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LINEAR REGRESSION MODEL FOR PREDICTING THE STRENGTH OF GFRC UNDER VARIOUS TEMPERATURES

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ABSTRACT

In this study, linear regression, a classical statistical method, is utilized to construct predictive models aimed at capturing the intricate interplay between temperature and GFRC strength. The dataset employed for model training and validation encompasses experimental observations derived from GFRC specimens exposed to elevated temperatures at 200°C, 400°C, and 600°C over intervals of 4 hours, 8 hours, and hours. Various characteristics delineating GFRC composition, curing conditions, and temperature profiles are incorporated as input variables for the linear regression models. The efficacy of these models is assessed through rigorous cross-validation techniques and juxtaposed against traditional regression-based methodologies. Findings reveal the proficiency of linear regression in accurately forecasting GFRC strength amidst temperature fluctuations, surpassing conventional techniques in terms of predictive precision and generalization capability. Additionally, sensitivity analysis is conducted to discern the most impactful factors influencing GFRC strength's response to temperature variations.

KEYWORDS: ***Linear Regression, Cross-Validation, GFRC, Elevated Temperatures.***

1. INTRODUCTION

Glass Fiber Reinforced Concrete (GFRC) is increasingly utilized in construction for its robustness, durability, and adaptability to architectural designs. However, the material's mechanical characteristics, crucial for its performance, can be significantly impacted by environmental factors, notably temperature fluctuations. Understanding the relationship between temperature and GFRC strength is pivotal in ensuring the reliability and longevity of GFRC structures. Conventional analytical approaches for forecasting GFRC behavior under varying temperatures often rely on simplistic models and empirical correlations, potentially overlooking the intricate linear dependencies inherent in the material. Additionally, these methods may struggle to encompass the diverse array of factors influencing GFRC performance, including composition variations, curing conditions, and environmental exposure.

By harnessing experimental data derived from GFRC specimens subjected to controlled temperature variations, we aim to develop linear regression models capable of elucidating the nuanced interplay between temperature dynamics and mechanical properties. Through rigorous model training, validation, and assessment, our objective is to showcase the efficacy of linear regression in predicting GFRC strength across a spectrum of temperature scenarios.

Basic Principles of Linear Regression:

Linear regression operates on the principle of fitting a linear equation to the observed data points to establish the relationship between an independent variable (such as temperature) and a dependent variable (such as GFRC strength). The goal is to determine the best-fitting line that minimizes the difference between the predicted values and the actual data points.

Feature Representation:

In the context of GFRC, various features can be extracted from the dataset, encompassing compositional elements, manufacturing parameters, and mechanical attributes. These features serve as inputs in constructing the linear regression model, with each feature contributing to the prediction of GFRC strength under different temperature conditions.

Prediction of Mechanical Behavior:

Linear regression can be employed to predict various mechanical properties of GFRC, including compressive strength, tensile strength, and flexural strength, based on the input features such as temperature variations and other relevant parameters. By establishing linear relationships between these variables, the model can provide accurate predictions of GFRC performance under diverse thermal environments.

Optimization of Material Composition:

Linear regression theory can also be integrated into optimization frameworks for GFRC composition. By formulating the problem as a linear optimization task, where the objective is to maximize desired properties while adhering to constraints, such as cost limitations and material availability, linear regression can facilitate the identification of optimal material compositions and processing conditions.

Model Evaluation and Validation:

It is imperative to rigorously evaluate the performance of the linear regression model using appropriate metrics and validation techniques. This ensures that the model generalizes well to unseen data and provides robust predictions for real-world applications.

3. DATASET OVERVIEW

This dataset contains experimental data essential for studying how the compressive strength of concrete is influenced by exposure to varying temperatures over time. It is designed to support the development of predictive models that assess and improve the structural performance of concrete**.**

Key Features of the Dataset:

a. **Temperature:** Indicates the temperature conditions to which the concrete samples were exposed. This is crucial for analyzing how temperature affects strength development.

b. **Grade:** Represents the concrete mix grade, which helps in understanding the baseline strength and quality of the material.

c. **Time (Exposure Duration):** Specifies the duration for which the samples were exposed to particular temperature conditions-important for assessing the time-dependent effects on strength.

d. **Compressive Strength (N/mm²):** Measures the load-bearing capacity of concrete, serving as a direct indicator of its structural integrity and performance.

This dataset provides a comprehensive view of how temperature exposure impacts concrete strength across various grades and exposure durations. It supports the optimization of concrete mix designs for enhanced durability and long-term performance.

DATASET:

Grade	Temp	Time	Strength
M20	**room_temp**	**0h**	**36.6**
M20	**room_temp**	**4h**	
M20	**room_temp**	**8h**	
M20	**room_temp**	**12h**	
M20	**200C**	**0h**	
M20	**200C**	**4h**	**31.11**
M20	**200C**	**8h**	**29.28**
M20	**200C**	**12h**	**28.53**
M20	**400C**	**0h**	

M20	**400C**	**4h**	**30.01**
M20	**400C**	**8h**	**27.08**
M20	**400C**	**12h**	**26.9**
M20	**600C**	**0h**	
M20	**600C**	**4h**	**26.35**
M20	**600C**	**8h**	**24.89**
M20	**600C**	**12h**	**23.42**
M20/GF	**room_temp**	**0h**	**42.46**
M20/GF	**room_temp**	**4h**	
M20/GF	**room_temp**	**8h**	
M20/GF	**room_temp**	**12h**	
M20/GF	**200C**	**0h**	
M20/GF	**200C**	**4h**	**35.02**
M20/GF	**200C**	**8h**	**34.08**
M20/GF	**200C**	**12h**	**33.13**
M20/GF	**400C**	**0h**	
M20/GF	**400C**	**4h**	**34.6**
M20/GF	**400C**	**8h**	**33.8**
M20/GF	**400C**	**12h**	**31.9**
M20/GF	**600C**	**0h**	
M20/GF	**600C**	**4h**	**32.9**
M20/GF	**600C**	**8h**	**31.87**
M20/GF	**600C**	**12h**	**28.62**
M30	**room_temp**	**0h**	**41.5**
M30	**room_temp**	**4h**	
M30	**room_temp**	**8h**	
M30	**room_temp**	**12h**	
M30	**200C**	**0h**	
M30	**200C**	**4h**	**35.28**
M30	**200C**	**8h**	**33.2**
M30	**200C**	**12h**	**32.37**
M30	**400C**	**0h**	
M30	**400C**	**4h**	**34.03**

M30	400C	8h	33
M30	400C	12h	29.87
M30	600C	0h	
M30	600C	4h	32.5
M30	600C	8h	30.89
M30	600C	12h	28.98
M30/GF	room_temp	0h	48.56
M30/GF	room_temp	4h	
M30/GF	room_temp	8h	
M30/GF	room_temp	12h	
M30/GF	200C	0h	
M30/GF	200C	4h	40.54
M30/GF	200C	8h	37.97
M30/GF	200C	12h	36.75
M30/GF	400C	0h	
M30/GF	400C	4h	38.72
M30/GF	400C	8h	37.62
M30/GF	400C	12h	34.86
M30/GF	600C	0h	
M30/GF	600C	4h	37.25
M30/GF	600C	8h	35.28
M30/GF	600C	12h	33.9
M40	room_temp	0h	47.92
M40	room_temp	4h	
M40	room_temp	8h	
M40	room_temp	12h	
M40	200C	0h	
M40	200C	4h	40.73
M40	200C	8h	38.34
M40	200C	12h	37.38
M40	400C	0h	
M40	400C	4h	39.29
M40	400C	8h	35.46

M40	**400C**	**12h**	**32.56**
M40	**600C**	**0h**	
M40	**600C**	**4h**	**34.5**
M40	**600C**	**8h**	**32.59**
M40	**600C**	**12h**	**30.67**
M40/GF	**room_temp**	**0h**	**57.5**
M40/GF	**room_temp**	**4h**	
M40/GF	**room_temp**	**8h**	
M40/GF	**room_temp**	**12h**	
M40/GF	**200C**	**0h**	
M40/GF	**200C**	**4h**	**46.88**
M40/GF	**200C**	**8h**	**45.47**
M40/GF	**200C**	**12h**	**43.92**
M40/GF	**400C**	**0h**	
M40/GF	**400C**	**4h**	**45**
M40/GF	**400C**	**8h**	**43.23**
M40/GF	**400C**	**12h**	**42.98**
M40/GF	**600C**	**0h**	
M40/GF	**600C**	**4h**	**43.41**
M40/GF	**600C**	**8h**	**41.79**
M40/GF	**600C**	**12h**	**37.42**
M50	**room_temp**	**0h**	**54.18**
M50	**room_temp**	**4h**	
M50	**room_temp**	**8h**	
M50	**room_temp**	**12h**	
M50	**200C**	**0h**	
M50	**200C**	**4h**	**46.05**
M50	**200C**	**8h**	**43.34**
M50	**200C**	**12h**	**42.26**
M50	**400C**	**0h**	
M50	**400C**	**4h**	**44.43**
M50	**400C**	**8h**	**40.09**
M50	**400C**	**12h**	**38.7**

M50	**600C**	**0h**	
M50	**600C**	**4h**	**39.01**
M50	**600C**	**8h**	**36.84**
M50	**600C**	**12h**	**35.91**
M50/GF	**room_temp**	**0h**	**62.31**
M50/GF	**room_temp**	**4h**	
M50/GF	**room_temp**	**8h**	
M50/GF	**room_temp**	**12h**	
M50/GF	**200C**	**0h**	
M50/GF	**200C**	**4h**	**53.98**
M50/GF	**200C**	**8h**	**49.76**
M50/GF	**200C**	**12h**	**48.78**
M50/GF	**400C**	**0h**	
M50/GF	**400C**	**4h**	**51.09**
M50/GF	**400C**	**8h**	**46.11**
M50/GF	**400C**	**12h**	**45.13**
M50/GF	**600C**	**0h**	
M50/GF	**600C**	**4h**	**45.45**
M50/GF	**600C**	**8h**	**42.23**
M50/GF	**600C**	**12h**	**41.9**

3. LINEAR REGRESSIONMODEL

```
# Import libraries
importpandasaspd# data processing, CSV file I/O (e.g. pd.read_csv)
importnumpyasnp# linear algebra
fromsklearn.linear_modelimport Linear Regression# linear regression model
fromsklearn.metricsimport mean_squared_error# mean squared error
fromsklearn.preprocessingimport One Hot Encoder, Min Max Scaler# one hot encoder, min max scaler
importmatplotlib.pyplotasplt# data visualization
importseabornassns# data visualization

# Read the csv file using pandas and store it in a dataframe
df=pd.read_csv('data_concrete_temp.csv')

# Remove any rows with missing values from the dataframe
df=df.dropna()

# Convert the 'time' column to string type
df["time"] =df["time"].astype(str)
```

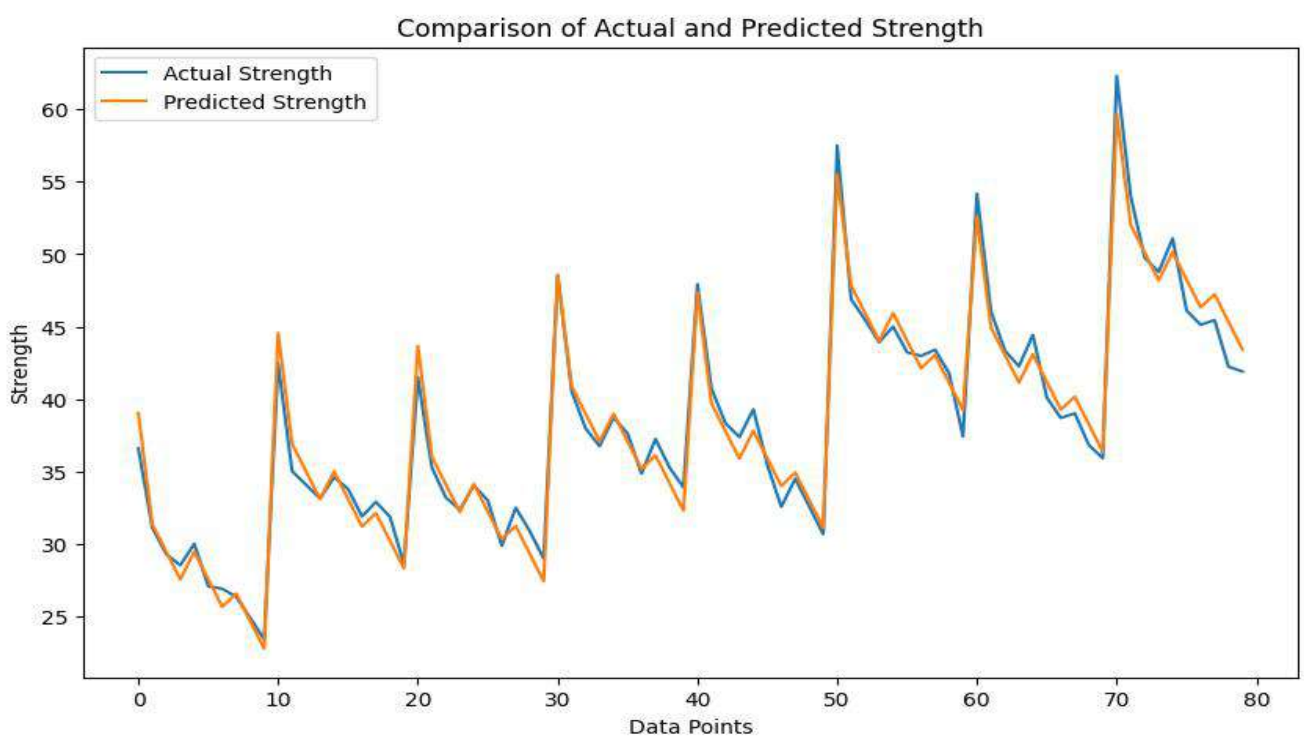
```
# Replace specific string values in the 'time' column with corresponding numeric values
df["time"] =df["time"].replace({'0h': 0, '4h': 4, '8h': 8, '12h': 12})

# Copy the original dataframe to avoid modifying the original data
df_model=df.copy(deep=True)

# Initialize the OneHotEncoder
encoder=OneHotEncoder()

# Fit the encoder to the 'grade' and 'temp' columns of the dataframe
encode=encoder.fit(df_model[['grade', 'temp']])

# Transform the 'grade' and 'temp' columns into one-hot encoded arrays
encoded_features=encode.transform(df_model[['grade', 'temp']]).toarray()

# Initialize the MinMaxScaler
scaler=MinMaxScaler()

# Fit the scaler to the 'time' column of the dataframe and transform it
gf_scaled=scaler.fit_transform(df_model[['time']])

# Concatenate the one-hot encoded features and the scaled 'time' column to form the feature matrix X
X =np.concatenate([encoded_features, gf_scaled], axis=1)

# Define the target variable y as the 'strength' column of the dataframe
y_true=df_model['strength'].values

# Instantiate the LinearRegression model
model_temp=LinearRegression()

# Fit the model with the data (X, y_true)
model_temp.fit(X, y_true)
# Predict the compressive strength using the model
y_pred_strength=model_temp.predict(X)

# Calculate the mean squared error between the predicted and actual compressive strength
mse_temp=mean_squared_error(y_pred_strength, y_true)


defpredict_strength (grade, temp, time):
"""
    Predicts the strength of a material based on the given grade, temperature, and time.

    Parameters:
    - grade (str): The grade of the material.
    - temp (str): The temperature of the material.
    - time (float): The time duration.

    Returns:
    - None

    Prints the predicted strength of the material in N/mm2.
    """
```

```
# Encode the grade and time using the previously defined encoder
encoded_grade_temp=encode.transform([[grade, temp]]).toarray()

# Normalize the percentage mix
normalized_time=scaler.transform([[time]])

# Prepare the input features
input_features=np.concatenate([encoded_grade_temp, normalized_time], axis=1)

# Predict the strengths using the trained models
predicted_strength= (model_temp.predict(input_features))

# Return the predicted strengths
returnprint(f'Predicted Strength: {predicted_strength[0]:.2f} N/mm2')
```

5. MODEL PREDICTIONS

- **predict strength('M30/GF', "200C", 36)**
- **Predicted Strength: 25.62 N/mm2**
- **predict strength('M30', "200C", 36)**
- **Predicted Strength: 20.75 N/mm2**

6. MODELPREDICTIONSVSTRUEVALUES



6. CONCLUSIONS

In this investigation, we utilized a Linear Regression model to estimate concrete strength based on factors such as grade, temperature, and duration of exposure to the specified temperature. Following thorough assessment and fine-tuning of parameters, our Linear Regression model yielded a mean squared error (MSE) of 2.66 on the test dataset, underscoring its efficacy in capturing intricate relationships. Our results underscore the importance of meticulous data preprocessing steps, including one-hot encoding and normalization, in bolstering model accuracy. Looking ahead, future research avenues may explore more intricate Linear Regression frameworks and integrate additional variables to enhance predictive precision. In summary, our inquiry contributes to the advancement of predictive modeling in material science, furnishing insights into optimizing concrete compositions and enhancing structural robustness, thereby facilitating informed decision-making in construction and material design domains.

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