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Machine learning-based techniques to facilitate the production of stone nano powder-reinforced manufactured-sand concrete

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Abstract. This study aims to examine four machine learning (ML)-based models for their potential to estimate the splitting tensile strength (STS) of manufactured sand concrete (MSC). The ML models were trained and tested based on 310 experimental data points. Stone nanopowder content (SNPC), curing age (CA), and water-to-cement (W/C) ratio were also studied for their impacts on the STS of MSC. According to the results, the support vector regression (SVR) model had the highest correlation with experimental data. Still, all of the optimized ML models showed promise in estimating the STS of MSC. Both ML and laboratory results showed that MSC with 10% SNPC improved the STS of MSC.
Keywords: machine learning; manufactured-sand concrete; stone nano-powder; tensile strength

1. Introduction

The demand for engineering constructions is increasing day by day at a higher rate. Therefore, examining the mechanical properties of structural materials has a special place among engineers and researchers (Cai *et al*. 2023, Jin *et al*. 2023, Liu *et al*. 2023, Wang *et al*. 2023, Zhou *et al*. 2021). One of these important materials is concrete (Huang *et al*. 2020, 2021, 2022, Zhou *et al*. 2023a, b). Every year, the global construction sector consumes and produces at least 10 billion metric tons of concrete (Zhang *et al*. 2020). This number is anticipated to increase due to the growing interest in these services. Over-extraction of river sand has occurred in specific locations due to the widespread use of river sand in making concrete. Since river sand is a finite resource, its depletion poses severe ecological risks. Therefore, it is essential to establish regulations for sand extraction and locate a long-term replacement for river sand. Achieving long-term economic and development objectives requires using locally available, durable aggregates. This will aid in minimizing the building's overall operating costs, energy consumption, and carbon footprint. Evidence shows that manufactured sand (MS) can be a sustainable substitute for river sand. Thus, manufactured sand concrete (MSC) has become an essential and environmentally benign part of the building industry (Zhao *et al*. 2017).

MS may be extracted from waste rock stockpiles by crushing them. As a result, MS is more angular than river sand and has a rougher surface (Li *et al*. 2011). However, at the same water content, MS is less workable than river sand due to the particles' inability to pack together (Zhao *et al*. 2017). Micro-fines (5-20% particles that pass through a 75-m screen) introduced during the production of MSC significantly impact the workability, compressive and flexural strengths, and freezing resistance of concrete (Li *et al*. 2011). Therefore, more considerations than those needed for river sand concrete are required when attempting to predict the mechanical properties of MSC. Preparing many samples for laboratory testing to extract patterns from tangible features requires significant time and money. Studying concrete's mechanical characteristics in the lab is fraught with difficulties. Concrete designers have turned to machine learning (ML) technology in droves in an effort to solve this conundrum (Dutta and Barai 2019).

In recent years, a number of engineering variables have benefited from the application of ML techniques like support vector machines (SVMs) and artificial neural networks (ANNs) (He *et al*. 2023, Moradi *et al*. 2021, Peng *et al*. 2021, Yuan *et al*. 2022). Gandomi *et al*. (2016) employed genetic programming (GP) to predict concrete creep. According to a recent study (Dao *et al*. 2019), an adaptive neuro-fuzzy inference system (ANFIS) may successfully approximate the CS of geopolymer concrete. Ling *et al*. (2019) evaluated the CS in marine environments using the support vector machine and the K-fold cross-validation technique. Compared to the DT and ANN

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models, the relative error of the SVM was lower. Yaseen *et al*. (2018) evaluated the extreme ML model and found it helpful in compressive strength (CS) modeling for lightweight foamed concrete. There are several examples in the literature of other uses of ML in the modeling of concrete characteristics (Amlashi *et al*. 2019, Ashrafian *et al*. 2018, Lokuge *et al*. 2018, Rathakrishnan *et al*. 2022, Ziyad Sami *et al*. 2023).

This research aims to assess the viability of four ML techniques for predicting MSC's mechanical characteristics. Support vector regression (SVR), multilayer perceptron regression (MLPR), and gene expression programming (GEP) are some of these techniques. Some of these techniques are new to the field. Despite its importance, splitting tensile strength (STS) has been overlooked in favor of UCS in ML-based studies of concrete's mechanical characteristics (Zhang *et al*. 2020). That's why the STS parameter is treated as a model output here. Previous studies show that the UCS and STS of MSC are significantly impacted by the proportion of stone powder used in its formulation (Zhao *et al*. 2017). So far, little research has been provided to create ML-based models that consider the impact of stone powder on the strength of the MSC. Only stone micropowder was utilized in the few tests that were done. In this research, stone nanopowder (SNP) was used to manufacture MSC samples for the first time. 310 data points from the lab were used to train and validate the models, with 80% used for training and 20% for validation. These data points included nine characteristics that were shown to significantly impact the mechanical properties of MSC. The effects of the curing age (CA), the W/C ratio, and the stone nanopowder content (SNPC) on the STS of MSC were also investigated. When everything was said and done, the performance of each ML model for predicting the STS of MSC was compared with the laboratory data to choose the best model.

2. ML models

This study uses four supervised ML methods for regression, including GEP, SVR, LSTM, and MLPR. Academics have accepted these methods in various tasks, most notably geotechnical analysis and domain stability, due to their relevant properties and advantages. The benefits are briefly summarized here.

- For classification and regression, they can handle both linear and nonlinear data.
- They employ a decision boundary in the form of a hyperplane, node, or neuron to categorize people into distinct sets.
- Costs and potential benefits are examined alongside alternatives and decisions, leading to the computation of capabilities and blunders.
- Error and calculation accuracy may be examined in proportion to the complexity of the research, and the possibility of using them throughout all stages of evaluation and stabilization is reduced.
- They make making more accurate predictions possible, ultimately saving time and money.
- Their application is simple and productive.

In SVR, the term "hyperplane" describes the straight line used to fit the data. The purpose of an SVR algorithm is to locate an n-dimensional hyperplane that can accurately classify the input points. The data points on each side of the hyperplane closest to the hyperplane are known as support vectors. Because these elements impact the hyperplane's position and tilt, they build the SVR.

LSTM is a type of recurrent neural network architecture that captures long-term dependencies in sequential data. It uses specialized memory cells and gates to selectively store, forget, and propagate information through the network. LSTM networks have found wide applications in various domains and have proven effective in sequential data analysis tasks.

MLPR is a neural network model used for regression tasks. It consists of multiple layers of perceptrons that learn the nonlinear relationships between input features and the target variable. MLP regression is capable of capturing complex patterns and making accurate predictions. It is widely used in various domains for regression analysis.

GEP is a computational technique combining genetic algorithms and programming to evolve computer programs for solving optimization, regression, and classification problems. It represents programs as linear sequences of genes and applies genetic operations to create and improve generations of programs. GEP has been proven effective in various domains and is particularly useful for symbolic regression tasks.

3. Dataset

Both the direct tensile strength (DTS) and the shear tensile strength (STS) tests may be used to determine a concrete's tensile strength (TS). The DTS is more difficult to implement in specifications and recommendations, but it is more likely to be used since it more accurately represents the tensile qualities of concrete. The STS is preferred over the DTS in scientific and technological endeavors because of its convenience, consistency, and low variability. Furthermore, cylindrical and cube-shaped objects are the norm in STS testing (Zhao *et al*. 2017). The outcomes of tests conducted on cylindrical specimens (300 mm, 150 mm diameter) and cubic specimens (150 mm dimension) are the same. In light of the significance of the TS of MSC applied in reinforced concrete structures and the absence of research into the TS development of MSC, this paper presents the test results of the STS of MSC with varying water-to-cement (W/C) ratios and stone nanopowder content (SNPC) for a curing age (CA) up to 388 days. In order to make the MSC samples, the SNPC-absorbed water was added to the starting mixing water. The sand ratio was increased by around 2% for concrete using natural sand and dropped by about 1%–2% for every 2%–3% rise in SNPC in manufactured sand. Finally, after determining the necessary CA for each sample, the STS test was carried out on 310 cube-shaped samples (15*15*15 cm). Each sample had a unique mixing design. Finally, 310 data points were produced, comprising nine effective parameters on the STS of the concrete, by recording the laboratory findings for each of the MSC samples. The ML models were trained

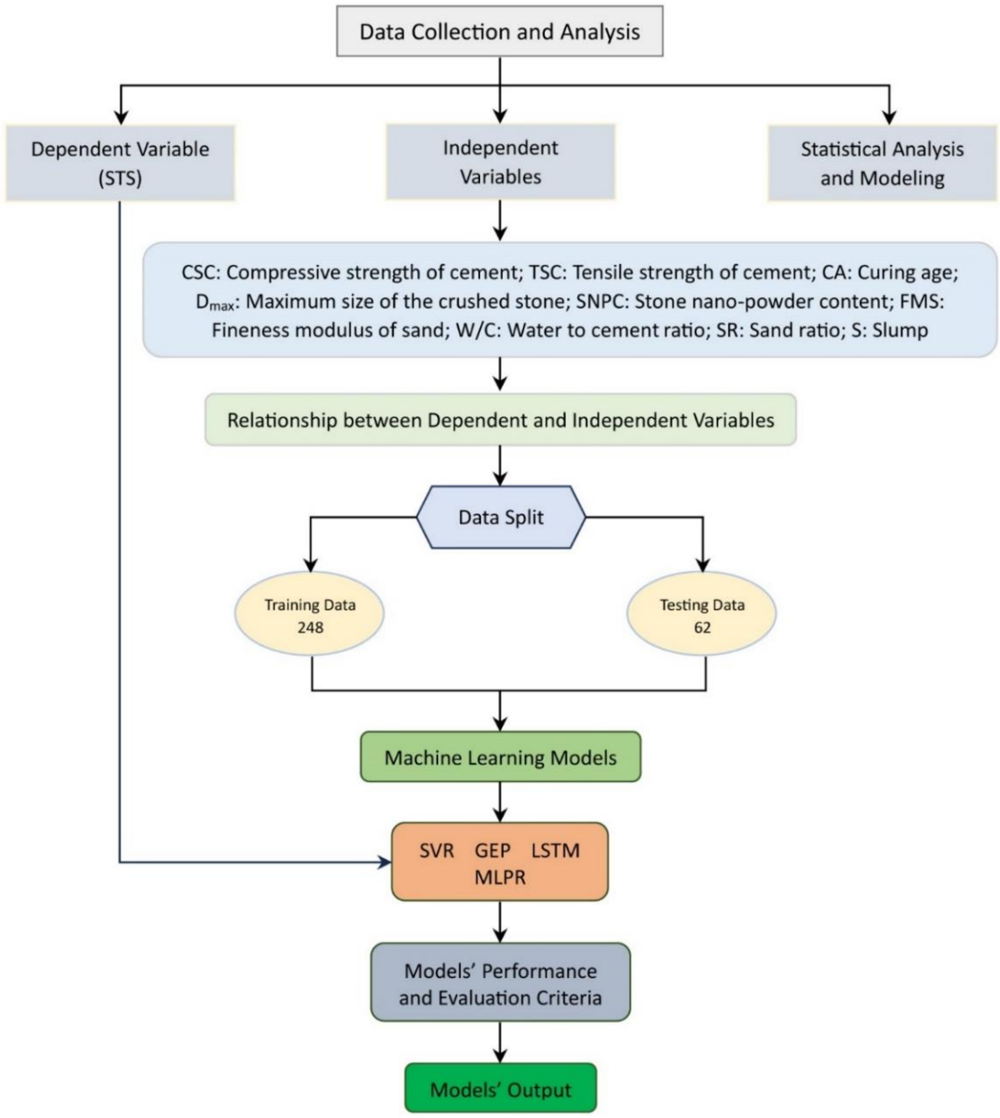

Fig. 1 Flowchart of the methodology

using 80% of the dataset and then put to the test with the remaining 20%. The flowchart of the methodology is depicted in Fig. 1.

The principal component analysis (PCA) results indicate that the first two principal components account for 66% of the overall variance in the dataset. This suggests that these two components capture the data's most significant patterns and trends.

Fig. 2, which presents the scree graph, helps determine the number of principal components to consider. The scree graph shows the eigenvalues of each principal component, representing the amount of variance explained by that component. In this case, the graph indicates that the first two principal components (PCs) have relatively high eigenvalues, suggesting they are the most important in describing the variance in the dataset.

Fig. 3 displays the scatter plot of the first two PCs. The scatter plot visualizes the data points in a two-dimensional space, each representing an observation in the dataset. The lack of distinct clusters or anomalies in the scatter plot suggests that the data does not exhibit clear natural groupings or outliers.

4. Statistical metrics

The accuracy performance of the ML models employed in this work to forecast the STS of MSC was evaluated using five statistical measures, including coefficient of determination (R^2), root mean square error (RMSE), mean absolute percentage error (MAPE), variance accounted for (VAF), and a10–index.

5. Results and discussion

One of our current objectives is to compare the accuracy of ML models with that of laboratory tests in predicting the STS of MSC. The a–10index metric is used to compare the predicted results from each ML model to the actual

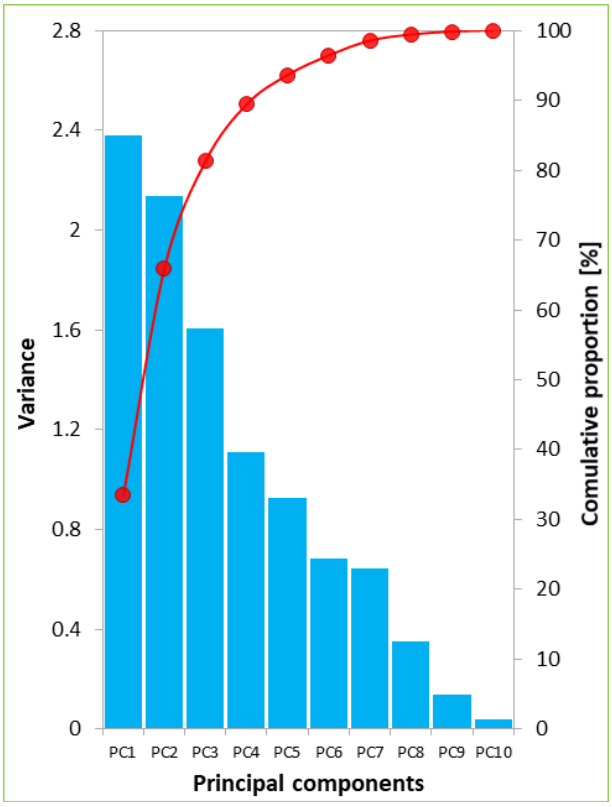

Fig. 2 Scree plot for the first ten PCs

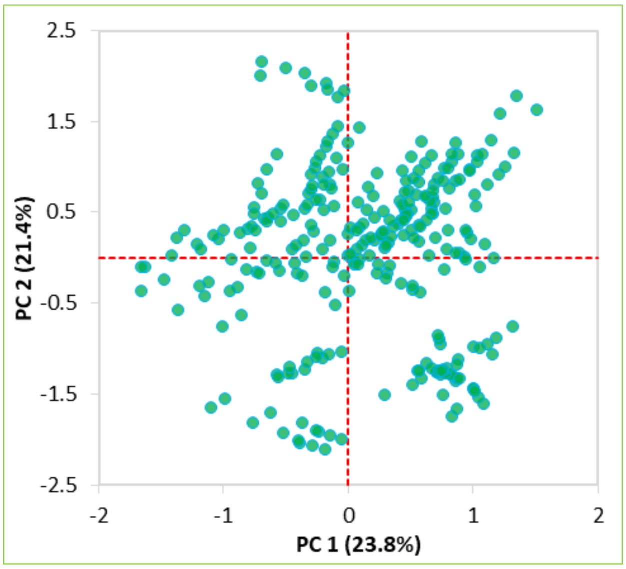

Fig. 3 Scatter plot of the PC1 against the PC2

laboratory findings in Fig. 4. All of the ML models agree well with the experimental data and provide exact estimates of STS. The STS of concrete may be estimated with the greatest and least precision using the SVR and MLPR models, respectively (a–10index = 0.87 and 0.56). Following is a ranking of the models' accuracy as determined by the a10–index: SVR > GEP > LSTM > MLPR.

We then evaluate the ML models' efficacy concerning various statistical measures, with the highest-scoring model being the most reliable option. Table 1 shows the calculated values for the different statistical metrics used in the analysis. For each metric, the model with the highest score was the one that best served the end user. The total number of points earned by each model is shown in the last column of Table 1.

The graphical representation of the ML models' ranking scores can be found in Fig. 5. In Fig. 5, the results obtained in Table 1 can be seen graphically. As it is clear from this figure, the highest total scores of statistical metrics are related to the SVR model. The GEP, LSTM, and MLPR models have obtained the scores of the metrics from higher to lower, respectively. The SVR and MLPR models fared the best and the worst in accuracy, with a ranking score of 15 and 5, respectively. The following is a ranking of the ML models' ability to predict the STS of MSC, based on the full findings in Table 1. SVR > GEP > LSTM > MLPR.

In reality, it's crucial to emphasize that all of the ML models adequately predicted the STS of MSC. Although the results of various models are shown here, there is a slight variation between them. Therefore, these models can forecast the STS of concrete with an accuracy comparable to that obtained in a laboratory setting.

The STS of MSC can now be correctly predicted using several ML models. Instead of relying exclusively on cross-correlation evaluation, it is preferable to investigate input trends and output patterns to guarantee the models' generalization capabilities. To do this, some variables are adjusted within a narrow range while all other factors are constant. At first, we'll check how well the models do by changing only the CA parameter within its allowed range (Table 2) while leaving the rest of the inputs the same. We now only consider 10 test datasets in which just the CA parameter is changed. The STS was determined by conducting laboratory tests on ten samples from the present test set.

That is to say, save the CA, all attributes of a second set of 10 samples analyzed in the lab and modeled using ML were kept the same. ML models and laboratory experiments are compared in Fig. 6. Both the laboratory experiments and the ML models show that the STS of the concrete increases when the CA lengthens from 3 days to 90 days. Only minor shifts in the STS value have occurred after we increased the CA from 90 to 390 days. In response to a change in CA value, all ML models have shown behaviors consistent with laboratory studies. The SVR model, however, showed the most incredible precision.

For the first time, nanoparticle-sized stone powder has been included in the MSC mixture, as indicated above. As was said before, this study is the first to use stone powder of nanoparticle size in the MSC mixture. To provide the highest potential strength, it is essential to carefully examine the MSC composition for the ideal quantity of this addition. For this reason, eleven new concrete examples were cast, and it was assumed that all attributes, except for the SNPC parameter, would remain constant (see Table 2).

Consequently, the SNPC parameter was raised from 0 to 20% in 2% increments throughout the preparation of the first eleven samples. These samples were analyzed in the lab and included in the ML models as fresh test data. In Fig.

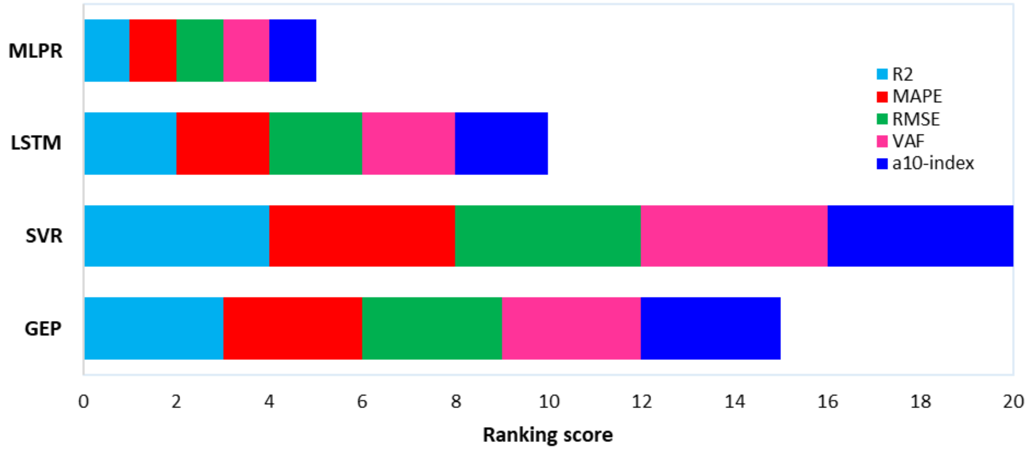

Fig. 5 The total score of the statistical metrics for each of the machine learning models

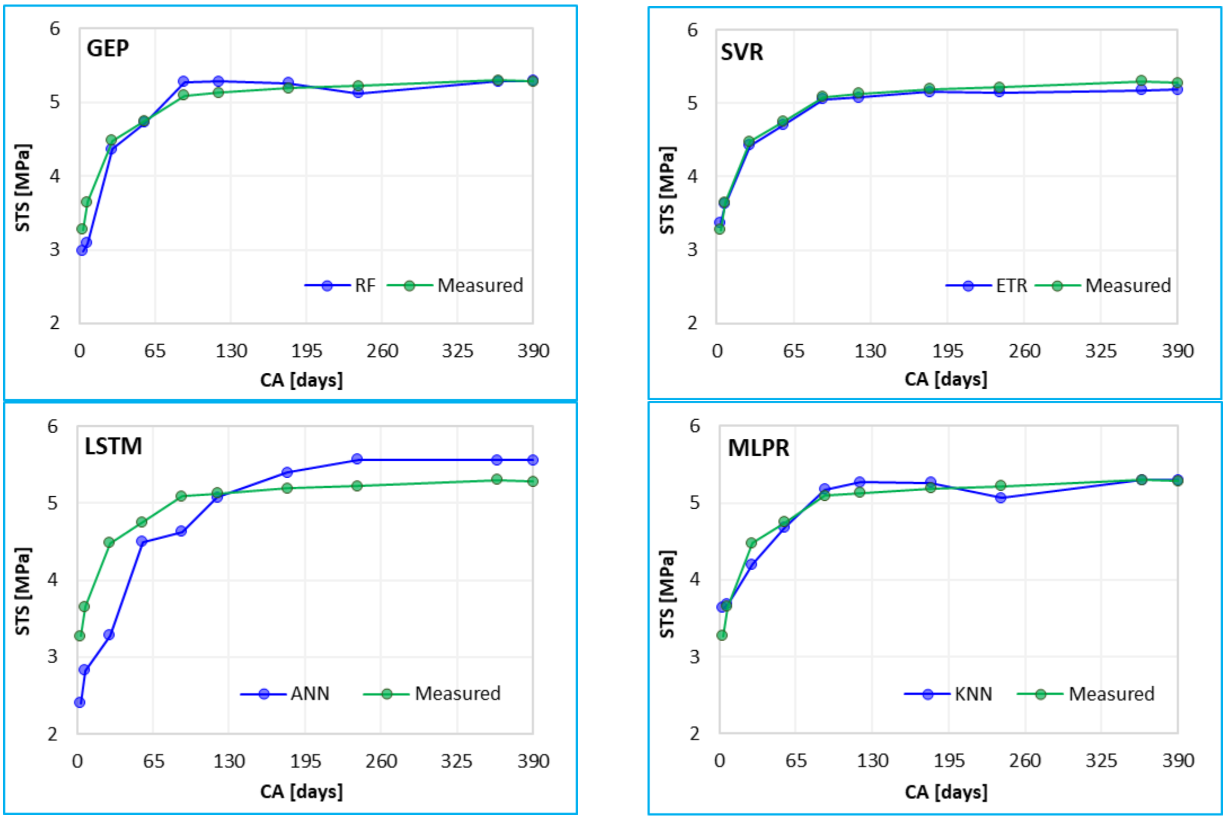

Fig. 6 Comparison of the laboratory tests and ML models in relation to the change of parameter CA

Table 1 Scoring the value of statistical metrics for each ML model

	R^2	Score	MAPE	Score	RMSE	Score	VAF	Score	a10_index	Score
GEP	0.8853	3	0.049	3	0.414	3	95.1	3	0.82	3
SVR	0.9432	4	0.042	4	0.318	4	97.3	4	0.87	4
LSTM	0.8721	2	0.054	2	0.438	2	92.9	2	0.75	2
MLPR	0.8417	1	0.076	1	0.485	1	89.4	1	0.56	1

Table 2 Constant values considered for the input parameters in order to evaluate the generalization of the ML models

CSC [MPa]	TSC [MPa]	CA [days]	D_{max} [mm]	SNPC [%]	FMS	W/C	SR [%]	S [mm]
50	7	3	35	10	3	0.45	35	90

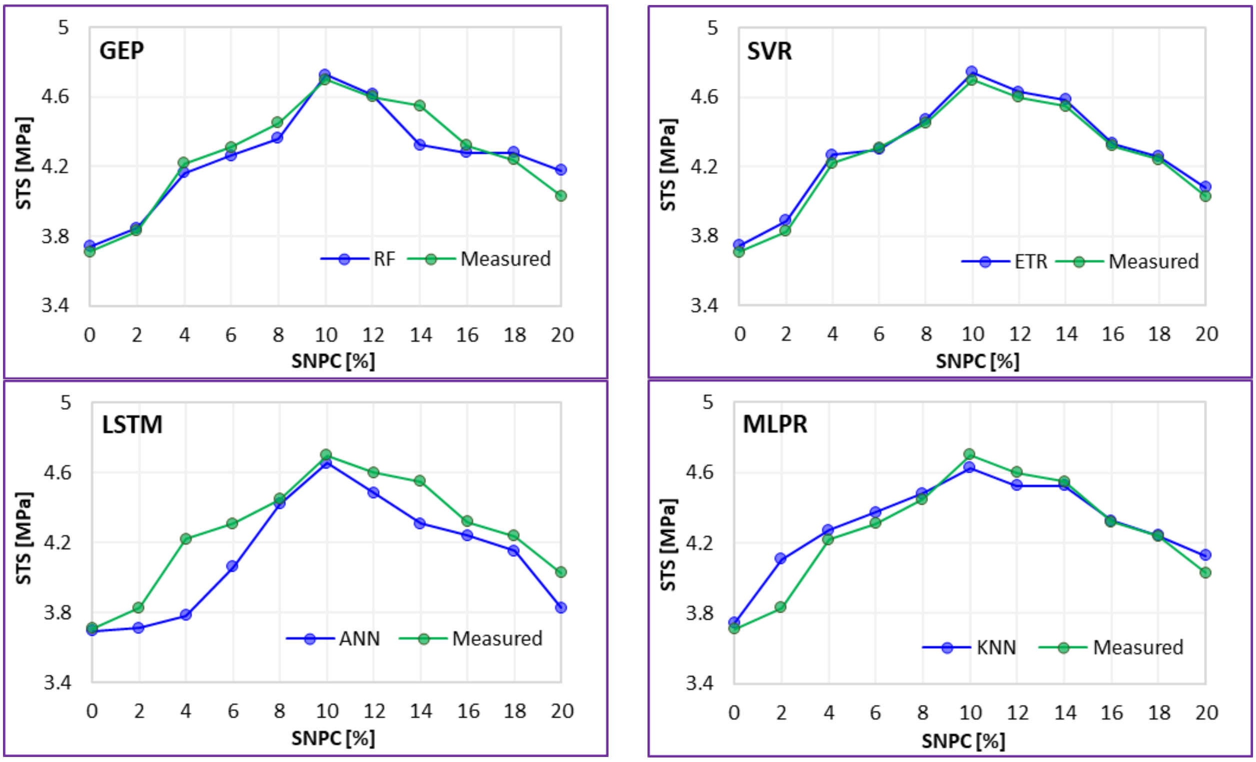

Fig. 7 Comparison of the laboratory tests and ML models in relation to the change of parameter SNPC

7, the findings from each ML technique are contrasted with the laboratory results for these 11 samples. The ML models and the laboratory experiments agree exceptionally well in this instance. The SVR model, however, showed the most consistent behavior with the experimental data. All of the ML models' outputs and the data from the lab show that raising the SNPC from 0 to 10% increases STS. The STS of concrete made with 10% SNPC is increased by about 27% compared to concrete made without SNPC. Increasing the SNPC content of the concrete from 10% to 20% prevented the STS rise from occurring and ultimately caused it to decline. This research concludes that 10% SNPC is the sweet spot for the MSC blend.

6. Conclusions

This study's findings support the following hypotheses:

- The predictions made by the ML models were quite similar to the actual outcomes of the trials. According to a number of statistical measures, the ML models proposed in this study successfully predicted the STS of SNP-enhanced MSC. ON THE OTHER HAND, the SVR and MLPR models came up with the highest and lowest quality estimations, respectively.

- The models were graded according to how well they estimated values by comparing their forecasts with experimental results. The following is the sequence of appearance: SVR > GEP > LSTM > MLPR.

- The SVR model was the most accurate model for predicting the STS of MSC by comparing the models' behavior to laboratory testing in which one input parameter was altered while the others were maintained constant.

- The MSCs had the greatest STSs for 90-day CAs, 0.3-to-1 W/C ratios, and 10% SNCs, all of which were consistent with laboratory and ML findings.

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