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APPLICATIONS OF ARTIFICIAL NEURAL NETWORKS IN MODELLING THE USE OF ADMIXTURE IN CONCRETE: A STATE OF THE ART REVIEW

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ABSTRACT
The application of artificial neural networks (ANNs) in modelling the use of admixtures in concrete has gained significant attention in recent years due to the complex, non-linear nature of concrete mix designs. This state-of-the-art review explores the various methodologies and approaches employed in leveraging ANNs to predict and optimize the properties of concrete when different admixtures are used. The review covers key aspects such as data collection, network architecture, training algorithms, and performance evaluation metrics. It also highlights the challenges and potential solutions in implementing ANN models, including the need for large datasets, the selection of relevant input variables, and the interpretation of model outputs. The findings suggest that ANNs offer a robust and efficient tool for improving concrete performance, particularly in optimizing the proportions of admixtures to achieve desired mechanical properties, durability, and sustainability. This review provides valuable insights for researchers and practitioners in the field of civil engineering, paving the way for future advancements in smart concrete technologies.
Keywords: *Artificial Neural Networks, Concrete Admixtures, Concrete Mix Design, Machine Learning, Optimization, Mechanical Properties, Durability, Smart Concrete Technologies, Civil Engineering, Non-linear Modelling.*

I Introduction
1.1 Background of the Study
Concrete, one of the world's most extensively used building materials, is a composite material made up of coarse aggregate joined with fluid cement that hardens over time[1]. Concrete mixture optimization is an important part of construction engineering, with the goal of improving concrete performance qualities like as strength, durability, and workability[2]. One of the most common strategies for achieving this optimization is to employ chemical and mineral admixtures. Admixtures are compounds that are added to concrete before or during mixing to change its characteristics in either the fresh or hardened condition[3]. Accelerators, retarders, superplasticizers, and air-entraining agents are some of the most common admixtures. The conventional technique of improving concrete mixes is based mainly on empirical approaches and considerable trial-and-error testing, which may be time-consuming and expensive. However, as computational technology evolve, new techniques emerge to speed and enhance the optimization process. One interesting option is the use of Artificial Neural Networks (ANNs)[4].
Artificial neural networks are computer models based on the structure and function of the human brain[5]. They are made up of linked nodes or neurons that analyze and learn from incoming data before making predictions or judgments. Because of its capacity to represent nonlinear connections and manage massive datasets[6], ANNs have shown great promise in tackling complicated engineering challenges. In the context of concrete admixtures, artificial neural networks (ANNs) may be used to forecast concrete qualities based on different mix parameters and additive combinations[7]. By training a neural network using a large dataset of concrete mixes and their performance characteristics, it is feasible to create a model that can reliably predict the results of novel combinations without requiring substantial physical testing. This predictive capacity allows engineers to explore a large design space and determine optimum admixture combinations that suit specified performance requirements[8]. ANNs may also assist detect trends and patterns that standard analytic approaches may miss. This may

result in the discovery of novel additive formulas and the creation of high-performance concrete with customized qualities for specific purposes. For example, ANNs may improve the balance of strength and workability, minimize environmental effect by reducing cement content, and increase durability for constructions exposed to harsh conditions. The use of Artificial Neural Networks to the optimization of concrete admixtures marks a major leap in construction technology[9]. Engineers may use ANNs' predictive capability to produce more efficient and effective optimization procedures, resulting in increased concrete performance, cost savings, and the possibility for innovation in concrete mix design[10].

1. 2 Concrete admixtures and its types

Admixture is used as an additional ingredient in the concrete mix other than water, cement, and aggregates[11]. Admixture is a blend of chemical compounds used to modify the characteristics of fresh or hardened concrete. It allows engineers to tailor the mixture as per the project requirements. It can influence various aspects of concrete, such as setting time, strength development, permeability, durability, and workability.

1. 2. 1 Types of Admixtures

- **Accelerating Admixtures**

This type of admixture expedites the setting time of concrete for faster strength development. They increase the hydration rate of hydraulic cement when added to mortar or grout[12]. They are composed of compounds like calcium chloride, calcium nitrate, or triethanolamine. They are utilized in situations where faster setting times are required, such as in cold weather conditions or for rapid construction schedules.

- **Retarding Admixtures**

Retarders work oppositely to accelerators. They slow down the setting time of concrete. These are helpful when the concrete needs to travel long distances in special mixers or when it is hot outside. Retarding admixtures are especially handy as a grouting mix and work to reduce the water used. The hydroxyl carboxylic acid is a type of admixture that makes concrete with a bit less water than the quantity of water used in a regular mix. Using these admixtures can make the concrete last longer and be sturdier[13].

- **Water-reducing admixtures**

These are the types of admixtures that enable the reduction of water content in the concrete mix without compromising its workability[14]. They enhance the flowability of concrete, allowing for easier placement and better compaction. Using this admixture comes in handy in various scenarios. Pouring concrete is tricky because there are lots of bars or other elements in the way. Also, when the mix of concrete is tough, like when crushed rocks are used, this admixture can make the concrete more workable. Additionally, by adding this admixture, the cost of cement used in making concrete can be reduced by a notable amount. Common water-reducers include polycarboxylate ethers and lignosulfonates.

- **Air-entraining admixtures**

These admixtures introduce microscopic air bubbles into the concrete mixture during mixing. By altering the surface tension of the mixing water, they allow air bubbles to form and disperse uniformly throughout the concrete[15]. These bubbles enhance the concrete’s durability by improving its resistance to freeze-thaw cycles, reducing bleeding, and improving workability. These are composed of agents like vinsol resin or salts of petroleum acids.

- **Super plasticising admixtures**

Superplasticizers are advanced water-reducing agents that greatly enhance the workability of concrete without increasing water content. They significantly improve the flow characteristics of concrete, allowing for easier placement in congested reinforcement areas. Compounds such as sulfonated naphthalene formaldehyde condensate (SNF), polycarboxylate ethers (PCE), and melamine-based superplasticizers fall into this category.

1.3 Introduction to artificial neural networks (ANN)

As you read this, which organ is actively processing it? The brain is the culprit! However, are you really aware of how the brain works? Neurons, or nerve cells, make up the majority of the brain and nervous system. These neurons are in charge of taking in sensory data from the surroundings, processing it, and producing an output that may be sent to the subsequent neuron[16]. Complex networks are formed by the precise connections made by synapses between individual neurons. You may be wondering how this relates to artificial neural networks. The composition and operation of human neurons serve as an inspiration for artificial neural networks. Let's examine their characteristics and information-processing methods in more detail.

- **Artificial Neural Networks**

Artificial neurons, sometimes called units, are the building blocks of artificial neural networks. These units are arranged into layers to create the network as a whole[17]. These layers may comprise a few hundred or millions of units, depending on the complexity needed to extract the underlying patterns in a dataset. The three primary layers of an artificial neural network are input, hidden, and output.

The network has to process or learn from the data that is received from the external world via the input layer. After that, the input is turned into information that the output layer may utilize by passing through one or more hidden layers. The output layer subsequently produces the network's final response to the input.

The majority of neural networks include connections between units at different layers, and each link has a weight. The impact of one unit on another is determined by these weights. The weights are modified as the input flows through the network, allowing it to gain and improve its comprehension of the data before generating an output at the output layer[18].

1.4 Applications of Artificial Neural Networks:

Artificial neural networks are widely employed in a wide range of industries, including as marketing, social media, healthcare, and personal help. For example, Facebook's 'People You May Know' tool suggests people you may know in real life based on an analysis of your profile, hobbies, and relationships with friends. You can then accept friend requests from these suggested persons. Facial recognition, which employs convolutional neural networks to find important reference points on a person's face and compare them with those in a database, is another often used social networking application.

On e-commerce platforms like Amazon and Flipkart, neural networks are utilized in sales and marketing to provide personalized product recommendations based on your browsing history[19]. Similar to this, apps like Zomato and Swiggy recommend restaurants based on your past purchases and likes. Customized marketing is a tactic that enables firms to effectively tailor their marketing efforts by using artificial neural networks to assess client preferences, past purchases, and dislikes.

In oncology, artificial neural networks are being used to develop algorithms that, at the microscopic level, can detect malignant tissues with an accuracy comparable to that of highly qualified medical personnel. It is also possible to detect uncommon diseases early on that manifest as physical characteristics by using facial analysis technologies on patient photographs. The widespread use of artificial neural networks in healthcare is expected to improve diagnostic abilities among medical professionals and raise the bar for healthcare delivery worldwide.

For the personal assistants that most of us are familiar with, like Siri, Alexa, and Cortana, to interact with users and provide pertinent replies, natural language processing is necessary. Because they use artificial neural networks to carry out a range of tasks, including language grammar, semantics, accurate pronunciation, and carrying on conversations, these personal assistants are effective and simple to use.

II LITERATURE REVIEW

Malo Charrier et al. (2022) reviewed a study titled "Artificial neural network for the prediction of the fresh properties of the use of ANNs for the purpose of foretelling the future characteristics of these materials (cementitious materials). An integral component of 3D printing ink, cement paste has its fresh characteristics studied in relation to admixtures. The combination included nanoclay, an accelerator, a material-changing ingredient, and calcium silicate hydrate seeds, in addition to the superplasticizer. The experiment was factorial in design. Using a rheometer to measure the cement paste's yield stresses, they contrasted and compared the findings from the mini-slump test. It was postulated that the mini-slump and the dynamic yield stress would have an empirical link. We confirmed that the material can keep its form even when printed in a single layer by calculating the critical yield stress. Predicting mini-slump and dynamic yield stress using certain admixture ratios was taught to artificial neural networks (ANNs). To assess the neural networks, we replicated several mixtures in simulation and contrasted the yield stress and mini-slump results from the two sets of data. The critical yield stress was used by the ANN to determine the quantity of each admixture [20].

Tahereh Korouzhdeh et al. (2021) In this research, a hybrid artificial neural network with optimization based on biogeography was used to analyze the impacts of cement fineness on mechanical characteristics and environmental impact of frozen and thawed cement mortar. The primary goal of the research was to decrease cement use and pollution via meticulous mix design, as it is well recognized that cement plants have a substantial impact on the environment. The researchers thoroughly examined the effects of cement fineness in three separate cement strength classes (CSC 32.5, 42.5, and 52.5 MPa) and different sand/cement ratios on porosity, flexural strength, and compressive strength under five separate freezing/thawing cycles. They used 54 mix designs and 810 specimens for the experiments. For better forecasts, they used a hybrid ANN that was fine-tuned using biogeographic data[21].

Junfei Zhang et al. (2019) proposed a method to optimize the proportions of concrete mixes by using metaheuristic algorithms and machine learning, considering several goals. In their study titled "Multi-objective optimization of concrete mixture proportions using machine learning and metaheuristic algorithm," the authors took on the task of maximizing three objectives at once: strength, cost, and slump—all while dealing with constraints that were significantly nonlinear. They chose the best performing ML model as the optimization target after benchmarking it for its ability to predict concrete objectives. Using a multi-objective particle swarm optimization approach, they improved the combination proportions to produce the optimum outcomes[22].

Venkata Subash Koneru et al. (2020) used artificial neural networks to assess the strength qualities of self-compacting concrete (SCC). They assessed compressive and splitting tensile strength in their research titled "Assessment of strength characteristics for experimental based workable self-compacting concrete using artificial neural network." Extensive testing was carried out to generate 123 practical SCC mixtures. But that wasn't all the researchers accomplished. Using inputs such as cement content, water-cement ratio, and types and percentages of admixtures, they trained the Marquardt backpropagation technique to employ artificial neural networks (ANN) to anticipate these strength characteristics[23].

Furqan Farooq et al. (2021) analyzed and optimized prediction models for eco-friendly high-performance concrete made from industrial waste using ensemble learning. According to the article "Predictive modeling for sustainable high-performance concrete from industrial wastes: A comparison and optimization of models using ensemble learners," a number of machine learning algorithms were used to foretell the compressive strength of the concrete. Methods like decision trees, ensemble learning (including bagging and boosting), and support vector machines were part of these approaches. To verify the models, k-fold cross-validation and statistical performance indicators were used[24].

S.N. Londhe et al. (2021) made use of ANNs and GP to predict the carbonation coefficient of the concrete. In their study titled "Predicting carbonation coefficient using Artificial neural networks and genetic programming," the authors aimed to replicate the carbonation phenomenon with more accuracy than was previously possible using methods such as multiple linear regression. They accomplished this by making use of a massive dataset. They used knowledge extraction approaches to comprehend the impact of each input on the result[25].

Emadaldin Mohammadi Golafshani et al. (2020) developed hybrid models that used the Grey Wolf Optimizer in conjunction with artificial neural networks and artificial non-linear feature extraction to forecast the compressive strength of both ordinary and high-performance concretes. "Predicting the compressive strength of normal and High-Performance Concretes using ANN and ANFIS hybridized with Grey Wolf Optimizer," a study that obtained a large dataset and evaluated several optimization procedures, found that hybrid models improved the accuracy of predictions[26].
Ali Mardani-Aghabaglou et al. (2021) evaluated and forecasted the flow behavior of cement paste using an innovative ANN model trained with the Teaching-Learning Based Artificial Bee Colony (TLABC) Algorithm. In their study titled "Assessment and prediction of cement paste flow behavior; Marsh-funnel flow time and mini-slump values," the researchers determined that ANN-TLABC was the most effective modeling tool after comparing it to other methods. Additionally, they identified significant characteristics that impact paste flowability[27].
Amirreza Kandiri et al. (2020) computed concrete compressive strengths using GGBFS, which included a hybridized multi-objective artificial neural network and a salp swarm approach. As part of their study titled "Estimation of the compressive strength of concretes containing ground granulated blast furnace slag using hybridized multi-objective ANN and salp swarm algorithm," the authors developed prediction models. They then tested these models using various error metrics and discovered that ANN models performed better than M5P model tree techniques[28].
Phillip D. McElroy et al. (2021) The use of artificial neural networks (ANNs) to determine the unconfined compressive strength (UCS) of nanoparticle-enhanced cement for usage in oil and gas wells was shown. For their paper titled "Artificial neural network (ANN) approach to predict unconfined compressive strength (UCS) of oil and gas well cement reinforced with nanoparticles," the scientists trained an ANN model using a dataset consisting of 195 cement samples with varying doses of nanoparticles. Good prediction accuracy was attained by the model[29].
Ali Ashrafian et al. (2020) created an AI/Hybrid model to forecast FCLT's compressive strength. They demonstrated a Multivariate Adaptive Regression Splines model optimized with the Water Cycle Algorithm (MARS-WCA) in "Compressive strength of Foamed Cellular Lightweight Concrete simulation: New development of hybrid artificial intelligence model," and it was determined to be the most effective model compared to other models[30].
Amir Ali Shahmansouri et al. (2021) to forecast the compressive strength of environmentally friendly geopolymer concrete using silica fume and natural zeolite, an ANN model was suggested. They used experimental data and input variables like specimen age and silica fume and natural zeolite content to build an artificial neural network model to forecast the compressive strength of environmentally friendly geopolymer concrete[31].
Paul O. Awoyera et al. (2020) estimated the geopolymer self-compacting concrete's tensile characteristics using machine learning algorithms. According to the study "Estimating strength properties of geopolymer self-compacting concrete using machine learning techniques," the authors used ANN and genetic programming to model the strength characteristics of concrete with mineral admixtures. The results showed that ANN was a better predictor, while genetic programming produced more straightforward equations[32].

2.1 Research Gap:

Despite the extensive application of Artificial Neural Networks (ANN) in optimizing and predicting various concrete properties, several research gaps remain. There is a need for integrating multiple optimization techniques and focusing on newer, environmentally sustainable concrete types. Long-term performance predictions, holistic property assessments, and real-world validations are limited. The development of dynamic, adaptive, and hybrid models incorporating advanced machine learning and genetic algorithms is underexplored. Additionally, incorporating environmental and economic considerations into ANN models, adopting cross-disciplinary approaches, and enhancing data quality and quantity for better model training are crucial areas that require further research to advance concrete technology.

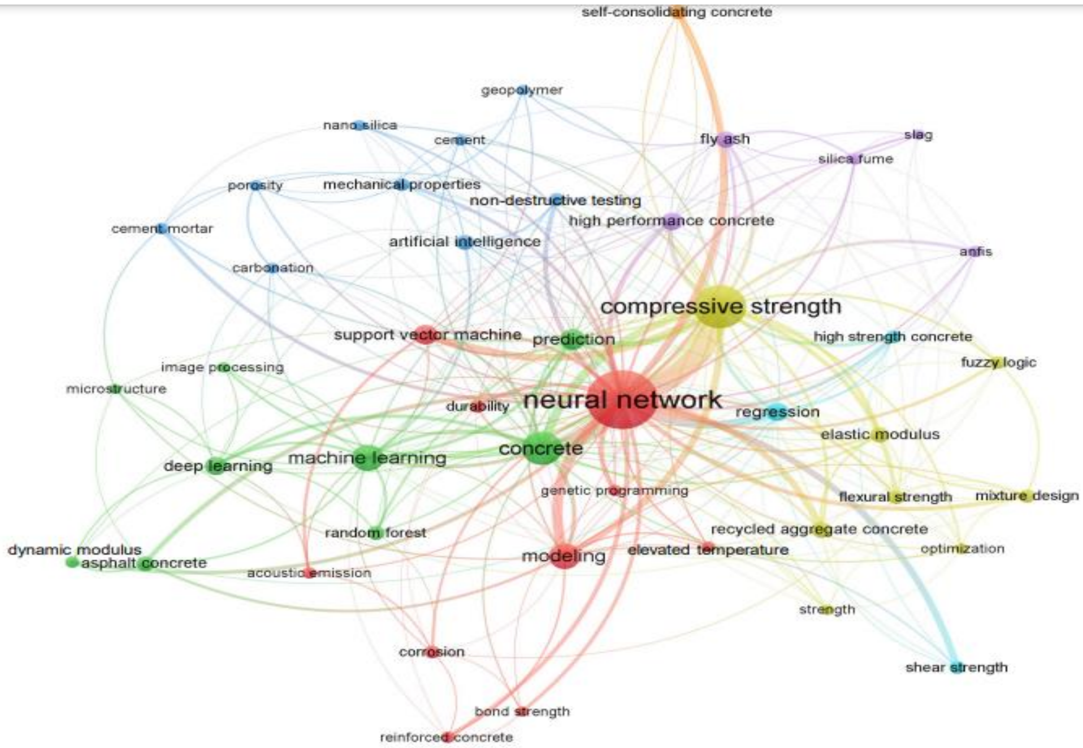

Figure 1: Network of co-occurring keywords related to research on AI in concrete materials (cluster view).

Figure 1 showcases the growing research interests in the application of AI within the field of concrete science, where certain keywords such as "modeling," "prediction," "regression," and "optimization" frequently appear in publications. These terms reflect the primary goals of using AI in this domain, which include modeling concrete behavior, predicting its properties, and optimizing mixture designs to achieve desired performance outcomes. Notably, "neural network" emerges as the most prominent keyword, emphasizing its widespread use as the preferred model in this area. This is particularly evident in its strong association with "compressive strength," a key parameter in construction that directly impacts concrete's mechanical and durability properties.

Figure 1 illustrates the diverse applications of AI in concrete science through distinct clusters of keywords, each representing different research focuses. For instance, the yellow cluster contains terms related to the physical performance of concrete, such as "strength," "flexural strength," "elastic modulus," "mixture design," and "optimization." This suggests a significant focus on optimizing concrete mixtures to improve their physical properties. On the other hand, the green cluster highlights emerging topics like "machine learning," "deep learning," and "image processing," pointing to a growing interest in these advanced AI techniques. These color-coded clusters not only map current research trends but also indicate potential areas for future exploration in AI-driven concrete science.

III 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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