DEVELOPMENT OF A MACHINE LEARNING-DRIVEN INTERFACE FOR INDIGENOUS PLASTERING MACHINE: A MIX DESIGN OPTIMIZATION APPROACH

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Abstract

Plastering in buildings is still ineffective due to inconsistent mix designs and reliance on manual knowledge. The goal of this project is to maximise mortar mix compositions by creating a machine learning-powered user interface for an automatic plastering machine. Four regression models: Random Forest, SVR, Bayesian Ridge, and Naïve Bayes were evaluated using 189 mortar samples. Random Forest exposed the best accuracy with R^2 = 0.816. Material estimate driven by artificial intelligence assures consistency and helps to lower waste by means of real-time monitoring and automated mix optimisation guarantees. This study advances automated, sustainable plastering for India's expanding infrastructure, so raising building efficiency and quality.

Key Words: Bayesian ridge and naïve bayes; Indigenous Plastering machine; Machine learning; Random forest model; SVR.

1. INTRODUCTION

India is in a phase of fast infrastructure development, hence innovative, high-quality building solutions are required. While advances in building technology and materials have substantially increased efficiency in many disciplines. One crucial element plastering remains mainly unoptimized. As a lack of consistent knowledge among employees on appropriate mix designs limits the quality of plastering, so causing weak adhesion, surface fissures, and inefficiencies in material consumption. Plastering is sometimes disregarded and resulting in poor building performance and shortened structural lifetime[1]. Although the quality and durability mostly rely on plaster work, the alarming reality is that plastering -quality has become a pervasive issue in India's construction landscape[2-3].

To address the challenges in plaster work, the demand of automated plastering equipment designed for Indian conditions becomes ever more evident [4-[7]. Plastering tools and equipment in India are mostly designed for onsite application by labourers, resulting in inconsistent and low-quality results. This research presents the development of an AI powered Automatic Plastering Machine for India's infrastructure[8]. Currently in development, an indigenous automated plastering machine closes this gap and improve the plastering process by combining artificial intelligence (AI), the Internet of Things (IoT), and advanced machine learning (ML) techniques. Hence, designed to automate the whole plastering process including weigh batching, material mixing, spraying, and finishing.

This next-generation plastering equipment Integrated with AI and IoT technologies assures accuracy, uniformity, and real-time monitoring of the plastering process. This greatly increases efficiency and reduces material waste.

This research focuses on development of a smart user interface for the weigh-batching system utilizing ML models[9]. This ML methods optimises mix designs in real time and gives accurate compressive strength. The deployed ML model is trained using extensive datasets on plastering materials, including cement, ground granulated blast furnace slag (GGBS), water-cement ratio, and admixtures so enabling correct material estimations for quality mix design[10-11]. This approach ensures outstanding plastering quality, hence less reliance on human knowledge is required and building efficiency is greatly increased. Moreover, the developed approach reduces material waste and optimum use of resources helps to promote sustainability.

This research illustrates how artificial intelligence-driven automation and ML-based regression modelling can be applied to improve plastering technology, therefore contributing to ongoing transformation of the construction industry[12-13].

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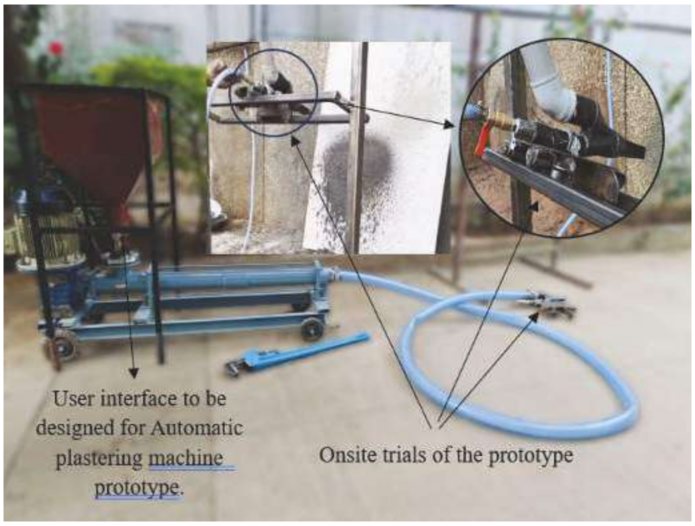

Figure 1: Prototype of automatic plastering machine

This study bridges the gap between traditional process and opens the road for more intelligent, efficient, and sustainable plastering procedures adapted for the evolving infrastructure needs of India and beyond.

2. SCOPE

This research focusses on the development of a plastering machine interface powered by AI, IoT, and machine learning. Machine learning models are used to optimise material composition based on experimentally collected data from mortar mix designs. The study entails evaluating multiple regression models using extensive statistical analysis to determine the most appropriate one. Key statistical measures are used to assess model performance, ensuring that the most reliable and accurate method for predicting material quantity in mix designs is selected. Furthermore, the study incorporates material development, utilising data-driven insights to improve mix performance and efficiencies.

3. METHODOLOGY

3.1 Materials and mortar mix designs

Appropriate Indian Standard (IS) codes are referred for consistency and quality control [14]. For plaster mortar, cement and crushed sand were the raw ingredients. Ordinary Portland Cement 43 grade and 53 grade gives enough strength and durability based on IS: 269 (1989) [15-17].Well-graded crushed sand conforming to IS: 1542 (1992) and IS: 383 (2016) criteria was used. round granulated blast furnace slag (GGBS) confirming to IS: 16714 (2018) is used as cement replacement (0 – 40 %)[18-20] . Admixture confirming to IS: 9103 (1999), a polycarboxylate ether (PCE) based superplasticizer was used, with dosage starting at 0 to 1.5 % of cementitious material [21]. Admixtures helped to maintain workability of 200–250 mm mini slump flow. This workability was obtained with a water-cement ratio between 0.6 to 0.85. The 1:4 ratio cement to sand was maintained for quality mortar mix. For indigenous plastering machine the workability was kept constant for all the mix designs. Strength testing applied with a compression testing machine (CTM) followed IS: 516 (1959)[22]. Testing for compression strength, 7.06 cm cube of size after 56 days of curing[23-24]. The compression strength data of 189 mortar cube samples were obtained during the experimental process. Collected data managed for a prediction model based on machine learning. Machine learning-based predictive modelling promises pragmatic relevance as well as scientific accuracy.

3.2 Machine learning

The user interface for the automatic plastering machine was made by observing the experimental data on compression strength, raw material proportions, mix design, and curing time. Machine learning models were trained using standardised, cleaned, data. With an eye towards optimising accuracy, processing time, and material use, four regression models were chosen and assessed [25]. This work intends to accelerate prediction, lower testing times, and greatly over time always increase resource efficiency by using these machine learning approaches.

3.3 Machine learning models

The analysis employed four machine learning models to evaluate their predictive capabilities for compressive strength using the input parameters cement, water-to-cement ratio, GGBS content and Admixtures and output parameters compressive strength[26]. In all four ML models prediction is based on the above specified parameters. The first model Random Forest Regressor functions as an ensemble learning method that uses multiple decision trees to enhance prediction accuracy and decrease overfitting problem. The second model Support Vector Regression (SVR) method RBF kernel used in this model enables it to detect non-linear relationships between input variables and output as compressive strength. The third model Bayesian Ridge Regression implements Bayesian inference to prevent overfitting which results in robust predictions when training data is scarce[27].

The fourth model Naive Bayes (Gaussian NB) uses probability distributions to classify strength categories which makes it appropriate for discrete strength classification.

3.4 Data preprocessing

The data for the experimental mortar mix design of this study was stored in CSV format. The research data were split into two parts, 30 % for testing and 70 % for training, to evaluate the performance of models[25]. As standard input is preferred in machine learning models, the feature values were normalised using Standard Scaler normalisation. Normalising input features is important as SVR, Bayesian Ridge Regression and Naïve Bayes models are sensitive to changes in feature scales. Naïve Bayes classification necessitated discrete compressive strength values from continuous data[28]. The target variable that refers to concrete strength quality was discretized into 3 bins. Using three bins, the model is trained to classify concrete quality by strength. The use of probabilistic learning helped in correctly predicting regressions.

3.5 Model evaluation and performance analysis

The developed models were evaluated using key performance criteria. Mean Absolute Error (MAE), which measures the average discrepancy between actual and predicted values. Mean Squared Error (MSE), which computes the average of the squared discrepancies. Root Mean Squared Error (RMSE), which evaluates the standard deviation of prediction errors. R^2 Score, which indicates the efficacy of the model in clarifying the variation in compressive strength. The evaluation of model's accuracy relied on scatter plots that showed actual versus predicted value relationships. The analysis includes a tabular comparison of statistical metrics to evaluate model performance.

3.6 Statistical comparison and selection

This research uses statistics to compare how well different machine learning models, such as Random Forest, Support Vector Regression (SVR), Bayesian Ridge, and Naive Bayes, can predict the compressive strength of plaster. The objective is to find the most accurate model that can be built into the user interface of an automatic plastering machine. This will improve the functionality and dependability of automatic plastering machines in the long run. The 'pandas DataFrame ' a data structure used to store and organize the performance metrics of various machine learning models, is used for facilitating statistical analysis to determine the most accurate model. The model selection occurred through evaluating R^2 scores and error values to achieve maximum predictive accuracy. The research outcomes help improve concrete mix design methods while reducing material waste and enhancing construction structural dependability.

4. RESULTS AND DISCUSSION

4.1 Compression strength of Mortar mix

The mortar cube compression test produced a wide range of compressive strengths ranging from 8.698 MPa to 39.017 MPa. The ideal mix of 40 % GGBS substitution, 1.5 % admixture, and 0.61 w/c ratio producing the highest compressive strength of 39.017 MPa. The compressive strength of GGBS mortar mixes was much improved by GGBS substitution; CSGB10, CSGB15, CSGB20, CSGB25, CSGB30, CSGB35, and CSGB40 showed increases of 30.65, 59, 107.8, 118, 150, 219, and 348.5 %, respectively as compared to the control mix i.e CSGB0. The results demonstrate a clear trend, where increasing GGBS substitution, admixture dosage, and decreasing water-to-cement ratio all contribute to improved compressive strength. This highlights the importance of optimal mix design parameters in achieving enhanced mortar strength.

4.2 Machine learning models

4.2.1 *Random forest model*

As shown in Figure 2 strength of mortar can be predicted by random forest regression (RFR) model by means of element analysis comprising the cement-to-sand ratio, GGBS percentage, water-cement ratio, and admixture dosage. The model achieved a low mean absolute error (MAE) of 1.448 MPa, indicating highly accurate results. Its lower MSE shows that it controls outliers also more successfully than SVR. The RMSE which is 1.848 MPa shows dependability since it rather closely corresponds to actual values. With R^2 = 0.816, explaining 81.6 %

Table 1: Mix design proportions

SR. NO	SAMPLE ID	MIX DESIGN 1: 4 RATIOS	W/C RATIO	ADMIXTURE	COMPRESSIVE STRENGTH (MPa)
1.	CSGB0	Cement + Crushed Sand	0.800	0.5	8.698
2.	CSGB10	Cement + 10 % GGBS + Crushed Sand	0.768	0.75	11.359
3.	CSGB15	Cement + 15 % GGBS + Crushed Sand	0.728	0.9	13.876
4.	CSGB20	Cement + 20 % GGBS + Crushed Sand	0.688	1	18.077
5.	CSGB25	Cement + 25 % GGBS + Crushed Sand	0.680	1.1	19.034
6.	CSGB30	Cement + 30 % GGBS + Crushed Sand	0.656	1.2	21.690
7.	CSGB35	Cement + 35 % GGBS + Crushed Sand	0.616	1.4	27.786
8.	CSGB40	Cement + 40 % GGBS + Crushed Sand	0.610	1.5	39.017

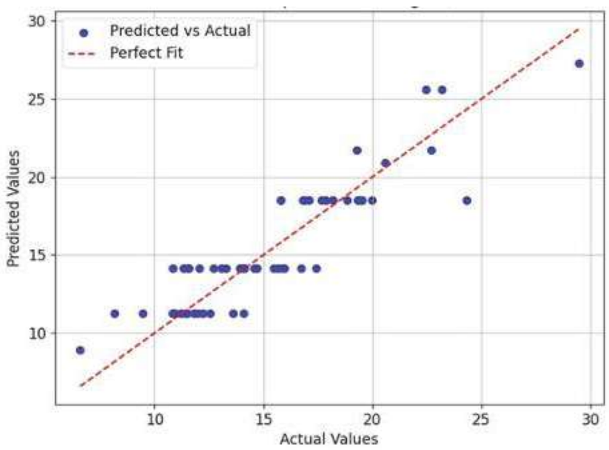

Figure 2: Actual vs predicted compressive strength (Random forest)

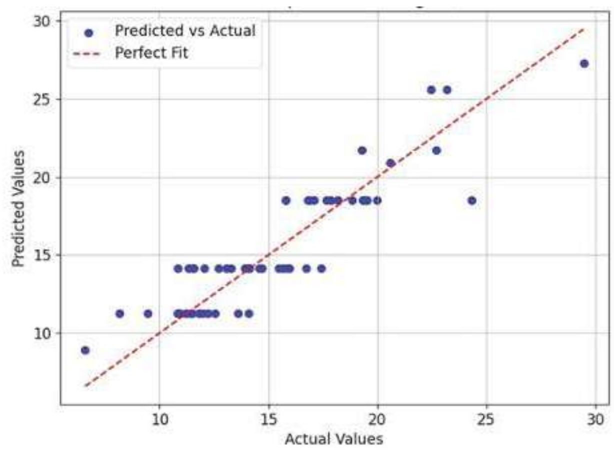

Figure 3: Actual vs predicted compressive strength

of strength fluctuations fits rather nicely with real data. Reducing overfit and increasing accuracy will help Random Forest to estimate mortar strength.

4.2.2 *Support vector regression (SVR) model*

As shown in Figure 3 for SVR model with an MAE of 1.46 MPa, the little variation in expected and actual compressive strengths emphasises model accuracy. While the RMSE of 1.85 MPa guarantees dependability, a low MSE shows most forecasts remain rather close to real values. With R^2 = 0.815, the SVR model chooses 81.5 % of compressive strength fluctuations . Most of the data points closely follow the 45-degree line, indicating a strong correlation. SVR is a better option than linear models even if it is not perfect since its RBF kernel helps it to detect complex patterns.

4.2.3 *Bayesian ridge model*

As shown in Figure 4 for Bayesian Ridge Regression model works on projected compressive strength by a probability-based method, thus reducing overfitting. With an MAE of 1.51 MPa, it is less exact than Random Forest and SVM. It indicates more frequent significant errors since its MSE, 3.44 MPa², was higher than the 3.42 MPa² of Random Forest. The model has an RMSE of 1.92 MPa which shows worse generalisation. Outperforming naïve bayes but trailing SVR and Random Forest, it explained 80.2 % of strength variation (R^2 = 0.802). Scatter plots revealed more mistakes at extreme values, hence underlining the difficulty of the model with regard to complicated mortar mix projections.

4.2.4 *Naïve bayes (GaussianNB) model*

As per Figure 5, matching mortar compressive strength to SVR and Random Forest proved challenging for naïve bayes (Gaussian NB). This model had higher errors, with an MAE of 1.72 MPa and RMSE of 2.43 MPa, resulting in predictions that were frequently inaccurate. Just covering 68.2 % of the strength variance, it is far less than SVR *i.e*, 81.5 % and Random Forest *i.e.*, 81.6 %. Naïve Bayes struggled to capture the complex interactions between materials and generated regular errors especially at particular strength levels because it assumes the input factors to be independent. The figure 5 scatter plot reveals anomalies that helps to explain its erratic behavior.

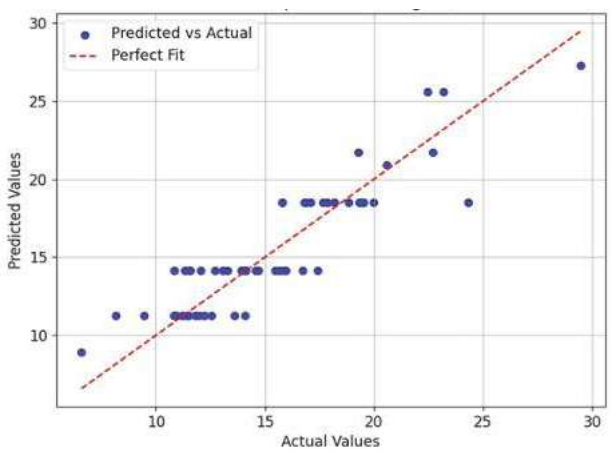

Figure 4: Actual vs predicted compressive strength (Bayesian model)

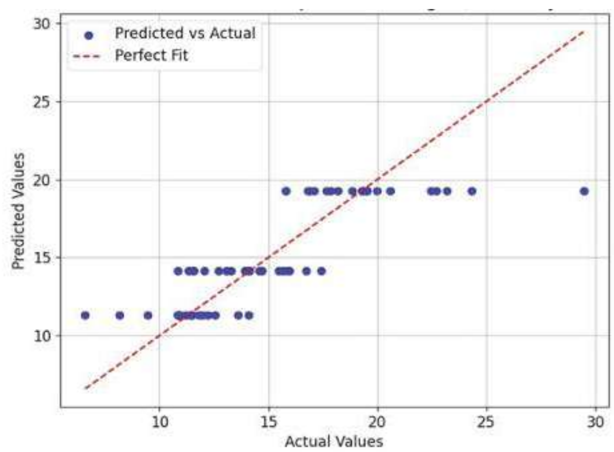

Figure 5: Actual vs predicted compressive strength (Naive bayes)

Table 2: Statistical analysis

	MAE	MSE	RMSE	R^2
Random forest	1.449	3.418	1.849	0.816
SVR	1.469	3.436	1.854	0.815
Bayesian ridge	1.511	3.676	1.917	0.802
Naïve bayes	1.715	5.915	2.431	0.681

4.3 Statistical analysis of models

Four machine learning models SVR, Random Forest, Naïve Bayes, and Bayesian Ridge evaluation driven by error metrics MAE, MSE, RMSE and accuracy R^2 score. By evaluating these metrics Random Forest was the most consistent model for compressive strength estimate among those with lowest errors and best R^2.

SVR's R^2 = 0.815 though similar with random forest it generated more errors and required careful tuning. With its linear character MAE 1.51 MPa, R^2 (0.802), Bayesian Ridge struggled with complicated data. Naïve Bayes scored highest RMSE (2.43 MPa) and lowest R^2 (0.682) depicting.

5. CONCLUSION

The experimental investigation of mortar cubes compression test revealed that the optimal combination of Ground Granulated Blast Furnace Slag (GGBS) substitution significantly enhances the compressive strength. Specifically, 40 % GGBS substitution, yielded the highest compressive strength of 39.07 MPa. These findings emphasize the importance of careful mix design optimization to achieve high-performance concrete. A comparative analysis of machine learning models for compressive strength prediction reveals that Random Forest is the most reliable choice, offering superior accuracy and low error rates. Support Vector Regression (SVR) demonstrates competitive performance, but its requirement for substantial computational resources is a notable drawback. The recommended model for compressive strength prediction is Random Forest; in cases of sufficient computational resources and SVR is a good replacement. Although Bayesian Ridge is computationally efficient, it lacks the flexibility to capture intricate relationships and Naive Bayes is not recommended since it performs poorly for regression problem.

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