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AI-based Optimization of Tensile Strength of the Cement Concrete Incorporating Recycled Mixed Plastic Fine used in Road Construction

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Abstract: One of the main problems in materials science and engineering is predicting the tensile strength of materials. In this study, we investigate how to model and forecast tensile strength (Tensile Strength in Mpa) based on different material attributes using Support Vector Regression (SVR) using Linear and Polynomial Kernels. The dataset includes the following details: plastic type, fine aggregate ratio, water/cement ratio, cement content, and associated tensile strength values. This work has two main goals: (1) to assess the predictive power of SVR models with various kernel functions and (2) to examine the significance of unique material attributes for prediction. To simulate the link between the input features and tensile strength, we used SVR in conjunction with a Linear Kernel. The final model included insightful information on how each feature affected the forecast. Our results show that the Polynomial Kernel SVR model may better reflect the complex interactions among the material attributes than the Linear Kernel SVR model, despite being more interpretable. Better prediction performance was offered by the Polynomial Kernel SVR, which also revealed the non-linear dependencies in the data.
Keywords: Road Construction; Tensile Strength; Artificial Intelligence; Optimization

I. INTRODUCTION

Modern technology and industry rely heavily on materials science and engineering, which is the foundation for designing and developing cutting-edge materials for a range of uses. Tensile strength, which indicates a material's resistance to axial stretching forces, is one of the many mechanical properties of materials that makes it stand out as an important metric [1-7]. Precise estimation of tensile strength is crucial in numerous domains, including as building, aircraft, automobiles, and materials science. Tensile strength prediction has historically been a difficult and complex endeavor since it depends on a variety of material properties and how those factors interact, often in nuanced ways. While conventional regression models work well for linear interactions, they may not be able to adequately address the non-linear dependencies that are often present in datasets related to materials.

Recent years have seen the emergence of machine learning techniques as potent tools for predicting material properties and modeling intricate interactions [8-14]. Because it can handle both linear and non-linear regression issues, Support Vector Regression (SVR), a machine learning technique based on the ideas of Support Vector Machines (SVMs), has drawn a lot of interest in the materials science community.

The use of SVR models—more specifically, SVR with linear and polynomial kernels—for tensile strength prediction is the main goal of this research project. Our goals are twofold: first, we want to find out how well these SVR models predict tensile strength; second, we want to investigate the role that specific material features play in the prediction process.

A number of important material properties are included in the dataset under evaluation, such as the amount of cement, the ratio of water to cement, the amount of fine aggregate, and the kind of plastic utilized in the material. Although it has been demonstrated that each of these characteristics affects tensile strength, the intricate interactions between them call for a reliable and adaptable modeling strategy. In order to create a linear regression model that serves as a foundation for comprehending the contributions of various material parameters to tensile strength, we use SVR in conjunction with a linear kernel in the first section of our inquiry. The model's findings provide the groundwork for a more thorough analysis of the non-linear dependencies in the dataset. Then, to take into consideration any non-linear interactions between the material properties, we employ SVR with a Polynomial Kernel. By using this more intricate model, we are able to increase the precision of tensile strength forecasts and reveal the subtleties that are concealed in the data.

This work attempts to shed light on the relative merits of various SVR techniques in materials science by contrasting the results of the Linear and Polynomial Kernel SVR models.

Furthermore, by providing a distinct viewpoint on the relative significance of material attributes in influencing tensile strength, the coefficients produced from these models improve our comprehension of the behavior of materials.

II. MACHINE LEARNING IN INDUSTRIES

Machine learning has emerged as a disruptive technology enabling more accurate and faster predictions of the mechanical properties and microstructure characteristics of materials across diverse manufacturing industries. For predicting mechanical properties like strength, hardness, toughness etc., supervised learning approaches like regression models, artificial neural networks, and support vector machines are being increasingly leveraged [15-18]. These data-driven models can capture the intricate non-linear relationships between a material's composition, processing conditions, microstructure features and final mechanical performance. In contrast with traditional physically-derived analytical models, the machine learning models are highly adaptable and can account for complex interactions given sufficient training data. For instance, past studies have successfully employed neural networks to predict yield strength and ultimate tensile strength in steel alloys, elastic modulus of porous materials, and fracture toughness of composite laminates among other properties just from the constituent make-up and processing parameters [19-24]. Such machine learning models can potentially reduce expensive, time-consuming experimental testing for mechanical characterization. Regarding microstructure prediction, image analysis techniques like segmentation and feature extraction allow automated characterization of microstructural features from micrographs such as grain size, morphology, crystal structure, porosity, precipitates etc. By correlating these microstructure descriptors to processing conditions using supervised learning approaches, models can now predict microstructural evolution during critical processes such as solidification, thermomechanical working, heat treatment, powder sintering and more. For example, convolutional neural networks have been applied to predict crystal sizes and orientations in polycrystalline nickel alloys from electron backscatter diffraction images. Figure 1 shows the typical prediction process of AI-based algorithms.

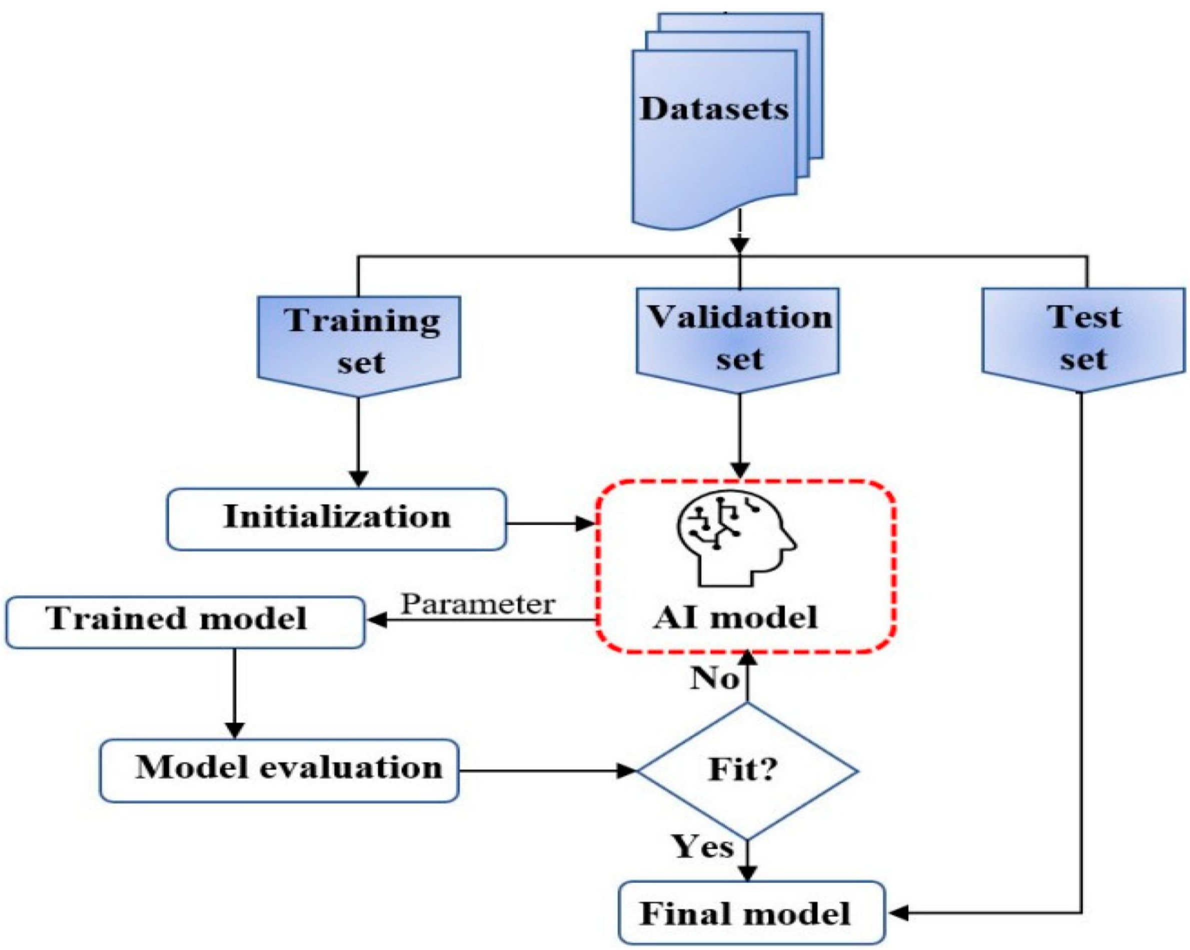

Figure 1. Typical artificial intelligence (AI) prediction procedure [25]

III. EXPERIMENTAL PROCEDURE

The study utilized Portland cement, natural sand (continuously graded based on modified Fuller-Thompson particle size distribution), granite gravel, and mixed plastic fine aggregate (MPFA) produced from post-consumer plastic waste using a twin-screw extruder. The MPFA was used to replace the 2-4mm size fraction of natural sand at 10-20% by volume in the concrete mixtures. The water-cement ratio, cement content, and fine aggregate ratio were varied based on a Taguchi experimental design at three levels each. A superplasticizer was incorporated and its dosage adjusted to maintain workability. The concrete samples were prepared by mixing the dry ingredients for 3 minutes followed by the addition of water and superplasticizer for another 3 minutes in a pan mixer. The fresh concrete was cast into 100mm cube molds for compressive strength, 400x100x100mm beam molds for flexural strength, and 300x150mm cylinder molds for split tensile strength testing. The samples were demolded after 24 hours and then cured in water at 28±3°C and 95% RH until testing at 7 and 28 days. The slump test was used to measure workability as per BS EN 12350-2 standard. The hardened concrete samples were tested as per BS EN standards to determine compressive, flexural and tensile strengths. A Taguchi experimental design was implemented to optimize the mix proportions based on multiple quality criteria including tensile strength. The Best-Worst multi-criteria decision-making technique was used to integrate the results from the different response variables. The optimal mix was identified using the signal-to-noise ratio. This systematic approach provided the experimental dataset on tensile strength of concrete containing recycled mixed plastic fine aggregate. The collected data as shown in Table 1were further prepared as excel file and, on this data, SVR based algorithms were used to find MSE and MAE value.

Table 1. Experimental Data

Cement Content	Water/Cement Ratio	Fine Aggregate Ratio	Plastic Type	Tensile Strength (Mpa)
400	0.43	0.43	HDPE	4.5
425	0.45	0.44	LDPE	4.2
375	0.4	0.45	PP	3.8
450	0.5	0.475	PET	5.1
400	0.43	0.43	HDPE	4.7
425	0.45	0.44	LDPE	4.3
375	0.4	0.45	PP	3.9
450	0.5	0.475	PET	5.3

IV. RESULTS AND DISCUSSION

An essential visual aid in the exploratory data analysis procedure is the pairplot depicted in Figure 2. We can see pairwise correlations between numerical variables thanks to it. The correlation or interaction between two variables is shown by each scatterplot in the lower and upper triangles of the pairplot. Furthermore, the pairplot's diagonal displays kernel density estimation (KDE) plots that show the distributions of each individual variable. For identifying trends, patterns, and possible dependencies in the dataset, the pairplot is quite helpful. For example, it can assist in determining whether variables tend to rise or fall together or whether there are non-linear correlations. This is especially useful when variables are color-coded, as in this instance with various "Plastic Types."

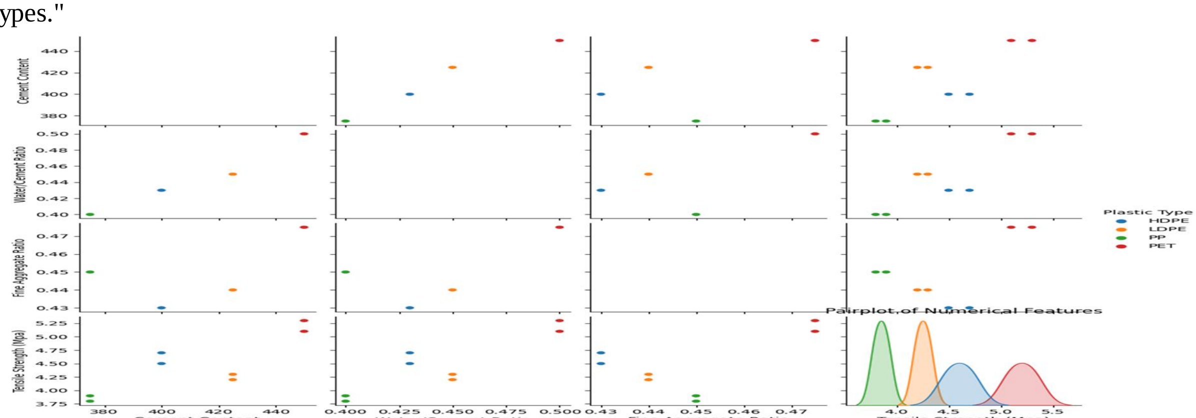

Figure 2. Obtained Pairplot

Boxplots are particularly helpful for comparing across categorical variables since they provide a clear and understandable breakdown of the distribution of data within several groups or categories depicted in Figure 3. The boxplot of "Tensile Strength" by "Plastic Type" in this instance shows the distribution, the central tendency, and any possible outliers in the tensile strength of each type of plastic. It is useful for determining material property variations and determining whether a given type of plastic has more variability or outlier values when it comes to tensile strength.

By displaying the degree and direction of association between numerical variables, the correlation heatmap sheds light on these interactions as shown in Figure 4. Significant relationships between variables are indicated by high positive or negative correlation coefficients. When choosing features for predictive modeling, it can be crucial to comprehend these associations. When evaluating the effect of features on the objective variable—in this case, tensile strength—a high positive correlation between two variables, for example, may suggest that they behave similarly.

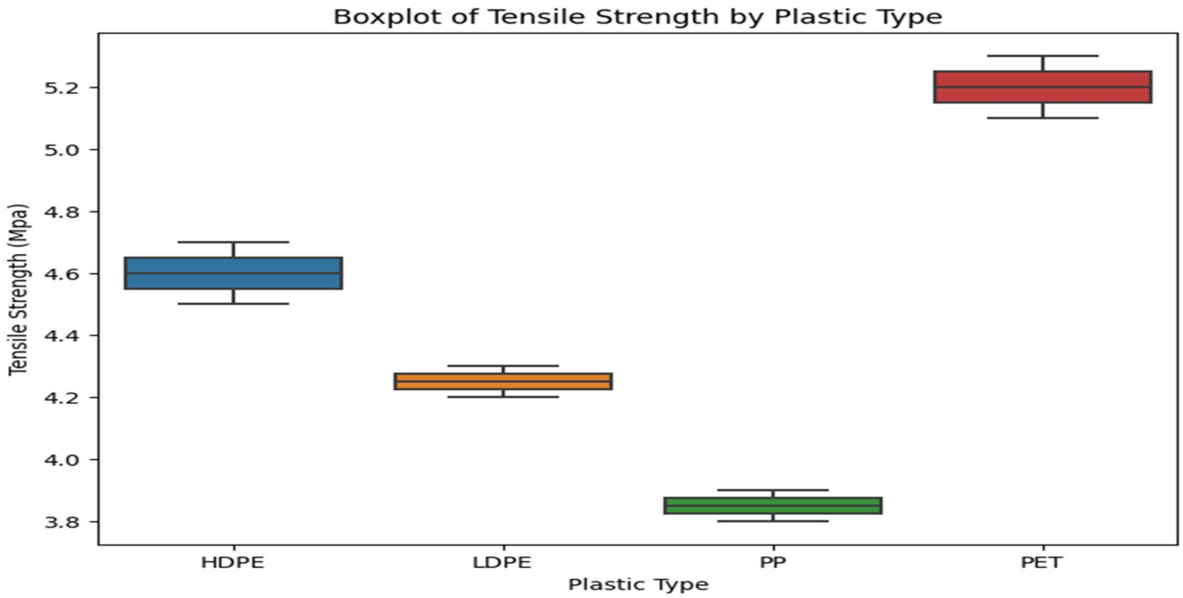

Figure 3. Obtained Boxplot

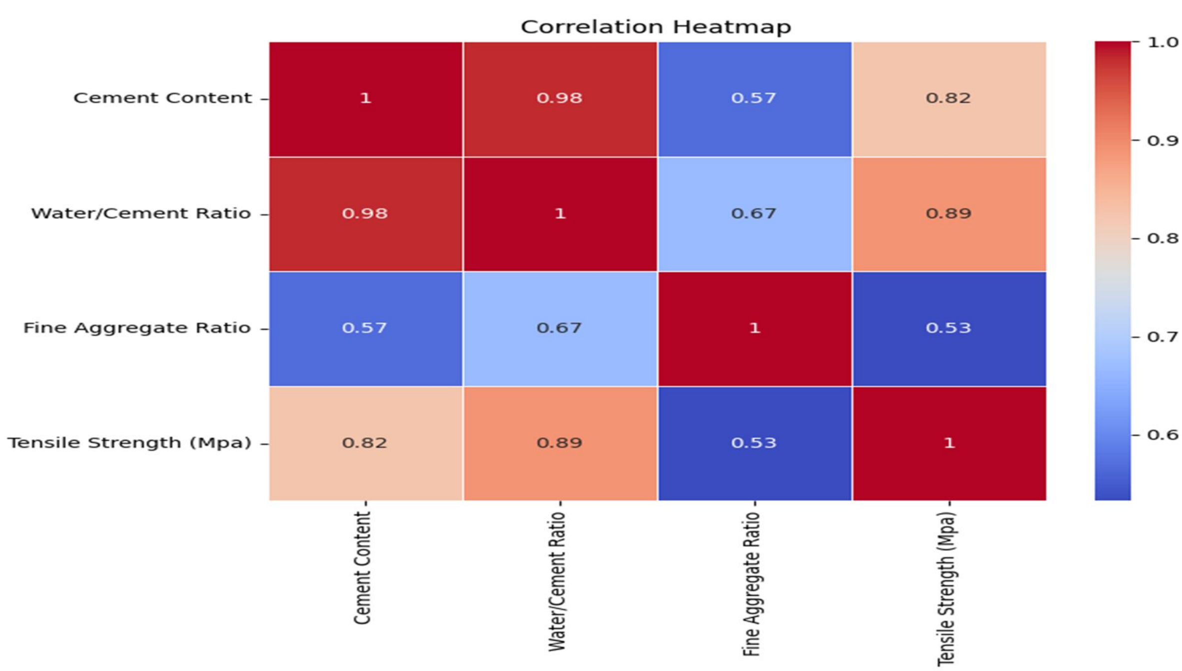

Figure 4. Obtained Heatmap

When analyzing the distribution of individual numerical variables, histograms are essential depicted in Figure 5. They assist us comprehend the central tendency and spread of the data by revealing its structure. Histograms in this dataset show the frequency or density of values within each variable visually, giving information about the symmetry, skewness, and possible outliers of the distribution. By displaying the distribution of tensile strength values for "Tensile Strength (Mpa)," the histogram helps us determine whether the distribution closely resembles a normal distribution or if there are any notable deviations.

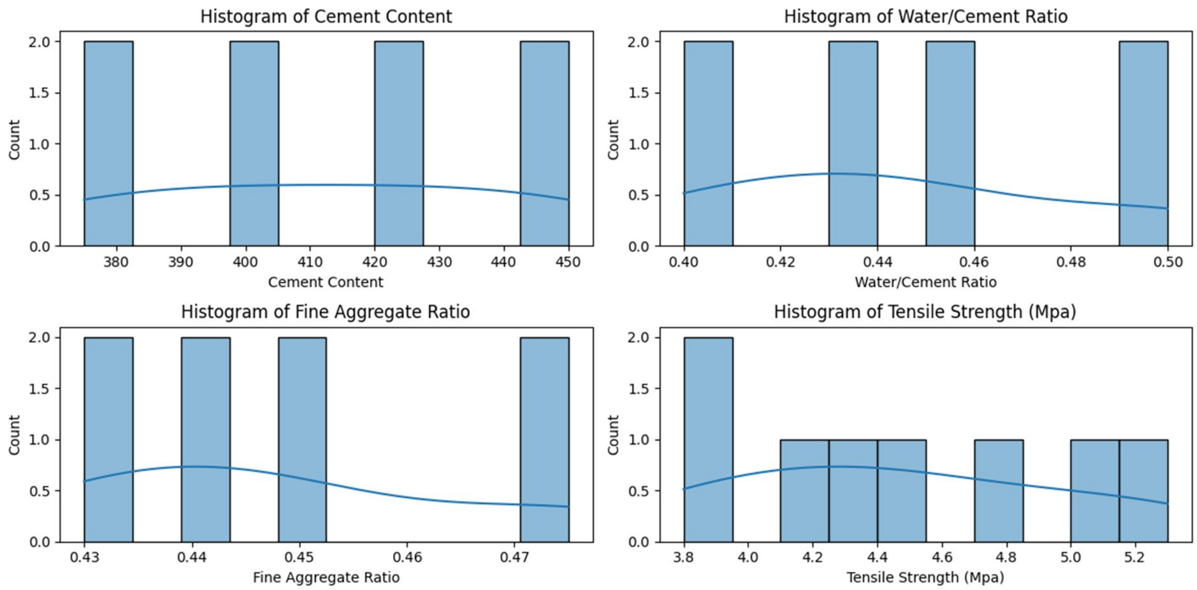

Figure 5. Obtained Histograms

Table 2 shows the obtained metric features for both Linear and Polynomial based SVR kernel.

Table 2. Obtained Results

Used Algorithm	MSE Value	MAE Value
SVR-Linear Kernel	0.5269	0.72420
SVR-Polynomial Kernel	0.2892	0.5354

The MSE and MAE of the SVR model with a linear kernel are 0.5269 and 0.72420, respectively. These numbers imply that, in comparison to the actual values, the linear model's predictions show a modest degree of error. Whereas the MAE gauges the average absolute difference, the MSE quantifies the average squared difference between the expected and actual values. This could lead to a modest degree of prediction error since the Linear Kernel might not be able to fully capture all the complex and non-linear relationships found in the data. With a lower MSE of 0.2892 and a lower MAE of 0.5354, the Polynomial Kernel SVR model performs better than the Linear Kernel model. Complex modeling is made possible by the Polynomial Kernel, which takes into account non-linear correlations between features and the goal variable. It can therefore capture a greater amount of the variability in the data, leading to more precise forecasts. The Polynomial Kernel model offers a closer fit to the real data, lowering the prediction error, as shown by the reduced MSE and MAE values.

V. CONCLUSION

In this research project, we set out to use Support Vector Regression (SVR) to predict tensile strength in materials, a crucial mechanical attribute in materials science and engineering. We looked into two SVR methods, Linear and Polynomial, each with a different kernel. We were able to glean important information about the relevance of the chosen kernels and their implications for materials science research through this investigation. Our analysis's findings were instructive. It became clear that the predictive performance of SVR models is significantly influenced by the kernel selection. The SVR model with a Linear Kernel was shown to have limitations in capturing the non-linear subtleties present in the dataset, but offering a foundational grasp of the correlations between material parameters and tensile strength.

Although reasonable, the corresponding MSE and MAE scores showed a considerable level of prediction inaccuracy. These results have implications for materials engineering, design, and construction, where precise tensile strength prediction is critical. Researchers and practitioners can improve the accuracy of their models and make better decisions by using the insights acquired from this study to help identify suitable SVR kernels for comparable prediction tasks.

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