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Ensuring reliable water level measurement for flooding: A redundancy-based approach with pressure transducer and computer vision

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Abstract

Fluid level measurement is essential in many fields, including industrial and civil sectors, especially for urban flood detection, where there is a high risk of mortality and economic losses. However, although contact-based methods that employ pressure transducers can achieve a high degree of precision, they are susceptible to damage from direct contact with the fluid. This study adopts a redundancy-based approach that combines pressure transducer measurements with computer vision to provide enhanced reliability and reduce the risk of sensor failures. Our approach entails training a deep-learning model that uses pressure sensor data to mitigate this potential risk of damage and avoid the need for manually annotating sets of images. The results show that the pressure transducer has high accuracy, with a mean absolute error (MAE) of 1.21 cm, and that the computer vision model which is trained on pressure sensor data, achieves a comparable MAE of 6.67 cm. This approach also makes the system more robust and includes a dependable backup measurement method in case the primary sensor fails. Furthermore, the model trained on the sensor data led to results that were very similar to those trained directly on ground-truth data.

Keywords
Computer vision, deep learning, flood prediction, pressure transducer, water level

Introduction

Urban floods can have deleterious effects on vulnerable areas, especially in urban environments. It is essential to be able to forecast severe flooding so that effective flood risk management can be carried out through damage control measures (McDermott, 2022). Reliable techniques to detect the depth of a water body involve continuous monitoring of urban rivers or creeks, and these make it possible to predict dangerous patterns that arise before they lead to an overflow. These kinds of data might supply physical (Triana et al., 2019) or data-driven (Brito et al., 2023) models of systems for water level forecasting and flood risk assessment.

Measurement systems generally leverage sensors or cameras to monitor water bodies (Fernandes Junior et al., 2021; Moreno et al., 2019). Contact approaches, such as the adoption of differential pressure transducers (Gold et al., 2023), assume that the sensors might directly contact the liquid. Although these sensors might lead to accurate predictions, they are susceptible to damage or being submerged by floods and accompanying debris and sand (Lo et al., 2015). In contrast, non-contact measurement approaches, such as ultrasonic sensors or light detection and ranging (LiDAR) (Ranieri et al., 2024), are less susceptible to damage but less accurate.

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Computer vision (Iqbal et al., 2021; Vandaele et al., 2021) tasks offer an alternative solution that may rely on cost-effective techniques that involve images from monitoring cameras positioned towards the water body. However, these have the disadvantage of being sensitive to the features of the water surface target, such as reflectance, low opacity, poor illumination, or changes in the camera positioning. These factors make image processing a challenging task since it relies on consistent and clear visual data to perform an accurate analysis. Although the problem can be partly overcome by using deep learning, a large volume of labeled data in different conditions would be needed for a generalized solution to be defined beyond a specialized environment.

In this research, a redundancy-based approach is adopted that combines a pressure transducer and a computer vision-based method that consists of an especially designed visual gauge coupled with a deep-learning system. The purpose of this was to evaluate whether the measurements from the pressure sensor could be used as a reliable target to train the computer vision model, which in turn could be used as a redundancy method with reasonable error rates for making predictions in case of sensor failure. This approach enables a continuous retraining paradigm (Kreuzberger et al., 2023) to be formed, which allows to switch to an up-to-date computer vision system when the pressure transducer fails.

A data collection procedure was followed in a controlled environment to assess the performance of the combined system in ideal conditions. The visual gauge, consisting of a plain plate with a simplified barcode pattern printed into it as described by Domingues Filho et al. (2023), was fixed to the wall of an experimental water tank which was made available at the Hydraulics Laboratory of the São Carlos Engineering School, University of São Paulo. The pressure sensor was installed at the bottom of the tank within an embedded system, and made special use of an ATmega family microcontroller. The pressure sensor was linked to the analog pin of the microcontroller, which allowed sensor data to be gathered and processed. We used the lab's resources to control the water so that the measurements from the pressure transducer, that were synchronized with images from the tank with the barcode panel taken from two angles, could be recorded at different water levels.

In seeking to achieve the objectives of our study, which include (a) developing a redundant water level measurement system that combines pressure transducers and computer vision techniques, and (b) evaluating the performance and reliability of the measurement system, we formulated two questions to guide our research. As a result, our methodology sought to answer the following research questions:

- **RQ1:** Are there significant differences in accuracy between pressure transducers and computer vision, when measuring water levels?
- **RQ2:** Is it feasible to utilize a pressure transducer for training a computer vision algorithm?

The remainder of this article is structured as follows. The "Background" establishes section the basic principles of water level measurements by means of different types of sensing devices. The "Related work" section discusses related work and assesses our research with respect to current academic literature. The "Methodology" section outlines the design of our research and discusses the experiments that were conducted to answer the research questions. The "Results" section shows the results for the pressure sensor and the computer vision-based methods. The "Discussion" section carries out a discussion, in an attempt to answer the research questions on the basis of the results. The "Conclusion" section summarizes the conclusion of the article.

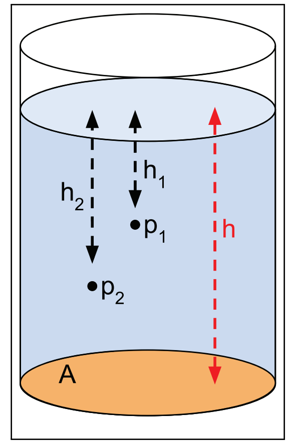

Figure 1. Fluid tank with differential pressure. Adapted from Pisano (2021).

Background

This section establishes the basic principles of water level measurement technologies. Level measurement can be divided into two categories: contact and non-contact.

Contact measurement

Contact measurement can be defined as when the sensors have direct contact with the contents/substance, either liquid or solids. The pressure transducer and float-type water level can be fitted into this category (Hanni and Venkata, 2020).

Pressure transducer. Submersible pressure transducers are widely used to measure water levels. The Stevin theorem was followed to determine the depth of the water column by hydrostatic pressure (Lipták and Venczel, 2016). Figure 1 shows a tank with a differential pressure where Stevin's theorem is applied.

To achieve this objective, the effect of atmospheric pressure must be removed from the sensor readings. A vented cable can be applied as a measuring device to compensate for the atmospheric pressure (Panagopoulos et al., 2021; World Meteorological Organization , WMO). In accordance with Stevin's theory, pressure sensors can directly measure the liquid level. The pressure point P is proportional to the liquid level h multiplied by its specific gravity, as shown in the following equation:

$$P = \rho g h, \tag{1}$$

Figure 2. Pressure sensor after a flood event.

where ρ is the density and g is the gravitational acceleration. However, this sensing method is not effective in flood situations. When debris in a river is in contact with water, in the event of a flood, it can sweep the sensor away (Lo et al., 2015; Panagopoulos et al., 2021). Figure 2 displays an installed pressure sensor which has been damaged by a flood, causing it to become buried and shift from its optimal configuration.

Float-type water level meter. Float-operated devices are widely used in utility services and as alarm switches (Lipták and Venczel, 2016). This technique uses floats to sense the change to the water level (up or down the river) and directly records the rate of transmission by mechanical means (Chen et al., 2022; Issachar, U.S. Patent US6028521A, 1997; Todd, U.S. Patent 4386337A, 1980). Although float type measurement can obtain a high degree of accuracy, its performance is unsatisfactory in flood situations (Chen et al., 2022).

Capacitive level measurement

That is a probe-type sensor that is immersed in the fluid (Lipták and Venczel, 2016). The operating principle of the interdigital capacitive sensor is similar to that of two parallel plate capacitors (Chetpattananondh et al., 2014). The capacitor converts a change in the level or properties of the dielectric material into an electrical signal (Kumar et al., 2014). The capacitance changes almost linearly with the level of the liquid (Esmaili et al., 2020). Capacitive sensors are operated by varying any of the three parameters of a capacitor: the distance between the plates (d), the area of capacitive plates (A), and dielectric constant (ϵ_r); as shown in the following equation:

$$C = f(d, A, \epsilon_r). \tag{2}$$

Non-contact measurement

Non-contact measuring devices are available that use water surface sensing methods such as ultrasonic acoustic wave transmission, radio wave (radar) transmission, and laser transmission (World Meteorological Organization , WMO). In addition, there are computer vision-based methods that determine the water levels by means of satellite, airborne, or ground camera images (Iqbal et al., 2021).

Ultrasonic level measurement. The ultrasonic measurement method uses a high-frequency acoustic transducer to propagate a sound wave that is carried through the air to the water surface (World Meteorological Organization , WMO). The transducer receives the reflected acoustic wave back. By measuring the wave's time-of-flight (i.e. the time between the pulse's emission and reception), the wave's traveled distance and, hence, the water level can be calculated.

Ultrasonic water level meters have a good performance in terms of metric accuracy and are easier to install in complex environments. However, they are vulnerable to changes in the environment (Chen et al., 2022). The transmitted and reflected signals may be affected by obstacles such as snow, rain, dust, and turbulent water surfaces (Bae and Ji, 2019a; Panagopoulos et al., 2021). Furthermore, Panagopoulos et al. (2021) have proved that temperature and relative humidity can affect the ultrasonic sensor operations.

LiDAR-based measurements of level. LiDAR is an active remote sensing technology that uses electromagnetic waves at optical and infrared wavelengths (McManamon, 2019). The system transmits a sequence of laser signals and collects their received signals. In the same way as in the ultrasonic method, the traveled distance of the laser's pulse (range) is calculated by the wave's time-of-flight (Matos et al., 2024).

Image-based level measurement. Image-based level measurement is a visual-sensing technique that carries out the reading of the water line via images (Zhang et al., 2019). A typical method is to take a series of images and manually determine the gauge reading of each one (Lin et al., 2018). However, by-eye manual readings are inefficient and often distorted or inaccurate, especially when the image is low-quality. However, there are several methods that can automatically recognize the water line (Chen et al., 2022), including YOLOv5s and convolutional neural networks (CNNs) (Eltner et al., 2021; Kuo and Tai, 2022; Qiao et al., 2022).

Apart from the problems with image quality and poor ambient illumination, there are other limitations to employing computer vision, which we intend to overcome through our method. Water line detection is a challenging task to carry out through traditional image processing (Nair and Rao, 2016) such as noise removal and morphological operations. They often fail to pick up complex semantic information, especially when faced with challenging conditions like occlusion and blurred boundaries (Wu et al., 2023). Thus there is a need for deep learning methods, such as CNNs and attention mechanisms, which can obtain better detection results by learning feature representations and semantic information. However, these require large labeled datasets, which are difficult to construct and often lack generalizability across different environments (Wu et al., 2023).

Furthermore, there are problems with the accuracy of the level calculations. Calculating water level rise involves extracting water lines and using gauge information or homography to find pixel-world coordinates (Wu et al., 2023). The main challenge in tracing gauge information is visibility, which can be impaired by reflections, obstructions, or damage (Wu et al., 2023). Moreover, as Wu et al. (2023) points out, combining data from different sensors is one of the recommended ways to improve the accuracy and robustness of solutions. Our approach involves using a barcode visual marker and combining a pressure transducer with computer vision to simplify dataset labeling and overcome the obstacles to line and water surface detection.

Related work

This section reviews studies on liquid-level measurement systems, including infrared and ultrasound techniques. Additionally, we discuss some research that relies on machine learning approaches and applications in urban flood monitoring.

Pressure transducer

Panagopoulos et al. (2021) monitored a river level by adopting different approaches. They compared ultrasonic level measurements with differential pressure transducer measurements installed at the same point. The results of a statistical and graph analysis showed that the differences between the two sensors never exceeded 7%. Furthermore, it was observed that the river flow turbulence and ambient temperature influence ultrasonic measurements. In effect, there was no fluctuation in the level measurement when pressure transducers were employed, although this may not be helpful in flood scenarios because, in these situations, there is a risk of damage to the submersible instruments.

Esmaili et al. (2020) provided a level-measuring instrument that is based on a differential pressure sensor design to measure the level of liquid. The instrument was tested in a varied ambient temperature variation and fluid sloshing conditions. The obtained results show a combined uncertainty rate that is lower than 1 mm, which is largely constrained by the sloshing conditions.

LiDAR-based sensors

Paul et al. (2020) investigated the LiDAR time-of-flight system for measuring water levels in a wide range of environmental conditions. The authors employed a near-infrared (905 nm) LiDAR sensor, and tested its performance in different conditions, such as distance measurement, surface roughness, air temperature, water turbidity, and angle measurement.

Tamari and Guerrero-Meza (2016) showed that an inclined (TOF) LiDAR might be able to measure a river level when the water is extremely turbid. They used an industrial range-only LiDAR with an incidence angle of 64° and showed that if the river water is turbid, an inclined LiDAR might be able to monitor flash floods. Tamari et al. (2016) also evaluated the capacity to measure the river level by using LiDAR with an incidence angle in a range of 30°–70°. The experiments were carried out in turbid water scenarios and they were able to measure the level with an uncertainty lower than ± 0.08 m.

The study conducted by Ranieri et al. (2024) measured the water level with a one-dimensional LiDAR, ultrasonic sensor, and inertial measurement units. The researchers assessed the sensor measurements in a controlled laboratory setting, by manipulating variables such as distance, incidence angle, and water turbidity to determine their impact on the accuracy of the water level predictions. The study employed machine learning techniques to synthesize data from the distance and inertial sensors, with the aim of improving the predict accuracy to an extent that exceeded what individual sensors can achieve.

Ultrasonic sensors

Some studies concentrated on liquid-level measurement systems that employ ultrasonic sensors. For example, Hanan et al. (2019) designed a water surface-level detection system that used the HC-SR04 ultrasonic sensors and the ESP8266-12E module. The system detects the water depth and sends the information to the module. Similarly, Prafanto and Budiman (2018) examined a wireless sensor network-based system for automatic, real-time detection of river water levels by means of ultrasonic sensors. The system transmits the water level data to a web server, which allows the public to monitor the depth of the river in real-time.

Sahoo and Udgata (2020) put forward a system to increase the accuracy of water level measurements in storage tanks of varying depths by means of HC-SR04 ultrasonic sensors. The authors' system overcomes these challenges by applying a Levenberg–Marquardt backpropagation artificial neural network architecture to reduce the risk of measurement errors.

Bae and Ji (2019b) created a data processing algorithm concerned with outlier removal and data smoothing for the water level data collected by HC-SR04 ultrasonic sensors in stream-scale channels. The authors used modified Z-scores based on the median absolute deviation. The processed data were then smoothed by means of an exponentially weighted moving average method.

Computer vision level measurement

Lo et al. (2015) presented a method that employed computer vision for monitoring water levels to detect and assess floods. The system serves as a cyber-surveillance tool for monitoring and early warning systems. The authors address the challenge of accurately predicting floods, which affect large regions of the country and have a long lead time, which makes it difficult to obtain precise forecasts for small areas. While cameras have been used to measure water levels, good lighting conditions and image quality are crucial for accurately detecting the water's surface. The authors discussed the use of aerial and remote images, such as satellite and synthetic aperture radar imagery, for flood analysis. However, the complex process of acquisition and post-processing procedures lead to delays, which constrains the real-time applicability of satellite or aerial images for flood detection and emergency warnings in small areas.

Righetti et al. (2022) designed a monitoring and flood warning system based on the machine learning and computer vision. This compares different IoT architectures, such as cloud and edge computing. Multiple metrics are used to compare these approaches, for example, processed frames per second, latency, memory, and CPU utilization. The image analyses achieved a better performance in the cloud computing system because of the cloud computational power, which was much higher than with edge computing approach. However, the application, that is, flooding monitoring and warning, requires low latency, fast decision-making, better reliability, and scalability. These requirements are best addressed through edge computing.

Pan et al. (2018) designed a low-cost surveillance system with measurement stations and a monitoring center. The authors used video cameras, a signal processing unit to calculate and transmit the water level, and wireless connections. They also employed three methods to evaluate the system: the difference method, dictionary learning, and deep learning. Finally, they showed that the best results with regard to accuracy and stability can be obtained from deep learning method based on the CNNs.

Chen et al. (2022) employed a method for recognizing water levels from water gauge images and examined its application in Wuyuan City, Jiangxi Province, China. They used a fully convolutional one-stage, an object detection model, which was enhanced by incorporating a contextual adjustment module to ensure edge computing compatibility and a significant detection accuracy rate. Additionally, they made use of the contextual adjustment module in Deeplabv3+ to segment the water gauge area above the water surface, and thus enabled the water level line to be positioned with precision.

Zhang et al. (2019) employed a method that leverages surveillance cameras for monitoring. Their work was based on the hypothesis that the water level is usually characterized by a significant variation in the grayscale on the water gauge. By employing image processing techniques, in particular the maximum mean difference between gray levels and edges, they achieved an accuracy rate of 90%. However, they faced difficulties in flood conditions caused by water vibrations and floating debris in front of the water gauge.

Lin et al. (2018) introduced a method for automatic water-level detection by using a single camera paired with a water gauge. They applied image processing techniques and co-linearity equations to determine the water level while reducing the problem of noise. Additionally, photogrammetric techniques were used to track the camera movements. Their results suggested that this method could effectively cope with varying weather conditions and unexpected camera movements when detecting water levels. Nonetheless, extreme changes in the camera position and severe weather conditions can impair the accuracy of this method.

Vandaele et al. (2021) devised a deep learning-based approach for automated semantic water segmentation to estimate river water levels from different camera angles. They configured their dataset from the Severn and Avon rivers in the United Kingdom. By comparing their results with nearby water gauge markers, they concluded that this method is both easy to put into practice and cost-effective, particularly in environments where there is a lack of water gauges.

Table 1 summarizes the related works, with a focus on LiDAR, ultrasonic sensors, pressure sensors, and camera-based applications.

Methodology

Our system envisions a symbiotic interaction between images obtained through a video camera, pressure sensor readings, and the machine learning pipeline. We created a controlled scenario with the aid of a tank at the Hydraulics Laboratory of the São Carlos Engineering School at the University of São Paulo which was designed to assess this system. Data collected in this environment were used to assess the feasibility of the predictive system.

The barcode panel

The model derived from computer vision relied on a panel imprinted with a visual marker, as shown in Figure 3. This is

Table 1. Related works focusing on liquid level measurement techniques: light detection and ranging (LiDAR), ultrasonic, pressure transducer, and computer vision.

Work	LiDAR	Ultrasonic	Pressure	Computer vision
Paul et al. (2020)	●	○	○	○
Tamari and Guerrero-Meza (2016)	●	○	○	○
Ranieri et al. (2024)	●	●	○	○
Hanan et al. (2019)	○	●	○	○
Prafanto and Budiman (2018)	○	●	○	○
Bae and Ji (2019b)	○	●	○	○
Sahoo and Udgata (2020)	○	●	○	○
Panagopoulos et al. (2021)	○	●	●	○
Esmaili et al. (2020)	○	○	●	○
Lo et al. (2015)	○	○	○	●
Righetti et al. (2022)	○	○	○	●
Pan et al. (2018)	○	○	○	●
Chen et al. (2022)	○	○	○	●
Zhang et al. (2019)	○	○	○	●
Lin et al. (2018)	○	○	○	●
Vandaele et al. (2021)	○	○	○	●
Our work	○	○	●	●

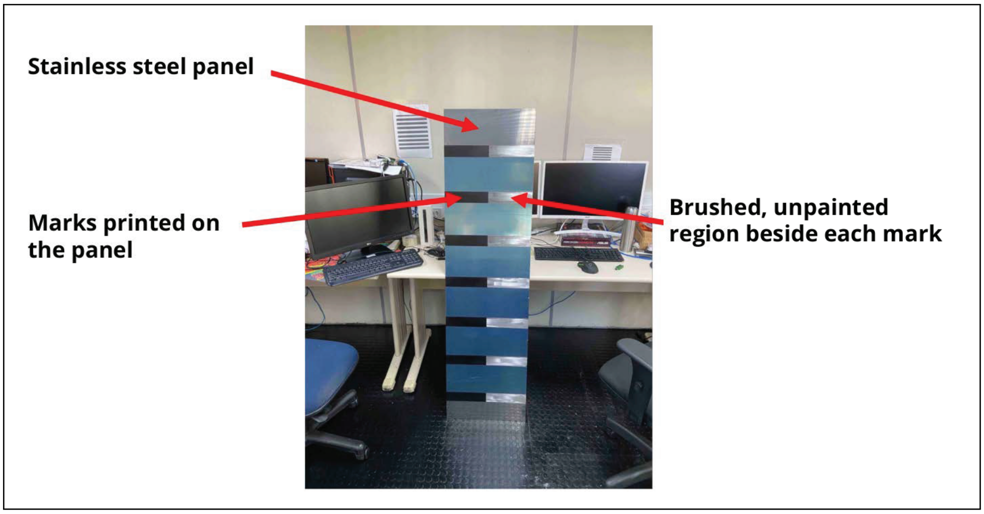

Figure 3. Barcode panel for water level measurement using computer vision.

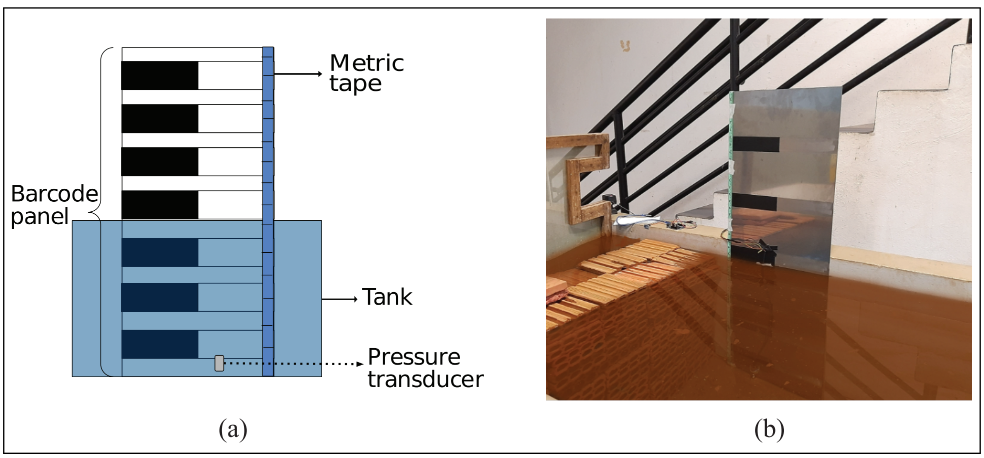

Figure 4. Barcode panel used as a marker for the computer vision model: (a) experimental setup and (b) sample image from the dataset.

the so-called barcode panel, originally designed by Domingues Filho et al. (2023).

The panel should be made of stainless steel. The prototype used in this study was 1.50 m long and 0.20 m wide, and the barcode consisted of seven bars, each 5 cm high, positioned with precise spacing and surface treatment process. The first bar was placed 15 cm from the top edge of the plate, with each subsequent bar separated by a 15 cm gap. When actually deployed in the field, the height and length of the panel, the number of bars, and the height of each bar must be adapted accordingly.

If required, the surface treatment can involve brushing the stainless steel to create a polished appearance solely for the barcode bars, while the rest of the plate remains untreated. The left section of each bar should be painted black, whereas the right section, which will be gray, should be brushed but left unpainted to retain the natural color of the stainless steel. This distinction between painted and unpainted sections makes it easier to read the barcode. High-quality paint should be used to prevent chipping or fading, and thus maintain the integrity of the barcode over a period of time.

Data collection

A P51-15-G-UC-I36-5V-R pressure transducer manufactured by SSI Technologies was fixed into the lower position of the barcode to measure the hydrostatic pressure of the bottom of the tank.

The barcode panel and the pressure transducer were placed in an empty tank, since this would enable us to simulate a range of water level scenarios by filling the tank incrementally. Figure 4(a) illustrates the experimental setup, while Figure 4(b) displays a sample image that shows three bars of the barcode panel above the water level.

A wide range of water level scenarios were simulated by using the bars of the panel as a reference point. The starting point, endpoint, and spacing between the bars were employed to establish differences in the depth of the water. A metric tape was used to measure all of these distances so that they could be used as the ground truth. A brown mask with an opacity of 60% was included to resemble the water turbidity, as usually observed in urban creeks during rainfall. During rain events, the level of turbidity increases significantly more than

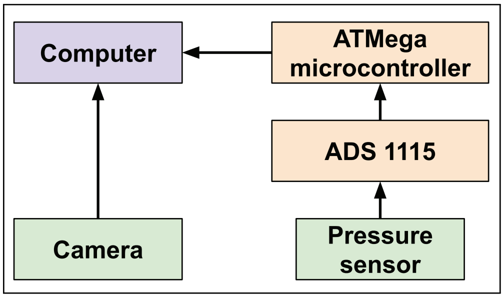

Figure 5. Measurement chain for the experiment.

in dry periods. Factors such as the resuspension of sediment and high sediment loads from runoff are responsible for this rise (Girardi et al., 2016; Sadauki et al., 2022).

To improve the sensor resolution, an ADS 1115 16-bit external analog-to-digital converter (ADC) was connected to the ATmega family microcontroller. This setup significantly enhances the accuracy of the sensor readings when compared with the built-in ADC of the microcontroller. During our data collection, the pressure sensor measure an analog signal that corresponds to the water level, which is then converted into a digital signal by the ADS 1115 ADC. This digital signal is transmitted to the microcontroller for processing and storage. At the same time, a camera captures water level images, and thus ensures visual verification and correlation with the sensor data. We captured 30 ADC readings along with a corresponding image for each scenario at water level. These collected data points were then analyzed to ensure the accuracy of the sensor readings. The measurement chain of the experiment is shown in Figure 5.

As a ground-truth measurement, the depth of the water was analogically measured with the aid of a metric tape, which was compared to the median of the ADC reads. These data were used to make an indirect calibration of the pressure transducer.

Predictive models

We have adopted a redundancy-based approach in our system to ensure that the computer vision system can take over if the pressure sensor malfunctions. However, training a deep neural network once and deploying it for future use, may result in an outdated model when it is actually needed. The following subsection discusses some of the reasons for this and seeks potential solutions to address this problem, which is central to our system . Afterwards, there is a description of the deep learning architecture that is used.

Maintenance of the model

When in production, machine learning-based systems must follow certain maintenance procedures that are more complex than those needed for other types of software (Sculley et al., 2015). This is because the model induced by the initial data collection is unable to maintain its performance indefinitely. Either the features of the data fed into the production system change over time, or changes in the desired targets mean they must be redefined. These issues are known as data drift and concept drift, respectively.

In our scenario, data drift may occur as a result of oxidation and other effects that alter the appearance of the panel with barcode codes or lead to the camera lens wearing out, for example. From a software engineering perspective, continuous data collection and model retraining are necessary. This can be achieved through a CI/CD/CT development paradigm (where CI stands for continuous integration, CD stands for continuous deployment, and CT refers to continuous training), as opposed to the common CI/CD practices used in other types of software (Kreuzberger et al., 2023). Thus, the machine learning model can be continuously updated with new data.

Nonetheless, for a supervised learning model, retraining will only be possible if account is taken of an implementation paradigm that involves the continuous collection of labeled data (Lakshmanan et al., 2020). Since the pressure sensor can make accurate measurements when fully operational, these data can be used as targets for continuous model retraining.

If this approach is adopted, an initial data collection is only necessary for the system's initial implementation when a dataset has not yet been created to induce the first models. Once new data from the production system becomes available, model maintenance can be carried out automatically. By monitoring pressure sensor readings, we will be able to detect any anomalous behavior and make measurements directly from the computer vision model.

An experimental procedure was followed to assess a scenario, in which images were trained for regression. These required the following: (i) metric tape measurements (manual annotations) as the targets training and validation; (ii) the readings from the pressure transducer as targets for training, and validation; and (iii) the readings from the pressure transducer as targets for training, and the metric tape measurements as targets for validation.

Deep learning architecture

The images utilized in our experiment were gathered in a controlled environment, which ensures the absence of invalid samples and significant variations in illumination or other sources of noise. Moreover, we utilized CNNs as the models for identifying the water level based on the images. These models offer feature extraction in addition to the classification or regression mechanisms found in traditional neural networks. Therefore, there is no need to perform preprocessing steps such as noise filtering before feeding the image to the model, as the CNN itself will execute the necessary operations through sequential convolutional and subsampling layers (Bengio et al., 2017).

Deep neural networks, such as CNNs or vision transformers, are effective for carrying out image-based tasks because they can automatically learn and optimize feature representations directly from raw image data, as well as by eliminating the need for manual feature extraction. This is particularly useful in dynamic environments where water levels might change rapidly on account of weather conditions or other external factors.

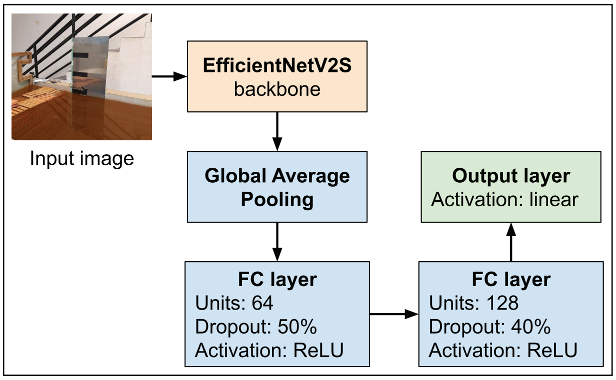

Figure 6. Neural architecture used for regression.

The EfficientNetV2 architecture (Tan and Le, 2019) introduces the compound coefficient technique for scaling up CNNs effectively. This technique entails scaling the width, depth, and resolution of the neural network through a fixed set of scaling coefficients. The authors also employed AutoML to form eight models that provide a trade-off between model complexity and accuracy, ranging from EfficientNetB0 to EfficientNetB7. EfficientNetV2 (Tan and Le, 2021) is an optimized version of the original EfficientNet and provides state-of-the-art accuracy with reduced complexity.

It is important to use an architecture as simple as possible for real-time applications such as water level measurement, in which timely and accurate predictions are essential for effective monitoring and response. Additionally, the model needs to be able to run and be retrained on edge devices, which have limited computing capability, making larger models unsuitable. In this work, we employed the EfficientNetV2-S architecture, the smallest within the EfficientV2 family, to build a simple yet accurate model.

By leveraging transfer learning, the model weights were initialized with pre-trained values on ImageNet and fine-tuned during the training phase through the dataset that was created. Figure 6 shows the neural architecture that was implemented, which used the EfficientNetV2S as a backbone. Our model introduced two fully connected (FC) layers which had ReLU activation, with 64 and 128 units, respectively, and ReLU activation. Dropout regularization was included to prevent overfitting, with rates of 50% and 40%. The output layer consisted of a single neuron with a linear activation function to predict the continuous measurement of the depth of the water.

The data were split into training and validation sets based on a stratified train-test-split, and this ensured that the distribution of samples for each number of bars above the water surface is preserved in both sets. The mean squared error (MSE) was chosen as the loss function. The MSE was also employed as an additional metric for monitoring the training process.

Figure 7 shows the mean absolute error (MAE) over 25 epochs, and illustrates its performance during the training and validation phases. Both the training and validation MAEs should decline and stabilize, and this signals that both effective learning and errors have been handled by the neural network. Any significant divergence between these lines might give rise to factors like overfitting, where the model performs well when training data but poorly when validating data.

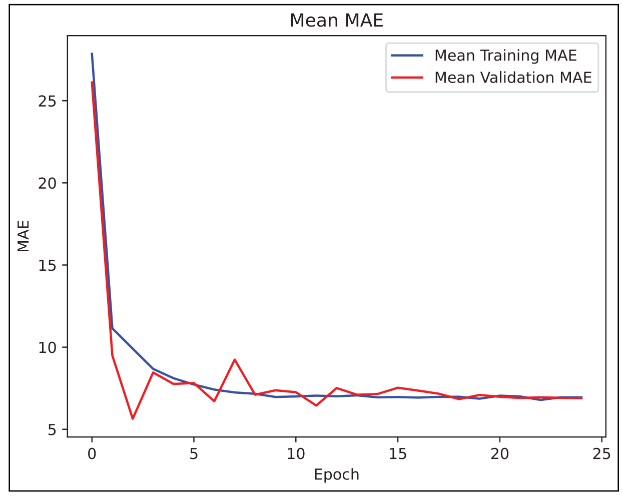

Figure 7. Mean absolute error (MAE) performance during training and validation.

The Adam optimizer (Kingma and Ba, 2014), with an initial learning rate of 0.5×10^{-3}, was used to train the model. The learning rate schedule employed a policy of decaying, by a factor of 0.2 whenever there was no improvement on the loss after five consecutive epochs. The procedure was repeated until the learning rate reached a minimum of 0.2×10^{-6}. The model was trained for 25 epochs (limited to 70 steps each), with a batch size of 32.

Results

The system depends on the pressure transducer as its primary source of data because of its high accuracy. However, if there is a pressure transducer failure, the computer vision-based model can be used as a backup. As the computer vision system is based on deep learning, it has to be continually retrained to maintain its accuracy. This can be done automatically by using the readings from the pressure transducer as training targets, which is a part of the redundancy-based approach that is recommended . The results of this system are discussed further in the following subsections.

Pressure transducer calibration

Considering the sensor's application in various environments, it is essential to note that the relationship between pressure and liquid level can be nonlinear depending on the shape of the container. In a rectangular tank, this relationship remains linear because the cross-sectional area is constant at all levels. In river/creek/lake application, the pressure transducer must be installed at the bottom in a location with a uniform cross-section, such as in a river, where this linear relationship holds. As noted in the literature, submersible pressure transducers are a suitable and cost-effective method for monitoring a river depth, particularly at control cross-sections where the rating

Table 2. Pressure transducer results.

	MAE	MSE	R^2
Pressure transducer	1.21	2.51	0.99

MAE: mean absolute error; MSE: mean squared error.

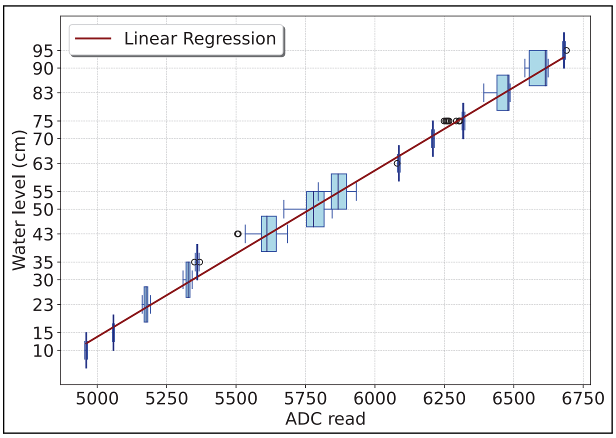

Figure 8. Sensor's indirect calibration.

relation is stable and unlikely to change (Phillips and Eaton, 2009).

Therefore, we used linear regression to estimate the pressure transducer calibration. Table 2 and Figure 8 show the results achieved by the model. There was a determination coefficient (R^2 score) of 0.99, an MSE of 2.51, and an MAE of 1.21. This suggests that the calibration model is highly accurate and can provide reliable results. With regard to error, the results show that the sensor's readings or measurements have a high degree of precision and accuracy. The calibration equation obtained was $y_1 = 0.05x_1 - 221.95$, where x_1 is the ADC reading, and y_1 represents the level in centimeters. Using the sensor's voltage output, we calculated the pressure (PSI) and also used linear regression to calibrate the sensor for converting pressure to level (cm). The calibration equation obtained was $y_2 = 250.45p - 220.33$, where y_2 is the level in centimeters and p the pressure gauge in PSI.

Computer vision and the redundancy-based approach

The trained model was used to predict the water depth for the validation of the images. The predicted values were compared with the corresponding human-measured water levels (metric tape). The performance of the model is set out in Table 3. The MAE is given in centimeters and the MSE, in squared centimeters.

Figure 9 shows the scatter plots of the models trained for the sensor data or the ground-truth (i.e. metric tape) targets. The red, dashed, straight lines correspond to an ideal model that always predicts the ground-truth target.

The equations for each approach were evaluated. In the case of the model trained with the metric tape data, the obtained

Table 3. Computer vision results.

Training targets	Evaluation targets	MAE	MSE	R^2
Metric tape	Metric tape	6.84	79.20	0.89
Sensor	Metric tape	6.67	58.78	0.91

MAE: mean absolute error; MSE: mean squared error.

equation is $y_3 = 1.05x_2 + 2.37$. This equation suggests that for the increase in the predicted value of each unit, the actual value increases by $\sim$ 1.049 units, with a baseline value of 2.37 when the predicted value is zero. The regression standard error is 8.89. Additionally, the 95% confidence interval for the predictions is ± 2.47, which gives a range within which we can be 95% confident about what the true values are. This interval provides an estimate of the uncertainty about the predictions, and provides a better understanding of the model's reliability.

In the case of the ground truth trained model, we obtained a residual norm through the Euclidean distance of 64.13. This value represents the overall magnitude of the prediction errors. Additionally, the model's p-value was found to be $< 10^{-4}$. Since this p-value is much less than the statistical significance level of 0.05, the null hypothesis that the slope is zero can be rejected. This suggests that there is a statistically significant linear relationship between the actual and predicted values.

In the case of the model trained by using sensor measurements as labels, the linear equation obtained was $y_4 = 1.17x_3 - 3.57$. This equation suggests that for each increase in the unit of predicted value, the actual value increases by $\sim$1.1702 units, after accounting for an offset of -3.5658. Moreover, the model achieved a standard error of 7.66. The 95% confidence interval for the predictions is ± 2.24. Additionally, the Euclidean norm of the residuals, calculated as the square root of the sum of squared residuals, is 54.22, and a p-value $< 10^{-4}$.

After the two models had been trained and validated, it was found that the model trained with sensor targets had a slightly lower MAE, MSE, and R^2 than the model trained with metric tape annotations as targets. The reason for this can be understood by analyzing Figure 9. Although the model trained on metric tape annotations yielded more results that were closer to the actual values, it led to a few errors on a larger scale, especially for measurements around 30 cm. Since the MSE penalizes errors on a larger scale, this metric was able to underline this difference.

Moreover, the results showed that when the computer vision model was trained with the aid of either the ground-truth targets (metric tape) or the sensor readings, it resulted in similar error metrics, which differ only by a few millimeters. We conducted an ANOVA test to compare the predicted values from two models. The test resulted in an F-statistic of $\sim$ 0.013 and a p-value of $\sim$ 0.91. The high p-value suggests that there is no statistically significant difference between the predicted values in the two models, indicating consistent predictions across the two datasets. This finding suggests that the proposed redundant approach can be employed in an autonomous setting that enables continuous retraining with

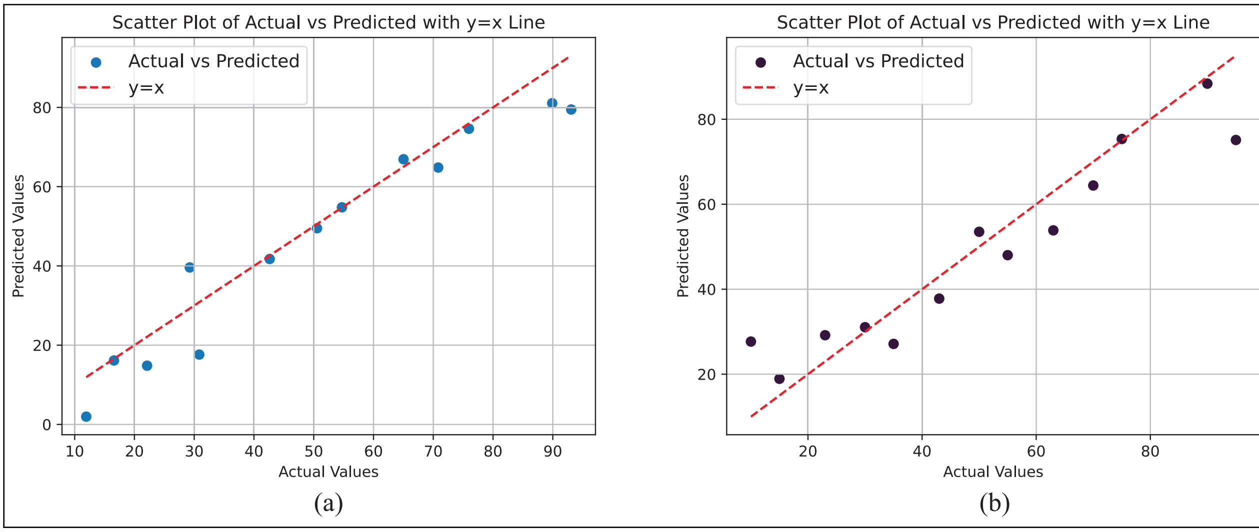

Figure 9. Scatter plots for the models trained on the sensor and on the tape (ground-truth) data. All evaluations were made using the tape data: (a) trained with the ruler tape targets and (b) trained with the sensor targets.

automatic labels. These results suggest that the model can learn the complex relationship between the visual features in the river images and the corresponding water depths measured by different instruments.

Discussion

The results of the computer vision approach demonstrated that employing computer vision as a redundant mechanism is a suitable means of ascertaining water levels in a body of water, and serves as an alternative to the primary pressure sensor system. The image classification model based on the EfficientNetV2S architecture achieved a notable performance in accurately determining the water level on the basis of a barcode panel, which was correlated with the water level.

In scenarios, where the primary pressure sensor experienced limitations or failure, the computer vision model served as a reliable backup, by showcasing its capacity to act as an independent and supplementary method for monitoring water levels. By carrying out extensive evaluation of a diverse dataset, the model displayed robustness and generalizability, and proved able to find a viable redundancy solution in critical situations where continuous and accurate water level monitoring is paramount. This redundancy mechanism offers increased reliability and resilience in monitoring systems, and can safeguard against the risk of sensor malfunctions or unforeseen technical obstacles to water level assessment.

The trained computer vision model provided valuable redundancy for the existing pressure sensor system. There are several advantages from using the model in conjunction with the pressure sensor. Its predictions provide a means of verifying the pressure sensor readings and thus increasing overall confidence in the water level measurements. For example, if the sensor reading deviates significantly from the prediction, it could mean something might be wrong with the sensor and prompt further investigation. If the pressure sensor malfunctions, the computer vision system can continue to make estimates of the water depth, albeit with slightly lower accuracy but still within an acceptable range (as shown by the validation results in the metric tape data).

A response can be given to the research questions on the basis of results shown in the "Results" section.

RQ1: Are there significant differences in accuracy between pressure transducers and computer vision, when measuring water levels?

The calibration of the pressure transducer was found to be more precise than the model obtained by training the computer vision system with the aid of the metric tape values as labels. The pressure transducer achieved a MAE of 1.21 cm, whereas the computer vision system obtained an MAE of 6.84 cm. This shows that the pressure sensor is capable of measuring water levels with high accuracy despite its limitations in flood situations.

RQ2: Is it feasible to utilize a pressure transducer for training a computer vision algorithm?

The level measurements from the pressure transducer were used to label the image dataset and train the deep learning algorithm. As a result, we achieved an MAE of 6.67 cm, and a standard error of 7.66. The 95% confidence interval for the predictions is ± 2.24 cm, which is evidence of the precision of our estimates. The p-value for the model was $< 10^{-4}$, which suggests there is a statistically significant linear relationship between the actual and predicted values. This approach is beneficial in two ways : (i) the fact that another sensor is used for image dataset labeling and (ii) it offers online training for a machine vision level measurement algorithm. This is because in certain conditions, a well-trained machine vision algorithm can be more effective in flood scenarios than a pressure transducer.

Conclusion

This study examines a redundant method for measuring water levels that combines the precision of pressure transducers with the flexibility of computer vision-based techniques. The purpose of this was to design a dependable system that could overcome the constraints of contact-based sensors, especially in extreme weather conditions like floods, where sensors are at risk of damage or being submerged. Additionally, the system makes use of pressure transducer measurements to train the computer vision algorithm, while making it unnecessary to manually label the image set whenever the models have to be trained.

In the experiment, we created a controlled environment to measure water levels by means of a pressure transducer and a computer vision model trained on a barcode-patterned visual gauge. The deep learning model relied on the EfficientNetV2S architecture, which was improved with the aid of transfer learning which included weights and biases obtained by training on the ImageNet dataset. When it is deployed, the model is expected to be continuously retrained through the pressure sensor readings, so that it can maintain its accuracy.

The results showed that the pressure transducer provided high precision with an MAE of 1.21 cm, which was significantly lower than the MAE of 6.84 cm obtained by the computer vision model trained with metric tape values. However, the computer vision model trained on pressure sensor data achieved a similar MAE of 6.67 cm, which shows that it can act as a reliable backup method.

The recommended system has several advantages: (i) increased reliability—this is because integrating a computer vision model allows the system to make water level estimates even if the pressure transducer fails; (ii) continuous retraining—pressure sensor readings can be used for subsequent retraining to ensure that the computer vision model remains accurate over a period of time, and (iii) improved accuracy in adverse conditions—the combination of methods mitigates the weaknesses of each approach, as well as making the system more reliable in adverse conditions.

Future work will concentrate on conducting field experiments to enhance the variability of the dataset and evaluate the combined measurement strategies in a wide range of environmental conditions. Additional sensors could be integrated to improve the accuracy of the measurements and deep learning approaches.

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Data availability statement

The dataset used in this research is available at https://doi.org/10.34740/kaggle/ds/4760342.

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