WATERNET: INTELLIGENT WATER QUALITY MONITORING FOR SUSTAINABLE DRINKING AND IRRIGATION SOLUTIONS

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ABSTRACT

For plants, animals, and humans to survive, water is an essential necessity. Quality water is not always suitable for drinking, household, or industrial usage, despite its significance. Numerous variables, including mining, industrialisation, pollution, and natural events, affect the quality of water by introducing or changing several characteristics that limit its fitness for general use or human consumption. Guidelines from the World Health Organisation specify the minimum amounts of several parameters that must be present in water samples that are meant for irrigation or human consumption. Metrics used to represent the level of these indicators and ascertain the overall water quality are the Water Quality Index (WQI) and the Irrigation WQI (IWQI). It may be quite difficult to gather water samples from multiple sources, test the many properties present, and compare these results to pre-established standards while following varied transportation and measurement protocols. In order to do this, this paper suggests a network architecture that would gather water parameter data in real-time and utilise Machine Learning (ML) algorithms to automatically assess if water samples are suitable for irrigation and drinking. The LoRa-based monitoring network that has been built takes into account the topography of the land. A partial mesh network design was shown to be the most suitable by the results of simulations conducted in Radio Mobile.

Large, publicly available datasets on drinking and irrigation water were lacking, therefore datasets suitable for ML model training were created. For the water classification process, three machine learning models—Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM)—were taken into consideration. The findings indicated that SVM was more appropriate for irrigation water, while LR was the best model for drinking water. The three ML models were then coupled using recursive feature reduction to determine which water parameter had the most impact on each model's classification accuracy.

1. INTRODUCTION

Water access is currently seen as a fundamental human right and is essential to human existence. One of the 17 Sustainable Development Goals (SDG) established by the UN in 2015 to provide a brighter future for all is access to clean water [1].In particular, the sixth objective, which is to provide and maintain universal access to water and sanitation [2]. The third SDG goal, "good health and well-being," can also be related to potable water because tainted water can spread diseases like cholera, typhoid, and diarrhoea, which together account for the highest rates of mortality (particularly among children) in developing countries in Asia and Africa [3]. Food production and agriculture both depend on water. According to recent data, malnutrition affects over 10% of the world's population, with developing nations suffering the most, while hunger accounts for roughly 45% of newborn deaths [5]. Therefore, ensuring food security on a global scale is crucial. Food security has been identified as a crucial necessity, which is why it is one of the Sustainable Development Goals (SDGs) (goal 2), with a particular emphasis on eradicating hunger via the advancement of sustainable agriculture and better food distribution. Water is essential to agriculture and food production since it is used for irrigation and animal feed. For agricultural purposes, it is therefore important to guarantee the availability and sustainable management of water.

Rivers, streams, rainfall, and groundwater (obtained through wells and boreholes) are some of the water sources for drinking and agriculture. A water source's type and attributes are frequently important determinants of the components of water samples taken from it. In addition to natural causes, chemical waste from human endeavours like mining, the extraction of crude oil, and industrial waste frequently finds its way into rivers, streams, and other water sources, altering the characteristics of these bodies of water. After that, these fluids are utilised for household chores, drinking, feeding animals, or irrigating crops in houses or farms. Drinking this kind of water might be fatal or have serious health effects. Therefore, it is crucial to implement an appropriate procedure to provide continuous water monitoring from the source to the final point of consumption. Samples of water must be taken at each monitoring location in order to evaluate its quality or "fitness for use" for irrigation, residential (or industrial) purposes, and human (and animal) consumption.

Numerous models have been created to evaluate the quality of water, and they all take into account different factors, such as chemical (like pH, calcium, oxygen, and sulphate levels), microbiological (like E. Coli, rotaviruses, and Entamoeba, among others), and physical (like temperature and clarity). The result of these models is a unit statistic called the Water Quality Index (WQI). WQI has been calculated using many guidelines that have been modified globally. For example, the National Sanitation Foundation Water Quality Index (NSFWQI) and the Canadian Council of Ministers of the Environment Water Quality Index (CCMEWQI) are the most widely used in North America, while the British Columbia Water Quality Index (BCWQI) and the Scottish Research Development Department (SRDD) are used in some parts of Europe. While the South African National Standard for drinking water (SANS 241-1) and the Kenya Bureau of Standards (KEBS) are noteworthy standards in Africa, the Bureau of Indian Standards (BIS) is well-known in Asia, particularly India. A review of some of these models may be found in

[6]. It is significant to remember that a large number of these national standards are essentially regional modifications of the World Health Organization's (WHO) standards [7]. The WHO and South African guidelines served as the foundation for this study.

As it frequently entails following a strict set of guidelines when collecting the water samples, maintaining predetermined conditions during transportation to the test laboratories, using standard methodologies when analysing the samples, and generally guaranteeing quality control, measuring water parameters for various water samples can be a time-consuming and intimidating task. A few of these procedures (together with the rules that go with them) are listed in [8], [9]. The results of these procedures show whether or not the water sample is suitable for human consumption. In this study, we provide a machine learning-based alternative model to assess the potability of water samples as well as a cyber-physical network architecture for real-time monitoring of water parameters across a metropolis. Similar to [10]_[13] [14], our approach ignores the biological aspects of water and solely concentrates on its physical and chemical characteristics. This is because, as far as we are aware, there are no physical sensors for monitoring biological factors like the presence of E. coli in water, and our model is intended to be sensor-based (in the context of the Internet of Things). We do not downplay the significance of microbiological water factors, and our suggested model may be modified to take them into account by just adding appropriate physical sensors (if any are available) or virtual/soft sensors, like the one suggested in [15], to our model.

2. LITERATURE SURVEY

‘‘Transforming our world: Implementing the 2030 agenda through sustainable development goal indicators,’’

The United Nations' 2030 Agenda for Sustainable Development recognizes violence as a threat to sustainability. To serve as a context, we provide an overview of the Sustainable Development Goals as they relate to violence prevention by including a summary of key documents informing violence prevention efforts by the World Health Organization (WHO) and Violence Prevention Alliance (VPA) partners. After consultation with the United Nations (UN) Inter-Agency Expert Group on Sustainable Development Goal Indicators (IAEG-SDG), we select specific targets and indicators, featuring them in a summary table. Using the diverse expertise of the authors, we assign attributes that characterize the focus and nature of these indicators. We hope that this will serve as a preliminary framework for understanding these accountability metrics. We include a brief analysis of the target indicators and how they relate to promising practices in violence prevention.

‘‘Water research in support of the sustainable development goal 6: A case study in Belgium,’’

Reaching the Sustainable Development Goal (SDG) 6 on water and sanitation is fundamentally important and conditional to the achievement of all the other SDGs. Nonetheless, achieving this goal by 2030 is challenging, especially in the Global South. Science lies at the root of sustainable development and is a key to new solutions for addressing SDG 6. However, SDG 6-related scientific outputs are often unknown, forming disconnections between academic world and practitioners implementing solutions. This study proposed a bibliometric and text mining method to qualitatively and quantitatively characterize the contribution of water research to the achievement of SDG 6. The method was applied for water research produced by Belgian-affiliated authors with a focus on the Global South collaboration. Despite accounting for less than one percent of the total global publications, Belgian water research has had a relatively high publication rate compared to its neighboring countries. We observed longstanding collaborations between Belgian and scientists from worldwide countries, and an increasing collaboration rate with countries from the Global South. The biggest share of publications focused on topics related to the targets 6.3, 6.4, 6.5, and 6.6, with the main hotspots for Belgian water research being water treatment, water stress, water pollution, climate change, and water modeling. The findings of the bibliometric search have been integrated into an online, user-friendly dashboard to facilitate the identification of research body and experts for practitioners and policy makers. The presented methodology is sufficiently generic and can be used to optimize other science programs in relation to the 2030 Agenda in other countries and regions. In this case study, the findings support shaping the Belgian cooperation and development policy in the water sector, and creating appropriate synergies between Belgian water researchers and their counterparts in the Global South.

‘‘Modification of the water quality index (WQI) process for simple calculation using the multicriteria decision-making (MCDM) method: A review,’

Human activities continue to affect our water quality; it remains a major problem worldwide (particularly concerning freshwater and human consumption). A critical water quality index (WQI) method has been used to determine the overall water quality status of surface water and groundwater systems globally since the 1960s. WQI follows four steps: parameter selection, sub-indices, establishing weights, and final index aggregation, which are addressed in this review. However, the WQI method is a prolonged process and applied to specific water quality parameters, i.e., water consumption (particular area and time) and other purposes. Therefore, this review discusses the WQI method in simple steps, for water quality assessment, based on two multi-criteria decision-making (MCDM) methods: (1) analytical hierarchical process (AHP); and (2) measuring attractiveness by a categorically based evaluation technique (MACBETH). MCDM methods can facilitate easy calculations, with less effort and great accuracy. Moreover, the uncertainty and eclipsing problems are also discussed—a challenge at every step of WQI development, particularly for parameter selection and establishing weights. This review will help provide water management authorities with useful knowledge pertaining to water usage or modification of existing indicators globally, and contribute to future WQI planning and studies for drinking, irrigation, domestic, and industrial purposes.

3. EXISTING SYSTEM

In [12], a network for measuring and monitoring water parameters in a metal producing city in Brazil was developed. Twelve water monitoring stations were setup to measure several physico-chemical water parameters, including pH, dissolved solids, Zinc, Lead etc. Finally, obtained results were analysed using principal component analysis. In a similar manner, [13] developed a system to monitor water quality in Limpopo River Basin in Mozambique and set up 23 monitoring stations to measure physico-chemical and microbiological parameters, and ultimately assess the quality of water in the river basin. To address the challenges of optimal placement of gauges and sampling frequencies, which are often faced when developing water monitoring systems, the authors in [14] developed an economically viable model that combined genetic algorithm with 1-D water quality simulation. Though the work was only simulated by using genetic algorithm, the authors were able to solve the NP hard problem of optimally placing monitoring stations.

Monitoring water parameters often entails periodically sampling a body of water to capture relevant metrics. These metrics might include physico-chemical and microbiological measurements, such as potential of hydrogen (pH), temperature, sodium levels etc. In a water monitoring network, measured parameters need to be transferred to a base station where relevant decision(s) would be taken. Due to the sparse nature of transmitted data, light weight communication protocols capable of transmitting relatively small data over long distance are required for water monitoring networks. From literature, Low Power Wide Area Network (LPWAN) technologies have been favoured for such applications. An extensive discussion on LPWAN technologies was done in [19]. The work compared a few sub-GHz solutions including Sig- Fox, LoRa, Ingenu and Telensa, with respect to their range,
transmission rate, and channel count. Ingenu was reported to have the longest range in city settings at 15 km, followed by SigFox at 10 km (in cities) and 50 km (in rural areas); then LoRa at 5 km (in cities), and 15 km in rural settings.

Regarding the assessment of communication technologies, there has been a long-drawn debate over the efficacy of software simulations versus real-world testing. Though this debate still rages, several researchers have shown that simulation results are often at par with real-world tests. For instance, using LoRa, the authors in [20] compared simulation results with real world test for intervehicle communication. They used NS3 as a simulation platform and an Arduino UNO C Dragino LoRa module for the real-world tests, while Propagation loss, coverage Packet Inter-reception (PIR), Packet Delivery Ratio (PDR) and Received Signal Strength Indicator (RSSI) level were used as benchmark metrics. They concluded that the results of the simulator were consistent with those of the real-world tests. In a similarwork,

Hassan [21] also compared the efficacy of simulation results (from Radio Mobile simulator) with real-world tests (using micro controllers C LoRa modules) when using LoRa as a bridge for Wi-Fi. Unlike [20], [21] did not give a side-byside comparison of simulated vs. real-world results for each metric considered but concluded that the simulator performed well. [22] set up seven pairs of XBee modules and compared communication performance using both the 800/900MHz
and 2.4GHz frequencies. They concluded that simulation results from the Radio Mobile simulator corroborated with those of real-world tests.

Disadvantages

- An existing methodology doesn't implement DATA PRE-PROCESSING & LABELLING method.
- The system not implemented Calculating WQI for Irrigation Water for prediction in the datasets.

4. PROPOSED SYSTEM

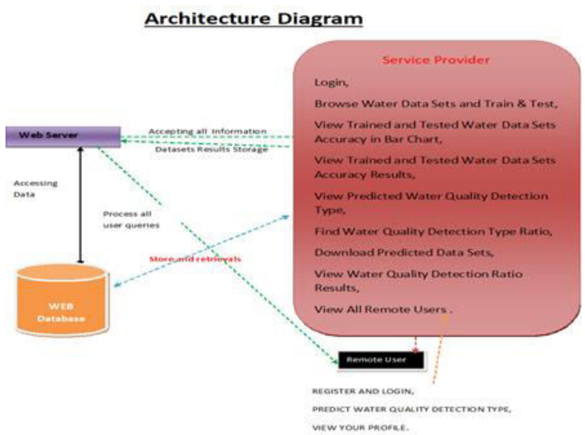
The water monitoring network proposed in this work is to be deployed in the City of Cape Town in Western Cape, South Africa, with the intention of monitoring water parameters in water storage dams and/or water treatment plants across the city. Data gathered by the monitoring network are then passed through Machine Learning (ML) models to determine their suitability for consumption or irrigation purposes.

1) Build a network for real-time collection and monitoring of water quality across water storage dams in the city of Cape Town. This network takes into consideration the unique geographical features of Cape Town, such as mountains and elevations that might obstruct radio frequency propagation.
2) Curate ample sized datasets on drinking and irrigation water that can be used to train (and test) machine learning models to automatically determine the `fitness for use'' of a sample of water for drinking and/or irrigation purposes.
3) Build models that determine the most critical parameters that influence the accuracy of machine learning models in analyzing water for drinking or irrigation.

Advantages

- The purpose of WaterNet is to gather data on water parameters from dams across the city. These parameters are then used to assess the quality of water with regards ``fitness for use'' for drinking and irrigation purposes.
- In this work, rather than relying on instrumental and physico-chemical analysis carried out in laboratories to assess water parameters, we propose the use of machine learning (ML) models, which take the numerous water parameters into consideration and automatically determine if a sample of water is potable or fit for agricultural use.

5. SYSTEM ARCHITECTURE



After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like REGISTER AND LOGIN, PREDICT WATER QUALITY DETECTION TYPE, VIEW YOUR PROFILE.

6. IMPLEMENTATION

Modules

Service Provider

In this module, the Service Provider has to login by using valid user name and password. After login successful he can do some operations such as Login, Browse Water Data Sets and Train & Test, View Trained and Tested Water Data Sets Accuracy in Bar Chart, View Trained and Tested Water Data Sets Accuracy Results, View Predicted Water Quality Detection Type, Find Water Quality Detection Type Ratio, Download Predicted Data Sets, View Water Quality Detection Ratio Results, View All Remote Users.

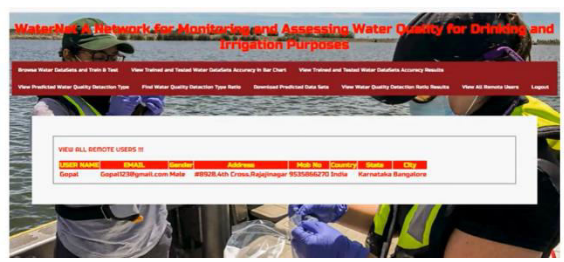
View and Authorize Users

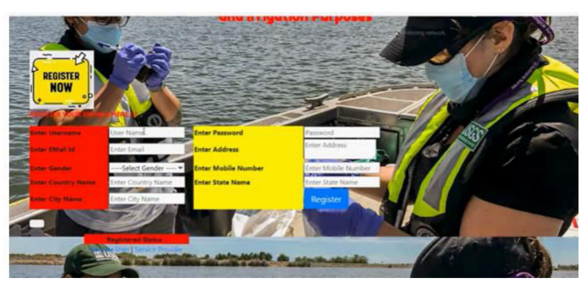
In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

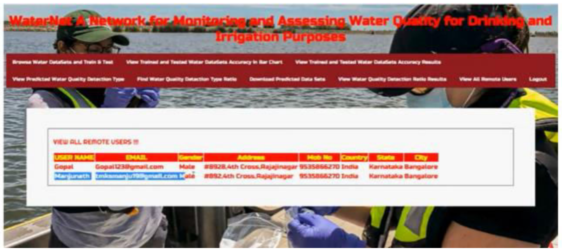
Remote User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database.

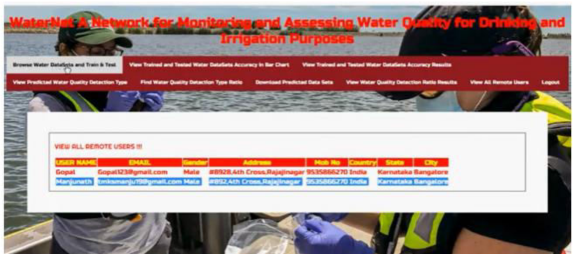
7. RESULTS






VIEW ALL REMOTE USERS !!!


PREDICTION OF WATER QUALITY TYPE !!!
ENTER ALL WATER DATASETS DETAILS HERE !!!
RID
State
District_Name
Place_Name
ph
Hardness
Solids
Chloramines
Sulfate
Conductivity
Organic_carbon
Trihalomethanes
Enter Turbidity
Predict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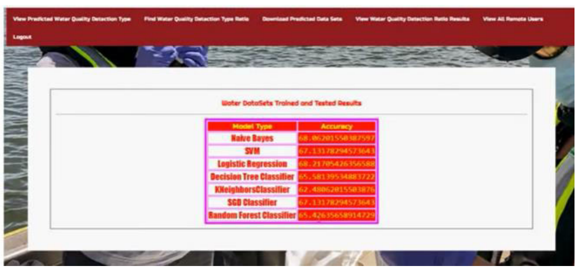
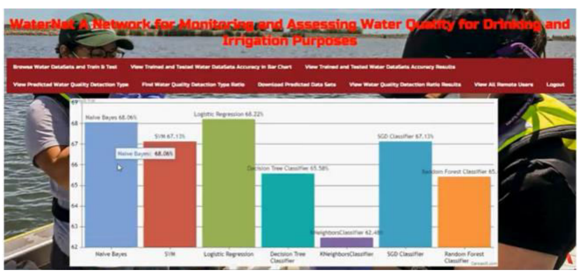
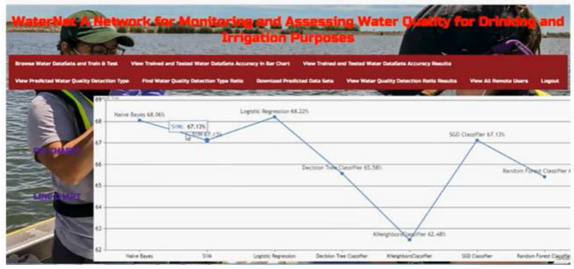
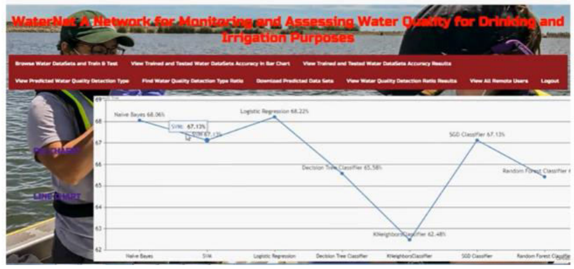
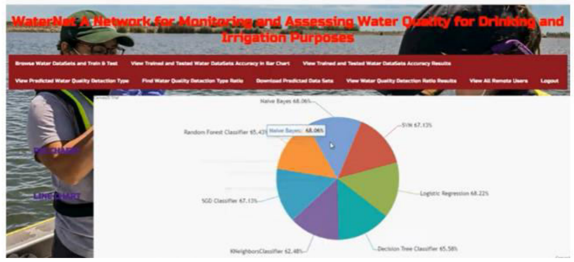
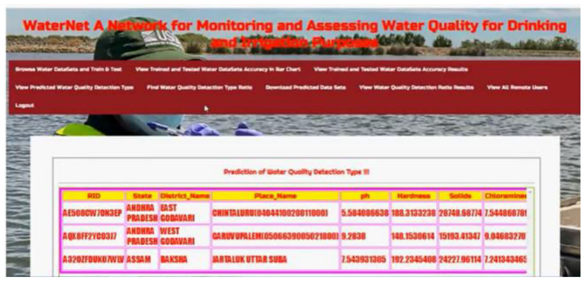

Water DataSets Trained and Tested Results
Model Type
Accuracy
Naive Bayes
68.06201550387597
SVM
67.13178294573643
Logistic Regression
68.21705426356588
Decision Tree Classifier
65.58139534883722
KNeighborsClassifier
62.48062015503876
SGD Classifier
67.13178294573643
Random Forest Classifier
65.42635658914729

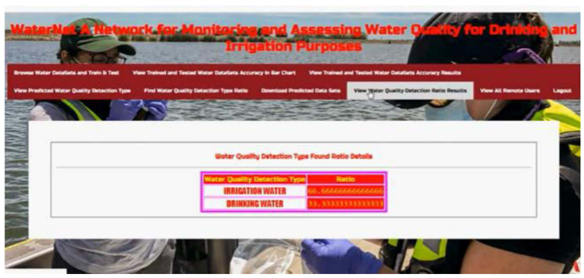


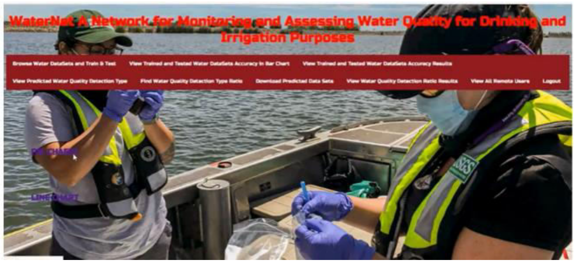


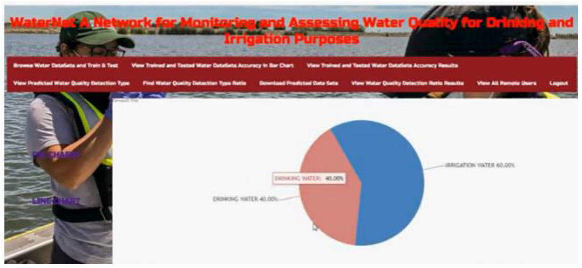





WaterNet A Network for Monitoring and Assessing Water Quality for Drinking and Irrigation Purposes
Prediction of Water Quality Detection Type !!!


Water Quality Detection Type Found Ratio Details
Water Quality Detection Type
Ratio
IRRIGATION WATER
DRINKING WATER





8. CONCLUSION AND FUTURE ENHANCEMENT

Two main ideas were the subject of this work. The first was the suggestion of a real-time water monitoring network to collect water parameter data from bodies of water. The second is the use of machine learning (ML) models to evaluate the quality of water. The City of Cape Town served as a case study for the development of the water monitoring network, which is based on Lo Ra, a low power long range data transmission protocol. The results of Radio Mobile's simulation showed that the best network architecture for covering the metropolis was a partial mesh network. Ideally, the data collected from this monitoring network would be combined on a cloud server, where machine learning algorithms could be used to determine if the water is appropriate for irrigation or drinking. Since there were no pertinent datasets, two appropriate datasets were created for this study and utilised to train and evaluate the three machine learning models that were taken into consideration: Random Forest (RF), Logistic Regression (LR), and Support Vector Machine (SVM). According to the test results, SVM was more appropriate for irrigation water, while LR performed best for drinking water since it provided the highest classification accuracy and the fewest false positive and negative values. Recursive feature elimination (RFE) was then used to investigate a model for determining the most significant water parameter or parameters in relation to the classification accuracies of the ML models. The findings indicated that SSP had the least impact on irrigation water while pH and total hardness had the least impact on drinking water.

Despite acknowledging the potential value of deep learning models, the authors did not employ them in this study. Future research might build on this work by including deep learning models, such as the different neural network variations. Future research might examine the use of unsupervised machine learning models as alternatives to manually computed water quality indicators, which were previously used to evaluate the "fitness for use" of water. Similarly, alternative methods like multi-criteria decision making might be used to find influential factors instead of RFE. Lastly, there may be ways to advance this study by identifying the sources of water contaminants and integrating consumption prediction models and microbiological monitoring into the water network.

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