Prediction of Concrete Grade Using Machine Learning

Project

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Jamia Millia Islamia

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Bachelor of Technology

(Civil Engineering)

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Certificate

This is to certify that the project entitled **"Prediction of Concrete Grade Using Machine Learning"** submitted in partial fulfilment for the award of the degree of **Bachelor of Technology (Civil Engineering)** is a record of the bona fide work carried out by **Hyfa Hanief, Mohammed Naved, Mohd Asad Naqvi, Sania Shakil and Mohd Faizan** under my supervision and guidance.

To the best of my knowledge, the matter embodied in this project has not been submitted in part or full to any other University/Institution for the award of any degree

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Declaration

We, Hyfa Hanief, Mohammed Naved, Mohd Asad Naqvi, Sania Shakil, Mohd Faizan students of Bachelor of Technology (Civil) hereby declare that the report titled "**Prediction of Concrete Grade using Machine Learning"** which is submitted by us to the Faculty of Engineering and Technology, Department of Civil Engineering, Jamia Millia Islamia, New Delhi in partial fulfilment of the requirement for the award of the degree of Bachelor of Technology (Civil) has not previously formed the basis for the award of any Degree, Diploma, Associate ship, Fellowship or other similar title or recognition.

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May 2024

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Abstract

The construction industry heavily relies on accurate predictions of cement compressive strength for ensuring the structural integrity and durability of concrete. Traditional methods for estimating compressive strength are often time-consuming and subject to various uncertainties. This project explores the application of machine learning techniques to predict cement compressive strength, offering a more efficient and accurate alternative. The project utilizes a dataset comprising laboratory experiments obtained from kaggle.com – an open database. The dataset comprises of 1030 observations having 9 quantitative variables comprising of cement content, slag, fly ash, water content, super-plasticizers, coarse aggregate, fine aggregate, age of the sample at the day of testing and the corresponding compressive strength The input data includes various ingredients of the concrete mix and its age, while the target variable is the compressive strength. A descriptive analysis of the input and output variables has been carried out in this project.

In the first part of the project, an analysis of data pertinent to concrete compressive strength has been carried out. Heatmaps, pair plots and box plots and bar plots were used to extract meaningful insights and patterns in the data. The Python libraries employed include but are not limited to Pandas, NumPy, Matplotlib, and Seaborn facilitating efficient data manipulation, statistical analysis, and visualization. The data analysis conducted herein serves as a crucial precursor to the machine learning model development. A concrete mix design based on the provisions of IS 10262:2019 has been carried out. Using MS excel sheet, target mean strengths for different grades of concrete have been computed.

Following the data analysis, deep neural network models were developed to predict the compressive strength of concrete. The first model used the original dataset of 1,030 observations, with 70% of the data employed for training and the remaining 30% for prediction. Performance metrics showed that this model performed well, with most predictions exhibiting only small errors. To enhance efficiency and precision, a second model was created using a filtered dataset, excluding outliers with compressive strengths less than 10 or greater than 60, as these grades are not often used in practice. This model significantly reduced errors and improved the accuracy of predictions compared to the unfiltered dataset. The third model combined the filtered dataset with results from laboratory cube tests.

In conclusion, the machine learning model based on the filtered dataset outperformed the other two models. The models developed in this project demonstrate significant potential for cost and time savings by reducing reliance on labor-intensive and time-consuming laboratory tests. This project demonstrated the potential of artificial intelligence in transforming the construction sector, leading to more innovative and efficient uses of concrete technology.

Keywords: Compressive Strength, Prediction, Artificial Neural Network, Concrete, Performance Metrics

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1 Introduction

Cement concrete, widely utilized in construction, comprises four primary ingredients: cement, sand, aggregates, and water. Its popularity stems from numerous benefits: Concrete's high compressive strength and durability makes it ideal for building structures like buildings, bridges, roads, and dams. Its versatility lies in its adaptability to different shapes, sizes, and designs, catering to specific construction needs and enabling innovative and creative architectural expressions. Moreover, concrete's inherent fire resistance enhances safety in fire-prone structures. The fundamental components of cement concrete – cement, sand, and aggregates – are both easily accessible and economical, making it a practical choice for construction projects of various magnitudes. These attributes of concrete – strength, durability, flexibility, and cost-effectiveness – contribute to its widespread preference in diverse construction activities.

The process of mix design, or concrete mix proportioning, is crucial for producing concrete with the required compressive strength and workability. This process involves two key steps: (1) selecting the right ingredients, and (2) determining their precise quantities to create concrete that offers optimal workability, strength, and durability, while also being cost-effective. The ratio of these ingredients depends on their unique properties. For specific concrete-making materials, factors to consider include the cement to aggregate ratio, water to cement ratio, sand to coarse aggregate ratio within the aggregate, and the quantity of admixtures used. The ultimate aim of mix design is to identify and utilize the most economical and suitable combination of available materials, ensuring the production of concrete that meets the desired performance criteria.

1.1 Background

The background of predicting concrete grade using machine learning lies in the challenges associated with traditional methods of assessing and determining the quality of concrete in construction projects. Traditionally, concrete quality is often determined through laboratory testing, which involves time-consuming and manual procedures. This process may not capture the dynamic and complex nature of concrete mixtures in real-world construction settings. Machine learning offers a promising alternative by leveraging computational models to analyse vast amounts of data and identify patterns that may be challenging for humans to discern. The prediction of concrete grade using machine learning involves developing models that can accurately forecast the strength and properties of concrete based on various input factors such as the composition of the mixture, curing conditions, and environmental factors.

1.2 Motivation

The compressive strength of concrete is influenced by multiple factors, including its age and the specific ratios of its components. The link between the proportions of these ingredients and the concrete's compressive strength is non-linear and becomes even more intricate in the case of high-performance concrete (HPC). Unlike traditional concrete, which consists of Portland cement, fine and coarse aggregates, and water, HPC necessitates additional components like fly ash, blast furnace slag, and chemical additives such as superplasticizers. Conducting traditional experimental tests to assess how different ingredient proportions affect HPC's characteristics is not only expensive but also time-consuming. Moreover, current empirical formulas found in various codes and standards, designed for estimating compressive strength, typically don't account for supplementary cementitious materials used in HPC.

Given these challenges, the primary goal of present project is to develop machine learning models, particularly deep neural networks (DNNs), with optimized hyperparameters for the prediction of the compressive strength of concrete, considering the composition of ingredients and the concrete's age. This approach represents a significant advancement in accurately predicting concrete strength, utilizing the power of machine learning to handle the complexity of variables involved in determination of compressive strength of concrete.

1.3 Project objectives

The major objective of the present project is to apply artificial neural network for predicting the grade of cement concrete

Specific objectives

1. To obtain and analyse a dataset of compressive strength tests on concrete
2. To analyse the effect of various parameters on the compressive strength of concrete
3. To develop machine learning models for the prediction of grade of concrete
4. Analyse and interpret the results obtained from the ML model

1.4 Project organization

Chapter 1 gives the introduction of the project. The objectives and the methodology has been described in this chapter.

Chapter 2 describes the artificial intelligence techniques, particularly the artificial neural network model

Chapter 3 describes the analysis of the available database of experimental results on concrete compressive strength

Chapter 4 describes the Python programming language and different libraries used in this project for the analysis of the available data

Chapter 5 describes the calculations for a concrete mix design based on the provisions of IS10262: 2019

Chapter 6 describes the development of ML models based on different datasets.

2 Literature Review

Numerous applications of ML techniques to civil engineering problems have been reported in the literature (e.g., Kaya 2010, Pandey et al. 2018, Asim et al. 2021, Kumar et al. 2023). Applications of ML techniques to prediction of compressive strength of concrete, in particular have been investigated in different forms by several researchers. Aiyer et al. (2014) explore the use of Least Square Support Vector Machine (LSSVM) and Relevance Vector Machine (RVM) methods to assess the compressive strength of self-compacting concrete. Their findings indicate that RVM is a particularly effective and reliable technique for this purpose. Kaya (2010) demonstrates that artificial neural networks can accurately predict scour depth patterns around bridge piers. The study highlights the potential of computational methods in enhancing our understanding and management of civil engineering challenges, paving the way for improved bridge design and safety. Stoński (2010) compares model selection methods for predicting high-performance concrete's compressive strength using neural networks. The research emphasizes the importance of techniques like cross-validation in preventing overfitting, and optimizing neural network models, thereby improving reliability in computational structural engineering.

Chou and Pham (2013) show that using an ensemble of AI techniques, including neural networks significantly improves the accuracy and robustness of predicting high-performance concrete compressive strength. Their work underscores the value of ensemble methods in construction materials engineering. Khashman and Akpinar (2017) shows that neural networks can predict concrete compressive strength using non-destructive tests like ultrasonic pulse velocity and rebound hammer readings. This method offers accurate, efficient strength estimates, reducing the need for destructive testing and improving construction safety and cost-effectiveness. Nguyen et al. (2021) show that advanced machine learning models, like support vector machines and decision trees, can accurately predict concrete strengths. These models outperform traditional methods, improving prediction accuracy and efficiency, and helping optimize concrete mix design and quality control in construction.

Deng et al. (2018) proposed a machine learning model utilizing a Convolutional Neural Network (CNN) to predict the compressive strength of recycled concrete, concluding that the CNN model outperformed the traditional Artificial Neural Network (ANN) model. Feng et al. (2020) detailed the use of an adaptive boosting approach to predict the compressive strength of concrete based on ingredient composition and curing time, comparing it against ANN and Support Vector Machine (SVM) methods. Kaloop et al. (2020a) examined the use of a multivariate adaptive regression spline model for feature extraction to identify optimal inputs for high-performance concrete (HPC) design, subsequently using these features in a gradient tree boosting machine learning technique to predict concrete compressive strength. Kaloop et al. (2020b) discussed four soft-computing approaches for estimating the slump flow and compressive strength of concrete. Liu et al. (2021) explored the application of machine learning models to predict the carbonation depth in recycled aggregate concrete.

Tran et al. (2022) discuss using hybrid models to predict the compressive strength of concrete made with recycled concrete aggregates. They concluded that combining a gradient boosting model with particle swarm optimization achieved the highest prediction accuracy. Ly et al. (2021) developed a Deep Neural Network (DNN) model to predict the compressive strength of rubber concrete, demonstrating superior prediction accuracy compared to earlier results from various other machine learning algorithms. Khursheed et al. (2021) examined the use of various machine learning techniques to predict the compressive strength of fly ash concrete. Li and Song (2022) applied four ensemble learning models—AdaBoost, GBDT, XGBoost, and random forest—to predict the compressive strength of high-performance concrete (HPC), concluding that the GBDT model outperformed the others. Bello et al. (2022) utilized deep neural networks to predict the water requirements for a normal concrete mix. Chi et al. (2023) incorporated electrical resistivity as an additional input parameter to enhance the prediction of concrete compressive strength.

3 Artifical intelligence

Artificial Intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think and learn like humans. The term can also be applied to any machine that exhibits traits associated with a human mind, such as learning and problem-solving. The primary goal of AI is to enable machines to perform intellectual tasks, such as decision making, problem solving, perception, understanding human language (natural language processing), and even artistic creation.

AI can be classified into two broad types:

Narrow AI: Also known as Weak AI, this type of AI operates within a limited context and is a simulation of human intelligence. Narrow AI is often focused on performing a single task extremely well and while these machines may seem intelligent, they operate under far more constraints and limitations than even the most basic human intelligence.

General AI: Also known as Strong AI, this type of AI would outperform human intelligence across a wide range of domains. General AI would have the ability to think, understand, and learn in a genuinely intelligent way. However, this level of AI has not yet been achieved and remains a subject of speculative fiction and future studies.

AI technologies include machine learning (where computers are trained to learn from and process data), neural networks (which mimic the processes of the human brain to help computers learn), and robotics (a branch of AI where physical robots are used). AI has applications across numerous fields, from advanced analytics and automation in industries in improving health care, environmental conservation, and enhancing customer service. The development and implementation of AI raise important ethical and safety considerations, including concerns about job displacement, privacy issues, and the need

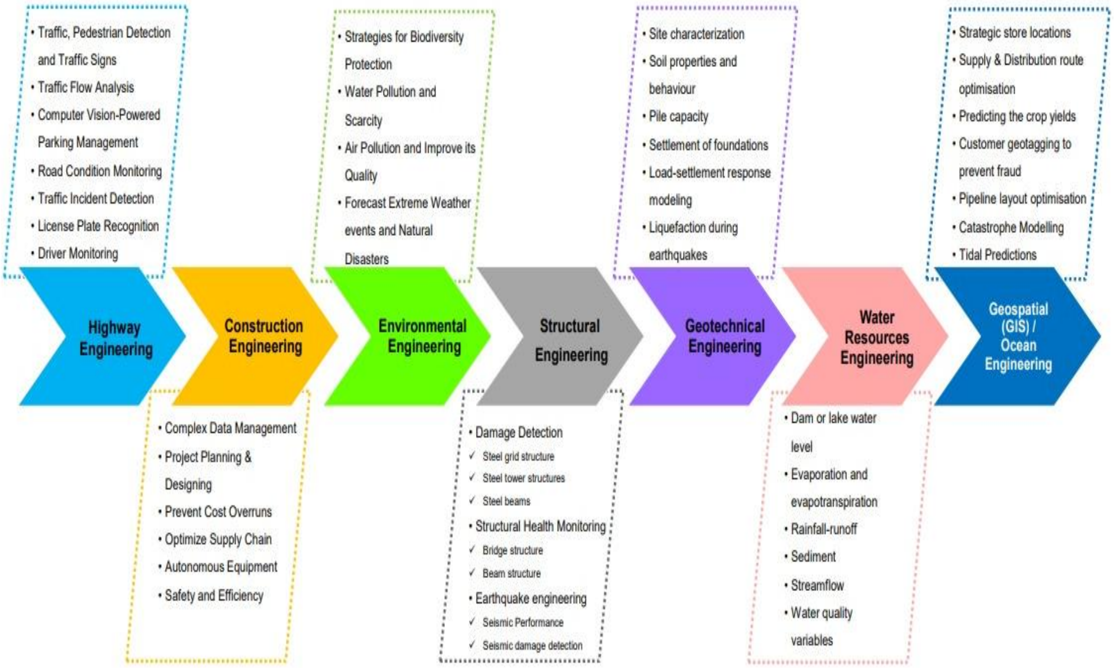

Figure 3.1 Role of AI in Civil Engineering

3.1 Machine Learning

Machine learning is a subfield of artificial intelligence (AI) that focuses on the development of algorithms and statistical models that enable computers to perform tasks without being explicitly programmed. In simpler terms, machine learning enables computers to learn from data and make decisions or predictions without programming it.

At its core, machine learning is all about creating and implementing algorithms that facilitate these decisions and predictions. These algorithms are designed to improve their performance over time, becoming more accurate and effective as they process more data. In traditional programming, a computer follows a set of predefined instructions to perform a task. However, in machine learning, the computer is given a set of examples (data) and a task to perform, but it's up to the computer to figure out how to accomplish the task based on the examples it's given.

For instance, if we want a computer to recognize images of cars, we don't provide it with specific instructions on what a car looks like. Instead, we give it thousands of images of cars and let the machine learning algorithm figure out the common patterns and features that define a car. Over time, as the algorithm processes more images, it gets better at recognizing cars, even when presented with images it has never seen before.

Machine Learning Concepts:

Algorithms: Machine learning algorithms are designed for tasks like classification, regression, etc.

Training: During the training phase, the model tries to adjust its internal parameters and optimize its ability to make accurate predictions or decisions

Testing and Evaluation: After training, the model is tested using new, unseen data to evaluate its performance.

Prediction or Inference: Once trained and evaluated, the machine learning model can be used to make predictions or decisions on new, unlabelled data.

Machine learning has numerous applications across various domains such as:

- Image recognition
- Speech recognition
- Natural language processing
- Autonomous vehicles
- Medical diagnosis and much more.

3.2 Artificial Neural network (ANN):

An artificial neural network (ANN) is a computational model inspired by the way biological neural networks in the human brain work. It is a key component of machine learning and a subset of deep learning, which refers to neural networks with three or more layers (including an input layer, one or more hidden layers, and an output layer).

Artificial Neural Networks (ANNs) play a significant role in various aspects of our day-to-day lives, often behind the scenes in technologies and applications that we use regularly. Here are some examples of how ANNs are utilized in different areas:

Voice Assistants and Speech Recognition: Voice-activated systems like Siri, Google Assistant, and Alexa use ANNs for natural language processing and speech recognition. ANNs help these systems understand and respond to spoken language.

Image and Video Recognition: ANNs are extensively used in image and video recognition applications. This includes facial recognition on social media, content recommendation systems on platforms like YouTube and Netflix, and image recognition for security purposes.

Online Shopping and Recommendations: E-commerce platforms leverage ANNs for recommendation systems. Algorithms analyse user behavior, preferences, and purchase history to suggest products that users might be interested in, enhancing the overall shopping experience.

Healthcare and Medical Diagnosis: ANNs are employed in medical imaging for tasks such as the detection of abnormalities in X-rays, MRIs, and CT scans. They can assist in diagnosing diseases, predicting patient outcomes, and recommending treatment plans.

Financial Services: In finance, ANNs are used for fraud detection, credit scoring, and stock market predictions. They can analyse large data sets to identify patterns and anomalies that may be indicative of fraudulent activities.

Autonomous Vehicles: Neural networks are crucial in the development of self-driving cars. They help process data from various sensors, such as cameras and lidar, to make real-time decisions about navigation, obstacle avoidance, and traffic interactions.

Language Translation: ANNs are employed in machine translation services like Google Translate. These systems use neural networks to understand and generate human-like translations between different languages.

Social Media and Content Personalization: Social media platforms use ANNs to personalize content feeds for users. Algorithms analyse user interactions, interests, and behaviour to show relevant content, advertisements, and suggestions.

Email Filtering and Spam Detection: ANNs are utilized in email services to filter spam. They can learn from patterns and characteristics of spam emails to automatically identify and quarantine them, improving the accuracy of spam filters.

Smart Home Devices like smart thermostats, lighting systems, and security cameras often use ANNs for pattern recognition and learning user preferences to optimize energy usage and enhance home security.

3.2.1 Neurons (Nodes):

In an artificial neural network, nodes are often called neurons. Neurons receive input, perform a computation, and produce an output. The output from one neuron becomes the input for another.

3.2.2 Layers:

Neurons in an artificial neural network are organized into layers. The three main types of layers are:

Input Layer: The layer that receives the initial input data.

Hidden Layers: Layers between the input and output layers that process the input data. Deep neural networks have multiple hidden layers.

Output Layer: The final layer that produces the network's output.

3.2.3 Weights and Biases:

Neurons in a neural network are connected by weights, which represent the strength of connections between neurons. Biases are additional parameters that help adjust the output of neurons. During training, the network adjusts these weights and biases to minimize the difference between predicted and actual outputs.

3.2.4 Activation Function

Each neuron typically has an activation function that determines its output based on the weighted sum of its inputs. Common activation functions include the sigmoid, hyperbolic tangent (tanh), and rectified linear unit (ReLU).

3.2.5 Feedforward and Backpropagation

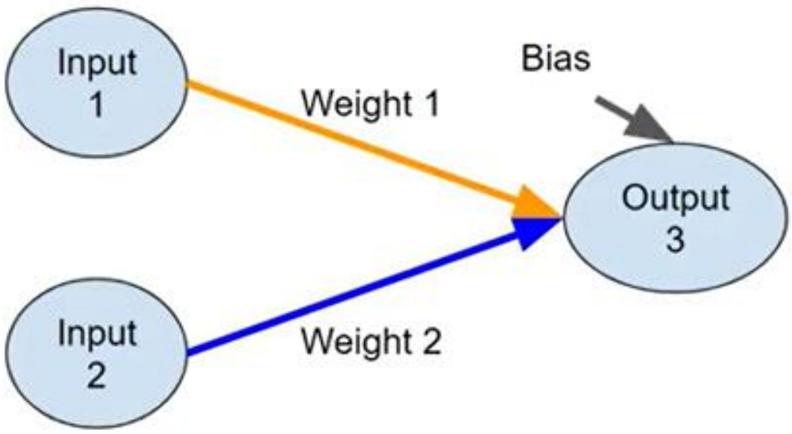

Figure 3.2 Activation Function

In the training phase of a neural network, the process involves feedforward and backpropagation. Feedforward is the forward pass where input data is passed through the network to produce predictions. Backpropagation is the backward pass where the network's errors are calculated, and the weights and biases are adjusted to minimize these errors.

3.3 Illustrative Example

Consider that the shear capacity of FRP beams depends upon the following parameter.

- Effective depth, d
- Concrete strength, f_c
- Shear span to depth ratio, a/d
- Ratio,E_f/E_c
- Fiber reinforcement ratio,ρf
- d, f_c , a/d, E_f/E_c and ρ_f are known as input variables.
- The shear capacity of the beam, Vu is the label (output variable)
- The ANN is trained using the set of examples of input and output data
- Once trained, the ANN is expected to compute the value of V_u for a given set of d, f_c , a/d, E_f/E_c

3.4 Activation Function:

An activation function is a crucial component in artificial neural networks (ANNs). It is a mathematical operation applied to the output of each neuron (or node) in a neural network, determining whether the neuron should be activated or not based on the input it receives. Activation functions introduce non-linearity to the network, allowing it to learn complex patterns and relationships in the data.

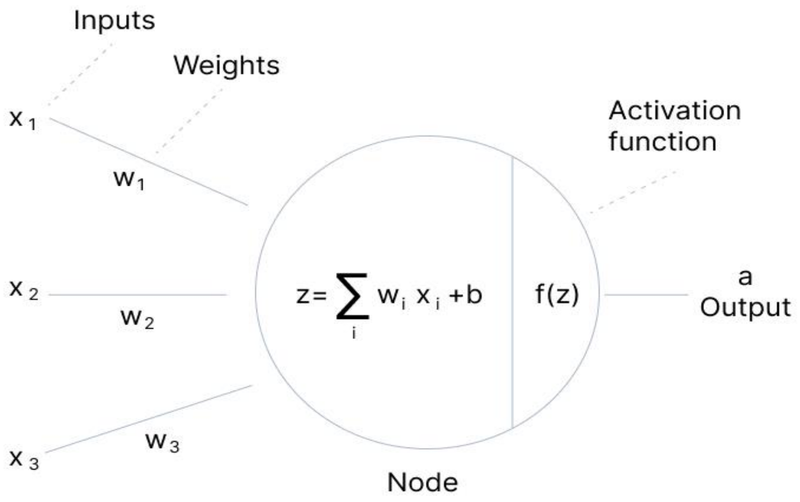

Figure 3.3 A typical artificial neural network

4 Methodology and Dataset

4.1 Methodology

The various steps in the methodology to be followed are:

1. Feature engineering will be used to prepare the database so that it can be input to ML model

2. Analysis of the affect of different variables on the compressive strength of concrete will be carried out

3. Artificial Neural Network model will be implemented in Python

4. Performance of the model will be evaluated through performance metrics such as accuracy of the model

Data Collection and Preprocessing

Gather a comprehensive dataset containing relevant information about concrete mixtures, including ingredients, proportions, age at the day of testing, and the corresponding compressive strength values. Preprocess the dataset to handle missing values, outliers, and ensure data consistency.

Data Analysis:

Identify and select the most relevant variables that that significantly contribute to the concrete strength prediction. Explore the possibility of creating new features through engineering to enhance the predictive power of the model.

Model Development:

Choose appropriate machine learning algorithms for regression tasks that are well-suited for predicting concrete compressive strength. Train and optimize the selected models using the prepared dataset. Explore the use of techniques like cross-validation to ensure the model's generalization to new data.

Model Evaluation:

Assess the performance of the machine learning models using appropriate evaluation metrics (e.g., Mean Absolute Error, Mean Squared Error) to measure the accuracy and reliability of predictions. Compare the performance of different models to determine the most effective one for concrete strength prediction.

Validation and Testing:

Validate the trained models on a part of the dataset to ensure that they generalize well to unseen data. Perform rigorous testing to verify the robustness and reliability of the model predictions.

Continuous Improvement:

Establish a framework for continuous monitoring and improvement of the model's performance as new data becomes available. Consider updating the model periodically to enhance its accuracy and relevance.to prevent AI systems from perpetuating or amplifying biases.

4.2 Programming Language

Python is a popular programming language due to its simplicity, readability, and versatility. It has applications in various domains, including web development, data science, artificial intelligence, scientific computing, and more. Python has become a dominant language in the field of machine learning (ML) due to its simplicity, versatility, and the rich ecosystem of libraries and frameworks that support ML development.

In Python, a library is a collection of modules and packages that contain pre-written code to perform specific tasks. Libraries provide reusable functions, classes, and routines that can be easily incorporated into your Python programs, saving time and effort.

Some of the libraries used in this project include:

4.2.1 Numpy

NumPy is a powerful numerical computing library in Python. It provides support for large, multi-dimensional arrays and matrices, along with a collection of mathematical functions to operate on these arrays. NumPy is a fundamental package for scientific computing with Python and is widely used in various fields such as machine learning, data science, engineering, and more.

4.2.2 Pandas

Pandas is a popular open-source data manipulation and analysis library for Python. It provides data structures for efficiently storing and manipulating large datasets, along with tools for working with structured data. Pandas is built on top of the NumPy library and is widely used in data science, machine learning, and other domains.

4.2.3 Matplotlib

Matplotlib is a popular 2D plotting library for Python that allows you to create a wide variety of static, animated, and interactive plots. It provides a high-level interface for drawing attractive and informative statistical graphics. Matplotlib is often used for data visualization and presentation in scientific and engineering applications.

4.2.4 Seaborn

Seaborn is a statistical data visualization library based on Matplotlib in Python. It provides a high-level interface for creating informative and attractive statistical graphics. Seaborn comes with several built-in themes and color palettes to make it easy to create aesthetically pleasing visualizations. It is particularly well-suited for exploring and visualizing complex datasets.

4.3 Jupyter Notebook

Jupyter Notebook is a versatile and interactive web-based application that has become a cornerstone in the toolkit of data scientists, researchers, and educators. One of the key strengths of Jupyter Notebook lies in its ability to foster an interactive computing experience. Users can write and execute code in a step-by-step manner, observing immediate feedback in the form of output, plots, or errors. This iterative workflow is invaluable for data analysis, exploratory data science, and prototyping machine learning models. The support for various programming languages and the integration of popular data science libraries, such as NumPy, Pandas, Matplotlib, and Scikit-learn, make Jupyter a central hub for a wide range of tasks.

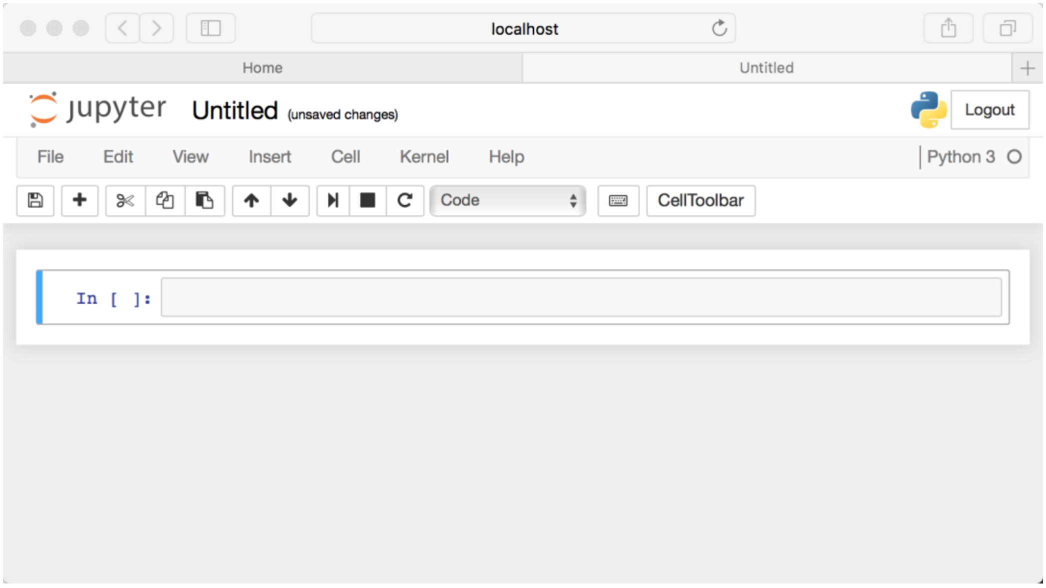

Figure 4.1 Jupyter Notebook Interface

4.4 Dataset

The dataset utilized in this project is publicly available on Kaggle.com. It comprises 1030 observations and consists of nine quantitative variables. The dataset is complete, as no missing values have been reported by the providers. Table 1 provides descriptive statistics of all the input and output variables. To create DNN and regression models, 70% of the experimental data was utilized for training the models, while the remaining 30% was used for testing purposes. For the efficient training of the DNN models, the input data variables have been normalized in the range of 0 to 1. The input variables (features) considered for the training of the DNN models include amount of cement (CM), slag (SL), fly ash (FL), water (WT), superplasticizer (SP), coarse aggregates (CA), and fine aggregates (FA). Additionally, the strength of concrete depends on its age (AG), and therefore AG is also included as an input variable.

Table 4.1 Descriptive Statistics

Notation	Parameter	Maximum	Minimum	Mean	Standard deviation
CM	Cement(Kg/m^3)	540.0	102	281.16	104.50
SL	Slag (Kg/m^3)	359.4	0.00	73.89	86.27
FL	Fly Ash (Kg/m^3)	200.1	0.00	54.18	63.99
WT	Water (Kg/m^3)	247.0	121.75	181.56	21.35
SP	Superplasticizer (Kg/m^3)	32.2	0.00	6.20	5.97
CA	Coarse	1145.0	801.00	972.91	77.75

	Aggregates (Kg/m^3)				
FA	Fine Aggregates (Kg/m^3)	992.6	594.00	773.57	80.17
AG	Age (days)	365.0	1.0	45.66	63.16
CS	Compressive Strength (N/mm^2)	82.6	2.33	35.81	16.70

4.5 Pair Plots

Python Command for pair plots:

sns.pairplot(df)

```
In [6]: sns.pairplot(df)
Out[6]: <seaborn.axisgrid.PairGrid at 0x26e95ea6810>
```

Figure 4.2 Command for Pair plot

A pair plot allows us to plot pairwise relationships between variables within a dataset. This creates a nice visualisation and helps us understand the data by summarising a large amount of data in a single figure.

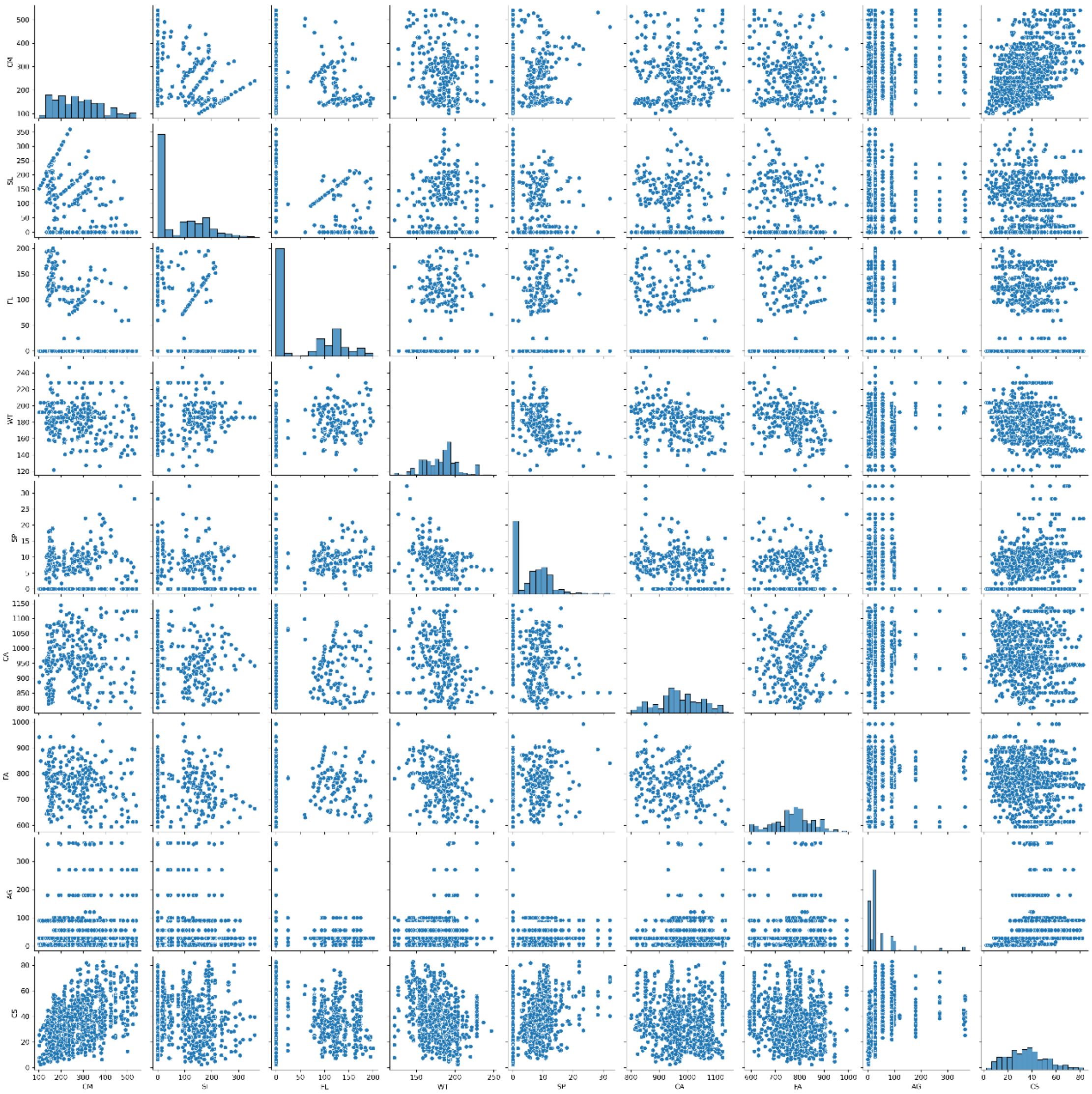

Figure 4.3 Pair plot

4.6 Bar Plots

Python Command for bar plot:

ages = [28, 3, 7, 56, 14, 90,100,180,91,365,270,360,120,1]

values = [315, 134, 126, 91, 62, 54,52,26,22,14,13,6,3,2]

plt.bar(ages, values, width=5)

plt.xlabel(‘Age of Concrete')

plt.ylabel('Number of Observations')

plt.title('Age vs. Number of Observations')

plt.show()

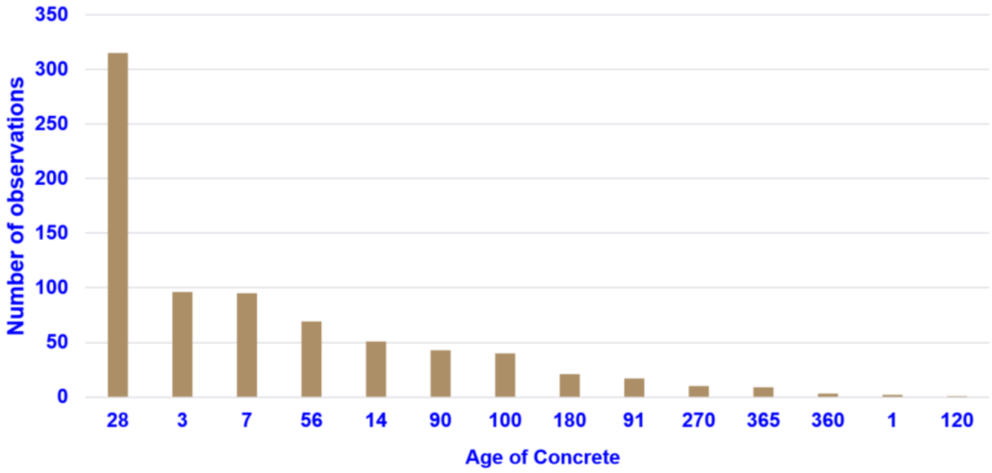

Figure 4.4 Bar Plot

A bar plot is a type of chart that uses rectangular bars to represent and compare different categories or groups of data. The length of each bar corresponds to the quantity or value of a specific variable, allowing for a visual comparison between the categories. Bar plots are commonly used to show the distribution of data, compare the sizes of different groups, or display changes in values over time. They provide a straightforward way to present information and make it easy for viewers to interpret and compare data points at a glance.

4.7 Box Plot

A box plot, also known as a box-and-whisker plot, is a graphical representation of the distribution of a data set. It provides a summary of key statistical measures, such as the median, quartiles, and potential outliers. Box plots are useful for visually assessing the spread and central tendency of a data set.

Here are the main components of a box plot:

Box: The box represents the interquartile range (IQR), which is the range between the first quartile and the third quartile. The length of the box illustrates the spread of the central 50% of the data.

Line (Whisker) or "Hinges": Lines extend from the box, called whiskers, representing variability outside the upper and lower quartiles. Data points beyond this range are often considered potential outliers and are plotted individually.

Median: A line inside the box represents the median of the dataset, which is the middle value when the data is sorted.

Outliers: Individual data points outside the whiskers are considered outliers and are usually plotted individually.

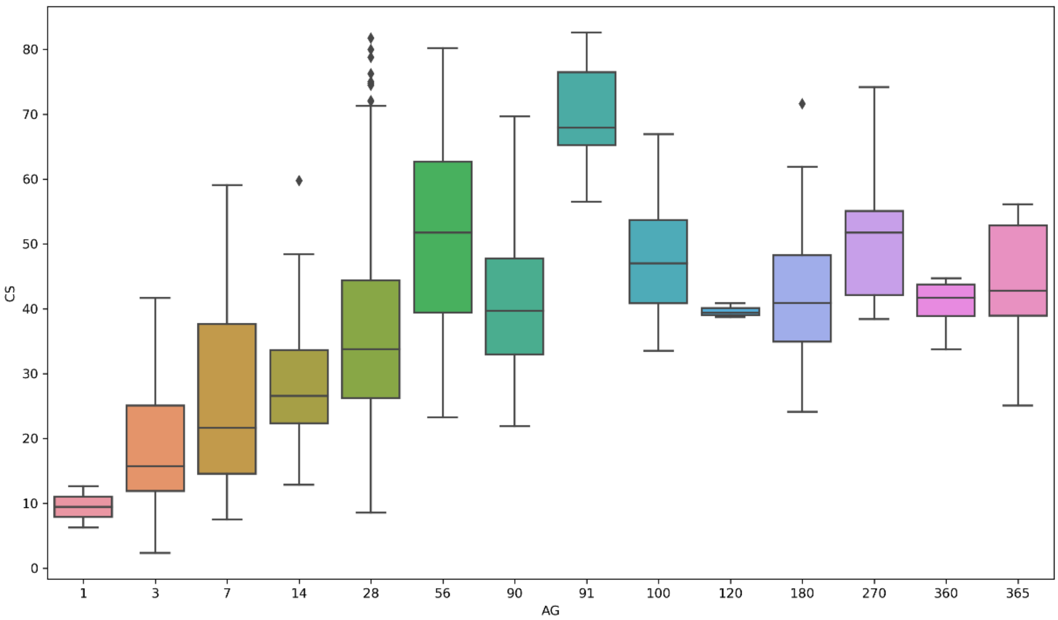

Figure 4.5 Box plots of compressive strength for different ages of concrete

Box plots are useful for comparing the distribution of different datasets or visualizing the spread of a single dataset. They provide a concise summary of the data's central tendency, spread, and potential outliers. Additionally, box plots are particularly effective when dealing with skewed datasets or datasets with outliers, as they are less influenced by extreme values compared to some other types of plots.

4.8 Heatmap

Python Command for heat map:

```
plt.figure(figsize=(14,8))

sns.set_theme(style="white")

corr = df.corr()

heatmap = sns.heatmap(corr, annot=True, cmap="Blues", fmt='.1g')
```

Figure 4.6 Heatmap

A heat map is a graphical representation of data where values in a matrix are represented as colors. It is an effective way to visualize and explore complex datasets, especially those with two-dimensional structures (e.g., a matrix or a table). Heat maps use color gradients to represent variations in data values, allowing patterns and trends to be easily identified.

5 Concrete mix design

The Indian standard code of practice for concrete mix design is IS:10262 (2019). Several examples of concrete mix design are provided in IS:10262 (2019).

5.1 Concrete Mix

A concrete mix is a combination of five major elements in various proportions: cement, water, coarse aggregates, fine aggregates (i.e., sand), and air. Additional elements such as pozzolanic materials and chemical admixtures can also be incorporated into the mix to give it certain desirable properties. The process of determining the specific proportions of these ingredients to achieve the desired properties is known as mix design. Mix design involves considering factors such as the required strength, workability, durability, exposure conditions, and any special requirements for the concrete.

Concrete mix design is the process of finding right proportions of cement, sand and aggregates for concrete to achieve target strength in structures. So, concrete mix design can be stated as concrete mix-Cement, Sand. Aggregates. The concrete mix design involves various steps, calculations and laboratory testing to find right mix proportions. This process is usually adopted for structures which require higher grades of concrete such as M25 and above and large construction projects where the quantity of concrete consumption is huge.. Benefits of concrete mix design is that it provides the right proportions of materials, thus making the concrete construction economical in achieving required strength of structural members. As, the quantity of concrete required for large constructions are huge, economy in quantity of materials such as cement makes the project construction economical.

5.1.1 Key components in a typical concrete mix:

Cement: Cement is a binding agent that, when mixed with water, forms a paste that holds the aggregates together. Common types of cement include Portland cement, Portland pozzolana cement, and others.

Water: Water is used to hydrate the cement and initiate the chemical reaction that leads to the hardening of the concrete. The water-cement ratio is a critical factor in determining the strength and workability of the concrete.

Aggregates:

Fine Aggregates (Sand): Fine sand is used to fill the voids between coarse aggregates and cement particles, contributing to the overall strength and workability.

Coarse Aggregates (Gravel or Crushed Stone): These provide bulk and stability to the concrete. The size and quality of coarse aggregates influence the strength and durability of the concrete.

Admixtures: Admixtures are optional ingredients added to the mix to modify certain properties of the concrete. Common admixtures include plasticizers (to improve workability), superplasticizers (to enhance flow), retarders (to slow down the setting time), and accelerators (to speed up the setting time).

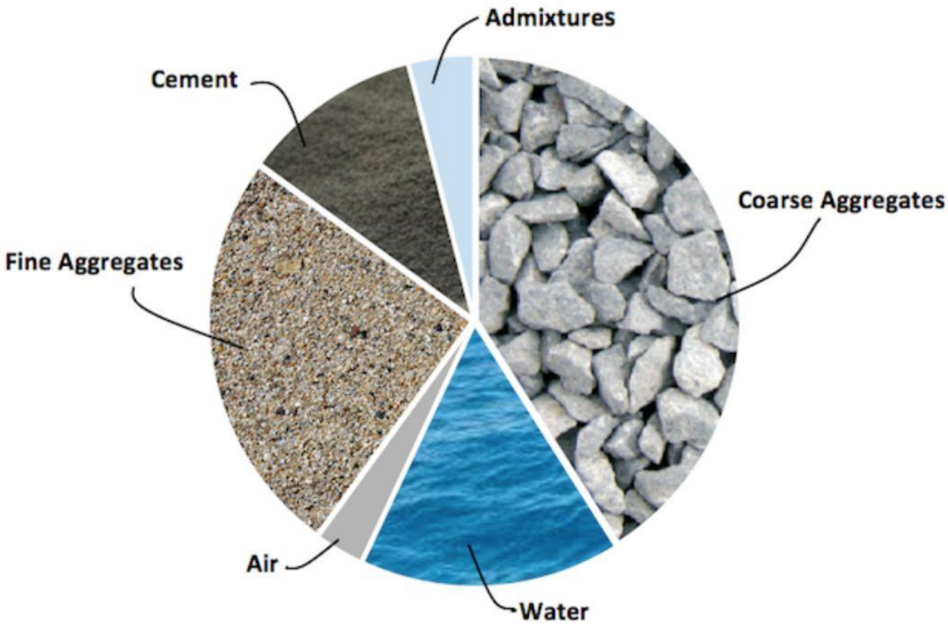

Figure 5.1 Concrete Mix

There are two types of mixes of concrete: nominal mix and design mix.

5.2 Nominal Mix

In the nominal mix concrete, all the ingredients and their proportions are prescribed in the standard specifications. These proportions are specified in the ratio of cement to aggregates for certain strength achievement. The mix proportions like 1:1.5:3, 1:2:4, 1:3:6 etc. are adopted in nominal mix of concrete without any scientific base, only on the basis on past empirical studies. Thus, it is adopted for ordinary concrete, or you can say, the nominal mix is preferred for simpler, relatively un-important and small concrete works.

As per the 'Indian Standard- IS 456:2000', nominal mix concrete may be used for concrete of M20 grade or lower grade such as M5, M7.5, M10, M15.

Table 5.1 Proportions for Nominal Mix as per IS 456:2000

Grade of Concrete	Total quantity of dry aggregate by mass per 50kg of cement to be taken as the	Proportion of fine aggregate to coarse	Maximum quantity of water per	Proportion

	sum of the individual masses of fine and coarse aggregate	aggregate (by mass)	50kg of cement	
M5	800	Generally, 1:2 but subjected to an upper limit 1:1.5 and a lower limit of 1:2.5	60	1:5:10
M7.5	625		45	1:4:8
M10	480		34	1:3:6
M15	330		32	1:2:4
M20	250		30	1:1.5:3

5.2.1 Advantages of Nominal Mix Concrete

- The nominal mix is the prescriptive type of concrete because a proportion is pre-decided.
- It is easy to make at the construction site.
- It doesn't take much time to decide the proportion because proportions are already given by standard code.
- No need to get skilled persons for making the nominal mix concrete.

5.2.2 Disadvantages of Nominal Mix Concrete

- The major drawback of nominal mix is, it's based on the experience and past empirical studies, and it lacks a proven scientific approach.
- It may or may not create exactly designed strength unless all the other factors like compaction, w/c ratio, curing of concrete are strictly followed.
- The water-cement ratio is considered by assumption so, if we don't take care of it, sometimes it leads to bleeding and segregation of concrete resulting in poor strength and accordingly it hampers the durability of concrete.
- There is no consideration for properties of aggregates such as grading and density of aggregate etc.
- In the nominal mix, sometimes cement content is used higher than the requirement, which increases the overall cost of the construction.
- No laboratory tests are conducted to ensure the quality of fresh concrete.
- This mix does not consider and check specific properties of individual ingredients. For example, if we take cement as an element, the fineness of cement, the grade of cement and type of cement, size and grading of aggregate etc. are generally not counted individually while making this nominal mix concrete

5.3 Design Mix

In design mix concrete, proportions of the ingredients are properly determined with their relative ratio to achieve the concrete of desired strength. Not only the desired strength but also according to the properties of fresh concrete like workability or performance of concrete with the certain specifications are taken in detail consideration.

All the materials are tested before the use and the entire process is found based on trial and error of various options from available materials designated for the work.

5.3.1 Advantages of Mix Design Concrete

- Design mix is more scientific than the nominal mix.
- Mix design is widely used for more extensive and important concrete works.
- Mix design is based on the actual available material to be used in construction work.
- If the locally available material can satisfy the standard criteria, it can be used for making mix design concrete so that the mix can reduce the cost of importing material from outside.
- The quantity of the ingredient to be used are rational, i.e. it's neither overused nor underused.
- It is based on the laboratory trial/error experiment method.
- It gives an assurance of strength.
- Mix design concrete is performance-based concrete.
- The designer can use admixtures rationally to modify the properties of concrete according to their requirement.
- Slump and strength can be related, i.e. for strength. We can use different slump by changing water/cement ratio with or without the use of admixtures so that it suits the concreting of different elements, i.e. for footing it may have less slump, i.e. less water-cement ratio, but for thin elements like chhajja or thin walls, it may need a larger slump, i.e. higher w/c ratio or more quantity of admixture. This is not possible in the use of the nominal mix.

5.3.2 Disadvantages of Mix Design Concrete

- Mix Design is time consuming.
- If the type or quality of desired ingredient gets changed during the progress of work, all the proportion will get changed of mix design concrete. Strict supervision is required as it is important, or we may end up making a fresh design which may delay the entire project.
- It is always better to have a mixed design with 2/3 possible brands of cement and to have aggregate from different sources.
- Need the involvement of the skilled persons to prepare the mix design

5.4 Characteristic Compressive Strength

The compressive strength of the concrete is given in terms of characteristic compressive strength of 150 mm sized cubes that is tested at 28 days (f_{ck}). The characteristic compressive strength is defined as the strength of the concrete below which not more than 5% of the test results are expected to fall. The compressive strength of the cube samples, although exhibit variations, when plotted on a histogram are found to follow the shape of a bell shape curve, as shown below.

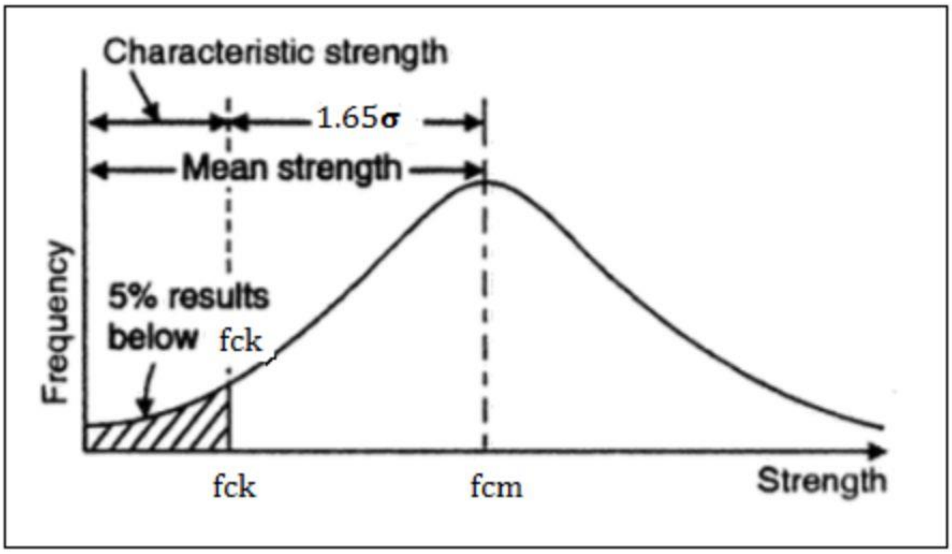

Figure 5.2 Characteristic Compressive Strength (Source IS 456: 2000)

5.4.1 Factors Affecting Compressive Strength

- Water-Cement Ratio (W/C Ratio):
    - The water-cement ratio is a crucial factor affecting the strength of concrete. A lower water-cement ratio generally results in higher strength. Excess water can lead to a porous and weaker concrete matrix.
- Cement Type and Quality:
    - The type of cement used, such as Ordinary Portland Cement (OPC), Portland Pozzolana Cement (PPC), or others, can impact the compressive strength. Additionally, the quality and fineness of the cement play a role.
- Aggregate Properties:
    - **Size and Grading:** Well-graded aggregates with a proper mix of particle sizes contribute to a denser concrete, potentially improving strength.
    - **Shape:** Angular and rough-textured aggregates provide better interlocking and improve strength compared to rounded or smooth aggregates.
- Admixtures:
    - **Plasticizers and Superplasticizers:** These can be used to improve workability without increasing the water content, contributing to better strength.
    - **Retarders and Accelerators:** Influence the setting time, which can affect the strength development.
- Mix Proportions (Mix Design):
    - The proportions of cement, water, aggregates, and admixtures in the concrete mix are critical. A well-designed mix ensures the desired strength and durability.
- Curing Conditions:
    - Proper curing is essential for the hydration process, which directly affects the strength development of concrete. Inadequate curing can lead to reduced strength and durability.
- Temperature:
    - Both the ambient and concrete temperatures during mixing and curing can influence the rate of hydration and strength development. Extreme temperatures can have adverse effects.

- Age of Concrete:
  - The compressive strength of concrete continues to increase over time. While the 28-day compressive strength is commonly specified, longer curing periods can result in higher ultimate strength.
- Testing and Quality Control:
  - Proper testing procedures and quality control measures during concrete production are crucial to ensuring that the actual strength meets or exceeds the specified strength.
- Construction Practices:
  - Proper placing, compaction, and consolidation of concrete during construction are essential for achieving the intended strength.
- Porosity and Void Content:
  - The presence of excessive voids or porosity in the concrete matrix can weaken the structure and reduce compressive strength.
- Environmental Conditions:
  - Exposure to harsh environmental conditions, such as aggressive chemicals or freeze-thaw cycles, can affect the long-term strength and durability of concrete.

5.5 Target Mean Strength

Target mean strength (f_m) is defined as the design strength determined for the manufacture of reinforced concrete. Target mean strength is determined by the formula:

$f'_{ck} = f_{ck} + 1.65S$ or $f'_{ck} = f_{ck} + X$, whichever is higher.

where, f'_{ck} = target mean compressive strength at 28 days, in N/mm2;

f_{ck} = characteristic compressive strength at 28 days, in N/mm2;

S = standard deviation, in N/mm2 (see 4.2.1); and

X = factor based on the grade of concrete,

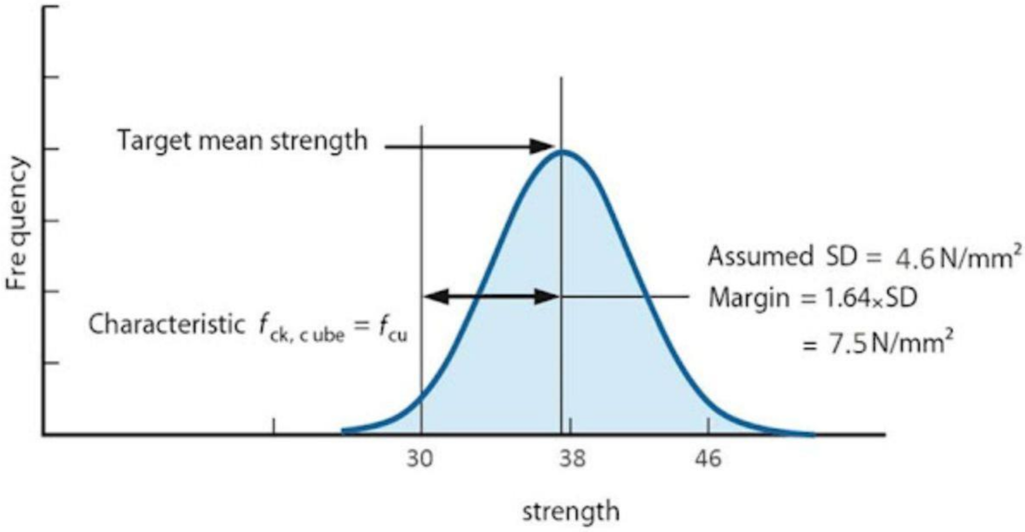

Figure 5.3 Target mean strength

A M20 concrete implies a concrete with characteristic compressive strength of 20 N/mm^2. But in real practice, in order to make a concrete with a strength of minimum 20 N/mm^2, we need to design a concrete with a higher value. Only then, after all possible losses if any, we finally get a concrete equal or greater than 20N/mm^2. A higher strength value more than intended is fine, but a lesser value is not acceptable.

5.6 Illustrative Example on Concrete Mix Proportioning

An example illustrating the mix proportioning for a concrete of M2 The following data is assumed as per the mix design calculation of M20 grade

Characteristic compressive strength: 20Mpa

Cement type: OPC 53 grade

Maximum size of coarse aggregates: 20mm

Workability required at the construction site: 100mm

Exposure condition: Moderate

Concrete placing method: pump able concrete

Specific gravity of cement: 3.15

Specific gravity of coarse aggregates: 2.80

Specific gravity of fine aggregates: 2.70

Fine aggregates sieve analysis: conforming to zone II of table IS 383

Mix design of M20 grade concrete

The following steps are considered in the mix calculation of concrete as per IS 10262 and IS 456 code standards.

Step 1: Calculation of target strength

Target strength is calculated by using $f'_{ck} = f_{ck} + 1.65S$, where S = standard deviation value considered from Table 1 of IS 10262.

Table 5.2 Standard deviation values

S. No.	Grade of Concrete	Assumed standard deviation, N/mm^2
1	M10	3.5
2	M15	
3	M20	4.0
4	M25	
5	M30	5.0
6	M35	
7	M40	
8	M45	
9	M50	
10	M55	
11	M60	
12	M65	6.0
13	M70	
14	M75	
15	M80	

From the above table the standard deviation value for M20 grade concrete mix is 4

So, Target strength = 20+1.65(4) = = 26.6 N/mm^2

Step 2: selection of water cement ratio

The water cement ratio is taken from table number 5 of IS 456: 2000 code related to the exposure condition as shown in Table 5.3.

Table 5.3 Water Cement Ratio as per Table 5 of IS 456:2000

S.No.	Exposure	Plain Concrete			Reinforced Concrete		
		Maximum Cement Content, Kg/m^3	Maximum free water cement ratio	Maximum grade of concrete	Maximum cement content kg/m^3	Maximum free water cement ratio	Minimum grade of concrete
1	Mild	220	0.6	-	300	0.55	M20
2	Moderate	240	0.6	M15	300	0.50	M25
3	Severe	250	0.5	M20	320	0.45	M30
4	Very Severe	260	0.45	M20	340	0.45	M35
5	Extreme	280	0.40	M25	360	0.40	M40

For the moderate condition related to the plain concrete the value of water cement ratio is 0.6. Based on the number of trials using concrete mix adopt the water cement ratio of 0.55.

Here 0.55 < 0.6 hence it is safe.

Step 3: Selection of water content

The value of the water content is selected from table 2 of IS 10262:2019 code of practice. The below specified water content is related to the various size of coarse aggregates

Table 5.4 Water Content as per IS 10262 Table 2

S. No.	Nominal maximum size of aggregates	Maximum water content
1	10	208
2	20	186
3	40	165

For the maximum size of 20mm aggregates, the value of water content is taken as 186 liters. This water content is applicable for 25 to 50mm slump value, and for every increase in 25mm slump value the water content is needed to increase by 3%. Here, in this case the slump value is 100mm. The value of water content increased by 6% and final water content = 186+(6/100)186 = 197.16 liters

Step 4: Calculation of cement content

For the available values of water content and water cement ratio we can easily determine the cement content.

From step 3 and 4 we have W/C = 0.55, Water content = 197.16

Cement = 197.16/W = 197.16/0.55 = 358.47 kg/m^3 < 450 kg/m^3 (maximum cement content), Hence ok.

Step 5: Proportion of volume of coarse aggregates and fine aggregates

The volume of coarse aggregates per unit volume of total aggregates values are initially considered from table 3 of IS 10262 code provisions related to the different fine aggregates zone condition

Table 5.5 Volume Of Coarse Aggregates Per Unit Volume Of Total Aggregates

S. No.	Nominal maximum size of aggregate	Volume of coarse aggregate per unit volume of total aggregate for different zones of fine aggregates			
		Zone IV	Zone III	Zone II	Zone I
1	10	0.50	0.48	0.46	0.44
2	20	0.66	0.64	0.62	0.60
3	40	0.75	0.73	0.71	0.69

Volume of coarse aggregates per unit volume of total aggregates

As per the zone II of 20 mm size aggregates

Volume of coarse aggregates per total aggregates = 0.62

This value of volume of aggregates is valid for 0.5 w/c ratio, for every increase in 0.05

W/C ratio the value of volume of coarse aggregates per total aggregates decreased by 0.01, in the same process for every decrease in 0.05 W/C ratio the value of volume of coarse aggregates per total aggregates increased by 0.01.

Hence, the final volume of coarse aggregates becomes = 0.62-0.01 = 0.61

Now the volume of fine aggregates = 1-0.61 = 0.39

Step 6: Estimation of concrete mix calculation

a. Assume volume of total concrete = 1m^3

b. Volume of cement = $\frac{Mass\ of\ Cement}{Specific\ Gravity}$ x (1/1000)

= (358.47/3.15)*(1/1000)

= 0.1138m^3

c. Volume of water =$\frac{Mass\ of\ Water}{Specific\ Gravity\ of\ Water}$ x (1/1000)

= (197.16/1) * (1/1000)

= 0.19716

d. Total volume of aggregates = 1-b-c = 1- 0.1138-0.19716 = 0.68904

Mass of coarse aggregates = d x volume of coarse aggregates x specific gravity of coarse aggregates * 1000

= 0.68904*0.61*2.8*1000

= 1176.88 kg/m^3

Mass of fine aggregates = d x volume of fine aggregates x specific gravity of fine aggregates x 1000

= 0.68904 x 0.3961 x 2.7 x 1000

= 736.90 kg/m^3

Calculation of mix proportion for trial

Cement = 358.47 kg/m^3

Fine aggregates = 736.90 kg/m^3

Coarse aggregates = 1176.88 kg/m^3

Water = 197.16 kg/m^3

Final mix of M20 grade concrete as per IS 10262 code

Cement : Fine aggregates : Coarse aggregates at W/C

358.47 : 736.90 : 1176.88 at 197.16

Divide entire values with cement

We get final mix proportion as 1: 2.055 : 3.283 at 0.55

5.7 Laboratory tests

Cube test was carried out in the materials laboratory of the department. The results of the cube test were added to the existing database to increase the size of the filtered dataset. The proportions of concrete were decided as per the mix design in accordance with IS 10262-Guidelines for concrete mix design proportioning.

A total of 18 cubes were casted for different grades of concrete namely-M25, M30, and M35. For each grade of concrete tests were carried out on 7, 14, and 28 days.

The procedure to carry out the cube test is prescribed in IS 516 (1959): Method of Tests for Strength of Concrete. The concrete sample is poured into moulds. Concrete cubes are typically formed in moulds with dimensions of 150mm x 150mm x150mm. Each mould is filled, levelled, compacted, and tampered. The cubes are then transferred to the temperature-controlled lab, where they are kept for 24 hours before being demoulded and placed into water tanks to cure. When the curing period is complete, each cube is

placed into a concrete crusher. The machine applies force to the cube until it breaks,

measuring the compressive strength at the point of failure. Once the specimens have been cured for the duration outlined in the project specifications, they are placed in a compressive strength testing machine and following processes take place:

- The machine begins to apply a load to the cube at a controlled rate, typically around 140 kg/cm^2 per minute.
- The load continues to increase gradually and uniformly. The machine ensures that the load is applied evenly across the cube's surface.
- During the loading process, the machine continuously measures and records the applied load
- The load is applied until the concrete cube fails, meaning it cracks or crushes under the pressure.
- At the point of failure, the maximum load applied is recorded. This load is used to calculate the compressive strength of the concrete using the formula.
- The results are analysed to determine if the concrete meets the required strength specifications. This data helps in assessing the quality and suitability of the concrete for its intended use.

5.8 Results of the cube test

The following table summarises the results of the tests performed

Table 5.6 Results of the cube test

S.No	CM (Kg)	SL (Kg)	FL (Kg)	WT (Kg)	SP (Kg)	CA (Kg)	FA (Kg)	AG (days)	CS (N/mm^2)
1	3.351	-	-	1.508	0.016	11.258	7.978	7	17.3
2	3.351	-	-	1.508	0.016	11.258	7.978	14	26.8
3	3.351	-	-	1.508	0.016	11.258	7.978	28	30.6
4	3.624	-	-	1.74	0.018	11.380	8.130	7	21.5
5	3.624	-	-	1.74	0.018	11.380	8.130	14	31.1
6	3.624	-	-	1.74	0.018	11.380	8.130	28	37.3
7	3.807	-	-	1.827	0.019	11.258	7.978	7	25.7
8	3.807	-	-	1.827	0.019	11.258	7.978	14	36.5
9	3.807	-	-	1.827	0.019	11.258	7.978	28	42.8
10	3.351	-	-	1.508	0.016	11.258	7.978	7	17.8
11	3.351	-	-	1.508	0.016	11.258	7.978	14	27.1
12	3.351	-	-	1.508	0.016	11.258	7.978	28	30.2

13	3.624	-	-	1.74	0.018	11.380	8.130	7	22.3
14	3.624	-	-	1.74	0.018	11.380	8.130	14	30.5
15	3.624	-	-	1.74	0.018	11.380	8.130	28	37.4
16	3.807	-	-	1.827	0.019	11.258	7.978	7	26.2
17	3.807	-	-	1.827	0.019	11.258	7.978	14	37.3
18	3.807	-	-	1.827	0.019	11.258	7.978	28	42.6

6 Model Development

This chapter describes the development of different ML models based on deep neural networks (DNNs). These are a type of networks that consists of multiple layers of interconnected nodes, inspired by the structure of the human brain. Each layer processes information in a hierarchical manner, with each subsequent layer learning more abstract features from the input data. In DNNs, there are typically three types of layers: input layers, hidden layers, and output layers. Input layers receive the initial data, hidden layers process this data through weighted connections and activation functions, and the output layer produces the final result. DNNs are capable of learning complex patterns and representations from large amounts of data, making them powerful tools for various tasks such as image and speech recognition, natural language processing, and many others. They are trained using algorithms like backpropagation and optimization techniques like gradient descent to minimize prediction errors and improve performance.. In order to predict the compressive strength of concrete, two deep neural network (DNN) models were developed. The first model was run with the help of the ReLu activation function whereas the second one, whereas the second one used the tanh function. The purpose of creating two models was to do a comparative study of using different activation functions and hyperparameters and minimise the loss function.

The python code for DNN model 1

```
model=Sequential()

model.add(Dense(8,activation='relu'))

model.add(Dense(8,activation='relu'))

model.add(Dense(8,activation='relu'))
```

```
model.add(Dense(1))

model.compile(optimizer='adam',loss='mse')
```

The python code for DNN model 2

```
model=Sequential()

model.add(Dense(8,activation='tanh'))

model.add(Dense(8,activation='tanh'))

model.add(Dense(8,activation='tanh'))

model.add(Dense(1))

model.compile(optimizer='adam',loss='mse')
```

6.1 Hyperparameters Utilised

There are several hyperparameters that drives DNNs

- **Number of hidden layers**

  In a neural network, the hidden layers are the layers between the input and output layers where the actual computation is performed. The number of hidden layers refers to how many of these layers are present in the network architecture. For the DNN model used in predicting the compressive strength of concrete the number of hidden layers were kept equal to three

- **Number of neurons in hidden layers**

  Neurons, or nodes, are computational units within each layer of a neural network. The number of neurons in the hidden layers refers to how many of these units are present in each hidden layer. For the model developed there were 8 neurons in each hidden layer.

- **Number of epochs**

An epoch is one complete pass through the entire training dataset during the training of a neural network. The number of epochs specifies how many times the algorithm will work through the entire training dataset. Increasing the number of epochs allows the model to potentially learn more from the data, but it may also increase the risk of overfitting. An optimum value of 400 epochs was chosen

- **Learning rate**

The learning rate is a hyperparameter that controls the size of the step taken during the optimization process of training a neural network. It determines how much the model parameters are adjusted with respect to the loss gradient. A higher learning rate can lead to faster convergence but may risk overshooting the optimal solution, while a lower learning rate may converge more slowly but with more precision. A learning rate of 0.001 was adopted for this model

- **Type of activation function**

Activation functions introduce non-linearities into the output of a neuron in a neural network. They help the network to learn complex patterns by enabling it to model non-linear relationships. The activation function used for the first DNN model is the rectified linear unit (ReLU) function, whereas for the second DNN model created, the activation function was changed to tan hyperbolic (tanh)

6.2 Performance Metrics

Performance metrics in DNN model building are specific criteria or measures used to assess and quantify the accuracy, effectiveness, and overall performance of a neural network model. These metrics provide a numerical evaluation of how well the model predicts or classifies data and help in identifying areas for improvement. These performance metrics help us understand how well our model has performed for the given data. In this way, we can improve the model's performance by tuning the hyperparameters. Each ML model aims to generalize well on unseen/new data, and performance metrics help determine how well the model generalizes on the new dataset.

Some of the common performance metrics are

Mean Absolute Error (MAE)

Mean Absolute Error or MAE is one of the simplest metrics, which measures the absolute difference between actual and predicted values, where absolute means taking a number as Positive.

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$

Mean Squared Error (MSE)

Mean Squared error or MSE is one of the most suitable metrics for Regression evaluation. It measures the average of the Squared difference between predicted values and the actual value given by the model. Since in MSE, errors are squared, therefore it only assumes non-negative values, and it is usually positive and non-zero. Moreover, due to squared differences, it penalizes small errors also, and hence it leads to over-estimation of how bad the model is. MSE is a much-preferred metric compared to other regression metrics as it is differentiable and hence optimized better.

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Root Mean Squared Error (RMSE)

The Root Mean Squared Error (RMSE) is one of the main performance indicators for a regression model. It measures the average difference between values predicted by a model and the actual values. It provides an estimation of how well the model is able to predict the target value (accuracy). The lower the value of the Root Mean Squared Error, the better the model is. A perfect model (a hypothetic model that would always predict the exact expected value) would have a Root Mean Squared Error value of 0. The Root Mean Squared Error has the advantage of representing the amount of error in the same unit as the predicted column making it easy to interpret

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}}$$

R- Squared

R squared error is also known as Coefficient of Determination, which is another popular metric used for Regression model evaluation. The R-squared metric enables us to compare our model with a constant baseline to determine the performance of the model. To select the constant baseline, we need to take the mean of the data and draw the line at the mean. The R squared score will always be less than or equal to 1 without concerning if the values are too large or small

Table 6.1 Computed performance metrics

Model	**Training Data**				**Testing Data**			
	MSE	**RMSE**	**MAE**	**R^2**	**MSE**	**RMSE**	**MAE**	**R^2**
Dataset 1	33.931	5.8251	4.557	0.879	34.8920	5.9070	4.5310	0.831
Dataset 2	18.682	4.3223	3.605	0.884	26.5851	5.1560	3.8497	0.877
Dataset3	20.825	4.5636	3.472	0.874	31.6058	5.6219	4.1729	0.816

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6.3 Data set 1

The first dataset comprises of a total of 1030 observations obtained from the web Kaggle.com . It comprises of nine quantitative variables

The nine quantitative variables are

1. Cement
2. Slag
3. Fly ash
4. Water content
5. Super plasticizers
6. Coarse aggregate
7. Fine Aggregate
8. Age of Concrete
9. Compressive strength

Dataset 1 which is the unfiltered dataset consists of compressive strengths ranging from 2.33 N/mm^2 to 8.599 N/mm^2

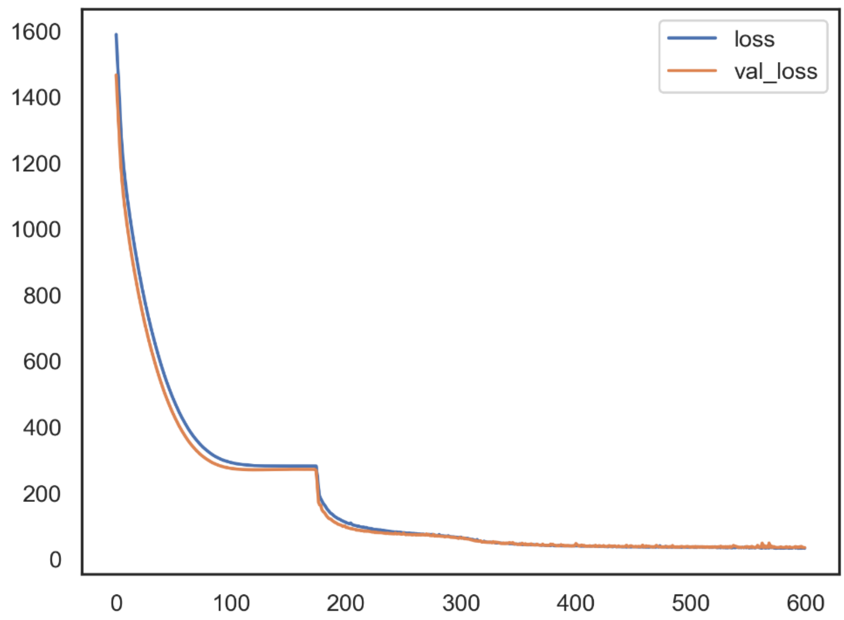

Figure 6.1 Loss curve for dataset1

The loss curve for the data set 1 is shown in Figure 6.1. It can be seen from Figure 6.1 that the loss curve, which first rapidly decreases both training and validation losses, suggests that the model is learning important patterns quickly. This suggests that the model training is effective. After a steep decline in losses around the 170th epoch—likely brought on by a learning rate reduction—both losses then stabilize and gradually decline, showing strong generalization. The model is not overfitting and appears to have reached a point where more training produces little gains when the losses stabilize at the end without divergence. All things considered, the curve shows a well-tuned training procedure and a model that performs well on untested data.

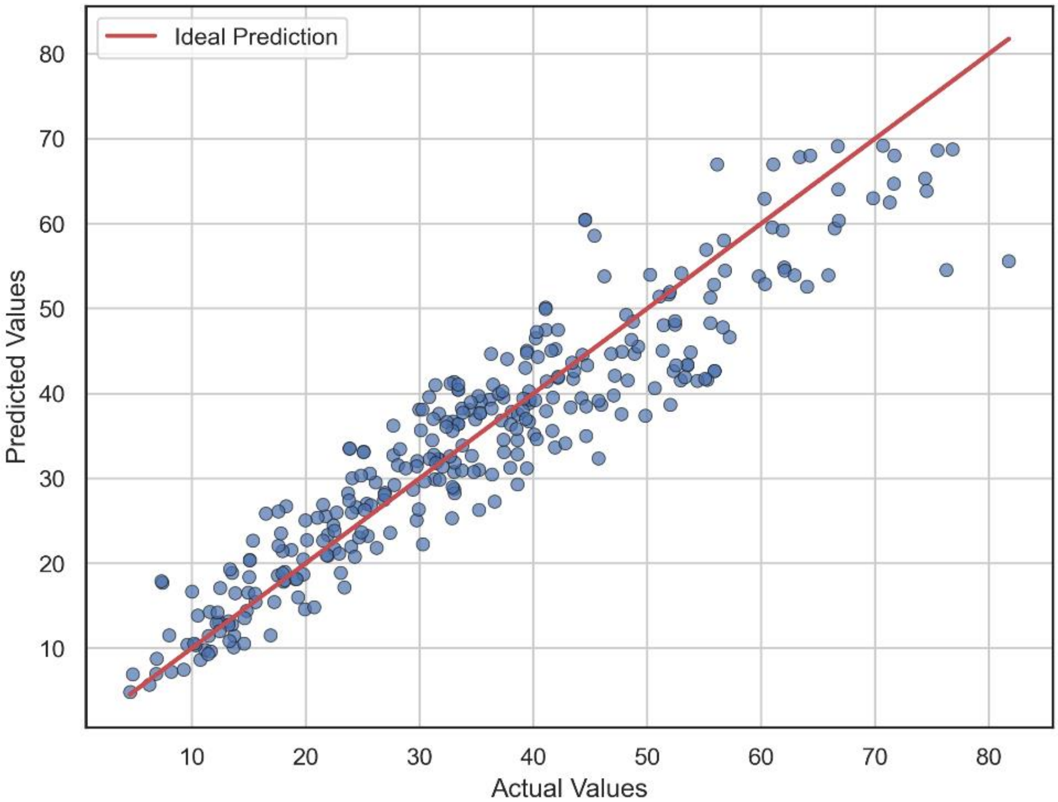

Figure 6.2 Scatter plot for dataset1

The scatter plot shown in Figure 6.2 compares the predicted values to the actual values. The red line represents perfect predictions, where predicted values would match actual values exactly. The points cluster closely around this line, indicating that the model's predictions are generally accurate. However, there is some scatter, particularly at higher values, suggesting slight prediction errors. Overall, the model performs well, with most predictions being close to the actual values

6.4 Data set 2

The second dataset comprises of 721 observations that were filtered from the original unfiltered dataset. Filtering is used in the data processing and analysis to refine and extract useful information from the raw data. It aids in removing unnecessary or irrelevant data, thereby improving the efficiency and accuracy of data analysis . Filtering is widely used across multilple fields including machine learning.

Key features of filtering include :

- Efficient data cleaning by excluding irrelevant data.
- Ability to handle large datasets
- Easy customization of filters to meet specific requirements.

In our case the filtered dataset is obtained by identifying the outliers, that is, removing the values for compressive strength less than 10 and greater than 60 since these values of compressive strength are rarely encountered.

Filtering the dataset improves the performance of our model in the following ways:

Increased Accuracy:

Machine learning models' output can be highly influenced by outliers, which makes it difficult to forecast compressive strength accurately. The model might focus on discovering the underlying patterns in the data by eliminating outliers, which will lead to more precise predictions.

Enhanced Generalization:

It may be difficult for models that were trained on datasets containing outliers to adapt successfully to new, untested data. Improved generalization performance results from the model's ability to more fully represent the underlying relationships in the data by eliminating outliers.

Enhanced Robustness:

Machine learning models that contain outliers may be more susceptible to minute variations in the data, which could lead to less reliable predictions. Eliminating outliers makes models stronger and less susceptible to extreme values.

Improved Interpretability:

It might be difficult to grasp the analysis's findings when outliers mask the underlying patterns and relationships in the data. When outliers are eliminated, the final model is frequently easier to understand and provides more information about the variables affecting compressive strength.

In conclusion, eliminating outliers from compressive strength calculations by machine learning can result in models that are more precise, reliable, and understandable, therefore enhancing the prediction process' performance

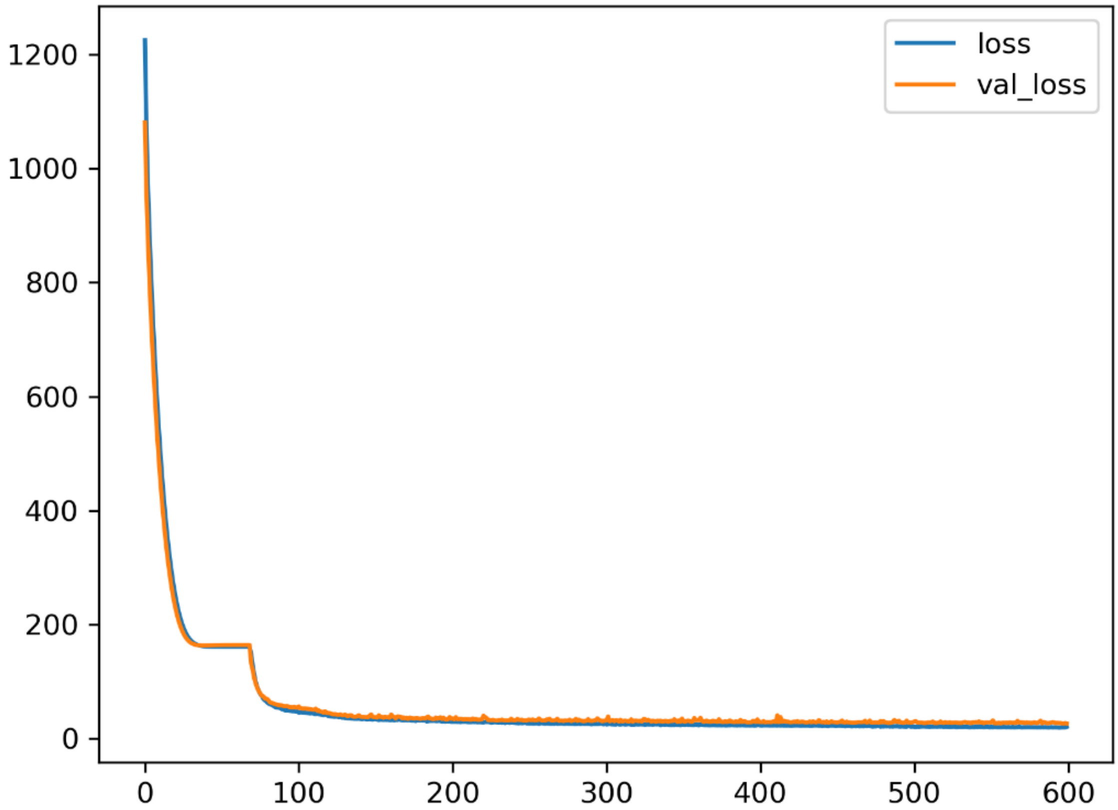

Figure 6.3 Loss curve for dataset2

The loss curve for dataset 2 shown in Figure 6.3 depicts that both training and validation losses start high and drop rapidly in the first 50 epochs, indicating that the model quickly learns the main patterns. After this, the losses level off and decrease slowly, stabilizing around the 100th epoch and remaining low and close together for the rest of the training. This suggests that the model is learning well and generalizing effectively to new data, without signs of overfitting.

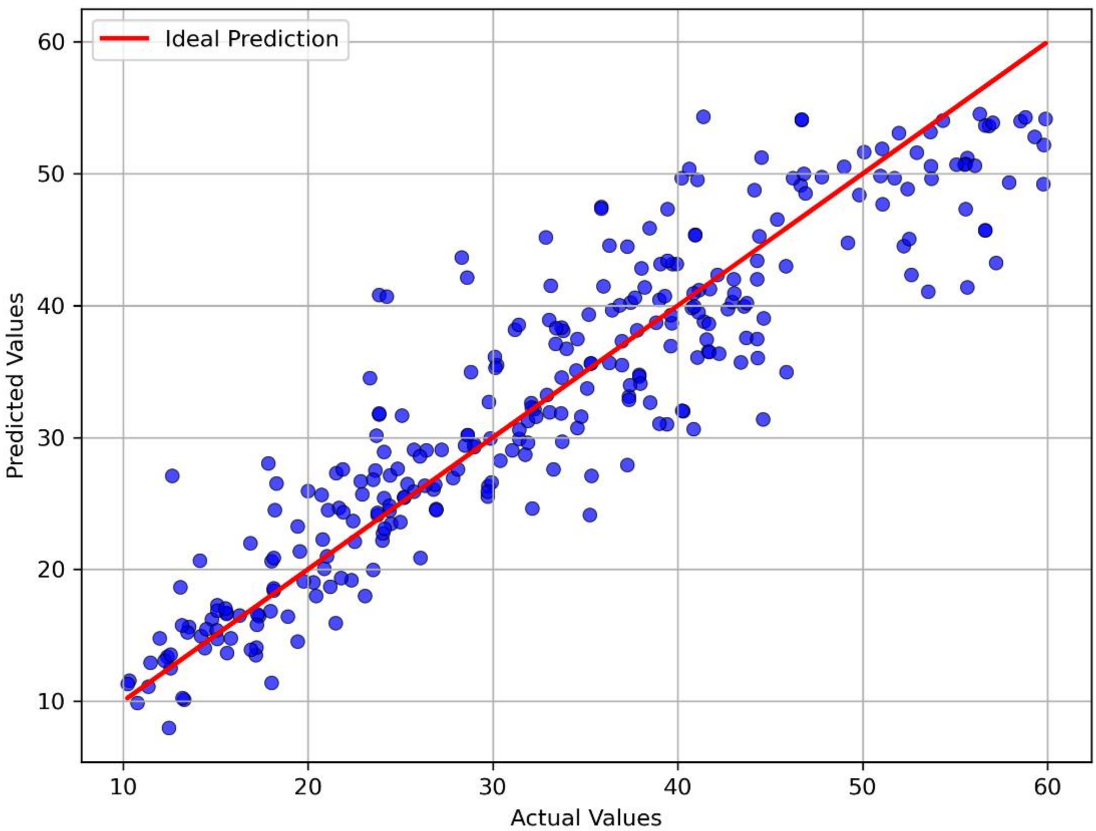

Figure 6.4 Scatter plot for dataset2

The scatter plot for dataset 2 shown in Figure 6.4. The red line displays the line of ideal predictions where the predicted value is equal to the actual value. The spread of the blue dots around this red line suggests that the predictions are generally close to the actual values, though there is some variability, indicating that the model's predictions are reasonably accurate but not perfect. Points above the line represent overpredictions, while those below indicate underpredictions.

6.5 Data set 3

The Data set 3 is a compilation of the filtered dataset merged with the results from laboratory cube tests conducted according to the specifications outlined in IS 10262:2019. Different design mixes were prepared as per these specifications, and subsequently, 18 cube tests were performed in the laboratory. The results obtained from these tests were then integrated with the filtered dataset.

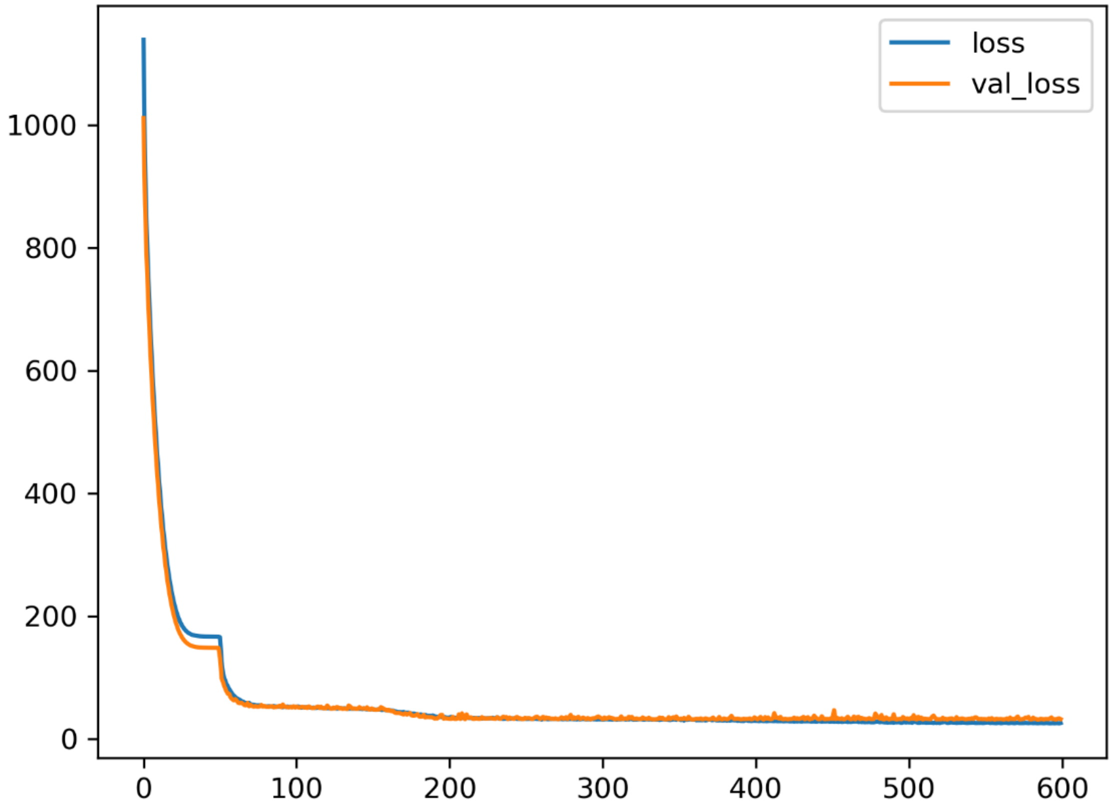

Figure 6.5 Loss curve for dataset3

The loss curve for dataset 3 shown in Figure 6.5 depicts the training loss (blue line) and validation loss (orange line) over 600 epochs. Both loss values start very high and decrease rapidly within the first 100 epochs, indicating that the model is learning and improving quickly during the initial training phase. After this steep decline, the loss values stabilize and continue to decrease gradually, converging towards a lower value, suggesting that the model's performance is improving steadily without overfitting. The close alignment of the training and validation loss curves indicates good generalization of the model to unseen data.

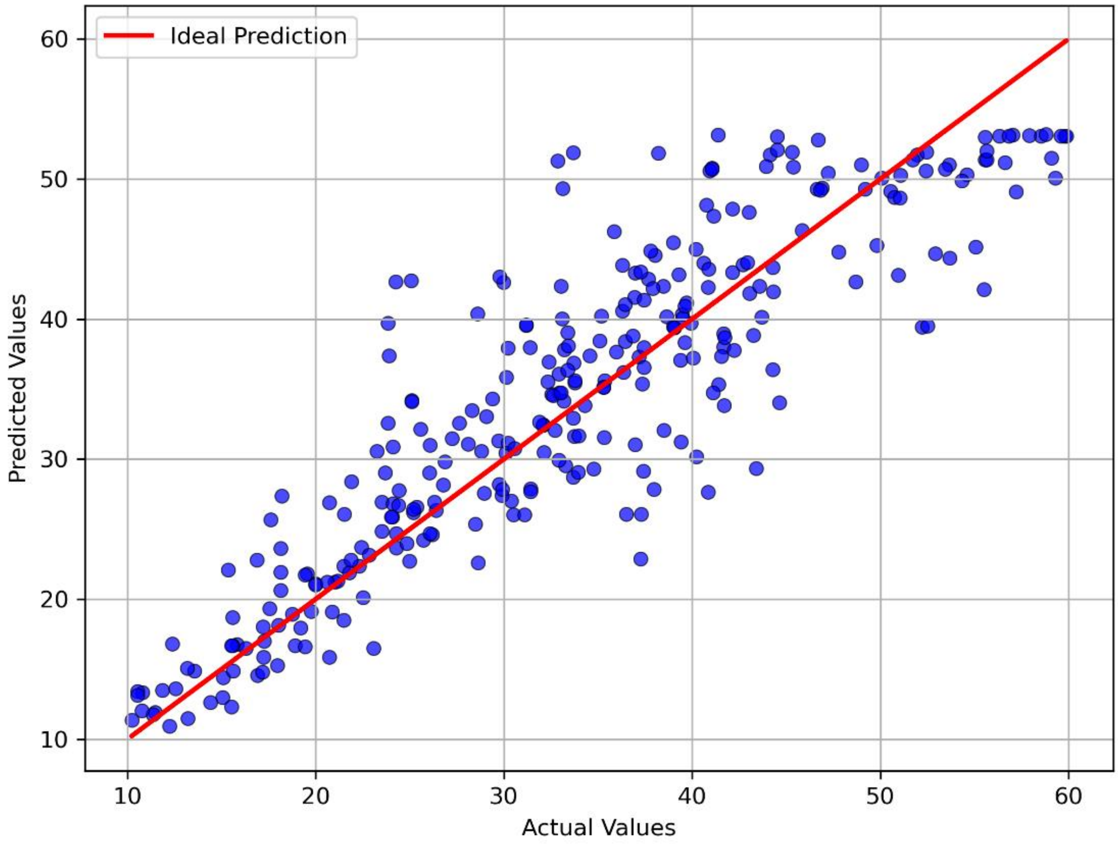

Figure 6.6 Scatter plot for dataset3

The scatterplot for dataset 3 shown in Figure 6.6 depicts clustering of blue dots around the red line indicating that the model's predictions are generally close to the actual values. However, there is noticeable spread, suggesting some variance in prediction accuracy. Points above the line indicate overpredictions, while points below it indicate underpredictions, reflecting areas where the model's performance could be further improved.

7 Conclusions

The major objective of the present project was to develop machine learning models for the prediction of compressive strength of concrete. The database considered in this project was obtained from Kaggle.com. The database comprises of 1030 observations having 9 quantitative variables comprising of cement content, slag, fly ash, water content, super-plasticizers, coarse aggregate, fine aggregate, age of the sample at the day of testing and the corresponding compressive strength The input data includes various ingredients of the concrete mix and its age, while the target variable is the compressive strength. A descriptive analysis of the input and output variables has been carried out in this project. The project has explored the relationship between different variables with the goal of enhancing the power of machine learning to optimize concrete mix proportions. Heatmaps, box plots, bar plots, and pair plots were used to analyse and determine the relationships within the data. The use of Jupyter Notebook and its libraries, such as Numpy, Pandas, Matplotlib, and Seaborn allowed for a thorough analysis of the dataset.

Following the dataset analysis, deep neural network models were developed to predict the compressive strength of concrete. For the first model, the original database of 1,030 observations was used, with 70% of the data employed to train the model and predict the compressive strength for the remaining data. Various performance metrics indicated that the model performed well, with most predictions showing only slight errors. To enhance efficiency and precision, the second model was created and run using a filtered dataset. Outliers, where the compressive strength was less than 10 or greater than 60 were discarded as these grades are not often used in practice. Running the model on the filtered dataset significantly minimized errors and reduced the gap between actual and predicted values. The performance of the model based on filtered dataset was better than the model based on unfiltered dataset. The third model comprises of the filtered dataset merged with the results from the cube tests conducted in the laboratory.

In conclusion, the machine learning model based on filtered dataset performed better than the remaining two models. The machine learning models developed in this project show a substantial potential for cost and time savings by reducing the reliance on labor-intensive and time-consuming laboratory tests. This project demonstrates how artificial intelligence (AI) has the potential to transform the construction sector, thus leading to a more creative and effective uses of concrete technology.

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