Appendix A

Reference Code:	

(Fill up by RMC)

International Collaborative Research Funding (ICRF) Application Form

A	**TITLE OF PROPOSED RESEARCH:** Towards An Autonomous System of Intelligent Asset Integrity
B	**DETAILS OF RESEARCHER**
B(i)	**Name of Project Leader: Dr. Ariana Yunita** **IC / Passport Number:**
B(ii)	**Position (Please tick (√)):** ☐ **Professor** ☐ **Assoc. Prof. / Dr.** ■ **Sen. Lect./ Lecturer**
B(iii)	**Faculty /School/Centre/Unit (Please provide full address):** Computer Sciences Department, Universitas Pertamina Griya Legita Building, 3rd Floor Jl. Teuku Nyak Arief, Simprug, Kebayoran Lama, Jakarta Selatan
B(iv)	**Office Telephone No.:** **Handphone No.: +6281217040411**

B(v)	**E-mail Address: ariana.yunita@universitaspertamina.ac.id**
B(vi)	**Date of first appointment with this University: 1 March 2016**
B(vii)	**Type of Service (Please tick *(√)*):** ■ **Permanent** ☐ **Contract (State contract expiry date):**
C	**RESEARCH INFORMATION**
C(i)	**Research Area (Please tick** *(√):* ☐ Self sustainable living: Green and Clean Technology ☐ Smart Mobility: Propulsion & Transport Infrastructure Technology ☐ Personalised Care: Health Analytics Technology ☐ Hydrocarbon Recovery: Enhanced Oil Recovery Technology ☐ Gas Contaminant Management: Purification Technology of Contaminated Gas √ Autonomous Facilities: Autonomous System & Technology Other:... Please Specify:
C(ii)	**Location of Research:** Computer Sciences Department, Universitas Pertamina, Jalan Teuku Nyak Arief, Jakarta Selatan

C(iii) **Duration of this research (Maximum 12 month):**

Duration: 12months

From : May 2023

To : May 2024

C(iv) **Other Researchers:**
(Please include your curriculum vitae, if necessary)

Bil	Name	Institution Details	Specialization	Role in the Project
1	Dr. Tasmi	UP	Mathematical Modelling and Optimization,	To be involved in model development and also model optimization.
2	Muhammad Zaki Almuzakki, M.Si, M.Sc.	UP	Nonlinear Control Systems	To be involved in model development and also model optimization.
3	Dr. Emelia Akashah P. Akhir	UTP	Machine Learning	To be involved in the process of data preparation and model validation.
4	NorShakirah Aziz	UTP	Business Intelligence	To be involved in the process of data preparation and model validation.
5	Nurul Aida Osman	UTP	Machine Learning	To be involved in model development and also model optimization.
6	Ahmad Afdhal	UP	Machine Learning (undergraduate student)	Research Assistant To be involved in data preprocessing
7	Yusril Albi	UP	Optimization (undergraduate student)	Research Assistant To be involved in data preprocessing

C **Research projects that have been completed or ongoing by researchers for the last three years. Please provide title of research, duration, year commence and year ending.**

(v)	Title of Research	Duration	Start Date	End Date
	Personalized Adaptive Gamification supported by Machine Learning	1 year	21/03/2022	21/03/2023

C (vi)	**Please furnish information on academic publications that has been published by the researchers for the last three (3) years. (Example: Journals, Books, Chapters in books, etc)**	
	Title	**Journal**	**Year**
	‘Everything is data’: towards one big data ecosystem using multiple sources of data on higher education in Indonesia	Journal of Big Data	2022
	Finding Contributing Factors of Students' Academic Achievement Using Quantitative and Qualitative Analyses-Based Information Extraction	International Journal of Emerging Technologies in Learning	2022

C (vii)

Executive Summary of Research Proposal (maximum 300 words)

(Please include the background of research, literature reviews, objectives, research methodology and expected outcomes from the research project)

Asset integrity is important for oil and gas industry, since asset’s capacity should run effectively and accurately, whilst also protecting the wellbeing of all personnel and equipment. Asset integrity that is supported by Artificial Intelligence (AI), namely Intelligent Asset Integrity (IAI), aims to optimize the maintenance of industrial assets such as pipelines, machinery, and equipment. The goal of this IAI is to improve the safety and reliability of assets, reduce maintenance costs, and prevent unplanned

	downtime. Companies can reduce the need for manual inspections and maintenance checks. Instead, they can rely on data-driven insights to prioritize maintenance activities and allocate resources more efficiently. This can result in cost savings and increased uptime, as well as improved safety, compliance and lower their carbon footprint. 45% of decarbonization goals can be tackled through better adoption of a circular economy. Companies can reduce the need for manual inspections and maintenance checks. Instead, they can rely on data-driven insights to prioritize maintenance activities and allocate resources more efficiently. Resolving repeat failures that cause process trips or shutdowns, stopping flaring and venting, ensuring operating parameters have not moved significantly from original efficiency levels, as well as finding and fixing asset-integrity issues that contribute to fugitive emissions are not just emission mitigation solutions, but offer substantial cost efficiencies and potential monetization opportunities for surplus power or captured gas. This research aims to build a model for IAI using a machine learning technique. Recurrent Neural Network, one of Deep Learning model, a state of the art of model that suit with time series data, is chosen for modelling the condition of asset. In general, the asset data will be gathered, processed, modeled, and evaluated for predicting asset. Expected outcome for this research is a predictive model for IAI as a basis for automation system for intelligent asset integrity.
C (viii)	**Detailed proposal of research project:** **(a) Research background including Hypothesis /Research Questions and Literature Reviews**. Asset integrity monitoring is a critical process in the oil and gas industry to ensure the safe and reliable operation of equipment. A lot of methods, such as Machine Learning method, have been used for asset integrity monitoring. Setiawan et al (2021), focused on using quantitative methods in regression analysis with multiple correlation variables. This study succeeded in showing which variables have a significant effect on the coating lifetime of the asset integrity they studied. Another study by Tang et al (2019), focused examines using the concept of risk analysis using a Streamline Failure Mode Effects and Criticality Analysis (SFMECA) method to calculate risk assessments that have the potential to occur in assets, including the risk of losing their integrity. Then this risk analysis is continued with the Borda Scoring method of the assessment that has been obtained. This research produces a worksheet that can provide data support for the failure diagnosis, state monitoring, health evaluation, and trend prediction of the existing equipment and facilities on asset integrity. A lot of Machine Learning algorithms that have been used for integrity asset monitoring is Random Forest (RF), Support Vector Machine (SVM), Artificial Neural Network (ANN). Al-Maythalony et al. (2019), RF was used for predicting the corrosion rate of oil and gas pipelines. The authors found that RF was able to achieve high accuracy in predicting the corrosion rate. Sun et al. (2019) detects pipeline

leaks based on acoustic emission signals using SVM. Furthermore, Sun et al. (2020), used ANN for predicting the remaining useful life of bearings. The authors found that ANN was able to achieve high accuracy in predicting the remaining useful life.

Other machine learning methods for intelligent asset integrity are Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) and Recurrent neural networks (RNNs).
CNN is a supervised learning algorithm that is commonly used for image recognition tasks. It is particularly useful in asset integrity monitoring as it can process large amounts of image data. For example, in a study by Yang et al. (2020), CNN was used for detecting cracks in wind turbine blades based on images. The authors found that CNN was able to achieve high accuracy in detecting cracks.

LSTM is a type of recurrent neural network (RNN) that is commonly used for time-series prediction tasks. It is particularly useful in asset integrity monitoring as it can capture temporal dependencies in data. For example, in a study by Zhou et al. (2021), LSTM was used for predicting the remaining useful life of wind turbines. The authors found that LSTM was able to achieve high accuracy in predicting the remaining useful life.

Furthermore, another method, Recurrent neural networks (RNNs) have several advantages in asset integrity monitoring, including their ability to capture temporal dependencies and handle non-linear relationships in data.

One advantage of RNNs is their ability to capture temporal dependencies in time-series data. This is particularly useful in asset integrity monitoring, where the health and performance of equipment can change over time. For example, in a study by Yang et al. (2018), RNNs were used for predicting the remaining useful life of aircraft engines. The authors found that RNNs were able to capture the temporal dependencies in the data, leading to improved performance. Similarly, in a study by Gao et al. (2018), RNNs were used for predicting the remaining useful life of gas turbines. The authors found that RNNs were able to capture the temporal dependencies in the data, leading to improved performance.

Another advantage of RNNs is their ability to handle non-linear relationships in data. This is particularly useful in asset integrity monitoring, where the relationship between sensor measurements and equipment health can be complex and non-linear. For example, in a study by Li et al. (2020), RNNs were used for predicting the remaining useful life of bearings. The authors found that RNNs were able to capture the non-linear relationship between vibration signals and bearing health, leading to improved performance. Similarly, in a study by Wang et al. (2019), RNNs were used for detecting anomalies in wind turbines. The authors found that RNNs were able to capture the non-linear relationship between sensor measurements and turbine health, leading to improved performance.

In addition to these advantages, RNNs have also been shown to be effective in handling missing data. This is particularly useful in asset integrity monitoring, where sensor data can be missing due to sensor failure or other issues. For example, in a study by Zhou et al. (2021), RNNs were used for predicting the remaining useful life of wind turbines. The authors found that RNNs were able to handle missing data, leading to improved performance.

In conclusion, RNNs have several advantages in asset integrity monitoring, including their ability to capture temporal dependencies, handle non-linear relationships in data, and handle missing data. These advantages make RNNs a valuable tool in asset integrity monitoring.

One limitation of RNNs in asset integrity monitoring is their inability to handle long-term dependencies. This issue has been highlighted in a study by Yang et al. (2017), where the authors used RNNs for predicting the remaining useful life of aircraft engines. The authors found that RNNs were not able to capture long-term dependencies, leading to poor performance. Similarly, in a study by Wang et al. (2018), RNNs were used for predicting the remaining life of bearings. The authors found that RNNs were not able to handle long-term dependencies, leading to poor performance.

Another limitation of RNNs in asset integrity monitoring is their sensitivity to noisy data. This issue has been highlighted in a study by Zhang et al. (2019), where the authors used RNNs for detecting anomalies in industrial equipment. The authors found that RNNs were sensitive to noise in the input data, leading to unstable predictions and poor performance. Similarly, in a study by Yu et al. (2018), RNNs were used for predicting the remaining useful life of bearings. The authors found that RNNs were sensitive to noise in the input data, leading to poor performance.

In addition to these limitations, RNNs can also suffer from overfitting. Overfitting occurs when a model becomes too complex and starts to memorize the training data instead of learning general patterns. This issue has been highlighted in a study by Guo et al. (2020), where the authors used RNNs for predicting the remaining useful life of bearings. The authors found that RNNs were prone to overfitting, leading to poor performance on new, unseen data.

Despite these limitations, there have been efforts to overcome them in the context of asset integrity monitoring. For example, in a study by Chen et al. (2021), the authors used a hybrid model that combined RNNs with a convolutional neural network (CNN) for predicting the remaining life of bearings. The hybrid model was able to capture both temporal and spatial dependencies in the data, leading to improved performance. Similarly, in a study by Zhou et al. (2021), the authors used a hybrid model that combined RNNs with a long short-term memory (LSTM) network for predicting the remaining useful life of wind turbines. The hybrid model was able to capture long-term dependencies in the data, leading to improved performance.

In conclusion, RNNs have limitations that can affect their effectiveness in asset integrity monitoring. However, by combining them with other machine learning techniques or preprocessing the data, these limitations can be overcome, and RNNs can be a valuable tool in asset integrity monitoring.

The above literature led to the following research questions:

1. What are the current machine learning techniques used in monitoring asset integrity in oil and gas plants to reduce carbon emission?
2. How can improvised machine learning techniques be used to develop a predictive model for monitoring asset integrity in oil and gas plants?
3. How effective is the developed machine learning model for its intended purpose?

Objectives:

1. To review the current state of asset integrity monitoring in the oil and gas industry and its impact on the environment.
2. To investigate the potential of machine learning methods in monitoring asset integrity in oil and gas plants to reduce carbon footprint.
3. To develop a predictive model using machine learning techniques to monitor asset integrity in oil and gas plants.
4. To evaluate the effectiveness of the developed model in reducing carbon footprint in oil and gas plants.

References

Al-Maythalony, B. A., et al. (2019). Predicting corrosion rate of oil and gas pipelines using machine learning algorithms. Journal of Petroleum Science and Engineering, 173, 502-512.

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Chen, W., et al. (2021). Bearing remaining life prediction using a hybrid model of convolutional neural network and recurrent neural network. Mechanical Systems and Signal Processing, 148, 107427.

Chen, J., Wang, S., & Wu, X. (2017). Research on carbon reduction of preventive maintenance in manufacturing industry. Procedia Engineering, 174, 548-556.

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Guo, X., et al. (2020). A novel approach to remaining useful life prediction of rolling element bearings based on deep learning with one-class classification. Mechanical Systems and Signal Processing, 136, 106415.

Kumar, P., Arora, V. K., & Vardhan, H. (2015). Energy conservation through preventive maintenance in wastewater treatment plant. Procedia Environmental Sciences, 29, 99-100.

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Li, J., et al. (2020). Deep learning-based fault diagnosis of rolling bearings considering the time-frequency domain features of vibration signals. Sensors, 20(16), 4586.

Setiawan, R., & Santosa, B. (2021, February). Regression analysis in predicting coating application lifetime on asset integrity project. In IOP Conference Series: Materials Science and Engineering (Vol. 1072, No. 1, p. 012040). IOP Publishing.

Tang, Y., et al. (2019). Risk identification and quantitative evaluation method for asset integrity management of offshore platform equipment and facilities. Mathematical Problems in Engineering, 2019.

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Yang, W., et al. (2018). A survey on deep learning for remaining useful life estimation. IEEE Transactions on Industrial Informatics, 14(8), 3807-3818.

Yang, W., et al. (2017). Deep learning for remaining useful life estimation: A case study on bearings. IEEE Transactions on Industrial Electronics, 64(1), 510-519.

Yang, F., et al. (2020). Automatic crack detection in wind turbine blades based on convolutional neural networks. Renewable Energy, 154, 1102-1113.

Yu, Y., et al. (2018). A deep learning approach to bearing remaining useful life prediction. IEEE Transactions

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(b) Objective (s) of the Research

This study embarks on the following objectives:

1. To review the current state of asset integrity monitoring in the oil and gas industry and its impact on the environment.
2. To investigate the potential of machine learning methods in monitoring asset integrity in oil and gas plants to reduce carbon footprint.
3. To develop a predictive model using machine learning techniques to monitor asset integrity in

oil and gas plants.

4. To evaluate the effectiveness of the developed model in reducing carbon footprint in oil and gas plants.

(c) Methodology

Please state in the form / Sila nyatakan di borang ini

1. Description of Methodology

There are four research phases in this study.

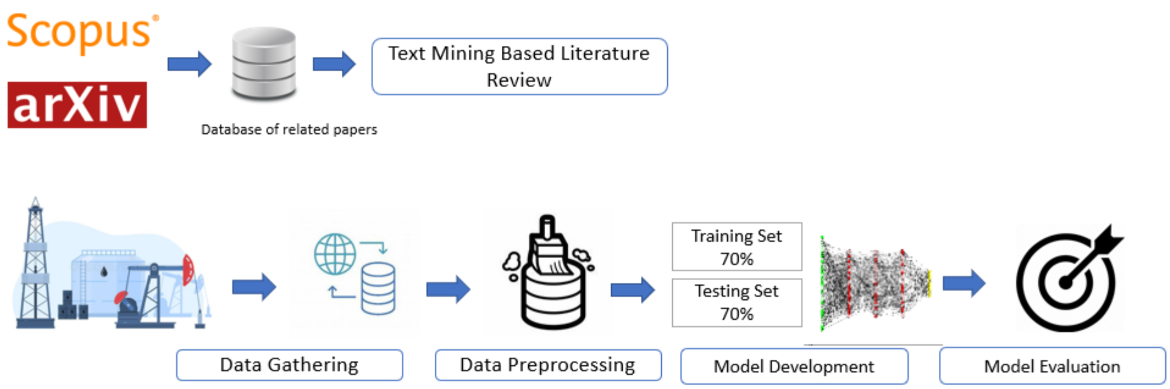


Figure 1. Research Phases

I. Literature Review

A systematic review of existing literature will be conducted to identify the current state of asset integrity monitoring in the oil and gas industry and the impact on the environment. The review will also identify the potential advanced and techniques in monitoring asset integrity to reduce carbon footprint.

Input: Related papers from reputable academic database

Technique: Text Mining based Literature Review (Latent Dirichlet Allocation for Topic Modelling)

Output: Review of Intelligent Asset Integrity and state-of-the-art of the technique

II. Data Collection

Data will be collected from sensors and other relevant sources in oil and gas plants. The data will include information on equipment performance, operating conditions, and other relevant metrics.

Input: Review of Intelligent Asset Integrity and state-of-the-art of the technique

Technique: Collecting Data from sensors

Output: Dataset

III. Model Development

The collected data will be used to develop a predictive model using advanced algorithms. The model will be trained on the data to identify patterns that can predict potential failures or anomalies in the equipment.

Input: Dataset

Technique: Data pre-processing, training

Output: Model

IV. Model Evaluation

The developed model will be evaluated by comparing its performance to traditional monitoring methods. The evaluation will include metrics such as accuracy, efficiency, and carbon footprint reduction.

Input: Testing Set, Model

Technique: Machine Learning Algorithms

Output: Accuracy, Precision, Recall

2. *Flow Chart of Research Activities*

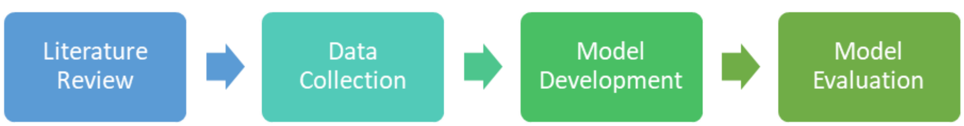
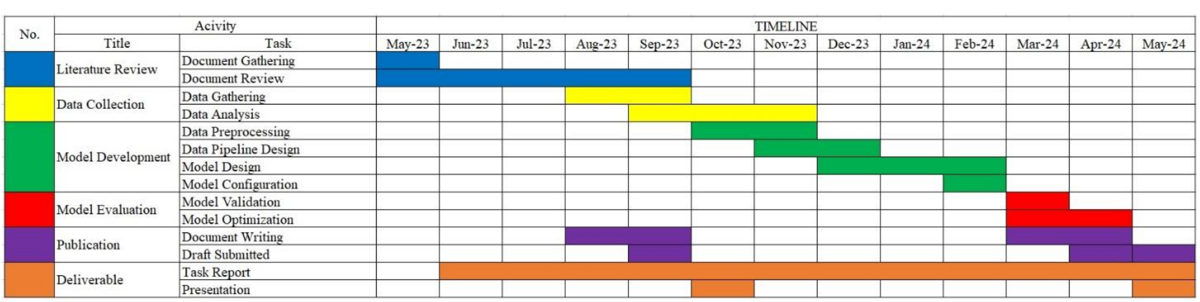


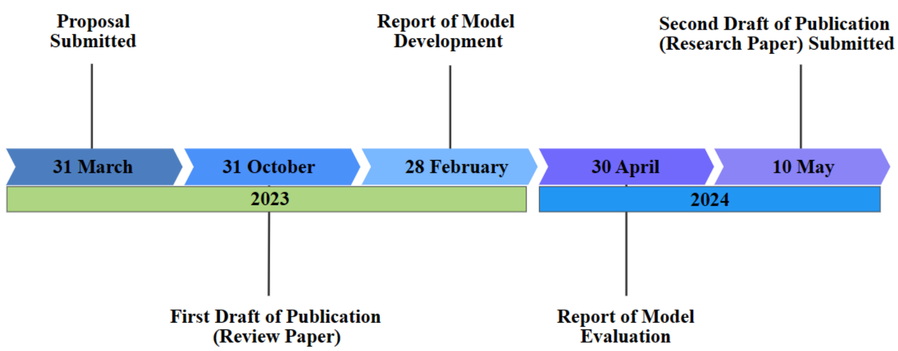
Figure 2. Research Activities

In general, there are four research activities: Literature review, collecting data, model development, and model evaluation. The explanation of each activity is explained in the previous section. Below is the Gantt Chart for this study.

3. Gantt Chart of Research Activities



4. Milestones and Dates



(d) Expected Results/Benefit

1. Novel theories/New findings/Knowledge

I. Enhanced of the current state of asset integrity solutions in the oil and gas industry and its impact on the environment.

II. An evaluation of the potential intelligent techniques in monitoring asset integrity to reduce carbon footprint.

III. An optimized model of the current operating parameters for monitoring asset integrity in oil and gas plants.

IV. An evaluation of the effectiveness of the developed intelligent model in reducing carbon footprint in oil and gas plants.

2. Research Publications

i- To publish in SCOPUS journal "International Journal of Advanced Computer Science and Applications (IJACSA)" - Q3

ii- To publish in journal proceeding IEEE / Scopus indexed journal

3. Two research assistants (Undergraduate students)

D	**ACCESS TO EQUIPMENT AND MATERIAL**		
	Equipment	**Location**	
	Example / *Contoh:*		
E	**BUDGET BREAKDOWN**		
	Please indicate your estimated budget for this research and details of expenditure according to the guidelines attached.		
	Budget details	**Amount requested by applicant (USD)**	**Description of the budget**
E(i)	**Vote 11000 - Wages and Allowances for Temporary and Contract Personnel**	**1000 USD**	2 Research Assistants 2 x 200 hours x Rp 36.000,00 = Rp 14.400.000,00 (1000 USD)
E(ii)	**Vote 21000 - Travel and Transporta**	**3200 USD**	**Trip to UTP 2700 USD** - Data Collection to UTP

	tion		- Evaluation and Engagement No of trip : 2 Cost per trip USD 1,350 per trip *Flight Tickets 3 researchers, Batik Airlines (Jakarta to KL), USD 200/return trip, Total:USD 600 *Accommodation, USD 50/night x 3 researchers; Approx. 4 nights per trip, Total: USD 600 *Local Transportation and Meal 4 days, for 3 researchers Total: USD 150 **International Conference – 500 USD** Flight 300 USD Accommodation 100 USD Transportation and Meals 100 USD
E (iii)	**Vote 24000 - Rental**		
E (iv)	**Vote 27000 - Research Materials & Supplies**	**200 USD**	Upgrade Google Colab Pro – 4 months 50 USD x 4 months = 200 USD

E (vi)	**Vote 29000 - Special Services**	**1300 USD**	Publication Fee for Journal 600 ("International Journal of Advanced Computer Science and Applications (IJACSA)" - Q3 - 600 USD Proofread 2 manuscripts = 2 x 250 USD = 500 USD Publication Fee for Proceedings IEEE = 200 USD
E (vii)	**Vote 35000 - Special Equipment and Accessories**	**300 USD**	Consumption Meetings 200 USD Stationery 100 USD
TOTAL AMOUNT		**6000 USD**	
F	**DECLARATION BY APPLICANT (Please tick *(√)*)**		

I hereby confess that:

V **1.** **All information stated here are accurate, the secretariat has right to reject or to cancel the offer without prior notice if there is any inaccurate information given.**

V ***2.*** **Application of this fundamental research is presented for the Universiti Teknologi PETRONAS-International Collaborative Research Funding.**

☐ ***3.*** **Application of this research is also presented for the other reasearch grant/s (grant's name and total amount)**

Date : 31 March 2023 **Applicant's Signature :**

G	**RECOMMENDATION** ***(Vice Chancellor/Deputy Vice Chancellor (Research and Innovation)/Director of Research Management Center)***
	Please tick (√) **Recommended:** ☐ ***A.*** **Highly Recommended** ☐ **B. Recommended** ☐ **C. Not Recommended (*Please specify reason*)** **Comments:** -- -- -- -- -- -- -- -- **Name:** **Signature:** **Date:**

Note: APPLICATIONS SUBMITTED WILL BE TREATED IN FULL CONFIDENCE. THE DECISION OF THE UTP-ICRF APPROVAL COMMITTEE IS FINAL.