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Potable Water Identification with Machine Learning: An Exploration of Water Quality Parameters

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Abstract- In this research, we aim to determine the water potability using three machine learning classification algorithms: decision tree, gradient boosting and bagging classifier. These algorithms were trained and tested on a dataset of water quality measurements. The outcomes of the experiment showed that the gradient boosting algorithm achieved the highest F1-score of 0.78 among all the algorithms. This indicates that the gradient boosting algorithm was most effective in correctly identifying both the safe and contaminated water samples. The results of this study demonstrate that gradient boosting is a promising approach for determining water potability and can be used as a reliable method for water quality assessment.

Keywords- Water Quality; Machine Learning; Water Potability; Classification

I. INTRODUCTION

Water potability refers to the quality of water that is safe for human consumption. It is a crucial aspect of public health and sanitation, such as having access to sanitary drinking water is essential for maintaining a healthy lifestyle. Water contamination can occur due to a variety of factors such as industrial and agricultural pollution, natural disasters, and improper sewage treatment. Contaminated water can cause a range of health issues, including diarrhea, cholera, and typhoid fever [1-4]. In severe cases, it can lead to death. To ensure water potability, water is tested for a variety of contaminants, including bacteria, viruses, and chemicals such as lead and arsenic. These tests are conducted by government agencies and independent organizations, and the results are made available to the public. However, even with regular testing, it can be difficult to detect all contaminants in water [5-8]. This is where machine learning comes in. Machine learning is able to recognise patterns and trends in water quality data that may not be immediately obvious to human researchers by applying sophisticated algorithms. In the end, enhanced water potability can result from the more precise and effective detection of water pollutants. In addition to the public health benefits, ensuring water potability also has economic benefits. Because it supports increased agricultural production, industrial development, and tourism, access to clean, safe drinking water is crucial for economic progress. Overall, water potability is a critical issue that affects the health and well-being of individuals and communities. The use of machine learning in potability detection can help improve the accuracy and efficiency of water testing, ensuring access to clean and safe drinking water for all. Machine learning is a rapidly growing field that is revolutionizing many industries, including manufacturing, healthcare, and transportation. In manufacturing, machine learning is used to improve productivity and efficiency [9-15]. For example, machine learning algorithms can be utilized to optimize production schedules, forecast equipment failures, and improve product quality. Additionally, machine learning can be used to improve supply chain management by predicting demand and optimizing inventory levels. These benefits are resulting in cost savings and increased competitiveness for manufacturing companies. [16-20] In healthcare, machine learning is used to improve patient outcomes and reduce costs. For example, machine learning

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algorithms can be used to envisage patient outcomes, identify patients at high risk of complications, and optimize treatment plans. Additionally, machine learning can be used to improve medical imaging by identifying diseases and detecting abnormalities [21-24]. As a result, healthcare providers are able to deliver more effective and efficient care to patients.In transportation, machine learning is used to improve safety and efficiency. For instance, route optimization and traffic pattern prediction using machine learning algorithms can improve travel times and reduce congestion [25-28]. Additionally, machine learning can be utilized to advance the protection of autonomous vehicles by detecting and responding to potential hazards. These benefits are helping to make transportation more efficient and safer for everyone.

II. PROBLEM STATEMENT

The availability of clean and safe drinking water is a basic human need, yet in many places of the world, getting access to potable water is still very difficult. Traditional methods for detecting water potability, such as chemical testing and visual inspections, can be time-consuming and costly, and may not provide accurate results in all cases.

The goal of this research is to create a machine learning model that can quickly and reliably determine if water is potable. The model should be able to analyze data from a variety of sources, including water samples, sensor readings, and environmental factors, to identify patterns and predict the presence of contaminants.

The proposed solution will leverage the power of machine learning algorithms to detect water potability, with the goal of providing a more accurate and efficient method for ensuring the safety of drinking water. Additionally, the model will be able to learn from data over time, allowing it to continuously improve its predictions and adapt to changing water conditions.

This work will have a significant impact on the public health and well-being, by providing a powerful tool for detecting water potability and ensuring access to clean and safe drinking water for communities around the world. It will also help to reduce the costs associated with traditional methods of water potability testing, and make it more accessible for developing countries.

III. EXPERIMENTAL PROCEDURE

A key element of effective health protection measures and a fundamental human right, access to clean drinking water is essential for good health. This is important as a health and development issue on a national, regional, and local level. Because they lower unfavourable health consequences and medical costs more than they cost to implement, investments in water supply and sanitation have been demonstrated to generate a net economic advantage in some locations. In the present work, the dataset file includes measurements of water quality for 3276 dissimilar frames of water. The input parameters are pH, Hardness, Solids (Total dissolved solids - TDS), Chloramines, Sulfate, Conductivity, Organic carbon, Trihalomethanes, Turbidity while Potability will be the output parameter. The given dataset will be subjected to classification-based machine learning algorithms for the forecast of the potability of the water. In the present work, the output parameter i.e. Water potability is labelled as 0 if its not potable and labelled as 1 if the water is potable. Supervised machine learning classification algorithms are a type of algorithm used to classify data into different categories or classes. These algorithms work by training a model on a labeled dataset, where the data points are already associated with a specific class or label. The algorithm's objective is to identify the underlying links and patterns in the data so that it may utilise this understanding to anticipate the outcomes of new, upcoming data. The process of training a supervised machine learning classification algorithm typically begins with the selection of a suitable algorithm, such as decision trees, logistic regression, or support vector machines. Then, a training set and a testing set are created from the labelled dataset. The model is trained using the training set, and its performance is assessed using the testing set. During the training process, the algorithm iteratively analyzes the data and learns the patterns and relationships that are associated with each class. This is done by adjusting the model's parameters, such as the weights of the features, to minimize the error between the predicted and true labels. Once the training is complete, the model is tested using the testing set, and the performance is appraised using system of measurement such as accuracy, precision, recall, and F1-score. If the performance is satisfactory, the model can then be used to classify new, unseen data points. The implemented framework used in the present work is shown in Figure 1.

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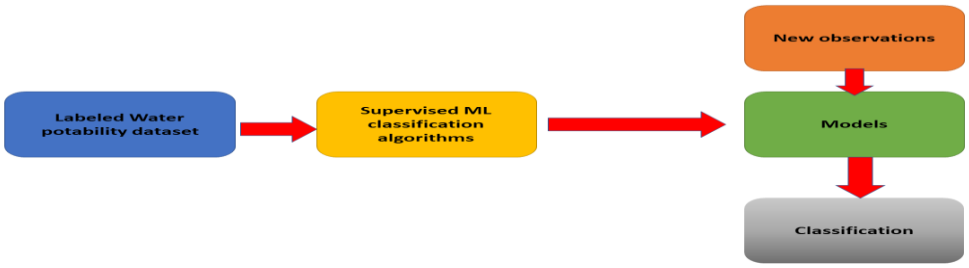

Figure 1. Machine Learning classification-based framework implemented in the present work

RESULTS AND DISCUSSION

Table 1 shows the statistical analysis results of the present dataset.

TABLE I. STATISTICAL ANALYSIS RESULTS

a~	mean	std	min	25%	50%	75%	max	
ph	2785.000000	7.080795	1.594320	0.000000	6.093092	7.036752	8.062066	14.000000
Hardness	3276.000000	196.369496	32.879761	47.432000	176.850538	196.967627	216.667456	323.124000
Solids	3276.000000	22014.092526	8768.570828	320.942611	15666.690297	20927.833607	27332.762127	61227.196008
Chloramines	3276.000000	7.122277	1.583085	0.352000	6.127421	7.130299	8.114887	13.127000
Sulfate	2495.000000	333.775777	41.416840	129.000000	307.699498	333.073546	359.950170	481.030642
Conductivity	3276.000000	426.205111	80.824064	181.483754	365.734414	421.884968	481.792304	753.342620
Organic_carbon	3276.000000	14.284970	3.308162	2.200000	12.065801	14.218338	16.557652	28.300000
Trihalomethanes	3114.000000	66.396293	16.175008	0.738000	55.844536	66.622485	77.337473	124.000000
Turbidity	3276.000000	3.966786	0.780382	1.450000	3.439711	3.955028	4.500320	6.739000

Statistical analysis is a key component of machine learning, as it is used to appreciate, interpret, and type predictions grounded on the data. By applying statistical methods, machine learning algorithms can extract useful information and patterns from data, and use this knowledge to make predictions or decisions.

One of the main results obtained by statistical analysis in machine learning is the estimation of model parameters. This is done by fitting a statistical model to the data, which involves finding the values of the parameters that best explain the data. Finding coefficient values that minimise the sum of squared errors between the predicted and true values, for instance, is the objective in linear regression. Another important result obtained by statistical analysis in machine learning is the assessment of model performance. This is accomplished by assessing the model's predictions' accuracy using various measures, including accuracy, precision, recall, and F1-score. These metrics give a mechanism to measure how well the model can categorise or forecast the results of fresh, unforeseen data points.

Statistical analysis also helps in understanding the feature importance and variable selection. By performing statistical tests, like chi-square test, we can understand which feature has a stronger relationship with the target variable. This helps us in selection of important features to be considered while building the model and also helps in reducing the dimensionality of the data.

Exploratory Data Analysis (EDA), which aids in understanding the underlying patterns and relationships within the data, is a vital phase in the machine learning process. By using EDA, we may find any outliers, missing numbers, and other anomalies in the data as well as learn more about the distribution and structure of the data at its core. Finding significant features is one of the key outcomes of EDA in machine learning. By visualizing the data and calculating summary statistics, we can gain insights into which features are most important for the problem at hand. This information can then be used to guide feature selection and dimensionality reduction. Another key result obtained by EDA in machine learning is the understanding of the relationship between features and the target variable. By

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creating visualizations such as scatter plots and heatmaps, we can identify any linear or non-linear relationships between the features and the target variable. These insights can help in selecting the appropriate model and fine-tuning the model's parameters.

EDA also helps in understanding the distribution of data and identifying any outliers. By visualizing the data distribution, we can identify any data points that fall outside the range of normal values. This is particularly useful for identifying errors in the data and for making decisions about data cleaning. Figure 2 shows the feature distribution plot obtained in the current work. Figure 3 shows the obtained pair plot in the current work.

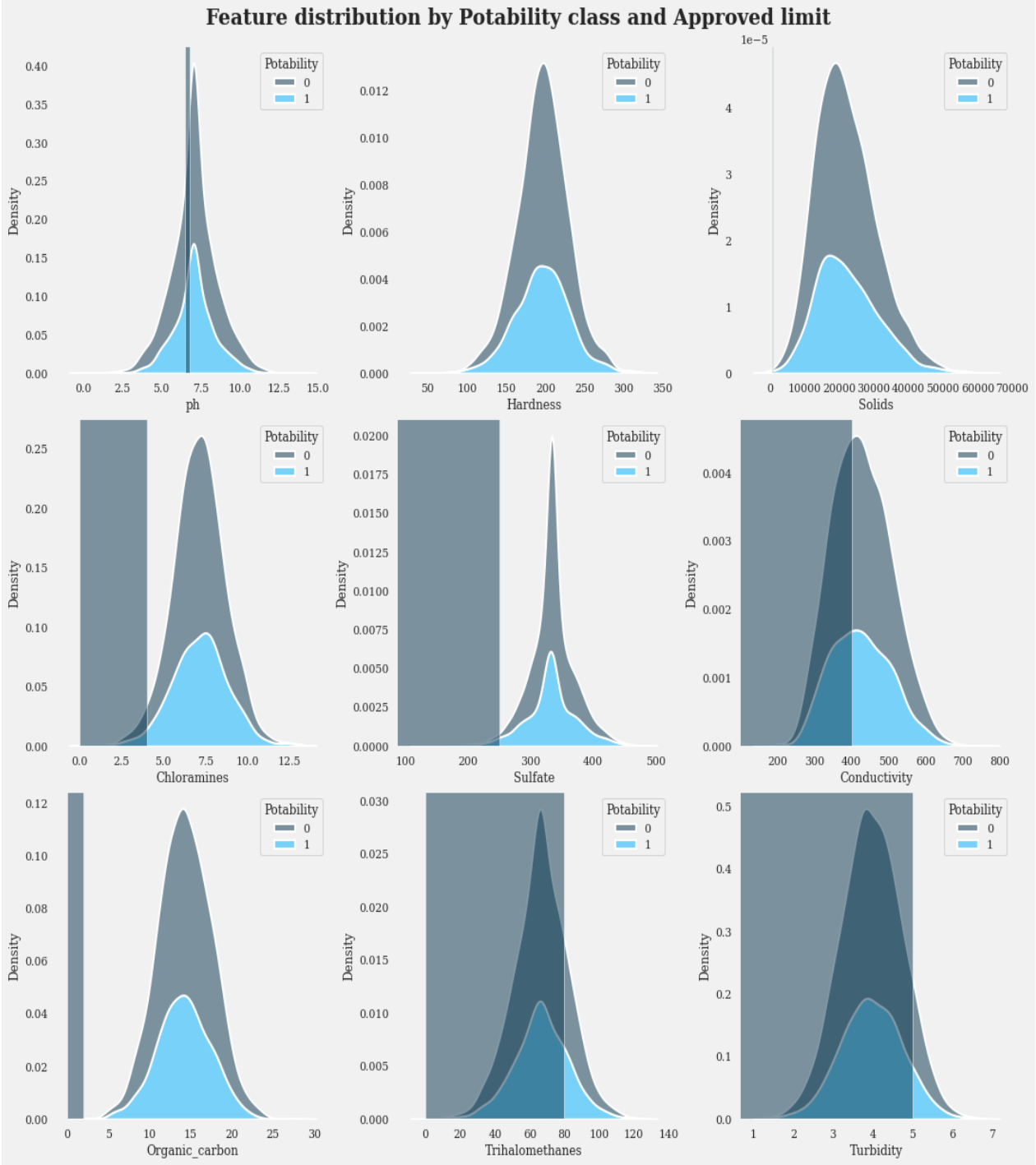

Figure 2. Feature distribution plot obtained in the current work

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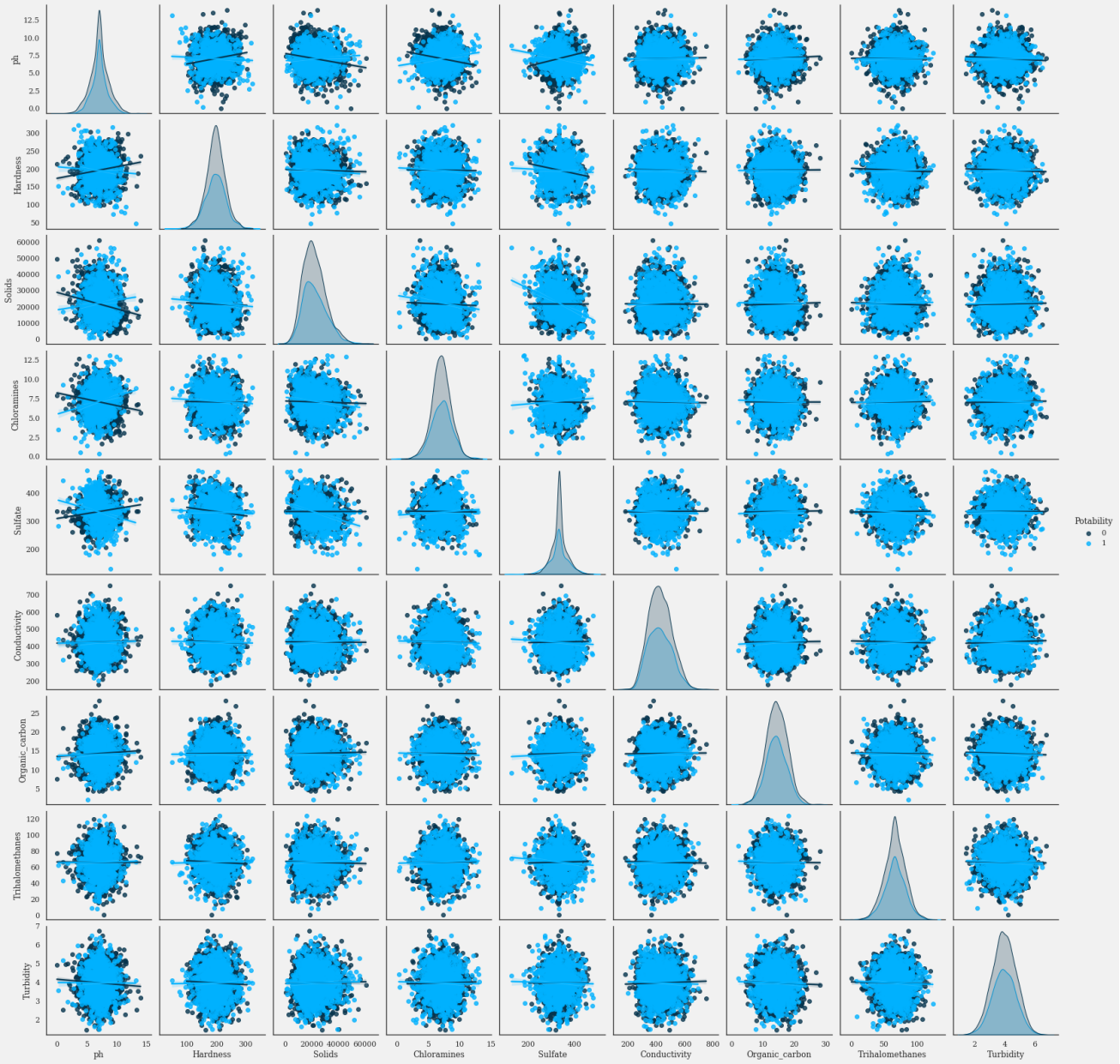

Figure 3. Obtained pair plot in the present work

For the purpose of determining the potability of water in the current work, three machine learning classification-based algorithms—Decision Tree, Gradient Boosting, and Bagging Classifier—have been applied. A popular supervised learning technique for classification and regression applications is the decision tree. It is a decision-making model that resembles a tree with potential outcomes. Recursively dividing the dataset into subgroups according to the values of an input feature is how the tree is constructed. A test on an input feature is represented by each internal node of the tree, the test's result is represented by each branch, and the class label is represented by each leaf node. The characteristic that best divides the dataset into subsets is chosen as the root node to start the decision tree classification process. Using a criterion like information gain or gain ratio, the features are chosen. The root node is chosen as the characteristic having the highest value of the criterion.

The feature that divides each subset most effectively is then chosen to further divide the subsets produced by the root node. As long as there are samples of the same class in all of the subsets, this process is repeated recursively for each internal node. The class labels of the samples in the respective subsets are represented by the leaf nodes. By moving up the tree from its root to one of its leaf nodes, the tree can be utilised for categorization. The anticipated class label for a new sample is the class label of the leaf node. Decision trees have the benefit of being simple to comprehend and interpret,

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which is one of its key advantages. The model's decisions are clearly and understandably explained by the tree structure. As a result, decision trees are frequently used in combination with ensemble methods like random forest, which use several decision trees to arrive at a final conclusion. Decision trees, however, can be sensitive to slight alterations in the data and can overfit readily.

An ensemble machine learning method called gradient boosting is employed for both classification and regression problems. The method is built on the notion of creating a model iteratively by including weak learners who fix the errors of the prior models. Decision trees are frequently used in gradient boosting as weak learners. Gradient boosting classification's mechanism begins with a straightforward model, like a decision tree with a single split. On the basis of the training data, this model is used to create predictions, and the errors are determined. The following stage is to match a fresh model to the flaws in the old one. Iterations of this process are repeated indefinitely, or until the model's performance plateaus. The new model concentrates on the data that the old model misclassified in each iteration. This is accomplished by giving the incorrectly identified samples a greater weight. The new model is taught to fix the errors committed by the old model. The final model is the weighted sum of each weak model, with each model's weight based on how well it performed on the training set of data. When compared to a single decision tree, gradient boosting exhibits state-of-the-art performance on a variety of classification and regression problems and is robust to overfitting. This is so that the variance can be reduced by the final model, which combines numerous weak models. However, it can be sensitive to the selection of hyperparameters and is also computationally expensive.

A bagging classifier is an ensemble technique that combines a number of base classifiers in order to enhance the model's overall performance and lower its variance. The basis classifiers are trained using several bags created from the training data. Through majority vote or by averaging the predictions of the basic classifiers, the final prediction is determined. The mechanism of bagging classifier begins with selecting a random subset of the training data, with replacement, to train each base classifier. This is done to introduce randomness and diversity among the base classifiers. The original dataset's data points are randomly chosen using replacement to form the subsets, sometimes referred to as bags. This implies that while certain data points might be chosen more than once in a bag, others might not be chosen at all. The basis classifiers are trained on these subsets of data after the bags have been produced. Combining the basis classifiers' predictions yields the final prediction. There are two ways to combine the predictions: majority voting and averaging. In majority voting, the class that is predicted by the majority of the base classifiers is chosen as the final prediction. In averaging, the predictions of the base classifiers are averaged to produce the final prediction.

Bagging classifiers are known to be effective in reducing the variance of the model. By training the base classifiers on different subsets of data, the model is able to capture different patterns in the data, which helps to reduce the variance of the model. Bagging classifiers are also known to be robust to noise in the data.

Table II. shows the obtained results for measuring the performance of the implemented algorithms.

Table II. OBTAINED RESULTS OF THE ML ALGORITHMS

Algorithms	**Precision for 0 and 1**	**Recall for 0 and 1**	**Overall F1-Score**
Decision Tree	0.66 and 0.56	0.90 and 0.22	0.65
Gradient Boosting	0.86 and 0.67	0.77 and 0.80	0.78
Bagging Classifier	0.81 and 0.68	0.80 and 0.69	0.76

It is observed that Gradient boosting is resulting in the highest F1-Score value. Gradient boosting is a powerful ensemble method that combines multiple weak learners to create a strong classifier. It is a popular choice for classification problems because of its ability to achieve high accuracy. The main reason why gradient boosting is so effective for classification is its ability to adapt to non-linear decision boundaries. Gradient boosting uses decision trees as its base learners, which are known for their ability to model complex and non-linear relationships in the data. By combining multiple decision trees, gradient boosting is able to capture more intricate patterns in the data, resulting in a more accurate classifier. Another key aspect of gradient boosting that contributes to its high accuracy is its ability to identify and correct errors made by previous base learners. The method does this by focusing on the samples that were misclassified by previous base learners and giving more weight to those samples when training the next base learner. This allows the classifier to improve upon its performance with each iteration. Gradient boosting also has a built-in feature

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selection mechanism which is known as "shrinkage", which helps to reduce overfitting. Shrinkage reduces the influence of each base learner by adjusting the learning rate of the model, which helps to stabilize the final predictions. This is particularly useful when working with high-dimensional data, as it helps to reduce the risk of overfitting.

IV. CONCLUSION

In summary, this study used three machine learning classification algorithms—the decision tree, gradient boosting, and bagging classifier—to assess the potability of the water. The results of the experiment showed that the gradient boosting algorithm achieved the uppermost F1-score of 0.78 among all the algorithms, indicating that it was most effective in correctly identifying both the safe and contaminated water samples. These results demonstrate that gradient boosting is a promising approach for determining water potability and can be used as a reliable method for water quality assessment. It is crucial to remember that this study was based on a particular dataset, and that in order to validate the results, additional research should be done using different datasets and under different circumstances.

As for future work, one could explore using other ensemble methods like Random Forest or LightGBM and compare the performance with Gradient Boosting. Additionally, incorporating other features like location, weather conditions etc. that may have an impact on water quality can be added to the dataset to evaluate if the model's accuracy increases. As an alternative to conventional machine learning techniques, the usage of deep learning models like Convolutional Neural Networks (CNNs) can also be investigated.

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