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Determine Water Turbidity by Using Image Processing Technology

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Abstract*:* The current study includes the measurement of water turbidity using image processing technology, as this technology is one of the most promising modern technologies due to the development in the field of imaging devices, the possibility of communication with various modern devices among themselves. In this study uses a deep learning method through an image-based convolutional neural network (CNN) to estimate water turbidity. In this way, samples of different values of water turbidity were prepared, which were measured in the laboratory by one of the devices specialized in turbidity in the laboratory, and then they were photographed in a suitable way for the purpose of entering them into the network. The network was created using Python programming, which is easily downloaded and using the (Colab Google) platform. After preparing a program for five levels of turbidity and testing its success, the results of the proposed system were compared with the results of the turbidity scale. The results showed that the performance of the proposed method by adopting five groups of turbidity degrees is good. The categories of water turbidity were detected with an accuracy of 91.6% only due to the accuracy of the imaging as well as the number of images entered.

Keywords: *Image processing, Water turbidity, Fresh*

1. Introduction

Turbidity is the cloudiness of the liquid due to the large numbers of particles in it, which are either visible or invisible to the naked eye. Turbidity is measured with a special test to determine the water quality, as it is measured in NTU, which is the unit of measurement of turbidity. For pure water it should be less than 5 NTU. The highest value is NTY 1000 for highly turbid water.

The process of monitoring and evaluating water quality is one of the modern and ongoing fields of research, as this field has witnessed clear development over the past two decades.

In today's world, measuring the turbidity of domestic water supplies has become very important, because the water treatment and purification process can be affected by turbidity. Turbidity may cause many problems if it is not taken into account, for example, it affects filters and prevents them from working effectively, filling tanks and pipes with mud and silt, stopping valves and taps from working, etc. are the harmful effects of high turbidity. While the low turbidity prevents the chlorine from killing germs in the water efficiently during chlorination. Hence, turbidity detection is of great significance for environmental protection, aquatic ecosystems, and drinking water safety

Due to the amount of water consumed by filtration plants and water treatment plants, there is an urgent need to improve monitoring and control procedures for the operation of these plants, to be able to improve procedures to work appropriately for the most extreme operating conditions and worst cases.

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With the great development of the computer, specifically in the field of image processing, as it has become one of the most widely used fields of artificial intelligence at the present time, where many technologies related to speed, identification and positioning, recognition of faces, vehicles, plant quality, etc. have been developed, and this technology has been applied in monitoring water quality, such as the detection of chlorophyll and the oxidizing agent. The determination of turbidity based on computer applications is not only useful for research and protection of the aquatic environment, but also plays an important role in the environmental awareness of citizens.

Computer vision technology has made great progress in practice in recent years, and it also as broad application prospects in turbidity detection. A recent paper proposed a system for measuring water turbidity using digital image processing of water samples. After taking pictures of them, the images are optically enhanced and filtered before being converted to grayscale images. Results obtained after comparison of the histogram values of grayscale images of water samples with NTU values determined by standard laboratory procedures [3].

In another study, a real-time monitoring system consisting of a video camera, a personal computer, an image processing unit, and software was developed and tested to monitor the distribution of turbid water. The test results show that it is possible to monitor the distribution of turbid water and estimate the turbidity value [4].

Another research adopted a new automated system for estimating the turbidity of liquids. Visualization of effluent samples through the property of light absorption as a function of the depth of the liquid. Computer vision processing techniques are used to determine the turbidity of this property [6].

This study presents a solution to the problem of measuring turbidity in terms of using a new technique to determine the degree of turbidity, by using water samples of different degrees of turbidity for study and defining their data visually. The based on the principles of artificial intelligence, more specifically in operating blocks and several layer of neurons that work together to mimic the functioning of the visual cortex of mammals, which are called convolutional neuronal networks (CNNs).

2. Turbidity Measuring

One of the preferred methods of testing water for turbidity is to use a turbidity meter, or a turbidity meter and probe. The turbidity probe works by sending a beam of light into the water to be tested. This light will then be scattered by any suspended particles. A light detector is (usually) placed at a 90-degree angle to the light source, and detects the amount of light that is reflecting off it. The amount of reflected light is used to determine the particle density within the water. The lighter detected, the more molecules there are in the water.

2.1. Units of Turbidity Measurement

- Nephelometric Turbidity Unit (NTU): scattered light from the sample at a 90-degree angle from the incident light.
- Formazine nephelometric unit (FNU) scattered light from the sample at a 90-degree angle from the incident light
- Formazine attenuation unit (FAU) – transmitted light through the sample at an angle of 180 degrees to the incident light.
- Formazine Turbidity Unit (FTU) – as the primary reference standard for turbidity

2.2. Systems of Determining Turbidity

Two basic functions are needed which are as follows.

1- Analog/digital conversion of video images: The images are processed to extract the turbid water distribution digitally in real time.

2- Converting the digital image data into a turbidity value: The degree of influence of turbidity is evaluated according to the turbidity.

3. Proposed Theoretical System

3.1. Convolutional Neural Networks

The Convolutional Neural Network (CNN or Convent) is a subtype of Neural Networks that is mainly used for applications in image and speech recognition [10].

The term convolutional network (CNN) is used to describe an architecture for applying neural networks to two-dimensional arrays. Figure (1) shows the architecture of a CNN with two layers of convolution weights and one output processing layer. Neural weights in the convolution layers are arranged in 2-D filter matrices, and convolved with the preceding array [11].

Inside convolutional neural networks

1- Artificial Neural Networks (ANNs) are an essential component of deep learning algorithms.

2- Recurrent Neural Network (RNN) which uses sequential or temporal data as input.

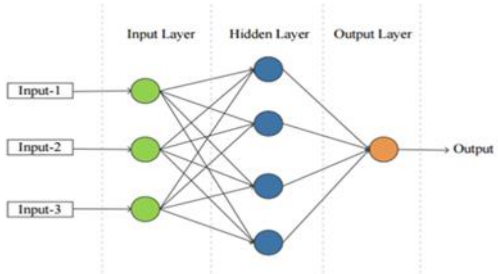


Fig 1. Architecture of a CNN with a single convolutional neuron in two layers.

3.2. Deep learning Mechanism

Deep learning is a part of machine learning that uses multiple layers to process special signals such as sound or images. In this way, the computer turns a complex concept into a simple one, and when the process continues, we get the basic concepts that allow the computer to make decisions directly [7,8]. Figure (2) shows the mechanism of deep learning.

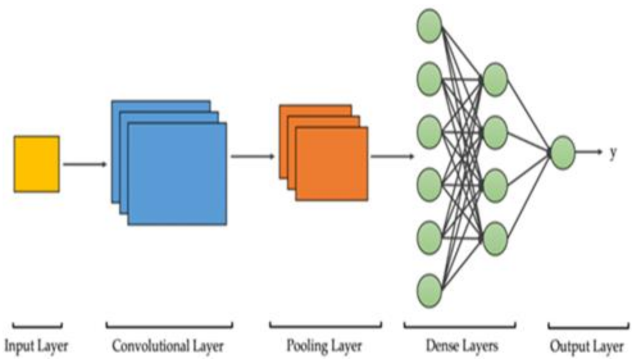


Fig 2. Architecture of a Mechanism of Deep Learning.

4. Proposed Experimental Method

4.1. Preparation of Datasets

In the proposed method, we take several images for each sample of water whose turbidity has been examined previously, where (30 samples with different degrees of turbidity starting from 9 NTU up to 950 NTU) were prepared and the examination was performed using the "Lovaione" shown in figure (3) for the purpose of establishing a rule data for images (creating an image datasets) [9].

Fig 3. Image of Turbidity Meter

Image of the samples was taken using a standard quartz beaker with the use of a standard blue background at a distance from the breaker with diffused white light shining at a certain height to avoid shadows and using a modern mobile phone equipped with a 12-pixel camera installed on a special holder to avoid movement and vibration when taking photos

and a specific distance from the beaker which containing the water samples. The selection of the blue color behind the samples when photographed was chosen to compare the change in it when the turbidity increased in the water samples when photographed, as shown in Figure (4).

Fig 4. Image of experimental sample photos

4.2. Preprocessing for Dataset

The study relied mainly on sand dunes found in river water, and to obtain accurate results, sand dunes were used and mixed with water samples in different proportions to obtain samples of varying degrees of turbidity, thirty liquid samples were prepared figure (5).

Fig 5. Image of samples used

The degree of turbidity of these samples was measured in the laboratory by using a turbidity measuring device to determine the degree of turbidity for all samples and to obtain varying degrees in proportional degrees, this is organized by selecting some samples and re-mixing them to reach the degrees of turbidity of the samples [8] as shown in Table (1)

Table 2. Units for magnetic properties

Sample	**1**	**2**	**3**	**4**	**5**	**6**
NPT	**9**	**16**	**20**	**28**	**35**	**46**
Sample	**7**	**8**	**9**	**10**	**11**	**12**
NPT	**50**	**65**	**71**	**85**	**95**	**122**
Sample	**13**	**14**	**15**	**16**	**17**	**18**
NPT	**172**	**210**	**265**	**281**	**313**	**334**
Sample	**19**	**20**	**21**	**22**	**23**	**24**
NPT	**389**	**416**	**473**	**492**	**654**	**687**
Sample	**25**	**26**	**27**	**28**	**29**	**30**
NPT	**707**	**734**	**782**	**860**	**923**	**965**

4.2.1. Increase the Dataset

To obtain successful results from processing requires huge amounts of data to ensure that neural networks work with great practice [9]. The arrangement of the images used in learning may be insufficient or unbalanced. Reproduction is performed in the dataset in order to enhance the rate of incomplete evidence used in learning.

Additional data for the training dataset is generated via the copy data method. This is done in several ways, including rotation, scaling, and others. In this study, we use a variety of rotation angle that is arbitrary within a spectrum of 0 angle and a given another angle.

4.2.2. Dataset Implementation

The architecture consists of four basic layers: (Conv2D layer, MaxPool2D layer, Flattening layer, and Dense layer). The function layer consists of two layers, the Relu layer and the softmax layer. After processing the images consisting of (pre-processing, segmentation, feature extraction, and cracking) as shown in Figure (6). This section will explain the steps for creating the proposed architecture, including mentioning the libraries on which the architecture is based. In order to classify turbidity, a dense convolutional neural network (CNN) architecture model was constructed.

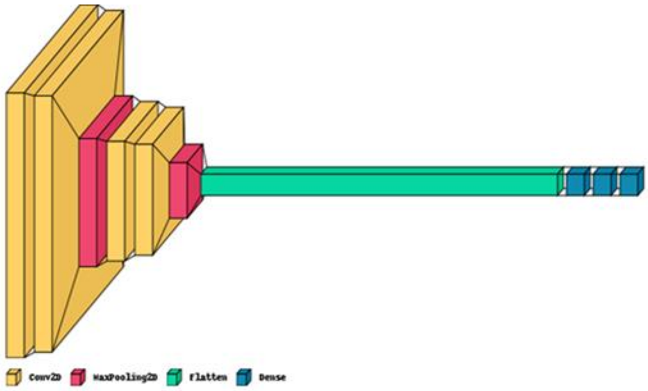


Fig 6. Shows proposed model for detection of turbidity

The first phase is building and organizing the base layers, followed by testing the series of training steps, activation functions, and finally introducing the optimizer to the model. Activation functions reach a maximum value of (0, x) where they will return x only if the relationship between x and 0 is greater than 0 and then this function returns 0 if it is not called.

When filters are applied to the input matrix, the spatial volume of the output volume shrinks. The output size will shrink as more convolutional layers are applied. It is sometimes preferable to keep as much data as possible from the source input matrix. As a result, the focus is kept on the output size as frequently as the input size as shown in Figure (7).

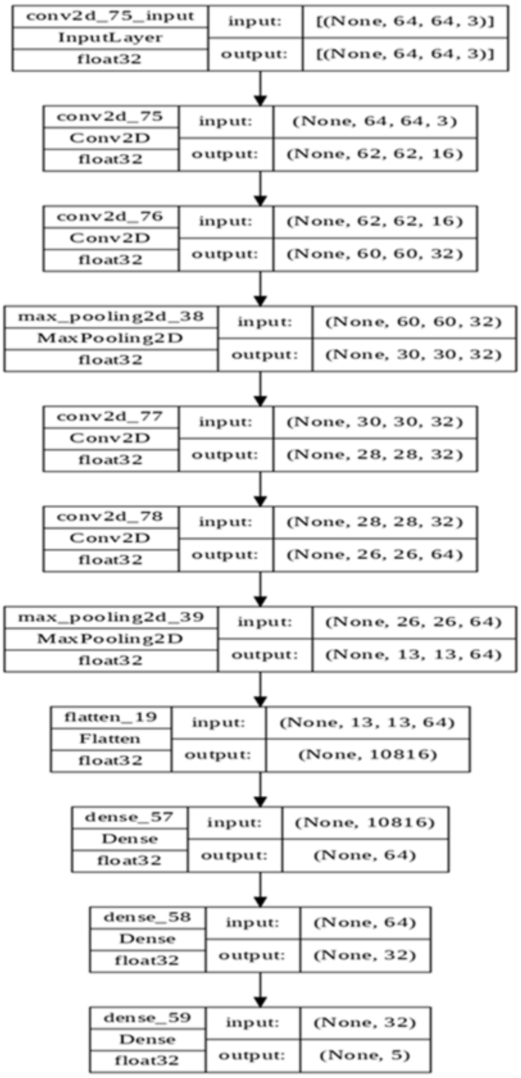
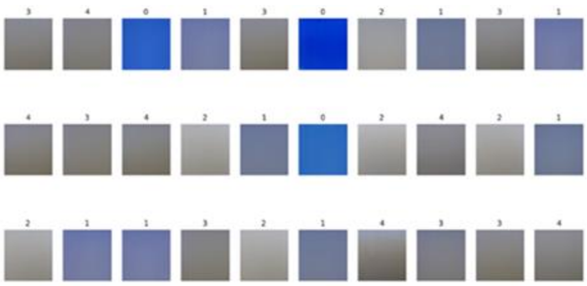


Figure (7): Shows a Processing the Images

5. Result and Discussion

In this section, the models were divided into five groups close in terms of color spectrum, and each group contains the same number of images to ensure that the code works correctly. The figure (8) shows the acceptance of input and random recall of images from the models



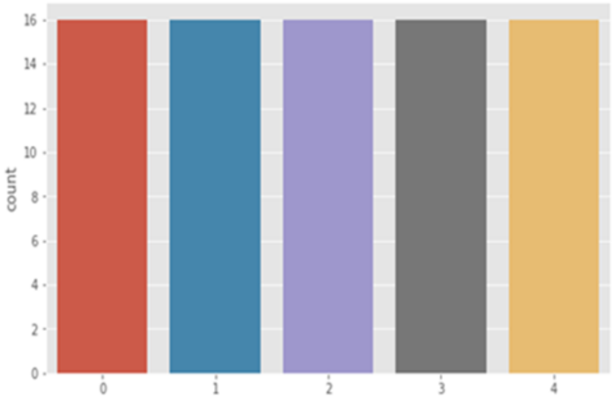


Fig 8. Images After Data Augmentation.

The measurement of accounts using the confusion matrix application, which has four indicators, is presented. True positive (TP), false positive (FP), false negative (FN), and true negative (TN) values are assigned to the indices. By applying the mentioned equations in Table (2), we were able to derive the final values of the classification. Table (3) shows all the equations that were used with a simplified definition [10].

Table 2: The Performance Measures That Were Employed in This Work, Together with Their Description

Dataset Relation		Description
Accuracy	$\frac{TN+TN}{TN+FP+FN+TN}$	The model's overall accuracy
Sensitivity	$\frac{TP}{TP+FP}$	The model's ability to anticipate the true positives of each given class
Specificity	$\frac{TN}{TP+FP}$	The model's ability to anticipate the true negatives of each given class
Precision	$\frac{TP}{TP+FP}$	The number of true positives with false positive

The results of all datasets were represented by four plots (confusion matrix, training test accuracy, loss accuracy, and ROC). The results of applying the proposed model and its implementation were presented on datasets. We divided the dataset into 60% for training, 20% for validation, and 20% for testing. The results for accuracy, specificity, sensitivity, accuracy, and receiver operational characteristics (ROC) were presented with a 5 × 5 noise matrix for each dataset.

After testing the Dense-CNN model on the eight datasets, we get in Figure (9) represents the plotted results for testing-training accuracy, the Figure (10) represents the plotted results for testing training loss and Figure (11) represents the confusion matrix for datasets used.

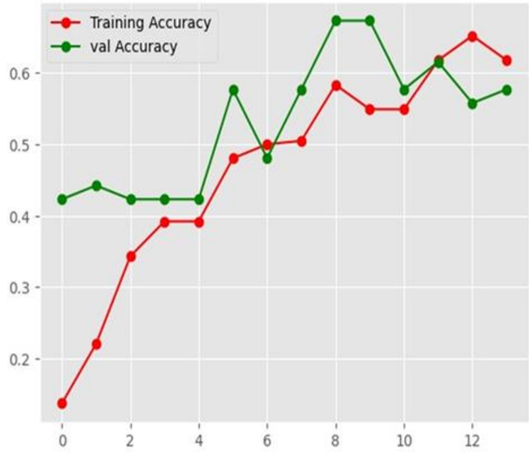


Fig 9. Shows the testing-training accuracy

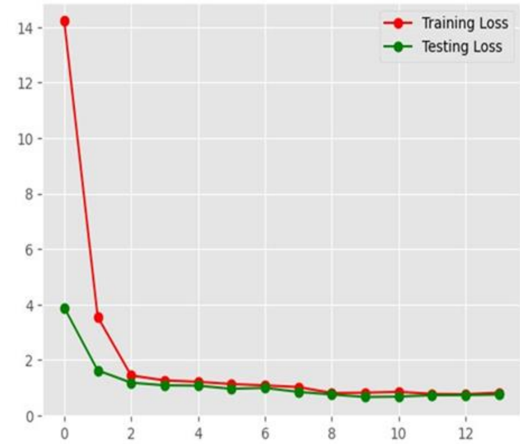


Fig 10. Shows the confusion matrix for the datasets used

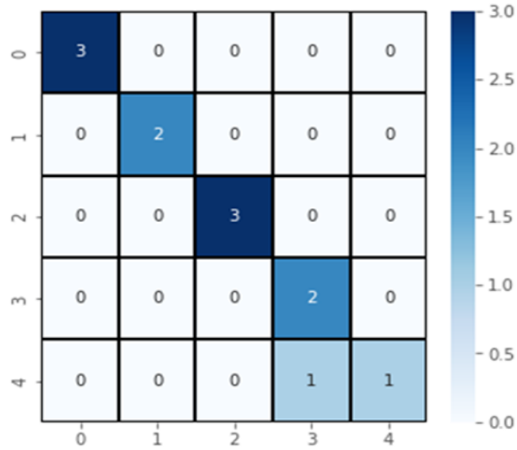


Fig 11. Shows the confusion matrix for the datasets used

The results of relevant studies dealing with the determination of turbidity degrees by applying them to a variety of models as well as a variety of datasets. Here we try to focus mainly on studies that dealt with the implementation of neural networks in all their models. We believe that comparing the results of the CNN used in previous studies and our own, will give more reliable results. Through the results, it is clear to us that our model has achieved results of accuracy, specificity, sensitivity, and accuracy that are much better than those of previous studies. The experimental results of the proposed model showed that the accuracy of the model was 91.6% when applying our model to the image data set that was distributed into five groups. We believe that the reason for the good results we obtained is due to several factors:

1- The strength of the model designed to contain several layers of Convolutional neural network-

2- Having three dense layers with RELU activation functions

3- Do not use the transferred learning method because we have created and trained the model.

6. Conclusions and Recommended

A new technique was proposed to identify the degree of turbidity (within specific aggregates) from the images entered in this work. The proposed technique succeeded in determining the turbidity within any group of the five aggregates, where turbidity can be determined within any category of these aggregates. To ensure the development of this work in future studies, we suggest:

1- Using a much larger data set so that the network can be properly trained. Because increasing the number of images entered and adding them to the images of our current work leads to an increase in accuracy.

2- Increasing the number of images enables us to increase the totals to 10 or more, which enables us to increase accuracy in determining the degree of turbidity.

3- Using other conditions that differ from our working conditions, for example, changing the blue color to another color, re-working with the same technology, studying the results and comparing them with our results.

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