Prediction of Durability and Mechanical Properties of Blended Cement Concrete Using Machine Learning Techniques

A PROJECT REPORT

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SUBMITTED BY

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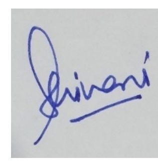
CONTENTS

CANDIDATE'S DECLARATION

I, Shivani Malhotra, Roll No 2K20/STE/20 of M.Tech (Structural Engineering), hereby declare that the project Dissertation titled "Prediction of Durability and Mechanical Properties of Blended Cement Concrete Using Machine Learning Techniques" which is submitted by me to the department of Civil Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirement for the award of the degree of Master of Technology, is original and not copied from any source without proper citation. The work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.



Place: Delhi

Date: Shivani Malhotra

CERTIFICATE

I hereby certify that the Project Dissertation titled "**Prediction of Durability and Mechanical Properties of Blended Cement Concrete Using Machine Learning Techniques**" which is submitted by **Shivani Malhotra** Roll No 2K20/STE/20, Department of Civil Engineering, Delhi Technological University, Delhi in partial fulfilment of the requirements for the award of **Master of Technology Degree** in **Civil Engineering** with specialization in Structural Engineering at Delhi Technological University, Delhi, is a record of the project work carried out by students under my supervision. To the best of my knowledge and based on student deceleration, the work has not been submitted to any other university/institute for the award of any degree or diploma.

Place: Delhi

Date: 30.5.2022

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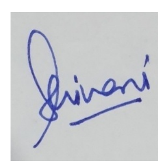

Shivani Malhotra

Abstract

Correlations have been important since the beginning; in some circumstances, they are required because it is challenging to quantity the value directly, and in others, they are beneficial since the results of other tests may be verified by correlations. Machine learning techniques like artificial neural networks (ANN) and support vector machines (SVM) were used to create prediction models to estimate the required parameters. Compressive strength and durability of blended cement concrete have been modelled in this research. The compressive strength of blended cement concrete was anticipated given its composition and other characteristics such as time, curing, and so on in the first problem.

In the second problem, the carb0nation depth of fly-ash c0ncrete has been predicted from input factors such as exposure-time, curing, relative humidity, temperature, CO2 concentration, fly-ash percentage, cement per cum and studied predictability of ensemble methods were f0und to be precise.

In last problem, prediction of sulphate resistance of blended cement concrete c0ntaining fly-ash and silica fume was done using ANN model.

The results of the performance was compared and revealed that the machine learning techniques are an effective tool for reducing uncertainty in concrete mix design projects. Soft computing may give new ideas and methodologies for reducing the risk for correlation inconsistency.

List of Figures

List of Tables

List of Symbols, abbreviation

AI	Artificial Intelligence
ANN	Artificial Neural Network
CART	Classification and regression trees
CS	Compressive Strength
DT	Decision Tree
HPC	High-performance concrete
ML	Machine Learning
RF	Random Forest
SVM	Support Vector Machines

CHAPTER 1

Introduction

Empirical connections are commonly employed in engineering to analyse specific engineering features of engineering materials. These connections are usually derived using statistical approaches using data from extensive laboratory or field testing. Artificial machine learning includes artificial neural netw0rks (ANN), supp0rt vect0r machines, decision trees, random forest, and other regression models. Even though the fundamental linkages are unclear or the physical understanding is challenging to describe, these methods train from the sets supplied to them in order to arrest the relational connections amongst the data. This differs from most standard experimental and analytical methods, which require previous knowledge of the attributes of the data associations. As a result, AI is highly adapted to modelling the complex behaviour of most engineering materials, which display extreme erraticism by their own nature. This modelling power, besides the capability to be trained from previous training/learning, has given AI an improvement over many conventional modelling methods, as there is no necessity to create hypothesis about the elementary rules which govern the question at that time.

Although several researchers have made efforts to modify and explain, ANN remains a "black box" technology with minimalism. Support vector machines is a new prediction model, the theories such as statistical learning theory and structural risk minimization has been used. While SVM is trained, it on restricted minimization, and punishes the errors to reduce the error margin. Since the SVM's the error function is a convex, it is more robust to generalisation than ANN.

Despite the fact that AI techniques have outperformed other traditional methods for modelling complicated engineering material performance, it has been criticised for its not being transparent, difficulty in understanding information abstraction process, and model ambiguity. To combat this, improvised AI techniques are being developed.

1.1 Need of Study

The properties of concrete is dependent on variable factors such as mix, curing, raw material etc. and testing of the concrete specimen is time consuming. The empirical formulas have been developed to design the mix of concrete. The requirement of producing high performance concrete or blended cement concrete necessities a simpler design approach. For this purpose, the scope of machine learning algorithms in evaluation of compressive strength and durability properties such as carbonation depth, sulphate resistance of concrete has been studied. To estimate particular technical qualities and materials, empirical relationships are employed extensively.

• Computational approaches learn from data samples so as to capture relational linkages amongst data, even if the underlying relations between variables are unknown or the physical relevance is unclear.

• The majority of classic experimental and statistical methods necessitate previous information of the nature of data interactions.

• Machine Learning techniques can be used to simulate the multifaceted performance of most engineering materials that are highly inconsistent.

1.2 Objectives

In spite of the great extent of study undertaken to evaluate the compressive strength and durability properties of concrete, the necessity for vigorous models and more varied datasets is the basis to develop dependable information on the results of the substitution of fly-ash, Rice-husk, or any blending material in cement. ML objectives at generating models which after training from definite training database can project precise estimation on the data which was never taken while creating a model, i.e., a model that can generalise. The use of blending materials will reduce cost of concrete used by the construction industry. It will also lead to the use of industrial waste in production which will not only reduce cost of disposal of waste but also generate revenue from the waste.

Consequently, the objects of this thesis are drawn below:

- To apply various machine learning methods like ANN, SVM, decision trees, random forest, and other regression models in parametric estimation of engineering problems.
- To do an investigation of prior study/research on the use of ML approaches to forecast the carbonation depth of original concrete technology accessible in the open research works. Consequently, define the benefits and shortcomings of the all the algos used for analysis and their attained accuracy is summarized, emphasizing their contributions to the building of mainstream concrete mixtures. Thereafter, model carbonation depth of concrete containing fly-ash and slag as an admixture.
- To make a huge and representative dataset to forecast the compressive strength of blended cement concrete, safeguarding that the ML models produced thereafter can generalise the fundamental rules of the compressive strength of blended cement concrete. Thereafter, model for compressive strength of blended cement concrete
- To make a machine learning model to forecast of the carbonation depth of blended cement concrete taking into consideration the increasing acknowledgement that the durability properties of concrete are altered by the substitution of blending materials and comparison of the carbonation-depth ML model to prior theoretic models and experimental results which were based on experimentation.

1.3 Methodology for Machine-Learning

The analysis of the mechanical & durability properties of blended cement concrete was done in this project. The difficulties of the vastly non-linear relation between the properties of concrete and its mix components is tackled using ML models. The observations of the this dissertation includes:
1. An previous research of the Machine Learning applications to forecast the compressive strength of concrete was reviewed, taking into consideration that prior research has analysed wider applications of Machine Learning methods in material engineering.

2. Created huge datasets so as to evaluate the compressive strength of concrete with admixture using prediction model, thus warranting the generalisation capacity of the models established in this research. Previous research works have used smaller database which may compromise the generalisation ability of the final model.
3. Machine Learning methods are applied to predict the carbonation depth of concrete with blended cement.

Three methods were applied to make predictions as given below:

(i) Artificial Neural Network (ANN)
(ii) Ensemble Machine Learning
(iii) Regression Machine Learning Algorithm

Artificial Neural Network (ANN)

A widely used function approximator which is quick to measure novel records. Artificial Intelligence (Al) approaches such as Artificial Neural Networks (ANNs) has got a lot of interest in recent times. In principle, ANN is an information technology that learns from familiarity and generalises from earlier examples to produce new output-target variable by extracting necessary features from input-variables in a arrangement of variable interconnected weights among the processing elements, similar to the human brain and nervous system. When the problem involves qualitative or complicated quantifiable reasoning, traditional statistical and mathematical approaches are insufficient, the factors are extremely interrelated, and the data is innately noisy, inadequate, or error prone, ANNs are more powerful than traditional methods (Bailey and Thompson, 1990). Figure 1.1 depicts segments of AI and ML.

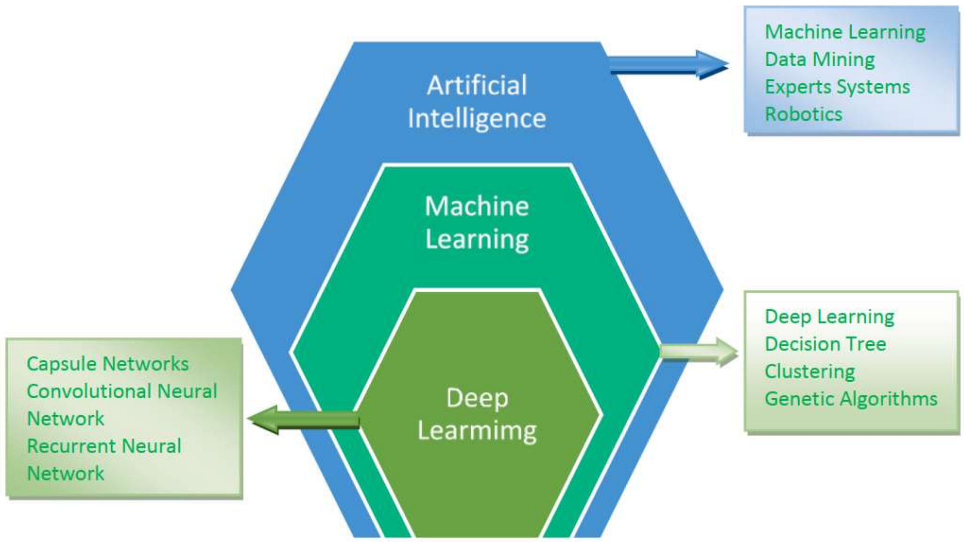

Figure 1.1 Depicting the subparts of the artificial intelligence.

ANNs provide numerous benefits over outdated modelling methods. To begin with, ANNs are data determined self-adaptive approaches that may arrest refined functional links amongst the dataset's records even if the essential interactions are unidentified or difficult to express, as contrast to traditional mathematical and statistical methods. Second, ANNs are more accurate at capturing complicated nonlinear relationships (Rumelhart et al. 1994). Third, ANNs have a significant advantage over mathematical and statistical models in terms of adaptableness. ANN system can modify their weights aut0matically to augment their behaviour. Classificati0n, clustering, vect0r quantification, pattern ass0ciation, functi0n approximati0n, contr0l, optimizati0n, and search have all been done with neural networks.

An artificial neural network (Mehrotra et al., 1997) is a c0mputational m0del with 4 parameters: kind of neur0ns, connecti0n architecture, learning alg0rithm, and recall alg0rithm.

ANNs are artificial neural networks that replicate the human nervous system. Processing components, that is an artificial m0del of a human neur0n, interc0nnections, which act similarly to the ax0n, and synapse, which are the juncti0ns where an interconnecti0n meets a neuron, are the three essential components. An input pattern is created by signals received from other neurons. This input pattern encourages the neuron to become more active. If there is enough activity, the neuron produces a single output signal, which is sent to additional neurons via a connection. Figure 1.2 shows structure of a neuron.

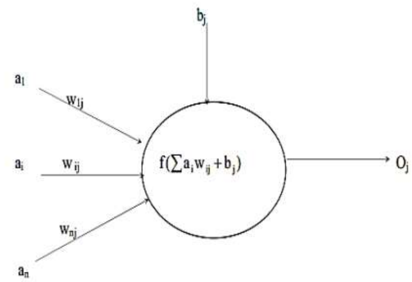

Figure 1.2 Pictorial representation of neuron

To make good ANN mode, it necessities determination of independent input variables, such that the weighted input variables produce one or more dependent target variables. The performance of ANN network is dependent on data pre-processing and hyperparameter selection. In the last step, the model is validated with the set of examples which it has never seen before. The series of steps followed to ANN prediction model is described in Figure 1.3.

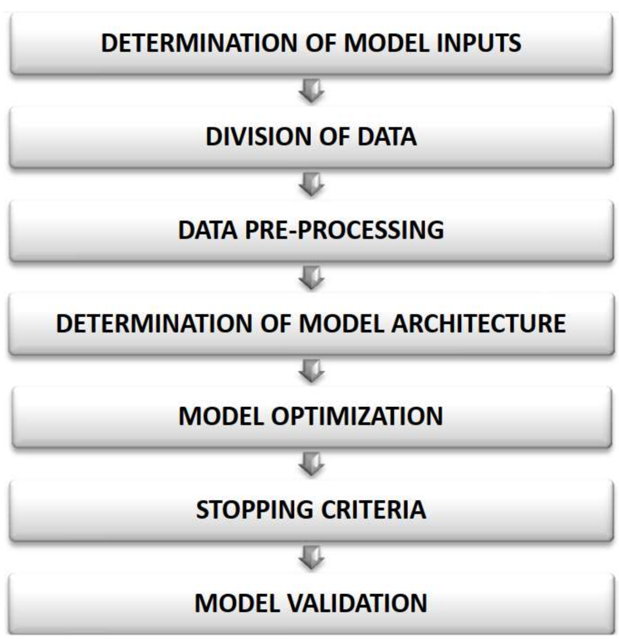

Figure 1.3 Flow chart describing ANN model

- **Ensemble Machine Learning**

What exactly are ensemble methods? The ensemble ML techniques are a category of ML technique that incorporates various base models to create a single best-fit predictive model.

Categories of Ensemble Methods:

1) Bootstrap AGGregating, or BAGGing. The term BAGGing originates from the point that it agregates Bootstrapping and Aggregation into a lone ensemble model. Numerous bootstrapped set of samples are taken form a trial data for Decision Tree (DT). DT is made using subsamples after bootstrapping. An algorithm is utilised to aggregate over the DT results into the most competent forecaster once each subsample DT is made. The Figure 1.4 below will clarify the process of aggregation.

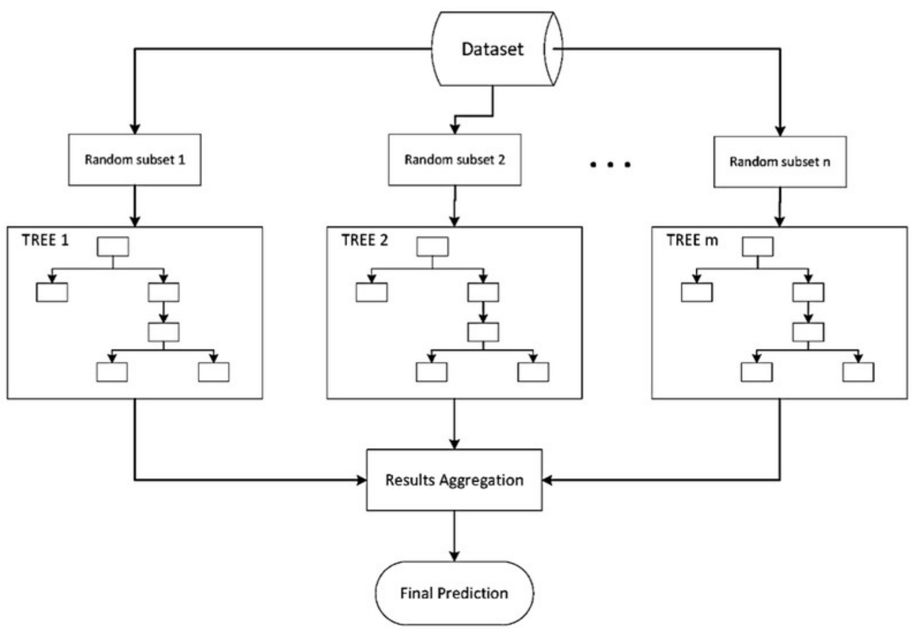

Figure 1.4 Flow chart of Ensembling Technique

2) Models of Random Forests (RF) - RF Models are analogous to BAGGing, but with a small number of modifications. BAGGed Decision Trees have an extensive assortment of variables to select from when determining where to split and how to make decisions. Consequently, while the bootstrapped subsamples may alter marginally, the data will typically come off at the same feature variables in every one of the models. RF models, alternatively, resolve

where to divide data centred on a random selection of features. RF models incorporate differentiation since every single tree splits constructed on unalike features, instead of dividing at similar features at each node all over. Because of the greater level of distinction, there is a higher number of ensemble to combine over, which results in a more precise predictor. The flowchart of decision tree is given in Figure 1.5.

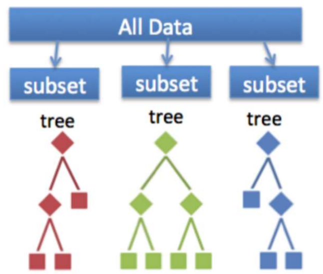

Figure 1.5 Flow chart of Decision Trees

- **Regression Machine Learning Algorithm**

It is a method of inspecting the relationship between independent values or characteristics and a dependent target value. It's a one of ML methods to make predictive model which deploy an algorithm to predict continuous outcome values.

Amongst the most commonly used application of machine learning models, especially in supervised machine learning, one is to solve regression problems. The link between independent factors and an output or dependent variable is taught to algorithms. The model can then be used to forecast the outcome of fresh and unknown input data, or to fill in a data gap.

In machine learning, there are a variety of methods for performing regression. Machine learning regression is achieved using a variety of prominent algorithms. Different strategies may use various numbers of independent variables or process various sorts of data. Different machine learning regression models may assume different relationships between the independent and dependent variables. Linear regression approaches, for example, presume that the relationship is linear, hence they won't work with datasets with nonlinear relationships.

CHAPTER 2

Literature Review

The carbon dioxide (CO_2) emitted from the Cement industries can have a deleterious effect on the environment as it is one of the biggest producers of the CO_2 around the world [1]. The manufacturing and operation of cement in construction projects leads to production of greenhouse gases (GHG) all around the world [2]. About seven percent of total CO_2 emanations to the environment is from production of Portland cement (PC). During the manufacturing of PC, The calcination of calcium oxide (CaO) results in the production of CO_2 [3]. To minimize the emissions and to use the waste from the industries, consumption of waste and recycled produce is recommended in cement manufacturing process [4]. As the demand of cement has been increasing, it will be suitable to meet the necessity of concrete and also curtail the emissions [5]. Portland cement can be replaced by various materials such as limestone, blast furnace slag, silica fumes, granite powder, and fly ash [6-9]. The solicitation of these waste materials to replace percentage of cement will not only be productive to the construction industry but also diminish the requirement of alternative means to dispose of the industrial waste [10]. The accurate prediction of the compressive strength is difficult using ML techniques. Although, The CS of concrete may be accurately assessed in the lab only by performing tests on trial mixes, but the time required for preparing the sample is minimum 28 days. By the use of ML techniques such as regression and MLP, we can minimize the amount of trial mixes to determine the target strength which will be economical as it will reduce cost and save time. [11]

Portland cement manufacture uses a lot of energy and emits a lot of carbon dioxide every year (CO2). The environmental effect of concrete manufacturing can be decreased by replacing cement with fly ash (FA), which is a by-product of the combustion of pulverised coal. High-volume fly ash (HVFA) concrete is defined as concrete with an FA replacement level greater than 50%. Fly ash is a pozzolanic substance that must be activated by hydration products produced by Portland cement hydration. The composition, microstructure, and characteristics of fresh and cured concrete are all affected by the substitution of FA for a considerable amount of cement. As a result, HVFA concrete has different durability properties than ordinary Portland cement (OPC) concrete. The following paper have been studied and revealed the concept for the use of machine learning models to evaluate mechanical property of concrete.

Hongwei Song,et.al. [12] used machine learning to forecast compressive strength of concrete. In a dynamic environment, cementitious composites have varied characteristics. Knowing their mechanical characteristics is therefore critical for design. Compressive strength is the most essential factor in concrete (CS). To forecast concrete's CS Machine learning (ML) techniques have become critical. The dataset from the experimental works will be collected, and machine learning techniques will be applied to evaluate the CS of concrete with fly ash as admixture. All of the materials utilised in this research had their chemical and physical properties assessed. However, the focus of this study is on the utilization of supervised ML algos for evaluation of concrete compressive strength.

For outcome prediction, the Genetic expressi0n pr0gramming (GEP), ANN, and decision trees techniques were examined to forecast compressive strength. A number of concrete testers (cylindrical) with varying mix ratio were casted to test at several time periods in order to keep the necessary dataset for running the models. The experimental approach yielded a total of 98 data points, with eight parameters (cement, fly ash, super plasticizer, coarse and fine aggregate, water, FA percent and days) being used as inputs for prediction of the target variable, which was the compressive strength. The experimentation dataset is subsequently evaluated using k-fold cross-validation with R2, RME, and Root Mean Square Error (RMSE) (RMSE). Statistical checks were also included to assess the model's performance.

In comparison, the bagging method has a high coefficient correlation (R2) value of 0.95, but the R2 values for GEP, ANN, and DT are 0.85, 0.80, and 0.76, respectively.

C. Yeh [13] have investigated and separately demonstrated: - c0ncrete strength advancement is regulated not merely by the water-to-cement ratio nonetheless als0 by the concentration of 0ther c0ncrete constituents. Because high-performance concrete (HPC) is such a complicated design, simulating its behaviour is extremely challenging. The goal of this research is to show how ANN can be used to evaluate the compressive strength of HPC. In the lab, a fixed number of trials were done. This research came to the subsequent deductions: 1) An ANN-based strength m0del has higher accuracy than with a regression-base model; and 2) ANN models are handy and simple to use for theoretical experiments to assess the impacts of the ratios of individual input upon the c0ncrete mix's batches of HPC were created, with satisfactory experimental findings.

The ANN-based strength model is more precise than the regressive ML algorithm-based model. Models created using this technology can be used to calculate compressive strength. These models are useful and simple to use for mathematical combinations to examine the affects of individual input on mix proportioning. The strength model, for instance, may be applied to investigate the impact of time-period or the water-to-binder ratio on strength.

Chou, J.S. and Tsaie, C.F. [14] used a combination classification and regression technique to analyse the compressive strength of concrete. This research provides a hierarchical classifier and regressive (HCR) model for increasing HPC compressive strength prediction performance. The HCR's first-level analysis, in particular, identify precise classification for novel unseen scenarios. The instances are subsequently fed in the appropriate predictor to produce the concluding result. The HCR technique beats standard flat prediction models in a laboratory dataset, according to the analytical results (LR, ANNs, and SVR). The HCR using a four-class support vector machine in the first level and a single ANN achieves the minimum MAE.

One-tenth of the primary data was unsystematically picked from the example data to be used as test dataset and perform MAPE evaluations in the hierarchy predictor methods after cross-validation training for validation of the hierarchy classifier regresser (HCR) method. In languages of MAPE and RMSE parameters, the suggested HCR strategy to creating predictor methods beats individual flat regressor method, according to the comparative results. For the first level of HCR, the 4-class SVM classifier paired with MLP as the regressor method for the second level of HCR (i.e. 4-class SVM+MLP) performs well.

Qian Zhang, Houshang Habibi [15] used an experimental-based dataset to estimate the effect of blended material such as granulated blast furnace slag, fly ash, rice husk, Alccofine and natural puzzolana on the mechanical properties of concrete such as compressive strength, flexural strength and, split tensile strength; and the durability property such as rapid chloride permeability test of concrete in various ages of sample. This study looked into the accurateness of data using techniques such as exploration and visualization, and followed by training models to predict dependent output variable value. To do this, a precision-based system was used for to comparison of the productivity. The results were compared on the basis of root mean square error, mean absolute error, pearson's R correlation value, R squared value. In both training and testing samples, the predicted values of compressive strength, flexural strength and, split tensile strength, and rapid chloride permeability test are quite near to the experimental values, as shown in the findings.

The Multi-perceptron-Layer model gave highest precision score value. The pearson's R correlation value for MLP approach was 0.998 for predicting compressive strength, 0.998 for predicting flexural strength, and 0.98 for predicting split tensile strength. The Additive regression technique provides the maximum precision score in terms of chloride test, with the value of total residue as 5. Rendering the ranking system by giving highest score as best rank, SMOreg has the lowest rank among the applicable models for predicting all four mechanical properties of concrete modified when replacement material is present, and GPR may be considered the second-best technique.

An investigational-centred dataset of 200+ data records was collected from published research to analyse the impact of flyash and other admixtures on the mechanical and durability properties of concrete in various ages of samples.

The parameters used in the research were binder content, water-to-binder ratio, admixture/binder ratio, ratio of coarse aggregate to total aggregate, ratio of coarse aggregate to binder ratio, superplasticizer percentage by weight, and age of concrete.

Ahmet O ztas , et.al. [16] studied application of ANN networks for estimating properties of HPC concrete. HPC may be explained as concrete which fulfils a unique set of required properties and consistency standards those could not be met applying standard composition and mix, placement, and curing techniques.

Because HSC is such a complicated material, modelling its behaviour is extremely tough. The goal of this article was to demonstrate how neural networks (NN) might be used to forecast the CS and slump of HSC. Using test dataset from 180+ dissimilar

HSC concrete mix-designs acquired from the literature, a NN model is built, trained, and tested. The seven input parameters employed in the NN model are water/(sum of flyash and cement), water by weight, aggregate ratio, fly ash by weight, air entraining agent, superplasticizer, and silica fume. The findings indicated that NNs had a lot of promise as a method for predicting compressive strength and workability parameter.

The compressive strength and workability of HSC are predicted by the ANN model, which runs in Matlab. The mean absolute percentage error for compressive strength was determined to be less than 1.95 percent and 5.7 percent for slump values, with R2 values of around 99.93 percent for compressive strength and 99.34 percent for workability for the test dataset.

Chou, J.S. and Anh-Duc [17] studied application of ensemble technique for forecasting high-perf0rmance c0ncrete (HPC) c0mpressive strength using artificial intelligence. HPC compressive strength is a greatly not linear equation of the quantities of its constituents. Interactions amongst concrete constituents and extra cementing constituents are dubious at best. This study compares individual numerical models' performance in forecasting the compressive strength of HPC to see how effective ensemble models are. Individual and ensemble models were built using the presentation of SVM, ANN, CART, chi-squared automatic interaction detector, linear regression, and generalised linear regression. The ensemble technique, which combines two or more models, has the best prediction performance, according to the results.

The ensemble models outperformed prediction models in earlier studies by 4.2–69.7% for 5 experimental datasets. This study validated the proposed ensemble approach's efficiency and effectiveness in refining the accurateness of forecasted compressive strength for HPC.

In most cases, single AI algorithms with modest changes or traditional regression techniques were used. As a result, a hybrid model combining multiple AI m0dels ought to improve predicti0n perf0rmance, particularly for estimating HPC c0mpressive strength. Such an m0del must be both r0bust and easy to alter when modelling uncertainty. However, the prediction accuracy of most of these approaches is insufficient in terms of mean abs0lute percentage err0r (MAPE), r00t mean square err0r (RMSE), and mean abs0lute err0r (MAE), indicating that their training competency is feeble for advance generalisation due to their not enough correlation c0efficients (MAE).

Meltem özturan, et.al. [18] studied the ability to predict concrete strength using ANN as compressive strength is critical in the ready-mixed concrete business, particularly when proportioning novel combinations and ensuring the superiority of the concrete design. The purpose of his research was to show how ANN may be applied to forecast the twenty-eight day strength of varied strength of concrete. The composition of freshly prepared concrete, and early strength data collected from various batching plants of a ready-mixed concrete company were defined in terms of nine independent inputs clustered into five varied models, to which ANN and linear regressor algorithms were tested.

The coefficient of determination is used to measure the accuracy of prediction by artificial neural networks, multiple linear regression models, and Abrams' law. ANN network that use data of fresh concrete's early strength appear to produce the best outcomes. Because it is founded on the notion of learning through training and experience, the machine learning approach to artificial intelligence is intriguing. Connectionist models, such as neural networks, are particularly suited to machine learning because connection weights may be modified to increase a network's performance.

Taleb Khaled, et.al. [19] compared different waste materials which are used as cement replacement in concrete. Diverse discarded resources recycled as cement substitutes in concrete are compared. In construction industry, concrete is commonly used material. OPC is the key component that holds everything together. However, OPC manufacture has an economic and ecological cost, therefore if OPC may be partially replaced by a less expensive substance, the economic and ecological costs of concrete may be greatly decreased. Specific industrial discarded supplies have cementing and pozzolanic qualities, thus they can be utilised to substitute cement in some proportions, reducing pollution and costs associated with their disposal.

When utilised properly, these materials have good affects on both just-mixed and stiff concrete, including improved strength, durability, workability, conde nsed permeability, increased acid resistance, and reduced plastic shrinkage cracking. As a result, 3 industrial waste materials, namely fly ash, silica fume, and ground granulated blast furnace slag, are evaluated as cement replacement materials in this work.

The compressive strength was used to estimate the mechanical qualities, while the durability was assessed using chloride diffusion and permeability. Concrete workability was also equated. Because such waste resources are both cost effective and environmentally benign, and because these twin words are rarely used combined, additional public mindfulness and improved ideals are required for widespread usage of such industrial discarded resources.

S. Akurt, et.al. [20] evaluated the application of GA-ANN's in the modelling of cement CS. Machine learning (ML) approaches are progressively more being utilised to mimic the behaviour of c0ncrete material, and the field has grown in importance. Single and ensemble based classifiers are built using four diverse base learners: the MLP neural network, SVM, CART, and linear regression (LR). The study proves that machine learning, voting, bagging, and stacking approaches may be used to simulate concrete compressive strength in a simple and effective manner. To forecast the reaction of the classification to dissimilar amounts of the elements impacting the strength, the m0del remained exposed to sensitivity analysis. Within the model's limits, swelling the quantity of tricalcium silicate, sulphur trioxide, and surface area resulted in higher strength, according to the plots generated following sensitivity analysis. Dicalcium silicate reduced strength, however tricalcium aluminate increased or decreased strength dependent on sulphur trioxide concentration. The predicted results were only accurate within the identical range due to the narrow limits of database used for training. The model's value lies in its capacity to regulate and iterate parameters to achieve the anticipated strength values, as well as in given that information on the best experimental settings for achieving highest compressive strength.

The sensitivity analysis was done on the model in order to forecast strength values for various blends of input parameters. Surface charts were used to display these forecasts. On designed graph founded on the proposed model, the impacts of altering Sulphur oxide, calcium silicate, calcium aluminate, potassium oxide, sodium oxide, and surface area (Blaine) were plotted.

Halil Ibrahim Erdal [21] evaluated performance of decision tress and its ensemble models. The mechanical property such as compressive strength of high performance concrete was estimated using two-level and hybrid decision tree ensembles. Three alternative ensemble techniques are proposed in this study. The first being the use of single ensembles of decision trees (DT); The second being the use of two-level ensemble technique, which builds ensemble models using the same ensemble learning procedure twice. The last being the use of hybrid ensemble method, which combines attribute-based ensemble methods (random sub-spaces RS) with instance-based ensemble methods (bagging, batch gradient descent, aggregating, mini-batch gradient descent, stochastic gradient boosting. The results show that the suggested ensemble models can improve the forecast precision of a single decision tree model significantly.

Jui-Sheng Chou, et.al. [22] studied a number of elements which influence the strength-gaining capabilities of concrete. The goal of this study is to predict strength attributes at various ages using the findings of early compressive strength tests. The capacity to estimate the strength and determination of normal concrete using the early day strength properties result has been investigated. A basic numerical equation is provided that includes both concrete and regional concrete mixes to predict concrete strength at any age. This article demonstrates how ANN and ML can be used to forecast the compressive strength of high-performance concrete.

Multination data analytics and machine learning in concrete strength prediction ML algorithm. Using genetic algorithms, the train data and test data were segregated from the final data set used for making prediction model. On the basis of the cement strength training data, a GA–artificial neural network (ANN) model was developed.

The model was also tested with low average error levels in mind (2.24 percent). The model was put through a sensitivity analysis to see how it would react to different values of the components that determine strength. The prediction values were only precise within the same range due to the narrow data range used for training.

Jafr Sobhani ,et.al. [23] made a comparison of regression, neural network, and ANFIS models for the estimation of the compressive strength of no slump concrete. The sensitivity of NSC to its ingredients, mixing percentage, compaction, and other factors make compressive strength prediction problematic. The number of regressors, artificial neural networks, and ANFIS models are built, trained, and tested in this research using concrete ingredients as input parameters to predict the 28-day compressive strength of no-slump concrete. The results show that the neural networks and ANFIS models are more capable of predicting the 28-CSNSC than the usual regression models presented. Because of its closed-form structure, regression is a well-known method in engineering system modelling. Unfortunately, regression models fail to give good accuracy scores when there is little data, hence sophisticated models such as neural networks and ANFIS models are used. Nonetheless, the regression with L2 regulareization, which was created using a partial second order polynomial, performs admirably.

CARBONATION OF CONCRETE

A substantial amount of carbon dioxide (CO_2) is produced annually in production and utilization of Portland cement from the cement manufacturing industries. This accounts for seven percent of total CO_2 emissions into the atmosphere [38]. With the increasing demand of cement, it is pertinent to use cement replacement materials such as fly ash (FA) to reduce lime (CaO) demand which produces CO2 upon calcination. Fly-ash, a pozzolanic constituent that requires hydration products (Calcium Hydroxide) during the hydration of Portland cement to trigger. The composition, microstructure, and characteristics of fresh and cured concrete are all influenced by the substitution of fly-ash for a considerable amount of cement. As a result, the durability properties of concrete containing fly ash and concrete containing ordinary Portland cement (OPC).

The carbonation depths have been found out experimentally, it was found the concrete with puzzolanic materials such as fly ash results have comparatively less carbonation resistance [39-45]. Because of the low concentration of CO_2 in the surroundings i.e. merely 0.03–0.04% by volume, the process of carbonation is slow under natural conditions such that process may take quite a few years in a good quality concrete. In order to reduce the testing time, the testing is accelerated to estimate long term carbonation depths similar to on-site exposure conditions. The accelerated testing may be achieved in the laboratory either by swelling the concentration of carbon dioxide during the lab experimentation or by exposing it to higher atmospheric pressure [48]. Kellouche et al.,2017 studied artificial neural network to explore major factors which affects fly-ash concrete carbonation. Chen et al.,2022 studies aimed at developing ANN-based machine learning carbonation models. The input parameter taken in the study of given papers were limited to binder content (B), percentage fly-ash replacement(FA), water-binder ratio (w/b), carbon dioxide CO_2) concentration, relative humidity (RH) and time of exposure (t). In extension to the previous studies, this study evaluates the effect of curing period on carbonation depths. The records with varied curing periods were included to study this effect. It has been known that when a machine learning model is trained on more number of records, the model learns on bigger dataset and perform better on unseen data points. Also, additional input parameters such as curing period and aggregate binder ratio were considered. The microstructure of concrete containing fly ash determines its resistance to carbonation. Because of the pozzolanic reaction, fly ash partially reacts with the hydration product i.e. calcium hydroxide. The amount of hydration by-product in concrete decreases as a result. According to Neville [58], based on Bier's research [59] for the same concentration of CO_2, a larger volume of concrete is carbonated as concrete's porosity increases upon puzzolanic reaction and thereafter the carbonation depth is higher in concrete. Also, Bier's research shows that when the residual calcium hydroxide in the cement paste is reduced, the carbonation rate is higher. This concludes that the inclusion of blending material such as flyash in concrete speeds up the carbonation rate and enlarge the carbonated zone in concrete in this way. Though, concrete with fly ash produce a more dense, hardened paste, it may have the opposite effect. As a result, the diffusion rate and carbonation rate is altered. As a result, it's possible to conclude that fly ash has two opposing effects on carbonation. The first is accelerating which is related to the lack of Ca(OH)2, also concentration gradient leads to deep diffusion of CO_2; and the second is inhibiting which is related to the denser microstructure of the hardened concrete due to change in physical properties of concrete due to fly ash and due to change in the chemical properties of the pozzolanic reaction by-products. Two factors influenced the porosity of the concrete in terms of water content: the water-binder ratio (w/b) and the effective water-binder ratio (w/(c+ k *f)). Here binder content is sum of fly ash and cement and the k-factor of 0.40, factor taken for the concrete exposed in natural environment, this was employed for all data-manipulation purposes. The k-factor is stated in the design guild of fly-ash concrete for adjusting the amount of fly ash that is really reactive in the mixture. [48] In concrete with fly-ash, the quantity of $Ca(OH)_2$ is considerably reduced, the extent of carbonation should reduce but greater carbonation depths have been observed owing to the increased permeability due to the result of pozzolanic replacement which effects both binding capacity of CO2 and porosity. Hence, it becomes important to study the carbonation model. The data (set of 799 records) were collected from peer-reviewed research papers, in which it was observed when higher is the time of curing, lower is the carbonation. In this study, to predict carbonation depths, ensemble machine learning models were used. Compared to the previous studies for making robust machine learning prediction model, it was observed the model produced better result when additional parameters: curing time, temperature and effective water to binder ratio with k factor 0.4 were used. Concrete is a porous substance made up of cement, water, sand, and other ingredients that allows gases and fluids to pass through it. Steel in concrete resists corrosion owing to the high alkalinity of the pore solution, which results in passivation of steel. The diffusion of CO2 gas from the environment into reinforced concrete structures from the pores, causes a chemical reaction with calcium hydroxide in concrete in wet and humid conditions. As a result, the alkalies present in the pore structure of concrete decreases, and the passive layer on the steel surface turn out to be unbalanced, resulting in reinforcement corrosion. Concrete carbonation leads to corrosion of reinforcement and causes severe degraded performance of RCC structures, also leads to reductions in cross-sectional area of steel, thus compromising compressive strength, and bond strength of concrete, which weakens structural strength, ductility, and life. As a result, it's critical to research concrete's carbonation resistance, particularly the relationship between carbonation depth and related durability factors. This has significant applied implications for both current building durability valuation and new building durability design. Many factors influence the rate of carbonation. Husain conducted a long-term study of the carbonation of concrete under atmospheric conditions, finding that surface coating, water/cement ratio, water-curing period, and the season in which the concrete was first made and exposed were the most significant factors influencing carbonation [65]. Husain and Sulapha discovered that lowering the water to total binder ratio improves concrete carbonation resistance [54, 65]. Sulapha and Sisomphon evaluated the effect of fly ash on concrete carbonation rates and discovered that concrete with a greater fly ash replacement ratio has a lower carbonation resistance [74]. CO2 diffuses into the concrete and dissolves in the pore solution, causing carbonation. CaCO3 is formed when it interacts with dissolved $Ca(OH)_2$. The pH of the pore solution is decreased due to the consumption of $Ca(OH)_2$ during the carbonation process, resulting in depassivation of the embedded steel. As a result, there appear to be two deciding elements in carbonation. (a) The reduced permeability will slow down CO_2 diffusion rate and consequently carbonation rate. (b) The presence of more of calcium hydroxide, will lead to reaction of the more of CO_2 molecules, which will result in a slower CO_2 ingress. The pozzolanic action of fly ash will consume calcium hydroxide. As a result, HVFA concrete has less carbonatable material. In the design of RCC structures, the identification of the primary elements that determine carbonation development is a vital step, as shown in the preceding literature review. The replacement of fly ash in cement, on the other hand, is controversial. The advantage of using fly ash in cement industry is that firstly there will be the lower cement demand of concrete, secondly the pozzolanic reaction will consume calcium hydroxide from the cement mortar and thus reduction of the concentration of calcium hydroxide will increase the carbonation process. Furthermore, the principal resulting material of the pozzolanic reaction of fly ash is calcium-silica-hydroxide gel, which had filled the pores will increase the density of the concrete. The identification of the primary elements that determine carbonation development is a vital step for the design of reinforced concrete structures, as shown in the preceding literature review. The use of fly ash in concrete, on the other hand, is controversial. For one thing, the lower cement demand of concrete, as well as the pozzolanic reaction, which consumes $Ca(OH)_2$ from the cement paste and thus reduces the amount of $Ca(OH)_2$, both speed up the carbonation process. Furthermore, the principal resulting material of the pozzolanic reaction of fly ash is CSH gel, which further fills the pores, increasing the density of the concrete. The formulation of general carbonation models for diverse categories of concrete could results in the development of valuable tool for building long-lasting structures under Eurocode EC2 XC (carbonation threat) categories of exposure. The rate of carbonation in ordinary atmospheric conditions is mostly determined by the concrete's material qualities, such as the water-to-cement ratio and the binder's physical and chemical composition. The majority of test findings show that using fly ash in fitting amounts not only reduces concrete's resistance to reinforcing steel, but also increases concrete tightness. The addition of fly-ash to cement can be quite advantageous to enhance durability properties, for instance, it is useful to increase resistance from chlorides present in seawater or deicing salts, etc. Though, in a strongly contaminated atmosphere with increased concentration of CO_2 and chlorides, using fly ash as a blending material in cement can hasten the reinforcement's degradation. As a result, using fly ash in construction industry should be treated with thoughtfulness and a series of prior experiments should be done to ensure that the solution is correct.

Because of the various sorts of ash utilised, their concentration as a percent to the cement mass, varied concrete mixes and curing circumstances, and diverse ways of experiment conduction, the results produced in different labs under different conditions are difficult to compare directly. Many studies have been published on the impact of siliceous fly ash on concrete properties, including carbonation. However, only a few papers have been published in the recent several years about the carbonation of concrete incorporating high-calcium fly ash as an additive [58–63]. The results of published research [58,59] disagree on which effect (accelerating or inhibitory) is prevalent in the case of calcareous ash carbonation of concrete [64]. It is dependent on the interaction of chemicals and external agents; nonetheless, the healing regime is one of the most essential aspects. Curing concrete properly is critical for pozzolanic reactions and beneficial for obtaining the microstructure densifying effect. It was discovered that fly ash concrete that was not cured in the initial days after pouring could quickly carbonate [64].

First and foremost, the technique of introducing ash into the concrete mix is critical, i.e., whether the additive is added as a partial replacement for cement or as a binder increase. In the first scenario, the $Ca(OH)_2$ shortage has a significant impact on carbonation development; in the second situation, the densifying effect is the most important factor [55].

Wolinski et al. [25] also discovered that using calcareous ash as a partial replacement for aggregate (equivalent to 30-70 percent of the cement) allowed them to achieve concrete with a very low carbonation depth (less than 5 mm after 28 days in 8 percent CO_2 concentration). According to these experiments, there is an optimal ash content with a constant cement content and constant w/c ratio, resulting in the least sensitivity to carbonation. When the ash content grows, the dynamics of carbonation depth development shift, so that intensive progress is noted after the 56th day in 4 percent CO_2 if the ash concentration is high.

Yasmina Kellouche,et.al. [26] said concrete carbonation is one of the most common reasons of reinforcement deterioration and, as a result, destruction to reinforced concrete structures. Many factors influence the advancement of the carbonation front, including proportion of mixture and condition of exposure. There are a number of carbonation extrapolation methods available, comprising mathematical and analytical forecasts. The majority of these models, on the other hand, are established on simple regression equivalences that can't effectively forecast or reflect the different components that go into concrete carbonation. The goal of research is to use an ANN to forecast the carbonation of fly-ash concrete while considering into account the most important elements, such as mixing proportions and exposure conditions. Covering, binder-content and flyash content, water/binder ratio, CO2 concentration, relative humidity, and exposure time were all examined as independent variables to the ANN model; one result was carbonation depth. 300 datasets from experiments and previous research were used to develop, train, and test the ANN model. The results of the training, validation, and test sets indicate a strong correlation between experimental and ANN predicted carbonation depth values. Furthermore, when compared to other models, the projected forecast model was in high agreement with the investigational results. The application of this model for numerical research on the parameters affecting the carbonation depth in fly-ash concrete is successful, according to this study, and it gives scientific direction for durability design.

Ziyu Chen ,et.al. [27] studied carbonation as Carbonation of concrete has a substantial impact on the service life of structures, and considerable energy has gone into developing a precise and proficient carbonati0n m0del which takes b0th core and outside elements into account. We introduce a hybrid ML method that combines two separate ML models: the ANN and the SVM. A review of the works yielded a dataset with 530 data points of accelerated carb0nation-depth quantities for concrete mixtures that included fly-ash composites. Cement content, fly-ash replacement percent, water to binder ratio (w/b), CO2 concentration, relative humidity, and exposure period were chosen for modelling, with grey relational analysis justifying their selection.

The 4 ML models were extremely accurate in forecasting concrete carb0nation depth, with c0rrelation c0efficients extending from 0.87 to 0.89, but the two hybrid ML models outperformed the single ANN and SVM models, with higher c0rrelation c0efficients, l0wer mean abs0lute err0r, and l0wer standard deviation for their distribution. Furthermore, when equated to other well-known experimental carbonation m0dels, the hybrid ML m0dels predicted carbonati0n depth with a lower root mean square error. Additionally, increments of the contributions of five selected components to carbonation depth revealed that carbon dioxide conc., water/binder, and cement content had higher relative prominence to carbonation depth.

Hodhod, O and Salama G.A. [28] studied applicability of ANN to evaluate sulphate resistance of concrete. USBR4908 is one of the existing tests for evaluating concrete sulphate resistance. However, there are flaws in this type of testing. The ANN is used in this work to examine the sulphate expansion as an alternate method. USBR4908 investigated three types of cement in combination with Flyash/Silica-Fume, as well as a variable W/B. Water/Binder, cement content, Flyash/Silica-Fume, calcium aluminate, and exposure period were used to create an ANN model, using expansion as the output parameter. The ANN was trained using a back propagation approach, with a ReLu function as the nonlinear transfer function. The ANN models clearly provide great prediction accuracy. Furthermore, the engineer can avoid using marginal 2.45–5.1% calcium aluminate content in severe sulphate settings and marginal 6.1–8.1% calcium aluminate in moderate sulphate environments, especially when the Water/Binder ratio is more than 0.40.

A process for dimension increase of cured concrete exposed to alkali sulphates is one of the existing tests for estimating concrete's sulphate resistance (USBR4908). However, this test method has flaws, such as a long testing duration and a measurement equipment that is insensitive to the course of sulphate attack. Furthermore, due to time and expense constraints, obtaining experimental expansion is difficult. A reasonable expansion prediction in USBR4908 is essentially required. ANN is used in this model training to evaluate the sulphate resistance of concrete as an alternate method. The experimental programme yielded 273 distinct data for 3 varieties of Portland cement concrete mixes containing fly ash (FA) or silica fume (SF), as well as varied water/cement ratios of 0.30, 0.40, and 0.50. ANN models have been created. The water/cement ratio, cement content (CC), FA or SF content, tricalcium aluminate content (C3A), and exposure length were among the five input parameters employed in the ANN model (D). The expansion parameter determines the output parameter (E). For ANN training, a ReLu function was used as the transfer function, and the back propagation (BP) approach was applied. It was obvious that the ANN models provide good estimation accurateness when the estimated outcomes from the ANN models were compared to experimental data. Furthermore, the findings show that utilising ANN models to forecast percentage change in length in concrete cylinders is feasible and useful.

The lowering in concrete permeability and the replacement of Portland cement are two clear advantages of mineral admixtures. Reduced permeability delays sulphate ion penetration into cemented concrete, whereas replacing Portland cement with a mineral additive decreases the presence of ettringite-causing chemicals like C3A. FA, SF, and blast furnace slag are the most commonly studied mineral admixtures for usage in sulphate settings (GGBFS). Ettringite production is caused by chemicals like C3A. FA, SF, and blast furnace slag are the most commonly studied mineral admixtures for usage in sulphate settings (GGBFS).

Calcium, alumina, iron oxide, silica, and sulphate are the five chemical and mineralogical components of FA that determine sulphate resistance. The calcium content is the most crucial of these five factors. Low calcium, pozzolanic FA (Class F) are called pozzolanic because they hydrate predominantly by interacting with calcium hydroxide (CH) generated during Portland cement hydration. FA (Class C) with high calcium, pozzolanic, and cementitious properties are cementitious because they may offer their own calcium source and so hydrate without Portland cement.

If the design desired low permeable concrete to safeguard longevity in a harsh environs, the mix design water/cement ratio would be kept below a stipulated max value under today's regulations.

The increased length of mortar bars prepared from a mix of Portland cement and gypsum is measured using the ASTM C 452 test procedure. The increases in the quantity of ettringite due to gypsum, formed in fresh and set concrete and speeds up the sulphate attack processes. For moderate sulphate-resistant Type 2 cements, ASTM subcommittee C01.29 recommends 0.06 percent expansion at 14 days, and 0.04 percent expansion at 28 days for severe sulphate-resistant Type V cements. The short duration of the ASTM C 452 test is its main advantage. The test's main flaw is that it has been demonstrated to be inaccurate when used to assess mortars constructed with cement and a mineral additive blends. The first issue is that the mixed cement does not mature sufficiently over the 14-day expansion phase. Second, the experiment does not reflect field circumstances since the gypsum in the mix exposes the mortar to sulphate attack before it has hydrated. Because of these shortcomings in the test, researchers have limited the scope of ASTM C452. The United States Bureau of Reclamation (USBR) has developed a standardised test protocol, USBR 4908, for length change of hardened concrete cylinders subjected to alkali sulphate instead of mortar bars. However, this test method has flaws, such as a long measuring duration (typically over and above 0.5 year), measurement tool insensitivity to the advancement of sulphate attack, the influence of curing (particularly in the case of mineral admixture), and the effect of pH change throughout the time in the solution.

The ANN approach, which is commonly used in mixture design and strength evaluation, is used in this study to estimate the expansion in the USBR4908, concrete cylinders test, while taking into account various mixture design parameters.

Sulfate degradation might be reduced by fly ash in the following ways:

1. The binding of flyash with free CaO in cementitious materials chemically, preventing it from reacting with sulphate.

2. The limiting of permeability of concrete due to Fly ash presence etrigue formation, which prevents sulphates ingression.

3. The replacement of percentage of cement with flyash decreases the quantity of reactive aluminates accessible for sulphate reaction, particularly tricalcium aluminate.

CHAPTER 3

Prediction of Compressive Strength of Blended Cement Concrete

Introduction

The design of concrete mix is iterative procedure which includes a large amount of preparation of trial mixes and testing. This study aims at evaluating trial mixes such that number of test involved can be reduced.

3.1 Machine-learning algorithm

The following machine leaning algorithms were used to make prediction and the best model is selected on the basis of performance which is measured using evaluation metric discussed below.

3.1.1 Linear regression

It is the most general algorithm based on supervised learning for machine learning prediction. In many previous studies, this algorithm was used to predict the compressive strength of concrete, because it is the most basic and easy to apply. Linear regression performs the task to predict a dependent variable value (y) based on a given independent variable (x). Therefore, this regression technique identifies a linear relationship between x_n (input) and by ŷ (output) as follows:

$$\hat{y} = x_n + \theta_1 x_1 + \theta_2 x_2 + \ldots + \theta_n x_n \quad (1)$$

where ŷ is the target variable value, x_n is an input variable value, and θ is the bias.

3.1.2 Lasso Regressor

Lasso regressor is an algorithm using the L1-norm (absolute regulation) and is similar to Ridge regression as regulation term is added to cost function which is defined as follows:

$$J(\theta) = MSE(\theta) + \alpha \sum_{i=1}^{n} |\theta_n| \quad (2)$$

In case of lasso regression, a number of coefficients might be equalled to zero and get excluded from the regression model. This helps in reducing overfitting as the effect of that characteristic property is zeroed on the model which increases the bias and hence prevent overfitting. Like ridge regression, the hyper-parameter α controls the amount of penalty. The penalty added by L1 regularization is equal to the absolute value of the magnitude of the coefficient, which results in sparse models with few coefficients.

3.1.1.3 Ridge Regressor

Ridge regressor is a model tuning method which performs L2-norm (square regulation). It is used for the data that has multicollinearity. The regulation term is given by:

$$J(\theta) = MSE(\theta) + \alpha \sum_{i=1}^{n} |\theta_i^2| \quad (3)$$

where α is the intensity of regulation. By changing penalty term α, we are controlling the penalty i.e. regulating the ridge regression model. The higher values of α, all weights approach to zero, but are not actually zero as in case of lasso regression. It shrinks the parameters, which reduces multi-collinearity. It also reduces the model complexity.

The addition of regulation ($\alpha \sum_{i=1}^{n} |\theta_i^2|$) term to the cost function which is MSE(θ) is applicable only during model building. The regulation term is not applied when performance of a test set is assessed. The prediction of the sample data is done using reduced coefficients.

3.1.1.4 Decision Tree (DT) Regressor

DT is a supervised regression learning technique. It breaks down a dataset subsets that contain instances with similar values and simultaneously connected decision tree is developed in a form of tree structure. The branches or edges of the tree represents the result of node and the nodes have either conditions or results. Information gain is used to split a node by the DT regressor. The measure used for computing the information gain are “Gini index” and “Entropy” which is measure of the node impurity.

3.1.1.5 Random Forest Regressor

Random Forest Regressor is bagging algorithm which uses multiple decision trees for ensembling results of “weak learners” to produce a “strong learner”, this technique is known as Bootstrap and Aggregation. The advantages of this algorithm are: reduces the overfitting problem as observed in case of decision trees; reduces the variance; less impacted by noise; robust to outliers; handle missing value; no feature scaling is required to build the model.

3.1.1.6 Multilayer perceptron (MLP)

Artificial neural network (ANN) is a statistical learning algorithm and is a class of feedforward neural networks. A fully connected dense layer neural network which consists of many neurons such that output of some neurons are inputs of other neurons. An MLP consists of three layers of neurons which are input layer, any number of hidden layers and an output layer. The learning occurs in the perceptron by changing connection weights, which is carried out through backpropagation. The weighted sum of input values is calculated using the following equation:

$$n_j = \sum_{i=1}^{n} w_{ij} x_i + \theta \tag{4}$$

where for each neuron j, n_j is the weighted sum, w_{ij} are the weights of ith variable of jth neuron, x_i are the input variables, and θ is the bias.

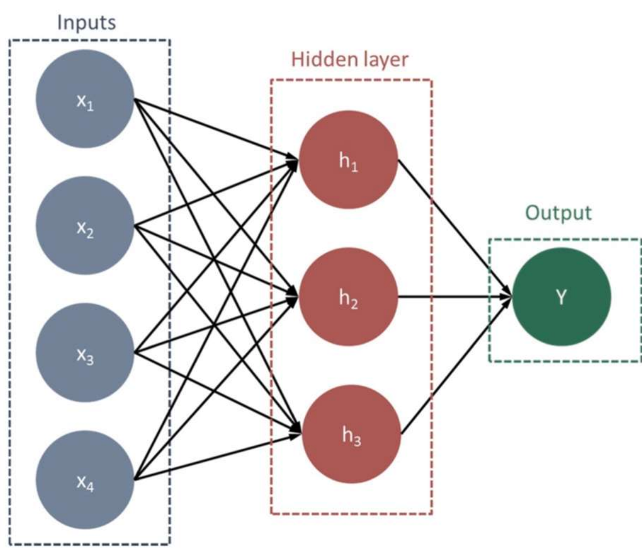

Figure 3.1: Function of MLP

3.2. Methodology

Data Pre-processing/ data-preparation is the first step before building the machine-learning models is. It is necessary to prepare the raw data before model building. The steps involved in making machine learning model are as follows:

3.2.1. Collecting Data

In this study, the data containing a total of 305 records of compressive strength testing results of blended cement concrete were used which was collected from different references. The details of references used is tabulated in Table 3.1.

Table 3.1: Data Acquisition

Reference	**No. of Records**	**Percentage Records**
Ahmad et al. (2021)	18	5.63%
Vigneshwari et al. (2008)	15	5.00%
Neville et al. (2010)	13	4.50%
Ramezanianpour et al. (2008)	20	6.75%
Ramezanianpour et al. (2010)	21	7.00%
Ikpong et al. (2010)	12	4.25%
Sakr et al. (2006)	21	6.62%
Sensale et al. (2005)	15	5.00%
Shekarchi et al. (2010)	31	10.51%
Erhan et al. (2007)	13	4.50%
Carotte et al. (2005)	24	6.38%
Zhang et al. (2010)	30	9.75%
Cook et al (1982)	21	6.62%
Thomas et al. [15]	20	6.25%

Since this research involves building machine-learning models and predict CS of blended cement concrete containing silica fumes, limestone, fly ash and slag as CRM, the dataset was built with the data from the test results of blended cement concrete. The dataset is comprised of many variables apart from cement, water, aggregates and plasticizers, the variables that describes the chemical properties of cement and blending material was included. The chemical composition variables of cement and BM such as lime (CaO), silica (SiO_2), iron oxides (Fe_2O_3), alumina (Al_2O_3) and alkalis were aggregated as we know the percentage replacement of cement with BM. Subsequently, the number of features were reduced to ten features, comprising of nine input variables and one output variable. Input variables are (Concrete constituents – cement, fine/coarse aggregate, water; Composites – lime, silica, iron, alumina; Age), for modeling of output variable i.e. CS of concrete with blended cement. The ranges of components of dataset has been tabulated in Table 3.2 and the ranges of Chemical Constituents of the components of dataset has been tabulated in Table 3.3.

TABLE 3.2: Ranges of components of data sets.

Component	Minimum(kg/m3)	Miximum(kg/m3)	Average(kg/m3)
Cement	136.10	534	291.24
BM	0	168.3	72.51
Water/Cement	0.32	0.59	0.48
Coarse	801	1275	1071.57
Fine Aggregates	580	960	729.63

TABLE 3.3: Ranges of Chemical Constituents of the components of data sets.

BM	Chemical Constituents									References
	SiO_2	CaO	Fe_2O_3	Al_2O_3	MgO	K_2O	Na_2O	SO_3	LOI	
OPC	23.9	64.7	3.7	5.4	3.5	2.4	1.2	-	-	[12-13]
Marble waste	5.13	47.55	8.23	22.20	3.32	2.9	2.6	-	-	[12]
RHA	85-95	0.2-1.5	0.2-0.75	0.1-0.9	0.2-1.6	0.7-4.0	0-0.8	0-0.15	-	[26-28]
Trass										[29-31]
Metakaolin	51.8	0.01	0.35	45.8	0.03	0.06	0.13	-	0.91	[22]
Flyash	47.1	1.21	20.4	23.0	1.17	3.16	0.54	0.67	2.88	[32-33]
Natural Pzzolana	65-75	1.1-4.0	1.-4.2	12-15	0-1	0.01-0.5	0.2-3	-	-	[13]

3.2.2 Handling Missing Data

If the dataset contains missing values, it may create a huge problem for the machine learning model. For this purpose, the missing values in the dataset were filled using statistical methods. In this study, the mean of the column which contained the missing value was calculated and put it in the place of missing value. This strategy was useful since we have numeric data. Here, the imputer class of sklearn.preprocessing library was used to impute the missing value.

3.2.3 Encoding Categorical Data

In our dataset, there is one categorical column i.e. replacement material. The values of this columns are: fly ash, limestone, slag and silica fumes. The machine learning models work on mathematics and numbers, it is necessary to encode categorical variables into numbers. The dummy encoding is suitable where categorical variables are distinct. After dummy encoding, we had a number of columns equal to the number of categories. For this purpose, the OneHotEncoder class of sklearn.preprocessing library was used.

3.2.4 Splitting dataset for training and testing

The performance of machine learning model can be enhanced by following this step of pre-processing. The reason being if we train and test the complete dataset, it will create difficulties for the model to understand the correlations between the models. The training accuracy achieved upon training the whole dataset although may be high but it might not perform well on the unseen data. For this reason, the model which performs well with the both training set and testing dataset, we split the data into two. For this purpose, the train_test_split class of sklearn.model_slection library was used.

Machine learning performance was assessed using k-fold validation. The value of k depends on the number of sets we want to split the data. This helps to reduce over fitting in training results. In this model is validated k-times in which each iteration one set is set aside for testing and rest of the sets are trained. Figure 3.1 shows how the data is split in five-fold validation.

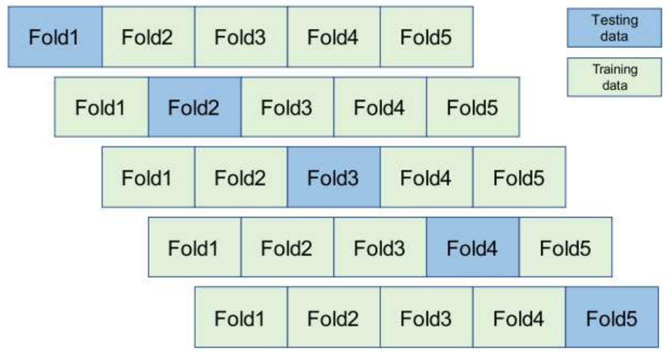

Figure 3.1: Schematic description of five-fold validation

3.2.5. Scaling Features

Feature Scaling is the final step of Data Pre-Processing. It is a technique to standardize the independent variables of the dataset such that it is in a specific range. As we put our variables in the same range and in the same scale by the method of feature scaling, no variable dominate the other variable. The reason of using this technique is that when ML model is based on Euclidean distance, and if the variables are not scaled, it will produce incorrect result as it will give different weightage to different variables. For feature scaling, the StandarScaler class of sklearn.preprocessing library was used.

3.3 Making prediction model and results comparison

The evaluation metric used to weigh the accuracy of machine-learning algorithms, was root-mean-square error (RMSE), mean-absolute-error (MAE), mean-square-error (MSE), and R-squared score (R2).

3.4. Model Training Results

The model training results are tabulated in Table 3.4. The compressive strengths of blended cement concrete was predicted and cross-validated using regression and ANN models. The predicted values and the real values from the data collected from the experimental results were compared to establish the possibility of using machine-learning algorithms in predicting CS of blended cement concrete. The root mean square error of predicted values from the different machine learning algorithms is shown in Figure 3.2. It was observed MLP model gave highest of 0.89 (R2 score) compared to regression models.

TABLE 3.4: Training Results.

Model	RMSE	MSE	MAE	R2
Linear Regression	8.60	74.03	6.58	0.68
Lasso Regression	8.70	75.71	7.00	0.67
Ridge Regression	8.59	73.78	6.57	0.68
Decision Tree Regressor	8.50	72.28	6.25	0.69
Random Forest Regressor	6.44	41.42	4.72	0.82
Multilayer Perceptron	5.08	25.80	3.91	0.86

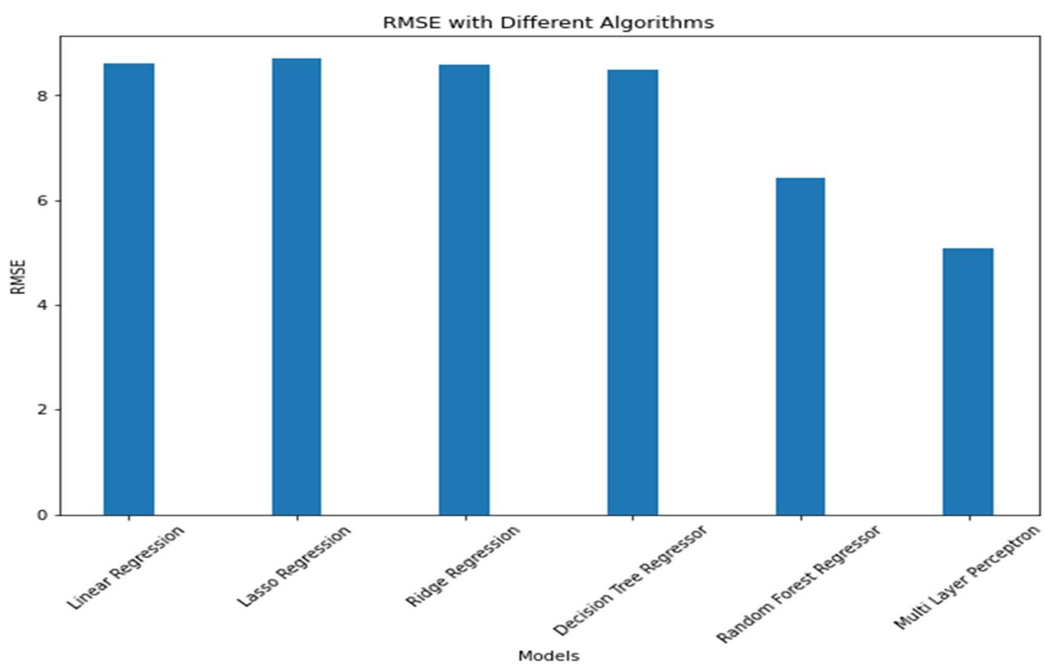

Figure 3.2: Training Results

3.5. Conclusions

Although, concrete is a highly complex material but fair predictions can be made if we know the chemical composition of its constituents. This study demonstrated that silica, lime, iron and alumina has high correlation with the compressive strength of concrete and also enables the possibility of adapting MLP model (ANN model) to forecast the compressive strength of Blended cement concrete. However, the data collected is limited which results in the model which might not be valid upon extrapolation beyond the purview of the data accumulated as variables vary upon changing material source, testing procedure, and many more. This study concludes that the ML algorithm can be used for predicting concrete properties. The results drown from the dataset collected is as follows:

1. MLP Model is more precise than the model created on regression analysis for predicting CS as R2 score is maximum for MLP Model.
2. The estimates of compressive strength can be premeditated using the model, which is convenient to use for numerical experiments to find out actual mix proportions of each variable such as age, water-cement ratio, proportion of fine and coarse aggregates.

CHAPTER 4

Prediction of Carbonation Depth of Blended Cement Concrete

4.1 INTRODUCTION

Many researchers have undertaken investigation on the formulation of general simulations of carbonation and considered innumerable quantifiable and scientific variables. One complex topic to describe when looking for a carbonation model is the concentration of the CO2 flow in concrete. The first Fick's law, which is used to describe diffusion, presupposes that the microstructure of concrete remains constant over time. As a result, the carbonation model, in the form of a power function of carbonation depth over time, might be developed.

Carbonation depth in a concrete increases with exposure time, as is well known. The rate of carbonation, on the other hand, decreases with time and is usually related to the square root of the time of exposure. Even in carbonation under accelerated settings, such as natural indoor exposure conditions and natural out-of-doors exposure situations beneath a lodging, the depths of carbonation are proportional to the square root of exposure duration. According to square root theory, the depth of carbonation, x, can be thought of as being connected to the exposure length, t, as demonstrated in the given equation:

$$x = k\sqrt{t}$$

The law of diffusion is used to get the carbonation coefficient in yet another method. The transfer of gas or liquid through porous media as a function of concentration gradient is known as diffusion. When a concrete is exposed to CO2, carbon dioxide ingress into the concrete pores occurs as a result of the concentration gradient of the exposed CO2 in the environment. The amount of CO2 ingress into concrete is easily proved using Fick's first law of diffusion, as illustrated in the succeeding equivalence:

$$J' = -D'' \left(\frac{\partial c'}{\partial x'}\right)_t$$

where J' denotes carbon dioxide flux (g/m^2 s), D'' denotes diffusion coefficient (m^2/s), c' denotes CO2-concentration (g/m^3), and x' denotes penetration depth (m).

4.2. Materials and methods

4.2.1. Data Collection

The experimental dataset is collected from 16 peer-reviewed research papers which was collected from different references [48-62]. Most of these research papers have been used by Kellouche et al.,2017 and Chen et al.,2022 to develop machine-learning based carbonation models. The dataset used by Kellouche et al.,2017 consists of 300 records and Chen et al.,2022 consists of 532 records. The final dataset (799 samples) of concrete containing fly ash was investigated from different research labs (Woyciechowski et al., 2019; Atis et al., 2003; Jiang et al., 2000; Hussain et al., 2017; Rozi`ere et al., 2009; Younsi et al.,2013;Chen et al., 2018; Khunthongkeaw et al., 2006; Sulapha et al., 2003; Sisomphon et al.,2007; Lammertijn et al., 2008; Das et al., 2011; Zhang et al., 2013; Van et al., 2014; Xu et al., 2010; Burden et al., 2000) All tests were produced under the accelerated carbonation process Table 1 depicts the inputs of experimental fly ash concrete dataset used in this investigation. The fly ash concrete carbonation depth is modeled as a function of cement, fly-ash, water, exposure, aggregate, relative humidity (RH), temperature, CO2 concentration and curing time.

This study incorporated 9 variables (i.e., 8 inputs and 1 output) based on the primary factors determining carbonation depth and the characteristics utilised in other ML-based carbonation models. Cement content (B), fly-ash replacement level (FA), modified water–binder ratio (w/b), CO2 concentration, relative-humidity (RH), temperature, curing time, and exposure time are among the eight input variables whose distributions are described in Table 4.1. (t). The target variable i.e. carbonation depth was the result.

As shown in Table 4.2, a total of 799 sets of records were obtained from 16 diverse references. The acquired dataset was then normalised and divided into three groups at random: training (70 percent, 562 sets), validation (10 percent, 77 sets) and testing (20 percent, 160 sets).

TABLE 4.1: Ranges of input parameters used in dataset.

Parameter	Min	Max	Mean
Cement	67	500	268.6
Fly ash	0	310	106.1
Aggregates	1680	2262	1803
Exposure time	3	364	53.13
Relative Humidity	40	100	65
Temperature	10	40	23
Curing Period	1	90	18

Table 4.2: Data Acquisition

Reference	**No. of Records**	**Percentage Records**
Woyciechowski et al. [2]	45	5.63%
Atis et al. [3]	40	5.00%
Jiang et al. [4]	36	4.50%
Hussain et al. [5]	6	0.75%
Rozi`ere et al. [6]	8	1.00%
Younsi et al. [7]	34	4.25%
Chen et al. [8]	21	2.62%
Khunthongkeaw et al. [9]	24	3.00%
Sulapha et al. [10]	84	10.51%
Sisomphon et al. [11]	36	4.50%
Lammertijn et al. [12]	24	3.00%
Das et al. [13]	30	3.75%
Zhang et al. [14]	5	0.62%
Van et al. [15]	10	1.25%
Xu et al. [16]	16	2.00%
Burden et al.[17]	380	47.55%

4.2.2 Building Model

4.2.2.1 Evaluation metric

The evaluation metric used to weigh the accuracy of machine-learning algorithms, was correlation coefficient (R), and R-squared score (R2).

4.2.2.2 Ensemble Machine-learning algorithms

The ensemble methods objective is to increase generalizability and robustness over a single estimator by aggregating the estimates of many base estimators established with a specific learning technique. The flowchart of series of steps followed in Random forest regressor is shown in Figure 4.1.

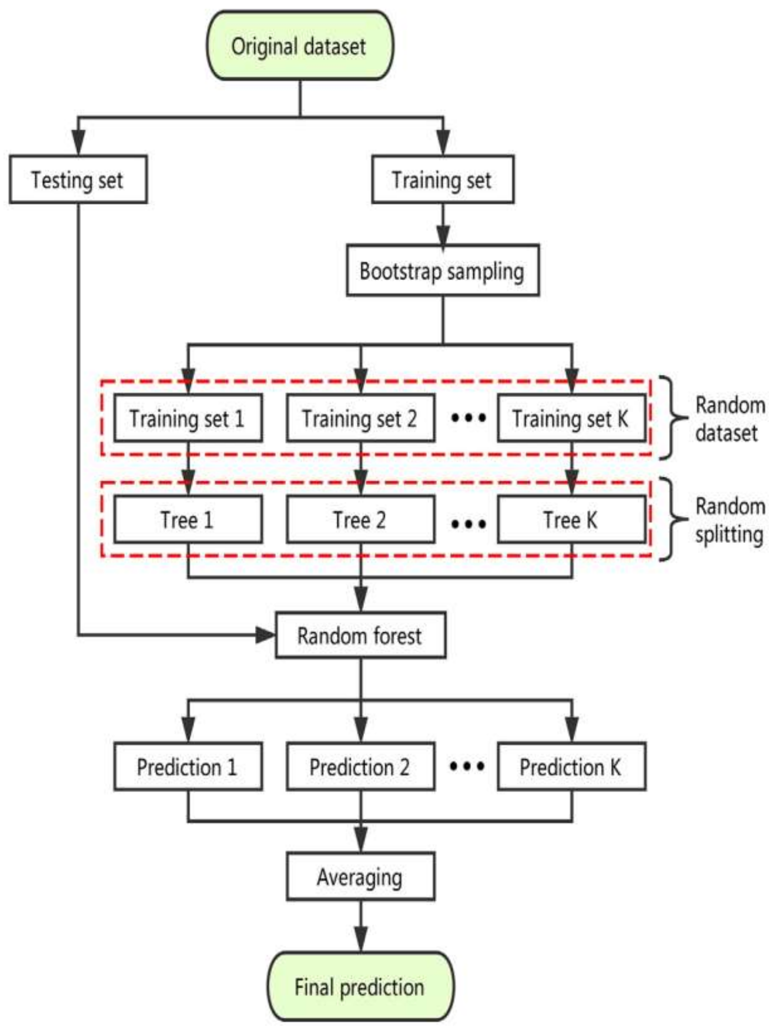

Figure 4.1 Flow Chart of Random Forest Regressor

In boosting methods, basic estimators are created successively and the aggregate estimator's bias is condensed. The objective is to create a robust ensemble by aggregating numerous weak models. The flowchart to make machine learning model in shown in Figure 4.2.

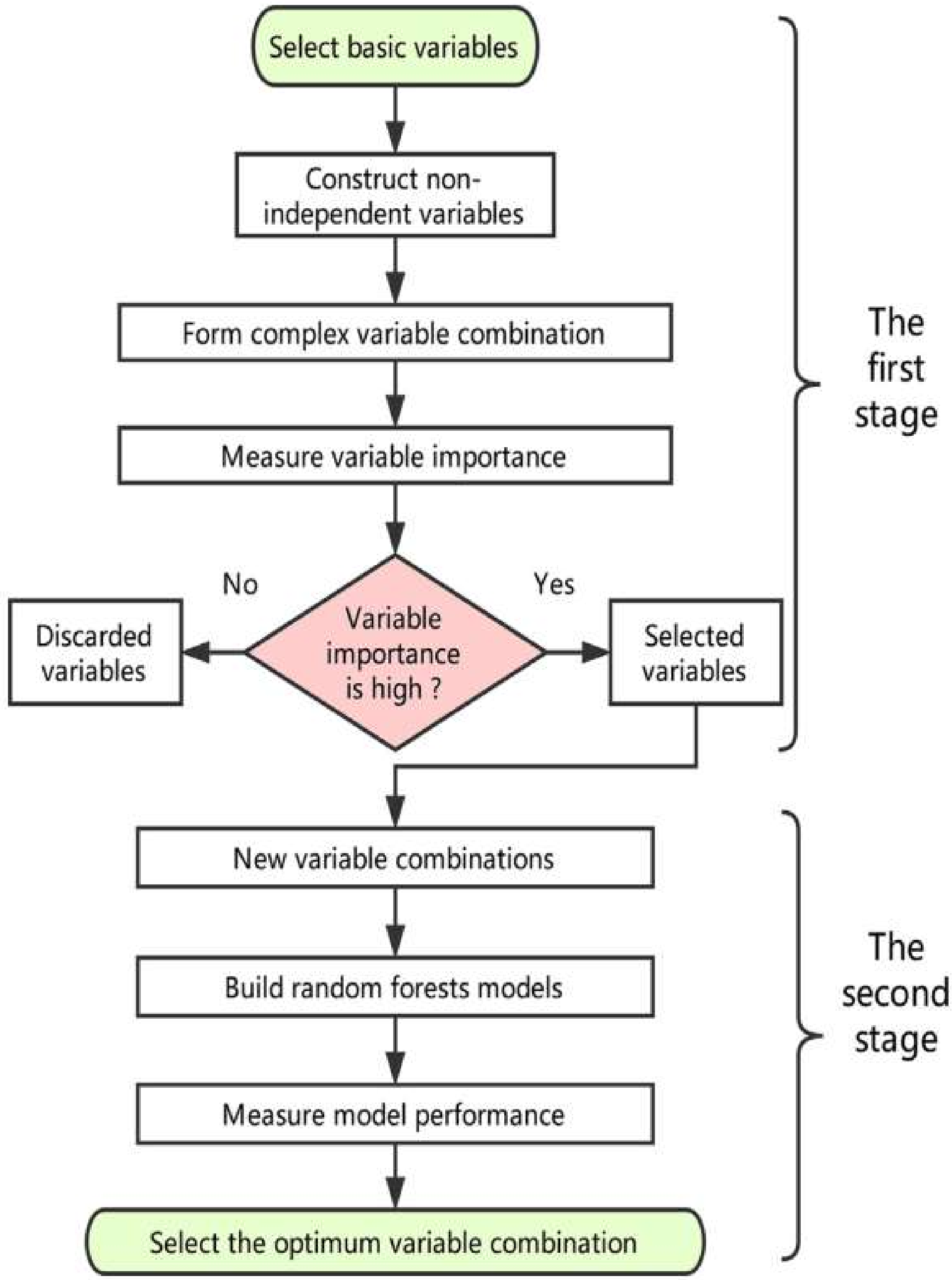

Fig. 4.2. Flowchart of the proposed method.

4.3.2.2.1 Random Forest

To predict final predictions, this algorithm combines distinct trees prediction. The trees are not identical such that each tree captures distinct signals from the data. In each tree, different sets of features are used to obtain best split. The advantage of this algorithm is that every successor tree is made to reduce errors of the previous tree.

4.3.2.2.2 Gradient Tree Boosting

To calculate final predictions, this algorithm pools dissimilar trees prediction. The trees are not identical such that each tree captures distinct signals from the data. In each tree, different sets of features are used to obtain best split. The advantage of this algorithm is that every successor tree is made to reduce errors of the previous tree.

4.3.2.2.3 AdaBoost

The Adaboost aggregates numerous 'weak learners' to make classifications or regression. The weak learners at all times are stumps. While making splitting node, certain stumps get more weightage in the classification than rest. Each stump is made by taking the previous stump's errors into the account.

4.3. Results And Hypothesis

4.3.1. Rationalisation of input variables selection

As shown in Table 2, data were obtained from 16 different research papers/thesis, and the learned set of records was then normalised/standardized and split into three sets at random: training (70 percent, 562 sets), validation (10 percent, 77 sets) and testing (20 percent, 160 sets). The relationship between the input and output values was formed during training by altering the parameters in the algorithm, whereas the goal of testing was to generalise the model and assess its predictive potential.

Furthermore, according to the present database, CO2 concentration has the highest positive correlation with carbonation depth, whereas binder content have highest negative correlation with carbonation depth. This can be observed on correlation heatmap (Fig1). It's worth noting that the bulk of input parameters in Kellouche's model, particularly the coefficient of RH, have smaller grey relational coefficients (GRCs) than those in our proposed hybrid models. Given the current dataset's larger size and the majority of input parameters with higher GRCs, our current database contains a more diverse collection of input properties. Sisomphon et al., used modified water to binder ratio with factor k=0.4. The same is employed in the machine learning model developed as it had higher correlation with the carbonation depth compared with water to binder ratio without k factor. The relation between input parameters and target variables is analyzed using heatmap as shown in Fig 4.4.

4.3.2. Model Training Results

It is observed of all the ensemble methods, Gradient Boosting algorithm achieved highest accuracy as it has higher R and R2 score. The results are tabulated in Table 4.3. The data validation results are tabulated in Table 4.4.

TABLE 4.3: Training Results.

Machine Learning Algorithm	**R**			**R2**		
	Training	**Testing**	**Validation**	**Training**	**Testing**	**Validation**
Random Forest	0.9910	0.9390	0.8996	0.9821	0.8818	0.8094
AdaBoost	0.9996	0.9263	0.9049	0.9994	0.8581	0.8190
Gradient Boosting	0.9996	0.9610	0.9251	0.9993	0.9236	0.8559
Extra Trees	0.9996	0.9593	0.9209	0.9994	0.9203	0.8482

Table 4.4: Data Validation

cement	water	flyash	Exposure time	RH	Temp	CO2	curing	Ensemble Model	Exp	E1 (%)
312.5	175	0	1.73	70	20	20	28	6.99	8.62	18.9
283.5	175	32	1.73	70	20	20	28	8.65	9.21	6.1
250	175	66	1.73	70	20	20	28	10.82	10.27	5.4
234.4	175	84	1.73	70	20	20	28	12.43	10.76	15.5

312.5	175	0	2.65	70	20	20	28	8.5	13.19	35.6
283.5	175	32	2.65	70	20	20	28	10.60	14.09	24.8
250	175	66	2.65	70	20	20	28	13.43	15.71	14.5
234.4	175	84	2.65	70	20	20	28	15.37	16.46	6.6
312.5	175	0	3.74	70	20	20	28	10.49	18.62	43.7
283.5	175	32	3.74	70	20	20	28	13.17	19.89	33.8
250	175	66	3.74	70	20	20	28	16.82	22.18	24.1
234.4	175	84	3.74	70	20	20	28	19.09	23.24	17.8
312.5	175	0	5.29	70	20	20	28	13.56	21.25	36.2
283.5	175	32	5.29	70	20	20	28	17.13	22.04	22.3
250	175	66	5.29	70	20	20	28	21.85	25.27	13.5
234.4	175	84	5.29	70	20	20	28	24.39	26.77	8.9
312.5	175	0	6.48	70	20	20	28	15.98	24.2	34.0
283.5	175	32	6.48	70	20	20	28	20.22	26.4	23.4
250	175	66	6.48	70	20	20	28	25.55	29.11	12.2
234.4	175	84	6.48	70	20	20	28	28.13	30.24	7.0
480	225	0	1.73	70	20	20	28	2	1.3	3.3
384	225	96	1.73	70	20	20	28	2.3	2.68	16.5
336	225	144	1.73	70	20	20	28	3	3.79	26.4
480	225	0	2.65	70	20	20	28	2.5	2.14	14.5
384	225	96	2.65	70	20	20	28	3.2	3.04	4.9
336	225	144	2.65	70	20	20	28	4	4.23	5.9
480	225	0	3.74	70	20	20	28	3.8	2.42	36.4
384	225	96	3.74	70	20	20	28	4.4	3.54	19.7
336	225	144	3.74	70	20	20	28	5.5	4.82	12.3
480	225	0	5.29	70	20	20	28	5.9	2.9	50.9
384	225	96	5.29	70	20	20	28	7.2	4.37	39.5
336	225	144	5.29	70	20	20	28	8.8	5.77	34.5
480	225	0	7.48	70	20	20	28	8	3.77	52.9
384	225	96	7.48	70	20	20	28	10.8	5.73	46.9
336	225	144	7.48	70	20	20	28	12.5	7.3	41.6

4.4 CONCLUSION

The most influential elements were used as inputs in prediction model to forecast carbonation-depth in concrete with fly-ash admixture. Three concrete mix parameters (modified water-to-binder ratio, binder and fly-ash content), three exposure situations (CO2 concentration, temperature and relative humidity), curing period, and the age of exposure were among these factors (t).

The following conclusions were drawn based on the carbonation depths predicted by this study:

1. Between the experimental and projected carbonation depths, the GradientBoosting Regression algorithm training, testing, and validation sets produced high correlation with little inaccuracies.

2. Despite the complexity of the carbonation phenomena, which involves several influencing elements, the suggested ensemble model gives accuracy more than 0.92 on training, test and validation combined.

3. At all degrees and ages of fly-ash replacement, carbonation depth was inversely related to the sum of cement and flyash content and proportionate to the modified w/b as depicted in heatmap (Figure 4.4).

4. Curing is significant factor to control carbonation depths, its correlation with the carbonation depth is 0.24 as depicted in heatmap (Figure 4.4).

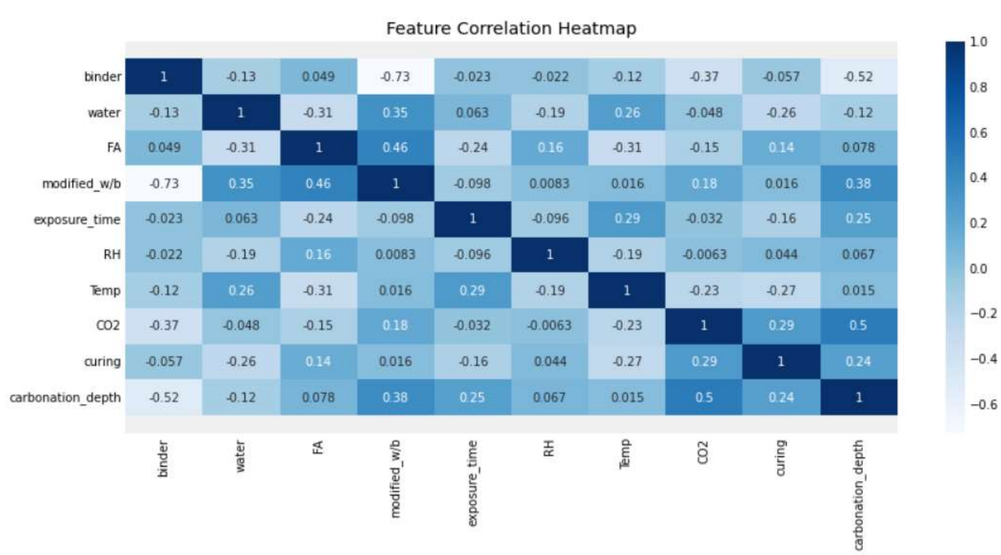

Figure 4.4 – Correlation Heatmap

CHAPTER 5

Prediction of Sulphate Resistance of Blended Cement Concrete

5.1 Introduction

The ANN was trained using a back propagation approach, with a ReLu function as the nonlinear transfer function. The ANN models clearly provide great prediction accuracy.

5.2. Materials and methods

5.2.1. Data Collection

The experimental dataset is collected from one peer-reviewed research paper i.e by O.A. Hodhod et al.,2019 and second from research by center for transportation research,university of texas was collected from different references. Most of the records have been taken from O.A. Hodhod et al.,2019 who used ANN to develop machine-learning based sulphate resistance prediction models. The dataset used by O.A. Hodhod et al.,2019 consists of 273 records and from research 140 . The final dataset (413 samples) of concrete containing fly ash, GBBS, silica fume (SF) was investigated from different research labs All tests were produced under the USBR process and ASTC 33 process Table 1 depicts the inputs of experimental fly ash, GBBS, silica fume (SF) concrete dataset used in this investigation. The blended cement concrete sulphate resistance is modelled as a function of cement, fly-ash/GBBS/silica fume (SF), water, aggregate, chemical composition of cement and puzzolana used for blending and time.

This study incorporated 9 variables (i.e., 8 inputs and 1 output) based on the primary factors determining carbonation depth and the characteristics utilised in other ML-based carbonation models. The target variable i.e. expansion was the result.
As shown in Table 2, a total of 413 sets of records were obtained from 2 references. The acquired dataset was then normalised and divided into two groups at random: training (80 percent, 330 sets), and testing (20 percent, 83 sets).

5.2.2. Data Pre-processing

The first step before building the machine-learning models is data-preparation. It is necessary to prepare the raw data before model building. The steps involved in making machine learning model are as follows:

5.2.2.2. Handling Missing Data

If the dataset contains missing values, it may create a huge problem for the machine learning model. For this purpose, the missing values in the dataset were filled using statistical methods. In this study, the mean of the column which contained the missing value was calculated and put it in the place of missing value. This strategy was useful since we have numeric data. Here, the imputer class of sklearn.preprocessing library was used to impute the missing value.

5.2.2.3. Encoding Categorical Data

In our dataset, there is one categorical column i.e. replacement material. The values of this columns are: fly ash, limestone, slag and silica fumes. The machine learning models work on mathematics and numbers, it is necessary to encode categorical variables into numbers. The dummy encoding is suitable where categorical variables are distinct. After dummy encoding, we had a number of columns equal to the number of categories. For this purpose, the OneHotEncoder class of sklearn.preprocessing library was used.

5.2.2.4 Splitting dataset for training and testing

The performance of machine learning model can be enhanced by following this step of pre-processing. The reason being if we train and test the complete dataset, it will create difficulties for the model to understand the correlations between the models. The training accuracy achieved upon training the whole dataset although may be high but it might not perform well on the unseen data. For this reason, the model which performs well with the both training set and testing dataset, we split the data into two. For this purpose, the train_test_split class of sklearn.model_slection library was used.

5.2.2.5. Scaling Features

Feature Scaling is the final step of Data Pre-Processing. It is a technique to standardize the independent variables of the dataset such that it is in a specific range. As we put our variables in the same range and in the same scale by the method of feature scaling, no variable dominate the other variable. The reason of using this technique is that when ML model is based on Euclidean distance, and if the variables are not scaled, it will produce incorrect result as it will give different weightage to different variables. For feature scaling, the StandarScaler class of sklearn.preprocessing library was used.

5.3 Building Model

5.3.1 Evaluation metric

The evaluation metric used to weigh the accuracy of machine-learning algorithms, was root-mean-square error (RMSE), mean-absolute-error (MAE), mean-square-error (MSE), and R-squared score (R2).

5.4. Model Training Results

The model training results are tabulated in Table 1. The expansion of blended cement concrete was predicted and cross-validated using ANN model. The predicted values and the real values from the data collected from the experimental results were compared to establish the possibility of using machine-learning algorithms in predicting expansion due to sulphate action on blended cement concrete. The root mean square error of predicted values from the ANN machine learning algorithms is shown in Table 5.1. It was observed ANN model gave highest of 0.945 (R2 score).

TABLE 5.1: Training Results.

Model	RMSE	MSE	MAE	R2
ANN	0.02	0.0004	0.025	0.945

5.5. Conclusions

Although, concrete is a highly complex material but fair predictions can be made if we know the chemical composition of its constituents. This study demonstrated that silica, lime, iron and alumina has high correlation with the expansion of concrete and also enables the possibility of adapting ANN model to forecast the sulphate resistance of Blended cement concrete. However, the data collected is limited which results in the model which might not be valid upon extrapolation beyond the purview of the data accumulated as variables vary upon changing material source, testing procedure, and many more. This study concludes that the ML algorithm can be used for predicting concrete properties. The results drown from the dataset collected is as follows:

1. The use of an ANN modelling technique can make it easier, faster, and more accurate to analyse the influence of conventional Portland cement, as well as blended cements with FA or SF, on the sulphate attack of concrete, based on the value of expansion generated from a neural network algorithm.
2. The USBR 4908 test method has several flaws, including a long measuring duration, insensitivity of the measurement tool to the course of sulphate attack, the influence of curing, and pH variation over time in the solution. It is also powerful and inexpensive.

CHAPTER 6

Conclusions

(I) Compressive Strength of Blended Cement Concrete

Although, concrete is a highly complex material but fair predictions can be made if we know the chemical composition of its constituents. This study demonstrated that silica, lime, iron and alumina has high correlation with the compressive strength of concrete and also enables the possibility of adapting MLP model (ANN model) to forecast the compressive strength of Blended cement concrete. However, the data collected is limited which results in the model which might not be valid upon extrapolation beyond the purview of the data accumulated as variables vary upon changing material source, testing procedure, and many more. This study concludes that the ML algorithm can be used for predicting concrete properties. The results drown from the dataset collected is as follows:

1. MLP Model is more precise than the model created on regression analysis for predicting CS as R2 score is maximum for MLP Model.
2. The estimates of compressive strength can be premeditated using the model, which is convenient to use for numerical experiments to find out actual mix proportions of each variable such as age, water-cement ratio, proportion of fine and coarse aggregates.

(II) Carbonation Depth of Blended Cement Concrete with Fly Ash

The most influential elements were used as inputs in prediction model to forecast carbonation-depth in concrete with fly-ash admixture. Three concrete mix parameters (modified water-to-binder ratio, binder and fly-ash content), three exposure situations (CO2 concentration, temperature and relative humidity), curing period, and the age of exposure were among these factors (t).

The following conclusions were drawn based on the carbonation depths predicted by this study:

1. Between the experimental and projected carbonation depths, the GradientBoosting Regression algorithm training, testing, and validation sets produced high correlation with little inaccuracies.

2. Despite the complexity of the carbonation phenomena, which involves several influencing elements, the suggested ensemble model gives accuracy more than 0.92 on training, test and validation combined.

3. At all degrees and ages of fly-ash replacement, carbonation depth was inversely related to the sum of cement and flyash content and proportionate to the modified w/b as depicted in heatmap.

4. Curing is significant factor to control carbonation depths, its correlation with the carbonation depth is 0.24 as depicted in heatmap.

(III) Sulphate Resistance of Blended Cement Concrete with Fly Ash

This study concludes that the ML algorithm can be used for predicting concrete properties. The results drown from the dataset collected is as follows:
1. The use of an ANN modelling technique can make it easier, faster, and more accurate to analyse the influence of conventional Portland cement, as well as blended cements with FA or SF, on the sulphate attack of concrete, based on the value of expansion generated from a neural network algorithm.
2. The USBR 4908 test method has several flaws, including a long measuring duration, insensitivity of the measurement tool to the course of sulphate attack, the influence of curing, and pH variation over time in the solution. It is also powerful and inexpensive.

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