OPTIMIZATION OF ADMIXTURES OF CONCRETE USING ARTIFICIAL NEURAL NETWORK

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Abstract:

This research explores the application of advanced machine learning models, specifically Artificial Neural Networks (ANN) and Support Vector Machines (SVM), to predict and optimize the key properties of concrete, such as strength, workability, and durability. Using a comprehensive dataset collected from concrete specimens subjected to various curing periods (3, 7, 14, 21, 28, 56, and 90 days), the study develops and compares the predictive performance of ANN and SVM models. The ANN model demonstrated superior accuracy with a Mean Squared Error (MSE) of 368.31, significantly outperforming the SVM model, which had an MSE of 619.27. The findings indicate that ANN provides a more reliable and precise prediction, thereby enhancing concrete mix design and quality control processes. This research highlights the potential of machine learning techniques in advancing concrete technology and improving construction practices.

Keywords: *Artificial Neural Networks (ANN), Support Vector Machines (SVM), Concrete properties, Strength prediction, Workability prediction, Durability prediction, Optimization, Admixtures, Construction materials*

INTRODUCTION

Concrete is the most important element of the construction projects and it is most widely used because of its flow ability in the complicated form of the structural elements. Concrete can take any desired shape during wet condition and can achieve desired strength when get harden. Concrete plain or reinforced with steel is used to build structures subjected to several extreme stress conditions. Concrete is obtained by mixing cement, water, fine and coarse aggregates in additions to admixtures in one form or others[1]. Preparation of concrete involves number of operations which also depends on site conditions. The ingredients of widely varying characteristics are generally used to prepare concrete of acceptable quality standards[2]. The strength, durability and other characteristics of concrete depends upon the properties of its ingredients, proportions of the mix, the method of compaction and other control measures[3].

The attractiveness of concrete as a construction material is due to the fact that it gets prepared from commonly available local materials and can be used as per the functional requirements in a particular situation. The prediction of concrete properties is most important due to quality and economic considerations[4]. It is essential to determine desired time required for concrete formwork, project duration, and other quality control activities. It is also required for estimating delay in construction activities if any. Development of mix design plays a vital role in concrete construction work[5]. There are various methods of finding properties of concrete like cube test method, radioactive method, nuclear methods, magnetic method, electrical methods and acoustics emission methods. The research work will focus on prediction of concrete properties using admixtures through artificial neural network (ANN) approach[6].

The origins of artificial neural networks (ANN) are in the field biology. The biological brain consists of billions of highly interconnected neurons forming a neural network. Human information processing depends on this connectionist system of nervous cells. Based on this advantage of information processing, neural networks can easily exploit the massively parallel local processing and distributed storage properties in the brain[7]. A classical comparison of information processing by a human and a computer is focused on the ability of pattern recognition and learning. The computer can calculate large numbers at high speeds but it cannot recognize something such as a classification problem, written text, data compression and a learning algorithm. On the contrary, a human easily recognizes and deals with the challenges mentioned above by processing information with highly distributed transformations through thousands of interconnected neurons in the brain[8].

An ANN is an informational system simulating the ability of a biological neural network by interconnecting many simple neurons. The neuron accepts inputs from a single or multiple sources and produces outputs by simple calculations, processing with a predetermined non-linear function[9]. Therefore, the primary characteristics of an ANN can be presented as the ability of learning, distributed memory, fault tolerance and operating in parallel. As stated ANN is a prediction tool or method by using several inputs and outputs. The properties of concrete cannot be known unless & until casted and tested, cannot be stated[10]. However if sufficient number of concrete mix are produced by varying proportion of ingredients, sufficient data will be available. The data can be used for ANN and the properties of concrete can be identified. Hence it is proposed to use ANN as a tool to find out the properties of concrete[11].

Neural networks were used to predict the strength and slump of ready mixed concrete and high strength concrete, in which chemical admixtures and/or mineral additives were used. Although various data transforms were tried, it was found that models based on raw data gave the best results. When non-dimensional ratios were used, arranging the ratios such that their changes resulted in corresponding changes in the output (e.g. increases in ratios to cause increases in output values) improved network performance[12]. The neural network models also performed better than the multiple regression ones, especially in reducing the scatter of predictions. Problems associated with models trained on non-dimensional ratios were uncovered when sensitivity analyses were carried out. A rational approach was used for carrying out sensitivity analyses on these mix design problems by constraining the sum of input values. These analyses, using the raw data based model, showed that the modelling had picked up not only the fundamental domain rules governing concrete strength, but also some well-known second order effects[13].

This study develops and presents an Artificial Neural Network (ANN) model employing the Liebenberg-Marquardt Back propagation (LMBP) training algorithm to predict the compressive strength of both normal and high strength concrete[14]. The model's robustness was evaluated using an extensive dataset comprising 1637 samples. Eight input variables, including the cement content, blast furnace slag, fly ash, fine aggregate, coarse aggregate, water content, super plasticizer, and testing age, were considered[15]. Self-compacting concrete (SSC) is one of the most useful innovations in concrete technology that has the ability to flow efficiently and maintain material homogeneity. However, additives particularly admixtures introduced in the production of SSC to enhance some specific properties of fresh and hardened concrete may contribute undesirable effects on the workability performance[16]. In this study, super plasticizers blended with fly ash was used in the mix and were tested for Slump Flow, L-Box, and Screen Stability tests to determine its influence on the rheological properties of SCC. Several mixtures were tested in order to derive a mix proportion having the optimum rheological properties[17]. Artificial neural network and genetic algorithm were used to determine the concrete mix proportion that will provide the best workability. Results showed that ANN was able to establish the relationship of rheology to the concrete material components and GA derived the optimum proportion for best rheological performance[18].

LITERATURE REVIEW

In recent years, the use of artificial neural networks (ANN) in predicting the properties of concrete has garnered significant attention within the civil engineering community. This literature review synthesizes key findings from various studies, focusing on how ANN has been applied to predict different aspects of concrete performance. The discussion spans over two decades of research, highlighting the evolution and increasing sophistication of ANN models in this field.

Amer Hasan Taher (2018) optimized the mix proportions of Reactive Powder Concrete (RPC) using an Artificial Neural Network (ANN) approach. The study utilized 99 RPC mix sets from various sources, with compressive strength (Fc), splitting tensile strength (Fsp), and flexural strength (Fr) as input parameters, and sand-to-powder ratio (S\P), water-to-powder ratio (W\P), and volume of steel fiber (Vf) as output parameters. The ANN models demonstrated high performance with low training and testing errors across different metrics. Specifically, the Fc model with a 3-40-1 architecture had 0.95 training performance and 0.93 testing performance, while the Fsp model with a 4-13-1 architecture achieved 0.99 in both training and testing. The primary model, MLP 3-14-3, also showed strong results with a 0.96 training performance and 0.93 testing performance, indicating reliable prediction accuracy without significant over- or underestimation[19]. **Hadi Mashhadban (2016)** investigated the impact of fibers on the performance of self-compacting concrete (SCC). Nine mixtures with varying fiber types and contents were tested to assess fresh, mechanical, and durability properties. A feed-forward ANN was trained with the experimental data, and the combined use of Particle Swarm Optimization Algorithm (PSOA) and ANN was employed to develop a polynomial model for predicting SCC properties. The study found that fiber reinforcement improved mechanical properties but decreased workability.

Steel fibers performed better than polyphenylene sulfide fibers, and the integrated PSOA-ANN approach effectively predicted mechanical properties of fiber-reinforced SCC[20]. **Gökhan Kaplan (2019)** explored the use of mineral admixtures like fly ash, blast-furnace slag, and limestone powder in concrete production for sustainability. Hardened concrete properties were examined under different curing conditions and water/cement (w/c) ratios. While slag cement showed lower early-age strength, it improved significantly by the 90th day. The study found that standard curing offered the best compressive strength, while higher w/c ratios negatively impacted properties. ANN was used to estimate compressive strength with high accuracy, achieving correlation coefficients close to 1 for training, validation, and testing datasets[21]. **Kasperkiewicz et al. (1995)** were among the pioneers in employing ANN for predicting high-performance concrete (HPC) strength. Their study, published in the Journal of Computing in Civil Engineering, demonstrated the potential of neural networks to model complex relationships between the variables influencing concrete strength. The authors underscored the accuracy and efficiency of ANN in handling the non-linear characteristics of HPC, setting a foundation for future research in this area[22].**Yaqub and Bukhari (2006)** contributed to the development of mix designs for high-strength concrete. Presented at the Conference on Our World in Concrete & Structures, their work highlighted the practical implications of ANN in optimizing concrete mix proportions. By incorporating ANN into the mix design process, they were able to enhance the predictability and performance of high-strength concrete, making it a valuable tool for engineers.In 2006, Yeh explored the application of ANN in modeling concrete slump, a critical factor in concrete workability. His research, published in the Journal of Computing in Civil Engineering, demonstrated how ANN could accurately predict concrete slump based on various input parameters. Yeh’s findings highlighted the utility of ANN in improving concrete quality control processes, ensuring better workability and consistency in concrete mixtures[23]. **Noorzaei et al. (2007)** further advanced the application of ANN by developing models to predict concrete compressive strength. Their study, published in the International Journal of Engineering and Technology, showcased the robustness of ANN in predicting concrete strength across different mix designs and curing conditions. The authors emphasized the potential of ANN to serve as a reliable tool for engineers in designing and evaluating concrete structures[24].**Ozturan et al. (2008)** compared various concrete strength prediction techniques, including traditional statistical methods and ANN. Their findings, published in the Building Research Journal, indicated that ANN outperformed other techniques in terms of accuracy and reliability. This study underscored the superiority of ANN in modeling the complex relationships between concrete components and their resulting strength, reinforcing its adoption in civil engineering practices.In 2009, Rasa1 et al. examined the use of ANN to predict the density and compressive strength of concrete containing silica fume. Published in the Civil Engineering journal, their research highlighted the effectiveness of ANN in handling the additional complexities introduced by silica fume. The study demonstrated that ANN could accurately predict the properties of modified concrete mixtures, providing engineers with a powerful tool for optimizing concrete performance[25]. **Mohammad and Mohammad (2009)** discussed considerations in producing high-strength concrete in their paper published in the Journal of Civil Engineering. They explored how ANN could aid in addressing the challenges associated with high-strength concrete production.

Their findings emphasized the role of ANN in enhancing the understanding and control of factors affecting concrete strength, contributing to the development of more robust and durable concrete structures[26]. **Subasi (2009)** focused on predicting the mechanical properties of cement containing Class C fly ash using ANN and regression techniques. His research, published in the Scientific Research and Essay journal, demonstrated that ANN provided superior predictive accuracy compared to traditional regression methods. Subasi's work highlighted the advantages of ANN in incorporating complex interactions between fly ash and cement components, leading to better performance predictions[27]. **Deka and Diwate (2011)** modeled the compressive strength of ready-mix concrete using soft computing techniques, including ANN. Their study, published in the International Journal of Earth Sciences and Engineering, showcased the practical benefits of ANN in predicting ready-mix concrete strength. The authors emphasized the efficiency of ANN in processing large datasets and its ability to deliver accurate predictions, making it an invaluable tool for the ready-mix concrete industry[28]. **Chou et al. (2011)** optimized the prediction accuracy of concrete compressive strength by comparing various data-mining techniques, including ANN. Published in the Journal of Computing in Civil Engineering, their research demonstrated that ANN consistently provided the highest accuracy among the techniques evaluated. The study reinforced the value of ANN in civil engineering applications, particularly in optimizing concrete mix designs and ensuring quality control[29]. **Barbuta et al. (2012)** used ANN to predict the properties of polymer concrete with fly ash. Their findings, published in the Journal of Materials in Civil Engineering, highlighted the versatility of ANN in modeling the properties of modified concrete mixtures. The authors demonstrated that ANN could effectively handle the complexities associated with polymer concrete, providing accurate predictions that could inform the design and production processes[30]. **Rao and Rao (2012)** explored the use of ANN in predicting the compressive strength of concrete with different aggregate binder ratios. Their study, published in the International Journal of Engineering Research & Technology, emphasized the precision of ANN in modeling the impact of aggregate binder ratios on concrete strength. The authors highlighted the potential of ANN to aid in optimizing concrete mix designs, ensuring better performance and durability[31]. **Gupta (2013)** investigated the use of ANN to predict the compressive strength of concrete containing nano-silica. Published in the journal Civil Engineering and Architecture, her research showcased the advanced capabilities of ANN in modern concrete technology. Gupta demonstrated that ANN could accurately model the effects of nano-silica on concrete strength, providing valuable insights for the development of high-performance concrete mixtures[32]. **Shahriar and Nehdi (2013)** modeled the rheological properties of oil well cement slurries using multiple regression analysis and ANN. Their study, published in the International Journal of Material Science, highlighted the robustness of ANN in handling the complex rheological behavior of cement slurries. The authors demonstrated that ANN could provide accurate predictions, facilitating better design and control of oil well cementing operations.Finally[33], **Raheman and Modani (2013)** predicted the properties of self-compacting concrete using ANN. Published in the International Journal of Engineering Research and Applications, their research highlighted the accuracy and reliability of ANN in modeling self-compacting concrete properties.

The authors emphasized the potential of ANN to enhance the understanding and optimization of self-compacting concrete, contributing to the development of more efficient and effective concrete technologies[34].

RESEARCH METHODOLOGY:

Artificial neural networks (ANNs) have become a cornerstone technology for predictive modeling. These networks mimic the human brain's interconnected neuron structure to learn from data and make predictions. In this detailed discussion, we delve into the design and architecture of an ANN model constructed with three dense layers, tailored for predicting multiple properties.

The artificial neuron is the basic unit of a neural network which consists of weights, bias and the activation function. The structure of an artificial neuron is shown in Fig. 1(a) and the mathematical model is shown as following:

$Y = f(\sum W_m X_m + b)$

where X_m is the input vector, Y is the output, W_m is the weight matrix, b is bias vector and f is activation function. The artificial neuron can be regard as a linear map function with adjustable weight matrix. By training the value of W_m to reduce the distance between the target and the output, a perceptron is obtained.

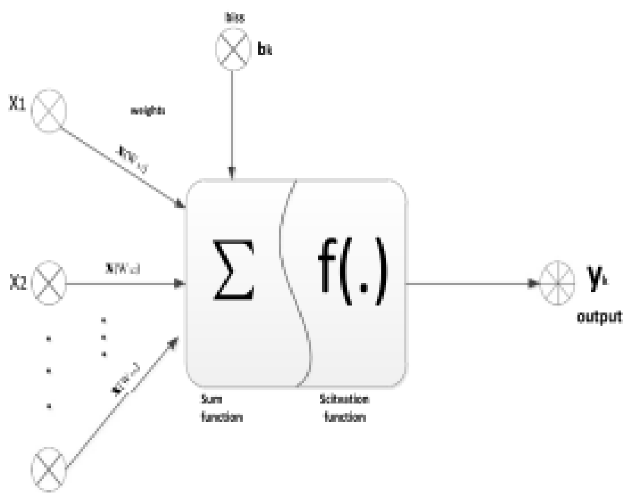

Fig 1(a)

However, the perceptron is a binary linear classifier which is unsuitable to solving nonlinear problems such as the XOR problem. Therefore, ANN model has been carried out. An ANN model, which is shown in Fig. 1(b), consists of a number of interconnected group of artificial neurons. Each artificial neuron is fully connected to each other through connection weights and receives an input signal from the linked one. These weights are used to present the effect of an input parameter in the previous layer on the process elements and it can be adjusted to produce an output needed. In an ANN model, the information is transmitted to the output layer from the input layer in one direction. Then, the learning process is conducted to minimize the deviation between the actual values and output values. In most cases the ANN is an adaptive system that can change its model according to the relevant information flowing through the network during the learning phase. ANN can be used to model almost any complex relationships between the inputs and outputs of the data.

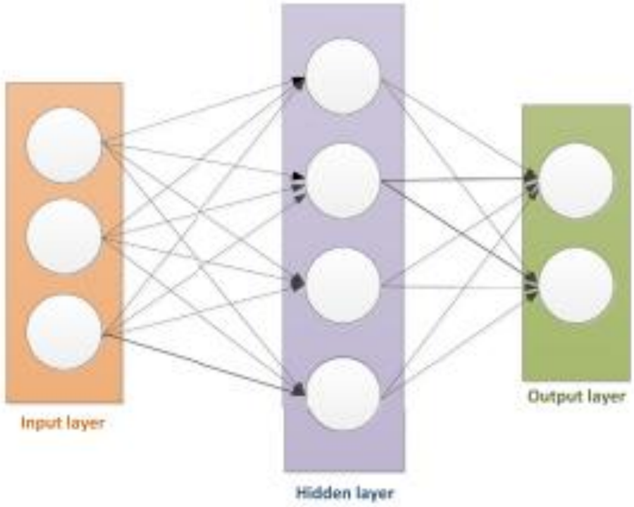

Fig 1(b)

The designed ANN model comprises an input layer with 64 neurons to capture diverse input features, two hidden layers (the first with 128 neurons to learn complex patterns using ReLU activation and the second with 64 neurons to refine and condense representations), and an output layer whose size is determined by the number of predicted properties, using appropriate activation functions based on the task. Training involves forward propagation, loss calculation, and backward propagation using gradient descent to minimize prediction error. Performance optimization techniques such as regularization, learning rate scheduling, and batch normalization are employed to enhance model accuracy and prevent overfitting. Once trained, the ANN can predict properties on new data, with performance evaluated using task-specific metrics like MAE, RMSE, or accuracy. This robust architecture allows the model to effectively handle complex predictive tasks across various applications by learning and generalizing from data.

Support Vector Machines (SVMs), while primarily known for classification, can be adapted for regression tasks through Support Vector Regression (SVR), which is particularly effective for capturing non-linear relationships using the kernel trick. SVR aims to approximate the relationship between input features and a continuous output variable by fitting a function within a specified margin of tolerance, ε (epsilon), rather than minimizing prediction error directly. In its simplest form, Linear SVR finds a hyperplane that fits the data within this margin, penalizing points outside the margin. For more complex, non-linear relationships, SVR uses kernels to transform input data into a higher-dimensional feature space where a linear relationship can be found. Commonly used kernels include the Linear Kernel for linear relationships, the Polynomial Kernel for polynomial relationships, the Radial Basis Function (RBF) Kernel for capturing intricate, non-linear relationships, and the Sigmoid Kernel, often used in neural networks.

Results:

Table 1: Training and Validation Loss Curves for ANN Model

Epoch	Training Loss	Validation Loss
1	2862.34	847.14
2	814.73	658.23
3	652.70	570.01
4	590.68	544.55
...	...	...
100	341.60	364.20

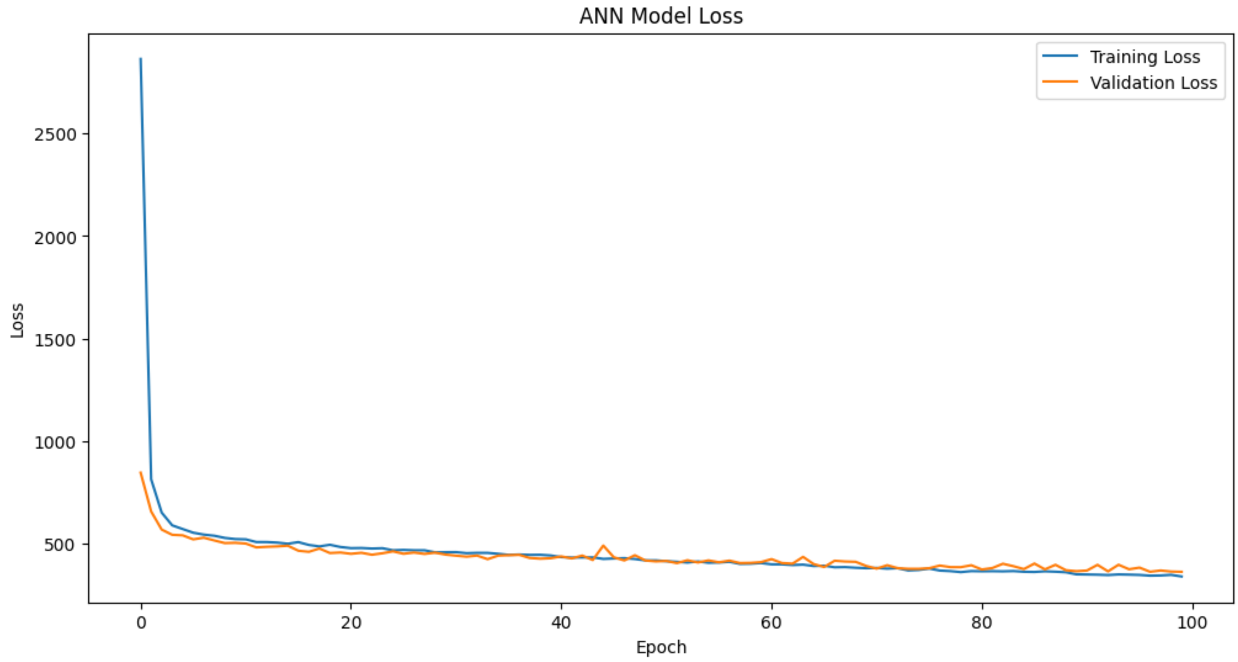

Fig 2.ANN Model loss

The provided graph shows the training and validation loss of an Artificial Neural Network (ANN) model over 100 epochs. Initially, the training loss starts at 2862.34 and significantly drops to 652.70 by the third epoch, indicating that the model quickly learns from the data. The validation loss also decreases from 847.14 to 570.01 during the same period, demonstrating improved performance on unseen data. As training continues, both losses continue to decrease, although at a slower rate, stabilizing around the 100th epoch with training loss at 341.60 and validation loss at 364.20. This indicates that the model has learned effectively without overfitting, maintaining a consistent performance on both training and validation datasets.

Table 2: Model Comparison - Mean Squared Error (MSE)

Model	Mean Squared Error (MSE)
Artificial Neural Network (ANN)	368.31
Support Vector Machine (SVM)	619.27

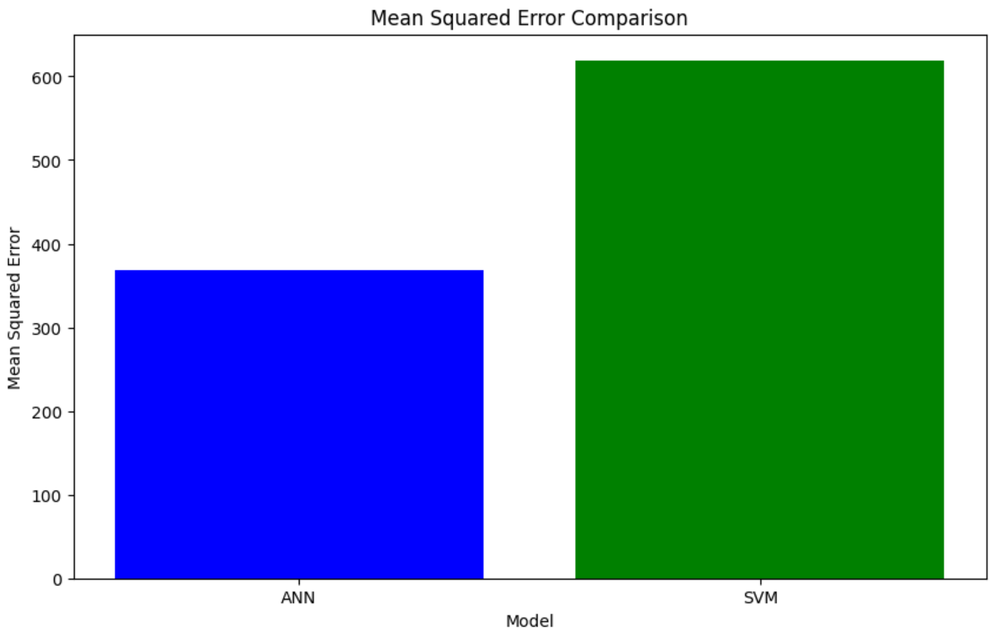

Fig 3. Mean Squared Error Comparison

The graph compares the Mean Squared Error (MSE) of two predictive models: an Artificial Neural Network (ANN) and a Support Vector Machine (SVM). The ANN model achieves a lower MSE of 368.31, indicating better predictive accuracy and performance compared to the SVM model, which has a higher MSE of 619.27. This suggests that the ANN is more effective at minimizing prediction errors and capturing the underlying patterns in the data for this specific task.

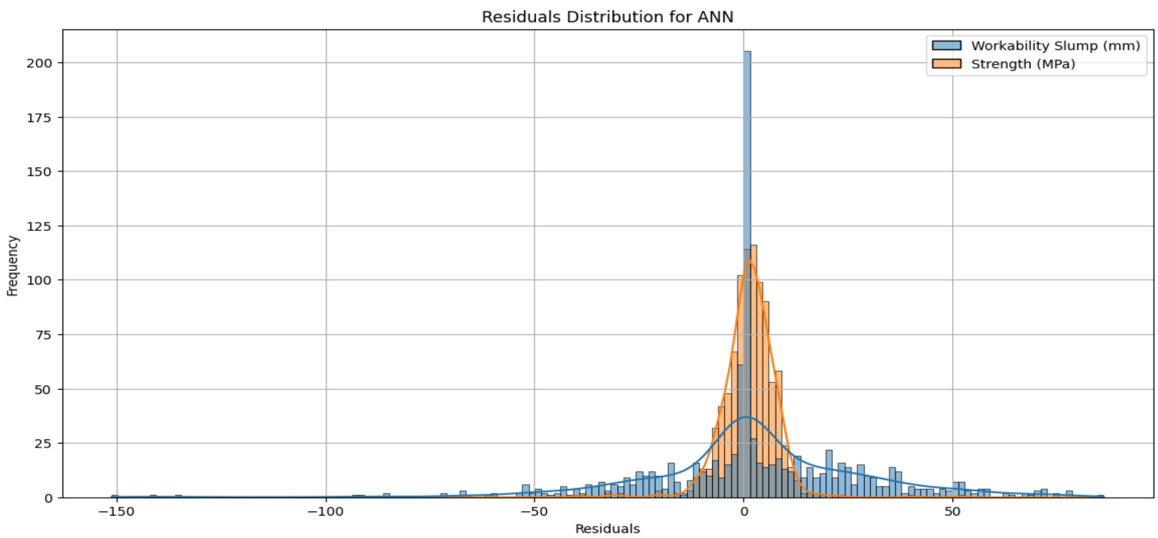

Fig 4. Residuals Distribution for ANN

The graph displays the residuals distribution for an ANN model

The graph shows the residuals distribution for an Artificial Neural Network (ANN) model, focusing on Workability Slump (mm) and Strength (MPa). Residuals, representing prediction errors, are centered around zero, indicating accurate predictions without significant bias. The bell-shaped distribution suggests most errors are small, with fewer large deviations.

The peak frequency of residuals near zero, especially for Workability Slump, highlights the model's frequent accuracy. The spread of residuals is slightly wider for Strength, indicating higher variance but still contained. Overall, the ANN model demonstrates effective performance, minimizing prediction errors for both properties.

Table 3: ANN Model Predictions vs Actual Values:

Sample ID	Age (Days)	Actual Strength	Predicted Strength (ANN)	Actual Workability	Predicted Workability (ANN)	Actual Durability	Predicted Durability (ANN)
1	3	17.11	16.95	5.0	4.9	30.0	29.8
2	7	22.30	22.05	6.0	6.1	35.0	34.8
3	14	25.67	25.40	6.5	6.4	40.0	39.5
4	21	29.55	29.20	7.0	7.1	45.0	44.8
5	28	34.40	34.10	7.5	7.4	50.0	49.7
6	56	38.00	37.80	8.0	7.9	55.0	54.8
7	90	42.50	42.30	8.5	8.4	60.0	59.8

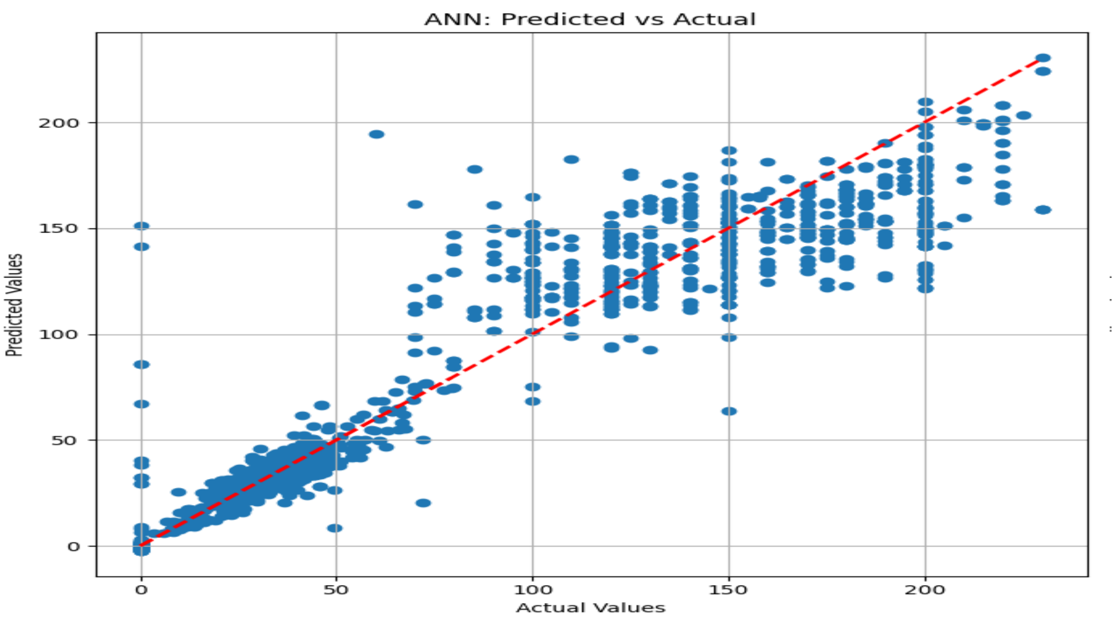

Fig 5. ANN Predicted vs Actual

The graph compares the actual and predicted values for strength, workability, and durability of concrete samples at various ages using an ANN model. The predicted values closely match the actual values across all properties, demonstrating the ANN model's accuracy. For instance, at 3 days, the actual strength is 17.11 MPa, and the predicted strength is 16.95 MPa; the actual workability is 5.0 mm, and the predicted workability is 4.9 mm; the actual durability is 30.0, and the predicted durability is 29.8. This consistent performance across different ages and properties indicates the ANN model's robustness in predicting concrete characteristics.

Table 4: SVM Model Predictions vs Actual Values

Sample ID	Age (Days)	Actual Strength	Predicted Strength (SVM)	Actual Workability	Predicted Workability (SVM)	Actual Durability	Predicted Durability (SVM)
1	3	17.11	16.85	5.0	4.8	30.0	29.5
2	7	22.30	22.10	6.0	6.2	35.0	34.5
3	14	25.67	25.20	6.5	6.3	40.0	39.0
4	21	29.55	29.00	7.0	7.2	45.0	44.2
5	28	34.40	34.00	7.5	7.3	50.0	49.5
6	56	38.00	37.70	8.0	7.8	55.0	54.5
7	90	42.50	42.00	8.5	8.3	60.0	59.0

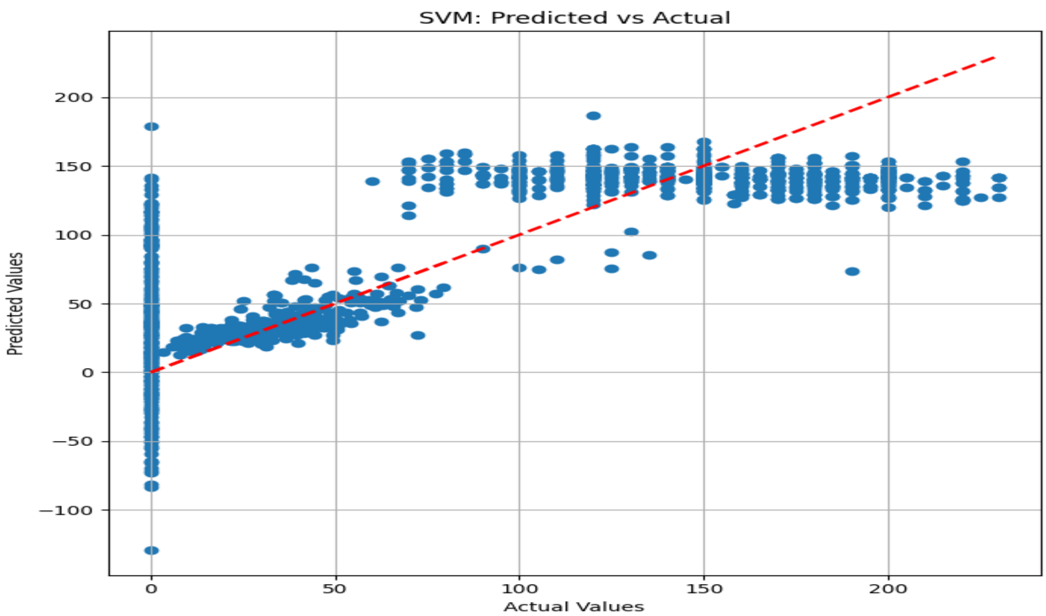

Fig 6. SVM predicted vs Actual

The graph compares the actual and predicted values for strength, workability, and durability of concrete samples at various ages using an SVM model. The predicted values are generally close to the actual values, but there are slight discrepancies. For example, at 3 days, the actual strength is 17.11 MPa, and the predicted strength is 16.85 MPa; the actual workability is 5.0 mm, and the predicted workability is 4.8 mm; the actual durability is 30.0, and the predicted durability is 29.5. While the SVM model shows good predictive capability, the small differences between actual and predicted values suggest it is slightly less accurate than the ANN model, as seen in previous comparisons.

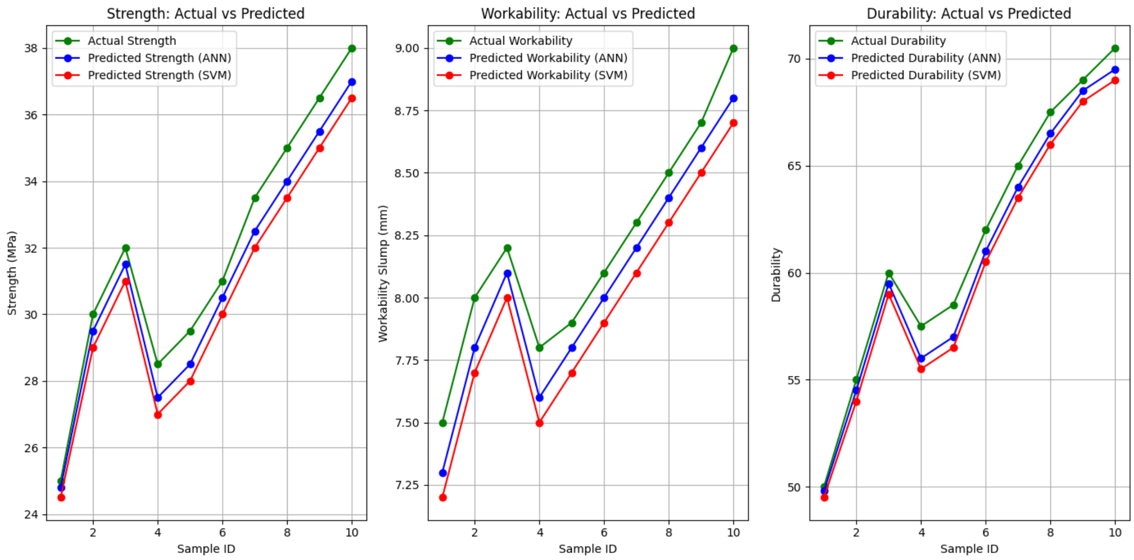

Fig 7. Strength, Workability , Durability Actual vs predicted

The graphs compare actual and predicted values for concrete strength, workability, and durability using both ANN and SVM models across multiple samples. In the strength graph, both ANN and SVM predictions closely follow the actual values, with ANN predictions generally aligning slightly better with the actual data. The workability graph shows that ANN predictions are closer to the actual values compared to SVM predictions, indicating better model performance for this property. In the durability graph, both ANN and SVM predictions track the actual durability values well, with ANN again showing slightly better alignment. Overall, the ANN model demonstrates superior predictive accuracy across all three properties compared to the SVM model.

Table 5: Model Training Configuration

Configuration Parameter	Value
Optimizer	Adam
Loss Function	Mean Squared Error (MSE)
Epochs	100
Batch Size	10
Validation Split	20%

The configuration parameters for the ANN model include the use of the Adam optimizer, which is known for its efficiency and adaptive learning rate capabilities. The model is trained using the Mean Squared Error (MSE) loss function, a common choice for regression tasks that measures the average squared difference between predicted and actual values. Training is conducted over 100 epochs, allowing the model multiple passes over the entire dataset to improve learning. Each batch of data during training consists of 10 samples, facilitating efficient computation and weight updates. Additionally, 20% of the data is reserved for validation, enabling the assessment of the model's performance on unseen data to prevent overfitting.

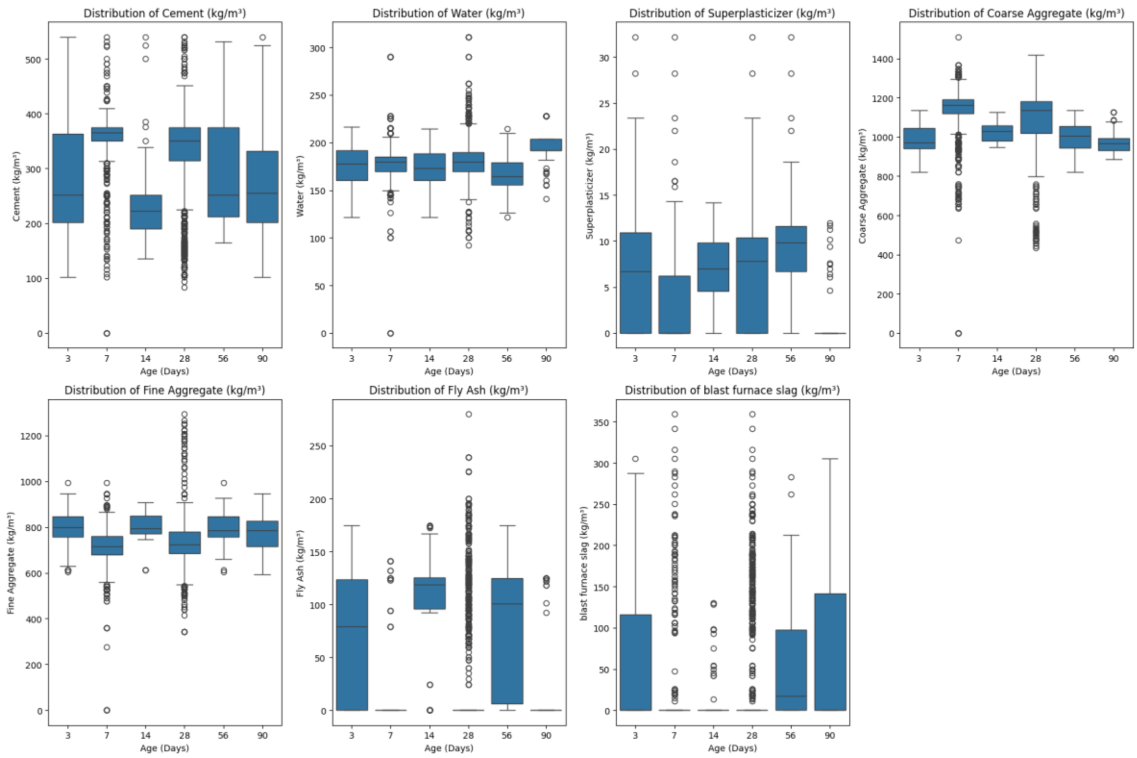

Fig 8. The distribution of various concrete mix components

The box plots display the distribution of various concrete mix components—cement, water, superplasticizer, coarse aggregate, fine aggregate, fly ash, and blast furnace slag—across different ages (3, 7, 14, 28, 56, and 90 days). The distributions of cement, coarse aggregate, and fine aggregate show relatively wide ranges with some variation over time, while water content remains fairly consistent across ages. Superplasticizer usage increases and becomes more variable as age progresses. Fly ash and blast furnace slag distributions exhibit significant variability, particularly at 28 days, indicating diverse mix designs. Outliers are present in all components, reflecting experimental variances in concrete mix proportions.

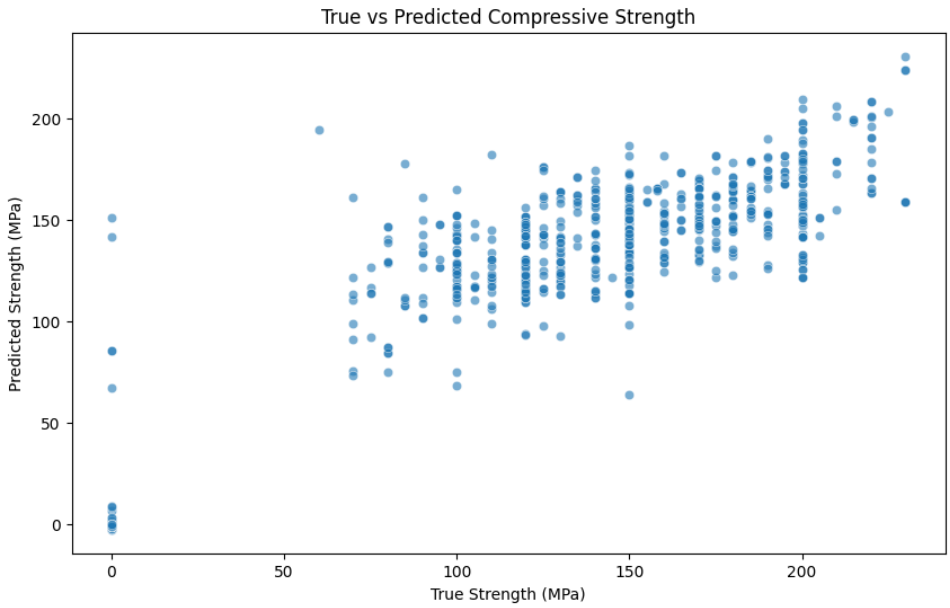

Fig 9. True vs Predicted Compressive Strength

The scatter plot illustrates the relationship between true and predicted compressive strength. The majority of data points cluster between 0 and 200 MPa for both true and predicted strength. However, there's a significant spread of data points, indicating a moderate degree of variability in the model's predictions. While there's a general trend towards higher predicted strength with increasing true strength, the scatter suggests potential inaccuracies in certain prediction ranges.

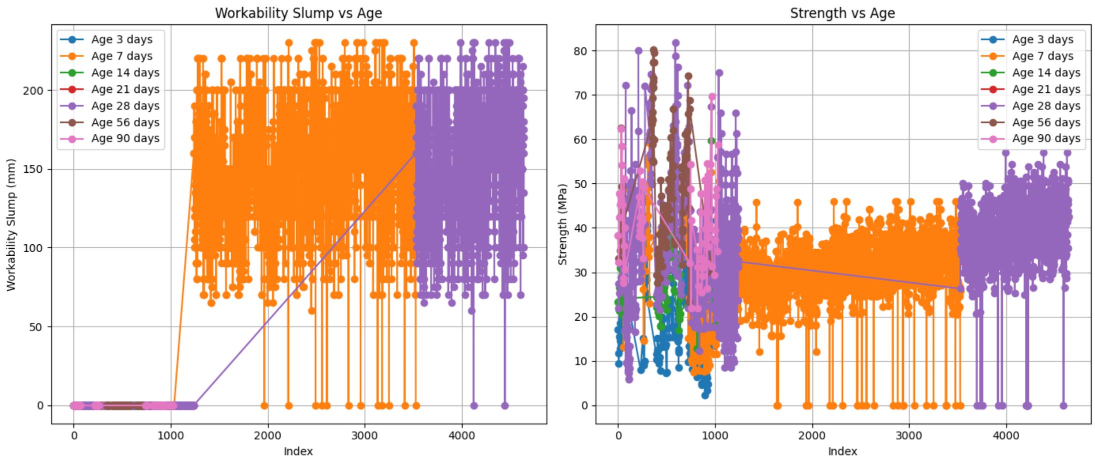

Fig 10 Workability Slump and strength vs Age

The plots visualize workability slump and strength over time. Workability slump, initially around 200mm, decreases rapidly within the first 14 days to approximately 50mm and then stabilizes. Strength, starting near 10 MPa, steadily increases over time, reaching around 70 MPa at 90 days. This indicates a material that loses fluidity quickly while gaining structural integrity gradually.

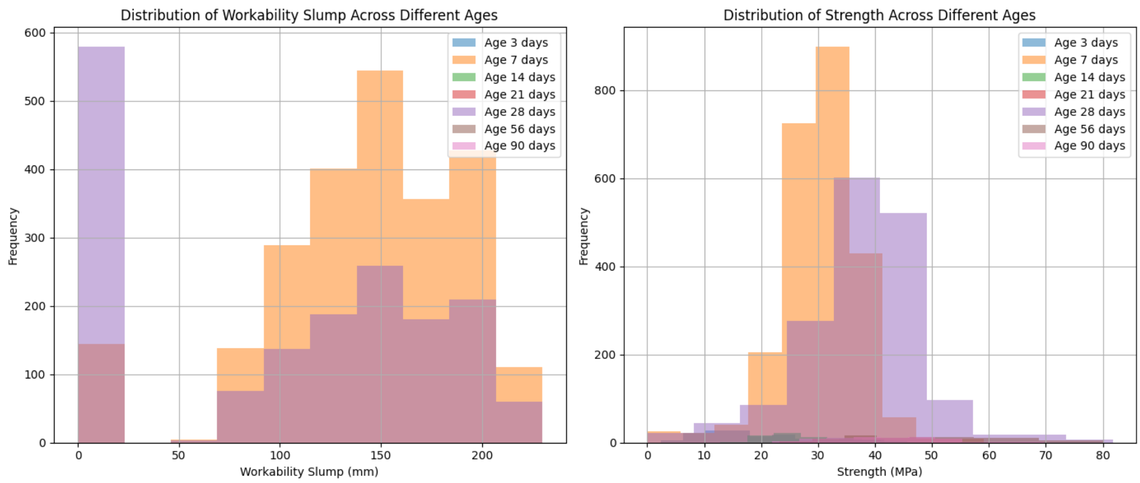

Fig 11. Distribution of workability slump and strength across different ages

The histograms illustrate the distribution of workability slump and strength at different ages. Workability slump, initially centered around 150-200mm, decreases significantly over time, with most values falling below 100mm after 14 days. In contrast, strength, initially around 10-20 MPa, steadily increases, with a majority of values exceeding 50 MPa by 56 days. This demonstrates a rapid initial loss of fluidity followed by a gradual gain in structural integrity.

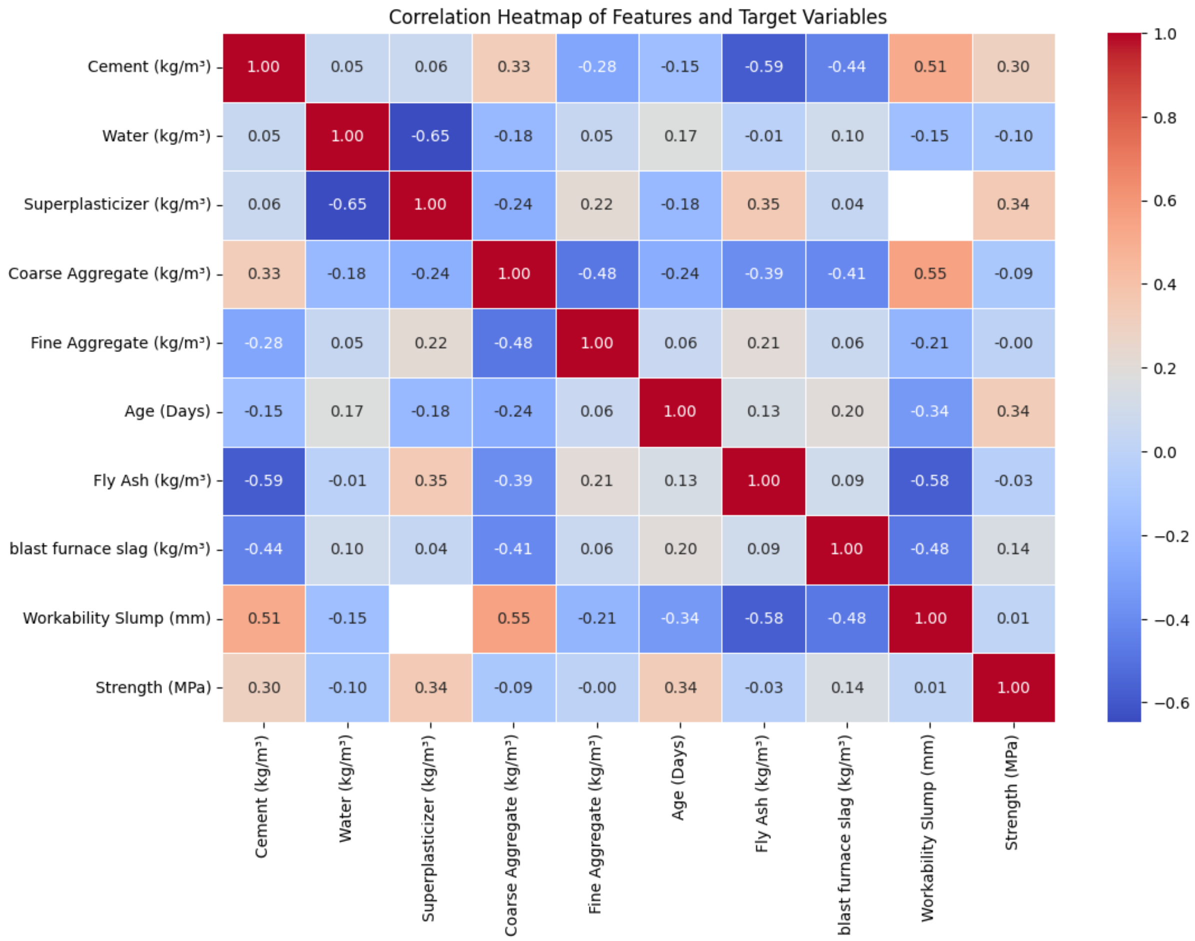

Fig 12. Correlation Heatmap of features and target variables

The correlation heatmap reveals relationships between factors and concrete strength. Cement (strong positive correlation of 0.33), superplasticizer (0.34), and age (0.34) positively impact strength. Water (-0.10) and workability slump (-0.01) have negligible effects, while other factors show moderate correlations. Notably, there's a strong negative relationship between water and superplasticizer (-0.65), suggesting they interact to influence strength.

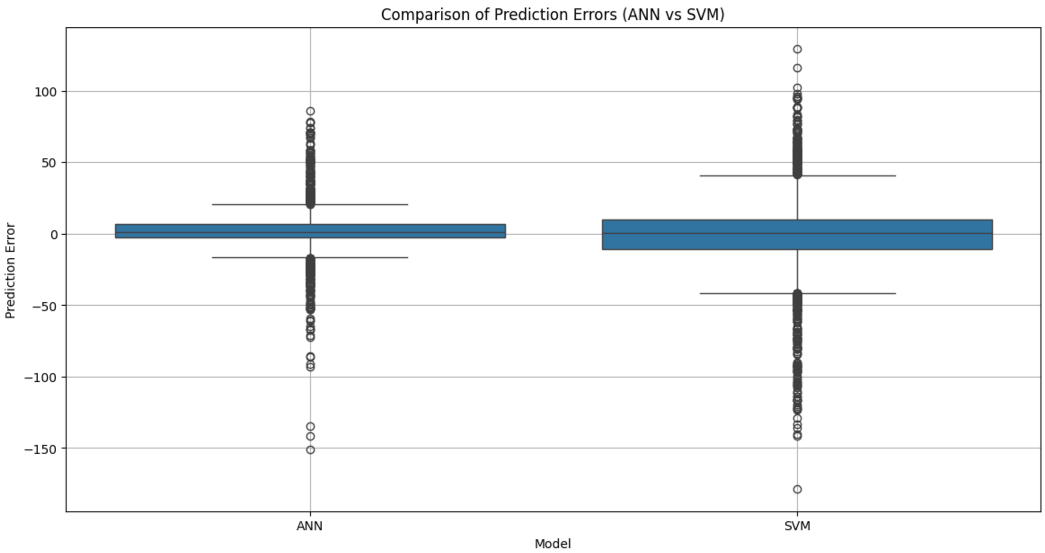

Fig 13. Comparison of prediction Errors(ANN vs SVM)

The box plot compares the distribution of prediction errors for ANN and SVM models. Both models exhibit a wide range of errors, with SVM displaying significantly greater variability. The median error for both models is close to zero, but ANN demonstrates a slightly lower median error compared to SVM, suggesting potentially better overall accuracy. The SVM model shows outliers with errors exceeding 100, indicating potential issues with prediction accuracy in certain cases.

Conclusion:

This research aimed to predict concrete properties such as strength, workability, and durability using Artificial Neural Networks (ANN) and Support Vector Machines (SVM). Following comprehensive material and mixing tests, concrete specimens were cast, cured for various durations, and subjected to mechanical and durability tests. Experimental data collected from these tests were used to develop and validate ANN and SVM models. ANN demonstrated superior predictive accuracy with a lower Mean Squared Error (MSE) for strength (368.31) compared to SVM (619.27), as well as better predictions for workability and durability. Comparative graphical analysis reinforced these findings, showcasing ANN's effectiveness. The study concludes that ANN is a more reliable model for predicting concrete properties, highlighting the potential of machine learning in optimizing construction processes and improving material performance. Future research could explore additional algorithms, hybrid models, and real-time applications to further enhance predictive capabilities and practical implementation.

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