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REVIEW ARTICLE

Advancements and Applications of Artificial Neural Networks in Structural Engineering: A Comprehensive Review

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ABSTRACT

Artificial Neural Networks (ANNs) have revolutionized the field of civil engineering by offering efficient and accurate solutions for complex material behavior predictions. This paper reviews the applications of ANNs in civil engineering, emphasizing their role in pre-dicting the load capacities of structural components under various conditions. The study highlights the development and application of a deep feed forward neural network (FFNN) for predicting the load capacities of post-installed adhesive anchors in cracked concrete. Additionally, it explores a hybrid methodology combining nonlinear finite element (NLFE) techniques with FFNN to enhance prediction accuracy and reduce computational effort. The research demonstrates the significant potential of ANNs in diverse civil engineering applica-tions, including crack detection, structural analysis, design optimization, and strength esti-mation. Despite challenges such as data quality, computational resources, model interpreta-bility, and generalization, the opportunities for enhanced prediction accuracy, reduced com-putational effort, and adaptability to various applications are substantial. The study particu-larly emphasizes the potential for ANN adoption and development in Ethiopia, presenting opportunities for capacity building and infrastructure improvement. The findings under-score the robustness and efficiency of ANNs, particularly deep FFNNs, as a vital tool in advancing structural engineering practices.

Keyword: *Keywords: Artificial Neural Networks (ANNs), Civil Engineering, Deep Feedfor-ward Neural Network (FFNN), Nonlinear Finite Element (NLFE), Load Capacity Prediction, Structural Analysis, Crack Detection, Hybrid Methodology, Machine Learning, Ethiopia, Infrastructure Development.*

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1. INTRODUCTION

Artificial Neural Networks (ANNs) are powerful tools that utilize existing experimental data to predict the behavior of materials under various testing conditions. Emerging from the field of artificial intelligence (AI), ANNs have been instrumental over the past decade in modeling engineering problems, particularly in understanding the mechanisms of composite materials. ANNs serve as effective regression tools, capable of capturing complex, nonlinear interactions among variables without requiring prior knowledge about these interactions. Once properly trained and validated with comprehensive experimental data, ANNs can provide reliable results efficiently, enabling designers to explore numerous design possibilities quickly and make informed decisions. The concept of artificial neurons was first introduced by McCulloch and Pitts as models of biological neurons. [1] These artificial neurons, interconnected to form neural networks, process information through a connectionist approach. Unlike real biological systems, artificial neural networks (ANNs) are designed either to mimic biological neural networks or to solve AI problems. A biological neuron comprises dendrites, a cell body, an axon, and synapses. Similarly, an artificial neuron consists of input variables, weights, a processing unit, and an output. In a feedforward network, neurons are organized in layers, with each layer receiving input from the previous one and sending output to the next, ensuring unidirectional information flow.

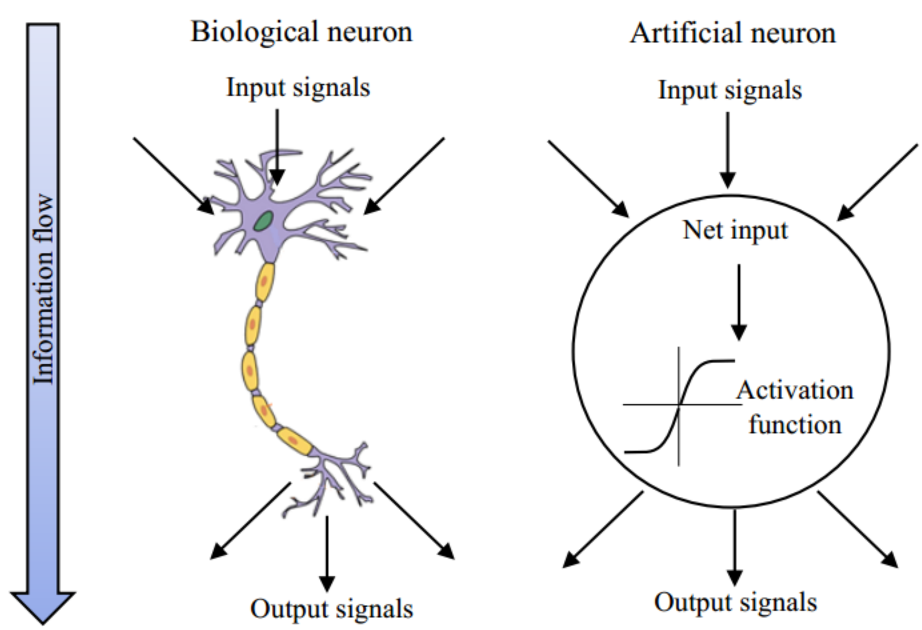

Fig. 1. Biological and artificial neurons.

Recent years have witnessed a significant rise in applying soft computing techniques in civil engineering, spanning earthquake engineering to water resources. Unlike conventional analytical methods, which seek exact solutions, soft computing techniques provide approximate solutions quickly and accurately, often with less computational effort. AI, particularly machine learning, plays a crucial role in this domain. Machine learning, a subset of AI, learns patterns from data and generalizes this knowledge to new inputs, useful for classification, regression, and clustering tasks. ANNs, a prominent machine learning technique, are extensively used in civil engineering for data classification and regression.

In structural engineering, one notable application of ANNs is predicting the load capacity of anchors installed in concrete. These anchors are crucial for securing non-structural components to buildings, especially for wind load resistance. With climate change potentially intensifying hurricanes, the importance of reliable anchor systems is growing. While several studies have applied ANNs to predict the load capacities of anchors in uncracked concrete, this paper reviews various ANN types and their recent applications in civil engineering and other fields.[34] It also demonstrates the development and application of a deep feed forward neural network (FFNN) to predict the load capacities of post-installed adhesive anchors in cracked concrete. Additionally, a hybrid methodology combining nonlinear finite element (NLFE) techniques with the developed FFNN is presented, offering more accurate predictions with reduced computational effort compared to standalone NLFE analyses. ANNs consist of interconnected cells called neurons, which adapt based on the information they process, akin to biological learning processes. Each neuron applies an activation function to its input to produce an output, which is modified by weights and biases before being passed to the next layer. The main types of ANNs include feed forward, radial basis, Kohonen self-organizing, recurrent, convolutional, and modular networks.[34] Feed forward neural networks (FFNNs) are among the simplest forms, with information flowing in one direction from inputs to outputs. FFNNs, especially deep ones with multiple hidden layers, have been successfully employed to predict the load capacities of structural members, such as concrete anchors. However, previous studies have primarily focused on anchors in uncracked concrete, limiting their applicability to other conditions. This paper provides a comprehensive review of artificial neural networks (ANNs) in civil engineering.

2. Recent application of ANN

2.1 Crack Detection

SDNET2018 is a comprehensive annotated image dataset designed for training, validating, and benchmarking artificial intelligence algorithms aimed at detecting cracks in concrete. It contains over 56,000 images featuring both cracked and non-cracked concrete surfaces, including bridge decks, walls, and pavements. The dataset showcases a wide range of crack widths, from as narrow as 0.06 mm to as wide as 25 mm. It also presents various obstructions such as shadows, surface roughness, scaling, edges, holes, and background debris. SDNET2018 is particularly valuable for advancing the development of deep convolutional neural networks (DCNNs) for concrete crack detection, a key area of research in structural health monitoring [2]. Structural fibers enhance the post-cracking tensile strength of concrete, but experimental characterization of this property introduces design uncertainties, hindering new fiber development and optimization.[16] The research presents a multilayer perceptron neural network to predict the behavior of fiber-reinforced concrete (FRC) in the Barcelona Test. The optimal network architecture is identified from 9,216 configurations, with performance validated through repeated random sub-sampling. The model accurately predicts residual tensile strength (fctR) at various cracking stages. A parametric analysis confirms the coherence between predictions and known FRC behavior. Automatic crack detection is essential for reducing costs and improving the quality of surface inspections required for infrastructure maintenance. This research developed a novel system to detect steel cracks and estimate their depth from 2D images, aiming to create an affordable, user-friendly alternative to expensive 3D measurement devices. The system uses a learning strategy, testing various structures to find the most suitable one. Neural networks were trained using the average intensities of 2D steel crack profiles and maximum crack depths measured by a laser microscope. A feed forward backpropagation neural network achieved an average testing error of 18.81%, which is 10% lower than the previous error using the updated 3D Make toolbox for depth estimation.[35]

2.2 Structural Analysis and Design Using ANN

Neural networks are computationally efficient techniques increasingly applied to structural engineering problems due to their simplicity in simulating real-world scenarios. This paper reviews several applications of neural networks in structural analysis and design, demonstrating that they offer a more efficient and accurate method compared to conventional approaches. Neural networks excel at representing complex input/output relationships without requiring complex or expensive programming. Their architecture mimics the knowledge acquisition and organizational skills of the human brain, enabling them to perform tasks beyond the scope of traditional processors. These networks can recognize patterns within large data sets and generalize them into recommended actions. A key advantage of neural networks is their ability to easily simulate problems without the need for intricate programming. Recent applications in structural engineering have highlighted their effectiveness and benefits in solving various challenges in the field. [36]

Artificial Neural Network (ANN) used for the preliminary design of reinforced concrete beam-columns.[3] Traditional methods to determine the required dimensions and reinforcing steel area for specific axial loads and moments involve complex, iterative calculations using column design interaction curves. To simplify this process, an ANN back-propagation model was developed. This model predicts the column cross-section based on inputs such as concrete compressive strength, column type (tied or spiral), reinforcing steel ratio, factored axial load (Pu), and moment (Mu). Various ANN models were tested, with the best performance achieved by a multi-layered network using a logistic activation function. This optimized ANN model demonstrated excellent statistical performance and accurately predicted designs compared to actual data.

Designing steel structures is an iterative process that can become complex without a good initial guess, typically derived from past design experience. Such an initial guess can significantly reduce the number of analysis and design cycles. However, forming declarative rules to capture human intuition and experience is challenging. Additionally, finding the optimal design solution is often computationally expensive and time-consuming. Artificial Neural Networks (ANNs) offer a promising solution by performing cognitive tasks like learning and optimization. The research explores the application of ANNs in the design process to enhance efficiency. Its goal is to train ANNs to find optimal solutions while considering design constraints and practicalities. An example is provided involving the design of a compression member, where an initial guess is crucial.[38]

Neural networks can predict the stress-strain relationships of reinforced concrete sections. Numerical analysis algorithms simulated existing experimental data. Neural networks, specifically back-propagation algorithms, were implemented for predictions.[32] The technique's efficiency is demonstrated by reconstructing previous experimental work and evaluating parameters that align with experimental results. This approach establishes valid mathematical relationships through numerical data manipulation without relying on a specific algorithm.

Artificial neural network (ANN) can rapidly and accurately assess the seismic response of existing reinforced concrete (RC) buildings.[17] The research focused on buildings in the outskirts of Bologna, developing 928 finite element models based on common structural data. By varying input parameters and conducting modal dynamic and non-linear static analyses, a comprehensive dataset of seismic responses was created. This dataset was used to train an ANN function to predict the seismic behavior of RC structures.

In addition, a generalized regression neural network (GRNN) model is used to predict the corrosion potential values and corrosion current densities of ASTM A572-50 steel specimens in nine soils with varying physiochemical properties. Experiments measured the corrosion current densities and potential values of the steel in these different soils.[5]

2.3 Estimation of strength

Recent research focuses on reusing recycled concrete aggregate from demolished buildings for its economic and environmental benefits. Hamed Dabiri et.al study uses machine learning to evaluate how replacing natural aggregate with recycled material affects concrete strength over 3, 7, and 28 days.[7] The most accurate model, Random Forest, shows minimal impact on strength when incorporating recycled aggregate, with fine aggregate having less effect than coarse or both. Sustainable construction promotes using recycled materials in place of traditional concrete. Priyanka Singh et.al study focuses on predicting the bond strength of environmentally friendly concrete made with waste materials, aiming to reduce construction costs, energy consumption, and CO2 emissions.[9] Machine learning is employed to forecast the bond strength, leveraging patterns in data. Specifically, an Artificial Neural Network (ANN) model is used, trained on various concrete mixes from technical literature. The model employs linear regression analysis to make predictions based on input attributes.

Faezehossadat Khademi et.al evaluates the 28-day compressive strength prediction of recycled aggregate concrete using three data-driven models: Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR). Fourteen input parameters, including dimensional and non-dimensional ones, were considered. Results suggest that ANN and ANFIS outperform MLR in predicting compressive strength. MLR is recommended for preliminary mix design, while ANN and ANFIS are better suited for mix design optimization and higher accuracy needs. Additionally, the inclusion of non-dimensional parameters improves model accuracy. The study also examines the impact of each non-dimensional parameter on model performance and explores the effect of the number of input parameters on compressive strength. [22]

Behzad A. et.al study's explores the use of Artificial Neural Networks (ANN) to predict the compressive strength (CS) of "green" concrete, which utilizes alternative materials like fly ash, Haydite lightweight aggregate, and Portland limestone cement. The aim is to understand how these materials affect concrete properties. The study employs a feed-forward Multilayer Perceptron (MLP) model, testing two input methods (relative and numerical) for accuracy and flexibility. Results indicate that concrete with Portland limestone cement shows slightly better CS. Both input methods yield accurate CS predictions, suggesting that a properly configured MLP model can effectively predict the CS of "green" concrete.

Masonry, one of the oldest and most commonly used building materials, lacks a reliable method to predict its strength based on its components' characteristics. This is due to the complex relationship between compressive strength and these properties. Panagiotis G. et.al study explores the use of artificial neural networks, specifically back-propagation models, to predict masonry strength based on experimental data. Results show the effectiveness of neural networks in reliably estimating masonry strength. [14]

Masoud Ahmadi etal's paper aims to develop new design formulas using Gene Expression Programming (GEP) and Artificial Neural Networks (ANNs) to determine shear stress in steel fiber-reinforced concrete (SFRC) beams without stirrups. The formulations consider various geometrical and material properties of reinforced concrete beams and fiber properties. To validate these formulations, a comparative assessment was conducted between calculated and measured shear stresses. Results show that the proposed formulations exhibit acceptable accuracy across a wide range of shear span to effective depth ratios.[18] J. Amani and R. Moieni compares Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) models to predict RC beam shear strength, with inputs including concrete strength and reinforcement details. The ANN model outperforms ACI and ICI codes in accuracy, while ANFIS shows comparable performance.[31]

Varinder Kumar Bansal et.al's study presents three models—Taguchi, ANN, and ANFIS—to predict compressive strength in concrete with industrial by-products replacing cement and fine aggregates. Different replacement levels were tested, with fixed water-to-binder ratios and curing ages. Using data from 90 experiments, ANFIS showed better accuracy in prediction compared to ANN.

Predicting concrete compressive strength is challenging due to various factors. Different methods have been proposed, with varying success rates. Faezehossadat Khademi's study aims to assess the effectiveness of an Artificial Neural Network (ANN) model in predicting 28-day compressive strength. By using specific concrete characteristics as input variables, the ANN model accurately predicts concrete strength. [23]

Emre Sancak's studyalso produced load-bearing concrete samples using pumice aggregate and silica fume. Cement was partially replaced with silica fume at 5% and 10% of its weight. Fresh concrete properties were assessed, followed by compressive strength tests at 28 and 90 days. Pullout tests on cubic samples were conducted on the 90th day to determine reinforcing steel-concrete bond strength. Data from these tests were used in Artificial Neural Networks (ANN) to predict bond strength values, which closely matched experimental results. The study suggests that ANN can efficiently predict bond strength in both normal and lightweight concrete, reducing the need for extensive laboratory work.[25]

Adriana T. etal also developed Artificial Neural Networks (ANNs) models to predict the compressive strength of concretes containing Construction and Demolition Waste (CDW) at different ages: 3, 7, 28, and 91 days. Experimental data from literature, totaling 1178 entries, were used to construct the models. Seventeen input parameters were used to predict compressive strength. The results from both training and testing phases demonstrate the effectiveness of ANN in predicting the compressive strength of CDW-containing concretes at various ages. [27]

Ahmed M. etal conducted two phases. The first phase involved validating a neural network to predict mortar and concrete properties affected by sulfate attack, including expansion, weight loss, and compressive strength loss. In the second phase, concrete compressive strength over a 200-year period under sulfate attack was assessed. The neural network model proved effective in predicting compressive strength, expansion, and weight loss due to sulfate attack. Additionally, design charts were developed to predict concrete compressive strength loss based on cement content, water-cement ratio, C_3A content, and sulfate concentration, providing a convenient method to predict strength loss for various concrete compositions at different ages and sulfate concentrations.[29]

Recent studies have begun using artificial neural networks (ANN) to simulate events in civil engineering. O P Akintunde etal's research focuses on developing an ANN model to predict how the addition of bentonite affects concrete compressive strength. The model was trained and tested using data from 200 experimental samples with various mix proportions from existing literature. The ANN model consists of seven input variables, one hidden layer with ten neurons, and output values for compressive strength at 3, 7, and 28 days. Evaluation shows that the ANN model reliably predicts concrete compressive strength with bentonite at different ages. [33]

In response to the ongoing waste disposal crisis, Sourav Ray et.al study examines the effectiveness of response surface methodology (RSM) and artificial neural network (ANN) in predicting the mechanical strength of concrete made with fine glass aggregate (GFA) and condensed milk can fibers (CMCF).[6]

2.4 Classification, Registration and Identification

Sirca et.al reviews structural system identification research published in journals since 1995, categorizing it into five approaches: conventional model-based, biologically-inspired, signal processing-based, chaos theory, and multi-paradigm. While much of the research focuses on small and academic problems, identifying large, real-life structures with nonlinear behavior and unknown dynamic loading poses a significant challenge. The research suggests that a multi-paradigm approach is the most effective strategy for system identification in such cases. [37]

A. Serwa and M. Saleh’s research introduces a new registration method for bridge structures using artificial neural networks (ANN). The method aims to align as-built laser data with global design reference data accurately. A software implementing ANN is developed for this purpose and tested on a steel bridge structure. The results demonstrate the reliability of the registration method, with an error of less than 5% between the as-built and design models. The study suggests potential improvements using deep learning (DL) for better results in future applications. [19]

Sujith Mangalathu and Jong-Su Jeon addresses the crucial task of predicting failure modes in circular reinforced concrete bridge columns after seismic events, which informs operational and recovery strategies. Three failure modes (flexure, flexure-shear, and shear) are analyzed using machine learning methods. Data from 311 specimens are collected from experimental studies. Various machine learning models are tested, with artificial neural network showing the highest performance. The neural network achieves 91% accuracy in classifying failure modes, outperforming other methods and highlighting its effectiveness in failure mode recognition for bridge columns.[13]

As industrial processes become more automated, there's a growing demand for intelligent decision-making tools, especially in non-destructive evaluation. While analysis is often automated using software, the decision-making process still involves humans. Tomasz R. etal introduces a damage classification algorithm for identifying structural damage in composites from X-ray computed tomography scans. The algorithm, based on deep neural networks, shows promising results in achieving high classification accuracy. The study demonstrates the effectiveness of the approach and suggests avenues for further algorithm development. [8]

3 Challenges and Opportunities

3.1 Challenges

a) Data Availability and Quality: One of the primary challenges in developing accurate ANN models is the availability and quality of experimental data. Inconsistent or insufficient data can lead to poor model performance and unreliable predictions. This is particularly relevant in the Ethiopian context, where comprehensive datasets might be scarce or difficult to obtain.

b) Computational Resources: While ANNs reduce computational costs compared to some traditional methods, training deep networks still requires significant computational power. Limited access to advanced computational resources can be a barrier, especially in regions with fewer technological advancements.

c) Model Interpretability: ANNs, especially deep networks, are often considered "black boxes" due to their complex inner workings, making it difficult to interpret how they arrive at specific predictions. This lack of transparency can be a concern in critical structural engineering applications where understanding the rationale behind predictions is essential.

d) Generalization to Different Conditions: Ensuring that ANN models generalize well to different conditions, such as varying environmental factors and material properties, is challenging. Models trained on specific datasets may not perform well under different or unforeseen circumstances.

e) Integration with Traditional Methods: Integrating ANNs with conventional engineering practices and convincing practitioners of their reliability and accuracy can be difficult. There is often resistance to adopting new technologies without extensive validation and demonstration of their benefits.

3.2 Opportunities

a) Enhanced Prediction Accuracy: ANNs offer the potential for significantly improved prediction accuracy for complex engineering problems. Their ability to model nonlinear interactions and handle large datasets makes them ideal for tasks such as predicting load capacities of structural components under varied conditions.

b) Reduction in Computational Effort: Once trained, ANNs can provide rapid predictions with minimal computational effort. This efficiency can lead to substantial time and cost savings in engineering design and analysis processes.

c) Adaptability to Various Applications: The versatility of ANNs allows them to be adapted to a wide range of civil engineering applications, from structural health monitoring to material property prediction. This adaptability opens up numerous avenues for research and practical implementation.

d) Hybrid Methodologies: Combining ANNs with traditional finite element methods, as demonstrated in this study, can enhance the accuracy and efficiency of structural analyses. Hybrid approaches can leverage the strengths of both techniques, providing robust solutions to complex problems.

e) Capacity Building in Ethiopia: The adoption and development of ANN technologies in Ethiopia present an opportunity for capacity building in the engineering sector. Training engineers and researchers in these advanced techniques can foster innovation and improve infrastructure development in the region.

f) Scalability and Flexibility: ANNs can be scaled and customized for different project requirements, making them a flexible tool for engineers. Their scalability allows for handling both small-scale projects and large, complex systems with varying degrees of complexity.

4 Conclusion

Artificial Neural Networks (ANNs) have proven to be invaluable tools in civil engineering, offering efficient and accurate solutions for complex problems without extensive computational costs. This paper reviewed the various types of ANNs and their applications in civil engineering, particularly in the Ethiopian context. The development and application of a deep feed forward neural network (FFNN) to predict the load capacities of post-installed adhesive anchors in cracked concrete were highlighted as a significant contribution. This study demonstrated the FFNN's ability to provide reliable predictions by leveraging its capacity to model complex, nonlinear relationships among variables.

The introduction of a hybrid methodology combining two-dimensional nonlinear finite element (NLFE) techniques with the FFNN further enhanced the accuracy and efficiency of load capacity predictions. This integrated approach accounted for real-life adverse effects such as concrete cracking, wind-induced beam bending, and elevated temperatures, thus providing a comprehensive solution to a challenging problem.

The critical review of ANN concepts and their applications underscored the potential of these networks in various structural engineering tasks, including predicting concrete strength and analyzing concrete-filled steel tubular (CFST) members. The study also provided valuable insights into the basic concepts of ANNs and the software tools used for developing ANN models, serving as a resource for design engineers to assess concrete mix proportions and estimate compressive strength accurately.

In conclusion, ANNs, particularly deep FFNNs, offer a robust and efficient alternative to conventional methods for solving complex engineering problems. Their ability to model intricate interactions and provide accurate predictions with minimal computational effort makes them a vital tool in advancing structural engineering. The findings of this study highlight the prospective applications of ANNs in improving the design and analysis of structural components, with a specific focus on enhancing infrastructure in Ethiopia. Particularly in the Ethiopian context, the opportunities they present for improving accuracy, efficiency, and adaptability in engineering practices are substantial. Addressing these challenges through strategic research, investment in computational resources, and capacity building can unlock the full potential of ANNs in advancing the field of structural engineering. Following this paper we were able to identify 100 research topics related with neural networks.

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