MECHANICAL AND DURABILITY ANALYSIS OF COMPLETELY REPLACEDNATURAL AGGREGATE CONCRETE WITH RECYCLED AGGREGATE CONCRETE USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

A

THESIS

Submitted in partial fulfilment of the requirements for the award of the degree of

MASTER OF TECHNOLOGY
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CIVIL ENGINEERING

With specialisation in

STRUCTURAL ENGINEERING

Under the supervision of

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STUDENT'S DECLARATION

I hereby state that the project report titled **"Mechanical and Durability Analysis of Completely Replaced Natural Aggregate Concrete with Recycled Aggregate Concrete using Artificial Intelligence and Machine Learning"** submitted in partial fulfilment of the requirements for the Master of Technology degree in Civil Engineering at the **Jaypee University of Information Technology, Waknaghat** is an authentic record of our work conducted under the supervision of **Mr. Chandra Pal Gautam and Mr. Kaushal Kumar.** This work has not been submitted for any other degree or credential consideration. The project report's content is entirely my Authority.

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CERTIFICATE

This is to certify that the work which is being presented in the project title **“Mechanical and Durability Analysis of Completely Replaced Natural Aggregate Concrete with Recycled Aggregate Concrete using Artificial Intelligence and Machine Learning ”** in partial fulfilment of the requirements for the award of the degree of Master of Technology in Structural Engineering and submitted to Department of Civil Engineering, **Jaypee University of Information Technology, Waknaghat** is an authentic record of work carried out by **Ayush(212652)**for a period from July 2022 to December 2022 under the supervision of**Mr. Chandra Pal Gautam and Mr. Kaushal Kumar(Assistant Professor Grade-II)** Department of Civil Engineering, Jaypee University ofInformation Technology, Waknaghat.The above statement made is correct to the best of my knowledge.

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ABSTRACT

Natural aggregates have long been used in construction, but the rising need for building supplies and the limited supply of natural resources have prompted researchers to look at substitutes. Since they can be made from construction and demolition waste, recycled aggregates have gained popularity as a sustainable alternative to natural aggregates. This reduces the amount of waste that is dumped in landfills. Recycled aggregates can be used in place of natural aggregates in a variety of building applications, such as paving, concrete, and masonry, according to substantial research on the subject. To guarantee the quality and longevity of the produced products, problems like the unpredictability of recycled aggregates and the potential for contamination must be solved.Despite these obstacles, the use of recycled aggregates can benefit the environment, the economy, and the development of a more circular and sustainable economy.Construction and demolition (C&D) waste is the waste produced during the building's construction, upkeep, repair, and disposal phases. The issue of managing C&D trash affects not only India but the entire world as the amount of garbage created accounts for a significant portion of the mass generated by solid waste. In addition, as environmental consciousness grows, pressure is mounting for construction materials to be recycled rather than discarded. It is theoretically possible and might even be advantageous for the environment in some cases to use construction debris as an aggregate for creating new concrete products.Thus, Recycled aggregate has been used in concrete because society is more cognizant of the need to safeguard natural resources. In order to properly utilise the waste materials, recycled aggregate (RA) has been introduced as the coarse aggregate in concrete mixtures. In contrast to concrete made with natural aggregate, however, recycled aggregate concrete, also known as recycled aggregate concrete, was rarely or never utilised.In order to ensure environmental sustainability, the current government campaign to ban sand mining emphasises the necessity to recycle, reuse, and substitute natural aggregates. The goal of this research project is to conduct an experiment in which recycled aggregates are made from C&D waste, paving the path for the efficient management of concrete debris.Each building has an age after which the building is demolished and we are left with a huge debris of construction material after demolition.Till now, this debris was considered recyclable and used mainly for filling purposes. The Indian govt showed concern regarding this and made provision for it to be utilized and in 2021 Schedule of Requirements(SOR)of the Indian Government made provisions for RCA.The goal of this research project is to conduct an experiment in which recycled aggregates are made from C&D waste, paving the path for the efficient management of concrete debris. As a replacement for natural coarse aggregates in proportions of 100%, or completely replaced Recycled aggregates, concrete waste was collected from the waste yard on the college campus and AIREF construction sites. This concrete waste was segregated, manually crushed, sieved and washed before being used for concreting for a mix proportion of M40 grade of concrete. The testing revealed that the compressive strength was lower than that of a Normal M40 concrete mix. However, it was determined to be appropriate for M30 grade construction projects. As a result, the usage of recycled concrete aggregate demonstrated satisfactory performance in terms of mechanical qualities.Additionally, by using data science, we predicted how much of raw material to use in order to achieve a good compressive strength, which will save us a lot of time and effort.So, in order to predict the quality, we analysed the dataset for concrete compressive strength and created a machine learning model too.

Keywords: Recycled Aggregate, compressive strength, Normal design mix,

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LIST OF ABBREVIATIONS

CA	Coarse Aggregates
C&D	Concrete and Demolition Waste
CS	Compressive Strength
FA	Fine Aggregates
GHG	Green House Gases
LPR	Linear Polarization Resistance
NAC	Natural Aggregate concrete
OPC	Ordinary Portland Cement
OPC	Ordinary Portland Cement
RCA	Recycled Concrete Aggregate
RCC	Reinforced Concrete
RMSD	Root Square Deviation
RMSE	Root Mean Square Error
SOR	Schedule of Rate
SG	Specific Gravity
SHM	Structural Health Monitoring
SSD	Saturated Surface Dry

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CHAPTER 1

INTRODUCTION

1.1GENERAL

Recycled aggregate concrete (RAC) is a potential strategy for environmentally friendly building. RAC is created by substituting aggregate made of demolition debris for natural aggregates in concrete. This conserves natural resources and lessens the quantity of waste that is transferred to landfills. Additionally, RAC has been demonstrated to have properties similar to those of conventional concrete and can be used in a variety of construction projects, including bridges, buildings, and pavements.

The characteristics of RAC are influenced by a number of elements, including the standard of the recycled aggregates, the kind of cement used, and the mixing procedure. High-quality recycled aggregates, like those derived from crumbled concrete, can produce RAC with qualities similar to those of conventional concrete [1].

Research has demonstrated that RAC can have a number of positive effects on the environment and the economy. It can lower the demand on natural resources, lessen the amount of waste disposed of in landfills, and lower the cost of transportation for waste removal. Additionally, RAC has been shown to have a lower carbon footprint than conventional concrete because producing recycled aggregates uses less energy.

However, using RAC is not without its difficulties. The variety of recycled aggregates, which can impact the strength and durability of the final concrete, is one of the key difficulties. The characteristics of the final concrete may also be adversely affected by impurities in recycled aggregates, such as leftover mortar or metals.

Various standards and guidelines for the use of RAC have been developed to address these issues. These specifications include advice on RAC testing and characterization, RAC design and construction, and the calibre of recycled aggregates.

In conclusion, employing RAC is a viable strategy for environmentally friendly building. Despite the difficulties involved in using recycled aggregates, RAC is a practical choice for a variety of construction applications due to its economic and environmental conditions.The usage of RAC is expanding thanks to the creation of standards and norms, and it is anticipated to play a bigger part in sustainable construction methods in the future. Whatever waste we get from construction, test sites, demolition are covered in recycled aggregates. It may consist of broken tiles, stones, ceramics and any construction waste.

RCAs are known for having high water absorption and lower strength as compared to its competitor natural aggregates like sand and gravel. This is due to its high pore pressure due to the outer layer being crushed stratum of concrete known as attached mortar. Since this attached mortar affects the strength and properties, hence special attention should be paid to monitor its effects and take its action into accountability.

The demolition of Industry can also create RAC and all other kinds of waste from construction industry also contributes towards the creation of RCA. This abundance of RCA can thus be used to create new cement-based techniques to utilise the usage of these RCAs. These can be used to create an eco-friendly alternative to the commercial cement and concrete used.

1.2 UTILIZATION OF RECYCLED AGGREGATES

The concrete which is used from the demolition waste of existing buildings and pavements constitutes crushed concrete and these aggregates are suitable to form Recycled concrete. It is is what is meant by the recycled concrete aggregate seen in Figure 1.1. It is a combination of the paste of cement and the mortar of cement. As with many natural aggregates, processing typically entails crushing, grading, and washing.

RCA is made of aggregate bits that have been covered with cement mortar or cement paste. Processing often requires crushing, grading, and washing, as it does with many natural aggregates.

By doing this, contaminating contaminants such remaining formwork, gypsum board, reinforcing steel, and other foreign components are removed. The resulting coarse aggregate can subsequently be used to create concrete. However, the fine aggregate frequently contains a substantial proportion of old cement paste and mortar.Problems with an unworkable mix and strength as well as an increase in drying shrinkage are frequently the result of this..

By far, the most common application for recycled concrete aggregate is in the construction of concrete sub-base for highways, bank protection, noise barriers, and embankments, as well as several types of general bulk fills and fill materials for drainage systems.
following the removal of impurities by air purification, screening, or selective demolition. For foundations of bridges, gutters, and roadways, crushed concrete can be used in place of fresh concrete. Additionally, it can be used to create goods like bituminous concrete, structural grade concrete, soil-cement pavement bases, and moulded concrete bricks and blocks.Recycled concrete was used for some of the structural slabs of a high-rise building in Japan, although there was little information available on this project.

Recycled aggregates are nowadays used in South Australia for just around 7% of the material used in road construction, according to Australian study. For their road base building projects, Victoria Road also uses recycled aggregate, while Main Roads in Queensland does not at the moment. Therefore, in the present research we will be using processed recycled aggregatesalso and study it effects on the desired compressive strength.

Fig 1: Waste concrete cubes

1.3RESEARCH OBJECTIVES

Initially the objective was to make high strength concrete (M40) using natural aggregates with conventional mixing approach. After that we made use of processed recycled and replace it by 100% recycled concrete aggregate.The purpose of this project is to compare the characteristic strength and durability characteristics of a concrete sample with 100% demolition aggregates with those of naturally found aggregates and to identify the most affordable and premium, concrete made of recycled material options available in South East Queensland in order to minimise any negative environmental impacts.Also, we compared the durability properties like compressive strength of the cubes after 7th, 14thand 28th days of curing. Another important consideration for achieving the appropriate longevity is concrete strength. It took 28 days to calculate the characteristic strength which is a considerate period of time.. Thus, by using ML, we can predict the amount of raw material needed to use in order to achieve a good compressive strength, which saves us a lot of time and effort.

The scope of this project:

- Read, understand and carry out the literature review regarding the use of recycled aggregates in place of normal aggregate concrete.

- Research the important issues in the production and application of the recycled concrete aggregate in the production of the concrete cubes.

- Construct the concrete cubes with the NAC and RAC (100%) of M40 grade and carry out the laboratory testing to find the characteristic strength after 28 days.

- Analyse the test result and compare the characteristic compressive strength of recycled and normal concrete aggregates.

- Predicting the durability and properties of concrete data with the help of Machine learning and Python code.

- Findings and recommendations from this study which can be used for further research in the particular research project.

1.4LAYOUT OF REPORT

This report is structured in the following format.

- Chapter 2 consist of a survey of pertinent literature on recycled concrete aggregates. This chapter also covers any problems discovered during earlier investigations and studies of recycled aggregate conducted globally.

- Chapter 3 deals with the origins of the concrete and the procedure and price for collecting and transporting recycled aggregate concrete. The process for creating high-quality recycled concrete aggregate, including the necessary level of screening will also be covered in this. Thechapter addressed the material employed, along with its composition and qualities, as well as the thorough experimental process.

- Chapter 4 deals with the prediction of Characteristic strength of concrete using AI and ML with the aid of Python programming.

- Chapter 5 deals with the Final outcomes of the compressive strength test and comparison of characteristic strength between normal aggregate concrete and recycled aggregate concrete are shown. It presents the finding from the Machine Learning utilising Python code, a model trained on data with features including cement, water, CA,FA, and age is needed to estimate the compressive strength of concrete.

- Chapter 6 deals with the conclusion and future scopes of the research work mentioned in this thesis

CHAPTER 2

LITERATURE REVIEW

2.1 GENERAL

In this lesson, we'll take a quick look at the research on how recycled aggregate affects concrete's compressive strength. The literature on various methods for gauging compressive strength after substituting recycled materials for natural aggregate was also discussed. The research done in the past by many researchers to examine the various methodologies utilised in comprehending test design and outcomes is discussed in this chapter. A thorough summary of the results is provided in this chapter, along with recommendations for further investigation.

The literature analysis offers a thorough overview of the state of the art with relation to concrete's compressive strength and emphasises the significance of choosing the right mix designs and curing conditions to reach the necessary strength levels. The review also identifies gaps in our knowledge of the subject and offers ideas for future research possibilities. For scholars and professionals concerned in the design and assessment of concrete structures, this review is a useful resource.

2.2 LITERATURE SURVEY

Peng Zhanget al[1] examined how the admixture of recycled concrete and the temperature for curing affect GPRAC potential, which aids in optimising ratio design and curing conditions. It also offers recommendations for the RAC in concrete consisting of geopolymer. and provides theoretical backing for the use of GPRAC in subsequent practical engineering applications.

The research on the mechanical characteristics, robustness, and microscopic features of GPRAC is summarised in this paper. With various strength tests including chemical , and chloride penetration resistance are among the materials whose constituents have been reviewed. It has been discovered that GPRAC can be improved by altering the curing temperature, employing various pre assigned materials, including fibres and nanoparticles, and establishing ideal mix ratios. When compared to employing just one precursor material, using several precursor materials in synergy generally shown greater performance. The apparent density was comparable to that of NA, respectively, when modified recycled aggregates were used.

Rashad, Alaa. Et al[2]In this work, the mechanical characteristics of recycled aggregate concrete (RAC) that uses recycled glass aggregate (RGA) to replace some of the natural coarse aggregates (NCA) are examined. The RGA replacement levels by volume of NCA 0-100%.Characteristic strength, spli tensile strength, elastic modulus, and bond strength between the concrete and steel reinforcement were among the parameters assessed. The findings demonstrated that when the RGA replacement improved the test values. The RGA replacement level had no impact on the bond strength between the concrete and steel reinforcement, though. Although the mechanical qualities of the RAC incorporating RGA were inferior to those of the traditional NCA concrete, they were nonetheless suitable for use in building.

According to the research, RGA can be used as a sustainable substitute for NCA in the manufacture of RAC, thereby lowering the demand for virgin aggregates and promoting the circular economy of building materials.

M. D. B. Filho, T. V. F. Junio et al [3]In this study, recycled aggregates from construction and demolition debris (CDW) completely overtake use of the concrete with natural aggregates (NA) in concrete to evaluate its performance. The RA concrete's physical, mechanical, and durability characteristics were contrasted with those of the NA concrete. According to the findings, the RA concrete was more porous, less dense, and less compressive than the NA concrete. However, the RA concrete's splitting tensile strength, elastic modulus, and drying shrinkage were comparable to those of the NA concrete. The RA concrete's resistance to carbonation, chloride diffusion, and water absorption was comparable to that of the NA concrete. According to the results, RA from CDW can be utilised as a sustainable substitute for NA in the production of concrete, lowering the environmental impact.

The study's findings suggest that:

-With more porosity and lesser density, the RA concrete's physical qualities were subpar compared to those of the NA concrete.

-The RA concrete's mechanical qualities, including its compressive strength, were likewise inferior to that of NA concrete. The elastic modulus of the RA concrete were comparable to those of the NA concrete, though.

-The RA concrete’s durability characteristics, including its resistance to carbonation, water absorption, and chloride diffusion, were comparable to those of the NA concrete.
-By lowering the requirement for virgin aggregates and preventing waste from going to landfills, the usage of RA from CDW can support the circular economy of building materials.

M. Hosseini, M. R. Esfahani et al [4] This study examines how concrete performs when NA is completely replaced with RA from CDW. The RA concrete’s physical, mechanical, and durability characteristics were contrasted with those of the NA concrete. According to the findings, the RA concrete was less dense, absorbed more water, and had lower compressive strength than the NA concrete. However, the tensile strength, elastic modulus, and drying shrinkage of the RA concrete were comparable to those of the NA concrete. The RA concrete’s resistance to carbonation and chloride diffusion was comparable to that of the NA concrete. According to the research, RA from CDW is a potential alternative to NA for producing concrete sustainably.

The study’s findings suggest that:
-The RA concrete’s physical characteristics, such as its lower density and greater water absorption, were inferior to those of the NA concrete.
-The RA concrete’s mechanical qualities, including its compressive strength, were likewise inferior to those of the NA concrete. The strength tests of the RA concrete were comparable to those of the NA concrete, though.
-The RA concrete’s durability characteristics, including its resistance to chloride diffusion and carbonation, were comparable to those of the NA concrete.
-By lowering the demand for virgin aggregates and preventing waste from going to landfills, the use of RA from CDW can support the circular economy of building materials.
R. M. Abadíaet al [5] In this study, the mechanical characteristics and toughness of concrete constructed entirely from RA from CDW are assessed. Comparing the RA concrete’s facial, and other characteristics to those of a reference concrete built with natural aggregates (NA). The findings indicate that compared to the NA concrete, the RA concrete had a lower density, a higher porosity, and a lower characteristic strength.. The split and elastic modulus test of the RA concrete were comparable to those of the NA concrete, though. The RA concrete’s resistance to carbonation and chloride diffusion was comparable to that of the NA concrete.

The final outcome shows that there’s a chance to produce concrete using 100% RA from CDW, but to achieve the best results, mix design and production procedures may need to be changed.

The study’s conclusions showed that the RA concrete’s physical characteristics—lower density and more porosity—were inferior to those of the NA concrete.
The RA concrete’s mechanical qualities, including its compressive strength, were likewise inferior to that of the NA concrete. The split tensile strength test and elastic modulus of the RA concrete were comparable to those of the NA concrete, though.
The RA concrete’s durability characteristics, including its resistance to chloride diffusion and carbonation, were comparable to those of the NA concrete.
100% RA from CDW can be used to produce concrete, but to maximise the RA concrete’s qualities, mix design and production methods may need to be changed.

F. P. N. P. Ferreira, M. A. G. Silva et al [6] In this work, the physical characteristics of concrete are examined with (RA) made from precast concrete scraps completely replacing natural aggregates (NA). Strengths in compression and splitting tensile, elastic modulus, and flexural strength are among the parameters that were assessed. The outcomes are contrasted with those of a NA-made reference concrete. The study also examines the impact of the ratio to determine replacement curing period, and ratio determining water-to-cement contenton the physical attributes of the samples. The prediction indicate that it is possible to use RA made from precast concrete waste as a full substitute for NA, as it has compressive and splitting tensile strengths that are on par with those of the reference concrete. Additionally, the outcomes show that the mechanical properties are significantly influenced by the replacement ratio, curing duration,..

The study’s conclusions show that:
-Complete replacement of Natural Aggregates with RA made with precast concrete waste is achievable, and its strength tests are on par with those of the control concrete.
-The flexural strength and elastic modulus of the RA concrete, however, were lower than those of the reference concrete.

-The strength properties of the Recycled concrete are significantly influenced by the replacement ratio, curing period, and water-to-cement ratio.
-A reduced RA replacement ratio causes the concrete’s mechanical characteristics to decline.
-Lower water-to-cement ratios result in less workable concrete but higher strength tests.
-The study emphasises the possibility of employing RA from precast concrete waste as a sustainable substitute to Natural aggregates in the manufacturing of concrete, but it also makes the case that mix design and production procedures may need to be adjusted to best utilise the RA concrete’s qualities.

M. K. Bhattacharyya, S. B. Bagchi et al [7] The study examines the compressive and rest of the strength tests of 100% RCA concrete and compares the findings to 100% NCA concrete. The study also looks at how other variables, like the ratio of water to the cement, curing duration, and RCA change ratio, affect the mechanical qualities of the concrete. The results indicate that 100% RCA concrete can be used as a substitute for NCA since its compressive and rest of the strength tests are on par with those of NCA concrete. However, RCA concrete has a lower modulus of elasticity than NCA concrete. The study also discovered that the mechanical properties of RCA are significantly connected by the replacement ratio, ratio of water to cement, and curing duration.

The study’s findings suggest that:
-With compressive and rest of the strength tests that are on par with NCA concrete, 100% RCA can be used as a substitute.
-Higher compressive and other strength tests are produced by a reduced water-cement ratio, but this also reduces workability.
-Higher compressive, breaking tensile, and flexural strengths are produced by extended curing times, but the modulus of elasticity is unaffected.
-The study indicates that RCA can be a practical substitute for NCA in the production of concrete, but it also makes the case that modifications to mix design and manufacturing procedures could be required to maximise the attributes of RCA concrete.

F. F. de Oliveira, F. M. Rodrigueet al [8]This study examines the mechanical properties and environmental effects of concrete produced using recycled aggregates (RA) manufactured from precast concrete waste (PCW) in place of all natural aggregates (NA). The study looks at the concrete’s strength tests and elastic modulus in addition to the environmental effects of its energy use and greenhouse gas (GHG) emissions. The results indicate that it is possible to replace NA with RA from PCW since it has mechanical qualities that are similar to those of NA concrete. The study also discovered that RA concrete has a lower environmental impact than NA concrete, with up to 50% less energy used and GHG emitted.

The study’s conclusions show that it is possible to completely replace NA with RA from PCW since it has all the required test values that are on par to those of NA concrete.
With savings in energy use and GHG emissions of up to 50%, RA concrete has a lower environmental impact than NA concrete.
According to the study, substituting RA from PCW for NA in concrete can help reduce waste and GHG emissions in the construction industry while keeping concrete’s desirable mechanical qualities.
The study also emphasises the significance of taking into account construction materials’ environmental effects in addition to their mechanical performance when making judgements about material selection and construction practices.

M. Q. Liu, Z. L. Chen Et al [9] In this study, the scientists used Python to create a ML model to predict the characteristic strength of the concrete sample made with recycled aggregate. The model was created using multiple linear regression and artificial neural network techniques, and its performance was measured against that of conventional statistical models. The outcomes demonstrated that when compared to conventional statistical models, the machine learning model created in Python had a greater predictibility in forecasting the characteristic strength of recycled aggregate concrete.
A. B. A. Ghani, M. M. AlkassEt al [10] For the fabrication and construction of high-strength concrete bodies, the prediction of compressive strength is a crucial concern. For the purpose of forecasting the characteristic strength of high-strength concrete sample, (ANN) models were created in this study. The mix proportions and the characteristic strength of 295 Good -strength specimens of concrete were among the experimental data used to train the models. The models’ performance was measured statistically, and the findings showed that the ANN models were capable of predicting the characteristic strength of high-strength concrete with high accuracy. The study also depicted that the ANN models could be applied to high-strength concrete mix optimisation, which would aid in lowering the cost of high-strength concrete building.

Findings:

-ANN models for forecasting the characteristic strength of good strengthening concrete have been made.

-used a library of experimental data to train the models, which contained information on the mix ratios and the characteristic strength of 295 specimens of high-strength concrete.

-Statistical performance indicators were used to evaluate the models, and it was discovered that the models successfully predicted the characteristic strength of better quality concrete

Depicts that ANN models may be used to save building costs by optimising the consistency of better quality concrete.

Jiang, X. ZhangEt al [11] the paper discusses that In order to forecast the characteristic strength of sample of concrete, an (ELM) method is put forth in this study. The principle component analysis (PCA) approach is used in the suggested method to minimise the dimensionality of the input features, and a differential evolution strategy is used to optimise the ELM model's parameters. The effectiveness of the suggested approach is assessed and contrasted with that of existing machine learning techniques, including as regular ELM, support vector regression, and backpropagation neural networks (BPNN). The findings demonstrate that, compared to previous approaches, the suggested method achieves higher accuracy and better generalisation ability when forecasting the compressive strength of concrete.

Findings:The differential evolution algorithm and PCA, together with the suggested improved extreme learning machine (ELM) technique, can successfully predict the compressive strength of concrete. The suggested approach outperforms other machine learning approaches, such as backpropagation neural networks (BPNN), support vector regression (SVR), and conventional ELM, in terms of accuracy and generalizability. According to the study, the suggested method may serve as a helpful resource for foretelling the characteristic strength of concrete in actual applications.

J. Li, X. ZhangEt al [12] This study uses machine learning techniques to predict the compressive strength of concrete. Using a sample space 1,200 samples of concrete with different mix proportions and ages, five algorithms—artificial neural networks, support vector regression, decision trees, random forests, and gradient boosting regression—were trained and put to the test. Utilising MAE and COD(R^2) values the models' performance was assessed. With an R-squared value of 0.96 and a mean absolute error of 1.88 Mpa, gradient boosting regression performed the best overall among the five algorithms tested in the results. The study finds that machine learning algorithms can accurately forecast the characteristic strength of sample of concrete and may be employed as a tool for concrete design.

S. Singh Et al [13] In this study, the effectiveness of multiple linear regression (MLR) and artificial neural networks (ANN) for predicting concrete's compressive strength is compared. An important consideration in determining how long concrete structures will last is the concrete's compressive strength. Cement, water, coarse and fine aggregates, and curing time were used as the value to be manually inserted in research. Concrete's characteristic strength is the returning value. A dataset of 200 samples was used to train the ANN and MLR models, and a dataset of 50 examples was used to test them. Using the (MAE) and the COD (R2), the models' performance was assessed.

It was discovered that the ANN model performed better in predicting the compressive strength of concrete than the MLR model. Compared to the MAE of the MLR model, which was 2.59 Mpa, the MAE of the ANN model was 1.79 Mpa. The ANN model's R2 score was 0.981, whereas the MLR model's score was 0.936. The study comes to the conclusion that the ANN model has the ability to increase the precision of predictions of concrete's compressive strength.

K. Krzemińskiet al [14] In this study, convolutional neural networks (CNNs) are suggested as a way for forecasting the characteristic strength of concrete. In order to extract features from picture of the concrete surface and estimate the characteristic strength of the concrete, the suggested technique processes the image of the concrete surface using a CNN. A dataset of 103 concrete samples was used to calculate the decided method. The output showed that the method achieved results that were on par with or better than those reported in the literature for other methods, including a mean absolute error (MAE) of 3.5 MPa and a COD (R2) of 0.87.The authors discovered that their proposed strategy produced outcomes that were on par with or better than those produced by other methods in the literature.

S. Yadav et al [15] The study demonstrated that concrete compressive strength may be accurately predicted using machine learning methods. With an R2 score of 0.9774 and an MAE of 1.936, the ANN process performed all the other process in basis of performance. According to the findings, using an ANN model to predict the characteristic strength is a good strategy. The study also demonstrated how machine learning algorithms can be used to estimate concrete's tcharacteristic strength more precisely and save time and money by removing the need for costly and time-consuming experimental testing.

M. RahmanEt al [16] 500 concrete samples were utilised in the study, and there were 8 input variables, including the quantity of cement, water, aggregates, and curing time. 70% of the dataset was used to train the ANN models, while 30% was used to test the models.

The research discovered that the ANN model could forecast the characteristic strength of concrete with an efficiency of 3.04 Mpa for Mean Absolute Error (MAE) and 3.92 Mpa for Root Mean Squared Error (RMSE). The Multiple Linear Regression (MLR) model and the ANN model's performance were examined by the researchers. The MLR model calculated the MAE of 4.11 Mpa and RMSE of 5.24 Mpa, respectively.

3. **M. A. ElshaerEt al**[17] According to the study, machine learning algorithms had an R2 value of 0.96 and a Mean Absolute Error (MAE) of 3.52 Mpa when it came to accurately predicting the the characteristic strength. Four ML processes were tested: Support Vector Regression (SVR), Artificial Neural Network (ANN), followed by Decision Tree (DT), and ultimately with the help of Random Forest (RF). The results of the tests were compared. The ANN model performed better than the other models, as seen by its R2 value of 0.978 and MAE of 3.04 Mpa.

The study's findings imply that machine learning algorithms, in particular ANN, can be utilised as a practical tool for forecasting the characteristic strength. This can help to optimise the mix design and lessen the requirement for experimental testing.

F. Fazal, N. Iqbal et al [18] According to the study, machine learning algorithms had an R2 value of 0.96 and a Mean Absolute Error (MAE) of 3.52 Mpa when it came to accurately calculating the characteristic strength. Support Vector Regression (SVR), Decision Tree (DT), Random Forest (RF), machine learning processes, Artificial Neural Network (ANN), along with the Adaptive Neuro-Fuzzy Inference System (ANFIS) were the five machine learning methods that the researchers compared for performance. The ANFIS model performed better than the other models, as seen by its R2 value of 0.997 and MAE of 1.18 Mpa.

The study's findings imply that machine learning algorithms, in particular ANFIS, can be utilised as a useful tool for anticipating the characteristic strength ,that can help in optimising the mix design and lowering the demand for experimental testing.

S. Al-Safadi Et al [19] With an R2 value of 0.94 and an RMSE of 2.1 Mpa, the study discovered that the combination of artificial intelligence methodologies was capable of properly predicting the characteristic strength of SCC. The performance of four artificial intelligence techniques—Artificial Neural Networks (ANNs), Decision Trees (DTs), Random Forests (RFs), was compared by the researchers. With an R2 amount of 0.95 and an Root Mean Square Error of 2.0 Mpa, the final value demonstrated ensemble of all four approaches outperformed the individual models.

The study's findings imply that a combination of artificial intelligence methods can be utilised as a powerful tool for forecasting the compressive strength of SCC, which can aid with mix design optimisation and minimise the requirement for experimental testing.

Z. Wu et al [20] The goal of Z. Wu, X. Wu, and W. Chen's study was to use machine learning to foreshadow the characteristic strength of fly ash geopolymer concrete. By employing ML techniques namely Python programming, linear progression etc., they gathered data on the compressive strength of fly ash geopolymer concrete and created a model. With an R-squared value of 0.93, they discovered about extreme gradient boosting approach gave the ultimate prediction at predicting the characteristic strength the concrete taken. Their research illustrates how well machine learning predicts the characteristic strength of concrete made with fly ash geopolymer.

2.3 RESEARCH GAPS

a) Most of the literatures are concerned about compressive strength detection in RCC structure using destructive method.
b) There is lacuna in literature about the effect of using processed Construction and demolition aggregates and its impact on characteristic strength.
c) There hasn’t been much research regarding the complete replacement of Natural aggregate with Recycled processed aggregate concrete.
d) There has been a lacuna in the prediction of characteristic strength of normal and recycled concrete aggregates combined.

CHAPTER 3

EXPERIMENTAL INVESTIGATION

3.1 GENERAL

Different material properties, as well as a thorough experimental programme and process, have been covered in this chapter. Testing was done on cement, fine aggregate, and coarse aggregate. Cement has undergone tests for normal consistency, beginning and final setting times, and compressive strength. Grading and specific gravity of fine aggregates. While the specific gravity and water absorption of coarse aggregate were measured in accordance with the corresponding Indian Standards codes. The experimental programme can be created to explore the induced degrees of corrosion on various reinforce concrete samples by discussing a variety of elements that either directly or indirectly affect the characteristics of concrete.

This part includes the production of concrete cubes of M40 grade firstly, with the help of natural aggregates as a control and then creating the design mixfor recycled aggregates After this, the concrete cubes were cast using recycled aggregates and their compressive strengths were calculated at 7^{th}, 14^{th} and 28^{th} day of curing. After this the compressive strength of recycled concrete aggregates cubes and normal aggregate concrete cubes were compared to each other .The next part of the experiment deals with prediction of compressive strength using data from training as well as testing processesand putting it into a machine learning (ML) and python programming to predict the characteristic strength and to also check the various mechanical properties of recycled aggregate concrete which will help in durability..

This chapter addressed the material employed, along with its composition and qualities, as well as the thorough experimental process. At first, key concrete characteristics were noted, and further cement ingredients were constrained.In order to set up an experiment to analyse the relative impact on concrete qualities, it's important to describe the concrete properties that affected by some materials either directly or indirectly.

3.2 RESEARCH METHODOLOGY

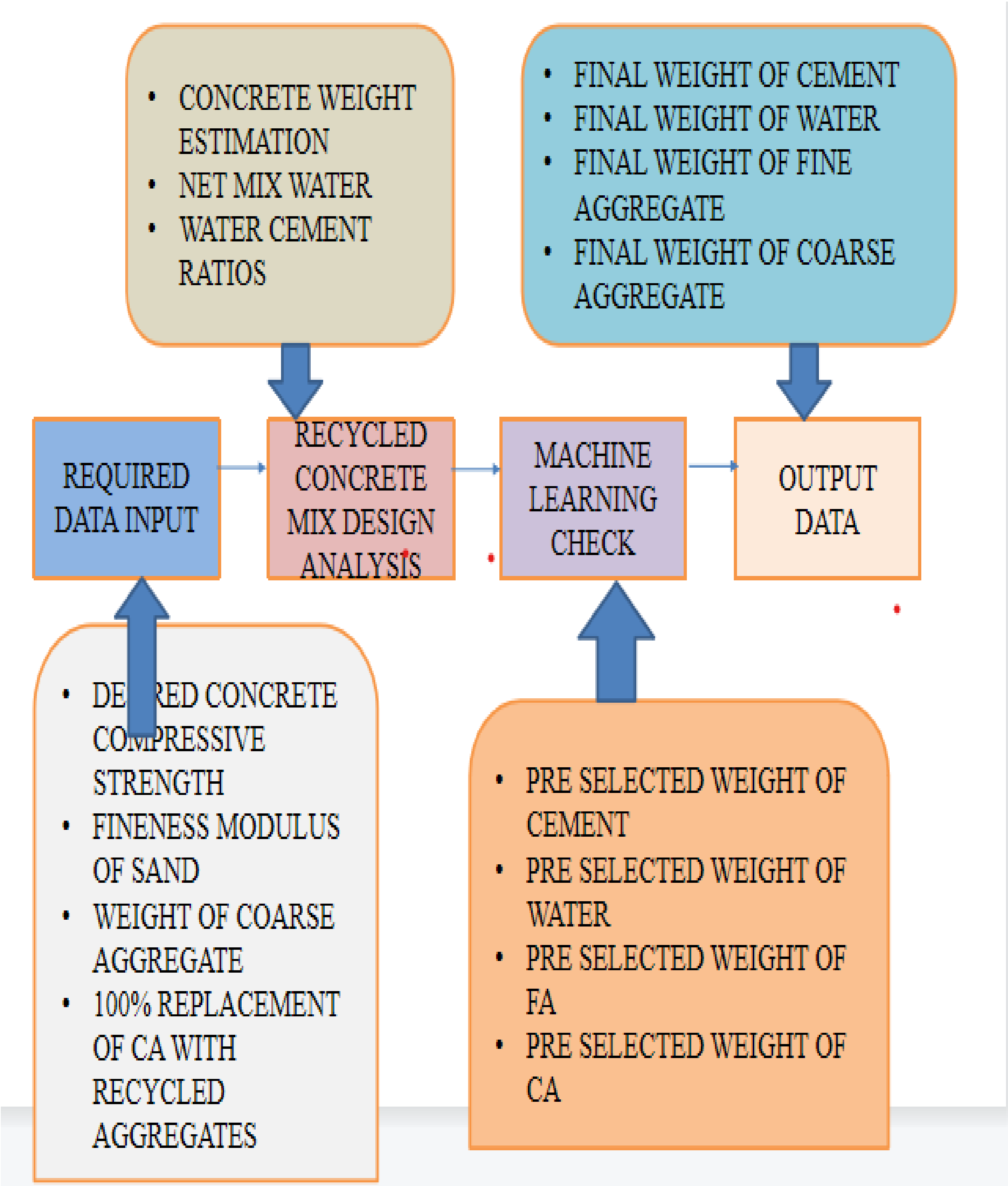


Fig 2: Research Methodology

3.3 MATERIALS USED

Concrete is a solid compound with cementitious media that has particles implanted inside of it. The level of its compaction have an important impact on the potential quality and power of concrete at a given mix proportion. The sections that follow provide an examination of the materials used in concrete planning.

3.3.1 Aggregates

As a base material for foundations, roads, and railways as well as a component of concrete and asphalt composite materials, aggregates are one of the most crucial building elements. They provide the volume, strength, wear and tear resistance, physical shapes,density to the structure or to the cube samples [21]. They also make up around 75% of the volume of concrete, which means they have a considerable impact on various concrete properties.

Natural aggregate and artificial aggregate are additional categories for normal weight aggregate. Sand, for instance, is a natural aggregate, while air-cooled slag, shattered brick, etc. are artificial aggregates. Depending on their size, aggregates can potentially be further classified.

a) Coarse aggregate (more than 4.75 mm)

b) Fine aggregate (less than 4.75 mm)

3.3.2 Classification based on size of aggregates:

1. Fine Aggregate
2. Coarse aggregate

Coarse aggregate is defined as having a size greater than 4.75 mm, and fine aggregate is defined as having a size of 4.75 mm or less. The workability of the concrete is affected by the aggregates' shape, which is an important attribute. It contributes significantly to the production of high-strength concrete. For most structural uses, coarse aggregate with a maximum size of 40mm is used.

The bedrock is where most natural aggregates are found. Due to their typical characteristics of being challenging, resistant, and dense, these three igneous stones make concrete very rewarding]. High pressures and temperatures can influence both igneous and sedimentary rocks, causing metamorphism, which changes the surface and internal structure of the stones.The concrete's functionality, durability, strength, weight, and shrinkage are all significantly impacted by the placement, size, and shape of the aggregate. The workability of the concrete is affected by the aggregates' shape, which is an important attribute.

Material Used	Size/ Grade
Cement	PPC (IS 8112)
H2O	Uncontaminated
FA	2.36 mm
CA	>10 mm
CA	<20 mm
Ceramic dust	Zone I
SuperPlasticizer	Polytan Crete NGT

Table 1: Quantity of materials for concrete using Recycled Aggregates

3.4 Testing of Materials

Before the casting of cube different tests were conducted on the cements, compression and tensile test as well as all the tests performed for cement samples.. The results were well within the range as specified in their respective IS codes.

3.4.1Tests for Plain Pozzolana Cement (PPC)

1. **Fineness Test**

This test is done to calculate the soundness of cement samples. The test is performed on basis of IS 4032. It is dependent upon the percentage of cement sample which was retained , with the weight of cement size no higher than 90 microns..

Numbering	Samples	Wt 1 (cement sample)	Wt 2 (cement retained 90 days)	Fineness of cement (Wt2/Wt1) *100
I.	Sa 1	100	6.55	6.56%
II.	Sa 2	100	7.39	.7.28%
III.	Sa 3	100	8.53	8.42%

Table 2: Fineness Test of OPC

Average of the three samples = 7.49%
Percentage fineness = 7.42%

2 Normal Consistency Test:

IS 4031 is used as the standard code for conducting this cement test for consistency.

This test is conducted to calculate the amount of water which is expressed as percentage of weight of cement and can be used to interpolate natural consistency of cement.

S No.	Data of samples	Weight of the sample of cement	H20 Percentage added	Wt of water to be added (ml))	The penetrating capacity
1	Sample1	320	30	90	32
2	Sample 2	330	31	100	37
3	Sample 3	320	32	98	32

Table 3: Test results for normal consistency

Normal Consistency of cement= 32%

3.4.2 TEST ON AGGREGATES

1. Abrasion Test

The abrasion test is done with the help of Los Angeles Abrasion Testing Machine. In this the normal aggregates. Are exposed to a lot of intense load and steel balls are added to the mixture to amplify the process of degradation on surface of the sample.

The LA Abrasion machine rotates, the samples are placed in a steel drums after which it is given rotation along with the sample inside it, As the drum revolute at a speed of x rpm, it keeps on hitting the samples, thus resulting in the contents being removed.Percentage loss is calculated.

Weight of sample (Wt 1) in g	Weight of sample passing through IS 1.70 mm (W2) in g	Percentage abrasion {(Wt1-Wt2)/Wt1} *100
6000	4100	48

Table 4: Abrasive value of Coarse Aggregates

Abrasion Value = 38%

2. Impact value Test

The method outlined in IS 2386 is used to determine the Impact test of coarse aggregates. Engineers evaluate the sudden load resisting power of material and predict its function in actual circumstances using the impact test. When the limitations are found and impacts the structure then, cracks, etc, many materials degrade rapidly.

Apparatus: - a device that has a metal base and can be used for testing and weighs 45-60 kgs and at least 30 cm in dia., A concrete floor with minimum thickness of 45 cm level.

Weight of the cylindrical sample +Aggregates Wt2 (g)	Weight of fine aggregates passing through IS 2.36 mm Wt1 (g)
400	80

Table5: Impact Value Test of coarse aggregates

Impact test value = (W1/W2) *100 = 20

3. CRUSHING TEST

The method for evaluating coarse aggregates for their crushing test value is called IS 2386. Aggregate Crushing Value Tests are typically used to determine the strength of coarse aggregates or their resistance to crushing under the applied force.

Apparatus: CTM machine. Sieves of IS specification 12.5 mm, 10 mm and 2.36 mm, a steel cylinder which has open ends

Weight of Aggregates + Cylinder Wt 1 (g)	Aggregate weight going through 2.36 mm sieve Wt 2 (g)	Aggregate crushing value (%) = (Wt 2/Wt 1) *100
5000	1100	22

Table 6: Crushing value of coarse aggregates

Aggregate crushing value = 22

4. Specific gravity and Water Absorption Test

The 2 aggregate exams mentioned above must be conducted and are of utmost importance. These two aggregate characteristics or parameters are crucial for the mix design of concrete. Since aggregate makes up between 70 and 80 percent of the volume of concrete, evaluating it before usage is crucial..

Apparatus: - an oven with a thermostat that maintains a constant interior temperature of between 100 and 110 °C.A low depth flat container, 2 clothes that are absorbent in nature and are atleast 75*45 cm in size.,a container with holes with thin wire hangers so that we can hang it from the weighing balance, a wire bucket with sieve size not bigger than 6.3 mm.

Weight of suspended aggregates in Water+ Bucket (Wt 1)	2.430kg
Weight of Bucket submerged into the water (Wt 2)	1.470kg
Weight of dry aggregates fully saturated in air (Wt 3)	3.21kg
Weight of aggregates (Wt 4)	2.65kg

Table 7: Specific gravity and Water Assortation Values

Specific gravity of Coarse Aggregates = (Wt4/Wt3) - (Wt1-Wt2) = 2.5

Water absorption ratio of the sample = [(Wt3-Wt4)/Wt4] *100 = 0.22

3.5Preparation and Grading of the Aggregates

After the completion of tests on cements, natural and recycled aggregates were arranged with 10mm-20mm size.

Unprocessed recycled aggregates were extracted from the concrete boulders manually with the help of hammer.Processed recycled aggregates (PRA) were produced by introducing the unprocessed recycled aggregates (UPRA) in Loss Angeles abrasion machine with 11 steel balls/ charge and at 33rpm.The stone dust was used in place of natural sand . The grading of the fine aggregate was done using IS: 383-1970.

Weight of the sample taken was 1000g. The zone of the fine aggregate came out to be grading zone II.

Figure3: Demolished concrete

Figure 4: Los Angeles Abrasion Machine

Figure 5: Recycled Aggregates before water-wash and grading

Figure 6: Processed Recycled Aggregates after water wash

Figure 7:Water washing the aggregates **Figure 8: Drying up the aggregates**

Figure 9: Sieve Analysis in Sieve shaker **Figure 10: Manual Sieving**

Figure 11: Impact Test

Figure 12: Crushing Strength test

Figure 13:Test Cubes of NA and RAC

Figure 14: Test Beams of NA&RAC

Figure 15: NA testing at 7 days

Figure 16:RAC testing at 7 days

Figure 17: Compressive Strength test on Samples

3.6 Mix Proportion and Mixing Approach

Mix ratio: - 0.35:1:3.043:1.472:0.01998

SNo	Material	Quantity (kg/m3)
1.	PPC-43 grade	475
2.	Water(h2o)	150
3.	Fine aggregate	650
4.`	Coarse aggregate	1300
5.	Water cement ratio	0.45
6.	Super plasticizer	6.064

Table 8 : Quantity of key ingredients

CHAPTER –4
CODE TO PREDICT THE COMPRESSIVE STRENGTH

Dataset:

We used a dataset which consisted of compressive strength values taken from the Kaggle and some of the data was taken from the testing. The link to the dataset has been provided.**C:\Users\ASUS\Downloads\concrete_data (1).csv**

- **Number of Instances: 500 (350- Taken from Kaggle, 150 – Testing data from Lab preparation)**
- **Number of attributes- 9**
- **Attributes breakdown – 8 Quantitative inputs, 1 Quantitative Output**

Dataset knowledge:

Cement: A substance that si used in construction industry and it hardens when water is added to it . It is used as a binding agent and provides strength to the structure.

Slag: It is a mixture of metal oxides and silicon dioxide.

Fly ash: It is a product of coal combustion and consists of particles which are extracted from boilers fired by coals together with the flue gases.

Water: A thick paste can be made using it.

Superplasticizers: High-strength concrete is made with the use of superplasticizers.

Coarse aggregate: the cost of obtaining rocks from subsurface deposits.

Fineaggregate: is aggregate that is smaller than 4.75mm in size.

Age: As people get older, the rate at which they build strength slows down.

Concrete strength is measured in csMPa

4.1 STEPS FOR THE PREDICTION OF COMPRESSIVE STRENGTH :

Step 1: Importing Modules

We need to import **Pandas** for the process of analysis of data , **NumPy** is used for the calculation of N-dimensional array**, seaborn and matplotlib** are the libraries used for the visulisation of data.

```
In [1]: # Compressive Strength prediction of concrete
```

```
In [2]: # Importing libraries
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import seaborn as sns
import numpy as np
import itertools as it
from sklearn.linear_model import LinearRegression  # Linear regression
from sklearn.metrics import mean_squared_error        # Compute mean square error
from sklearn.model_selection import train_test_split   # Splitting dataset into training and test data
from sklearn.linear_model import Lasso                #Lasso Regression
from sklearn.neighbors import KNeighborsRegressor    #KNN Neighbor
from sklearn.svm import SVR          # SVM
from sklearn import metrics
%matplotlib inline
from sklearn.preprocessing import PolynomialFeatures
from sklearn.preprocessing import PolynomialFeatures
import statsmodels.api as sm
```

Step 2: Reading Data

For this purpose, we generally take a file in CSV format and to analyse the CSV file we use the pandaslibrary.

```
In [3]: # Loading of dataset
df=pd.read_csv('concrete_data.csv', sep=',') # Create a dataframe
df.head(10)    #Reading of first 10 rows
```

Out[3]:

	cement	blast_furnace_slag	fly_ash	water	superplasticizer	coarse_aggregate	fine_aggregate	age	concrete_compressive_strength
0	332.5	0.0	0.0	228.0	0.0	932.0	594.0	28	40.27
1	332.5	0.0	0.0	228.0	0.0	932.0	594.0	28	41.05
2	198.6	0.0	0.0	192.0	0.0	978.4	825.5	28	44.30
3	266.0	0.0	0.0	228.0	0.0	932.0	670.0	28	47.03
4	380.0	0.0	0.0	228.0	0.0	932.0	594.0	28	43.70
5	380.0	0.0	0.0	228.0	0.0	932.0	594.0	28	36.45
6	266.0	0.0	0.0	228.0	0.0	932.0	670.0	28	45.85
7	475.0	0.0	0.0	228.0	0.0	932.0	594.0	28	39.29
8	198.6	0.0	0.0	192.0	0.0	978.4	825.5	28	38.07
9	198.6	0.0	0.0	192.0	0.0	978.4	825.5	28	28.02

Step 3: Study of Dataset and Handling of Null values

After we have done Step 2 ie making the program read the data ,we need to take out the values from the dataset.For this we employ the use :

```
In [4]: # Data Structuring
        print('Number of rows',df.shape[0])
        print('Number of columns',df.shape[1])
        print(df.info())

Number of rows 500
Number of columns 9
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 500 entries, 0 to 499
Data columns (total 9 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   cement                         500 non-null    float64
 1   blast_furnace_slag             500 non-null    float64
 2   fly_ash                        500 non-null    float64
 3   water                          500 non-null    float64
 4   superplasticizer               500 non-null    float64
 5   coarse_aggregate               500 non-null    float64
 6   fine_aggregate                 500 non-null    float64
 7   age                            500 non-null    int64
 8   concrete_compressive_strength  500 non-null    float64
dtypes: float64(8), int64(1)
memory usage: 35.3 KB
None
```

This function showed us the count of null values in each of the features of the dataset and also tells us the data types of the particular feature which is present in our dataset.

```
In [5]: # Missing Values
        print('Number of missing values in dataset', df.isnull().sum())
        'The dataset contains no missing values'

Number of missing values in dataset cement                           0
blast_furnace_slag               0
fly_ash                          0
water                            0
superplasticizer                 0
coarse_aggregate                 0
fine_aggregate                   0
age                              0
concrete_compressive_strength    0
dtype: int64

Out[5]: 'The dataset contains no missing values'
```

Describe() method is used to calculate the various calculation in each datset.

Step 4:Correlation Plot

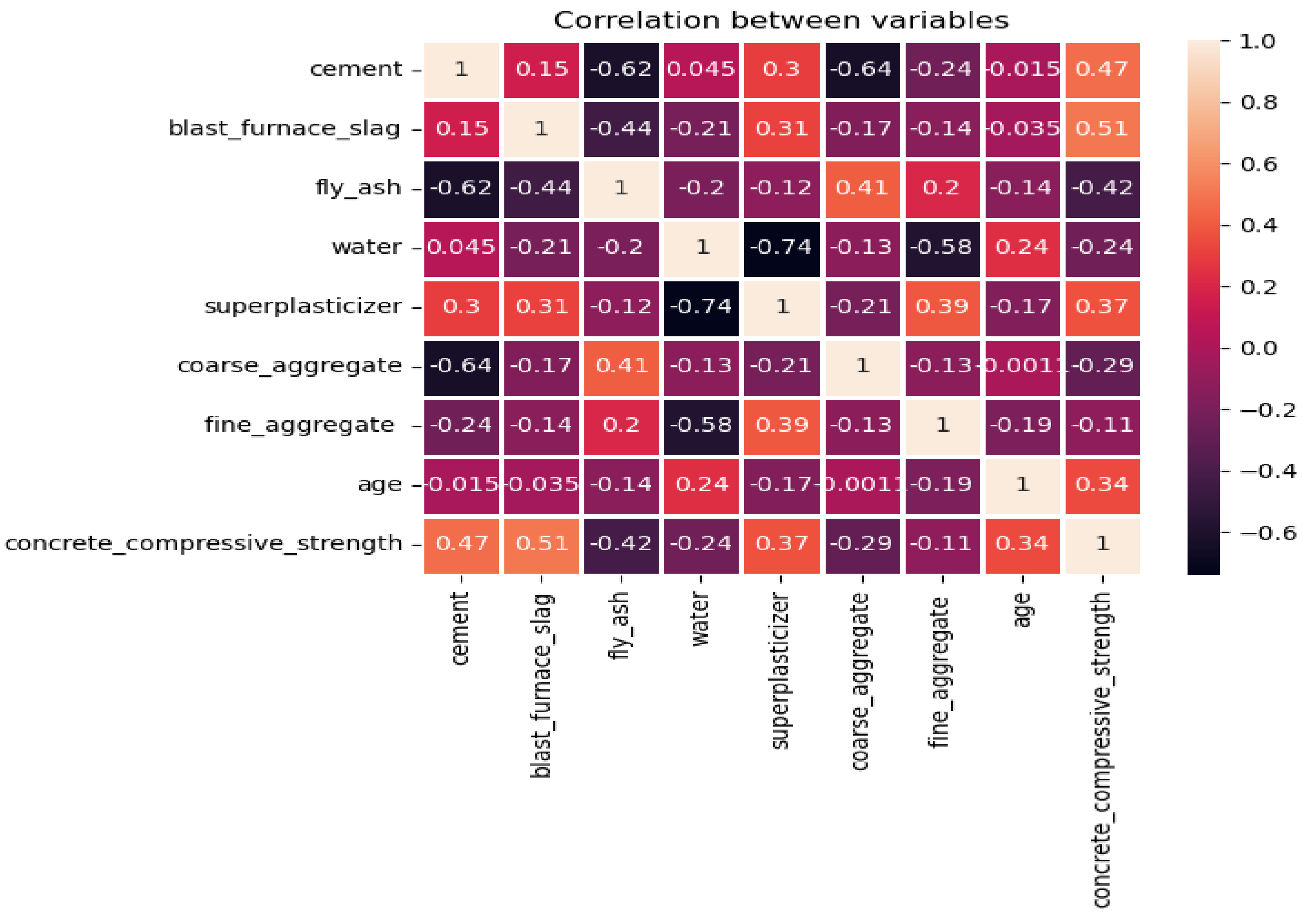
This is used to view the correlation coefficient when different variables are given.The plot consists of the table which resembles to the correlation matrix..

Now visualisation of the relationship between two variables are shown by the plot points.

```
In [6]: # Data visualization
        #1 Correlation Matrix
        sns.heatmap(df.corr(), annot=True, linewidth=2)
        plt.title("Correlation between variables")
        plt.show()

        #2 Pair plot
        sns.pairplot(df,markers="h")
        plt.show()

        #3 Distribution plot
        sns.distplot(df['concrete_compressive_strength'], bins=10, color='b')
        plt.ylabel("Frequency")
        plt.title('Distribution of concrete strength')
```



Step 5:Exploratory Data Analysis(EDA)

This is one of the most crucial path to construct aArtificial intelligence and Machine learning project, It is a method of analysing data sets to summarise their key properties, and it is a crucial phase in the development of any machine learning project. By simply looking at the plots and graphs, we may learn about features with the aid of EDA.

Thus we used some periodically applied visualisation processess for analysing the data present:

Pair Plot: In the dataset, it draws a couple wise association and builds an axis grid in which the y-axis corresponds to the rows whereas the x-axis to the columns.

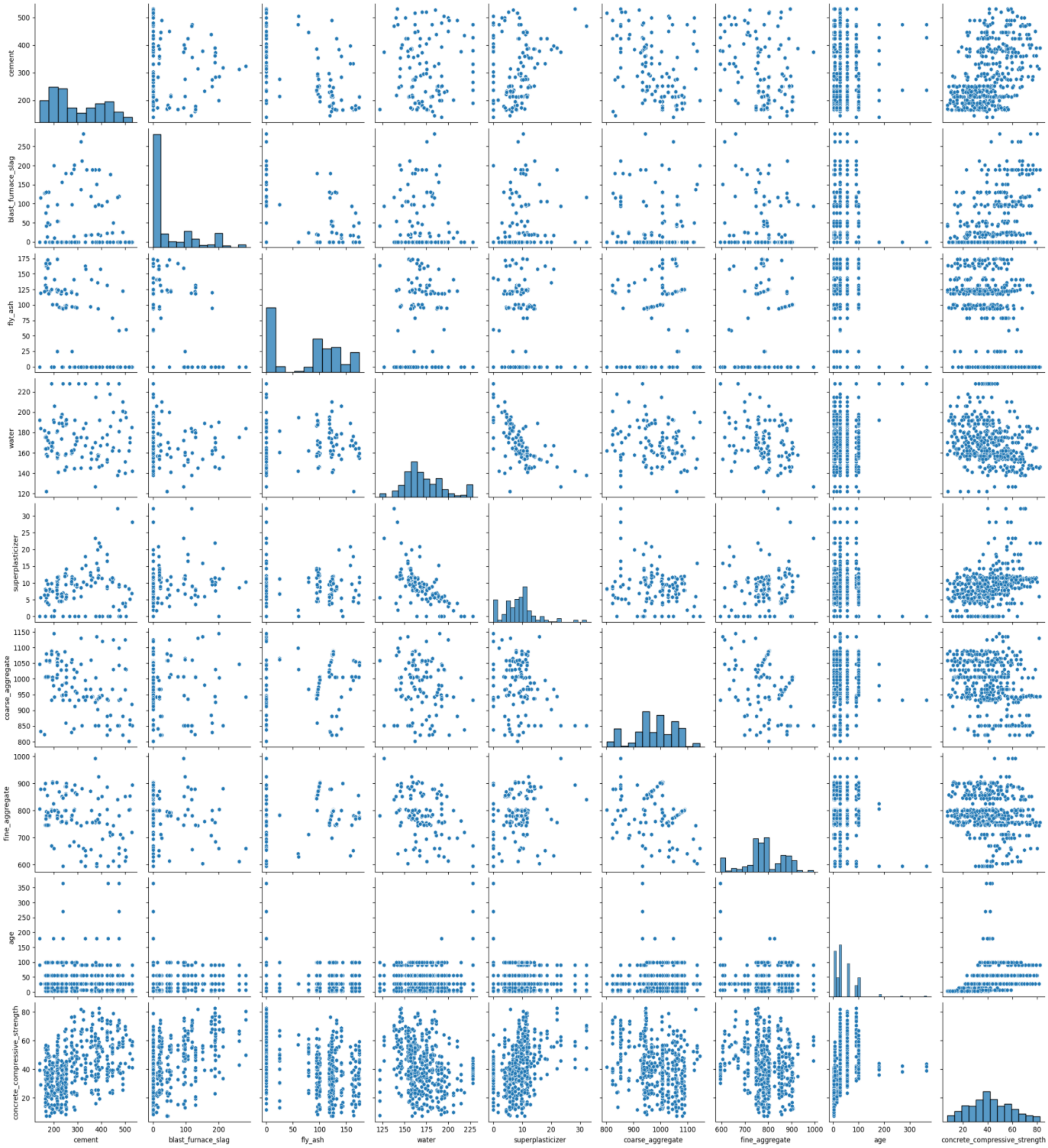
```
# pair plotting the data frame of samples
sb. pair plot( df )
```

When the variable in a given dataset is continuous or can be assigned into the category,the relationship betwwen their datas is visually represented with the help of Pair plot.Thus,in a dataset, pairplot describes the pairwise relationship.

The Pairplot module provides the user with an interface which is premium level and creates a aesthetically and educationally relevant visuals..

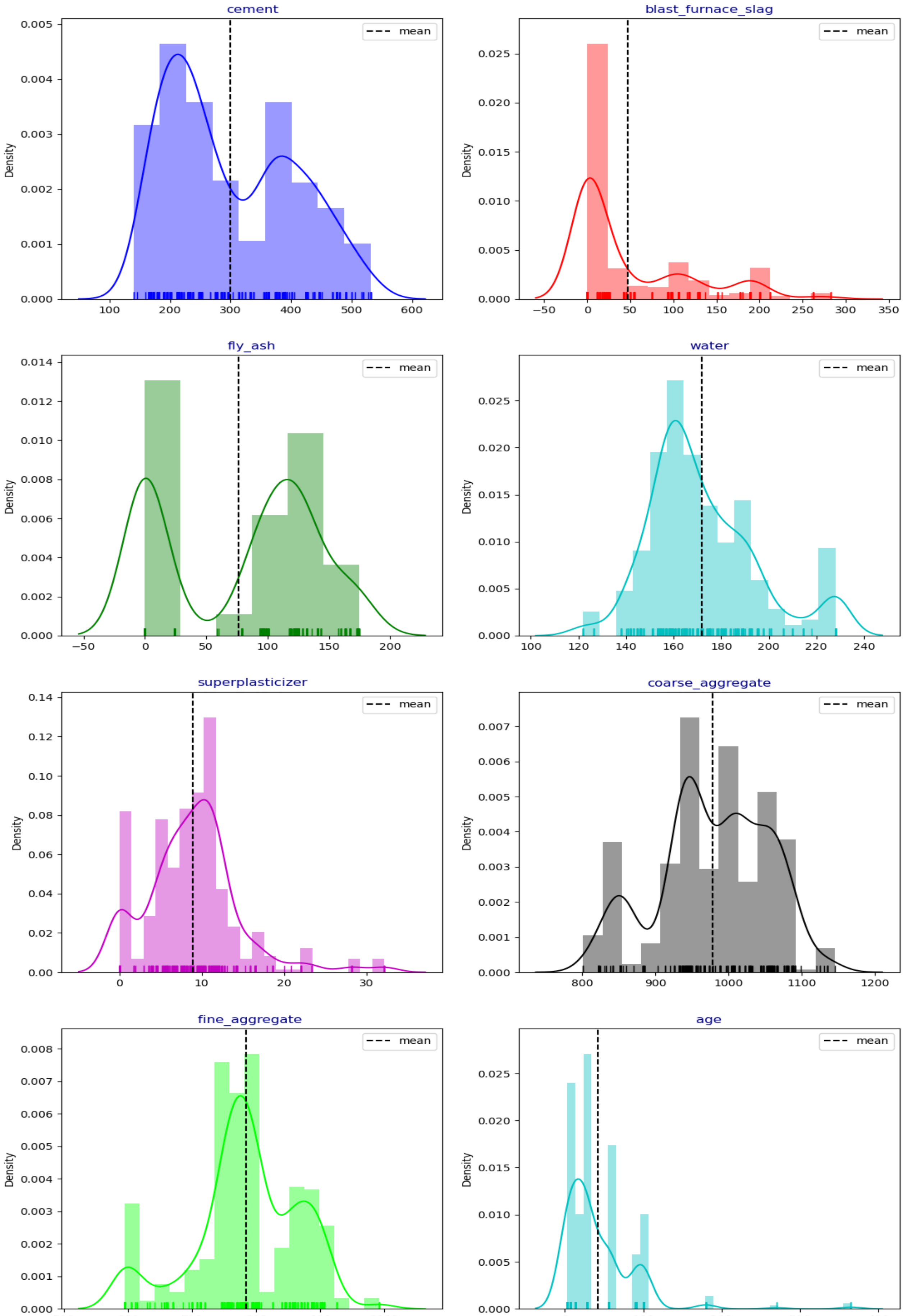
We can see in this scatter plot that it was created using matplotlib that the dependent variable, csMPa, has data points that range from 0 to 80 on the y-axis and 100 to 500 on the x-axis, respectively.

The scatter plot indicates that as we add more cement to the concrete, the quality of the concrete may also improve.In light of this, we can also draw the relationship between any other two dataset features. Plotting a scatter plot between csMPa and flyash is suggested.

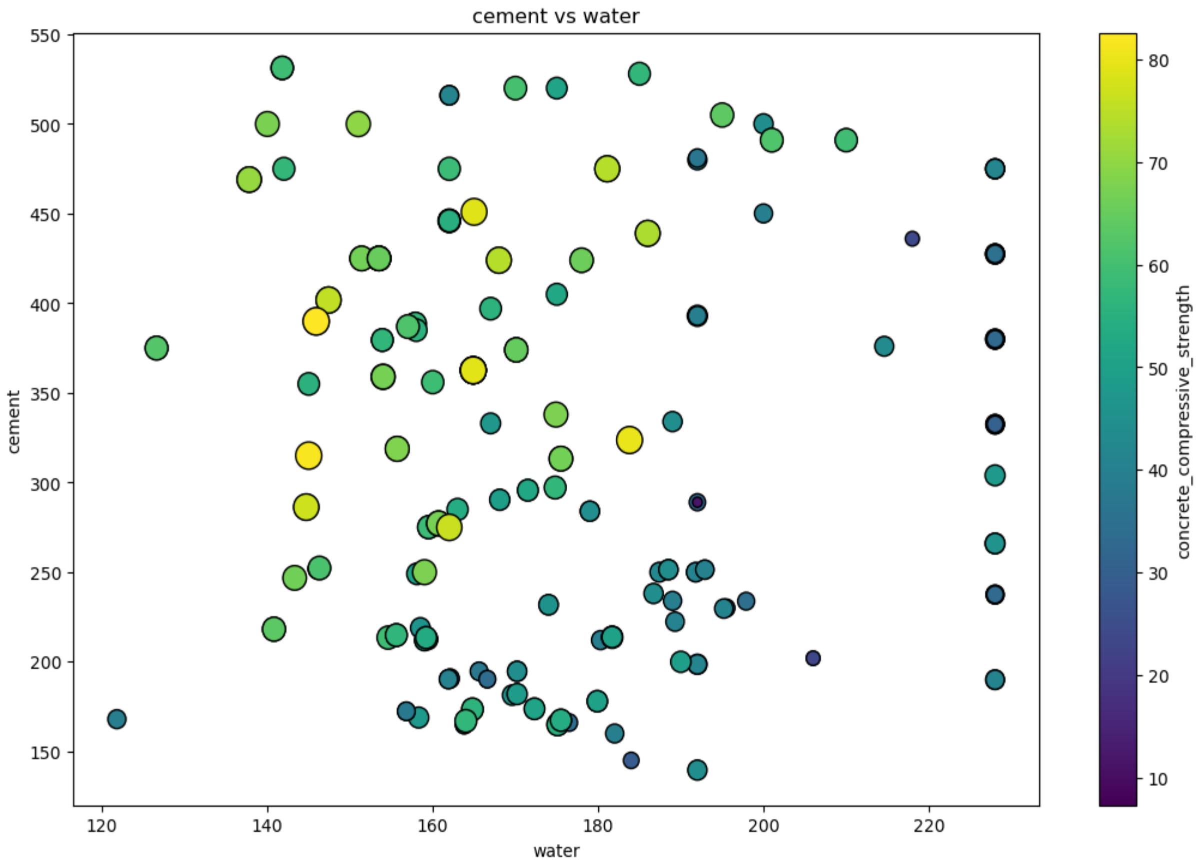


In [7]:
```
# Distribution of components of concrete
cols = [i for i in df.columns if i not in 'compressive_strength']
length = len(cols)
cs = ["b","r","g","c","m","k","lime","c"]
fig = plt.figure(figsize=(13,25))

for i,j,k in it.zip_longest(cols,range(length),cs):
    plt.subplot(4,2,j+1)
    ax = sns.distplot(df[i],color=k,rug=True)
    ax.set_facecolor("w")
    plt.axvline(df[i].mean(),linestyle="dashed",label="mean",color="k")
    plt.legend(loc="best")
    plt.title(i,color="navy")
    plt.xlabel("")
```


cement
blast_furnace_slag
fly_ash
water
superplasticizer
coarse_aggregate
fine_aggregate
age
mean
Density

```
In [8]: # Scatterplot between components
fig = plt.figure(figsize=(13,8))
ax = fig.add_subplot(111)
plt.scatter(df["water"],df["cement"],
            c=df["concrete_compressive_strength"],s=df["concrete_compressive_strength"]*3,
            linewidth=1,edgecolor="k",cmap="viridis")
ax.set_facecolor("w")
ax.set_xlabel("water")
ax.set_ylabel("cement")
lab = plt.colorbar()
lab.set_label("concrete_compressive_strength")
plt.title("cement vs water")
plt.show()
```



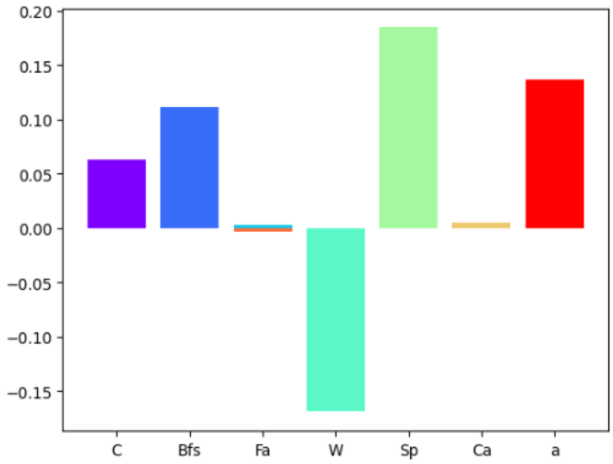

```
In [9]: # Data Splitting
# The dataset is divided into a 70 to 30 splitting between training data and test data

train,test = train_test_split(df,test_size =.3,random_state = 0)
train_X = train[[x for x in train.columns if x not in ["concrete_compressive_strength"] + ["age_months"]]]
train_Y = train["concrete_compressive_strength"]
test_X  = test[[x for x in test.columns if x not in ["concrete_compressive_strength"] + ["age_months"]]]
test_Y  = test["concrete_compressive_strength"]
```

```
In [10]: #Model 1= Multiple linear regression
# fit a model
lm = LinearRegression()
model = lm.fit(train_X, train_Y)
predictions = lm.predict(test_X)
m1=model.score(test_X, test_Y)
RMSE1=np.sqrt(metrics.mean_squared_error(test_Y, predictions))
print('Accuracy of model is', model.score(test_X, test_Y))
print('Mean Absolute Error:', metrics.mean_absolute_error(test_Y, predictions))
print('Mean Squared Error:', metrics.mean_squared_error(test_Y, predictions))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(test_Y, predictions)))
```

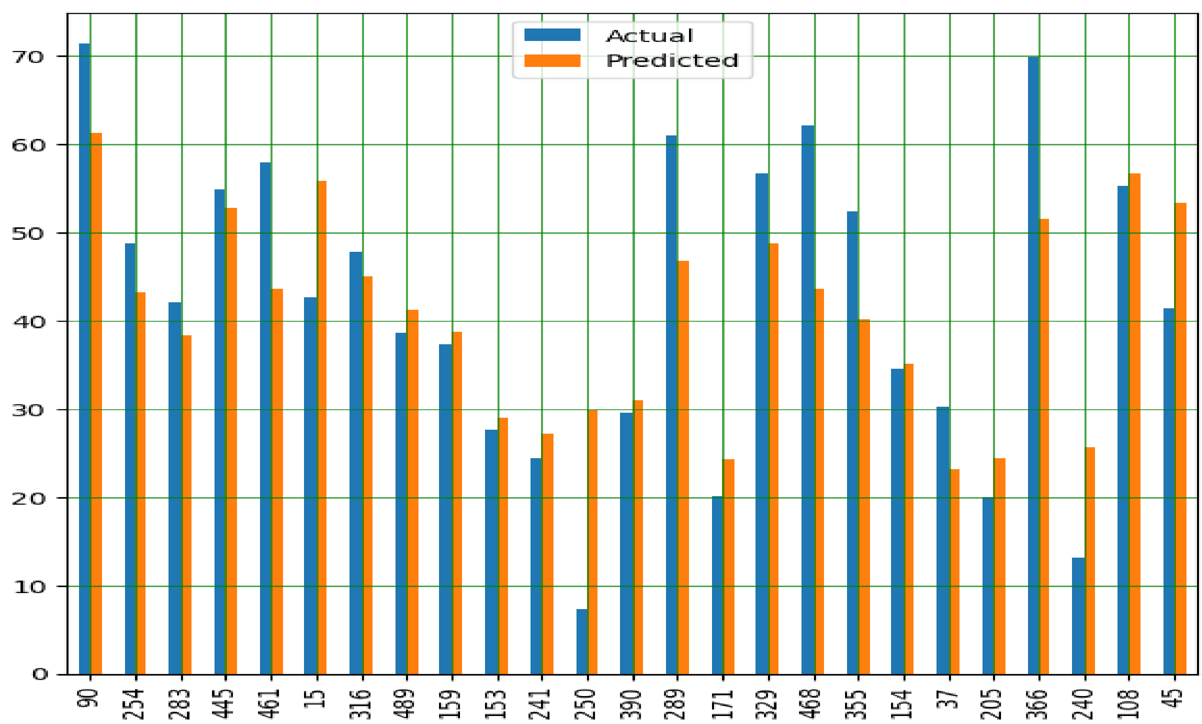
```
Accuracy of model is 0.5278044056345028
Mean Absolute Error: 9.711705853772068
Mean Squared Error: 143.13666083696225
Root Mean Squared Error: 11.963973455209697
```

In [11]:
```
# Features Importance
coef=pd.DataFrame(lm.coef_.ravel())
coef['feat']=train_X.columns
c=coef['feat'].rows=['C','Bfs','Fa','W','Sp','Ca','Fa','a']
num_colors = 8;
colors = cm.rainbow(np.linspace(0,1,num_colors))
plt.bar(c, coef[0], color=colors)
plt.show()
'where C:Cement, Bfs: Blast_furnace_slag, Fa: Fly_ash, W:water, Sp:Superlasticizer, Ca:Coarse_aggregate, Fa: Fine_aggregate, a:
```



Out[11]: 'where C:Cement, Bfs: Blast_furnace_slag, Fa: Fly_ash, W:water, Sp:Superlasticizer, Ca:Coarse_aggregate, Fa: Fine_aggregate, a: Age'

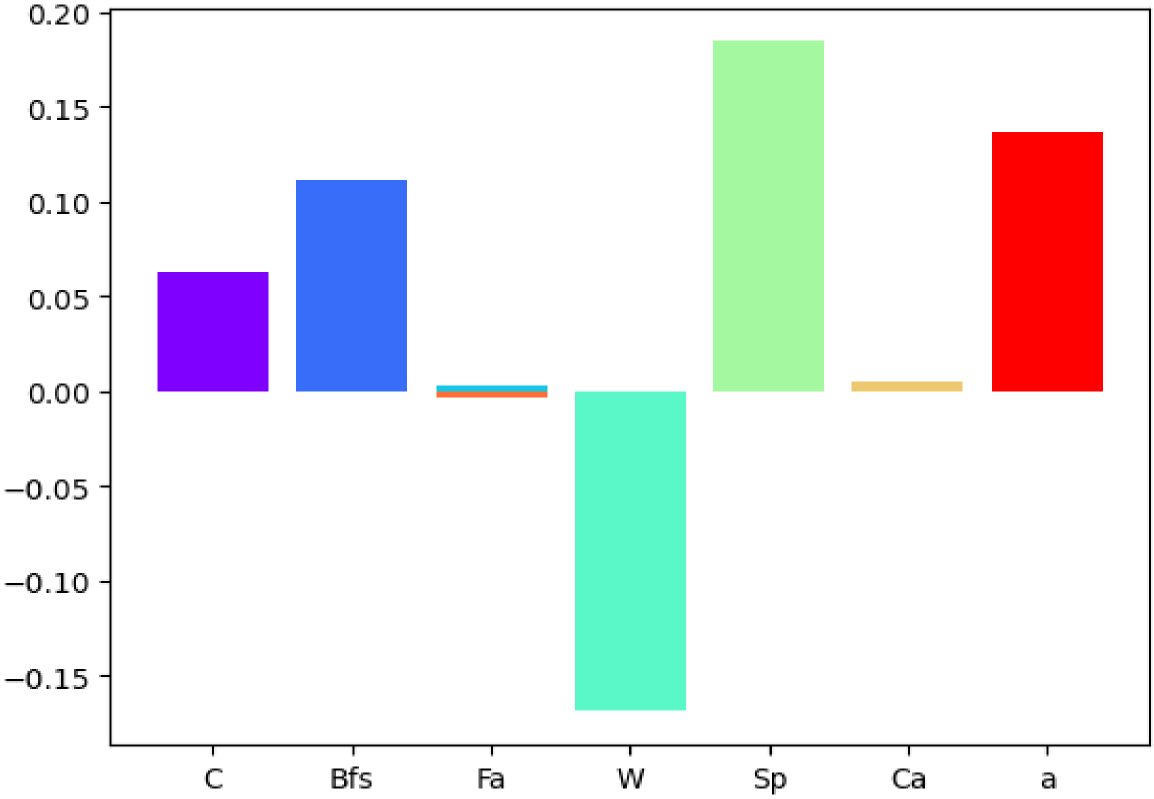
In [12]:
```
#Plot of true value vs. predicted values
dat = pd.DataFrame({'Actual': test_Y, 'Predicted': predictions})
dat1=dat.head(25) #just a sample which shows top 25 columns
dat1.plot(kind='bar',figsize=(7,7))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



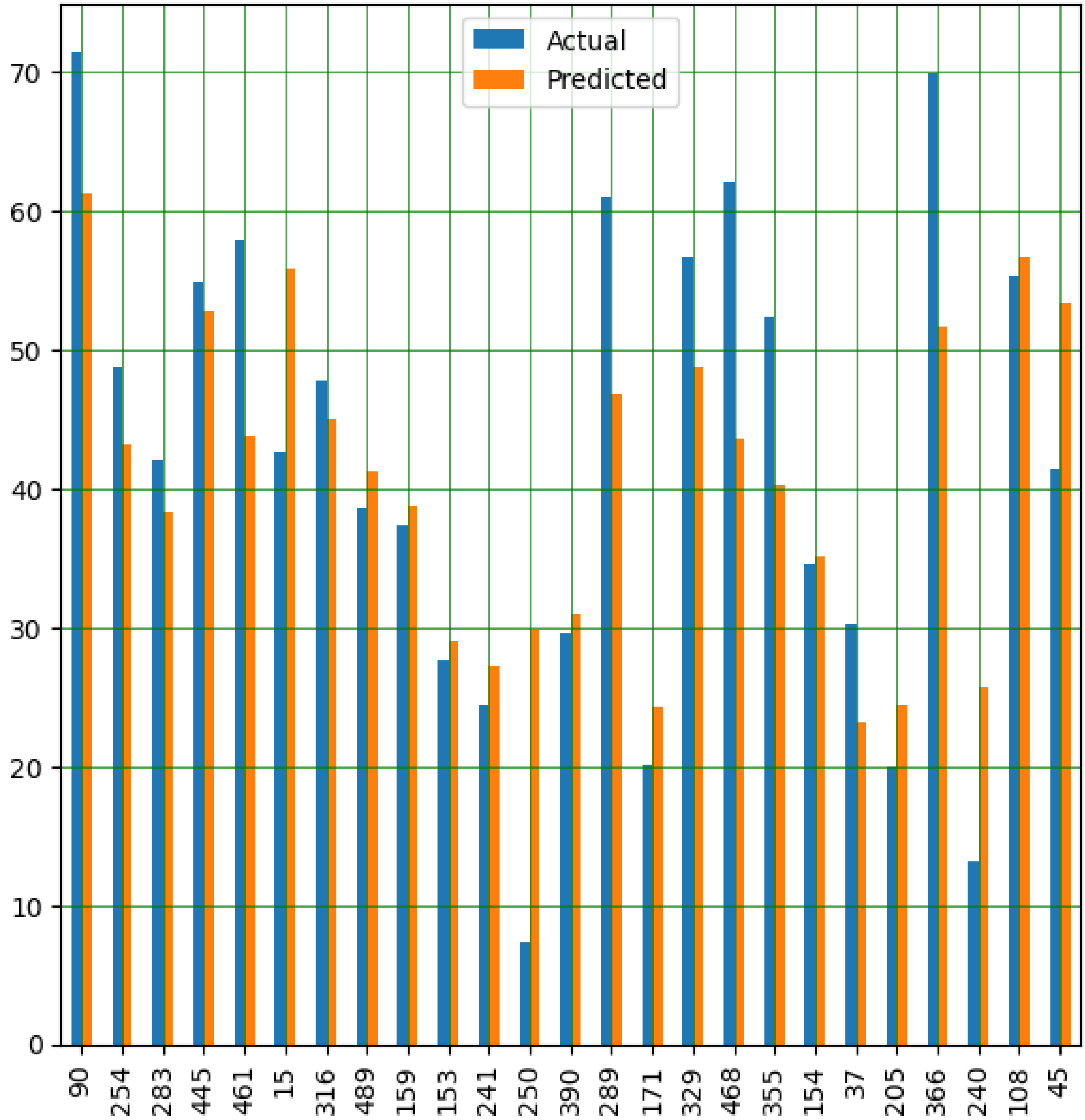
In [13]:
```python
# Model 2: LASSO Model
las = Lasso(alpha=0.1)
model2 = las.fit(train_X, train_Y)
predictions2 = las.predict(test_X)
m12=model2.score(test_X, test_Y)
RMSE12=np.sqrt(metrics.mean_squared_error(test_Y, predictions2))
print('Accuracy of model is', model2.score(test_X, test_Y))
print('Mean Absolute Error:', metrics.mean_absolute_error(test_Y, predictions2))
print('Mean Squared Error:', metrics.mean_squared_error(test_Y, predictions2))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(test_Y, predictions2)))
```

```
Accuracy of model is 0.5281974252228898
Mean Absolute Error: 9.70872005748586
Mean Squared Error: 143.01752480054748
Root Mean Squared Error: 11.958993469374 73
```

In [14]:
```python
# Feature selection
coef1=pd.DataFrame(las.coef_.ravel())
coef1['feat']=train_X.columns
c1=coef['feat'].rows=['C','Bfs','Fa','W','Sp','Ca','Fa','a']
num_colors = 8;
colors = cm.rainbow(np.linspace(0,1,num_colors))
plt.bar(c1, coef[0], color=colors)
plt.show()
```



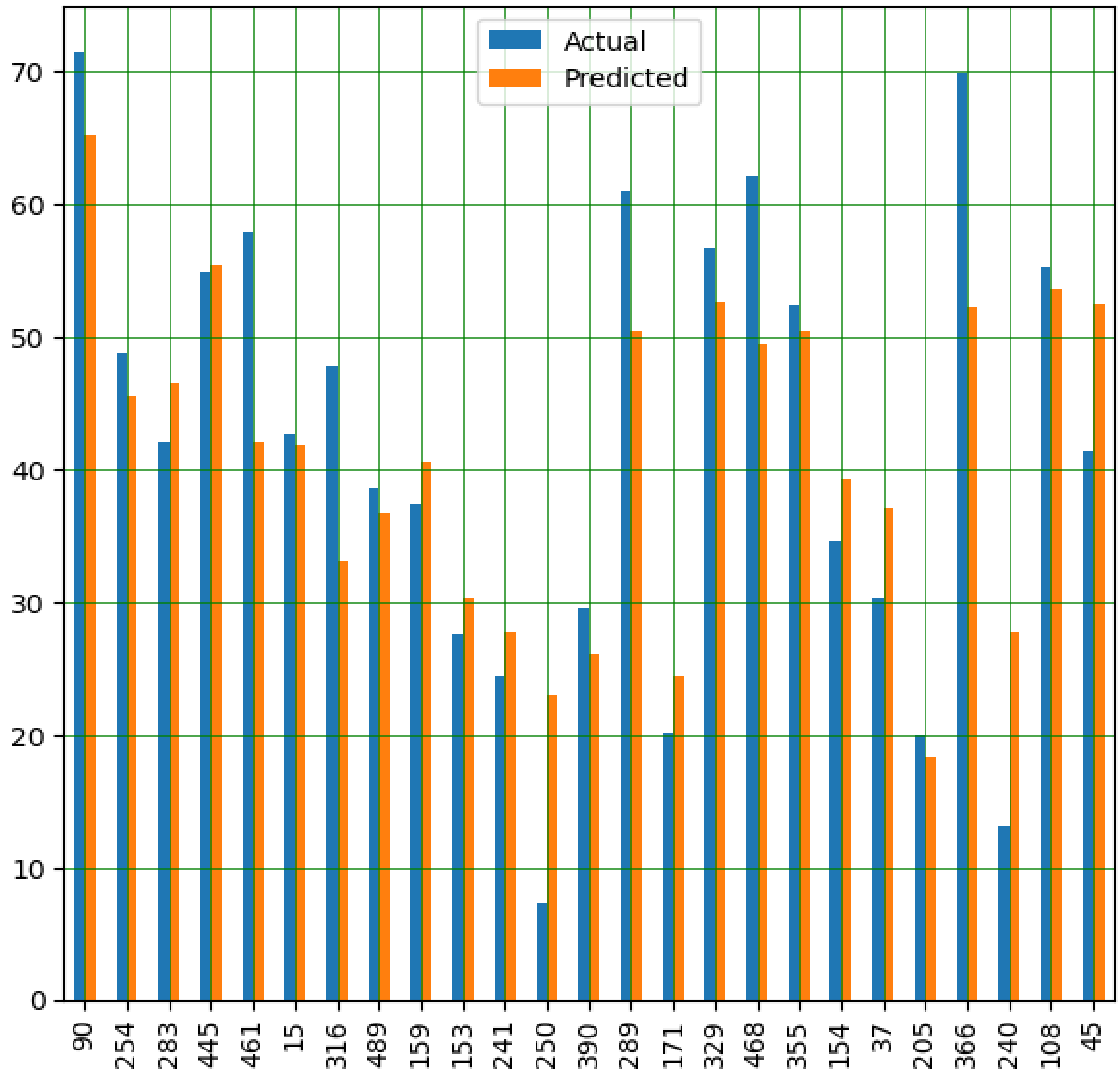
In [15]:
```python
#Plot of true value vs. predicted values
dat = pd.DataFrame({'Actual': test_Y, 'Predicted': predictions2})
dat1=dat.head(25) #just a sample which shows top 25 columns
dat1.plot(kind='bar',figsize=(7,7))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



In [16]:
```
# Model 3: KNN Neighbor
knn = KNeighborsRegressor()
model3=knn.fit(train_X,train_Y)
predictions3 = knn.predict(test_X)
m13=model3.score(test_X, test_Y)
RMSE13=np.sqrt(metrics.mean_squared_error(test_Y, predictions3))
print('Accuracy of model is', model3.score(test_X, test_Y))
print('Mean Absolute Error:', metrics.mean_absolute_error(test_Y, predictions3))
print('Mean Squared Error:', metrics.mean_squared_error(test_Y, predictions3))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(test_Y, predictions3)))
```

```
Accuracy of model is 0.6025398023424395
Mean Absolute Error: 8.393493333333332
Mean Squared Error: 120.48211839999999
Root Mean Squared Error: 10.976434685270076
```

In [17]:
```
dat = pd.DataFrame({'Actual': test_Y, 'Predicted': predictions3})
dat1=dat.head(25) #just a sample which shows top 25 columns
dat1.plot(kind='bar',figsize=(7,7))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```



CHAPTER -05

RESULTS AND DISSCUSSION

5.1 GENERAL

In this part of the lesson, Final outcomes of the characteristic compressive strength test are compared between normal aggregate concrete and recycled aggregate concrete are shown. After the completion of Compressive strength test, the results of M40 grade Normal aggregate concrete and equivalent grade of recycled aggregate concrete were compared. In this lesson, ,the results derived by performing the tests on Plain cement concrete(PCC)are shown and their successive values are explained. The test result have been discussed furthermore for better understanding of concepts. The values obtained through compressive strength tests atafter7th, 14thand28thdaysofcuringare firstly obtained .After this ,the split tensile strength performed on the concrete beams on the 7th and 28th days prior curing was obtained. The test was peformed on concrete using both Normal aggregate concrete (NAC) blocks and Recycled aggregate Concrete (RAC) blocks. It tells the outcome of 150 concrete cubes of M40 grade (140 RAC cubes and 10 NAC cubes).

Also, the chapter presents the finding from the Machine Learning utilising Python code, a model trained on data with features including cement, water, coarse aggregate, fine aggregate, and age is needed to estimate the compressive strength of concrete.This programme loads a dataset called **concrete_data.csv** that includes information about cement, water, coarse and fine aggregates, age, and values for compressive strength. It consists of 500 cube samples (350 observations from Kaggle and 150 samples from Testing data). It had 8 quantitative inputs and 1 quantitative output.

5.2 TESTS CONDUCTED

To check the compressive strength of concrete, CTM (Compressive testing Machine) was used and flexural Strength Test was also done on concrete beams.

5.2.1 Flexural Strength Test

5.2.2 Compressive Strength Test

5.2.1 Flexural Strength Test

A crucial characteristic that assesses concrete's capacity to withstand bending or cracking under stress is its flexural strength. The test process is applying a load at the centre of a rectangular concrete beam specimen during a three-point bending test until the beam fails or cracks. A formula that considers the load at failure, the distance between the supports, the width, and the depth of the specimen is used to determine the flexural strength of concrete.

Concrete's flexural strength is affected by a number of variables, including the mix design, the curing environment, and any flaws or cracks in the specimen. The concrete's strength and stiffness, and consequently its capacity to withstand bending, are influenced by the mix design. In order to ensure that the concrete reaches its maximum strength potential, regular curing processes must be followed. Curing conditions play a significant effect in how strong the concrete becomes.

The dimensions of the rectangular concrete beam specimen should be (150*150*700)mm The specimen's surface should be flawless and devoid of any holes or fissures. The beam should be treated using the conventional concrete curing techniques.

Fig 18- Flexural Tensile Strength Testing Machine

Setting up the testing apparatus: The apparatus should be calibrated and set up in accordance with the accepted testing practises. The bottom surface of the specimen should be pointing upward as it is supported by the supports.

Loading procedure: The centre of the beam should be loaded with a load using a loading device. The specimen should be subjected to the load gradually until it fails or cracks. The loading speed should fall between 0.02*10^6 Pa/s and 0.05 *10^6 Pa/s.

Calculating Flexural Strength: The formula below can be used to determine the concrete's flexural strength

Flexural Strength (MPa) = (3 x P x L) / (2 x b x d^2)

5.2.1.1Results of Flexural Strength Test

Final result of Flexural strength of Normal concrete aggregates after 28 days

S No.	Samples	Flexural Strength
1	S1	15
2	S2	14.8
3	S3	15

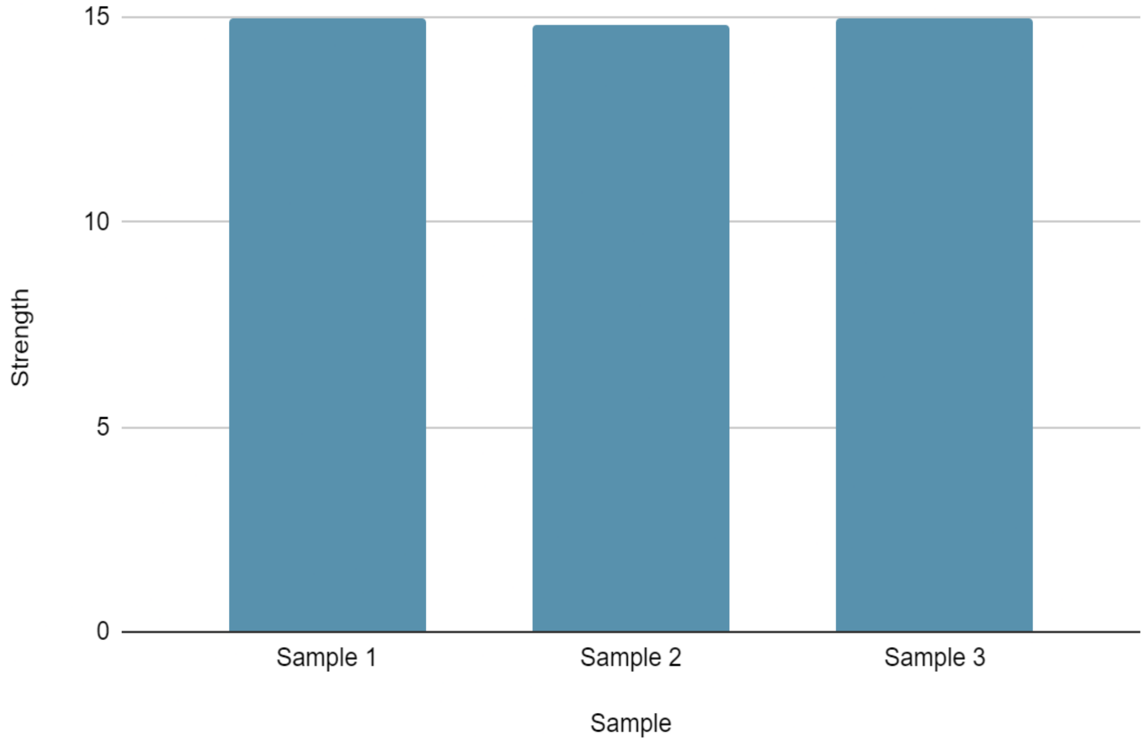


Fig 19: flexural strength of Normal concrete after 28 days

Final result of Flexural strength of Recycled concrete aggregates after 28 days

S No.	Samples	Flexural Strength
1	S1	13.6
2	S2	14.5
3	S3	14

TABLE 9: Result for flexural strength of Recycled concrete in 28 days of curing

5.2.1.2 Comparison of Flexural strength at 28 days

After twenty-eight days of curing, a comparison of the flexural strengths of recycled concrete and regular concrete is made.

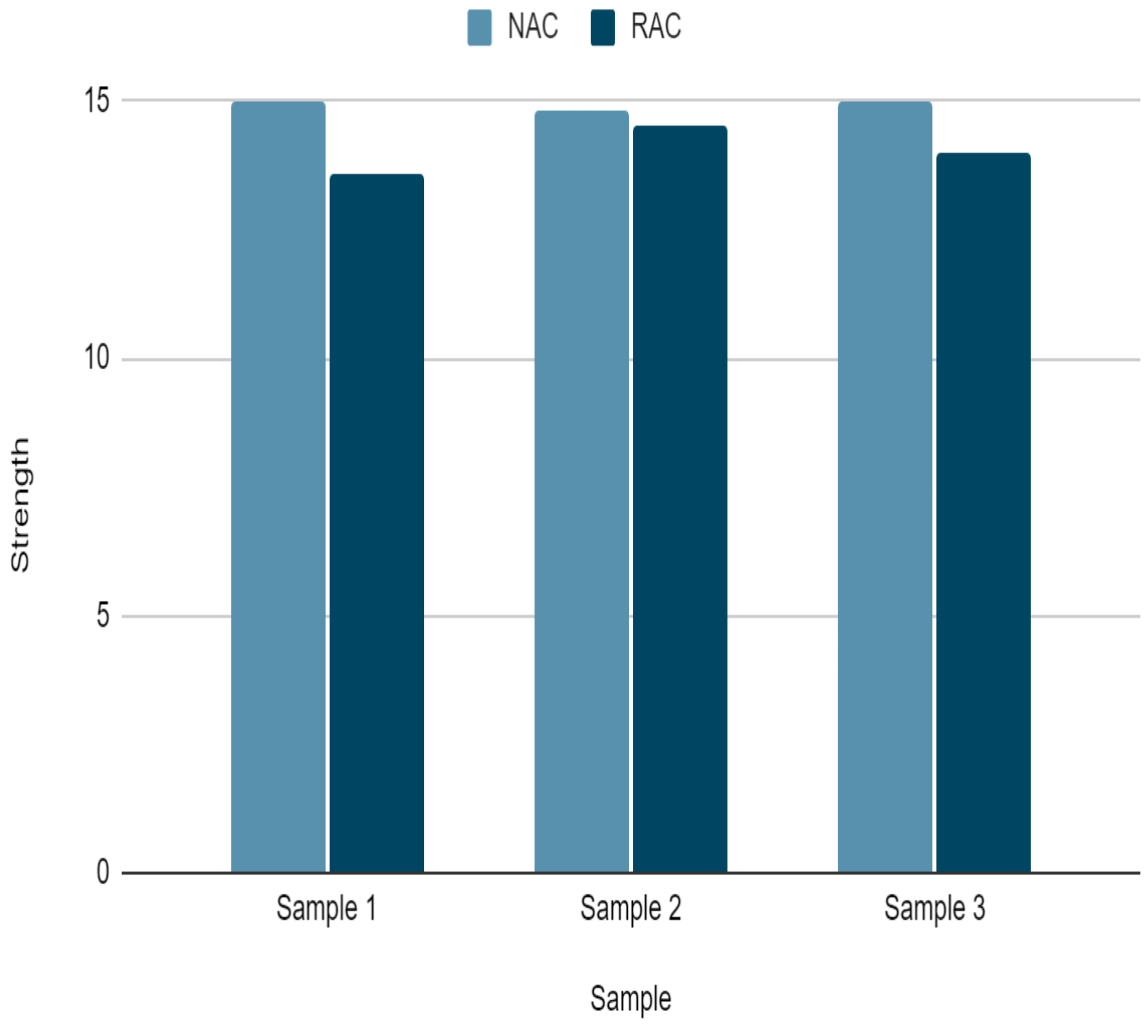


Figure 20: Comparison of flexural strength b/w the normal and recycled concrete after 28 days

5.2.2 Compressive Strength Test

The strength of concrete, rough and fine aggregates, water, and various admixtures are all controlled through proportioning. The ratio of water to cement is the major component in determining the strength of concrete. When using a low water-cement ratio, the compressive strength is increased. Currently, the strength of concrete is expressed in megapascals (MPa) in SI measurements and pounds per square inch (psi) in US values. Usually, this is brought on by the compressive strength of genuine fc/fck. For typical field applications, concrete with a strength range of 10 MPa to 60 MPa can be used. Ultra-high strength concrete, or concrete with high compressive strengths in the range of 500 MPa, is made for specific uses and designs. Or chemically active concrete powder.

Fig 21: Characteristic Strength Testing Machine(CTM)

Compression evaluation is the most frequent test that may be performed on hardened concrete, in part because it is a straightforward procedure and can reveal more useful, practical features of concrete. The characteristic compressive strength of 150-millimeter-size cubes measured at 28 days (fck) is used to determine the concrete's compressive strength (as shown in Figure). The members of concrete must determine their own strength. To determine the strength of concrete, concrete specimens have been cast and examined while being subjected to compressive loadspowdered active concrete.Concrete with quality control was prepared under controlled exposure conditions for this study's work. They are poured into cubical moulds(150x150x150mm) and set on a table to reduce air trapped inside the moulds in order to prevent any impact on the compressive strength. After one day, the moulds were removed, but the specimens were left in the moulds so they could heal at room temperature before testing. There are 9 cubes of each grade available for the Compressive evaluation. 27 cubes in all were examined in one test routine. It was repeated for total of 150 cubes to also predict the compressive strength using Machine learning.And python codes.

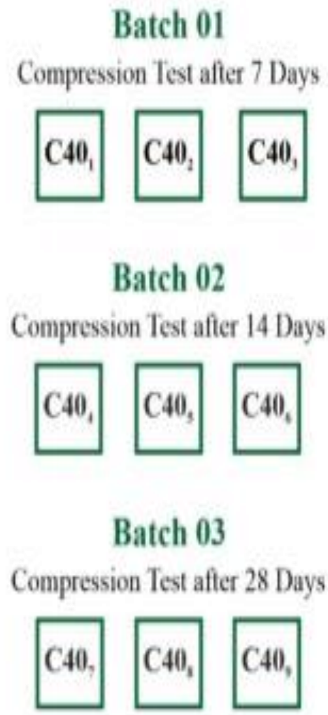


Fig 22: M40 concrete Samples

5.2.2.1 Results of Compressive Strength of concrete of both NAC and RAC

Batch 1(NAC)			Batch 2(NAC)			Batch 3(NAC)		
1 WEEK			2 WEEK			4 WEEK		
Compressive Strength (MPa)								
S1	**S2$_2$**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
28.10	29.89	28.10	42.89	42.41	42.41	46.34	46.34	47.89
Average compressive Strength(MPa)								
28.69			42.57			46.83		

Table 10: Compressive strength of NAC(M40) on 7th, 14th and 28th days

Batch 1(RAC)			Batch 2(RAC)			Batch 3(RAC)		
1 WEEK			2 WEEK			4 WEEK		
Compressive Strength (MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
25	28	28	35.25	38.39	32	38	40.23	34.25
Average compressive Strength(MPa)								
27			35.21			37.49		

Table 11: Compressive strength of RAC (M40)on 7th, 14th and 28th day

Batch 4(RAC)			Batch 5(RAC)			Batch 6(RAC)		
1 WEEK			2 WEEK			4 WEEK		
Compressive Strength (MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
24	29.89	25	28.25	32.25	28.30	32.25	34.00	30.25
Average compressive Strength(MPa)								
26.29			29.93			32.16		

Batch 7(RAC)			Batch 8(RAC)			Batch 9(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
28.10	29.89	28.10	30.20	32.41	33.41	32..34	34..34	35.89
Average compressive Strength(MPa)								
28.69			32.00			34.19		

Batch 10(RAC)			Batch 11(RAC)			Batch 12(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
28.10	29.89	28.10	32.89	32.41	32.41	36.34	36.34	37.89
Average compressive Strength(MPa)								
28.69			32.57			36.83		

Batch 13(RAC)			Batch 14(RAC)			Batch 15(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
25.10	24.89	24.10	28.89	27.41	26.41	32.34	31.34	30.89
Average compressive Strength(MPa)								
24.69			27.57			31.52		

Batch 16(RAC)			Batch 17(RAC)			Batch 18(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	S2	S3	S4	S5	S6	S7	S8	S9
28.10	29.89	28.10	32.89	32.41	32.41	36.34	36.34	37.89
Average compressive Strength(MPa)								
28.69			32.57			36.83		

Batch 19(RAC)			Batch 20(RAC)			Batch 21(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	S2	S3	S4	S5	S6	S7	S8	S9
28.10	29.89	28.10	32.89	32.41	32.41	36.34	36.34	37.89
Average compressive Strength(MPa)								
28.69			32.57			36.83		

Batch 22(RAC)			Batch 23(RAC)			Batch 24(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	S2	S3	S4	S5	S6	S7	S8	S9
25.10	26.89	25.10	30.89	32.41	30.41	34.34	36.34	34.89
Average compressive Strength(MPa)								
25.69			31.23			35.19		

Batch 25(RAC)			Batch 26(RAC)			Batch 27(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
28.10	29.89	28.10	32.89	32.41	32.41	36.34	36.34	37.89
Average compressive Strength(MPa)								
28.69			32.57			36.83		

Batch 28(RAC)			Batch 29(RAC)			Batch 30(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
28.10	29.89	28.10	32.89	32.41	32.41	36.34	36.34	37.89
Average compressive Strength(MPa)								
28.69			32.57			36.83		

Batch 31(RAC)			Batch 32(RAC)			Batch 33(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
25.10	26.89	25.10	30.89	32.41	30.41	34.34	36.34	34.89
Average compressive Strength(MPa)								
25.69			31.23			35.19		

Batch 34(RAC)			Batch 35(RAC)			Batch 36(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
28.10	29.89	28.10	30.20	32.41	33.41	32..34	34..34	35.89
Average compressive Strength(MPa)								
28.69			32.00			34.19		

Batch 37(RAC)			Batch 38(RAC)			Batch 39 (RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
28.10	29.89	28.10	32.89	32.41	32.41	36.34	36.34	37.89
Average compressive Strength(MPa)								
28.69			32.57			36.83		

Batch 40(RAC)			Batch 41(1RAC)			Batch 42(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
25.10	24.89	24.10	28.89	27.41	26.41	32.34	31.34	30.89
Average compressive Strength(MPa)								
24.69			27.57			31.52		

Batch 43(RAC)			Batch 44(RAC)			Batch 45(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
25	28	28	35.25	38.39	32	38	40.23	34.25
Average compressive Strength(MPa)								
27			35.21			37.49		

Batch 46(RAC)			Batch 47(RAC)			Batch 48(RAC)		
1 WEEK			2 WEEK			4 WEEK		
CC Strength(MPa)								
S1	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**S9**
24	29.89	25	28.25	32.25	28.30	32.25	34.00	30.25
Average compressive Strength(MPa)								
26.29			29.93			32.16		

CHAPTER-6

CONCLUSIONS AND FUTURE SCOPE

6.1 GENERAL

The main objective was to make use of Recycled aggregate concrete more mainstream in use in construction industry especially in RCC works. The research was done in order to lessen the demand for natural resources like gravel and sand and to promote the sustainable use of building and demolition debris, recycled concrete are typically used in place of natural aggregates. This strategy supports the goals of the circular economy, which are to minimise environmental impact, enhance resource efficiency, and eliminate waste.

Utilising recycled aggregates can also result in cost savings on shipping, landfill fees, and raw material costs. Additionally, by reducing the need for energy-intensive extraction and transportation of natural aggregates, recycled aggregate concrete used in concrete can aid in lowering the carbon footprint of construction activities.

6.2 CONCLUSION

- The study's findings suggested that high-strength recycled aggregate concrete (RAC), which contains up to 100% recycled aggregate, can satisfy the necessary durability standards. According to the study, high-strength RAC, which uses fewer natural resources and less waste to fill landfills, can be a sustainable substitute for ordinary concrete. However, to guarantee that the desired strength and durability are realized, correct mix design and processing processes are required.

- In accordance to the result, the determined compressive strength of M40 grade of concrete cubes prepared with the help of concrete containing Natural aggregates (NAC) is comparatively greater to te occurring characteristic strength of cubes prepared from concrete containing recycled aggregates (RAC) .The results indicated that the strength in terms of compressive as well as Split tensile strength decreased while 100% RCA was employed.

- However, the results conclude that 100% replacement of natural aggregates with RCA is feasible and can be an efficient way to recycle construction and demolition waste, provided that the mix design and processing techniques are optimized to ensure all the characteristics of concrete are desirable. The final result displays that the characteristic strength of concrete along with split tensive strength of the concrete reduced the efficiency of 100% RCA.

- From the compressive strength prediction, following conclusions can be made:

  - Except for cement, there aren't any strong relationships between compressive strength and other properties, which should be the case with stronger materials.
  - The other two characteristics that have a substantial correlation with compressive strength are age and super plasticizer.
  - Super Plasticizer appears to have favorable relationships with Fly ash and Fine Aggregate and negative associations with Water

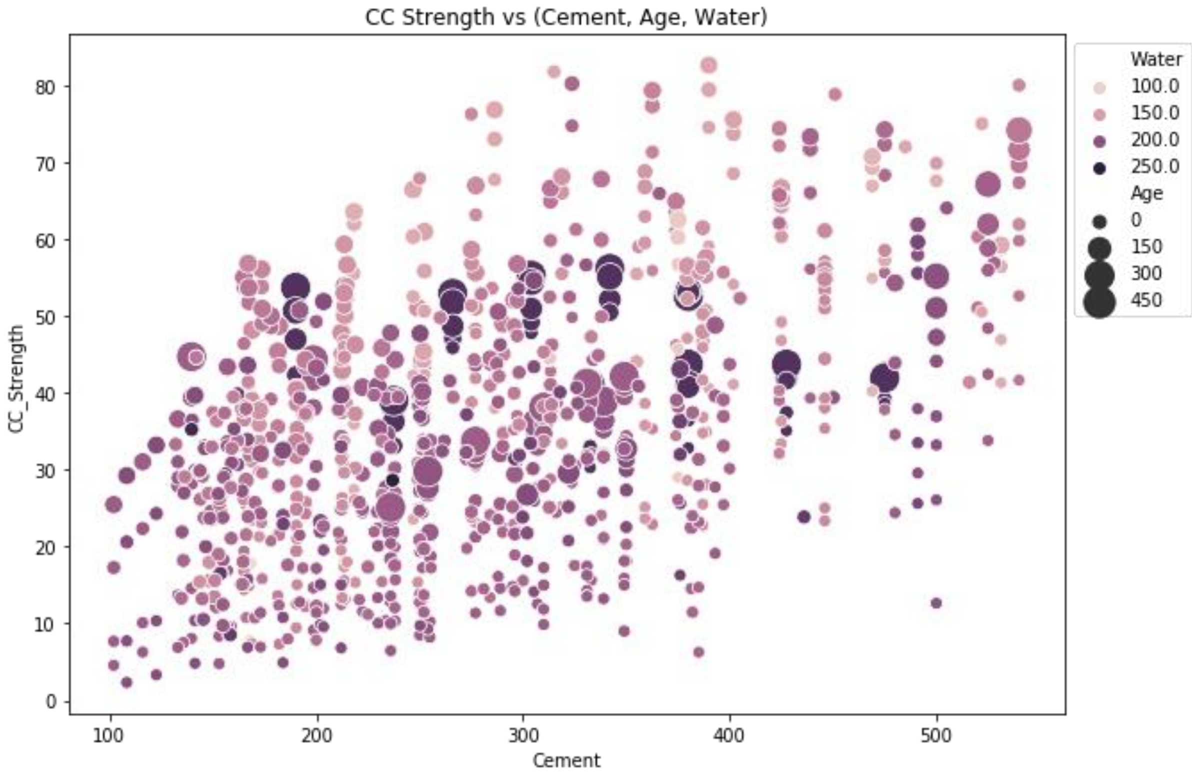


Fig 23:CC strength vs(Cement,Age,Water)

- Following observation were made from CC Strength vs (Water, Cement and Age)

  - With **more cement, compressive strength rises.**
  - With **age, compressive strength rises.**
  - For **greater strength,** younger cement needs **more cement.**
  - **More water** is needed.for **older cement**
  - **Less water** is needed to prepare concrete, which **increases its strength**.

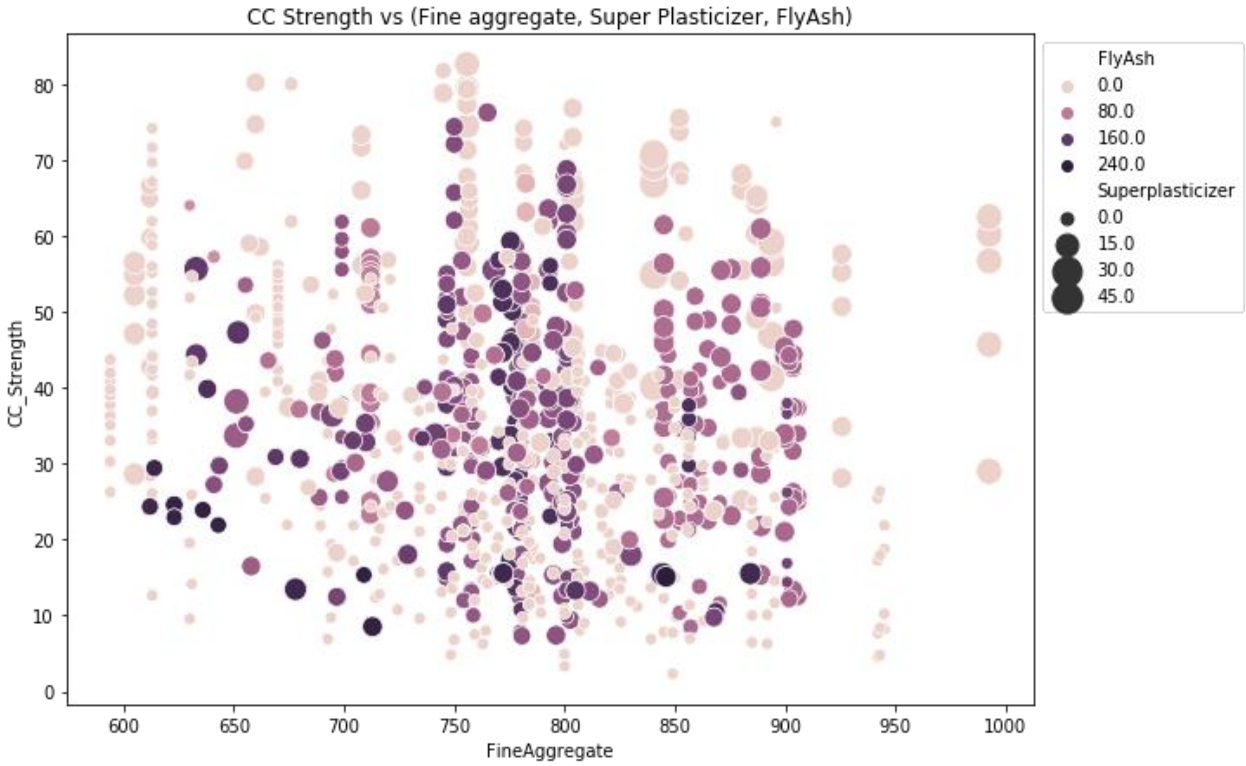


Fig 24:CC strength vs (Fine Aggregates, Superplasticizers, Fly Ash)

- Following observation were made from CC strength vs (FA, Superplasticizers and Fly Ash)

  - As the quantity of **Fly ash increases**, the **compressive strength increases**
  - **Strength increases** with the **increase in Superplasticizers**.

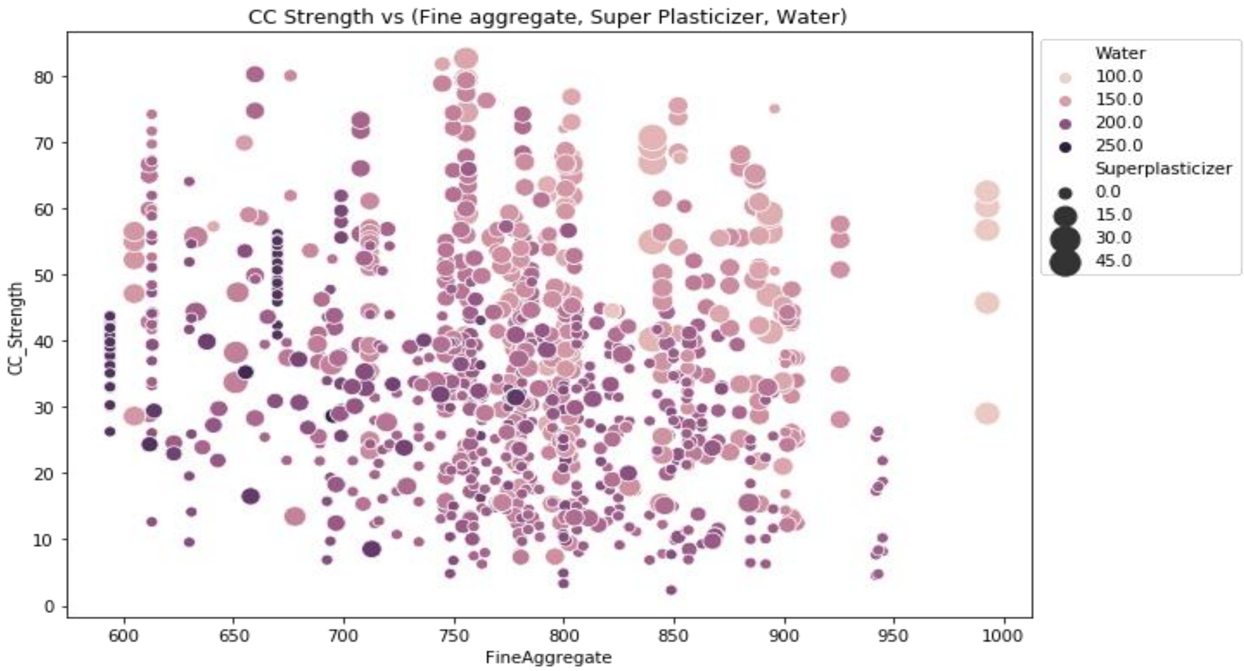


Fig 25: CC strength vs (Fine Aggregates, Superplasticizers, Water)

- Following Observations made from CC strength vs (CA, water, Superplasticizers)

  - **Strength decreases** with **increase in water**, **strength increases** with **increase in Super plasticizer** (already from above plots)
  - **More Fine aggregate** is used when **less water**, **more Super plasticizer** is used.

6.3 FUTURE OUTCOMES:

In future researches, following points can be considered for more flexible outcomes in the mechanical as well as durability analysis of concrete using recycled concrete.The application of artificial intelligence (AI) and machine learning (ML) in the study of concrete with recycled aggregate totally replacing natural aggregate has a lot of potential. The following are some examples of the area's probable future scope:

- **Predictive models**: They can be created using AI and ML to forecast the characteristics of concrete made from recycled aggregates. Large datasets of material properties can be used to train these models, which can then be used to improve the concrete mix design to attain the desired properties. Thus, we can use, AI and ML to predict the compressive strength of Higher grade recycled concretes too.

- **Real-time quality control** of concrete generated from recycled aggregates is possible with the help of AI and ML. Concrete qualities can be measured using sensors, and the ML algorithms can be utilized to identify any variations from the required properties. This can assist in preventing flaws and enhancing the concrete's general quality.

- **Material selection:** AI and ML can be used to examine the characteristics of several recycled aggregate kinds and determine which ones are best for use in concrete. This can maximize the utilization of recycled aggregates and reduce the environmental impact.

- **Environmental Impact Assessment** of the environmental impact of employing recycled aggregates in concrete can be done using AI and ML. This can assist in locating any potential harmful effects and creating plans to lessen them

Overall, the study of concrete that totally substitutes natural aggregate with recycled aggregate using AI and ML has the potential to revolutionise the building sector and advance ecologically friendly and sustainable practises.

CONFERENCE PUBLICATION

[1] Attended and presented the work on **“Effect of Processed and Unprocessed recycled aggregate concrete on the Compressive strength of High Strength concrete”** at 3rd International Conference on Futuristic and Sustainable Aspects in Engineering and Technologyat GLA University, Mathura ,UP.

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Certificate

This is to certify that

Mr. Ayush

has participated and presented a paper titled “Effect of Unprocessed and Processed Recycled Concrete Aggregate on the Compressive Strength of High Strength Concrete” in 3rd International conference on **“Futuristic and Sustainable Aspects in Engineering and Technology (FSAET-2022)”** held on **11th - 13th November, 2022** which was organized by **Department of Civil Engineering. GLA University, Mathura.**

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GLA University, Mathura

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