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Research Article

Assessment of Heavy Metal Contamination and Its Impact on Water Quality and Aquatic Life in Mine Surface Plant Areas

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Abstract

The Copper mining industry accounts for the country's largest export earning and creates several jobs. Despite this the mines have been known to be the major contributor to the environmental pollution. It has been observed that in one province of the country, there is high presence of iron and other heavy metals in the surrounding areas. Unfortunately these heavy metals find themselves in water bodies and consequently affect the aquatic life. This study was conducted to develop suitable machine learning prediction models that estimate the impact of mine pollutants on fish production in the Kalumbila area of North-Western Province. The Machine Learning techniques employed include Multiple Linear Regression (MLR), Artificial Neural Networks (ANN), Random Forest (RF) and K-Nearest Neighbors (KNN). These models were evaluated and, in terms of Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) with the values of 0.25 (25%) and 0.22 (22%) indicating that Random Forest appear to be the best-performing models in terms of prediction accuracy compared to other models. In addition, the RF model also achieved the highest R2 score of 0.94, indicating its ability to explain a greater proportion of the variance in the dependent variable compared to the other models. This means that RF provides a strong prediction accuracy than other models in terms of determining heavy metal contamination in impact on Water Quality and Aquatic Life in Mine Surface Plant Areas. Therefore this study shows the potential of Machine Learning models to assist decision makers in understanding the pollution levels in water bodies.

Keywords

ML, Aquaculture, Prediction, Mining, Influents, Machine Learning, Random Forest, Prediction

1. Introduction

The Sentinel copper mine, situated in the Kalumbila district of the North Western Province, Zambia, stands as one of Africa's largest copper-producing mines, boasting significant copper reserves on a global scale [28]. Operational since 2016, the mine is under the ownership and management of Kalumbila Minerals, a wholly-owned subsidiary of the Canadian metals and mining company First Quantum Minerals. Utilizing conventional open-pit mining techniques, the operation employs fleets of electric face shovels, hydraulic excavators, and haul trucks with capacities of 330t and 240t. Extracted ore undergoes in-pit crushing and is subsequently transported to a nearby processing plant via an overland conveyance system.

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Unfortunately, this extraction process results in the release of heavy metal discharge residuals into the environment. Zambia Environmental Management Agency (ZEMA) categorizes these emitted heavy metals as some of the most critical pollutants [31].

Aquaculture, acknowledged for its reliability and low environmental impact in generating high-quality proteins for human consumption, is considered more efficient than alternative forms of agriculture due to higher food convergence. However, the discharge of heavy metal residues significantly impacts the aquatic ecosystem.

As an example, the fisheries and aquaculture measurements: Yearly Report" published by the Office of Fisheries Zambia in 2020 provides an overview of the state and performance of the fisheries and aquaculture sectors within the country. The report explains the sustainable fishing practices, conservation efforts, and the impact of environmental factors on fish stocks and aquaculture productivity [3].

Recognizing this, there is a need to monitor and reduce heavy metal pollution to safeguard the health of aquatic ecosystems and the dependent species. Consequently this study was aimed to develop Machine Learning Model that uses mine influents to soil and Aquarium water to predict future changes. This proactive approach aims to mitigate the environmental impact of heavy metal discharge and ensure the sustainable coexistence of mining activities and aquatic ecosystems.

2. Literature Review

According to the Auditor General's 2014 report on environmental degradation caused by mining, it was observed that very little is being done to reduce further degradation of the ecosystem because of mining activities. The Auditor's General report [30] further noted that ZEMA has no capacity to ensure that there is environmental compliance by all mining firms in Zambia. As a result, contamination of water by heavy metals is one of the serious environmental problems in Zambia and has significant implications for human health and aquatic organisms [7].

Aquatic ecosystems in Zambia are crucial for the livelihoods of many local communities, who depend largely on them for fishing and for supporting small-scale agriculture. [8]. Studies have shown that there are challenges associated with the usage of polluted water for irrigation of farming [9]. These include the absence of adequate information in the changes in concentration of heavy metals in water being used for irrigation, crops and soil [14]. Although there are challenges in using polluted water for farming, farming remains a major source of livelihood for most communities living near the mines [22].

The study by Daga et al [6] discussed various applications of IoT in agriculture, such as precision farming, smart irrigation systems, livestock monitoring, soil health monitoring, and crop management. These applications help optimize resource use, increase efficiency, and improve yield.

Other studies [12, 13] present an automated monitoring system for fish farms, emphasizing the use of sensors and automated controls to maintain optimal conditions. Both studies highlight the importance of continuous monitoring and automated systems in enhancing the efficiency and sustainability of aquaculture operations, demonstrating how technology can optimize conditions and reduce manual labor in fish farming environment.

Although mining is a major contributor to resource rich countries income and economy, it has contributed to the challenges of local communities in developing countries [21]. Literature shows that discharge of metals and dissolved salts into rivers, streams and groundwater, through mining activities, is a major challenge affecting the whole environmental eco-system, as the water bodies spread out [2]. The mining activities in Zambia, along with their aftermath, have presented numerous obstacles to the nation, many of which persist today, particularly concerning water contamination.

According to a study Chen et al [15], the primary components of an intelligent aquaculture cage system include sensors, controllers, and actuators. Sensors are used to monitor water quality parameters such as pH, temperature, and dissolved oxygen levels. Controllers are used to process the data from the sensors and to make decisions about the management of the cage environment. Actuators are used to control the various systems that maintain the growing conditions in the cage, such as aeration systems, water circulation systems, and feeding systems.

The presence of copper undermines fish resilience against diseases by interfering with their migration, disrupting normal swimming behavior, inducing oxidative damage, impeding respiratory processes, and causing structural and functional abnormalities in critical organs like gills, kidneys, liver, and various types of stem cells. [19]. Copper exposed different fish species posed behavioural changes such as decrease in swimming ability and food intake and increase in operculum movements [23, 24]. According to Arslan et al., extended exposure periods saw a return to normalcy regarding these modifications. In stinging catfish (Heteropneustes fossilis), rainbow trout (Oncorhynchus mykiss), and North African catfish (Clarias lazera), copper exposure led to a decline in muscle and liver glycogen levels while increasing serum glucose levels [25]. Arslan et al. hypothesized that these shifts could be linked to fish adapting to hypoxic conditions caused by the presence of copper.

The Aquacon system [9] employs sensors and additional monitoring devices to acquire data on multiple parameters, encompassing temperature, pH levels, dissolved oxygen levels, and other relevant factors. This data is then analyzed and processed using machine learning algorithms to provide valuable insights into the health and growth of the aquatic organisms being cultured. This information is then used to optimize the aquaculture conditions, such as feeding and water quality, to ensure optimal growth and survival of the organisms.

According to Alpaydin [1], machine learning is a scientific discipline that focuses on developing algorithms and statistical models that enable computers to perform tasks without explicit instructions.

The study by [11] focused on the development and application of an Adaptive Neural Fuzzy Inference System. ANFIS combines neural networks and fuzzy logic principles to create a model that can learn from data and make decisions based on uncertain or imprecise information. This system was particularly useful in complex environments like aquaculture.

Idachaba and Kodali [16-18] focused their studies on innovative technologies for enhancing fish farm management through real-time monitoring systems. Idachaba and colleagues developed an IoT-enabled real-time fishpond management system that uses various sensors to monitor environmental parameters such as water temperature, pH, and dissolved oxygen levels. This system allows for continuous data collection and analysis, enabling timely interventions to maintain optimal conditions for fish growth and health.

Finally the study by Doe [29] aimed at developing Enhanced Prediction Models that made use of advanced machine learning models, including Random Forest and Deep Learning that significantly improved the accuracy of predicting water quality and fish health metrics in aquaculture systems. However this study did not consider the quality of water for aquatic life in mine surface plant areas, which this study investigated thoroughly.

2.1. Problem Statement

The issue of water quality in ecosystems impacted by mining activities poses a significant environmental challenge, particularly in regions such as the Kalumbila District of the North-Western Province, where the Sentinel Mine has been operational. The discharge of mine influents into water bodies, shown by the Chisola Dam, can introduce varying concentrations of heavy metals, including Copper (Cu), Iron (Fe), and Cobalt (Co), potentially affecting the pH levels and overall aquatic health.

Understanding the complex relationships between mine influents and water quality is critical for developing effective environmental management strategies. Current practices often rely on periodic manual measurements, lacking the ability to anticipate future changes. There is an urgent need for an advanced predictive tool that leverages machine learning techniques to analyze historical data and forecast potential alterations in soil and aquarium water quality based on mine influents.

The study findings across these papers highlight the growing role of artificial intelligence (AI) and machine learning (ML) in optimizing water treatment processes and water quality management. Alam et al. [26] discuss the application of AI in automating and optimizing adsorption processes in water treatment, noting recent advancements and future prospects. Nasir et al. [27] demonstrate the effectiveness of machine learning algorithms in classifying water quality, enhancing monitoring accuracy. Li et al. [28] review the use of AI and ML for analyzing nonlinear relationships and controlling processes in drinking water treatment, showcasing their potential to improve system efficiency and decision-making. These studies collectively emphasize the transformative impact of AI and ML on water management, offering innovative solutions for improving water quality and treatment efficiency.

This research aims to address this gap by developing a robust machine learning model capable of predicting future changes in water quality, providing valuable insights for proactive environmental conservation efforts in mining-affected areas [17].

2.2. Objectives

The following are the objectives of the study:

1. To assess the level of heavy metal contamination (Cu, Fe, Co and pH) in water at mine surface plant areas by measuring key physical and chemical using a multi-parameter instrument.
2. To investigate the relationships between measured water quality parameters (Cu, Fe, Co and pH) and their impact on the optimal levels of heavy metals suitable for aquatic life.
3. To develop a Machine Learning Model that utilizes data on mine influents (Cu, Fe, Co and pH) to predict potential future changes in heavy metal contamination levels.

3. Methodology and Materials

3.1. Preparation of Dataset

The dataset consisted of 252 samples (observations) of surface water taken from Chisola Dam for the period 2015 to 2022. The dataset was systematically arranged based on the recommendation from ZEMA and how the pollutants are determined.

3.2. Study Area

This study was conducted at Kalumbila mine in Kalumbila District of North-Western Province. The mine is currently approximately 100 m deep and is expected to reach a depth of approximately 200 m. The width is in excess of 1000 m and the current length is approximately 1500 m, extending to approximately 8000 m. a dam wall was constructed upstream of Sentinel Mine, as the Chisola Dam actually flowed through the surface mine’s footprint.

Figure 1. *Chisola Dam.*

3.3. Physical and Chemical Measurements of Properties of Water

The contaminated water possessed a particular pH value and contained Copper (Cu), Iron (Fe), and Cobalt (Co) as heavy metal contaminants. The assessment of these levels in the initial sample set was carried out on location using the WTW pH330i multi-parameter instrument (Wissenschaftlich–Technische Germany). Calibration of the pH probe was accomplished using buffer solutions having a pH of 7.00.

3.4. Selection of Inputs

In this study four dependent variables were measured and predicted based on how their levels determines the levels of heavy metals in water. The four dependent variables were pH, Copper (Cu), Iron (Fe) and Cobalt (Co). The dataset distribution was as follows: 70% of the data samples, selected randomly from the entire dataset, for the training phase of a forecast model of the dependent variable. The remaining 30% of the samples was used to verify network performance while training the network and to avoid over-learning. The aim was to test the predictive validity and effectiveness of these models which ranged from 15% for the test and 15% for the validation respectively.

3.5. Linear Regression for Data Formatting

To assess the relationship between the independent and dependent variables of this study, linear regression was applied using the formula:

$$Y=\beta 0+\beta 1\cdot X1+\beta 2\cdot X2+\beta 3\cdot X3+\beta 4\cdot X4+\varepsilon$$

Where:

Y - is the dependent variable (optimum levels of heavy Metals for aquatic life)

X1, *X2*, *X3*, *X4* - are the independent variables (pH, Copper (Cu), Iron (Fe), and Cobalt (Co)) respectively.

β0 - is the intercept (constant term)

β1, β2, β3, β4 - are the coefficients for each independent variable, representing the change in Y for a one-unit change in the corresponding X.

ε - is the error term, representing unobserved factors influencing Y that are not accounted for in the model.

The data was normalized in order to improve the convergence speed and calculation accuracy of the water quality prediction model and eliminate the impacts caused by differences in the data.

3.6. Comparison of Machine Learning Models

To develop a Machine Learning Model that uses mine influents to soil and Aquarium water to predict future changes, various machine learning models were considered and compared:

3.6.1. Multiple Linear Regression (MLR)

Multiple Linear Regression (MLR) is a fundamental statistical technique that models the relationship between a dependent variable and multiple independent variables by fitting a linear equation. It assumes a linear relationship between the predictors and the response, making it suitable for scenarios where such relationships exist. However, MLR has limitations in capturing complex nonlinear patterns in the data and can suffer from multicollinearity issues when predictors are highly correlated [4].

3.6.2. Artificial Neural Networks (ANN)

In contrast, Artificial Neural Networks (ANN) are versatile models inspired by the structure and functioning of the human brain. They excel in capturing nonlinear relationships and can handle large and complex datasets effectively. ANNs use interconnected nodes arranged in layers to learn complex patterns and relationships from the data through iterative optimization algorithms [5].

3.6.3. Random Forest (RF)

On the other hand, Random Forest (RF) is an ensemble learning method that combines multiple decision trees to improve predictive performance and reduce overfitting. RF builds a multitude of decision trees during training and aggregates their predictions to make more accurate and robust predictions. It is capable of handling high-dimensional data and can capture complex interactions between variables without requiring extensive preprocessing [10].

3.7. Modelling Techniques Developed

In the development of a machine learning model aimed at predicting future changes in soil and aquarium water based on mine influents, the Random Forest ensemble method was employed. Random Forest was particularly well-suited for this task because it excels in handling diverse datasets with multiple features. In this case, the model leveraged data from mine influents, integrating information on pH levels, concentrations of heavy metals such as copper, iron, and cobalt, and other relevant parameters under consideration in this study.

4. Results and Discussion

The results of the study were presented according to the objectives presented II. The following were the objectives:

Objective One: *To assess the level of heavy metal contamination (Cu, Fe, Co and pH) in water at mine surface plant areas by measuring key physical and chemical using a multi-parameter instrument.*

Table 1. *In-situ measurement results.*

Parameter (Pollutants)	Optimum Recommended Level	Current	Difference
pH	6.5	4.0	2.5
Copper (Cu)	< 0.02-6.0 mg/L	18–28 µg/L	17.98-22 µg/L
Iron (Fe)	0.1 - 2.0 mg/L	≤ 0.07 mg/L	0.03 µg/L
Cobalt (Co)	0.01 mg/L	60 mg/L	59.99 µg/L

The findings from the in-situ measurements of key physical and chemical properties, including pH, Copper (Cu), Iron (Fe), and Cobalt (Co), reveal notable disparities between the current levels and the optimum recommended levels for fish survival. The pH level is notably lower than the recommended range, with a difference of 2.5, potentially indicating increased acidity in the water. Copper (Cu) concentrations exceed the upper limit of the recommended range (18–28 µg/L), with a difference of 17.98-22 µg/L, posing a potential risk of toxicity to aquatic life. Iron (Fe) levels are significantly below the recommended range, with a difference of 0.03 µg/L, suggesting a potential deficiency in this essential trace element. Cobalt (Co) concentrations are considerably higher than the recommended level, with a difference of 59.99 µg/L, raising concerns about the potential adverse effects on aquatic organisms. These findings underscore the importance of continuous monitoring and highlight the potential implications of the observed deviations from optimal water quality conditions for the well-being of the aquatic ecosystem.

Objectives Two: *To investigate the relationships between measured water quality parameters (Cu, Fe, Co and pH) and their impact on the optimal levels of heavy metals suitable for aquatic life.*

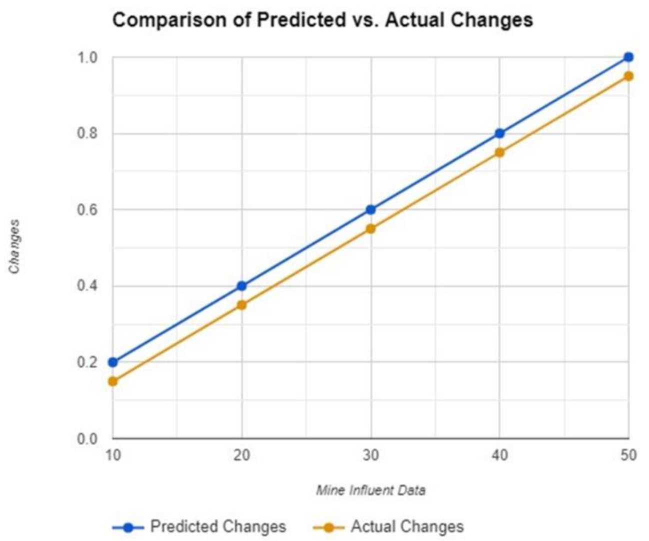

Figure 2. *Comparison of Predicted and Actual Values.*

The third objective was to apply linear regression analysis to quantify the relationships between the selected independent variables (pH, Copper, Iron, Cobalt) with regards to the predicted variable and the dependent variable (optimum levels of heavy metals for aquatic life). According to the results obtained and as depicted in the figure above, the results shows that the new system shows a better and more consistent smoother plot than the old system in terms of predicting the mine influents emitted in the atmosphere.

Objective Three: *To develop a Machine Learning Model that utilizes data on mine influents (Cu, Fe, Co and pH) to predict potential future changes in heavy metal contamination levels.*

To measure the third objective above, the study investigated three prediction models (RF, MLR and ANN) and applied three statistical tools (Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) the coefficient of determination (R2 score) to assess their performance. The results are shown below in table 2 and Figure 1 respectively:

Table 2. *Performance of ML Models.*

Model	MAE	RMSE	R^2
MLR	0.40	0.45	0.78
ANN	0.35	0.38	0.82
RF	0.25	0.22	0.94

According to the results depicted in the table above, the Mean Absolute Error (MAE) were estimated as 40% for MLR, 35% for ANN, 30% for KNN and 25% for RF. The Mean Absolute Error (MAE) was used because it helps calculates the average absolute difference between the actual and predicted values, giving thereby giving an idea of how wrong the predictions were. In a MAE, a lower MAE signifies a better performance of the model as it indicates smaller deviations from the actual value. Therefore, in our study the RF model yielded the lowest MAE (25%), indicating that on average, the RF model's predictions deviated least from the actual water-quality indices.

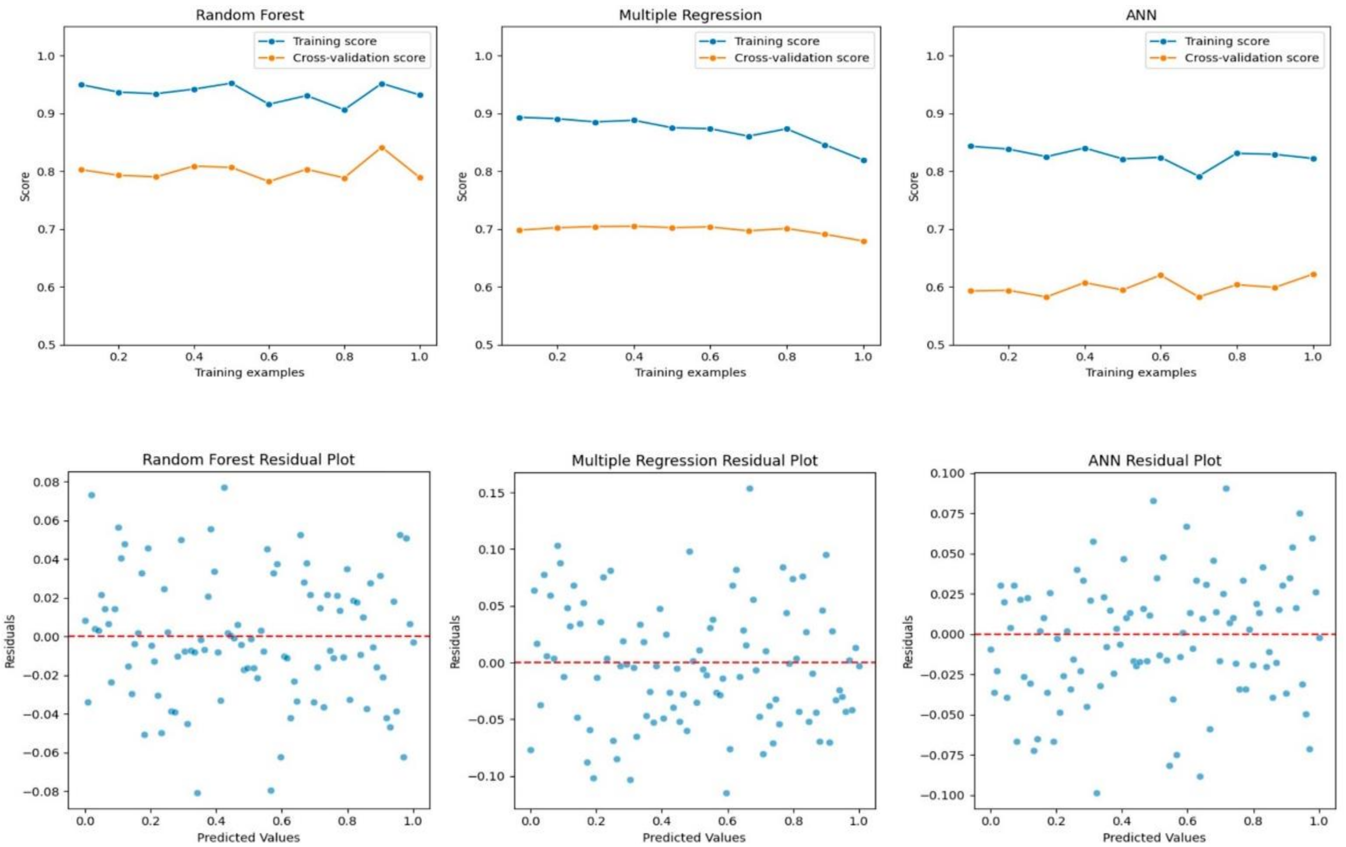

Figure 3. *Simulation and Prediction.*

According to the results obtained and as depicted in the diagram above, Random Forest and better performance in terms of both predicting accuracy and its ability to capture relationship among the variables involved than other algorithms.

5. Results Discussion

The main objective of this study was to of a Machine Learning Model that uses mine influents to soil and Aquarium water to predict future changes. According to the results obtained, as illustrated in Table 1, there was a significant differences between current levels and optimum recommended levels of heavy metals in aquarium water for fish survival. The observed lower pH level (4.0) compared to the recommended range (6.5) suggests a potential increase in water acidity, potentially impacting aquatic life. The results correlates with the findings of Emmanuel Sakala (2020) who established that, high level of pH concentration means the presence of heavy metals in water.

The study also revealed that Elevated Copper (Cu) concentrations (18–28 µg/L) exceeding the recommended range, with a difference of 17.98-22 µg/L, indicate a risk of toxicity. Suboptimal Iron (Fe) levels (≤ 0.07 mg/L) and excessive Cobalt (Co) concentrations (60 mg/L), with differences of 0.03 µg/L and 59.99 µg/L respectively, raise concerns about nutrient deficiencies and potential adverse effects on aquatic organisms, emphasizing the need for continuous monitoring and intervention.

Moving on to Objective Two, the developed Machine Learning Model effectively captured complex relationships between mine influents, particularly copper, and physical and chemical properties of soil and aquarium water, as shown in Figure 1. The model highlighted the crucial role of pH in determining concentration levels, indicating that high pH concentrations in mine surface plant water may limit fish growth, while lower levels increase sensitivity to toxic metals. This underscores the model's ability to predict future changes and its potential for proactive environmental management.

In pursuit of Objective Three, the application of linear regression analysis to quantify relationships between independent variables (pH, Copper, Iron, and Cobalt) and the dependent variable (optimum levels of heavy metals for aquatic life) yielded insightful results, as depicted in Figure 3. The new system demonstrated improved consistency and predictive accuracy compared to the old system, providing a more effective tool for quantifying the relationships between mine influents and the optimal levels of heavy metals for aquatic life [20]. These findings collectively emphasize the significance of integrating machine learning models and advanced analytical techniques for enhancing predictive capabilities and informing sustainable environmental practices.

6. Conclusion

In this study the development and implementation of a machine learning model utilizing mine influent data to predict future changes in soil and aquarium water quality at Kalumbila Mine in has been developed. Through a thorough preparation and analysis of a comprehensive dataset sourced from Chisola Dam, encompassing seven years of surface water samples, this study successfully employed linear regression for data formatting and subsequently employed the Random Forest ensemble method for robust modeling. The model, adept at handling diverse datasets with multiple features, incorporated key physicochemical measurements and delivered reliable predictions for the concentrations of heavy metals specifically, pH, Copper, Iron, and Cobalt. The results not only provide valuable insights into the intricate relationships between mine influents and water quality but also establish a foundation for proactive measures in mitigating potential adverse effects on aquatic ecosystems. The predictive validity demonstrated by the model underscores its potential applicability in anticipating future changes in water quality, offering a valuable tool for environmentalists, regulators, and stakeholders in safeguarding the integrity of aquatic ecosystems impacted by mining activities.

7. Recommendation

Based on the above discussion and conclusion, this study recommends that the findings be integrated into environmental monitoring and management practices at Kalumbila mine and similar settings. The predictive capabilities of the Random Forest model, combined with insights from linear regression analyses, offer a valuable tool for anticipating alterations in pH, Copper, Iron, and Cobalt concentrations. This information can aid in proactive decision-making to mitigate potential adverse effects on aquatic ecosystems. Additionally, the study recommends ongoing collaboration between environmental authorities, mining companies, and data scientists to continually refine and update the predictive model, incorporating new data for improved accuracy.

Abbreviations

ZEMA	Zambia Environmental Management Agency
ZDA	Zambia Developmental Agency
ML	Machine Language
AI	Artificial Intelligence
ANN	Artificial Neural Networks
RF	Random Forest
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error

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Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work the author(s) used

Google Bard in order to refine the language. After using this tool, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Conflicts of Interest

The Authors declare no conflicts of interest.

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