Prediction Analysis of Laboratory Equipment Depreciation Using Supervised Learning Methods

Geovanne Farell [1], Nizwardi Jalinus [2], Asmar Yulastri [3], Sandi Rahmadika [1], Rido Wahyudi [1]

[1] *Department of Electronics Engineering, Universitas Negeri Padang, Padang, Indonesia*
[2] *Department of Mechanical Engineering, Universitas Negeri Padang, Padang, Indonesia*
[3] *Department of Family Welfare, Universitas Negeri Padang, Padang, Indonesia*

***Abstract* – Asset management in Indonesia still poses problems in terms of securing state-owned property. These concerns make it difficult for analysts to predict laboratory equipment depreciation. Therefore, this research aims to create a new model to address this issue. Additionally, to support laboratory managers in gaining insights, a technology-based framework in the form of a laboratory equipment depreciation prediction model has been developed. A new model has been created in this research, which integrates supervised learning models with linear regression algorithms, and subsequently employs a waterfall system development approach. The testing results of the model for predicting laboratory equipment depreciation showed a high level of accuracy, reaching 93%. Furthermore, the comparison between the prediction model and the laboratory equipment data tested directly by technicians demonstrated an accuracy rate of 100%. Finally, the numerical results demonstrate that our framework provides a valuable solution to the difficulties in predicting laboratory equipment depreciation, offering an innovative and practical approach to laboratory equipment maintenance.**

DOI: 10.18421/TEM123-33
https://doi.org/10.18421/TEM123-33

Corresponding author: Geovanne Farell,
Department of Electronica Engineering, Padang State University, Padang, Indonesia.
Email: geovannefarell@ft.unp.ac.id

Received: 30 May 2023.
Revised: 28 July 2023.
Accepted: 16 August 2023.
Published: 28 August 2023.

***Keywords* – Machine learning, supervised learning, linear regression, laboratory equipment.**

1. Introduction

Assets are resources owned or controlled by individuals, businesses, or countries, which are expected to be valuable and useful in the future. Property refers to rights owned by an entity that cannot be traded as they are the entity's ownership rights [1]. These assets possess names, places or locations, purchase years, and other data. Asset management in Indonesia still faces challenges in terms of securing state-owned property. The complexity arises from state-owned property whose location is unknown or is nearly damaged but cannot be proposed for removal. Assets are goods individuals or institutions own with economic, commercial, and exchange value.

With the advancement of technology in every institution, the number of assets or items continues to increase yearly. The need for good asset information and data is crucial as it can support the performance of an institution. As stated in Government Regulation Number 28 of 2020, Article 1 Number 3, the Good Managers is an official legally responsible for providing guidelines and recommendations in addition to handling state or regional-owned goods [2].

In the management of state-owned assets, there is also depreciation of state-owned assets regulated by the Ministry of Finance of the Republic of Indonesia Regulation Number 65/PMK.06/2017 regarding the Depreciation of State-Owned Goods in the Form of Fixed Assets [3]. According to Article 1, number 03 of the Central Government Institution: "the depreciation of state-owned assets, such as fixed assets" hereinafter referred to as "depreciation of fixed assets," it is a systematic process of allocating the value of fixed assets that can be depreciated over their useful period.

The Department of Electronic Engineering, Universitas Negeri Padang, Sumatera Barat, Indonesia, is one of the leading study programs in the field of electronics engineering, offering five study programs: Electronics Engineering Education, Informatics Engineering Education, Electronics Engineering, Informatics, and Animation. Each study program has several learning facilities, such as laboratories. The laboratory equipment includes various fixed assets, such as computers, projector and other laboratory equipment, which will naturally experience depreciation. To obtain primary data, observations and interviews were conducted with the laboratory managers of the E60 Electronic Engineering Department.

Based on the interview results with the laboratory managers, it is apparent that the current system for managing laboratory equipment depreciation is conditional when there is a request from the faculty or university. Therefore, laboratory managers require a tool that can estimate the equipment's depreciation in the laboratory and predict the depreciation by efficiently calculating future procurement needs. This tool would help determine the usable lifespan of laboratory equipment, making it easier for laboratory managers to predict which items will become damaged or unusable within a specific timeframe.

In this paper, the authors present a new approach to address the aforementioned problem. This approach consists of determining a research model and machine learning techniques that will assist laboratory managers in estimating equipment depreciation in the laboratory. This research involves creating a model by combining supervised learning models and linear regression algorithms. The model development process follows the waterfall approach for system implementation. This approach concludes with deploying the entire framework, offering various services and incorporating different functionalities, which will be further explained in this research paper.

The remainder of the paper is structured as follows: After the current introduction section, we transition to the literature review and scientific works related to our research. Next, we will explain the methods used in this research. In the results and discussion section, after processing the data with various algorithms and training the data, a model is generated, and the accuracy of the model is tested. Then, testing is conducted based on actual data from technician assessments using the developed model. Finally, we conclude this paper with a conclusion.

2. Related Work

A comprehensive summary of various techniques and algorithms used in machine learning can be found in several publications and academic articles. After thoroughly analysing the existing literature, relevant studies are presented in Table 1 as part of the subsequent comparison.

Using auto-regressive integrated moving average (ARIMA) taken from various sources, the emerging trends and patterns slitting machine sensors will be analyzed to forecast potential failures and quality deficiencies which will enhance the entire manufacturing process. Therefore, the application of machine learning demonstrates its importance in IoT and has applications in quality management and quality control, as well as minimizing maintenance expenses and optimizing the overall manufacturing process [4].

The success rate achieved when using this algorithm alone in the Predictive Churn Analysis research is higher compared to the hybrid method developed using logistic regression and Naive Bayes. On the other hand, the artificial neural network approach has the highest prediction accuracy rate (91%) [5].

The artificial neural network model developed for this study Fault Analysis and Predictive Maintenance of Voltage establishes current values at specific times and categorizes data as either error-free or having specific faults. Afterward, the model is connected to the actual using the motor to precisely identify and categorize faults to facilitate subsequent actions [6].

The development of machine learning classifier models used in industrial equipment failure forecasting with classifiers has shown their ability to detect several pattern changes and sensor features 5-10 minutes before industrial equipment failures occur [7].

Maintenance planning verifies the effectiveness of various application features, for example, the time needed for data processing, as part of system research for improving the efficiency of heating equipment. The outcomes of the prediction method suggest that the data processing system and model accuracy need to be adjusted. As the data size increases, the processing time increases, and the sub-second precision decreases below 50%. The evaluation shows that because the solution can detect over 30% of failures, user convenience increases [8].

Table 1. Relevant research on prediction analysis of laboratory equipment depreciation (Z1=Data, Z2=Accuracy, Z3=Model, Z4=Application)

Authors	Objectives	Methods	Z1	Z2	Z3	Z4
Kanawaday et al. [4]	Predictive Maintenance of Industrial	1. ARIMA 2. Forecasting	Yes	Yes	Yes	No
Gunay et al. [5]	Predictive Churn Analysis	1. Logistic Regression 2. Decision Tree 3. Support Vector Machines	Yes	Yes	Yes	No
Kavana et al. [6]	Predictive Maintenance of Induction Motor	1. Fault Analysis 2. Artificial Neural Network (ANN)	Ye	Yes	Yes	No
Kolokas et al. [7]	Forecasting faults of industrial equipment	1. Classification 2. Time Series 3. Forecasting	Yes	Yes	No	No
Santiago et al. [8]	Predictive Maintenance of Heating Equipment	1. Heating, Ventilation, and Air-Conditioning (HWVAC)	Yes	Yes	Yes	No

3. System Architecture

The system architecture of this research encompasses several crucial stages. At its core lies the creation of the research model, which will employ the linear regression algorithm to establish relationships between variables. This will be followed by data collection, gathering relevant data from diverse sources. Subsequently, data analysis will unveil patterns and insights, guiding the pre-processing phase where data is refined. Training data will then enable the model's parameter adjustments for accurate predictions, leading to the final step of building the model. These interlinked components form the backbone of the research's systematic approach.

3.1. The Research Model

To build a new system approach, research was conducted using the waterfall method to obtain a detailed overview of both local characteristics and overall outcomes. Waterfall is a type of application development model and falls under the classic lifecycle, emphasizing sequential and systematic phases. Researchers chose this method because its development stages are structured, thereby minimizing errors. The following are the stages of the waterfall method:

1. Requirements Gathering and Analysis
   The author will first conduct a requirement analysis in the requirement gathering and Analysis phase to determine what is needed in the system development. This includes analyzing the current system and analyzing the proposed system.
2. Systems Development
   In the system development step, the author designs the interface of the program. The interface design includes the design of desired displays and menus that will be present in the program. The design language used is UML, which is used to create use cases, activity diagrams, sequence diagrams, flowcharts, and interface diagrams.
3. Systems Implementation and Coding
   In order for machines, specifically computers, to comprehend the prior design, it must be translated into a machine-readable form, During the coding process, which is a stage involving the implementation of the design phase, programmers will execute the instructions using the programming language.
4. Testing
   The author uses black box testing during the testing phase because it provides more detailed and accurate testing of the system and determines whether the application is feasible or not. System testing begins with finding bugs, program imperfections, and errors in program lines that cause failures in the execution of the software system.
5. Development
   In this deployment phase, the author will launch this application into web hosting to make it easily accessible.
6. Systems Operation and Maintenance
   Software maintenance is highly necessary, including its development, because software is not always perfect upon creation. Even during its runtime, there might be minor errors that went unnoticed earlier or additional features that are still missing from the software.

3.2. Linear Regression

In this research, the model to be created will use the linear regression algorithm.

Linear regression is a regression analysis that describes the correlation between a response variable (dependent variable) and multiple predictors (independent variables) that influence it. In this dataset, there is a column labeled "which" that serves as the target output of the model. The model is trained using a set of training data and then classifies or predicts the output based on predefined labeled data. Backpropagation, support vector machines, random forests, linear regression, naive Bayes, and other popular algorithms are used in supervised learning [9].

The regression model will use input variables (features) and output variables (labels) to discern the correlation or pattern between the input and output variables.

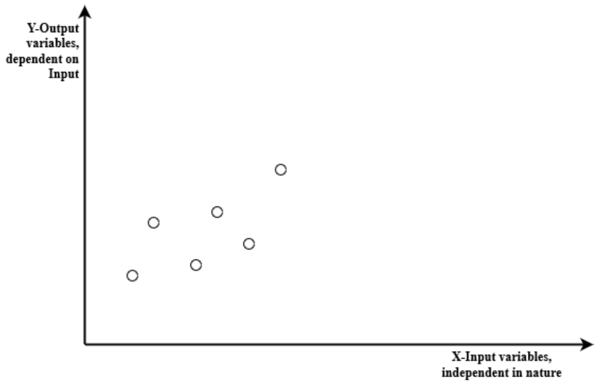

Figure 1. The correlation between the dependent variable and the independent variable.

The multiple linear regression calculation used is located at

$$Y = a + b1X1 + b2X2 + \ldots + bnXn$$

Information:

- Y = dependent variable (related variable)
- X1, X2, ..., Xn = independent variables (unrelated variables)
- a = constant
- b1, b2, ..., bn = regression coefficients

Linear regression is employed to examine the linear correlation between independent variables (features) and dependent variables (labels). The linear relationship suggests that as the value of an independent variable increases or decreases, the value of the dependent variable also changes correspondingly (increases or decreases).

The formula for linear regression is

$$y = a + bX$$

Regression model performance evaluation calculates the difference between the actual values (y_test) and the predicted values (y_pred), which is called the error. The evaluation of the accuracy of the regression model using the root mean square error (RMSE) value. RMSE is commonly used to evaluate the performance of forecasting models, measuring the precision and efficiency of the forecasts. A low RMSE value indicates that the predicted values closely match the original values. Conversely, a large RMSE value indicates that the accuracy of the predictions deviates significantly from the original values.

The Root Mean Squared Error (RMSE) is calculated by taking the square root of the Mean Squared Error (MSE).

$$\text{RMSE} = \frac{\sum_i n = \sqrt{(yi+yi\hat{})^2}}{n}$$

Information:

- yi = initial data
- y^ = final data
- n = number of data points

The RMSE value, the smaller, the better the performance of the regression model. To calculate the RMSE value, the functions mean absolute error from scikit-learn and mean squared error can be used.

3.3. Data Collection

Lab Equipment data is used to determine the condition of each Lab equipment that has been used up to the present. Data collection in this research was conducted through field observations and literature review. Observations were conducted to determine the actual conditions and damages that have occurred in the laboratory equipment of the Department of Electronics, Faculty of Engineering. Unfortunately, the lab equipment data cannot be included in this paper as it is private data. Generally, lab equipment data used in this research consists of 247 data entries with several labels including item name, acquisition date, brand, and quantity. The data will be processed in the following table format:

Table 2. General format of laboratory equipment data

No	Name	Date of Acquisition	Brand	Quantity
1	Uninterruptible Power Supply (UPS)	13/12/2010	LAPLACE GTX 1150	2
2	Personal Computer	22/09/2017	HP ProOne 400G2	5
…	…	…	…	…
…	…	…	…	…
247	CPU	31/12/2005	P.4 2,66 GHz/Black	4

3.4. Data Analysis

Before focusing on building predictive models, the data from the equipment lab is analyzed. Then, regression statistics is calculated, which can be seen in Table 2. Next, ANOVA table to examine the mean comparison between two or more groups is used. This facilitated the analysis of multiple different sample groups with minimal risk of error. The results of the ANOVA table can be found in Table 3, and the regression coefficients, representing the target variables serve as the ground truth for validating the trained models in all prediction tasks, can be found in Table 4. We also performed a coverage analyzing the available data points to identify potential correlations and decrease the data's dimensionality.

1. Regression Statistics Table

Table 3. Regression statistics

Regression Statistics	
Multiple R	0,432271927
R Square	0,186859019
Adjusted R Square	0,173306669
Standard Error	5,506647241
Observations	62

- In Table 3, the regression statistics provide an overall measure of fit: R2 = 0.186859019
- The correlation among y and x is 0.432271927 (when squared, it gives the squared correlation = 0.186859019 = R2).
- The standard error is described as an estimate of the standard deviation of the error term u.
- Sometimes, this is also represented as the standard error of the regression. It is equal to sqrt (SSE/(n-k)).

2. ANOVA Table

Table 4. ANOVA table

	df	SS	MS	F	Significance F
Regression	1	418,09	418,09	13,78	0,000450577
Residual	60	1819,38	30,32		
Total	61	2237,48			

- Table 4 illustrates how the ANOVA (Analysis of Variance) breaks down the sum of squares into individual components.
- So $\Sigma_i\ (y_i - \text{ybar})^2 = \Sigma_i\ (\text{yhat}_i - \text{ybar})^2 + \Sigma_i\ (y_i - \text{yhat}_i)^2$
- The total sum of squares = regression (or explained) sum of squares + residual (or error) sum of squares.

3. Regression Coefficients
The regression model parameters include

$$y = \beta1 + \beta2\ x + u$$

These crucial assumptions in regression analysis enable us to make dependable predictions and draw significant conclusions from the model's outcomes.

3.5. Pre-processing

Preprocessing is a technique used to transform collected data for further processing. Preprocessing is used to address data issues such as missing values, redundant data, outliers, or data formats that are not compatible with the system, as these factors can interfere with the output results. In this research, several preprocessing techniques will be used, including Normalizer, MinMax Scaler, and Standard Scaler. These methods will be applied separately to compare the different preprocessing approaches.

The first preprocessing technique is the normalizer. The normalizer is a preprocessing method that applies normalization to each data sample. The normalizer method is used on datasets that have many zero values and attributes with different scales. The normalizer is used to handle outlier data. The specific normalizer to be used is the L2 Normalizer, which ensures that the data has a sum of squares equal to 1.

The second comparative preprocessing method is MinMax Scaler. MinMax Scaler is a preprocessing method that transforms features by scaling each feature individually to a specific range. MinMax Scaler preprocessing is performed to ensure that the range of each sample in a feature is not too large. The formula for MinMaxScaler is shown in equation (1), where X represents the sample value.

$$P = \frac{X - \min(x)}{[\max(x) - \min(x)]}$$

The last preprocessing method used for comparison is Standard Scaler. Standard Scaler is a preprocessing method where standardizing features involves subtracting the mean value and scaling to unit variance. This process is applied to each feature in the sample.

This preprocessing technique is performed to prevent data with significantly larger values from dominating the training process compared to other values. The formula for Standard Scaler is shown in Equation (2), here, μ represents the mean of the sample values and σ represents the standard deviation.

$$S = \frac{Xi - \bar{X}}{\sigma}$$

3.6. Training Data and Building the Model

1. Data Exploration
   Before building a machine learning model for laboratory equipment depreciation prediction analysis, we need to go through several steps, one of which is data exploration. In this research the pandas library software will be used. The purpose of this exploration is to determine the data dimensions, namely the number of rows and columns, to see if our data is too large or too small. If the data is too large, it will take longer to train the model, while if the data is too small, the performance of the resulting model may not be satisfactory as it may not be able to recognize patterns accurately.
2. Data Preprocessing: Scaling
   Next is to perform data scaling process, as some variables may have significantly different ranges. Therefore, we need to normalize them first. Data rescaling is done within the range of 0 and 1, so that all features fall within that range, with the maximum value being 1 and the minimum value being 0.
3. Features & Label
   The dataset needs to be split into features and label/target. The feature variables will consist of variables declared as X, and the [age of the item] is the target variable declared as y.
4. Training and Test Dataset
   Next, we will train the model based on the laboratory equipment dataset and test the dataset with a training dataset to test dataset ratio of 80:20. We will allocate 80% of the data for training and reserve 20% for the testing process.
5. Predict Model
   The Predict Model is used to perform classification predictions on a previously trained model. Next, we will use this model to predict the labels of the testing dataset (X_test) using the.predict() function.
6. Save Model
   After performing various tests to evaluate the previously created model, we will proceed to save the model into a file named 'model-prediction-laboratory.joblib'.

4. Results and Discussion

The model is created after the data is processed using linear regression techniques and training data. The model built with the help of linear regression techniques needs to be saved as a file for future use. The output of the model will then be evaluated using a confusion matrix. The confusion matrix is created as a table that includes four possible combinations of predicted and actual values. The results of classification, True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN), are represented in the Confusion Matrix (FN). In Figure 2, the Confusion Matrix represents the negative class as the number 0, the neutral class as the number 1, and the positive class as the number 5.

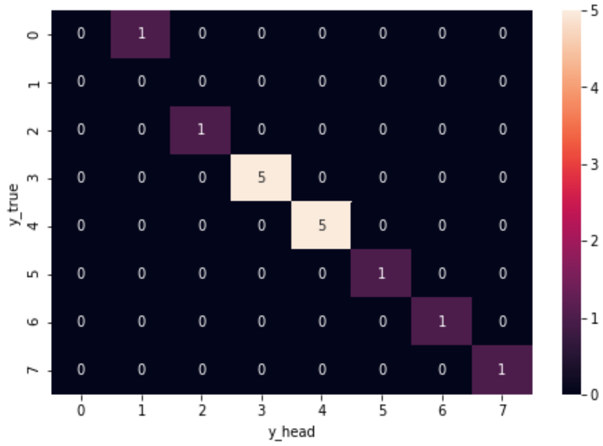

Figure 2. Confusion matrix.

- TP (True Positive)
  The count of data points where both the actual class and the predicted class are positive.
- FN (False Negative)
  The total of data points with a positive actual class but a negative predicted class.
- FP (False Positive)
  The count of data points with a negative actual class but a positive predicted class.
- TN (True Negative)
  The count of data points with a negative actual class and a negative predicted class.

Next, the accuracy of the model is assessed and constructed using the confusion matrix. It is possible to ascertain the accuracy of the model using performance metrics such as accuracy, recall, and precision. The outcomes of the model testing are presented in Table 5. We obtained an accuracy of 0.93 or 93%. Based on the test results, we will compare the previous data to determine if the model has the same values as the actual results. As shown in Figure 2.

Table 5. Performance metrics

	precision	recall	f1-score	support
1.0	0.00	0.00	0.00	1
2.0	0.00	0.00	0.00	0
10.0	1.00	1.00	1.00	1
17.0	1.00	1.00	1.00	5
18.0	1.00	1.00	1.00	5
21.0	1.00	1.00	1.00	1
23.0	1.00	1.00	1.00	1
30.0	1.00	1.00	1.00	1
accuracy			0.93	15
macro avg	0.75	0.75	0.75	15
weighted avg	0.93	0.93	0.93	15

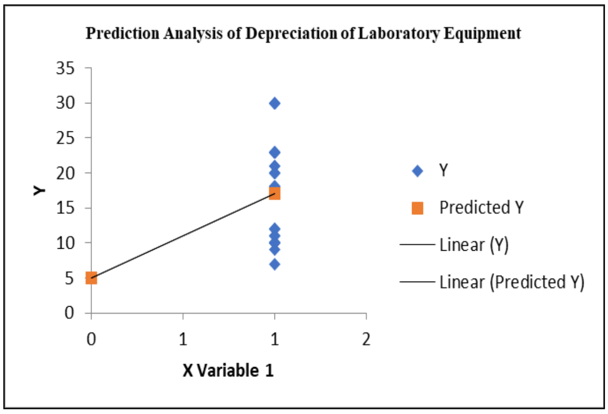

Figure 3. Graph of model testing results

Table 6. Model testing results

No	Name	Date of Acquisition	Identification Results	Result Accuracy
1	Personal Computer	28/11/2012	Bad	1
2	Personal Computer	28/11/2012	Bad	1
3	P.C Unit	20/12/2011	Bad	1
4	P.C Unit	22/09/2017	Good	1
5	P.C Unit	22/09/2017	Good	1
6	P.C Unit	22/09/2017	Good	1
7	Note Book	13/12/2016	Bad	1
8	CPU (Mainframe Equipment)	31/12/2004	Bad	1
9	CPU	31/12/2005	Bad	1
10	(Mainframe Equipment)	31/12/2005	Bad	1

Actual testing findings from technician inspections combined with laboratory equipment depreciation prediction analysis, while Table 6 shows that the accuracy of all testing findings is rated as 1. The column "Accuracy of Result Value 1" indicates that the results produced by the system and the reported technician results are identical. You can use calculations to determine the accuracy of the results in the form of a percentage.

$$P_{(E)} = \frac{X}{N} \text{ x } 100\%$$

In this particular context, several key symbols are used to represent significant elements. The letter "P" is employed to denote Probability, signifying the likelihood of an event occurring. "E" stands for Event, representing the specific occurrence under consideration. The symbol "X" represents the count or number of occurrences of the event "E." Lastly, "N" refers to the total number of events.

$$P_{(Accurate)} = \frac{Result\ Level\ 1}{Number\ of\ tests} \text{ x } 100\%$$

$$= \frac{10}{10} \text{ x } 100\%$$

$$= 100\ \%$$

$$P_{(Not\ Accurate)} = \frac{Result\ Level\ 0}{Number\ of\ tests} \text{ x } 100\%$$

$$= \frac{0}{10} \text{ x } 100\%$$

$$= 0\ \%$$

From the equation, we can observe that the accuracy value of the system when combined with the technician's choice in determining the laboratory equipment depreciation prediction analysis is 100%. Based on the testing findings and the accuracy rate exceeding 100%, this research is highly effective in quickly, accurately, and precisely identifying the laboratory equipment depreciation prediction analysis.

Table 7. Prediction Analysis of Laboratory Equipment Depreciation (Z1=Data, Z2=Accuracy, Z3=Model, Z4=Application)

Authors	Objectives	Methods	Z1	Z2	Z3	Z4
Geovanne 2023	Prediction Analysis of Depreciation of Laboratory Equipment	1. Supervised Learning 2. Linear Regression	Yes	Yes	Yes	Yes
Jalali et al. [10]	Predicting Time to Failure of Plasma Etching Equipment	1. Support Vector Machines 2. Deep Neural Networks (DNNs)	Yes	Yes	Yes	No
Alshboul et al. [11]	Forecasting Liquidated Damages for Highway Construction Projects	1. Linear regression 2. Multiple linear regression (MLR)	Yes	Yes	No	No
Theissler et al. [12]	Predictive maintenance for automotive industry	1.. CNN (Convolutional neural network) 2. Extreme learning machines (ELMs)	Yes	Yes	No	No
Jyh-Yih Hsu et al. [13]	Predictive Maintenance through Statistical Process Control	1. Decision Trees 2. Fault Diagnosis 3. Random Forest	Yes	Yes	Yes	No

5. Conclusion

Supervised learning methods using linear regression algorithms can generate models with an accuracy of 0.93 or 93%. The testing results achieved up to 100% accuracy rate when compared to actual technician data samples. The laboratory equipment depreciation prediction analysis using supervised learning method can provide high accuracy in identifying damages through predictive identification. It is believed that as the system evolves, increasing the number of samples and incorporating parameters that influence lab equipment degradation will enhance the predictability of the results. It is expected that as the system continues to advance, adding more samples and factors that affect lab equipment degradation will further improve the predictive capabilities of the system.

References:

[1]. Dari-Mattiacci, G. (2018). The Theory of Business Organizations. *Forthcoming in Encyclopedia of Law & Economics, Corporate Law and Economics Adam Badawi, ed., Amsterdam Law School Research Paper*, (2018-32).

[2]. Sitindaon, I. V. L., Febrian, F., Ridwan, R., & Rumesten, I. (2022). Reconstruction of Utilization Arrangements for the State Assets in the Form of Land to Increase Non-Tax State Revenue. *SASI*, *28*(2), 268-278.

[3]. Hartati, S., Sintara, D., & Maryani, H. (2022). Utilization Of State Property By Partners In The Perspective Of Utilitarianism Legal Theory. *Veteran Law Review*, *5*(1), 15-26.

[4]. Kanawaday, A., & Sane, A. (2017). Machine learning for predictive maintenance of industrial machines using IoT sensor data. *2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS)*. Doi:10.1109/icsess.2017.8342870.

[5]. Gunay, M., & Ensari, T. (2018). Predictive churn analysis with machine learning methods. *2018 26th Signal Processing and Communications Applications Conference (SIU).* Doi:10.1109/siu.2018.8404467.

[6]. Kavana, V., & Neethi, M. (2018). Fault Analysis and Predictive Maintenance of Induction Motor Using Machine Learning. *2018 International Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT).* Doi:10.1109/iceeccot43722.2018.9001543.

[7]. Kolokas, N., Vafeiadis, T., Ioannidis, D., & Tzovaras, D. (2018). Forecasting faults of industrial equipment using machine learning classifiers. *2018 Innovations in Intelligent Systems and Applications (INISTA).* Doi:10.1109/inista.2018.8466309.

[8]. Santiago, A. R., Antunes, M., Barraca, J. P., Gomes, D., & Aguiar, R. L. (2019). Predictive Maintenance System for Efficiency Improvement of Heating Equipment. *2019 IEEE Fifth International Conference on Big Data Computing Service and Applications (BigDataService).* Doi: 10.1109/BigDataService.2019.00019

[9]. Ray, S. (2019). A quick review of machine learning algorithms. In *2019 International conference on machine learning, big data, cloud and parallel computing (COMITCon)*, 35-39. IEEE.

[10]. Jalali, A. et al. (2019). Predicting Time-to-Failure of Plasma Etching Equipment using Machine Learning. *2019 IEEE International Conference on Prognostics and Health Management (ICPHM).* Doi:10.1109/icphm.2019.8819404.

[11]. Alshboul, O., Alzubaidi, M. A., Mamlook, R. E. A., Almasabha, G., Almuflih, A. S., & Shehadeh, A. (2022). Forecasting Liquidated Damages via Machine Learning-Based Modified Regression Models for Highway Construction Projects. *Sustainability*, *14*(10), 5835. https://doi.org/10.3390/su14105835.

[12]. Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., & Elger, G. (2021). Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. *Reliability engineering & system safety*, *215*, 107864. https://doi.org/10.1016/j.ress.2021.107864.

[13]. Hsu, J.-Y., Wang, Y.-F., Lin, K.-C., Chen, M.-Y., & Hsu, J. H.-Y. (2020). Wind Turbine Fault Diagnosis and Predictive Maintenance through Statistical Process Control and Machine Learning. *IEEE Access*, *8*, 1–1. Doi:10.1109/access.2020.2968615.