Quest Journals
Journal of Research in Mechanical Engineering
Volume 12 ~ Issue 3 (May. – June. 2026) pp: 01-09
ISSN(Online):2321-8185
www.questjournals.org

Research Paper

ANN Technique Modelling of Machines Replacement in Industry

[1] F. E. Edet, [2] C.M.Orazulume, *[3] W. A. Akpan, [4] E.J. Awaka-Ama, [5] V. A. Amba
[1] *Department of Mechanical Engineering, University of Uyo, Akwa Ibom State, Nigeria*
[2] *Department of Electrical and Electronics Engineering, Faculty of Engineering, TopFaith University Mkpatak, Akwa Ibom State, Nigeria.*
[3] *Department of Mechanical Engineering, School of Engineering and Engineering Technology, Federal University of Technology, Ikot Abasi, Nigeria*
[4] *Department of Mechanical Engineering of Mechanical Engineering, Faculty of Engineering University of Uyo, Akwa Ibom State, Nigeria.*
[5] *Department of Mechanical Engineering of Mechanical Engineering, Faculty of Engineering University of Uyo, Akwa Ibom State, Nigeria*
**Corresponding author*

Abstract

Companies whether big or small are increasing faced with the problem of equipment. It becomes more tasking and challenging with large companies facing competitions in the global where survival and returns on investment are crucial.Traditional methods of equipment replacement can no longer be relied upon in this technological age. ArtificialIntelligence is the way forward. Artificial Neural Network (ANN) has been developed in this research to demonstrate its effectiveness.Five years of cost data was collected using eMaint computerized maintenance management system. for 100 machines. A replacement point was established using the ANN model. This indicates that the model is a promising for predicting machine replacement.ANN is therefore viable and highly recommended.

Keywords: Modelling, ANN, optimum replacement, inflation, salvage value.

*Received 02 May., 2026; **R**evised 10 May., 2026; **A**ccepted 12 May., 2026 © The author(s) 2026.*
P**ublished with open access at **www.questjournals.org

I. Introduction

As equipment age, they deteriorate and most likely to break down, leading to high operating and maintenance (O and M) costs and declining salvage values.This will lead lower production rates and anserious economic impact. [**1**] determined the optimum machine replacement schedule.

Traditional method of machine failure prediction is difficult to apply in complex technical systems [**2**]. Newer assets that are more efficient and better in retaining their value may exist in the marketplace and could provide a better choice.

Therefore, public and private companies that maintain specialized or general equipment must periodically decide when to replace equipment parts of their machines. These equipment replacement decisions are usually based upon a desire to minimize [3].[4] used net present value to support decisions.[5] used optimization model for equipment problem**s.**

ANNs learn the relation between inputs and outputs of the system through an iterative process called training. Neural networks are trained for input data and the output is computed. The error obtained by comparing outputs with a desired response is used to modify the weights with a specific training algorithm. The potential of ANN in problems solving have been presentedby [6],[7],[8], and [9] respectively.

The objective of thisresearch is to present a machinery replacement model using ANN. The model has three inputs; the increased purchaseprice (IPP (%)), decreased operating cost (DOC (%)) and decreased maintenance cost (DMC (%)).The model followed several steps to facilitate its development. The core of this neural network prediction will rely on the ability to establish salvage (resale) valueand replacement decisions module.

The use of Artificial neural network in model development owes largely to its ability to handle the complexities of non-linear relationships between variables, with large datasets. The non-linearity exists dues variance of the combination of the factors such as equipment wear and tear, usage pattern, market fluctuation, which altogether makes it a multifaceted relationship. The methodology is shown in Figure 1.

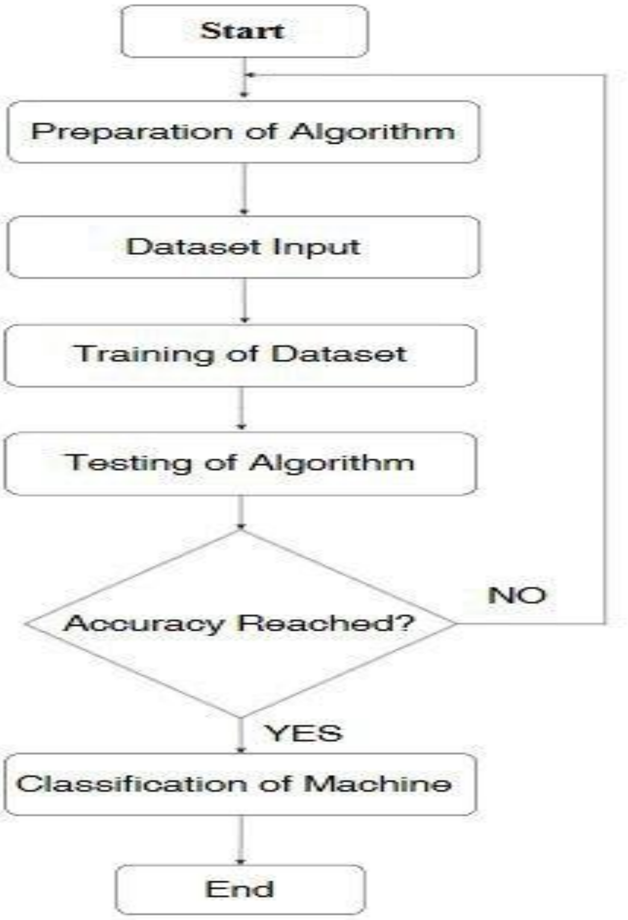

Figure 1: **Flowchart showing Methodology**.

Furthermore, dataset training as apre-processing of dataset, which is a process of reshaping the dataset to a usable form after bykeras library was imported and the dataset trained using the imported library, tensor flow, the dataset and the algorithm. The research thereafter developed a model to enable the dataset to be trained. The model developed was thereafter validated and tested with different dataset in other to determine the efficiency of the model. The research also obtained other metric values which were, Fi-Score, Recall, Precision, Training and validation accuracy, training and validation losses which helped in giving a broader understanding of the efficiency of the model developed.

Data Collection and Preparation

Five years of cost data was collected using eMaint computerized maintenance management system. The eMaint CMMS database contains information about the operational condition of the case plant such as, Type scenario and Normal. Since manufacturing is not a continuous process, the operating cost can be estimated by considering the utilisation of the machine. The model's input parameters includedMachinery ID, Age, Repair Time in hours, Repair Frequency, Corrective Spare Part Cost, Corrective Labor Cost, Preventive Spare Part Cost, Preventive Labor Cost, and Replacement Decision. The corrective and preventive maintenance costs were calculated as real costs. The dataset once obtained was evaluated with MS Excel and rows with NaN values were removed.

Data Normalization

In order to achieve analysis and improve the efficiency of network training, was correctly processed (Oreta, 2004). Pre-processing data by scaling improves the training of the neural network. However, new input data was scaled before being presented to the network and the corresponding predicted values was un-scaled before use. The linear scaling equation is expressed in Equation 1[10]**.**

$X_s = \left(\frac{0.8}{\Delta}\right) X + (0.9 - \left(\frac{0.8X_{max}}{\Delta}\right)$ Equation 1

where X_s represents the scaled value of input variables and X represents the un-scaled value of input variables. The input variables are IPP, DOC and DMC. Equation (3.1) is used here for an IPP, DOC and DMC between minimum increasing or decreasing percentage 1% (X_{min}) and maximum increasing or decreasing percentage 50% (X_{max}), such that, Equation 2 is evolved.

$\Delta = X_{max} - X_{min}$ Equation 2

The data stored in the machinery fault database is acquired with the help of sensory equipment attached to the machine fault simulator as shown in Figure 2.

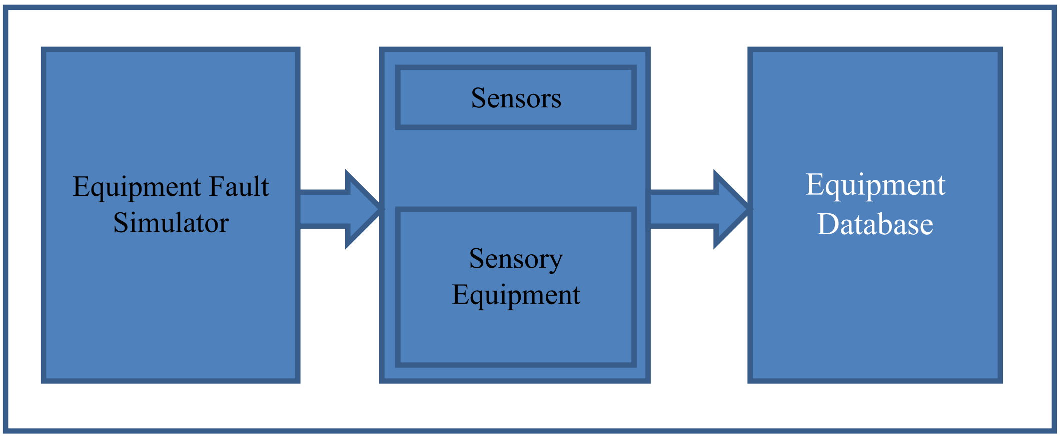

Figure 2: Equipment data acquisition

This procedure is performed using training data set until a convergence criterion is met. Neuralnetworks have different learning algorithms for training. The trainingperformance is evaluated using the following performance measures, namely the Mean SquareError (MSE) average sum of square errors and Correlation Coefficient (R**),** given by Equation 3 and Equation 4 respectively:

$MSE = \sum_{j=10}^{p} \sum_{i=0}^{N} \left(d_{ij} - y_{ij}\right)^2$ Equation 3

$R = \frac{\frac{\Sigma(x_i - x_{mean})\,(d_i - d_{mean})}{NP}}{\left[\left(\frac{\Sigma(d_i - d_{mean})^2}{N}\right)\left(\frac{\Sigma(x_i - x_{nean})^2}{N}\right)\right]^{0.5}}$ Equation 4

where P is number of output processing elements; N is number of exemplars in the data set; yijis network output for exemplars i at processing element j; and dijis desired output for exemplars i at processing element j.

A normalization model where a value (p) of the data having the minimum value (p min) and maximum value (p max) is converted into a normalized value (pn). The normalized values lie between -1 and +1.

$pn = \frac{2(p - pmin)}{P_{max} - P_{min}} - 1$ Equation 5.

Model Formulation and Calculation of ANN Input

The term 'total cost value' is defined asthe summation of the machine purchase price (PP), operating cost (OC), maintenance cost (MC)and resale value S (t) over a long period, with replacements occurring at intervals of n periods.

Therefore,C_m, C_{cm}*and* $P_m$are given in Equations 6.7 8. 9 and 10 respectively.

$C_m = C_{cm} + P_m$ Equation 6

$C_{cm} = SP_c + LCc$ Equation 7

$P_m = SP_p + LC_p$ Equation 8

where Cm is the maintenance cost, C_{cm} is the corrective maintenance cost, Pm is the preventivemaintenance cost, $SP_c$is the spare part cost for corrective maintenance, $LC_c$is the labour cost for corrective maintenance, SP_p is the spare partcost for preventive maintenance and LC_p is the labour cost for preventive maintenance.
The resale value is calculated in Equation 3.7;

$$S(t) = PP * a * (1 - Dr)^t \; t = 1, 2, 3, 4, 5, 6, \ldots, 60 \; (month) \qquad \text{Equation 9}$$

where a is the percentage that is multiplied by the machine purchase price to give the value of themachine on the first day of use. The rate of depreciation is given in Equation 10

$$D_r = 1 - \left(\frac{SV}{BV_1}\right)^{\frac{1}{L}} \qquad \text{Equation 10}$$

where; D_r is the rate of depreciation,, V is the salvage value
The total cost value of the machine is calculated from Equation 11

$$TC_{value} = [\{PP + [\textstyle\sum_{K=1}^{RT} MC_k + OC_k] - S(t)\} X N] \qquad \text{Equation 11}$$

where;
PP is the purchased price, RT is the replacement time
MC_k is the maintenance cost at k value, OC_k is the operating cost at k value
S(t) is the resale value; N is the number of machine replacements as shown in Equation 12

$$N = \frac{T}{RT} \qquad \text{Equation 12}$$

where T is the optimisation time horizon
Eight neurons and six layers were used. Weight initialization, forward propagation, backpropagation, and gradient descent were used during training and validation. Epoh of the model andefficiency of the model were evaluated to minimize error and calculate the effeciency.-usingF1 score, Recall and Precision value

Data Partitioning

After preparing the data, the general practice is to first divide the data into three sets; training set, which is used for computing the gradient and updating the network weights and biases. The validation set which is used to ensure generalization of the developed network during the training phase and finally the test set which is used to examine the final performance of the network. This research had partitioned the dataset into 80% for training set, 10% for validation set and the remaining 10% of the data for test. This enabled different set of data to be used during training, validation and testing so as to ensure that proper evaluation of the performance of the model during validation and testing phases.

Network Development

The ANN architecture was carefully designed to handle the binary classification task. The input layerconsisted of nodes corresponding to each input parameter, where the number of input nodes matched the number of input features present in the dataset. To capture intricate patterns and relationships in the data, two hidden layers were added between the input and output layers. The specific number of hidden layers and the number of nodes in each layer was determined through experimentation and optimization to find the most suitable configuration.

For effective learning and representation of nonlinear decision boundaries, the chosen activation function for the hidden layers was the sigmoid function. The sigmoid functionintroduced non-linearity to the model, enabling it to approximate complex mappings between the input features and the target variable. The output layer had a single node representing the binary decision for machine tool replacement: 1 (Replacement needed) or 0 (Replacement not needed). This presents a robust model where evaluation of machine parameters and subsequent replacement of machine are done without human inference, which further ensures that human errors are eradicated.

Network Training

The training process utilized the binary entropy loss function, which is well-suited for binary classification tasks. The loss function measured the discrepancy between the predicted probabilities and the actual target labels, guiding the model to make more accurate predictions.

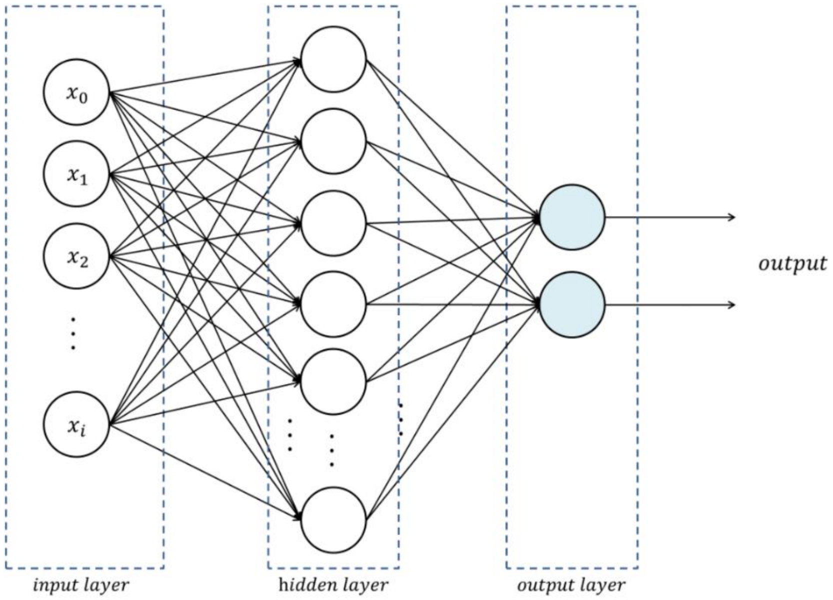

Figure 3: A Binary Classification Model of the MRP (Developed by the researcher using[11]

In Figure 3, eight neurons and six layers were used. During training, various crucial processes took place, such as weight initialization, forward propagation, backpropagation, and gradient descent. Weight initialization involves setting the initial weights of the connections between nodes randomly, which influences the convergence of the training process. Forward propagation occurs when the input data flows through the network, and predictions are generated based on the learned weights. Backpropagation, in conjunction with gradient descent, is used to calculate the gradients of the loss function with respect to the model's weights and update the weights to minimize the loss, progressively improving the model's performance.

Training Algorithm

The back-propagation algorithm has proven very good and has been used extensively in neural network applications in literature. It is a gradient based optimization procedure in which the network learns a predefined set of input-output sample pairs by using a two-phase propagate-adapt cycle. After the input data were provided as stimulus to the first layer of network unit, it was propagated through each upper layer until an output was generated. See appendix I for the algorithm.The algorithm offers a learning platform where weights and biases of interconnected neurons are adjusted to map the input and output parameters. The process, being like human brain, employed back-propagation. This ensured errors were reduced to the barest minimum.

However, the following processes took place during the learning process:

(i) Backpropagation: This offers a platform where the neural network performs iterative adjustment of the internal parameters of the hidden layer to ensure that the difference between the predicted and the actual values are reduced to the barest minimum. The errors recorded in the system between the predicted outcome and the actual outcome were also evaluated.

(ii) Weight Adjustment: This is a process of modification of the strength of connections between the learnable neurons during training. Input variables are multiplied by specific weight which forms the input for hidden layers. The summation of the weighted inputs is then done in the neurons. However, biases are activated, which scales up weighted sums that are zero to meet system’s response. These biases have weight and input which are equal to 1. A threshold value is therefore set to limit the results obtained in the previous layer to a desired value. The activation function is thereafter set to transfer function so as to obtain the desired output. Weight adjustment is a mechanism designed to correct the differences that had occurred during backpropagation. This was done by ensuring that every input layer is properly mapped to the output parameters. This mechanism helped in ensuring that the parameters were optimize to yield optimal solution.

(iii) Gradient Descent: This method helped in finding the best set of parameters for the model through minimization of cost functions, representing the error inherent in the predicted and the actual values.

(iv) Iterative Process: The iteration process involved continuously feeding the dataset through the network, which enables the model to calculate errors and constantly adjust weights until the desired accuracy is reached.

Stopping Criteria

The Back-propagation algorithm is a first order approximation of the steepest-descent technique in the sense that it depends on the gradient of the instantaneous error surface in weight space[12].

Network Training

Training of dataset refers to the process of training a model with the training set. It involves a continuous process where the parameters of the network are continuously being adjusted until inputs are properly mapped to their outputs accurately. However, this followed an iterative process where the training set were subjected to repeated iterative training until the desired accuracy was reached.

However, accuracy and losses recorded during each Epoch was also found, which tracks the progress of the model during training. This shows how well a model performed during the learning period – how well the patterns and features in the input data were learnt during training. However, a high value of training accuracy means that the model had learnt the features in the training set well but cannot represent the assumption that the model will do well in unseen data. However, while a high value of accuracy means that the model is fitting the training data well, a low training accuracy means that the model performed poorly during the training process.

Similarly, training losses are metric values which represents errors or discrepancies the output obtained during training and the ground truth. However, a decreasing loss means improved ability of the model in learning from the training data while an increasing training loss means that the model was unable to learn the features on the training set. Increasing losses values can be remedied by continuously adjusting the weights and biases of the systems until the required accuracy is reached.

Network Validation

Validating a model is simply exposing a model to validation data that was not involved in its training. The model's performance was thoroughly evaluated and fine-tuned to ensure its effectiveness and applicability in practical scenarios.

The ultimate goal of this binary classification ANN was to develop a reliable and accurate predictive model for machine tool replacement decisions. By leveraging real cost data, the model assists decision-makers in making informed choices regarding machine tool maintenance and replacement, optimizing operational efficiency, and reducing downtime. Validation network enables appraisals to be done on the training process and identify cases of overfitting where remedial measures could be taken to ensure that the training yields the desired parameters and results. The results obtained during validation enabled the performance of the model to be evaluated on unseen data, which assesses how well the neurons had learnt the featured of the dataset presented before it during the training process.

However, the validation accuracy was obtained by dividing the number of correct predictions by the total number of predictions made. Validation accuracy was represented as probability of obtaining correct prediction which is measured against a scale of 1 and as a percentage.

Validation loss is also an important metric value that appraises the errors inherent in the model. Validation losses were calculated in each Epoch to evaluate the performance of the system. Simply put, validation losses measure how well a model generalizes on unseen data. It is evaluated on dataset which is different from the one used during training, and it identifies the portion of the training where the model performs well in training but poorly during validation.

Epoch of the Model

Epochs are typically the repetitive process of training and validating a model during the training and validation phases of the model. However, the training and validation phases in artificial intelligence are done in a repetitive manner so as to allow the learnable neurons to learn the features of the dataset, where the process gets to an end when the desired accuracy is reached. This repetitive process, called Epoch enables the parameters of the model to be repeatedly adjusted each time the training or validation takes place until the desired output is obtained. In this study, the model had 100 Epochs, which indicates that the training and validation process was done repeatedly for 100 times. This helped in minimisation of error, in ensuring optimum yield of the output was attained.

Model Efficiency

The efficiency of the model was measured in terms of training and validation accuracy, training and validation losses, test accuracy, F1-Score, Precision and Recall, which altogether gave a clearer understanding of how well the model performed during training, validation and testing phases. However, aside from the accuracy and loss values, the model had also found the F1-Score, Recall and Precision value. The deductions from these metric values are thus:

(i) Precision: This evaluates how accurate the model was at making positive predictions. A high precision values are indicative of the ability of the model to avoid false positive predictions. Simply put, precision is the ratio of correct positive predictions to the total predicted positives – proportion of positive predictions that were actually positive. It is evaluated as True Positive divided by (true positive plus false positive)

(ii) Recall: This metric measures how well a model can identify all relevant positive instances in a dataset. It is a ratio of true positive correctly identified to the total number of actual positive instances in the dataset.

Actual positive in this case are a combination of the true positives and the false negative that was incorrectly classified as negative. Recall is therefore calculated as TP ÷ (TP + FN). Where TP means true positive and FN means false negative. A higher recall value indicates that the model was able to find actual positive instances, regardless of the errors in classification.

(iii) F1-Score: F1-Score represents the harmonic mean of recall and precision, which balances both metrics. F1-Score is a single metric that evaluates the performance of the model, which would provide a balance between how well a model predicts and how well it recalls true positive cases. F1 = 2(product of precision and recall) ÷ (sum of precision and recall). A high F1-Score signifies that the model has a good balance between precision and recall, which means it was able to identify true positive scenarios and minimize errors. This metric becomes an important metric to be considered when the cost of error is high.

II. Results

Figure 4 shows optimum equipment replacement period with time.

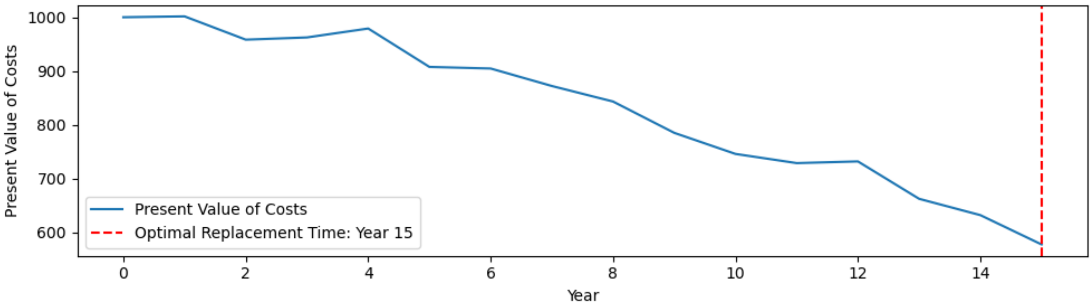

Figure 4: Optimum Replacement Time

III. Discussion of Results

Training and Validation Accuracy

The training started with a relatively high loss and gradually decreased with each epoch, indicating that the model was effectively learning from the training data. As a result, the accuracy improved over time, reaching a high value by the end of training.The accuracy of the model on both the training and validation sets increased as the training progressed. This implies that the model was successfully capturing the patterns in the data and making better predictions.

The training and validation accuracies were consistent throughout the training process, suggesting that there was no overfitting in the model during the training period. The model's performance on unseen validation data was close to its performance on the training data.

Test Accuracy

Upon exposure to further test data, the developed ANN model predicted the replacement decisions of the machine tools with an accuracy of 0.8667 or 86.67%. This means that the model correctly classified 86.67% of the samples in the test dataset. This also implies that the learnable neurons were able to learn the features presented to them during data training and was able to recognize these features and make deductions on any dataset presented to it based on the features that was learnt during training.

Training and Validation Losses

It visualizes how errors in the model changes with time during the course of training. It shows how much the prediction of the model differed from the actual value during each epoch.

Confusion Matrix

A confusion matrix is a table that is used to evaluate the performance of a classification model. It summarizes the results of the model's predictions compared to the actual labels of the test dataset as presented in Figure 5.

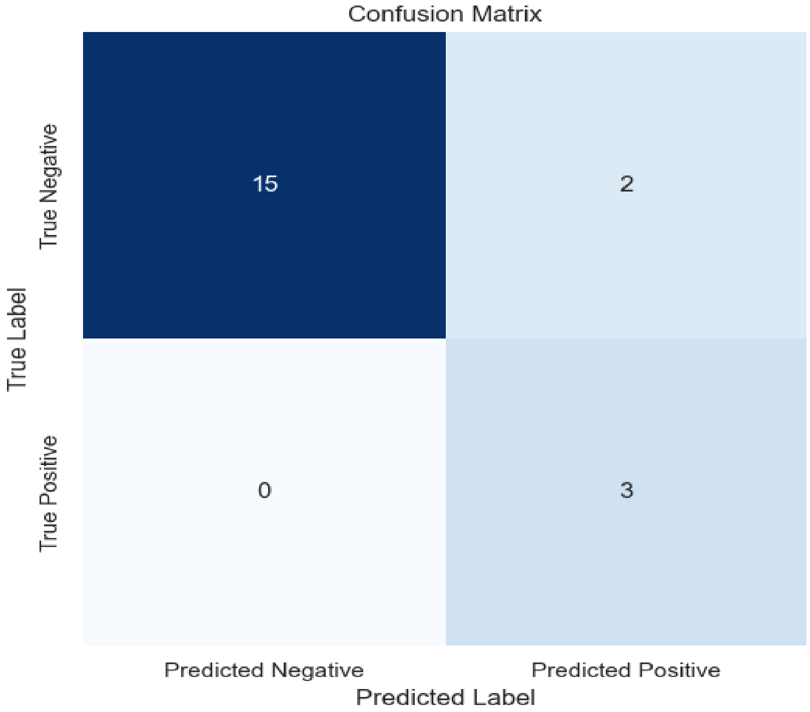

Figure 5: Confusion Matrix

The confusion matrix shows the performance of a binary classification model. It indicates that 15 instances were correctly classified as class 1, 0 instances were incorrectly classified as class 1, 3 instances were incorrectly classified as class 2, and 1 instance was correctly classified as class 2.The confusion matrix revealed the model's competence in correctly predicting Class 0 samples with an 88% recall. For Class 1, the model demonstrated a remarkable recall of 100%, correctly identifying all positive samples. The low precision of 60% for Class 1 can be attributed to the inherent challenge of class imbalance in the obtained dataset.

Precision, Recall and F1- Score

The values of the medel's precision, recall and F1-score is presented in Table 4.2. For Class 0, the model achieved a near-perfect precision of 100%, indicating its accuracy in classifying samples as Class 0. Additionally, both classes demonstrated high recall, indicating the model's capability in identifying true positive samples. The F1-scores for Class 0 and Class 1 were 0.94 and 0.75, respectively, further validating the model's balanced performance.

Effect of Deterioration

The deterioration function within this analysis examined the gradual decline in the asset's value over time. This exploration considered real-world scenarios where asset deterioration can fluctuate based on factors such as usage patterns, maintenance practices, and environmental conditions. As the asset's condition deteriorates, its current value decreases, resulting in a higher present value of future maintenance and replacement costs. Deterioration is often due to wear, tear and a combination of other factors, which reduces the functions and market value of assets with time.

Inflation directly impacts the replacement cost, which is the cost of acquiring a new asset at the end of its useful life. A higher inflation rate indicates that the replacement cost will be higher in the future. This, in turn, increases the present value of future replacement costs, potentially influencing the optimal timing for asset replacement. A prolonged inflationary trend could lead to misrepresentation of the true future value of an asset. This leads to overestimation of the salvage value of an asset which could make difficult to make replacement plans, as the asset's nominal salvage value seems higher than its real value. However, an inflation graph helps in an understanding of how the purchasing power of money changes with time, which influences the estimated value of the asset at the end of its useful service life.

Effect of Rate of Return

The discount rate, or rate of return, is used to determine the present value of future costs. A higher discount rate reduces the perceived value of future costs, making it less costly to replace the asset sooner. Conversely, a lower discount rate increases the perceived value of future costs, making it more cost-effective to postpone replacement.

Salvage value calculations

The salvage value is the estimated value of the asset at the end of its useful life. A higher salvage value reduces the overall cost of ownership, as it can offset some of the replacement cost. Conversely, a lower salvage value increases the overall cost of ownership.

The salvage value represents the estimated residual value of the asset at the end of its useful life. A higher salvage value can offset some of the replacement cost, reducing the overall cost of ownership. Conversely, a lower salvage value increases the overall cost of ownership.

Here is a snippet of part salvage value calculation done using python.

IV. Conclusion

Traditional methods of equipment replacement can no longer be relied upon in this technological age. Artificial Intelligence- Artificial Neural Network (ANN) should be employed for machinery replacement. Applications of other artificial intelligence methods in solving this problem is proposed for further work

REFERENCES

[1]. S.H. Gokler and S. Brown (2022‘Determining Otimal Machine Part Replacement Time Using a Hybrid ANN-GA Model’, Transaction of E. Industrial Engineering, Sharif University of Technology ScientiiaIranica, Turkey. https.//scientiairanica.sharif.edu.

[2]. M. M. Gyazova, I.D. Vlaznev (2020) ‘Mathematical Method of Artificial Neural Networks in Aircraft Maintenance, Repair and Overhaul’ TEM Jornal ,Volue 9, Issue 4, Pp 1372-1383

[3]. S. Aperranthis, P. Zacharia, A. Chatzopoulos and M. Papousidakis (2024) ‘ Preditive MaintenANCE OF Machinery with Rotating Parts Using Convolutinal Neural Networks’, htptps://doi.org/10.3390/electronics13020460.

[4]. E.Pourahimian, R. Ead, M. Elmenshawy and S. Abourizk (2024) A Decision Support system for Equipment Replacement. Proceedings of Canadian Society of Civil Engineering Annual Conference 2023, Volumw 3, P75-188.

[5]. E. O. Abensur, B. P. Santos and A.A. Bandeira (2023) Optimization Models as Applied to Equipment Replacement Prblems : Review and Trends, Applied Mathematical Programming. Gestao and Producao, 3o, e4022.Htpps://dio.org./10/10.1590/1806-9649-2023v30e4022.

[6]. A. Ahmed, N. Yub Huran, S.Wagas, U. Arshad and S. ALI Ghalib (2024)‘ Optimization of Operational Parameters Using Artificial Neural Network’. ACA Publications Vol.9 Issue 24.

[7]. Z. Kang, C. Catal, B. Tekinerdogan’ Remaining Useful Life (RUL) Prediction of Equipment in Production ( ) PMCID: PMC7866836 PMID:33573297

[8]. O. Sovlijanski, B. Lncar, L. Pet, A. Anatomic, S. Brunet, V. Filipovic, J. Filipovic, J. C. Brunet, G. Cetkovic, V. Traviac’ Unloking the Potential of ANN Optimization in Sweet Potato Varieties Drying Processes PMCID:PMCID778433 PMID:38201161.

[9]. S.Mondal, R. Maity and A. Nag( ) An Efficient Artificial Neural Network Based Optimization

[10]. Techniques for Early Prediction Coronary Heart Diseases: Comprehensive Analysis

[11]. S.T. Yousif, Artificial neural network modelling of elasto-plastic plates, Ph.D. thesis, College ofEngineering, Mosul University, 2007.

[12]. S. Rajasekaran; G,A.Vijayalashmi Pai Neural Networks, Fuzzy Logic and Genetic Algorithms : Synthesis and Applications, PHI Learning Private Limited, New Delhi-110001 2012

[13]. S. Hykin, Neural Networks: A Comprehensive Foundation, 2nd ed., New Jersey: Printice-Hall, 1999. [Google Scholar]