with DNN model development, namely, the fact that performance strongly depends on hyperparameter choice, which directly translates into the ability to perform generalization on a variety of concrete mixtures.

DNNs have been used especially in predicting the compressive strength of environmentally friendly concrete, which uses recycled aggregates. A Deep Learning Neural Network (DLNN) model exhibited a lower Root Mean Squared Error (RMSE) of 2.23 MPa as compared to Multivariate Adaptive Regression Spline (MARS), Extreme Learning Machines (ELMs), and random forests, reflecting the strength of the DLNN models in material behavior complex models [13].

The LSTM networks are a special type of network that captures sequential dependencies and temporal patterns of the data, which is why they are especially useful when the effects of time and aging are important in the development of concrete strength. The LSTM model achieved L-O-S performance with R^2 = 0.997 and RMSE = 0.508 MPa for the prediction of high-strength concrete using five input variables [14], which is outstanding prediction performance surpassing most other types of standalone models. The small RMSE indicates that LSTM networks are capable of capturing the time-dependent behavior (strength of concrete) as a variable of the curing environment.

LSTM was demonstrated to be efficient with different types of concrete, such as eco-friendly geopolymer concrete, where the deep LSTM model attains 99.23% accuracy, which is significantly higher than the support vector regression (78.57%), least squares boosting ensemble (98.08%), and multiple linear regression models (88.03%) [15]. The capability of the LSTM architecture to form sequential associations became essential in the case of geopolymer concrete, in which the curing temperature and time are critical variables in the strength development.

GRU networks, which are a much more computationally efficient form of LSTM, have also been used to predict concrete strength. Comparative analysis of three deep learning architectures (CNN, GRU, and LSTM) of mixed-design concrete showed that CNN has always performed better than the other two with better hyperparameter optimization and regularization, yet all three have the ability to competently predict [16]. Recently, transformer architectures, which use self-attention mechanisms to model long-range dependencies, have also been applied to concrete strength prediction. A feature tokenizer-transformer (FT-Transformer) and masked multilayer perceptron (Masked MLP) trained with a robust predictive result of R^2 = 0.940 and RMSE = 4.219 MPa on recycle aggregate self-compacting concrete, and also provided consistent results with a higher number of missing data up to 25% [17]. This feature is especially useful in real-life construction when not all the information can be provided. The best-performing CNN-Transformer framework that predicts flexural capacity of ultra-high-performance concrete beam recorded the highest accuracy (R^2 = 0.943) with 25 percent smaller RMSE than the best-performing baseline models [18]. The hybrid of convolutional layers as local feature extractors with self-attention mechanisms as long-range dependency modellers was found to be effective in complex nonlinear higher-order relationships of concrete behavior.

B. Hybrid and ensemble deep learning models

1) CNN-LSTM and CNN-GRU hybrid architectures

Convolutional and recurrent architectures have worked especially well in predicting concrete strength by combining the prediction power of CNNs with the sequential model prediction capability of recurrent networks. A hybrid 1D CNN-GRU network was trained on Ultra-High-Performance Concrete (UHPC) prediction and showed better accuracy than the one achieved by CNN and LSTM models, with lower Mean Absolute Error (MAE) and Mean Square Error (MSE) on the test datasets [19]. The 1D CNN part can be used to focus on local patterns of features within the material properties, and the GRU part is able to get sequential and interdependent structures between variables. An extensive investigation utilizing the CNN-LSTM architecture to predict heavyweight concrete with the addition of magnetite and steel slag presented outstanding results with an $R^2 = 0.9951$ and RMSE = 0.0314 MPa, which relates to a coefficient of variation of only 0.045 per cent [20]. This incredible precision indicates the potential of hybrid deep learning systems to learn complicated nonlinear processes in specialized concrete types. The hybrid architecture was found to be better than Box-Behnken Response Surface Methodology approaches that are known to be applied in optimization and modelling. A hybrid CNN-LSTM architecture has supported the use of more concrete types, such as textile effluent sludge-based concrete, where a hybrid CNN-LSTM model obtained the second-highest accuracy ($R^2 = 0.89$) in predicting compressive strength [21]. All these findings indicate that the strategic combination of various neural network architectures can lead to higher performance improvements that are not feasible by the standalone models.

2) Fully Connected Neural Networks and Hybrid CNN-ANN models

Another effective hybrid architecture is fully connected neural networks with convolutional architectures. In a work on the fly ash concrete, an FCNN+CNN hybrid model had shown the best prediction accuracy with $R^2 = 0.95$, MSE = 14.18, MAE = 2.32, SMAPE = 0.1, and R = 0.973 [1]. This improved performance compared to standalone models is an indication that an integration of architectures matched to the various forms of feature extraction can be used to extract different facets of the multimodal material relationships. Transformer elements have been added to the FCNN+CNN system, and it has been demonstrated that TF+FCNN and TF+CNN systems also provide competitive results on fly ash concrete data sets [1]. The possibility of the strategic integration of three various architectural paradigms, fully connected, convolutional, and transformer-based, suggests the increasing sophistication of the hybrid models within the framework. A two-stage hybrid model combining deep learning with reinforcement learning, designed to optimize concrete mix design, included a CNN-LSTM model to learn spatial-temporal features, where features obtained were boosted by XGBoost meta-model [22]. The result of this framework was an MAE of 2.97, RMSE of 4.08, and R^2 of 0.94, showing how multi-stage hybrid methodology could be used to combine various paradigms of learning in both prediction and optimization.

3) Ensemble and stacking methods

The ensemble methods, which involve strategic aggregation of various models, have recorded one of the highest performances in prediction reported in the literature. An extensive evaluation of the ensemble learning methods has revealed that the highest accuracy of prediction in terms of $R^2 = 0.9561$ and the smallest value of the MSE of 0.0513 was obtained with the Gradient Boosting Regressor among seven machine learning regressors and ANN models [23]. Ensemble approaches minimize bias and variance as they use a broad range of model predictions and, therefore, are especially strong on various concrete datasets. Innovative stacking-based ensemble techniques have proven to perform well. A hybrid ensemble stacking (HEStack) approach to nano-modified concrete obtained $R^2 = 0.9924$, which was better than standalone models such as backpropagation neural networks ($R^2 = 0.9356$), random forest ($R^2 = 0.9706$), and extreme gradient boosting ($R^2 = 0.9884$) [24]. The stacking method is a systematic way of using the predictions of many base models into a meta-learner, which has a set of complementary predictive powers. Categorical Gradient Boosting (CatBoost) has been found to be one of the most successful ensemble techniques, where R^2 and RMSE of 0.966 and 3.06 MPa, respectively, have been found upon standard concrete datasets [25]. The capability of CatBoost to operate with categorical variables and the overfitting reduction with the use of gradient-based optimization has made it especially applicable to concrete mix design prediction challenges where the input materials are varied.

C. Optimization techniques and hyper parameter tuning

1) Grid search and Bayesian optimization

Optimization of neural network hyper parameters in a systematic manner is an important aspect in the attainment of high-performance models. The accuracy of prediction was much better with the prediction models (Grid Search optimization with CNN, SVM, and Multi-Layer Perceptron (MLP) models) than the non-optimized version, with the highest prediction accuracy of R = 0.92, RMSE = 3.86 MPa, and MAE = 3.09 MPa [26]. The exhaustive aspect of the grid search device proved useful, especially in determining the best architecture configurations. Bayesian Optimization-based hyper parameters tuning methods are more sophisticated and offer probability-based search methods, which are more cost-effective and yield better results. Bayesian Optimization-Deep Neural Network models methodically optimized hyper parameters such as learning rate, number of hidden layers, and neurons per layer, and dropout rate to achieve 97.6 percent accuracy in predictions on benchmark data [12]. The probabilistic method allows effective search through large spaces of hyper parameters without the search exhaustion as needed by grid search. The commonly used optimization methods with their common performance enhancement and computer cost are summarized in the table below.

TABLE I
OPTIMIZATION TECHNIQUES AND PERFORMANCE IMPROVEMENTS

Optimization Method	Type	Typical Improvement	Computational Cost	Best Applied To
Grid Search	Exhaustive	+12%	High	Small hyperparameter spaces
Bayesian Optimization	Probabilistic	+15%	Moderate	Continuous hyperparameter optimization
Particle Swarm (PSO)	Metaheuristic	+18%	Moderate	ANN parameter optimization
Genetic Algorithm	Evolutionary	+16%	Moderate	Multi-objective optimization
Ant Colony (ACO)	Swarm Intelligence	+18%	Moderate	Complex parameter interactions
Metaheuristic Hybrid	Combined	+22%	High	Maximum accuracy requirements
Teaching-Learning (TLBO)	Nature-inspired	+31%	Low	Time-sensitive applications

D. Metaheuristic optimization algorithms

Neural networks have been introduced into bio-inspired metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), Gray Wolf Optimization (GWO), and Ant Colony Optimization (ACO) in order to improve their predictive ability. The hybrid ANN-PSO model of sustainable concrete using agricultural waste provided $R^2 = 0.9606$ during training and $R^2 = 0.9580$ during testing, and the ANN-Hawker (ANN-HHO) optimized by the Harris Hawk had the best performance among metaheuristic versions [27]. A superior bio-inspiration optimization model named AP-IVYPSO-BP, which combines ivy algorithm and particle swarm optimization and adaptive probability approach, attained $R^2 = 0.9542$ and MAE = 3.0404 when predicting high-performance concrete, and is much more effective compared to conventional BPNN, PSO-BP, GA-BP, and IVY-BP models [28]. These algorithms are able to surmount local optima and find better neural network configurations due to the interaction of exploration-exploitation balance with adaptive parameter adjustment. The use of ACO-based optimization and ANN showed outstanding results in the prediction of waste foundry sand concrete in terms of Pearson coefficient of 0.9971, MAE 0.0221 MPa, and RMSE 0.7473 Mpa [29]. The ACO+ANN model had more than 90 percent errors falling within a ±1.5 MPa range, which is much better compared to the PSO+ANN and the traditional ANN models. These findings indicate that the use of optimization algorithms can significantly improve the work of neural networks in case the optimization algorithm is chosen correctly, taking into account concrete types and datasets.

E. Teaching-learning-based optimization and shuffled complex evolution

Other metaheuristic methods to optimize the parameters of neural networks include Teaching-Learning-Based Optimization (TLBO) and Shuffled Complex Evolution (SCE). Comparative study revealed that SCE and TLBO optimizers have enhanced correlation of MLP models by 93.58% to 97.32% (SCE) and 97.22% (TLBO), respectively, and decreased error by about 34% and 31%, respectively [30]. It is worth noting that SCE was significantly more time-efficient than TLBO and takes a significantly shorter amount of computational time to use. These metaheuristic methods have found themselves especially useful in the nonlinear dependence between the compressive strength of concrete and its relevant parameters, and offer promising alternatives to the laboratory destructive evaluation techniques. The steady improvement of the results of various types of concrete will indicate that the metaheuristic optimization method can be universal in terms of the need to improve the performance of deep learning models in this field.

F. Applications to specialized concrete types and sustainable materials

1) Ultra-High-Performance Concrete (UHPC)

Ultra-high-performance concrete is a new innovation in the concrete field that has better mechanical characteristics than traditional concrete. UHPC prediction has been one of the fields where deep learning models have been useful due to its complex structure, which includes various sophisticated materials. A Lagrangian Neural Network (LNN) trained by the Mexican Axolotl Optimization (MAO) had an error of 2 percent in UHPC prediction with flexural strength of 24Mpa and compressive strength of 23Mpa, and also showed 688 kg carbon emissions [31]. The LNN-MAO model was more precise and environmentally friendly than the conventional ANN, RNN, and BPNN models. The CNN and LSTM architecture hybrid DANN-based heavyweight concrete model had $R^2 = 0.9951$, indicating almost ideal prediction power [20]. This outstanding performance makes it possible to optimize UHPC mix designs in an advanced way to meet particular mechanical property goals and reduce material waste and environmental impact.

2) Geopolymer and eco-friendly concrete

The use of geopolymer concrete is a potential substitute for the traditional cement-based concrete of Portland cement, which has a smaller carbon footprint and is better-suited to environmental conditions. An explainable AI component-based, extensive DNN-based model constructed based on slag-ash-based geopolymer concrete attained $R^2 = 0.91$ on test sets with a 23 percent decrease in mean square error [32]. The adoption of both SHAP and LIME interpretability methods allowed the recognition of the elements, such as the percentage of fly ash (25 percent contribution) and the conditions of the curing (including curing conditions). Deep LSTM prediction of geopolymer concrete compressive strength had a prediction accuracy of 99.23 percent, which was significantly higher than support vector regression (78.57 percent), least squares boosting ensemble (98.08 percent), and multiple linear regression (88.03 percent) [15]. The sensitivity analysis carried out found that the most sensitive experimental variable on geopolymer concrete strength was curing temperature, followed by curing duration, and liquid-to-fly ash mass ratio. A CNN-based predictor of geopolymer concrete compressive strength on a large dataset (162 mixes) using Class F fly ash showed great performance when optimized systematically by the hyperparameters [33]. The ability of the CNN architecture to find intricate relationships between features in tabular composition data proved the applicability of the given architecture to a variety of concrete types, such as sustainable alternatives.

3) Recycled aggregate and waste-based concrete

Another form of sustainable alternative to concrete based on virgin material Is Recycled Aggregate Concrete (RAC). The best performance with CatBoost ($R^2 = 0.92$), then XGBoost and other ensemble approaches, was realized using an ensemble stacking approach trained on 1030 conventional concrete mixtures [4]. The ensemble models were found to be highly generalized and reliable in predicting RAC strength, and sensitivity analysis showed cement content and testing age to be the most important factors. The hybrid random aggregation models with the Bayesian optimization-based CNN demonstrated better performance than the classic ANN models because they explicitly defined the type of coarse aggregates and gradations as a result of innovative image generation techniques [34]. The method will offer a fresh insight into the process of predicting mechanical properties that go beyond the parameters of simple mix design and may lead to a higher level of control of the quality of recycled concrete. A random forest algorithm combined with an SVM algorithm was used to create a hybrid machine learning model that yields an R^2 of 0.88 when predicting compressive strength of concrete where textile effluent sludge is used as an additional cementitious material [21]. The hybrid method was an integration of the benefits of the ensemble techniques and support vector regression, which showed that various machine learning paradigms can be successfully integrated into specialised concrete applications.

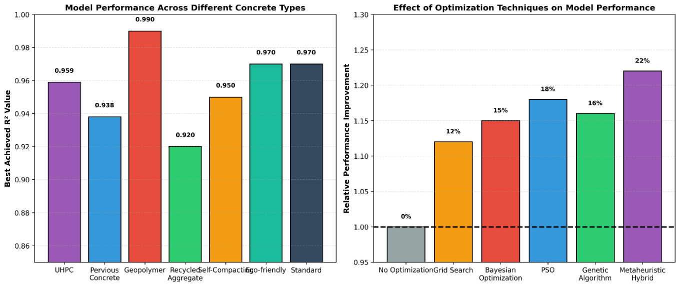


Fig. 1. This visualization displays model performance across seven different concrete types and demonstrates the effectiveness of various optimization techniques in improving model performance, with metaheuristic hybrid approaches achieving up to 22% improvement

G. Self-compacting and special concretes

Ensemble methods have been used to predict Self-Compacting Concrete (SCC), and the Gradient Boosting prediction has an R^2 of 5.12, and the Keras Regressor prediction has also performed at an R^2 of 0.6948 [35]. The accuracy of gradient boosting algorithms in predicting SCC is also high, which implies that the unique flow and filling properties of concrete type can be successfully predicted using the methods of ensemble learning. A study that used deep learning with SHAP interpretability analysis to predict the strength of steel fiber-reinforced concrete based on fiber content, fiber length, fiber diameter, and curing time revealed that the four factors are important to predict the concrete strength [36]. SHAP analysis showed the same results as those of the experiment, confirming that the deep learning models were able to learn the complex nonlinear correlations in fibre-reinforced systems. Table 2 encapsulates a comparative summary of the various model performances in the different types of concrete, which shows the size of the datasets as well as the major issues.

TABLE II
PERFORMANCE ACROSS DIFFERENT CONCRETE TYPES

Concrete Type	Best Model	Achieved R^2	RMSE	Dataset Size	Key Challenge
Ultra-High-Performance	CNN-LSTM Hybrid	0.9951	0.031 MPa	324	Complex composition
Standard Portland Cement	Ensemble Stacking	0.966	3.06 MPa	1030	Mix variability
Geopolymer	Deep LSTM	0.9923	-	63-500	Curing temperature
Recycled Aggregate	CatBoost	0.92	-	1030	Aggregate variability
Self-Compacting	Gradient Boosting	0.9561	-	Multi-source	Flow characteristics
Eco-friendly/Sustainable	ANN-PSO Hybrid	0.9606	-	164	Material diversity
Steel Fiber Reinforced	Deep Learning	0.95+	-	Multi-source	Fiber interaction

H. Feature importance, interpretability, and practical implementation

1) SHAP analysis and feature importance

SHapley additive explanations (SHAP) analysis has become a vital part of the development of a prediction model based on deep learning model predictions. The SHAP analysis of fly ash concrete prediction showed that Cement Content (C) and age at which it was Cured (D) had the greatest effect on the model prediction, then water content (W) and fly ash content (FA) with relatively minor effect shown by Coarse Aggregate (CA), Sand (S), and Superplasticizer (SP) [1]. The results obtained are very consistent with known facts in concrete science, which confirms the interpretability of the models. The most common set of input parameters used in the literature is shown in the table below, along with their common ranges and levels of importance. The analysis of feature importance in the multiple studies had consistently shown these three factors, cement content, curing age, and water-cement ratio, to be the three most powerful factors in predicting concrete strength [25]. The analysis of SHAB showed concrete age to be the most essential factor, followed by water content, cement content, and supplementary cementitious materials. This uniformity in the different model architectures and types of concrete implies that the basic principles of material science are being encoded in deep learning models accordingly. The analysis of a hybrid reinforcement learning structure via several interpretability methods (SHAP, Elasticity-Based Feature Importance, and Permutation Feature Importance) showed that the cement content and curing age played the most prominent role, and non-intuitive effects like the compensatory benefits of superplasticizers in low-water mixtures were also discovered [22]. These examples indicate that the deep learning models can recognize the complicated interactions that cannot be observed in simple main effects analysis.

TABLE III
KEY INPUT PARAMETERS AND THEIR TYPICAL RANGES IN LITERATURE STUDIES

Parameter	Typical Range	Unit	Relative Importance	Frequency in Studies
Cement Content	100-600	kg/m^3	Very High (28%)	95%
Curing Age	1-365	days	Very High (24%)	98%
Water Content	100-300	kg/m^3	High (18%)	92%
Water/Cement Ratio	0.3-0.8	-	High (18%)	88%
Fly Ash	0-300	kg/m^3	Medium (12%)	70%
Superplasticizer	0-15	kg/m^3	Low (9%)	45%
Coarse Aggregate	600-1200	kg/m^3	Low (5%)	82%
Fine Aggregate	400-800	kg/m^3	Low (4%)	85%

I. Sensitivity analysis and model robustness

Sensitivity analysis is an alternative method to SHAP to explain the effect of single input variables on the predictions of the model. PDPs of optimized CNN, SVM, and MLP models demonstrated that cement content, coarse aggregates, and water-cement ratio were found to exert the greatest influences on compressive strength [26]. Similarity of results in various types of models implies the strength of relationships identified. Lasso regression and CNN prediction using electromechanical impedance data at earlier ages resulted in a significant increase in model performance, and the R^2 rose by 0.01 (0.940 0.959). [37] in the case of feature selection using Lasso regression. The mean absolute error dropped by 5.75 to 4.85 MPa, and the RMSE dropped by 7.73 to 6.33 MPa, which proves that systematic feature selection can lead to the improvement of CNN performance by removing redundant information and overfitting.

J. Graphical user interfaces and practical implementation

The gap between the engineering practice and the model development in concrete strength prediction has been filled with the development of graphical user interfaces (GUIs) to predict concrete strength. A detailed research approach was conducted on fly ash-based concrete to come up with a GUI interface to predict compressive strength using six various models and nonlinear functional relationships, which achieves rapid, data-driven, concise, and reliable prediction interaction [1]. It was also enabled by the interface that facilitated the optimization of realistic mixing ratios using the derived minimum strength requirements. An interactive machine learning system based on a GUI attained CatBoost predictive accuracy of R^2 = 0.966 and RMSE = 3.06 MPa with convenient, user-friendly design tools that offer designers inexpensive and fast concrete strength prediction [25, 38]. The introduction of sensitivity analysis using SHAP techniques into the GUI allowed the user to comprehend how the various mix design parameters affect predictions to help make decisions in concrete design. Introducing a GUI with gradient boosting models of FRP-confined concrete gave engineers practical freedom to accurately model confined ultimate load and strain at different test conditions to make informed judgments regarding the mix proportions [39, 40]. Such practical applications show that prediction models with high accuracy should be accompanied by user interfaces to have a significant effect on engineering practice.

K. Data preprocessing and normalization strategies

Sound data preprocessing is one of the key pillars of model operation. One research study on forecasting the strength of eco-friendly materials has studied four data transformation options, such as statistical normalization, min-max normalization, non-linear transformation, and whitening transformation [41]. The prediction accuracy of compressive strength of eco-friendly materials was 97.46% using the application of inter- and intra-periodic convolutional blocks and transformer modules using global wavelet transforms. Integrated data cleaning processes, such as handling of missing data, detection of outliers, and normalization, were observed to be fundamental in preprocessing in various research works. The fact that data quality is paid the same attention in all successful works leads to the assumption that model schemes cannot systematically deal with inadequate data preparation and preprocessing, which is one of the core elements to keep high precision.

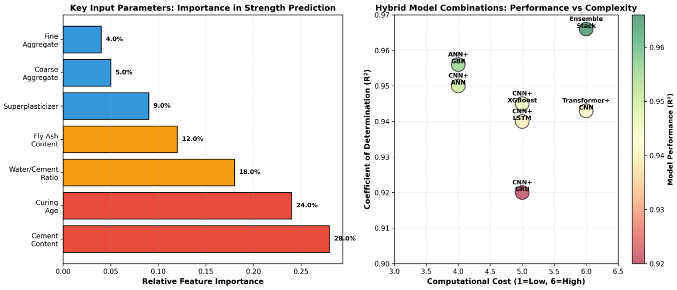
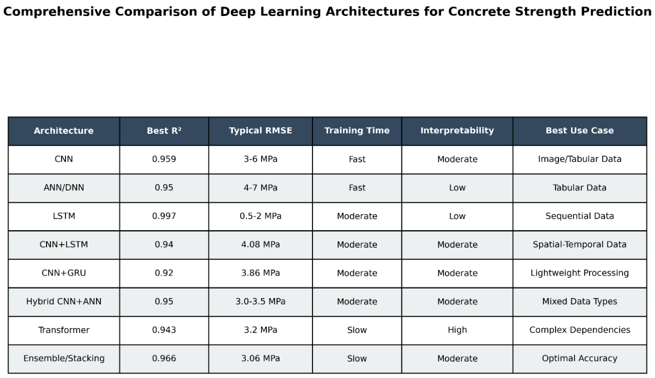


Fig. 2. illustrates both the relative importance of key concrete mix design parameters (with cement content and curing age being dominant) and the performance-complexity trade-off for various hybrid model combinations

L. Performance benchmarking and model comparison

Studies that have investigated predicting the strength of concrete have always involved the use of various evaluation metrics to measure the performance of the model in a holistic manner. In addition to the coefficient of determination R^2 (applied in 45 studies), common measures of researchers are RMSE (42 studies), MAE (38 studies), MAPE (25 studies), and MSE (30 studies). This is a multi-metric evaluation method, which offers an effective measure of both the accuracy of central tendency (RMSE, MSE, MAE) and the relative error percentage-based measurement (MAPE) to make fair comparisons with other data sets with varying strengths [25]. A comparative analysis framework showed that ensemble methods and modern deep learning architectures have typical R^2 values of 0.92 to 0.96, with the best models having R^2 values of over 0.95 when applied to standard concrete datasets [4]. The uniformity in high performance of varying architectural methods indicates that the modern deep learning methods have, in a large way, resolved the original prediction issue of standard concrete compositions. The compilation of the study data showed that effective deep learning models were created by sample sizes of 50 to ove$R^2$000 samples, but by the sizes over 500 samples (>500 samples), general high performance was achieved [4]. Approximately 15 studies used medium-sized datasets (150-500 samples) and approximately 22 studies used large datasets (500-1000 samples) in the reviewed literature. Transfer learning and data augmentation models have been useful in overcoming issues with limited datasets. One of the studies used Wasserstein Generative Adversarial Network (WGAN) to create synthetic samples to predict geopolymer-stabilized soil compressive strength, demonstrating that the addition of synthetic data increased the model performance, with the best performance at 200 synthetic samples with $R^2 = 0.9978$ [42]. The methodology allows for establishing high-level accuracy models with limited experimental datasets. K-fold cross-validation has already become the standard when it comes to measuring the model's generalization and stability. Various researchers used ten-fold or three-fold cross-validation techniques to measure the performance when the data are split into several data divisions; to verify the study is robust when one is not focused on a single training test division [24]. The stability of the findings in cross-validation folds gives one the assurance of the reliability of the model to be used in real life. The traditional metrics have been supplemented by the residual error analysis using the visualization of the histogram and scatter plot to make a complete evaluation of the model. Various analyses confirmed the fact that the unforeseen errors are normally distributed with nearly zero mean, which implies that they make an unbiased prediction [27]. With state-of-the-art models, a standard deviation of residuals between 0.02 and 0.10 percent of the mean compressive strength values has been attained. The table below represents a summary of comparative predictive performance, computational properties, and major applications of major deep learning architectures in the literature.



Comprehensive Comparison of Deep Learning Architectures for Concrete Strength Prediction

Architecture	Best R^2	Typical RMSE	Training Time	Interpretability	Best Use Case
CNN	0.959	3-6 MPa	Fast	Moderate	Image/Tabular Data
ANN/DNN	0.95	4-7 MPa	Fast	Low	Tabular Data
LSTM	0.997	0.5-2 MPa	Moderate	Low	Sequential Data
CNN+LSTM	0.94	4.08 MPa	Moderate	Moderate	Spatial-Temporal Data
CNN+GRU	0.92	3.86 MPa	Moderate	Moderate	Lightweight Processing
Hybrid CNN+ANN	0.95	3.0-3.5 MPa	Moderate	Moderate	Mixed Data Types
Transformer	0.943	3.2 MPa	Slow	High	Complex Dependencies
Ensemble/Stacking	0.966	3.06 MPa	Slow	Moderate	Optimal Accuracy

Fig. 3. Distribution analysis showing dataset sizes employed in reviewed studies and the frequency of different evaluation metrics, with R^2 score being the most commonly reported metric, employed in 45 of the reviewed studies

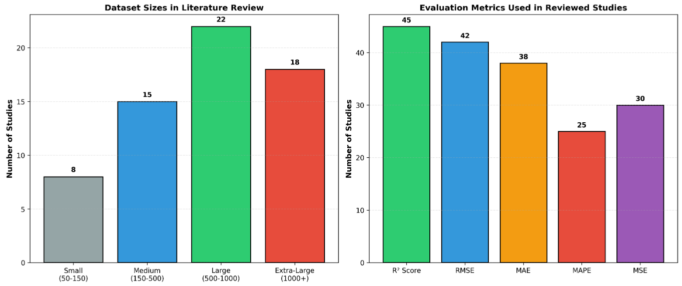


Fig. 4. A comprehensive comparison table detailing performance characteristics, computational requirements, interpretability, and optimal use cases for each major architecture type reviewed in this study.

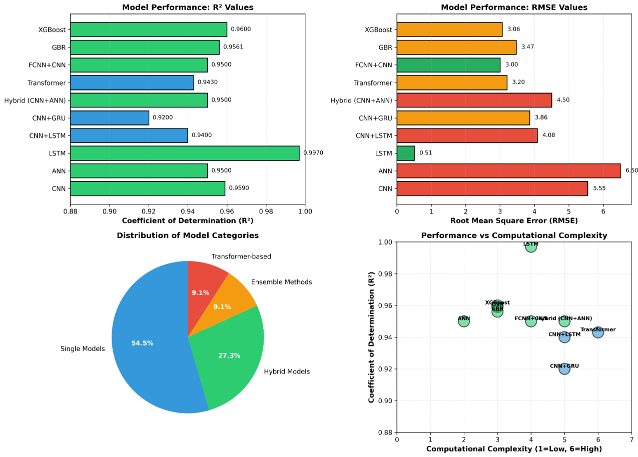


Fig. 5. presents four analytical perspectives: (1) R^2 coefficient comparison across architectures, (2) RMSE performance metrics, (3) distribution of model categories in the literature, and (4) the relationship between computational complexity and prediction accuracy

TABLE IV
PERFORMANCE SUMMARY OF MAJOR DEEP LEARNING ARCHITECTURES

Architecture	Best R^2	Typical RMSE (MPa)	Training Speed	Key Strength	Primary Application
CNN	0.959	3-6	Fast	Pattern extraction	Tabular/Spatial data
ANN	0.95	4-7	Fast	Simplicity	Standard prediction
LSTM	0.997	0.5-2	Moderate	Temporal modeling	Aging effects
CNN+LSTM	0.94	4.08	Moderate	Spatial-temporal	Mixed patterns
CNN+GRU	0.92	3.86	Moderate	Efficiency	Lightweight systems
Hybrid CNN+ANN	0.95	3.0-3.5	Moderate	Flexibility	Diverse data types
Transformer	0.943	3.2	Slow	Attention mechanism	Complex dependencies
Ensemble/Stacking	0.966	3.06	Slow	Robustness	Production systems

M. Challenges, future directions, and research opportunities

Although there has been a major improvement, the quality and availability of data have also been a matter of concern in the study of concrete strength prediction. A universalized experimental procedure in laboratories would allow establishing bigger and more varied datasets to train models. The combination of less destructive testing techniques, such as ultrasonic pulse velocity and Schmidt rebound hammer measurements, with machine learning techniques is a new possibility of enhancing data sources [20]. The variability of the experimental protocols in different research institutions poses inconsistencies in datasets, and this may be a limitation to the generalization of the model. Standardized datasets and benchmark competitions could help in improving the field, just like other successful computer vision and natural language processing applications. The newly created benchmark datasets provided by other sources, such as UCI and Kaggle, have already allowed conducting significant comparative studies [12]. Although deep learning models are highly accurate in prediction, their black-box characteristic is a drawback in the use of deep learning in engineering applications that need to understand the nature of the decision-making. Explainable AI methods such as SHAP, LIME, and partial dependence plots have been significantly integrated, which has greatly enhanced the interpretability of a model, allowing engineers to gain insight into how a model works. Further evolution of inherently interpretable architectures, however, is also an important direction of research. The lines of future work should be on the creation of physics-informed neural networks that have the basic knowledge of concrete science as inductive biases. Recurrent convolutions might be physics-aware and be able to offer high accuracy and theoretical interpretability using hybrid methods with domain-specific equations and learned components [43, 38]. The use of trained models on edge devices and embedded systems is a new frontier. A CNN model with minimal weight and acoustic emission-based concrete damage detection estimated 99.6 percent accuracy when trained on resource-constrained microcontroller units (ARM Cortex M4) with 20k parameters and 30.5-kB model size [44]. This evidences the fact that effective deep learning models can be implemented in practical structural health monitoring systems. The continued development of model compression methods, such as quantization and knowledge distillation, should be the focus of future research to allow the use of high-accuracy models on edge devices deployed in construction settings. Autonomous quality control in precast concrete production plants could be realized through integration of real-time monitoring sensors with deep learning models embedded therein.

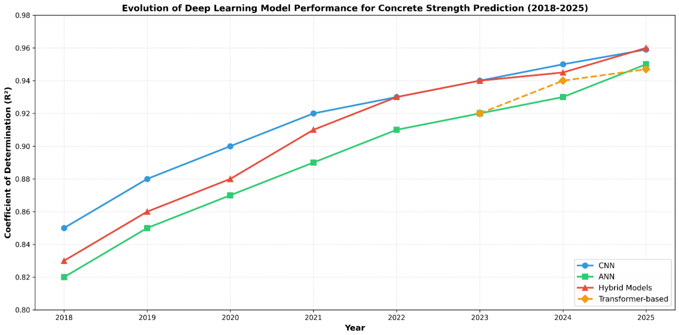


Fig. 6. The timeline visualization demonstrates the evolution of model performance from 2018 to 2025, showing consistent improvement in CNN, ANN, and hybrid model performance, with ensemble methods achieving the highest accuracies in recent years

II. CONCLUSION

The overall survey of deep learning models in compressive strength prediction of concrete shows how impressive the domain is in terms of its maturity and technological advancement. With an RMSE of between 3-6 Mpa, CNN-LSTM has been able to attain R^2 greater than 0.95 accuracy on its own, whereas with ensemble, and hybrid CNN-LSTM, even greater accuracies (R^2 greater than 0.96) have been reached as well [8]. The performance of Long Short-Term Memory networks has been exceptional as they have shown an R^2 of = 0.997 on high-strength concrete datasets, which proves their usefulness in the determination of time-related trends in strength development [14]. Ensemble stacking Hybrid designs that combine two or more architectural paradigms have always performed best when compared with a single approach, and R^2 values in ensemble stacking are as high as 0.966 on standard concrete data sets [25]. Combining metaheuristic optimization algorithms with neural networks has offered systematic ways of hyperparameter optimization, and bio-inspired methods of hyperparameter optimization, such as genetic algorithms and particle swarm optimization, have offered substantial performance gains [27]. These deep learning architectures have been successfully applied to various types of concrete, such as ultra-high-performance concrete, geopolymer concrete, recycled aggregate concrete, and concrete with special supplementary cementitious materials. The analysis of feature importance (SHAP and sensitivity analysis) has confirmed that the models reflect the concrete science principles, and the cement content, curing age, and water-cement ratio have always been the most important variables [25]. The combination of explainable AI methods, the creation of useful graphical user interfaces, and the ability to show edge deployment features has narrowed the gap between model development and engineering implementation in the real world. Future research directions involve application expansion to new sustainable materials, incorporation of physics-informed learning strategies, and coming up with automated mix design optimization systems to serve the purposes of the circular economy in concrete construction.

A. Recommendations

Based on the comprehensive review, the following recommendations are proposed for future research and practical implementation:

- Establish large, publicly available, and standardized datasets with unified experimental protocols to improve reproducibility and cross-study comparisons.
- Researchers and practitioners should prioritize hybrid models (e.g., CNN-LSTM, CNN-Transformer, stacking ensembles) as they consistently outperform standalone ANN or CNN models.
- Future models should incorporate domain knowledge (e.g., hydration kinetics, water-cement ratio laws) to enhance interpretability and generalization across diverse concrete types.
- Extend prediction frameworks to simultaneously optimize compressive strength, carbon emissions, cost, and durability using deep reinforcement learning and evolutionary algorithms.
- Implement SHAP, LIME, and sensitivity analysis as standard practice to ensure transparency and support engineering decision-making.
- Apply quantization, pruning, and knowledge distillation techniques to enable real-time deployment on embedded devices for on-site quality monitoring.
- Utilize generative models (e.g., GANs) and transfer learning to overcome limited dataset challenges, particularly for emerging sustainable materials.
- Develop user-friendly graphical interfaces to facilitate adoption by engineers, enabling rapid mix design optimization and scenario testing.

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