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# IoT-Based Aquatic Pollution Monitoring using Convolutional Neural Networks

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***Abstract: The continuously decreasing quality of drinking water is of great concern across the globe. Due to the incessant mixing of unprocessed industrial and domestic wastes, the contamination rate of water is rapidly increasing.The contaminations are of physical, organic, and chemical nature. Owing to this rise in pollution, the idea proposed is to build a model equipped with a visual device such as a camera, and other sensors, that by means of floating on water, can constantly monitorthe water body. Using techniques of computer vision, floating or other debris is detected on the surface of water. The use of sensors can help to keep in check the physical as well as the chemical parameters of water. Conditions like temperature, pH, turbidity, conductivity etcetera can be used either directly or indirectly to judge the overall quality of water.The optical device captures real-time images and a debris detection algorithm using Convolutional Neural Network (CNN) sends vital measurements to the user. The processed dataafter converting intoa user-understandable format can be used to get a general idea of whether the water is safe for consumption, that is, to determine whether it is potable or could be made potable by some treatment. Secondly, it could be used to monitor the balance in marine ecosystems.***

***Keywords: Water Monitoring, Computer Vision, Deep Learning, CNN, Aquatic Pollution, IoT, Image Processing***

## I. INTRODUCTION

Aquatic Debris is essentially any form of waste found in water bodies that contributes negatively to the health of a marine ecosystem. It is no secret that most of our sources of water are highly polluted – most people are aware of this fact. However, the extent of this damage remains largely unknown to the majority. It is estimated that about 1.2 billion people in the world are forced to drink water that is of poorer quality than that used in the toilet of an average urban home. Such is the plight of those individuals, and it all roots from one major issue – human activities that foul these bodies of water without giving thought to the damage trail that is left behind by their actions. Extensive damage has been done to water sources by artificial sources - with civilization mostly responsible for the same.

More effort is needed in undoing whatever damage has been caused to these natural sources in the past, and hence, this project seems befitting in the current scenario. The scope is not just restricted to whether the water is potable either. Depending on the context and the region of use, the device may be used to ensure that the water quality is always suitable for the marine ecosystems as well. The versatility of the project enables the model to be deployed for more purposes than one.

The underlying concept of the undertaken project is the creation of a device, capable of being deployed in water, which keeps the user informed of the current level of pollution in the area where it is situated. The device will consist of a mounted camera module and other sensors to measure and inform the user about the water quality in its current location. Sensors are employed to aid in the task of image processing as well as geolocating the device. A durable floating model is devised in which the optical sensor is to be mounted in such a way that it periodically captures the images of the water body that will be used for further analysis.

The pollution level in the water can be categorized into two types in the context of this project. The first is the debris which can be detected visually by virtue of its size and the fact that it floats on the surface of water. This waste is detected by using the camera module. The second type would be the pollutants that go undetected by just looking at the water body that is under consideration.

Additional sensors to the device will enable it to monitor parameters that the optical device cannot monitor by visual means such as the temperature of water or its pH. All these modules integrated together could provide a wholesome idea about the quality of water in a region. To sum up, debris that is not detected by chemical devices, such as plastics, are spotted visually. Likewise, the parameters not detectable by visual means are taken care of by the other sensors.

Finally, a network device sends this data to a receiver that uses the data to carry out the tasks of judging the suitability of the water source. Results may be in raw form consisting of current parameters of the water body. Using intelligent algorithms, it may be possible to provide suggestions in the form of actions that may be taken to improve the situation in the region of measurement.

## II. LITERATURE REVIEW

In this section, we briefly explain various practical approaches and classification methodologies available for analyzing the water quality.As the trend moves towards Artificial Intelligence based solutions in every field of life,likewise during the last decade, tremendous research has been noticed for water quality monitoring. In [9]recently, motivated by the remarkable success of deep learning, convolutional neural networks (CNNs) have been applied to analyze river images into classes as ‘Muddy’ and ‘Clear’. [15]proposes an Internet of Things (IoT) based water quality systemcapable of measuring the quality of water in near real-time. The hardware solutionsends data to the cloud for real-time storage and processing.They used four machine learning algorithmsincluding Support Vector Machine (SVM), k Nearest Neighbor (kNN), single-layer neural network and deep neuralnetwork for classification of water qualityand experimental results revealed that deep neural networkoutperforms all other algorithms with an accuracy of 93%.

Yu Wang et al. [8] proposed the use of a Horizon-based Image Registration for detecting the presence of waste in a water body. This works by aligning images taken at different time instants into one coordinate system. This was necessary to counter the shaking caused by waves. Foreground pixels are used as initial seed points and connected to represent the candidate debris objects. A threshold-based approach is used to distinguish objects based on their activity speeds. The results returned were complicated by the dynamic task offloading which performs part of the estimations in situ and part by uploading to the cloud.

Yong Wang et al. in [4] put forward the idea of using Block-based Compressive Sensing for floating debris detection. In this method, first, image frames are captured by the camera module and then they are reconstructed in sequence based on block-based compressive sensing. A strategy called adaptive block size is used. It means that the size of the image is determined automatically according to the environmental disturbances. Compressive reconstruction reduces the dimensions of the image while retaining most information. Then, motion detection is performed on these reconstructed frames. This serves as a method for floating debris detection to check moving objects. This is the first floating debris detection. Once the existence of moving objects is confirmed, the next detection is carried out to realize the continuous tracking of the contaminants in dynamic waters.The method is effective, but accuracy can be further improved by using CNN.

## III.PROPOSED SYSTEM

### *A. Sensors*

To detect the presence of chemical impurities like industrial effluents, chemical sensors are needed. By using these sensors, the presence of impurities can be inferred by indirect means. Water parameters need to be estimated and analysed on the basis of prediction or alarm threshold models with respect to (World Health Organization) WHO standards for each parameter [1][3].

1) *pH Sensor:* pH is an important limiting chemical factor for aquatic life. Streams generally have pH values ranging between 6.5 and 8.5, depending upon the presenceof dissolved substances that come from bedrock, soils and other materials in the watershed. pH shows the concentration of hydrogen ions in water [2].
2) *Turbidity Sensor:* Increased levels of turbidity raises water temperature as heat is absorbed by suspended particles. Incidentally, the dissolved oxygen content of water decreases resulting in loss of water quality. Monitoring the degree of water transparency is crucial to an aquatic system.
3) *Temperature Sensor:* Temperature is a key factor in water chemistry. Temperature affects the dissolved oxygen levels in water, the rate of photosynthesis and metabolic rates of organisms. Aquatic organisms depend on particular temperatureranges for their health.
4) *Conductivity Sensor:* The measurement of specific conductivity in aqueous solutions is important for the determination of metallic impurities in water. The presence of heavy metals in water is critical to the marine life of a system. Mercury and other metals are poisonous even in small concentrations.

TABLE I
WATER PARAMETER SAFE RANGES

| SR.NO. | PARAMETERS | RANGES |
|---|---|---|
| **1** | pH | 6.5 to 8.5 |
| **2** | Turbidity | 0 to 5 NTU |
| **3** | Conductivity | 2000 cm |

### *B. Camera Module*

In [4], the problemwith solely using sensors in a wireless sensor network is that it is difficult to analyse water quality just by using statistical and threshold comparison models. The approach may tell us about 'what we can't see' in the water but fails to report 'what we can see' i.e. the floating debris which at times may be present in remote areas of the water body. This floating debris is also those pollutants that lead to changes in water quality and detecting them is also important. The approach specified [4] fails to report such waste and therefore, we find a need for better or modified contamination detection means.

The camera sensor captures images and interprets data using a suitable method that will be discussed in a later section. This interpreted data is passed on to a sensing platform along with the position parameters from GPS in Raspberry Pi 3 to the control console in the cloud, which analyses the data and shows the presence of floating debris at a particular location.

### *C. GPS Module*

GPS Module for Raspberry Pi is a small electronic circuit that allows you to connect to your Raspberry Pi board to get position and altitude, as well as speed, date and time on UTC (Universal Time Coordinated). This is essential to know the exact location of the debris in the region where it is detected. Since the flow of the water body could contribute to the change in the position of the waste the exact time and location at which it is detected by the device is critical.

### *D. Prototype*

The paper by Laut J et al. [5] proposes the idea of an Unmanned Surface Vehicle (USV) for capturing images and video on the surface of the water. This approach is helpful in detecting the debris while reducing the costs compared to an autonomous underwater vehicle[6] which costs about $70000 per unit. The drawbacks of this paper are that the USV is very large in size which makes it difficult to control and deploy. Also, the literature stresses more on the USV rather than the image acquisition algorithms. The algorithm employed by the authors has a high computational complexity.The high computational complexity algorithm indicates that there is little attention given to resources and there is no resourceconstraint as such which makes this approach expensive.

Fig. 1Prototype selected [7]

Yong Wang et al. [7]proposed the following model whose main body, which is the carrier, is a buoy box made up of waterproof foam board.This contains the sensing platform. Customized node components: Raspberry Pi 3 which includes a 64-bit ARMv8 processor with a maximum speed of 1.2 GHz. It also has a built-in Wi-Fi and Bluetooth facility and an external SIM808 module which helps realizes remote communication based on GPRS. A 16-G micro SD card is also present which is used to store the Operating system for the Raspberry Pi and all the data including images, detection results and other information from various sensors.The camera adopts OV5647, a small-sized low power 5-megapixel CMOS image sensor that supports video and snapshot operations. It also provides a programmable resolution.The main control board is responsible for signal sensing, processing and motion control of aquatic sensor nodes. Sensors like pH, turbidity, dissolved oxygen, temperature, etc. and GPS may be connected to the board.

For powering the platform, a 12V lithium battery is used for the propulsion system. In the case of long-term deployment of the device, a 520x420mm monocrystalline silicon solar panel is used which is mounted on the top of the device. The battery pack is connected to the solar panel for re-charging through a power regulator that controls and protects the battery from overcharge or over-discharge. The battery capacity is 8400mAh.

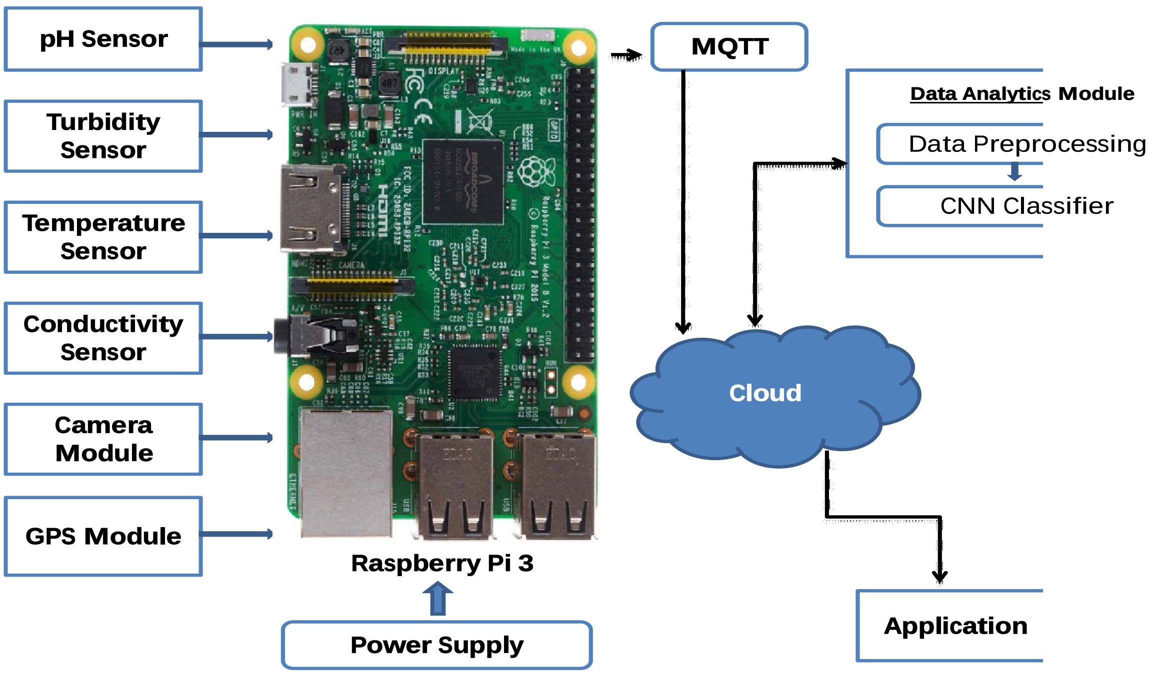


Fig. 2 Proposed Architecture

*E. Workflow*

The proposed device consists of 4 sensors that detect the non-visual parameters of the water body in the region it is deployed. The sensors are immersed in water and constantly send the raw data to the Raspberry Pi. The Camera Module is an integral component of the system. The image processing aspects of the proposed device start at the camera module. The optical device captures images in real-time. The data from the 4 sensors and the camera module are bundled together with the GPS data obtained from the GPS module.The device is powered by means of a solar panel mounted on top of the buoy that is connected to a 12V Lithium battery that ensures that the device is capable of functioning for a long duration.

MQTT protocol is apublish-subscribe based protocol. The published data is in JSON format. A program file resides at Cloud that subscribes to the topic on the MQTT server to obtain published data. The sensor data obtained from the MQTT server is in JSON format. The Pi camera can be controlled using a Python script. Once the image is taken, encode the image as Base64, then split it into segments to publish.

Using this MQTT protocol, the data is pushed to the cloud. The suggested cloud service provider is Amazon Web Services (AWS). AWS's Internet of Things Applications and Solutions provides a platform for IoT data computation and storage. It provides the public key, private key and the certificate for authentication of the MQTT protocol. The Raspberry Pi module can be connected with MQTT by using Node-RED platform.

*F. Classification Methodology:Convolutional Neural Networks (CNN)*

A convolutional neural network (CNN) is a specific type of artificial neural network that uses perceptrons, a machine learning unit algorithm, for supervised learning, to analyse data.Like other kinds of artificial neural networks, a convolutional neural network has an input layer, an output layer, and various hidden layers. Some of these layers are convolutional, using a mathematical model to pass on results to successive layers. This simulates some of the actions in the human visual cortex.CNN image classifications take an input image (here in our case image related to water bodies), process it and classify water quality under certain categories. Computers see an input image as an array of pixels, and it depends on the image resolution. Based on the image resolution, it will see h x w x d (h = Height, w = Width, d = Dimension).E.g., An image of 28 x 28 x 3 array of matrix of RGB (3 refers to RGB values). Each input image will pass through a series of convolution layers with filters (kernels), pooling, fully connected layers (FC) and apply Softmax function to classify an object with probabilistic values between 0 and 1.

We need to apply pre-processing to estimate water quality accurately. Images of rivers contain different regions such as grass, sand, sky, and tree. These regions often produce worse results of water quality estimation and these are easily removed using semantic segmentation methods. Hence, we apply pre-processing before training of CNNs using a semantic segmentation methodwith better result accuracy.Semantic segmentation is a natural step in the progression from coarse to fine inference. The origin could be located at classification, which consists of making a prediction for a whole input. The next step is localization detection, which provides not only the classes but also additional information regarding the spatial location of those classes. Finally, semantic segmentation achieves fine-grained inference by making dense predictions inferring labels for every pixel so that each pixel is labelled with the class of its enclosing object or region [9][10].

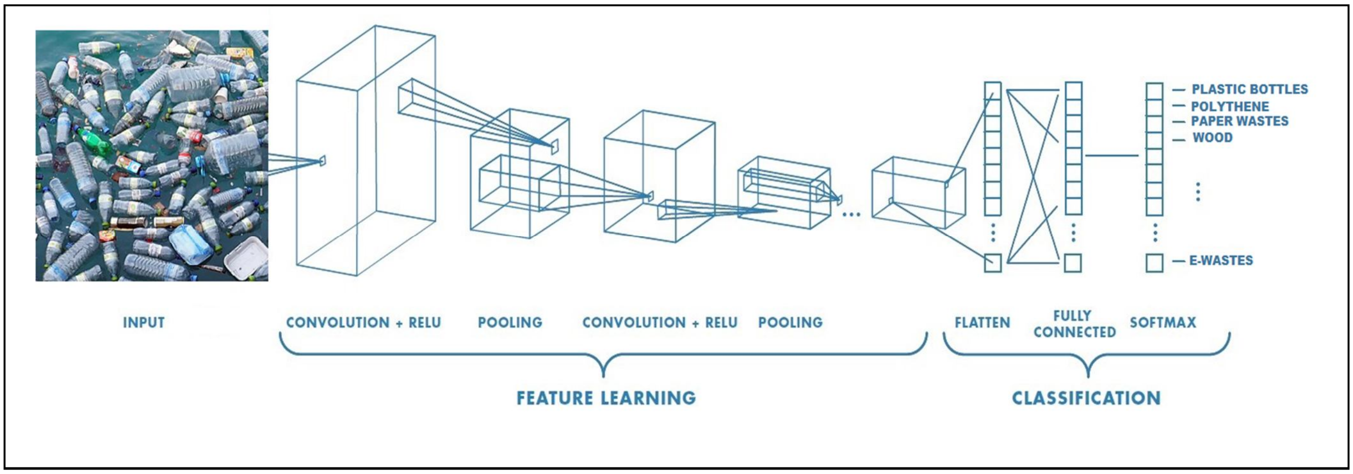


Fig. 3 Proposed CNN Architecture

## IV. FEASIBILITY

The proposal is technically feasible as the main tools and technologies associated with the project are readily available. Each of the tools is freely available except for the AWS Cloud Platform and the Raspberry Pi. The technical skills required to use these technologies are manageable. The time limitations of the product development and the ease of implementing using these technologies are synchronized.

The main body of the device should be designed in a cost-effective manner such that it will include the Raspberry Pi, the sensors and the camera module and yet will be able to fulfil its basic function of floating on the water surface. The body will be designed in such a way that the weight of the water it displaces will be equal to its weight, which, according to Archimedes' Principle will theoretically make the device float in water. The major cost incurred during the project will be for the various sensors employed in the device and the main camera module. At the initial stage, the potential market space will be lakes and rivers.

## V. CONCLUSION

In this paper, we proposed an IoT based solution to monitor the water quality in real-time after reviewing and analyzing the drawbacks in various pieces of literature. Owing to the emerging water crisis, there is a dire need for systems to measure water quality. The deep multi-layered neural network (CNN) has been applied for the classification of floating debris into different classes with improved results. The proposed model counters the drawbacks in the current methods of monitoring water quality and presents a comprehensive point of view for combating aquatic pollution. There is scope for improvement in the existing systems and hopefully, this paper will be useful in constructing a suitable model free from most of the drawbacks.

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