THESIS

ON

NEURAL NETWORK APPROACH TO PREDICT THE COMPRESSIVE STRENGTH OF CONCRETE UTILIZING ULTRASONIC PULSE VELOCITY & DIGITAL IMAGES

Submitted By

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DECLARATION

This thesis titled 'NEURAL NETWORK APPROACH TO PREDICT THE COMPRESSIVE STRENGTH OF CONCRETE UTILIZING ULTRASONIC PULSE VELOCITY & DIGITAL IMAGES' prepared and submitted in the partial fulfilment of the requirements for the degree of Master of Civil Engineering (with specialisation in Structural Engineering) at Jadavpur University for the academic session 2023-2024.

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RECOMMENDATION CERTIFICATE

It is hereby certified that this thesis titled 'NEURAL NETWORK APPROACH TO PREDICT THE COMPRESSIVE STRENGTH OF CONCRETE UTILIZING ULTRASONIC PULSE VELOCITY & DIGITAL IMAGES' is prepared and submitted in the partial fulfilment of the requirements for the degree of Master of Civil Engineering (with specialisation in Structural Engineering) at Jadavpur University by ARNAB MANDAL, a student of 2nd year of the said course for the session 2023-2024, under my supervision and guidance. It is also declared that no part of this thesis mentioned above has been presented or published elsewhere.

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ABSTRACT

Concrete compressive strength is the most important property which signifies the quality of concrete. Several nondestructive and semi destructive test can be conducted to evaluate the concrete compressive strength, but there is an issue regarding the direct corelations between compressive strength and different non destructive test results. However, in the present study a image based concrete compressive strength prediction model using machine learning techniques with the help of ultrasonic pulse velocity (UPV) test has been proposed. In the present investigation 3 different concrete mix has been prepared of grade M20, M25 and M30 respectively. Several images at different zoom have been captured using digital microscope after cutting the concrete sample. In addition to that, all the sample have been tested for UPV values followed by destructive compressive strength. The images and corresponding UPV data and compressive strength have been used to predict the compressive strength from the image using the above mentioned methodology. The study clearly reveals that models exhibits better prediction model for estimating compressive strength using the digital microscopic images. The findings from the present investigation corroborate that UPV DATA can be used efficiently to predict cement mortar and concrete compressive strength. Thus, present study demonstrate the applicability of different machine learning technique using UPV values and digital microscopic images as an alternative nondestructive/semi destructive test method for predicting compressive strength of concrete.

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Introduction

1.1 General

Concrete is one of the most widely used materials globally, surpassed only by water in its prevalence. Although concrete was developed long ago, its application in civil engineering projects is still broadening. The key reasons for this are its cost-efficiency and simple production process, along with the absence of any material that can substitute its unique properties [1,2]. Strength refers to the measurement of the stress required for a material to deform or fail. The primary factor tested to estimate the strength of concrete is compressive strength. This parameter is crucial for designing reinforced concrete structures and serves as a key indicator for monitoring the health of existing structures.

The available tests for assessing concrete strength include: (a) Destructive tests (b) Non-destructive tests and (c) combination of both tests. The widely used destructive testing methodology for obtaining the compressive strength is the cube test. Cube testing is carried out on fresh concrete samples that are prepared using the same proportions of raw materials as those used in new concrete members [3,4]. This method is useful for estimating the strength of newly created concrete members but is challenging to predict the strength of existing structures. The measurement of the strength of existing structure are typically conducted using non-destructive testings, as they do not necessitate any destructive procedure for sample collection and are both simple and quick to use. Examples of tests that can be applied non-destructively on site include ultrasonic pulse velocity, rebound hammer, and sonic rebound (SonReb) tests [5–10]. NDT can be utilized for testing both old and new structures. It's primary applications for new structures are quality control and addressing material or construction quality issues. Evaluating existing buildings centers on determining their structural soundness or suitability. The ultrasonic pulse velocity test and the rebound hammer test are frequently employed non-destructive testing methods for assessing the mechanical properties of concrete, whether in a laboratory setting or on-site.

An artificial neural network (ANN) is a form of computational algorithm modelled after the neurons in the human brain, and it is commonly utilized for forecasting of data [11–13]. Neural networks can learn and analyse extensive datasets derived from experiments or trials. However, when addressing an image classification task with an ANN, converting a 2D image into 1D vectors before training can significantly raise the number of parameters that need to be learned as the image size grows. To overcome these challenges, convolutional neural network (CNN) models are employed across various fields and are especially prevalent in image and video analysis tasks [14].

1.2 Need for present study

Evaluating the load-bearing capacity of existing concrete constructions is a significant matter, increasingly capturing the attention of scholars, particularly in recent times. A precise approach for forecasting concrete characteristics is necessary, as it would be advantageous for the construction sector. The primary factor tested to estimate the strength of concrete is compressive strength. This parameter is crucial for designing reinforced concrete structures and serves as a key indicator for monitoring the health of existing structures. The primary evaluation of concrete compressive strength mainly involves the destructive testing procedure. Determination of the concrete strength using NDT methods has been intensively investigated. In global literature, various correlations have been suggested that link the compressive strength of concrete with the velocity of ultrasound. The primary limitation of these methods is the wide variation in the predicted values and the considerable discrepancy from the actual (experimental) compressive strength of the concrete. Nowadays, various machine learning algorithm like Support Vector Machine (SVM), Artificial Neural Network (ANN), Fuzzy Inference System (FIS), Adaptive Fuzzy Inference system (ANFIS), Convolutional Neural Network (CNN) etc have been used for prediction purpose and it can be used for estimating concrete properties.

1.3 Objective and scope of the work

The objective of the present study is Assessing Compressive Strength of Concrete using Digital Images by Different Machine Learning Technique. This paper explores the use of ANNs to forecast the compressive strength of concrete structures. To develop the ML models, information from experiments regarding ultrasonic pulse velocity and images taken from cube samples were employed, along with compressive strength tests performed on the same samples.

The scopes of the work are as follows

- Determine the UPV values of concrete.
- Determine the compressive strength of concrete.
- Capturing image data and preprocessing the image data.
- Train The ANN model.
- Prediction of the compressive strength by machine learning technique.
- Statistical analysis of the results.

1.4 Organization of thesis

The thesis has been divided into five chapters. The table and figures have been presented in a sequence as they appear in the text.

Chapter 1 an attempt has been made to introduce the problem along with need for present research, scope and objectives of the work and organization of thesis.

Chapter 2 furnishes a detailed literature review on the relevant topic.

Chapter 3 presents the methodologies adapted for experimental program and data collection.

Chapter 4 discussed about the results obtained form the experimental program.

Chapter 6 depicts the concluding remarks along with major findings, draw backs and future study.

References is furnished at the end.

Literature review

2.1 General

The non-invasive testings (NDT) of concrete holds significant scholarly and pragmatic value. The ultrasonic pulse velocity (UPV) technique is a widely utilized non-invasive method for evaluating concrete characteristics [15]. In 1976, Malhotra provided an extensive literature review of the non-invasive techniques typically employed for testing and evaluating concrete [10]. Leshchinsky outlined the benefits of non-destructive tests in comparison to core testing [16]. The application of UPV for the non-destructive evaluation of concrete properties were thoroughly researched for decades and is among the most widely used non-destructive technique [17]. This testing method is suitable for evaluating the uniformity and comparative quality of concrete and detecting the presence of voids and cracks. However it seems overly confident and difficult to try to develop an ultrasonic testing method for determining concrete strength. It is important to note that a vast amount of experimental data and theoretical correlation relationships between compressive strength and UPV value have been introduced and suggested [15,18–23]. which help us in finding the strength of concentrate members using pulse velocity.

Recently, techniques based on computer vision and machine learning are being suggested to guess the physical properties and classification. Employing machine learning techniques for image classification shows great potential for addressing this type of issue [24]. Different machine learning technique can be applied including support vector machine (SVM), Artificial Neural Network (ANN), Deep Convolution Neural Network (DCNN) for image classification. These methods were successfully applied in different field like recognition of hand written digits [25], face recognition [26], pest detection [27], plant disease [28,29], autonomous vehicles [30], medical diagnosis [31,32] etc. Further, a number of successful applications of the different machine learning method were applied in the field of civil engineering [33–35]. Asteris et al. [15] assessed the concrete compressive strength using ANN, drawing on experimental data from NDT tests: UPV and Rebound Hammer. Behnam et al. [36] predicted the compressive strength of concrete using ANFIS (adaptive neuro-fuzzy inference system), with slump flow and mixture proportions as inputs. Several successful applications of various image-based machine learning methods have been implemented in civil engineering, such as: identification of pavement crack [37,38], detection of structural damages [39].Recently quite a few breakthrough researches promoted the use of image processing technique (IP) to forecast the compressive strength of concrete. Başyiğit et al. [40]

conducted various regression analyses using IP to predict concrete's compressive strength, in which he attains an accuracy of 94.8%. Lopez et al. [41] used image analysis to examine characteristics of lightweight high-performance concrete, including unit shrinkage, deformation, elasticity and yield. Dogan et al. [42] utilized an ANN model to assess the compressive strength utilizing image processing technique. Shiuly et al. [43] concluded in their study that compressive strength can be predicted using images of concrete using various DCNN models and achieved a satisfactorily result. In the study conducted by Dantas et al. [44], ANN models were created to forecast the compressive strength of concrete with Construction and Demolition Waste (CDW) at ages of 3, 7, 28, and 91 days. Jang et al. [45] effectively employed contemporary DCNN models to forecast the compressive strength using a limited number of cement concrete samples captured with a digital microscope at specific resolution and reported that ResNet produced satisfactory results.

H.G. Ni, J.-Z. Wang explores the use of neural networks to predict the 28-compressive strength of concrete. A multi-layer feed-forward neural networks (MFNNs) was developed, considering a 11-7-1 architecture, meaning the model consists of 11 input nodes, each representing a distinct factor (or component of an input vector) such as grade of cement, water-to-cement cement ratio, cement content, dosage of water, max size of coarse aggregate, fine modulus of sand, the sand-aggregate ratio,the aggregate-cement ratio, slump, dosage of admixture, effect of admixture. The hidden layer contains seven nodes, which process the information from the input layer. The network's output layer has a single node that corresponds to the 28-day compressive strength of the concrete. The study involved two datasets: one from the authors' laboratory experiments and another from a concrete plant in Beijing. Each dataset was split into two subsets: a learning set for training the neural network and a testing set for evaluating its performance. The first batch of data consist of 65 mixes and the second batch having 100. he neural network model achieved high accuracy in predicting compressive strength, with a max relative error of 5.86% for the 1st batch and 12.81% for the second batch. The trained neural network (NN) models can be employed to simulate how various factors influence concrete strength. The authors used these models to establish functional relationships between the compressive strength and the relevant influencing factors. The study found that the compressive strength of concrete is almost directly proportional to the amount of cement used, assuming a constant water dosage of 190 kg/m^3. The strength is roughly directly proportional to the cement dosage, and the higher the grade, the greater the concrete strength. The sand-to-aggregate ratio in concrete mixtures can influence the strength, though the effect might be subtle but the effects of the fine module of sand on concrete strength are greater than the sand/aggregate ratio.

Breccolotti et al. explores the presence of spatial correlation in rebound hammer and ultrasonic pulse velocity test readings through experimental assessments on two reinforced concrete walls. The impact of this correlation is then incorporated into concrete strength assessment using the established SonReb method. Monte Carlo simulations, performed to evaluate the accuracy of the SonReb standard procedure, revealed a significant risk of both under- and over-estimation, as well as considerable absolute errors in predicting the mean compressive strength of the structural elements tested. To address these issues, the paper proposes a modification to the standard procedure. This adjustment, which involves increasing the distance between individual test locations, improves the accuracy of the SonReb evaluation. By applying this modification, the maximum overestimation error is reduced from approximately 15% to 5%, enhancing the reliability of the strength assessment.

Y. Zhang, F. Aslani introduces two models for predicting the compressive strength of lightweight aggregate concrete: a regression model and a back-propagation neural network (BPNN). The BPNN model integrates ultrasonic pulse velocity (UPV) data to meet various accuracy requirements. To achieve this, a comprehensive database was created, including 603 data sets from 26 different studies. This database covers a broad range of coarse aggregate sizes (4 mm – 40 mm) and lightweight aggregates (0.65 mm – 30 mm), as well as various volume ratios of coarse aggregate to binder (0.53 – 9.66) and sand to aggregate (0 to 5.99), lightweight aggregate volume fractions (0 – 100%), water-to-binder ratios (0.3 – 0.89), and curing times (1 day to 120 days). Statistical analysis shows that both the regression model and the BPNN model can provide reasonable estimates of compressive strength for lightweight aggregate concrete, although their accuracy levels differ. Consequently, the two models offer adaptable options for different accuracy requirements.

Asteris et al. proposed the application of artificial neural networks (ANNs) for predicting the compressive strength of concrete for existing structures. In this study artificial neural networks have been systematically employed to predict the compressive strength of concrete by incorporating data from both ultrasonic pulse velocity and Schmidt rebound hammer tests from vast amount of data found in numerous literature. An experimental database has been compiled from data sets available in the literature. Specifically, the database includes 209 datasets derived from experimental results reported in the PhD thesis by Logothetis. Each of the 36 batches (with the exception of one) consisted of 6 specimens. Initially, each specimen underwent non-destructive testing, starting with ultrasonic pulse velocity measurements followed by Schmidt hammer rebound tests. After completing these non-destructive assessments, each specimen was subjected to a uniaxial compressive test to determine its compressive strength. In the present study, a back propagation neural network (BPNN) is implemented and trained using the UPV and rebound number as input and the compressive strength as an output. The ANN models were trained using over 140 data points, which represents 66.99% of the total 209 data points. The remaining 69 data points were used for validation and testing. Specifically, 35 data points (16.75%) were allocated for validation, while 34 data points (16.27%) were used for testing the trained ANN. The comparison of the results obtained from the ANN models with experimental findings and existing analytical formulas in the literature highlights the promising potential of using back-propagation neural networks for accurately and reliably estimating concrete compressive strength based on non-destructive testing measurements. Additionally, the proposed neural network models can continuously be retrained with new data, allowing them to adapt and expand their applicability as more data becomes available.

Trinik et al. discussed in their paper the corelation between the ultrasonic pulse velocity test result and comprehensive strength of concrete. Accurately evaluating concrete compressive strength using ultrasonic pulse velocity (UPV) can be challenging because UPV values are influenced by various factors that do not necessarily affect compressive strength in the same way or to the same extent. This paper examines these factors and their impact on the velocity-strength relationship. Additionally, the study analyses the relationship between ultrasonic pulse velocity, static and dynamic Young's modulus, and shear modulus. Factors such as aggregate type, initial concrete temperature, cement type, environmental temperature, and water-to-cement (w/c) ratio were also investigated. Based on the experimental results, a numerical model was developed, employing a multi-layer feed-forward neural network. The paper shows that artificial neural networks are effective for modelling the velocity-strength relationship. This model facilitates the easy and reliable estimation of concrete compressive strength using only the ultrasonic pulse velocity and certain mix parameters. In this study the influence of the amount of aggregate, type of aggregate, nominal maximum aggregate size, and aggregate shape on the velocity-strength (Vp–S) relationship is examined. The impact of the aggregate amount in concrete is illustrated for mixtures with a water-to-cement (w/c) ratio of 0.54. It is evident that the quantity of aggregate plays a significant role in affecting the Vp–S relationship. It also concluded that within a specific range of values, the influences of initial temperature (Tini), environmental temperature (Tenv), cement type, and water-to-cement (w/c) ratio on the Vp–S relationship were not significant.

P. Turgut established a relationship between concrete strength and ultrasonic pulse velocity (UPV) using data from numerous cores extracted from various reinforced concrete structures with different ages and unknown concrete mixture ratios. This new formula allows for the practical estimation of concrete strength in existing structures where records of concrete mixture ratios are unavailable or not present.

Nash et al. aims to establish a unified relationship that connects the results of various non destructive tests and correlates them with the crushing strength of concrete cubes. Statistical methods are used to analyse laboratory tests conducted on concrete cubes with different mixing ratios and curing conditions. The goal is to develop correlation curves that improve the prediction of concrete strength. The study involves 161 test results from 161 concrete specimens, each with dimensions of 150x150 mm. Some of these specimens were created using mixtures formulated specifically for this research with ordinary Portland cement adhering to the Iraqi standard (No. 5), featuring target strengths of 15 and 25 N/mm^2 and subjected to various curing conditions. Other specimens were sourced from an M.Sc. thesis, primarily using ordinary Portland cement, except for 6 specimens made with sulphate-resistant Portland cement. These latter specimens were cured by immersing them in water for 30 days before testing. The age of the specimens in both categories ranged from 7 to 138 days. All specimens were made with fine aggregate falling within Zone 1 and coarse aggregate sizes ranging from 5 to 19 mm. An Ultrasonic Pulse Velocity (UPV) test was performed on each cube by averaging two readings (one from each of the opposite faces) using the commercially available PUNDIT equipment with a pulse frequency of 54 kHz. Following this, a Schmidt Hammer test was conducted on the same cube. The cube was fixed in a compression testing machine applying a force of approximately 2.5 N/mm^2, and the average of 10 rebound number readings from the Schmidt Hammer was recorded. Finally, the cube was subjected to a crushing test, and the crushing force was documented. He concluded that relying on a single test method (whether the Schmidt Hammer or UPV) is insufficient for accurately predicting in-situ concrete strength. The highest percentage of results explained by using only one method was 77%.

G.F.Kheder utilized two non-destructive test methods, ultrasonic pulse velocity and Schmidt hammer, along with concrete mix proportions and density, to develop mathematical models using multiple linear regressions for estimating concrete compressive strength. These models were applied to both wet and air-dry concrete conditions. A total of 103 different mixes were tested at ages ranging from 7 to 90 days. For more accurate estimates, a second stage involved correlating the initial strength estimates with actual strengths obtained from a limited number of cores taken from the structure. This approach was tested on two separate building projects, yielding reliable predictions. The standard error of estimate was 2.95 MPa for concrete with strengths ranging from 15.7 to 33.8 MPa in the first case study, and only 0.91 MPa for concrete with strengths ranging from 12.5 to 23 MPa in the second case study.

H.Y.Qasrawi The paper summarizes the author's experience with estimating concrete strength using combined non-destructive testing methods. The study utilized both the traditional rebound hammer and ultrasonic pulse velocity tests. The research aimed to develop a straightforward chart that relates rebound number and ultrasonic pulse velocity to concrete crushing strength. The goal was to create a chart that is easy for engineers to use on-site. This chart was subsequently utilized for evaluating the strength of various concrete samples. Standard cubes with a side length of 150 mm were prepared using various concrete mixes and immersed under water for a minimum period of 24 h before testing. The rebound number was obtained by taking three measurements on each of the four faces of the cube, with the rebound hammer positioned horizontally for all measurements. The results were evaluated following the guidelines of ASTM C 805. After completing the rebound hammer test, each of the two surfaces of the cube was prepared for the ultrasonic pulse velocity test. After completing the non-destructive testing on each cube, the cube was subjected to a loading test until failure, and the maximum load was recorded. With the help of this data a corelation between the comprehensive strength and the two non destructive test value the rebound number (RN) and the UPV vale ar proposed. The r^2 value was found to be 0.88 for RN and 0.9562 for UPV.

Shariati et al. focuses on the advanced prediction of the compressive strength of concrete mixtures that incorporate furnace slag and fly ash as partial cement replacements. For this investigation, a dataset consisting of 1030 samples with nine input parameters (related to the concrete mix composition and the age of the concrete) and one output parameter (the compressive strength) was gathered. Instead of utilizing the absolute values of the inputs, their relative proportions were employed. A novel method combining an artificial neural network with a genetic algorithm (ANN-

GA) was applied to carry out the study. The performance of the ANN-GA model was assessed by comparing it to another artificial neural network (ANN), which was developed and optimized using a traditional backpropagation (BP) algorithm. The findings revealed that the ANN-GA model not only could be effectively developed and applied for predicting the compressive strength of concrete but also achieved better results when compared to the ANN-BP model.

Behnam Vakhshouri & Shami Nejadi, developed a ANFIS models to establish a relationship between compressive strength as the output and slump flow along with mixture proportions as inputs across eighteen different combinations of input parameters. The data used in this study are derived from 55 previously conducted experimental studies. The impact of each parameter on compressive strength and its significance within the developed model has been thoroughly examined. By analysing the error in each combination, the weighting factor and importance level of each parameter are evaluated to apply correction factors, aiming to achieve the most optimized relationship. The results indicate that the model incorporating all input data (slump flow and mixture proportions) provides the most accurate prediction of compressive strength. Excluding slump flow from the combinations significantly impacts the compressive strength prediction, though not as much as the influence of maximum aggregate size and aggregate volume in the mixture design. Additionally, varying values of powder volume, aggregate volume, and paste content in the mixture exhibit different ascending and descending effects on compressive strength.

Başyiğit et al. delves into evaluation the compressive strength values of various concrete classes using image processing techniques. To achieve this, seven different water/cement ratios were produced across different concrete series. Physical and mechanical tests were performed on the resulting specimens, and image processing techniques were applied for further analysis. The study sought to establish correlations between the compressive strength values of the concrete specimens and the results obtained through image processing. A strong correlation ($R^2 = 0.9847$) was observed between the aggregate volume determined via image processing and the aggregate volume theoretically calculated during the mixture design. Regression analyses were conducted using the results from image processing and non-destructive testing. To compare the performance of the regression techniques, R^2, RMSE, SSE, and MAPE metrics were evaluated for each analysis. The findings suggest that the image processing technique used in this study could serve as a supplementary tool to both destructive and non-destructive testing methods.

Dogan et al. tried to predict the mechanical properties of concrete non-destructively, using a novel alternative method. To achieve this, 96 cylindrical concrete samples were produced, utilizing five distinct parameters: water/cement ratio, curing, cement content, compression, and additives. Images of the samples were captured before they underwent compression testing, and the pressure readings obtained in the laboratory were used to train and test both Artificial Neural Network (ANN) and Image Processing (IP) models. Additionally, 48 of the concrete samples were randomly selected to verify the ANN and IP predictions. A remarkably high correlation, ranging between 97.18% and 99.87%, was observed between the ANN and IP outcomes and the actual results for both the training/testing samples and the verification samples. The findings suggest that when ANN and IP are used together, this method offers a strong alternative to the traditional destructive and non-destructive techniques currently employed for determining the mechanical properties of concrete.

Shiuly et al introduces a new image-based machine learning method for predicting the compressive strength of concrete, evaluating six different models in the process. These models include a support-vector machine model and several deep convolutional neural network models: AlexNet, GoogleNet, VGG19, ResNet, and Inception-ResNet-V2. The investigation involved preparing cement mortar samples with cement ratios of 1:3, 1:4, and 1:5, using water ratios of 0.35 and 0.55. Additionally, cement concrete samples were prepared with cement:sand aggregate ratios of 1:5:10, 1:3:6, 1:2:4, 1:1.5:3, and 1:1:2, all using a water ratio of 0.5. The samples were cut, and multiple images of the cut surfaces were captured at various magnifications using a digital microscope. The samples were then subjected to destructive compressive strength testing. The captured images, along with the corresponding compressive strength data, were used to train the machine learning models to predict compressive strength based on the image data. Among the models tested, the Inception-ResNet-V2 model provided the most accurate compressive strength predictions. The findings support the effectiveness of using machine learning models to estimate the compressive strength of cement mortar and concrete from digital microscopic images, offering a viable alternative to traditional nondestructive or semi-destructive testing methods, with potential cost advantages.

M. Bilgehan & P. Turgut This article proposes an artificial neural network (ANN) approach to evaluate the relationship between concrete compressive strength and ultrasonic pulse velocity (UPV) values, using data obtained from numerous cores extracted from various reinforced concrete structures of different ages and with unknown concrete mixture ratios. The proposed method offers a practical way to estimate the compressive strength of concrete in existing reinforced concrete structures where the records of concrete mixture ratios are unavailable or missing. As a result, researchers can conveniently assess the compressive strength of concrete specimens based on their UPV values.

2.2 Critical appraisal of literature

On the basis of above literature survey following observations may be made.

- Compressive Strength prediction are not done using DCNN model and UPV testing data.
- Conducted on very few data points.
- It is done with particular zoom levels, so variations with different zoom are needed.
- A separate ANN model needs to be develop to incorporate both image data and UPV data.

Methodologies

3.1 General

In this section the details of all the methodology were discussed briefly. This investigation concentrate on finding a suitable and reliable CNN model for forecasting of data. It is important to note that the entire procedure is divided into four fundamental steps: acquisition of experiment data, preprocessing of data, training of the network and classification and evaluation of data.

3.2 Ultrasonic Pulse Velocity test

The ultrasonic pulse velocity (UPV) technique is one of the most frequently utilized non-destructive method for evaluating concrete characteristics [15]. However, accurately evaluating the concrete compressive strength using this method is challenging because UPV values are influenced by various factors that do not necessarily impact concrete compressive strength in the same manner or to the same degree [46]. The details of the UPV test can be found in IS 516 (Part 5/Sec 1) [46] ASTM C597 [47] (1991) and BS 1881-203 [48]. In this study only INDIAN STANDARD CODE has been followed.

An electro-acoustical transducer generates the ultrasonic pulse. When this pulse is introduced into the concrete by the transducer, the pulse undergoes numerous reflections at the boundaries of the various material phases within the concrete. A sophisticated network of stress waves forms, encompassing longitudinal (compressional), shear (transverse), and surface (Rayleigh) waves. The receiving transducer detects the arrival of the longitudinal waves, which travel the fastest. The velocity of these pulses is nearly unaffected by the geometry of the material they traverse and depends solely on its elastic properties. Consequently, longitudinal waves are termed primary or P waves, whereas transverse waves are referred to as secondary or S waves [46,49]. The time it takes for the pulses to travel through the concrete is recorded during the test. The velocity is subsequently calculated using the following formula:

$$V_p = \frac{L}{T} \tag{1}$$

where V_p represents the pulse velocity (Km/s), L is the length (m), and T is the effective time (s) [46]. The dynamic modulus of elasticity for a uniform and isotropic material can be assessed by measuring the velocities of P and S waves. The velocity of the waves can be related to the dynamic modulus of elasticity E_d and Poisson's ratio ν through the following formulas [49]:

$$V_p = \sqrt{\frac{E_d}{\rho(1-2v)(1+v)}} \quad (2)$$

$$V_s = \sqrt{\frac{E_d}{2\rho(1+v)}} \quad (3)$$

Where ρ represents the density of the substance, and VP and VS denote the primary and secondary wave speeds in the material, respectively.

The condition of concrete regarding consistency, presence or absence of internal defects, cracks, and segregation (reflecting the standard of the mixing) can be evaluated according to the guideline proposed in Table 1 by IS 516 (Part 5/Sec 1) [46].

Table 1: Concrete Quality as Determined by UPV as per IS 516 (Part 5/Sec 1)

Average Value of Pulse Velocity by Cross Probing in km/s	**Above 4.4**	**3.75 to 4.4**	**3.00 to 3.75**	**Below 3.00**
Concrete Quality Grading	Excellent	Good	Doubtful	Poor

This table is solely for grading concrete quality and should not be used to predict the grading of concrete or its strength based on ultrasonic pulse velocity values. It is important to recognize that an abundance of empirical data and theoretical models relating compressive strength to pulse velocity have been introduced and suggested. Table 2 sums of the most accepted and widely recognised models [15].

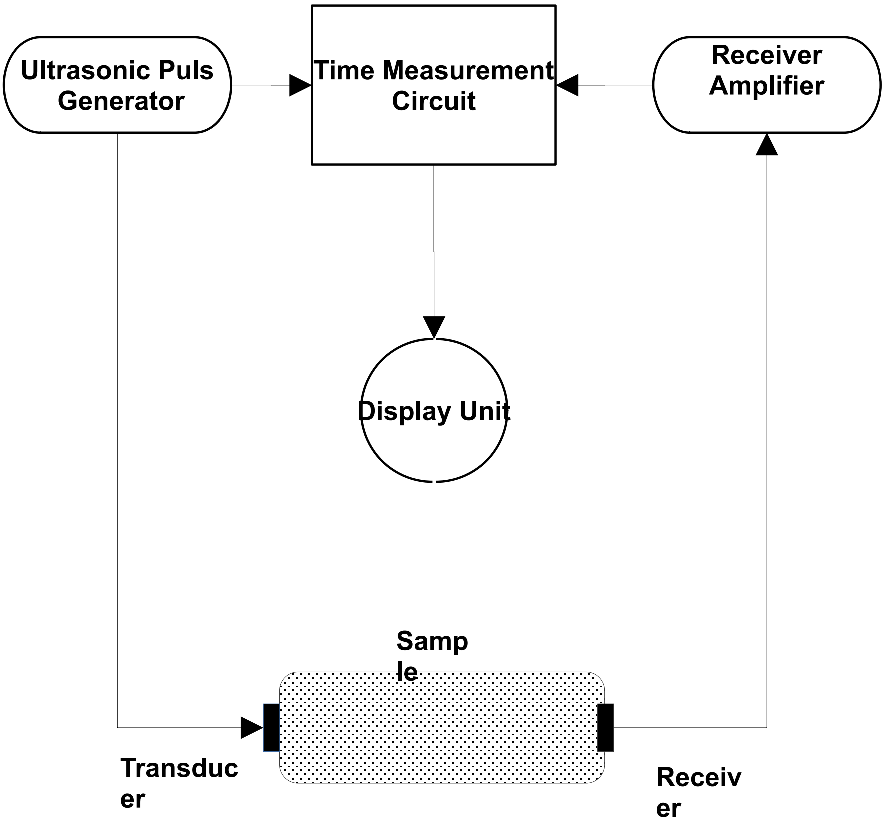


Fig 1: Diagrammatic representation of the ultrasonic pulse velocity testing setup.

Fig 2: A typical UPV apparatus with calibration rod

Table 2 Empirical Formulas for Estimating Concrete Compressive Strength (f_{ck})

Sl. No.	Equations	Reference
1	$f_{ck} = 1.146\,e^{0.77 V_p}$	[19]
2	$f_{ck} = 0.0854\,e^{1.288 V_p}$	[18]
3	$f_{ck} = 1.119\,e^{0.715 V_p}$	[20]
4	$f_{ck} = 1.2 \text{ X } 10^{-5}(1000\,V_p)^{1.7447}$	[21]
5	$f_{ck} = 36.73\,V_p - 129.007$	[22]
6	$f_{ck} = 176.9 - 96.46\,V_p + 13.906(V_p)^2$	[23]

3.3 Artificial Neural Networks

An artificial neural network (ANN) is a form of computational algorithm, modelled after the neurons in the human brain, and it is commonly utilized for forecasting of data. The architecture of Artificial Neural Networks (ANNs) are extensively parallel, consisting of numerous processing units interconnected by links. They are engineered in such way so that they can learn from provided experimental or theoretical data. These models can classify information, predict outcomes, and aid in selection-making tasks.

ANNs operate in a way that is analogous to the biological networks of human brain [50,51]. The artificial neuron serves as the fundamental unit of an ANN; essentially, it is a mathematical model engineered to emulate the function of a biological neuron. The architecture of an ANN consist of three layers namely- a) a input layer which receives the input data, b) one or several hidden layers which process the inputs, c) output layer which generates the result. When neurons are arranged in multiple layers, the network is referred to as a multilayer ANN. Input information is fed into the artificial neuron and, after undergoing processing through a mathematical function, it gives an output as a result. weights are assigned to the input parameters before input data are passed to the neurons, to replicate the stochastic characteristics of a biological neuron.

ANNs can learn and analyse extensive datasets derived from experiments or trials. However, when addressing an image classification task with an ANN, converting a 2D image into 1D vectors before training can significantly raise the number of parameters that need to be learned as the image size grows. To overcome these challenges, convolutional neural network (CNN) models are employed across various fields and are especially prevalent in image and video analysis tasks. In this present study a Deep Convolution Neural Network (DCNN) is implemented and described.

3.3.1 Overview of DCNN

In recent years, the performance of Deep Convolutional Neural Networks (DCNNs) have demonstrated significant advantages in image classification. DCNNs are a type of deep learning algorithm designed to process image data in the form of multiple arrays. They focus on extracting specific features, while handling variations such as shifting, rescaling, noise, and other types of data distortions [52]. The architecture of a hidden layer of a typical DCNN model primarily consists of convolutional layers, pooling layers, and fully connected layers [53]. Notably, the convolutional layer, succeeded by a pooling layer, includes several convolutional kernels known as Filters that are used to generate various feature maps (Fig. 3). The general formulation for the g^{th} feature map of the h^{th} layer in a convolutional neural network,

$$f_g^h = \sigma\left(\sum_{k=1}^{K^{(h-1)}} W_k^{(h)} * f_k^{(h-1)} + B^{(h)}\right) \tag{4}$$

Where f_g^h is the value of the h^{th} feature map in the l^{th} layer, σ is the activation function, such as ReLU, sigmoid, etc [54]. $K^{(h-1)}$ is the number of feature maps in the $(h\text{-}1)^{th}$ layer. $W_k^{(h)}$ is the convolutional kernel associated with the k^{th} feature map from the $(h-1)^{th}$ layer to the h^{th} feature map in the ^{hth} layer. $f_k^{(h-1)}$ is the k^{th} feature map of the $(h-1)^{th}$ layer. (*) denotes the convolution operation and $B^{(h)}$ is the bias term for the h^{th} layer. This equation captures the essence of how convolutional neural networks build higher-level features from lower-level ones through repeated convolution and activation operations. Following a convolutional layer, a pooling layer is introduced to integrate features, decrease parameters, and achieve shift-invariance by reducing the resolution of the feature maps. Following a convolutional layer, a pooling layer is introduced to integrate features, and achieve a smaller shift-invariance by reducing the resolution of the feature maps. The pooling layer in a convolutional neural network typically applies a downsampling operation to the input feature maps, if we represent ζ as the pooling operator then the output of the the pooling layer can be written as :

$$P_g^h = \zeta\left(f_g^h\right) \tag{5}$$

Next to the above mentioned layers, some architectures include several fully connected layers to learn higher-level features. These layers connect every neuron in one layer to every neuron in the next, which necessitates a large number of weight parameters. This full connectivity allows the network to model intricate relationships and patterns in the data. At the final layer of a neural network, a layer called softmax is typically introduced to transform the last out put of the end layes to a probability distribution.

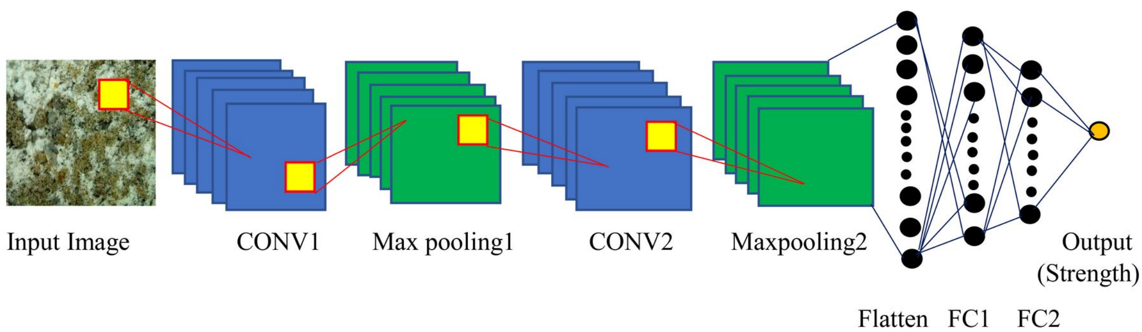


Fig. 3 Diagrammatic representation of a basic architecture of DCNN model

3.4 EXPERIMENTAL PROGRAM

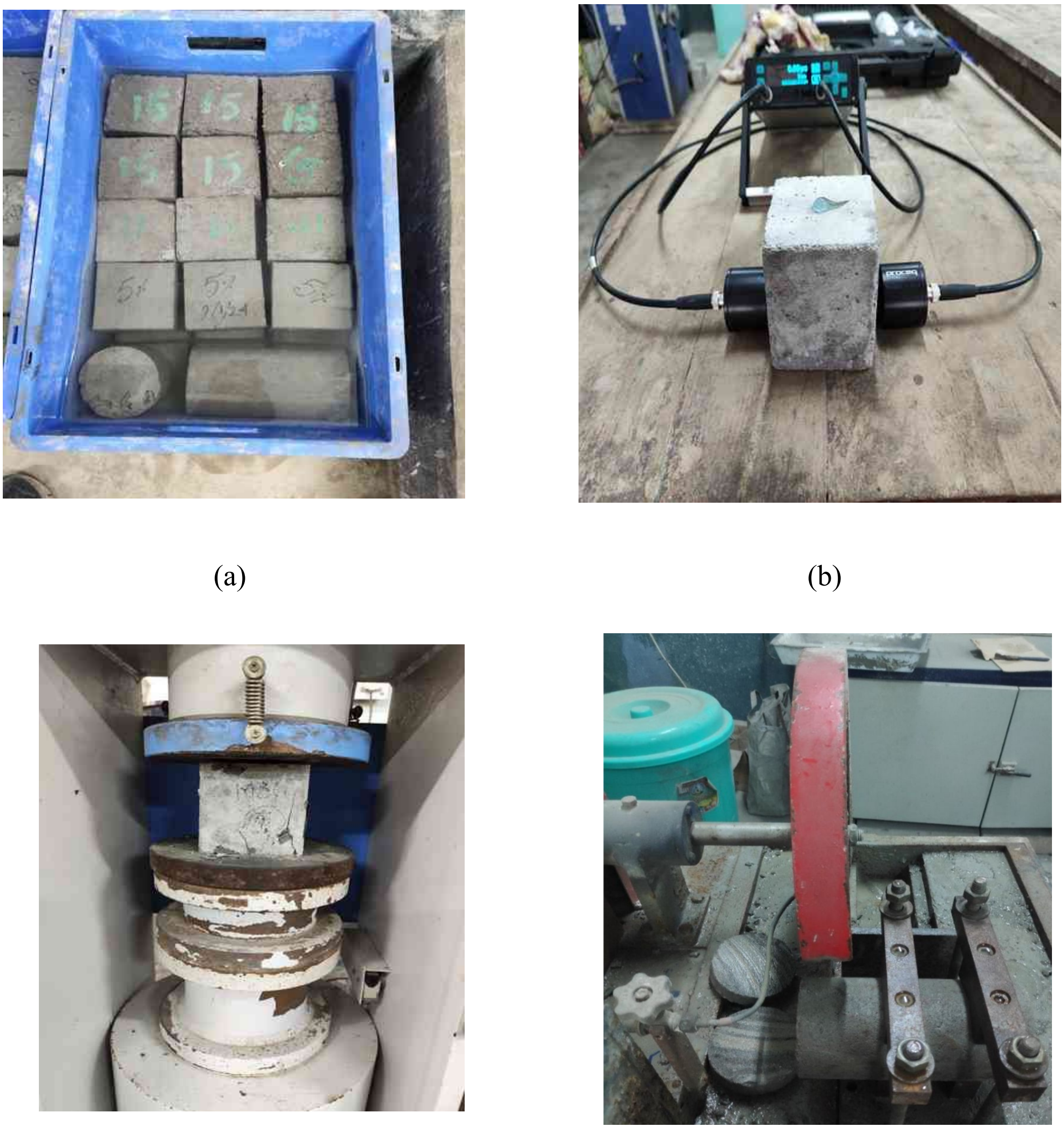
3.4.1 Sample preparation

In this present study compliance to IS 456: 2000 and IS 10262: 2019 concrete cube of 100 mm^3 of grade M20 M25 and M30 for 75 mm slump were cast and all the specimen were cured for 7 days, 28 days and 90 days respectively compliance to IS 1199(Part 5): 2018. In addition to that three concrete cylinder of diameter 100 mm and hight of 300 mm were also cast for each concrete group and cured for the same period as the cubes.

Three cubes of each group were first tested at an interval of 7 days, 28 days, 90 days of curing non-destructively for UPV measurement with the help of PUNDIT followed by compression testing according to IS 516(Part 5/Sec 1): 2018 and IS 516(Part 1/Sec 1): 2021. One cylinders from each group were cut radially at an interval of 7, 28 and 90 days respectively for capturing of images for the training of the neural network. Fig. 4 represents the experimental procedure which has been conducted for UPV and compressive strength test.

3.4.2 Acquiring of image database & preprocessing of image data

In this current investigation images have been captured of the concrete using digital microscope. Arbitrarily 60 number of images have been captured for each grade of concrete at 1x, 20x and 40x zoom level for end of each above mentioned curing periods, with the help of Caliper Pro Live software for capturing, processing and storing of the images digitally. In this research, all images underwent random cropping and horizontal flipping. Specifically, an image originally sized 1600 × 1200 was resized to 112 × 112. Subsequently, a random seed was generated within an 18 × 18 section. Then, an 84 × 84 segment of the image was selected using this random seed. Ultimately, the 9 sets of concrete images, each comprising 120 or 100 images, were divided into a training set (90%) and a testing set (10%). Furthermore the training images were further divided into 80% and 20% for training and validation set. Fig. 5 depicts the image capturing procedure and Fig. 6 shows a sample of images obtained.



(a) (b)

(c) (d)

Fig. 4 Sample preparation and testing of concrete. (a) prepared samples for UPV and compressive testing, (b) testing of UPV value of a cube sample after 28 days, (c) compressive testing apparatus, (d) cutting of samples for image acquisition

(a) (b)

Fig. 5 process of capturing images of samples (a) prepared samples of M25 concrete, (b) capturing of images using microscope

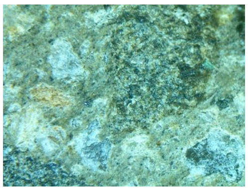
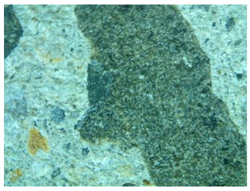
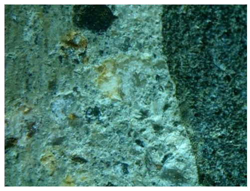
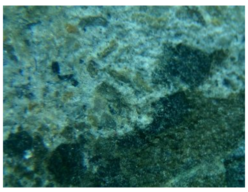
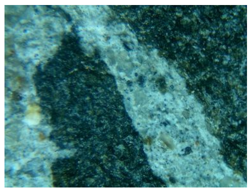
	Zoom Level	7 Days	28 Days	90 Days
	1x			
M30 concrete sample after 28 days	20x			
	40x			

Fig. 6 Images of concentrate

3.4.4 Normalisation of Data

Normalising or standardisation of dataset is regarded as the most vital phase in the field of soft computing including artificial neural network approaches. In this present study Min-Max Normalisation methods have been applied. The input variables (Table 3) and the sole output variable have been scaled using the Min-Max scaling technique. The input and output variables in this study have been scaled to fall within the range of [0.10, 0.90].

Table 3 Input and Output parameters for training the neural network

Parameter	Unit	Type	Data		
			Min	Average	Max
Ultrasonic pulse velocity V_p	km/s	Input	3.96	4.35	4.98
Compressive Strength	MPa	Output	11.20	27.47	38.67

Results and discussion

4.1 Test-database

An experimental test database consist of the results of UPV test data and compressive test data has been prepared. The results of both of the tests are presented in Table 4 and Table 5 respectively. Each sample was first evaluated using non-destructive methods; i.e. ultrasonic pulse velocity assessments were performed. Once the non-destructive tests were completed, each sample underwent a uniaxial compression test to determine it's compressive strength. A third database consist of experimental databases from previously mentioned experimental results has been prepared. This database consist of 3 batches of datasets each having 9 data-points based on experimental results conducted. The extended database is presented in Table 6.

Table 4 Compressive Strength (f_{ck}) Result of Concrete-specimens

Grade	Sl. No.	7 days	28 days	90 days
M 20	1	11.2	25.8	27.4
	2	12.5	26.7	28.1
	3	11.7	28.2	27.9
	Average	**11.8**	**26.9**	**27.8**
M 25	1	14.8	33.2	34.9
	2	13.7	35.9	36.2
	3	15.35	33.5	35
	Average	**14.6**	**34.2**	**35.37**
M30	1	21.6	36.2	37.55
	2	21.4	37.3	38.67
	3	21.6	37	38.45
	Average	**21.5**	**36.8**	**38.22**

Table 5 Ultrasonic Pulse Velocity Test Results (V_p) of Concrete-specimens

Grade	Sl. No.	7 days	28 days	90 days
M 20	1	3.96	4.17	4.15
	2	4.02	4.25	4.22
	3	3.98	4.18	4.13
	Average	**3.98**	**4.20**	**4.16**
M 25	1	4.08	4.55	4.42
	2	4.08	4.72	4.52
	3	4.46	4.55	4.46
	Average	**4.21**	**4.60**	**4.47**
M30	1	4.41	4.88	4.98
	2	4.08	4.52	4.59
	3	4.12	4.50	4.57
	Average	**4.20**	**4.46**	**4.71**

Table 6 Extended test results

No.	**Sample**		**Input Parameter**	**Output parameter**
	Batch	**Specimen No.**	V_p	f_{ck}
1	**M 20**	1	3.96	11.2
2		2	4.02	12.5
3		3	3.98	11.7
4		4	4.17	25.8
5		5	4.25	26.7
6		6	4.18	28.2
7		7	4.15	27.4
8		8	4.22	28.1
9		9	4.13	27.9

10		1	4.08	14.8
11		2	4.08	13.7
12		3	4.46	15.35
13		4	4.55	33.2
14	**M 25**	5	4.72	35.9
15		6	4.55	33.5
16		7	4.42	34.9
17		8	4.52	36.2
18		9	4.46	35
19		1	4.41	21.6
20		2	4.08	21.4
21		3	4.12	21.6
22		4	4.88	36.2
23	**M 30**	5	4.52	37.3
24		6	4.50	37
25		7	4.98	37.55
26		8	4.59	38.67
27		9	4.57	38.45

4.2 DCNN model development

In this study we have used DCNN as backbone with added ANN structure for enabling UPV values as input beside the input image. In order to achieve a fair comparison of the predictions of the various ANNs used, the datasets are split into training, validation and testing sets. Few number of different DCNN models have been developed and implemented and trained with over 648 images (72% of total sample points) and 27 data points and the validation and testing were done using remaining data pints. Table 7 shows the hyper parameters used for training the ANN,

Table 7 Hyper parameter used in different DCNN model

Model	Used loss funtion	epoch	Optimiser	Learning Rate	Pooling	Bias learn rate factor	Activation
DCNN	Categorical cross entropy	200	adam, sgdm	0.0003	avg, max	10	softmax

The proposed model (Fig. 8) uses the feature of Inception-v3 and Densenet-121, factorisation and dense connection and since it is multi-modal, it also contain ANN to have UPV input value which influences the model to perform better than the existing models. The graphical presentation of model accuracy and loss function of training and validation dataset for concrete at 28 d curing of a pictures captured at 20× zoom, is shown in Fig. 7. A brief discussion abut the above mentioned models are presented in the next segment.

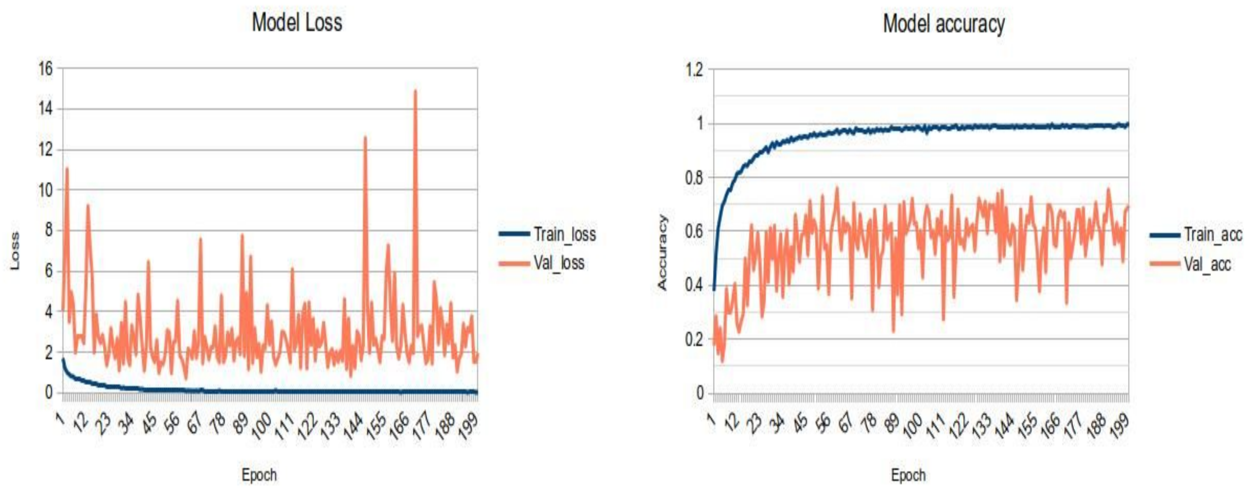


Fig.7 Model accuracy and loss of training and validation datasets

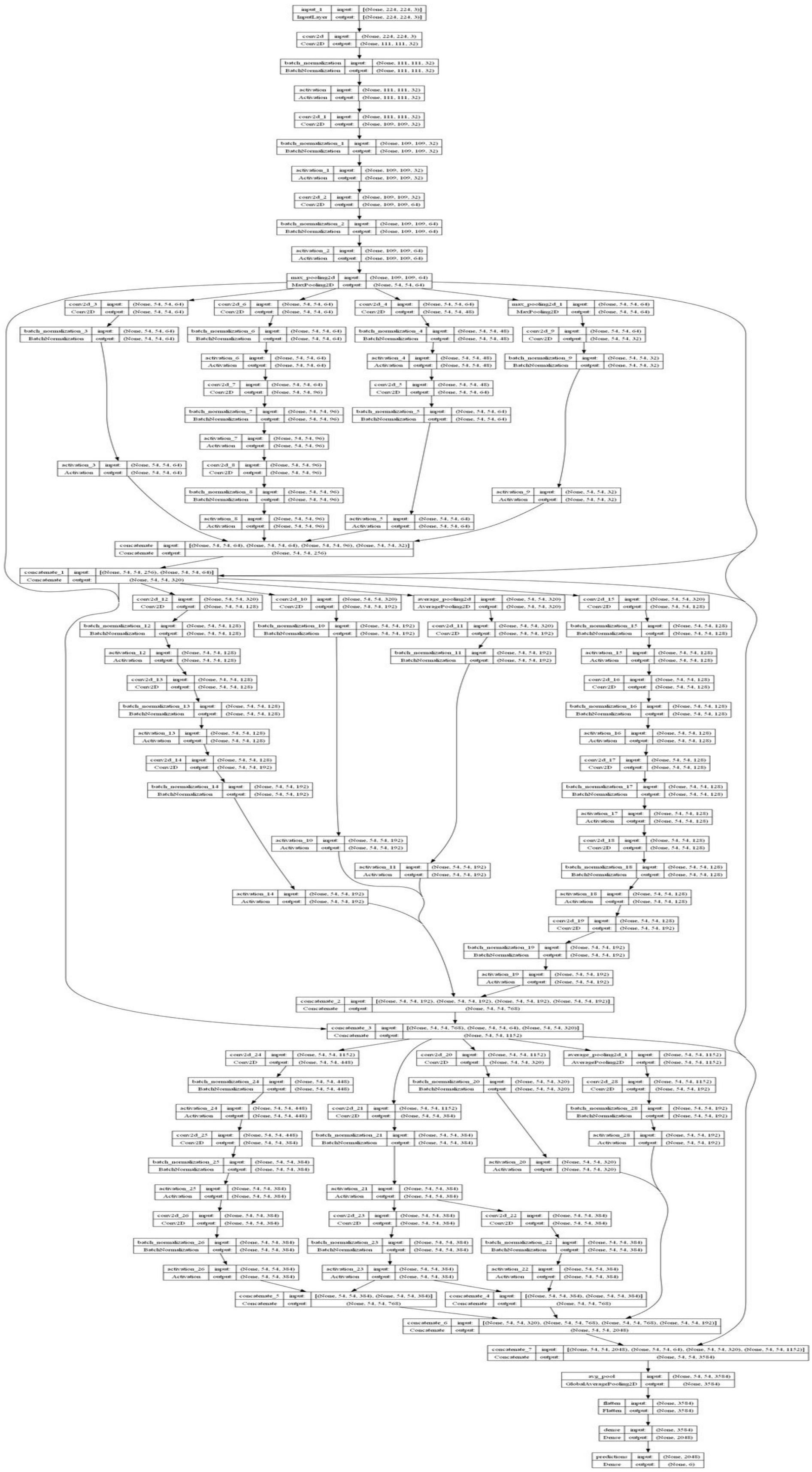


Fig 8: Architecture of the proposed DCNN model

4.2.1 Inception-v3

Inception-v3 is a convolutional neural network (CNN) architecture that has revolutionized the field of computer vision. Introduced in 2015 by Christian Szegedy et al. [55], Inception-v3 is the third iteration of the Inception family of models, which have consistently pushed the boundaries of image classification accuracy. The network is divided into three main components: the stem, the inception modules, and the classification head. The stem is the initial component of the network, responsible for processing the input image. It consists of a series of convolutional and pooling layers that reduce the spatial dimensions of the image while increasing the number of channels. The inception modules are the core building blocks of Inception-v3. These modules are designed to capture features at multiple scales simultaneously, using a combination of convolutional and pooling operations. Each module consists of four branches, each with a different filter size, allowing the network to capture both local and global features. The classification head is the final component of the network, responsible for producing the output probabilities. It consists of a global average pooling layer, followed by a fully connected layer and a softmax activation function. The details of the network is presented in Fig. 9.

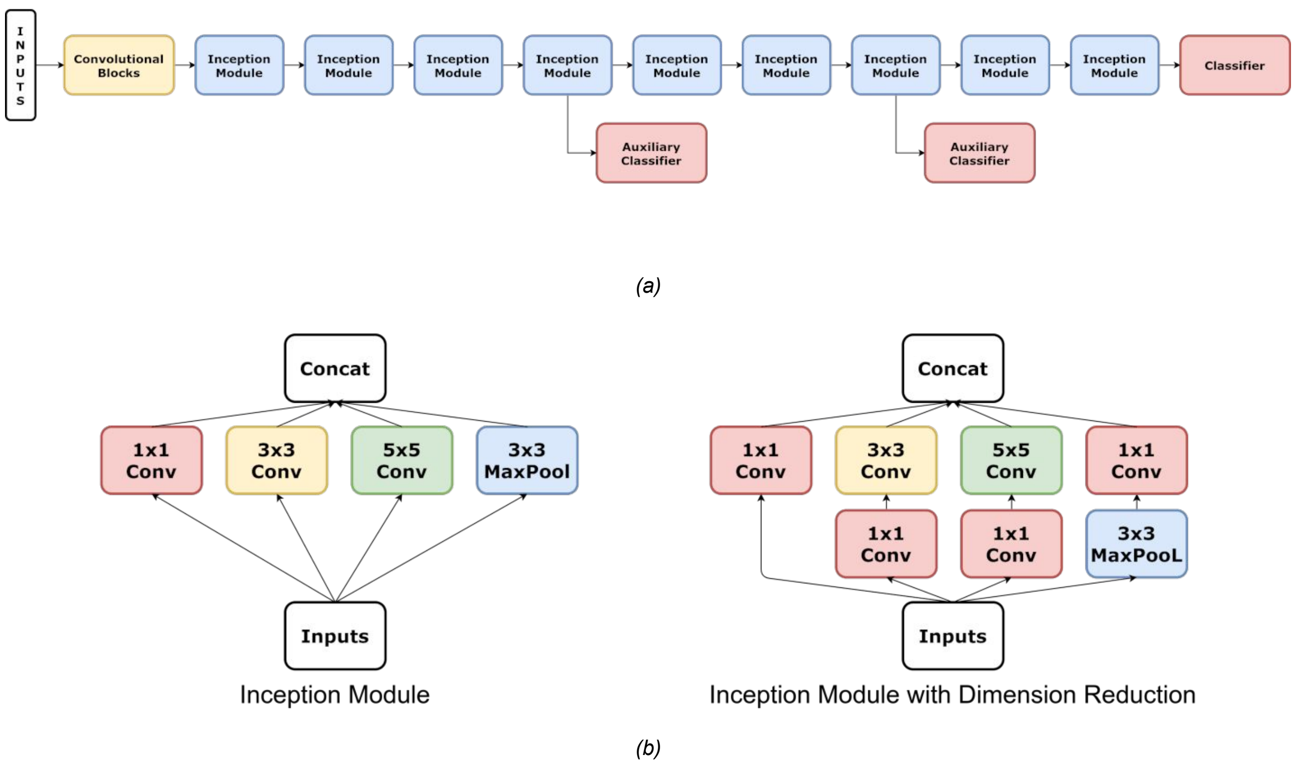


Fig. 9: Architecture of Inception-v3, (a) Inception-v3 mode (b) A Fundamental Component of the Inception-v3 Framework. On the Right-Hand Side is a Traditional Sub-Component, and on the Left-Hand Side is a Compactness-Enhanced Sub-Component [Image by dvgodoy/CC BY]

4.2.2 DenseNet-121

DenseNet-121 is a specific configuration of the DenseNet architecture [56], characterized by its 121 layers, growth rate of 32, and four dense blocks. This unique design enables feature reuse and reduces the vanishing gradient problem, resulting in improved accuracy and reduced parameters. The architecture comprises four dense blocks, interspersed with transition layers that perform downsampling and feature map reduction. This design not only enhances the network's capacity to learn complex features but also helps in managing computational resources effectively. A defining feature of DenseNet-121 is its use of dense connections within each dense block. Unlike traditional CNNs where each layer only receives input from the previous layer, DenseNet-121 connects each layer to every other layer in a feed-forward fashion, allowing for feature reuse and improved information flow. The growth rate of 32 enables the network to increase its capacity without exponentially increasing the number of parameters. The use of transition layers reduces the spatial dimensions and number of channels, preventing the network from becoming too computationally expensive.

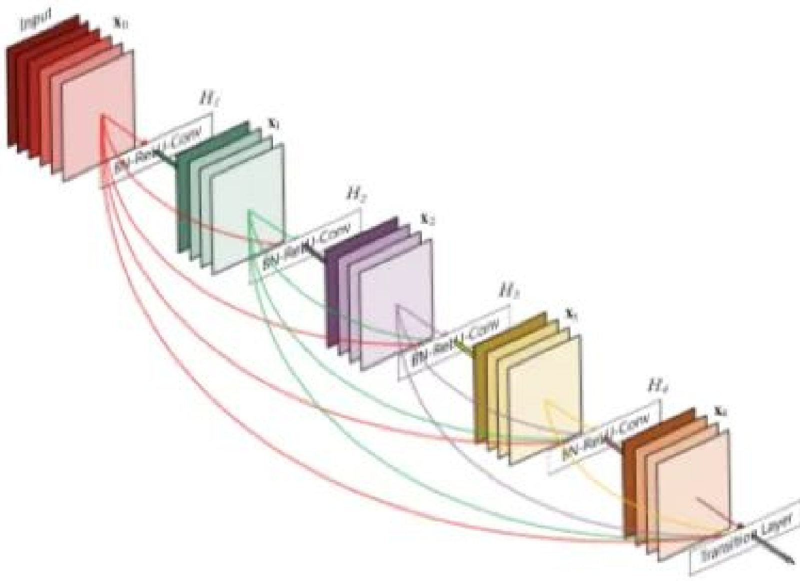


Fig. 10: Schematic diagram of DenseNet [56]

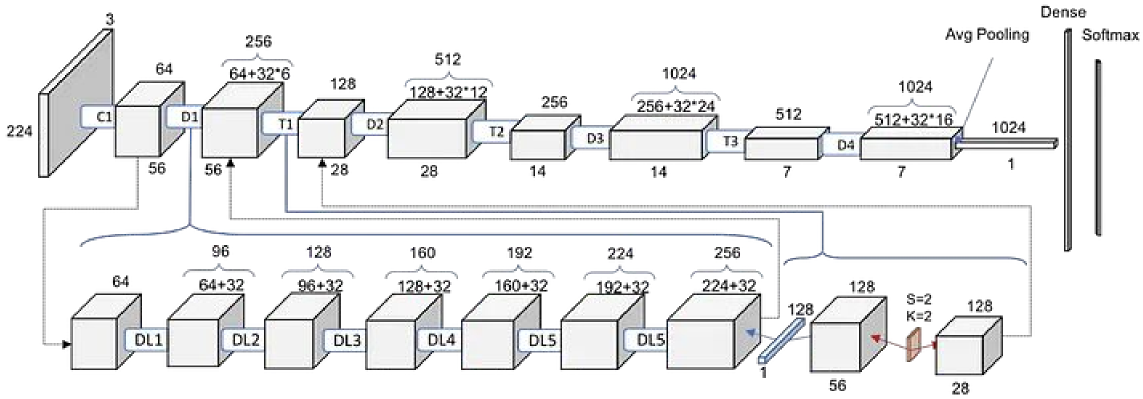


Fig. 11: Architecture of DenseNet-121 [Image by Pablo Ruiz]

4.2.3 Prediction of compressive strength

Based on the above a number of CNN models have been developed and investigated in order to find the optimum model. The developed ANN models were sorted in a decreasing order based on the validation accuracy and the model showed in Fig. 8 has been chosen as the best fitting model according to the validation results. Fig. 12 depicts the comparison between of the experimental values and the predicted values of the ANN for images taken at 20x zoom level. It is worth noting that all samples used for the testing process have a deviation less than ± 20%.

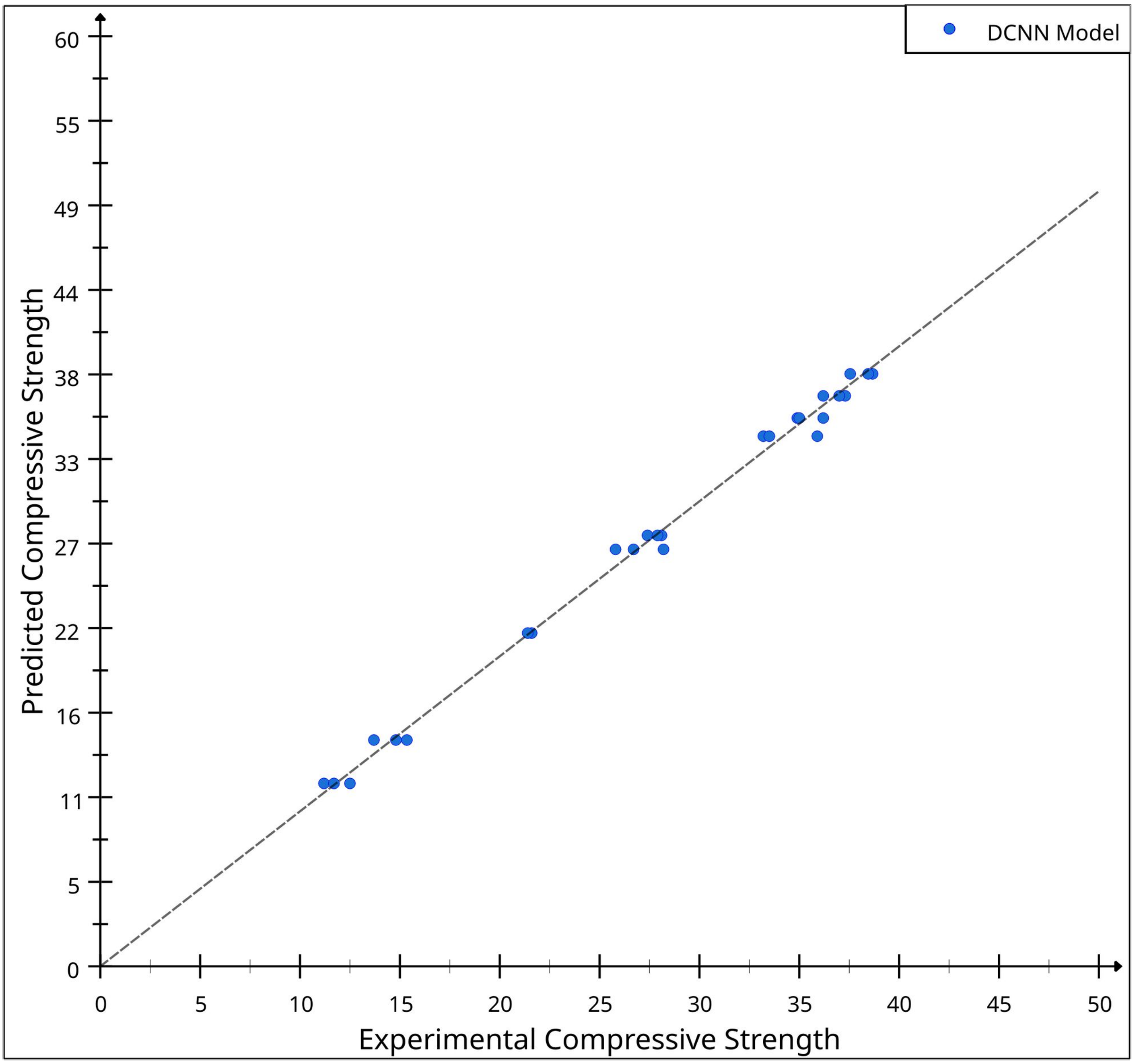


Fig. 12 Experimental compressive strength vs. Predicted compressive strength (for images taken at 20x zoom level)

4.3 Validation of results

Two distinct statistical metrics were utilized to assess the performance of the developed neural network model, as well as the existing formulas in the literature for estimating concrete compressive strength based on nondestructive testing. Root mean square error (RMSE) and Pearson Correlation Coefficient R^2 are used in this study. It is to be mentioned that higher R^2 signifies how well the independent variable are related to the dependent variable and R^2 close to 1 signifies, the better the prediction power. RMSE represents the absolute difference of actual and predicted compressive strength i.e. error in prediction of the compressive strength, and the lower RMSE values represent more accurate prediction results. The coefficient of and RMSE can be defined as

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{\sum_{i=1}^{n} (x_i - y_i)^2} \right) \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (x_i - y_i)^2} \tag{7}$$

where n denotes the total number of datasets, and x_i and y_i represent the predicted and target values, respectively. Additionally, the a20-index is introduced for evaluating the reliability of the developed artificial neural network (ANN) model [15].

$$a20 - index = \frac{m20}{N} \tag{8}$$

Where N stands for the amount of data samples, m20 represents the count of samples showing the ratio between Experimental-value and Predicted-value. Note that for an ideal predictive model, the a20-index values are anticipated to be 1.

4.4 Comparisons of test results

In Table 8 the predicted results for images taken at 20x zoom level of the proposed neural network's as well as the 6 bibliographical suggestion presented in Table 2 are presented. Additionally, the ratio of experimental vs prediction values of compressive strength of all the above mentioned models are presented in Fig. 13. It is clearly depicted in Fig. 12 and Fig. 13, that most of the data points predicted by the proposed ANN model are well predicted and they are situated near the centre line of the graph.

The R^2 and RMSE metrics of the relations between predicted and actual compressive strength of concrete for the ML model along with the proposed empirical suggestions are charted in Fig 14. It is observed that the proposed neural network performed the best in terms of the R^2 value among all the mathematical models. It also produced the least RMSE value. Previously Shiuly et al. [43] reported that InceptionResNet-v2 yielded the best results (R^2 values close to 0.85).

Table 8 Value of proposed index of different mathematical models

Sl. No.	Mathematical model	R^2	RMSE	a20-index
1	DCNN Model	0.99	0.67	1
2	EQ.1	0.57	8.51	0.63
3	EQ.2	0.52	7.41	0.37
4	EQ.3	0.58	6.53	0.33
5	EQ.4	0.62	7.16	0.52
6	EQ.5	0.63	7.05	0.63
7	EQ.6	0.55	8.59	0.33

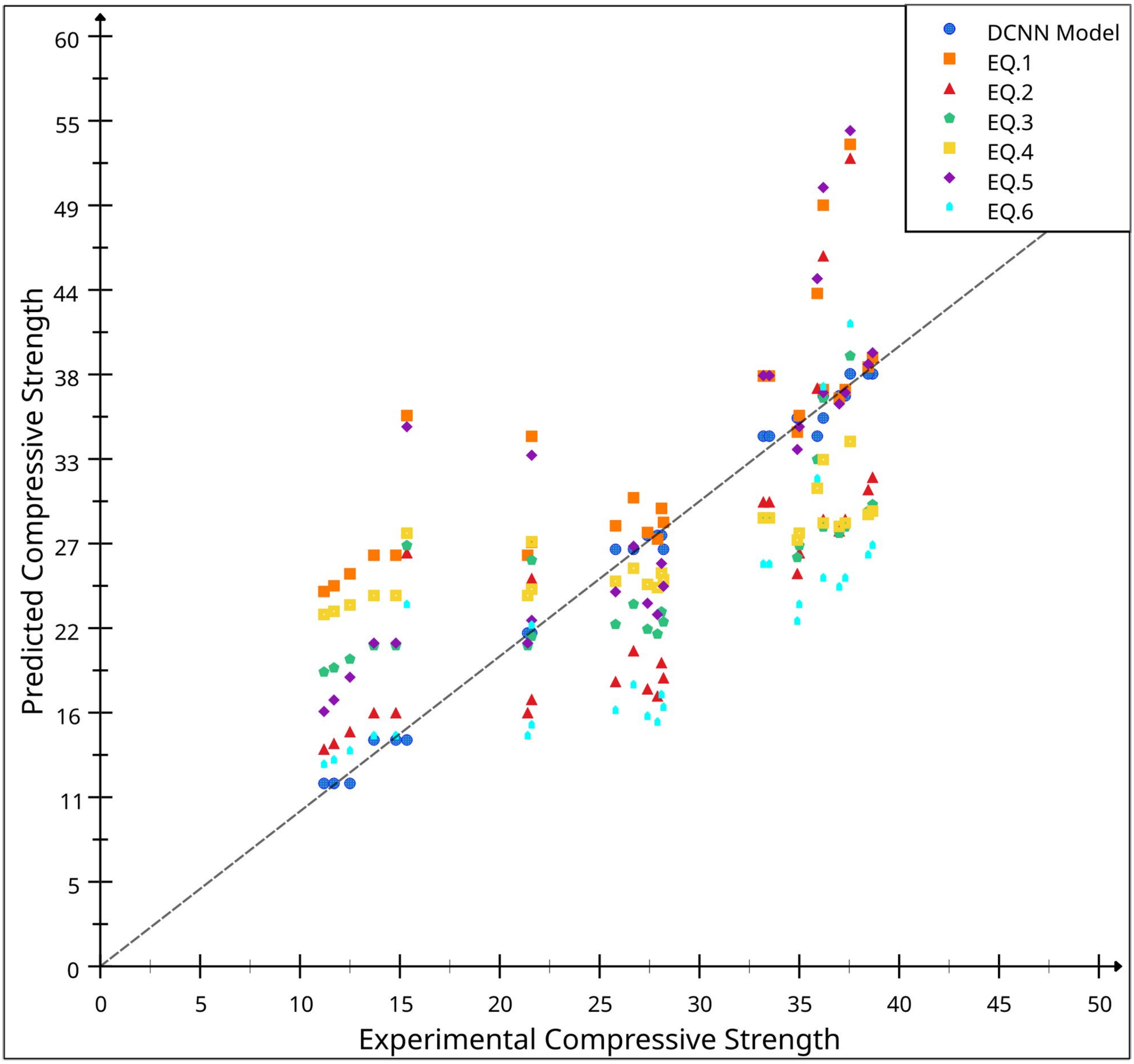


Fig. 13 Experimental compressive strength vs. Predicted compressive strength of all the mathematical models (for images taken at 20x zoom level)

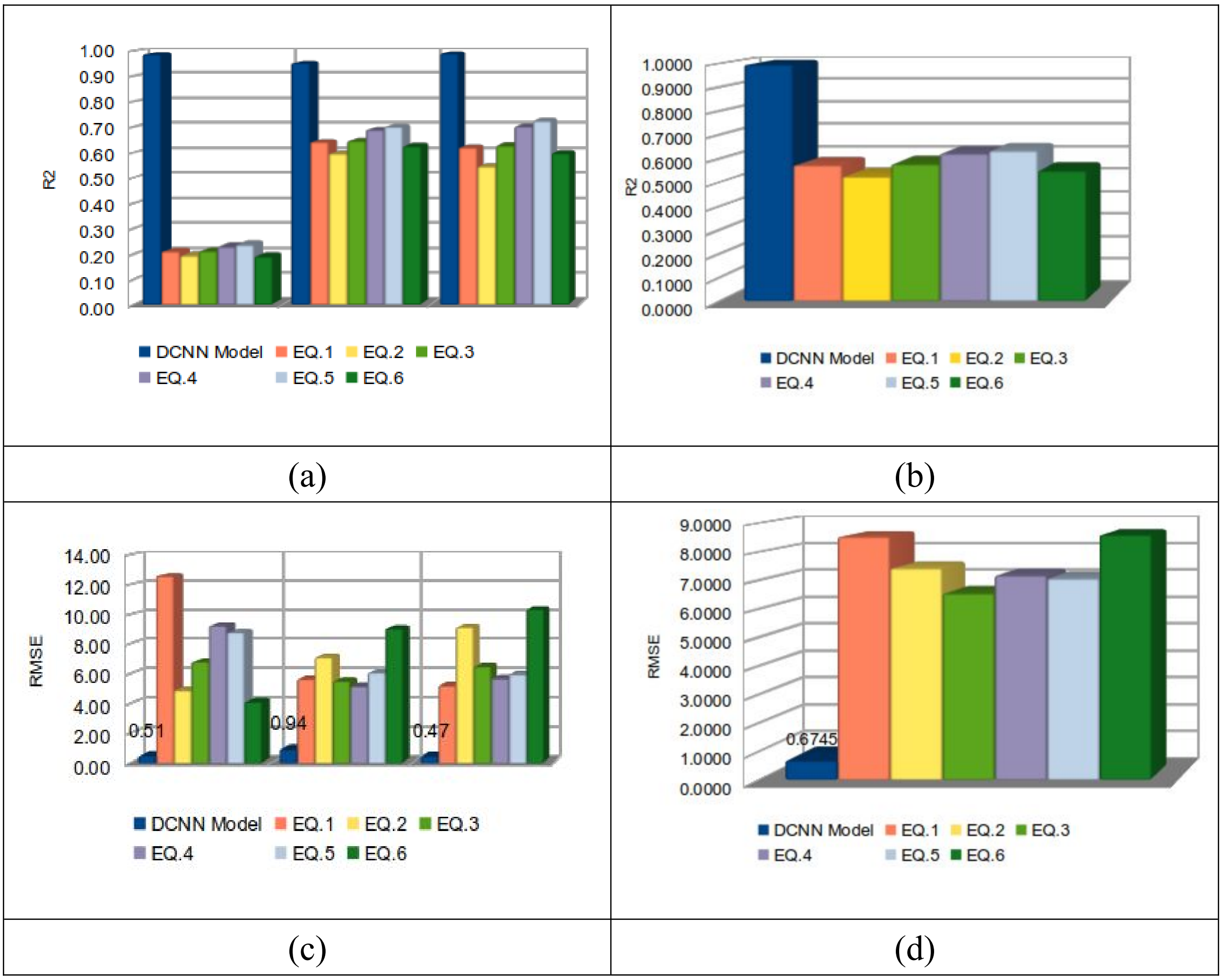


Fig. 14: The R^2 and RMSE metrics of compressive strength. (for images taken at 20x zoom level). (a) R^2 value of concrete at different curing time. (b) R^2 value of overall result.(c) RMSE value of concrete at different curing time. (b) RMSE value of overall result.

Conclusion

5.1 General

Due to it's heterogeneity, accurately predicting the compressive strength of concrete is extremely challenging. Numerous studies utilizing non-destructive methods for estimating concrete compressive strength have been conducted. However, the challenge of accurately estimating concrete compressive strength remains unresolved because the formulas available in the literature often exhibit significant variability in their estimates and substantial deviations from the actual (experimental) compressive strength values of the concrete.

The present study attempts to establish a relation between concrete compressive strength and ultrasonic pulse velocity by using machine learning technique. In the present study, an attempt has been made to predict the compressive strength concrete using the UPV values and concrete surface images with the help of machine learning technique. For carrying out the whole experiment, concrete sample of different grade were prepared and cured for 7 days, 28 days and 90 days respectively. Ultrasonic pulse velocity tests were performed followed by uniaxial compressive test at the end of each curing stage. Pictures were taken at different zoom level at during this time. A deep convolutional neural network model was developed and trained using the gathered data with UPV and images being the input and the compressive strength as the output value.

5.2 Findings

The comparison between the obtained results and the experimental data and existing analytical formulas in the literature highlights the promising potential of using machine learning for reliably and accurately approximating the compressive strength of concrete based on non-destructive measurements. The results clearly signify that among all the methods, the model developed using Inception-v3 and DenseNet yields best results for predicting compressive strength concrete with highest value of R^2 (about 0.98) and lowest values of RMSE. Additionally, the proposed neural network models can continuously retrain with new data, allowing them to adjust effectively to new information and expand their range of applicability.

Limitations

The proposed neural network model can only be implemented if both the experimental value of UPV test results as well as the images of the concrete surface are present. It is important to emphasize that the machine learning systems are best utilized for variable ranges spanning from the minimum to the maximum levels of each variable (as outlined in Table 3). The diversity of the image and experimental test dataset generated in this study is restricted. Thus, it will produce inaccurate compressive strength predictions for any new image with a UPV value outside the input range. It is also important to emphasize that no test has been conducted to check the durability properties of concrete.

Scope for further research

1. Durability properties should be measured like RCPT, sorptivity etc
2. Durability properties should be also checked by image processing.
3. More samples should be tested for accurate results.
4. Image processing should be conducted more preciously.
5. Image processing can be done for high strength concrete

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