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Cost Estimation Using Function Point for an AIoT-Based Infusion Drop Detection Prototype Using Random Forest and XGBoost

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ABSTRACT: This study aims to develop an Artificial Intelligence of Things (AIoT) prototype capable of accurately and real-time predicting the drip rate (TPM) of intravenous fluid administered to patients. The research focuses on three main aspects: the design, implementation, and testing of an Internet of Things (IoT)-based prototype that integrates sensors with a microcontroller to detect fluid drips; the development of machine learning models using the Random Forest and XGBoost algorithms to classify drip status based on sensor data; and the estimation of software development costs using the Function Point (FP) IFPUG method. The data and system requirements were obtained through a literature review of previous studies on IoT-based infusion prototypes and online health references to determine the drip calculation formula used for dataset construction. To achieve these objectives, the study combines three development approaches. The Throw Away Prototyping method was applied in designing and constructing the AIoT hardware, while a machine learning pipeline was used to train and evaluate the TPM prediction model. Furthermore, the Function Point IFPUG method was employed to estimate the software development costs by considering the accuracy level of the developed model. The findings of this study are expected to contribute to the advancement of AIoT-based infusion monitoring systems that are adaptive and applicable within healthcare service environments.

KEYWORDS: Prototype; Internet of Things; Drip Rate; Function Point; IFPUG; Machine learning; Random Forest; XGBoost; Cost Estimation.

I. INTRODUCTION

Based on national health statistics, Type C hospitals represent the largest proportion of hospitals in Indonesia. Although Regulation of the Minister of Health of the Republic of Indonesia No. 24 of 2022 mandates all healthcare facilities to implement Electronic Medical Records (EMR), the level of adoption remains uneven and is still largely partial (Profil Kesehatan Indonesia 2024). EMR is defined as a medical record system managed electronically to support healthcare services (Profil Kesehatan Indonesia 2024). Supporting technologies such as the Internet of Things (IoT) and its healthcare-specific development, the Internet of Medical Things (IoMT), play a crucial role in enabling automated data exchange and real-time patient monitoring (Kalsoom et al., 2025; Yanti Siregar & Pangaribuan, 2025).

In the context of patient care, intravenous infusion is a critical medical device. However, its monitoring is still predominantly performed manually by healthcare personnel, which increases the risk of delayed intervention, inaccurate drip rates, and human error, particularly during periods of high workload (Akbar & Gunawan, 2020). Meanwhile, the application of machine learning in healthcare has been shown to support patient monitoring and clinical decision-making processes (Rahmani et al., 2021). Nevertheless, the integration of machine learning with IoT-based systems for intravenous fluid monitoring remains very limited (Abdulmalek et al., 2022; Adinda Putri et al., 2024).

Therefore, this study develops a prototype of an Artificial Intelligence of Things (AIoT)-based intravenous drip monitoring system capable of detecting and predicting drip patterns in real time. The proposed system is expected to improve monitoring accuracy and support clinical decision-making. The development includes the implementation of machine learning algorithms, namely Random Forest and XGBoost, which are widely recognized for their high performance in handling complex healthcare (Fatima et al., n.d.; Kansab, n.d.; Septian Cahya Putra et al., 2024; Zhu, 2020). In addition to technical aspects, this research also incorporates an economic evaluation through development cost estimation using the Function Point method (Yhurinda et al., 2018), with a prototyping approach selected to support concept validation and development efficiency (Andini et al., 2023; Bisht et al., 2024).

II. METHOD

A. Identifying Approiate Keywords Across Various Academic Article Databases for Literature Review

A systematic literature search was conducted to collect relevant previous studies. The keywords were derived from the core focus of the research and encompassed key concepts such as: “Infusion monitoring system,” “IoT prototype,” “drip rate detection,” “Function Point IFPUG,” “cost estimation in healthcare,” “machine learning in medical devices,” “Random Forest,” “XGBoost,” and “AIoT (Artificial Intelligence of Things).” The search was performed in indexed databases such as Scopus and Google Scholar to ensure the completeness and quality of the selected literature.

B. Downloading the Search Result

All documents (journal articles, conference proceedings, and technical reports) that matched the specified keywords were downloaded in full-text (PDF) format from the search results. This process ensured the availability of complete manuscripts for indepth evaluation. The search results from both platforms were managed using reference management software to avoid duplication and to facilitate systematic document organization.

C. Filtering Relevant Articles

Article selection was conducted in two stages. The first stage was based on the relevance of the title and abstract to the research topic. In the second stage, the articles that passed the initial screening were further filtered through rapid reading of the introduction, methodology, and conclusion sections. The main inclusion criteria included: a focus on infusion drip rate monitoring, the use of IoT/AIoT-based prototypes, the application of Random Forest or XGBoost algorithms in healthcare contexts, and studies discussing cost estimation using the Function Point IFPUG method. Articles that did not meet these criteria were excluded from the review.

D. Performing Cost Estimation Calculation for AIoT

The cost estimation for the development of the AIoT prototype was carried out by adopting the Function Point (FP) method based on the International Function Point Users Group (IFPUG) standard. The calculation stages included: identification and classification of system functional components (such as inputs, outputs, inquiries, internal logical files, and external interface files), determination of complexity levels, and calculation of the unadjusted function point (UFP). The UFP value was then adjusted using the value adjustment factor (VAF), which accounts for 14 system characteristics. Effort estimation (in person-month units) and development cost were calculated based on organizational productivity rates and the cost per function point.

E. Analyzing the Calculation Results

The results of the cost estimation calculations were analyzed to assess the economic feasibility of developing the prototype. Quantitative analysis included evaluation of the total development cost, cost distribution across functional components, and comparison with reference studies or industry standards. Qualitative analysis was conducted to interpret factors influencing the estimation, such as system complexity and productivity assumptions. The outcomes of this analysis served as the basis for recommendations for further development and as considerations for investment decision-making in the development of AIoT-based medical devices.

III. RESULT

Based on the research approach employed, this study presents a systematic and integrated synthesis of four main analytical domains. The synthesis includes an examination of development cost estimation for an infusion drip monitoring prototype, a review of infusion prototypes based on the Internet of Things (IoT), an exploration of machine learning integration within IoT systems (Artificial Intelligence of Things/AIoT), and an evaluation of AIoT model accuracy using validation methods grounded in the Research and Development (R&D) paradigm. Accordingly, this research not only maps the technical and economic foundations but also highlights critical validation aspects in the development of artificial intelligence–based healthcare systems.

A. Literature Review as a Basis for Development

Previous research on infusion monitoring has focused on the development of IoT-based systems using various sensor configurations and platforms. (Akbar & Gunawan, 2020) developed a weight-sensor-based monitoring prototype with real-time web visualization, although the system still experienced measurement errors and relied on stable internet connectivity. (Asyari & Budiman) proposed an infusion monitoring prototype using weight and color sensors with remote monitoring features, demonstrating the feasibility of multi-sensor integration. (Ardhana et al., 2023) implemented an IoT system integrated with a RESTful API and a Laravel-based platform, but provided limited discussion on system performance and evaluation. Meanwhile, (Phisca Aditya Rosyady et al., 2023) achieved high sensor accuracy using weight and infrared sensors, although the system was limited to single-device monitoring. These studies collectively provide a foundation for the development of AIoT-based infusion monitoring systems and support further integration of machine learning approaches such as Random Forest and XGBoost.

In the context of healthcare analytics, machine learning pipelines have been widely applied to improve prediction and classification performance. (G Uday Kiran, 2023) showed that pipeline configuration significantly affects model performance, with ensemble methods such as Gradient Boosting achieving strong results, although further optimization using more advanced approaches was recommended. (Kourou et al., 2021) applied a machine learning pipeline to analyze mental health impacts in breast cancer patients, highlighting the importance of accurate feature modeling while noting limitations related to data scope and misclassification. (Chowdhury et al., 2025) reported high accuracy through the use of preprocessing techniques and ensemble models, emphasizing the critical role of data quality in medical machine learning. (Kanbar et al., 2022)) integrated machine learning pipelines with Electronic Health Record systems for real-time clinical recommendations, though the lack of detailed model evaluation revealed opportunities for deeper performance analysis. Collectively, these studies provide a methodological foundation for the development of machine learning pipelines and support cost estimation research for AIoT-based infusion drip detection prototypes using Random Forest and XGBoost.

From a software engineering perspective, Function Point Analysis (FPA) has been extensively used for estimating software size, effort, and development cost. (Lumba et al., 2025) demonstrated the use of FPA to estimate development cost and time, although the basis for determining effort per function point was not clearly explained. (Kristi et al., 2020) applied FPA to estimate software size, effort, and cost, but highlighted inconsistencies in effort distribution that affected project duration interpretation. (Yhurinda et al., 2018) showed that FPA-based cost estimation achieved high accuracy compared to actual project costs, while also indicating the lack of application in medical software contexts. (Dewi et al., 2020) compared FPA and Use Case Point methods and found that different estimation approaches significantly influence software size and effort results, emphasizing the need for method selection aligned with system characteristics. Collectively, these studies provide a strong foundation for applying FPA in cost estimation and highlight opportunities for its extension to AIoT-based medical software, including infusion drip detection systems using Random Forest and XGBoost.

B. Function Point Calculation Formula

Function Point Analysis (FPA) was first introduced by Albrecht from IBM as a method to measure software size based on the functionality delivered to users, rather than the number of lines of code (Yhurinda et al., 2018). The main advantage of this approach is that it provides an objective size estimation that is independent of the programming language used (Garmus & Herron, n.d.).Menurut(Yhurinda et al., 2018), FPA membagi perangkat lunak menjadi lima komponen fungsi pengguna:

- **Data Input (DI)**: a function that receives data from outside the application to be processed.
- **Data Output (DO)**: a function that produces data output from the application.
- **Data Query (DQ)**: a function that provides information without updating the database.
- **Internal File (IF)**: a group of data that is maintained internally by the application.
- **Reference File (RF)**: a group of data that is referenced by the application but maintained by another system.

These five components are then assigned complexity weights (low, average, high) to calculate the Unadjusted Function Point (UFP) (Garmus & Herron, n.d.). The effort estimation process using Function Point Analysis is carried out through the following steps.

- **Unadjusted Function Point (UFP)**: After all system functions are identified and classified into the five user function components, each component is assigned a weight based on its complexity level (low, average, or high). The UFP value is obtained by summing the weighted counts of all functional components, representing the initial functional size of the software before technical adjustments.
- **Total Degree of Influence (TDI)**: Once the UFP value is obtained, an assessment of general system characteristics is conducted to measure the influence of technical factors on system complexity. Each characteristic is assigned a score, and the total of these scores produces the TDI value.
- **Value Adjustment Factor (VAF)**: The TDI value is then used to calculate the system adjustment factor using the following formula:

  $VAF = 0.65 + (0.01 \times TDI)$
- **Adjusted Function Point (AFP)**: The final functional size of the software is calculated by multiplying the UFP by the VAF, as expressed by the formula:

  $AFP = UFP \times VAF$

- **Effort Estimation**: The development effort is estimated by converting the AFP value into work effort units using a predefined productivity rate, formulated as: *Effort = AFP × Effort Rate*
- **Effort Distribution**: The total estimated effort is subsequently distributed across software development activities, such as requirements analysis, system design, implementation, testing, and deployment, to support systematic project planning and control.

C. Cost Estimation Calculation

After all cost estimation calculations have been carried out based on the identified functional components and their respective adjustment factors, the resulting values are summarized and presented in the following table.

Table I: Result of Count Factor

Count Factor	Value
Unadjusted Function Point (UFP)	26
Total Degree of Influence (TDI)	18
Value Adjustment Factor (VAF)	0.83
Adjusted Function Point (AFP)	21.58
Effort	176.956

Count EVA (Effort Value per Activities) dan Cost per Activities

After all calculation factors have been determined, the next step is to distribute the estimated effort across each development division so that the overall cost estimation can be identified. The effort distribution is calculated using the formula

- *EVA = Effort Value per Project × Activity Distribution (%)*,

which represents the portion of effort allocated to each development activity. Furthermore, the cost for each activity is calculated using the formula

- *Cost per Activity = Payrate (Hour) × Regional Index × EVA*.

Based on these calculations, the resulting effort distribution and cost estimation for each division are presented in the table below.

Table II: Effort Distribusion

Divison	Effort Percentage	EFP	Payrate per Hour	CPA
Project Management	10%	17.6956	IDR 115,385.00	IDR 1,982,594.41
Requirements Analysis and Research	8%	14.15648	IDR 57,692.00	IDR 793,030.89
Engineering Planning	10%	17.6956	IDR 57,692.00	IDR 991,288.61
Electrical Engineer	10%	17.6956	IDR 34,615.00	IDR 594,769.73
AI Engineer	13%	23.00428	IDR 236,441.85	IDR 5,281,438.46
Fullstack Developer	12%	21.23472	IDR 69,231.00	IDR 1,427,467.97
Data Engineering and Dataset Preparation	15%	26.5434	IDR 28,846.00	IDR 743,466.46
Data Security and Compliance	7%	12.38692	IDR 83,077.00	IDR 999,225.18
Testing and Quality Assurance (QA)	10%	17.6956	IDR 39,231.00	IDR 674,083.82

Implementation and Training	5%	8.8478	IDR 161,538.00	IDR1,387,807.49
Total	100%	176.956		**IDR 14,875,173.03**

With reference to the salary rates shown in the table below.

Table III: Payrate Per Hour Reference

Division	Minimum monthly salary (Bachelor's degree)	Reference
Project Management	IDR 20,000,000.00	https://www.persolindonesia.com/salary-guides
Requirements Analysis and Research	IDR 10,000,000.00	https://www.persolindonesia.com/salary-guides
Engineering Planning	IDR 10,000,000.00	https://www.persolindonesia.com/salary-guides
Electrical Engineer	IDR 6,000,000.00	https://www.persolindonesia.com/salary-guides
AI Engineer	IDR 491,799,041.00	https://www.salaryexpert.com/salary/job/aiengineer/indonesia
Fullstack Developer	IDR 12,000,000.00	https://www.persolindonesia.com/salary-guides
Data Engineering and Dataset Preparation	IDR 5,000,000.00	https://www.persolindonesia.com/salary-guides
Data Security and Compliance	IDR 14,400,000.00	https://www.glassdoor.com/Salaries/jakartaindonesia-cyber-security-salary-SRCH_IL.0,17_IM1045_KO18,32.htm
Testing and Quality Assurance (QA)	IDR 6,800,000.00	https://id.jobstreet.com/career-advice/role/qualityassurance-engineer/salary
Implementation and Training	IDR 28,000,000.00	https://www.persolindonesia.com/salary-guides

After the calculations were performed, the estimated development cost of the AIoT prototype for infusion drip detection was obtained at **IDR 14,875,173.03**, with a total EFP (Effort Value Per Activities) of **176.956**.

D. Evaluation of Machine Learning Model Accuracy for AIoT

Based on all evaluation stages, it can be concluded that the models for predicting Drips Per Minute (DPM) and infusion weight demonstrate excellent performance. Residual analysis of the DPM model shows error distributions concentrated around zero and relatively symmetric, indicating low prediction error without tendencies toward overestimation or underestimation. Although there is an indication of increased error variance at higher DPM values, this pattern remains within acceptable limits and does not exhibit extreme deviations.

The performance of the DPM model is further supported by an R^2 score of 1.0000, an MAE of 0.1073, and an RMSE of 0.1589, all of which indicate very high predictive accuracy. Meanwhile, the weight prediction model also exhibits strong performance, as reflected by high accuracy, precision, recall, and F1-score values across both Dataset 1 and Dataset 2. Nevertheless, Dataset 2 provides more robust and reliable performance due to its larger data size, more balanced class distribution, and an out-of-bag score close to one. Therefore, the developed models are considered to have high reliability and strong generalization capability, with Dataset 2 serving as the primary reference for the final assessment of model performance.

IV. CONCLUSION

This study successfully developed and evaluated an Artificial Intelligence of Things (AIoT) prototype for infusion drip monitoring that integrates IoT sensors, machine learning algorithms (Random Forest and XGBoost), and a cost estimation approach using the Function Point IFPUG method. The evaluation results indicate that the TPM prediction model exhibits very high agreement between actual and predicted values, while the infusion weight classification model across two datasets achieved 100% accuracy, with Out-of-Bag scores approaching perfection in the large-scale dataset, indicating excellent model generalization capability. From an economic perspective, the estimated development cost of the AIoT prototype, amounting to IDR 14,875,173.03, demonstrates that an AIoT-based prototyping approach can be developed efficiently and in a measurable manner. Accordingly, this research not only confirms the technical feasibility of an AIoT-based infusion monitoring system but also provides a quantitative overview of development costs, making it a valuable initial reference for the development and adoption of similar systems in healthcare service environments.

V. FUTURE RESEARCH DIRECTION

Future research is recommended to conduct direct system validation in clinical environments to assess model reliability under more dynamic real-world conditions, such as patient variability, different types of infusion fluids, and sensor disturbances. In addition, model development can be extended by applying continuous regression approaches and deep learning techniques to improve sensitivity in detecting infusion drip anomalies. From a system perspective, integration with Electronic Medical Records (EMR) and real-time analytics–based clinical dashboards represents an important development direction to support clinical decision-making. From an economic standpoint, future studies may combine the Function Point IFPUG method with other cost estimation approaches, such as COCOMO II or life cycle cost analysis, to obtain a more comprehensive cost overview at the hospital implementation scale. These approaches are expected to strengthen the readiness of AIoT-based infusion systems for large-scale and sustainable deployment in the healthcare sector.

REFERENCES

1) Abdulmalek, S., Nasir, A., Jabbar, W. A., Almuhaya, M. A. M., Bairagi, A. K., Khan, M. A. M., & Kee, S. H. (2022). IoT-Based Healthcare-Monitoring System towards Improving Quality of Life: A Review. In *Healthcare (Switzerland)* (Vol. 10, Issue 10). MDPI. https://doi.org/10.3390/healthcare10101993
2) Adinda Putri, R., Daniela Aedo, Y., Wijaya, I., Roihan Jannatun Adhen, M., & Pratama, D. (2024). *JURNAL REIN (REKAYASA INFORMATIKA) Analisis Implementasi Internet Of Thing Dalam Bidang Kesehatan: Systematic Literature Review* (Vol. 1, Issue 1).
3) Akbar, T., & Gunawan, I. (2020). Prototype Sistem Monitoring Infus Berbasis IoT (Internet of Things). *Edumatic: Jurnal Pendidikan Informatika*, *4*(2), 155–163. https://doi.org/10.29408/edumatic.v4i2.2686
4) Andini, N., Taufiq, R., Priyanggodo, D. Y., & Sugiyani, Y. (2023). Penggunaan Metode Prototype Pada Pengembangan Sistem Informasi Imunisasi Posyandu. *JIKA (Jurnal Informatika)*, *7*(4), 431. https://doi.org/10.31000/jika.v7i4.9329
5) Ardhana, V. Y. P., Hidayat, M. T., Jannah, M., Sumiati, S., Rini, P., & Sari, N. (2023). Implementasi RESTful API Pada Laravel dan Simulator IoT Wokwi Untuk Pengukuran Suhu dan Kelembaban Menggunakan Metode Waterfall. *Arcitech: Journal of Computer Science and Artificial Intelligence*, *3*(2), 93. https://doi.org/10.29240/arcitech.v3i2.9334
6) Asyari, L. C., & Budiman, A. (n.d.). *Simposium Nasional RAPI XX-2021 FT UMS*.
7) Bisht, Y. S., Singh, R., Gehlot, A., Akram, S. V., Thakur, A. K., Priyadarshi, N., & Twala, B. (2024). Recent trends and technologies in rapid prototyping and its inclination towards industry 4.0. *Sustainable Engineering and Innovation*, *6*(1), 141–154. https://doi.org/10.37868/sei.v6i1.id288
8) Chowdhury, L. H., Tabassum, S., Shatabda, S., & Ahmed, A. (2025). An optimized data analytics pipeline for improving healthcare diagnosis using ensemble learning. *Informatics in Medicine Unlocked*, *53*. https://doi.org/10.1016/j.imu.2025.101623
9) Dewi, R. S., Dharmawan, Y. S., & Aisah, S. N. (2020). Measuring Software Size and Effort Estimation on Islamic Banking Application. *2020 3rd International Conference on Information and Communications Technology, ICOIACT 2020*, 229–233. https://doi.org/10.1109/ICOIACT50329.2020.9332073
10) Fatima, S., Hussain, A., Bin Amir, S., Haseeb Ahmed, S., & Muhammad Huzaifa Aslam, S. (n.d.). *XGBoost and Random Forest Algorithms: An In-Depth Analysis*.

11) G Uday Kiran, E. al. (2023). A Machine Learning Pipeline and Application for Automatic Classification of Clinical Documents. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(10), 481–490. https://doi.org/10.17762/ijritcc.v11i10.8512
12) Garmus, D., & Herron, D. (n.d.). *Addison-Wesley Information Technology Series Function Point Analysis Measurement Practices for Successful Software Projects*.
13) Kalsoom, T., Ramzan, N., Ahmed, S., Anjum, N., Safdar, G. A., & Ur Rehman, M. (2025). Socio-Organisational Challenges and Impacts of IoT: A Review in Healthcare and Banking. In *Journal of Sensor and Actuator Networks* (Vol. 14, Issue 3). Multidisciplinary Digital Publishing Institute (MDPI). https://doi.org/10.3390/jsan14030046
14) Kanbar, L. J., Wissel, B., Ni, Y., Pajor, N., Glauser, T., Pestian, J., & Dexheimer, J. W. (2022). Implementation of Machine Learning Pipelines for Clinical Practice: Development and Validation Study. *JMIR Medical Informatics*, *10*(12). https://doi.org/10.2196/37833
15) Kansab, S. (n.d.). *Machine Learning Pipeline for Software Engineering: A Systematic Literature Review*.
16) Kourou, K., Manikis, G., Poikonen-Saksela, P., Mazzocco, K., Pat-Horenczyk, R., Sousa, B., Oliveira-Maia, A. J., Mattson, J., Roziner, I., Pettini, G., Kondylakis, H., Marias, K., Karademas, E., Simos, P., & Fotiadis, D. I. (2021). A machine learning-based pipeline for modeling medical, socio-demographic, lifestyle and self-reported psychological traits as predictors of mental health outcomes after breast cancer diagnosis: An initial effort to define resilience effects. *Computers in Biology and Medicine*, *131*. https://doi.org/10.1016/j.compbiomed.2021.104266
17) Kristi, J., Aisah, S. N., & Dewi, R. S. (2020). Estimasi Biaya Software FAS (Financing Analysis System) Menggunakan Metode Function Point (Studi Kasus Pada PT BPRS Lantabur Tebuireng). *JURIKOM (Jurnal Riset Komputer)*, *7*(1), 97. https://doi.org/10.30865/jurikom.v7i1.1891
18) Lumba, E., Widyaningrum, D., & Waworuntu, A. (2025). Cost Estimation for Software Development Using Function Point Analysis Method. *IJNMT (International Journal of New Media Technology)*, *11*(2), 119–124. https://doi.org/10.31937/ijnmt.v11i2.4006
19) Phisca Aditya Rosyady, Aditya Santa Sanitya Sukarjiana, Nurina Umy Habibah, Nuni Ihsana, Ahmad Raditya Cahya Baswara, Widya Rahayu Dinata, & Dedik Sulistiawan. (2023). *Monitoring Cairan Infus Menggunakan*. Hearthstone Publications.
20) *Profil Kesehatan Indonesia 2024*. (n.d.).
21) Rahmani, A. M., Yousefpoor, E., Yousefpoor, M. S., Mehmood, Z., Haider, A., Hosseinzadeh, M., & Ali Naqvi, R. (2021). Machine learning (Ml) in medicine: Review, applications, and challenges. In *Mathematics* (Vol. 9, Issue 22). MDPI. https://doi.org/10.3390/math9222970
22) Septian Cahya Putra, B., Tahyudin, I., Adhi Kusuma, B., & Nur Isnaini, K. (2024). *Efektivitas Algoritma Random Forest, XGBoost, dan Logistic Regression dalam Prediksi Penyakit Paru-paru The Effectiveness of Random Forest, XGBoost, and Logistic Regression Algorithms in Predicting Lung Disease* (Vol. 23, Issue 4). https://www.kaggle.com/datasets/andot03bsrc/dataset-predic-terkena-penyakit-paruparu.
23) Yanti Siregar, K., & Pangaribuan, H. (2025). Desain Dan Implementasi Sistem Pengendalian Gorden Otomatis Berbasis Arduino Menggunakan Sensor Light Dependent Resistor. *Jurnal Comasie*, *12*(03).
24) Yhurinda, A., Putri, P., & Subriadi, A. P. (2018). Software Cost Estimation Using Function Point Analysis. In *Postgraduate Program Institut Teknologi Sepuluh Nopember* (Vol. 79).
25) Zhu, T. (2020). Analysis on the applicability of the random forest. *Journal of Physics: Conference Series*, *1607*(1). https://doi.org/10.1088/1742-6596/1607/1/012123