Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Developing a Predictive Model of Concrete Performance with Fly Ash and Steel Fiber Using Machine Learning Algorithm

Edgardo Cruz [1], Miguel Lagarto [2*], Jonathan Madrazo [3], Fay Morales [4]
[1, 2, 3, 4] School of Civil, Environmental, and Geological Engineering, Mapua University, 658 Muralla St., Intramuros, Manila, 1002 Metro Manila, Philippines
**Corresponding Author: Miguel Lagarto, lagm64233@gmail.com*

ARTICLE INFO

Received: 18 Dec 2024
Revised: 17 Feb 2025
Accepted: 28 Feb 2025

ABSTRACT

This research paper aims to develop an AI model that predicts the performance of concrete containing Fly Ash and Steel Fiber. Fly Ash is a byproduct of coal combustion in electric power plants, causing environmental concerns due to its sizeable global production. Steel Fiber is a specialized reinforcement material for concrete used in various applications. The study addresses the lack of international guidelines for evaluating concrete with Fly Ash and Steel Fiber performance. The model uses machine learning algorithms and neural networks to forecast key performance metrics such as compressive strength, cracking behavior, and bending stress. The objectives include assessing these properties and building a network model for analysis. This research promotes construction practices by reducing carbon emissions and endorsing Fly Ash and Steel Fiber as eco- substitutes for traditional Portland cement. The AI predictive model can optimize concrete mix designs, predict long-term performance trends, and evaluate environmental factors influencing behavior. It seeks to improve project outcomes, lower testing costs, and advance construction methods. The study examines concrete strength and split tensile strength with Fly Ash and Steel Fiber, emphasizing machine learning techniques for modeling. It also explores how machine learning methods like networks can predict concrete compressive strength. Theoretical frameworks like networks and ensemble learning theory are introduced to enhance accuracy. The methodology section provides insights into research design elements, data collection procedures, instruments used, and statistical analyses applied in developing the model. A quantitative approach was used to gather data and conduct analyses. The research took place at Mapua University laboratory using a Universal Testing Machine and AI tools.

Keywords: Algorithm, Confusion Matrix, Fly Ash, Machine Learning Algorithm, Multivariate Regression, Steel Fiber.

INTRODUCTION

This study is focused on predicting the performance of a concrete mixture of Fly Ash and Steel Fiber as an additive determining its performance through making a predictive model using Artificial Intelligence (AI). This study assessed the variables of Fly Ash with Steel Fiber, such as Fly Ash to Cement Content, Water to Cement Ratio, and Aggregate Properties. Furthermore, the researchers found an appropriate machine-learning algorithm in artificial intelligence as a predictive model for predicting the performance of concrete.

Currently, the local and international concrete codes lack provisions for assessing the performance of Fly Ash with Steel Fiber as an additive mixture to concrete. The material economy and structural stability of civil infrastructure greatly depend on the capacity to forecast specific strengths accurately. [12] If concrete's inherent durability is not sufficiently acknowledged, cement may be used needlessly, increasing carbon dioxide emissions. Fly ash is one of the essential components of the cement mixture due to the increase in compression strength, flexural strength, and hardness of the concrete. [3] The components of fly ash are pozzolan, silica, alumina, and calcium-based substances that chemically combine with the free line in the fly ash to generate a cementitious material. [3] Artificial intelligence

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

(AI) has been a significant factor in society's advancement due to the vastly evolving technological improvement. The predictive models that illustrate the relationship between the strength of concrete and its constituent parts have been the subject of extensive research in recent times. While traditional methods have been essential in determining strong relationships between important variables like cement dosage, aggregate fraction, and air void content concerning concrete strength, analyzing the compound effects of these features is still complex. [25] With these circumstances, the researchers aimed to incorporate artificial intelligence to augur the specific strength of concrete. Ideally, a prediction model should provide meaningful insights that enhance physical buildings with remarkable constructability and durability while reducing expenses.

This study uses artificial intelligence to create a predictive model of concrete performance utilizing Fly Ash and Steel Fiber. Creating this predictive model of concrete performance with artificial intelligence technologies helps the industry be efficient. Artificial intelligence has a significant advantage over traditional predictive models or methods since predictions in artificial intelligence can be made without knowing the relationships between the variables.[39] Although many research studies have used predictive models to predict the performance of the said concrete, the studies were able to predict the compressive strength of concrete with an accurate prediction. This study widens parameters by not only being able to get the compressive strength of Fly Ash with Steel Fiber concrete, but this study will also predict the Compressive Strength and Split Tensile Strength of the concrete mixture through a predictive model with the help of Artificial Intelligence by using machine learning algorithms. The predictive model produced in this study will be compared to the existing models to get the best prediction accuracy and accurate results.

MATERIALS AND METHODS

Research Design:

In this study, the research used Experimental Design. The raw data, Fly Ash with Steel Fiber concrete mixture content, Water Cement ratio, and Aggregate Properties, are gathered in a laboratory setting with controlled variables. Furthermore, the obtained variables were trained under a machine learning algorithm to develop a predictive model. The study followed a quantitative approach, focused on developing a predictive model to predict the performance of fly ash with steel fiber as an additive mixture to concrete using artificial intelligence (AI). Furthermore, it entails gathering raw data from laboratory tests and developing models utilizing AI through machine learning algorithms to ensure the accuracy and reliability of the predictive model. The primary objective of this quantitative study is to address the gap in local and international concrete codes that lack provision for calculating the mechanical performance of concrete with Fly Ash with Steel Fiber as an additive mixture.

Research Setting:

The production and testing of concrete with Fly Ash with Steel Fiber as an additive mixture was done in the Laboratory of Mapua University in Intramuros Campus. The concrete with Fly Ash with Steel Fiber mixture specimen underwent a concrete test using a Universal Testing Machine (UTM) to test and measure the Compressive Strength and Split Tensile Strength. The validation of the results from the UTM Test, statistical treatment, and Predictive Model development was carried out using MATLab and Microsoft Excel, which is integrated with Python.

Data Gathering Instruments:

The research instruments used in this study are the Universal Testing Machine, Microsoft Excel integrated with Python, and Matlab. The usage of the Universal Testing Machine will be able to compute the compressive strength and the split tensile strength. In addition, with a standard Portland cement, the testing of each ground granulated blast furnace slag concrete would be compared to that standard to determine the difference and the relationship between the variables. For data analysis and model development, machine learning algorithms would be used to train for the data by Microsoft Excel integrated with Python. Lastly, Matlab integrated with multivariate regression would be used for model development to find the relationship and predict the model.

Data Gathering Procedure:

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

The data-gathering procedure in this study started with the gathering the raw data of Concrete to Fly Ash with Steel Fiber, Water Cement Ratio, and Aggregate Properties from the Universal Testing Machine (UTM) in order to determine the compressive strength and split tensile strength. The constant variables, the Water Cement Ratio, the cement aggregate ratio, and the curing, took 28 days. The independent variable for this experiment is the ratio of fly ash that would be replaced with the amount of cement; the steel fiber would also have different percentages that would be added in the experiment. The dependent variable will be the result, particularly the compressive and split tensile strength. The researchers also provide a standard Portland cement to compare with the Ground Granulated Blast Furnace Slag Mixture in different ratios for compressive strength and split tensile strength. After achieving the raw data, the researchers then trained the data using a Machine Learning Algorithm using Excel with integration with Python to train the model and check the compatibility of the data to use for the predictive model. The researchers then used Matlab to train the predictive model using multivariate regression to develop the predictive model and check the significance of the relationship between the variables of the data set trained in the machine learning algorithm model. Lastly, the researchers would then integrate the multivariate regression with the predictive model with the input and output mainframe and deploy it for end-users.

Statistical Treatment:

The researchers used various plotting models, such as scatterplot, histogram, and surface plot. The primary purpose of these descriptive statistical tools is to find the relationship between the variables and analyze the trend with the variables and how it would affect the dependent variable. The statistical treatment involved is descriptive statistics to answer objectives 1 and 2.

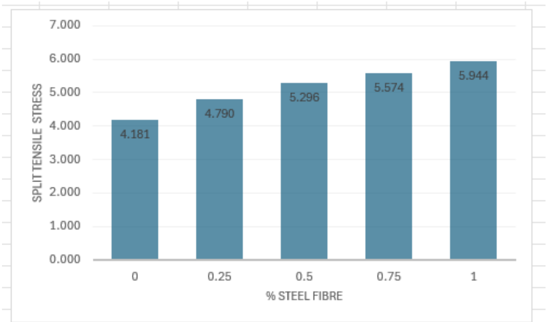


Figure A. Histogram Example

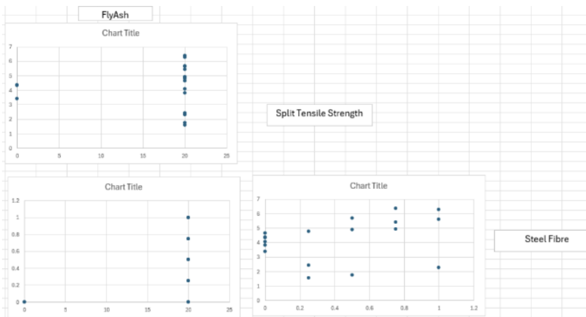


Figure B. Scatter Plot Example

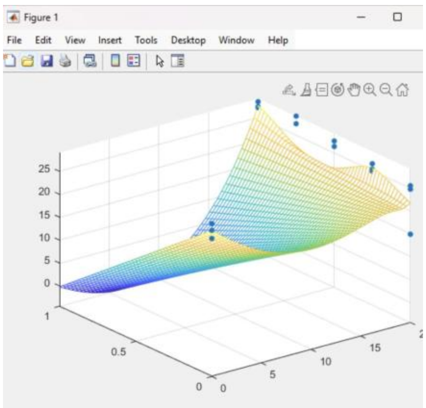


Figure C. Surface Plot Example

In answering objectives 3 to 5, inferential statistics and Matlab coding were used to analyze and present the needed output for the objectives. A machine learning algorithm was used to train the data, and the confusion matrix was used to show how the data would fit the predictive model. The machine learning algorithm represented the generalization

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

for the unseen data. In addition, Matlab is used for regression analysis, in which the code could run the program using multivariate regression to get the relationship and the significance of the predictive modeling. In addition, the program would also run to check for the computation of the T-test per value, the F1-score for the whole regression analysis, and the P value for the entire regression analysis.

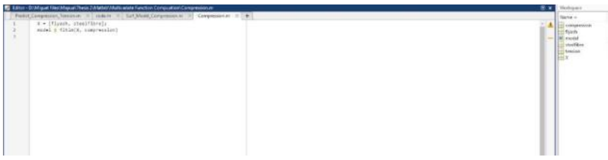


Figure D. MATLab Code

```
y ~ 1 + x1 + x2

Estimated Coefficients:
                   Estimate       SE        tStat     pValu
                   ________    ________    _______    ______

    (Intercept)      28.208     0.59156     47.684    3.9311e
    x1             -0.15217    0.037414    -4.0672     0.0028
    x2               3.2444     0.74828     4.3358     0.0018
```

Figure E. Multivariate Regression Analysis

```
Command Window
  model =

  Linear regression model:
      y ~ 1 + x1 + x2

  Estimated Coefficients:
                     Estimate       SE        tStat       pValue
                     ________    ________    _______    __________

      (Intercept)      28.208     0.59156     47.684    3.9311e-12
      x1             -0.15217    0.037414    -4.0672     0.0028113
      x2               3.2444     0.74828     4.3358     0.0018889

  Number of observations: 12, Error degrees of freedom: 9
  Root Mean Squared Error: 0.837
  R-squared: 0.724,  Adjusted R-Squared: 0.663
  F-statistic vs. constant model: 11.8, p-value = 0.00305
>>
```

Figure F. Validity Test of the Regression Analysis Strength.

RESULTS AND DISCUSSION

3.1 Presentation, Analysis, and Interpretation of the Data

The Table 1. Compressive Strength and Split Tensile Strength Results

% Fly Ash	% Steel Fiber	28 days (Mpa)	28 days (Mpa)	28 days (Mp
0	0	25.723	28.927	27.489
20	0	24.673	25.434	14.863
20	0.25	26.403	24.736	25.216
20	0.5	11.097	26.317	27.517
20	0.75	27.459	29.102	11.12
20	1	28.413	27.132	27.334

*Color red is failed or hollowed concrete cylinders (Standard Strength is 20Mpa)

Table 1.1. Compressive Strength Results

% Fly Ash	% Steel Fiber	28 days (Mpa)	28 days (Mpa)	28 days (Mp
0	0	25.723	28.927	27.489
20	0	24.673	25.434	14.863
20	0.25	26.403	24.736	25.216
20	0.5	11.097	26.317	27.517
20	0.75	27.459	29.102	11.12
20	1	28.413	27.132	27.334

*Color red is failed or hollowed concrete cylinders (Standard Strength is 20Mpa)

Table 1.2. Split Tensile Strength Results

The table above shows the Compressive and Split Tensile Strength Results. The data above was tested using the UTM Testing Machine at Mapua University. The researchers got the data with specific ratios that were done during the design of the experiment. Table 1 is the result of the Compressive Strength. It showed that when more steel fiber was added, the compressive strength increased from 24.673 to 29.102. It has a somewhat positive linear relationship, but looking at the fly ash percent, when it was from 0, the compressive strength was more significant than that of the 20 percent fly ash. The researchers further analyzed that with the help of steel fiber, the experiment increased the compressive strength lost due to Fly Ash.

On the other hand, similarly to the compressive strength, the researchers interpreted from the tensile stress that it is directly proportional; the steel fiber and the split tensile strength are directly proportional. Further analysis, the researchers can also add that the fly ash directly correlates with the split tensile strength. In addition to that, the

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

addition of the steel fiber has caused the improvement of split tensile strength in the mixture, which has a direct proportional relationship with fly ash and steel fiber. In Table 2 above, the researchers also say that with the addition of steel fiber, the split tensile strength has almost doubled compared to the standard Portland cement mixture.

In summary, the researchers concluded that fly ash and steel fiber have a positive linear relationship with compressive strength and are directly proportional to the split tensile stress.

Figure 1. Scatter Plot of the relationship between FlyAsh and Steel Fiber with Compressive Strength and Split Tensile Strength

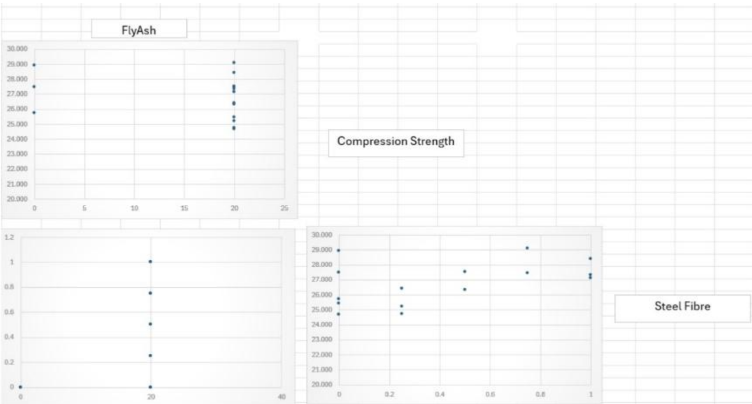


Figure 1.1 Scatter Plot of the Relationship between Fly Ash and Steel Fiber with Compressive Strength

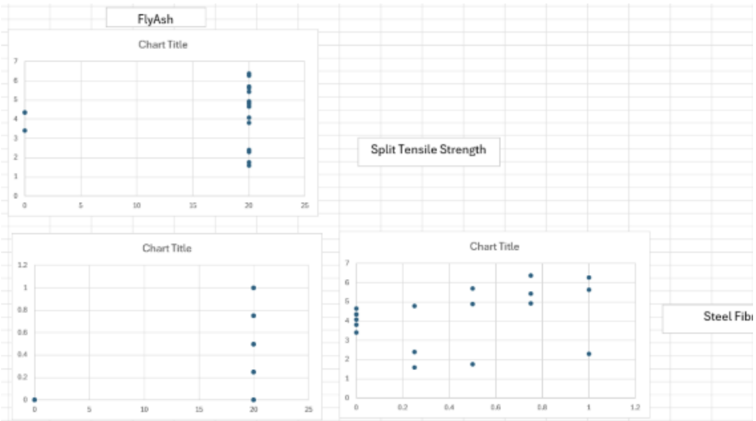


Figure 1.2 Scatter Plot of the relationship between FlyAsh and Steel Fiber with Split Tensile Strength

The figures above the scatter plot show the relationship between Fly Ash and Steel Fiber with Compressive Strength and Split Tensile Strength. For the first Figure 1.1, the data showed a positive increase with the corporate data. The bigger the value of the Fly Ash and Steel Fiber is, the bigger the compressive strength is. In addition, Figure 1.2 shows a more direct proportion, which the researchers can also explain. The more significant the Fly Ash and Steel Fiber value is, the bigger the split tensile strength. The researchers can conclude that there is a relationship between Fly Ash and Steel Fiber with Compressive Strength and Split Tensile Strength.

Figure 2. Histogram for the relationship of Steel Fiber with Compressive Strength and Split Tensile Strength

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

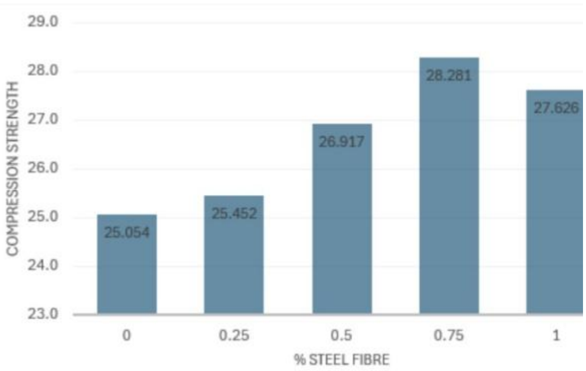


Figure 2.1. Histogram for the relationship of Steel Fiber with Compressive Strength

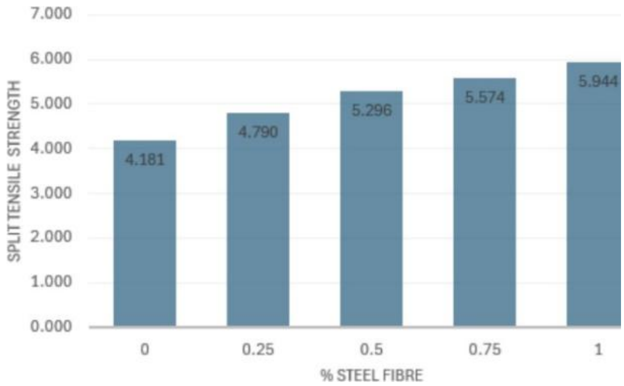


Figure 2.2. Histogram for the relationship of Steel Fiber with Split Tensile Strength

The figure above represents the direct relationship between steel fiber with Compressive Strength and Split Tensile Strength. In Figure 2.1, the data is interpreted as that steel fiber is directly related to compressive strength. In addition, figure 2.2 shows that Steel Fiber and Split. Tensile Strength are directly proportional. With the help of the histogram, the researchers were able to conclude the upward trend with the steel fiber with the compressive strength and the split tensile strength from the results and that the steel fiber has a relationship with the compressive strength and the split tensile strength.

Figure 3 Surface Plot In Matlab with the relationship of Fly Ash and Steel Fiber to Compression Strength code and figure

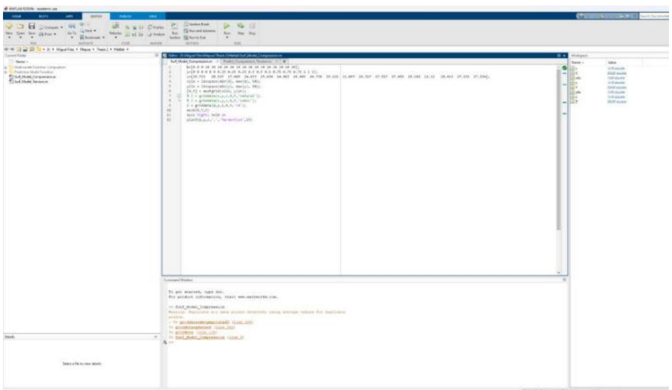


Figure 3.1. Surface Plot In Matlab with the Relationship of Fly Ash and Steel Fiber to Compression Strength Code

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

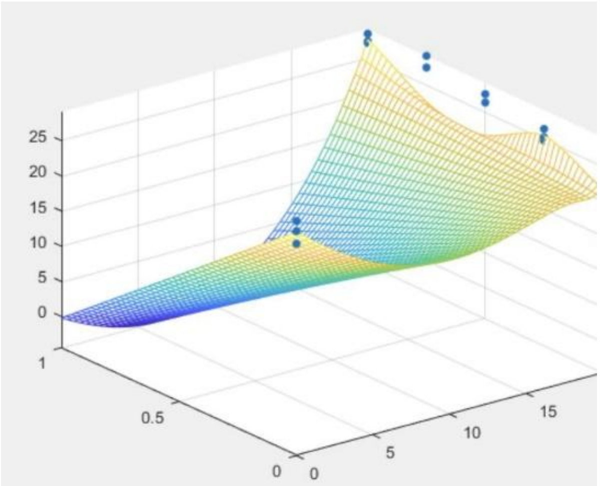


Figure 3.2. Surface Plot In Matlab with the relationship of Fly Ash and Steel Fiber to Compression Strength figure

From the figure above, the code shown is the process of manipulating the graph, written in rows but still with the same data as the table above. Figure 3.2 is the surface plot that represents the increase in fly ash and steel fiber, which also causes an increase in compression strength, according to the plot. As the figure shows, the larger the value for the Fly Ash and Steel Fiber is, the larger the compression strength is. In addition, with the surface plot's help, the researchers quickly identified the trends and patterns. They had a better insight into the multivariable data from the testing.

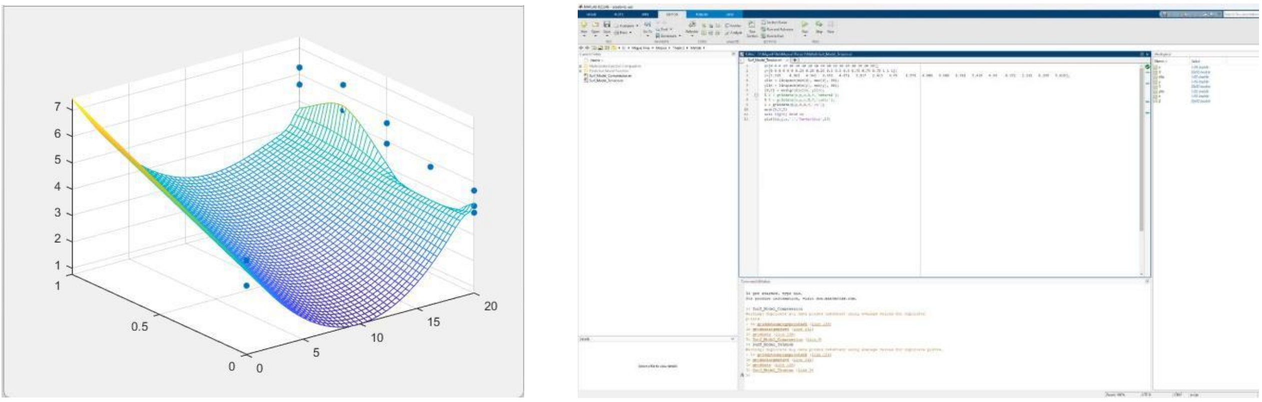


Figure 4. Surface Plot In Matlab with the relationship of Fly Ash and Steel Fiber to Split Tensile Strength code and figure

From the Figure above, the code shown is the process of manipulating the graph, which is similar to Fig. 3, in which it is written in rows but still with the same data as the table above. However, the dependent value shown in this Figure is for the Split Tensile Strength. Fig. 3.2 is the Surface Plot that represents the increase of Fly Ash and Steel Fiber, which also causes the increase of Split tensile, which is analyzed in the Figure. As the Figure shows, the larger the Fly Ash and Steel value, the bigger the value for the Split Tensile Strength.

Figure 5 Compressive Strength Data Training Using Machine Learning Algorithm in Excel Integrated with Python

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

% Fly Ash	% Steel Fibre	Test	Label	Mpa
0	0	1	>=20	25
0	0	1	>=20	28
0	0	1	>=20	27
20	0.25	1	>=20	24
20	0.25	1	>=20	25
20	0.25	0	<=20	14
20	0.5	1	>=20	26
20	0.5	1	>=20	24
20	0.5	1	>=20	25
20	0.75	0	<=20	11.
20	0.75	1	>=20	26
20	0.75	1	>=20	27
20	1	1	>=20	27
20	1	1	>=20	28
20	1	1	>=20	28
20	1.25	1	>=20	26
20	1.25	1	>=20	27
20	1.25	0	<=20	11.

Figure 5.1 Data Set

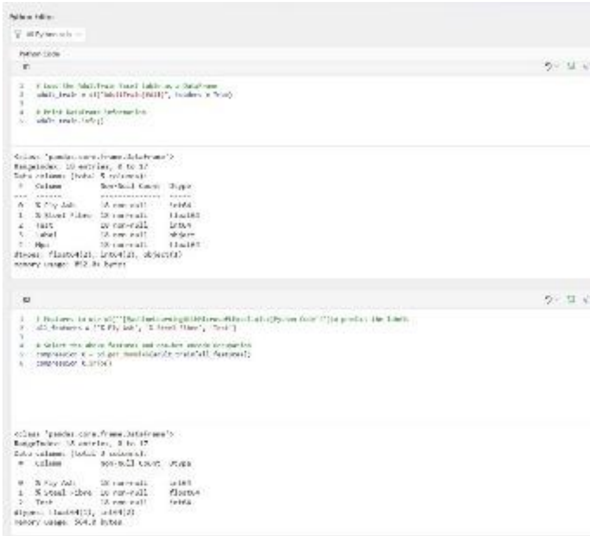


Figure 5.2.1 Python Editor in Excel Interface

Figure 5.2.2 Python Editor in Excel Interface

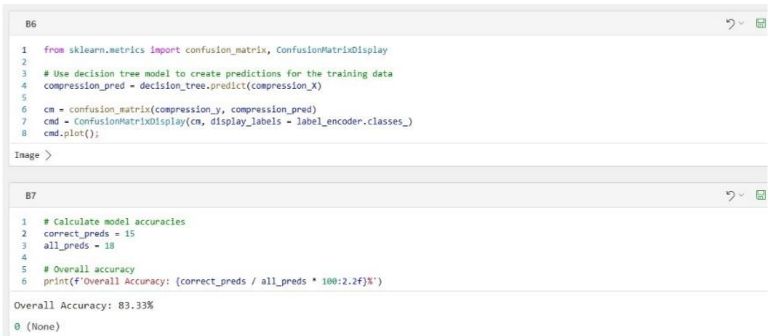


Figure 5.2.3 Python Editor in Excel Interface

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

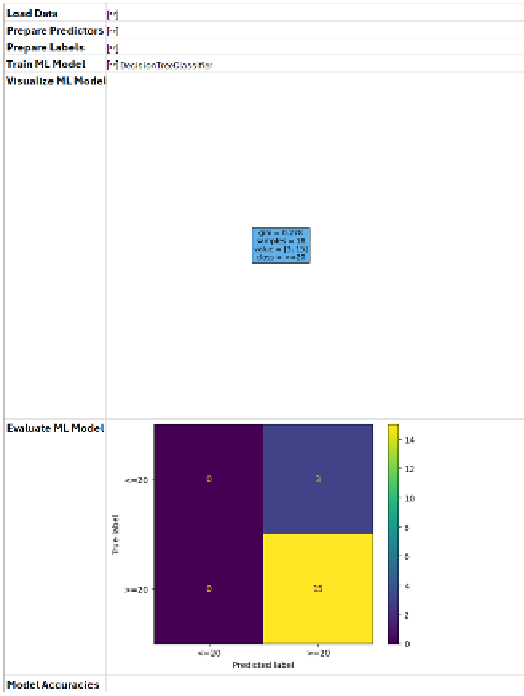


Figure 5.3 Machine Learning Model

Figure 5.1 represents the data set chosen to be trained in the machine learning algorithm. It mainly comprises the percent of fly ash, steel fiber, and the compressive strength based on the results from the UTM. The researchers chose the data based on this study's dependent and independent variables. The following figure, figure 5.2, is the series of coding used to run the machine learning algorithm model. In this series of codes, figure 5.2.1 represents the type of variable the model will train and the data set selection, which is the whole data. The next step in the figure showed that the dependent and the independent are segregated from each other, and the researchers were to choose which data sets are the independent variables and which are the independent variables for the machine learning algorithm to train. Figure 5.2.2 represents the labeling of the data and how to qualify the data. The researchers decided that to qualify data, it has to pass the minimum requirement of strength, which is from the ratio m20, so the qualification needed to pass the data is 20 Mpa. After labeling the data, the researchers then decided to code for a decision tree in which, in this tree, it is decided what primarily affects the labels of the structure. Figure 5.2.3 states that the decision tree model was used to create a prediction for the training data. In this figure, the algorithm predicted 15 that passes 20 Mpa, while in the actual data, 15 also passes the 20 Mpa mark. On the other hand, the algorithm predicted three more that passed 20 Mpa, but the actual data stated that it was less than 20 Mpa, which is a False Positive, which is a wrong prediction. The machine learning algorithm model has a prediction accuracy of 83 percent, which is still significant, and it can generalize the unseen data; in other words, the data can be used in a predictive model.

In conclusion, the figure above interpreted that the machine learning algorithm model could be used to generalize the unseen data and that the model has 83 percent of the predicted unseen data trained from the actual data given above. Furthermore, it can represent future prediction with an 83 percent credibility for the prediction model with the provided data.

Figure 6 Split Tensile Strength Data Training Using Machine Learning Algorithm in Excel Integrated with Python

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

% Fly Ash	% Steel Fibre	Test	Label	Mpa
0	0	1	>=3	3
0	0	1	>=3	4
0	0	1	>=3	4
20	0.25	1	>=3	4
20	0.25	1	>=3	4
20	0.25	1	>=3	3
20	0.5	0	<3	2
20	0.5	1	>=3	
20	0.5	0	<3	1
20	0.75	1	>=3	4
20	0.75	1	>=3	5
20	0.75	0	<3	1
20	1	1	>=3	5
20	1	1	>=3	
20	1	1	>=3	6
20	1.25	0	<3	2
20	1.25	1	>=3	6
20	1.25	1	>=3	5

Figure 6.1 Data Set

Figure 6.2.1 Python Editor in Excel Interface

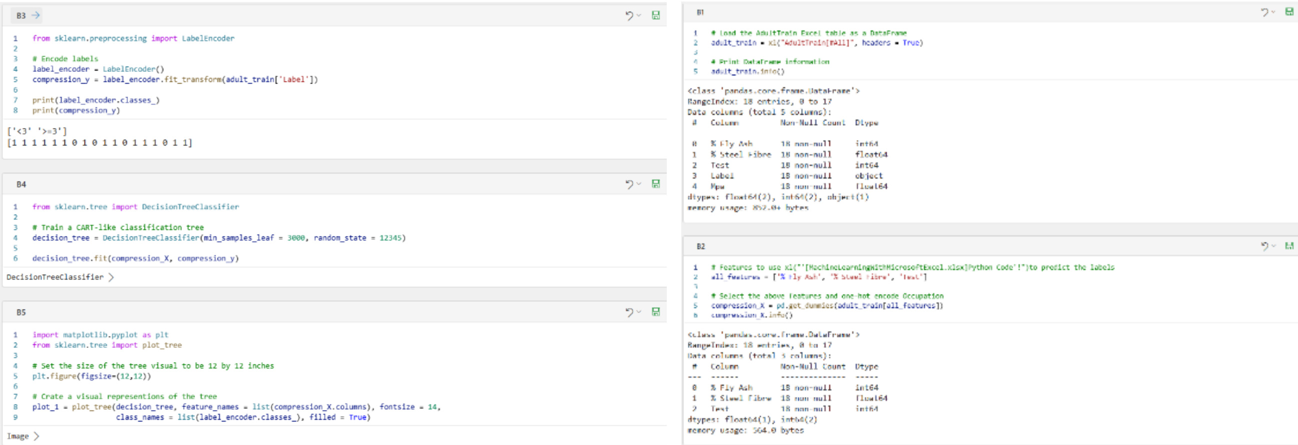


Figure 6.2.2 Python Editor in Excel Interfac

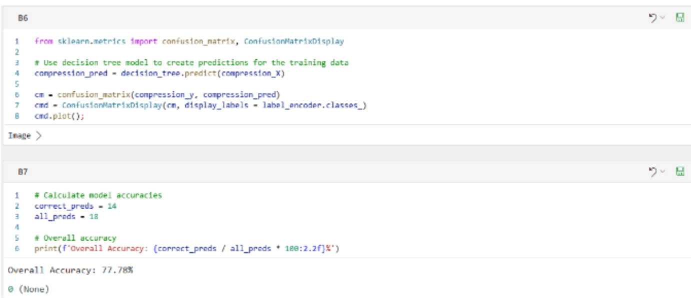


Figure 6.2.3 Python Editor in Excel Interface

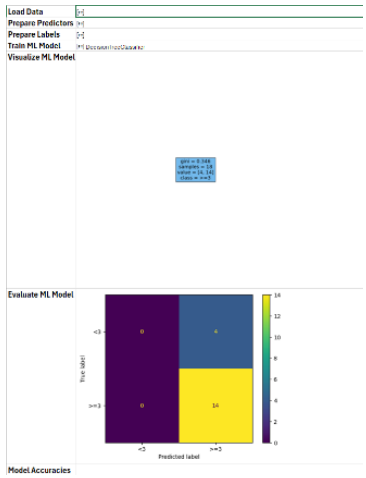


Figure 6.3 Machine Learning Model

Figure 6.1 represents the data set chosen to be trained in the machine learning algorithm. It mainly comprises the percent of fly ash, the percent of steel fiber, and the split tensile strength from the results of the UTM testing. The researchers chose the data based on this study's dependent and independent variables based on the selection. The following figure, figure 6.2, is the series of coding used to run the machine learning algorithm model. In this series of

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

codes, figure 6.2.1 represents the type of variable the model will train and the data selection, in which case the whole data includes the split tensile strength values. The next step in the figure showed that the dependent and the independent are segregated from each other, and the researchers were to choose which data sets are the independent variables and which are the independent variables for the machine learning algorithm to train. Figure 6.2.2 represents the labeling of the data and how to qualify the data. The researchers decided that to qualify data, it must pass the minimum strength requirement, which is 15 percent from the ratio m20, so the qualification needed to pass the data is three mpa. After labeling the data, the researchers then decided to code for a decision tree in which, in this tree, it is decided what primarily affects the labels of the structure. Figure 5.2.3 states that a decision tree model is used to create a prediction for the training data. In this figure, the algorithm predicted 14 that passes 3 Mpa, and at the same time, in the actual data, 14 also passes the 3 Mpa mark. On the other hand, the algorithm predicted four more that passed 3 Mpa, but the actual data stated that it is less than 3 Mpa wh, which is a False Positive, which is a wrong prediction. The Machine Learning Algorithm model has a prediction accuracy of 77.78 percent, which is still significant and close to percent, and it can generalize the unseen data, or, in other words, the data can be used in a predictive model.

In conclusion, the figure above interpreted that the machine learning algorithm model could be used to generalize unseen data and has a 77.78 percent chance of predicting these unseen data trained from the abovementioned data. Furthermore, it can represent future predictions with a 77.78 percent credibility for the prediction model with the given data for the prediction of the split tensile stress.

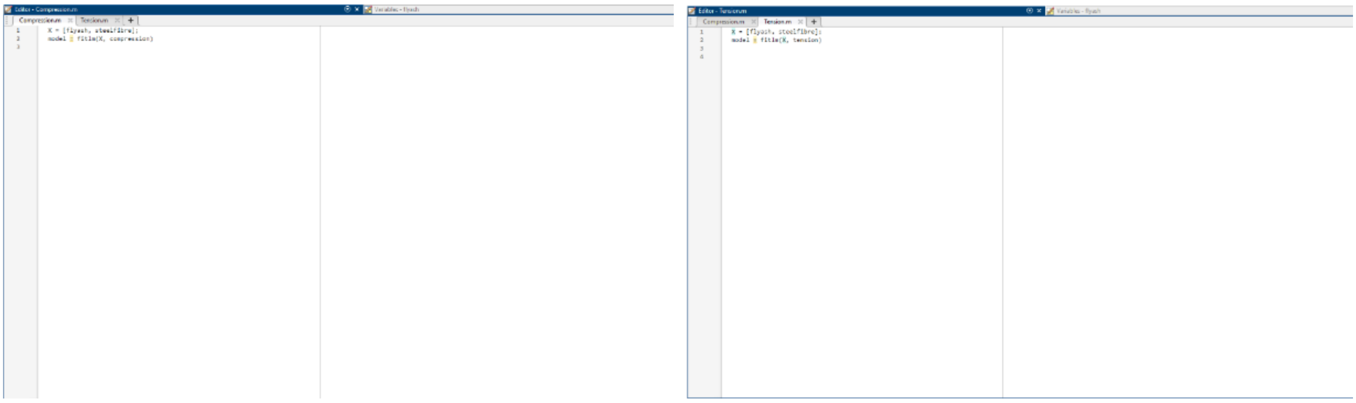


Figure 7 Predictive Model Optimization using Multivariate Regression in Matlab

From the figure above, the researchers used Matlabs as a medium to generate and form the Multivariate Regression to create Predictive Modelling. By doing this, Multivariate Regression can improve the prediction accuracy by incorporating different predictors; the regression would capture more complex relationships with the variables and not just straight direct linear proportionality, which is impossible if it is analyzed by simple linear regression. In addition, multivariate regression also has a better generalization of data; it tends to generalize unforeseen data and helps overfit the data by considering parameters that contribute to the effect of the dependent data. Figures 7.3 to 7.5 show the data set the researchers chose to analyze the predictive modeling. The researchers filtered out the lower results and put the results nearer to each other to lessen the error of human error during the prediction.

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Figure 8 Compressive Strength Results for Multivariate Regression

```
Command Window

model =


Linear regression model:
    y ~ 1 + x1 + x2

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    ________    _______    _________

    (Intercept)      28.208     0.59156     47.684    3.9311e-12
    x1             -0.15217    0.037414    -4.0672     0.0028113
    x2               3.2444     0.74828     4.3358     0.0018889


Number of observations: 12, Error degrees of freedom: 9
Root Mean Squared Error: 0.837
R-squared: 0.724,  Adjusted R-Squared: 0.663
F-statistic vs. constant model: 11.8, p-value = 0.00305
>>
```

Figure 8.1 Compressive Strength Results for Multivariate Regression

```
Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    ________    _______    _________

    (Intercept)      28.208     0.59156     47.684    3.9311e-12
    x1             -0.15217    0.037414    -4.0672     0.0028113
    x2               3.2444     0.74828     4.3358     0.0018889
```

Figure 8.2 Analysis of Compressive Strength Results for Multivariate Regression per Coefficient

```
model =


Linear regression model:
    y ~ 1 + x1 + x2

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    ________    _______    _________

    (Intercept)      28.208     0.59156     47.684    3.9311e-12
    x1             -0.15217    0.037414    -4.0672     0.0028113
    x2               3.2444     0.74828     4.3358     0.0018889


Number of observations: 12, Error degrees of freedom: 9
Root Mean Squared Error: 0.837
R-squared: 0.724,  Adjusted R-Squared: 0.663
F-statistic vs. constant model: 11.8, p-value = 0.00305
>>
```

Figure 8.3 Analysis of Compressive Strength Results for Multivariate Regression as a whole model

From Figure 8.1, the researchers found a relationship between fly ash and steel fiber with compressive strength. From the result of the Multivariate Regression, we would be able to get a formula of y = 28.208 - (0.15217 * x1) + (3.2444*x2) in which x1 is the percentage of fly ash, x2 is the percentage of the steel fiber. Further, by diving into analysis and looking at figure 8.1, the researchers can also state that with the analysis of the t stat, the researchers

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ Research Article

can clearly state that steel fiber has a very significant relationship with compressive strength. On the other hand, fly ash has only a somewhat relationship with the model. In addition to that, the P-Value has a parameter if the value is lower than 0.05 then, which would mean that the data relationship is significant with the independent and the dependent variable and that it has the most significant impact on the regression is fly ash and steel fiber which is significant for the results of the regression. In addition to that, the researchers can say that we can reject the null hypothesis and are in favor of the alternative hypothesis in which There is a significant impact from altering the Fly Ash to cement ratio and adding Steel Fibers to concrete. These factors do not have a measurable effect on the concrete's performance (compressive strength and split tensile strength), which can be predicted by the predictive model using multivariate regression and machine learning algorithms.

Furthermore, analyzing Figure 8.3, the researchers examined the data and did an F-test for the regression model. The researchers were able to get a value greater than 4, meaning it is significant and that this regression model can understand the relationships well. The F-value implies that the regression model is a good fit for the data and that the predictors are related and have a relationship with the data. Diving into it more profoundly, the independent variable as a group provides a significant explanation and relationship of the changes in the dependent value, and there is a strong chance that the model can be used for prediction. It is not because of random probability.

Additionally, the regression model can also state that the predictors are reliable and valid, making the regression model statistically significant and providing better evidence that the independent variable has an essential relationship with the dependent value. Moreover, the researchers gained a very low p-value of the p-test and a value lower than 0.001, which the researchers can conclude is highly significant for the study and conclude that the null hypothesis can be rejected as a whole model. There is a substantial impact from altering the Fly Ash to cement ratio and adding Steel Fibers to concrete. These factors do not have a measurable effect on the concrete's performance (compressive strength and split tensile strength), which can be predicted by the predictive model using multivariate regression and machine learning algorithms. The researchers also stated that with the low value of p, the independent variable is highly likely to be an impactful variable with the dependent variable, making it a significant predictor for the regression and that this p-value plays an important role in the impact of the dependent value for the model in which in another word the researcher can conclude that it has the effect with the result of the predictive model.

Figure 9 Split Tensile Strength Results for Multivariate Regression

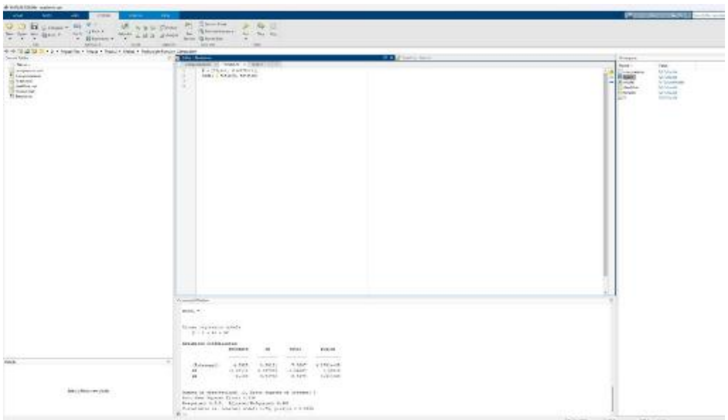


Figure 9.1 Split Tensile Strength Results for Multivariate Regression

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

```
Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    ________    ________    __________

    (Intercept)      4.3525     0.59131      7.3607    4.2781e-05
    x1             -0.02117    0.037398    -0.56607       0.58518
    x2                2.182     0.74796      2.9173      0.017108
```

Figure 9.2 Analysis of Split Tensile Strength Results for Multivariate Regression per coefficient

```
Command Window

model =


Linear regression model:
    y ~ 1 + x1 + x2

Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    ________    ________    __________

    (Intercept)      4.3525     0.59131      7.3607    4.2781e-05
    x1             -0.02117    0.037398    -0.56607       0.58518
    x2                2.182     0.74796      2.9173      0.017108


Number of observations: 12, Error degrees of freedom: 9
Root Mean Squared Error: 0.836
R-squared: 0.515,  Adjusted R-Squared: 0.408
F-statistic vs. constant model: 4.79, p-value = 0.0384
fx >>
```

Figure 9.3 Analysis of Split Tensile Strength Results for Multivariate Regression as a whole model

From Figure 9.1, the researchers found a relationship between fly ash and steel fiber with the split tensile strength. From the result of the Multivariate Regression, we would be able to get a formula of y = = 4.3525 - (0.048445 * x1) + (2.182*y2) in which x1 is the percentage of fly ash, x2 is the percentage of the steel fiber and y is the result for the predicted split tensile strength. Further diving into analysis, looking at figure 9.1, the researchers also can state that with the analysis of the t stat, the researchers can clearly state that steel fiber has a very high significant relationship with the split tensile strength. On the other hand, fly ash is related to the model but has a very low t-stat score. In addition to that, the P-value has a parameter value lower than 0.05 then, which would mean that the data relationship is significant with the independent and the dependent variables and that it has the most significant impact on the regression is steel fiber, which is significant for the results of the regression. However, fly ash has a significant relationship with the split tensile strength. In addition to that, the researchers can say that we can reject the null hypothesis and favor the alternative hypothesis in which There is a significant impact from altering the Fly Ash to cement ratio and adding Steel Fibers to concrete. These factors do not have a measurable effect on the concrete's performance (compressive strength and split tensile strength), which can be predicted by the predictive model using multivariate regression and machine learning algorithms.

Furthermore, analyzing Figure 9.3, the researchers analyzed the data and did an F-test for the regression model. The researchers were able to get a value greater than 4, meaning it is significant and that this regression model can understand the relationships well. As said in the above figure, the F-value implies that the regression model is a good fit for the data and that the predictors are related and have a relationship with the data. Therefore, the regression model can also state that the predictors are reliable and valid, making the regression model statistically significant and providing better evidence that the independent variable has a significant relationship with the dependent value.

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

Moreover, the researchers gained a very low value of the p test and a value lower than 0.04, which the researchers can conclude is significant for the study, and the null hypothesis can be rejected as a whole model. There is a significant impact from altering the Fly Ash to cement ratio and adding Steel Fibers to concrete. These factors do not have a measurable effect on the concrete's performance (compressive strength and split tensile strength), which can be predicted by the predictive model using multivariate regression and machine learning algorithms. The researchers also stated that with the low value of p, the independent variable is highly likely to be an impactful variable with the dependent variable, making it an important predictor for the regression and that the researchers can use this model as the predictive model for the said study due to passing all the parameters. With Figures 8 and 9, the researchers were able to deeply analyze the significance of the independent variables with the dependent variable and that it has a significant relationship and can be used for the predictive model due to its high validity and significance

Figure 10 Predictive Model integration with Multivariate Regression Input and Output

Figure 10.1 Predictive Model Integration with Multivariate Regression Code Data

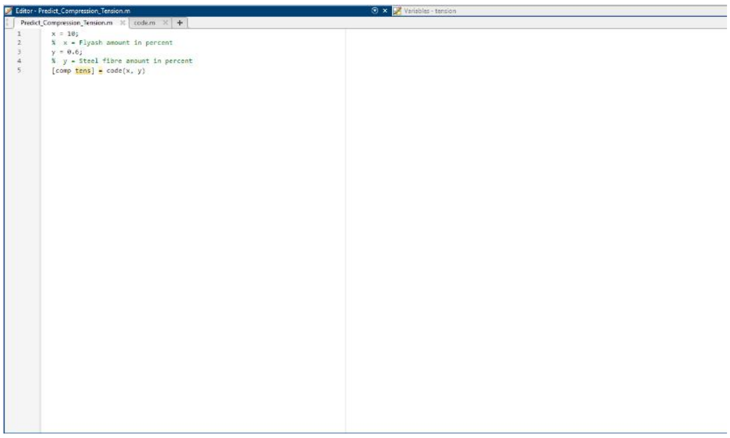
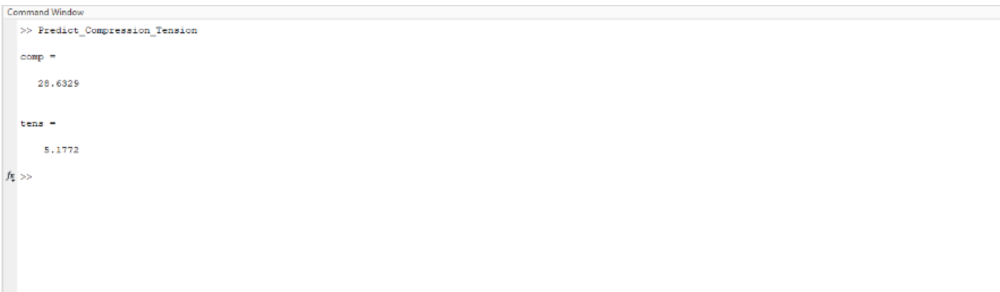


Figure 10.2 Predictive Model Integration with Multivariate Regression Input



Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Figure 10.3 Try Run for Predictive Model Integration with Multivariate Regression Output

The figure above shows the deployment of the predictive model and a trial run of the model with the data trained from the machine learning algorithm and the function from the multivariate regression. Figure 10.1 shows the integration of the function with the model; it is the running code and how the code would be computed. However, the variable we get from the regression model is not automatic in this code. It would automatically be input to the Predictive model; the researchers are the ones to change the values to the code of the Predictive model itself. Figures 10.2 and 10.3 are the output and inputs for the predictive model, and this is the interface in which the end-user will input the needed value. The outcome will be released, and the end-user will be able to get compressive strength and the split tensile strength. In addition to that, there is a parameter, and only the input ranges from 0 - 20 for the percent of fly ash and 0 to 1 for the percent of steel fiber can be inputted in the data; inputting data outside the parameter would cause the inaccuracy of the data and is not supported within the study.

CONCLUSION

Based on the findings, the study can conclude the identification of the relationship between the compressive strength and split tensile strength of concrete with a given Fly Ash with Steel Fiber concrete. The Study successfully determined the relationship between the compressive strength and split tensile strength of concrete with a given Fly Ash with Steel Fiber concrete and also provided the multivariate regression relationship in the study. The Study Successfully retrieved data from the UTM testing and gathered the data set for the needed experiment with the controlled variables considered. The Study was able to plot out and assess the trend of Fly Ash and Steel Fiber to the compressive strength and split tensile strength. The Data set was trained and was able to be incorporated in the machine learning algorithm and gained positive results therefore backing the study, providing validity and generalization for the unseen data. The study was able to emphasize the significance of the relationship through the usage of the T-test, the F-scores and the P-test and to prove that there is a significant relationship between the variables and can be used for the predictive model. The researchers were able to integrate the Multivariate Regression and develop a predictive model with an input and output function. The study was able to reach a milestone in developing a model in which can be considered used in the industry field.

Appendix:

An appendix may be included (and is often helpful) in mathematical or computational modeling.


Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Acknowledgements:

The successful completion of this thesis is attributable to the invaluable contributions and support provided by numerous individuals and organizations, and the researchers wish to convey their heartfelt appreciation to: To Engr. Edgardo Cruz, the researchers want to show heartfelt gratitude for the expert in guidance and support which was a big contribution for the deeper understanding for this research. To one of the friends and coworkers met during the process, the researchers want to give you a heartfelt thank you for providing the materials during this study. To the Researchers' Family, thank you for the never-ending support and perseverance for always being there for us and trust for this successful thesis. To Members of the Panel, the researchers want to thank for the ideas and guidance which is a big part in shaping and structuring the direction of the research. To the Almighty, thank you for the unwavering support, and the wisdom that you provided us leading us success.

REFERENCES

[1]. Abraham GK, V.S. Jayanthi, Bhaskaran P. Convolutional neural network for biomedical applications. Elsevier eBooks. Published online January 1, 2020:145-156. doi: https://doi.org/10.1016/b978-0-12-820604-1.00010-8

[2]. https://www.irjmets.com/uploadedfiles/paper/volume_3/issue_8_august_2021/15771/final/fin_irjmets1629611659.pdf

[3]. Alterary, S. S., & Marei, N. H. (2021). Fly ash properties, characterization, and applications: A review. Journal of King Saud University - Science, 33(6), 101536–101536. https://doi.org/10.1016/j.jksus.2021.101536

[4]. Asteris, P. G., Kolovos, K. G., & Livas, J. N. (2016). Prediction of concrete compressive strength using artificial neural networks and multiple linear regression. Construction and Building Materials, 102, 1099-1108. https://doi.org/10.1016/j.conbuildmat.2015.06.084

[5]. Almottiri, F. (2011). Physical properties of steel fiber reinforced cement composites made with fly ash. Jordan Journal of Civil Engineering, 5. https://jjce.just.edu.jo/Download.ashx?f=DzD17AOU98xYOyISmVfcf%2Bz3gq%2Bxw 1l9o8GybfmtkYk%3D

Journal of Information Systems Engineering and Management
2025, 10(43s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

[6]. Azmee, N. M., & Nuruddin, M. F. (2017). IMPACT PERFORMANCE OF LOW CEMENT ULTRA-HIGH-PERFORMANCE CONCRETE. WIT Transactions on Ecology and the Environment, 1, 481–488. https://doi.org/10.2495/sc170421
[7]. Chi L, Wang M, Liu K, et al. Machine learning prediction of compressive strength of concrete with resistivity modification. Materials today communications. 2023;36:106470- 106470. doi:https://doi.org/10.1016/j.mtcomm.2023.106470
[8]. Gandomi, A. H., Alavi, A. H., & Fratta, D. (2014). Multivariate adaptive regression splines-based modeling of post-liquefaction settlement. Engineering Geology, 177, 112-119. https://doi.org/10.1016/j.enggeo.2014.05.013
[9]. Hadi B, Ziyad F, Kumar P, et al. Feasibility analysis for predicting the compressive and tensile strength of concrete using machine learning algorithms. Case studies in construction materials. 2023;18:e01893-e01893. doi:https://doi.org/10.1016/j.cscm.2023.e01893