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A.T. Sekerbaev

Cyprus International University, Nicosia, Cyprus
(E-mail: sekerbaevarystan2006@gmail.com)

Classification of water transparency (turbidity) by level based on deep learning

Accurate classification of turbidity is essential to maintain water quality in a variety of contexts, from drinking water to industrial processes. Traditional turbidimeters face challenges, including the resistance of colored objects, changes in the shape and size of parts, and the need for constant calibration and maintenance. In this document, a convolutional neural network (CNN) is implemented to classify water samples according to their degree of turbidity. The data set consisted of images taken in laboratory conditions where blur levels were monitored, measured using a 2100p portable turbidimeter. CNN achieved 97.00% classification accuracy in laboratory parameters. When tested on samples of water bodies in the real world, the model retained 85.00% accuracy. The results show that deep learning can effectively classify blur levels, offering a promising solution to overcome the limitations of traditional methods. The study demonstrates the potential of CNN for accurate and effective measurement of turbidity, balancing accuracy and the possibility of practical application in field conditions.

Keywords: water quality, deep learning, accuracy, drinking water quality, blur level detection, image-based analysis.

Introduction

Water quality is a comprehensive term that encompasses the various physical, chemical and biological characteristics of water, defining its suitability for various purposes such as drinking water [1,2], recreational activities [3], agricultural irrigation [4,5] and industrial processes [6]. Water quality assessment involves measuring a number of parameters to understand the presence and concentration of pollutants and the overall health of a water body [7]. Physical characteristics such as temperature, color, smell, taste, and turbidity provide important information about conditions in the aquatic environment. Temperature affects the metabolic rate of aquatic organisms and the solubility of gases, and color can indicate the presence of organic matter, pollutants or minerals. Smell and taste often indicate organic compounds, microbial activity, chemical pollutants, and turbidity affecting light penetration and aquatic ecosystems [8,9,10]. Chemical aspects, including pH, dissolved oxygen (DO), nutrients, heavy metals, and organic compounds, are very important in determining water quality. The pH level indicates the acidity or alkalinity of water, which can affect various biological and chemical processes. DO is very important for the survival of aerobic organisms and low levels often mean pollution. Nutrients such as nitrogen and phosphorus are essential for plant growth, but can lead to eutrophication when in excess. The presence of heavy metals such as lead, mercury and arsenic, even in low concentrations, poses significant health risks. At the same time, organic compounds, including pesticides, herbicides, industrial chemicals, can harm humans and Wildlife [11,12,13,14]. Finally, some biological factors are important indicators of water quality. Bacteria and viruses can pose health risks by expressing fecal contamination and causing disease [15]. Algae blooms, often caused by nutrient pollution, can consume oxygen levels and release toxins that are harmful to aquatic life.

The physical characteristic of opacity is the cloudiness or opacity of a liquid due to many particles that are usually invisible to the naked eye [7]. Lameness is measured using turbidimeters that estimate the amount of light scattered at an angle of 90 degrees to the incident light [16]. These particles scatter and absorb light, reducing the transparency of the liquid. The measurement process involves several steps. First, usually a beam of light from an LED or laser is directed through the sample with a wavelength selected according to the size and type of particles expected in the sample. The liquid sample is placed in a transparent container called a cuvette, allowing light to pass through it. As light moves through the sample, it interacts with the suspended particles, causing scattering, which is measured by detectors located at different angles, usually 90 degrees to the incident light. The intensity of scattered light directly proportional to the turbidity of the sample is converted by turbidimetric electronics to the turbidity value, which is usually expressed in Nephelometric Turbidity units (NTU) or formazine Nephelometric units (FNU). These steps require knowledge and training in the use of turbidimeters. In addition, the measurement of blur faces many difficulties. The interference of colored objects in water can absorb incident light, making it difficult to underestimate blur and accurate readings in color or painted samples [17]. The assumption of uniform particle sizes and shapes increases the complexity, as natural samples often contain different particles that scatter light differently, causing discrepancies and inaccuracies in readings [18]. Turbidimeters also require periodic calibration with standards such as formazan and meticulous cuvettes and maintenance of optical components to ensure accuracy, which can be time-consuming and expensive. Moreover, the detection range of these meters is limited; very high particle concentrations can cause many scattering events, leading to nonlinear responses and inaccurate readings at high blur levels. External factors such as ambient light, temperature fluctuations and vibration can interfere with the measurements, which requires appropriate shielding and environmental monitoring to obtain reliable data.

Metodology

High accuracy in the assessment of turbidity is crucial for maintaining healthy aquatic ecosystems and ensuring safe drinking water. Advances in machine learning provide promising solutions to improve the accuracy and efficiency of blur measurement, to address traditional challenges and limitations in this important area. For example, the regression model achieved 91.23% accuracy in the range of 0.02 - 60 NTU with RGB sensors for бұлың 2 blur. However, environmental factors such as temperature, light, and pH can affect sensor performance, introducing measurement variability [22]. This system requires careful calibration and testing to maintain accuracy, which is time-consuming and resource-intensive. In contrast, the recursive neural network (RNN2) model, using underwater sensors and UAV image data, achieves a prediction accuracy of 94.10% for Blur values from Qingtan Weir in Taiwan [23]. However, UAV operations are sensitive to weather conditions, which can affect the stability of data collection. The gradient amplification Solution Tree (GBDT) model shows 88.00% accuracy in the range of 0.94 to 103.43 NTU, but requires careful adjustment of hyperparameters and a significant amount of training data to achieve high accuracy [24]. The transfer learning method achieved a classification accuracy of 96.86% with the risk of over-docking that could compromise performance with new data [25]. The self-organizing multi-channel deep learning system (SMDLS) for monitoring river turbidity, evaluated in a comprehensive data set from nine locations over a year, increases accuracy by about 14.27% compared to other models based on psnr, MSE and NMGE metrics [26]. However, its computational efficiency is limited due to the need to train seven subnets and combine their results. For measurements of turbidity and total suspended solids (TSS), the CNN implementation achieved an accuracy of 98.24% for TSS and 97.20% for turbidity through the use of white light; however, it is very important to accurately control the lighting distance and camera position, which can be difficult in field conditions without special equipment [27]. In addition, a study used by CNN to accurately classify the turbidity of water samples containing a relatively small data set of 200 images achieved a total accuracy of 97.5% in classifying the turbidity from 0 to 250 NTU, noting the need for a larger data set to increase the generalization accuracy of the model [28].

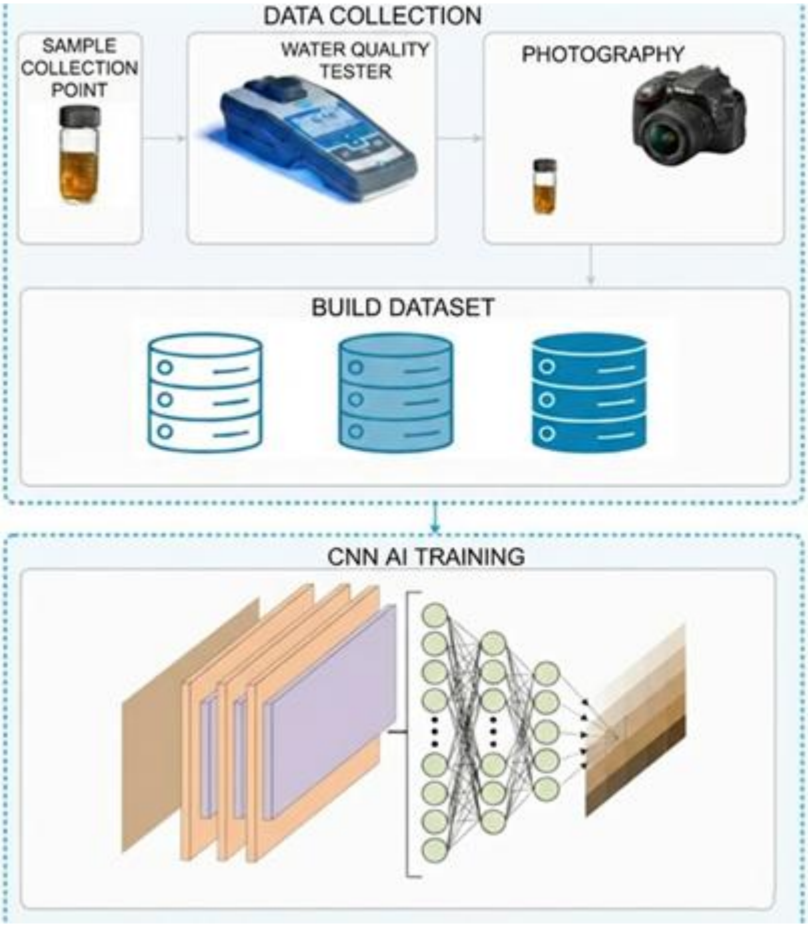

Figure 1. CNN opacity classification methodology review

This document describes the result of a comprehensively adapted data set for CNN training. The data set is carefully balanced to ensure that the samples are evenly distributed in five different classes. Each image has been carefully selected to be clear and noise-free with precise marking to provide high-quality reading data for CNN. Each sample is associated with a specific NTU value, which is accurately measured using a turbidimeter. The novelty of this study lies in its simple classification process, which requires low computing resources due to the characteristics of the presented CNN and data sets. Unlike previous studies, this study collects water samples with NTU values ranging from 200 to 800 and achieves high accuracy in their classification. The images were taken by experimental setup to reduce external interference and ensure correct classification, as shown in Figure 1. Although simple, this installation is very important to achieve reliable results. The classification process achieves an impressive 97.00% accuracy of turbidity classification, indicating the ability of this approach to accurately select classes in muddy water applications.

Research results

CNN's performance in real conditions remains competitive compared to other samples in the literature, a test bench and calibration method were used for classification, an accuracy of 91.23% was achieved with the K-nearest neighbor classifier, indicating the importance of controlled experimental conditions for reliable results. Along with higher R-square values of 20.89 during training and 36.11 during testing, 99.30% for training and 94.10% for testing, Sentinel-2 demonstrates significant predictive accuracy despite its own complexity and computational demands aimed at obtaining data through the correct processing of satellite images and the removal steps of pre-cloud provision images, atmospheric effects. This made it possible to collect accurate spectral reflection data, which is important for reliable blur assessment. On the other hand, it relied on a large river turbidity control dataset containing 11,681 data points from nine registered locations during the year, which improved accuracy by 14.27% over other models, even though it faced computational inefficiency due to the large amount of data and processing requirements. Finally, using the CNN architecture

(AlexNet) in a data set that uses liquid samples illuminated by LEDs and recorded by a smartphone camera, it has achieved an accuracy of 97.20%, taking advantage of different lighting conditions and the ability to take high-quality pictures. In contrast, the proposed CNN achieves an accuracy of 97.00% with a simple classification process and a carefully balanced data set that includes actual NTU values of 200 to 800, indicating a demand for low computing resources while maintaining high accuracy. The controlled experimental setup highlighted the ability to effectively and accurately classify blur in practical applications, reducing external interference.

In light of the above analysis, this study demonstrates the effectiveness and practicality of the proposed CNN in various parameters, highlighting its competitive advantage and potential for real-world applications in blur estimation.

Conclusion

The proposed CNN demonstrates competitive performance compared to other models in the literature, such as RGB sensors, rnn2, GBDT, transfer learning method, and regression model such as SMDLS, while maintaining high accuracy and practical applicability. Although some samples show high accuracy rates, they often require large-scale calibration, accurate monitoring of environmental conditions, or significant computing resources. The methodology used to create a data set of merit measurements allowed CNN to achieve high accuracy with a significant accuracy of 97% for laboratory measures and 85% for specific samples. This rigorous data set is critical to CNN's success. In addition, the proposed CNN simplicity and lower computational requirements make it a viable option for field applications, especially in less controlled environmental conditions. However, further tuning and adaptation is required to increase its resistance to environmental changes. In general, the proposed CNN offers a promising solution for measuring blur in real-world conditions, effectively balancing accuracy and practicality.

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A. T. Sekerbaev

Терең оқыту негізінде судың мөлдірлігін (лайлануын) деңгей бойынша жіктеу

Лайланудың нақты жіктелуі ауыз судан бастап өндірістік процестерге дейінгі әртүрлі контексттерде судың сапасын сақтау үшін өте маңызды. Дәстүрлі турбидиметрлер түрлі-түсті заттардың кедергісін, бөлшектердің пішіні мен өлшемдерінің өзгеруін, үнемі калибрлеу мен техникалық қызмет көрсетуді қажет ететін қиындықтарға тап болады. Бұл құжатта су үлгілерін лайлану дәрежесіне қарай жіктеу үшін конволюциялық нейрондық желі (CNN) енгізілген. Деректер жинағы 2100p портативті турбидиметр көмегімен өлшенетін бұлыңғырлық деңгейлері бақыланатын зертханалық жағдайларда түсірілген суреттерден тұрды. CNN зертханалық параметрлерде 97,00% жіктеу дәлдігіне қол жеткізді. Нақты әлемдегі су объектілерінің үлгілерінде сыналған кезде модель 85,00% дәлдікті сақтап қалды. Нәтижелер терең оқыту дәстүрлі әдістердің шектеулерін еңсерудің перспективалы шешімін ұсына отырып, бұлыңғырлық деңгейлерін тиімді жіктей алатынын көрсетеді. Зерттеу cnn-дің бұлыңғырлықты дәл және тиімді өлшеу, дәлдікті теңестіру және далалық жағдайларда практикалық қолдану мүмкіндігі үшін әлеуетін көрсетеді.

Түйін сөздер: судың сапасы, тереңдетіп оқыту, дәлдік, ауыз судың сапасы, бұлыңғырлық деңгейін анықтау, кескінге негізделген талдау.

A. T. Sekerbaev

Классификация прозрачности (мутности) воды по уровням на основе глубокого изучения

Точная классификация мутности необходима для поддержания качества воды в различных условиях, от питьевой воды до промышленных процессов. Традиционные турбидиметры сталкиваются с проблемами, в том числе с устойчивостью окрашенных объектов, изменением формы и размера деталей, а также необходимостью постоянной калибровки и технического обслуживания. В этом документе реализована сверточная нейронная сеть (CNN) для классификации проб воды в соответствии со степенью их мутности. Набор данных состоял из изображений, сделанных в лабораторных условиях, где отслеживались уровни размытости, измеренные с помощью портативного турбидиметра 2100p. CNN достигла точности классификации лабораторных параметров на 97,00%. При тестировании на образцах водоемов в реальном мире точность модели составила 85,00%. Результаты показывают, что глубокое обучение может эффективно классифицировать уровни размытости, предлагая многообещающее решение для преодоления ограничений традиционных методов. Исследование демонстрирует потенциал CNN для точного и эффективного измерения мутности, точности балансировки и возможности практического применения в полевых условиях.

Ключевые слова: качество воды, глубокое обучение, точность, качество питьевой воды, определение уровня размытости, анализ на основе изображений.

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