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Optimizing Asset Management by using Double Declining Balance and The KNN Algorithm

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Abstract Satker PTN is a ministry work unit whose entire income goes into the state account and is not given ownership of its assets. One of the Satker PTN in Indonesia is the Bacharuddin Jusuf Habibie Institute of Technology (ITH). ITH's operational procedures follow the rules of Satker PTN: not given asset ownership rights. The management of BMN ITH assets has not been optimal due to limited human resources which cause difficulties in the maintenance process, checking asset conditions and procurement of goods so that digitalization tools are needed that can be used to increase the efficiency of decision making and asset data analysis. This study optimizes asset management at ITH by using the depreciation method, namely the Double Declining Balance Method to determine asset depreciation. The Multilabel Classification Method uses the K-Nearest Neighbor Algorithm to classify good asset conditions, checking needs improvement. This study evaluates the depreciation of Chromebook, HDMI Cable, Electronic Plug, LCD Projector and Microphone assets over a 5-year period. Based on the results of the study, the DDB method produces a lower Final Book Value with a faster depreciation rate. The DDB method is effective in accelerating the depreciation of high-tech assets that tend to have shorter economic lives. The kNN algorithm classifies asset conditions based on historical asset lending data that includes features related to asset depreciation and usage. The results of the comparison of the kNN and Random Forest models in asset data classification are evaluated in Cross Validation, Confusion Matrix and ROC Analysis. Evaluation of the kNN Cross Validation Model with a value of k = 27 with 5 and 10 folds with an AUC value of 0.982, accuracy of 0.981, F1 score of 0.980, precision of 0.984, recall of 0.981, and MCC of 0.871. Evaluation of the Random Forest Cross Validation Model using 50 decision trees and 5 folds with an Auc value of 0.979, accuracy, F1 score, precision, recall and MCC are the same as the kNN model. The results of the kNN and Random Forest Confusion Matrices provide similar results and are a more detailed picture of prediction errors, including false positives and false negatives, which helps in understanding and improving the model. The results of the ROC Analysis evaluation show the Threshold values of the Checking, Good, Repair categories, namely 0.794, 0.259, 0.083 for kNN and 0.692, 0.247, 0.102 for Random Forest. Based on the evaluation results, this study shows that the kNN model is able to distinguish asset categories, is accurate in predicting asset status and can reduce false positives so that only assets that really need attention can be followed up. This study combines the DDB and KNN methods can be easily implemented, accelerate asset depreciation, classify asset conditions effectively, reduce repair operational costs and can optimize asset management by implementing models in asset applications.

Keywords Asset Management, Depreciation, DDB, Classification, KNN

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1. Introduction

*S*tate Higher Education, often referred to as PTN, is Higher Education organized by the Government. UUD No 12/2022 categorizes State Universities into 3, one of which is a Work Unit (Satker) [1]. PTN Satker is a ministry work unit where all revenue will go into the state account before use. PTS Satker is not given ownership of its

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assets. PTN Satker's assets are state property provided through the Director General. There are several Satker PTNs in Indonesia, one of which is the Bacharuddin Jusuf Habibie Institute of Technology PTN, or ITH. ITH is a PTN Satker under the Ministry of Education and Culture, Research and Technology.

ITH follows PTN Satker rules in operational work procedures, is not given asset ownership rights. General The section that manages state property assets at ITH, namely Facilities and Infrastructure. Asset management at ITH is not yet optimal due to limited human resources, so digitalization tools are needed that can be used to improve the efficiency of decision making and data analysis. ITH has several state-owned assets that support teaching and learning activities, such as projectors, HDMI, chrome books, and others. These state-owned assets are used by students, staff, and lecturers use this state of property assets. The lending process goes through a general team, where the available officers will register the borrower name, item borrowed, time of use, etc. The Double Declining Balance (DDB) method is effective in accelerating the reduction in asset value, especially for assets with a short economic life such as high technology assets. Asset optimization is also very important to maximize asset life. The use of modern information and analytical technologies such as IoT and machine learning offers great potential in improving asset management efficiency. This technology makes it possible to monitor asset conditions and optimize maintenance schedules based on asset lending data. Several studies related to depreciation methods and classification methods.

Researchers calculate asset values using the Double Declining method Balance method and get the asset value in 5 years. Machine learning is compared with traditional statistical modeling, discussing its current applications in accounting and auditing research [23]. This method is used because it is suitable for assets that experience a rapid decline in value at the beginning of their helpful lives [2]. ITH assets tend to experience more significant physical depreciation or are exposed to rapid technological changes in optimizing asset management using various methods. Research [3] manages asset repair operations from simple to optimizing complex systems from several units using the multi-unit method. In this study, assets are maintained in the hospital, which is integrated with the supply sector using the ERP system [4]. Research [5] defines dynamic inspection intervals for efficient distribution network asset management. Research [6] applies depreciation to determine the profit from selling 3 kg LPG Gas.

The advanced method used in this research is the Multi-Label Classification Method using the k-nearest Neighbor Classifier algorithm to classify assets based on good categories, checking, and needing improvement. The Multi Label Classification method is used to classify data with more than one category or label [7]. Double Declining Balance and straight-line methods are applied in this study to present a precision graph of typical current values. In managing the company's operational activities, this research compares the Straight-Line and Double Declining Balance Method [8]. The research applies the Tweet Multilabel model to student social media to classify complaints—a multi-label classification method to identify unsupervised persons [9]. Several studies have used the K-Nearest Neighbor to classify economic capability, productive waqf assets, groundwater quality, and the classification of documents based on information [10, 14]. This research aims to integrate the DDB method for asset depreciation with the KNN approach in asset condition classification to improve operational efficiency and maintenance of ITH assets.

2. RESEARCH METHODS

2.1. Research Stages

The data used comes from ITH asset borrowing data for 2022 and 2023. The data attributes used in this study are Asset Name, Asset Price, Total Asset Usage (year), Asset depreciation price and Asset Category.

2.2. Double Declining Balance Method

The DDB method is an accelerated depreciation method, which means that the annual depreciation rate is higher at the start of the set useful life and decreases over time. DDB is an accelerated depreciation method used to calculate the depreciation of an asset over time. In this method, depreciation occurs more rapidly at the beginning of the asset's life and then slows down over time. DDB results in higher depreciation charges at the beginning, based on the assumption that the asset may experience faster depreciation early in its useful life. The following is the DDB formula[15, 16]:

1. Initial Book Value: the previous value of the asset before depreciation
2. Accumulated Prior Depreciation is the amount of depreciation that has been calculated for the last years.
   (a) First year:
   $$Depreciation \quad Expense \quad = Initial \quad Bood \quad Value \quad \times DDB \quad Depreciation \quad Rate \tag{1}$$
   (b) The following years:
   $$Annual \quad Depreciation \quad (DDB) = (Initial \quad Gradebook \quad - \quad Accumulated \quad PriorDepreciation) \times DDB \quad Depreciation \quad Rate \tag{2}$$
3. The DDB depreciation rate is twice the straight-line depreciation rate. If the economic life of the asset is n years, then the DDB depreciation rate is:
   $$Rate \quad of \quad Depreciation \quad DDB = \frac{2}{n} \times 100\% \tag{3}$$
4. Determination of Ending Book Value (EBV)
   $$EBV \quad = \quad Acquisition \quad Cost \quad - \quad Accumulated \quad Depreciation \tag{4}$$

2.3. K-Nearest Neighbor Algorithm

This method explains clearly how the author conducted the research. This method requires a clear description of the research design, reproducible research procedures, and how the data will be summarized and analyzed[22]. The K-Nearest Neighbor (K-NN) algorithm in this study is used to classify data to become new information. In analyzing the data, researchers used Microsoft Excel files and orange software. The K-NN algorithm is divided into training data and testing data as test data. kNN is a machine learning algorithm used for classification and regression. This algorithm is based on the distance between data and decisions based on the nearest neighbor data. The advantages of the kNN model are that it is simple, easy to implement and does not require an explicit training model. The following are the stages of the K-NN method [13, 17].

1. Find the value of K (number of nearest neighbors)
2. Compute the squared Euclidean distance of each object (query instance) using the provided sample data.
3. Classify these objects with minimum Euclidean distance.
4. Collection Category Y.

Equation 2 is the Euclidean distance formula:

$$distance = \sum_{i=1}^{n} (Xi_{training} - X_{testing})2 \tag{5}$$

dengan :
Xi training : data training ke i;
X testing : data testing
i : record (baris) ke-i dari table;
n : amount of testing data

3. Result and Discussion

3.1. Data description

The data used in this research is ITH asset lending data for 2022-2023 with attributes namely (Name of Asset, Initial Price of Asset, Number of Uses. Total loan data ITH assets total 676 data. In calculating asset depreciation, researchers used five types of assets. From the results data collection that has been carried out, researchers obtained five lists of assets from asset lending data, namely Chrome Book, HDMI Cable, Electrical plug, LCD Projector, and Microphone. Figure 1 shows the research stages using the DDB and KNN methods. Stage 1, collecting 676 asset data. Stage 2 is calculating the depreciation price for each asset over 5 years using the DDB method. Stage 3 is classifying asset conditions based on usage data and asset depreciation prices using the KNN method. KNN model testing becomes a reference for the success of the asset classification results. The following is a link to the asset data. In this study, the asset data used was only electronic asset data because the type of asset depreciates quickly.**https://github.com/Khaeratunnisa/Data-asset**.

3.2. Double Declining Balance Method

From the results of data collection that has been done, researchers get 5 Alternatives (List of items to be maintained) In Table 1 is a list of ITH assets that will be used as alternatives in calculating DDB. Beginning Book Value is the initial book value for each alternative. The alternative (asset) is obtained in 2022 and calculated in 2023, so that the initial book value is the same as the purchase price. Depreciation Expense is the value of the depreciation expense for each alternative. To use the DDB method, here are the general calculation steps for each alternative:

1. Determine the Asset Acquisition Cost Initial costs of acquiring fixed assets. The Initial Cost of each alternative (asset) has been determined in table 1.

Table 1. Alternative (Asset List)

Alternative	Beginning Book Value	Depreciation Expense
Chrome Book	5.160.000.00	2.064.000
HDMI Cable	88.000	35.200
Electrical plug	175.000	70.000
LCD projector	13.733.000	1.493.200
Microphone	95.000	38.000

2. Determine the Useful Life of the Asset Researchers first determine the useful life of each alternative. Useful life refers to the time period of each asset. The useful life is determined in years before reaching the Salvage Value of each alternative. Salvage Value is determined as the residual value at the end of the useful life of each alternative in table 2.

Table 2. Determine the Useful Life

Alternative	Useful Life	Salvage Value
Chrome Book	5	100.000.00
HDMI Cable	5	100.000.00
Electrical plug	5	5.000
LCD projector	5	100.000.00
Microphone	5	1.000

3. Determine the DDB Depreciation Rate Determine the Depreciation Rate for each alternative. Researchers use Regular Depreciation values because all alternatives have a depreciation rate of 1 year.

$$Rate \quad of \quad Depreciation \quad DDB = \frac{2}{1} \times 100\% = 20\% \tag{6}$$

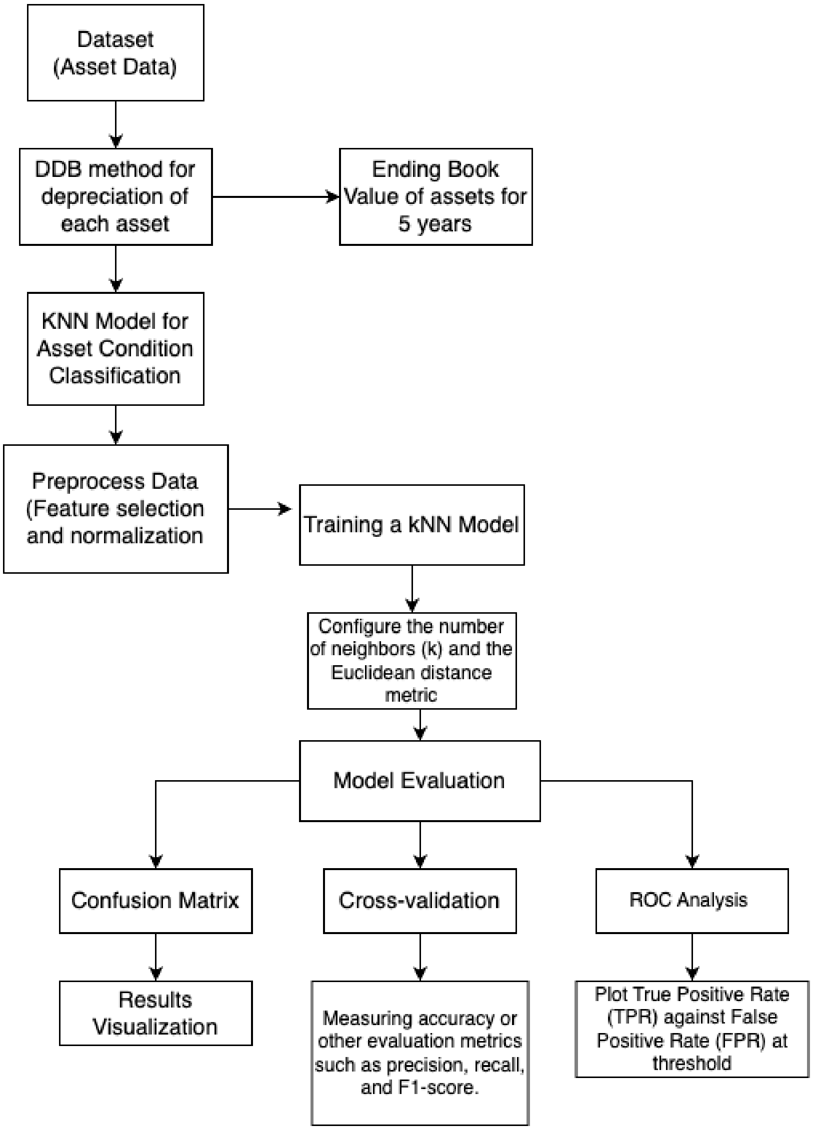


Figure 1. Research stages

4. Calculate Annual Depreciation Expense Annual depreciation expense using the DDB method is calculated based on the book value of the asset at the beginning of the depreciation period.Calculation of depreciation expense using formulas 1 and 2.The following is an example of manually calculating Chrome Book assets.

   Useful life : 5
   Salvage Value : 100.000
   Reguler Depreciation Rate : 20%

   After determining the useful life salvage value and regular depreciation rate, then do the calculations manually starting from year 1 to year 5 and calculate the ending book value for chrome book assets.
   Year 1 : 5.160.000.00
   Year 2 : 5.160.000.00 - 2 x 5.160.000.00 x 20%

Year 3 : 3.096.000.00 - 2 x 5.160.000.00 x 20%
Year 4 : 1.857.600.00 - 2 x 5.160.000.00 x 20%
Year 5 : 1.114.560.00 - 2 x 5.160.000.00 x 20%
Ending Book Value:668.736.00 - 2 x 5.160.000.00 x 20%
Ending Book Value: 401.241.60

In tables 3, 4, 5, 6, 7 are the results of alternative calculations using the Double Declining Balance method using Matlab. Table 8 is the result of Depreciation Expenses, namely the acquisition price of alternatives (assets) each year which reflects the decline in the price of each asset.

5. Accumulated Depreciation Accumulated depreciation is the total depreciation expense recognized from year 1 to year 5. In table 9. Ending Book Value is the remaining price of the asset at the end of the year after depreciation. Chrome Book Asset Data shows a significant decline in value from year to year. The steady decline indicates the depreciation method is successful in rapid asset depreciation. HDMI values show a more steady decline compared to Chrome book. The consistent decline shows that the depreciation method can be well controlled over a 5 year period. Plug assets show moderate value. The moderate decline indicates good management of this asset. The factor is due to a longer economic life or higher residual value. The LCD shows a larger depreciation and indicates a faster depreciation method. This is due to the speed of technological change in electronic equipment. The microphone shows a smaller alignment. The small decrease is due to the microphone having a longer economic life.

   Based on the results of the Ending book Value calculation obtained from each alternative, this analysis can be used to assist in planning and managing depreciation and asset maintenance strategies. The EVB data information will then be displayed used to classify the useful life of assets, repairs or replacements using the KNN method.

Table 3. Chrome book asset calculation results using Matlab

Chrome Book	**Year 1**	**Year 2**	**Year 3**	**Year 4**	**Year 5**
Beginning Book Value	5.160.000.00	3.096.000.00	1.857.600.00	1.114.560.00	668.736.00
Depreciation Expense	(2.064.000.00)	(1.238.400.00)	(743.040.00)	(445.824.00)	(267.494.40)
Ending Book Value	3.096.000.00	1.857.600.00	1.114.560.00	668.736.00	401.241.60
Assumptions					
Useful Life (years)	5				
Salvage Value	100.000.00				
Reguler Depreciation Rate	20%				

3.3. *K-Nearest Neighbor Algorithm*

The KNN method is used to classify the condition of Asset Data. The stages of the KNN method are as follows:

1. Data Processing Stage. Selection of relevant asset data features using the KNN method (Asset Name, Asset Price, Amount of Use, Asset Depreciation Price (Per year), Asset Class.
2. Normalize the data (asset data is normalized in numerical form)
3. Train the KNN model by setting the number of neighbors (k) and distance metrics. To choose the K value, researchers have explored values starting from low to high values. In the table 10 are the results of selecting the K value. Researchers have carried out experiments on vulnerable k values 1-27. The value K=27 was chosen to obtain a more stable and accurate estimate of model performance. In the kNN model, potential

Table 4. HDMI Cable asset calculation results using Matlab

HDMI Cable	Year 1	Year 2	Year 3	Year 4	Year 5
Beginning Book Value	88.000.00	52.800.00	31.680.00	19.008.00	11.404.80
Depreciation Expense	(35.200.00)	(21.120.00)	(12.672.00)	(7.603.20)	(1.404.80)
Ending Book Value	52.800.00	31.680.00	19.008.00	11.404.80	10.000.00
Assumptions					
Useful Life (years)	5				
Salvage Value	100.000.00				
Reguler Depreciation Rate	20%				

Table 5. Electrical plug asset calculation results using Matlab

Electrical plug	Year 1	Year 2	Year 3	Year 4	Year 5
Beginning Book Value	175.000,00	105.000.00	63.000.00	37.800.00	22.680.00
Depreciation Expense	(70.000.00)	(42.000.00)	(25.200.00)	(15.120.00)	(9.072.00)
Ending Book Value	105.000.00	63.000.00	37.800.00	22.680.00	13.608.00
Assumptions					
Useful Life (years)	5				
Salvage Value	5.000.00				
Reguler Depreciation Rate	20%				

Table 6. LCD Projector asset calculation results using Matlab

LCD Projector	Year 1	Year 2	Year 3	Year 4	Year 5
Beginning Book Value	3.733.000.00	2.239.800.00	1.343.880.00	806.328.00	483.796.80
Depreciation Expense	(1.493.200.00)	(895.920.00)	(537.552.00)	(322.531.20)	(193.518.72)
Ending Book Value	2.239.800.00	1.343.880.00	806.328.00	483.796.80	290.278.08
Assumptions					
Useful Life (years)	5				
Salvage Value	100.000.00				
Reguler Depreciation Rate	20%				

Table 7. MICROPHONE asset calculation results using Matlab

MICROPHONE	Year 1	Year 2	Year 3	Year 4	Year 5
Beginning Book Value	95.000.00	57.000.00	34.200.00	20.520.00	12.312.00
Depreciation Expense	(38.000.00)	(22.800.00)	(13.680.00)	(8.208.00)	(4.924.80)
Ending Book Value	57.000.00	34.200.00	20.520.00	12.312.00	7.387.20
Assumptions					
Useful Life (years)	5				
Salvage Value	1.000.00				
Reguler Depreciation Rate	20%				

bias can arise from the selection of inappropriate K parameters. A K value that is too small makes the model more sensitive to outliers, namely data that does not follow a general pattern. A K value that is too large makes the model too general which causes underfitting (the model cannot capture the pattern). The solution

Table 8. The results of calculating Depreciation Expense using Matlab software

Depreciation Expense	Year 1	Year 2	Year 3	Year 4	Year 5
Chrome Book	2.064.000.00	1.238.400.00	743.040.00	445.824.00	267.494.40
HDMI Cable	35.200.00	21.120.00	12.672.00	7.603.20	1.404.80
Electrical plug	70.000.00	42.000.00	25.200.00	15.120.00	9.072.00
LCD Projector	1.493.200.00	895.920.00	573.552.00	322.531.20	193.518.72
Microphone	38.000.00	22.800.00	13.680.00	8.208.00	4.925.80

Table 9. The results of calculating the Ending Book Value using Matlab software

Ending Book Value	Year 1	Year 2	Year 3	Year 4	Year 5
Chrome Book	3.096.000.00	1.857.600.00	1.114.560.00	668.736.00	401.241.60
HDMI Cable	52.800.00	31.680.00	19.008.00	11.404.80	10.000.00
Electrical plug	7 105.000.00	63.000.00	37.800.00	22.680.00	13.608.00
LCD Projector	2.239.200.00	1.343.880.00	806.328.00	483.796.80	290.278.08
Microphone	57.000.00	34.200.00	20.520.00	12.312.00	7.387.20

to finding a good K is through cross-validation. The use of the distance matrix in kNN to clarify how the model performs classification based on proximity to nearest neighbors. Consider more nearest neighbors, the model predictions become more consistent as more information from the large amount of training data is used [18, 19].

Table 10. Classification with the KNN model

Number of neighbors	Matric	Weight
27	Euclidean	By Distances

4. Evaluate the Model using:

   (a) Cross-validation: In table 11 Can evaluate model performance objectively by dividing the dataset into several folds, training the model on some parts, and testing on other parts. Of the 676 data, 80% (540 data) of the data were used for training data and 20% (136 data) were used for testing data. The process of dividing the dataset used random sampling by covering all criteria in the dataset so that each data has an equal chance of entering the training or testing data. In the table is a test score test using cross validation with a dataset of 676. The stages of cross validation are as follows.

      i. Determine the number of folds, for example 5-fold or 10-fold. If using 10-fold, the data will be divided into 10 parts.
      ii. Training and testing, this process is carried out for each fold. In a certain iteration, one fold is selected as the testing data while the other folds are combined to form the training data.
      iii. Evaluation, the results of the model tested on the test fold are measured using evaluation metrics.
      iv. The training and testing process is repeated for each fold, so that each part of the data has been test data.
      v. After all folds are tested, the results of the accuracy evaluation of all iterations are averaged to provide an overview of model performance

   Cross Validation helps reduce bias, providing a more stable assessment of model performance. In this study, the test score value at k = 27 showed higher stability and consistency compared to k = 26. This is due to several factors, namely:

      i. At k=27, the selection of the number of neighbors in the kNN model reaches the optimal point, which reduces prediction variations caused by small changes in the training data.

Table 11. Accuracy value with the KNN model

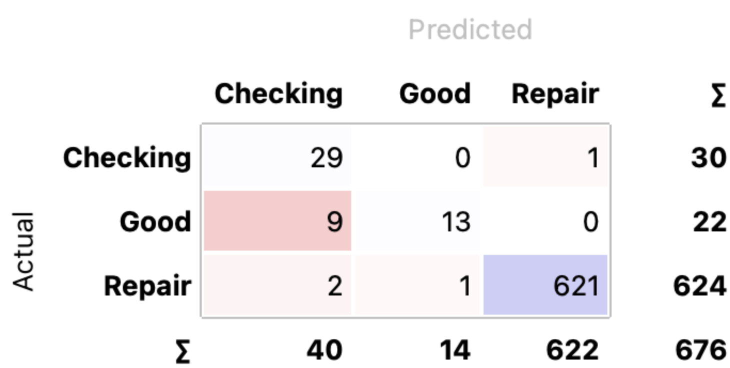
Number of neighbors	Cross Validation	AUC	CA	F1	Prec	Recall	MCC
k= 26	5-Fold	0.982	0.981	0.980	0.984	0.981	0.871
k= 26	10-Fold	0.981	0.981	0.980	0.984	0.981	0.871
k= 27	5-Fold	0.982	0.981	0.980	0.984	0.981	0.871
k= 27	10-Fold	0.982	0.981	0.980	0.984	0.981	0.871

ii. Dividing the data into folds 5 and 10 at k=27 produces a more representative subset of the data, ensuring that each fold has a similar data composition.

iii. The model at k=27 shows the right balance between complexity and generalization, reducing the risk of overfitting and underfitting. Therefore, the stability of the kNN algorithm at k=27 allows the model to handle variations in the data more effectively, producing consistent and reliable test score values.

iv. Conclusion for Test Score AUC: shows the model has a good ability to differentiate between positive and negative classes CA: has a very high level of accuracy showing that 98.1% of model predictions are correct. F1: shows a good balance between precision and recall in a balanced classification Prec: High precision shows that most of the model's positive predictions are correct Recall: A good recall level shows that the model is able to capture most of the true positive instances MCC : Good correlation between prediction model and actual labels

(b) Confusion Matrix: is a more detailed description of the types of errors the model makes, such as false positives and false negatives. To create an appropriate confusion matrix, researchers arrange actual and predicted data into a table in the following table 12 and ficture 2. In table 13 Calculating the Confusion Matrix from actual and predicted data, namely True Positives (TP): 3 False Positives (FP): 1 False Negatives (FN): 5 [19, 20, 21].



	Checking	Good	Repair	Σ
Checking	29	0	1	30
Good	9	13	0	22
Repair	2	1	621	624
Σ	40	14	622	676

Figure 2. Predicted Data and Actual Data results

The following is an Interpretation and Conclusion from the Confusion Matrix: The model has a precision of 0.75, which means 75% of positive predictions are correct. The recall is 0.375, indicating that the model can only capture 37.5% of all true positive instances. The accuracy of this confusion matrix is 0.333, which shows that the model only correctly predicts about 33.3% of all predictions. Evaluation of the confusion matrix shows that this model has high precision (0.75), but has low recall (0.375). These values indicate that the model is good at identifying correct positive predictions but fails to capture most of the true positive instances.

Table 12. Predicted Data and Actual Data

Actual	Predicted	Match
13	13	TP
0	9	FN
1	0	FN
9	0	FN
29	29	TP
2	1	FN
0	1	FP
1	2	FN
621	621	TP

Table 13. Calculating Confusion Matrix

	Predicted Positive	Predicted Negative
Actual Positive	(TP)3	5(FN)
Actual Negative	1(FP)	-

i. Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{3}{3+1} = \frac{3}{9} = 0.33 \tag{7}$$

ii. Precision

$$Precision = \frac{TP}{TP + FP} = \frac{3}{3+1} = \frac{3}{4} = 0.75 \tag{8}$$

iii. Recall

$$Recall = \frac{TP}{TP + FN} = \frac{3}{3+5} = \frac{3}{4} = 0.375 \tag{9}$$

iv. F1 Score

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision \times Recall} = 2 \times \frac{0.75 \times 0.375}{0.75 \times 0.375} = 0 \tag{10}$$

(c) ROC (Receiver Operating Characteristic) Analysis. A graph depicting the performance of a classification model at various decision thresholds. In the KNN model, ROC plots the True Positive Rate (TPR) or sensitivity to the False Positive Rate (FPR) at various classification thresholds. Target Checking. Threshold 0.704 TPR 0.97 indicates the KNN model is very good at detecting assets that need to be checked. FPR 0.02 is very low indicating the model is very accurate in distinguishing assets that do not need to be checked Target Good. Threshold 0.259 TPR 0.59 indicates that the KNN model can detect 59% of assets that are truly ”Good”. FPR 0.01 indicates that the KNN model has little problem classifying ”Not Good” assets as ”Good”. Target Repair. Threshold 0.083 TPR 1.00 indicates that all instances that actually need to be repaired are successfully detected as needing repair. FPR 0.71 indicates that 17% of instances that do not actually need to be repaired are classified as needing repair.

Table 14. Predicted Data and Actual Data

Target	Threshold	TPR	FPR
Checking	0.704	0.97	0.02
Good	0.259	0.59	0.01
Repair	0.083	1.00	0.17

3.4. Random Forest Algorithm

1. Data Processing Stage. Selection of relevant asset data features using the Random Forest method (Asset Name, Asset Price, Amount of Use, Asset Depreciation Price (Per year), Asset Class.
2. Normalize the data (asset data is normalized in numerical form).
3. Determine the parameters of Random Forest, such as the number of trees. In determining the number of trees using various values to provide the best performance, for example 50, 100, 200, 300 etc. With 676 data, the best performance of the model is at 50 trees [24].
4. Model Performance Evaluation. Cross Validation (eg 5 fold or 10 fold) is a tool used to evaluate model performance with various numbers of trees [25].
   (a) Cross-Validation: The cross validation stages are as follows.
      i. Data division. The data is divided into 5 folds. 4 folds are used to train the model and 1 fold is used to test the model.
      ii. Training and validation. This process is repeated 5 times according to the number of folds. Each iteration, a different subset is used as test data and the rest is used as training data. So each subset will be test data once.
      iii. Model Building. The Random Forest model was built using 50 decision trees. The number of trees 50 was chosen because it was considered to provide stable results.
      iv. Random Forest works by creating multiple decision trees and then combining the results to make good predictions.
      v. Evaluation. After the model is trained, predictions are made on the test data, and performance metrics such as Accuracy, Precision, Recall, and Auc are calculated.

   From the Cross Validation results in table 15, the model uses 50 decision trees with 5 folds with an AUC value of 0.979, indicating that the Random Forest model is very effective in distinguishing between classes. A CA value of 0.981 means that 98.1% of the model's predictions are correct. An F1 Score of 0.980 indicates that the model has a good balance between precision and recall. This model is efficient in predicting the positive class without too many false positives. Recall 0.984, the model is very effective in detecting the positive class. MCC 0.871 indicates that the model has very good predictive ability with a good balance between positive and negative classes [26].

   (b) Confusion Matrix: is a more detailed description of the types of errors made by the model, such as false positives and false negatives. The results of the Confusion Matrix for the Random Forest model provide the same results as the KNN Model with the following description:
      i. The classification performance of the model is similar. both models produce very similar predictions for the same dataset, so the number of correct and incorrect predictions for each class is similar. This shows that KNN and Random Forest have comparable capabilities in handling the data provided.
      ii. The same class distribution. This means that KNN and Random Forest are able to recognize patterns in the data with the same level of success.
      iii. Similar Evaluation Metrics. Other evaluation metrics calculated from this matrix include accuracy, precision, recall and F-1 score. This is in accordance with the calculation results in table 15 where the F1, Recall, and MCC values for both models are the same.

Table 15. Accuracy value with the Random Forest model

Number of trees	**Cross Validation**	**AUC**	**CA**	**F1**	**Prec**	**Recall**	**MCC**
50	5-Fold	0.979	0.981	0.980	0.984	0.981	0.871
50	10-Fold	0.978	0.981	0.980	0.984	0.981	0.871
100	5-Fold	0.979	0.981	0.980	0.984	0.981	0.871
100	10-Fold	0.978	0.981	0.980	0.984	0.981	0.871

(c) ROC (Receiver Operating Characteristic) Analysis. A graph depicting the performance of a classification model at various decision thresholds. In the Random Forest model, ROC plots the True Positive Rate (TPR) or sensitivity to the False Positive Rate (FPR) at various classification thresholds. In table 16 Target Checking 0.692 TPR 0.97 is also very high indicating that Random Forest is also very effective in detecting assets that need to be checked. FPR 0.02 indicates that the Random Forest model is also very accurate in distinguishing assets that do not need to be checked. Target Good. Threshold 0.247 TPR 0.64 indicates that the Random Forest model can detect 64% of assets that are truly "Good". FPR 0.01 indicates that the Random Forest model also has good performance in minimizing negative classification errors for "Good" assets. Target Repair. Threshold 0.102 TPR 1.00 indicates that all instances that need to be repaired are correctly detected. FPR 0.10 indicates that 10% of instances that do not actually need to be repaired are classified as needing to be repaired.

Table 16. Predicted Data and Actual Data

Target	**Threshold**	**TPR**	**FPR**
Checking	0.692	0.97	0.02
Good	0.247	0.64	0.01
Repair	0.102	1.00	0.10

3.5. Comparative Analysis of KNN and Random Forest

From the results of the evaluation of the KNN and Random Forest models carried out in classifying asset data checking, Good, Repair, both models provide good results. However, in the case of asset classification at ITH, the KNN model is very necessary for the following reasons:

1. From the Cross Validation Evaluation. The Cross Validation value of kNN is k = 27 5 and 10 folds with an AUC of 0.982 while the Random Forest value is 50 decision trees 5 folds and an AUC of 0.979. The KNN AUC value is higher than that of Random Forest, this indicates that KNN's performance is better in distinguishing between positive and negative classes overall. CA value 0.981, F1 0.980, Prec 0.984, Recall 0.981, MCC 0.871 for kNN and Random Forest. However, the model performance in F1 Score, MCC, Recall, Precision for kNN is the same and indicates that the overall classification quality of the model is equivalent.
2. From the results of the Confusion Matrix Evaluation, the KNN and Random Forest models give the same results, this means that both KNN and Random Forest make the same classification errors.
3. From the results of the ROC Analysis Evaluation, the KNN model has a higher average Threshold value, namely Checking 0.704, Good 0.259, Repair 0.083 compared to Random Forest. The ROC Analysis value for the Random Forest model is Checking 0.692, Good 0.247, Repair 0.102. With a high threshold value, kNN tends to be more selective in grouping assets into the positive category, thus requiring a higher probability to classify assets as "Checking", "Good", or "Repair". KNN is more conservative in making positive predictions than Random Forest. On the other hand, Random Forest with a low Threshold tends to classify more assets into the positive category, with a higher risk of false positives.

4. Conclusion

In this study, researchers found that the Double Declining Balance (DDB) method is effective in accelerating asset depreciation. DDB is very suitable for assets that include high-tech equipment and machinery because by accelerating depreciation, the ITH campus can reduce some of the risks of having technological assets that are quickly obsolete or irrelevant. This allows the company to continue using more sophisticated and efficient equipment. The results of the evaluation of the kNN and Random Forest models show that in this study the KNN Model was chosen in this study because KNN is a simple algorithm that is easy to implement. KNN uses a combination of high test scores and detailed evaluation through the Confusion Matrix shows that the KNN model with a k = 27 configuration and 5 and 10 cross-validation folds is a good choice for asset condition classification. Stable performance and clear interpretation of the types of errors made by the model provide additional confidence in the use of this model in making decisions. KNN works well on datasets that are not too large, with a moderate amount of data KNN can provide fast and accurate results. Based on the higher AUC value, KNN is able to distinguish asset categories (Checking, Good, Repair). KNN is more accurate in predicting the actual asset status and can help prevent unnecessary repair costs. KNN has a higher threshold value, KNN can reduce false positives, so that only assets that really need attention will be followed up and help reduce repair costs. KNN is a better choice in asset management, especially for applications that require a simple, efficient model and have good discrimination ability in asset classification. Suggestions for further research are to compare the performance of DDB with other depreciation methods such as Straight Line Depreciation, Unit of Production and combine the DDB approach with other analysis techniques to predict the residual value of assets or improve the accuracy of depreciation estimates. Other suggestions are to conduct evaluations with larger or varied data and consider a hybrid approach between kNN and methods, SVM, Artificial Neural Networks to determine the strength of the model in classifying asset conditions.

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