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EMPOWERING WATER TREATMENT THROUGH CONVOLUTIONAL NEURAL NETWORK CLASSIFICATION

Chowdam Vinaya Sri
Department of Computer Science Engineering
Sharda University, Greater Noida
Uttar Pradesh, India

Ayushman Arya Kumar
Department of Computer Science Engineering
Sharda University, Greater Noida
Uttar Pradesh, India

K. Suman Kumar Bohara
Department of Computer Science Engineering
Sharda University, Greater Noida
Uttar Pradesh, India

ABSTRACT

With significant development of Internet of Things and substantial advancements in sensors, researchers can now readily obtain photos of the water and use them to understand what is happening in the ecosystem. In essence, expanding data size and category helps address issues related to water contamination. In this research, we concentrate on categorizing water photos into subcategories of clean and contaminated water in order to provide real-time feedback of an IoT-based water pollution monitoring system. Water picture categorization is difficult as collected images have large intra-class and minimal inter-class differences. Motivated by the capacity to derive very distinctive characteristics from Convolutional Neural Networks (CNNs), We wish to construct an attention neural network for the classification of gathered water photographs that appropriately encodes channel-wise and multi-layer characteristics in order to accomplish feature representation augmentation. Before building a local and global hierarchical attention neural network, we propose the VGG 19 model with a channel-wise attention gate structure. We carried out comparative experiments with a water surface image dataset from many publications, proving the effectiveness of the proposed attention neural network for classifying water photos. We integrated the proposed neural network as an essential part of an image-based water pollution monitoring system, allowing users to monitor water pollution breaches in real time and take timely corrective action.

Index Terms: Water Treatment, CNN, Image Analysis, Water Quality, Machine Learning for Environmental Applications, Deep Learning Classification, VGG19

I INTRODUCTION

The rapidly expanding human civilization poses a major danger to river, lake, and marine ecosystems. The category, volume, and quality of relevant data that is collected have all improved steadily as a result of the development of sensor technology and the Internet of Things (IoT). Using the data collected, researchers may design systems that instantaneously monitor, control, and reduce pollutants, protecting aquatic environments in the process. The broad growth of employing artificial intelligence to conceptually assess relevant data in the context of the Internet of Things has benefitted both environmental protection and water resource management. Within the topic of water ecosystem monitoring, this is an important research question. Numerous pertinent water data are now easily accessible due to the use of drones, security cameras, and other Internet of thing's technology. Big data technology consequently drastically changes the water pollution monitoring system, replacing manual sampling procedures with instantaneous and automatic monitoring and analysis.[10] The improvement's advantage is that there is no discernible delay for government users in precisely determining the location and timing of pollution occurrences. Therefore, the primary challenges of this kind of monitoring system are to effectively evaluate the data gathered by IoT technologies in order to provide exact pollution information.We concentrate on one of the most prevalent categories among the various water-relevant data sources, which is water photography. In order to accomplish the purpose of monitoring water contamination, we also carry out image content interpretation. More specifically, our goal is to build a unique water pollution monitoring system that can carry out two categorization jobs in an Internet of Things setting. First, by classifying input water photos into fundamental categories like clean and contaminated, such a system may identify areas where contamination is occurring [6] The system should determine the subcategories of input water photographs based on the general kind of water images. These subcategories might give users enough information to enable them to take further action. Stated differently, this technology can distinguish between four subcategories of clean water photographs: fountain, lake, ocean, and river. It can also detect the type of water pollution that is present, such as fungus, dead animals, industrial pollution, oil, and rubbish. Water is a valuable resource that is required for many human activities as well as the sustenance of life. Having access to clean, safe water is crucial for industry, agriculture, public health, and the overall well-being of society, making it one of the most significant human rights. However, a number of problems, including as pollution, population increase, climate change, and fast urbanization, have made it more difficult to provide a steady supply of clean drinking water and to treat wastewater adequately. In this regard, the application of cutting-edge technologies—in particular, machine learning classification—has shown promise as a means of enhancing water treatment systems and tackling these complex issues. [8] Historically, water treatment systems have purified water using well-established chemical and physical processes. Although these techniques have mostly proven successful, they are frequently resource- and energy-intensive, and they are less flexible when it comes to the changing needs and quality of water. Cutting-edge machine learning classification methods provide a game-changing approach by enabling predictive analytics, intelligent decision-making, and real-time monitoring in water treatment operations. Machine learning classification comprises many algorithms and techniques that are capable of analyzing intricate information and arriving at wellinformed conclusions by identifying patterns and trends. By using these methods in the changes in water quality, improve energy efficiency, identify anomalies, integrate various data sources, and react quickly to contamination incidents. This study explores the potential to transform the water treatment sector and the significant effects of enabling water treatment using sophisticated machine learning categorization.[17]. This research article intends to shed light on the possible advantages and difficulties connected with

II LITERATURE REVIEW

After classifying the relevant techniques into two groups—water picture classification and attention mechanism—we provide thorough explanations. Classification of Water Images Numerous research projects have been conducted to address the issue of water contamination. Sorting different sorts of pollution in water photos is one of the most crucial problems among them. Actually, a number of related strategies, such as the development of cloud-based monitoring systems, have been established to the advantage of precisely monitoring water information. Initially, reflected contour detection was accomplished using a flip invariant form detector. Their suggested approach uses contour location to accomplish water picture segmentation after finding reflected contours with edge characteristics. Lastly, in order to accomplish the goal of water surface identification, their suggested approach collects characteristics from sub-regions. In accordance with their concept, water bodies are located precisely by using sky reflection, which computes intensity value similarity. [10] Subsequently, it was suggested that water identification be carried out using the dynamic texture recognition guided

water treatment process, we may anticipate

incorporating machine learning into water treatment systems through a thorough investigation of these ideas and their practical consequences. By doing this, it hopes to advance the conversation on effective and sustainable methods of managing water resources, which will ultimately lead to the development of water treatment systems that are safer, more robust, and ecologically friendly for communities all over the world.

segmentation method, which models and learns the texture-related properties of

pictures using entropy.In [12] used many techniques to detect changes in the water's surface. Their suggested method may result in a multi-spectral image that has been refined for classification, offering a high accuracy outcome. In conclusion, traditional methods to the problem of water pollution often include manual feature extraction and classifier construction techniques, which are challenging, costly, and time-consuming Appl. Sci. 2020,10, 909 4 of 16 to complete water image segmentation. Finally, their proposed technique gathers features from sub-regions to achieve the aim of water surface identification. Rankin et al. [14] used this idea as a model to identify bodies of water by employing sky reflection, which uses the similarity of intensity values to locate locations accuratelyThe dynamic texture identification guided segmentation approach, which models and learns the texture-related features of the water photos by utilizing entropy, was then proposed as a way to recognize changes in the water surface. Their proposed approach may provide a multi-spectral image that has been enhanced for classification, providing a result with a high degree of accuracy. In conclusion, traditional approaches addressing the problem of water pollution often include labor-intensive, costly, and time-consuming manual feature extraction and classifierdesign operations. Since deep learning structures are developing so quickly [17–19], four researchers have used additional deep networks to classify photos of water. A CNN was trained to carry out classification tasks on Inputs picture patches by Zhao et al. [20], who were inspired by the CNN models to analyse the close range photography. They came to the conclusion that CNN is far superior to SVM, the conventional classification approach, and has a lot of promise for use in SAR picture interpretation after performing comparison research , with a focus on water surface as a significant object category. Because R-Vane is based on the spectral and spatial properties of HSI data, it can achieve greater accuracy even with less training datasetsTheir suggested technique divides an input picture into high-quality super pixels, then creates a task-specific CNN to extract semantic characteristics from the water surface. This CNN is then used to categorise the super pixel's class label—water or no-water—after it has been segmented. The classification target of the suggested technique is comparable to that of Chen et al. [22]. But unlike the problem they studied, we do ambiguous classification at the picture level as opposed to binary classification at the pixel level. Panet al. [25] developed a low-cost water monitoring system with cameras serving as the main sensors. A deep CNN structure was used to automatically estimate the water level. The development of cloud edge computing and the construction of a CNN-based model for water interpretation served as the foundation for this system [23, 24]. Notable advancements have been made in the fields of irrigation water categorization and water quality evaluation, especially when using cutting-edge data processing methods. Meireles and associates. (2010) [26] put out a revolutionary technique of classification for irrigation water, highlighting the significance of accurate water classification. Yıldız and Karakuş (2020) [27–29] demonstrated the potential of data-driven models in water quality assessment by introducing an optimal model for calculating the irrigation water quality index. Furthermore, highlighting the necessity for data-driven insights, Hasan et al. (2020) [34] provided a dataset assessing hadrochemical parameters for groundwater suitability in Bangladesh. An increasing amount of research demonstrates the use of IoT and sensor networks in a variety of fields outside of water treatment. Kamakya et al. (2021) [38] covered complicated systems connected to intelligent transportation, whereas Bagula et al. (2021) [36] investigated the reliability of cyber-physical systems. Mbayo et al. (2021) [41] presented (IoT)-based pollution checking model in the environmental sector, highlighting the need of real-time environmental data. According to Janssen et al. (2020),[43], the integration of sensor technologies improves communication and range capabilities, which aids in data collecting. The City of Cape Town (2018), Ilium (2022) [45], and ScienceDirect Data Brief (2022) are a few more sites that provide useful tools and platforms for doing data-intensive research and gaining access to datasets. Together, these initiatives demonstrate how data-driven approaches and technological integration are developing in the fields of environmental monitoring and water quality evaluation. The advantages and possible uses of this approach in the context of sensor networks are also covered. Next, [18] explores cloud computing and concerns related to quality of service, providing insight into the difficulties and advancements in cloud computing as well as how they affect the calibre of services provided. This study provides insightful information on how the cloud computing industry is changing. The field of low power wide area networks (LPWAN) is then examined in [19], where a summary of LPWAN technologies and their uses is given. The importance of LPWAN in allowing low-power, long-range connectivity for Internet of Things devices is covered in this study. In order to assess the performance of LoRa (Long Range) technology for vehicular communications in real-world circumstances vs simulated ones, a research published in [20] contrasts experimental and simulation studies. Determining the viability of utilizing LoRa in automobile Internet of things applications is crucial. [21] examines the use of LoRa as a radio connection technology for remote-controlled electric switch systems using network bridge radio-nodes. This work clarifies if LoRa is suitable for specific industrial applications. The study in [22] focuses on long-distance wireless sensor networks and highlights the disparities between simulation and real-world performance. This is helpful in comprehending the constraints and difficulties associated with implementing wireless sensor networks in large-scale situations. Now that we are talking about The research in [30] goes a step further by presenting an optimal model for estimating irrigation water quality index, highlighting the significance of accurate models for agricultural water quality evaluation.The environmental issues, assessments of water quality are included in the literature review. [23] looks at many water quality index models and their uses to assess surface water quality, which is crucial for environmental monitoring and management.introduces the development of a universal water quality index (UWQI) for South African river catchments, highlighting the necessity of tailoring water quality evaluation to local conditions and requirements [24]. The research in [25] addresses soil salinity as a significant environmental issue and examines the potential mitigation strategies including microorganisms that promote plant growth. Our grasp of sustainable agriculture practises is improved by this research. In the context of agricultural irrigation, [26] provides an IoT-based prediction model for the water quality index, illustrating how IoT technology may be used to guarantee water quality appropriateness for agriculture.The emphasis in [27] switches to machine learning techniques for irrigation-related groundwater quality forecasts, highlighting the significance of data-driven methods for guaranteeing groundwater appropriateness.Numerous research on irrigation water quality indices are included in the survey. [28] looks at the evaluation of an irrigation water quality index (IWQI) in a specific location in Iraq in order to emphasize the need of area-specific water quality assessments for agriculture.provides a comprehensive approach to irrigation water quality classification in [29], which offers a suggestion for irrigation water classification. dataset in [31] adds to the data resources available for water quality evaluation by offering useful hadrochemical parameters for evaluating groundwater suitability for irrigation in a particular location in

Bangladesh.The literature review delves into the applications of IoT and sensor networks across several domains, extending beyond water quality. [32] shows how IoT cyber-physical systems for dependability monitoring. presents the idea of cyber-healthcare kiosks and shows how they might be used to leverage IoT and sensor technology to support healthcare in underdeveloped nations [33].explores sophisticated transportation-related systems and sensors in depth, providing insights into how sensors may improve safety and transportation systems.

The research in [35] explores portable devices, active RFID, and networked wireless sensors for contemporary car park management, offering a thorough overview of IoT-based parking facility management. examines the idea of Environment 4.0, an technology might improve the reliability of important systems by discussing the usage of

Internet of Things-based pollution monitoring approach that might be useful for managing and monitoring the environment.Understanding the possibilities and constraints of LoRa technology in various contexts requires an understanding of the work in [47], which explores the range and study of LoRa 2.4 GHz communication lines.The literature review includes information about cloud computing resources for data-intensive research, data briefs for various research areas, and documents from the City of Cape Town about water services and the urban water cycle [48, 52], in addition to references to relevant sources and standard.

III METHODOLOGIES

Existing System: Image Classification of Water Numerous research projects have been conducted to address the issue of water contamination. Sorting various forms of pollution in water images is one of the most important issues. Actually, a number of comparable tactics have been developed with the benefit of accurately monitoring water information, such as the development of cloud-based monitoring systems.. The training model and classification, with a 92% accuracy rate, is the Vgg 16 model.20]

Proposed System: The VGG 19 model is the suggested approach for the classification objective. But unlike the problem they studied, we do ambiguous classification at the picture level as opposed to binary classification at the pixel level. A low-cost water quality prediction system was created using a deep CNN structure and a CNN-

As deep learning structures are developing quickly, more deep networks are being used by researchers to classify photographs of water. Motivated by CNN models to examine up-close shots.A multiplicity of decision trees are used to create RF [52]. It may be applied to issues involving both classification and regression.

Disadvantages Of Existing System:

• It uses a cloud-based technique and image processing

•It uses vgg16 with less training layers. based model for water interpretation. This system could automatically forecast water levels.

Benefits of the Submitted System: predicts water quality photos automatically and without any human interaction. Permit the detection of noteworthy water quality The model has more accuracy than previous approaches.

Advantages of Proposed System: Automates process of prediction of water quality images without human interface. Permit the detection of noteworthy water quality The model has more accuracy than previous approaches

A: Proposed Model

Overview The system requirements, operating environment, system and subsystem architecture, file and database design, input and output formats, layouts for human-machine interfaces, detailed design, processing logic, and external interfaces are all included in the system design document.

B: Modules

Data Collection: We used an internet collection of water photos for our study, which is divided into three groups of five categories. Each folder contains 50 photos that are used for training; pixel values from the images are used as input, while labels are utilised as output.

Pre-Processing: One method to enhance visualization and increase picture quality is pre-processing. In order to improve the image quality, image processing is a crucial step in water quality imaging. In order to acquire precise and good results in the next phases of the proposed method, this can be one of the most crucial components. Pictures depicting the condition of the water may have several issues that make the image difficult to see. Inadequate or low-quality photos might produce disappointing outcomes. We carried out picture propagation until the ideal weights are found and only the strongest and most predictive neurons are turned on to provide predictions.

• For each tagged picture, forward propagation compares the difference between the actual and projected objective in order to compute the loss and cost improvement, noise reduction, background removal, and removal of unnecessary blood supply during the preprocessing stage.

Splitting the Train-Test and Model Fitting

In our dataset, we now divide the data used for testing and training. This split aims to assess how well our model performs on unknown data and determine how much it has generalized on training data**.** A model fitting, which is a crucial stage in the model-building process, comes next. Assessment of the Model and Forecasts: This last stage evaluates the model's performance on testing data using a variety of scoring measures; I have chosen to use the 'accuracy score' to do this.The process begins with the creation of a model instance. Next, the fit 17 technique is used to fit the model to the training data. Lastly, the forecast technique is used to make predictions about the testing data or the x test. Next, the forecasts are stored in a variable called "y test hat." The results will be kept in a variable called test accuracy, which will represent the testing accuracy of our model. The y test and y test hat will be supplied into the accuracy score function for model assessment

functions. The model trains over several epochs of this procedure.

Gradient descent is used in backward propagation to update each neuron's weights and bias, assigning the highest weight to the neurons with the best prediction accuracy until it discovers the optimal combination of activations.

• As the model gains more experience, it becomes more adept at predicting the goal, which lowers the loss measure.
• To get overall performance, the cost function considers the average loss across all samples.

Incorporate adversity to help your model learn to identify your goal in improbable situations:

- Change the orientation of the picture
- Include pictures of people who look like your target.
- Include hazy and grainy renditions

To improve model efficiency, reduce the model load:

- To reduce the image's dimensionality, use max pooling in between the layers to compress spatial size and parameters.
- After a given number of epochs, if your model reaches a peak in accuracy, it will stop looking for an even higher accuracy. This will assist in avoiding overfitting.
- Use fewer epochs for training to reduce processing time.
- Consider using an alternative activation function, such as ReLU, which is more effective than sigmoid or tanh since it only stimulates certain neurons.
- Consider dropout to reduce network computation by ignoring randomly chosen neurons during training.
- Steer clear of huge pixel pictures (224 by 224 is usual), as adding more clarity to an image doesn't really help learning.

To carry out technological and operational research and analysis, as well as to

In addition to testing with various model hyper-parameters, you may also perform the following actions to enhance your model:

encourage the sharing and advancement of techniques and instruments for operational analysis in relation to defence issues.

Input And Output Designs

Logical Design:

"Logical design" refers to an abstract representation of a system's inputs, outputs, and data flows. Modeling is often employed to do this, using an excessively abstract (and sometimes graphical) representation of the actual system. are included in the systems design framework. Logical design includes Entity Relationship Diagrams, or ER Diagrams.

Physical Layout

The methods for entering data into a system, validating it, processing it, and displaying the results are all outlined here. The following system requirements are chosen during physical design.

- requirements for input
- needs for output
- Needs for storage
- Needs for Processing
- Backup and recovery procedures for the system.

Put differently, there are three minor jobs that make up the physical part of systems design:

- Design of User Interfaces
- 2. Information Architecture

IV SYSTEM IMPLEMENTATION

User interface design is centered on how users enter data into the system and how the system obtains and presents data. Data design deals with how data is represented and stored inside the system. In the end, process design is about how and where information is verified, secured, and/or altered, as well as the flow of data into, though, and out of the system. At the end of the systems design phase, documentation detailing the three subtasks is produced and made available for use in the following phase. The physical arrangement of an information system is not what is meant to be understood by "physical design" in this sense. To provide an analogy, a personal computer's physical design comprises of keyboard input, CPU processing, and output via a display, printer, and other devices. It wouldn't matter how the hardware was physically arranged; on a PC, this would include the monitor, CPU, motherboard, hard drive, modems, video/graphics cards, USB ports, and so on. It comprises a detailed design of a user, a database structure processor for the product, and a control processor. We provide a unique H/S personal specification for the proposed system.

Input and Output Diagrams

Design of Input

The input design serves as the user-information system interface. In order to convert transaction data into a format that can be handled, it involves developing standards and data preparation techniques. People can enter data directly into the system or the computer can read data from a written or printed document to do this.The primary objectives of input design are to minimize errors, avoid delays, control the amount of input required, remove pointless steps, and streamline the procedure. The input is done in a way that provides security and usability without compromising privacy. Considerations for Input Design included the following:

Which data sets are appropriate for input?

• How should the information be coded or organized?

• The discussion to guide the contribution of the operating personnel.

• Steps for creating input validations and what to do if something goes wrong.

Goals

Input design is the process of converting a user-oriented description of the input into a computer-based system. This design is essential for avoiding data input mistakes and giving management the proper direction on how to get correct data from the computerized system. To manage massive amounts of data, it is achieved by creating user-friendly data entry interfaces. The main goal of input design is to provide error-free data entry. The data entry page's architecture makes it feasible to manipulate any type of data.. There are ways to see records as well. When the data is input, it will check that it is accurate. Data entry can be aided by using screens. Notifications are given appropriately when needed to keep the user from becoming lost in the present. Thus, creating an intuitive input layout is the aim of input design.

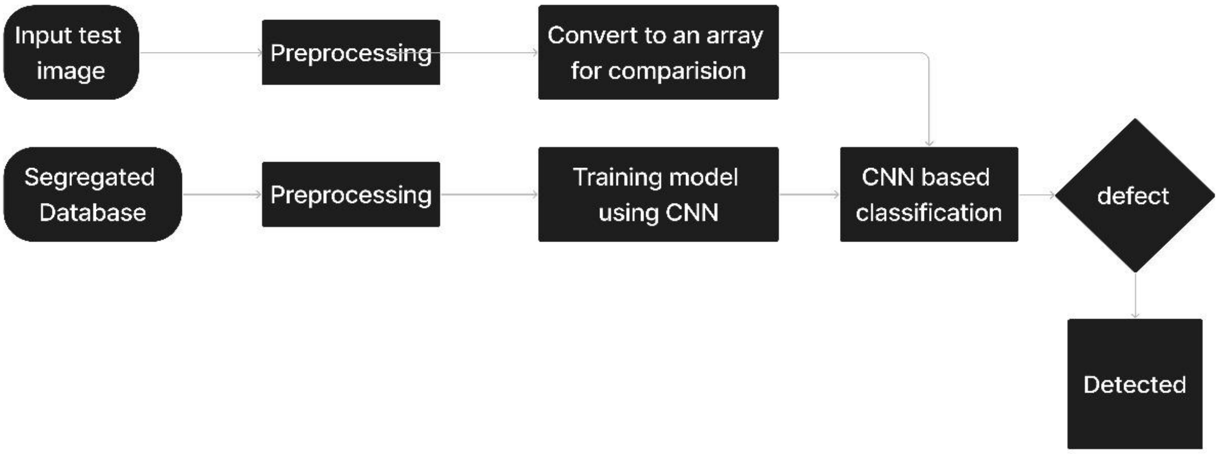

Figure 1: system input design

Design of Output

An output that meets the needs of the end user and effectively conveys the information is considered high quality. Any system's outputs are how processing results are shared with users and other systems. How information is displaced for immediate use and the hard copy output is decided in output design. For the user, it is the most significant and immediate source of information. Effective and thoughtful output design strengthens the connection between the system and facilitates user decision-making.

a. The process of designing computer output should be methodical and well-planned; appropriate output should be created while making sure that every output component is made in a way that makes the system simple and efficient for users to utilise. When analysing computer output, designers should pinpoint the precise output required to satisfy specifications.

b. Choose how to show the information. c. Generate reports, documents, or other formats containing data generated by the system.

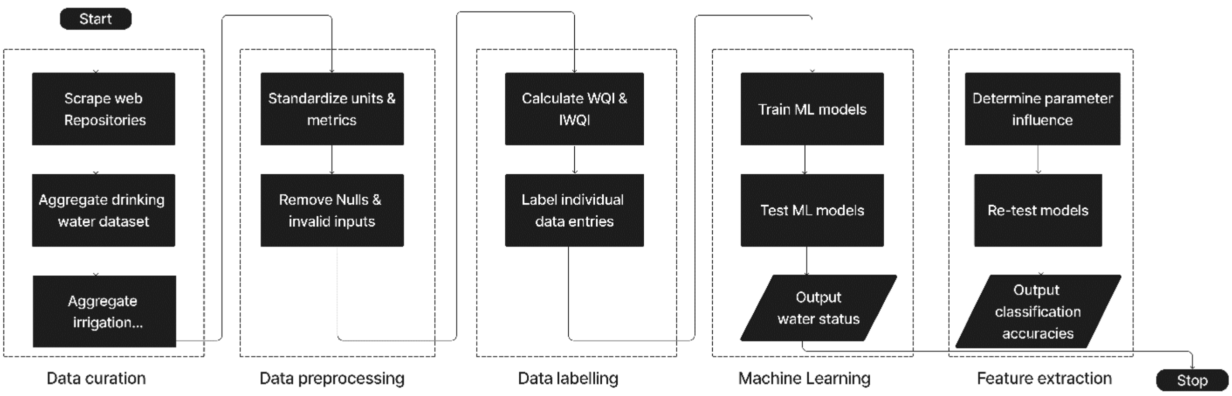

Figure 2. procedure flow for ML-based water quality assessment.

V OUTPUT

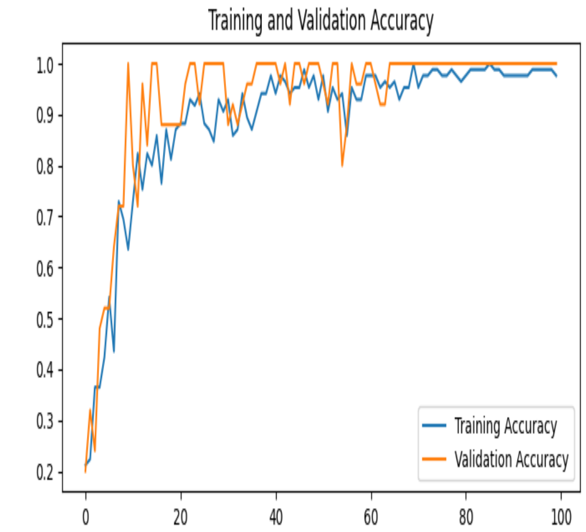

Figure 3: **Training and validation Accuracy**

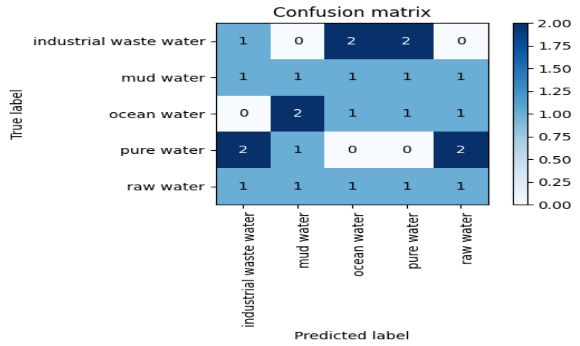

Figure 5:Confusion matrix

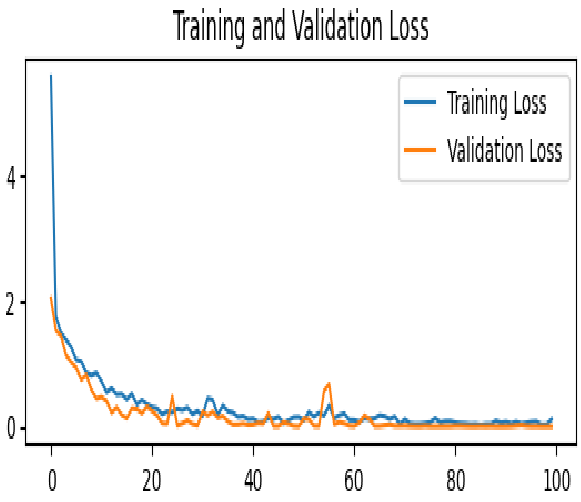

Figure 4.Training and Validation loss

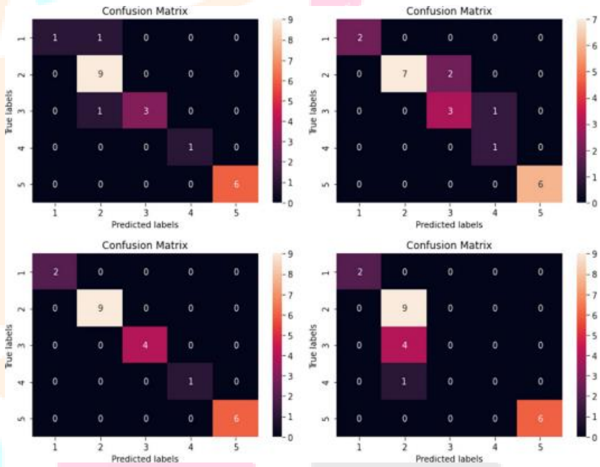

Fig. 6. Confusion matrix for classification algorithm. A. Random Forest Classifier B. Support Vector Classifier C. Classifier using Gradient Boosting d. AdaBoost Classifier

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Model	Accuracy	Precision	Recall	F1-score
Random Forest Classifier	.91	.96	.85	.89
Support Vector Classifier	.86	.82	.91	.84
Gradient Boosting Classifier	1.0	1.0	1.0	1.0
AdaBoost Classifier	.77	.53	.60	.56
Convolutional Neural Network	.97	1.0	1.0	1.0

Evaluation of the classification model's output

Python is used to implement many methods for classification. Table 1 displays the outcomes of several categorization models. Out of all the models, the Gradient Boosting Classifier has proven to be the most accurate and practical for forecasting the quality of water.. The Random Forest Classifier is the second-best model; nonetheless, it is outperformed by the Support Vector Classifier when it comes to recall calculations. In comparison to the other methods, the Ada-Boost Classifier model is determined to be less successful. Fig. 6 displays the confusion matrix for the models.As seen in Fig. 6, the Gradient Boosting Classifier properly identified all of the testing data according to the water quality level, despite the fact that some of the testing data had been wrongly classified by previous models

Table 2 Performance comparison of the suggested approach with earlier research in the literature

Name	Location	Total Specimens	Prediction Method	Classification Method	Prediction Accuracy	Classification Accuracy
Wang et al. (2017)	China	22	SVR	–	92%	–
Yilma et al. (2018)	Ethiopia	12	NN	–	93%	–
Samsudin et al. (2019)	Malaysia	13	SDA-ANN	–	71%	–
Ahmed et al. (2019)	Pakistan	4	GB	MLP	74%	85%
Ho et al. (2019)	Malaysia	6	–	DT	–	81%
Bui et al. (2020)	Iran	10	BA-RT	–	94%	–
Jia Uddin (2021)	Bangladesh	9	PCR	GBC	95%	100%
Proposed model	India	6	CNN	VGG19	97.65 %	100%

Performance comparison with other studies

It is clear that the PCR and GBC techniques have outperformed the earlier models developed in terms of WQI prediction and classification. These models comprised hybrid (SDA-ANN, BA-RT), deep neural network (NN, MLP), and standalone machine learning (SVR, GB, DT). The maximum accuracy was found by Bui et al. (2020; accuracy = 94%). But they had not provided a model for classification. Yilma et al. (2018) and Wang et al. (2017) achieved 92% and 93% prediction accuracy, respectively, using support vector regression and artificial neural networks. However, since the majority of the water specimens were studied in laboratories, those approaches required 12 and 22 water specimens, which may be seen as costly. Furthermore, Samsudin et al. (2019), Ahmed et al. (2019), and Ho et al. (2019) used fewer water specimens in their WQI classifications and forecasts. But the accuracy of their model is less than 85%. In this experiment, utilizing just six water specimens, the recommended models demonstrated 100% classification accuracy and 97.65% prediction accuracy, in contrast to the previous techniques.

VI COCLUSION

We propose to use VGG-19 for water picture classification, which dynamically modifies the context of channel-wise and multi-layer features to enhance feature maps. During the construction process, we first propose a channel-wise attention gate, which we subsequently employ to construct a hierarchical attention model. We performed comparative experiments with many prior studies utilizing an image dataset of the water's surface, showcasing the special ability of the proposed attention neural network to classify photos of water. With a 97.65% accuracy rate, the model outperforms the present standard.

VII FUTURESCOPE

CNNs have several more possible uses in the water treatment industry in addition to these particular examples. CNNs, for instance, might be utilised for:
Determine and categorise water pipe leaks
Observe the infrastructure for water treatment.
Create models that forecast water quality.

CNNs have a bright future ahead of them in the water treatment industry, and they will be crucial to its evolution. CNNs may contribute to ensuring that everyone has access to safe and clean water by providing water treatment specialists with up-to-date data and insights.

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