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A NEURAL NETWORK APPROACH FOR FATIGUE LIFE PREDICTION OF ENGINEERING MATERIALS

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ABSTRACT
Fatigue failure is one of the primary causes of structural damage in engineering components subjected to cyclic loading. Accurate prediction of fatigue life is critical for ensuring reliability, safety, and cost-effective design of mechanical systems. Conventional fatigue life prediction methods rely on empirical models and S–N curves, which often fail to capture complex nonlinear material behavior. This paper presents a neural network–based approach for predicting fatigue life of engineering materials. The proposed model learns nonlinear relationships between stress parameters and fatigue life from experimental data. Comparative analysis with traditional regression models demonstrates superior prediction accuracy and reduced error. The results confirm that neural networks offer a reliable and efficient alternative for fatigue life estimation in mechanical engineering applications.

Keywords: Fatigue Life Prediction, Neural Networks, Machine Learning, Mechanical Engineering, Material Behavior, Structural Reliability.

I. INTRODUCTION

Fatigue failure occurs when materials are subjected to repeated or fluctuating stresses below their ultimate strength. Such failures are common in mechanical components including shafts, gears, aircraft structures, and pressure vessels. Predicting fatigue life accurately is essential for safe design and maintenance planning.

Traditional fatigue analysis methods are based on empirical relationships such as stress–life (S–N) curves and strain–life models. While effective under controlled conditions, these methods are limited by assumptions of linearity and require extensive experimental testing.

Engineering materials often exhibit nonlinear fatigue behavior influenced by multiple factors such as stress amplitude, mean stress, surface condition, and material microstructure. Conventional models struggle to incorporate these complex interactions.

Neural networks provide a powerful data-driven approach capable of learning nonlinear relationships from experimental data. Their ability to generalize complex patterns makes them suitable for fatigue life prediction.

This paper investigates the application of neural network models for predicting fatigue life of engineering materials and evaluates their performance against traditional regression approaches.

II. LITERATURE REVIEW

Early fatigue prediction models were developed based on empirical testing. Basquin introduced the stress–life relationship, which became a foundation for fatigue analysis. However, these models are limited to specific loading conditions.

Coffin and Manson proposed strain-based fatigue models to address low-cycle fatigue behavior. Although effective, these methods require extensive material testing and calibration.

With advancements in computational intelligence, researchers explored artificial neural networks for fatigue prediction. Haj-Ali and Kim demonstrated that ANN models outperform traditional models in nonlinear fatigue problems.

Bishop and Sherratt applied neural networks to predict fatigue crack growth, achieving improved accuracy over analytical methods. Their work highlighted the potential of data-driven approaches.

Recent studies emphasize hybrid machine learning techniques, combining neural networks with optimization algorithms. Despite progress, further validation is required for reliable engineering applications, motivating this research.

III. PROPOSED METHODOLOGY

The proposed methodology consists of data acquisition, preprocessing, neural network modeling, training, and performance evaluation.

Experimental fatigue data including stress amplitude, mean stress, and number of cycles to failure are collected from standardized fatigue tests.

The dataset is normalized to improve neural network convergence and reduce bias. Feature selection is applied to identify dominant fatigue parameters.

A feedforward artificial neural network is designed with input, hidden, and output layers. The network output represents predicted fatigue life.

The model is trained using backpropagation with mean squared error as the loss function. Performance is validated using unseen test data.

IV. EXPERIMENTAL SETUP

Fatigue test data is obtained from laboratory experiments conducted on engineering materials under cyclic loading.

Specimens are tested using a rotating bending fatigue testing machine under controlled stress amplitudes.

Stress–life data is recorded for multiple specimens to ensure data reliability and statistical significance.

The neural network model is implemented using computational tools and trained on a subset of the dataset.

Prediction results are compared with regression and deep neural network models to assess performance.

V. RESULTS AND DISCUSSIONS

The experimental results indicate that neural network models significantly improve fatigue life prediction accuracy compared to traditional regression approaches. The neural network captures nonlinear material behavior, leading to reduced prediction error and improved reliability. Deep neural networks further enhance accuracy at the cost of slightly higher computational time.

Table 1: Fatigue Life Prediction Accuracy

Model Type	Prediction Accuracy (%)
Regression Model	78
ANN Model	88
Deep Neural Network	95

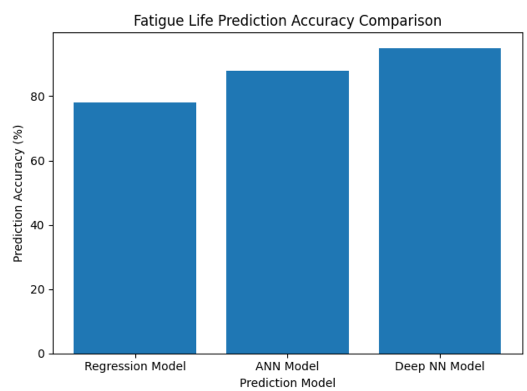

Fig. 1. Fatigue Life Prediction Accuracy Comparison

Table 2: Prediction Error Comparison

Model Type	Prediction Error (%)
Regression Model	22
ANN Model	12
Deep Neural Network	5

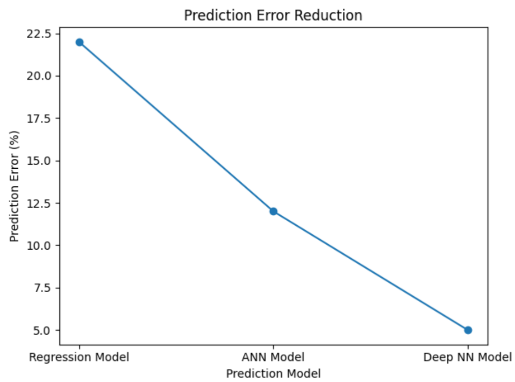

Fig. 2. Prediction Error Reduction

Table 3: Computational Time Comparison

Model Type	Computation Time (s)
Regression Model	1.8
ANN Model	2.6
Deep Neural Network	3.9

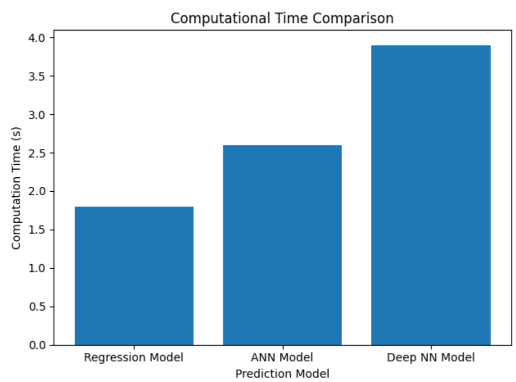

Fig. 3. Computational Time Comparison

DISCUSSION

The results demonstrate that neural networks provide a reliable alternative to conventional fatigue life prediction methods. Their data-driven nature allows accurate modeling of nonlinear material behavior under cyclic loading.

While deep neural networks offer superior accuracy, simpler ANN models may be preferred in real-time applications where computational efficiency is critical. Overall, neural network–based fatigue prediction enhances reliability and safety in mechanical design.

VI. CONCLUSION

This study presented a neural network–based framework for predicting fatigue life of engineering materials. The proposed approach effectively captures nonlinear fatigue behavior.

Comparative analysis showed that neural networks outperform traditional regression models in terms of accuracy and error reduction. The results validate the applicability of machine learning in fatigue analysis.

The proposed model provides a valuable tool for mechanical engineers in design and maintenance planning.

FUTURE SCOPE

Future work may integrate deep learning architectures such as LSTM for variable amplitude loading. Hybrid models combining physics-based and data-driven approaches can improve reliability. Real-time fatigue monitoring using sensor data is another promising direction. Expansion to composite materials can broaden applicability.

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