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ENHANCING EQUIPMENT FAILURE PREDICTION USING AI TECHNIQUE IN INDUSTRIAL PREDICTIVE MAINTENANCE

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Annotation. In terms of repair costs and production downtime, gearbox and machinery failures are expensive and frequently lead to whole plant failures. By using Artificial Neural Networks (ANN) to forecast machinery breakdowns, this study sought to reduce these losses by facilitating the application of predictive maintenance techniques. This strategy offers major operational gains by increasing machine dependability and attaining large cost savings. An ANN model that had undergone extensive training, validation, and testing procedures was used to gather and analyse sensor data. The outcomes showed a remarkable 97.3% prediction accuracy. The Mean Time Between Failures (MTBF) increased by 3,000 hours and the Mean Time to Repair (MTTR) decreased by 6.5 hours, two significant increases in key performance parameters. Predictive maintenance also resulted in 95 million Naira in cost savings. This study's use of AI approaches greatly increased the accuracy of failure prediction, enabling better predictive maintenance. This led to increased machine dependability and significant cost savings, highlighting the importance of incorporating cutting-edge AI techniques into industrial maintenance procedures.

Keywords: Artificial Neural Networks (ANN), Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), Artificial Intelligence (AI), Predictive Maintenance, Equipment, Failure, Industry, Enhance, Datasets, Confusion Matrix.

Аннотация. По затратам на ремонт и простоям производства отказы редукторов и машин дорогостоящие и часто приводят к отказу целого завода. Используя искусственные нейронные сети (ИНС) для прогнозирования отказов оборудования, в данном исследовании были предприняты попытки снизить эти потери за счет облегчения применения методов прогнозирования технического обслуживания. Эта стратегия предлагает значительные операционные выгоды за счет повышения надежности машин и достижения значительной экономии средств. Для сбора и анализа данных датчиков была использована модель ANN, которая прошла обширные процедуры обучения, валидации и тестирования. Результаты показали замечательный результат Точность прогноза 97,3%. Среднее время между отказами (MTBF) увеличилось на 3000 часов, а среднее время до ремонта (MTTR) уменьшилось на 6,5 часов, что является двумя значительными увеличениями ключевых параметров производительности. Прогнозируемое обслуживание также привело к экономии 95 миллионов Naira. Использование подходов искусственного интеллекта в этом исследовании значительно повысило точность прогнозирования неудач, что позволило лучше поддерживать прогнозы. Это привело к повышению надежности машин и значительной экономии затрат, что подчеркивает важность включения передовых технологий искусственного интеллекта в процедуры промышленного обслуживания.

Keywords: Artificial Neural Networks (ANN), Mean Time Between Failures (MTBF), Mean Time to Repair (MTTR), Artificial Intelligence (AI), Predictive Maintenance, Equipment, Failure, Industry, Enhance, Data Sets, Confusion Matrix.

Introduction

In order to minimize unexpected downtime of machinery, equipment, and processes and prevent system failures, failure prediction is a crucial part of industrial maintenance methods [1]. In order to schedule maintenance tasks in a timely manner, predictive maintenance depends on precise forecasts of future malfunctions. Failure prediction techniques examine data from the past and present that reflects system operations,

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events, and states. Machine learning (ML), which makes it possible to train a prediction model from time-series data, assess the model's performance, and implement it in a productive context, is a technology that is being utilized more and more for failure prediction [2]. Improvements in machine learning algorithms, their integration into open-source software packages, and the increased availability and quality of industrial data within the framework of big data analytics and stream processing platforms have all contributed to the growing use of machine learning technology for failure prediction [3].

Evidence suggests that ML-based failure prediction models work well for a range of systems, such as ICT gadgets, wind turbines, agricultural machinery, aircraft components, and even production facilities [4-5]. Furthermore, there is comparable evidence for forecasts made extremely close to the failure time, like a few minutes, as well as predictions made far away, like several weeks. This diversity in the prediction job corresponds with a broad range of machine learning approaches that academics and practitioners can select from when creating a particular prediction model. The methods deal with the underlying machine learning algorithms, the conversion of operational data into features, the training of prediction models using historical data, and the evaluation of the models' performance.

Understanding machine learning techniques and how they affect prediction performance is essential to developing successful prediction models. Nevertheless, the growing body of evidence from earlier studies is poorly documented. Failure prediction has not been the subject of a review, despite the fact that the application of ML technology for predictive maintenance has been evaluated multiple times [6]. One set of reviews looked at methods for a wide range of industrial maintenance duties. Failure detection (did a failure occur?), failure diagnosis (why did the failure occur?), condition monitoring (what is the current condition?), failure prediction, and forecast of other variables, such deterioration and remaining useful life, were among the duties. For example, just three of the thirty-three research in a review by Zhang et al. looked at failure prediction [7]. Failure prediction and detection were examined in a review by Stetco et al [8]. However, it is not possible to compare and integrate research findings for one task with those for another [9]. As a result, the failure prediction task was left out of another set of reviews that concentrated on the failure diagnostic job.

When taken as a whole, the knowledge gleaned from existing evaluations is insufficient to guide the creation of ML-based failure prediction models and assess their effectiveness. By concentrating on the failure prediction task and carrying out a task-specific systematic review, this study fills this significant gap in the literature. Therefore, the goals of this study are to evaluate the use of machine learning technology in earlier studies looking at failure prediction in industrial maintenance and to summarize the published findings to recommend directions for further investigation.

Materials and Method

Study Area

This section outlines the research methodology employed in the study on the enhancement of equipment failure prediction using AI techniques in industrial predictive maintenance. It describes the research problem, data collection methods, data pre-processing, Artificial Neural Network model development, Artificial Neural Network Model Training and testing

Algorithm of the System

Problem Definition

This is the first stage in which the precise issue that has to be resolved with the ANN model is specified. It entails comprehending the project's objectives, limitations, and specifications. The issue may have to do with classification, pattern recognition, prediction, etc.

Data Collection

Predictive maintenance is based on data, and in order to create reliable models, it is essential to gather and pre-process the appropriate data. The following steps are included in the data collection process:

Sources of Data: In an industrial context, sensors, equipment logs, and maintenance records will be used to gather historical equipment data. Variables pertaining to operating parameters, maintenance operations, and equipment condition will be included in the data. Gearbox state, temperature, vibration, and alignment.

After Data Processing (Cleaning):

the data is gathered, it must be processed and cleaned to get rid of any errors, noise, or inconsistencies. In this step, missing values are handled, data is normalized, and raw data is transformed into an analysis-ready format.

ANN Model Development (MATLAB):

In this case, MATLAB is used to create the ANN model. Choosing the right kind of neural network, specifying the network design (number of layers, neurons per layer, activation functions), and establishing the initial parameters are all part of this process.

ANN Model Training

The ANN model is trained using the processed data. By modifying weights and biases throughout training, the model gains the ability to identify patterns and relationships in the data. In order to reduce the error between expected and actual results, this iterative step uses strategies like backpropagation.

ANN Model Testing:

A different dataset that was not utilized for training is used to test the model after it has been trained. The model's performance and capacity to generalize to fresh, untested data are assessed in this step. The model is evaluated using performance metrics like accuracy, precision, recall, and mean squared error.

ANN Model Evaluation

The trained model is carefully assessed in this step to make sure it satisfies the required performance standards. This entails evaluating the testing phase's outcomes and, if required, making additional model adjustments.

Results Presenting the outcomes of the model evaluation is the last stage. Reporting on performance metrics, model prediction versus actual outcome visualizations, and any analysis-derived insights or conclusions are all included in this. The outcomes aid in future model refinement or data-driven decision making. Each block denotes a critical stage in the creation and implementation of an ANN model, guaranteeing a methodical approach to using neural networks to solve challenging issues. Assurance of Data Quality: Missing values will be imputed when the data has been cleansed. To guarantee the quality of the data, anomalies and outliers will be found and dealt with. Data Integration: To create a complete dataset for model building, pertinent data from various sources will be combined.

Ethical Considerations The privacy and confidentiality of industrial data will be protected by this study's adherence to ethical standards and norms. The industrial setting's cooperation and consent will be sought, and any sensitive data will be safeguarded and anonymised to safeguard proprietary information. The algorithm is summarized in Figure 1's flowchart.

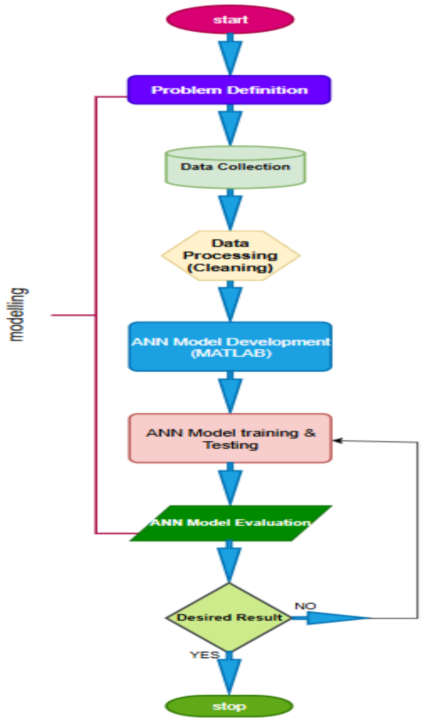
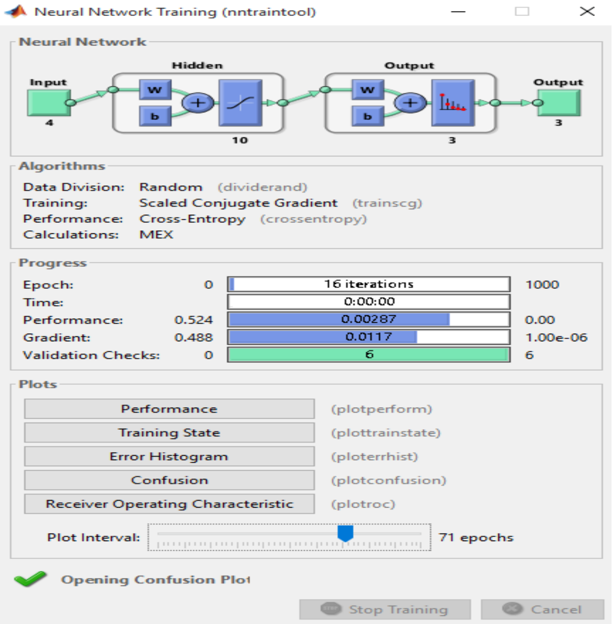


Fig 1. Flowchart of the system.

Results and Discussion. The research findings are arranged according to how well the created AI models forecast equipment failures and what it means for industrial predictive maintenance. Three types of samples are used: 10% for testing, 25% for validation, and 65% for training. Figure 2 illustrates how the training set is given to the network during training, and the network is modified based on its mistake. Network generalization is measured using validation sets, and training is stopped when generalization ceases to improve. Testing sets offer an impartial assessment of network performance both during and after training because they have no influence on training.

Implementation of the NN Model

The model is implemented in MATLAB as evident in figure 2:



Data Division: Random (dividerand)
Training: Scaled Conjugate Gradient (trainscg)
Performance: Cross-Entropy (crossentropy)
Calculations: MEX

Epoch:	0	16 iterations	1000
Time:		0:00:00	
Performance:	0.524	0.00287	0.00
Gradient:	0.488	0.0117	1.00e-06
Validation Checks:	0	6	6

(plotperform)
(plottrainstate)
(ploterrhist)
(plotconfusion)
(plotroc)

Plot Interval: 71 epochs

Opening Confusion Plot

Fig 2. Neural network training interface.

Figure 3 represents the performance of the ANN model during training, validation, and testing phases across multiple epochs.

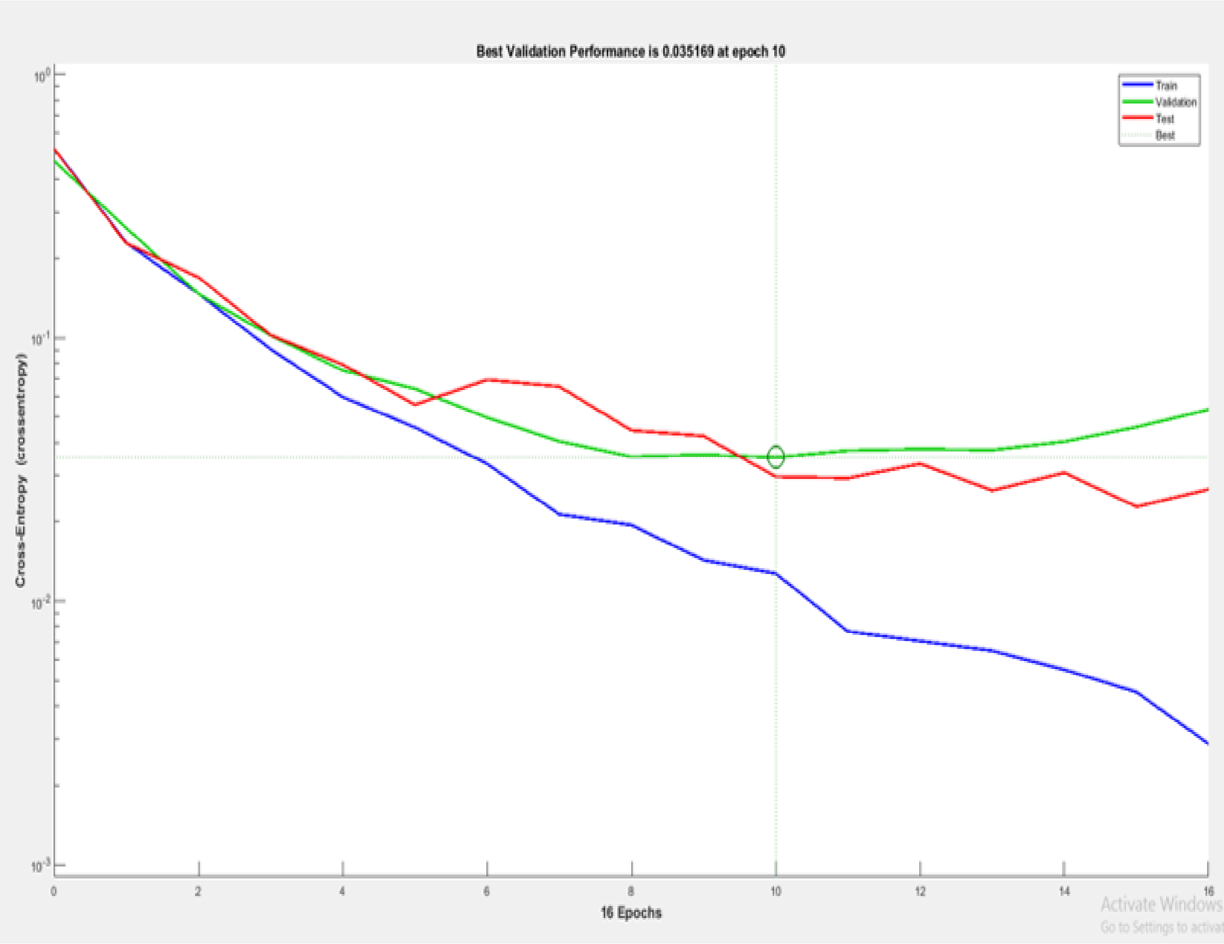
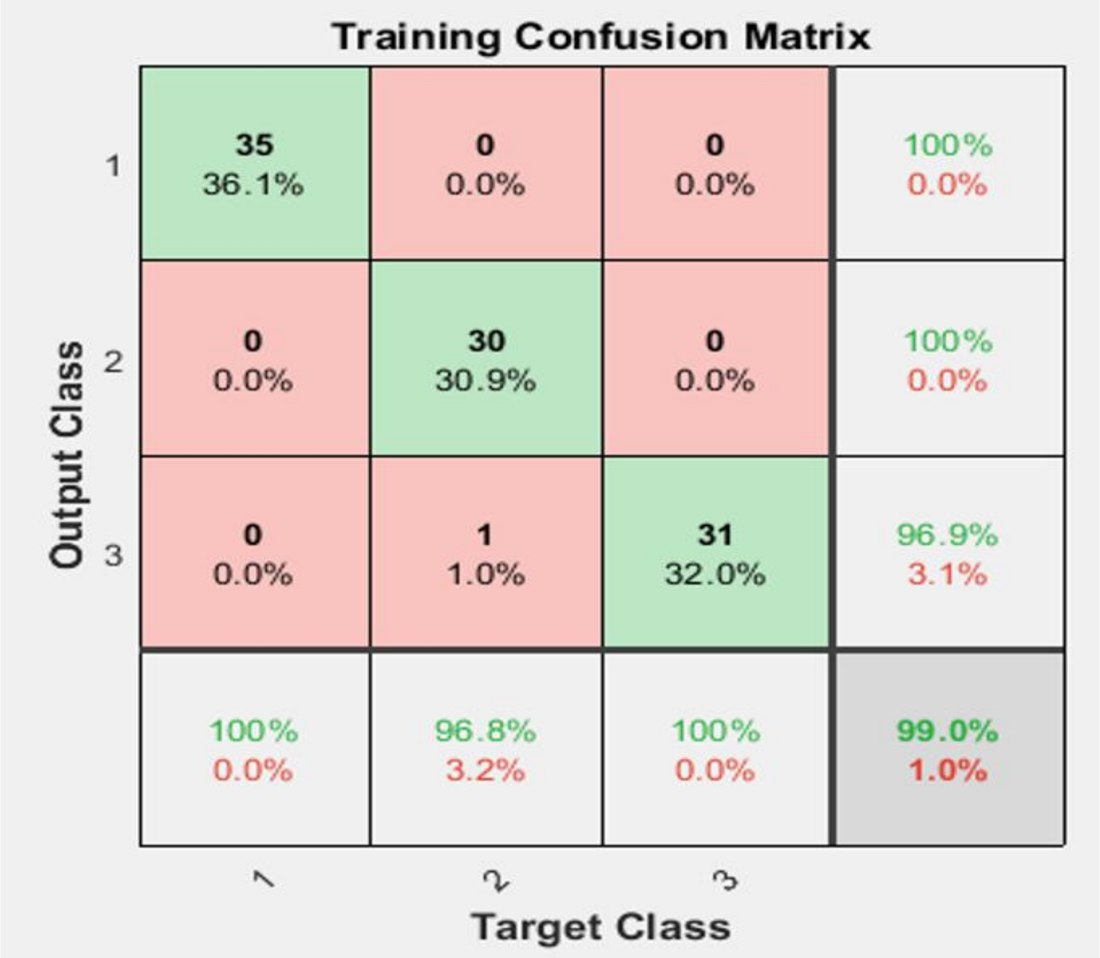


Fig 3. Training, validation and testing plot.

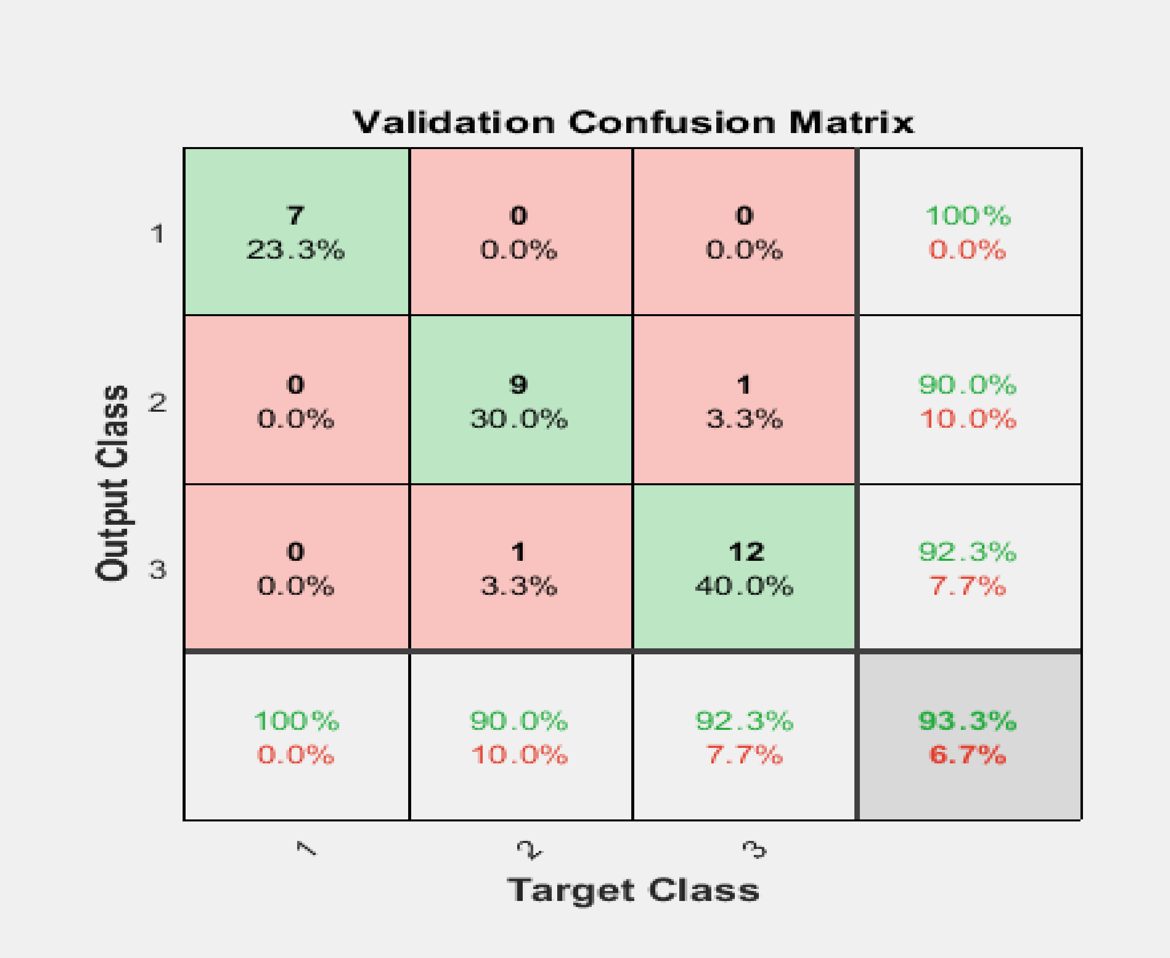
Here's an explanation of the elements in the figure 3:
Plotting cross-entropy loss against the number of training epochs, the diagram shows how a learning model behaves. The horizontal axis shows the epochs, each of which corresponds to a full pass through the training dataset, while the vertical axis shows the cross-entropy loss, which measures the difference between the predicted outputs and the true labels. Lower values indicate better model performance. There are three curves displayed: The green curve shows the validation loss, which is used to evaluate performance on unseen validation data and track overfitting; the blue curve shows the training loss, which gradually reduces over time, suggesting that the model is gradually learning patterns from the training data;
The graph highlights the point of optimal validation performance at epoch 10, which has the lowest validation loss of 0.035169. This optimum is indicated by a dotted reference line. Effective learning is first demonstrated by both the training and validation losses decreasing; however, after epoch 10, the training loss keeps down while the validation and test losses stable and slightly increase. The beginning of overfitting, in which the model becomes overly specialized to the training data at the price of generalization, is indicated by this divergence. Overall, the figure gives a clear picture of the training dynamics and shows that epoch 10 is the best place to stop in order to strike a compromise between generalization performance and learning accuracy.



Output Class \ Target Class	1	2	3	
1	35 36.1%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	30 30.9%	0 0.0%	100% 0.0%
3	0 0.0%	1 1.0%	31 32.0%	96.9% 3.1%
	100% 0.0%	96.8% 3.2%	100% 0.0%	99.0% 1.0%

Fig 4. Training confusion matrix.

A confusion matrix is a tool used to evaluate the performance of a classification model by comparing the predicted labels with the actual labels. Here's a detailed explanation of the confusion matrix of figure 4 above. Components of the system description is below.
Class 1 is Grey-box
Class 2 is Motor
Class 3 is Coupling
With rows denoting the model's outputs and columns denoting the real labels, Figure 4's confusion matrix clearly summarizes the model's classification performance by contrasting predicted classes with the actual target classes. Class 1, Class 2, and Class 3 record 35 (36.1%), 30 (30.9%), and 31 (32.0%) correctly identified occurrences, respectively. The majority of the entries lay along the diagonal, emphasizing valid predictions across all three classes. There are very few off-diagonal entries, which show misclassifications; only one case of class 2 was mistakenly forecasted as class 3, making only around 1% of the total.
The model's excellent performance is further shown by the marginal totals: class 1 and class 2 achieve 100% classification accuracy, while class 3 achieves 96.9% accuracy with a negligible error rate of 3.1%. In a similar vein, the prediction-wise accuracy reveals that almost every predicted label is accurate, with very little uncertainty between classes 2 and 3. Overall, the model provides high accuracy and dependable class discrimination, as evidenced by the dominance of diagonal values and the extremely small off-diagonal errors.



Validation Confusion Matrix

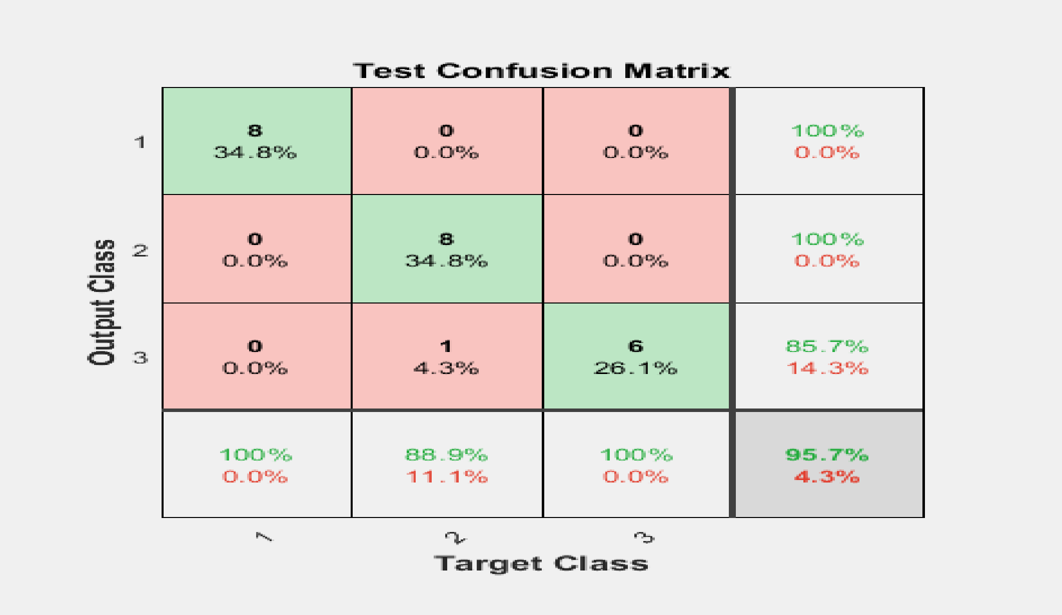
Output Class \ Target Class	1	2	3	
1	7 23.3%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	9 30.0%	1 3.3%	90.0% 10.0%
3	0 0.0%	1 3.3%	12 40.0%	92.3% 7.7%
	100% 0.0%	90.0% 10.0%	92.3% 7.7%	93.3% 6.7%

Fig 5. Validation model confusion matrix.

Figure 5's confusion matrix shows a high degree of classification accuracy throughout the three classes, with the majority of predictions falling along the diagonal. For class 1, there are seven (23.3%) correct predictions, nine (30.0%) for class 2, and twelve (40.0%) for class 3. There are just two instances of misclassifications, each accounting for 3.3% of the total: one sample from class 2 is mistakenly forecasted as class 3, and one sample from class 3 is mistakenly projected as class 2. Class 1 achieves 100% classification, while classes 2 and 3 achieve accuracies of 90.0% and 92.3%, respectively, with tiny error rates due to mutual confusion. This performance is further reflected in the class-wise accuracy.

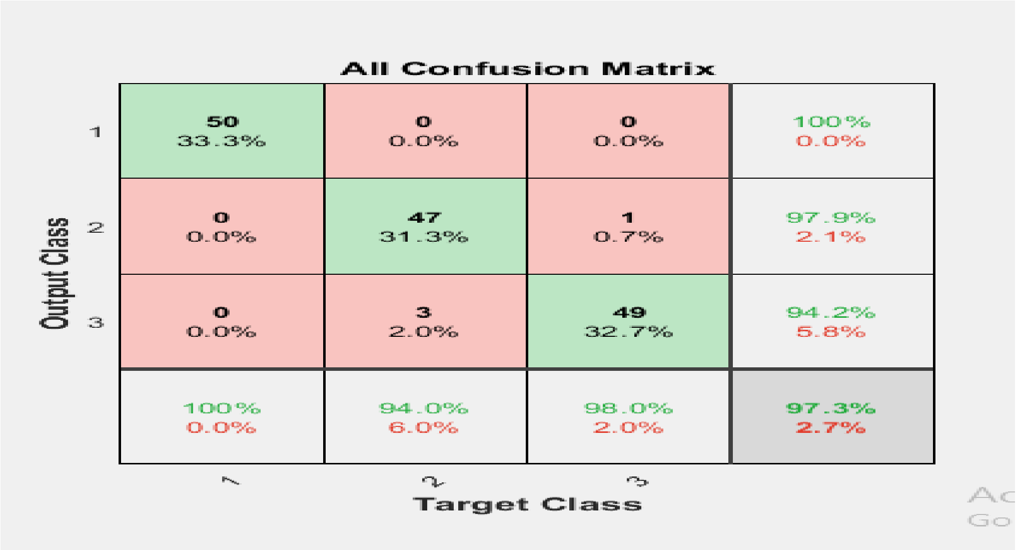
The strong diagonal entries in Figure 6's confusion matrix indicate that most samples are correctly identified. In particular, eight cases (34.8%) are correctly classified as class 1, eight more cases (34.8%) as class 2, and six cases (26.1%) as class 3. There is very little misclassification, just one instance of a class 3 sample being mistakenly classified as class 2, making up 4.3% of the total, while all other off-diagonal entries are zero. The model's efficacy is further supported by the class-wise performance, where classes 1 and 2 attain 100% accuracy but class 3 records a little lower accuracy of 85.7% as a result of this small confusion.

With very little overlap between classes 2 and 3, the data show good classification performance overall. While Tables 1, 2, 3, 4, and 5 show the Distribution of Equipment Reliability Matrix, Maintenance Cost Comparison, Maintenance Cost Breakdown, Percentage of Total Maintenance Cost & Time, and Cost Savings with AI Predictive Maintenance, respectively, Figure 7 displays the all-confusion matrix combining the training, testing, and validation.



1	8 34.8%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	8 34.8%	0 0.0%	100% 0.0%
3	0 0.0%	1 4.3%	6 26.1%	85.7% 14.3%
	100% 0.0%	88.9% 11.1%	100% 0.0%	95.7% 4.3%
	1	2	3	

Fig 6. Testing confusion matrix.



1	50 33.3%	0 0.0%	0 0.0%	100% 0.0%
2	0 0.0%	47 31.3%	1 0.7%	97.9% 2.1%
3	0 0.0%	3 2.0%	49 32.7%	94.2% 5.8%
	100% 0.0%	94.0% 6.0%	98.0% 2.0%	97.3% 2.7%
	1	2	3	

Fig 7. All confusion matrix.

Table 1.

Distribution of equipment reliability matrix

Equipment Type	MBTF Before (Hrs)	MBTF After (Hrs)	MTTR Before (Hrs)	MTTR After (Hrs)
A	480	1200	4	2
B	520	1600	6	3.5
C	600	1800	5	3

Table 2.

Maintenance cost comparison

Maintenance Strategy	Total Cost (#)
AI-Based Predictive	40,000
Reactive	75,000
Preventive	60,000

Table 3.

Maintenance cost breakdown

Equipment Type	AI-Based Predictive Maintenance (#)	Reactive Maintenance (#)	Preventive Maintenance (#)
A	15,000	20,000	18,000
B	10,000	18,000	14,000
C	25,000	37,000	30,000

Table 4.

Percentage of total maintenance cost

Maintenance Type	Percentage of Total Maintenance cost
AI-Based Predictive Maintenance (%)	22.85
Reactive Maintenance (%)	42.86
Preventive Maintenance (%)	34.29

Table 5.

Time and Cost Savings with AI Predictive Maintenance

Parameter	AI-Based Predictive Maintenance (#)	Traditional Maintenance (Reactive & Preventive)	Savings
Time (hours)	1320	1800	480
Cost (#)	40,000	135,000	95,000

The study's findings point to significant advantages for industrial predictive maintenance procedures. Early detection of possible equipment breakdowns through the use of AI-based models helps lower unplanned downtime and related maintenance expenses. These models' predictive power also facilitates better maintenance planning, enabling businesses to plan interventions ahead of time and distribute resources more effectively. Because there is a far lower chance of unexpected malfunctions, equipment dependability and operational lifespan are enhanced. Additionally, by reducing maintenance costs and averting production losses, preventing significant failures adds to overall cost savings. When taken as a whole, these benefits allow industries to take a more data-driven approach to maintenance management, which improves operational effectiveness and facilitates well-informed decision-making.

Conclusion

This study unequivocally shows that artificial intelligence, specifically, Artificial Neural Networks, offers a potent and useful option for predictive maintenance in industrial settings. The suggested AI-driven framework greatly increases the capacity to predict equipment problems before they happen by utilizing high-quality sensor data and ongoing monitoring, which enhances operational reliability and lowers maintenance costs. With a failure prediction accuracy of 97.3%, a significant improvement in Mean Time Between Failures of about 3,000 hours, and a decrease in Mean Time to Repair of 6.5 hours, the ANN model's results are impressive.

When compared to traditional reactive and preventative strategies, these performance advantages translated into significant economic benefits, resulting in maintenance cost reductions of over 95 million Naira. This clearly shows the financial viability of AI-based predictive maintenance. Additionally, improvements in equipment-specific metrics and the Equipment Reliability Index attest to the fact that implementing AI techniques significantly increases equipment lifespan and reduces unscheduled downtime, especially in critical systems like gearboxes and industrial machinery. All things considered, this study broadens our understanding of industrial predictive maintenance and offers compelling proof that using AI-based techniques can make maintenance procedures more effective, dependable, and economical. Additionally, it establishes a strong basis for further study and broader industrial use of intelligent maintenance systems.

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