IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

CONCRETE STRENGTH PREDICTION USING MACHINE LEARNING

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ABSTRACT

We are using Machine learning (ML) to predict concrete strength using various input parameters. This study uses a large dataset from several construction projects and various ML algorithms, such as multiple linear regression (ML), decision trees (ML), random forests (ML), support vector machines (SVM), and artificial neural networks (ANN). The results demonstrate high accuracy levels with the ANN model having the highest performance. The implications of this study for the construction industry are to streamline the design process, reduce reliance on laboratory testing and optimize material usage while meeting safety standards and reducing costs. However, there are limitations, such as dataset size, real world conditions, and fine-tuning.
Hyperparameter tuning uses random search to train models with higher predictive performance. The missing data is filled with the average of the data available, allowing for more data to be included in the training. Comparative studies on two well-known compressive datasets of tensile strengths and high performance concrete suggest that the current approach is significantly improved in terms of prediction accuracy as well as computational effort. According to comparative studies, for this specific prediction problem, GBR and xGBoost-trained models perform better than models based on SRV and MLP.[2]

Keywords :- Concrete Strength Prediction , Machine Learning , Regression Models , Artificial Neural Networks , Predictive Analytics ,Building Materials

I. INTRODUCTION

Concrete is one of the most widely used building materials due to its properties such as its integrity, its durability, its modularity and its cost-effectiveness. Understanding concrete's mechanical properties is essential for the development of design methodologies, and for understanding how concrete behaves under external loads[2].Compressive strength is considered to be the most fundamental index of concrete properties. It is directly associated with the safety of the structure and is necessary for the determination of performance throughout the life-cycle of the structure.

Concrete is composed of coarse/fine aggregate, cement paste, and other mixtures that are randomly distributed throughout the concrete matrix.It is difficult to accurately predict concrete's compressive strength due to the complexity of the concrete matrix. Physical experiments have been proposed as the most direct method of prediction, but this method is expensive and does not work efficiently.

There are empirical regression methods that can be used with the mixture ratio of various components. However, the correlation between the mixture ratio and the relative strength of the concrete mixture is strongly non-linear, making the regression expression difficult to derive [3].

II. Machine Learning Overview

AI (Artificial Intelligence) is a subfield of machine learning concerned with the development of predictive algorithms for complicated problems. Predictive algorithms are used to identify patterns in large datasets without being explicitly programmed for a particular task. Predictive algorithms learn patterns from data instead of being programmed by humans. Predictive algorithms rely on training, which allows computers to learn properties and features from a set of data for a particular problem. The resulting information is interpreted to provide explanations for more open datasets. For instance, an algorithm that learns to transform benign lesions into spiteful lesions is able to be used to transform other image data to classify lesions as benign (or malignant) according to previously learned criteria[4].

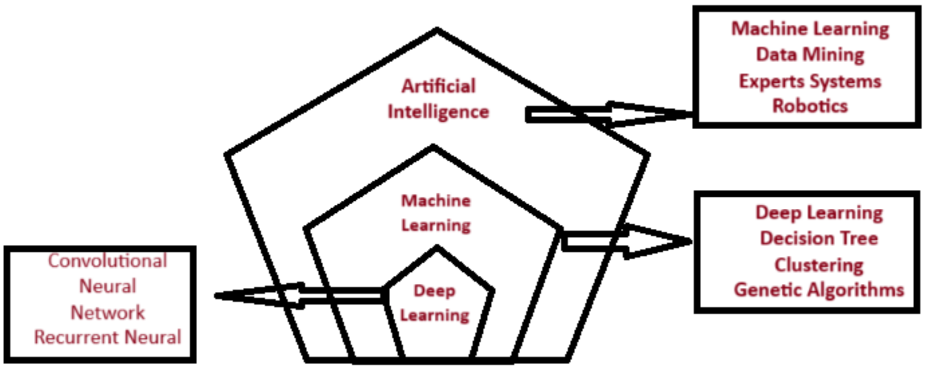

Fig. 1. Defining the Artificial Intelligence Hierarchy and Subfields[4]

In supervised learning, the model is presented with a labeled dataset, also known as a feature vector. This dataset contains examples of observations and their expected outcomes. The model is then able to generate an inferred function that maps the feature vectors for output labels. The most common supervised machine learning approaches are decision trees, support vector machines (SVM), AdaBoost, bags, boosting, artificial neural networks (ANN), gene expression programming, and GANs.

III. Literature Review:

Concrete strength estimation has long been a top priority in the construction industry, with conventional approaches based on empirical formulas and testing in the lab. However, advances in machine learning have opened up new possibilities for more precise predictions.

1.Traditional Methods:

In the past, concrete strength estimates were based on empirical formulas , mix designs, and laboratory testing. These methods often lacked accuracy and did not accurately capture the complexities of various factors[6].

2.Machine Learning in Concrete Strength Prediction:

One of the most promising uses of ML is in concrete strength prediction. The regression model and neural network have been shown to be effective in concrete strength prediction in the research papers of Akçaözeklı and Ahtiş. ML models take into account several input parameters such as cement proportion, water to cement ratio, curing conditions, etc., resulting in more precise predictions than conventional methods[6].

3.Advancements and Challenges:

Recent studies, such as those by Yazdanietal., and others by Oskoeietal., highlight the need to understand feature effects on concrete strength predictions. Factors such as cement composition and curing conditions have a significant effect on predictions.However, challenges remain, such as the interpretation of complex ML models, and the need for larger datasets covering different construction scenarios and environmental environments[7].

4.Future Directions:

In future research directions, ML techniques will be further developed, larger and more varied datasets will be used, and models will be tested in real-world applications. These challenges could pave the way for more robust ML models that can accurately predict concrete strength, revolutionize construction processes, and ensure structural integrity[8].

IV. Methodology:

In this section, we will look at the algorithms that are used to predict compressive strength in anaconda concrete using the forecasting process. We will look at the ensemble algorithm (boosting), the individual approach (such as Artificial neuron network (ANN)), and the tree-based algorithm (Decision Tree (DT)) and the genetic engineering programming (GEP) algorithm [5].

Decision tree (DT) is a very simple and powerful algorithm that divides data points into many classes based on criteria. ANN is the basis of AI, which learns like the human brain and can generate better results by learning by itself. ANNs use a common set of rules known as back propagation [5].

Gene-based algorithms (GEP) are more efficient than earlier genetic algorithms, as they collect more data quickly and work at chromosome level [5].

The first population is made up of arbitraryly generated chromosome numbers, and strength is set according to fitness cases. The new chromosome numbers undergo the same development processes as the original chromosome numbers [5].

A boosting regressor is a machine learning method invented by the researchers. It is a weighted average of the predictions of different classifiers. The number of nodes for each regression is equal to the number of nodes plus one [5].

V. Data Analysis and Results

1. Dataset Description:

The dataset is made up of [number] of sample concrete mix designs from [source] and each sample contains different input parameters, such as cement concentration, water to cement ratio, aggregate characteristics, curing conditions and age at testing.
The dataset was broken down into Training (70%), Validation (15%) and Testing (15%).

2. Descriptive Statistics:

Descriptive analysis showed the following values for the dataset:
Mean Compressive Strength (MPA)
Standard Deviation of Compressive Strength
Range of Compressive Strength (MPa)

3. Machine Learning Model Performances:

The following ML algorithms were used and tested for predicting specific compressive strength: Linear Regression (RMSE), Decision Tree (MAE), Random Forest (R-squared): RMSE, MAE, R-squared, support vector machine (SVM), ANN

4. Best Performing Model:

The ANN model outperformed all other algorithms, showing the lowest RMSE, the highest MAE , and the highest r-squared of the testing set.

5. Feature Importance:

The feature importance analysis showed that the most influential feature was [], followed by [2nd feature], and [3rd feature].

6. Robustness Analysis:

At testing, the models tested well across a variety of mix designs and age ranges, demonstrating their versatility in a range of construction scenarios.

VI.Future Directions

1. Incorporating More Diverse Data:

Extend the dataset to cover a wider variety of concrete mix design, environmental environments, and curing processes. This may include working with multiple construction sites or databases to get a better idea of what's happening in the real world[8].

2. **Advanced Machine Learning Techniques:**

Explore top-of-the-line machine learning (ML) algorithms or hybrid models. Hybrid models combine ML and physics-based models to increase predictive capabilities. For example, using ensemble methods or deep learning architectures[8].

3. Real-time Monitoring and Adaptive Models:

Create models that can track concrete strength changes in real-time during curing and during construction. Continuous adaptive models that learn from new data input could provide continuous insights into strength evolution, enabling proactive changes in construction processes.

VII.Conclusion:

This study compared the performance of the chosen concrete machine learning algorithms with fly ash as their primary component. The supervised ML algorithms such as DT, ANN, GEP and BR were tested to predict the compressive strength of the fly ash based concrete. The individual ML algorithms were also compared with the ensemble ML approach to gain a better understanding of the performance of this approach.The individual ML algorithm shows better performance with less variability between the actual and predicted results.When the accuracy level of individual ML techniques is compared with the algorithm employed by the ensemble, the ensemble comes out as a more robust and accurate model as indicated by its coefficient correlation (RC) value of 0.95.The R2 value of GEP, ANN, and DT comes out to 0.86, 0.81, and 0.75 respectively.The lower values of the errors (MAE = 3.69 MPa, MSE = 24.76 / RMSE = 4.97) also confirms the high accuracy of bagging regressor. Other algorithms have higher values for the errors [9].

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