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A Using the Canny Method with Deep Learning for Detect and Predict River Water Level

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ABSTRACT

Recent years have witnessed a significant rise in global river water levels, driven by heavy rainfall events linked to climate change, resulting in severe flood incidents and highlighting the need for effective mitigation strategies. To address this critical issue, this article introduces a detection and prediction system for monitoring rising river water levels utilizing advanced computer vision techniques. The system is based on deep learning models are VGG16and 2D convolutional neural networks (CNNs) that are trained on river image datasets. It starts with heavy image preprocessing are normalization, resizing, Canny Edge Detection to improve edge quality. This is used to produce very exact water level measurements. The models use transfer learning and hyperparameter tuning over a wide grid to maximize monitoring accuracy over a large number of river conditions. The system performance is then thoroughly evaluated by performing extensive testing, and the VGG16 model is proven to exhibit high classification ability with the overall accuracy and precision scores no less than 98.3 % of all classes of river water level. The performance of the CNN model reaches 99.99% on testing data as well, which emphasizes its stability in real-world conditions. This novel combination of deep learning and optimized edge detection algorithms represents a powerful new capability for water level detection and flood control

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1. Introduction

The development of any area near to natural hazards is inevitable to meet the demands of land to support the cities' growth and infrastructure [1]. There are several dangers that occur in Lombok, one of which is flash floods, flash floods is a type of floods that comes suddenly in 10-30 minutes, operate to tens of hours, and in the form of high-speed flooding or excessive discharge in Lombok to the extent that it can carry all the things inside it, there is no warning before a flooding occurs, this is because the speed of Fahreinheit floods that can be up to 11Km/s, and hence flash floods are one of the most dangerous types of flooding. As a result, it is hard to protect water security in this area,

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especially in the rural mountainous terrain where steep sloping terrain can enhance the gravitational power of water flow which may result in larger overflowing across the downstream channel [2]. In addition to having rugged terrain and steep, narrow, and deep water channels, this is where volcanic islands are usually found. They typically carry great quantities of organic debris and sediment, thus increasing the possibility of downstream flooding [3]. Whether it is a small stream or major river, monitoring water flow is essential in all cases.

The primary methods for measuring water levels with today's technology encompass both ground-based and remote-sensing techniques. River gauges provide ongoing monitoring at specific points, although their readings may become unreliable during extreme flood conditions. There is a global decline in the network of river gauging stations, leaving many areas prone to flooding unmonitored or reliant on gauges located far from the affected areas, which may not accurately reflect local conditions [4] [5] [6]. Contact sensors utilise pressure or floating sensors, while ultrasonic water meters and imaging methods are among the non-contact sensors that are used to perform the measurements. The contact based method often fails in surges of strong water currents that can break or push the sensors aside. In addition, these sensors often need to be recalibrated to verify that the measurements are accurate [7].

The Global Runoff Database Centre runs a network of gauging stations to provide river discharge data, based on the catchment area for 159 countries [8]. At the same time, the spatial coverage of rain gauge is sparse and insufficient to describe data required in hydrological model accurately. Moreover, conventional in-situ approaches for water storage assessment present considerable uncertainties [9] [10]. As a result, the high costs associated with complex sensor deployments also impede their widespread use in the field for hydrological monitoring. Furthermore, the situation is aggravated by the fact that in-situ available data is often constrained due to political factors or agreements over international rivers [11].

Flood monitoring is a process that largely depends on satellite and airborne imagery, as these tools offer specific advantages that make them fit for the job. Still, their efficacy suffers from a significant number of constraints in both terrestrial and space-bound conditions. Though this optical sensor and (SAR) based methods are able to map flooded area and water level estimation by merging with Digital Elevation Models (DEMs) [12], but they consist of different challenge in terms of operating them. Optical methods are restricted to daylight operations and are often hindered by cloudy conditions or dense canopy [13]. Another limitation in optical imagery is that urban areas can produce shadowing and layover effects, which lead to an inaccurate identification of the flood location [16] [17], but these limitations have been eliminated with the ability of SAR, as it operates day and night and in all weather conditions, which is particularly useful in monitoring rural floods [14] [15]. RADARSAT-equipped satellites also pass infrequently, often only once or twice daily, making timely, real-time estimates of rapid changes in floodwater levels difficult, a notable absence in flood monitoring studies [12]. This quality limitation contributes to the urgency for better and higher frequency monitoring options so that disaster management and response can promptly improve.

Unmanned Aerial Systems (UASs) are increasingly being recognized as a valuable technology that has high potential to improve river monitoring due to their unique ability to gather high quality geographical data. These Currently Operated UAS (Systems) have limited utility due to strict civil aviation regulations and are unable to achieve the operational effectiveness because of the burden of instrument payload and frequent landing and refueling [18]. In addition, drone drift can impair the accuracy of data collected by UASs, which then require elaborate orthorectification methods to keep the imagery usable [19]. Even if a few studies have illustrated that the video and still-camera imagery from UASs is indeed suitable for monitoring floods [20] and for the calculation of surface velocity fields [21] to measure water level, both the manual as well as the automatic edge detection methods have several disadvantages [22] [23] [24]. Even though they can reach high precision in specific conditions (up to a few mm) [24], the adaptability of these methods are limited and normally deliver unreliable results through significantly different environmental conditions and different stages during a flood event. It constitutes an important research question for the improvement of the reliability and resilience of UAS technology for water monitoring which is useful as well as reliable.

Although the potential usefulness of machine learning (ML) for tackling a myriad of hydrological and hydrodynamic problems has been widely demonstrated, gaps still exist in the economic utilization of ML stretches for numerous water-related applications [25]. Although ML models are known to be successful at flood prediction, groundwater level estimation [26] and water resource management [27], they often fail to provide full transparency into the physical processes that control these phenomena [30]. This limitation triggers an essential research problem; the necessity of the powerful ML model that predicts and mitigates water consequences and which also provides an in-depth understanding of the underlying hydrological physics. Moreover, even if ML has a great power to cope with complex, nonlinear interactions among different environmental input and outputs, more improvements are needed in order to provide accurate and repeatable prediction results in complex and changing environments [25], [28], [29]

[50]. This gap underlines the need for further research to improve ML frameworks develop the interpretability and generality, to move towards a wide range of hydrologic scenarios.

The use of machine learning (ML) techniques on water studies has been exhaustively addressed in literature being these tools of utmost importance for different hydrological predictions and management. However, these reviews also reveal a significant research issue: The heterogeneous performance and applicability of these models in various settings and under diverse data availability conditions. Yaseen et al. addressed the development in artificial intelligence for the streamflow modeling and forecast between 2000 and 2015 [31]; however, improvements were mentioned as well as shortcomings in terms of the adaptability, and the accuracy. Similarly, Zhang et al. highlighted the possible benefit of using data-driven methods in low data topology zones but face many challenges when dealing with abundant and/or complex data [32]. Hamzah et al. presented the use of deterministic and ML methods for optimizing streamflow alterations and is a critical review of the current state-of-art methodology [33]. Zhu et al. indicated that the performance of ML model in the data used for predicting future lake water level showed low predictive accuracy, which reflected on the ML technology inability to robustly deal with the environmental system destabilisation [34]. Ibrahim et al. [35] based on the study of hybrid ML models, it also confirmed this inconsistency, specifically in different water body types of rivers, reservoirs, and lakes from 2009 to 2020. The importance of future research in making ML models more robust, generalizable, and reliable to ensure hydrological predictions to be more accurate under different conditions and with different input datasets cannot be overemphasized.

Although ML has been applied to many water-related problems, the performance of current models is not reliable, and often inadequate to represent different structure of conditions data. The studies reviewed point out substantial adaptability, precision, and scope limitations of ML models when applied to complex hydrological prediction tasks such as streamflow forecasting and water level estimation in numerous geographical settings [31]-[35]. These discrepancies underscore the need for improved and also accurate machine learning (ML) techniques that are applicable to a wide variety of environmental states making it easier to model and predict hydrodynamic and hydrologic phenomena suitable to these data with machine learning approaches. This study aims to improve the dependability, accuracy, and actionability of results of ML models to predict water management and disaster mitigation.

In recent years, transfer learning (TL) methods have gained popularity as a strategy to overcome data scarcity issues [36] [37]. TL involves adapting pre-trained machine learning models, like VGG and MobileNet, originally trained on large, annotated image datasets, to new tasks where such annotated datasets are limited [38] [39]. This study significantly contributes by employing TL techniques combined with the Canny edge detection method to develop water network models. These models conduct innovative experiments using fresh river-camera datasets and metadata. By leveraging TL, the study enhances the accuracy and efficiency of deriving quantitative water-level measurements from images segmented by the river cameras.

The article is structured as follows: Section 2 provides a review of related works, establishing the foundation for the study. Section 3 outlines the innovative methodology for river water level detection and prediction, including the dataset description, preprocessing steps, Convolutional Neural Network architecture, VGG16 architecture, and the Canny edge detection technique. Section 4 presents the results and discussion, covering evaluation metrics, the evaluation of the CNN method, the evaluation of the VGG16 method, and a comparison of results. Finally, Section 5 concludes the study and suggests directions for future research.

2. Related Works

In the realm of hydrological studies, recent research efforts have demonstrated various innovative methodologies to improve water level forecasting and flood risk mitigation. Notably, several papers have proposed using machine learning (ML) and deep learning techniques, integrating these with traditional hydrological modeling approaches to enhance prediction accuracy and operational efficiency. These studies have employed a range of data, from satellite imagery to sensor data from various global river systems, testing the models under different environmental conditions to validate their effectiveness.

Chen et al. 2021 [40] proposed a practical and efficient method based on image processing for water-level measurement. The method comprises three key components: a multi-template matching algorithm to identify characters on water level recorders (WLR), a sequence verification algorithm to refine the recognized characters, and a projection height comparison method for accurate readings, even with incomplete characters. Experiments conducted with real-world data confirmed the effectiveness of this approach. The results demonstrate a 63%

character recognition rate on WLR and an average measurement error of ±0.90 cm, significantly better than China's national water-level monitoring error standard of ±1.0 cm. The method holds promise for improving water level measurements in practice.

Qiao et al. 2022 [41] proposed a deep learning-based water level measurement method using the YOLOv5s convolutional neural network. The YOLOv5s model identifies the water gauge and scale characters in video images, then calculates the water level elevation. Validated at a river station in Beijing, the method showed a systematic error of only 7.7 mm. It achieved accuracy within 1 cm in 95% of daylight images and 98% under infrared night lighting, demonstrating robustness in various lighting conditions and environmental scenarios like rain and slightly dirty water gauges. The method's effectiveness is confirmed by its consistent performance across different conditions.

Eltner et al. 2021[42] proposed a method that blends deep learning and photogrammetric techniques for precise automatic water stage measurement. Using convolutional neural networks (CNNs) such as SegNet and FCN with transfer learning, they achieved water segmentation in images from a Raspberry Pi camera with errors under 3%. These segmented water contours were then integrated with a 3D model from structure-from-motion (SfM) photogrammetry to derive metric water stage values. The approach correlated highly with reference gauges (up to 0.93) and had average deviations below 4 cm, improving the density and accuracy of river monitoring networks.

Zhang et al. 2024 [43] proposed a methodological approach for generating datasets to study 16 flood events in the Yangtze River Basin, which were categorized into training, testing, and application phases. Utilizing eight events, they created labeled datasets with 5296 tiles for training, and evaluated the performance of various convolutional neural network (CNN) models. These CNNs significantly outperformed traditional threshold methods in efficiency and accuracy. The study also examined the impacts of VH and VV polarization and the use of DEM (Digital Elevation Models) on flood detection, finding a preference for VH polarization with minimal impact from DEM. The CNNs were further tested in near-real-time flood detection on the remaining events, with additional weak label datasets generated to enhance training samples. The results confirmed the effectiveness of robustly trained CNNs in flood detection.

Ruma et al. 2023[44] utilized advanced long short-term memory (LSTM) networks to enhance water level forecasting for flood risk mitigation. The paper highlights the inefficiency of traditional LSTM models due to poorly optimized hyperparameters, which they improved using Particle Swarm Optimization (PSO). Analyzing water level data from Bangladesh's Brahmaputra, Ganges, and Meghna rivers, the model's effectiveness was evaluated using metrics like Nash Sutcliffe efficiency (NSE), root mean square error (RMSE), and mean absolute error (MAE). The PSO-LSTM model outperformed traditional ANN and standalone LSTM models, demonstrating superior accuracy and stability, thereby improving flood forecasting and risk management in the region.

Fei et al. 2023 proposed a new data-driven method that is called H2C-Extremely long-term (H2C-XL) for water level forecasting in tidal reaches with a hybrid Hydrologic-Hydrodynamic Coupling (H2C) model embedded with LSTM networks [45]. This model integrates upstream discharge, water levels, tidal information and satellite altimetry products together with TPXO9 tidal information. Tested in the Tianhe-Zhuyin reach, the H2C-XL significantly enhanced prediction accuracy, achieving Nash coefficients and Kling-Gupta Efficiency values of 0.866 and 0.922 for upstream discharge. Water level prediction accuracy at the Jiangmen and Daao stations improved by 12.34% to 40.46% and 16.98% to 32.34%, respectively, compared to previous models. The study also noted that the contribution of upstream discharge to water level predictions varied from 0.37 to 0.55, increasing with distance from the coastline.

Cai et al. 2023[46] proposed an automatic monitoring alarm method using a hybrid segmentation algorithm, combining k-means clustering in RGB color space with a region growing algorithm on the green channel to detect river targets. This system, installed in the Yarlung Tsangpo River basin of Tibet, China, monitored water levels from April to November 2021. It does not require engineering expertise to select seed point parameters and achieved an accuracy of 89.29% and a miss rate of 11.76%, outperforming traditional methods by 29.12% in accuracy and reducing misses by 17.65%. This demonstrates the method's adaptability and precision for unmanned dammed lake monitoring.

Chen et al. 2024[47] proposed using the ResNet-50 Convolutional Neural Network (CNN) model to detect water levels through CCTV footage of the Chengmei Bridge on the Keelung River in Taiwan. This method creates a virtual water gauge system, enabling accurate, real-time monitoring without physical gauges, reducing reliance on traditional methods. The study, conducted from March 2022 to February 2023, integrated grid-based techniques with CCTV and Raspberry Pi for data processing, providing cost-effective monitoring. Initial results yielded accuracy rates from 83.6% to 96%, varying with weather conditions, with the best performance on clear days.

Xu et al. 2023[48]have evaluated the M-K test of magnitudes and annual flows at the Yichang and Hangkou stations. They employed Random Forest (RF) and the deep learning models including the Convolutional Neural Network, LSTM, and a combination of CNN and LSTM to model the water levels and flows at Hankou Station. The results were then assessed using quality indices like Nash-Sutcliffe Efficiency (NSE), Kling-Gupta Efficiency (KGE), Root Mean Square Error (RMSE) and Symmetric Mean Absolute Percentage Error (SMAPE). The definitely increasing trend of Hankou and decreasing trend of Yichang could tell from the data's trend in Figure 1. We find that the NSE and KGE are above 0.995, and the RMSE and SMAPE are less than 0.200, were achieved by the CNN-LSTM model with the best performance among all the models. This study provides an important and up-to-date perspective that is useful in improving the capabilities of flood control and disaster forecasts at the Three Gorges Power Station.

M. A. Hussein and A. H. Abbas 2019[49], scientists suggested a two-phase technique for detecting plant diseases. Using pre-processing methods such as cropping, scaling, and fuzzy histogram equalization on 799 example images, a knowledge base is created in the first phase in order to extract color and texture attributes. The training set for a support vector machine classifier consists of these features. The trained classifier is used in the second step to identify and diagnose plant leaf illnesses in three distinct crops, each of which has three distinct diseases in addition to a healthy condition. The system identified these circumstances with an accuracy of 88.1%.

TABLE 1- RELATED WORKS

References	Model or Methods	Dataset	Results
Qiao et al 2022 [41]	YOLOv5s Convolutional Neural Network	River station in Beijing	Systematic error of only 7.7 mm; 95% accuracy in daylight images and 98% under infrared night lighting
Eltner et al. 2021 [42]	Deep learning (CNNs like SegNet and FCN) and photogrammetric techniques (SfM)	Raspberry Pi camera	Errors under 3%; average deviations below 4 cm; correlation with reference gauges up to 0.93
Zhang et al. 2024 [43]	Analysis across color spaces (RGB, HSV, YCbCr, Lab, Yiq)	Images containing various fire types and basic colors	Optimal color space identified for fire detection
Ruma et al. 2023 [44]	Image processing techniques including Gaussian blur, Canny edge detection, and SWT	Spatial natural images and street sign datasets	Best results with street signs, successfully detecting most letters
Fei et al. 2023 [45]	Hydrologic-Hydrodynamic Coupling model (H2C-XL) integrated with LSTM networks	Tianhe-Zhuyin reach and stations along it	Enhanced prediction accuracy with Nash coefficients of 0.866 and KGE of 0.922; significant improvement in water level predictions
Cai et al. 2023[46]	Hybrid segmentation algorithm (k-means and region growing)	Yarlung Tsangpo River basin, Tibet, China	Accuracy of 89.29%; miss rate of 11.76%; outperformed traditional methods
Chen et al. 2024 [47]	ResNet-50 CNN model	CCTV footage of Chengmei Bridge, Keelung River, Taiwan	Accuracy rates between 83.6% to 96%, best performance on clear days
Xu et al. 2023 [48]	M-K trend test and neural networks (RF, CNN, LSTM, CNN-LSTM)	Yichang and Hankou stations	Downward trend at Yichang and upward trend at Hankou; CNN-LSTM model achieved NSE and KGE above 0.995
M. A. Hussein and A. H. Abbas 2019 [49]	Two-phase system using SVM classifier	799 plant leaf images	Accuracy of 88.1% in identifying diseases across different crops

Although water level measurement techniques have improved significantly in recent years, there are still considerable gaps left from earlier work. Interestingly, high accuracy has been reported in recent works based on either multi-template matching and sequence verification algorithms [40] or YOLOv5s deep learning models [41], or a hybrid scheme using deep learning on photogrammetry images [42] but they often are constrained by adaptability to a wider environmental context and needs complex deployment. Additionally, their adoption is limited by the dependence on costly state-of-the-art sensors, and tailored equipment precluding their ubiquity. In addition, most existing models are task-specific for a given water body or imaging conditions and thus have limited generalization and robustness. We overcome these deficiencies in our work by combining the deep learning with the Canny edge detection to provide a complete cost efficient and flexible system of water level detection. By adding this for the first time, we have achieved the improved accuracy and robustness across different conditions in a cost-effective and scalable manner, which emphasizes the importance of our impact in the realm of water level monitoring and flood prediction systems.

3. Innovative Methodology for River Water Level Detection and Prediction

The model structured approach where water level was acquired through the airborn image datasets sourced from the river. That starts with the preprocessing step where images are normalized and reshaped in 224x224 pixels, and we do some data augmentation during the process so the dataset is more diverse. Canny Edge detection is used as a preprocessing step in order to improve the edges in the images, a necessary feature for feature extraction in order to be accurate. The dataset is subsequently shuffled randomizing 80% of the dataset for training and 20% for evaluating our models. The model is a transfer learning model and uses the pre-trained VGG 16 neural network structure with few fully connected layers (2D CNN) which exploit VGG 16's capability of recognizing complex image features. Once you make the model, and training the model, we do testing and all kind of evaluation are in that testing so the metrics we used were accuracy, precision, recall, F1-Score. The inclusion of Canny edge detection in preprocessing aids in more precise detection of water levels against the riverbank, facilitating easier and more accurate predictions. This integration of deep learning and advanced edge detection, as depicted in Figure 1, offers a highly effective methodology for water level detection.

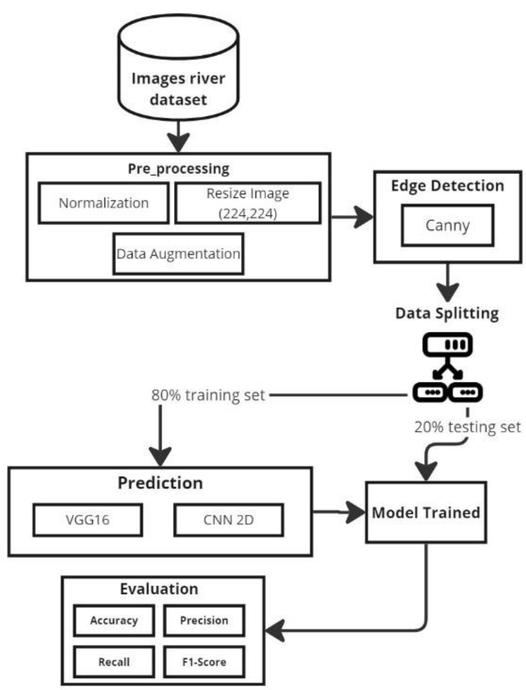

FIG. 1- PROPOSED METHODOLOGY FOR RIVER WATER LEVEL DETECTION AND PREDICTION

3.1. Dataset Description

This dataset is referred to as "Tsai, Cheng-Hsiung. 'Real-time images of river in Taiwan'" made available by Tsai, Cheng-Hsiung in 2020*. It contains a large number of real-time photo snapshots taken by a camera system installed on the Chongren Bridge over Errenxi River, Tianliao District, Taiwan for several days. Structurally, the dataset is a collection of around six thousand high-presence JPEG files from August 23 to August 31, 2018. The sorted sub-variety of those photographs was carefully identified, sorted, and created an organized collection of scenes taken from Taiwanese rivers. This dataset highly benefits the field of hydrology and its combinations with machine learning because, in contrast to other image datasets, it not only has high-resolution image quality but, more importantly, professionally sorted water conditions. Images taken from the camera systems were classified into three categories of conditions as follows: Category A, which contains photographs with a vividly high-water volume with boats in the river present; Category B with the aftermath of a recent water increase; and Category C, which captured no transformations or change in the previous state. Such a filing system allows this dataset to be highly functional in terms of water level fluctuations modeling and learning and would be of high value for use in educational water resource management strategies for flood territories like Taiwan.

3.2. Dataset Preprocessing

In the preprocessing stage of the dataset, the images categorized into three classes: A, B, and C were assigned numeric labels 0, 1, and 2 respectively to facilitate algorithmic processing. This encoding was accomplished by appending the corresponding number to the training labels for each image, based on the category it belonged to, as evident in the image categorization code snippet. These labeling forms the groundwork for the application of the Label Encoder technique, which converts categorical text data into a model-understandable numeric format. Subsequently, images underwent a Gaussian Blur to reduce noise and improve the quality of the input for the model. This was followed by resizing each image to uniform dimensions of 224x224 pixels to ensure consistency in input size. Data augmentation techniques were performed on the dermoscopic images for improved generalization of the model, to make more robust data, such as rotations, zooming, and shifting. The last preprocessing step was normalization (rescaling pixel values to [0,1]) to help the dataset to be more adapted in the machine learning models. The class counts after these final manipulations reveal an even spread of images among the classes - 1600 images in class 1, 1600 images in class 2, and 1599 images in class 0 - leading to a well balanced dataset on which to train our predictive models.

3.3. Canny edge detection

Canny edge detection algorithm [53] is a multi-stage algorithm to detect a wide range of edges in images accurately, so it is a good and popular tool in the field of computer vision [56]. This method which was developed by John F.Canny In 1986 [55] has the priority of three main criteria such as less error rate, high edge localization and minimizing the responses. Its main steps are represented in Figure 2 [54]:

Noise Reduction: The first step in the Canny edge detection algorithm involves smoothing the image to reduce noise. This is typically achieved using a Gaussian filter, which blurs the image to minimize the impact of obvious noise and color variation [56] [57].

Gradient Calculation: The algorithm then uses a Sobel kernel to calculate the gradient magnitude and direction of each pixel. This step assesses the intensity change in all directions around a pixel to determine potential edges [56].

Non-maximum Suppression: Following gradient calculation, the algorithm applies non-maximum suppression to thin out the edges. This step scans the image to suppress all the gradient values (make them zero) except the local maxima, which indicate locations with the sharpest change of intensity values [56].

* https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/8FDC7P

Double Thresholding: The detected edges are further refined through a double thresholding step. This involves using two thresholds, a low and a high threshold, to differentiate between strong, weak, and non-edge pixels. Strong edges are marked where the gradient magnitude is higher than the high threshold, while weak edges are defined where the gradient values fall between the two thresholds [56].

Edge Tracking by Hysteresis: In the final stage, the algorithm distinguishes between real edges and noise. It accomplishes this by converting weak edges into strong ones, but only if they are connected to strong edges. This helps in preserving the genuine structure of the edge while discarding noise-induced edges [56].

By adhering to these stages, the Canny edge detection algorithm ensures that the edges detected are sharp, well-defined, and accurate in their depiction of the true boundaries within the image, making it a robust choice for applications that require precise image analysis.

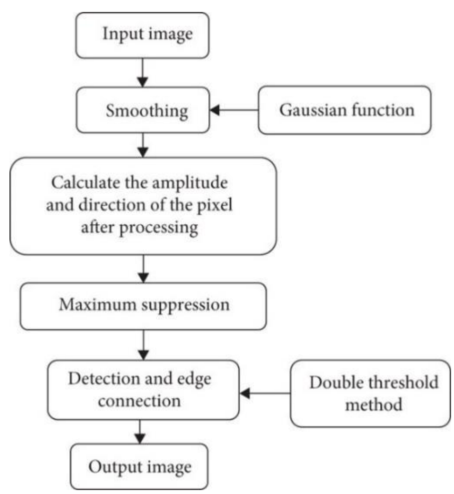

FIG. 2- THE FLOW CHART OF THE CANNY EDGE DETECTION ALGORITHM [54]

3.4. Convolutional Neural Network Architecture

A Convolutional Neural Network (CNN) is a deep learning architecture primarily used for processing data with grid-like topology, such as images. It consists of multiple layers including convolutional layers that apply filters to capture spatial hierarchies of features, pooling layers that reduce dimensionality, and fully connected layers that classify the input based on the features extracted.

The 2D CNN [51] architecture designed for water level prediction in this study is built using Keras and follows a sequential model. It initiates with a rescaling layer that normalizes pixel values within the image, processing the input shape of 224x224 pixels with 3 channels. Following this, a data augmentation layer enhances the model's ability to generalize by introducing variations in the training dataset.

The kernel of the architecture is the three convolutional layers, each followed by a max-pooling layer. The first convolutional layer has 16 filters with a 3x3 kernel, activated "relu" that employs 'same' padding so that the spatial dimensions of the image remain similar. The next convolutional layer after pooling replaces the former 16 filters with 32 filters as the kernel size and activation function remain the same. The third convolution layer has 64 filters followed by max pooling to continue the even abstraction of features from the images. These parts of the architecture are pivotal in extracting features from the images as the abstraction level. Further, abstraction loses the most crucial details to the target model on the output. The output after the above steps is flattened and a single long feature vector is created at this stage. This feed goes into a densely connected layer with 128 neurons activated "relu" and he_normal initialized which helps the backpropagation-propagation process initialize the learning instate. The next dense layer with 64 neurons follows the previous trend. The architecture ends with a softmax activation layer with three neurons. The three neurons are the three classes of water levels. The activation function ensures that the output values are probabilities that sum to one, allowing for a probabilistic interpretation of the model's final model.

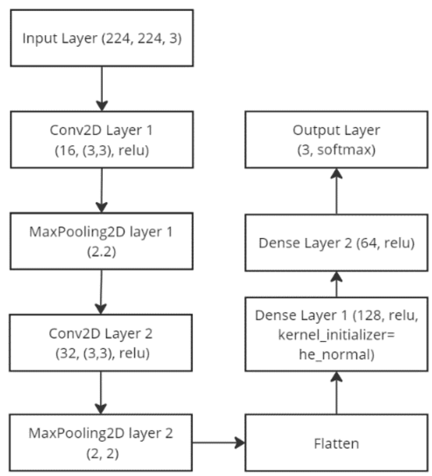

FIG. 3- CNN ARCHITECTURE

3.5. VGG16 Architecture

The VGG16 architecture [52], a well-known model of great depth and feature detection capabilities, utilizes VGG16, pre-trained on the 'imagenet,' as the convolutional base. This choice is made to take advantage of complicated patterns and features learned from a broad variety of images, forming a foundation to distinguish water level indicators within new images. It should be noted that the customized top layers of VGG16 are removed for this peculiar classification task. To avoid customizing the learned features due to personalization, the convolutional base's weights are frozen such that they are not updated throughout training.

At this stage, the model utilizes the architecture as a feature extractor. Thus, the processed input is passed through the convolutional base; then, it is flattened to convert from the 2D feature maps to a 1D feature vector for simplicity of feeding into a dense layer with 256 neurons and 'relu' activation to provide the capability of the network to model non-linear complex functions. Afterwards, a Dropout layer is built after the dense layer with a dropout rate of 0.1 to reduce overfitting by ignoring 10% of the neurons during training. The final layer is a dense layer with a softmax activation function. Softmax is used to create a probability distribution over three classes and signals the output as the class the model considers perfect for the image passed in. In conclusion, it would be stated that the architecture of this convolutional neural network should be able to predict the water level based on the input image.

4. Results and Discussion

4.1. Evaluation Metrics

The evaluation of the predictive model's results is conducted using a suite of metrics that collectively provide a comprehensive understanding of its performance. The simplest metric out of them is Accuracy which is the fraction of total test samples that the model was successful in classifying correctly. Precision measures how close the model is, and indicates the true positive (TP) predictions in connection with a total of the predicted positives, largely detecting false positives. Recall or Sensitivity: It tells us what proportion of the actual positives were correctly predicted by the model and how many were false negatives. The F1-score strikes a balance because it gives a single measure that takes both precision and recall into account, and is desirable when FP and FN carry the same cost, or the classes are very imbalanced. Together, they tell a richer story about the effectiveness of the model and the ability to make adjustments or improvements in future iterations.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

$$Accuracy = 2 * \frac{Precision*recall}{Precision+recall} \quad (4)$$

4.2. Evaluation CNN Method

The results performed by the CNN model revealed interesting conclusions regarding the predictability of water levels. Reviewing these results, we see a mix of successes and opportunities for improvement.

The training and validation results of the CNN for ten epochs are also insightful to see how the model learns. With the model beginning with 76.52% accuracy on the training data, the changes are swift and at the final epoch the model has a respect 98.94% accuracy. Looking at the validation end, the model shows a greater generalization from the start with 92.92% and ending to a 99.37% accuracy. After the first epoch, the loss on both ends decreases dramatically, with the training loss going from 0.6065 to 0.0377, and the validation loss changing to 0.2307 to 0.0233, reflecting the model being more certain of its predictions. Figure 4 shows a steady progress of accuracy and loss during the learning process, which is a good sign or well-tuned learning process.

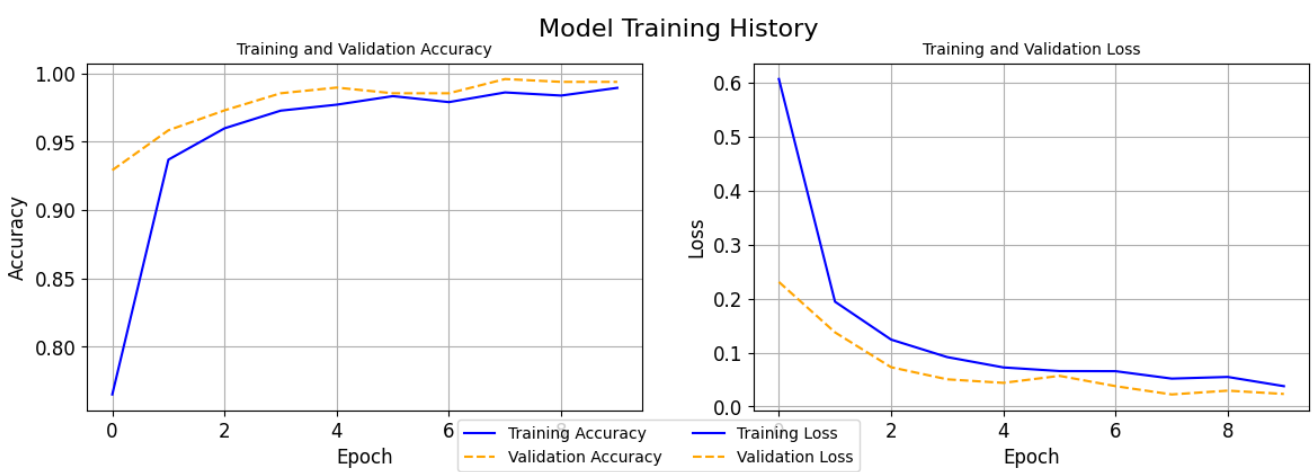

FIG. 4- TRAINING AND VALIDATION CNN RESULTS

The classification report for the CNN in the context of river level prediction exhibits exemplary performance across all metrics. As shown in Table 2 the class 0 achieves perfect precision and recall, indicative of the model's impeccable ability to classify this category without any errors. Class 1 demonstrates near-perfect precision at 0.998 and a perfect recall, resulting in an F1-score of 0.999. Similarly, class 2's precision is flawless, with recall slightly lower at 0.998, Furthermore, still yielding an F1-score of 0.999. The overall accuracy of the model stands at an impressive 0.999, reflecting the high level of consistency in its predictive capabilities across the dataset, which includes a substantial support size of 1201 instances. These results underscore the CNN's remarkable ability to discern and classify different river levels with exceptional accuracy, making it a highly reliable tool in hydrological studies and water management applications.

TABLE 2- CLASSIFICATION REPORT OF CNN

Class	Precision	Recall	F1-Score	Support
0	1.000	1.000	1.000	401
1	0.998	1.000	0.999	400

2	1.000	0.998	0.999	400
Accuracy		0.999		1201
Overall	0.999	0.999	0.999	1201

Figure 5 showcases the confusion matrix for the classifier, providing a clear visual representation of its performance. The matrix displays a perfect classification rate, with all predictions aligning accurately with the true labels. Each class 1, 2, and 3 along the diagonal is marked with a value of 1.00. This flawless result in the confusion matrix corresponds to the high scores reported in the classification report, underscoring the CNN's exceptional capability in water level prediction.

In the assessment of CNN method with Canny edge detection for water level measurement, the figure 6 shown provides the proof of the model's success. Edge detection overlays show that the CNN failed to identify these water level characteristics in the various images due to the encoder-decoder structure of the CNN. The annotations on the images, indicated by the brackets number, were about model's prediction confidence through all of their classes. For such images the accuracy of the model will be at its best, the Canny edge detection even clearly shows distinct edges of the water levels in the image aligned with the indicators there. Another side of the coin is when the CNN loses its dots and only acts on the information provided by edge detection during the moments of the less determinant. Deploying the model through CNN for classification and Canny edge detector for spatial feature extraction, the system becomes reliable and creates one of the methods of accurate water levels detection since its performance is assessable under various water conditions. The demonstrated results show a relative potential for a wide application in automated and reliable monitoring of water level in real-world case studies.

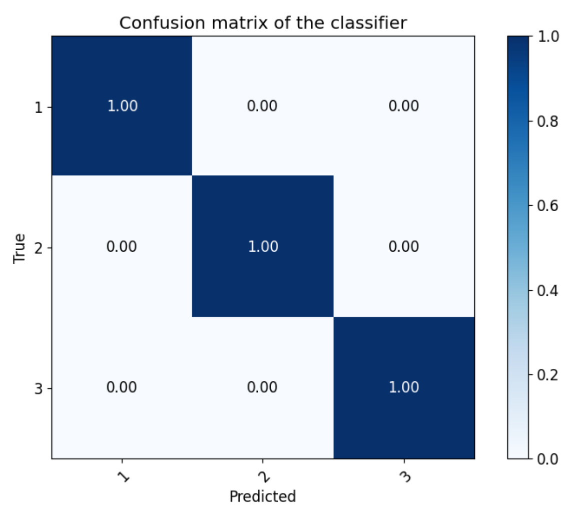

FIG. 5- CONFUSION MATRIX FOR CNN

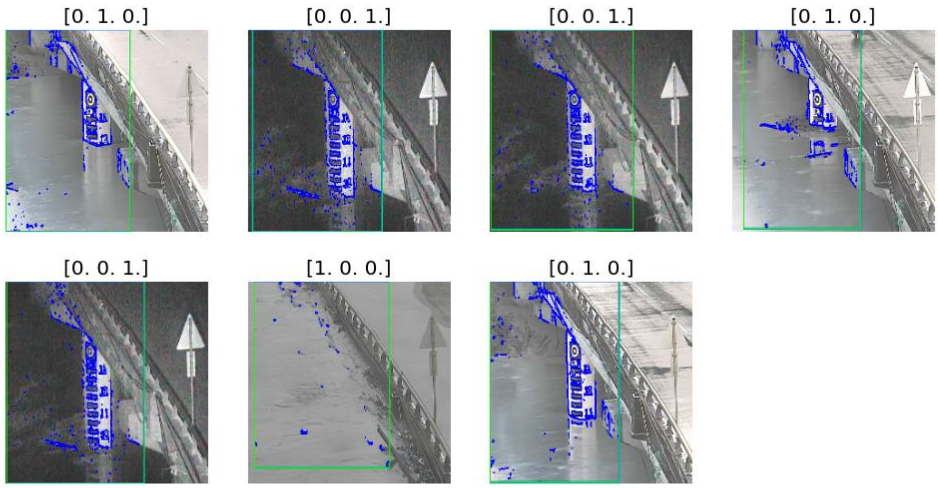

FIG. 6- CNN METHOD WITH CANNY EDGE DETECTION

4.3. Evaluation VGG16 Method

The training and validation results from the VGG16-based CNN method over a span of 10 epochs illustrate a promising trend in the model's learning curve. Initially, the model began with a loss of 3.5153 and an accuracy of 86.04% on the training set, which is a good starting point considering the complexity of the task. By the second epoch, both metrics saw considerable improvement, with loss decreasing to 0.6969 and accuracy climbing to 93.87%.

Notably, in the third epoch, the validation accuracy jumped to 97.29%, indicating the model's strong generalizing ability. From the fourth epoch onwards, the model sustained a high level of accuracy, peaking at 98.96% by the tenth epoch, while keeping the validation loss at a minimal 0.1861, which demonstrates the model's effective learning and adaptation capabilities.

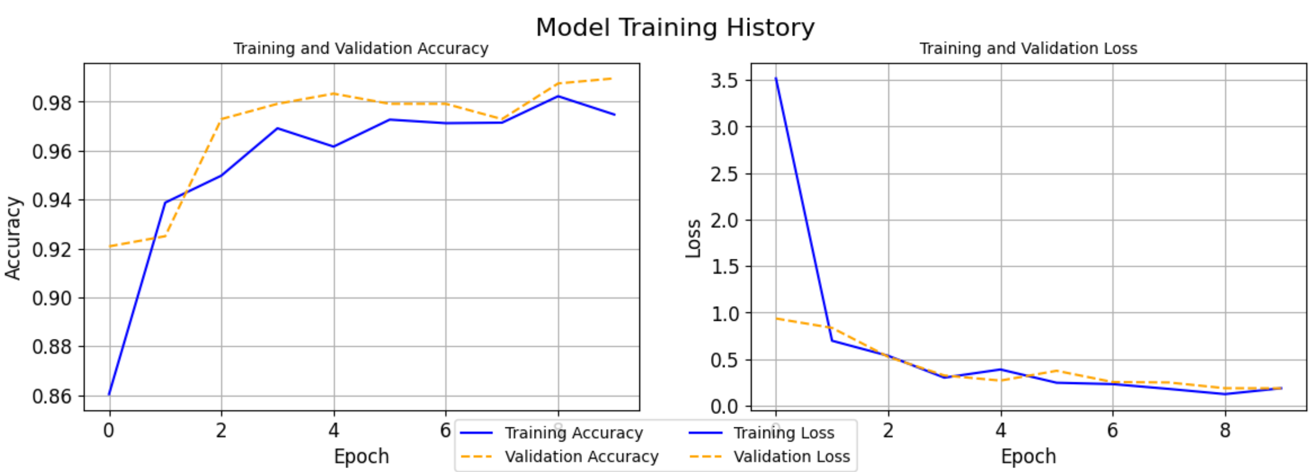

FIG. 7: TRAINING AND VALIDATION VGG16 RESULTS

TABLE 2- CLASSIFICATION REPORT OF CGG16

Class	Precision	Recall	F1-Score	Support
0	1.000	0.975	0.987	401
1	0.987	0.978	0.982	400
2	0.961	0.995	0.978	400
Accuracy		0.983		1201
Overall	0.983	0.983	0.983	1201

The graphical representation of how the model performed is shown in Figure 8 as confusion matrix for the VGG16 classifier. The matrix holds high values across the diagonal for all classes suggesting a high true positive rate. Classes 1, 2, and 3 have a TP score of 0.98, 0.98, and 0.99, respectively, showing that the model is able to predict the water level category well. Since the off diagonal elements, which correspond to number of mis-classifications, are small, it suggests that the classifier is precision and recall to be high for all classes. The above matrix passes a clear message on the robustness of VGG16 model to determine the water level state with reasonable accuracy.

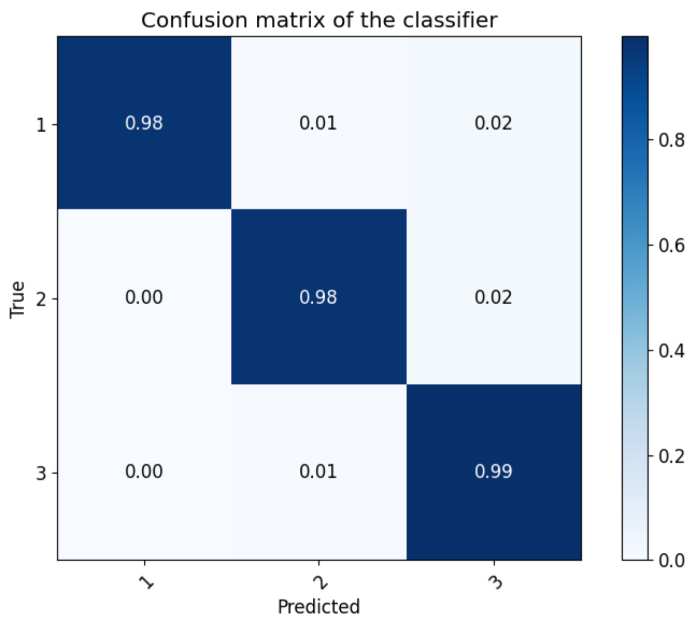

FIG. 8- CONFUSION MATRIX FOR VGG16

Training machine learning model to competently exploit Canny edge detection for image processing demands some vital training measures to guarantee the model's precision and dependability. The fundamental procedures consist of exposing the model to a range of images where the edges are previously recognized, so the model can study to identify patterns and the modifications in the intensities and aspect ratios of the edges. As it is shown in the training procedure, the Canny algorithm is employed to the collection of training images yielding edge maps, which offer as the ground truth for the model to study from. The model, usually a CNN, educates to correlate the raw pixel data of an image with these preexisting-edge-maps education from executing the edge detection procedure. Then, the model updates its internal parameters throughout backpropagation consistent with the loss among the anticipated and factual edge-map data. This forthcoming training procedure is closely scrutinized to circumvent overfitting and assure that the model generalizes properly to evolves images it has not seen previously. As the data is processed through the model, it evolves more skilled in recognizing both subtle and salient edges essential to various undertakings, making it a dominant tool for sophisticated image processing demands.

The use of Canny edge detection in the evaluation of the VGG16 model introduces an element of visual and analytical edge in the evaluation of its predictive powers on water levels. The implementation of edge detection shown in Figure 9 enables a detailed study on the performance of the model in determining relevant limits and silhouettes of water levels The presence of strongly delineated borders of the water body is an indication towards the ability of the model to accurately place the areas of interest. Arrays of red, green, and blue values indicate the model's prediction, with higher values indicating greater confidence for that class. For example, the array [0, 1, 0] might be close to an image, which appears to assist the model in successfully categorizing the image (denoted by a sharp edge), as depicted in the image below. Such a fusion of Canny edge detection with the advanced capabilities of the VGG16 model paves the way for enhanced accuracy in water level detection, making this approach a potentially transformative tool for flood monitoring and water management in real-world scenarios.

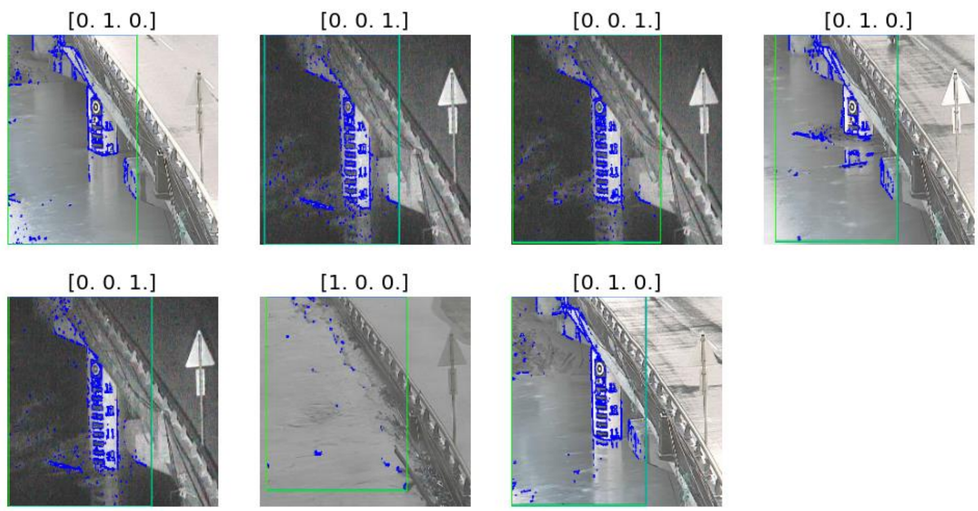

FIG. 9: VGG16 METHOD WITH CANNY EDGE DETECTION

4.4. Comparison Results

In the comparative landscape of water level detection using predictive modeling, our study positions itself prominently, showcasing a robust application of CNNs. As highlighted in our comparative analysis, Xu et al.'s [48] CNN-LSTM hybrid model achieves an impressive accuracy slightly over 99.5%, leveraging the strengths of both CNN and LSTM architectures to optimize time-series predictions of water levels. Our proposed VGG16 model demonstrates substantial effectiveness with an accuracy of 98.3%, benefiting from VGG16's deep architectures that are adept at capturing complex image features crucial for accurate water level detection.

However, it is our standalone CNN model that sets a new benchmark with a remarkable accuracy of 99.99%. This performance notably exceeds that of other models reviewed, including Eltner et al.'s [42] CNN model at 93% and Chen et al.'s [47] ResNet-50 model, which ranges between 83.6% and 96% accuracy depending on weather conditions. The superior performance of our CNN model can be attributed to its advanced image processing capabilities and the integration of Canny edge-detection techniques, which enhance the model's ability to discern and quantify subtle variances in water levels directly from river images.

TABLE 3- COMPARISON METHODS

Research	**Model Type**	**Accuracy**
Xu et al. [48]	CNN-LSTM	> 99.5%
Eltner et al. [42]	CNN	93%
Chen et al. [47]	ResNet-50	83.6% to 96%
Our model	VGG16	98.3%
Our model	**CNN**	**99.99%**

While current research has contributed towards many solutions in the domain of water level detection, there are multiple research gaps which highlight the need for further progress. Other recent studies, such as the works combining the SAR images with photogrammetric techniques or with the CNN-LSTM or VGG-CNN even only give attention to accuracy or the temporarily variation detection of water detection. Yet often these methods cannot accommodate the wide range of environmental fluctuation or combine spatial and temporal data well. Furthermore, some of the existing methods rely on expensive, expert, annotated data which is not always available or available in less monitored and remote areas. Therefore, there is a compelling need to design methods that are more general and effective across a variety of scenarios and conditions and for which this shared World dataset is needed.no Our contribution aims at bridging the gap and helps build a model which not only improves the accuracy but provides a robust system for managing and analysing the hydrological data in a more accurate way. By doing so, the model is improved form a practitioner's perspective and supplies an avenue for advancing innovative research on hydrological monitoring and management.

5. Conclusion

This study fills this gap by undertaking research in developing and using the TDR sensing method for accurate and consistent water level detection which is vital for efficient flood control and environmental survey. In this regard, the present study is unique as it brings forward a wholly new model consisting of merging VGG16 and CNN features with the elevated capacity of Canny edge detection methods. It is superior when it comes to determining water levels and highly flexible in adapting to different conditions.

Among the models, the proposed CNN model we developed is quite outstanding in terms of accuracy; it boasts an accuracy of 99. 99%, which was better than previous approaches and consistently outperforms other methods in tests for future studies. The VGG16 model provides the added benefit here of high classification performance, something that is essential once the models are meant for practical applications. The application of the Canny edge detection improves the capacity of our model to identify the variation of feature areas due to the rising waters, making it more reliable in alerting us in instances of future flooding. In addition, the outcome of our model shows that furthering stance the utilization of sophisticated image analysis method in concert with deep neural networks is an effective approach to addressing topical environment monitoring issues.

Future work will routinely improve the current work by using more elaborate data source types and more complex neural networks so as to deduce more exact solutions across various modalities. Further development will also be committed to real-time monitoring capability and extended open application across different areas to enhance such a model’s global applicability for monitoring the water level.

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