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ESTIMATION OF COMPRESSIVE STRENGTH OF PERVIOUS CONCRETE BY USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES

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Abstract: This study employs a deep learning strategy and a CNN model with three convolutional modules to improve the accuracy and applicability of existing mechanical performance prediction models for pervious concrete. The coarse and fine aggregate, water, admixture, cement, fly ash, and silica fume content are the eight input variables used in the model to predict the 28-day compressive strength of pervious concrete. There are 111 sample sets in the dataset, with an additional 12 sets added for robustness. Contrasted with Backpropagation (BP) brain organizations, the CNN model shows a higher coefficient of assurance (0.938) and a mean outright rate mistake of 9.13%, demonstrating predominant precision and general material.

Keywords: pervious concrete; convolutional neural network; compressive strength; prediction model

1. Introduction

Pervious cement is an imaginative and eco-accommodating development material known for its great porousness, antislip properties, erosion obstruction, and strength. Urban development and environmental protection are two areas where it can be used. Compressive strength is an essential presentation pointer, imperative for upgrading the plan and nature of designs utilizing this material. The effects of various materials and mix proportions on compressive strength have been the subject of extensive research into the performance indicators of pervious concrete. Studies have changed fly debris replacement rates, total sorts, and concrete assortments to figure out their effects. Late exploration has additionally analyzed the impact of novel materials, for example, filaments and development squander, on pervious substantial execution, close by factors like restoring conditions and porosity. High level strategies, including Examining Electron Microscopy (SEM), have been utilized to concentrate on pervious cement at the tiny level. For example, Kelly Patrícia Torres Vieira et al. found that rising reused total extent diminishes compressive strength, while Xiaoyan Zheng et al. examined salt-initiated materials' belongings utilizing field emanation SEM and X-beam diffraction. These examinations give itemized experiences into compressive strength varieties and guide future plan and development of pervious cement [1-4].

Due to varying materials and mix proportions, traditional empirical formulas frequently fail to accurately predict the compressive strength of pervious concrete, particularly as new materials emerge and regional construction methods differ. For accurate predictions of pervious concrete's 28-day compressive strength, it is essential to make use of existing data due to the limitations of previous research and resource-intensive experiments. Advances in deep learning and machine learning have demonstrated the capacity to predict concrete compressive strength from large datasets. Models like BP brain organizations and CNNs have exhibited high exactness. For example, a CNN model by Ziyue Zeng et al. accomplished a R^2 of 0.967 in foreseeing concrete compressive strength, outflanking customary techniques [5-7].

By incorporating the characteristics of the material and data from previous studies, this study develops a CNN model to predict the 28-day compressive strength of pervious concrete. The model's use of component content as input makes it easier to use and more practical. Important contributions include:

- Fostering a CNN model that shows prevalent execution in foreseeing compressive strength, as confirmed by decency of fit, normal outright rate blunder, root mean square mistake, and mean outright mistake.
- Integrating existing blend extent data into the model, lessening designers' responsibility.
- Accomplishing an integrity of fit more prominent than 0.9 and a normal outright rate mistake underneath 10%, showing dependable strength expectations across various materials. Insights for future research can be gleaned from this study's robust and practical method for predicting the strength of pervious concrete.

2. Testing of the Data Source and Model

This section will discuss the data sources used to train the CNN, the methods used to collect experimental data, the structural information of the CNN, and the particulars of the training and testing processes in order to guarantee experimental reproducibility.

2.1. Data Basis

We used experimental data from a variety of studies to confirm the universality of our CNN predictive model for pervious concrete, focusing on compressive strengths between 2 and 40 MPa. We included samples with standard mix compositions in order to improve the model's applicability in light of the diverse mix compositions that were reported. The types and contents of coarse and fine aggregate, water content, admixture content, cement content, fly ash content, silica fume content, and 28-day compressive strength were among the data gathered. Also, we led 12 new examinations to additional upgrade the dataset. To increase robustness, different sets were used for each model run, and each sample was randomly assigned to either the training set (70 percent) or the testing set (30 percent). To address the absence of freely accessible datasets with point-by-point blend extents, we dismissed explicit total and concrete sorts, zeroing in rather on approximating material planning during model preparation. The eight input variables and their 28-day compressive strength were the nine variables in the dataset for each sample. The CNN model is able to accurately predict the compressive strength of pervious concrete for a variety of materials and mix proportions thanks to this strategy [8].

2.2. CNN Structure

CNNs have been broadly investigated by analysts for anticipating concrete compressive strength. For example, Deng et al. fostered a brain network with a convolutional layer part and a secret layer containing four neurons, using four info highlights to foresee reused total cement. On the other hand, Zeng et al. contended that as the quantity of info pointers expands, the CNN's design ought to be changed likewise. As a result, they looked for the optimal number of neurons in the fully connected layer between 4 and 128 and increased the number of convolutional kernels. The convolutional structure is improved in line with the significant differences in raw materials between the samples in this study. A convolutional layer with a kernel size of 3 1 1, a pooling layer with a kernel size of 1 1, a batch normalization layer, and a ReLU activation function layer make up each convolutional structure. The gathered information enters the model through the information layer. In the wake of going through fundamental preparation with three convolutional structures, repetitive information is disposed of through dropout layers. Data fusion is then accomplished by fully connected layers. A regression layer is used to perform data prediction after the model has been trained [9].

3. Results and Discussion

3.1. CNN Model Predictive Performance

To outwardly exhibit the prescient capacities of the CNN model for the compressive strength of pervious concrete, this study presents results from a particular examination. The CNN model's predicted compressive strength over the course of 28 days is shown on the vertical axis, while the actual compressive strength is shown on the horizontal axis. In the subsequent diagram, information focuses group around the corner-to-corner line, showing areas of strength for a between the model's expectations and the noticed outcomes. This example recommends a serious level of concordance among anticipated and genuine compressive strength values, showing the model's exactness. The CNN model's ability to predict the compressive strength of pervious concrete is demonstrated by the data points' proximity to the diagonal line [10].

3.2. Improvements in CNN Model Training

3.2.1. Enhancements for Improved Robustness of the Model

However, the model's predictions for the compressive strength of pervious concrete within this range may be inaccurate due to a lack of training data in the 10 to 20 MPa range. Experimental data on the measured 28-day compressive strength in the range of 10 to 20 MPa will be added to the model to increase its robustness and ensure that minor variations in the material composition of pervious concrete do not significantly affect the prediction results. This extra information expects to expand the preparation set of the CNN prescient model, working on its relevance to various sorts of pervious cement.

3.2.2. Method for Enhancing Model Robustness

1) Experimental Materials

For the experiments on pervious concrete, this study used a variety of materials, including grade 42.5 Ordinary Portland Cement (OPC). The OPC has a standard consistency of 27.1%, a particular surface area of 357 m2/kg, an underlying setting season of 203 min, and a last setting season of 250 min. The Jinying Hardware Business Department's 5–20 mm aggregates from the Jiangning District in

Nanjing were chosen as the coarse aggregates. These aggregates have a crushing value of 3.04 percent, an apparent density of 3.0149 g/cm3, a bulk density of 3.0045 g/cm3, and a compacted bulk density of 2.9246 g/cm3. Additionally, Nanjing Thermal Power Plant low-calcium Class I fly ash with a density of 2.04 g/cm3, a water demand ratio of 0.95, and a fineness of 6% (remaining on the 45 m sieve) was utilized. A high-performance polycarboxylate superplasticizer from Wuhan Greelan Building Material Technology Co., Ltd., which is located in Wuhan City, Hubei Province, China, was introduced to improve the performance of concrete. This gray-white powdered superplasticizer reduces the amount of water in mortar by 25 to 30 percent and has a bulk density of 350 to 450 kg/m3. The water utilized in substantial blending stuck to the guidelines illustrated in JGJ63-2006 for substantial water utilization [11].

2) Experimental Procedure

In this review, twelve arrangements of pervious cement were ready with various blend extents, point by point in Table 1, utilizing the slurry covering strategy. At first, coarse totals were blended in with roughly 3% water for 30 seconds to guarantee exhaustive pre-wetting, upgrading bond to solidify. After that, all-cement water, additives, and cement were added, and the mixture was stirred for 180 seconds to form a highly flowable slurry that prevented aggregates from crushing and reduced friction between them. This cycle considered uniform covering of the totals, advancing a round structure and upgrading porosity. The new concrete was then filled 100 × 100 × 100 mm³ cubic molds, compacted by vibration, demolded following 24 hours, and relieved in a standard chamber for 28 days. The "Standard for Test Method of Mechanical Properties of Ordinary Concrete" (GB/T 50081-2002) was used to test the specimens' compressive strength. The experimental outcomes, recorded in Table 2, expected to fill the information hole in the 10-20 MPa range, showed moderately close compressive strength values with a standard deviation of roughly 4.63 MPa [12].

Table 1. Pervious Concrete Mix Ratios.

Mixture	**Coarse Cement Aggregates (kg/m (kg/m^3)**		**Fly Ash (kg/m^3)**	**Water (kg/m^3)**	**Fresh Concrete Bulk Density (kg/m^3)**
Mix 1	1532	300	90	90	1863
Mix 2	1532	300	178	110	1945
Mix 3	1532	300	279	111	2065
Mix 4	1532	350	74	94	1884
Mix 5	1532	350	144	109	1967
Mix 6	1532	350	237	123	2039
Mix 7	1532	400	40	94	1876
Mix 8	1532	400	115	109	1958
Mix 9	1532	400	189	120	2098
Mix 10	1532	450	10	98	1855
Mix 11	1532	450	69	104	1965
Mix 12	1532	450	159	117	2075

Table 2. Pervious Concrete Porosity and Compressive Strength Test Results.

Mixture	28 d Compressive Strength Measured Porosity (%) (MPa)	
Mix 1	24.9	10.8
Mix 2	20.4	12.9
Mix 3	15.9	16.4
Mix 4	24.3	12.8
Mix 5	19.2	14.6
Mix 6	16.5	18.8
Mix 7	23.2	16.3
Mix 8	21.1	18.9
Mix 9	14.3	24.4
Mix 10	24.5	18.9
Mix 11	21.1	21.8
Mix 12	15.3	25.6

3.2.3. Predictive Performance after Model Training Enhancement

Actual data from a variety of sources were compared to their corresponding predicted values, which were generated by the model, in order to visually demonstrate the predictive performance of the CNN developed in this study for estimating the compressive strength of pervious concrete with various material compositions. Quiet, the extra information consolidated in this concentrate effectively tended to the information hole inside the 10~20 MPa range. The CNN model had good predictive accuracy across all sample data following the retraining process, with data points tightly grouped around the diagonal line. Subsequent to integrating extra preparation information, the expectation execution of the CNN model on both the preparation and test. With very few absolute errors, it is evident that the model's predicted values closely match the actual values in the test and training sets. This indicates that the model, after being retrained with new data, has excellent predictive capabilities without experiencing issues with underfitting or overfitting. The model reliably accomplishes high exactness in anticipating the 28-day compressive strength of assorted kinds of pervious cement. This paper uses histograms to visually present the distribution of relative errors between predicted and actual values in both the training and test sets, in addition to the indicators previously mentioned. The calculations indicate that the training set's minimum relative error may reach 0.03%, while the test sets may reach 0.08%. Furthermore, more than 60% of the relative errors in the training set are below 10%, and a similar percentage of over 60% of the relative errors in the test set are below 10%. The training set has a relative error rate of 9.30%, while the test set has an error rate of 8.11%. These results show that the CNN model can accurately and reliably estimate the compressive strength of pervious concrete with different material compositions [13].

3.3. Comparative Analysis between CNN and Other Prediction Methods

This study trained and tested both models on the same dataset in order to emphasize the CNN model's superiority. The BP Neural Network is a widely used neural network. The outcomes showed that while the two models had information focuses bunched around the askew line, demonstrating great prescient execution, the CNN model's expectations were strikingly nearer to the real qualities. The CNN model's superior accuracy and dependability in predicting the 28-day compressive strength of pervious concrete was demonstrated by this visual comparison. A relative diagram was created to portray the anticipated qualities against the genuine qualities for the two models outwardly. The predictions made by the CNN model outperformed those made by the BP model because of their tighter clustering around the actual values. The CNN model had a higher overall predictive performance than the BP model, with a R2 of 0.931 as opposed to 0.893. The CNN model consistently outperformed the BP model, as evidenced by further examination of the Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE) metrics. More specifically, the BP model had a MAPE of 14.40%, which was higher than the desired 10% threshold and suggested that certain mix ratios might be off from the actual values. The CNN model, on the other hand, had all MAPE values below ten percent, indicating superior predictive performance. Consequently, the CNN model gives dependable and exact expectations to the 28-day compressive strength of pervious cement with different material organizations, making it more reasonable for down to earth applications [14-15].

4. Conclusions

This paper introduces a Convolutional Neural Network (CNN) model designed to predict the 28-day compressive strength of pervious concrete using eight input parameters related to mixture proportions. The model was trained and validated using a dataset comprising 123 samples gathered from literature and experimental studies. The study yields several significant findings: First, the CNN model demonstrated strong predictive accuracy with a Mean Absolute Percentage Error (MAPE) of 9.13% and an R^2 value of 0.938 on the test set. These metrics indicate that the CNN model effectively predicts the compressive strength of pervious concrete across diverse material compositions, underscoring its stability and ability to maintain prediction errors within acceptable limits. Second, comparative analysis with a traditional BP neural network showed that the CNN model outperformed in terms of both R^2 and lower prediction error metrics (RMSE, MAE, and MAPE), highlighting its superior predictive performance and robustness. Third, the study included experimental data covering a specific compressive strength range of 10-20 MPa for pervious concrete, enhancing the model's capability to predict data from various sources and experimental conditions. Despite these advancements, limitations exist due to factors such as aggregate characteristics, cement grades, and curing methods not being included as input variables, potentially impacting the model's performance across different types of pervious concrete. Future research directions should focus on integrating a broader array of material data and preparation conditions into CNN models, leveraging larger and more diverse experimental datasets to ensure comprehensive model validation and improve prediction accuracy. Additionally, as the dataset expands, optimizing hyperparameters like learning rate and decay factor will be critical, necessitating advanced algorithms to handle complexity and enhance the model's practical utility.

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