MACHINE LEARNING TECHNIQUES FOR ESTIMATING THE COMPRESSIVE STRENGTH OF FLY ASH CONCRETE.

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Submitted in partial fulfillment of the requirements of the degree of Master of Technology in Structural Engineering

Under the guidance of

Ms Osharani Sahoo

GALGOTIAS
UNIVERSITY

SCHOOL OF CIVIL ENGINEERING

GALGOTIAS UNIVERSITY

GREATER NOIDA

MAY 2020

To

My Parents

&

Family

CERTIFICATE

This is to certify that the project work entitled "**Machine learning techniques for estimating the compressive strength of fly ash concrete**" submitted by **Suhaila Khursheed** to the School of Civil Engineering, Galgotias University, Greater Noida, for the award of the degree of Master of Technology is a bonafide work carried out by her under my personal supervision and guidance. The thesis work in my opinion has reached the requisite standard, fulfilling the requirements for the award of the said degree.

The results contained in this report have not been submitted, in part or full, to any other college, university or institute for the award of any degree or diploma.

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APPROVAL SHEET

This project report entitled “**Machine learning techniques for estimating the compressive strength of fly ash concrete”** by **Suhaila Khursheed** has been approved for the degree of **Master of Technology** in **Civil Engineering.**

Examiner

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I, the undersigned solemnly declare that this report represents my own ideas in my words under the supervision of my guide and wherever I have used others' ideas, data, words and results I have properly cited them and provided proper reference of their original source. I further assure that I have strictly obeyed all ethics of academic sincerity and I have not at any point in this report misrepresented, formulated or incorrectly presented any idea, data, result and/or source. I am well aware that incase of any violation of the above mentioned cases, there will be a cause for disciplinary action by the Institute and can also evoke penal action from the sources which have not been properly cited or from whom proper permission has not been taken before using their work.

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ABSTRACT

Compressive strength of a concrete is the resistance against the external load. It is one of the most crucial properties of hardened concrete. Concrete is very strong in compression and its determination is of utter importance. For years the traditional method of determining compressive strength has been UTM test in which sample cubes are prepared, cured, and tested under load in the Universal Testing Machine thereafter compressive strength can be obtained from strength-load relationship. In early 1940s non-destructive tests were introduced in which compressive strength was determined indirectly by relatively less time taking but a complex calibrated process. However all these methods have time consuming and complexity drawbacks.

With the advent of Artificial Intelligence, Machine learning techniques are being used to predict the compressive strength. Various techniques have shown high accuracy in predicting the compressive strength. In this work I have used two important machine learning methods which are BackPropagation Neural network (BPNN) and Feed Forward Neural Network(FNN) for forecasting the 91 days strength of concrete. The actual data after normalization to reduce the range of data difference is segregated randomly into training and testing datasets which are fed to the MATLAB where from the predicted dataset is obtained. The relevance factor R is computed which establishes the relationship between actual and predicted data and it is highly important parameter for defining the accuracy of the used predicting model. On the basis of high valve of relevance factor and other parameters like VAF, RMSE, R^2, RSR, NS, mean, standard variation and variance, I arrived at the conclusion that BPNN was more accurate and efficient model for predicting the compressive strength of concrete than FNN.

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CHAPTER 1

INTRODUCTION

1.1 GENERAL

The compressive strength of concrete is one of the foremost vital properties of concrete. The main function of concrete is to resist the compressive stresses resulting in the structure due to loads. In a few cases where quality in tension or quality in shear is required, the compressive quality is utilized to calculate those properties indirectly. Hence the concrete fabricating properties of distinctive constituents of concrete are for the most part measured in terms of compressive quality. Furthermore Compressive quality is utilized as a qualitative measure for different other properties of concrete. Till now no actual direct relationship between compressive strength of concrete and various other properties of concrete viz flexural strength, strength in tension, young'a modulus of elasticity, resistance against fire, and permeability nor it is possible to be established in near future. However, in some cases, applied math relationships are determined and they provide a lot of helpful data to engineers. However it needs to be stressed that it can provide only the approximate results of those properties and if better results are needed other tests should be carried out to have appropriate valves for example with an decrease in size of the sample specimen the compressive strength increases on the other hand modulus of elasticity decreases and in that case the modulus of elasticity doesn't follow the compressive strength. When the concrete is subjected to freezing and thawing compressive strength does not indicate the helpful property of concrete. Concrete having about 6% entrained air which is generally weaker in quality is found to be more tough than thick and solid concrete. The compressive strength is primarily decided in the laboratory or at field by testing cubes or cylinder specimens under UTM or by non destructive methods.

Strength of the concrete is its resistance to cracking/failure under loads. It is decided in numerous ways such as quality in-tension, compression, shear and flexure of these shows quality with respect to a chosen method of testing. In the event that concrete structure falls flat beneath the compressive stack the failure is really a combination of smashing and shear failure

. This failure mechanism is often advanced phenomena. It's typically assumed that the concrete in resisting failure, generates every cohesion and internal friction. The cohesion and internal friction developed by concrete in resisting failure is found to be somehow related to one parameter that is water binder ratio.

Strength may be defined as the capacity of the concrete to stand up to failure once it’s subjected to the action of stresses caused by masses or the mix of all the masses The first common being compression, tension, bending and impact. The significance of sorting out the changed qualities is highlighted from the genuine reality that materials like stones and concrete have high compressive quality be that as it may slightest (1/5 to 1/50) tensile, bending and impact qualities. Compressive Quality is pointed out from tests on cubes, cylinders or prisms that unit of measurement ordinarily smaller for consistently homogenized materials and bigger for non homogenized ones.Prisms and cylinders have lower resistance than cubes of an identical cross-sectional zone, on the inverse hand crystals with heights littler than their sides have bigger quality than the cubes.

Flyash: Ash or pulverised fly ash (PFA) is the buildup from the burning of fine coal collected by mechanical or power separators from the pipe gasses or control plants. It comprises of 3/4th of the total ash made inside the plant.. The properties and composition of cinder shift wide, not totally between absolutely totally different plants but from hour to hour insides a comparative plant. Its composition depends on shape of fuel burnt and on the assortment of stack on the evaporator. The ash that's gotten from power precipitators is alright having a specific particular surface of 3500 cm^2/g as compared to ash gotten from violent wind separators that's comparatively coarse related contains an outsized extent of unburnt fuel. commonly it's or maybe better than cement. fiery remains comprises more often than not of circular particles, assortment of which may be like glass related empty and of on an irregular basis shaped particles of unburnt fuel or carbon. It ought to shift in color from light-weight dark to dull dark or indeed brown.

Effect of flyash on concrete on the next properties:

Water content: the use of flyash in restricted sums as a substitution for cement or as relate expansion to cement needs scarcely endless water for an indistinguishable droop since of fineness of the fiery debris. it is frequently in assention that the utilize of fiery remains, strikingly as relate admixture instead of as a substitution of cement, diminishes, isolation and harm. In the event that the sand is coarse the expansion of fiery remains produces supportive comes about; for fine sands, its expansion seem increment the water request for a given workability.

Compressive strength: Since the puzzolanic activity is exceptionally moderate, expansion of flyash upto time unit finishes up in decrease in compressive quality for 1 week and 4 weeks relate addition of ash up to thirty per cent may cause lower quality at 1 and 4 weeks respectively,but on the approach aspect twenty eight days the compressive will increase for half-hour substitution. If substituted on top of time unit the compressive strength is recognized to be decreasing.

Modulus of elasticity: owing to flyash the modulus of snap decreases within the intial day however goes on increasing at later stage.

Curing : there's result on action. Its same as that normal portland cement.

Shrinkage of concrete: Coarser fly ashes and society having a high carbon substance unit incalculable in threat of increment drying shrinkage than the better fly ashes and society having an intermittent carbon content. .

Permeability: The permeability of concrete diminishes on addition of ash to cement. twenty eight days fine-grained fly-ash-concrete is 3 times as permeable as ancient concrete but after 6 months it's on the point of be but 1/4th porous

Setting time: A thirty per cent substitution of ash may cause an increase of initial setting time up to two hours.

1.2 ARTIFICIAL INTELLIGENCE

Artificial intelligence, an extensive method, was developed in 1956 when the term was first used in a summer research project meeting held in Darthmouth college, New Hampshire, USA and on the basis of the interaction of various disciplines like computer science, linguistics, psychology, neurophysiology, information theory and cybernetics. The primary goal of artificial intelligence is to explore ways to imitate and function like the human brain.

Artificial intelligence (AI) is turning out to be a highly efficient alternate way of dealing with traditional modeling methods. Artificial intelligence is the branch of computer science that develops softwares which have the capability of solving a problem using human-like intelligence. In contrast with classical methods, AI can deal with problems that are complex in nature with high uncertainties and provide effective solutions by saving considerable amount of time and human efforts. AI makes the process of decision making relatively faster. It can be incorporated to predict a solution from existing data when testing isn’t possible.

In the pool of various AI techniques, machine learning (ML), pattern recognition (PR), and deep learning (DL) have effectively garnered wide consideration owing to their high output accuracy in civil engineering related problems mostly in structural designing engineering.

Machine learning (ML) is one of the main subfield of artificial intelligence (AI) that deals with the study, plan, and improvement of programs that can learn from the accessible information on their own and predict feasible solution to a problem using the learnt data without having the need of being programmed by user.It could be a information analytics method that enables com puters to do what comes naturally to people and creatures that's to learn from the experiences.It employs computational strategies to “learn” data specifically from information without depend ing on an already determined equation as demonstration.As the number of samples available fo r learning increases,the calculations adaptively move forward their execution Higher the numbe r of data sets is the ouput accuracy. Machine learning employs two sorts of procedures:

Supervised learning in which a model is prepared on known input and yield information sets so that future outputs can be anticipated with higher accuracy.

Unsupervised learning, in which covered up patterns or inborn structures are found in available input data sets without being labelled.

Common calculations for performing classification incorporate support vector machine(SVM), k-nearest neighbor, naïve bayes, calculated relapse and neural systems.

Reinforced learning works on the principle of feedback wherein the user feedback is used to improve the output accuracy.

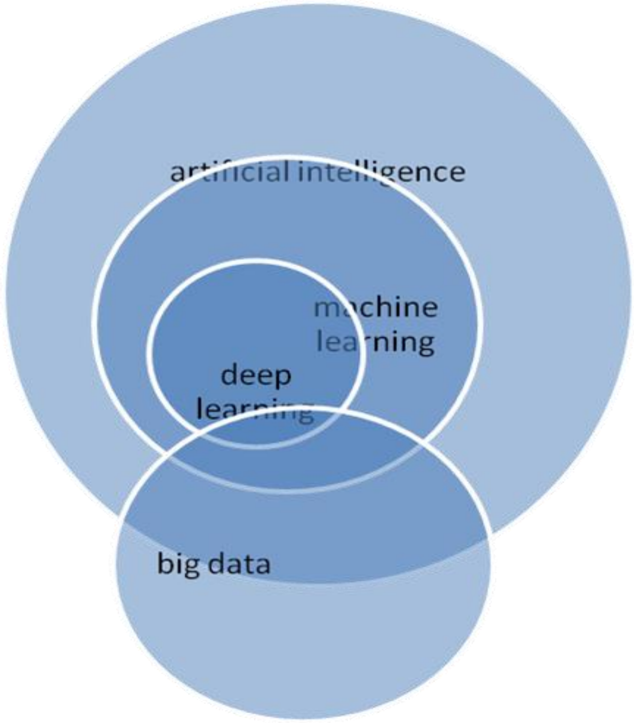

Figure 1.1 Relation between various AI techniques

.BPNN is an ANN based capable device which is utilized for apprehension of the incursion action.The neuron is the Fundamental component of BPNN that stores and processes information. The back propogation neural network (BPNN) was created by Rumelhart as a arrangement for the issue of planning multi-layer perceptrons. The basic advances interpreted by the BPNN were the consideration of a differentiable exchange function at each node of the framework and the utilization of error backpropogation to modify the internal system loads after each training span.BPNN can be utilized for both direct as well as non straight classification.

1.3 OBJECTIVES OF THE STUDY

1. To verify the capability of Back Propagation Neural Network (BPNN).
2. To make a comparative study between BPNN and FNN
3. To compute various statistical analysis.

1.4 AVAILABLE METHODS

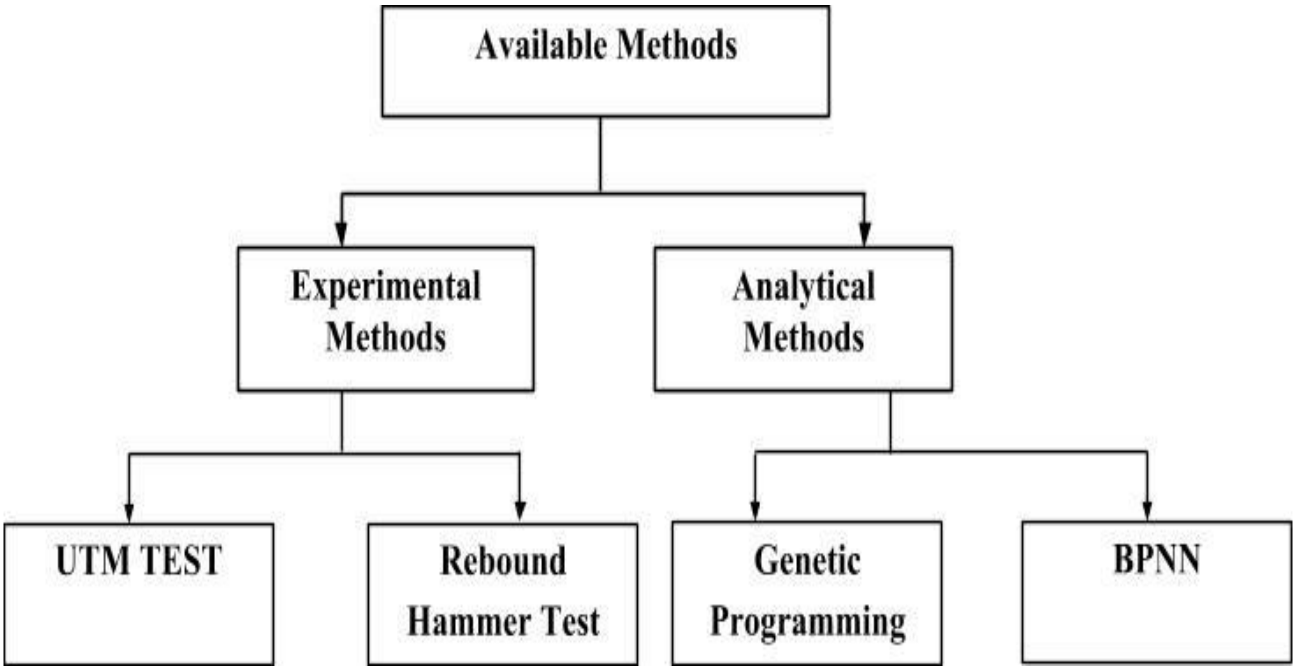

Figure 1.2: Flow chart of Available Method.

1.4.1 EXPERIMENTAL METHODS

UTM TEST

Compressive strength is the property of concrete due to which the concrete resist the loads without failing. UTM(universal testing machine) test is a destructive test in which the average of 3 cubes is taken to evaluate the valve of compressive strength just before failure under the load in the machine. Concrete of specified grade is prepared and filled in 3 cubical moulds of size 150x150x150 mm^3 or cylinders of 150mm diameter and 300mm high if size of aggregate is greater than 20mm. For size less than 20mm moulds of size 100*100*100 mm^3 are used. The concrete is placed in 3 equal layers of 50mm and compacted with tamping rod 35 times before the next layer in placed. The cubes are placed at standard room temperature i-e 27 $\pm 3^{\circ}$ for 24 hours ±30minutes which starts the moment water is added to the mixture while making concrete. The samples are then taken out and placed in water and are removed only before testing. The samples are placed in UTM and load is applied and gradually increased to

14Mpa per minute and continued till the sample is crushed and highest applied load just before failure is measured. The average of 3 samples is taken and compressive strength is obtained from the formula stated below

$$compressive\ strength\ f_{ck} \equiv \frac{P_{\max}}{A}$$

Where

f_{ck} is the compressive strength N/mm^2

P_{max} is the highest load before specimen is crushed(N)

A is area of x-section of the surface of cube under test(mm^2)

Figure 1.3 Cube under test in UTM

REBOUND HAMMER TEST

This test was developed by Schmidt in 1948 and is most commonly used non destructive test. This is a test of non destructive nature which is used to predict compressive strength. Since it is not possible to calculate compressive strength without destruction of the cubes therefore the strength is calculated indirectly by calibrated scale. The rebound hammer test is an easy test that takes less time than destructive test. The hammer is pulled against the specimen under test and the based on the strength of the wall under test the spring attached to rider along with guide scale is driven back which gives a number on the scale called rebound number. This test can be carried out at any angle but for each angle the results are different hence for every angle separate calibration is needed which is one of the drawbacks of this method.

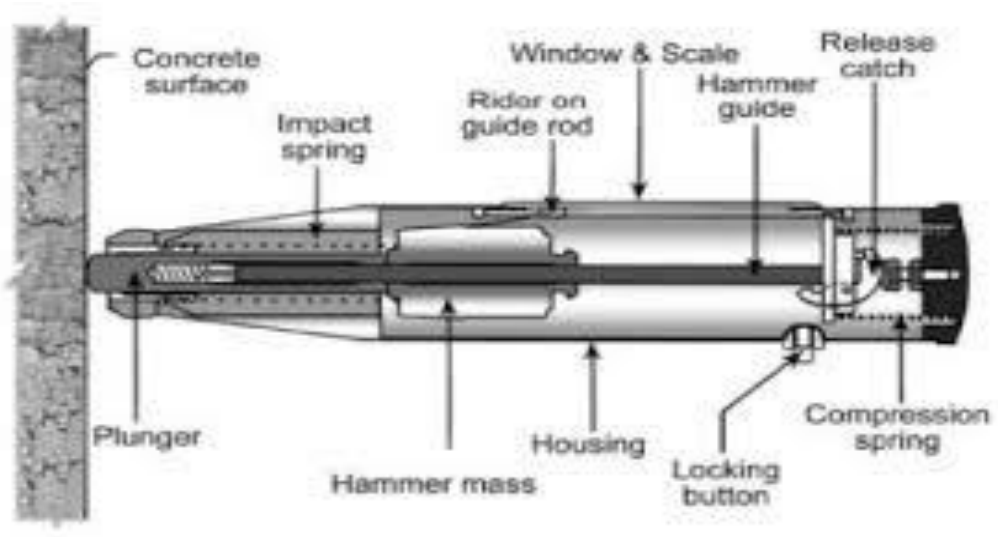

Figure 1.4 sectional view of rebound hammer test

The above experimental methods have following disadvantages:

Wastage of concrete.

Complex method for determining compressive strength.

Flaws can not be determined with accuracy.

1.3.2 ANALYTICAL METHODS

(a) Genetic Programming

•Genetic programming could be a bunch of directions and a wellness procedure to decide how efficiently a machine has played out a specific undertaking.

•It maybe a procedure utilized to enhance occupants of PC program in a line with a reasonabe site controlled by a program's capacity to complete prearranged computational condition.

(b) BPNN (Back Propagation Neural Network)

•

To defeat the confinement of recognition Rumelhart et al. in the year 1986 had portrayed anot her managed learning framework known as Back Engendering Neural Network(BPNN).

• BPNN(Back propogation neural systems) is an Artifical neural framework (ANN) based ground breaking method which is utilized for location of the interruption action. Fundamental part of BPNN might be a neuron, which stores and procedures the information. Part begins wit h organic model of neuron,trailed by computational demonstrate of neuron
which begins from normal model.

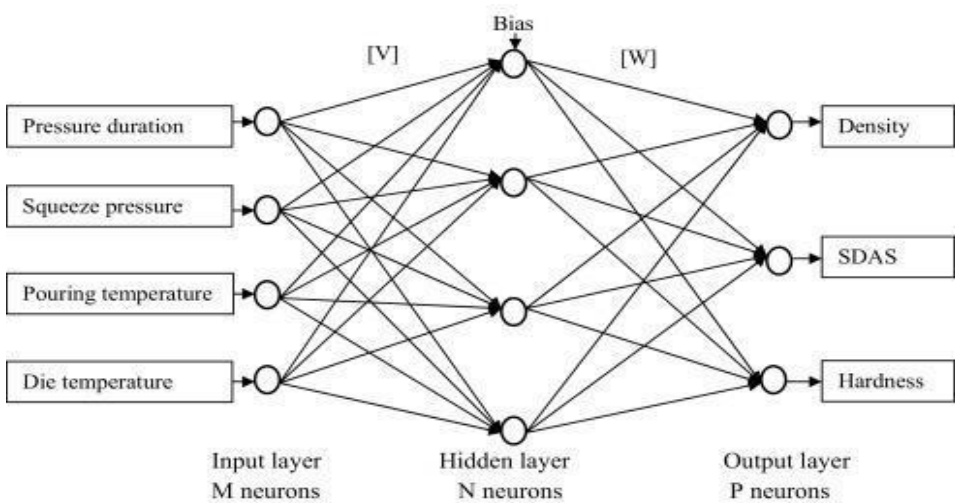

Figure 1.5 Structure of BPNN

Advantages of BPNN

- BPNN requires less labour work.
- BPNN takes less time in calculation.
- BPNN gives us the approx.(nearest value) result of given input.
- BPNN(Back propagation neural networks) is an Artificial neural network (ANN) based astonishing strategy that is utilized for identification of the interruption movement.
- It overcome the limitation of perception by another administered learning methodology referred as Back Propagation Neural Network(BPNN).

CHAPTER 2

LITERATURE REVIEW

INTRODUCTION

In this chapter various literatures on the impact of flyash partial replacement on compressive strength of concrete and machine learning techniques for solving problems in civil engineering have been surveyed, studied and following facts are reported briefly.

Compressive strength

Hwang et al. (1998) analyzed the impact on the compressive strength of concrete due to replacement of fine-aggregate by flyash. It was found out that strength and carbonation rate in concrete with water cement ratios of 0.3, 0.4 and 0.5. increased when fine aggregate was substituted by fly ash upto 1/4th and 1/2 by weight.

Siddique (2003) determined that with increase in flyash replacing fine aggregate compression strength in concrete increases upto a certain limit only after which it goes on decreasing. Further when fine aggregate was replaced by 50% compression strength increased upto 51% for 28 days and 67.1% for 365 days.

Alvin Harison et al. (2014) researched the increase and decrease of strength of concrete with change in percentage of amount of fly ash for 1 week, 4 week and 8 weeks strength. They found that by using flyash the 1 week strength was lesser than unsubstituted concrete but the strength went on increasing after 4 weeks. Upto 30% the strength increased fairly and decreased beyond that. The increase was more prominent 20% substitution..

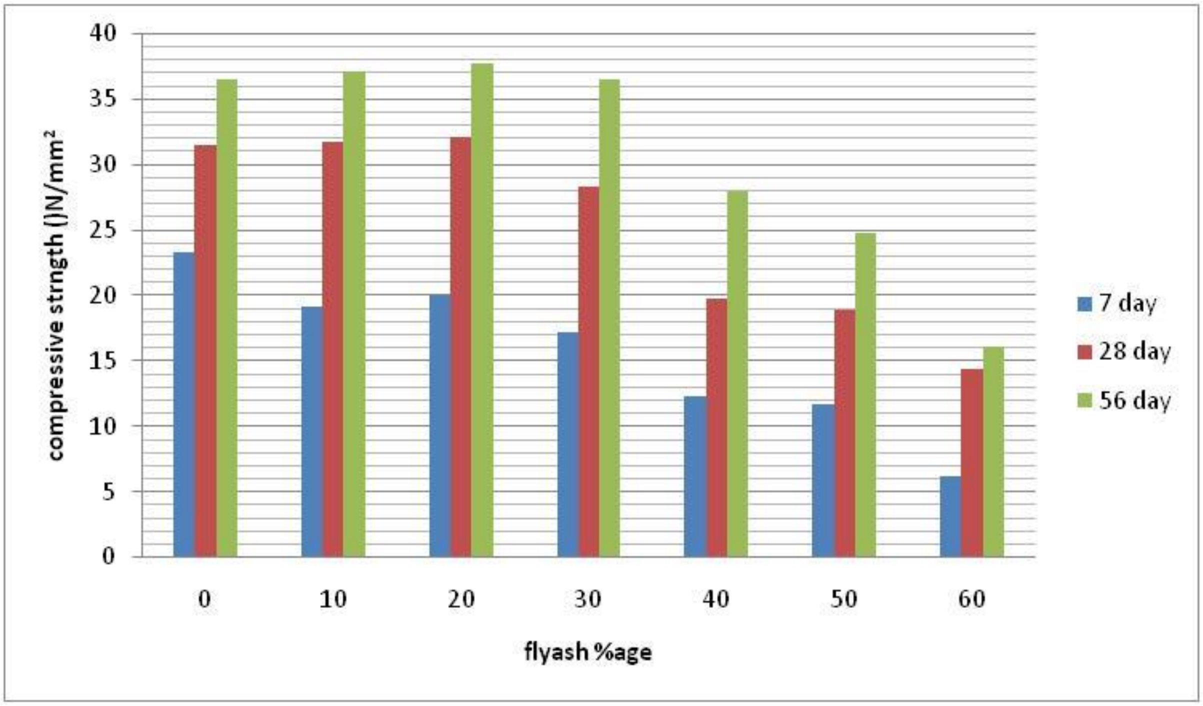

figure 2.1 compressive strength of flyash concrete Alvin Harrison et al.

Ashish Kumer Saha(2018) used class F flyash as partial replacement for binder concrete. Concrete mixed in controlled conditions and curing carried out in lime saturated water it was found out that the strength for 28 days reduced with increase in the flyash percentage but increased gradually beyond 28 days. Also the rate of hydration and subsequently drying shrinkage was reduced as compared to ordinary concrete. Besides these it was found out the density of binder matrix was increased due to pozzolanic action

Machine learning technique

Nurcihan Ceryan(2014) used prediction models SVM(support vector machine) and RVM(relevant vector machine) and compared their results with ANN to predict the Uniaxial Compressive Strength of volcanic rocks which normally is determined by tests which are expensive, destructive and time consuming in nature. The input parameters taken were porosity and P-durability. The above mentioned methods were successful as compared to ANN in areas of statistical performance criterion for training and testing data which are R^2 , adj. R^2, PI, VAF, RMSE, WMAPE. It was found that ANN produced very less accurate results and SVM, RVM performed with a great accuracy. These results are a way forward in use of prediction models for determination of UCS of volcanic rocks in quick time without involving physical tests and destructive tests.

Vinay chandwani et al(2015) hybridized two main techniques of artificial intelligence which are ANN(artificial neural networks) and GA(Genetic Algorithm) for modeling the slump of Ready Mix Concrete(RMC) based of six input parameters i-e cement, sand, coarse aggregate, flyash, admixtures and water cement ratio. The results of these hybrid techniques was compared with BPNN(back propagation neural network) model which is a subset of ANN. The accuracy of this hybrid model was very high and it can be used to forecast slump for a given mixed-design in short span without the need of performing different test with diverse design blend proportions.

Yeh (1998) used a modified BPNN for forecasting compression strength of concrete and used 7 input parameters viz water binder ratio, cement, fine aggregate, coarse aggregate, grain size, and testing age. Logarithmic neurons and exponent neurons were added as input and output layer in BPNN. The accuracy in prediction of BPNN was checked in modeling compressive strength and the results showed that the logarithmic neurons and exponent neurons improved the accuracy in developing the compressive strength model.

SZ Khan et al(2015) used Functional Neural Networks for estimating the residual strength of clay. They used the existing available data for predicting the strength using FN and compared the results with Support Vector Machine (SVM) and ANN on the basis of statistical parameters like Co-relation factor, Nashsutcliff coefficient of efficiency(E), absolute average error, Maximum average error, and Root Mean Square Error(RMSE).based on the result of comparison of these parameters it was found that FNN was a better prediction model for the data. However valves of E and R were found to be less than SVM. From this research a prediction equation was developed for future use in this field.

CHAPTER-3

METHODOLOGY

3.1 GENERAL

This part comprises of technical details of the utilized machine learning methods to predict the compressive strength of concrete with flyash. The following figure is a flowchart which briefs the technical steps required to achieve the objective.

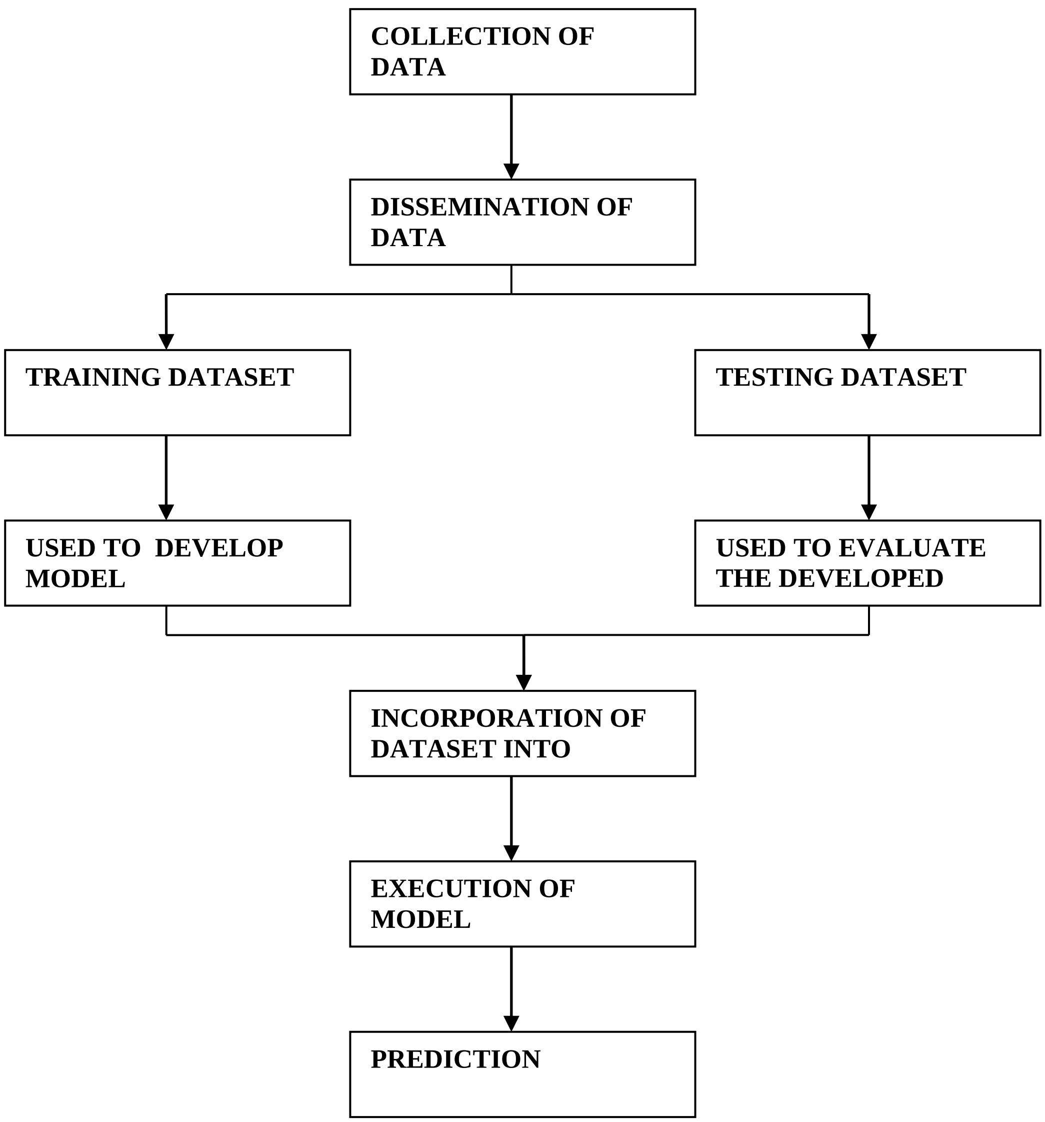

Figure 3.1: Methodology for the adopted technique.

Brief description of methodology flow chart:

1. First the data is collected and it is given as input. There are 6 input parameters here viz cement, water content, coarse aggregate, fine aggregate, flyash and water cement ratio.
2. Segregation of data. The data is randomly segregated into 70% and 30% as there is no thumb rule for it.
3. The 70% segregated data is used as training dataset to construct the model
4. The 30% segregated data is used as testing dataset to evaluate the datasheet.
5. Both the training and testing data is incorporated into the AI model.
6. Based on the inputs used the compressive strength can be predicted by the used model.
7. Statistical parameters like R, R^2, RMSE, WAP, VAF, PI, NMBE%, NS, RSR are used to justify the model.

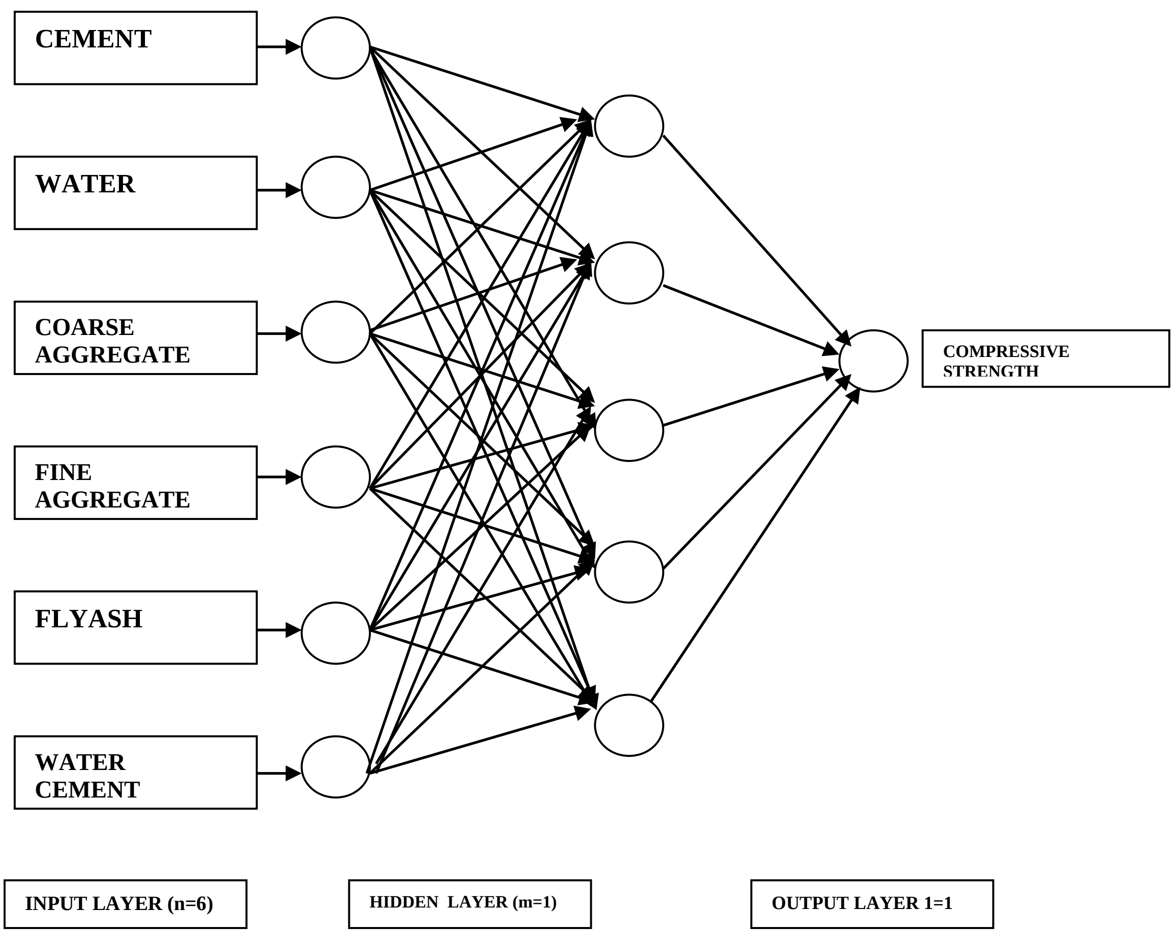

Figure 3.2: Typical BPNN architecture

In the above figure, totally six inputs are considered for accomplishing the target of compressive strength prediction for 91 days. The next layer is the unrevealed layer where the real work of this model held which was boosted by activation functions.

Back Propagation: Back propagation neural network is the subset of artificial neural networks to compute a gradient that's needed within the calculation of the weights to be utilized in the network. Simply BP refers to the "the backward propagation of errors," because if flaws are detected in the outcome it is disseminated behind beyond the network layers. It's very typically accustomed to practice the deep neural networks, a term bearing on neural networks with quite one hidden layer.

BPNN has the necessity of using the loss function with the allusion of the loss function to the output neuron to be revealed and it does not imply the required target value. It has the cause that the BPNN is to be for the supervised learning model for the generalization. However BPNN is also utilized in some unsupervised networks like auto-encoders.

Back propagation neural network is additionally happened according to the rule of delta to the multi pronged layered feed forward networks which is used to the chain norms for the individual layers. BPNN almost associated with the Gauss–Newton algorithm and is an element of constant investigates for the rear propagations. The weight associated with the function which can be activated by the neurons for stimulating the each and every neuron for its vectorizations.

The BPNN could be a multi layered feed forward neural network and it is too distant which was utilized more extensively. It's also reviewed the global way of induce the activation function from the bias to the précised neuron for the succinct libraries and implementing the matrix functions. BPNN operates by getting closer of the non linear kinship among the input and outcome by stimulating the internal values. In addition, the generalized input data for the cost function and its quadratic cost and the single training samples for the weights and bias. The Back Propagation Neural Network has two platforms as training and testing dataset. In the course of the training the network nurtured with the compiled input data and the respective output of the nurtured inputs.

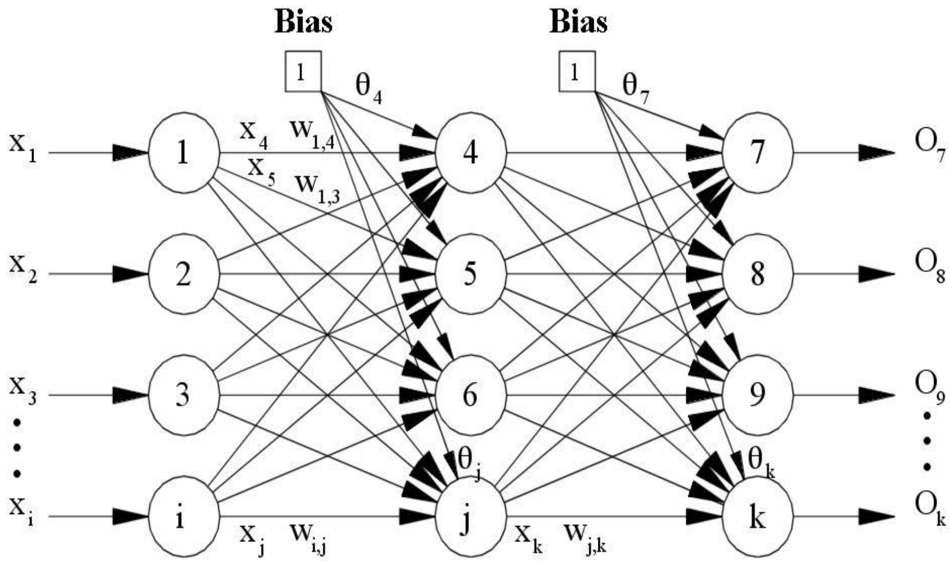

Figure 3.3 Topology of backpropagation.

The above figure shows the topology of the Back propagation neural network which comprises of input layers, hidden layers and the output layers along with the bias and the activation function. The execution of the BPNN involves in the static mapping of the input to the issues of the bias for the feed forward network which ensembles the recognition of patterns. In the recurrent propagation the flaws are determined and propagated in the rear end. The sensitivity of the noisy data can be considered as the con of this adapted method; however it can able to simplify the network pattern by diffusing the weighted links which has the least effect on the practiced network. The partial derivatives of the cost function calculate the intermediate quantity which is considered as the error from the earlier neuron in order to execute the propagations from the backward. These derived cost functions will lead the neurons to determine the error from the layered neuron so that the output by the activation function makes the each layer under propagation. There are four fundamental equations for the BPNN which are errors, gradients of the cost function, performances and the number of iterations. The working methodology of the back propagation totally depends on the input data. The second neuron determines the rate at which the activation function is changing. In case of quadratic cost the vector which has the partial derivatives as expressing the rate of variations of variables with respect to the activation function.

To check how well our machine learning model learns and categorizes the input data we have underfitting data and overfitting data to understand the accuracy of our model.

Underfitting data

A statistical model is said to have underfitting if it can not capture the underlying trend of the data. It is synonymous to trying to fit in a undersized garment. It destroys the accuracy of the model and signifies that the model is not doing justice to the input data. Underfitting often happens when the available input data is less because the main principle of machine learning is more the data higher is the accuracy.

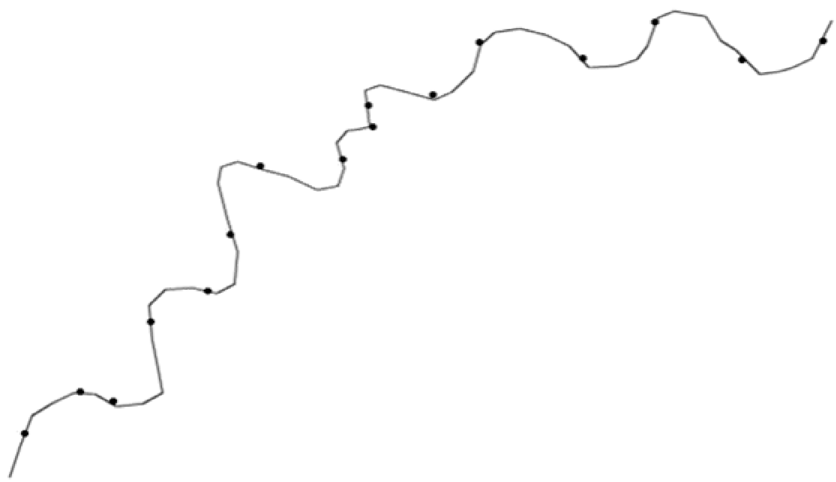

Figure.3.4 Under-fitting data.

Overfitting data

A statistical model is said to be overfitted when the input data for training is very high similar to fitting in an oversized garment. It happens when the data entered in the model is very high. When the model is trained with abundant data, it starts learning from the noise and incorrect data entries thus reducing its accuracy and building unrealistic model

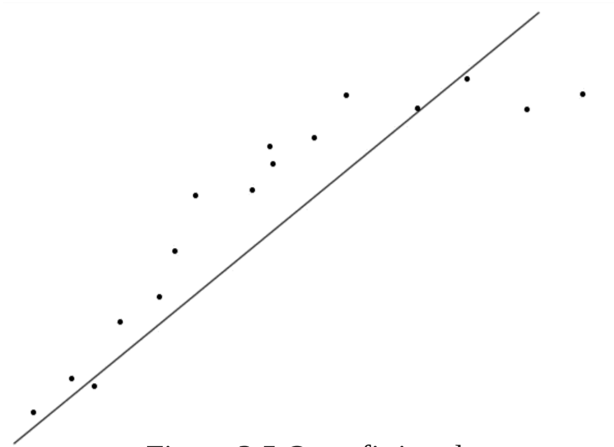

Figure.3.5 Over-fitting data.

Good fit

The statistical model is said to be good fit on the data if the model predicts results with 0 error. Although it is practically impossible to have 0 error but slightly less around 98-99% accuracy is deemed as good fit

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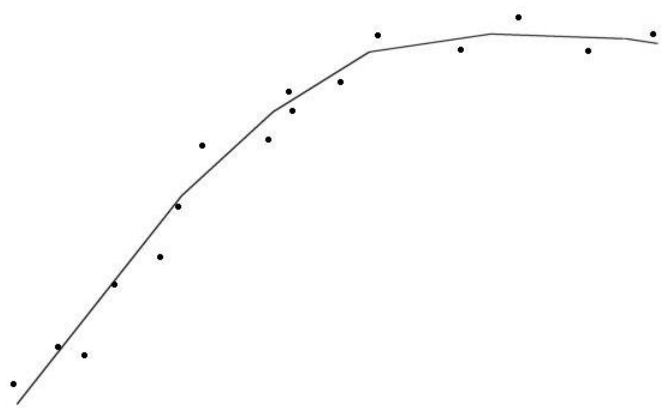

Figure 3.6 Good fit of the data

The basic step is it does the random initialization of the model and it identifies the point of initialization through various iterative learning and it attains the pseudo models. In the upcoming step, it does initializing the developing model at any random input in the event of checking the performance. In a spot, the real output of the arbitrarily initialized neural network and in another spot, the required outcome was learnt from the machine. A supervised neural network, at the best and simplest abstract representation, may be presented as a recorder with 2 methods learn and predict as following:

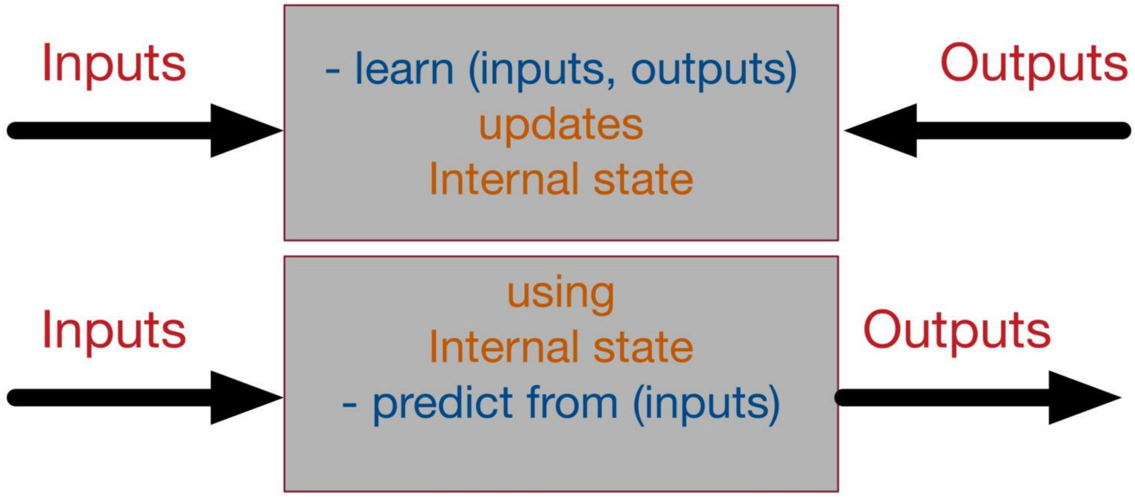

Figure.3.7 Neural Network as a black box.

FNN (Functional Neural Network)

Functional networks (FNs) blend the domain knowledge for determining the pattern of the networks, data and the unrevealed neuron function. FNN has the potential to fill the gap between the single and multi layered neural network. The elements of the input structure will be expanded as the each input data. Then the widened inputs were nurtured into the single layer neural network and from that the required output were derived. The collection of functions is made compiled for the enlargement of the specified function for the output from the older neuron to be as the input for the neuron. The dimension of the function can be inflated by using appropriation function. Relying upon the complexity of the problem the total number of layer and the count in neurons will change. During the widening of the counts of layers and neurons the training model becomes more laborious. Consequently, the various algorithms were dedicated to fail, however the FNN methods to derive the single layer neuron. The bias action used here for inducing the activation could be of various; however it can found out the train model which could be probably cannot be as per our expectation.

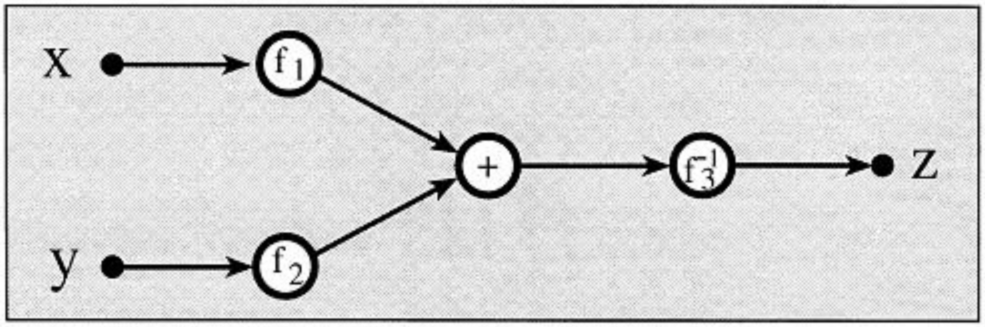

Figure 3. Typical view of FNN.

3.2 DATASET

The dataset used for determining the compressive strength of concrete with flyash was obtained from various research works- from PK Mehta et al.(1982), Ravina et al.(1988), L. Lam et al.(1998), Cengiz Duran Atiş(2003), Liu M et al.(2011) and Palika et al. (2016). The dataset consists of 6 parameters cement, fine aggregate, coarse aggregate, water content and fly ash and water cement ratio.

In machine learning it is important to perform normalization on data. The need for normalization arises due to large difference in range of data which could affect the accuracy of the model. The primary aim is to reduce to numerical valves in data to a common scale with small difference in range of valves, however in machine learning dataset with small range of differences does not need to be normalized

The compressive strength is normalized between 0 and 1 because the valves have a different range. It is done without distorting the difference in range of valves. The formula for normalization is

$$\text{Normalized value} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \qquad (3.1)$$

where x is the data, x_{min} – is the lowest value and x_{max} is the uppermost value.

Table 3.2 Dataset of compressive strength of fly ash concrete after 91 days.

Cement	**Fine Aggregate**	**Coarse Aggregate**	**Fly ash (FA)**	**Water**	**W/CM ratio**	**Compressive strength (N/mm^2)**
kg/m^3	kg/m^3	kg/m^3	kg/m^3	Kg/m^3		91days

400	440	1080	60	180	0.45	52.2
425	416.5	1045.5	63.75	178.5	0.42	55.75
425	463.25	1139	63.75	191.25	0.45	52.69
425	544	1096.5	63.75	199.75	0.47	50.42
450	441	1102.5	67.5	189	0.42	56.51
450	513	1057.5	67.5	198	0.44	53.11
450	562.5	1143	67.5	211.5	0.47	51.07
475	498.75	1040.25	71.25	199.5	0.42	57.7
475	541.5	1168.5	71.25	209	0.44	53.79
425	463.25	656.6	63.75	191.25	0.45	53.39
425	544	1096.5	63.75	199.75	0.47	50.5
450	441	1102.5	67.5	189	0.42	57.17
450	513	1057.5	67.5	198	0.44	53.67
450	562.5	1143	67.5	211.5	0.47	51.62
450	616.5	1228.5	67.5	220.5	0.49	48.08
475	498.75	1040.25	71.25	199.5	0.42	58.19
475	565.25	1168.5	71.25	209	0.44	54.12
475	584.25	1192.25	71.25	218.5	0.46	52.1
425	505.75	862.75	63.75	199.75	0.47	50.5
450	481.5	837	67.5	198	0.44	53.62
450	526.5	900	67.5	211.5	0.47	51.42
450	580.5	837	67.5	220.5	0.49	47.3
450	625.5	891	67.5	229.5	0.51	46.11
475	451.25	798	71.25	199.5	0.42	57.82
475	503.5	874	71.25	209	0.44	54.38
475	555.75	817	71.25	218.5	0.46	52.39
475	598.5	869.25	71.25	228	0.48	48.55
120	600	1200	280	116	0.29	41.1
200	600	1200	200	120	0.3	79.9
296	729	1050	144	172	0.39	66.62

348.5	589	1132	61.5	174.25	0.5	62.6
307.5	576	1132	102.5	153.75	0.5	53.7
225.5	549	1132	184.5	112.75	0.5	54.1
184.5	536	1132	225.5	92.25	0.5	41.4
210	975	975	60	208	0.1	27.6
135	895	1165	70	160	0.77	13.6
135	895	1160	70	155	0.76	12.5
135	900	1170	70	155	0.76	17.9
135	900	1170	70	155	0.76	17.8
135	830	1180	140	150	0.55	19.9
135	830	1180	140	150	0.55	15.5
120	900	1165	90	155	0.76	11.2
120	895	1165	90	155	0.76	11.9
120	905	1180	90	155	0.74	16.6
120	905	1180	90	150	0.73	14.8
120	805	1180	180	140	0.47	16.6
120	805	1180	180	140	0.47	15.2
105	900	1170	105	155	0.76	10.3
105	900	1170	105	155	0.74	9.8
105	900	1180	105	155	0.74	14.6
105	900	1180	105	155	0.74	12.9

This dataset was randomly segregated into training and testing dataset after the normalization of values. The same dataset was utilized for developing both the BPNN and FNN models.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 RESULTS

The capability of the developed BPNN and FNN models can be assessed by Pearson's Coefficient of Correlation (R) and it computes the statistical relationship among the variables. The correlation between observed and the forecasted values was rely upon the value of R, however if the relationship is non-linear it may give biased results. It's a known fact, when R is close to unity, then the adopted predictive model is good. The following is the formula for computing the value of R.

$$R = \frac{\sum_{i=1}^{N}\left(M - \bar{M}\right)\left(F - \bar{F}\right)}{\sum_{i=1}^{N}\left(M - \bar{M}\right)^2 \sum_{i=1}^{N}\left(F - \bar{F}\right)^2} \tag{4.1}$$

Where M is the measured value and $\bar{M}$ is the mean of the measured value; F is the forecasted value and $\bar{F}$ is the average of the forecasted value; N is the total number of data utilized.

The adopted BPNN model provides the best result when number of training epochs at 27 and 2 hidden neurons. The epochs here refer to the iterations performed by the model to arrive at most accurate output. The duration of obtaining the optimum value is 1 seconds and number of training epochs at 27 and 2 hidden neurons. The training function used in this model is Tansig & Tansig. The following figures explain the training and testing performance of BPNN in forecasting the long-run compressive strength of fly ash concrete.

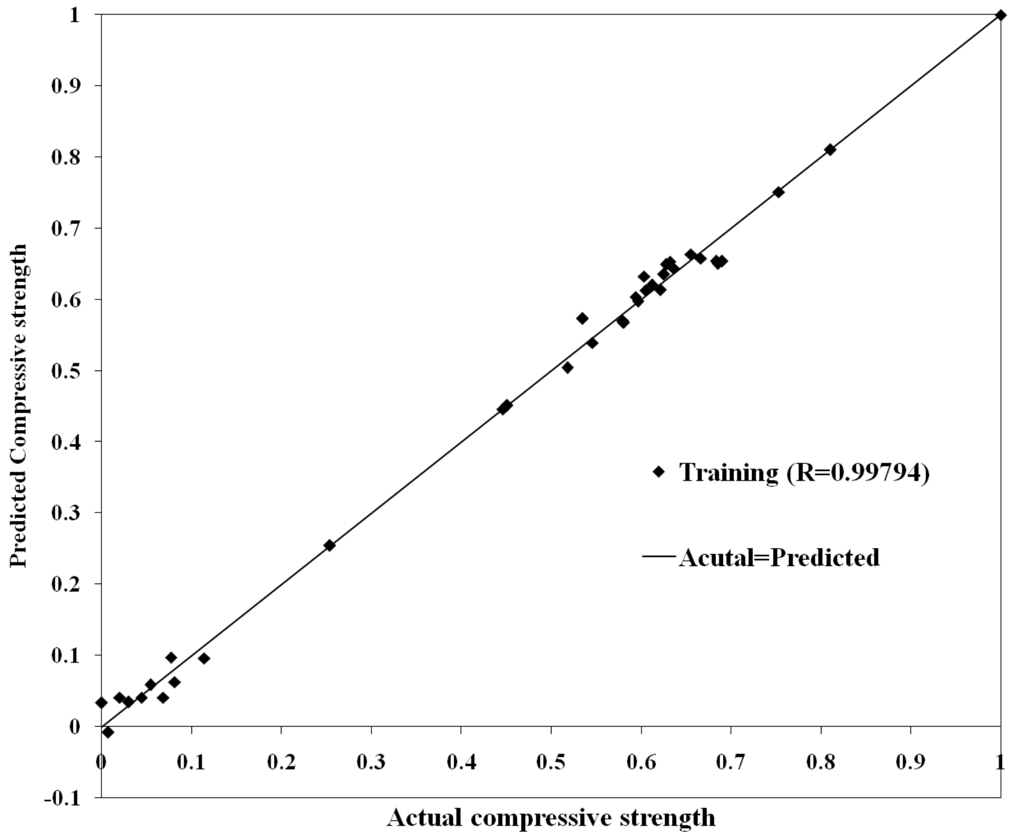

Figure 4.1: Training capacity of BPNN model

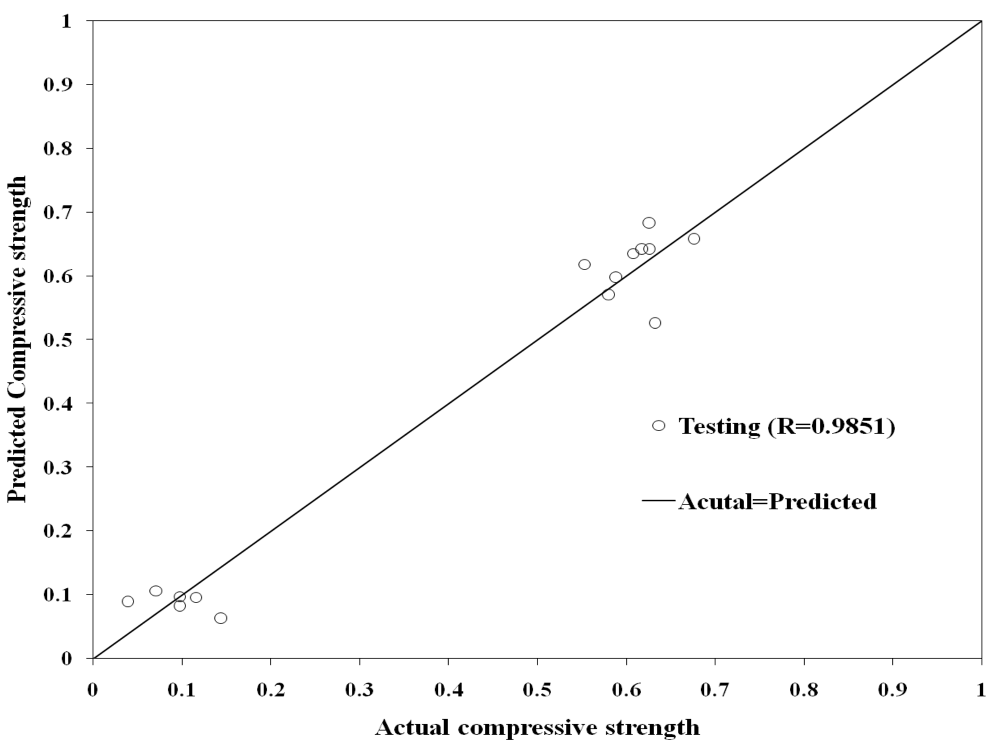

Figure 4.2: Testing capacity of BPNN model

The above figures 4.1 and 4.2 depict the potential of BPNN in foreseeing the mechanical property of concrete in which the co-efficient of co-relation R value is near to unity which depicts the potential of the developed model.

FNN model

The training function for FNN model is tanx. The below graphs show the relevance factor for this model in training data and testing data. Since the value of R is very close to unity it shows that FNN can be a good predicting model.

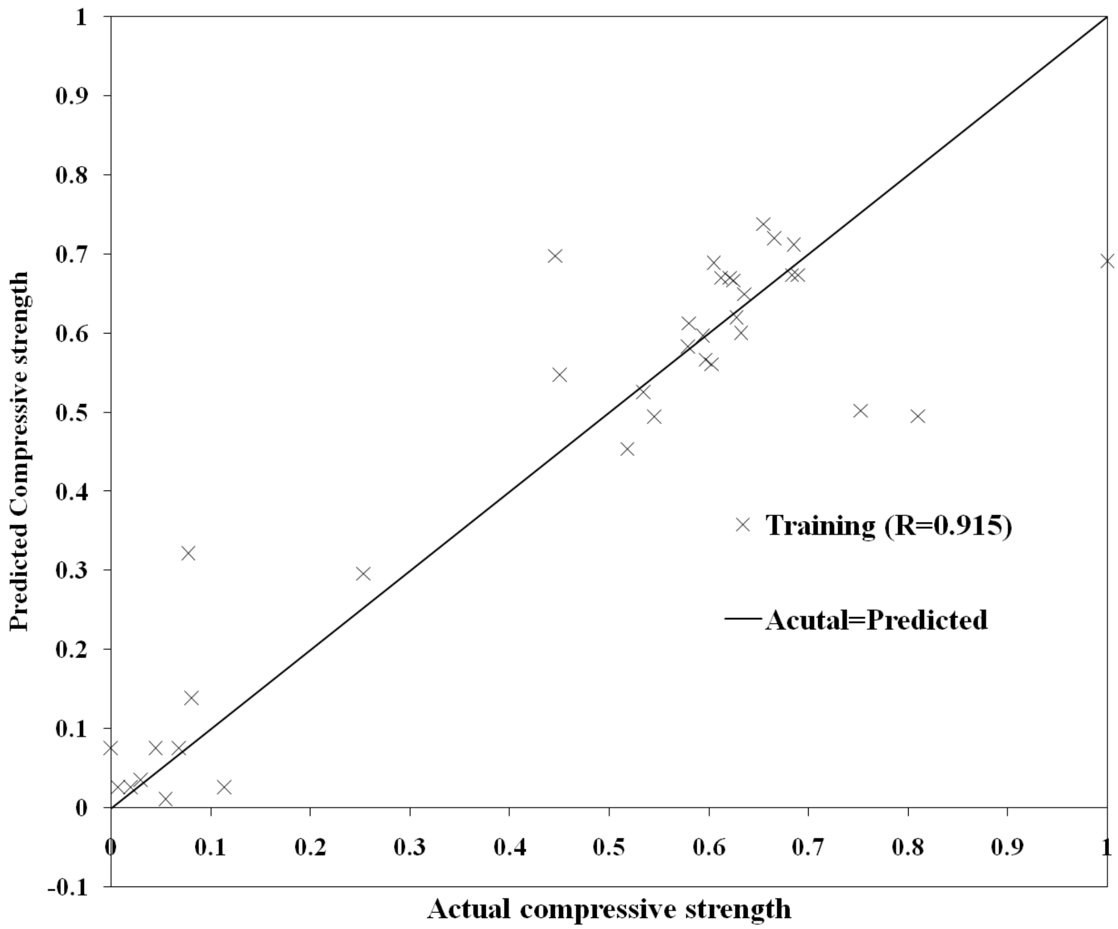

Figure 4.3: Training performance of FNN model

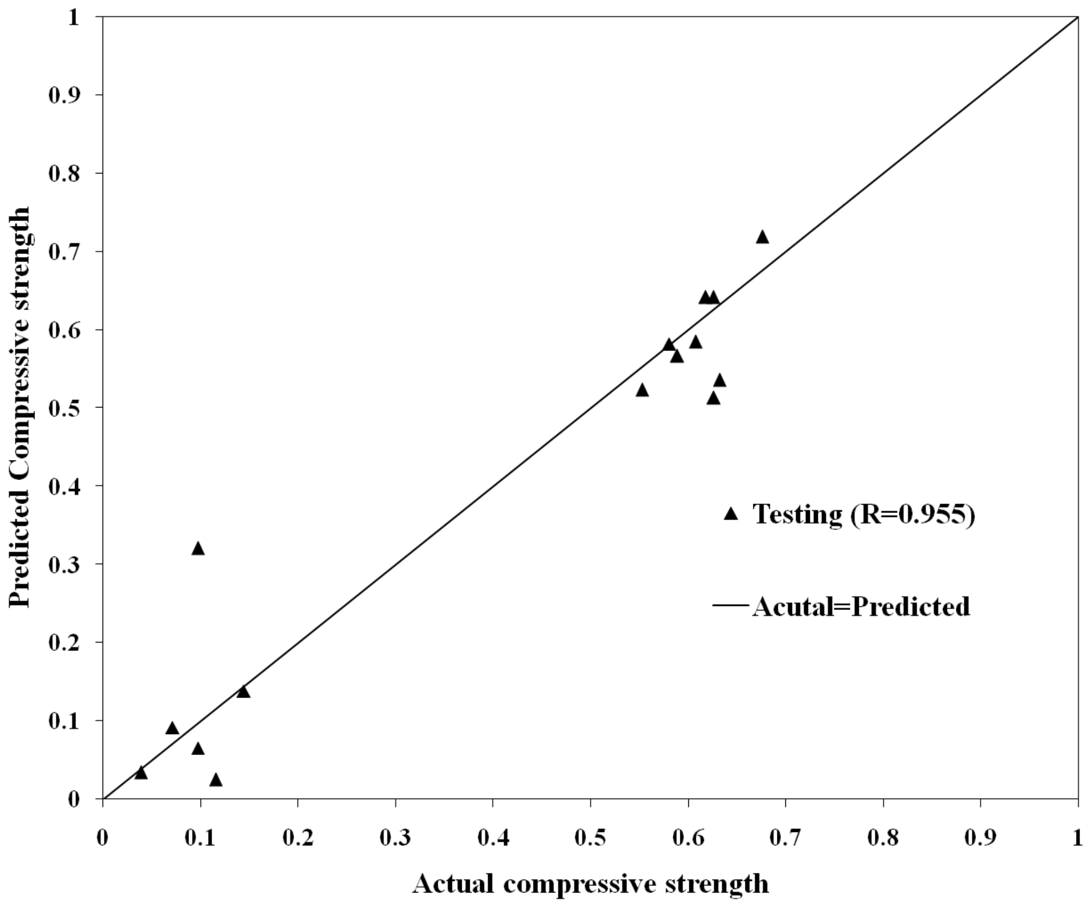

Figure 4.4: Testing performance of FNN model

To justify the BPNN and FNN model various other statistical parameters are computed including RMSE(Root Mean Square Error) (eq. 4.1), WMAPE(Weighted Mean Absolute Percentage Error)(eq. 4.2), Nash–Sutcliffe Co-effcient of efficiency(NS/E)(eq. 4.3), VAF(variance account factor)(eq. 4.4), NMBE(Normalized Mean Bias error)(eq. 4.5), RSR(standard deviation of measured data)(eq. 4.6), adj. R^2 (Eq. 4.7), and PI (eq 4.8)

RMSE matches with the target values and the estimated values and calculates the square root of the average residual error. If the valve of RMSE is low then model can be deemed as good predictive model. VAF gives the ratio of variance of error to the variance of actual data while NS gives an idea about the potential of the constructed BPNN and FNN model at invigorating the yield data from the average of actual data. RSR joins the advantages of mistake record insights and incorporates a scaling/standardization factor, with the goal that the subsequent measurement and revealed qualities can apply to different constituents (Chen, Xu, and Guo, 2012). The ideal estimation of RSR is zero. Subsequently a lower estimation of RSR demonstrates great forecast. NMBE measures the capacity of the model to foresee a worth which is arranged away from the mean worth. A positive NMBE shows over-expectation and a negative NMBE demonstrates under-forecast of the model (Srinivasulu and Jain, 2006). A consolidated utilization of the presentation measurements described above can give a fair gauge to expectation capacity of the neural system models.

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(T_{ai} - T_{pi}\right)^2} \tag{4.1}$$

$$WMAPE = \frac{\sum_{i=1}^{m}\left|\frac{T_{ai} - T_{pi}}{T_{ai}}\right| \times T_{ai}}{\sum_{i=1}^{m} T_{ai}} \tag{4.2}$$

$$NS = 1 - \frac{\sum_{i=1}^{m}\left(T_{ai} - T_{pi}\right)^2}{\sum_{i=1}^{m}\left(T_{ai} - \overline{T_{ai}}\right)^2} \tag{4.3}$$

$$VAF = 1 - \frac{\operatorname{var}\left(T_{ai} - T_{pi}\right)}{\operatorname{var} T_{ai}} \times 100 \tag{4.4}$$

$$NMBE\% = \frac{\frac{1}{m}\sum_{i=1}^{m}\left(T_{pi} - T_{ai}\right)}{\frac{1}{m}\sum_{i=1}^{m} T_{ai}} \times 100 \tag{4.5}$$

$$RSR = \frac{RMSE}{\sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(T_{ai} - \overline{T_{ai}}\right)}} \tag{4.6}$$

$$Adj.R = 1 - \frac{(m-1)}{(m-k-1)}\left(1 - R^2\right) \tag{4.7}$$

$$PI = adj.R^2 + 0.01VAF - RMSE \tag{4.8}$$

Where,

T_{ai} = actual value

T_{pi} = Predicted value

$\overline{T}_{ai}$ = mean of actual valves

m = Total no. Of datasets

k = no. of input parameters

The determined values of the statistical approaches for BPNN as well as FNN have been depicted in the table:

Table 4.5 Statistical Parameters for BPNN and FNN

Statistical Parameters	**BPNN**		**FNN**	
	Training	**Testing**	**Training**	**Testing**
RMSE	0.017765	0.046075	0.111695	0.075935
WMAPE	0.02784	0.088064	0.149962	0.122686
NS	0.995886	0.967589	0.837374	0.911969
VAF	99.58863	96.76663	83.73743	91.24646
R^2	0.995884	0.970422	0.837225	0.912025
Adj. R^2	0.995033	0.948239	0.803547	0.846044
PI	1.973155	1.869829	1.529227	1.682573
NMBE (%)	-0.01148	0.555844	0.000034	-1.40767
RSR	0.064138	0.18003	0.403269	0.2967

Briaud and Tucker (1988) emphasized that besides correlation coefficient (R) statistical criteria should also be used. The mean and standard deviation was also considered for evaluating the capability of the developed model (Abu-Farsakh and Titi, 2004; Das and Basudhar, 2006) The mean and standard deviation of predicted / target values serves as an crucial evidence of the exactness predictive techniques. An accurate model should have standard deviation to be 0 and mean value as 1.0. If value exceeds 1 it depicts over-prediction and vice versa is under-prediction.

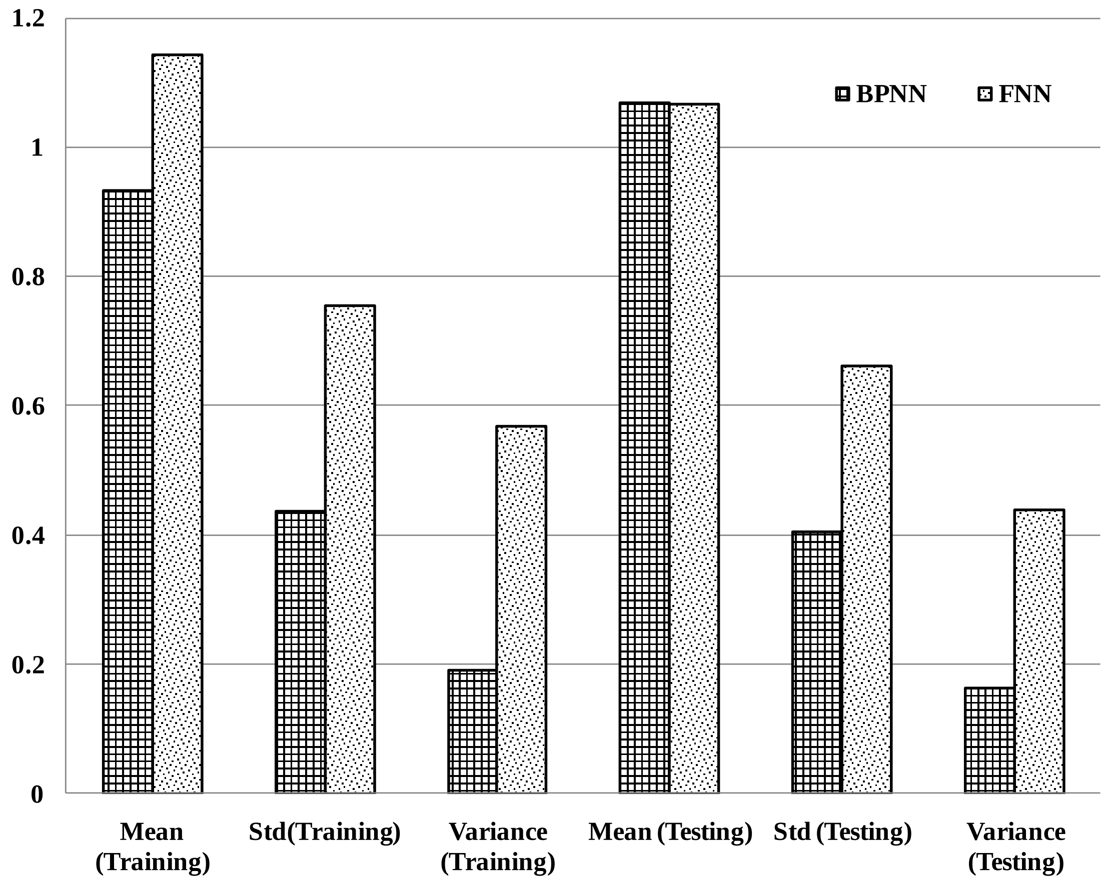

Figure 4.6 shows comparison of mean, standard deviation and variance of BPNN and FNN

There are other measures like cumulative dissemination and probability density function also considered for scrutinizing the models. If this dissemination is near to the unity, then it can be decided as the good model. The ratio of predicted value and the measured values are determined and its lognormal disseminations have to be computed. Those can be plotted in the following figures fig. 4.4 ,4.5, 4.6, 4.7.

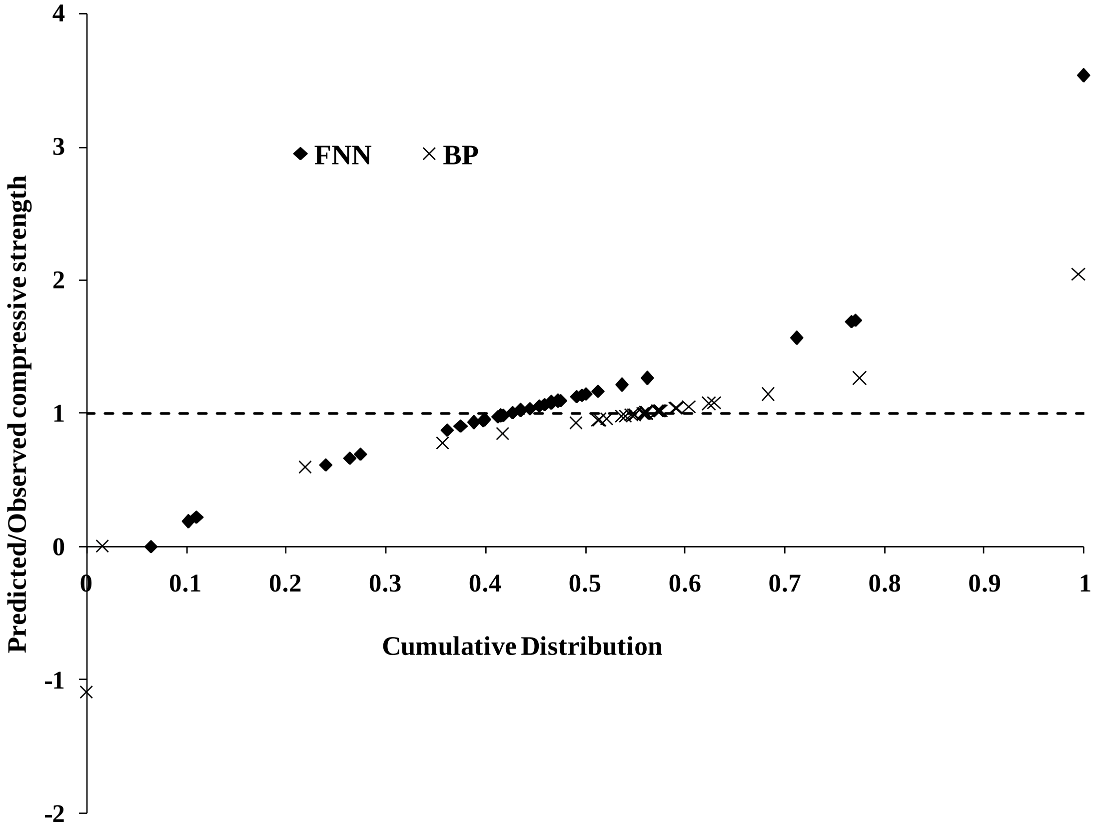

Figure 4.5 CDF plot of predicted vs observed compressive strength in training

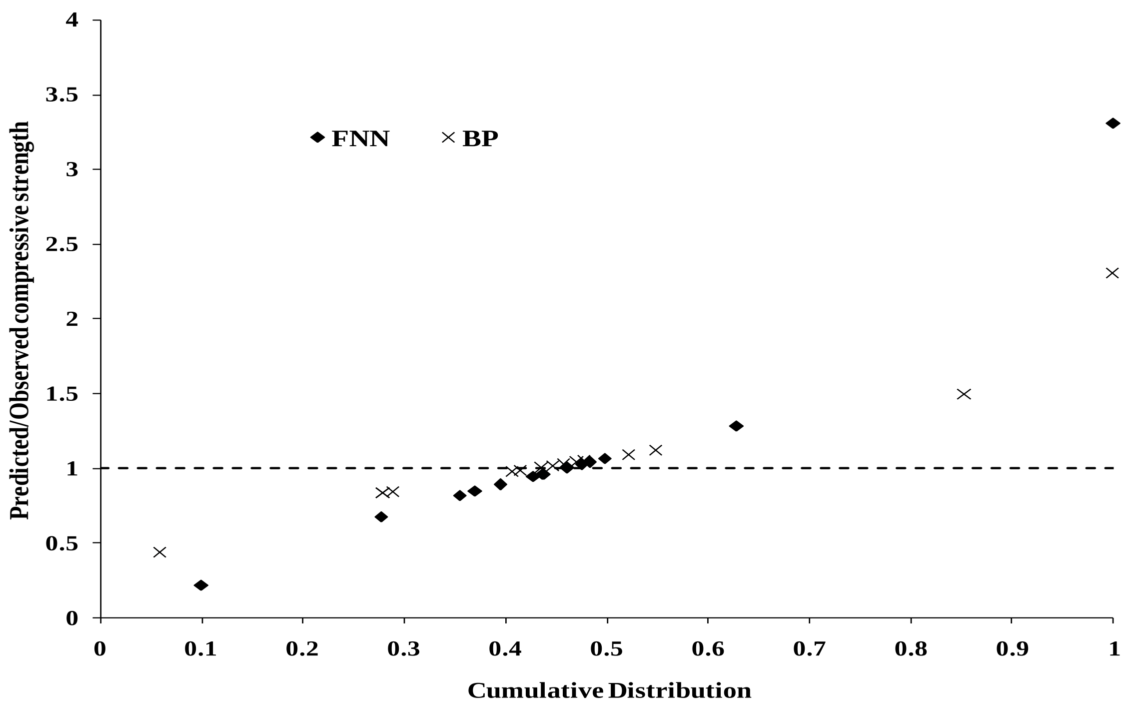

Figure 4.6 CDF plot of predicted vs observed compressive strength in testing

The above two figures 4.5 and 4.6 depicts the PDF for the developed models BPNN and FNN, and it is clear that most of the values fall nearby one. This also shows the potential of the developed models as accurate.

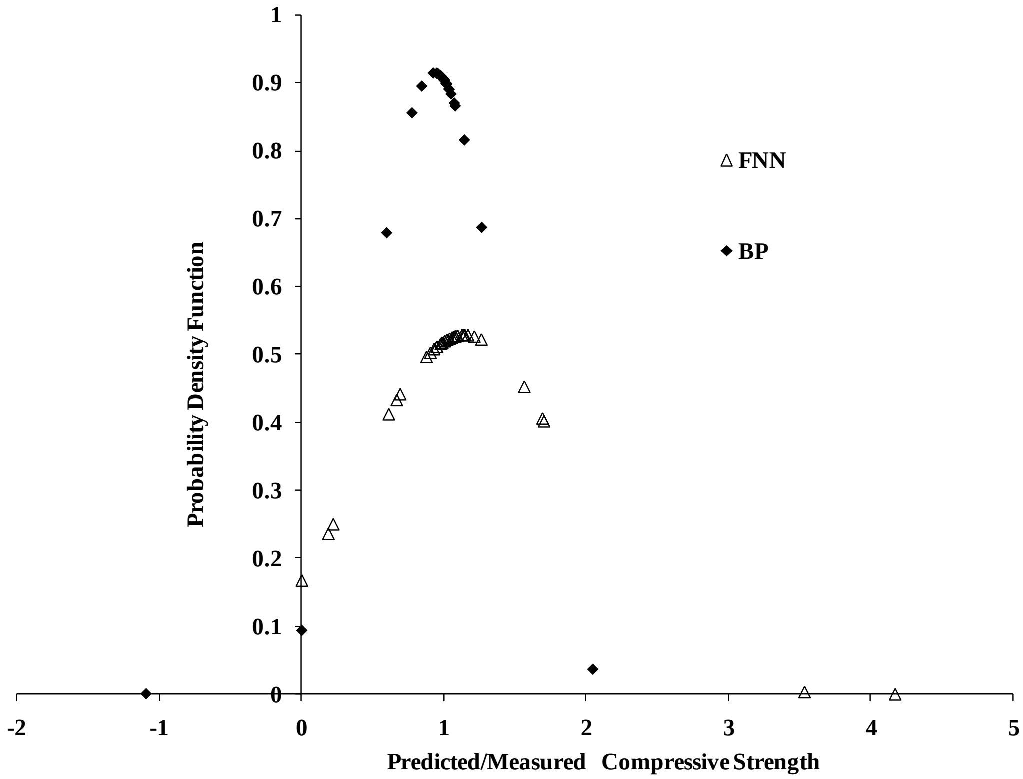

Fig 4.6 PDF plots of $f_{ck\ predicted} / f_{ck\ measured}$ for training

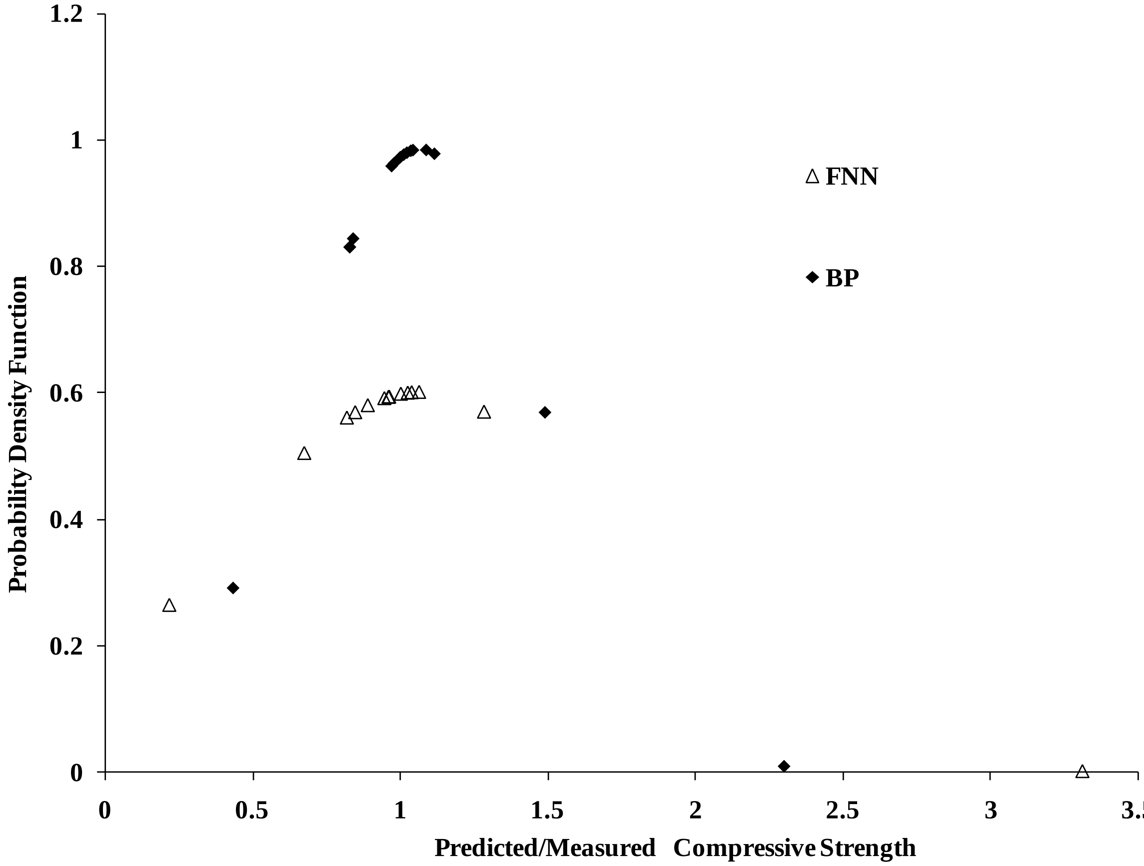

Fig 4.6 PDF plots of $f_{ck\ predicted}$ /$f_{ck\ measured}$ for testing

The above determined R values, statistical error calculations, Cumulative Distribution Function and Probability Density Function were determined and exposed in the form of tables and figures.

4.4 DENORMALIZED DATA

The results obtained from the machine learning techniques BPNN and FNN are in normalized form so denormalization is required to make it convenient to compare the results obtained. Following table shows the comparison of actual compressive strength with the predicted compressive strengths.

Fig.4.7 Comparison of denormalized compressive strength from BPNN FNN.

Cement	Fine Agg	Coarse Aggregate	Fly ash (FA)	Water	W/CM ratio	Measured compressive strength 91days	Predicted Compressive Strength for Machine Learning Models	
Kg/m^3	Kg/m^3	Kg/m^3	Kg/m^3	Kg/m^3		MPa	BPNN	FNN
340.2027	440	1080	60	179.9097	0.45	52.2	52.7713	58.04983
360.1351	416.5	1045.5	63.75	178.4069	0.42	55.75	56.31836	61.54782
360.1351	463.25	1139	63.75	191.1802	0.45	52.69	53.29004	56.78102
360.1351	544	1096.5	63.75	199.6957	0.47	50.42	49.757	50.5982
380.0676	441	1102.5	67.5	188.9261	0.42	56.51	55.91879	60.21592
400	565.25	1168.5	71.25	208.9626	0.44	54.12	55.56829	51.81794
400	584.25	1192.25	71.25	218.4799	0.46	52.1	54.12423	49.11208
400	498.75	1040.25	71.25	199.4453	0.42	57.7	55.63839	57.04039
400	541.5	1168.5	71.25	208.9626	0.44	53.79	55.30191	53.1919
360.1351	463.25	656.6	63.75	191.1802	0.45	53.39	52.82037	56.78102
380.0676	625.5	891	67.5	229.5	0.51	46.11	45.13741	41.61839
400	451.25	798	71.25	199.4453	0.42	57.82	55.365	59.65512
400	503.5	874	71.25	208.9626	0.44	54.38	54.93739	55.32995
380.0676	562.5	1143	67.5	211.4672	0.47	51.62	51.67073	49.53268
380.0676	616.5	1228.5	67.5	220.4836	0.49	48.08	47.59792	44.40136
400	498.75	1040.25	71.25	199.4453	0.42	58.19	55.63839	57.04039
180.7432	600	1200	200	119.8002	0.3	79.9	79.87196	58.22508
257.2838	729	1050	144	171.8951	0.39	66.62	66.58801	44.51352
360.1351	505.75	862.75	63.75	199.6957	0.47	50.5	49.56072	52.75728
380.0676	481.5	837	67.5	197.9425	0.44	53.62	54.32051	56.54969
380.0676	526.5	900	67.5	211.4672	0.47	51.42	52.11236	51.59362
380.0676	580.5	837	67.5	220.4836	0.49	47.3	49.95328	46.58147
168.3851	536	1132	225.5	91.99954	0.5	41.4	41.40809	48.10264
188.7162	975	975	60	207.9608	0.1	27.6	27.6054	30.58465
128.9189	895	1165	70	159.8732	0.77	13.6	13.89384	10.50801
105	900	1180	105	154.8641	0.74	14.6	12.66008	15.04348

105	900	1180	105	154.8641	0.74	12.9	12.66008	15.04348
116.9595	600	1200	280	115.7929	0.29	41.1	41.05058	58.73681
116.9595	900	1165	90	154.8641	0.76	11.2	12.66008	11.56652
116.9595	895	1165	90	154.8641	0.76	11.9	12.19742	12.20443
299.1419	589	1132	61.5	174.1492	0.5	62.6	62.43108	45.01123
116.9595	805	1180	180	139.8367	0.47	15.2	16.62073	32.31612
105	900	1170	105	154.8641	0.76	10.3	9.25322	11.56652
105	900	1170	105	154.8641	0.74	9.8	12.14835	15.04348
128.9189	900	1170	70	154.8641	0.76	17.8	16.53661	11.56652
128.9189	830	1180	140	149.8549	0.55	15.5	14.20929	19.50184
380.0676	513	1057.5	67.5	197.9425	0.44	53.11	54.78317	54.8042
380.0676	562.5	1143	67.5	211.4672	0.47	51.07	51.67073	49.53268
128.9189	895	1160	70	154.8641	0.76	12.5	16.01787	12.20443
128.9189	900	1170	70	154.8641	0.76	17.9	16.53661	11.56652
360.1351	544	1096.5	63.75	199.6957	0.47	50.5	49.757	50.5982
380.0676	441	1102.5	67.5	188.9261	0.42	57.17	55.91879	60.21592
380.0676	513	1057.5	67.5	197.9425	0.44	53.67	54.78317	54.8042
266.4527	576	1132	102.5	153.6118	0.5	53.7	57.6783	45.78233
201.0743	549	1132	184.5	112.537	0.5	54.1	46.65858	47.35958
400	555.75	817	71.25	218.4799	0.46	52.39	54.34855	50.78747
400	598.5	869.25	71.25	227.9973	0.48	48.55	53.14283	46.48333
128.9189	830	1180	140	149.8549	0.55	19.9	14.20929	19.50184
116.9595	905	1180	90	154.8641	0.74	16.6	15.53418	14.39155
116.9595	905	1180	90	149.8549	0.73	14.8	17.26565	16.22116
116.9595	805	1180	180	139.8367	0.47	16.6	16.62073	32.31612

CHAPTER 6

CONCLUSIONS

In this project, the nature inspired computational techniques have been adopted to determine the 91 day compressive strength. In this project the heuristic approach has been executed for figuring out the functions and design values. Back-propagation Neural Network (BPNN) as well as FNN training algorithm were framed and executed in MATLAB, proving their efficiency in determining the values of compressive strength. This can act as an assistance platform in order to benefit the engineering people to effortlessly estimate the technical values. This accuracy of our model proves that this methodology will nullify the elbow grease and minimize the time for the futuristic actions. The accessibility of the experimental data led to create a practicable tool for envisioning the compressive strength. But BPNN also has some drawbacks in which it takes some time for training and also the structure of BPNN is complex which do not provide any practical equations.

On the comparative analysis of BPNN and FNN techniques BPNN is more efficient and accurate as valve of R is 0.99794 for BPNN training and 0.9851 for testing as compared to 0.915 for training and 0.955 for testing in FNN. Higher the valve of co-efficient of co-relation (R) higher is the accuracy. Also the other parameters valves of RMSE, WMAPE, RSR are low for BPNN. In statistics, the value of co-efficient of determination, $R^2 > 0.8$, then it can be considered that the relation between the measured and the foreseen values of the adopted data. In the adopted models, the value of R^2 is greater than the ideal values; however BPNN has higher valve than the FNN model. For both techniques NMBE% is negative which indicates under-prediction but it is lesser for BPNN (-0.01%) Also the mean for BPNN model is closer to unity and Variance and standard deviation are closer to 0 than FNN model. In general dependent on the examination of the measurable parameters it very well may be inferred that BPNN may fill in as a solid prescient medium, for expectation of both experimental and on site data might give great and important express plan for some affable engineering applications.

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