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Comparative Analysis of Novel Deep Belief Network over Decision Tree Algorithm for the Detection of Cracks in Large Marine Structures

[1] Tumu Mani Sai Pavan*, [2] Monish Kumaar M, [3] Mohamed Nabhan, [4] Vasa Banu Sree, [5] Darisipudi Komal

[1] [2] [3] Department of Artificial Intelligence and Machine Learning, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India
[4] Department of Computer Science and Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India
[5] Department of Artificial Intelligence and Data Science, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India
Corresponding Author Email: [1] saipavantm5011.sse@saveetha.com, [2] monishkumaarm5014.sse@saveetha.com, [3] mohamednabhanmi5009.sse@saveetha.com, [4] vasabhanusreev1029.sse@saveetha.com, [5] komald4051.sse@saveetha.com

Abstract— ***Crack detection in large marine structures, particularly submarines, is a critical task for ensuring structural integrity, operational safety, and mission reliability under harsh underwater conditions. Traditional inspection methods face limitations due to poor visibility, high pressure, and restricted accessibility, making automated image-based detection techniques increasingly important. This study presents a comparative analysis of a Novel Deep Belief Network (NDBN) and a Decision Tree (DT) algorithm for detecting surface cracks in underwater submarine structures. A publicly available surface crack image dataset was used, comprising positive and negative crack samples. Both models were trained and evaluated using identical experimental conditions to ensure fairness in comparison. Performance was assessed primarily based on classification accuracy and statistical significance. Experimental results demonstrate that the Novel Deep Belief Network significantly outperforms the Decision Tree model, achieving a mean accuracy of 99.83%, compared to 83.09% obtained by the Decision Tree. Statistical validation using an independent sample t-test confirms that the observed performance difference is statistically significant ($p < 0.05$). The findings indicate that the hierarchical feature-learning capability of deep belief networks enables more robust and accurate crack identification compared to conventional tree-based methods. This work highlights the potential of deep learning approaches for reliable underwater structural health monitoring and supports their application in enhancing the safety, maintenance, and longevity of large marine structures.***

Index Terms— ***Crack Detection, Decision Tree, Deep Belief Network, Image Classification, Marine Structures, Structural Health Monitoring.***

I. INTRODUCTION

Crack detection in large marine structures, particularly submarines, plays a vital role in ensuring structural integrity, operational safety, and long-term reliability under harsh underwater environments. Submarines are continuously exposed to extreme hydrostatic pressure, corrosive saltwater, and cyclic mechanical stresses, which can gradually weaken structural components and lead to the formation of surface or subsurface cracks. If left undetected, these defects may propagate and result in severe structural failure, posing significant risks to crew safety, mission success, and the surrounding marine environment.

Conventional inspection techniques, such as manual visual examination and diver-based assessments, are often impractical for underwater structures due to limited visibility, accessibility constraints, and safety concerns. As a result, automated image-based crack detection methods have gained increasing attention in recent years. Advances in machine learning and computer vision have enabled the development of intelligent systems capable of analyzing large volumes of inspection data with improved accuracy and consistency.

Among various machine learning approaches, Decision Tree algorithms are widely used due to their simplicity and interpretability; however, their performance can degrade when dealing with complex image features and noisy underwater data. In contrast, deep learning-based models, particularly Deep Belief Networks, offer hierarchical feature learning capabilities that allow more effective representation of complex crack patterns. Motivated by these advantages, this study presents a comparative analysis of a Novel Deep Belief Network and a Decision Tree algorithm for detecting cracks in underwater submarine structures. The objective is to evaluate their performance in terms of accuracy and statistical significance, thereby identifying a more reliable approach for marine structural health monitoring.

II. MATERIALS AND METHODS

A. Experimental Setup

The experimental work was carried out at the Machine Learning Laboratory, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India. The study focuses on a comparative evaluation of two machine learning models—Decision Tree (DT) and Novel Deep Belief Network (NDBN)—for crack detection in underwater submarine structures. A total of 40 experimental samples were considered, with 20 samples allocated to each model. Statistical power analysis was conducted using G*Power with a significance level of $\alpha = 0.05$ and statistical power of 0.80 to validate the adequacy of the sample size. Since no human or animal subjects were involved, ethical approval was not required for this study.

B. Dataset Description

The dataset used in this research was obtained from the publicly available Kaggle repository. The dataset, titled *Surface Crack Detection*, consists of approximately 40,000 images, including 20,000 crack images and 20,000 non-crack images. These images represent surface-level crack patterns suitable for training and evaluating image-based classification models. The dataset was randomly divided into training and testing sets to ensure unbiased model evaluation.

C. Software and Hardware Configuration

All experiments were implemented using the Python programming language. Model development and execution were performed on the Google Colaboratory platform, which provides access to high-performance computational resources. The hardware configuration included an NVIDIA RTX 3050 GPU with 4 GB of dedicated memory, an AMD Ryzen 7 4800H processor, and 16 GB of RAM. Statistical analysis was carried out using IBM SPSS Statistics (Version 26). Additional software tools included Windows 11 and Google Chrome.

D. Novel Deep Belief Network Model

The Novel Deep Belief Network is a deep learning architecture composed of multiple stacked layers of Restricted Boltzmann Machines, enabling hierarchical feature extraction from input images. The model employs an unsupervised pretraining phase followed by supervised fine-tuning to improve classification performance. This layered learning strategy allows the network to capture complex and abstract crack features, making it well-suited for underwater image analysis. Hyperparameters such as learning rate and number of epochs were optimized experimentally to achieve stable convergence.

E. Decision Tree Model

The Decision Tree algorithm is a supervised machine learning technique that constructs a tree-based classification structure by recursively partitioning the dataset based on feature importance. At each node, the algorithm selects the optimal split using impurity measures to maximize classification accuracy. While Decision Trees are computationally efficient and easily interpretable, their performance may be affected by overfitting and limited generalization when handling complex image data.

F. Statistical Analysis

The performance of both models was evaluated primarily using classification accuracy as the dependent variable. Independent sample t-tests were performed using IBM SPSS to determine the statistical significance of performance differences between the Novel Deep Belief Network and Decision Tree models. A significance threshold of $p < 0.05$ was used to validate the results.

III. RESULTS

The experimental results demonstrate a clear performance difference between the Novel Deep Belief Network (NDBN) and the Decision Tree (DT) model for underwater crack detection. Model performance was evaluated using classification accuracy across 20 independent experimental iterations for each algorithm.

Table I presents the accuracy values obtained by both models over 20 runs. The Novel Deep Belief Network consistently achieved higher accuracy compared to the Decision Tree across all iterations. The NDBN recorded accuracy values close to 100% in every experiment, whereas the Decision Tree showed noticeable variability and comparatively lower accuracy.

Table I. Comparison of Accuracy Between Novel Deep Belief Network and Decision Tree

S. No.	Novel Deep Belief Network (%)	Decision Tree (%)
1	99.80	82.17
2	99.80	85.67
3	99.85	83.17
4	99.70	82.50
5	99.90	79.50
6	99.90	82.83
7	99.70	81.33
8	99.90	82.00
9	99.85	84.50
10	99.90	84.53
11	99.90	83.50
12	99.90	81.17
13	99.80	83.17
14	99.70	83.67
15	99.75	82.67

S. No.	Novel Deep Belief Network (%)	Decision Tree (%)
16	99.75	84.67
17	99.95	83.50
18	99.90	84.17
19	99.90	83.67
20	99.85	83.17

Table II summarizes the group statistics for both algorithms. The Novel Deep Belief Network achieved a mean accuracy of 99.83% with a low standard deviation of 0.07964, indicating high stability and robustness. In contrast, the Decision Tree model achieved a mean accuracy of 83.09% with a higher standard deviation of 1.42647, reflecting less consistent performance.

Table II. Group Statistics of Accuracy for Novel Deep Belief Network and Decision Tree

Algorithm	N	Mean Accuracy (%)	Std. Deviation	Std. Error Mean
Novel Deep Belief Network	20	99.8350	0.07964	0.01781
Decision Tree	20	83.0930	1.42647	0.31897

To validate the statistical significance of the observed performance difference, an independent sample t-test was conducted, and the results are presented in Table III. The analysis yielded a p-value of 0.000 ($p < 0.05$), confirming that the difference in accuracy between the two models is statistically significant.

Table III. Independent Sample T-Test Results Between Novel Deep Belief Network and Decision Tree

Metric	t-value	df	sig.(2-tailed)
Accuracy	52.406	38	0.000

(95% Confidence Interval: Lower = 16.095, Upper = 17.388)

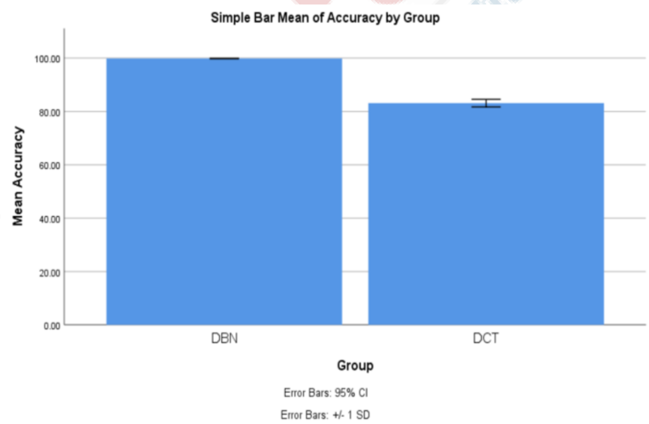

Figure 1. Mean accuracy comparison between Novel Deep Belief Network and Decision Tree

Figure 1 illustrates the mean accuracy comparison between the Novel Deep Belief Network and the Decision Tree model. The graphical representation further highlights the superior performance of the NDBN over the Decision Tree in detecting cracks in underwater submarine structures.

IV. DISCUSSION

The results obtained in this study demonstrate the effectiveness of deep learning–based approaches for underwater crack detection, particularly when compared with traditional machine learning techniques. The Novel Deep Belief Network exhibited superior performance in terms of accuracy and stability, highlighting its ability to learn complex hierarchical features from crack images. This advantage is especially relevant in underwater environments, where image data often suffer from noise, low contrast, and varying illumination conditions.

The comparatively lower performance of the Decision Tree model can be attributed to its reliance on hand-crafted feature representations and its limited capability to capture intricate spatial patterns present in crack images. While Decision Trees offer interpretability and computational efficiency, their susceptibility to overfitting and reduced generalization becomes evident when applied to high-dimensional image data. In contrast, the layered learning mechanism of the Novel Deep Belief Network enables robust feature abstraction, leading to improved classification outcomes.

The statistical analysis further reinforces these observations, as the significant difference in performance between the two models confirms that the improvement achieved by the Novel Deep Belief Network is not due to random variation. These findings align with recent trends in structural health monitoring, where deep learning models are increasingly favored for automated defect detection tasks.

Despite the promising results, this study has certain limitations. The experimental evaluation was conducted using a single publicly available dataset, which may not fully capture the diversity of real-world underwater crack scenarios. Environmental factors such as water turbidity, lighting variations, and sensor noise may influence detection performance in practical deployments. Future work should focus on validating the proposed approach using larger and more diverse datasets, as well as exploring real-time implementation and computational efficiency for operational underwater monitoring systems.

V. CONCLUSION

This study presented a comparative evaluation of a Novel Deep Belief Network and a Decision Tree algorithm for crack detection in large marine structures. The experimental results demonstrate that the Novel Deep Belief Network significantly outperforms the Decision Tree model in terms of accuracy and robustness, making it a more suitable approach for underwater crack detection applications. The hierarchical feature-learning capability of the deep belief network enables effective representation of complex crack patterns that are difficult to capture using conventional tree-based methods.

The findings of this work highlight the potential of deep learning techniques in enhancing automated structural health monitoring systems for underwater environments. By improving crack detection accuracy, such approaches can contribute to safer submarine operations, timely maintenance, and extended structural lifespan. Future research may focus on expanding the dataset, incorporating real-time monitoring scenarios, and evaluating additional deep learning architectures to further improve detection performance and practical applicability.

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Declarations:

Conflict of Interest:

The authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contributions:

Tumu Mani Sai Pavan contributed to literature review, data collection, model implementation, and manuscript preparation. Monish Kumaar M, Mohamed Nabhan, and Vasa Banu Sree assisted in data preprocessing, experimental analysis, and result validation. All authors reviewed and approved the final manuscript.

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