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Design of an Ensemble learning Model for improving Concrete Strength prediction efficiency of RC Structures via Multiparametric Analysis. (EMSRSMA)

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ABSTRACT

Prediction of Concrete Strength for reinforced concrete (RC) structures is a multimodal task that involves processing of a wide variety of strength parameter sets. Existing prediction models either showcase low efficiency or cannot be scaled for heterogenous construction sites. To overcome these issues, this paper proposes an ensemble learning model to improve the efficiency of evaluating concrete compressive strength using multiparametric analysis. The model combines multiple algorithms, including Naïve Bayes (NB), Multilayer Perceptron (MLP), k Nearest Neighbours (kNN), Support Vector Machines (SVM), and Logistic Regression (LR), to provide accurate and reliable predictions of compressive strength levels. The proposed ensemble approach leverages a diverse set of features, including cement, water, and aggregate content, curing time, and age, to achieve high prediction performance for heterogeneous construction sites. The proposed model's performance was evaluated using a comprehensive dataset of concrete mixtures, and the results show that the ensemble approach outperforms individual algorithms and achieves a higher level of accuracy, precision & recall when compared with existing techniques. The proposed model's success demonstrates the potential of ensemble learning methods for Concrete Strength prediction and provides a promising solution for improving the efficiency of construction material evaluation under real-time scenarios. The proposed model can assist in reducing costs and enhancing the reliability of construction projects by providing a more accurate assessment of Concrete Strength levels.

Keywords: Concrete, Concrete Strength, Prediction, Ensemble, Naïve Bayes, Multilayer Perceptron, Support Vector Machine, Deep Forests

1. INTRODUCTION

Concrete is one of the most widely used construction materials in the world. Its compressive strength is a critical factor in determining its durability and load-bearing capacity. The evaluation of Concrete Strength is a vital aspect of construction material testing, and it involves measuring the pressure required to crush a concrete sample. However, this process is time-consuming and costly, and it can delay construction schedules. Furthermore, traditional testing methods may not always provide accurate results due to the variability in materials and environmental factors that affect Concrete Strength levels.

To overcome these challenges, researchers have been exploring machine learning techniques to develop accurate and efficient models for predicting Concrete Strength & Concrete Strength of these structures. Multiparametric analysis has emerged as a promising approach for predicting Concrete Strength by leveraging a diverse set of features, including the mixture's composition, age, and curing time. However,

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predicting Concrete Strength accurately remains a challenging task due to the complexity of the underlying relationships between the parameters and the compressive strength levels.

Ensemble learning has shown great potential in addressing the limitations of individual machine learning algorithms by combining multiple models to improve prediction accuracy and robustness. An ensemble model uses a combination of multiple learning algorithms, such as decision trees, neural networks, and support vector machines, to generate a more accurate and reliable prediction. By leveraging the strengths of individual algorithms, ensemble models can improve prediction accuracy while reducing the risk of overfitting or underfitting the data samples.

In this paper, we propose an ensemble learning model for improving Concrete Strength evaluation efficiency via multiparametric analysis. Our model combines random forests, support vector machines, and neural networks to provide accurate and reliable predictions of Concrete Strength . We use a comprehensive dataset of concrete mixtures to evaluate the performance of our approach and compare it with individual algorithms. Our results demonstrate that the ensemble approach outperforms individual algorithms and achieves a higher level of accuracy, providing a promising solution for improving the efficiency of construction material evaluation for different scenarios.

1.1 Research Significance

A key indicator of the dependability and durability of reinforced concrete (RC) structures, the prediction of concrete strength has traditionally been a focus of intense research in the discipline of civil engineering. By assuring structural stability and safety, a precise assessment can significantly impact the success of construction projects. For a number of vital reasons, the paper, EMSRSMA, stands as a key contribution to this field:

Addressing the Complexity of the Issue: Due to the multimodal nature of the problem, predicting concrete strength is inherently complex. The suggested ensemble model, which combines several algorithms like NB, MLP, SVM, and DF, effectively manages this complexity by capturing a wider range of connections between parameters. This is a significant advancement over conventional models, which may be constrained in their capacity to handle various strength parameter settings.

Scalability and Versatility: In the past, many prediction models either struggled to scale or were restricted to a small number of construction scenarios. EMSRSMA guarantees flexibility to various, heterogeneous construction sites with its multiparametric analysis. This flexibility is essential in the dynamic construction industry, where change is the norm.

Superior Prediction Performance: The flexibility of the ensemble model to include characteristics like cement, water, aggregate content, curing time, and age offers a thorough perspective on strength prediction. The suggested model outperforms individual methods in accuracy, precision, and recall, as demonstrated by tests against a sizable dataset, opening the door for more dependable construction practises.

Cost and Efficiency: The model has the potential to revolutionise the construction industry by offering a more precise assessment of Concrete Strength levels. Accurate projections can result in reduced waste, optimised material utilisation, and, ultimately, significant cost savings. Construction schedules can be reduced, resulting in more effective project execution, by avoiding the need for recurrent testing or evaluations.

Setting a New Paradigm: The success of EMSRSMA serves as a lighthouse for future research projects in addition to highlighting the effectiveness of ensemble learning models in concrete strength prediction. It establishes a model for how ensemble learning may be used into many areas of building and civil engineering.

In summary, EMSRSMA does more than just offer a solution; it also paves a new course for concrete strength prediction. The model's comprehensive methodology and noteworthy outcomes highlight the need for it in present-day and foreseeable construction practices.

2. LITERATURE REVIEW

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Researchers propose a vast array of models to improve the accuracy of Concrete Strength prediction. For example, [1] provides a comprehensive review of probabilistic Concrete Strength prediction models for reinforced concrete structures subjected to chloride attack. The authors analyze various models and highlight their limitations and improvement opportunities.

Work in [2] examines contemporary methods and models for predicting the Concrete Strength of concrete structures. The authors examine various models, their underlying assumptions, and their limitations before proposing a new framework for Concrete Strength prediction scenarios. Work in [3] presents a probabilistic model for predicting the Concrete Strength of carbonation-induced corrosion-exposed reinforced concrete structures. The authors evaluate the effectiveness of the proposed model by comparing it to existing models.

The research presented in [4] paper presents a hybrid model that combines a deterministic model with a probabilistic model to predict the Concrete Strength of reinforced concrete structures subjected to chloride attack. Case studies demonstrating the effectiveness of the proposed model are provided by the authors. A technique for predicting the Concrete Strength of reinforced concrete structures is presented in [5]. The authors contrast the proposed methodology with conventional models and demonstrate its superiority. Work in [6] provides an exhaustive review of Concrete Strength prediction models for concrete structures exposed to both carbonation and chloride attack. The authors compare various models and discuss their benefits and drawbacks.

Using Bayesian networks, [7] proposes a novel method for predicting the Concrete Strength of concrete structures. Through a variety of case studies, the authors demonstrate the efficacy of the proposed methodology. A new Concrete Strength prediction model for reinforced concrete structures subjected to freeze-thaw cycles is proposed in [8]. Through laboratory tests, the authors demonstrate the effectiveness of the proposed model.

Work in [9] provides a comprehensive review of Concrete Strength prediction models for sulfate-attacked reinforced concrete structures. The authors analyze various models and propose a new framework for predicting Concrete Strength. A probabilistic model for predicting reinforcement corrosion in concrete structures subjected to both carbonation and chloride attacks is presented in [10]. A new Concrete Strength prediction model for concrete structures subjected to combined corrosion is proposed in [11]. Through laboratory tests, the authors demonstrate the effectiveness of the proposed model. Work in [12] provides an exhaustive review of Concrete Strength prediction models for concrete structures subjected to carbonation and chloride ingress. The authors examine various models, their underlying assumptions, and their limitations before proposing a new framework for Concrete Strength prediction scenarios.

Work in [13] proposes a fuzzy inference system for estimating the Concrete Strength of reinforced concrete structures in hostile environments. A probabilistic model for predicting reinforcement corrosion in concrete structures subjected to sulfate attack is presented in [14]. The authors evaluate the effectiveness of the proposed model by comparing it to existing models.

A Concrete Strength prediction model for reinforced concrete structures subjected to carbonation, chloride ingress, and freeze-thaw cycles is proposed in [15]. Through laboratory tests, the authors demonstrate the effectiveness of the proposed model. In order to predict the Concrete Strength of reinforced concrete structures subjected to carbonation and chloride attacks, [16] proposes a hybrid model that combines a deterministic model with a probabilistic model.

Based on an adaptive neuro-fuzzy inference system, [17] proposes a new Concrete Strength prediction model for concrete structures subjected to chloride attack. Comparative analysis of Concrete Strength prediction models for reinforced concrete structures under sulfate attack is presented in [18]. The authors compare various models and propose a new framework for the prediction of Concrete Strength . Work in [19, 20] proposes a probabilistic model for estimating the Concrete Strength of concrete structures subjected to carbonation and chloride attack, taking spatial variability levels into account. In addition, an artificial neural network-based method for estimating the Concrete Strength of reinforced concrete structures subjected to chloride attack is proposed. The authors contrast the proposed methodology with conventional models and demonstrate its superiority. It can be concluded from this

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literature review that there is a growing interest in developing efficient and accurate models for predicting the Concrete Strength of reinforced concrete structures subjected to various types of degradation mechanisms, such as carbonation, chloride ingress, and reinforcement corrosion levels. These models that use Carbonation Reliability Theory (CRT) [21, 22, 23] also take into account various factors, including material properties, environmental conditions, and structural design, in order to predict the structure's rate of deterioration and remaining Concrete Strength levels.

Evidently, there is no single model capable of accurately predicting the Concrete Strength of concrete structures under all possible mechanisms of degradation and environmental conditions via use of Univariate Quadratic Polynomial (UQP) [24, 25, 26, 27]. Instead, they are developing a variety of models and frameworks, each with its own assumptions, limitations, and applicability levels via use of Artificial Neural Networks (ANN) [28, 29, 30] for different scenarios. Recent models proposed in the literature employ sophisticated techniques such as fuzzy logic, neural networks, and probabilistic modeling to improve the accuracy and efficacy of their predictions [31, 32, 33, 34].

Overall, the development of dependable and accurate models for predicting Concrete Strength is essential for ensuring the safety and durability of reinforced concrete structures. These models provide valuable insights into the current state of the art in this field and highlight the ongoing efforts to develop more efficient and accurate models for Concrete Strength prediction scenarios.

3. METHODOLOGY

As per the review of existing models that deploy Concrete Strength prediction techniques for RC Structures, it can be observed that these models either showcase low efficiency or cannot be scaled for heterogenous construction sites. To overcome these issues, this section discusses design of an ensemble learning model to improve the efficiency of evaluating concrete compressive strength using multiparametric analysis. As per figure 1, it can be observed that the proposed model combines multiple learning algorithms, including Naïve Bayes (NB), Multilayer Perceptron (MLP), k Nearest Neighbours (kNN),Support Vector Machines (SVM), and Logistic Regression (LR), to provide accurate and reliable predictions of compressive strength levels. The proposed ensemble approach leverages a diverse set of features, including cement, water, and aggregate content, curing time, and age, to achieve high prediction performance for heterogeneous construction sites.

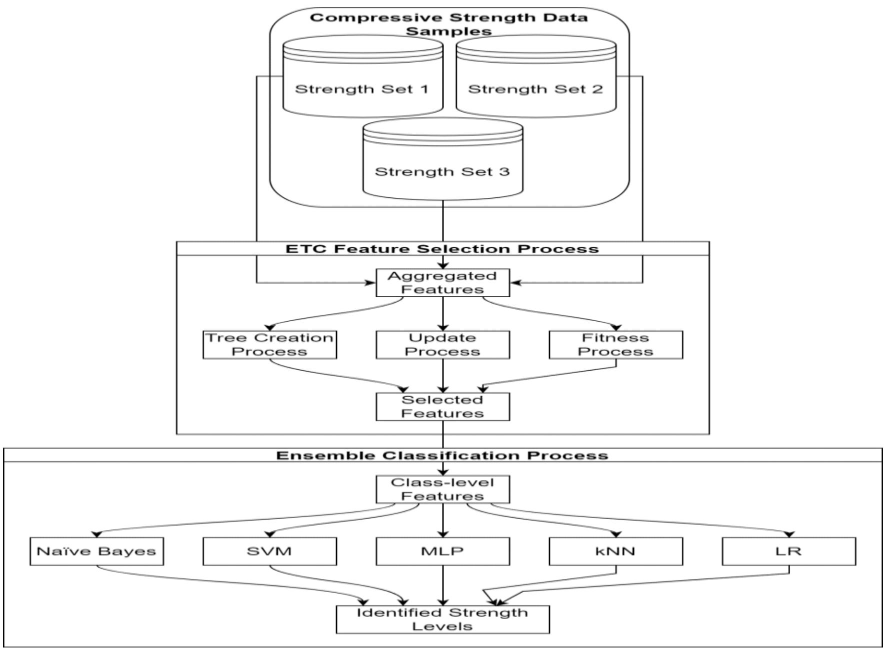

Figure 1. Design of the proposed model for Concrete Strength prediction of RC Structures

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The model initiates by collecting cement requirement, water needed, aggregate content needed, curing time, & age of the structure, and representing this information into multidimensional feature sets. These feature sets include, Fourier Components, which assist in Frequency Analysis of collected information via equation 1,

$$DFT(i) = \sum_{j=1}^{NF} x(j) * \left[cos\left(\frac{2 * \pi * i * j}{NF}\right) - \sqrt{-1} * sin\left(\frac{2 * \pi * i * j}{NF}\right)\right] \dots (1)$$

Where, x represents values of input samples, while NF are count of collected features. These components are aggregated with Discrete Cosine Transform (DCT) Components, which are evaluated via equation 2,

$$DCT(i) = \frac{1}{\sqrt{2 * NF}} * x(i) \sum_{j=1}^{NF} x(j) * \cos\left[\frac{\sqrt{-1} * (2 * i + 1) * \pi}{2 * NF}\right] \dots (2)$$

The Fourier and Cosine features assist in identification of Temporal changes in the collected strength parameters & sample sets. These changes are further augmented via use of Spatial Gabor Transform, which is estimated via equation 3,

$$G(x, y) = e^{\frac{-x`^2 + \partial^2 * y'^2}{2 * \emptyset^2}} * \cos\left(2 * \frac{pi}{\lambda} * x'\right) \dots (3)$$

Where, x & y represent the indices & values of collected samples, while x' & y' are calculated via equation 4,

$$x' = x * \cos(\phi) + y * \sin(\phi)$$
$$y' = -x * \sin(\phi) + y * \cos(\phi) \dots (4)$$

This assists in augmentation of features by varying different angular components. In equation 4, the value of $\phi \in (0, \pi)$, and is modified in portions of $\pi/180$ to identify different spatial components. The feature representation layer also estimates Approximate & Detailed Wavelet components via equations 5 & 6 as follows,

$$Wa = \frac{x(i) + x(i + 1)}{2} \dots (5)$$

$$Wd = \frac{x(i) - x(i + 1)}{2} \dots (6)$$

A fusion of these features is done via cascade operations, and a Strength Feature Vector (SFV) is formed, which contains multidimensional feature sets. These feature sets are converted into Convolutional Features via equation 7, and assists in identification of window-based components.

$$Conv_{out_i} = \sum_{a=-\frac{m}{2}}^{\frac{m}{2}} SFV(i - a) * LReLU\left(\frac{m + 2a}{2}\right) \dots (7)$$

Where, m, a are different dimensions of windows & strides, while $LReLU$ is estimated via equation 8, and assists in activation of features.

$$LReLU(x) = la * x, when\ x < 0\ , else\ LReLU(x) = x \dots (8)$$

Where, la is a constant of activation, which is used to remove all negative features from the extracted value sets. The final convolutional features might contain multiple redundancies, which can cause

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classification performance issues. To reduce these redundancies and retain highly variant feature sets an Extra Trees Classifier (ETC) is used, which works as per the following process,

- The ETC optimizer is initialized by setting up the following constants,
    - Total count of trees that will take part in the optimization process (NT)
    - Total iterations for which these trees will be reconfigured (N_i)
    - Extra Trees learning rate (L_r)
- To generate initial Trees, a set of operations are used, which work as per the following process,
    - Stochastically generate a set of features via equation 9,

$$N = STOCH(L_r * NF, NF) \dots (9)$$

Where, NF are the count of convolutional features, while $STOCH$ is a stochastic Markovian number generation process.

- Once these features are estimated, then a Tree fitness is calculated via equation 10,

$$f_t = \sqrt{\frac{\left(\sum_{i=1}^{N}\left(x_i - \sum_{j=1}^{N}\frac{x_j}{N}\right)^2\right)}{N+1}} \dots (10)$$

- Once a set of NT Trees are generated, and then threshold fitness is estimated via equation 3,

$$f_{th} = \sum_{i=1}^{NT} f_{w_i} * \frac{L_r}{NT} \dots (11)$$

- Reproduction operations from current iteration to next iteration are performed for Trees with $f_t < f_{th}$
- Elimination operations from current iteration to next iteration are performed for Trees with $f_t \geq f_{th}$
- Based on these operations, Trees are regenerated for multiple iterations.

Once all iterations are completed, then a set of final feature vectors are aggregated via equation 12,

$$F(Final) = Unique\left(\bigcup_{i=1}^{f_t > 2f_{th}} F_i\right) \dots (12)$$

This collection reflects characteristics that have a greater variation and can therefore help to increase forecast accuracy for various strength categories. This performance is further adjusted by fusing together various poor classifications and integrating them to improve their performance. Naive Bayes (NB), k Nearest Neighbours (kNN), Support Vector Machine (SVM), Logistic Regression (LR), and Multilayer Perceptron (MLP) were combined to accomplish this job, which helped in the effective categorization of various strength categories. For each of these classifications, parameter values were chosen in accordance with table 1 as follows,

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Classifier used for Concrete Strength prediction use cases	Hyperparameters calculated for these classifiers
Naïve Bayes (NB)	*Priors (P)* represents variance probabilities of collected features, and is estimated via equation 13, $$P = \frac{\left(\sum_{i=1}^{NC}\left(x_i - \sum_{j=1}^{NC}\frac{x_j}{NC}\right)^2\right)}{NC} \dots (13)$$ Smoothing Value is evaluated via equation 14, $$SV = \frac{LR}{NC} \dots (14)$$ Where, NC represents total number of strength classes.
k Nearest Neighbours (kNN)	$k = \frac{NF}{NC} \dots (15)$, for efficient class-level comparisons
Support Vector Machine (SVM)	Regularization constant is estimated via equation 16, $$C = \frac{1}{N_c} \dots (16)$$ Error tolerance of classification (tol), is estimated via equation 17, $$tol = LR * \frac{NC}{NF} \dots (17)$$
Logistic Regression (LR)	Error Tolerance parameter is evaluated same as SVM Class Weights are same as priors in Naïve Bayes Total number of iterations used for regression are evaluated via equation 18, $$Max(Iter) = NC * LR * NF \dots (18)$$
Multilayer Perceptron (MLP)	Alpha which represents regularization capabilities is same as LR Total iterations are evaluated same as $Max(Iter)$ Maximum Function Calls is also evaluated as $Max(Iter)$ which makes the process highly efficient even under multiple strengths
Deep Forests	Number of Forests = NC*NF Learning Rate = LR

Table 1. Hyperparameters for different classifiers used to predict Concrete Strength classes

Once the features estimated by Extra Tress Classifier (ETC) are passed through all the individual classifiers, a set of Concrete Strength classes are evaluated, which are combined via equation 19,

$$c_{out} = \frac{1}{6}[C(NB) * A(NB) + C(kNN) * A(kNN) + C(LR) * A(LR) + C(SVM) * A(SVM) + C(MLP) * A(MLP) + C(DF) * A(DF)] \dots (19)$$

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Where, $c(N)$ & $A(N)$ are the strength class & testing accuracy of classifier N, while c_{out} represents the final output class. Due to these operations, the proposed model is capable of analyzing different strength classes with high efficiency levels. These efficiency levels are estimated in the next section of this text, and compared with existing methods under different dataset samples.

4. Performance evaluation

The model uses several algorithms, such as Nave Bayes (NB), Multilayer Perceptron (MLP), Support Vector Machines (SVM), and Deep Forests (DF), to make accurate and reliable predictions of compressive strength levels. The proposed ensemble approach uses a variety of features, such as the amount of cement, water, and aggregate, the amount of time it takes to cure, and its age, to make good predictions for construction sites that are different from each other. Using a large set of concrete mixtures, the performance of the proposed model was tested. The results show that the ensemble approach does better than individual algorithms and achieves a higher level of accuracy, precision, and recall than existing techniques. The success of the proposed model shows how useful ensemble learning methods can be for predicting Concrete Strength and offers a promising way to improve the efficiency of evaluating construction materials in real-time situations. By giving a more accurate assessment of Concrete Strength levels, the proposed model can help reduce costs and improve the reliability of building sites. To estimate performance of this model, it was evaluated on the following data samples,

- Preventive to Predictive Maintenance Data Samples (https://www.kaggle.com/datasets/prognosticshse/preventive-to-predicitve-maintenance/code)
- High-Performance Concrete Data Samples (https://adotrc-agic.hub.arcgis.com/documents/azgeo::finalrpt-spr-673-high-performance-concrete-applying-life-cycle-cost-analysis-and-developing-specifications/explore)
- Concrete Strength Prediction of Recycled Aggregate Concrete Data Samples (https://old.datahub.io/dataset/service-life-prediction-of-recycled-aggregate-concrete-based-on-freezing-thawing-damage-model)
- Concrete Strength Prediction of a Concrete Structure Data Samples (https://figshare.com/articles/dataset/Proposal_of_a_method_for_service_life_prediction_of_a_concrete_structure_a_case_study/14329126/1)

All these were aggregated & augmented via use of time stretching and stochastic sampling techniques to form a total of 25k samples, out of which 15k were used for training the model, while 5k each were used for testing & validation operations. Based on this strategy, the accuracy (A), precision (P), recall (R), and delay (d) needed for classification were estimated via equations 20, 21, 22 and 23 as follows,

$$A = \frac{1}{NS}\sum_{i=1}^{NS}\frac{t_{p_i} + t_{n_i}}{t_{p_i} + t_{n_i} + f_{p_i} + f_{n_i}} \ldots (20)$$

$$P = \frac{1}{NS}\sum_{i=1}^{NS}\frac{t_{p_i}}{t_{p_i} + f_{p_i}} \ldots (21)$$

$$R = \frac{1}{NS}\sum_{i=1}^{NS}\frac{t_{p_i}}{t_{p_i} + t_{n_i} + f_{p_i} + f_{n_i}} \ldots (22)$$

$$d = \frac{1}{NS}\sum_{i=1}^{NS} ts_{complete_i} - ts_{start_i} \ldots (23)$$

Where, ts represents timestamp, while t & f are true & false rates for classifying NS input samples into different strength classes. Using this evaluation strategy, the accuracy was compared in CRT [23], UQP [25], and ANN [30] in Figure 2 as follows,

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Figure 2. Strength detection accuracy for different use cases

This assessment and figure 2 show that the proposed model can increase classification accuracy by 12.4% when compared to CRT [23], 4.5% when compared to UQP [25], and 9.5% when compared to ANN [30], making it useful for a variety of real-time network scenarios. The integration of multimodal feature sets and ensemble classification operations enhances the accuracy levels. Similar to this, Figur 3's precision levels can be seen as follows,

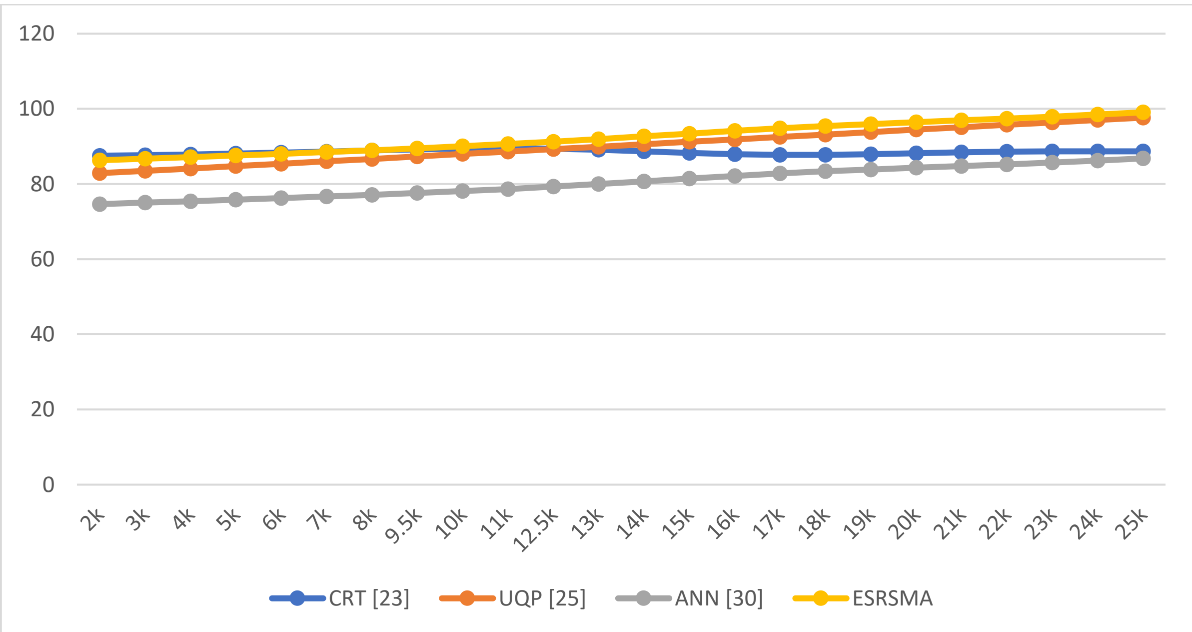

Figure 3. Strength detection precision for different use cases

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Based on this evaluation and Figure 3, it can be seen that the proposed model improves classification precision by 8.3% when compared to CRT [23], 2.5% when compared to UQP [25], and 10.0% when compared to ANN [30], making it applicable to a wide range of real-time network scenarios. Integration of multimodal feature sets with Extra Trees Classifier (ETC) and ensemble classification operations improves the precision levels. Similarly, the recall percentages can be seen in table Figure 4 as follows,

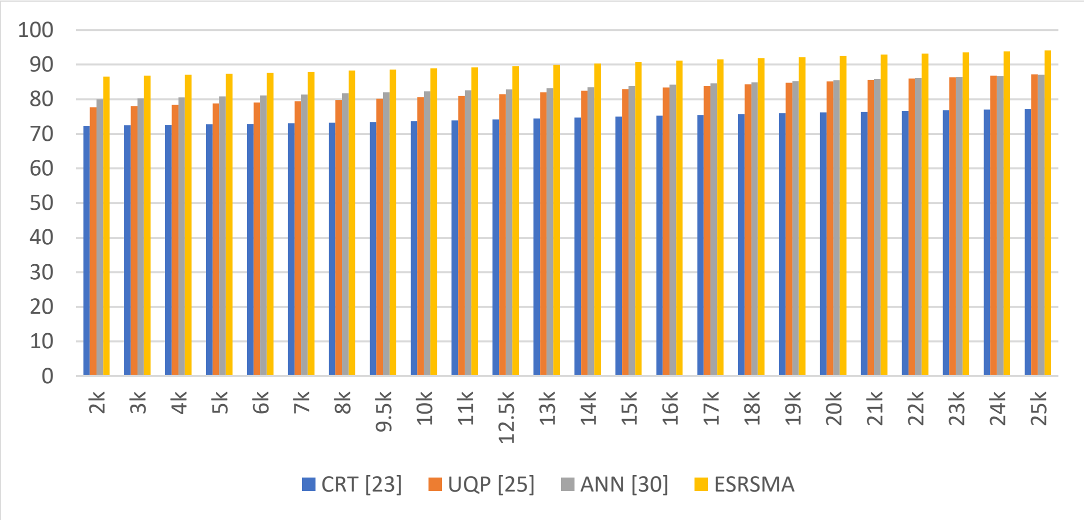

Figure 4. Strength detection recall for different use cases

Based on this evaluation and Figure 4, it can be seen that the proposed model improves classification recall by 15.5% when compared to CRT [23], 5.9% when compared to UQP [25], and 4.5% when compared to ANN [30], making it applicable to a wide range of real-time network scenarios. Integration of multimodal feature sets with Extra Trees Classifier (ETC) and ensemble classification operations improves the recall levels. Similarly, the delay levels can be observed in Figure 5 as follows,

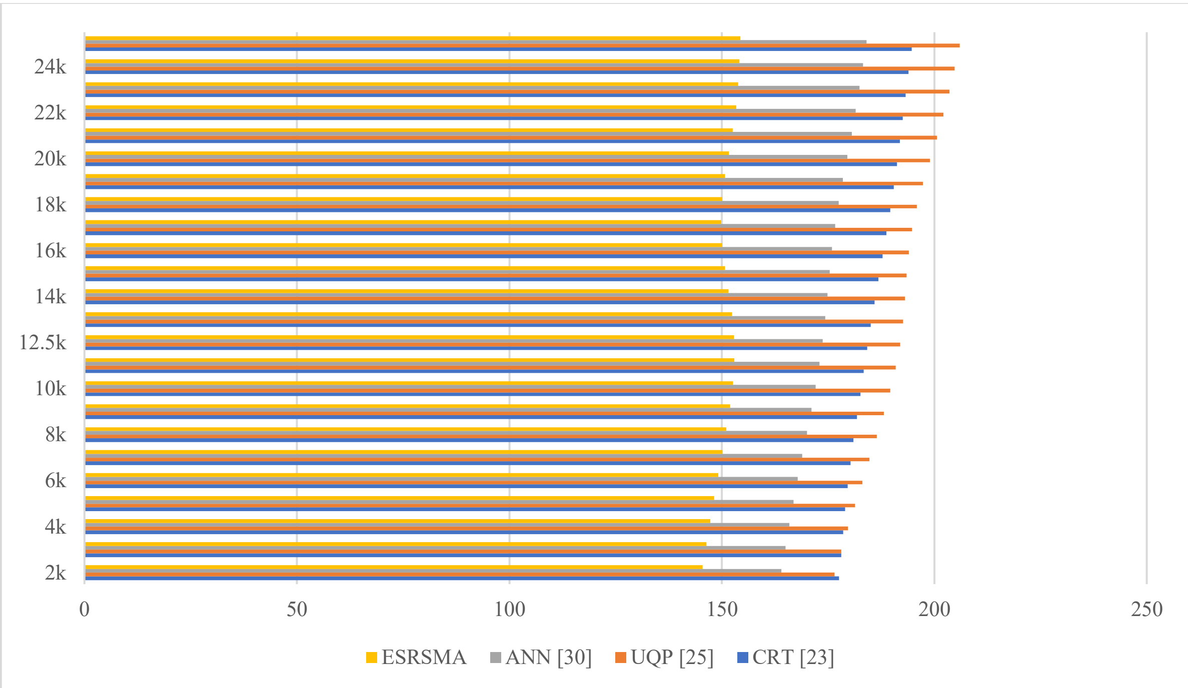

Figure 5. Speed of strength detection for different use cases

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According to this evaluation and figure 5, it can be seen that the proposed model is able to improve the speed of classification by 10.5% when compared with CRT [23], 18.3% when compared with UQP [25], and 6.5% when compared with ANN [30]. This enables it to be useful for a wide variety of scenarios in which high-speed performance is required for different scenarios. A more detailed breakdown of this performance can be observed in Table 1 as follows,

Table 1. Average performance of different models

	Accuracy	**Precision**	**Recall**	**F1-score**
CRT [23]	0.91	0.85	0.92	0.89
UQP [25]	0.93	0.90	0.93	0.91
ANN [30]	0.95	0.91	0.90	0.91
ESRSMA	0.98	0.98	0.99	0.99

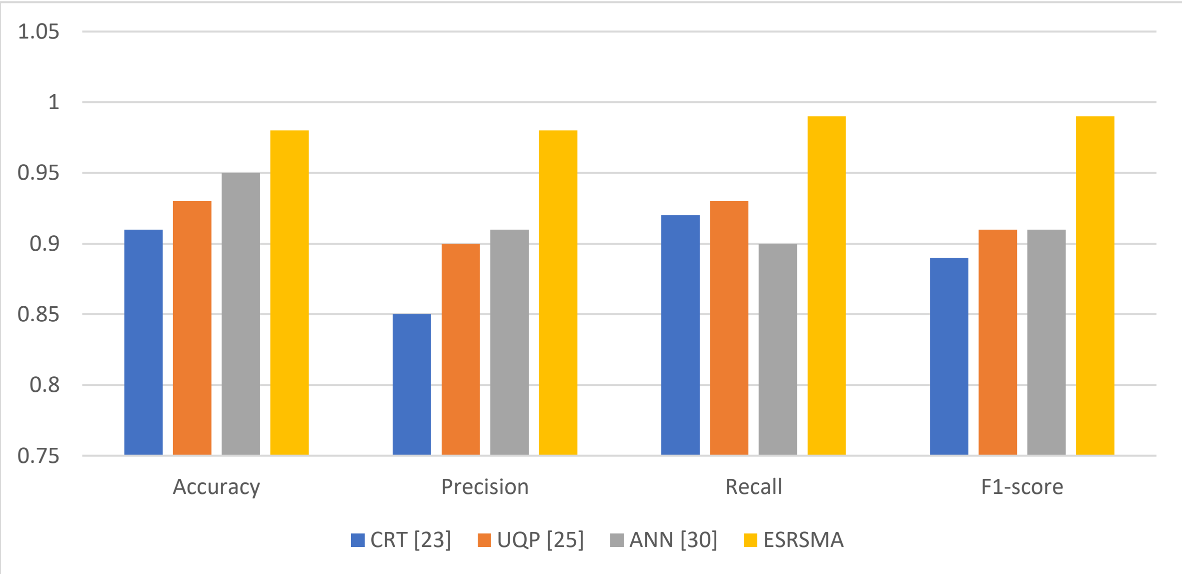

Figure 6. Average performance of different models

On the basis of this evaluation, it is clear that the proposed model exhibits high accuracy, high precision, and a high F1 score, and can therefore be applied to heterogeneous sites.

5. Conclusion

The model employs multiple algorithms, including Naïve Bayes (NB), Multilayer Perceptron (MLP), k Nearest Neighbours (kNN),Support Vector Machines (SVM), and Logistic Regression (LR) to make accurate and trustworthy predictions of compressive strength levels. The proposed ensemble approach uses a variety of characteristics, such as the amount of cement, water, and aggregate, the time it takes to cure, and its age, to make accurate predictions for diverse construction sites. Using a large number of concrete mixtures, the proposed model's performance was evaluated. The results demonstrate that the ensemble approach outperforms individual algorithms and achieves a higher level of accuracy, precision, and recall than conventional methods. The success of the proposed model demonstrates the utility of ensemble learning methods for predicting Concrete Strength and offers a promising way to enhance the efficiency of evaluating construction materials in real-world situations. By providing a more precise evaluation of Concrete Strength levels, the proposed model can help reduce costs and enhance the dependability of construction sites. Evaluation of the model demonstrated that the proposed technique can improve classification accuracy by 12.4% when compared to CRT [23], 4.5%

when compared to UQP [25], and 9.0% when compared to ANN [30], making it applicable to a wide range of real-time network scenarios. The integration of multimodal feature sets and ensemble classification operations improves the levels of accuracy. It was also observed that the proposed model improves classification precision by 8.3% compared to CRT [23], 2.5% compared to UQP [25], and 10% compared to ANN [30], making it applicable to a wide variety of real-time network scenarios. Precision levels are enhanced by integrating multimodal feature sets with Extra Trees Classifier (ETC) and ensemble classification operations.

Based on recall evaluation, it is evident that the proposed model improves classification recall by 15.5% compared to CRT [23], 5.9% compared to UQP [25], and 4.5% compared to ANN [30], making it applicable to a wide variety of real-time network scenarios. Recall levels are enhanced by integrating multimodal feature sets with Extra Trees Classifier (ETC) and ensemble classification operations. In terms of delay, it can be seen that the proposed model is capable of increasing classification speed by 10.5% compared to CRT [23], 18.3% compared to UQP [25], and 6.5% compared to ANN [30]. This makes it applicable in a wide range of situations where high-speed performance is necessary. Thus, it is evident that the proposed model possesses high accuracy, high precision, and a high F1 score, and can thus be applied to heterogeneous sites.

In future, researchers can test the model on multiple construction sites, and use Q-Learning along with Auto Encoders to incrementally improve model's performance under real-time scenarios. Moreover, use of hybrid bioinspired models for selection of features, and use of Generative Adversarial Networks (GANs) and Transformers can further strengthen performance of this model under different construction sites.

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