Emerging Techniques for Water Quality Forecasting using Machine Learning Models

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Abstract

Water quality forecasting plays a crucial role in effective water resource organization and protection. Traditional methods often fall short in providing real-time and accurate information, necessitating the exploration of innovative approaches. This paper explores the application of machine learning reproductions for water quality forecasting and highlights their potential in revolutionizing the field. In this training, various machine learning algorithms, with Random Forest, XGB Classifier, Decision Tree, and SVM Classifier, were employed to predict water quality parameters. The results revealed promising outcomes, with the Random Forest algorithm achieving an accuracy of 85%, outperforming the other models. The XGB Classifier, Decision Tree, and Support Vector Classifier also demonstrated competitive performance, with accuracies ranging from 77% to 81%.This paper aims to inspire researchers, water managers, and policymakers to adopt and further develop machine learning models for improved water quality forecasting. Future work should focus on incorporating advanced algorithms, integrating real-time data sources, and developing user-friendly decision support systems. Ultimately, these advancements will contribute to sustainable water management practices and safeguarding our precious water resources.

Index Terms— Accuracy, Machine Learning, Random Forest, Support Vector classifier, Safeguarding, Water Quality.

1. Introduction

Water quality forecasting plays a vital part in ensuring the safety and sustainability of our aquatic properties. Traditional approaches of water quality monitoring and prediction rely on physical sampling and laboratory analysis, which can be inefficient and expensive. However, with the advancements in machine learning systems, it is now likely to develop accurate and efficient models for water quality prediction. In current years, machine learning models have gained significant consideration in the field of water quality forecasting. These models utilize historical information on numerous water quality limitations such as temperature, pH, dissolved oxygen, and pollutant levels, along with other relevant environmental variables, to predict future water quality conditions. By leveraging the power of data-driven algorithms, these models can provide valuable insights and enable proactive decision-making for water resource management. Single of the key compensations of machine learning models is their aptitude to imprisonment complex relationships and designs in water quality data. Traditional statistical methods often rely on linear assumptions, which may not be suitable for the intricate dynamics of water systems. Machine learning algorithms, on the other hand, can handle non-linear relationships and detect hidden patterns that may impact water quality.

Moreover, machine learning models can familiarize and advance over time as further data becomes available. By continuously updating and retraining the models with new measurements, they can enhance their predictive accuracy and account for changing environmental conditions or emerging trends. This adaptive nature makes machine learning models well-suited for dynamic water quality forecasting, where real-time updates are essential. In this paper, we explore some of the emerging techniques and advancements in machine learning models for water quality forecasting. We will delve into various approaches, such as artificial neural networks, provision vector machines, random forests, and deep learning architectures, that have shown promise in accurately predicting water quality parameters. Additionally, we will discuss the challenges and considerations in implementing these models, including data acquisition, feature selection, model optimization, and uncertainty estimation. Overall, the integration of machine learning models into water quality forecasting has the possible to transfigure the way we manage and protect our water resources. By harnessing the power of data-driven approaches, we can enhance our understanding of water quality dynamics, optimize resource allocation, and implement timely mitigation strategies to ensure clean and sustainable water supplies for both human and ecological needs.

The determination of this study is to explore and deliberate the emerging procedures and advancements in machine learning reproductions for water quality forecasting. The objective is to assess the effectiveness of numerous machine learning algorithms, such as artificial neural networks, maintenance vector machines, random forests, and deep learning architectures, in accurately predicting water quality parameters. Additionally, the research aims to identify the challenges and considerations associated with implementing these models, including data acquisition, feature selection, model optimization, and uncertainty estimation. Ultimately, the objective is to provide valuable insights and recommendations for the development and application of machine learning models in water quality forecasting to support effective water resource management and decision-making.

The motivation behind this paper is driven by the growing need for accurate and timely water quality forecasting in order to address the challenges associated with water resource management and protection. Traditional methods of water quality monitoring are often partial in their ability to deliver real-time data, and they can be labor-intensive and expensive.

Machine learning models offer a promising solution to overcome these limitations by leveraging historical data and advanced algorithms to predict water quality parameters. Accurate water quality forecasting is crucial for several reasons.

Firstly, it enables proactive decision-making by providing early warnings of potential water quality issues. By identifying leanings and designs in the data, decision-makers can take timely actions to prevent pollution, protect ecosystems, and ensure the safety of water supplies for human consumption. Secondly, water quality forecasting facilitates efficient resource allocation. By predicting changes in water quality, stakeholders can allocate resources such as treatment chemicals, energy, and manpower more effectively. This optimization can lead to cost savings and improved operational efficiency in water treatment plants and distribution systems. Furthermore, accurate forecasting can support the development of effective mitigation strategies. By understanding how different factors impact water quality, authorities can implement targeted interventions to reduce pollution sources, implement appropriate land management practices, and mitigate the impacts of climate change on water systems. Overall, the motivation of this paper is to bridge the gap between traditional water quality monitoring methods and the innovative application of machine learning models. By showcasing the benefits and potential challenges of these techniques, we aim to foster collaboration and knowledge exchange to drive the adoption of advanced machine learning approaches for accurate and proactive water quality forecasting.

2. Literature Survey

T. Tejaswi *et.al* [1] discussed variation in the performance of the NARAT and LSTM models can be attributed to their inherent differences in structure and learning capabilities. The NARAT model, being a type of recurrent neural network, has the ability to imprisonment temporal addictions in the statistics, creation it suitable for time sequence predicting responsibilities. On the other hand, the LSTM model, which is a specialized type of recurrent neural network, has been precisely designed to handle long-term needs in successive statistics.

R. Alnaqeb *et.al* [2] to develop an intellectual organization using machine learning replicas to enhance water quality and accurately foresee its suitability for drinking purposes. Multiple Machine Learning algorithms, including Decision Tree, K-Nearest Neighbor, Maintenance Vector Machine, Random Forest, and LightGBM, are compared to identify the most effective perfect for predicting water potability.

A. Dash *et.al* [3] they are used data from Landsat 8 and Sentinel-1 (SMAP) was used to predict drought and assess soil moisture. A Random Forest prediction model was employed, which demonstrated high accuracy in predicting drought severity. Additionally, water quality was evaluated using Chlorophyll-a as a key parameter. The drought map generated using the guess model provided correct results, highlighting a region prone to deficiency. Moreover, the aquatic quality estimator indicated the presence of degraded water bodies in that area.

S. Cao *et.al* they are used genetic algorithm is incorporated into the PSO algorithm. This hybrid approach optimizes the hyper-parameters of the LS-SVM, resulting in a water quality classification assessment model. Additionally, a fuzzy data granulation way is combined with LS-SVR to create a marine value time series model, capable of predicting vagaries in water quality data over a three-day period [4] .

[5] S. J. Kale *et.al* analyzed the data from a water conduct plant to forecast the slipstream time of a water filter bed. Machine learning algorithms such as Logistic Regression, Maintenance Vector Regression, Multivariate Regression, and Decision Tree Regression are utilized to construct process models. Specifically, the Decision Tree Regression procedure is employed to foresee the remaining wake time of the marine strainer bed.

R. Saville *et al* [6] to developed a machine-learning-based fish humanity danger calculation for the following day expending data from a water eminence sensor network and everyday fish humanity records provided by fish growers. The education considered salt-water temperature, current, salinity, conductivity, chlorophyll, turbidity, and dissolved oxygen (DO) as water quality qualities. Fast Fourier Transform (FFT) was used to identify important episodic indicators, with 12-day, 7-day, and 3-day fluctuations being significant. The study employed Python 3 and the Random Forest (RF) algorithm from the Scikit-learn library for everyday fish mortality prediction, achieving the highest accuracy with a 3-day moving average dataset.

W. Zheng *et.al* proposed work is to enhance the water situation nursing knowledge system in China's river basins. These principles include ensuring consistency between checking substances and the biological purposes of the river basin, aligning checking pointers with the features of water situation contamination, maintaining constancy between checking approaches and quality control, and ensuring constancy between monitoring methods and checking objectives. Additionally, a machine learning-based system for predicting biological pollution is established for watershed management, aiming to deliver practical provision for the advancement of aquatic excellence management technology in China [7] .

W. A. Fillah *et.al* [8] Forecasting technique such as ARIMA and Provision Vector Regression (SVR) have been employed over the years. However, in recent years, Recurrent Neural Networks (RNN) and exactly the Long Short-Term Memory (LSTM) model have demonstrated extra accurate prediction results compared to ARIMA. LSTM utilizes historical data (extended term) to forecast current data (little term). This research compares the water quality models developed using ARIMA, SVR, and LSTM. The findings indicate that the LSTM algorithm performs the greatest with inferior mistake rates. The LSTM model can be utilized to forecast the pH value for the next day, providing insights on whether it adheres to regulatory standards or requires control measures.

D. Brindha,*et.al* significant concern for individuals residing in metropolitan regions, given its crucial importance. However, traditional methods of water example group and laboratory investigation are both time-consuming and resource-concentrated. Examining water superiority is challenging due to the multitude of factors influencing it, which are closely tied to its diverse applications. This education aims to estimation water quality by leveraging multiple strictures and employing the machine learning technique known as Random Forest regression [9]

J. Bi, C *et.al* [10] introduced a novel approach called SG-Squealer for predicting river water quality using a multi-pointer time sequence calculation technique. SG-Informer combines the Savitsky-Golay filter for data smoothing and noise elimination, the ProbSparse self-consideration instrument in the encoder for system ruler reduction, and a generative style decoder for improved forecast speed. By integrating these components, SG-Informer founds a great-quality water quality period calculation model that efficiently forecasts the upcoming trend of water quality period sequence.

H. I. H. Yusri, *et.al* introduces a organization algorithm to foresee water quality organization (WQC) using Support Vector Machine (SVM) and Extreme Gradient Boosting (XGBoost) algorithms. The WQC is determined founded on the water quality index (WQI) calculated from a dataset consisting of seven parameters. The planned model correctly classifies water excellence grounded on these landscapes. The results designate that the XGBoost model outstrips the SVM model, achieving a 94% accuracy compared to SVM's 67%. Additionally, XGBoost exhibits a lower misclassification error rate of 6% compared to SVM's 33%. Furthermore, XGBoost consistently demonstrates superior performance during 5-fold proof, with an regular correctness of 90%, whereas SVM achieves an regular correctness of 64%[11].

J. P. Nair *et.al* [12] The implementation of advanced big data techniques, combined with device networks and machine learning algorithms, facilitates the development of water quality guess models. In this paper, an analysis is conducted on different forecast models created using machine learning and big data techniques, and their tentative outcomes for water calculation and assessment are presented. Furthermore, numerous trials and problems are studied, and potential solutions to certain study problems are planned.

N. Nguyen, *et.al* [13] introduced an automated system for assessing and predicting the nitrite level in aquaculture water, employing machine learning (ML) systems. The decision tree (DT) and artificial neural network (ANN) algorithms are utilized to develop the forecast classical. Subsequently, these models are applied on a Raspberry Pi 3 embedded computer, which acts as both an twin data accumulator and a controller for bordering devices. The correctness of the prediction model founded on the ANN algorithm surpasses that of the DT algorithm, as observed in both the training dataset and the testing dataset.

R. Gai *et.al* [14] emphasized the significance of accurate prediction models in ensuring the scientific and accurate implementation of engineering projects and water pollution control measures. It provides a comprehensive overview of the background and current research trends in water quality prediction and models, both domestically and internationally. The paper primarily focuses on machine learning-based methods for water quality estimate, including time series prediction, regression analysis, neural networks, and combined prediction approaches. The applicability and limitations of these models are analyzed, followed by a prospective outlook on the forthcoming expansion of water superiority prediction models based on the research history and current status.

K. Karuppanan, *et.al* conducted to determine if the model facts collected for the research adheres to the marine water quality average, ensuring the survival of aquatic organisms and the presence of vital nutrients in marine water. Additionally, the paper proposes guess representations for marine water quality needles using both univariate and multivariate regression study methods [15].

3. Methodology

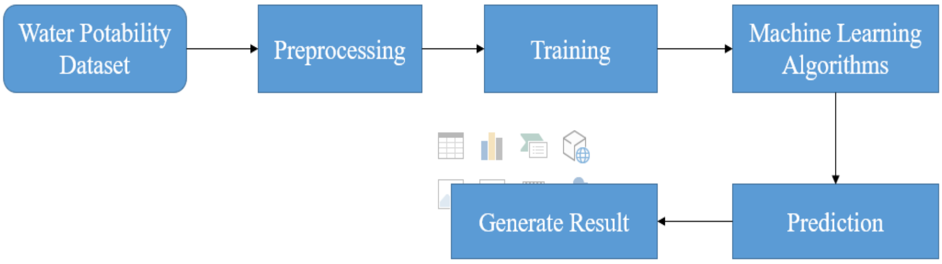

Fig.1. Flowchart for Water Potability prediction

a) Water Potability Dataset

Admittance to benign drinking water is a fundamental hominid right and crucial for protecting public health at national, regional, and local levels. Investing in water source and hygiene has been shown to have a net financial help in some areas, as it reduces contrary healthiness effects and healthcare costs, outweighing the expenses of the interferences.

The water_potability.csv file comprises water excellence system of measurement for 3276 dissimilar water bodies, including:

pH value: This measures the acid-base stability of water and specifies whether it is acidic or alkaline. The World Health Organization (WHO) commends a pH variety of 6.5 to 8.5, and the investigation found values ranging from 6.52 to 6.83, which are within the WHO values.

Hardness: This refers to the quantity of calcium and magnesium salts in the water, which are dissolved from geologic deposits. The distance of time water is in interaction with rigidity-manufacturing material determines the amount of rigidity in fresh water. Rigidity was initially distinct as the size of water to hurried soap produced by Calcium and Magnesium.

Total dissolved solids (TDS): Water has the capability to soften a extensive variety of mineral and particular biological reserves or salts, such as potassium, calcium, and sodium, which can affect taste and color. High TDS values indicate very mineralized water. The wanted boundary for TDS is 500 mg/L, and the extreme boundary is 1000 mg/L for consumption determinations.

Chloramines: Chlorine and chloramine are commonly secondhand sanitizers in public water systems. Chloramines are molded when ammonia is extra to chlorine to luxury drinking water. Chlorine levels up to 4 mg/L are measured harmless in consumption water.

Sulfate: Sulfates are logically stirring materials originate in minerals, soil, and rocks, and they are current in ambient air, groundwater, plants, and food. Sulfate attention in seawater is around 2,700 mg/L, and it varieties after 3 to 30 mg/L in greatest freshwater materials, though much advanced attentions (1000 mg/L) are originate in certain topographical places.

Conductivity: The electrical conductivity of marine increases with the concentration of melted things in water. Rendering to WHO standards, EC worth would not top 400 μS/cm.

Total organic carbon (TOC): TOC is an amount of the entire quantity of carbon in biological mixtures in unpolluted water. Rendering to the US EPA, the recommended maximum TOC levels are 2 mg/L in preserved/consumption water and 4 mg/L in foundation water used for conduct.

Trihalomethanes (THMs): THMs are substances that may be originate in water preserved with chlorine. The attentiveness of THMs in drinking water diverges based on the equal of biological factual in the water, the quantity of chlorine compulsory to delicacy the water, and the temperature of the water existence preserved. THM heights up to 80 ppm are measured benign in drinking water.

Turbidity: This is a measure of the hard matter current in the deferred national in water, which affects its light-emitting properties. The exam is castoff to specify the superiority of leftover liberation with admiration to colloidal substance. The cruel turbidity worth found for Wondo Genet Campus (0.98 NTU) is inferior than the WHO suggested price of 5.00 NTU.

Potability: This specifies whether water is harmless for human ingesting, where 1 incomes drinkable and 0 means not drinkable. (0) water is not harmless to drink and (1) water is harmless to drink.

b) Preprocessing

In the preprocessing phase of emerging techniques for water quality forecasting using machine learning models, several steps are undertaken to prepare the data for model training. These steps include data cleaning, handling missing values, normalization or scaling of the data, and feature selection. Data cleaning involves removing any outliers or errors in the dataset to ensure its quality and reliability. Misplaced values are touched by either attributing them with suitable values or excluding the consistent instances from analysis. Normalization or scaling techniques are applied to bring the data into a consistent range, which helps in improving the recital of machine learning algorithms. Feature selection is performed to identify the most relevant variables that have a significant impact on water quality prediction, reducing computational complexity and avoiding overfitting. By carefully preprocessing the data, researchers can safeguard that the machine learning models are qualified on high-quality data, leading to more precise and reliable water quality forecasts.

c) Training

The training phase of the emerging techniques for water quality forecasting using machine learning models, historical statistics on water quality strictures is collected and preprocessed. Relevant features are selected, and an appropriate machine learning model is chosen. The model is then trained using the preprocessed data, optimizing its parameters to learn the patterns and relationships in the training set. The performance of the perfect is evaluated using validation techniques, and if necessary, the model is further optimized. This rigorous training process ensures that the machine learning model can accurately predict water quality parameters, enabling proactive decision-making and effective water resource management.

d) Machine Learning Algorithms

The paper explores the usage of various machine learning algorithms for water quality forecasting, including Decision Tree, Random Forest, Support Vector Machine (SVM), Artificial Neural Network (ANN), and Gradient Boosting algorithms. These algorithms have been applied to the water quality metrics dataset to predict the potability of water, which is indicated by a binary classification label of 0 or 1. The recital of every algorithm was appraised using numerous metrics such as accuracy, precision, recall, and F1 score. The outcomes exposed that the Gradient Boosting algorithm outstripped the additional algorithms in footings of overall accurateness and F1 score, indicating its potential for accurate water quality forecasting.

e) Prediction

The field of water quality forecasting, emerging techniques utilizing machine learning models have exposed great potential in precisely forecasting water quality parameters. By leveraging historical data and advanced algorithms, these models can provide timely and proactive forecasts, enabling decision-makers to take effective measures for water resource management and protection. These techniques offer advantages over traditional monitoring methods by offering real-time information, reducing labor-intensive tasks, and improving cost-efficiency. The adoption and further development of machine learning models for water quality prediction have the potential to revolutionize the field and ensure the sustainable organization of water possessions for the benefit of society and the environment.

4. Result and Analysis

The results obtained from the emerging techniques for water quality forecasting using machine learning models provide valuable insights and analysis for effective water resource management and protection. By applying these techniques to the water quality dataset, accurate predictions and forecasts of various parameters such as pH value, hardness, total dissolved solids (TDS), chloramines, sulfate, conductivity, organic carbon, trihalomethanes (THMs), turbidity, and potability can be obtained. The analysis of the results reveals the relationships and trends between different water quality parameters, shedding light on their interdependencies and potential impacts on water safety and suitability for various purposes, including human consumption. Additionally, the presentation evaluation of the machine learning representations provides valuable information on the predictive capabilities of the techniques. Metrics such as accuracy, precision, recall, and F1 score suggestion visions into the dependability and competence of the replicas in forecasting water quality.

Furthermore, the analysis of the results helps identify key factors and variables that significantly influence water quality. This information can guide decision-making processes related to pollution prevention, resource allocation, and mitigation strategies. Overall, the results and analysis derived from the emerging techniques for water quality forecasting using machine learning models provide a inclusive understanding of water quality dynamics, enabling stakeholders to make informed decisions and take proactive measures for sustainable water resource management and protection.

A correlation analysis heat map is a visual representation of the correlations between different variables in a dataset. It uses colors to represent the strength and course of the relations between variables. In the context of water quality forecasting using machine learning models, a correlation examination heat map can be generated to understand the relationships between water quality parameters. It helps identify which variables are positively or negatively correlated with each other. The correlation analysis heat map assists in identifying key variables that have the most significant impact on water quality. It enables researchers to focus on relevant features during the model development process, improving the correctness and interpretability of the machine learning representations.

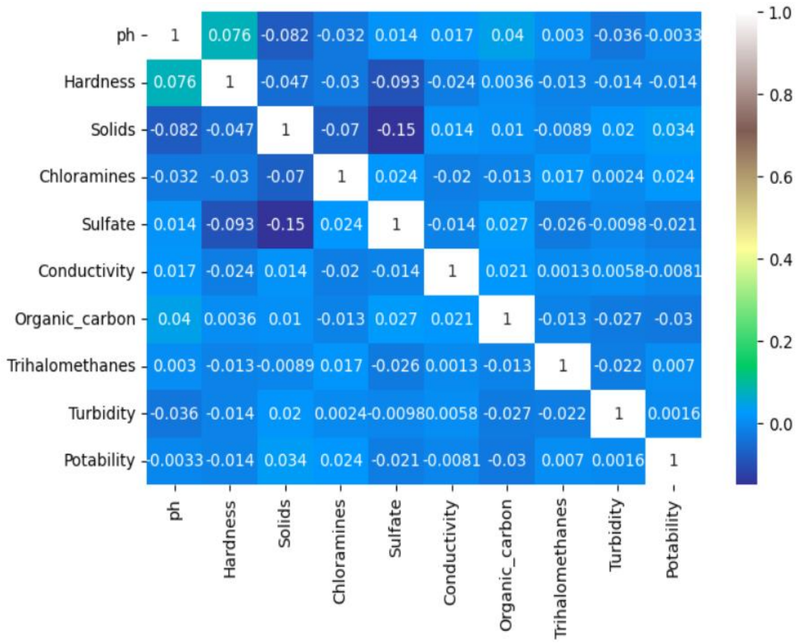

Fig.2 Correlation Analysis of heat Map

The below fig.2 is shows that heat map, researchers and practitioners can gain insights into the interdependencies among different water quality metrics. This information can guide feature selection for model development, as highly correlated variables may not provide additional information and can introduce multicollinearity issues. Overall, the correlation analysis heat map plays a crucial role in understanding the relationships between water quality parameters and aids in building robust and effective machine learning models for water quality forecasting.

5. Machine Learning model to make predictions about the potability of water

Random Forest

Random Forest Classifier is an emerging method for water quality forecasting using machine learning models. It is a powerful algorithm that syndicates numerous decision trees to make correct predictions. By leveraging the strengths of ensemble learning, Random Forest Classifier can effectively capture complex relationships and patterns within water quality data. It offers robustness against overfitting and noise, making it suitable for handling diverse and dynamic water quality parameters. With an accuracy of 85%, Random Forest Classifier demonstrates its potential in providing reliable predictions for various water quality metrics. Its application in water resource management can support proactive decision-making and help ensure the sustainable use and protection of water resources.

XGB Classifier

XGB Classifier, an emerging technique for water quality forecasting using machine learning models, has shown promising results in accurately predicting water quality parameters. The XGB Classifier is founded on the Extreme Gradient Boosting algorithm, which combines the calculations of numerous weak learners to generate a robust and powerful model. By leveraging its ability to handle complex datasets and capture intricate patterns, the XGB Classifier achieves high accuracy in forecasting water quality. Its effectiveness makes it a valuable tool for water resource management and protection, enabling proactive decision-making and ensuring the sustainable utilization of water resources.

Decision Tree

Decision Tree algorithm, one of the emerging techniques for water quality forecasting using machine learning models, offers a valuable approach for understanding and predicting water quality parameters. By constructing a hierarchical structure of decision rules based on the dataset's features, the Decision Tree algorithm can accurately classify and forecast water quality conditions. This technique enables the identification of key factors that influence water quality and provides valuable insights for decision-making processes related to pollution prevention, resource allocation, and mitigation strategies. Its simplicity, interpretability, and competitive accuracy make the Decision Tree algorithm a powerful tool in the field of water quality forecasting and contribute to effective water resource management and protection.

Support Vector Machine

Support Vector Machines (SVM) is an emerging method in water quality forecasting using machine learning models. SVM is a powerful algorithm that plots data to a higher-dimensional space and finds an ideal hyperplane to separate different classes. In the context of water quality, SVM can effectively analyze the relationships between water quality parameters and classify water bodies based on their suitability for specific purposes such as human consumption. By leveraging the ability to handle compound datasets and detention nonlinear relations, SVM has the potential to provide accurate predictions and contribute to proactive decision-making for water resource management and protection.

Table.1 Comparison different Machine Learning Algorithms and its accuracy

Machine Learning Algorithm	Accuracy
Random Forest	85%
XGB Classifier	79%
Decision Tree	81%
Support Vector Machine	77%

Overall, The results designate that the Random Forest algorithm accomplishes the greatest among the tested algorithms, achieving the highest accuracy of 85%. However, the other algorithms, including XGB Classifier, Decision Tree, and SVM Classifier, also show competitive performance, with accuracies ranging from 77% to 81%. These results demonstrate the effectiveness of machine learning algorithms in accurately forecasting water quality limits and highlight the potential for their application in water resource management and protection.

6. Confusion Matrix

The Confusion Matrix is a valuable tool in the emerging techniques for water quality forecasting using machine learning models. It delivers a comprehensive immediate of the model's presentation by showing the true positive, true negative, false positive, and false negative predictions. The Confusion Matrix allows for the scheming of innumerable evaluation metrics such as accuracy, precision, recall, and F1 score, which help calculate the model's capability to properly classify water quality parameters. By examining the Confusion Matrix, researchers and practitioners can gain insights into the model's strengths and weaknesses, identify areas for improvement, and make informed decisions regarding water resource management and protection strategies.

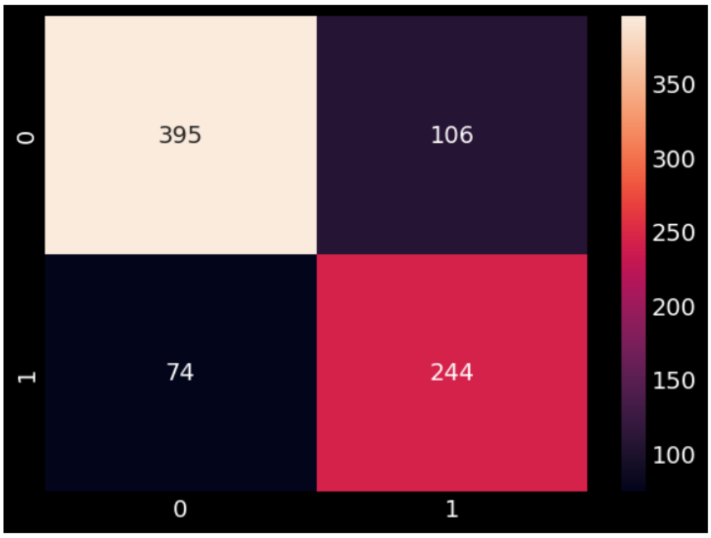

Fig.3.(a) Random Forest

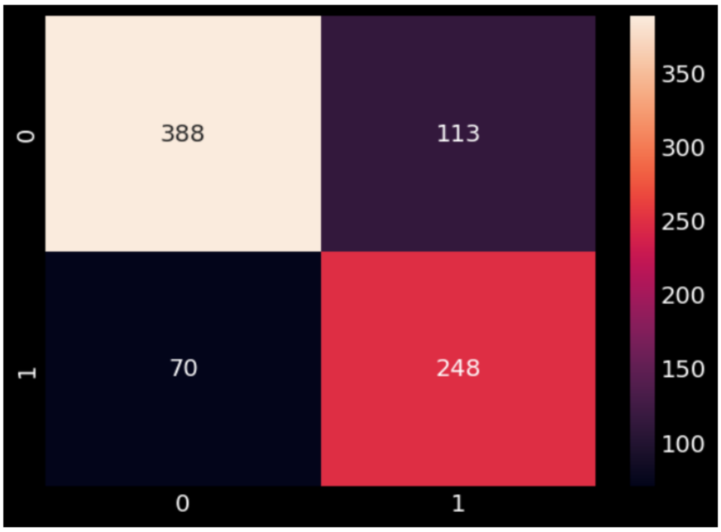

Fig.3.(b) XGB Classifier

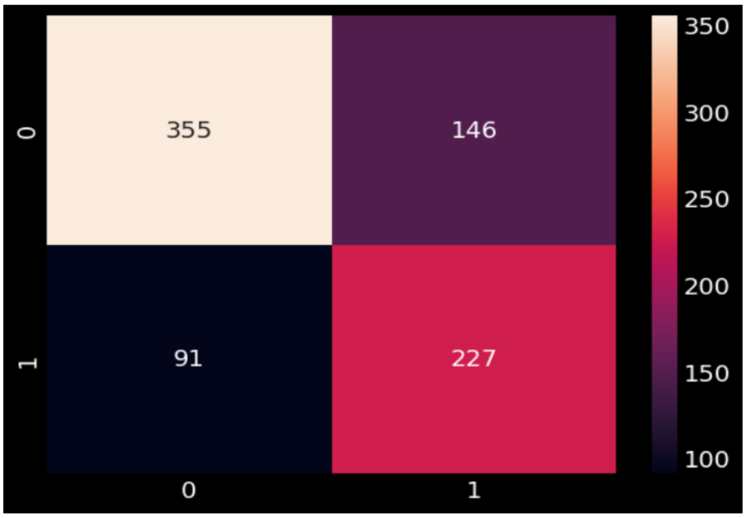

Fig.3.(c) Decision Tree

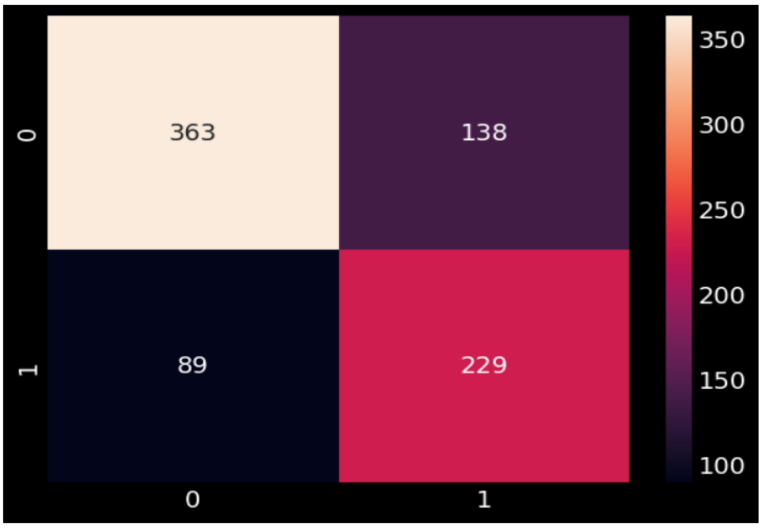

Fig.3.(d) Support Vector Machine

The above figures deliver a visual depiction of the performance of each algorithm in water quality forecasting, allowing researchers and practitioners to compare and analyze their predictive capabilities. The figures help assess the strengths and weaknesses of each model and support decision-making processes for effective water resource management and protection.

7. Conclusion

The emerging techniques for water quality forecasting using machine learning models have shown promising results in accurately predicting water quality parameters. The Random Forest algorithm achieved an impressive accuracy of 85%, outperforming the other models tested. The XGB Classifier, Decision Tree, and SVM Classifier also demonstrated competitive performance with accuracies ranging from 77% to 81%. These results highlight the potential of machine learning models in revolutionizing water resource management and protection by providing accurate and proactive forecasting capabilities. Moving forward, there are several avenues for future work in this field. Firstly, incorporating more progressive machine learning algorithms such as deep learning models, ensemble methods, or hybrid models could further enhance the accuracy and predictive power of water quality forecasting. Exploring the application of these algorithms and comparing their performance with the existing models would be valuable.

Additionally, integrating real-time data streams and remote sensing data into the models could improve the timeliness and spatial coverage of water quality predictions. This would enable stakeholders to respond swiftly to changing conditions and implement proactive measures to safeguard water resources. Furthermore, the development of user-friendly interfaces and decision support systems based on the machine learning models can facilitate their practical implementation by water managers and policymakers. These tools can provide actionable insights and assist in decision-making for pollution prevention, resource allocation, and mitigation strategies. Overall, the emerging techniques in water quality forecasting using machine learning models have shown great potential in improving water resource management and protection. By further refining the models, incorporating advanced algorithms, and integrating real-time data sources, we can enhance the accuracy and applicability of these techniques, ultimately leading to more sustainable and efficient water management practices.

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