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Comprehensive Review of River Water Level Detection and Prediction Technologies

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Abstract— This paper comprehensively reviews recent advancements in deep learning, focusing on detection, water level prediction, and water segmentation using deep learning techniques. Floods have become a growing concern, necessitating accurate and efficient methods for monitoring and predicting water levels. Leveraging the power of artificial intelligence and deep learning, this review explores various methodologies and algorithms employed. The review also critically evaluates the strengths and limitations of existing approaches, identifies challenges, and proposes potential future research directions. Key topics covered include image segmentation techniques, water level detection and prediction models, datasets, evaluation metrics, and the integration of multi-modal data fusion for improved flood detection and prediction accuracy. By addressing deficiencies and highlighting the significance of this critical field, this review serves as a valuable reference for researchers, practitioners, and policymakers working on flood management and disaster response.

Keywords: *Image Segmentation, Flood Detection, Water Level Prediction, Deep Learning, Convolutional Neural Networks، RNN, CNN, SVR, and GRU*

مراجعة شاملة لتقنيات الكشف عن مستوى مياه النهر والتنبؤ به

نسرين توفيق كريم - أستاذ جميلة الحربي

قسم علوم الحاسوب، كلية العلوم، الجامعة المستنصرية، بغداد، العراق

تستعرض هذه الورقة بشكل شامل التطورات الحديثة في التعلم العميق، مع التركيز على الكشف والتنبؤ بمستوى المياه وتجزئة المياه باستخدام تقنيات التعلم العميق. أصبحت الفيضانات مصدر قلق متزايد، مما يستلزم أساليب دقيقة وفعالة لرصد مستويات المياه والتنبؤ بها. من خلال الاستفادة من قوة الذكاء الاصطناعي والتعلم العميق، تستكشف هذه المراجعة مختلف المنهجيات والخوارزميات المستخدمة. تقوم المراجعة أيضًا بتقييم نقاط القوة والقيود في الأساليب الحالية بشكل نقدي، وتحدد التحديات، وتقترح اتجاهات البحث المستقبلية المحتملة. تشمل المواضيع الرئيسية التي يتم تناولها تقنيات تجزئة الصور، ونماذج الكشف عن مستوى المياه والتنبؤ بها، ومجموعات البيانات، ومقاييس التقييم، وتكامل دمج البيانات متعدد الوسائط لتحسين دقة الكشف عن الفيضانات والتنبؤ بها. من خلال معالجة أوجه القصور وتسليط الضوء على أهمية هذا المجال الحاسم، تعد هذه المراجعة بمثابة مرجع قيم للباحثين والممارسين وصانعي السياسات العاملين في إدارة الفيضانات والاستجابة للكوارث

الكلمات المفتاحية: تجزئة الصور، الكشف عن الفيضانات، التنبؤ بمستوى المياه، التعلم العميق، الشبكات العصبية التلافيفية، RNN، CNN، SVR، و GRU

1-INTRODUCTION

An image is a visual representation of anything that contains a load of helpful information. The analysis and information extraction from the image without changing the other qualities is one of the critical uses of digital image technology[1]. Image segmentation is fundamental for numerous computer vision applications, including scene understanding, human resolution, and autonomous driving. Due to its wide variety of uses, researchers highly value this technique[2]. The most essential stage of picture analysis is segmentation[3]. These methods are being used in increasing domains and subtasks, including indoor scene reconstruction and other activities that might significantly increase the final accuracy by estimating interior room layout. However, utilizing segmentation labels at the pixel level can result in costly annotation expenses [4]. Image segmentation is breaking down each frame of an image or video into various objects or regions and labeling each one appropriately. So far, image segmentation development has involved thousands of widely used segmentation methods and continuous image segmentation advances. They fall into region, threshold methods, edge, particular theory, and deep learning-based segmentation techniques. There was also the argument that image segmentation methods should use the same number or notation to identify pixels in a picture that are part of the same specific object. [5]. It's helpful for additional analysis to simplify the segmenting or transforming an image representation into a meaningful representation. [6]. The area of an image that needs to be segmented should be straightforward, homogeneous, and uniform in terms of texture, color, and greyscale. Adjacent pixels should also be markedly distinct from one another. In image processing, picture segmentation is a challenging task that distinguishes readily between the objects and the background. [7]

Machine learning has gained increasing traction in the field of research. It is employed in various applications, including social network analysis, image categorization, multimedia concept retrieval, text mining, etc. "Deep learning" is another name for representation learning, one of several machine-learning algorithms. [8]. The subfield of machine learning known as "deep learning" uses hierarchical architectures to try and extract high-level abstractions from data. It is a recent method widely used in conventional artificial intelligence applications.[9]. Automated feature extraction by deep learning algorithms enables researchers to extract discriminative characteristics which require less domain expertise and manual labor[10]. It is a neural network with many layers and parameters. Neural network architectures are used in the majority of deep learning approaches. Consequently, it is also known as deep neural networks. Deep learning employs a chain from several nonlinear process unity strata for feature extraction and conversion. The higher layer learns more complicated characteristics that are derivable from lower-layer features, while lowest layers nearer to the information input learns basic features. A powerful and hierarchical feature representation is formed by the structures; it implies that deep learning is suitable for assessing as well as extraction knowing of from massive numbers of information as well as information acquired from a variety of resources[11]. Deep learning enables computational models with several processing layers to learn and represent data with various degrees of abstraction, imitating how the brain processes multimodal information and implicitly capturing complex structures of large-scale data[12]. Deep learning considerably outperforms its previous, having its roots in conventional neural networks. It develops multi-layered learning models using graph technology and transformations among neurons. Numerous recent Deep Learning approaches have been introduced, showing hopeful outcomes in various uses, including audio and speech processing, visual data processing, natural language processing (NLP), and many other well-known ones [13].

1. Semantic Segmentation

Nowadays, one of the primary issues of semantic segmentation is a topic in computer vision. It can be utilized for static 2D photos, video, and even 3D or volumetric data. Looking at the large image, when considered holistically, semantic segmentation is one of the high-level processes that result in complete scene comprehension. [14].In the recent models of deep segmentation created for semantic segmentation, Image processing and analysis commonly involve the process of semantic segmentation. This gives each pixel a label, resulting in a set of areas in the output. [15]. Namely: the semantic segmentation model (SegNet) is a fully convolutional autoencoder. It comprises an encoder network, a matching decoder network, and a final layer of pixel-wise categorization. 13 convolutional layers include the encoder network, corresponding to the first 13 convolutional layers of the Visual Geometry Group network. (VGG16). Better segmentation accuracy results from the model's ability to transmit higher-resolution information between layers. [16]. The Pyramid Scene Parsing Network (PSPNet) utilizes the pyramid pooling module, depicted in Fig.1. , to transfer data from a higher to a lower layer. The pyramidal structure tries to send more contextual information between layers[17]. The architecture of the UNet, shown in Fig.2, was created for biomedical image segmentation working with a small number of training photos without compromising segmentation precision. The network leverages communication among levels to transfer contextual data to higher-resolution layers, giving rise to its U-shaped architecture, which gave rise to its name[18]. FCN32 employs a deep, fully convolutional network that integrates the fine layer outputs and the coarse layer's semantic data to provide precise and thorough segmentation, shown in Fig.3.[19].

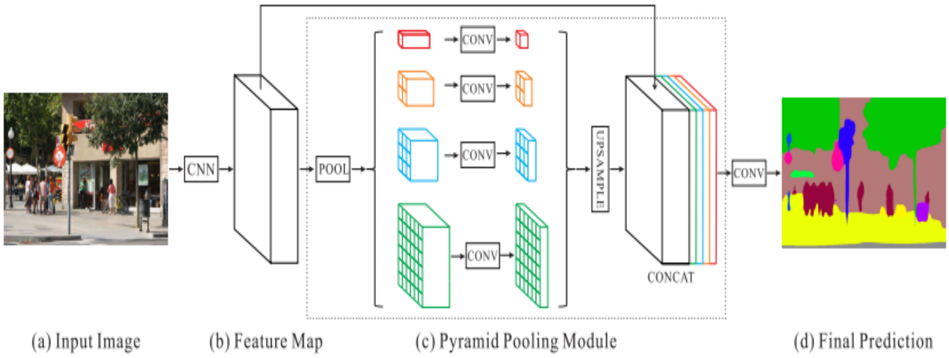

Fig.1: Overview of PSPNet [17].

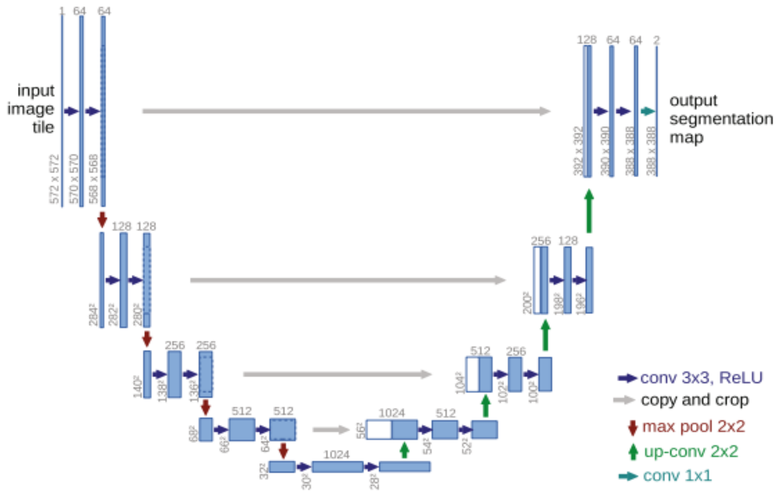

Fig.2: design of a U-network [18].

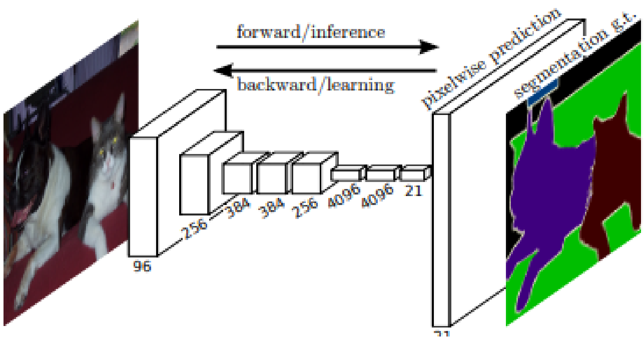

Fig.3: Fully convolutional networks(FCN) [19].

3. Image Segmentation Techniques and Water Level Prediction and detection Methods

Laura Lopez, et al. in (2017) [20],proposed an automatic detection of river flooding by segmenting videos used by surveillance cameras around the river. In case of an increase in water level, the proposed system issues a warning alarm.

Three semantic segmentation algorithms were investigated for this purpose, namely Fully convolutional networks for semantic segmentation (FCN-8s), Fully Convolutional DenseNets for Semantic Segmentation (Tiramisu), and Image-to-Image Translation with Conditional Adversarial Networks (Pix2Pix). In addition, the authors created their dataset consisting of 300 images from Google, cameras around the riverbeds, and self-captured images. 75% of the dataset was used for training the algorithms, whereas 25% were kept for testing. The performance of the algorithms was evaluated according to Mean Intersection over Union (MIoU) and pixel-wise accuracy (Pa) shown in Equations (3)and(4), respectively. The Tiramisu algorithms achieved the highest MIoU (81.91) and Pa (90.47), followed by Pix2Pix, whereas FCN-8s had the lowest MIoU and Pa values.

Faruq, et al. in (2019)[21], examined the efficiency of an LSTM network in forecasting the water level of Klang river in Malaysia depending on real-time data and the network's ability to learn and perform predictions from historical data. The LSTM network is made up of input layer, 200 memory cells in the hidden layer, and an output layer. The network is characterized by its ability to maintain and adjust its cell state, such that the learned information from the previous layer is kept and new information is added to it or removed depending on the input. In each cell state, the information to be removed is selected, the applicable information is kept, and the specific information are used through the functions of the forget gate, input gate, and output gate respectively. The LSTM network was trained by 80% of the standardized dataset (15207), whereas the simulation and prediction were carried out by 20% (3801). The LSTM model presented itself as a good solution for modeling and forecasting floods by achieving a root mean squared error RMSE value of 0.205, and R2 value of 0.844, it is expressed in Equations (1) and (2), respectively. the low RMSE value indicates that the predictions of the LSTM network are very close to the actual values.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y - y'|^2} \quad (1)\ [21]$$

$$R^2 = \frac{\sum_{i=1}^{n}(\acute{y} - \bar{y})^2}{\sum_{i=1}^{n}(y - \bar{y})^2} \quad (2)\ [21]$$

Where n is the count of points of data, y denotes the observed river water level at the time i, y′ indicates the river water level prediction values, and $\bar{y}$ indicates the mean value of the recorded data, whether it be actual or observed.

Alvin, et al. in (2020)[22], introduced an inference approach for flood detection by installing a flood detector near rivers in urban areas with the help of a camera near the bridge column. The main objective was to deliver a system alerting the authorities to evacuate the area before it's too late. The model consists of 3 colors dataset: red, blue, and green, referring to the height that the water reaches. The dataset was split by an 80:20 ratio for training and testing the proposed model and was annotated and labeled. The model was generated by MobileNet SSD v2, and the Pi camera was used to detect the water line by taking real-time images. In addition, a Simulated Bridge-Column Environment was created. The system was able to produce an 85.46% accuracy.

Mirko Zaffaroni and Claudio Rossi., in (2020)[15], aimed to determine the accuracy at which deep learning models can detect water in images, specifically through pixel-wise semantic segmentation. The assessment of deep learning algorithms took place on a dataset called "Water Segmentation Open Collection (WSOC) " introduced by the author and other datasets. The WSOC dataset comprises other public datasets: COCO, the Semantic Drone Dataset, MSRC v2, Video Label Propagation, and the River Dataset, in addition to new 490 images. The WSOC dataset contained 120061 images that were annotated and validated. Four DL models were developed and evaluated, with either of the following pre-trained backbones VGG16, ResNet50, MobilNet, in combination with one of the following segmentation algorithms SegNet, PSPNet, FCN32, and UNet. The evaluation metrics were Mean Intersection Over Union (MIoU) and Pixel Accuracy (PA) shown in Equations(3)and(4). Model-wise, SegNet achieved the highest entries, while metric-wise, ResNet-50 backbone models achieved the best results (0.85 and 0.94 values for MIoU and PA, respectively). In addition, training the models on the WSOC dataset allowed them to achieve better results than when trained on different datasets. The suggested method is represented in Fig.6.

$$MIoU = \frac{\frac{1}{c}\sum_{i}^{N} n_{ij}}{t_i + \sum_{j}^{N}(n_{ij} - n_{ii})} \qquad (3)\ [15]$$

The Pixel-wise Accuracy (PA) is also:

$$PA = \frac{\sum_{i}^{N} n_{ii}}{\sum_{i}^{N} n_{ii}} \qquad (4)\ [15]$$

Where ti is the total number of pixels in class i, nij is the number of pixels from class i that were incorrectly classed as being in a class j, nii is the number of pixels from class i that were correctly classified, and C is the overall count of classes.

Mingyang et al.in(2020)[23], discussed implementing GRU and CNN for water level detection through special-temporal data analysis. The GRU-based model consisted of 2 hidden GRU layers and a fully connected layer as an output layer, and it was used for predictions on 1 station (model 1) and 3 stations (model 2). The GRU-CNN model, it is made up of three convolution layers and 3 GRU layers. As for the dataset, the authors relied on IoT-based technologies such as auto-telemetry systems to collect data for Yangtze River, which resembles 30 years of data collection at 8 o'clock daily. Outliers in the dataset were replaced with average values, and denoising was also performed. The dataset was divided by 80:20 ratio for training and testing into 3 categories: dry season, middle season, and flood season. The performance of the models was evaluated according to NSE, MRE,in Equations (5) and (6), and RMSE in Equation (1), where GRU-based models perform better compared to LSTM and other models. Additionally, the best-performing model was the GRU-CNN model achieving the highest NSE value (0.9747), lowest MRE value (3.31%), and lowest RMSE value (0.1398).

$$NSE = \frac{\sum_{i=1}^{n}\left(y^{(i)} - \hat{y}^{(i)}\right)^2}{\sum_{i=1}^{n}\left(y^{(i)} - \bar{y}\right)^2} \qquad (5)\ [23]$$

$$MRE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y^{(i)} - \hat{y}^{(i)}}{y^{(i)}}\right| \qquad (6)\ [23]$$

Where y^i represents the observed value, yˆi represents the anticipated value, and y¯ represents the observed average.

Sang.Soo et al.in(2020)[24] , introduced a CNN-LSTM combined model to predict water levels in the Nakdong river basin. Water level data were acquired from the Water Resources Management Information System (WAMIS) in South Korea, and the simulation period was divided into a calibration period and a validation period between Jan 2016 and Nov 2017. CNN-part of the model is responsible for feature extraction from images, whereas the LSTM-part is responsible for identifying the pattern in time series. The CNN architecture was made up of a convolution layer for radar images, followed by an additional architecture (for temperature, evaporation, average water level in the last 3 days, etc..), and finally a fully connected layer. The epoch number for CNN was 1000 and the mini-batch was 16 with a learning rate of 0.001. The performance of the CNN model was assessed through R2 in Equation (2), NSE in Equation (5), and MSE in Equation (1). The model scored R2 value of 0.923, MSE value of 0.001, and NSE value of 0.933.

R´emy Vandaele, et al. in (2020)[25], examined the implementation of deep transfer learning as an approach for water segmentation and water level prediction. In order to do so, the authors selected two datasets: COCO-stuff (11,625 images total) and ADE20k dataset (1,927 images total). The authors followed three approaches. The first approach uses pre-trained networks. The second approach uses pre-trained semantic segmentation networks that are fine-tuned on one of the two datasets. In the third approach, only a fragment of the two datasets is used for fine-tuning the pre-trained networks. In the second approach, the network consists of Deeplabv2 with a ResNet101 encoder and atrous spatial pyramid pooling decoder 9, which is fine-tuned on the COCO-stuff dataset.

In contrast, the FCN network with a ResNet50 encoder and a UperNet decoder was fine-tuned on the ADE20k dataset. The networks were tested on new datasets, INTCATCH and LAGO, and evaluated according to pixel accuracy and MIoU). The results show that the Deeplabv2 network from the second approach scored the highest MIoU levels on the INTCATCH dataset (99.18) and 99.59 Accuracy. Similarly, the ResNet50-UperNet network from the second approach scored the highest MIoU levels on the INTCATCH dataset at 98.95 and the highest accuracy at 99.48.

Md. Imran, et al.in (2022)[26], suggested deep learning models to predict the Bahadurabad transit of Brahmaputra-Jamuna water levels . The prediction of water levels is proposed through three different DL models, namely Recurrent Neural Network RNN, Long Short-Term Memory, and Gated Recurrent Unit. For training these models, data was collected from Jan 2005 to Sep 2013, while the rest of the data (up till 2019) was used for testing the models. The variables that were taken into consideration were water level, discharge, and maximum velocity. The training and testing datasets were divided into explanatory and response variables. The discharge was used as the response variable, while the water level and maximum velocity were used as explanatory variables. For RNN, a straightforward model architecture was built with 100 'Simple RNN' units with the activation function Rectified Linear Unit. The RNN architecture consisted of 180 Long-Short Term Memory units in the first layer and 50 units in the second layer. After testing, the R2 value and the mean absolute percentage errors MAPE were calculated. This paper finds that all three models perform similarly, but the RNN has a better R2 value (0.9980) and less MAPE (0.49), indicating higher accuracy.

Punyanuch, et al.in(2022)[27], investigated the use of deep learning algorithms, namely Support Vector Regression ()SVR, LSTM, as well as a combination of both, as a method for river water height prediction. SVR can capture non-linear data through the use of non-linear kernels, whereas the LSTM model is made up of 2 stacked LSTM networks with 50 hidden nodes and 20 hidden nodes. The LSTM network possesses memory cells that allow the network to remember and delete inputs. On the other hand, the authors propose using LSTM to extract features and SVR to predict the final results. The assessment of the performance of the three models was done through mean absolute error (MAE) and root mean square error (RMSE) values. Data were recorded, cleansed, and validated, making 2880 samples for training and 688 for testing. By taking 4 different periods for prediction and different input dimensions, the total number of generated models was 32. The results show that the LSTM model provides the lowest error for all of the different interval inputs. However, the proposed LSTM-nonlinear SVR model achieves similar results but with better performance in predicting rapid temporal changes in data. The authors concluded that it is best to collect historical data with intervals that are equal to or more than the prediction time period to achieve optimal results.

Hashi,et al.in (2021) [28], suggested machine learning systems with emphasizing deep learning as a method for detecting floods based on real-time images. J48, Random Forest, Convolutional Neural Networks, and Naive Bayes were the proposed ML algorithms for this purpose. Initially, the authors collected their data by introducing water level sensor and the data was collected by monitoring a river in real-time using Arduino and GSM devices as hardware. The data was communicated with the microcontroller and was utilized to train the chosen models. According to the best performance, the algorithm was chosen, and according to its result, the result might be transmitted through an SMS to flood control authorities. The ML algorithm RF was able to achieve highest accuracy value (98.7%) even surpassing the DL algorithm CNN (87%). Fig 12 displays the proposed framework.

Qiao, et al. (2022) in [29], YOLOv5s as a solution to the challenges that arise in flood detection, specifically the lack of scene adaptability and weak robustness. The YOLOv5s model extracts the water gauge and character area, identifies the location of water surface line through image processing, and calculate the water level height. The dataset consists of on-site shooting data or data collected online about a river in Beijing, where the collected sample cover water gauge data such that the camera angle is adjusted to capture the data from different angles and the images of the water gauge are taken during different time periods and different lighting scenes, totaling 5000 images. In addition, SVHN dataset was taken into consideration containing a total of 73257 images. From these datasets, YOLOv5s had to perform water gauge detection and water surface line recognition before determining the actual level of water. The results showed that the YOLOV5s model performs well in detecting the water gauge with great precision (1.00) and only 2 misdetections in the transparent scene. The water gauge detection speed was 30FPS. YOLOv5s also found hardship in accurately detecting water surface lines in transparent scenes (it is off by more than 1cm), compared to daylight, nightlight, and infrared illumination scenes.

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Compared to traditional image processing methods, YOLOv5s achieved higher speed and lower error rates. Fig. 13 shows the structure of YOLOv5.

Table 1 summarizes the methodologies, results, and drawbacks for each of the previous works, while Table 2 explains the types of datasets used.

Table 1: summary of the previous works.

Author/year	Methodology	Dataset	Result	Drawback
In 2017, Laura Lopez-Fuentes et al.[20]	(FCN-8s), (Tiramisu), and (Pix2Pix).	Costume-made dataset 300 images	MIoU= 81.91 Pa= 90.47	-Small dataset
In 2020, A. Faruq et al.[21]	LSTM network	19008 input	RMSE= 0.205 R^2 = 0.844	-input variables are limited to 1.
In2020,Alvin Sarraga Alon et al.[22]	Raspberry Pi camera + MobileNet SSD v2	RBG Line Image Dataset 300 images	Accuracy= 85.46%	-A small dataset with 300 images only.
In 2020, Mirko Zaffaroni and Claudio Rossi.[15]	pre-trained backbones VGG16, ResNet50, MobilNet, with SegNet, PSPNet, FCN32, and UNet	WSOC dataset 120061 images	MIoU= 0.85 PA= 0.94	-ResNet achieved the best results, but it was the slowest algorithm.
In 2020,Mingyang Pan, et al.[23]	GRU and GRU-CNN	47,267 inputs from 4 river stations	NSE= 0.9747 MRE= 3.31% RMSE= 0.1398	-prediction for more than 5 days is not effective.
In 2020,Sang-Soo Baek et al.[24]	CNN	WAMIS dataset	R^2= 0.923 MSE= 0.001 NSE= 0.933.	- This approach must be replicated using other datasets.
In2020,R´emy Vandaele, et al.[25]	Deeplab, and ResNet50-UperNet	LAGO and INTCATCH datasets	MIoU=99.18 Acc= 99.59 MIoU= 98.95 Acc=99.48.	-Lack of in-depth analysis and statistical data
In 2022, Md. Imran Islam	Gated Recurrent Unit, Long Short-Term	BWDB (2005-	R^2= 0.998 MAPE=	-Historical data eliminate the external factors such

Rabbi et al.[26]	Memory, and Recurrent Neural Network	2019)	0.49%	as climate change.
In2022, Punyanuch Borwarnginn et al. [27]	SVR, LSTM, and combination of SVR and LSTM	3,568 samples from the Japanese River Website	RMSE= 0.016 ± 0.004 MAE= 0.012 ± 0.004	- LSTM is not able to apprehend quick changes in river height levels.
In 2021, Abdirahman Osman Hashi et al.[28]	CNN, J48, Naive Bayes, and Random Forest	Real-time data	Accuracy= 98.7%	-The dataset size is not indicated.
In 2022, Guangchao Qiao et al.[29]	YOLOv5s	Guage dataset= 5000 SVHN dataset= 73257	95% error that is less than 1 cm Processing time= 30 FPS	-Precision values were not indicated.

Table 2: Types of datasets used in the previous works.

Dataset Name	**Description**	**Purpose**	**Size**	**Source**
River Photos	Collection of river images from various sources, including drones, in-field observations, and social media.	Water segmentation, flood detection	Large	Lopez, et al. (2017) [20]
Klang River Data	Historical dataset of river water levels from the Klang River in a case study.	Water level prediction, flood forecasting	Large	Faruq, et al. (2019) [21]
Real-time Sensors	Real historical sensor data, including rain, total rainfall, and river water levels.	Water level prediction	Large	Punyanuch et al. (2022) [27]
Water Gauge Data	Dataset of CCTV images containing water gauge areas and scale	Water level measurement	Medium	Qiao et al. (2022) [29]

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	characters for water level measurement.			
Water Segmentation	Dataset incorporating flood-related photos from drones, in-field observations, and social media.	Water segmentation using deep learning	Large	Zaffaroni and Rossi (2020) [15]
Flood Images	Collection of RGB images representing different water levels under a bridge.	Flood level detection and alert system	Small	Alvin et al. (2020) [22]
River Monitoring	Dataset of images and metadata collected from a river monitoring station in Beijing.	Water level prediction using deep learning	Medium	Qiao et al. (2022) [29]

4. Discussion and Analysis models

The research on " River Water Level Prediction And Detection Based On Deep Learning Techniques: " explores various methods and approaches to tackle the challenges of flood detection, water level prediction, and water segmentation using different datasets. Let's discuss and analyze the methods used in some of the critical research papers mentioned in the review:

1. **Deep Learning for Water Segmentation:** Several studies, such as Lopez et al. (2017)[20] and Zaffaroni and Rossi (2020)[15], emphasize the effectiveness of deep learning methods, including Fully Convolutional Networks (FCNs), Tiramisu, and Conditional Adversarial Networks (Pix2Pix), for water segmentation from river photos. These methods leverage semantic segmentation and pixel-wise accuracy to achieve accurate results in detecting water regions from images. The superior performance of the Tiramisu framework, with over 5% better accuracy than other methods, showcases the potential of deep learning in water segmentation tasks. However, further research can explore using different advanced deep learning architectures to enhance accuracy and efficiency in this area.
2. **LSTM and GRU for Water Level Prediction:** Faruq et al. (2019)[21] and Mingyang et al. (2020)[23] proposed the use of Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) to predict river water levels. LSTM networks are especially suitable for time-series data, making them practical for forecasting river water levels. The LSTM network with the designated training group provided accurate water level predictions, demonstrated by low Root Mean Square Error (RMSE) and high R-squared (R2) values. However, one limitation in some cases was reduced

performance for long-term forecasts, suggesting further optimization to handle longer prediction intervals.

3. **CNN for water level detection to Flood Detect:** Research by Alvin et al. (2020) [22] demonstrated the use of Convolutional Neural Networks (CNNs) to develop a flood-level detection and alert system. The CNN-based model detected flood levels using color codes from images captured under a bridge. The model achieved high testing accuracy for detecting flooded areas (Green) and impending floods (Red), indicating its effectiveness as a real-time flood monitoring system. However, one limitation is the relatively small dataset size, which could impact the model's generalization to different scenarios and location

Overall, the research on " River Water Level Prediction And Detection Based On Deep Learning Techniques: A Review" highlights the potential of deep learning techniques, particularly CNNs, FCNs, LSTM, and GRU, water level prediction ,detection, and water segmentation tasks. However, several research papers noted limitations related to dataset size, generalization, and handling extreme conditions, indicating areas for further improvement and research. The review provides valuable insights into the state-of-the-art methods for flood-related tasks and lays the foundation for future advancements in this critical domain.

5. Challenges and Opportunities

5.1 Challenges:

- Data Quality and Availability: Obtaining high-quality and diverse datasets for flood-related tasks remains challenging. Inadequate data can lead to biased models and hinder their generalization to different environments. Additionally, accessing real-time and historical data from various sources can be challenging.

- Model Interpretability: Deep learning models, especially complex ones, often lack interpretability, making it challenging to understand the reasoning behind their predictions. Interpretable models are crucial for gaining trust and acceptance in critical applications such as flood prediction and disaster management.
- Extreme Events and Uncertainty: Modeling extreme flood events and dealing with uncertainty in flood forecasts are complex tasks. Handling uncertainty becomes essential in decision-making processes to avoid false alarms or missed warnings.
- Resource Constraints: Deploying and maintaining sophisticated deep-learning models require significant computational resources and memory. Implementing real-time flood detection systems on low-power devices and in resource-constrained areas is challenging.

- Data Privacy and Ethics: Leveraging social media and other user-generated content for flood detection raises privacy and ethical concerns. Ensuring that user data is used responsibly and with proper consent is essential.
- Integration of Multiple Data Sources: Integrating data from different sensors, satellite imagery, social media, and other sources presents challenges in data fusion and information extraction. Ensuring the seamless integration of diverse data for comprehensive flood monitoring is crucial.

5.2 Opportunities:

- Advancements in Deep Learning: Continual advancements in deep learning techniques offer opportunities to enhance flood detection and prediction models. Novel architectures, transfer learning, and self-supervised learning can contribute to improved accuracy and efficiency.
- Big Data and Cloud Computing: Leveraging big data technologies and cloud computing can help handle large datasets, accelerate model training, and enable real-time processing for flood monitoring systems.
- Interdisciplinary Collaborations: Collaboration between researchers, environmental scientists, data scientists, and policymakers can lead to more holistic flood management solutions. Integrating expertise from various domains can address complex challenges effectively.
- Internet of Things (IoT) and Sensor Networks: IoT devices and sensor networks can provide real-time data on water levels, rainfall, and other environmental variables. Integrating such data into flood prediction models can enhance accuracy and timeliness.
- Explainable AI (XAI): Advancements in XAI techniques can enable better interpretability of deep learning models, making them more transparent and understandable for decision-makers and stakeholders.
- Climate Change Resilience: Deep learning models can contribute to assessing the impact of climate change on flood patterns and developing adaptive strategies to improve resilience against changing environmental conditions.
- Public Awareness and Early Warning Systems: Integrating deep learning models with early warning systems can significantly improve public awareness and preparedness, reducing the impact of floods on communities.
- Automated Remote Sensing: Deep learning models can aid in automating the analysis of satellite and drone imagery, allowing for more frequent and comprehensive flood monitoring on a global scale.

6. Conclusions

The research presents a comprehensive overview of the methodologies and techniques utilized in water level detection and prediction, and water segmentation using various deep learning. The review highlights the effectiveness of deep learning methods, such as CNNs, FCNs, LSTM, and GRU, in addressing the challenges of flood-related tasks. Additionally, combining visual data from images and textual metadata has shown promise in enhancing the accuracy and robustness of flood detection systems. The study demonstrates that deep learning models, particularly FCNs and Tiramisu, offer superior performance in water segmentation tasks, providing accurate and consistent results in detecting water regions from river photos. LSTM and GRU-based models exhibit strong potential in accurately predicting river water levels, especially in short-term forecasts, aiding flood forecasting and management efforts.

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