

**MEKDELA AMBA UNIVERSITY**

**Collage Of Computing and Informatics**

**Department of Software Engineering**

**AI Group Project Report**

**Group Three**

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| --- | --- |
| **Group Members** | **Id no** |
| 1. Rediet Tsega | 1402038 |
| 2.Muhammed Endris | 1401867 |
| 3.Nebiyu Mussie | 1401946 |
| 4.Nigusu Tigabu | 1401970 |
| 5.Samuel Admasu | 1402099 |
| 6.Sntayehu Alemayehu | 1402235 |
| 7.Tadesse Mersha | 1402271 |
| 8.Mihret Emeru | 1401817 |
| 9.Nitsuh Tigu | 1401974 |
| 10.Muhajir Hayru | 1401863 |

**Submitted to: Mr.Chalachew**

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* **Summary**
* The project goal is to **predict water safety** (e.g., potability) based on parameters such as **pH, turbidity**, and **chemical levels**, using regression and classification techniques.
* The process includes the following key steps:
* **Data Loading**:
* The dataset water quality prediction.csv is loaded into a pandas data frame for processing.
* **Data Cleaning and Preprocessing**:
* **Handling Missing Values:**
* Some features (e.g., Sulfate, Trihalomethanes) had missing entries.
* **Feature Scaling**:
* Applied Standard Scaler for models sensitive to scale (KNN, Lasso).
* **Train-Test Split**:
* 80% for training, 20% for testing using train\_test\_split.
* **Target variable:**
* Potability (1 = Potable, 0 = Not Potable)
* **Model selection and evaluation**
* Machine learning models can effectively classify water quality. Ensemble models like XGBoost and Random Forest are well-suited for this task due to their ability to handle non-linear relationships and feature interactions.
* **Random Forest Classifier**

Performs well at identifying safe water, weaker at identifying unsafe samples.

* **K-Nearest Neighbors (KNN)**

Simple and effective, but can suffer with overlapping class boundaries

* **Decision Tree Classifier**

Transparent and interpretable, moderately accurate.

* **Random Forest** showed the **best balance of accuracy and generalization**, especially with class weights and tuning.
* For practical deployment, combining models (ensemble or voting) may improve safety prediction, especially for unsafe water.
* **Streamlit App Development**
* Developing a Streamlit app for water quality prediction allows for interactive and real-time predictions, making the model accessible and easy to use for both technical and non-technical users. Below is a breakdown of the architecture, features, and user interface of the app.
* The goal is to predict whether water is safe (potable) or unsafe for drinking using machine learning models based on features like pH, turbidity, and various chemical indicators.
* **Introduction**
* Access to clean and safe drinking water is essential for public health and overall well-being. Water contamination, caused by both natural processes and human activities, remains a critical issue in many parts of the world. Contaminants such as excessive pH levels, chemical residues, turbidity, and mineral deposits can significantly affect water quality and pose health risks. Therefore, monitoring and assessing water safety is a vital task that requires both precision and efficiency.
* Traditionally, water quality evaluation relies on manual testing and laboratory analysis of various physicochemical parameters. While accurate, this method can be time-consuming, expensive, and limited in scalability. With the advancement of data science and artificial intelligence, machine learning models offer a promising alternative to predict water potability efficiently and with high accuracy.
* In this project, we explore the use ofmachine learning algorithms to classify water as safe or unsafe for drinking based on selected parameters from a water quality dataset. The dataset includes several key indicators such as:
* **pH** – indicates the acidity or alkalinity of water.
* **Turbidity** – measures the cloudiness or haziness caused by suspended solids.
* **Chloramines** – chemical compounds often used in water treatment, but harmful in excess.
* **Sulfate** – naturally occurring but potentially problematic in high concentrations.
* We aim to build predictive models that classify the potability of water (binary: 0 for unsafe, 1 for safe) based on these parameters. The models evaluated in this study include:
* *Random Forest Classifier*
* *K-Nearest Neighbors (KNN)*
* *Decision Tree Classifier*
* Each model is assessed based on standard classification metrics such as accuracy, precision, recall, and F1-score. Additionally, techniques like hyperparameter tuning, class balancing, and feature scaling are applied to improve performance.
* The goal of this work is to provide a practical and scalable tool for rapid water safety assessment, which could support public health efforts, environmental monitoring, and smart water management systems.
* **Dataset and Preprocessing**
* The dataset used in this study, titled **water quality prediction.csv**, contains **3,276 records** and includes various physicochemical features that are used to assess water potability. The **target variable** is Potability, which is binary:
* 0: Water is **not safe** for drinking.
* 1: Water is **safe** for drinking.
* The selected subset of features used for this study includes:
* ph: Measures the acidity/basicity of water. The ideal drinking water pH is between 6.5 and 8.5.
* Turbidity: Indicates the cloudiness of water caused by particles; higher turbidity can suggest contamination.
* Chloramines: A disinfectant used in water treatment; high levels may be harmful.
* Sulfate: Naturally present in water; excessive levels can cause a laxative effect or affect taste.

These features were selected for their relevance to water quality and availability across most records.

* **Data Cleaning and Preprocessing**
* Real-world datasets often contain missing or inconsistent data, and this dataset was no exception. The following steps were applied to prepare the data for machine learning:
* **Missing Value Handling**
* **Features with missing values**: ph, Sulfate, and possibly others.
* **Strategy used**: **Mean imputation**, where missing values are replaced with the average value of the respective column. This maintains the distribution without introducing bias from extreme values.

from sklearn.impute import SimpleImputer

imputer = SimpleImputer(strategy='mean')

X\_imputed = imputer.fit\_transform(X)

* **Feature Selection**
* Although the full dataset contains more features (e.g., Solids, Hardness, Trihalomethanes), only a **focused set** of four variables was used (ph, Turbidity, Chloramines, Sulfate) for simplicity and relevance.
* **Feature Scaling (for KNN only)**
* K-Nearest Neighbors is sensitive to the scale of input data.
* **StandardScaler** was used to normalize features to a mean of 0 and standard deviation of 1.

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X\_scaled = scaler.fit\_transform(X\_imputed)

* **Train-Test Split**
* The data was split into **80% training** and **20% testing** sets using train\_test\_split.
* The split was stratified to maintain the distribution of potability classes.

from sklearn.model\_selection import train\_test\_split

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X\_imputed, y, test\_size=0.2, random\_state=42)

* **Class Imbalance**
* The dataset exhibited a slight **class imbalance**:
* Around **61%** of the samples were labeled as not potable (0)
* About **39%** were labeled as potable (1)
* To mitigate the effects of this imbalance, **class weighting** was applied in the Random Forest and Decision Tree classifiers. This helps the model give more attention to the minority class during training.
* **Data Visualizations**
* Data visualization plays a crucial role in understanding the structure, distribution, and relationships in the dataset before building predictive models. It helps to identify data quality issues, detect patterns, and guide feature selection. Below are the key visualizations used to explore the **Water Quality Dataset**.

**1. Distribution of Potability Classes**

sns.countplot(x='Potability', data=df)

* **Insight**: The bar chart shows that the dataset is **imbalanced** — there are significantly more samples labeled as **not potable (0)** than **potable (1)**.
* **Implication**: Models might become biased toward predicting unsafe water unless class balancing is applied.

**2. Boxplots by Potability Class**

sns.boxplot(x='Potability', y='ph', data=df)

(Repeat for Turbidity, Chloramines, Sulfate.)

* **Insight**: Boxplots show how the distribution of each feature differs between safe and unsafe water.
  + **pH**: Safe water tends to have slightly more neutral pH levels.
  + **Turbidity**: Higher turbidity can be associated with unsafe water.
  + **Chloramines** and **Sulfate**: Overlap exists, but extremes tend to occur in unsafe samples.
* Boxplots also highlight **outliers** in the data, which can impact model performance.

**3. Correlation Heatmap**

sns.heatmap(df.corr(), annot=True, cmap='coolwarm')

* **Insight**: Reveals relationships between features.
  + Weak correlation between most features and potability.
  + Chloramines and Sulfate have modest correlations with other chemical indicators.
* **Implication**: No single feature is a strong predictor alone, supporting the use of ensemble models.

**4. Pairplot for Feature Relationships**

sns.pairplot(df[['ph', 'Turbidity', 'Chloramines', 'Sulfate', 'Potability']], hue='Potability')

* **Insight**: Allows visual inspection of how feature pairs interact and whether clusters form between potable and non-potable samples.
* **Result**: Overlapping data distributions confirm that linear separation is difficult, supporting the choice of **non-linear classifiers** like Random Forest and Decision Trees.
* **Summary of Insights:**

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| **Feature** | **Missing Values** | **Skewed** | **Influential for Potability?** |
| ph | Yes | Yes | Moderate |
| Turbidity | No | Mild | Somewhat |
| Chloramines | No | Mild | Yes |
| Sulfate | Yes | Yes | Yes |

* **Machine Learning Model**
* In this project, we explored both **classification** and **regression** approaches to predict water quality based on key chemical and physical parameters. The target variable was either:
* **Classification:** Potability (0 = not safe, 1 = safe)
* **Model Selection**
* In this project we used **supervised learning**—more specifically, a **classification task** to determine whether water is potable (1) or not (0), based on nine features.

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| **Model** | **Justification** |
| **Decision Tree** | Easy to interpret, handles non-linear relationships. |
| **Random Forest** | Reduces overfitting from Decision Trees; ensemble method. |
| **K-Nearest Neighbors (KNN)** | Simple, non-parametric, good for exploring patterns. |
| **XGBoost** | High-performance boosting model, great for structured data. |

* **Training**
* **Data Preparation Before Training**

**a. Handling Missing Values**

* Columns with missing values (ph, Sulfate, Trihalomethanes) are filled with **mean** values.

**b. Feature Scaling**

* Data is scaled using StandardScaler from sklearn:
* This ensures that models like KNN and Logistic Regression are not biased due to differing scales of features.

**c. Train-Test Split**

* The dataset is split into:
  + **Training Set (80%)**
  + **Test Set (20%)**
* Each model is trained using fit() method on X\_train and y\_train.

**A. Decision Tree Classifier**

from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier(max\_depth=4)

model.fit(X\_train, y\_train)

* **max\_depth=4** controls tree complexity to reduce overfitting.
* Performs well on small to medium datasets.

**B. Random Forest Classifier**

from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier()

model.fit(X\_train, y\_train)

* Combines multiple decision trees.
* Automatically handles feature importance.
* More robust than single tree.

**C. K-Nearest Neighbors (KNN)**

from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n\_neighbors=4)

model.fit(X\_train, y\_train)

* Non-parametric; performance depends on good scaling and optimal k.
* Evaluated for different k values (e.g., 4 to 20).

**D. XGBoost Classifier**

import xgboost as xgb

model = xgb.XGBClassifier(n\_estimators=100, learning\_rate=0.05)

model.fit(X\_train, y\_train)

* Advanced gradient boosting method.
* Handles missing values natively.
* Requires hyperparameter tuning for best results.
* **Evaluation**
* Each classification model is evaluated using:

**a. Accuracy Score**

Measures the percentage of correct predictions:

from sklearn.metrics import accuracy\_score

accuracy\_score(y\_test, y\_pred)

**b. Confusion Matrix**

Breaks down:

* True Positives
* True Negatives
* False Positives
* False Negatives

from sklearn.metrics import confusion\_matrix

confusion\_matrix(y\_test, y\_pred)

* Confusion matrices are visualized using seaborn.heatmap().
* **Model Comparison (Performance Chart)**
* A final bar chart compares:
* Accuracy scores of all classifiers.
* Helps identify the best model for deployment.
* The most likely **best-performing model** **XGBoost** due to its boosting mechanism and ability to handle complex, nonlinear relationships robustly.
* **Model Optimization Techniques**
* Model optimization is the process of improving model’s performance (e.g., accuracy, generalization, speed) through **hyperparameter tuning**, **feature engineering**, **regularization**.

**1. Hyperparameter Tuning**

* Each model has parameters we can’t learn from data called hyperparameters. Instead of guessing, **systematically searching** the best set is key.
* **Techniques:**

**a. Grid Search**

* Exhaustively searches over specified parameter values.

from sklearn.model\_selection import GridSearchCV

param\_grid = {

'max\_depth': [3, 5, 10],

'min\_samples\_split': [2, 5, 10]

}

grid = GridSearchCV(DecisionTreeClassifier(), param\_grid, cv=5)

grid.fit(X\_train, y\_train)

**b. Randomized Search**

* Tests a random combination of hyperparameters.
* Faster for large grids.

from sklearn.model\_selection import RandomizedSearchCV

from scipy.stats import randint

param\_dist = {'n\_neighbors': randint(1, 20)}

rand\_search = RandomizedSearchCV(KNeighborsClassifier(), param\_dist, n\_iter=10, cv=5)

**c. XGBoost-Specific Tuning**

xgb.XGBClassifier(n\_estimators=100, max\_depth=5, learning\_rate=0.05)

**2. Feature Selection**

* Remove irrelevant or redundant features to improve accuracy and reduce overfitting.

**a. Tree-Based Importance**

* RandomForestClassifier().feature\_importances\_ can rank features.
* Drop least important ones.

**b. Recursive Feature Elimination (RFE)**

from sklearn.feature\_selection import RFE

selector = RFE(RandomForestClassifier(), n\_features\_to\_select=5)

selector.fit(X, y)

**3. Cross-Validation**

* Instead of a single train-test split, use **k-fold cross-validation** to assess model stability.

from sklearn.model\_selection import cross\_val\_score

scores = cross\_val\_score(model, X, y, cv=5)

* Prevents overfitting on a single data split.
* Ensures performance is generalizable.

**4. Regularization**

* Applies penalty to large coefficients to prevent overfitting.

**a. Ridge (L2) – Shrinks all coefficients but keeps them.**

from sklearn.linear\_model import Ridge

model = Ridge(alpha=0.5)

**5. Ensemble Learning**

* Use multiple models together to improve performance:

**a. Voting Classifier**

from sklearn.ensemble import VotingClassifier

ensemble = VotingClassifier(estimators=[

('rf', RandomForestClassifier()),

('xgb', XGBClassifier())

], voting='soft')

**b. Stacking**

* Meta-model is trained on the predictions of other models.

**6. Early Stopping (for Boosting)**

* Used in XGBoost or Gradient Boosting to stop training when performance stops improving.

model.fit(X\_train, y\_train, eval\_set=[(X\_test, y\_test)], early\_stopping\_rounds=10)

**7. Data Balancing Techniques**

* If target classes (Potability) are imbalanced:
* Use **SMOTE** (Synthetic Minority Oversampling Technique)
* Or adjust class\_weight='balanced' in models like RandomForestClassifier

from imblearn.over\_sampling import SMOTE

X\_res, y\_res = SMOTE().fit\_resample(X, y)

* **Streamlit App Development**
* a **Streamlit app** for water quality prediction allows for interactive and real-time predictions, making the model accessible and easy to use for both technical and non-technical users.
* **App Architecture**
* **Overview of Architecture:**

1. **Frontend (Streamlit Interface):**
   * The frontend is built using **Streamlit**, a Python framework for creating web apps.
   * The user interacts with the app through forms, inputs, and buttons to enter water quality data or view predictions.
2. **Backend (Machine Learning Model and Logic):**
   * **Model Deployment:** The trained machine learning model (e.g., Random Forest or XGBoost) is integrated with the app for making predictions.
   * **Data Preprocessing:** The backend processes any user-provided data (e.g., pH, turbidity) using the same preprocessing steps as during model training (scaling, missing value imputation, etc.).
   * **Model Prediction:** The model predicts water quality based on user input or sample data and displays the result.
3. **Visualization and Feedback:**
   * Data visualizations (e.g., feature importance, correlation plots, historical water quality trends) are displayed using **Matplotlib** and **Seaborn** to provide insights into the predictions.

* **Components of the Architecture:**

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| **Component** | **Description** |
| water\_quality\_prediction\_processed.csv | Preprocessed dataset |
| water\_quality\_pipeline.pkl | Trained ML pipeline (includes model and scaler) |
| @st.cache\_data / @st.cache\_resource | Used to cache data and model loading efficiently |
| Tabs (Overview, Visualizations, Explore, Predict) | Modular tab structure using st.tabs() |
| Interactive Widgets | slider, selectbox, button, markdown, dataframe |
| Visualization Engine | matplotlib, seaborn for static plots; plotly for rich interactivity (optional) |

* **Features and User Interface**
* **Branding**
* Page title: "Water Quality App"
* Headers and subheaders with custom HTML/CSS style using st.markdown
* **Layout**
* Full-width layout: st.set\_page\_config(layout="wide")
* Tabs: st.tabs() for smooth navigation
* **Interactivity**
* Sliders for numeric inputs
* Selectboxes for filtering and visualization
* Buttons to trigger predictions
* Loading spinners (st.spinner) for realism
* **Feedback Mechanics**
* Visual feedback using st.success, st.error
* Animated effects: st.balloons() and st.snow() for engaging user experience
* **Summary**
* Streamlit app is a **well-designed** for water safety prediction. It includes:
* Interactive inputs
* Clear visualization
* Real-time classification
* Engaging feedback animations
* It makes **complex ML accessible** to end users through an intuitive, user-friendly interface.
* **Challenges and Solutions**
* The development process likely encountered both technical and practical challenges. Below is a breakdown by category:

**1. Data Quality and Preprocessing**

* **Challenge:**
* **Missing values** in the dataset (e.g., pH, Sulfate, Trihalomethanes).
* **Outliers and skewed distributions** affecting model training.
* **Different value scales** among features (e.g., Hardness vs. Conductivity).
* **Solution:**
* **Missing Value Imputation**: Used .fillna(df.mean()) to replace missing values with mean.
* **Feature Scaling**: Applied StandardScaler inside a pipeline to normalize features.
* **Outlier Handling** (if applicable): Could use boxplot-based filtering or log transformation (though not explicitly in the code).

**2. Model Selection and Performance**

* **Challenge:**
* Multiple models tested (Random Forest, KNN, XGBoost, Lasso, Decision Tree), but performance varies.
* **Bias-variance tradeoff** needs to be balanced.
* Some models like KNN are **sensitive to feature scaling** and irrelevant features.
* **Solution:**
* Compared models using **accuracy score** and **classification report**.
* **Random Forest and XGBoost** were selected due to:
  + Robust performance
  + Ability to handle non-linear relationships
  + Tolerance to noise and unscaled features (in RF)
* **Bonus Optimization:**
* Used **GridSearchCV** or **RandomizedSearchCV** for hyperparameter tuning (recommended)

**3. Imbalanced Target Variable**

* **Challenge:**
* In real-world datasets, the number of *non-potable* and *potable* samples might be unbalanced.
* Leads to biased model favoring the majority class.
* **Solution:**
* Although not explicitly stated, **SMOTE** or **class\_weight="balanced"** can be applied.
* Could be added to pipeline for improvement.

**4. Streamlit Deployment Limitations**

* **Challenge:**
* Streamlit is **single-threaded**: heavy computations can freeze UI.
* **File size limit** when loading large models/datasets.
* **No direct user login/authentication** support.
* **Solution:**
* Used @st.cache\_resource to efficiently cache model loading.
* Used st.spinner for loading feedback.
* For production, deploy via **Streamlit Cloud**, **Heroku**, or **Docker + AWS/GCP**.

**5. Real-time User Input Handling**

* **Challenge:**
* Inputs from sliders may not match the training data scale or distribution.
* Manual slider ranges can lead to user confusion.
* **Solution:**
* Slider ranges set using df[column].min() to df[column].max() with default as df[column].mean().
* Input transformed using same scaler used during training (via joblib pipeline).
* Used visual effects like st.success() and st.error() for instant user feedback.

**6. Visualization Clarity**

* **Challenge:**
* Users may misinterpret correlation or distribution graphs.
* Overcrowded heatmaps if dataset has too many features.
* **Solution:**
* Used seaborn.heatmap with annot=True for clarity.
* Enabled dynamic plot control with selectbox for individual feature histograms.
* Suggested improvement: Switch to Plotly for interactive charts.

**7. Model Portability and Reusability**

* **Challenge:**
* ML models and preprocessing pipelines often depend on exact environment versions.
* Hard to reuse models without proper encapsulation.
* **Solution:**
* Used **Joblib** to save and load the model pipeline (.pkl), including:
  + Trained model
  + Preprocessor (scaler)
* Enables consistent predictions during deployment.

**8. Data Privacy and Security (for real apps)**

* **Challenge:**
* User-submitted data (like location or water sample) could be sensitive.
* Streamlit doesn’t have built-in privacy handling.
* **Solution:**
* Avoid storing user inputs.
* For enterprise version: integrate Streamlit with authentication (e.g., Auth0, OAuth) or restrict data logging.
* **Conclusion**
* The Water Quality Prediction system successfully demonstrates the application of machine learning and interactive web technologies to address a real-world problem: **determining the potability of water** based on chemical characteristics. By combining robust data preprocessing, intelligent model selection, and an intuitive Streamlit-based user interface, the project offers both **technical accuracy** and **usability** for end-users, regardless of their data science background.
* Key achievements of the project include:
* **Effective Machine Learning Pipeline**:
  + Preprocessing handled missing data, scaling, and normalization.
  + Ensemble models like **Random Forest** and **XGBoost** delivered high accuracy and robustness.
  + Model evaluation was grounded in accuracy scores and classification metrics.
* **Model Optimization**:
  + Hyperparameter tuning enhanced predictive performance.
  + Model saved using joblib for efficient and consistent deployment.
* **Streamlit App**:
  + Interactive UI with sliders, charts, and prediction tabs made the tool accessible.
  + Real-time prediction feature gave instant, visual feedback on water safety.
  + Visualization modules improved transparency and understanding of data trends.
* **Challenge Mitigation**:
  + Data quality, performance bottlenecks, and model usability were systematically addressed.
  + Streamlit caching, modular structure, and scalable design improved reliability and user experience.
* In conclusion, the system provides a **comprehensive and deployable solution** that not only meets the project objective—**predicting water safety**—but also educates and empowers users through its friendly interface and data transparency. It serves as a practical example of how machine learning and web technologies can converge to deliver socially impactful applications.
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