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Optimizing Bioleaching for Printed Circuit Board Copper Recovery: An AI-Driven RGB-Based Approach

Jordi Vives Pons [1], Albert Comerma [2], Teresa Escobet [3], Antonio D. Dorado [4] and Marta I. Tarrés-Puertas [1,*]

[1] Department of Mining, Industrial and ICT Engineering, Informatics Engineering Section, Universitat Politècnica de Catalunya—BarcelonaTech (UPC), 08242 Manresa, Barcelona, Spain;

[2] Serra Húnter Fellow, Department of Mining, Industrial and ICT Engineering, Electronics Engineering Section, Universitat Politècnica de Catalunya—BarcelonaTech (UPC), 08242 Manresa, Barcelona, Spain;

[3] Department of Mining, Industrial and ICT Engineering, Electronics Engineering Section, Universitat Politècnica de Catalunya—BarcelonaTech (UPC), 08242 Manresa, Barcelona, Spain;

[4] Department of Mining, Industrial and ICT Engineering, Chemical Engineering Section, Universitat Politècnica de Catalunya—BarcelonaTech (UPC), 08242 Manresa, Barcelona, Spain;

* Correspondence: marta.isabel.tarres@upc.edu

Featured Application: This AI-driven optimization research focuses on bioleaching for Cu recovery from e-waste, integrating RGB sensor data and machine learning to enable real-time monitoring and predictive maintenance. The IIoT-based approach improves recovery rates, lowers environmental harm, and promotes sustainable resource management across different operational scales in e-waste recycling plants.

Abstract: Recovering copper from end-of-life electronics, especially from printed circuit boards, provides significant economic benefits, reduces environmental impact, and supports a circular economy. This case study presents a data-driven approach to predicting copper recovery in the electrolysis stage of a bioleaching process by utilizing RGB sensor readings. We tested nine regression models using RGB values from experimental data. The gradient boosting model, optimized via response surface methodology (RSM), outperformed the others, with predictions matching 84% of observed patterns. These results demonstrate strong predictive capabilities, with scope for further accuracy enhancements. We offer an open-source, web-based digital twin designed specifically to monitor the bioleaching plant, enabling real-time and historical data analysis to support predictive maintenance. Our results underscore the potential to optimize the entire bioleaching process, marking a significant advancement for large-scale copper recovery. This study is the first to investigate predictive bioleaching continuous processes in a semi-industrial e-waste plant using RGB sensors, presenting a novel approach in the field.

Keywords: artificial intelligence; industrial systems; machine learning; Industrial IoT; real-time systems; digital twin; copper recovery; bioleaching

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1. Introduction

The Global E-waste Monitor 2020 analyzes global e-waste flows, emphasizing their role in the circular economy through resource recovery and recycling to reduce environmental impact and increase material reuse [1]. The BIOMETALLUM project [2] focuses on developing bioleaching-based plants for extracting valuable metals from e-waste, offering both extraction and maintenance services. Led by the BIOGAP group, this project develops an alternative process to recover metals from e-waste recycling using bio-based technology that offers environmental advantages compared to conventional methods. The process significantly reduces energy use and emissions compared to pyrometallurgy, while recirculation minimizes the consumption of reagents and the production of liquid waste in comparison to traditional hydrometallurgy [3]. Rooted in circular economy principles [1], it supports a local business model that reduces resource dependency and promotes sustainable material reuse, addressing both environmental and economic challenges. However, this article focuses solely on the technological aspect of the study, presenting initial results from the application of a digital twin based on the color information of the solution within the bioleaching process. This technological approach aims to demonstrate the potential of the implemented methodology, leaving the full evaluation of economic feasibility and broader impacts within the circular economy model for future work.

1.1. The Bioleaching Plant

Bioleaching leverages microorganisms to convert insoluble minerals into soluble forms through their metabolic processes, enabling the recovery of metals from low-grade ores where traditional mining and refining are not cost-effective [3,4]. A major advantage of bioleaching is its ability to efficiently process both primary and secondary resources with far less environmental impact than methods like pyrometallurgy [5].

Unlike conventional chemical leaching, bioleaching minimizes ecological harm by employing naturally occurring microorganisms, avoiding the use of toxic agents such as cyanide or sulfuric acid [3,4]. This makes the process safer and more sustainable. Economically, bioleaching provides a cost-effective solution, allowing the extraction of metals from low-grade ores that would otherwise be impractical. Additionally, bioleaching operates at ambient temperatures and pressures, reducing energy consumption compared to conventional chemical leaching, which typically requires high energy inputs due to extreme temperature and pressure conditions [6].

The BIOMETALLUM project operates a semi-industrial bioleaching plant at the EPSEM-UPC onsite facility dedicated to experimental research for enhancing and optimizing metal recovery, with a focus on copper (Cu (II)) and iron (Fe (III)) extraction from electronic waste like printed circuit boards (PCBs) from computers and mobile phones. Although the plant currently operates with an effective monitoring system, our research is advancing towards the integration of predictive, monitoring, and simulation technologies, including digital twins and machine learning models. These enhancements are expected to boost the precision and efficiency of metal recovery. These technologies could significantly reduce the environmental impact of the mining and chemical industries globally [7]. Figure 1 presents a graphical representation of the bioleaching plant, featuring a screenshot taken from the Biometallum web-based digital twin, accessible via [8]. The plant is structured into three primary stations, each assigned to distinct operational tasks.

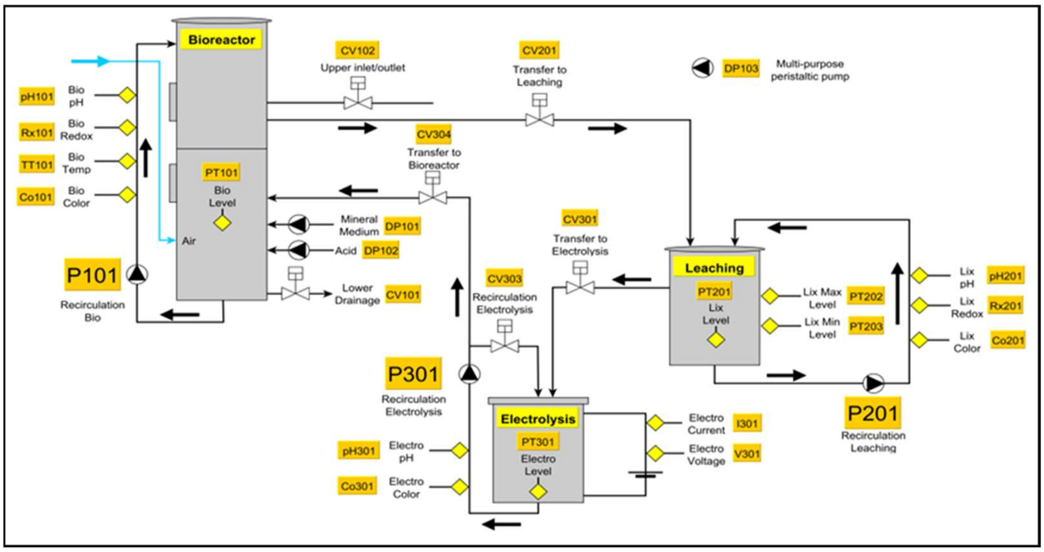

Figure 1. Diagram of the bioleaching plant, highlighting its key components: bioreactor, leaching tanks, and electrolysis unit.

Although the full industrial process is more intricate, a simplified overview of its operation is outlined below:

Bioreactor: The bioreactor is a vital component of the bioleaching system, responsible for maintaining and regenerating the biological agents that drive the leaching process. It continuously monitors key parameters, including redox potential, pH, temperature, and dissolved oxygen, all of which are essential for optimizing microbial activity and ensuring efficient system performance. The bioreactor operates continuously, using an air injector to maintain oxygen levels and to ensure uniform mixing of the bioleaching solution. The temperature is regulated at 31 °C, which is optimal for microbial growth. pH is supervised within the narrow range of 1.6 to 1.8 using two pumps: PB1 for acid addition and PB2 for base addition. This regulation is crucial, as any deviation could deactivate the microbial agents, disrupting the leaching process. Real-time monitoring of dissolved oxygen and redox potential ensures continuous adjustment of operational parameters, while a maximum liquid level sensor prevents overflow. In the event of anomalies, such as an abnormal pH increase or redox potential drop, the system automatically adjusts reagent addition or mixing intensity to restore optimal conditions.

Leaching Tanks: The leaching process transfers the biologically active solution from the bioreactor to the leaching tanks, where it interacts with the electronic waste material. Here, microbial agents facilitate the breakdown and dissolution of metal ions from the solid matrix. The tanks are equipped with sensors and actuators to maintain necessary environmental conditions. pH, temperature, and redox levels are monitored, while pumps and valves regulate the flow of leaching agents and removal of dissolved metals. High- and low-level sensors ensure tank volumes remain within safe limits to prevent overflow or underflow. Abnormalities trigger automated responses, such as halting the addition of new waste or activating recirculation pumps. The recirculation system, managed by pump PL1, ensures uniform distribution of bioleaching agents and prevents solid residue sedimentation. Additionally, colorimetric sensors measure the solution's red, green, and blue components to estimate metal ion concentration in real time, providing an indirect measure of the leaching process's efficiency.

Electrolysis Unit: Commonly referred to as the copper recovery unit, this stage constitutes the final step in the bioleaching process. Here, dissolved copper ions are separated from the solution and deposited as solid copper through the electrowinning technique, enabling efficient metal recovery. In this process, an electric current is applied to precipitate copper onto cathodes. The system includes sensors to monitor voltage, current, and solution composition. Circulation pump PB4 ensures continuous solution flow between the leaching tanks and the recovery unit, maintaining a steady supply of copper ions for deposition. Pressure and level sensors regulate the inflow and outflow of the solution to prevent imbalances that could disrupt the electrowinning process. Anomalies in voltage or current trigger automatic adjustments to operating parameters, ensuring efficient metal recovery and protecting the equipment from potential damage.

The bioleaching plant operates through a robust hardware and software system built around an industrial Arduino device integrated into a SCADA framework; further details are available in our previous work [9]. Key components like the ESP32-PLC, Raspberry Pi, and Node-Red form a flexible control structure. The ESP32-PLC serves as the main controller, interfacing with sensors and actuators, managing control loops, and adjusting parameters such as pH or halting pumps during emergencies. Data collected by the ESP32-PLC are transmitted to a Raspberry Pi running Node-Red, which processes and visualizes the data through a cloud-based Big Data System (BDS). The system uses the MQTT protocol for reliable, low-latency communication. Technicians can monitor and control operations in real time via a touchscreen panel onsite or remotely via the Telegram app, with manual overrides available for intervention when necessary.

A key feature of our semi-industrial bioleaching plant is the integration of an advanced RGB digital sensor at the bioreactor station. This non-invasive RGB sensor measures Fe (III) and Cu (II) concentrations by detecting color changes in the solution, eliminating the need for complex sampling and analysis. The application of RGB sensors in bioleaching is an underexplored area, offering potential for monitoring microbial activity. RGB sensors operate without direct contact with the corrosive and aggressive liquids involved in chemical processes, significantly extending their operational lifespan. They are not only cost-effective but also offer a clear and reliable correlation with reaction progress, facilitating rapid data acquisition. Unlike standard models that rely on sample extraction, extended analysis times, and manual result interpretation, these sensors enable real-time monitoring. Their implementation in our bioleaching plant can optimize operations by automatically halting the process at the optimal threshold, leading to substantial savings in time, materials, and labor costs. Its performance has been validated by comparing its readings with conventional methods, such as UV-VIS spectroscopy and atomic absorption, demonstrating its accuracy and reliability in the harsh bioleaching environment, as shown in our previous work [10]. This sensor can detect subtle color changes in the solution (see Figure 2), enabling real-time monitoring and analysis of metal dissolution and recovery processes.

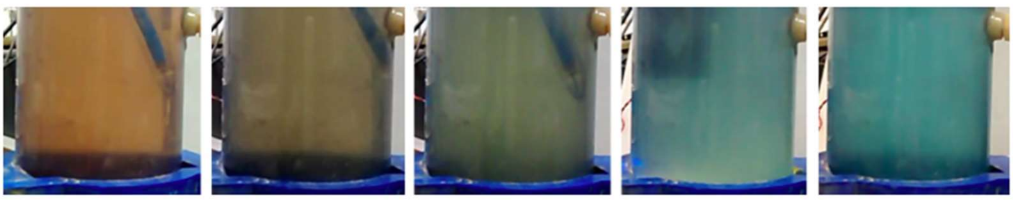

Figure 2. Color evolution at different stages of the redox reaction [10].

Multiple RGB BH1749NUC sensors [11] are strategically placed at critical points in the plant and isolated from the chemically aggressive pH range of 1.6 to 1.8, where the leaching process occurs, using custom 3D-printed enclosures mounted externally to the recirculation pipes (see Figure 3). These transparent enclosures are designed to fit around the pipes, allowing precise measurements. To minimize ambient light interference, a pulsed LED circuit (Figure 3) provides controlled illumination, ensuring accurate color data capture. The sensors demonstrated robustness and reliability in a 24 h ambient light test (day and night), further confirming their suitability for real-world bioleaching applications.

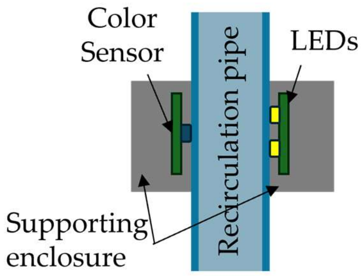

Figure 3. Integration of color sensors with recirculation pipes.

The RGB sensor, coupled with an ESP32-based programmable logic controller (PLC), processes and transmits data for analysis, enabling real-time monitoring. This system enhances the efficiency and sustainability of metal recovery compared to traditional methods and provides valuable insights for biotechnological research into metal recovery from electronic waste and other hydrometallurgical processes.

Data from the RGB sensor and other plant components are transmitted to a cloud-based Big Data System (BDS) via Web Sockets, facilitating both data visualization and command execution. Interactive dashboards display key metrics such as pH, temperature, and metal recovery rates, while historical data analysis helps identify trends, anomalies, and opportunities for predictive maintenance or process optimization.

Security is a fundamental aspect of the SCADA system. The plant's software securely stores client keys for server authentication, which are validated by a root certification authority (CA). This ensures that only authenticated devices can access the server, safeguarding against unauthorized access and data breaches. Encrypted communication channels and robust authentication protocols are employed to maintain the integrity and confidentiality of the transmitted data [9].

1.2. AI and Machine Learning Algorithms for Bioleaching Process Optimization

Artificial intelligence and machine learning offer significant potential to optimize bioleaching processes and extend their use in hydrometallurgy. The KEEN project [12] exemplifies the application of AI in enhancing efficiency, reducing development time, and lowering operational costs in engineering and production. AI is optimizing chemical processes, increasing energy efficiency, and improving metal recycling, as seen in copper leaching using neural networks [13,14]. AI is also applied in predictive maintenance, optimizing operations, and improving safety in bioleaching and chemical plants [15].

Standard models like *Linear Regression* can be applied to bioleaching but are limited in capturing its nonlinear relationships, such as interactions between microbial growth, particle size, and temperature. *Polynomial regression* offers an intermediate solution, balancing complexity, and performance, though high-degree polynomials risk overfitting noisy data. Both approaches are computationally efficient, with complexity primarily dependent on dataset size and the number of variables [16].

Bioleaching is a complex, nonlinear process influenced by variables like microbial growth, pH, temperature, particle size, and metal ion concentration. Decision trees effectively model these interactions by creating interpretable rules but are prone to overfitting, especially with deep trees. This can be addressed using pruning or ensemble methods like *Random Forests* to improve generalization and prevent overfitting [17].

In bioleaching processes, where data complexity and nonlinearity are common, *random forest regression* (RFR) and *gradient boosting machines* (GBMs) offer substantial advantages over traditional machine learning models. Their capacity to process complex, high-dimensional datasets and generate accurate predictions makes them invaluable for enhancing bioleaching efficiency and resource management. RFR and GBM outperform simpler models like linear regression or decision trees because they can effectively account for the nonlinear and interdependent nature of bioleaching factors. For instance, linear models are often too simplistic, failing to capture complex relationships between variables such as particle size, microbial growth, and temperature, which are key determinants of metal recovery rates [17].

AdaBoost effectively captures nonlinear relationships in bioleaching processes and can outperform simpler models like decision trees or support vector machines in terms of robustness and accuracy. However, *XGBoost* may perform better in handling missing or high-dimensional data [16]. For smaller-scale problems, simpler models such as decision trees or *support vector machines* (*SVR*) can be used [18], with *GBM* and *random forest regression* offering strong performance for parameter optimization and recovery rate predictions [16].

Artificial neural networks (ANN), including *multilayer perceptron* (*MLP*) [19], are effective for modeling complex bioleaching processes with interacting variables. While MLP outperforms linear and polynomial regression, methods like Random Forest and XGBoost may offer similar performance with lower computational cost. Research highlights the optimization of metal recovery in bioleaching, especially in electronic waste recycling. Studies using machine learning, such as ANN and SVM models, have achieved over 99% metal recovery efficiency in bio-Fenton processes [20].

From a computational perspective, the complexity of machine learning algorithms varies significantly. Gradient boosting machines (GBMs) and random forest regression (RFR) stand out due to their ensemble nature: GBM's iterative process can increase computational load, while RFR scales with the number of trees [21]. However, optimized implementations like XGBoost improve efficiency, making these models both computationally feasible and effective for large datasets.

Further studies applied machine learning to urban mining, optimizing copper recovery from PCBs, with *gradient boosting machines* (GBMd) yielding the best results for parameter combination optimization [20,22]. Additionally, random forest regression demonstrated the highest accuracy in predicting recovery rates in bioleaching processes, highlighting the importance of factors like resource type, particle size, and microorganism type in metal recovery predictions [20]. RFR and GBM excel at generalizing across unseen data, reducing overfitting, and ensuring reliable predictive models for bioleaching under diverse conditions.

The study in [16] presents the evaluation of 40 regression-based machine learning (ML) algorithms for bioleaching process optimization, identifying *random forest regression* as the most effective, achieving a prediction accuracy of 77%. The dataset, comprising 871 samples extracted from 206 journal articles, included nine independent variables—such as microorganism type, temperature, and particle size—while the recovery rate served as the target variable. Data were gathered using search keywords like "bioleaching" and "microbial leaching" from databases including Google Scholar, Scopus, and Web of Science. Building on this, the study in [16] applied random forest regression and reported promising results.

In our research, we analyzed the key machine learning algorithms applied to bioleaching data and achieved a prediction accuracy of 84% using a *gradient boosting machine* (GBM), underscoring its potential for optimizing bioleaching processes. Key parameters like pH, copper concentration, and innovative RGB-based metrics were incorporated to improve predictive performance. These results highlight the substantial potential of advanced machine learning techniques to enhance the efficiency and effectiveness of bioleaching.

1.3. Digital Twins in the Bioleaching Industry

Digital twins are virtual replicas of physical systems that enable real-time simulation, monitoring, and optimization. They can be classified by their functionality: Monitoring digital twins collect and visualize real-time data to track system status. Analytical digital twins use machine learning to identify patterns and predict issues. Predictive digital twins analyze both historical and real-time data to forecast future behaviors, while prescriptive digital twins suggest actions based on optimization models. The most advanced control digital twins interact directly with the physical system to adjust operational parameters in real time. In the chemical industry, digital twins enhance process efficiency, reduce costs, and minimize environmental impact by enabling real-time modeling and simulation of industrial processes [14]. In [7], the potential of digital twins in biomanufacturing is explored, demonstrating how this technology can improve production monitoring and control while integrating with AI to optimize production and minimize waste. Digital twins also facilitate machine learning model training, predicting system behavior and improving resource management [22,23].

The synergy of process intensification and digital twins offers significant benefits, such as reducing equipment size, energy consumption, and raw materials, while increasing productivity, safety, and sustainability. This combination is transforming the process industry, particularly in the energy transition. In both the mining and chemical industries, digital twins have proven effective in optimizing processes, including mineral beneficiation and reducing energy costs in separation processes [24,25].

By integrating AI-driven process intensification with digital twins, the stage is set for advanced methodologies in bioleaching. The next section outlines the methodology used in our study to apply an IIoT and machine learning framework to optimize bioleaching.

2. Materials and Methods

The state-of-the-art review of machine learning applied to bioleaching, presented in Section 1, identifies random forest regression as one of the leading algorithms for estimating recovery rates using variables such as initial pH and atomic number (e.g., [6]). Our approach introduces a novel approach, utilizing RGB data from smart sensors to predict copper and iron recovery. RGB sensors, as outlined in Section 1, provide real-time monitoring by tracking reaction progress without direct contact with corrosive liquids, enhancing durability and cost-efficiency.

In our research, we selected nine machine learning algorithms to analyze their performance in the bioleaching process of the electrolysis unit. These algorithms, ranging from standard models to those identified as top-performing in prior theoretical studies, are widely validated in the academic literature. Their proven efficacy in both practical applications and theoretical investigations ensures a robust foundation for reproducible and comparable results within the scientific community. In our analysis, the gradient boosting machine surpasses the random forest algorithm, showing greater predictive accuracy and efficiency. The compatibility of these algorithms with various data volumes and types is another reason for their selection. Methods like SVM and gradient boosting are particularly effective in contexts with high dimensionality or numerous explanatory variables, whereas tree-based and ensemble algorithms are more tolerant of missing values or asymmetric distributions.

2.1. Experimental System Setup

The bioleaching process was divided into four key operational stages to maintain consistency and control over experimental conditions:

Material Preparation: Shredded copper cables were chosen as the starting material and processed in a biologically active solution within a bioreactor. The solution was enriched with Fe (III) ions produced by iron-oxidizing bacteria, establishing a controlled environment for copper leaching.

Bioleaching Process: Operational parameters in the bioreactor were maintained within optimal ranges for microbial activity, specifically at 31 °C and a pH range of 1.6 to 1.8. These conditions facilitated efficient copper ion dissolution from the solid matrix into the solution, enhancing microbial effectiveness.

Sensor Network Monitoring: An array of sensors continuously measured critical parameters such as pH, temperature, and metal ion concentration during the bioleaching process. RGB sensors tracked color changes in the solution, which were linked to Fe (III) and Cu (II) concentrations, offering a non-invasive method to monitor metal dissolution, as explained in Section 1.

Data Transmission and Logging: Sensor data were transmitted in real-time to a central server via the MQTT protocol, ensuring low-latency and reliable data transfer. This setup enabled continuous data acquisition over multiple bioleaching cycles (72–96 h) and interval-based sample analyses, generating a comprehensive dataset for model training that captured both standard and edge-case operational conditions.

2.2. Experimental Data Acquisition

A comprehensive range of datasets was collected from real-time sensor data to develop and evaluate nine machine learning models for predicting copper recovery. These datasets were systematically gathered to ensure diversity and representativeness of the operational conditions. Emphasis was placed on data quality and consistency to facilitate accurate model training, cross-validation, and performance evaluation.

The model development pipeline comprised several key steps:

Data Preprocessing: The dataset underwent preprocessing to handle missing values using median imputation. Feature normalization was performed using min–max scaling to ensure all features had comparable ranges, preventing bias due to scale differences across variables.

Feature Engineering: Additional features were derived to improve model performance, including color intensity ratios and interaction terms extracted from the RGB sensor data. These engineered features aimed to capture more complex patterns in the data.

Model Training: The dataset was split into training (70%) and testing (30%) subsets. A variety of regression models were evaluated, including linear regression, decision tree regression, random forest regression, polynomial regression, multilayer perceptron (MLP), support vector regression (SVR), gradient boosting regression, XGBoost, and AdaBoost.

Model Evaluation: Model performance was assessed using several metrics, including root mean squared error (RMSE), mean absolute error (MAE), R^2 (coefficient of determination), and adjusted R^2. These metrics provided insights into the accuracy and robustness of each model.

K-fold Cross-Validation: To ensure reliable performance and mitigate overfitting, K-fold cross-validation was applied. This technique, which partitions the dataset into k subsets, helps validate the model and estimate its performance. In each iteration, one subset is used as validation data while the remaining subsets are used for training. The mean performance across all iterations provides an assessment of the model's accuracy. Common k-values are 5, 10, or 20. For our study, the training-to-testing set ratio was 70% to 30%.

To create each dataset, 25 bioleaching experiments were conducted to establish a correlation between the colors of Fe (II)/Fe (III) and their concentrations. Each experiment utilized a prototype plant column filled with 16 g of shredded cables and 10 g of a 3D-printed filler, combined with 1.3 L of Fe (III) solution produced by microorganisms. Throughout the experiments, multiple samples were collected to monitor Fe (II)/Fe (III) levels and to correlate ion concentrations with the solution color detected by the plant's smart color sensor and an onsite pH sensor. The solution samples were then analyzed for Fe (III) and Cu (II) concentrations, following the methodology outlined in [10]. Table 1 presents the measured concentrations of Fe (III) and Cu (II) ions obtained during the electrolysis stage of the experiment.

Table 1. Example of measured concentrations of Fe (III) and Cu (II) ions from an experiment.

Reaction Time (K_r), min	[Fe(III)], mg/L	[Cu(II)], mg/L
0	6,134.6	0.0
5	5,632.2	~0.0
10	5,144.2	310.66
15	4,915.9	514.71
25	4,064.9	1,063.42
35	3,557.7	1,405.33
45	3,564.9	1,622.24
75	2,247.6	2,348.35
105	1,882.2	2,577.21
195	1,521.6	3,081.80
225	1,185.1	3,081.8
342	1,341.3	3,250.00

After data collection, the data were formatted into a structure compatible with machine learning algorithms. The preprocessing steps included cleaning the data, addressing missing values (less than 5%) using median imputation, and normalizing the variables to a 0–1 scale through min–max scaling.

Data visualization and correlation analyses revealed key relationships between RGB values, pH, and copper concentration (Cu) during the bioleaching process. The correlation matrix in Figure 3 shows a negative correlation between the red component (C1R1) and Cu concentration (−0.44), indicating that higher C1R1 values correspond to lower Cu concentrations. Conversely, moderate positive correlations were observed between the green component (C1G1) and pH (pH1) with Cu concentration (0.44 and 0.36, respectively), suggesting that increases in these parameters are associated with higher Cu levels.

Figure 5 presents the scatter plot matrix, which visually confirms the correlations shown in Figure 4. It illustrates that Cu concentration typically decreases with higher C1R1 values, while positive trends are observed between C1G1, pH1, and Cu concentration, consistent with the numerical correlations. Figure 6 provides scatter plots of each predictor against Cu concentration, further highlighting the influence of each variable on Cu recovery, in alignment with the trends identified in the matrix analysis.

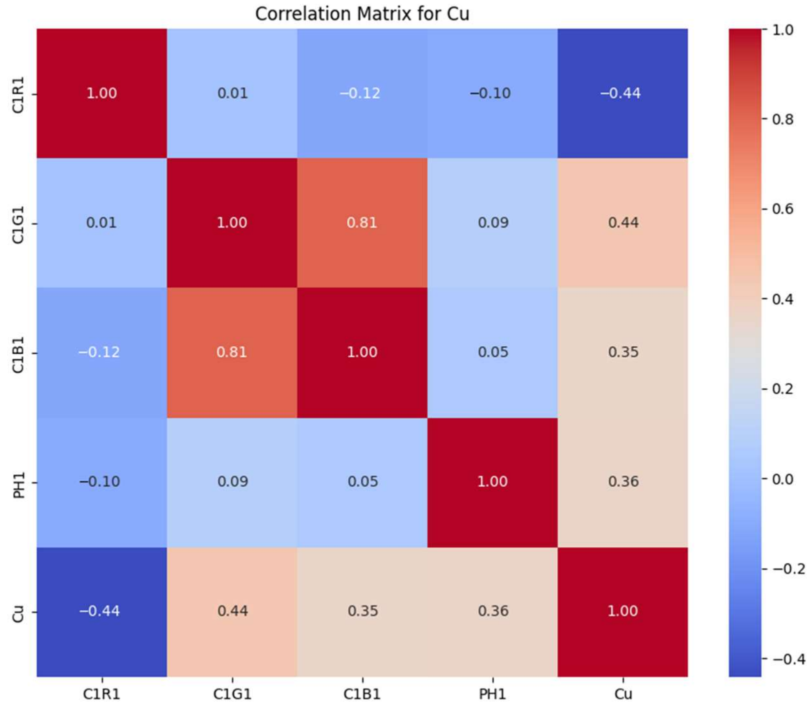

Figure 4. Correlation matrix or RGB–pH vs. Cu (II).

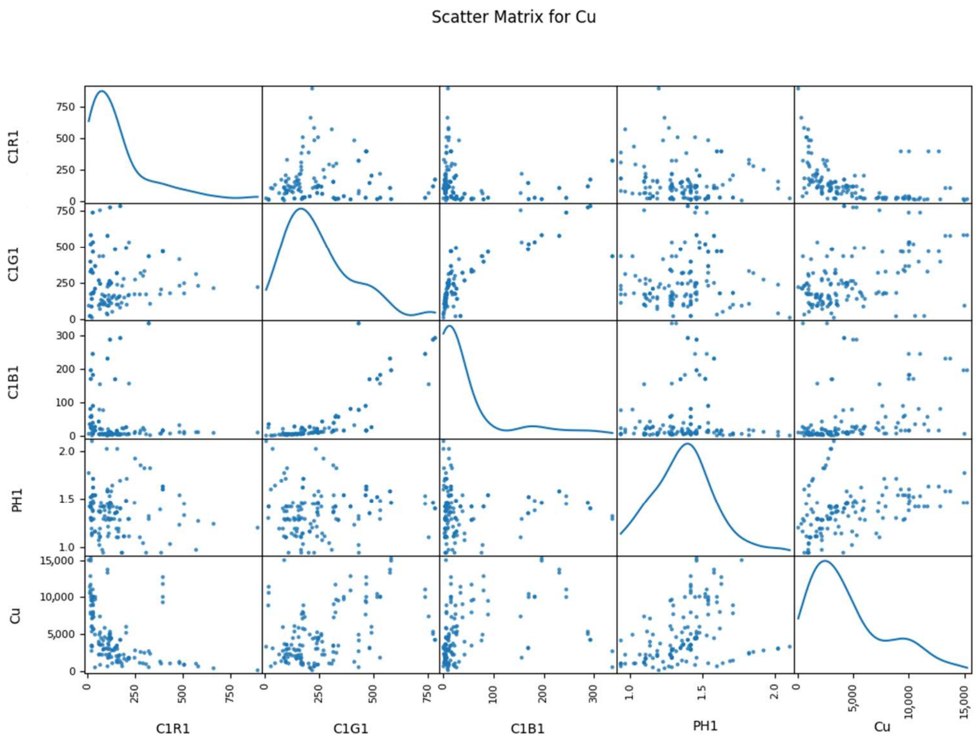

Figure 5. Correlation scatter matrix of predictors vs. Cu (II).

The correlation matrix of RGB–pH vs. Cu (II), the correlation scatter matrix of predictors vs. Cu (II), and the scatter plot of RGB and pH vs. Cu (II) collectively demonstrate a negative correlation between C1R1 and Cu concentration, along with positive correlations for C1G1 and pH with Cu concentration. These results highlight the importance of RGB and pH data as predictors for copper recovery, providing a basis for optimizing machine learning models to enhance bioleaching efficiency. Additionally, the figures reveal a strong correlation between the blue (C1B1) and green (C1G1) predictor variables, suggesting potential redundancy. To streamline the dataset and reduce complexity, we excluded the C1B1 feature, given its high correlation with C1G1, thereby improving model efficiency.

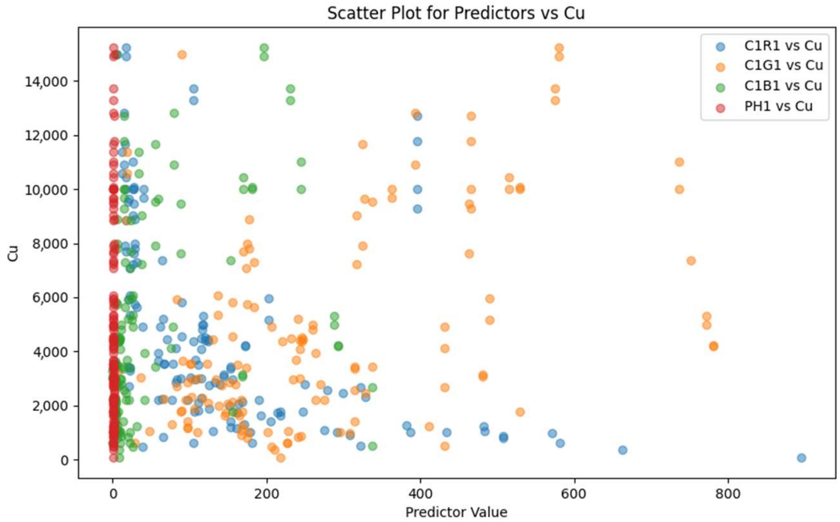

Figure 6. Scatter plot of RGB and pH vs. Cu (II).

Experiments and datasets from the electrolysis unit are continuously collected to train and validate the models, with cross-validation techniques used to ensure reliable performance. Future work will focus on evaluating the models on independent datasets from other stations of the bioleaching plant to confirm their generalizability and assess their effectiveness under varying operational conditions.

2.3. Computational Analysis Approach

We evaluated the performance of nine machine learning regression models for predicting Cu (II) recovery using R^2, Adjusted R^2, RMSE, and MAE. The models were designed and implemented in Python (version 3.8.2). For data manipulation, we used pandas (version 2.0.3), while scikit-learn (version 1.3.2) was employed for machine learning algorithms. Data visualization was performed using Matplotlib (version 3.7.5) and seaborn (version 0.13.2) for statistical visualizations. Numerical computations were handled with NumPy (version 1.24.4). The algorithms and dataset used in this research are available for public access on the project's GitLab repository [26].

Table 2 presents the performance metrics—R^2, adjusted R^2, RMSE, and MAE—for the machine learning models developed during the methodology phase. These models were tested to assess their ability to predict copper recovery during the electrolysis stage of the bioleaching process. Figures 7–10 present a comparative graphical analysis of the model performance metrics. The results indicate that the gradient boosting machine outperformed the other models, achieving the highest R^2 and the lowest error metrics on the test set, demonstrating its effectiveness in predicting copper recovery from sensor data.

Table 2. Comparative performance metrics of the regression models for predicting Cu (II) recovery.

Model	R^2	Adjusted R^2	RMSE	MAE
AdaBoost	0.77	0.74	1520.00	1122.49
Decision Tree	0.75	0.72	1600.96	1065.45
Gradient Boosting Machine	0.84	0.82	1277.41	863.08
Linear Regression	0.37	0.30	2536.57	1687.33
Multilayer Perceptron	0.82	0.80	1326.08	806.35
Polynomial Regression	0.76	0.73	1552.26	1250.35
Random Forest Regression	0.82	0.80	1339.43	936.40
Support Vector Machine	0.25	0.16	2772.20	1962.54
XGBoost	0.82	0.80	1351.92	956.50

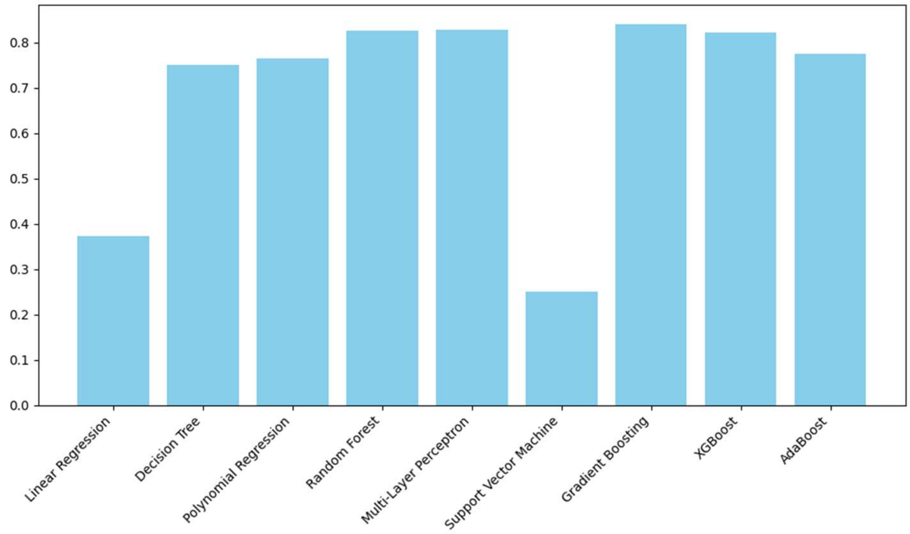

Figure 7. Comparative graph of the R^2 metric for each tested model.

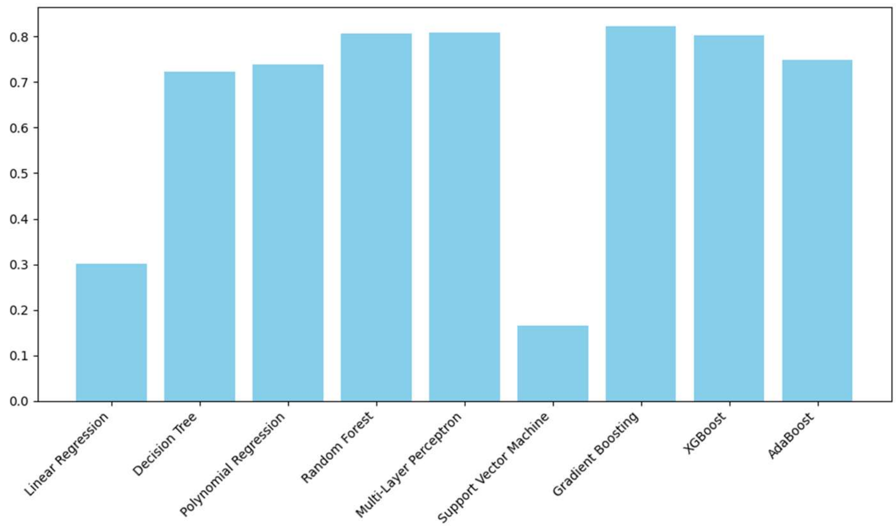

Figure 8. Comparative graph of the adjusted R^2 metric for each tested model.

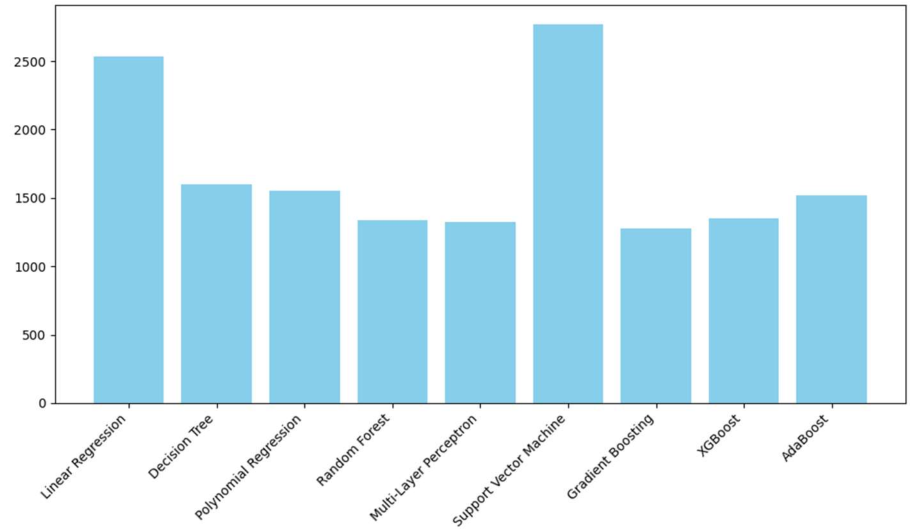

Figure 9. Comparative graph of the RMSE metric for each tested model.

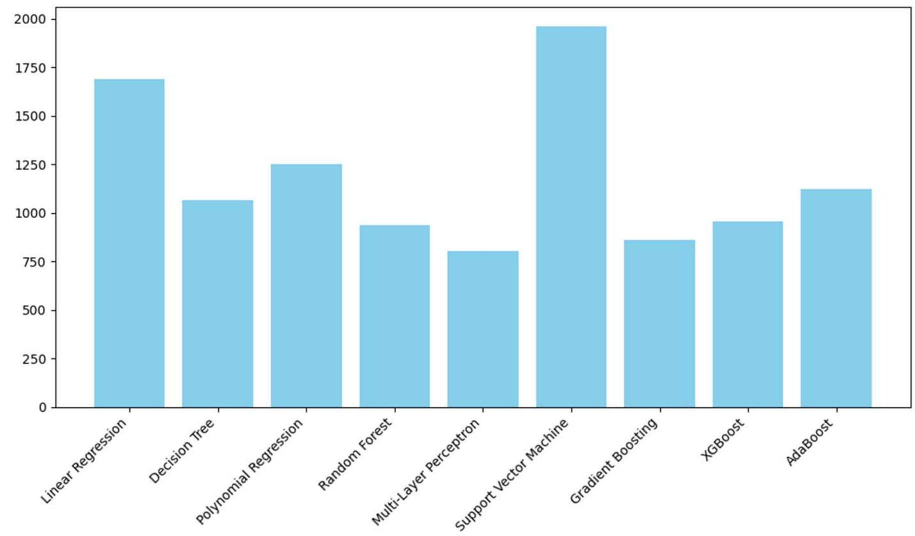

Figure 10. Comparative graph of the MAE metric for each tested model.

The following figures (Figures 11–19) present a graphical comparison of the predictions made by each tested model with the actual values from the experimental trials, as outlined in Table 2. These charts illustrate how well the predicted values align with the observed data, providing insight into each model's ability to capture the complex dynamics of the bioleaching process. Among the models, the gradient boosting machine shows the best performance (see Figure 12). Models with R^2 values below 0.8 (Figures 10, 11, 13, 15, and 17) are considered to be less reliable. Nevertheless, integrating this model into the SCADA system introduced specific challenges and opportunities, detailed in the Section 4.

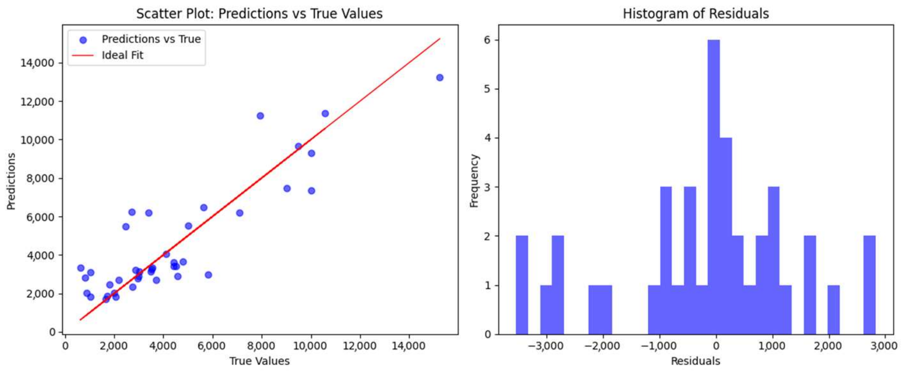

Figure 11. Predicted vs. actual copper recovery rates using AdaBoost.

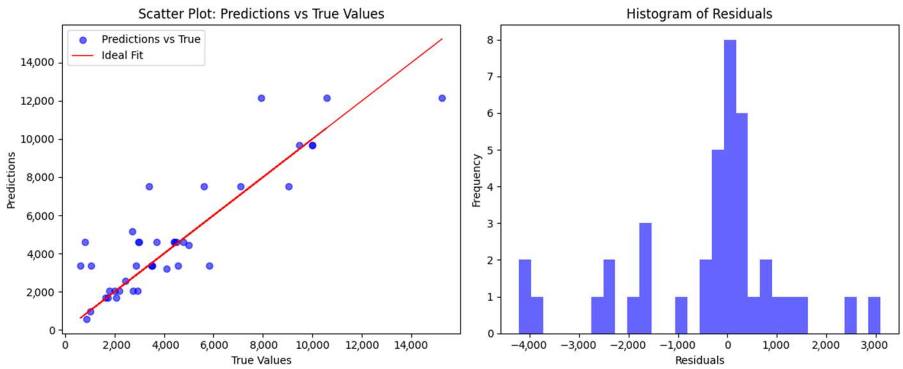

Figure 12. Predicted vs. actual copper recovery rates using decision tree.

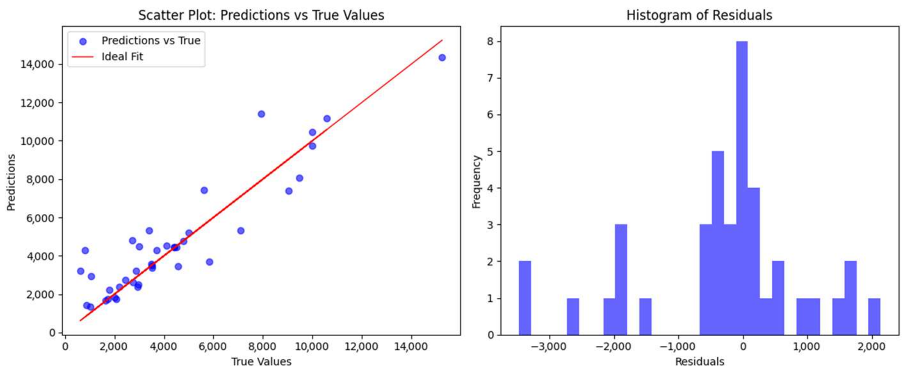

Figure 13. Predicted vs. actual copper recovery rates using gradient boosting machine.

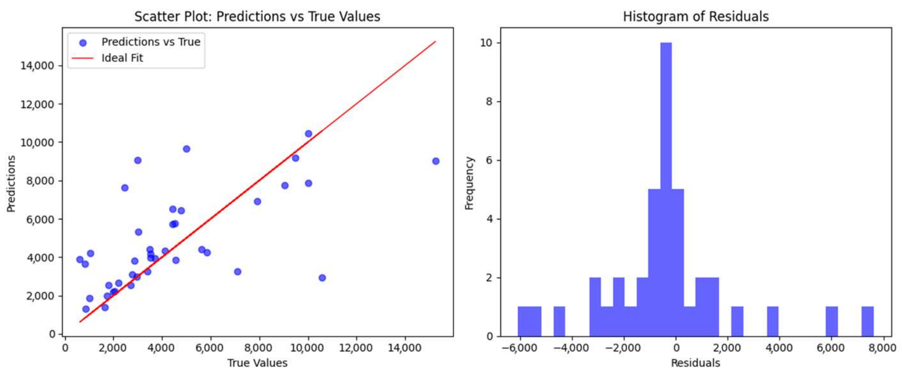

Figure 14. Predicted vs. actual copper recovery rates using linear regression.

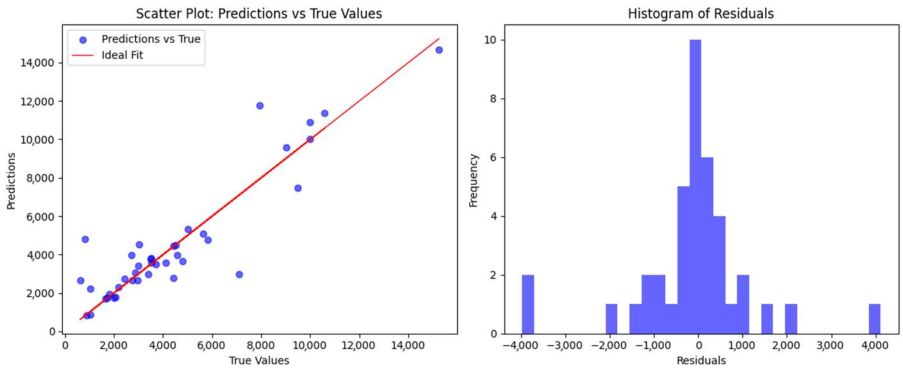

Figure 15. Predicted vs. actual copper recovery rates using multilayer perceptron.

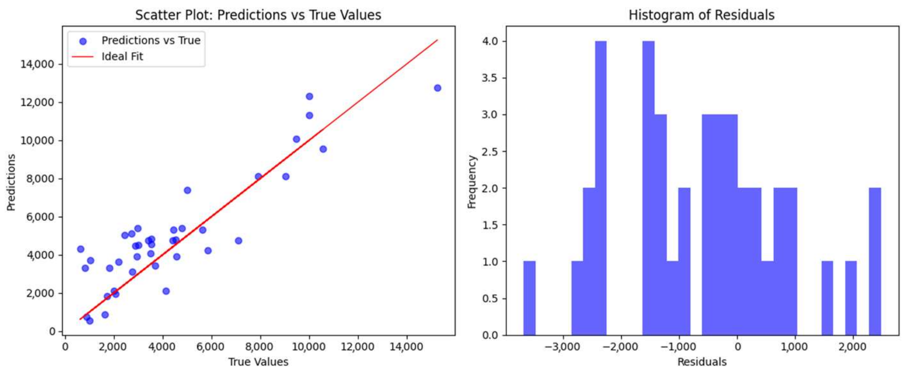

Figure 16. Predicted vs. actual copper recovery rates using polynomial regression.

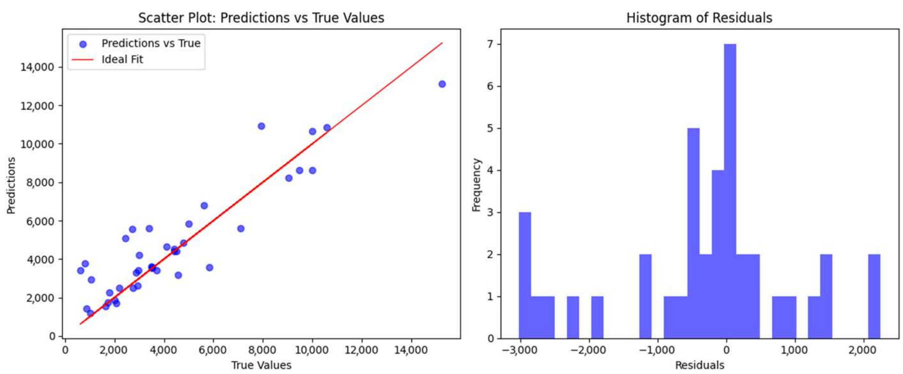

Figure 17. Predicted vs. actual copper recovery rates using random forest regression.

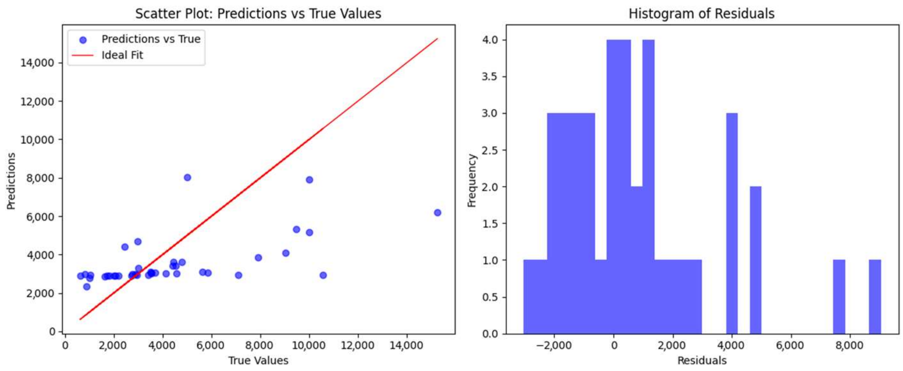

Figure 18. Predicted vs. actual copper recovery rates using support vector machine.

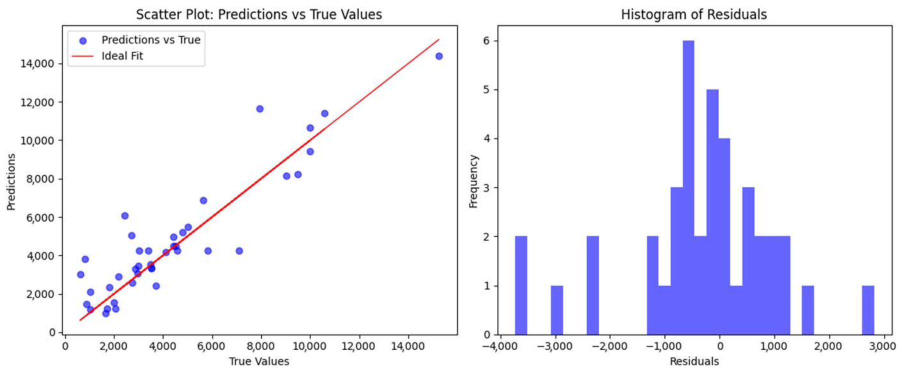

Figure 19. Predicted vs. actual copper recovery rates using XGBoost.

The computational complexity of the algorithms used in our research (see Table 2) for bioleaching processes is influenced by factors such as dataset size, model architecture, and the efficiency of supporting libraries. Frameworks like tensorFlow-2.14.0, PyTorch 2.x, and Scikitlearn 1.6.0 enhance performance through GPU/TPU acceleration, parallel processing, and optimized computation, allowing efficient handling of large datasets. Similarly, XGBoost 2.1.3 employs advanced gradient boosting techniques, including data pruning, feature selection, and distributed processing, to minimize computational overhead. Leveraging these libraries in our implementations [26] ensures scalability, reproducibility, and flexibility for experimenting with different configurations. These capabilities make the algorithms particularly well-suited for bioleaching, where high speed and scalability are essential.

2.4. The Web-Based Digital Twin System

Our previous research on plant monitoring and control software architecture [8] has been enhanced by integrating machine learning algorithms and implementing a web-based digital twin system. The entire infrastructure has been adapted from the initial prototype to a large-scale plant setup.

The new system, accessible at [8,26], integrates HTTPS encryption and advanced user authentication protocols to safeguard sensitive data and ensure that access is restricted to authorized personnel only. Access control is managed through role-based access control (RBAC), which assigns permissions based on user roles, ensuring that only authorized individuals can modify critical system parameters or access sensitive data. Additionally, cookie-based authentication enhances security for the web interface, with encrypted

HTTP cookies protecting the confidentiality and integrity of session data throughout user interactions.

For improved system performance and security, the server-side architecture uses Gunicorn in combination with Nginx, where Nginx acts as a reverse proxy and load balancer. This setup not only adds an extra layer of security but also optimizes system efficiency. Furthermore, SSL/TLS protocols encrypt all data communications between the Raspberry Pi and external devices, safeguarding against unauthorized interception and enhancing overall security.

The Flask-based web interface includes user-friendly, real-time dashboards with interactive charts and historical data, enabling trend analysis of key parameters. This functionality supports informed decision making and dynamic adjustments, promoting proactive process management to maintain optimal bioleaching conditions. Figures 20–24 are screenshots taken from the Biometallum web-based digital twin, accessible via [7]. Figure 20 illustrates the Dashboard Page, showing sensor readings and actuator statuses for the bioleaching plant described in Section 1 and depicted in Figure 1.

Additionally, the web application features a customizable data extraction interface, where operators can specify time ranges, sampling intervals, and choose sensors or actuators from various process stages. The Get Data page allows for immediate data visualization through generated graphs or CSV downloads for further analysis. CSV files are formatted with timestamps, sensor/actuator names, and recorded values, facilitating targeted analysis and informed decision making to enhance operational efficiency. Figure 21 shows graphical representations of sensor readings relevant to the biological stage of the process, with adjustable time period settings. Similarly, Figure 22 illustrates sensor readings for the leaching stage, also allowing for time period adjustments.

The system upgrade introduces predictive models to forecast behavior based on historical data. While still in the early stages, this functionality paves the way for integrating advanced machine learning algorithms to optimize metal recovery.

Currently, the system uses the methods detailed in Section 2 (AdaBoost, decision tree, gradient boosting machine, linear regression, multilayer perceptron, polynomial regression, random forest, support vector machine, and XGBoost) to analyze historical data and predict copper recovery efficiency under various conditions. This predictive capability enables technicians to make proactive adjustments, preventing critical thresholds from being surpassed. By incorporating these models, the system can optimize operational parameters, improving metal recovery efficiency and the sustainability of the bioleaching process. For instance, the system can identify patterns in copper dissolution rates, recommending optimal reagent addition times or adjusting leaching solution flow rates.

From the prediction page in Figure 23, plant technicians can input various parameters into the machine learning models to generate copper recovery predictions.

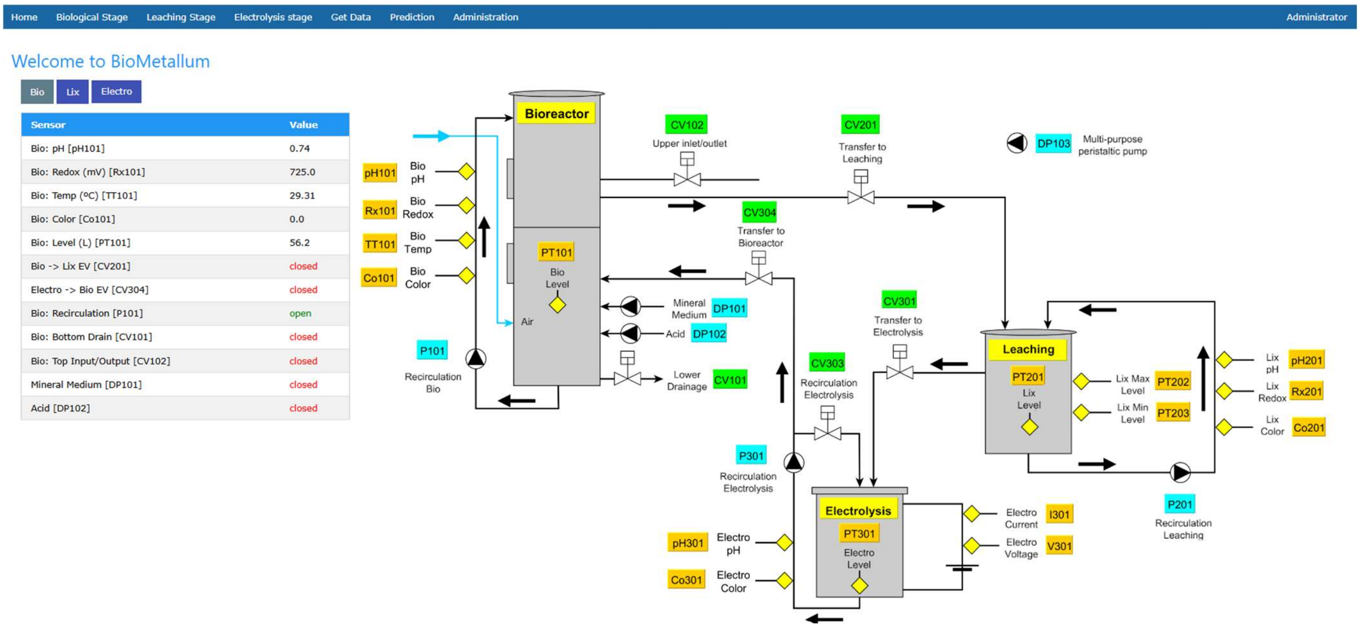

Figure 20. Overview of the dashboard page, displaying sensor readings and actuator statuses for the entire plant.

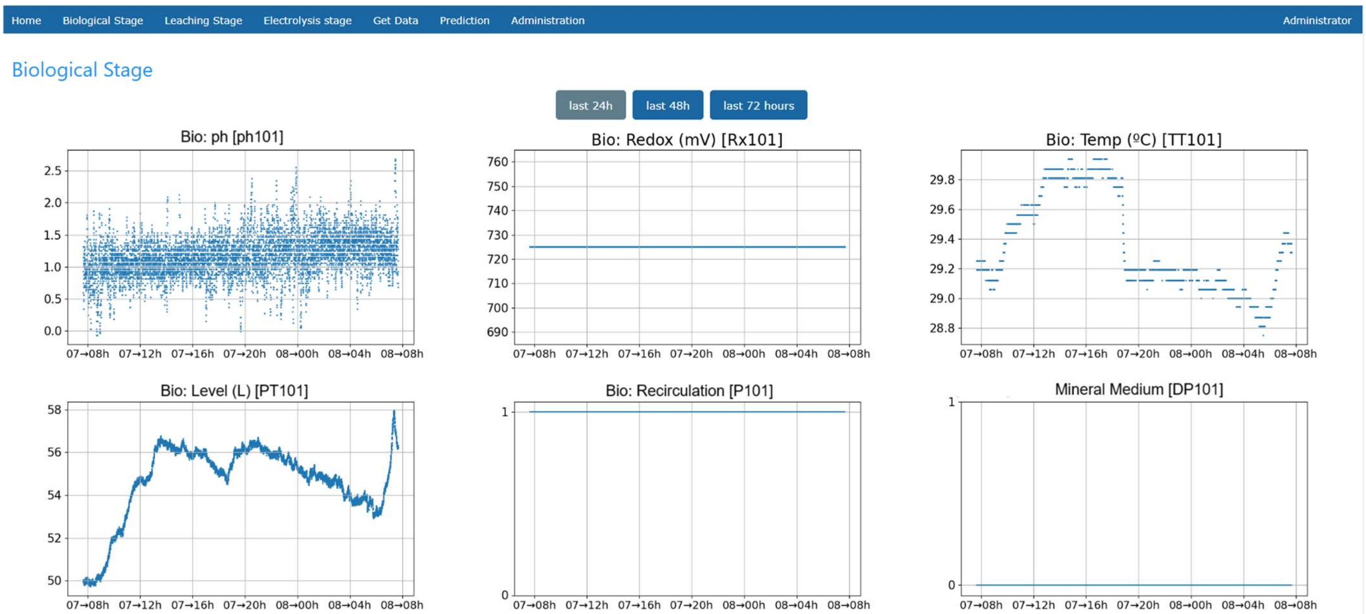

Figure 21. Sensor readings relevant to the biological stage page.

Figure 22. Sensor readings relevant to the leaching stage page.

Figure 23. Predictions on copper recovery from machine learning models.

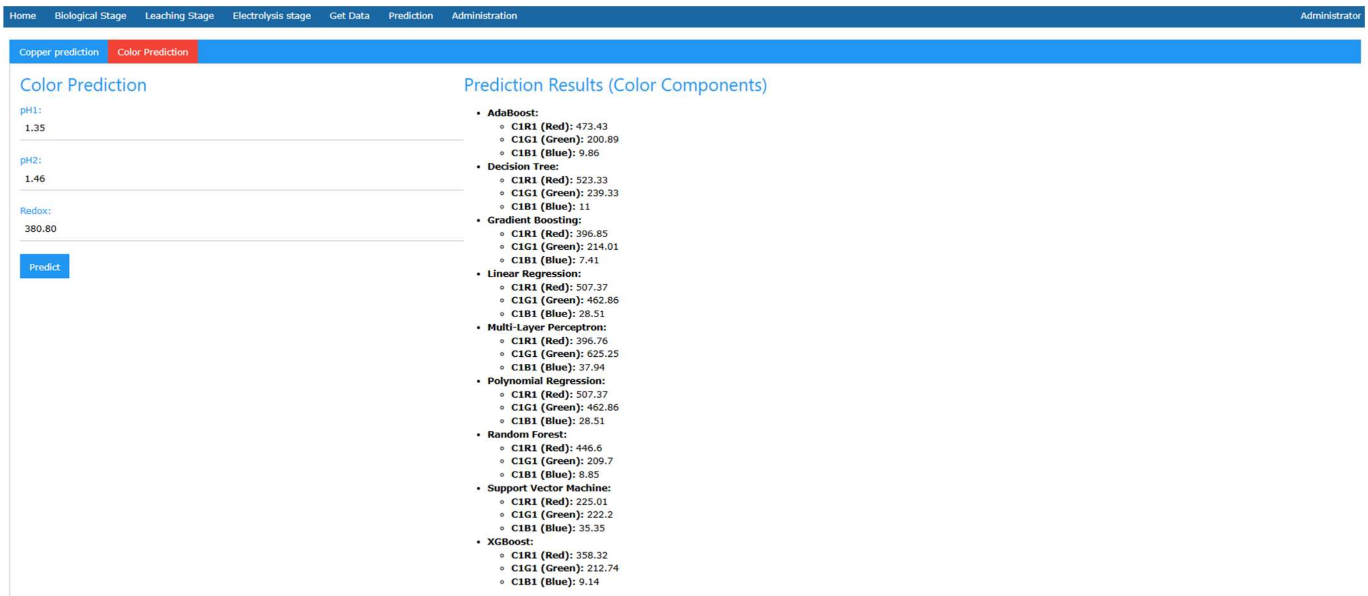

Figure 24. Color on copper recovery from machine learning models.

3. Results

The newly developed web-based digital twin integrates sensor data into a unified dashboard, accessible on both desktop and mobile devices. The intuitive interface enables technicians to monitor key parameters, such as Cu (II) and Fe (III) concentrations, pH levels, and temperature, in real time. Interactive charts and historical data visualizations facilitate trend analysis and anomaly detection, enabling prompt adjustments to maintain optimal conditions.

Remote accessibility enhances operational flexibility, enabling technicians to monitor and control the system offsite. This is especially valuable for bioleaching processes that require constant oversight, as it reduces the need for onsite presence, lowers labor costs, and ensures continuous operations.

Data export functionality supports process optimization by enabling the download of historical datasets for further analysis. This facilitates advanced analytics and machine learning, contributing to continuous improvements and refinements in system performance. Analyzing historical data identifies trends that inform operational adjustments.

To ensure security and data integrity, the system employs modern protocols, including encrypted communication and role-based access control. This ensures that only authorized personnel can access or modify plant data. Additionally, the system logs all user actions, creating an audit trail that promotes transparency and accountability.

Extensive testing was conducted during the development of the software architecture to ensure functionality, compatibility, and efficiency. The system underwent rigorous compatibility testing across various operating systems, including Windows 10, Android 12, and Ubuntu 24.04 LTS, and on different web browsers such as Chrome, Firefox, and Edge. These tests confirmed the web application's seamless operation across diverse platforms.

To optimize performance, the system integrates a gevent-based concurrency management configuration within Flask, enabling efficient handling of multiple simultaneous connections, which is crucial for real-time monitoring in industrial environments. Additionally, a caching mechanism was implemented to reduce data loading times, enhancing page speed and providing a smoother user experience during remote monitoring.

Preliminary testing demonstrated the system's ability to forecast process behaviors, detect anomalies, and reduce manual intervention, representing significant advancements in automation and operational efficiency. By analyzing real-time sensor data, including RGB colorimetric readings and pH values, the system accurately estimates copper recovery rates, enhancing resource efficiency, lowering costs, and promoting sustainability by minimizing non-productive runtime, preventing solution overexposure, and optimizing chemical and energy use. These capabilities, combined with substantial improvements in accessibility, usability, and scalability, position the architecture for deployment in larger-scale operations.

The integration of a web-based interface, predictive modeling, and real-time data access establishes a robust foundation for a more autonomous, efficient, and data-driven bioleaching plant. This scalable platform supports future enhancements, such as additional predictive models or advanced sensors, making it a powerful tool for optimizing bioleaching processes and advancing sustainable metal recovery.

4. Discussion

This study presents a novel approach for metal recovery from e-waste using bio-based technology. The process offers significant environmental advantages over conventional methods, including reduced energy consumption, lower emissions compared to pyrometallurgy, and minimized reagent use and liquid waste production compared to traditional hydrometallurgy [27]. These benefits highlight the potential of this approach to contribute to a circular economy and sustainable e-waste management.

While the current stage of development remains at the laboratory and semi-industrial scale, the focus of this study is not on evaluating its economic feasibility but rather on demonstrating its technical viability and environmental benefits. Economic feasibility will be addressed in future studies as the process advances toward full-scale industrial implementation.

The implementation challenges and complexities encountered during this study provide valuable insights into the technological hurdles that must be addressed during scale-up. However, the primary focus of this work remains on the potential applications and advantages of the proposed technology. By addressing these key aspects, this approach lays the groundwork for a sustainable and economically viable alternative to conventional recycling processes.

The challenges in ensuring reliable sensor data, including sensor drift, environmental interference, and calibration inconsistencies, have been addressed. A dedicated system leveraging RGB digital sensors has been developed to provide continuous, real-time monitoring of the bioleaching process, minimizing the impact of these factors. The non-invasive design of the RGB sensor system eliminates direct contact with corrosive solutions, thereby extending sensor lifespan and maintaining consistent measurement accuracy over time.

Additionally, the need for data validation to ensure consistency and reliability has been recognized. To ensure high-quality data, the RGB sensors have been validated against established methods, such as UV-VIS spectroscopy and atomic absorption, confirming their reliability in bioleaching environments. Integrating these advanced sensors with machine learning algorithms is expected to enhance both the accuracy and efficiency of the bioleaching process, effectively addressing challenges associated with sensor calibration and data variability.

Scalability and system load management offer opportunities for optimization. The architecture effectively supports remote monitoring and real-time data visualization, though performance may be impacted under high data volumes and simultaneous user access. This provides a valuable insight for future improvements, as the use of lightweight components like SQLite and Flask can be refined or replaced to better suit large-scale industrial applications.

The diverse range of algorithms tested, from interpretable linear models to advanced ensemble methods and neural networks, enabled a comprehensive evaluation of predictive performance in the bioleaching context. This strategic approach facilitated the identification of optimal methods for improving copper recovery processes while revealing the strengths and limitations of each model. The gradient boosting machine model performed well overall, but struggled to handle extreme values outside the normal operating range, suggesting a need for improved outlier detection and model refinement.

Lastly, the system still relies on manual intervention for predictive controls. While the models provide recommendations for process adjustments, operators must still make decisions regarding halting operations or adjusting parameters. This manual dependency can cause delays, especially if operators are not immediately available, highlighting the need for a fully autonomous control system to enhance responsiveness and operational efficiency.

These challenges underscore areas for improvement, particularly in data quality, scalability, automation, and security, which will guide future development efforts. Future developments will focus on the following aspects:

1. **Enhance model accuracy**: Integrate additional data sources, including microbial population density and solution flow rate, to improve predictive accuracy.
2. **Boost prediction precision and efficiency**: Apply time series models (TDSM), such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks, which are well-suited for capturing temporal patterns in evolving biological processes.

3. Create a **3D digital twin** of the physical system using game engines like Unity, enabling operators and researchers to:
    (a) **Visualize processes in real time**: Access live data in a virtual environment for quick insights.
    (b) **Simulate scenarios**: Experiment with parameter changes or simulate faults safely, without affecting the real plant.
    (c) **Enhance interaction**: Use interactive controls to explore and manipulate processes, boosting user engagement and comprehension.
4. **Advanced model optimization**: Validate advanced machine learning techniques, including deep learning models, to accurately capture complex interactions across all stages of the bioleaching process. Integrate these results into the digital twin to facilitate real-time analytics and improve informed decision making.

5. Conclusions

This study presents a bio-based technology for metal recovery from e-waste that significantly reduces energy consumption, emissions, and reagent and liquid waste compared to traditional methods. By combining machine learning with the Industrial Internet of Things (IIoT), the research enhances bioleaching efficiency by means of industrial process control. A key innovation is the development of a web-based supervision system implemented as a digital twin, enabling real-time monitoring and control of the bioleaching plant.

The system uses color data and sensor inputs to create a virtual model of the plant, improving decision making and process optimization. It overcomes the limitations of previous solutions developed by our research team based on Android or third-party apps, making plant management more efficient and collaborative. The study also highlights the use of non-invasive RGB sensors in the electrolysis unit, which avoid direct contact with corrosive solutions. These sensors offer advantages such as a longer lifespan, precise in situ measurements, and the elimination of sample extraction and analysis time consumption.

A predictive model built with gradient boosting achieved 84% accuracy, showcasing the potential of machine learning to improve bioleaching processes. The integration of the digital twin not only proves the technical viability of this approach but also provides notable environmental benefits. The design adheres to human-centered design principles, ensuring that the technology is intuitive, user-friendly, and accessible to operators, thereby promoting collaboration and improving the user experience. Additionally, the approach supports Industry 5.0 by fostering collaboration between humans and machines, enhancing decision-making and process control while meeting sustainability goals.

While economic feasibility and scalability will be explored in future work, the current findings lay a solid foundation for further development. This research is the first to apply continuous predictive techniques using RGB sensors and digital twin technology in a semi-industrial e-waste plant, marking a crucial step in optimizing and scaling bioleaching. Ultimately, the integration of advanced sensors, machine learning, and digital twin technology offers the potential to enhance the efficiency, sustainability, and scalability of bioleaching, with applications in both semi-industrial and full industrial settings.

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