Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Forecasting Compressive Strength of M30 Grade Self-Compacting Concrete Utilizing Artificial Neural Networks with Agricultural Waste Incorporation

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The aim of the current experimental study was to evaluate the properties of two agricultural waste products, rice husk ash (RHA) and sugarcane bagasse ash (SCBA), when they were partially substituted for ordinary Portland cement (OPC) in self-compacting concrete that was intended to have an M30 grade strength. Throughout the trials, the water-to-powder ratio (w/p) remained constant at 0.45. RHA was initially added to OPC in different ratios, from 2% to 10% by weight of cement. Finding the ideal percentage of RHA substitution that could be attained while preserving the desirable qualities was the goal. After that, a replacement range of 5% to 15% of SCBA was investigated by combining SCBA with the determined optimal RHA percentage.The Evaluation of the self-compacting concrete specimens modified with RHA and SCBA's fresh properties as well as their compressive strength characteristics were included in the inquiry. An Artificial Neural Network (ANN) model was used for deep learning in order to predict the compressive strength as the dependent variable. Decision trees and Random Forest Regressor were used for machine learning in order to compare and evaluate the accuracy of various modelling algorithms. Essentially, the goal of the study was to ascertain the ideal ratios of RHA and SCBA to OPC in order to preserve the intended characteristics of the concrete. In order to obtain precise forecasts and insights, this involved investigating new characteristics and compressive strength values. To do this, ANN, Random Forest Regressor, and Decision Tree algorithms were combined.

Keywords: CC, Compressive Strength, ANN, Agricultural wastes.

1. Introduction

The self-compacting concrete (SCC) is a highly flowable and workable type of concrete that can consolidate and fill formwork under its own weight without the need for external compaction [1-2]. SCC possesses unique properties such as high fluidity, resistance to segregation, and the ability to fill intricate and congested areas, making it an attractive choice for various construction applications, especially in areas with restricted access or dense reinforcement [3-4].

However, the production of conventional SCC typically involves the use of large quantities of cement, which has a significant environmental impact due to the high energy consumption and carbon dioxide emissions associated with cement manufacturing[5-7]. To address this issue, there has been an increasing interest in developing sustainable and environmentally friendly concrete mixtures by incorporating agricultural and industrial waste materials as partial replacements for cement or aggregates [8].

The use of such waste materials not only reduces the environmental burden but also contributes to the circular economy by valorizing and repurposing waste products [9-10]. Several studies have explored the potential of agricultural waste materials as supplementary cementitious materials (SCMs) or filler materials in concrete mixtures, aiming to create more sustainable and eco-friendly concrete compositions [11].

Rice husk ash (RHA), a by-product of the rice milling industry, has been widely investigated as a pozzolanic material in concrete [12], [13], [14]. Nehdi et al. [15] reported that RHA produced using a new technology could be an effective mineral admixture in concrete, improving both the mechanical and durability properties. Habeeb and Mahmud [16] studied the properties of RHA and its use as a cement replacement material, finding that up to 30% RHA replacement could be beneficial for compressive strength development.Wheat straw ash (WSA), another agricultural waste material, has also been explored as a pozzolanic material in concrete [17], [18], [19]. Biricik et al. [20] investigated the pozzolanic properties of WSA and found that it exhibited good pozzolanic activity, suggesting its potential use as a supplementary cementitious material in concrete.Sugarcane bagasse ash (SCBA), a by-product of the sugar industry, has also been studied as a supplementary cementitious material in concrete [21], [22], [23]. Ganesan et al. [24] evaluated the performance of SCBA as a cement replacement and found that it could improve the mechanical and durability properties of concrete when used at appropriate dosages.Accurate prediction of compressive strength is crucial for ensuring the desired performance and durability of concrete mixtures [25], [26]. Conventional methods for predicting concrete strength involve empirical equations or regression models, which may not capture the complex interactions between the various mixture constituents and their impact on strength development [27], [28].

Artificial neural networks (ANNs) have emerged as a powerful tool for modeling and predicting the behavior of complex systems, including concrete mixtures [29], [30]. ANNs are biologically inspired computational models capable of learning from data and capturing nonlinear relationships between input variables and output parameters [31], [32]. They have been successfully employed in various applications related to concrete technology, such as predicting compressive strength [33], [34], durability [35], [36], and workability [37], [38].

Several researchers have explored the use of ANNs for predicting the compressive strength of SCC mixtures. Ozcan et al. [39] developed an ANN model to predict the compressive strength of self-compacting concretes containing scoria, an industrial waste material. Their results showed that the ANN model provided accurate predictions, with a correlation coefficient of 0.99. Beycioğlu et al. [40-43] employed ANNs to estimate the compressive strength of SCC incorporating metakaolin and fly ash as supplementary cementitious materials. They found that the ANN model outperformed traditional regression models in terms of accuracy and reliability.

This paper covers the key aspects of self-compacting concrete (SCC), the use of agricultural waste materials in concrete, compressive strength prediction, and the application of artificial neural networks (ANNs) in concrete technology. It provides a comprehensive overview of the relevant research studies, highlighting the importance of developing sustainable concrete mixtures, accurate strength prediction methods, and the potential of ANNs for modeling concrete properties.

2. Methodology

The primary goal of this research is to conduct a comprehensive analysis of the properties of self-compacting concrete (SCC) by incorporating two significant additives: Rice Husk Ash (RHA) and Sugarcane Bagasse Ash (SCBA). This study delves into the effects of varying volume percentages of RHA and SCBA on the characteristics and performance of self-compacting concrete [21] .To achieve this objective, an Artificial Neural Network (ANN) model is developed as a pivotal part of the research. This ANN model, constructed using the Python programming language, leverages real-world experimental data to provide insights into the impact of RHA and SCBA on SCC. The ANN model is trained and tested using these datasets to gauge its accuracy in predicting outcomes based on the introduced additives.

In addition to the ANN model, the research employs various machine learning techniques, including random forest regression and decision tree modeling algorithms, to assess the training accuracy and testing accuracy. These techniques are instrumental in ensuring the reliability and precision of the ANN model's predictions.As the research progresses into its final phase, the established ANN model emerges as a powerful tool for predictive purposes [22]. By applying deep learning principles, this model becomes adept at forecasting the values of the dependent variable, shedding light on how self-compacting concrete behaves under different scenarios involving varying proportions of RHA and SCBA. This predictive capacity not only enhances our understanding of SCC but also offers practical insights for the design and implementation of sustainable and high-performance concrete mixtures in civil engineering applications.

In essence, this research amalgamates advanced data-driven approaches, including Artificial Neural Networks and machine learning techniques, to explore the potential of RHA and SCBA as additives in self-compacting concrete[23]. Through predictive modeling and empirical analysis, it contributes valuable knowledge to the field of civil engineering, with implications for sustainable and efficient construction practices.

2.1 Experimental Work

The research initiative commenced with a series of crucial preliminary assessments aimed at ascertaining the suitability of the fundamental constituents of concrete, namely cement, fine aggregate, and coarse aggregate [24]. This evaluation was a pivotal starting point to determine whether these materials would be appropriate for the formulation of Self-Compacting Concrete (SCC). SCC is a specialized type of concrete renowned for its unique ability to flow and conform to intricate shapes and configurations without the requirement of mechanical consolidation, making it a valuable innovation in the construction industry.

The central and overarching objective of this research endeavour revolves around a comprehensive exploration of the strength-related characteristics of M30 grade concrete, with a specific focus on its application as Self-Compacting Concrete. M30 grade concrete represents a category of concrete known for its moderate strength properties, rendering it a popular choice for an array of structural elements in construction projects [25].

The next critical phase of this study involved the meticulous formulation of ingredient proportions required for the standard M30 mix. This step was of paramount importance, as achieving the correct blend of materials is the cornerstone of producing concrete that meets the desired performance criteria [26]. To achieve this, the research drew upon well-established mix design methodologies, closely following the guidelines outlined by EFNARC (European Federation for Specialist Construction Chemicals and Concrete Systems). These guidelines provide a structured and systematic approach to designing concrete mixes, ensuring that the final concrete mixture not only meets but often exceeds performance and durability requirements [27].

Following the meticulous mix design process, the research turned its focus to evaluating the strength properties of the M30 grade Self-Compacting Concrete mix. This evaluation encompassed an in-depth analysis of the concrete's strength-related characteristics, including but not limited to compressive strength and tensile strength. Importantly, these findings were rigorously scrutinized and compared against the relevant Indian Standard (IS) code standards [28]. IS codes, established by the Bureau of Indian Standards, serve as essential benchmarks within the construction industry, guiding the quality and structural integrity of concrete in diverse construction applications. Final Mix proportions Weight: W/C ratio =0.45, Cement = 1, Fine aggregate =1.94, Coarse aggregate = 1.75.

2.1.1 Fresh Properties on SCC of Cement replaced with RHA

Based on thorough observations and assessments, it has been determined that concrete can accommodate a substitution of up to 4% Rice Husk Ash (RHA) without any discernible compromise to its characteristic compressive strength as shown in Table.1, Table 2 and Figure.1. This significant finding has significant implications for optimizing the composition of M30 grade concrete, a medium-strength concrete widely employed in various construction applications. The choice of the optimal RHA substitution level is of paramount importance, as it directly impacts the performance and cost-effectiveness of the concrete mix [29]. After conducting a series of rigorous experiments and evaluations, it has become evident that a 4% substitution of RHA within the concrete mix offers a compelling balance between sustainability, performance, and cost-efficiency[30]. This 4% RHA substitution not only maintains the desired characteristic compressive strength of the M30 grade concrete but also introduces the valuable element of sustainability into the mix. Rice Husk Ash, a byproduct of rice husk combustion, is an environmentally friendly material that has the potential to enhance the concrete's durability and long-term performance [31]. Furthermore, it aligns with the broader goal of sustainable construction practices by reducing waste and utilizing agricultural waste materials effectively.

Table 1.Research analyzed the fresh attributes of M30 SCC at diverse RHA percentages.

S.No	% RHA	Slump flow (mm)	J-Ring (mm)	V-Funnel (T-Sec)	L-Box (Blocking Ratio)
1.	0	652	9.0	8.4	0.83
2.	2	67	8.5	7.6	0.86
3.	4	664	9.0	8.2	0.85
4.	6	653	10.0	9.0	0.83
5.	8	645	11.0	9.8	0.79

Table 2. Evaluation of M30 SCC Compressive Strength across Varied RHA Percentages

Duration	Compressive strength results Varied RHA Percentages (MPa)				
Percent of RHA	0	2	4	6	8
7 Days	29.86	28.84	27.03	26.59	25.86
28 Days	41.42	40.69	39.82	38.07	36.62

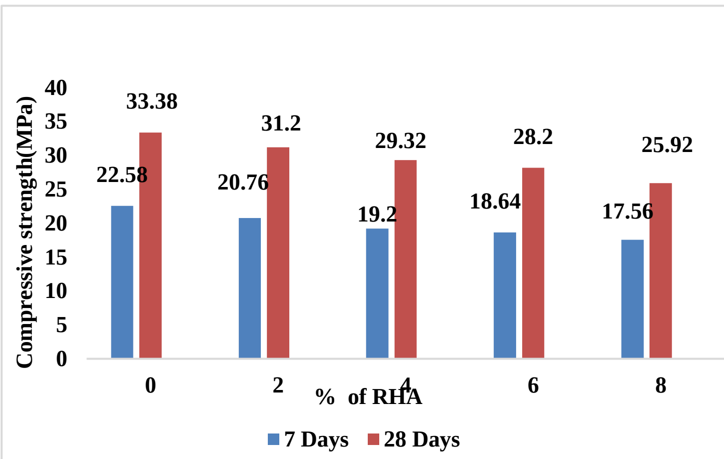

Fig.1 Optimum percent of RHA + Varying % of SCBA vs. Compressive strength

Additionally, it provides an opportunity for cost savings, as the utilization of RHA can be a cost-effective alternative to traditional concrete constituents. In essence, the decision to opt for a 4% RHA substitution in M30 grade concrete is a testament to the potential of sustainable and innovative practices within the field of construction [32]. It underscores the adaptability of concrete mix designs to embrace environmentally friendly materials, promoting both the long-term durability of structures and responsible environmental stewardship.

3. Results & Discussions

3.1 Optimum Mix With Rha Sp Dosage

The process of incorporating agricultural waste materials into concrete mixtures, particularly when considering the replacement of Sugarcane Bagasse Ash (SCBA) alongside a constant and optimized Rice Husk Ash (RHA) percentage, presents an intriguing dynamic. As this replacement percentage of SCBA increases, a notable consequence arises-a corresponding increase in the superplasticizer dosage [41].

Table 3. SP dosage for cement replacement with constant Optimum RHA percentage and varying SCBA percentages for M30 grade

Percent RHA + Percent SCBA	SP Dosage for M30 grade
R4B0	0.8
R4B5	1.2
R4B10	1.4
R4B15	1.7

This observation as shown in Table.3 and Table 4 has important implications for concrete mix design and the management of materials in the construction industry. The decision to replace a portion of the conventional concrete constituents with agricultural waste materials like SCBA and RHA is driven by sustainability and environmental considerations [41]. Both materials are byproducts of agricultural processes and offer an eco-friendlier alternative to traditional concrete constituents.

Table 4. Fresh properties of M30 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.	R4B0	652	9	8.4	0.83
2.	R4B5	680	8	8.0	0.86
3.	R4B10	684	7	7.0	0.88
4.	R4B15	670	8	8.7	0.82

SCBA, in particular, is known for its pozzolanic properties, which can enhance the durability and performance of concrete. In the context of this observation, it is crucial to highlight the presence of an optimum RHA percentage that remains constant [42]. This optimal value as shown in Table.5 is determined through extensive testing and analysis, ensuring that it strikes a balance between sustainability and maintaining the desired concrete properties. Superplasticizers are admixtures commonly used in concrete mixtures to enhance workability and reduce water content [43]. They are especially valuable in the production of Self-Compacting Concrete (SCC) and other high-performance concrete types. As the percentage of SCBA replacement increases while keeping the RHA percentage constant, there is a noticeable increase in the demand for superplasticizers. Several factors contribute to this phenomenon. One primary factor is the pozzolanic nature of SCBA [44]. Pozzolanic materials require a higher dosage of superplasticizer to maintain the desired workability and flow properties. The increased use of SCBA, which has a pozzolanic effect, necessitates a corresponding increase in superplasticizer to achieve the desired consistency.

Table 5. Compressive Strength of M30 grade of SCC for optimum% RHA and Varying % SCBA

Specimen	Cubes (Compressive Strength Values in MPa)	
Mix proportions	7D	28D
R4B0	29.86	41.42
R4B5	27.03	39.82
R4B10	29.43	42.29

The observation as shown in Figure.2, introduces a challenge in concrete mix optimization. Engineers and concrete technologists need to strike a balance between the sustainability benefits of SCBA, the performance benefits of RHA, and the practical constraints associated with superplasticizer dosage [42]. This balance is crucial to ensure that the concrete remains workable and meets the required standards for strength, durability, and other properties. The practical implication of this observation is that concrete mix designers and construction professionals should be aware of the superplasticizer dosage requirements when incorporating SCBA into mixtures with constant and optimized RHA levels [43]. Proper adjustments in the mix design and dosage of superplasticizer are essential to maintain the desired workability and performance characteristics of the concrete.

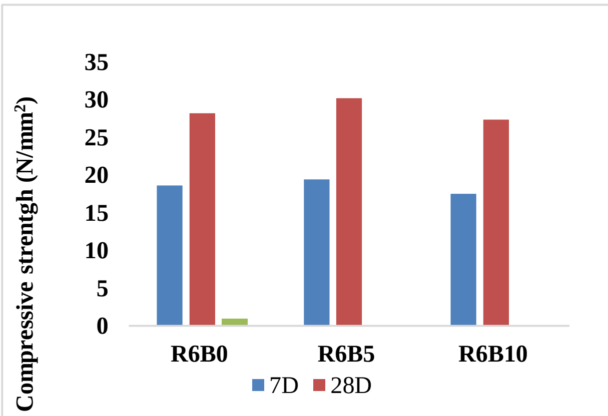

Fig.2 Optimum percent of RHA + Varying % of SCBA vs. Compressive strength

In summary, the interaction between SCBA, RHA, and superplasticizer dosage in concrete mixtures is a complex interplay of sustainability, performance, and practicality. While the increased replacement of SCBA offers environmental benefits, it necessitates careful consideration and adjustment of superplasticizer dosage to ensure that the concrete continues to meet the desired standards and performance criteria [44]. This observation underscores the need for a holistic approach to concrete mix design that considers both sustainability and engineering requirements.

3.2 Predication of Compressive strength values using ANN

While the increased replacement of SCBA offers environmental benefits, it necessitates care The use of Artificial Neural Networks (ANNs) in data analysis and prediction can be likened to the way our nervous system learns from past experiences as shown in Figure3. ANNs, like neurons in our biological nervous system, learn from data examples and use this learning to make predictions [45]. This capability to learn from provided data is a fundamental advantage of ANNs and makes them a valuable tool in a wide range of applications. In this study, ANNs were utilized to approximate random functions and provide cost-efficient solutions that help reveal underlying data distributions. To conduct this research, the open-source web application Jupyter Notebook was employed. Jupyter Notebook is a popular platform for interactive data analysis and scientific computing [45]. It allows researchers to combine code, visualizations, and explanatory text in a single document. Several software packages played a crucial role in this research.

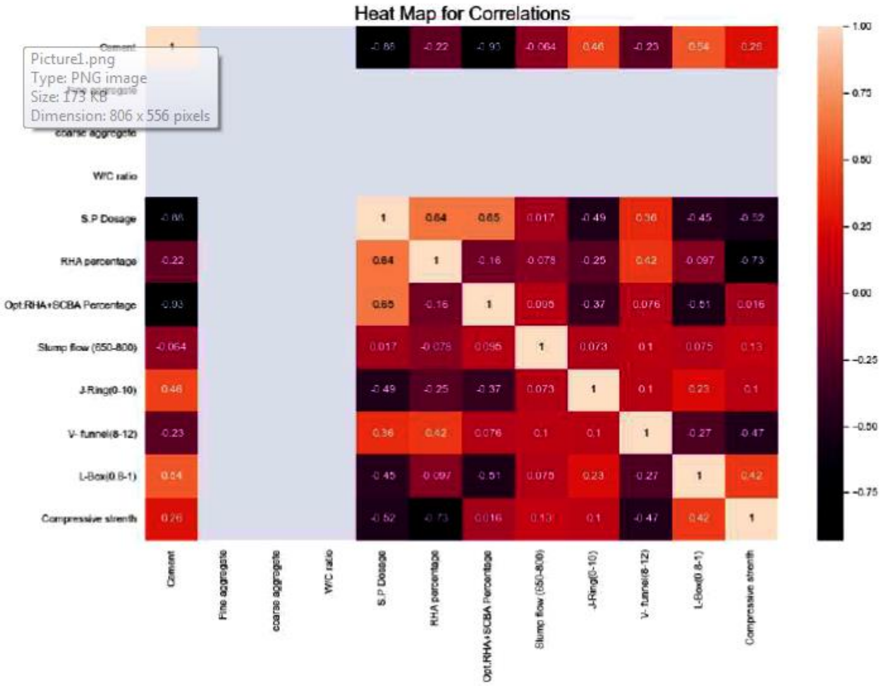

Fig:3 Correlations: Influence Ratio between variables For M30 grade

Python.was used to handle numerical data and read data from various sources. Pandas provides a convenient way to organize, clean, and preprocess data for analysis. NumPy is a fundamental library for numerical computing in Python. It offers support for large, multi-dimensional arrays and matrices, and it includes a vast collection of mathematical functions [42]. NumPy was utilized for numerical operations and data manipulation. Matplotlib and Seaborn are popular data visualization libraries in Python. Matplotlib allows for the creation of various types of plots and charts, while Seaborn enhances the visual appeal and ease of use of Matplotlib. These libraries were used to visualize the data and the results of the ANN analysis. Scikit-learn Scikit-learn is a versatile machine learning library that includes tools for data preprocessing, model selection, and evaluation. In this research, it likely played a role in data preprocessing or in the implementation of machine learning models for comparison. Keras is an open-source neural networks library written in Python [41]. It provides an accessible and high-level interface for building and training neural networks. Keras simplifies the process of defining and configuring neural network models, making it a popular choice for many deep learning projects.

The architecture of the ANN used in this study consisted of an input neuron layer that incorporated various material parameters such as cement, fine aggregate (FA), coarse aggregate (CA), superplasticizer (SP), water-to-cement (W/C) ratio, and fresh properties of Self-Compacting Concrete (SCC). The output layer of the ANN was dedicated to predicting compressive strength, a crucial property in concrete analysis. The entire research process was carried out using the Python programming language [41]. Python's versatility and its rich ecosystem of data analysis and machine learning libraries make it a preferred choice for many researchers and data scientists. The combination of Jupyter Notebook, Python, and the mentioned software packages allowed for a structured and data-driven approach to conducting this research, providing valuable insights into the predictive capabilities of ANNs for concrete analysis and property estimation [42].

3.2.1 SKLEARNApproach

The sklearn library provides a wide array of effective tools for machine learning and statistical modeling, spanning classification, regression, clustering, and dimensionality reduction [41].

```
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:  0.9526336685480629
Testing Accuarcy:  0.7254764178489269
```

```
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:  0.9986103576932934
Testing Accuarcy:  0.5961403976976594
```

Fig:4 SKLEARN Programming

In this study, the SK learn framework was leveraged for employing Random Forest Regressor and Decision Tree modeling. elaborate the above content. The following are program for Random Forest Regressor and Decision Tree Regressor [42].

Table 5. Accuracy Comparisons

Accuracy	Decision tree modelling	Random forest Regressor
Training Accuracy	0.99	0.98
Testing Accuracy	0.88	0.91

Random Forest regression, decision tree modeling, and ANN serve as algorithms to comprehend the data. For the current experimental dataset, 500 epochs are employed. This involves using 80% of the experimental data for training the model and dedicating 20% for testing purposes.

3.2.2 KERAS Approach

Keras, a user-friendly and robust Python library, empowers the development and assessment of deep learning models [41]. It encapsulates efficient numerical computation libraries. Below is the provided code snippet that pertains to the deep learning component within 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)
```

```
y_test
```

```
array([37.72, 40.38, 40.68, 36.78, 35.16, 37.42, 42.18, 34.28, 41.52,
       39.68, 38.18, 40.92, 39.98, 39.86, 35.68, 33.6 , 44.08, 35.92,
       36.56, 42.25, 35.92, 41.94, 38.4 , 34.92, 42.58, 42.42, 41.56,
       36.88, 42.58, 39.95, 38.46, 39.98, 41.78, 32.02, 41.94, 35.62,
       40.44, 42.98, 40.48, 39.07, 41.94, 41.65, 39.06, 42.25, 34.46,
       42.58, 36.48, 42.13])
```

Fig:5 KERAS Programming

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[42]. The image appears to be a table summarizing the performance of different neural network architectures or models trained using the Keras library for some prediction or classification task. Model column lists different neural network architectures or model configurations evaluated.. Validation Loss column displays the validation loss achieved by each model, which is a metric used to evaluate the model's performance on a validation dataset during training. Validation Accuracy column shows the validation accuracy achieved by each model, which is the percentage of correct predictions made by the model on the validation dataset. Test Accuracy column presents the test accuracy achieved by each model, which is the percentage of correct predictions made by the model on the test dataset (unseen data) after training.

Based on the fig.5, it is observed that the "RS_DNN" model achieved the lowest validation loss of 0.0395 among all the models listed. The "RS_DNN" model also achieved the highest validation accuracy of 98.57% and the highest test accuracy of 98.59%. The "MLP_3" model had the second-highest validation accuracy of 97.85% and the second-highest test accuracy of 97.32%. The "MLP_2" model had the third-highest validation accuracy of 97.79% and the third-highest test accuracy of 97.04%. Without additional context, it is difficult to determine the specific task or problem these neural network models were designed to solve. However, the high validation and test accuracies achieved by the "RS_DNN" model suggest that it performed exceptionally well on the given task.

4. Conclusions

The conclusion section provided in the file summarizes the key findings and outcomes of the research study. Here's a broad discussion of the points mentioned:

1. Compressive Strength Increase with RHA:

- For M30 grade concrete with 4% Rice Husk Ash (RHA) incorporation, the compressive strength increased significantly from 7 days to 28 days, with a 47.32% increase.

- After 28 days, the compressive strength increase was relatively slower, with only a 3% increase from 28 days to 56 days.

- This observation suggests that RHA plays a crucial role in enhancing the early-age compressive strength development of the M30 grade concrete.

2. Compressive Strength with RHA and SCBA:

- When both RHA (4%) and Sugarcane Bagasse Ash (SCBA) (10%) were incorporated into the M30 grade concrete, a 43.6% increase in compressive strength was observed from 7 days to 28 days.

- The combination of RHA and SCBA appears to have a synergistic effect on the compressive strength development, comparable to the effect of RHA alone.

3. Performance of Random Forest Regressor:

- In the machine learning approach, the Random Forest Regressor model outperformed the Decision Tree model in terms of prediction accuracy.

- Random Forest Regressor leverages the bagging technique, which combines multiple learning models, resulting in improved accuracy and robustness.

4. Accuracy Comparison:

- For the Random Forest Regressor model, the training accuracy was 0.95, and the testing accuracy was 0.72.

- For the Decision Tree Modeling, the training accuracy was 0.99, but the testing accuracy was lower at 0.59.

- The gap between training and testing accuracy suggests some degree of overfitting, where the models perform exceptionally well on the training data but struggle to generalize to unseen data.

Overall, the conclusions highlight the positive impact of incorporating agricultural waste materials like RHA and SCBA on the compressive strength development of M30 grade concrete. Additionally, the study emphasizes the superiority of the Random Forest Regressor model over Decision Tree Modeling in accurately predicting the compressive strength, potentially due to its ensemble learning approach.In Machine learning, at decision tree modeling training accuracy is 0.99 and the testing accuracy is 0.59

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