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Predictive Modelling of Concrete Compressive Strength Using Machine Learning Techniques

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Abstract:** Concrete compressive strength is a critical parameter in structural engineering, directly influencing safety and durability. Traditional experimental methods for determining compressive strength are time-consuming and resource-intensive. This study explores the application of machine learning (ML) algorithms to predict compressive strength using mix composition data. A dataset comprising 1030 samples with nine input variables (cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, and age) was utilized. Five ML models—Linear Regression (LR), Decision Tree (DT), Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Regression (SVR)—were developed and evaluated using Mean Absolute Error (MAE), Mean Squared Error (MSE), and coefficient of determination (R^2). Among all models, Random Forest demonstrated superior performance (R^2 = 0.88, MAE = 3.86, MSE = 30.49), followed closely by SVR (R^2 = 0.87). The results indicate that ensemble and non-linear models effectively capture complex relationships in concrete mixtures, enabling accurate and efficient prediction. This study highlights the potential of ML in optimizing mix design and enhancing construction efficiency.

***Keywords:** Concrete compressive strength, Machine Learning, Random Forest, SVR, Predictive modeling, Civil Engineering*

I. INTRODUCTION

Concrete is one of the most widely used construction materials due to its strength, durability, and cost-effectiveness. Among its properties, compressive strength is the most important indicator of structural performance. Conventional methods for determining compressive strength involve laboratory testing after curing (typically 28 days), which delays decision-making and increases project costs.

With advancements in computational techniques, machine learning (ML) has emerged as a powerful tool for predicting material properties. ML models can capture nonlinear relationships between input variables and output responses, making them highly suitable for predicting concrete strength based on mix proportions.

This study aims to develop and compare various ML models to predict compressive strength and identify the most accurate and reliable approach.

II. LITERATURE REVIEW

Previous studies have demonstrated the effectiveness of ML techniques in predicting concrete strength. Artificial Neural Networks (ANN) and ensemble methods such as Random Forest and Gradient Boosting have shown superior performance compared to traditional regression models.

Key findings from literature include:

- Ensemble models outperform individual models due to better generalization.
- ANN performs well with limited datasets.
- Boosting techniques achieve high accuracy (R^2 up to 0.96).
- Traditional linear regression often underperforms due to nonlinearity in data.

However, gaps remain:

- Limited studies combining multiple ML models for comparison.
- Insufficient datasets (>1000 samples) in many studies.
- Lack of consideration for full mix variability and curing conditions.

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III. METHODOLOGY

A. Dataset

The dataset consists of 1030 samples with the following input variables:

- Cement
- Blast Furnace Slag
- Fly Ash
- Water
- Superplasticizer
- Coarse Aggregate
- Fine Aggregate
- Age

Output variable:

- Compressive Strength (MPa)

B. Data Preprocessing

- Missing values handled using mean/median imputation
- Data normalized using StandardScaler
- Dataset split into 80% training and 20% testing

C. Machine Learning Models

The following models were implemented:

- Linear Regression (LR)
- Decision Tree (DT)
- Random Forest (RF)
- K-Nearest Neighbors (KNN)
- Support Vector Regression (SVR)

D. Hyperparameter Tuning

Grid Search with 5-fold cross-validation was used to optimize model parameters.

E. Evaluation Metrics

Models were evaluated using:

- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Coefficient of Determination (R^2)

IV. RESULTS AND DISCUSSION

A. Model Performance

Model	MAE	MSE	R^2
Linear Regression	7.75	95.97	0.63
Decision Tree	4.29	42.58	0.83
Random Forest	3.86	30.49	0.88
KNN	6.76	72.41	0.72
SVR	4.02	33.20	0.87

B. Key Findings

- Random Forest achieved the highest accuracy due to ensemble learning.
- SVR performed competitively, capturing nonlinear relationships.

- Linear Regression showed poor performance due to inability to model nonlinearity.
- Tree-based models handled outliers effectively.

C. Feature Importance

- Most influential features: Age, Cement
- Moderate influence: Water, Slag
- Least influence: Fly Ash, Aggregates

D. Discussion

The superior performance of Random Forest highlights the importance of ensemble learning in handling complex datasets. The results align with previous studies, confirming that nonlinear and ensemble models are more effective for predicting concrete strength.

V. CONCLUSIONS

This study demonstrates the effectiveness of machine learning techniques in predicting concrete compressive strength. Key conclusions include:

- Random Forest is the most accurate and reliable model.
- Ensemble and nonlinear models outperform traditional methods.
- ML models significantly reduce dependency on laboratory testing.
- Feature importance analysis helps optimize mix design.

VI. RECOMMENDATIONS

Future research can focus on:

- Incorporating real-time and site-specific data
- Exploring deep learning techniques (ANN, CNN)
- Using explainable AI tools (SHAP, LIME)
- Developing web-based prediction tools for field engineers

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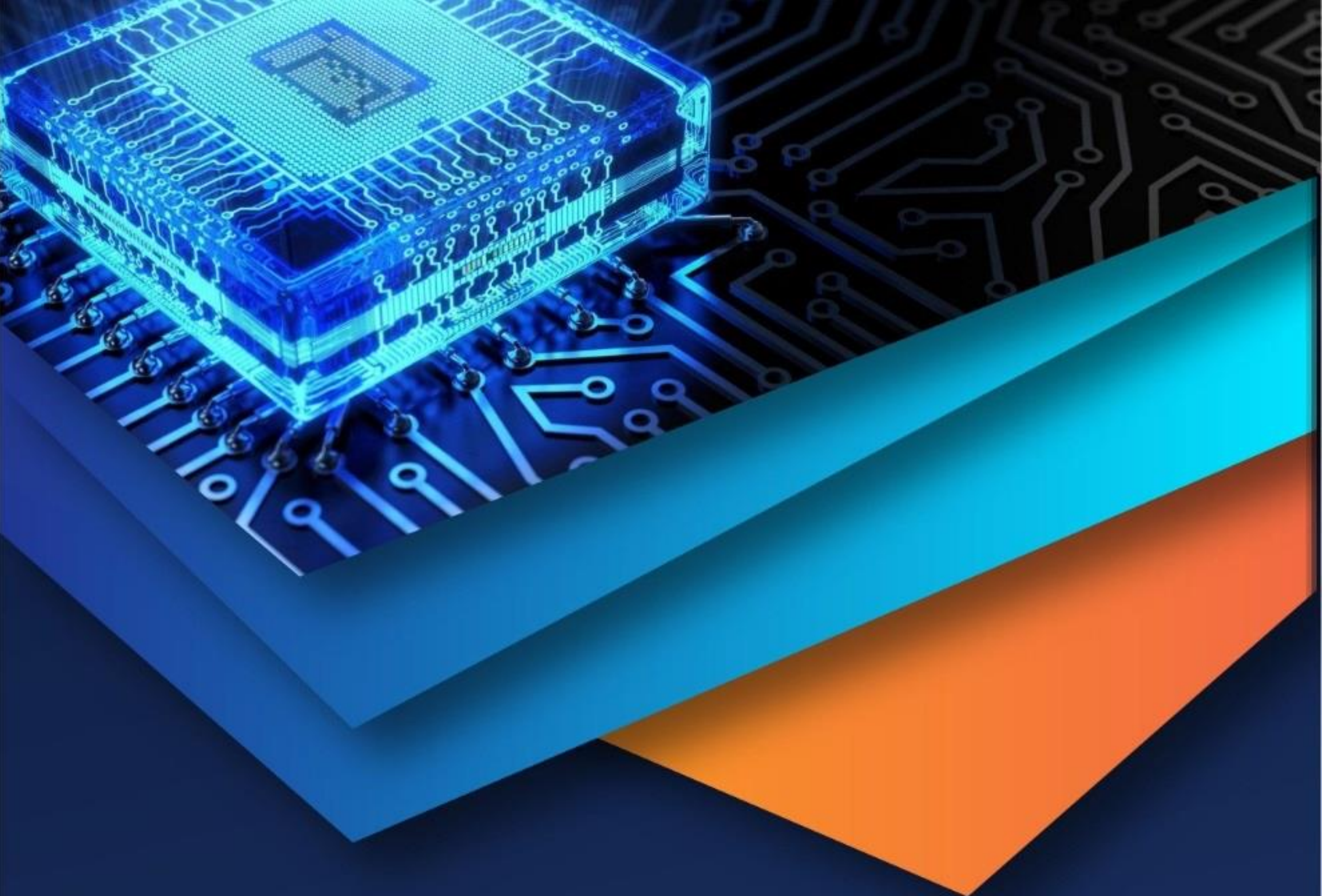

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