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Online Monitoring System for Water Quality Based on Machine Learning Algorithms

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ABSTRACT
The international attempt to develop sustainable, intelligent water delivery systems faces considerable challenges due to the urbanisation that has characterised modern cities. In urban planning, the quality of the water we use for aquaculture and we consume is becoming more crucial due to the environmental changes. The main focus of urban water quality control has historically been the physical, chemical, and biological categories of quality indicators. However, occurrences like widespread infections have increased in frequency in many big cities due to the biological indications' inevitability, worsening the threat to the fishes and public's health. We begin this task by outlining the problem at hand, going over its technical challenges, and outlining open research issues. Then, we suggest a potential solution by creating a methodology for risk assessment specific to the urban water distribution system. Using the indicator data we acquired from industrial activity, we can track changes in water quality and spot potential threats. We provide an Adaptive Frequencies Analysis (Adp-FA) approach that uses the frequency domain data of indicators for their internal linkages and individual prediction in order to produce results that can be explained. We also examine the approach's indicator, geographic, and temporal scalability. As a part of a larger study, we use data sets of industrial quality collected in four Norwegian cities (Oslo, Bergen, Strmmen, and Alesund). We put the proposed method to the test, comparing its spectrogram, prediction precision, and time commitment to better established AI techniques like the Artificial Neural Network, Random Forest, CNN, and LSTM. The results demonstrate that our strategy outperforms alternatives in most respects. Risk prediction for water quality are possible.

KEYWORDS: Water quality, Prediction, Training, Machine Learning

1. SCOPE

This system's primary goal is to foresee potential risks in the water for aquaculture. The physical characteristics of water, such as pH, turbidity, and temperature, are used in the proposed method to assess water quality. Utilising more accurate chemical parameters, such as dissolved oxygen, TDS, specific ion concentrations, etc., can help with this. There is room for improvement so that the exact number and kind of pollutants in the water can be utilized to get the outcome. The proposed method can be applied in a variety of aqua environments, including, the method can be used to check the water quality for mineral water producers. Our approach has the potential to give the general public access to a tool or method for hassle-free water quality testing.

2. INTRODUCTION:

Two major trends, urbanisation and information technology, have emerged in the early 21st century. By 2050, 68% of the world's population is anticipated to reside in urban regions, a first according to the United Nations' Bureau of Social and Economic Affairs (DESA). Networks for distributing water are crucial in cities all around the world. Without a smart water supply system that integrates sensors, controllers, cloud computing, and data technologies, future sustainable smart cities cannot be constructed. The program's ultimate goal is to ensure that rapidly growing urban areas have access to clean, reliable water. However, industrial, agricultural, and societal contamination pose significant threats to urban water quality. It is a truth nowadays that safe water distribution is essential in modern cities. Goal 6 of the Sustainable Development Goals, also known as the SDGs, addresses access to clean water and sanitation. These goals were established in 2015 by the UN's Sustainable Development Programme. Water that is safe to consume is becoming scarcer across the world, affecting an estimated 2.1 billion people. Numerous legal attempts, including the European Union Drinking Framework Directive and the US's Clean Water Act, reflect the contemporary society's worries about this problem. Management of water sources, purification, and distribution are the three main components of the current water supply process. Water treatment is followed by the standard practise of quality control. However, underground and surface water are the predominant contemporary water sources. The risk of chemical and microbiological contamination is high for them. Water treatment is followed by a quality control process that seems to slow down danger identification and decrease reaction time. The new Norwegian national norm for water quality is now being implemented in the source region. Physical abilities chemical, and biological markers are all used to assess water quality. Biological indicators are the most directly relevant to human health when evaluating water quality. Biological indicator levels provide the basis of most national standards. Escherichia coli, intestinal enterococci, clostridium perfringens, etc., are all examples of common coliform bacteria that serve as indicators. The outcomes of tests inform the next steps in the therapy process. Although coliforms alone seldom result in life-threatening disease, their existence serves as a warning indication that other pathogenic organisms are present and potentially harmful. Water poisoning is caused by some strains of E. coli. Bacterial a condition called end diverticulitis, and meningitis are all made worse by int, as are urinary tract infections. Laboratory bacterial culture is the primary basis for testing biological markers. It may take up to two days for this to happen. The risk is far larger than the time it takes to have an impact on the human body. Due to a delay in the findings of a bacteriological test, around two thousand five hundred persons, many of them small children, fell victim to a giardia epidemic in Bergen, Norway, in 2004. As a result, there is an urgent need for improved methods of early danger identification in intelligent water distribution networks. Experiments using data to regulate water quality have been conducted. Multiple indices of water quality were evaluated in Hounslow in 2018. demonstrated a panel of universal bacterial sensing cells for gauging water quality. Data usage for forecasting water quality is the subject of some investigation. The salinity of the Murray River, in Australia, was predicted using a synthetic neural network developed by Holger et al. Orouji and colleagues developed several models (ANFIS, GA, and Shuffled FLA) to forecast chemical indicators of water quality (sodium, potassium, magnesium, etc.) based on measurements taken at the Astane station on Iran's Sefidrood River. The NH3-H concentration in the Dahan Rivers in Taiwan, China, was predicted using an analytical methodology presented by Chang et al. However, they tend to focus on separate measures of quality rather than the connections between them. The present research, industry, and everyday life are all touched by the improved ubiquitous sensing technologies. More environmental indications can be detected, sent, and measured with their help. Multiple sensors are used in an environmentally friendly smart water delivery system for effective resource management and water quality monitoring. Here, data plays a crucial role in enhancing our comprehension of the systems we already have in place. Changes within the water distribution system may be detected by monitoring the data itself using the right techniques. In the field, we deployed a wide variety of pH, temperatures, conductivity, etc. sensors in key water-production regions. We are able to significantly enhance the water quality monitoring process thanks to the large amounts of data generated by those inexpensive sensors and the most up-to-date data analysis technology. These many sensors are now amassing data in the zettabytes. Simultaneously, more powerful tools for analysing data have been created. Indicators of water quality are a common kind of spatial-temporal variable. The analysis of correlation and numerical prediction evaluation are two branches of this study's investigation. Hardoon et al., an early group to employ correlation analysis, performed Kernel Correlation Analysis on the pictures and accompanying words of web pages. PCA, or principal component analysis, is often used when there are many independent variables to consider. Jolliffe et al. [20] compared traditional PCA with more recent innovations like Robust PCA and Adaptive PCA. Tensor model correlation analysis was used by Luo et al. for gait identification. However, they failed to take into account time-domain correlations. Almost all current research in the field of spatiotemporal data analysis involves dealing with enormous data sets. For instance, Gudmundsson et al. analysed the behaviour and predicted trajectories of team-sport players. When it comes to spatial and temporal data, Lecun et al. presented the ground-breaking notion of Deep Learning. Liu et al. used the cutting-edge LSTM technology to examine 3D human motion. Laptev et al. find outliers in the data collected by the industrial platform. However, their efforts depend on big training sets, which are presently unavailable in water distribution networks. Furthermore, the explanation provided by such techniques does not meet the standards for commercial use. In this work, we provide our first observations from Norway. We begin by examining the nature of the issue, the obstacles, and the research questions. Second, we offer a data-perception-based paradigm for analysing water quality using data gathered from various water distribution networks. Third, we provide a predictive risk identification technique based on an adaptive frequency analysis. This approach may be used to a wide variety of problems, from water quality indicators to spatial and temporal scales. In addition, we choose data sets of industrial quality by application from a nationwide project in the water systems of four Norwegian cities: Oslo, Bergen, Strmmen, and Alesund. We provide early results of our risk detection, prediction, and assessment study, as well as the frequency property link between water quality indicators. The efficiency and time spent predicting are compared with those of a traditional Artificial Neural Network and a Random Forest. Additionally, time-domain scalability is investigated. Several obvious reasons for doing this study. To begin, it uses advanced data analysis techniques to address the issue of water quality management in prospective Sustainability Smart Water Supply systems. This is achieved primarily via the sharing of information across several indicators, locations, and periods of time. Secondly, it is able to deal with real-world water source monitoring processes and make use of data gathered directly from the manufacturing process. This sidesteps concerns about the viability of the findings in the laboratory and their potential use in industry. The existing supply of water in urban infrastructure networks may also benefit from this. Third, it bridges the gap between simple physical as well as chemical indicators and more nuanced, but equally important to water quality risk, biological indicators. Finally, this study lays the groundwork for more investigation and deliberation about the contamination caused by commercial and domestic operations in the respective water source locations.

3. RELATED WORK

“Urbanization and climate change impacts on surface water quality: Enhancing the resilience by reducing impervious surfaces,”

Climate change and urbanisation are two key factors that will affect the quality of the water in urbanised catchments in the future. In this study, we assess how increasing temperatures and urbanisation affect receiving bodies of water's drinking water quality in the vicinity of a heavily populated watershed in northern Italy that is served by a combined sewage system (CSS). A two-year field effort and integrated modelling research establish the extent of the effect. Combined sewage overflows (CSOs) and, by extension, water quality in the receiving water body are strongly predicted by the amount of impervious urban surface and the intensity of rainfall, as shown by the case study findings. Reducing imperviousness by halting the development of new impervious land and cutting down on existing ones by no more than

15% was identified as a viable technique for adjusting to such circumstances. Using this knowledge to influence future design decisions could strengthen the resilience of these systems in the face of inevitable environmental and urbanisation shifts.

"Sustainable development ´ goals: A need for relevant indicators,"
The UN General Assembly's Open Working Group in New York recommended 17 goals and 169 targets for worldwide sustainable development. In addition, in March 2015, a pilot set of 330 indications was released. Some of the SDGs expand upon the Millennium Development Goals that came before them, while others are wholly new. An analysis of the available indicators for measuring sustainable development shows that they are of varying quality (with respect to meeting specific requirements). Users aren't always clear whether the indicators they're using are accurately measuring the phenomena they're keeping tabs on, even though there's been a lot of theoretical research on quality criteria for indicators. As a result, we place an emphasis on the need of making the Sustainable Development Goals' aims actionable and assessing the indicators' relevance, the most crucial quality attribute among the indicators' quality qualities. As a result, we propose for the establishment of a conceptual structure in order to choose suitable indicators for aims, either by using preexisting collections or by creating new ones. In order for consumers to get clear, unambiguous information, experts should place special emphasis on the "indicator-indicated fact" link in order to assure the indicators' relevance. To help with the massive amount of conceptualization required to create a firm basis for the creation of the ultimate indicators framework, we conclude with some advice for indicators suppliers.

"The eu drinking water directive: the boron standard and scientific uncertainty,"
European Community updated its Water for Human Use Directive in 1998 to ensure the safety of drinking water throughout the EU. The European Union has instituted a new limit for boron in potable water, setting the threshold at 1 milligramme per litre. However, we find that total compliance with the new water consumption standard for boron has been impeded due to scientific ambiguity surrounding the sources and scale of the boron issue in Europe throughout the regulatory standard-setting process. Boron's origins were up for debate before the standard was established, but we now know it comes from both natural and human-made processes. According to recent geological research, a lot of the contaminated boron comes from the environment. Accordingly, the new EU boron policy is proving more challenging and costly to implement in countries like Italy and Cyprus, which have significant naturally occurring boron amounts in their drinking water.

4. METHODOLOGY

In this study, we present a technique for identifying and quantifying possible risks to water supply systems. This model suggests that the process is divided into five separate phases. All the raw data is provided via sensor networks and laboratory studies of watershed regions. Included are all the significant indicators of water quality. Data is frequently transformed during pre-processing from its raw form into a more useful format for analysis. Standardising, matching, and organising. It is necessary to take into account the inconsistent, out-of-range, missing, and multi-resolution units in the raw data. It's critical to keep in mind that you are under no obligation to utilise clustering or declustering. This is intended to make it easy to organise the data from various angles and discover any underlying trends. Clustering and declumping, for instance, may take into account the temporally-dependent characteristics of water quality, using a range of epochs from days to seasons. After cleaning and preparing the data, we must determine the most crucial indications across a number of dimensions, perform a probability distribution, and create training and test data sets. This project's ultimate purpose is to identify any dangers to the quality of the water supply. To create the risk model, we worked with water quality control specialists. Here, we break down the framework for risk assessment into its constituent parts. Cycle identification is to identify the underlying cycle in time-series indicator changes. The peak value is determined in order to track and gauge the intensity of a multi-bacteria pandemic. Parameter adjustments in response to training data. In addition, we need to decluster the data and provide reliable trend and value predictions for the bacteria indicators. Depending on the rules for managing water sources that are actually put into practise in various places, these numbers may correspond to varying degrees of danger. In the future, water treatment facilities will include decision support systems that can switch between prediction and risk modes. In addition, when both sets of domain knowledge expand, the models must develop in real life

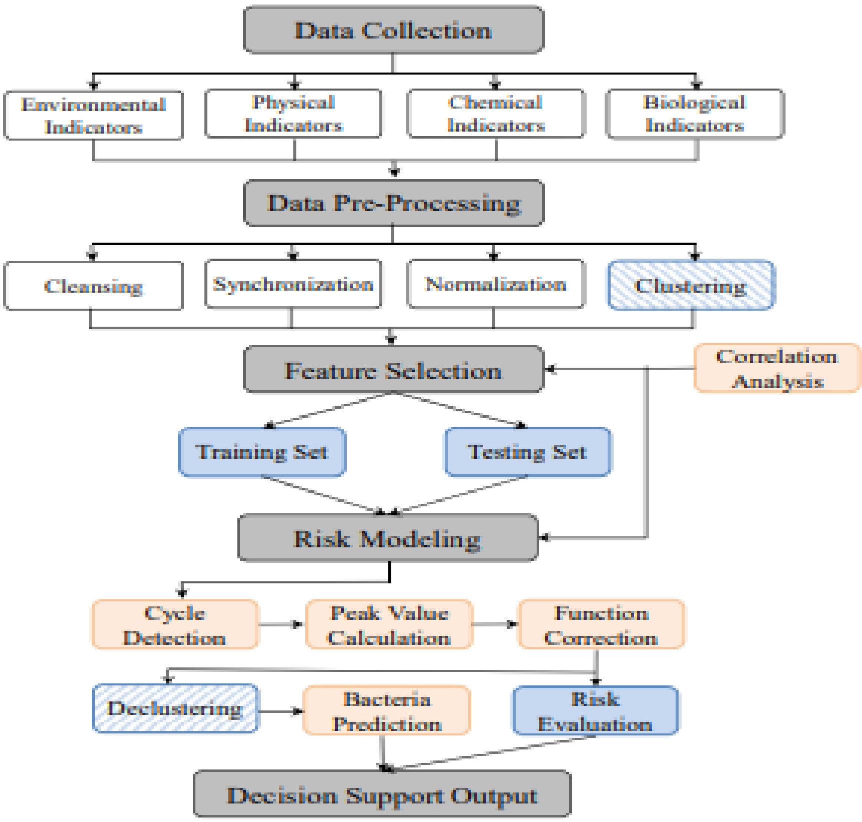

Fig 1 System Architecture

5. RESULTS

Biologic indicators of water quality are crucial for assessing risk in the water distribution system. In response to these modifications, the subsequent treatment procedure will adjust as needed. According to the results of our investigation presented in the levels at which these indicators peak provide useful data. Artificial neural networks (ANN), random forests (RF), proposed adaptive, CNN, LSTM algorithms are traditional approaches to prediction that we evaluate with our own frequency analysis techniques. There are three criteria by which we judge them. To begin, let's determine the typical accuracy of peak value forecasts. The risk model was used to determine the most appropriate peak values. The second measure is the overall forecast accuracy using the Root Mean Square Error (RMSE).

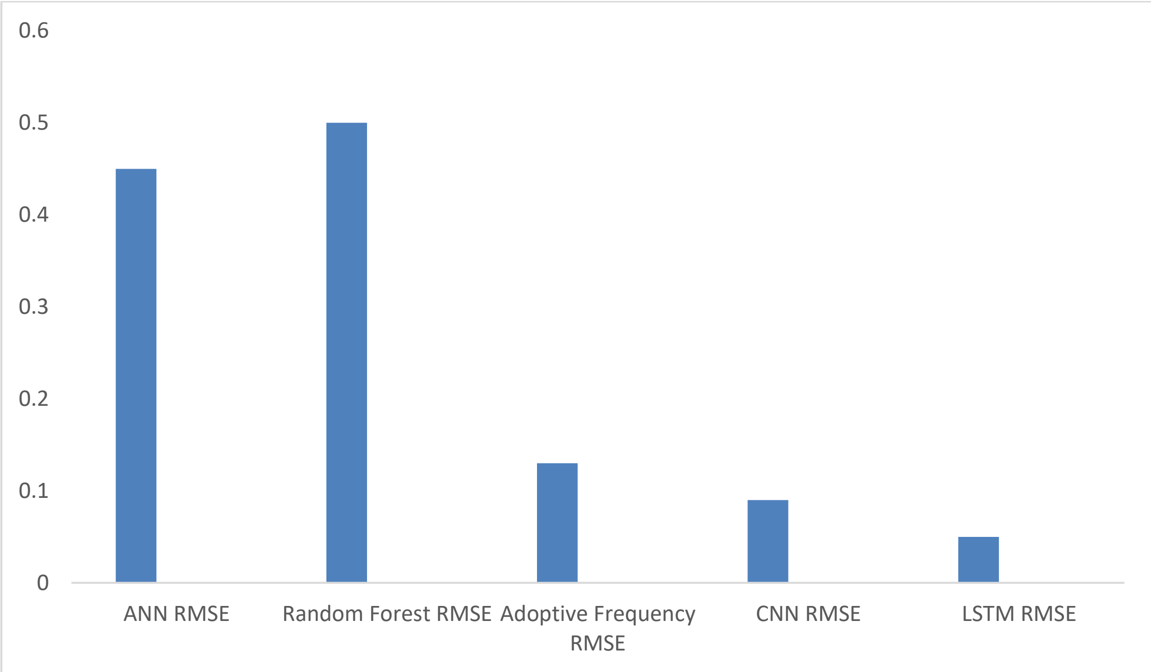

Fig 2 RMSE Comparison Graph of algorithms

As a third metric, we consider the amount of time required to calculate the effectiveness of various strategies. The physical and chemical markers used in this experiment are pH, Conductivity, or the Turbidity, and Colour. Coliform, Ecoli, and Int are all biological markers that may be derived from their outputs. Due to the scarcity of recordings, we divide our data into a 90%-10% training and testing set. Finally, our proposed adaptive method will allow us to determine whether or not a given set of test data poses a danger

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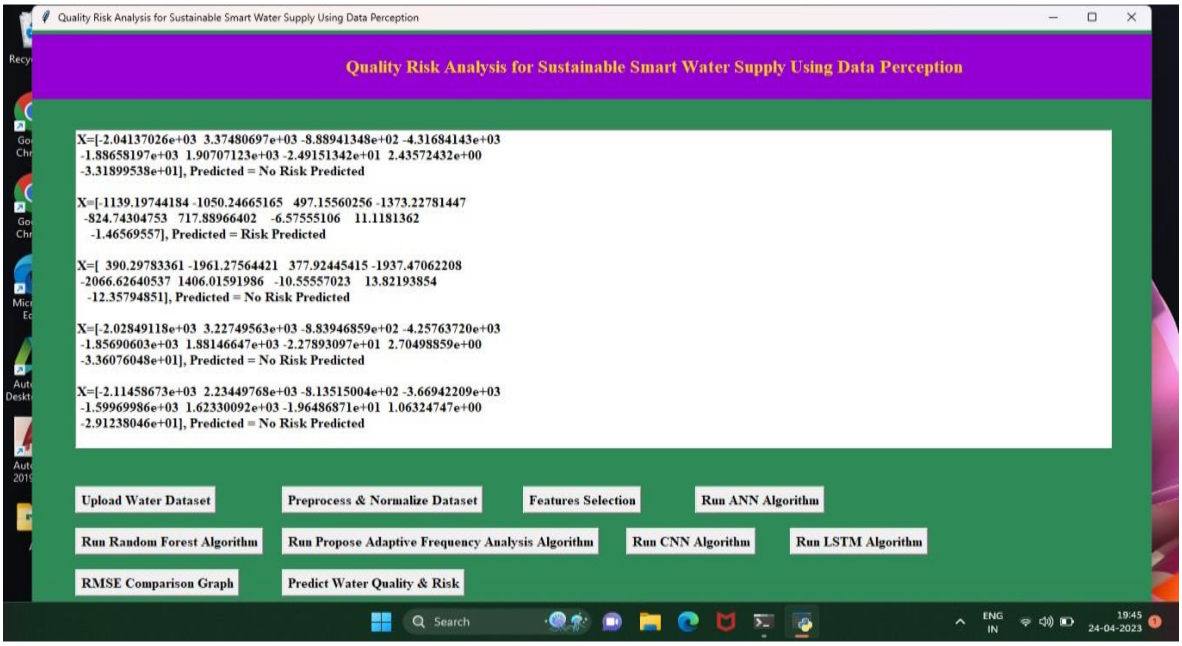

Fig 3 Risk prediction in water

6. CONCLUSION

For the sake of progress in maintaining water quality in aquaculture and Smart Water Supply systems, water quality has become an urgent problem in today's metropolitan centres throughout the globe. It is difficult to detect the spread of bacteria in a timely manner using traditional risk management and monitoring techniques, which also fall short in providing useful decision support. In this study, we advocate for the use of data perception to develop early warning systems for potential water quality risks. We have shown the approach's viability, accuracy, and efficiency via its implementation throughout four cities in Norway. Experts in the field have deemed the early evaluations to be quite encouraging. The following are main ways in which this effort helps: It uses free methods of data analysis to give an early warning about water. This method blends indicator and temporal domains, which lengthens the reaction time for preventative interventions and so that usable decisions can be made earlier before anything wrong happens. It offers a fresh angle on frequency domain analysis for establishing causality between variables and forecasts. This article's methodology is put to use on the actual industrial water supply networks in four Norwegian cities.

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