Prediction of compressive strength values using ANN for M20 Grade of Self-Compacting Concrete made from Agricultural Wastes

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Abstract
The present experimental investigation was carried out to evaluate the properties of agricultural wastes Rice Husk Ash (RHA) and Sugarcane Bagasse Ash (SCBA) when used as a partial replacement for Ordinary Portland Cement (OPC) in self-compacting concrete for M20 grade. The w/p ratio was taken as 0.45. Cement was replaced with 2-10% of RHA by weight of cement to obtain the optimum RHA % up to which cement can be replaced. After obtaining the optimum % of RHA, cement was replaced with 5-15% of SCBA to obtain optimum RHA and SCBA %. Fresh properties and compressive strength values were studied when replaced with RHA and SCBA. Using the ANN model understanding the machine learning random forest regressor and decision tree modelling algorithms are used for accuracies between the models. For the prediction of the dependent variable as compressive strength ANN is used for deep learning.

Key Words: SCC, Compressive Strength, ANN, Agricultural wastes
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1.0 Introduction
In recent years, the technology of Artificial Neural Networks has been applied to solve a range of issues in civil engineering applications through a subfield of artificial intelligence. With interconnected computational pieces, Artificial Neural Networks handle highly complicated problems. The processing elements of the neural system, which are many simple computational elements stacked into layers, are similar to Neurons in the brain.

An ANN is configured for a specific application, such as pattern recognition or data classification, through a learning process. Learning largely involves adjustments to the synaptic connections that exist between the neurons.

2.0STUDY AREA
This study focuses on SCC's characteristics with RHA and SCBA. Different volume percentages of RHA and SCBA are used to investigate the effect of the volume percentage of RHA and SCBA on the self-

compacting concrete After that create the ANN model for understanding the using the Python programming language to generate training and testing accuracies for experimental data and assess training accuracy and testing accuracy using random forest regression and decision tree modelling algorithms as part of machine learning. After that predict dependent variable values by using ANN as a part of deep learning.

3.0 METHODOLOGY

3.1.1. Steps followed in carrying out Experimental work Basic tests were conducted on cement, fine and coarse aggregate to check their suitability for SCC. The study aims to investigate the strength-related properties of concrete M20 grade Self Compacting Concrete with agricultural wastes. The proportions of ingredients of the control of M20 had to be determined by mix design as per EFNARC guidelines and the strength requirements are checked with respect to IS code.

Final Mix proportions Weight:
W/C ratio =0.45, Cement = 1, Fine aggregate =2.22, Coarse aggregate = 1.93

3.1.2. Fresh Properties on SCC of Cement replaced with RHA:

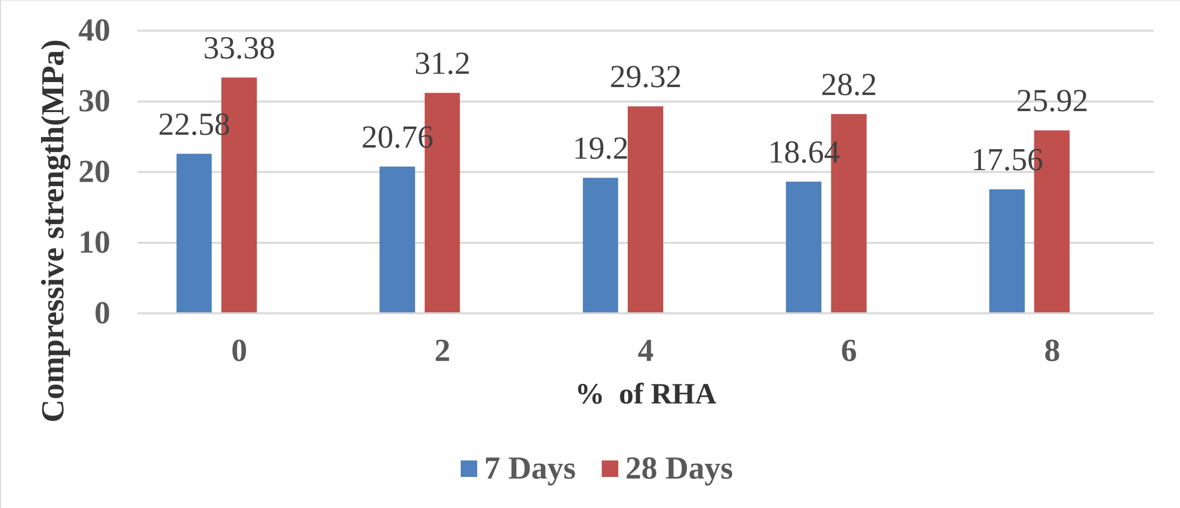
Table:1 Fresh properties of M20 grade of SCC for Various percentages of RHA

S.No	% RHA	Slump flow (mm)	J-Ring (mm)	V-Funnel (T-Sec)	L-Box (Blocking Ratio)
1.	0	680	5.0	10.48	0.83
2.	2	692	3.5	10.42	0.85
3.	4	683	4.0	10.54	0.84
4.	6	675	5.0	11.10	0.83
5.	8	664	6.0	11.21	0.82

Table 2 Compressive Strength of M20 grade of SCC for Various percentages of RHA

Duration	Compressive strength results for different percent of RHA(MPa)				
percent of RHA	**0**	**2**	**4**	**6**	**8**
7 Days	22.58	20.76	19.20	18.64	17.56
28 Days	33.38	31.20	29.32	28.20	25.92

Graph 1: varying percent of RHA for M20 grade vs. Compressive strength



As per the observations, concrete can be replaced up to 6 percent of RHA without any compromise on characteristic compressive strength. So, consider optimum RHA by 6 percent for the M20 grade.

3.1.3 TEST RESULTS FOR GETTING OPTIMUM MIX WITH RHA SP DOSAGE

Table:3 SP dosage for cement replacement with constant Optimum RHA percentage and varying SCBA percentages for M20 grade

percent RHA + Percent SCBA	SP Dosage for M20 grade
R6B0	0.80
R6B5	1.20
R6B10	1.40
R6B15	1.70

An increased percentage of replacement of SCBA with constant optimum RHA percentage results in a higher superplasticizer dosage.

Table:4 Fresh properties of M20 grade of SCC for optimum% RHA and Varying % SCBA

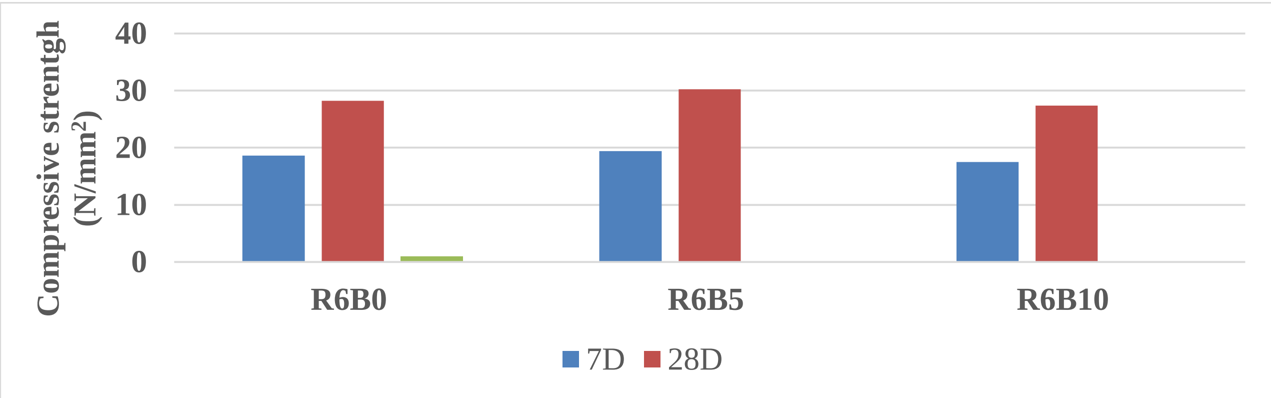
S.No	Optimum RHA+% SCBA	Slump flow (mm)	J-Ring (mm)	V-Funnel (T-Sec)	L-Box (Blocking Ratio)
1.	R6B0	675	5.00	11.10	0.83
2.	R6B5	685	3.00	10.56	0.82
3.	R6B10	660	3.50	10.48	0.81
4.	R6B15	678	4.20	11.02	0.84

For the M20 grade, after replacing 6 percent RHA and different percentages of SCBA 5 percent, 10 percent, and 15 percent with all variations. SCBA Up to 10 percent replacement of cement is fulfilling the fresh properties.

Table 5: Compressive Strength of M20 grade of SCC for for optimum% RHA and Varying % SCBA

Specimen	Cubes (Compressive Strength Values in MPa)	
Mix proportions	**7D**	**28D**
R6B0	18.64	28.2
R6B5	19.42	30.22
R6B10	17.52	27.36

Graph 2: Optimum percent of RHA + Varying % of SCBA vs. Compressive strength



At 10 % of SCBA with optimum RHA (i.e., 6% of RHA) target mean strength compared to remaining variations of self-compacting concrete.

3.2 ANN Packages

That is, just like how the neurons in our nervous system are able to learn from past data. similarly, the ANN is able to learn from the data and provide responses in the form of predictions. An important advantage of ANN is the fact that it learns from the example data sets. The most common usage of ANN is that of a random function approximation. With these types of tools, one can have a cost-effective method of arriving at the solutions that define the distribution.

In this present work jupyter notebook is the open-source web application considered.

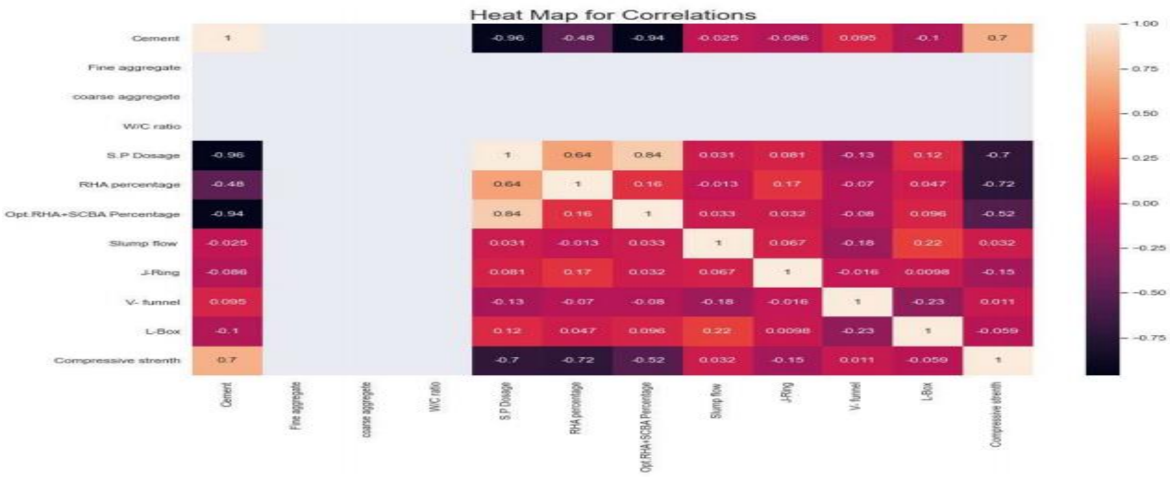
The following packages are used for this work.

- Pandas
- NumPy
- Matplotlib
- Seaborn

- Sk learn
- Keras

In these NumPy and pandas, packages are used for numerical data and read the data respectively. Code up the whole process in Python programming language. Seaborn and matplotlib are visualization techniques. In this present work, materials cement, FA,CA,SP,W/C ratio and fresh properties of SCC are considered as input neuron layer in ANN. Compressive strength is considered as output layer.

Fig:1 Correlations: Influence Ratio between variables For M20 grade



3.2.1 SKLEARN

The sklearn library contains a lot of efficient tools for machine learning and statistical modeling including classification, regression, clustering and dimensionality reduction. Random forest regressor and Decision tree modelling are used for SK learn in this work.

The following are program for RandomForestRegressor and Decision Tree Regressor.

```
from sklearn.ensemble import RandomForestRegressor

rf_model = RandomForestRegressor()
rf_model.fit(X_train, y_train)


rf_over_pred = rf_model.predict(X_test)

print("Training Accuracy: ", rf_model.score(X_train, y_train))
print('Testing Accuarcy: ', rf_model.score(X_test, y_test))
```

```
Training Accuracy:  0.9816873342795215
Testing Accuarcy:  0.9145039786862534
```

```
from sklearn.tree import DecisionTreeRegressor

tree_model=DecisionTreeRegressor()
tree_model.fit(X_train,y_train)
tree_over_pred=tree_model.predict(X_test)

print("Training Accuracy: ", tree_model.score(X_train, y_train))
print('Testing Accuarcy: ', tree_model.score(X_test, y_test))
```

```
Training Accuracy:  0.9919105506190533
Testing Accuarcy:  0.8852473541118833
```

Table:5 Accuracy Comparisons

Accuracy	Decisiontree modelling	Random forest Regressor
Training Accuracy	0.99	0.98
Testing Accuracy	0.88	0.91

Random Forest regression, decision tree modelling and ANN are the algorithms which are used for understanding the data. 500 epoch are considered for the present experimental data. Out of which 80 % of experimental data is used for training the model and 20% of experimental data is considered for testing.

3.2.2 KERAS

Keras is a powerful and easy-to-use free open source Python library for developing and evaluating deep learning models. It wraps the efficient numerical computation libraries.The following the code for part of deep learning in ANN.

```
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasRegressor
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
```

```
# importing the libraries
from keras.models import Sequential
from keras.layers import Dense

# create ANN model
model = Sequential()

# Defining the Input layer and FIRST hidden layer, both are same!
model.add(Dense(units=5, input_dim=11, kernel_initializer='normal', activation='relu'))

# Defining the Second layer of the model
# after the first layer we don't have to specify input_dim as keras configure it automatically
model.add(Dense(units=5, kernel_initializer='normal', activation='tanh'))

# The output neuron is a single fully connected node
# Since we will be predicting a single number
model.add(Dense(1, kernel_initializer='normal'))

# Compiling the model
model.compile(loss='mean_squared_error', optimizer='adam')

# Fitting the ANN to the Training set
model.fit(X_train,y_train ,batch_size = 1, epochs = 500, verbose=1)
```

The present experimental data is validated of the ANN developed by the inputs of experimental data used as variables. The variables are independent and also has influence by each on the other. The dependent variable is considered as output data. In these records are 240 rows and 13 columns

Fig:2 Prediction Values

```
y_test

array([24.92, 29.32, 32.52, 27.46, 25.58, 22.18, 29.04, 23.68, 31.64,
       24.86, 27.96, 25.12, 29.18, 31.64, 21.92, 22.56, 28.36, 27.22,
       21.92, 34.82, 24.92, 28.36, 28.2 , 22.96, 32.02, 33.3 , 26.46,
       24.92, 34.82, 31.64, 29.32, 29.96, 31.64, 22.96, 30.22, 25.9 ,
       31.64, 27.06, 30.3 , 27.96, 29.98, 32.52, 21.92, 33.3 , 25.9 ,
       33.38, 25.58, 33.38])
```

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4.0. CONCLUSIONS

1. For M20 grade of concrete with 6 % RHA from 7 days to 28 days, the compressive strength increased by 51.29 %, and from 28 days to 56 days, the compressive strength increased by 6.24%.
2. For M20 grade of concrete with 6 % RHA and 10 % SCBA there is a 56.16% increase in compressive strength from 7 days to 28 days.
3. Random forest predicts more accurate results than the decision trees. It is the supervised learning algorithm in machine learning that it uses the bagging method so that there is a combination of learning models which increases the accuracy of results.
4. In Machine learning, at decision tree modeling training accuracy is 0.99 and the testing accuracy is 0.86. The percentage variation between training and testing accuracies is 11.11% for M20 grade of concrete.
5. In Machine learning, at random forest regressor training accuracy is 0.98 and the testing accuracy is 0.91. The percentage variation between training and testing accuracies is 7.00% for M20 grade of concrete.

5.0. REFERENCES

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