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Artificial Neural Network for Concrete Mix Design

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Abstract: Artificial neural networks (ANNs) are being increasingly used for predicting various civil engineering characteristics, such as the prediction of compressive strength of concrete of various grades, fracture toughness, and determining the displacement in concrete reinforcement buildings, etc. In this study, comparison is made between feed forward back propagation (FFBP) and Cascade forward back propagation (CFBP) algorithms for concrete mix design. ANN models have been developed using cement quantity, fine aggregate, metal, water, super plasticizer, and aggregate cement ratio by weight as the input variables to forecast the compressive strength of concrete for 3, 7, and 28 days. The training and testing datasets were split into 50% and 70% respectively. The results revealed that both FFBP and CFBP algorithms are successful models for predicting the compressive strength, but the training dataset of 70% and FFBP algorithm gave more accurate results.

Keywords: *Artificial neural networks (ANNs), compressive, FFBP, CFBP, predicting*

1. Introduction

In the world, concrete is frequently used in construction. Cement, sand, aggregate, water, and other materials are used to make it. Therefore, it is highly practical to predict the compressive strength of concrete based on the proportioning design. The growing use of soft computing approaches in predicting concrete strength is due to the remarkable compressive strength of concrete and its capacity to be molded into various forms and sizes. Utilizing a prediction model allows for the estimation of compressive strengths for various mix designs, making it easier to choose those that meet the necessary strength for subsequent physical tests. This method reduces the necessity for multiple attempts, resulting in substantial time and financial savings. Furthermore, it enables the determination of the most financially efficient alternative among choices that necessitate compressive strength for economic reasons. Soft computing techniques, often known as data-driven models, utilize input-output data to achieve improved accuracy, significant time and cost savings. The Artificial Neural Network (ANN) approach, which consists of interconnected nodes that simulate biological neurons, is very remarkable.

Design and construction rules require an obligatory 28-day compressive strength test in the field of quality control and performance evaluation [1]. Nevertheless, this test is characterized by its technical complexity, lengthy duration, and susceptibility to experimental inaccuracies. Moreover, once the test is performed, there is no opportunity for rectification if the concrete does not pass the test after a long period of waiting. Hence, the pre-28-day assessment of compressive strength is extensively embraced due to its manifold advantages. By adopting this proactive strategy, it becomes possible to strategically plan operations like as prestressing and formwork removal, resulting in improved overall efficiency. Furthermore, it enhances quality control by ensuring that structures are more resilient, hence reducing undue stress during the initial stages.

Using ANNs and ANFIS models, the authors evaluated the 28-day compressive strength of the concrete [2]. ANN were employed to develop a new approach for determining the FRP-confined compressive strength of the concrete [3]. Nowadays, artificial intelligence is being applied to different fields such as damage detection in skeletal structures [4]. ANN are a frequently suggested technique for predicting concrete strength, with the back propagation network being the most widely used ANN network [5] [6]. However, some research found that the service life and durability of concrete using recycled aggregate were inferior to those of conventional concrete [7, 8], while other studies found that the durability of recycled aggregate-based concrete was superior to that of conventional concrete [9]. Although there is no commercial strategy for the use of high-quality recycled aggregate, the availability of additional data may nonetheless inspire customers to utilize more recycled aggregate.

For example, M5P (a tree model used to test the efficiency of ANNs) was used to predict the mechanical characteristics of concrete incorporating used foundry sand. Their findings demonstrate that the M5P tree model

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performs well in predicting the characteristics of concrete [10], [11].

ANN have become influential instruments in the realm of concrete mix design, providing inventive methods for maximizing the intricate connections among different mix constituents and the resultant concrete characteristics. The process of concrete mix design is of utmost importance in the construction sector, as it seeks to attain an equilibrium between the properties of workability, strength, and durability. Historically, this procedure depends on empirical techniques and rigorous experimental tests, resulting in a tedious and time-consuming process.

On the other hand, ANN offer a method that is based on data, allowing for the representation of complex nonlinear connections inside concrete mixture designs. These computational models replicate the learning process of the human brain, enabling ANN to adjust and extrapolate from available data, finally forecasting the ideal combination of ingredients for desired tangible characteristics. The employment of ANN in concrete mix design enables a more efficient and precise exploration of the extensive design possibilities, resulting in enhanced performance and optimal allocation of resources.

This introduction examines the incorporation of ANN into the field of concrete mix design, highlighting its capacity to transform and simplify this essential element of construction. Researchers and practitioners seek to improve the accuracy and effectiveness of concrete mix design by utilizing the capabilities of ANN. This effort aims to drive progress in the construction sector and promote sustainable infrastructure development.

To predict the compressive strength of concrete with ground granulated blast furnace slag, a hybrid ANN with a multi-objective salp swarm method was used [10]. In that study, it was demonstrated that the M5P tree model was outperformed by 13 out of 19 ANN. This have become powerful instruments with significant ramifications in different disciplines, within the ever-changing landscape of modern technological breakthroughs. The need to explore the complexities of FFBP in ANN is due to the unmatched capability these networks provide for addressing complicated problems, especially in the fields of predictive modeling and pattern recognition.

The main incentive arises from the innate ability of ANN to replicate the complex learning mechanisms of the human brain. With the advancement of technology, there is a growing need for autonomous systems that can adapt, generalize, and learn from data. ANN, particularly the feedforward backpropagation (FFBP) model, offer a chance to tap into this potential, facilitating the development of sophisticated applications in areas including image and speech recognition, medical diagnosis, financial forecasting, and beyond.

The exploration of Feedforward Backpropagation (FFBP) in ANN aims to tackle the complexities and non-linear patterns found in datasets. Conventional statistical techniques frequently prove insufficient in handling intricate patterns, rendering them unsuitable for jobs that entail subtle correlations and multifarious interdependencies. FFBP, due to its capacity to simulate complex connections and adjust to various datasets, emerges as a potent solution for navigating the complexities of real-world challenges.

The domain of concrete mix design involves complex interactions among different components, highlighting the necessity for advanced modeling tools. The objective of utilizing FFBP in this particular scenario is to optimize and improve the concrete mix design process. Our goal is to utilize the learning capabilities of FFBP to enhance the optimization of concrete component proportions, taking into account variables such as workability, strength, and durability. This not only accelerates the design process but also guarantees that the resulting concrete constructions fulfill the specified performance parameters.

Moreover, the reason for examining Feedforward Backpropagation (FFBP) in ANN is rooted in the wider context of promoting sustainable practices in the building sector. Optimizing concrete mix designs boosts resource efficiency, minimizes material waste, and ultimately improves the sustainability of construction projects. The objective goes beyond simple prediction; it is in line with a vision of developing more robust and ecologically responsible infrastructures.

FFBP, when employed in quality control, provides a strong and reliable method for forecasting the compressive strength of concrete well in advance of the conventional 28-day testing period. This not only expedites building schedules but also enables proactive modifications, so enhancing the overall efficiency and durability of structures. The objective is not solely to achieve accurate predictions, but rather to provide construction professionals with tools that facilitate informed decision-making and resource efficiency.

To summarize, the exploration of FFBP in ANN goes beyond the technical complexities, driven by motivation and purpose. It is in line with a more comprehensive goal of utilizing state-of-the-art technology to tackle practical problems, improve effectiveness, and promote sustainable and resilient practices in various industries. The FFBP model, as a component of ANN, provides a mechanism to explore novel opportunities, enabling the development of smarter, adaptable, and more efficient systems in the always changing realm of technology and industry.

This study aimed to investigate the effectiveness of the Artificial Neural Network in evaluating the compressive strength of concrete. The experiment comprised six concrete mix designs with a grade of M20, incorporating five specific mix factors, namely cement content, fine aggregate, metal, water, and aggregate cement ratio. The compressive strength of each mixture was evaluated following 3, 7, and 28 days of immersion in water for curing. Later on, soft computing techniques, particularly the Artificial Neural Network, were applied and simulated using MATLAB© 2015. The concrete mix parameters were used as input variables in this modeling procedure, with the compressive strength of concrete serving as the output parameter. The outcomes derived from these two models were subsequently refined and put to a comparison examination. The main goal was to assess the efficacy of the Artificial Neural Network in forecasting the compressive strength of concrete.

2. Methodology

2.1 Data collection

Data was collected by laboratory tests. The ratio of M20 concrete is 1:1.5:3. Displays below Mix no 1 the cement, sand, and aggregate ratio, which implies that 1.5 kilograms of sand and 3 kilograms of aggregate should be used for every kilogram of cement used to make concrete; that is, 1 part cement, 1.5 parts sand, and 3 parts aggregate. M20 Concrete, also known as nominal concrete, is a material that can be expertly constructed according to Indian Standard IS 456:2000, and has a compressive strength of 20 N/mm2 at 28.

Typically, concrete must be fully hydrated with 38% of its weight in water. A water-cement ratio of 0.45 to 0.50 is often used for M20 Concrete.

M20 concrete Used in RCC works like, Rigid Pavement Construction, used to construct structural members like slabs, beams, columns, etc (for small to medium structures only. Not suitable for heavy structures or work), Water retaining structures, piles, etc.

Required Water Cement Ratio for M20 concrete are for high-quality concrete works; 0.45 w/c ratio is specified, Minimum water-cement ratio: 0.45.

Below is an example of concrete mix proportioning. These examples are only meant to help with the procedure's explanation; the real mixing ratios must be determined using trial batches made using the supplied supplies.

Mix No.1

Strength at 28 days (N/mm2)	20 N/mm^2		
Characteristic strength	20 N/mm^2		
Target Design Strength	26.60 N/mm^2		
Workability			
a) Slump (mm)	70mm		
Degree of Control	Good		
Method of Compaction	Vibration		
Type of Cement	ACC O.P.C. 53 Grade		
Maximum Nominal Size of Aggregate (mm)	20		
Water Cement Ratio by Weight			
A Free	0.55		
B Actual	0.55		
Mix Proportion	**Cement**	**Fine Aggregate (Crushed Stone)**	**Metal 20mm**
Weight of Material (kg/m3)	350	818.5	1169.28
Proportion by Weight	1	2.34	3.34
Proportion by Volume	1	2.51	3.76
Water (lit/m3)	193		

Super plasticizer (Kg/m3)	1.1
Aggregate-cement Ratio by weight	5.68
Laboratory Cube Strength obtained	
Average of three test specimen	
after curing	
A S 3 days (Immerse Curing Method)	14.66 N/mm^2
B 7 days (Immerse Curing Method)	22.81 N/mm^2
C 28 days (Immerse Curing Method)	30.33 N/mm^2
Unit weight of fresh concrete (kg/m3)	2530.78
Cement Content (kg/m3)	350

2.2 Model Performance Evaluation

Four criteria were utilised for a comparative evaluation of the model's performance to assess the ANN's prediction accuracy. MSE, Mean Relative Error (MRE), and Correlation Coefficient (CC) are the norms that were used.

2.2.1 Mean Absolute Error (MAE):

The MAE is a quantitative measure used to evaluate the degree of agreement between a forecast or prediction and the observed outcomes. The determination is made by computing the mean of the absolute between the predicted values and the corresponding measurements within the validation dataset. Put simply, the mean absolute error measures the average size of differences between predictions and actual outcomes.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|observed - predicted|$$

2.2.2 Mean Square Error (MSE):

The MSE is a measure used to assess the difference between the projected values from an estimator and the actual values of the estimated quantity. The MSE is calculated by taking the total of the squared residuals or errors and dividing it by the degrees of freedom in the sum. It provides a quantification of the variance or estimate mistake. The mean squared error is computed by aggregating the squared discrepancies between anticipated and actual values, and subsequently dividing by the relevant degrees of freedom. This metric is highly important for evaluating the overall accuracy and precision of an estimator. It offers a quantifiable measure of how well the projected values coincide with the observed values. The mean squared error is a commonly used metric in statistical and machine learning domains. It enables practitioners to assess the effectiveness of estimators and models by examining the average of the squared discrepancies between anticipated and actual values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(observed - predicted)^2$$

2.2.3 Mean relative Error (%):

The absolute error is multiplied by the precise value's magnitude to get the relative error. It often takes the form of a percentage and aids in the calculation of the real error to true ratio. **MRE=1/n $\sum^{n}_{i=1}$ [X –Y] / [X] ×100**

2.2.4 Coefficient of correlation (Cc)

It is a gauge of how strongly two variables are correlated linearly. It is defined in terms of the variables' standard derivations divided by the (sample) covariance of the variables.

$$CC = \frac{\sum(x-x')(y-y')}{\sqrt{(x-x')(y-y')^2}}$$

2.3 TRAINING ALGORITHMS

a) Feed Forward Back Propagation Algorithm (FFBP)

The prevailing technique used to train feed-forward ANN is the error backpropagation method, which employs the gradient descent updating algorithm. The FFBP model, seen in Figure 1, is a commonly used approach for training ANN. This procedure encompasses two critical stages.

During the initial stage, every input pattern from the training dataset passes through the network's input layer in order to reach the output layer. In the second stage, an error is calculated by comparing the output of the network with the intended goal output. Subsequently, this error is transmitted in reverse to the input layer, while simultaneously modifying the weights to enhance the network's performance. The inquiry utilizes the FFBP paradigm for its construction.

The error backpropagation methodology, which incorporates the gradient descent update algorithm, is the principal approach used to train feed-forward ANN. The FFBP model, seen in Figure 1, is a commonly utilized method for training ANN. This paradigm adheres to a two-stage process that is essential for achieving successful learning. During the initial phase, every input pattern from the training dataset passes through the input layer of the network and moves towards the output layer. In the second stage, an error is calculated by comparing the network's output with the desired goal output. Subsequently, this error is transmitted in reverse to the input layer, accompanied by the modification of weights to enhance the network's performance.

The current research employs the FFBP model as the fundamental framework for building and training the Artificial Neural Network. The backpropagation of errors and weight adjustments in this method are essential for the learning process, enabling the network to adapt and enhance its predicting abilities using the available training data.

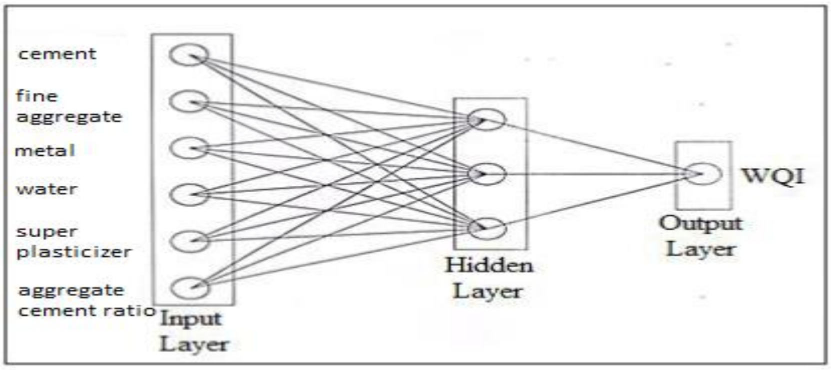


Fig.1: Feed-Forward Back Propagation (FFBP) Neural Network Architecture

b) Cascade Forward Back Propagation Algorithm (CFBP)

The Cascade Back-Propagation (CFBP) method, invented by Scott Fahlman from Carnegie Mellon in 1990, is a conceptual framework designed to enhance the speed of learning in ANN. The framework, seen in Figure 2, integrates components from both the back-propagation and cascade-correlation methods, thus acquiring its unique designation. The CFBP method describes a step-by-step approach to modify the weights of synaptic connections by moving in the direction of decreasing error in the vector space of these weights. This method is consistent with well-known algorithms used for learning in neural networks. Usually, the error measure is a quadratic function that represents the difference between the actual and desired outputs. Although feed-forward networks and CF models have similarities, CF models have additional weight connections from inputs to each layer and from each layer to subsequent layers. Artificial neural network (ANN) models have been developed in this context using MATLAB® 2015.

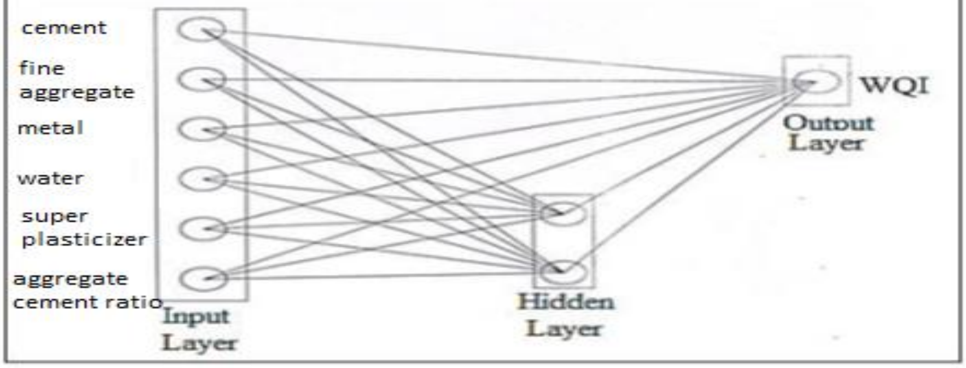


Fig.2: CFBP Neural Network Architecture

3. Result And Discussion

3.1 Artificial Neural Network Model

To determine the optimal configuration for predicting the compressive strength of concrete using Artificial Neural Networks (ANNs), a comprehensive exploration was conducted, varying the number of neurons in the hidden layer, the transfer function in the input layer, and the training methodology. Numerous ANN models were generated and evaluated with both 50% and 70% training datasets to discern the impact of data quantity on model performance. The crucial consideration in this exploration was striking a balance in the number of neurons in the hidden layer, recognizing that too few may compromise information gathering, while an excess might lead to overfitting issues.

The ANN model was structured with one input layer featuring five input variables, a hidden layer with neurons ranging from one to ten, and an output layer with a single neuron. The transfer functions employed in the hidden layer included logsigmoidal, transigmoidal, and purelinear. The evaluation criteria for identifying the optimal model were based on the correlation coefficient approaching one and achieving the minimum values for Mean Absolute Error (MAE) and mean relative error (MRE). This systematic exploration aimed to discern the interplay between the architectural components of the ANN and the training dataset size, striving to uncover an optimal configuration that ensures robust predictive performance in estimating concrete compressive strength.

From Fig. 3.1 to 3.3, it is observed that the ANN models' prediction for the compressive strength of concrete shows a good correlation with the observed compressive strength of concrete for almost all days (3, 7, and 28). This is because the predicted compressive strength of concrete by the ANN models correlates well with the observed compressive strength of concrete.

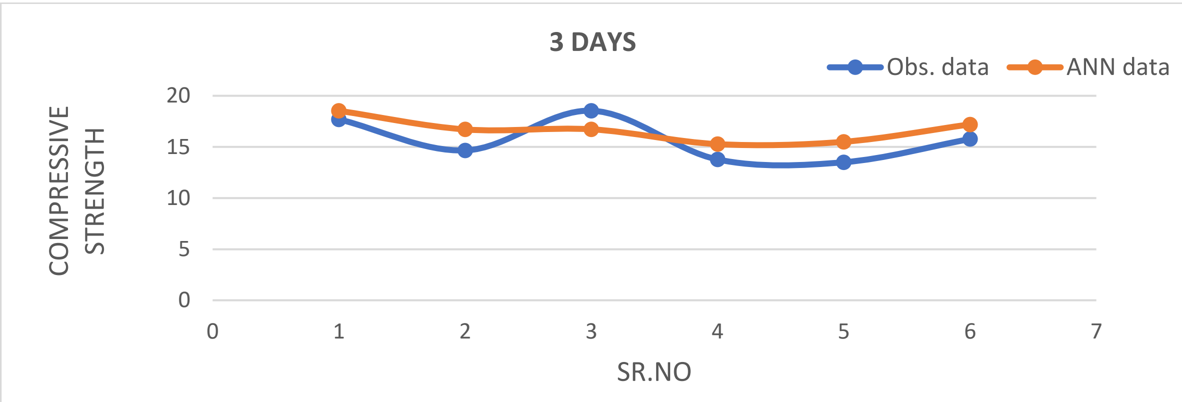


Fig.3.1 ANN prediction for 3-days Compressive Strength

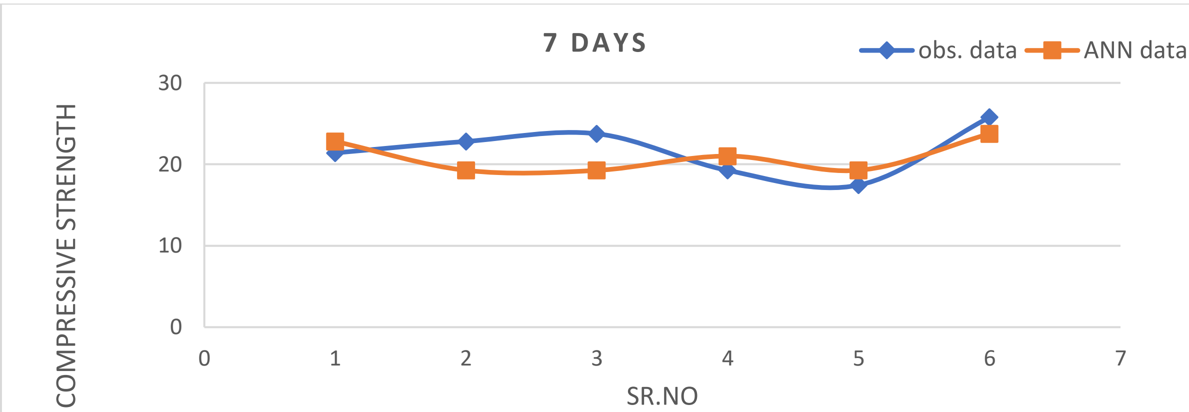


Fig.3.2 ANN prediction for 7-days Compressive Strength

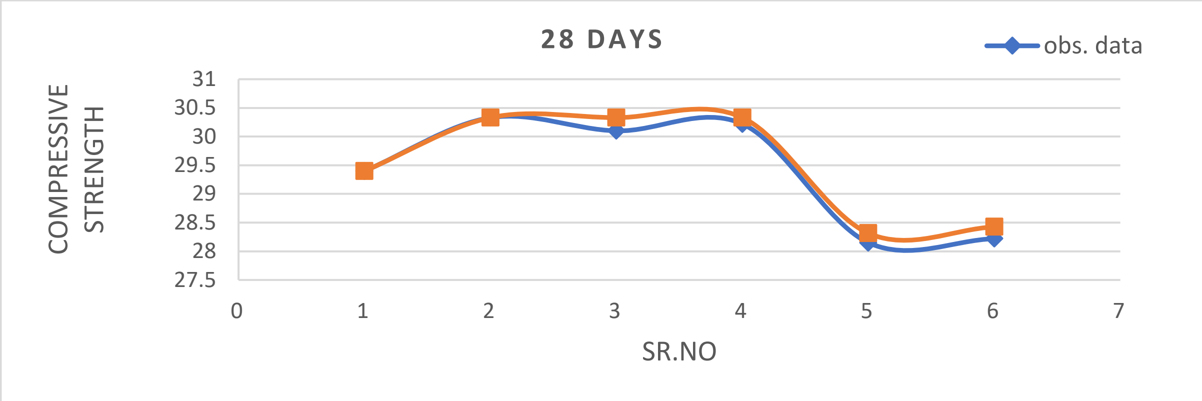


Fig.3.3 ANN prediction for 28-days Compressive Strength

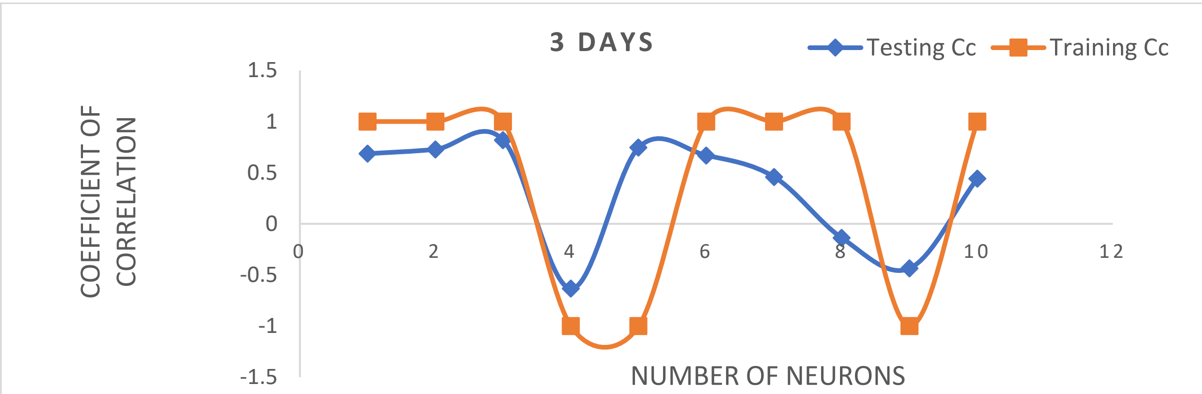
Fig. 3.1 to 3.3: ANN Predictions of compressive strength of concrete

3.2 Effect of transfer function

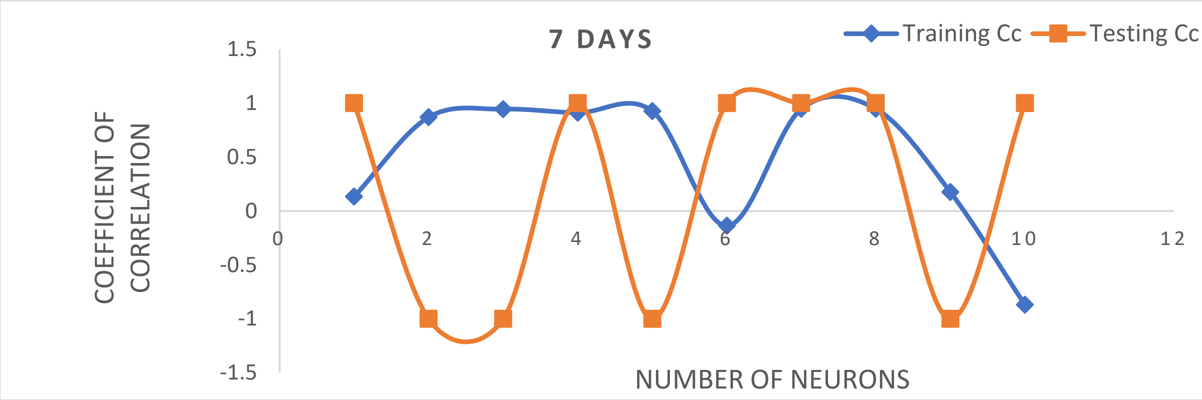
The table1 lists the typical error analysis for training and testing on various days (3, 7, and 28). It has been noted that model performances vary significantly with changes in the number of neurons in the hidden layers, the transfer function, and the ANN algorithm. The table 1 lists the best-fitting ANN model for each zone based on performance indices and transfer function. From the table1, it can be seen that for three days compressive strength, Logsigmoidal is the best transfer function, for seven days compressive strength, Purelinear is the best transfer function, and for twenty-eight days compressive strength, Tansigmoidal is the best transfer function.

3.3 Effect of number of neurons in hidden layers

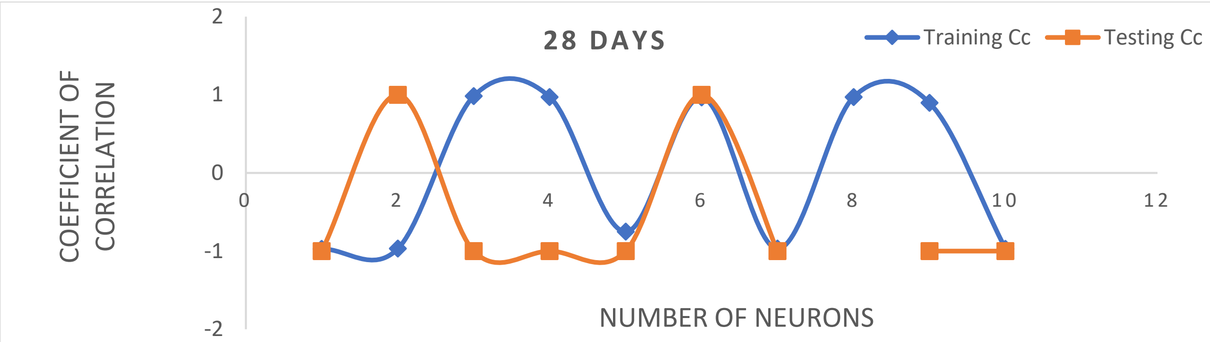
Fig. 3.3 displays how well the ANN model performed during training and testing for typical days (three, seven, and twenty-eight). It can be seen from Table 3 that a hidden layer structure with seven neurons works better for three days, eight neurons for seven days, and eight neurons for twenty-eight days. Due to daily variations in statistical variables, the structure of the best-fitting hidden layer varies.



A) Correlation Coefficient (Cc) in correlation with the number of neurons in the hidden layer for 3 days Compressive strength



B) **Correlation Coefficient (Cc) and the Number of Neurons in the Hidden Layer exhibit a relationship for 7 days Compressive strength**



C) **Correlation Coefficient (Cc) in relation to the Number of Neurons in the Hidden Layer for 28 days Compressive strength**

Fig.3.3: ANN Model Performance

3.4 ANN model performance

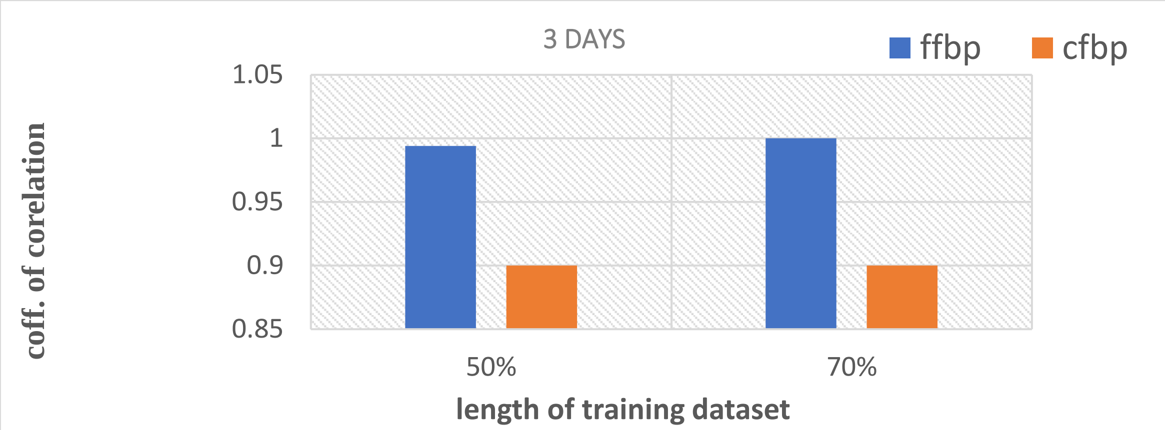
When ANN models with various hidden layer architectures have high coefficients of correlation that are often closer to one during training and testing, the best fitting model should be chosen based on MAE and mean relative error (MRE) from Figure 3.3. From Table 1, it is also clear that practically every predicted day (3, 7, and 28), the ANN models exhibit extremely high levels of correlation between observed and anticipated values.

3.5 Effect of length of dataset

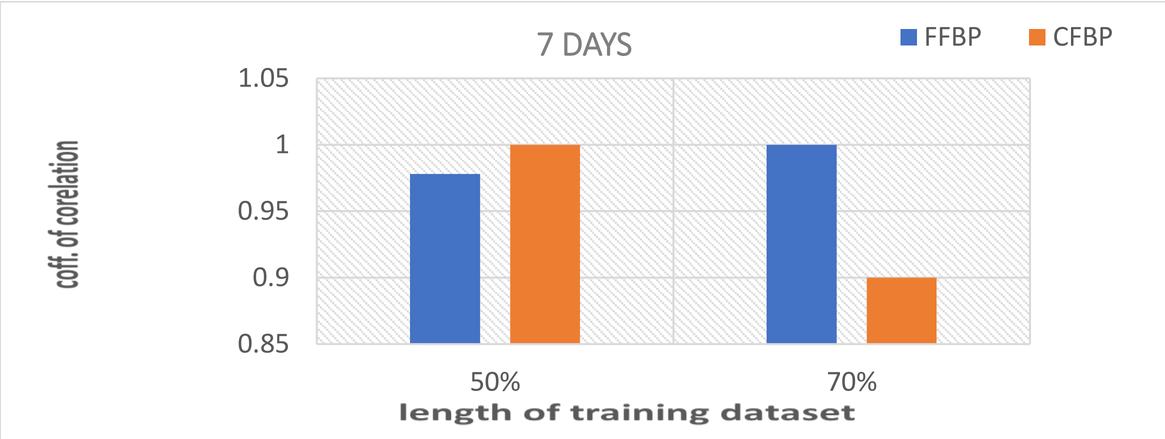
Three, seven, and twenty-eight days, respectively, are used to evaluate the impact of training dataset duration on prediction accuracy. Two distinct dataset lengths were first utilized to test how the model's performance was affected by the dataset's length. These two datasets training lengths are 50% and 70%, respectively. From Figures 3.6.1 to 3.6.2, as the duration of the dataset increases, the correlation coefficient (Cc) increases and the MAE and mean relative error (MRE) both decreases. At 70% of the length of the training dataset, the highest correlation and lowest mean relative error (MRE) are found. This can be attributed to providing a longer dataset for training. Error rises when the training dataset length exceeds 50%.

3.6 Comparative Analysis of CFBP and FFBP Algorithms.

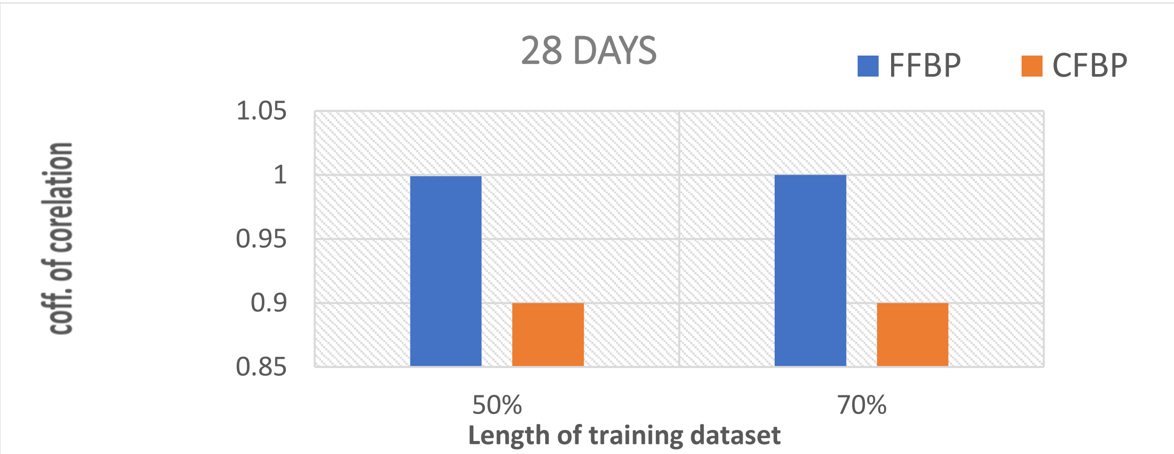
Cascade-forward and feed-forward backpropagation algorithms are used for predicting the compressive strength of concrete for three, seven, and twenty-eight days. Table 2 shows that feed-forward backpropagation performs better than cascade-forward.



Correlation (Cc) in relation to the Percentage of the Training Dataset Length.

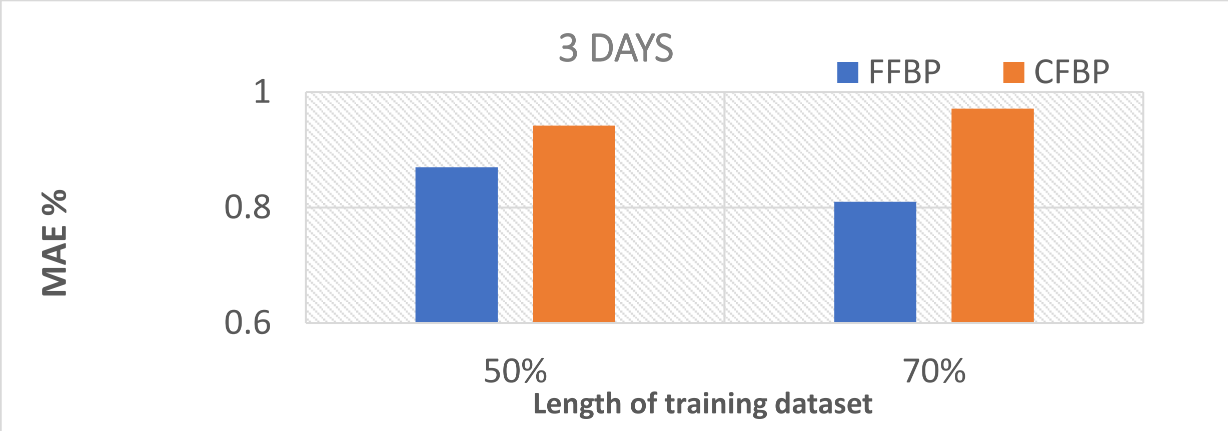


Correlation (Cc) as it pertains to the Percentage of the Training Dataset Length.

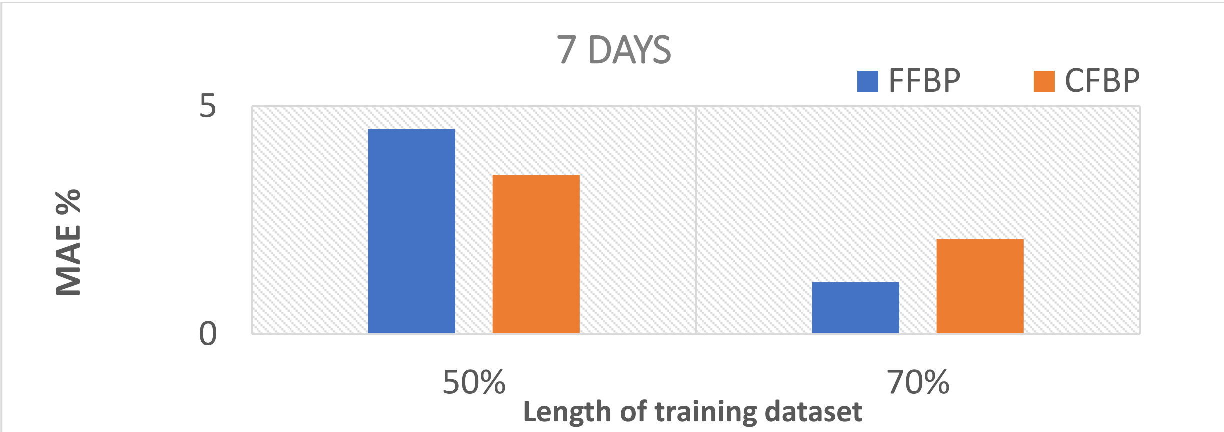


Correlation (Cc) in relation to the Percentage of the Training Dataset Length.

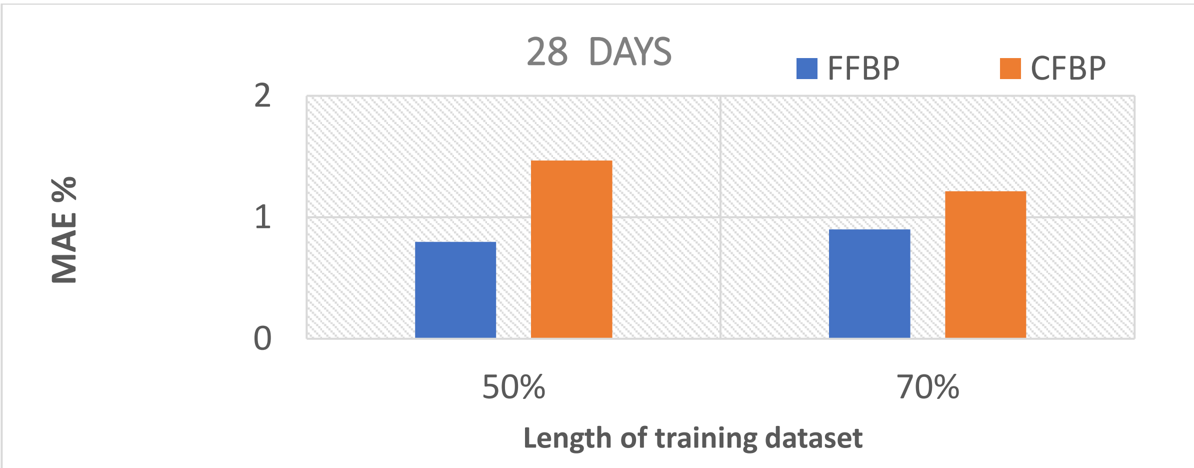
fig.3.6.1: Coefficient of Correlation



Relationship between Length of Training Dataset (%) and MAE %



Relationship between Length of Training Dataset (%) and MAE %



Relationship between Length of Training Dataset (%) and MAE %

fig.3.6.2: Mean absolute error

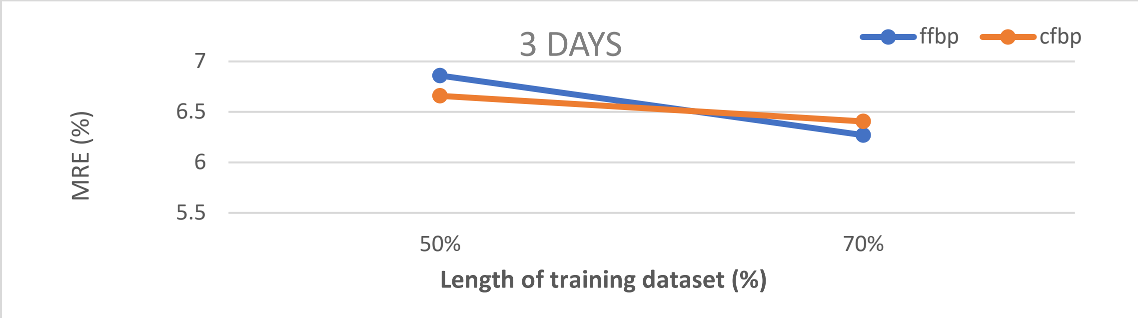


Fig.5.13: Relationship between Length of Training Dataset (%) and MRE %

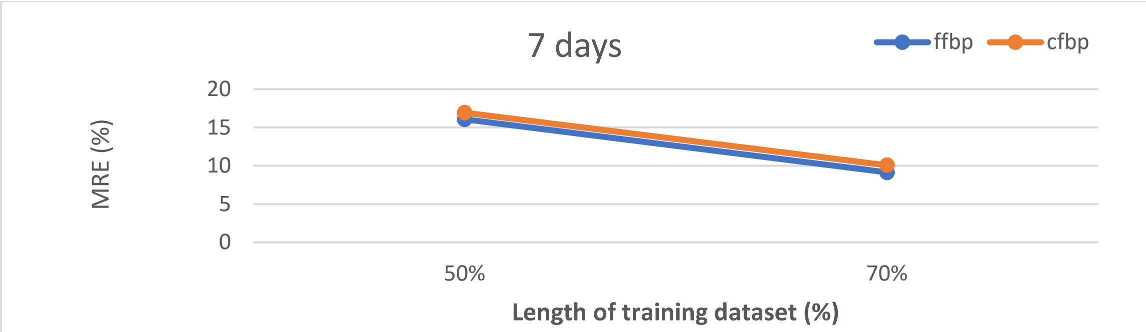


Fig.5.14: Relationship between Length of Training Dataset (%) and MRE %

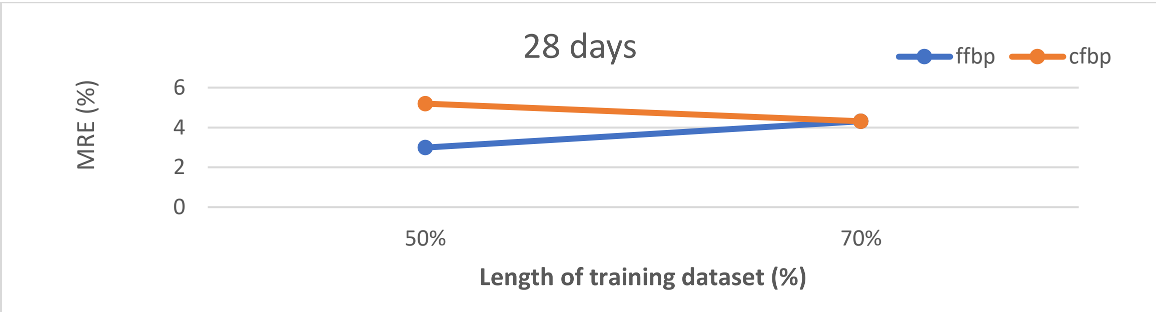


Fig.5.15: Relationship between Length of Training Dataset (%) and MRE %

fig.5.13 to 5.15: mean relative error

Table 1: Best fitting ANN model

Length of training dataset	Days	Type of neural network	Transfer function	No. of neurons	CC	MRE	MAE
70%	3	Feed	Logsig	7	1	6.27	0.91
	7	Feed	Purelinear	8	1	9.144	1.923
	28	Feed	Tansig	8	1	4.311	1.215

Table 2 Comparative Analysis of the Performance of CFBP and FFBP Algorithms

No. of Days	length of training dataet %	CFBP			FFBP		
		Cc	MAE	MRE	Cc	MAE	MRE
3	50	0.994056	0.942049	6.659196	0.994056	0.973881	6.86105
	70	0.999	0.971446	6.405908	1	0.919916	6.27318

7	**50**	1.00E+00	3.493333	16.93162	0.97802	11.33706	16.0705
	70	0.999	2.084917	10.06844	1	1.923662	9.144391
28	**50**	0.999557	1.466667	5.195064	0.99951	0.847217	2.997265
	70	0.999	1.215	4.310964	1	1.215269	4.311919

According to the data in Table 2, the performance measures show that FFBP performs better than CFBP in this particular situation. The figures from 3.6.1 to 5.15 provide visual depictions that demonstrate the connection between the size of the training dataset and important metrics such Coefficient of Correlation (Cc), MAE, and Mean Relative Error (MRE).

Table 1 presents data on the most suitable Artificial Neural Network (ANN) models, determined by different parameters. It emphasizes the efficacy of FFBP in predicting concrete strength on different days. The comparison presented in Table 1 clearly illustrates the improved performance of FFBP in terms of Cc, MAE, and MRE.

In addition, the comprehensive comparison presented in Table 2, which considers various sizes of training datasets and durations, highlights the persistent dominance of FFBP over CFBP. The FFBP model consistently demonstrates superior performance with higher Cc values and lower MAE and MRE percentages, which indicates its greater accuracy and reliability in predicting concrete compressive strength.

4. Conclusions

ANN models were used in the research to estimate the compressive strength of M20 grade concrete.

1) The study shows that hidden layer neurons and alterations to the transfer function have a significant impact on model performance. It is clear that on various study days, such as three days for Logsigmoidal, seven days for Purelinear, and twenty-eight days for Transigmoidal transfer functions, all performed better due to the significant nonlinearity between the input and output variables. The study also shows that hidden layer neurons and alterations to the transfer function have a significant impact on model performance.

2) It shows that a hidden layer structure with 7 neurons performs better for 3 days, 8 neurons perform better for 7 days, and 8 neurons perform better for 28 days.

The relationship between the size of the training dataset and the accuracy of predictions is a primary area of interest, since it provides valuable insights into the model's performance. More precisely, a dataset consisting of 70% training data exhibits higher prediction accuracy in comparison to a dataset containing only 50% training data. This is seen in the elevated correlation coefficient (Cc), which signifies a more robust linear association between the expected and actual values. In addition, the dataset including 70% training data demonstrates a decrease in MAE, showing a reduction in overall prediction errors, as well as a decrease in mean relative error (MRE), suggesting a more precise prediction in relation to the actual values.

A notable pattern arises as the size of the training dataset grows — there is a consistent enhancement in the accuracy of predictions. The decrease in error measurements, such as MAE and Mean Relative Error (MRE), indicates that when additional data is used for training, the model improves its ability to predict outcomes, leading to a more precise depiction of the actual relationships existing in the dataset. This trend highlights the significance of having a sufficient amount of training data to improve the model's capacity to generalize and generate precise predictions beyond the training set.

Essentially, the accuracy of predictions is heavily influenced by the magnitude of the training dataset. A more extensive training dataset, namely one consisting of 70% training data, leads to significant enhancements in correlation coefficient, mean absolute error, and mean relative error. The diminishing mistakes found as the training dataset lengthens highlights the crucial significance of data quantity in enhancing the model's prediction skills. These findings emphasize the significance of meticulously choosing and enhancing training datasets to guarantee the optimal performance of predictive models.

Feed-forward backpropagation approach performs better than cascade-forward backpropagation algorithm.

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