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IoT and Water Consumption Forecasting: A Green Accounting Study at a Coffee Shop in Cimahi

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Abstract

Uncontrolled water consumption is a serious challenge, especially in small businesses like coffee shops. Excessive water use can lead to waste and financial losses. To address this issue, IoT (Internet of Things) technology and data analysis are applied to monitor and predict water consumption. In this study, predictive models such as Random Forest, XGBoost, and LSTM are used to analyze water consumption data. The results show that Random Forest has the best performance with the lowest prediction error and the highest R-squared value, indicating this model's capability to explain nearly all the variance in water consumption data. Random Forest and XGBoost perform well as they can handle data with non linear features and complex interactions, while LSTM's lower performance is likely due to limited data and suboptimal hyperparameter tuning. The implementation of green accounting in this system enables effective tracking of water consumption costs. Suggested improvements include further exploration of LSTM hyperparameters, the use of ensemble techniques, and cost sensitivity analysis for water-saving policy decisions. This model is expected to provide an effective water saving solution for coffee shop owners.

Keywords— *water consumption, IoT, Random Forest, green accounting, coffee shop*

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1. INTRODUCTION

Uncontrolled water consumption is one of the serious challenges faced by the world today. Population growth, urbanization, and increasing economic activities have led to a rising demand for water, while the availability of clean water continues to decline. According to a report by the World Resources Institute (WRI), approximately 25% of the global population lives in regions experiencing extremely high water stress, where water demand significantly exceeds supply [1]. This issue not only affects the sustainability of natural resources but also increases the risk of social conflicts due to competition over water resources.

In small businesses such as coffee shops, excessive water consumption often goes unnoticed. However, these businesses contribute to water waste that could be managed more efficiently to reduce environmental impact. Poor water management can lead to significant financial losses. For instance, if water consumption exceeds the necessary amount by 20%, with an average water cost of IDR 5,000 per cubic meter, losses could range from approximately IDR 200,000 to IDR 500,000 per month, or IDR 2,400,000 to IDR 6,000,000 per year, depending on the scale of operations.

Therefore, a new approach that integrates IoT (Internet of Things)

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technology and data analytics is needed to monitor and predict water consumption. According to a study by Czajkowski [2], implementing IoT in water management has been proven to reduce water consumption by up to 15% through real time monitoring and optimization, enabling the adoption of more sustainable management policies.

The urgency of managing water consumption wisely is not only to ensure the sustainability of water resources for future generations but also to reduce the economic and environmental impacts of excessive water use. This case study will explore the implementation of IoT technology and machine learning for forecasting water consumption in a coffee shop in Cimahi, as part of a green accounting initiative to promote water use efficiency and environmental sustainability [3].

Problem Formulation:

1. How is the data collected?
2. What forecasting methods are used to predict water consumption?
3. How can green accounting reports be implemented?

2. METHOD

The research method is structured to address the problem formulation. We propose a prototype design with an architecture that integrates IoT, machine learning, and green accounting to answer the first research question regarding data collection.

In the input stage, an ultrasonic sensor will measure the water level in the storage tank. An ESP32 based microcontroller [4] will be embedded in this system. The device will transmit data using the HTTP protocol [5]. The collected data will be stored in a database and then processed for forecasting using machine learning. The processed results will be sent to a green accounting application (Figure 1). This study contributes by presenting an IoT-based water consumption architecture model.

We propose a water consumption architecture with a case study in a coffee shop. Data collection is conducted through an IoT-based-system (Figure 2). The ESP32 microcontroller is equipped with distance, temperature, humidity, and rain sensors to process and transmit data to the server daily at 6:00 PM WIB.

The dataset consists of a time series spanning 219 days, starting from January 1, 2023. Each incoming data entry is recorded under the 'date' feature, which serves as a timestamp for when the data is stored on the server. The 'date' feature is then processed to generate new features, such as 'day_of_week' and 'is_holiday.' The 'day_of_week' feature represents the numerical day of the week (e.g., 0 is Monday, 6 is Sunday). Meanwhile, the 'is_holiday' feature marks holidays (weekends) with a value of 1 if 'day_of_week' ≥ 5.

The 'temperature' feature represents the average temperature of the day in degrees Celsius. The 'is_rain' feature records whether it rained on a given day, assigning a value of 1 if rain occurred and 0 otherwise. The 'humidity' feature captures the average humidity percentage, ranging from 0 to 100%.

The 'water_consumption' feature determines water usage based on readings from the HCSR04 ultrasonic distance sensor. Table 1 presents the data successfully transmitted from the ESP32 using the HTTP protocol.

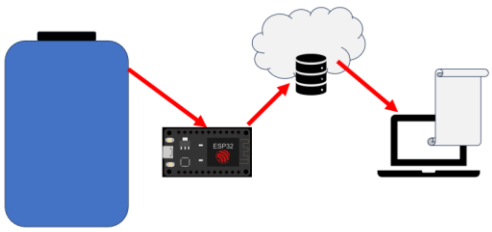

Figure 1. IoT Water Consumption Architecture

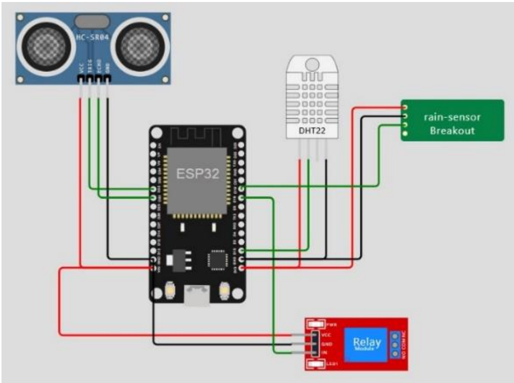

Figure 2. IoT Water Consumption Device Scheme

Table 1 Main Data

Date	Water_Consumption	Temperature	is_rain	Humidity	day_of_week	is_holiday
2023-01-01	0	28.745401	0	77.939727	6	1
2023-01-02	190	30.986585	0	52.019753	0	0
2023-01-03	182	29.592489	0	51.429007	1	0

Table 1 presents the data successfully transmitted from the ESP32 using the HTTP protocol.

To address the second research question regarding forecasting model development, the collected data undergoes various techniques, such as:

2.1.Feature Engineering

We applied feature engineering techniques [6], [7], including adding the 'month' feature to capture monthly cyclical patterns in the data. Additionally, we introduced the 'temp_humidity_interaction' feature by multiplying temperature and humidity to capture their interaction effects [8].

$$temp\_humidity\_interaction = temperature \times humidity$$

We added the 'heat_index' feature to estimate the heat index, considering the combined effects of temperature and humidity on thermal comfort.

Additionally, we applied the One Hot Encoding method [9], [10] to convert categorical features such as 'day_of_week' and 'month' into dummy variables. For the 'day_of_week' feature, each day of the week was transformed into a dummy variable (0 or 1) for each day category.

2.2.Data Normalization

We performed data normalization [11], [12] to facilitate the model training process. The steps taken include:

1. Scaler Initialization, creating a MinMaxScaler object for both features (scaler) and the target variable (scaler_y).
2. Feature Normalization, applying Min-Max normalization to

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numerical features to scale values between 0 and 1.

3. Target Normalization, separately normalizing the target variable Water_Consumption to ensure consistency in model training.

2.3. Adding Lag Features and Moving Averages

1. Lag Features, we added lag features [13] for Water_Consumption, ranging from 1 to 7 days prior, using the shift (lag) function. These features rely on historical Water_Consumption data.
2. 7-Day Moving Average, we introduced a 7-day moving average feature for Water_Consumption, calculated using a rolling mean over the past 7 days. This feature also depends on historical Water_Consumption data.
3. Handling NaN Values, we removed rows containing NaN values generated from the shift and rolling operations to maintain data integrity.

2.4. Splitting Data into Features and Target

The feature set (X) consists of all features except Water_Consumption, while the target variable (y) is derived from the Water_Consumption feature.

2.5. Splitting Training and Testing Data

We used the train_test_split function to divide the data into training and testing sets with a 60:40 ratio. To preserve the temporal order in the time series data, we disabled shuffling by setting shuffle=False.

2.6. Model Training

We utilized three machine learning models: Random Forest, XGBoost, and Long Short-Term Memory (LSTM), based on their suitability for capturing different patterns in time-series data and their proven performance in forecasting tasks.

XGBoost [14] was selected for its ability to handle structured data efficiently and its robustness to overfitting through regularization. We performed hyperparameter tuning [15] using Optuna [16], an efficient optimization framework. The objective function [17] used by Optuna minimized the Mean Squared Error (MSE) [18] on the test set. The model was trained using XGBRegressor with the optimal parameters determined through the tuning process.

Long Short Term Memory (LSTM) [19], was included to model temporal dependencies and patterns in sequential water consumption data that traditional models may overlook. We set the sequence length to 15, meaning the model considers the past 15 time steps to predict the next value. The model was built using a sequential architecture with specified parameters. We trained the model for 50 epochs, using a batch size of 16, and applied a validation split of 0.2, meaning 20% of the training data was used for validation.

We trained the Random Forest model [20] using Optuna for hyperparameter tuning. After training, we performed the following steps:

1. Inverse Transformation of Predictions, converting predicted values back to their original scale.
2. Using scaler_y.inverse_transform, Restoring both predicted and actual values to their pre-normalization scale.
3. Prediction Visualization
4. Model Evaluation. Assessing performance using Mean Squared Error (MSE) and R-squared (Coefficient of Determination).

To address the third research question, the green accounting process was conducted, which includes:

Utilization of Data in Green Accounting [21]

1. Integration of Forecasting in Green Accounting. The water consumption forecasting results are integrated into green accounting through environmental financial reports [22]. These reports include records of water consumption, associated costs, and any savings or penalties applied due to efficiency or wastage.
2. Cost and Savings Analysis. Actual water consumption is compared with the forecasted values to determine efficiency or wastage. Any discrepancies between actual and predicted consumption are calculated to assess the relevant environmental costs [23].

Environmental Cost and Savings Calculation.

1. Water Cost. The cost of water usage is calculated by multiplying actual consumption by the rate per liter.
2. Savings from Efficiency. Savings are determined when actual water consumption is lower than the forecasted amount, reflecting the cost successfully reduced.
3. Environmental Cost Due to Excessive Consumption. Additional costs or penalties are calculated for water usage that exceeds the target, serving as a measure to internalize the environmental impact of overconsumption

3. RESULTS AND DISCUSSION

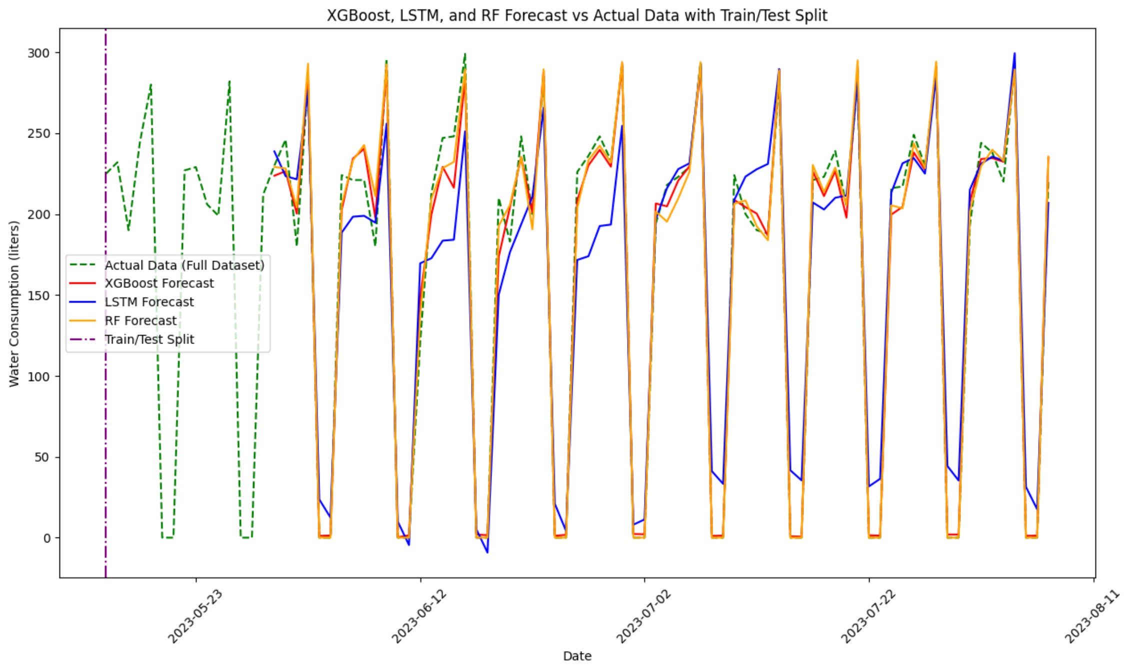

Figure 1 Forecast: XGBost, LSTM, Random Forest

In Figure 3, we can observe a comparison between the predicted water consumption from three different models (XGBoost, LSTM, and Random Forest) against the actual data. The dashed green line represents the actual water consumption.

There is a significant variation in water consumption, with periodic increases and

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decreases, particularly with lower consumption on holidays. Among the models, Random Forest demonstrates the best predictive performance, accurately capturing fluctuations in water usage during both high and low consumption periods.

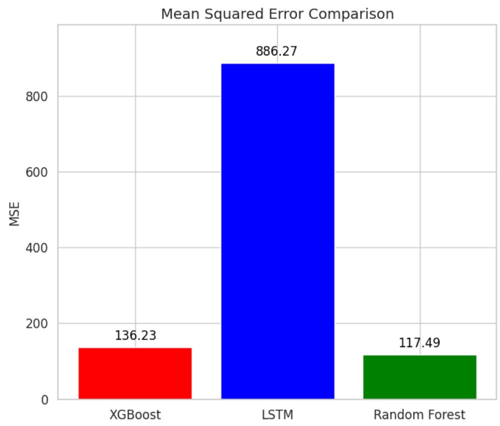

Figure 2 MSE Comparison

Figure 4 presents a comparison of the Mean Squared Error (MSE) for the three predictive models: XGBoost, LSTM, and Random Forest. MSE is an evaluation metric used to measure how closely the model's predictions align with actual values, where a lower MSE indicates better performance.

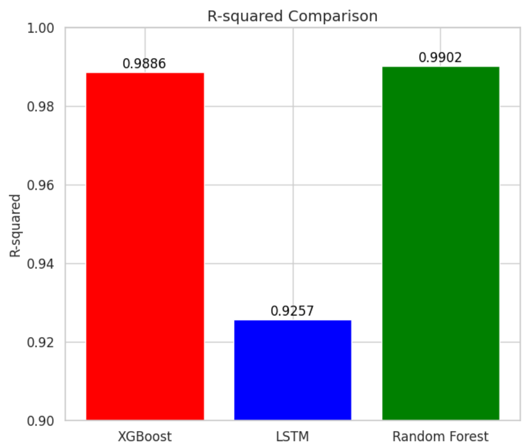

Figure 3 R-squared comparison

Figure 5 presents a comparison of R-squared values for the three predictive models: XGBoost, LSTM, and Random Forest. R-squared is a statistical metric that indicates how well a model explains the variance in actual data. A value close to 1 suggests a highly accurate predictive model.

Among the models, Random Forest achieves the highest R-squared value of 0.9902, meaning it explains approximately 99% of the variance in actual water consumption data. This result highlights Random Forest as the most effective model for capturing and modeling water consumption patterns.

An example of Random Forest input on 2024-01-10 is shown in Table 2.

Table 2 Forecast Random Forest

Parameter	Value
Date	2024-01-10
Temperature	25.00 °C
is_rain	0
Humidity	48.00 %

Predicted Water Consumption for 2024-01-10: 197.2634859981626 liters

Example of Green Accounting Implementation: Green Accounting is the process of incorporating environmental factors into accounting and economic decision-making. The forecasting results can be applied to green accounting through bookkeeping (Table 3) or environmental reporting (Table 4). The primary focus of green accounting is to integrate costs and benefits into financial and sustainability assessments.

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Table 3 Forecasted Water Consumption in Monthly Environmental Management Report

Period	Forecasted Water Consumption (Liters)	Actual Water Consumption (Liters)	Difference (Liters)	Status
January 2023	12,000	11,500	-500	Efficiency
February 2023	15,000	16,200	+1,200	Wastefulness
March 2023	13,500	13,300	-200	Efficiency
April 2023	11,500	11,500	0	On Target
May 2023	10,800	10,500	-300	Efficiency

This forecasting compares actual water consumption with the projected estimates. Efficiency or wastefulness is identified by analyzing the difference between actual and forecasted consumption. The insights gained from this comparison are then used to enhance water management strategies for future periods.

Table 4 Water Usage Costs and Environmental Savings

Periode	Water Consumption (Liters)	Water Cost (Rp)	Savings from Efficiency (Rp)	Environmental Cost Due to Wastefulness (Rp)
January 2023	11,500	1,150,000	50,000	-
February 2023	16,200	1,620,000	-	120,000
March 2023	13,300	1,330,000	20,000	-
April 2023	11,500	1,150,000	-	-
May 2023	10,500	1,050,000	30,000	-

Notes:

1. Water Cost is calculated by multiplying actual consumption by the rate per liter.
2. Savings from Efficiency reflect cost reductions when actual consumption is lower than the forecasted amount.
3. Environmental Cost Due to Wastefulness records additional costs or

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penalties for water usage that exceeds the target or surpasses sustainable capacity.

4. CONCLUSION

The IoT device successfully transmitted sensor data readings. Among the three models tested, Random Forest achieved the lowest MSE of 117.4869, indicating the smallest prediction error.

R-squared (R^2) measures the proportion of variance in the target variable that can be explained by the model. An R^2 value close to 1 suggests that the model effectively explains data variability. Random Forest achieved the highest R^2 of 0.9902, indicating that it explains 99.02% of the variance in water consumption data.

Random Forest slightly outperformed XGBoost. The performance difference may be due to how each algorithm handles data and feature interactions. Both Random Forest and XGBoost are decision tree-based models capable of handling non-linear relationships and complex feature interactions [14], [20] which appear well-suited for water consumption data.

LSTM, designed for time series data and long-term dependencies, performed worse than the tree-based models. Possible reasons include: limited data availability [24], suboptimal hyperparameter tuning and lack of strong time-series patterns in the data

While Random Forest and XGBoost both achieved R^2 values close to 1, which could indicate potential overfitting, the low MSE on the test data suggests that these models generalize well. Random Forest emerged as the best-performing model, with the lowest MSE and highest R^2.

The green accounting framework was effectively designed to incorporate forecasting and track actual consumption. This allows coffee shop owners to take appropriate actions, including monitoring monthly water usage and cost management.

5. RECOMMENDATIONS

Based on the experiment, further exploration of hyperparameter tuning for the LSTM model is recommended to improve its performance. Ensemble techniques can also be utilized to enhance model accuracy and stability. As more data becomes available over time, retraining new models can help assess their performance and adaptability. Regarding green accounting, conducting a sensitivity analysis on water costs can provide deeper insights into how fluctuations in water consumption impact expenses. This would enable more effective decision making for water conservation policies and financial planning.

REFERENCES

[1] WRI, “Updated Global Water Risk Atlas Reveals Top Water- Stressed Countries and States,” *Wri*, 2019.

[2] A. Czajkowski *et al.*, “Global water crisis: Concept of a new interactive shower panel based on iot and cloud computing for rational water consumption,” *Applied Sciences (Switzerland)*, vol. 11, no. 9, 2021, doi: 10.3390/app11094081.

[3] C. Sukmadilaga, S. Winarningsih, I. Yudianto, T. U. Lestari, and E. K. Ghani, “Does Green Accounting Affect Firm Value? Evidence from ASEAN Countries,” *International Journal of Energy Economics and Policy*, vol. 13, no. 2, 2023, doi: 10.32479/ijeep.14071.

[4] E. Systems, “ESP32 Series Datasheet,” 2021. [Online]. Available: https://www.espressif.com/sites/default/files/documentation/esp32_datasheet_en.pdf

[5] M. J. A. Baig, M. T. Iqbal, M. Jamil, and J. Khan, “Design and implementation of an open-Source IoT and blockchain-based peer-to-

peer energy trading platform using ESP32-S2, Node-Red and, MQTT protocol," *Energy Reports*, vol. 7, 2021, doi: 10.1016/j.egyr.2021.08.190.

[6] H. Dai, Q. Xiao, N. Yan, X. Xu, and T. Tong, "Item-level Forecasting for E-commerce Demand with High-dimensional Data Using a Two-stage Feature Selection Algorithm," *J Syst Sci Syst Eng*, vol. 31, no. 2, 2022, doi: 10.1007/s11518-022-5520-1.

[7] T. H. Kim *et al.*, "Simultaneous feature engineering and interpretation: Forecasting harmful algal blooms using a deep learning approach," *Water Res*, vol. 215, 2022, doi: 10.1016/j.watres.2022.118289.

[8] T. Wang, J. Chen, J. Vaughan, and V. N. Nair, "Interpretable Feature Engineering for Time Series Predictors using Attention Networks," *SSRN Electronic Journal*, 2022, doi: 10.2139/ssrn.4117900.

[9] V. Sarveswararao, V. Ravi, and Y. Vivek, "ATM cash demand forecasting in an Indian bank with chaos and hybrid deep learning networks," *Expert Syst Appl*, vol. 211, 2023, doi: 10.1016/j.eswa.2022.118645.

[10] M. Anjaneyulu and M. Kubendiran, "Short Term Traffic Flow Prediction Using Hybrid Deep Learning," *Computers, Materials and Continua*, vol. 75, no. 1, 2023, doi: 10.32604/cmc.2023.035056.

[11] F. T. Lima and V. M. A. Souza, "A Large Comparison of Normalization Methods on Time Series," *Big Data Research*, vol. 34, 2023, doi: 10.1016/j.bdr.2023.100407.

[12] J. Yu and K. Spiliopoulos, "NORMALIZATION EFFECTS ON DEEP NEURAL NETWORKS," *Foundations of Data Science*, vol. 5, no. 3, 2023, doi: 10.3934/fods.2023004.

[13] O. Surakhi *et al.*, "Time-lag selection for time-series forecasting using neural network and heuristic algorithm," *Electronics (Switzerland)*, vol. 10, no. 20, 2021, doi: 10.3390/electronics10202518.

[14] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2016, pp. 785–794.

[15] R. K. Vogeti, B. R. Mishra, and K. S. Raju, "Machine learning algorithms for streamflow forecasting of Lower Godavari Basin," *H2Open Journal*, vol. 5, no. 4, 2022, doi: 10.2166/h2oj.2022.240.

[16] T. Akiba, S. Sano, T. Yanase, T. Ohta, and M. Koyama, "Optuna: A Next-Generation Hyperparameter Optimization Framework," in *The 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, 2019, pp. 2623–2631.

[17] H. Ismail Fawaz, G. Forestier, J. Weber, L. Idoumghar, and P. A. Muller, "Deep learning for time series classification: a review," *Data Min Knowl Discov*, vol. 33, no. 4, 2019, doi: 10.1007/s10618-019-00619-1.

[18] A. C. R. Klaar, S. F. Stefenon, L. O. Seman, V. C. Mariani, and L. dos S. Coelho, "Optimized EWT-Seq2Seq-LSTM with Attention Mechanism to Insulators Fault Prediction," *Sensors*,

p-ISSN :1858-3911 , *e-ISSN : 2614-5405*
https://journal.fkom.uniku.ac.id/ilkom

vol. 23, no. 6, 2023, doi: 10.3390/s23063202.

[19] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput*, vol. 9, no. 8, pp. 1735–1780, 1997.

[20] L. Breiman, "Random forests," *Mach Learn*, vol. 45, no. 1, 2001, doi: 10.1023/A:1010933404324.

[21] H. A. Riyadh, M. A. Al-Shmam, H. H. Huang, B. Gunawan, and S. A. Alfaiza, "The analysis of green accounting cost impact on corporations financial performance," *International Journal of Energy Economics and Policy*, vol. 10, no. 6, 2020, doi: 10.32479/ijeep.9238.

[22] A. M. Islam and C. Deegan, "Motivations for an organisation within a developing country to report social responsibility information: Evidence from Bangladesh," *Accounting, Auditing and Accountability Journal*, vol. 21, no. 6, 2008, doi: 10.1108/09513570810893272.

[23] M. Yassin, A. Asfaw, V. Speight, and J. D. Shucksmith, "Evaluation of Data-Driven and Process-Based Real-Time Flow Forecasting Techniques for Informing Operation of Surface Water Abstraction," *J Water Resour Plan Manag*, vol. 147, no. 7, 2021, doi: 10.1061/(asce)wr.1943-5452.0001397.

[24] A. Althnian *et al.*, "Impact of dataset size on classification performance: An empirical evaluation in the medical domain," *Applied Sciences (Switzerland)*, vol. 11, no. 2, 2021, doi: 10.3390/app11020796.