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Artificial Neural Network Machinery Replacement Programme in Oil Industry

F. E. Edet[1*], W. A. Akpan[2], C.M. Orazulume[3], E.J. Awaka-Ama[4]

[1]Department of Mechanical Engineering, Faculty of Engineering, University of Uyo, Akwa Ibom State, Nigeria.

[2]Department of Mechanical Engineering, School of Engineering and Engineering Technology,Federal University of Technology, Ikot Abasi, Akwa Ibom State, Nigeria.

[3]Department of Electrical and Electronics Engineering, Faculty of Engineering, TopFaith University Mkpatak, Akwa Ibom State, Nigeria.

[4]Department of Mechanical Engineering, Faculty of Engineering, University of Uyo, Akwa Ibom State, Nigeria

ABSTRACT: Equipment replacement is one the problems many organizations are facing in the management of their assets. Most times some of these organizations have many equipment and the decision to determine when this equipment should be replaced or maintained becomes very challenging. Traditional methods of equipment replacement can therefore be relied upon. Artificial Neural Network (ANN) has been developed and presented in this research to guide in equipment replacement decision for industries. Five years of cost data was collected using eMaint computerized maintenance management system. for 100 machines. An overall condition of 15 and above served as a replacement point. A test accuracy of 86.67% was recorded using the ANN model. This indicates that the model is a promising for predicting machine tool replacement. The developed artificial neural network (ANN)is considered valuable for predicting machine replacement.

KEYWORDS: ANN, machine replacement, deterioration, operating cost, salvage value, oil industry.

1.0 INTRODUCTION

As assets age, they generally deteriorate and break down, resulting in rising operating and maintenance (O and M) costs and decreasing salvage values. Equipment is one of the key factors of any industrial operation. These machines are prone to degradation throughout their operational lives. This results in lower production rates and an adverse economic impact [1] determined the optimum machine part replacement and obtained useful results. The harsh working conditions of some machines can cause faster deterioration. Many companies are bothered by the decision of machine replacement seeking ways to maximize profit while minimizing expenses.

Breakdowns can cause a variety of issues. In some cases, they occur in support equipment when the production equipment is not in use. Lead times in obtaining replacement parts or extended repair time can cause outages that delay production, and result in missed deadline. Traditional methods of failure prediction are difficult to apply in complex technical systems[2]. These can have severe impacts in the short-term for loss of money from current contracts, and in the long-term will reduce the number of contracts and programmes. Furthermore, newer assets that are more efficient and better in retaining their value may exist in the marketplace and be available for replacement.

For this reason, public and private agencies 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 equipment costs and are often motivated by the conditions of deterioration and technological changes, either separately or together [3] detected the functional state of ball bearings.

Artificial neural networks (ANNs) are computational models that simulate how the nervous system and brain of living things process information. The system is made up of a vast number of networked processing units, also called neurons which work together to solve a given problem. [4] used net present value to support decisions. In essence, an ANN maps sets of random input–output vectors in a non-deterministic manner. Some advantages of these networks over statistical methods include the lack of any presumptive relationship between input-output quantities, in-built dynamism, and robustness against data errors. Some replacement models exclude resale value in the build-up of cost. Yet it is the value that is directly affected by deterioration. This missing link will be supplied by this research.

. With the increased availability of monitoring data on the condition of systems and equipment, neural networks are increasingly applied in the field of fault detection, fault diagnostics and for predicting the residual useful life for subsequent replacement.

An artificial neural network consists of interconnection of neurons. The neurons are usually assembled in layers. [5] used optimization models as applied equipment problem**s.** Each layer has a number of simple neuron processing elements called nodes or neurons that interact with each other by using numerically weighted connections.

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 potentials s of ANN in problems solving have been demonstrated in [6],[7],[8], and [9] respectively.

The objective of this research is to develop a machinery replacement model using classical machine learning method to predict the effect of deterioration on the salvage (resale) value and possible replacement date of industrial machines. The developed model has three inputs; the increased purchase price (IPP (%)), decreased operating cost (DOC (%)) and decreased maintenance cost (DMC (%)). The model followed number of steps to facilitate its development. The core of this neural network prediction will rely on the ability to establish salvage (resale) value and replacement decisions module. The overall objective of the model is to minimize costs in the manufacturing industry.

2.0 Methodology

This procedure is performed using training data set until a convergence criterion is met. Neural networks have different learning algorithms for training. The training performance is evaluated using the following performance measures, namely the Mean Square Error (MSE) average sum of square errors and Correlation Coefficient (R**),** given by Equation 1 and Equation 2 respectively:

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

Equation 1

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

Equation 2

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

The dataset here comprised asset’s characteristics and the maintenance history of the asset (machine) and the overall market conditions of the asset.

The research also employed other metric values like, Fi-Score, Recall, Precision, Training and validation accuracy,

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 was estimated by considering the utilisation of the machine. The model’s input parameters included machinery ID, age, repair time in hours, repair frequency, corrective spare part cost, corrective labor cost, preventive spare part cost, preventive labour 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.

The data was normalized using Equation 3

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

Equation 3

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 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 4 is evolved.

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

Equation 4

Before feeding the data into the ANN model, further preprocessing steps were applied. The dataset was divided into training and testing sets using the train-test-split function from the sklearn library to ensure the model's generalizability. Additionally, to achieve consistent scaling of the numerical features, the MinMaxScaler was applied, normalizing the input features to a range between 0 and 1. This was done in other to improve the accuracy of the model by ensuring equal contribution by all the features towards the learning process.

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.

Datta partitioning was done to enabled different set of data to be used during training, validation and testing to ensure that proper evaluation of the performance of the model during validation and testing phases.

Model Formulation and Calculation of ANN Input

The term ‘total cost value’ is defined as the 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.

$$C_m = C_{cm} + P_m \quad \text{Equation 6}$$

$$C_{cm} = SP_c + LCc \quad \text{Equation 7}$$

$$P_m = SP_p + LC_p \quad \text{Equation 8}$$

where Cm is the maintenance cost, C_{cm} is the corrective maintenance cost, Pm is the preventive maintenance 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 part cost for preventive maintenance and LC_p is the labour cost for preventive maintenance.

The resale value is calculated in Equation 3.7;

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

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

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

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

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

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

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

where T is the optimization time horizon

Eight neurons and six layers were used. Weight initialization, forward propagation, backpropagation, and gradient descent were used during training and validation. Epoch of the model and efficiency of the model were evaluated to minimize error and calculate the effeciency.-usingF1 score, Recall and Precision value.

3.0 RESULTS AND DISCUSSION

Results

Table 1 shows the training and validation losses and Table 2 shows classification report.

Table 1: Training and Validation values for Accuracies and Losses in Each Epoch

Epoch	Training Accuracy	Training Loss	Validation Accuracy	Validation Loss
1	0.1985	0.7523	0.500	0.7297
2	0.4356	0.7077	0.4375	0.6929
3	0.6313	0.6659	0.5625	0.6627
4	0.8081	0.6311	0.7500	0.6377
5	0.9247	0.5988	0.8125	0.6163
6	0.9024	0.5672	0.8125	0.5972
7	0.9063	0.5434	0.8125	0.5798
8	0.8868	0.5251	0.8125	0.5638
9	0.9063	0.4983	0.8125	0.5495
10	0.8946	0.4814	0.8125	0.5368
11	0.9219	0.4473	0.8125	0.5253
12	0.9063	0.4426	0.8125	0.5148
13	0.9063	0.4244	0.8125	0.5054
14	0.8985	0.4056	0.8125	0.4975
15	0.9063	0.3848	0.8125	0.4909
16	0.8946	0.3811	0.8125	0.4853
17	0.9180	0.3499	0.8125	0.4791
18	0.8985	0.3530	0.8125	0.4736
19	0.8829	0.3598	0.8125	0.4681
20	0.8907	0.3331	0.8125	0.4633
21	0.9102	0.3059	0.8125	0.4584
22	0.9063	0.3005	0.8125	0.4536
23	0.8946	0.3070	0.8125	0.4488

24	0.9024	0.2807	0.8125	0.4451
25	0.8985	0.2923	0.8125	0.4399
26	0.8985	0.2849	0.8125	0.4356
27	0.8829	0.2874	0.8125	0.4323
28	0.8907	0.2659	0.8125	0.4310
29	0.8985	0.2574	0.8125	0.4317
30	0.8946	0.2514	0.8125	0.4324

Table 2: Classification Report

Class	Precision	Recall	F1-Score	Support
0	1.00	0.88	0.94	17
1	0.60	1.00	0.75	3

Figure 2 shows training and validation accuracy, while Figure 2 shows their losses respectively.

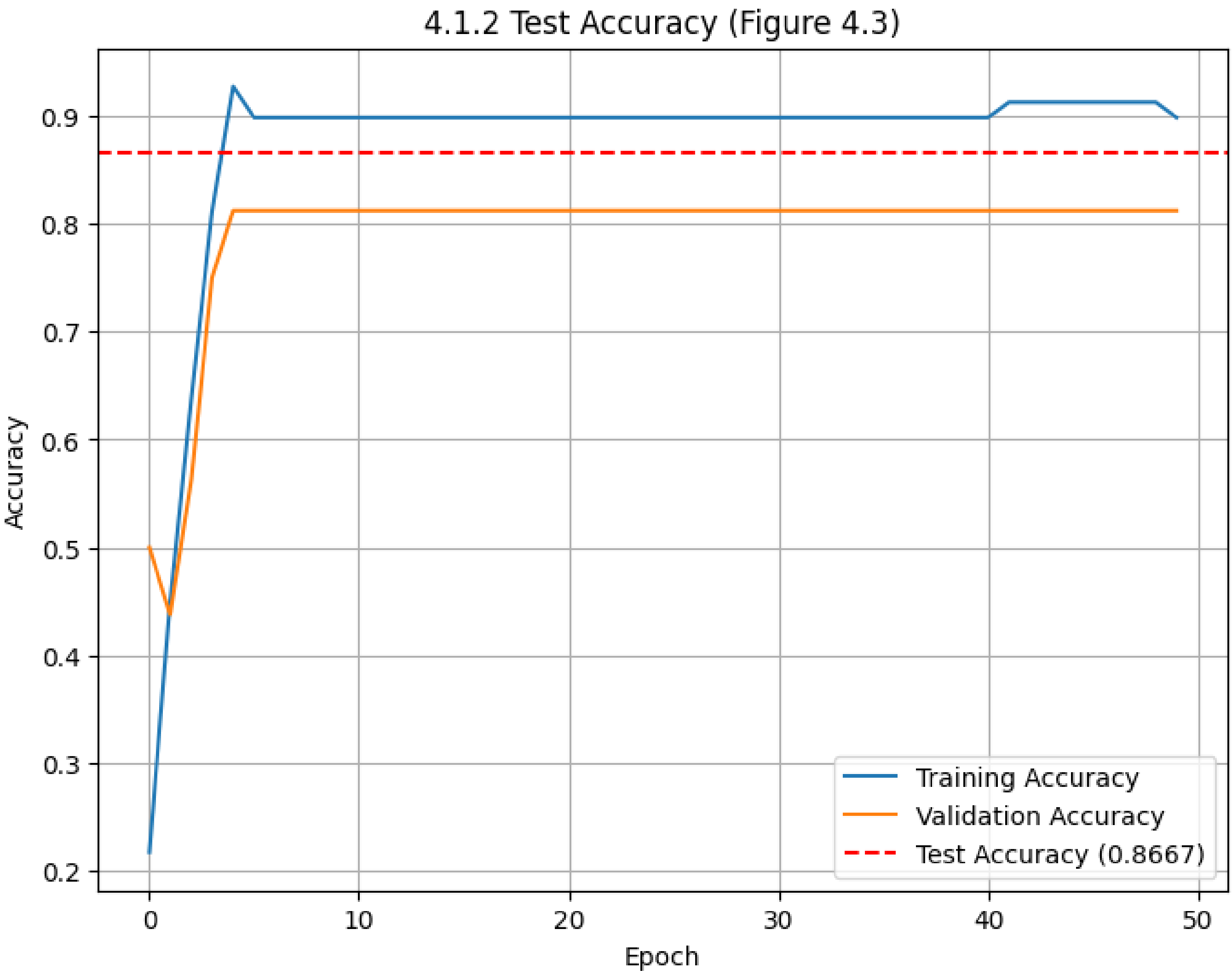

Figure 1: Training and Validation Accuracy

Figures 2 and 3 show the deteriorating rate and the salvage value and optimal replacement data.

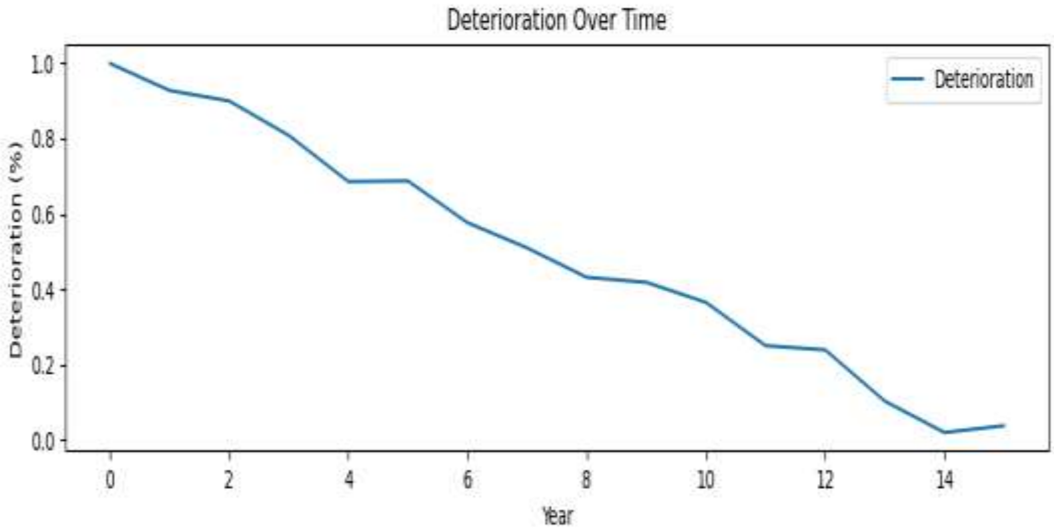

Figure 2: Deterioration over time

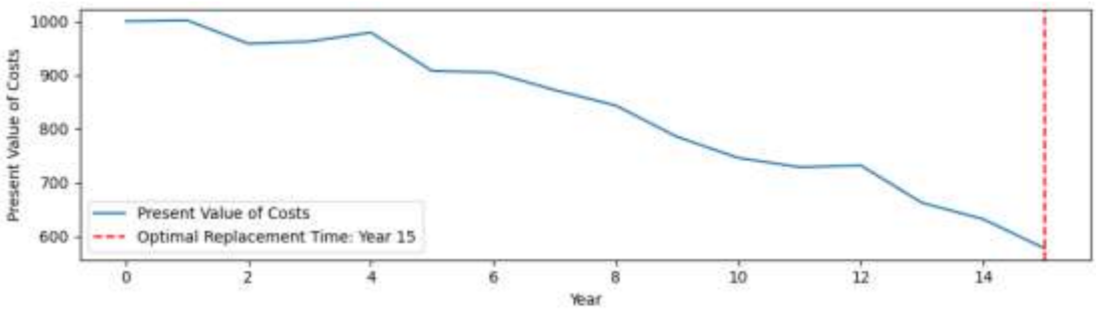

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Figure 3: Salvage value and Optimal replacement data

Table 2 shows the replacement date for the asset.

Table 2 Machinery Replacement Data Input Identification

Machinery ID	Age (years)	Repair Time (hours)	Repair Frequency	Corrective Spare Part Cost (₦)	Corrective Labor Cost (₦)	Preventive Spare Part Cost (₦)	Preventive Labor Cost (₦)	Total Spare Part Cost (₦)	Total Labor Cost (₦)	Overall Condition	Replacement Decision
1	11	24	3	1289	115	455	30	1744	145	13.3	Not Replace
2	12	34	4	1045	121	473	46	1518	167	17	Replace
3	6	39	5	1056	148	373	41	1429	189	15.7	Replace
4	12	6	3	1469	115	425	43	1894	158	8.4	Not Replace
5	4	15	5	1825	130	498	49	2323	179	7.5	Not Replace
6	4	30	5	1244	127	321	50	1565	177	12	Not Replace
7	11	5	3	1100	105	460	35	1560	140	7.6	Not Replace
8	1	15	2	1301	148	496	38	1797	186	5.4	Not Replace
9	5	10	1	1647	120	382	44	2029	164	5.7	Not Replace
10	5	27	2	1186	129	316	39	1502	168	11	Not Replace
11	14	14	4	1379	114	484	43	1863	157	12	Not Replace
12	10	20	1	1561	135	483	47	2044	182	11.2	Not Replace
13	1	24	5	1430	134	400	40	1830	174	8.7	Not Replace
14	7	17	3	1270	102	349	50	1619	152	9.2	Not Replace
15	1	19	2	1490	107	395	35	1885	142	6.6	Not Replace
16	10	24	1	1939	133	401	38	2340	171	12.4	Not Replace

17	2	33	3	1754	130	467	30	2221	160	11.5	Not Replace
18	4	7	1	1332	106	300	41	1632	147	4.3	Not Replace
19	10	24	5	1081	109	436	39	1517	148	13.2	Not Replace
20	6	10	4	1929	127	318	45	2247	172	6.8	Not Replace
21	7	21	3	1207	116	319	42	1526	158	10.4	Not Replace
22	3	38	1	1444	113	475	45	1919	158	13.1	Not Replace
23	5	29	2	1089	101	364	46	1453	147	11.6	Not Replace
24	5	13	3	1254	117	309	40	1563	157	7	Not Replace
25	4	36	3	1755	147	366	41	2121	188	13.4	Not Replace
26	2	27	3	1961	105	485	43	2446	148	9.7	Not Replace
27	6	10	3	1219	150	326	30	1545	180	6.6	Not Replace
28	6	24	5	1538	120	470	47	2008	167	11.2	Not Replace
29	11	30	5	1340	125	383	44	1723	169	15.5	Replace
30	3	20	3	1815	127	385	40	2200	167	8.1	Not Replace
31	4	27	3	1681	145	374	36	2055	181	10.7	Not Replace
32	5	10	3	1223	129	373	48	1596	177	6.1	Not Replace
33	8	11	4	1748	131	457	33	2205	164	8.1	Not Replace
34	13	12	5	1065	103	459	37	1524	140	11.1	Not Replace
35	7	9	1	1173	102	443	41	1616	143	6.4	Not Replace
36	9	12	3	1747	138	380	48	2127	186	8.7	Not Replace
37	12	8	4	1713	100	386	38	2099	138	9.2	Not Replace
38	5	40	5	1696	121	447	35	2143	156	15.5	Replace
39	6	20	5	1121	132	369	32	1490	164	10	Not Replace
40	3	7	3	1960	127	399	50	2359	177	4.2	Not Replace
41	4	18	2	1281	125	327	40	1608	165	7.8	Not Replace
42	15	25	5	1657	122	439	31	2096	153	16	Replace
43	12	30	3	1155	111	365	46	1520	157	15.6	Replace
44	1	23	4	1801	116	495	46	2296	162	8.2	Not Replace
45	11	37	5	1417	106	491	46	1908	152	17.6	Replace
46	11	19	1	1167	108	402	38	1569	146	11.4	Not Replace
47	2	14	4	1849	125	337	48	2186	173	6	Not Replace
48	6	16	4	1218	122	347	48	1565	170	8.6	Not Replace
49	10	18	2	1861	129	487	40	2348	169	10.8	Not Replace
50	5	36	2	1259	109	369	30	1628	139	13.7	Not Replace
51	12	35	2	1703	120	463	45	2166	165	16.9	Replace
52	7	7	3	1339	136	362	46	1701	182	6.2	Not Replace
53	3	26	5	1243	147	322	50	1565	197	10.3	Not Replace
54	10	26	5	1575	112	472	31	2047	143	13.8	Not Replace
55	7	32	2	1378	120	405	35	1783	155	13.5	Not Replace
56	9	12	1	1896	105	431	48	2327	153	8.3	Not Replace
57	4	39	5	1441	125	454	47	1895	172	14.7	Not Replace
58	6	12	2	1413	107	424	32	1837	139	7	Not Replace
59	4	29	3	1183	150	394	30	1577	180	11.3	Not Replace
60	7	15	4	1892	141	335	32	2227	173	8.8	Not Replace
61	1	10	2	1188	149	475	42	1663	191	3.9	Not Replace
62	11	10	2	1028	142	457	46	1485	188	8.9	Not Replace
63	5	21	3	1804	128	340	34	2144	162	9.4	Not Replace
64	6	25	2	1528	121	415	31	1943	152	10.9	Not Replace
65	9	12	5	1933	150	468	38	2401	188	9.1	Not Replace
66	13	40	2	1174	135	303	37	1477	172	18.9	Replace
67	11	8	1	1290	120	412	36	1702	156	8.1	Not Replace
68	5	34	2	1376	120	469	38	1845	158	13.1	Not Replace
69	11	28	3	1951	132	403	34	2354	166	14.5	Not Replace
70	9	31	3	1905	114	434	48	2339	162	14.4	Not Replace

71	5	18	1	1294	150	453	42	1747	192	8.1	Not Replace
72	10	14	3	1794	143	318	41	2112	184	9.8	Not Replace
73	7	7	3	1699	125	381	49	2080	174	6.2	Not Replace
74	15	26	3	1615	104	337	35	1952	139	15.9	Replace
75	1	10	3	1548	128	456	30	2004	158	4.1	Not Replace
76	7	7	2	1603	126	419	36	2022	162	6	Not Replace
77	14	32	3	1432	137	332	31	1764	168	17.2	Replace
78	4	32	5	1345	134	459	30	1804	164	12.6	Not Replace
79	12	22	2	1602	146	490	43	2092	189	13	Not Replace
80	1	28	5	1009	148	314	36	1323	184	9.9	Not Replace
81	9	34	1	1054	128	363	38	1417	166	14.9	Not Replace
82	8	31	3	1322	103	382	42	1704	145	13.9	Not Replace
83	12	25	4	1808	121	460	45	2268	166	14.3	Not Replace
84	11	31	1	1774	103	349	49	2123	152	15	Not Replace
85	13	12	1	1237	147	351	35	1588	182	10.3	Not Replace
86	11	28	4	1759	115	465	45	2224	160	14.7	Not Replace
87	14	13	2	1553	118	341	42	1894	160	11.3	Not Replace
88	10	10	1	1634	142	428	38	2062	180	8.2	Not Replace
89	3	22	5	1770	119	397	41	2167	160	9.1	Not Replace
90	11	6	4	1900	117	323	38	2223	155	8.1	Not Replace
91	12	17	3	1748	122	444	40	2192	162	11.7	Not Replace
92	3	15	1	1979	114	424	36	2403	150	6.2	Not Replace
93	13	16	4	1174	115	314	40	1488	155	12.1	Not Replace
94	7	26	1	1318	106	365	45	1683	151	11.5	Not Replace
95	10	39	5	1554	130	338	48	1892	178	17.7	Replace
96	5	26	3	1767	136	438	45	2205	181	10.9	Not Replace
97	4	24	3	1565	114	383	37	1948	151	9.8	Not Replace
98	15	23	3	1465	101	375	32	1840	133	15	Not Replace
99	10	10	1	1375	104	423	44	1798	148	8.2	Not Replace
100	7	20	2	1701	110	308	48	2009	158	9.9	Not Replace

DISCUSSION OF RESULTS

From Table1 the training and validation accuracy of the first Epoch was 0.1985 and 0.500 respectively, which corresponds to epoch 1. The values of training and validation accuracy increased progressively as the number of Epoch (iteration) increased before reaching momentary peaks of 0.9247 for the training accuracy and a value of 0.8125 for validation accuracy. The validation accuracy values had progressive and a constant value of 0.8125 was maintained from epoch 5 to the last epoch, while there was a slight drop in the value of training accuracies. Some of the high values recorded in training accuracy were 0.9102, 0.9180, 0.9219 and 0.9247 which occurred in epochs 21, 17, 11 and 5 respectively. The highest training accuracy occurred in epoch 47 which had an accuracy of 0.9331. Also, the plot reveals a narrow gap between training accuracy and validation accuracy. The validation accuracy of 0.8125 shows the performance of the model outside the dataset used in the training process. This is consistent with the work by [10].

The developed ANN model predicted the replacement decisions of the machine tools with an accuracy of 0.8667 or 86.67%.

The confusion matrix shows the performance of a binary classification model. The F1-scores for Class 0 and Class 1 were 0.94 and 0.75, respectively, further validating the model's balanced performance.

Figure 2 shows the deterioration of equipment over a given period. The plot shows a declining value of the set with time. The plot reveals the period 1 to 15 years, where the deterioration of the equipment was stable before further slump. The point where the graph flattens represents periods where terminal salvage value could be evaluated. It can also be seen that the rate deterioration of the equipment was high in the early years 0 to 2 years, which is synonymous with mechanical systems, caused by rapid wear and tear.

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.

The optimal replacement date is determined by minimizing the present value of future costs. This is shown in Figure 3. From Table 2, overall condition of 15 and above attracted replacement. This analysis considers factors such as asset deterioration, rising replacement costs due to inflation, the discount rate, and the salvage value. A higher deterioration rate or a higher inflation rate can necessitate earlier replacement, while a higher discount rate or a higher salvage value can delay replacement. The ANN model offers a more comprehensive simulation for machine tool replacement than traditional economic models like Terborgh's and Grant's, Orenstein's probabilistic approach, Dean's model. The developed Artificial Neural Network (ANN) model has provided superior baseline results.

4.0 CONCLUSION

This research has developed a machine learning model, utilizing an artificial neural network, to accurately predict machine tool replacement. The model recorded 89.07% and 81.25% as the accuracies of the last Epoch during training and validation respectively, which showed its ability to learn the features in the test dataset and make accurate predictions. A test accuracy of 86.67% was recorded during testing This indicates that the model is a promising for predicting machine tool replacement. Based on these findings, the developed artificial neural network (ANN) model can be considered a valuable asset for predicting machine tool replacement.

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