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Computer Vision Algorithm for Identifying Rivers as Indicators of Potential Flood

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***Abstract*– The project proposes the development of a computer vision algorithm using YOLO (You Only Look Once) and the Roboflow training platform to identify rivers and predict potential overflows. This solution aims to address the issue of flooding in Honduras, where flood seasons are a constant threat, but the ability to take preventive measures is limited.**

The algorithm will be trained with images and river data to achieve accurate detection of bodies of water. Subsequently, it will be enhanced to identify early signs of overflows, enabling timely alerts to be issued. Early detection of overflows will allow for preventive measures to be taken, safeguarding lives and property.

This computer vision approach holds the promise of providing an effective solution to anticipate and manage the risk of flooding in Honduras, where prevention and early warning are crucial to mitigate the devastating effects of these natural events.

Keywords- Flood Prediction; CNN; Algorithm; Overflow.

I. Introduction

The importance of having a precise and efficient monitoring system to assess the state of rivers lies in its ability to anticipate and respond to extreme weather events that can lead to floods and overflows. Water-related disasters, such as flash floods, can have a devastating impact on infrastructure, the economy, and, most importantly, on the safety of the population. Therefore, the implementation of an advanced river recognition system becomes a strategic priority for the SIT (initials or acronym). This report aims to provide an overview of the most current technologies, methods, and approaches used in the field of river recognition through images.

Through a review of specialized literature, the most recent advances in the use of computer vision, remote sensing, artificial intelligence, and other related disciplines for river detection and tracking will be explored. Additionally, successful cases and best practices in the implementation of similar systems in other regions and organizations will be addressed.

Ultimately, this paper will serve as a starting point for the SIT in its search for the most suitable and effective solution for its river recognition project. The information gathered here will provide a solid foundation for understanding the possibilities, challenges, and key considerations that must be considered in the planning and execution of an image-based river monitoring system, to ensure the safety and well-being of the population and the natural environment.

The implementation project of an image-based river recognition system to measure the riverbed and determine the risk of overflow is set within a context where several elements must be comprehensively considered. These elements come from various sources of information and experience.

First and foremost, it is essential to look to the past, examining past overflow events in the region. These events not only shed light on the history of river-related disasters but also provide a clear insight into their impacts on both the population and infrastructure. Understanding the underlying causes and risk patterns associated with previous events is crucial for effective planning.

Furthermore, the current state of monitoring technologies in use must be considered, including sensor systems and weather stations. This evaluation helps determine the effectiveness of existing solutions and points out areas where improvements can be introduced to address the specific needs of this project.

II. State of the Art

Recognizing rivers from images is an important task in various applications such as environmental monitoring, water resource management, urban planning, and detecting changes in the natural environment. The automation of this process through machine learning techniques, particularly neural networks, has gained relevance due to their ability to process large volumes of image data and learn complex patterns.

The computer vision is used to detect small details that humans' eyes cannot identify, also to automate a production line and reduce times and costs. Humans are being replaced by artificial vision because is faster, more precise and has more replicability. This also brings both operational and security benefits as human participation is diminished [1].

Image-based River recognition systems represent a valuable tool in water resource management and the prevention of natural disasters. These systems combine technologies such as remote sensing, computer vision, machine learning, and meteorology to gather detailed information about rivers, allowing for a precise assessment of riverbeds and the risk of overflowing. This theoretical framework examines the key elements involved in these systems and their relevance in flood mitigation and sustainable river management.

According to Reference [2], the use of machine learning has been aimed at maximizing available information or providing guidance on acquiring more data, whether to develop physical understanding or models when there's limited knowledge in physics (such as data-driven modeling) or when the computational cost of a detailed mechanical model is too high (as in surrogate models). Typically, employing these cutting-edge techniques requires a substantial amount of data to create accurate, stable, and reliable models.

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The importance of employing emerging datasets and analytical methods to enhance disaster resilience capacities is increasingly recognized, both in research communities and in practice. An example is the Sendai Framework for Disaster Risk Reduction 2015-2030 (UNDRR 2015), where the primary focus is on understanding disaster risk. This specific approach emphasizes the value of emerging data from social networks and mobile devices to create early warning systems, model risks, assess, map, and monitor disasters. Previous studies have demonstrated the use of various types of large datasets to anticipate early warnings, coordinate responses, and recovery during urban floods. These early alerts and predictions can help people avoid flood-prone areas, while quickly identifying impact and recovery patterns resulting from floods can greatly benefit disaster recovery decision-making and resource allocation [3].

HEC-RAS is a widely recognized hydraulic software tool developed by the US Army Corps of Engineers, used alongside the HEC-HMS platform to simulate hydrological aspects. HEC-RAS performs 1D flood routing under steady and changing flow conditions, applying a forward finite difference scheme between successive sections with flexible geometry [4].

After adjusting data for resampling and vertical errors, all resampled grid datasets were used to create a 1D HEC-RAS model. This tool is highly prevalent in flood modeling in Indonesia. The HEC-RAS parameters remained constant for different Digital Elevation Models (DEMs) to evaluate flood map sensitivity to topographic errors, avoiding creating a specific calibrated model for each topographic dataset [4].

Hydrodynamic models and geographic information systems are commonly used for such evaluations. In a specific assessment, a coastal digital elevation model was developed using hydrometric and elevation data to project the present and future impact of cyclonic waves on flooding levels at Pigeon Point. After obtaining flood potential analysis results using HEC-RAS software, flood areas and inundated zones along river areas can be identified using a geographic information system, which integrates with HEC - Geo RAS extensions to import data from HEC-RAS. This is relevant for predicting and better understanding river overflows and their impacts in specific areas [4].

The Hydrologic Engineering Center (HEC) in California, USA, produced the HEC-2 software package, which can be used to perform all necessary calculations to simulate flooding in a river system. The numerical implementation of the equation can be explained as follows [5]:

Assume a water surface elevation at the upstream cross-section WS2 for subcritical flow in the river channel while SW1 is known.

Based on the assumed water surface elevation, determine the corresponding total discharge. Determinations of areas and discharge for subsections are crucial for model application[5].

Solve the equation for SW2 and compare the calculated value of SW2 with the assumed value in step 1; repeat steps 1 to 3 until values match within an accuracy of 0.01 meters. The calculated SW2 will be used as SW1 for calculating water surface elevation toward the next upstream section [5].

The study examined time intervals for floods of 2, 5, 10, 50, and 100 years in the Juwana River. Hydrodynamic modeling was conducted using HEC-RAS 5.0.6 software to determine the extent and flow of floods in the river. The data used included primary information obtained through field observations and interviews, as well as secondary data collected through institutional surveys. Among the secondary data were DEMNAS records with an 8.1-meter resolution, accumulated precipitation data over 28 years, administrative maps, land use maps, and terrain type maps [6].

Reference [7] proposed using a Genetic Algorithm to reduce the complexity of possible solutions. Computing all possible combinations of fourteen suggested river levels along with a sample of 7 reservoirs would be very resource-intensive, especially in systems requiring real-time processing. The genetic algorithm is employed to create viable flow configurations. Its evaluation function is based on the optimal configuration for flood generation.

A. Object Detection

Data acquisition involves obtaining images of the Earth's surface covering areas where the rivers of interest are located. These images can come from different sources like Earth observation satellites, planes, drones, or ground-based cameras. A linear regression, gradient boosting regressor (machine learning), and multilayer perceptron (neural network, deep learning) are compared using various learning strategies, validation, and prediction. Preliminary results show that diverse strategies perform as well as the empirical delay-and- path model. Further improvements in creating learning and validation databases are being investigated [8].

There are many applications for object detection, such as pedestrian detection, robotics, intelligence in transportation, autonomous vehicles, forestry, urban planning, marine studies, among many others. Knowing the type of detection and its characteristics helps us select the most suitable type more precisely, thus achieving results that resemble the expected outcome, accompanied by time and resource savings [9].

Advancements in hardware performance, continuous optimization of intelligent algorithms, and the growth of Big Data have significantly contributed to the progress of computer vision. Object detection stands out as one of the essential components of computer vision [9].

Reference [9] argues that fundamental tasks in image processing involve a series of recognitions, including classification, localization, and object detection. Key challenges in these processes include precision, speed, and complexity. Convolutional neural networks (CNNs) stand as an important basis for object detection.

Reference [9] summarizes convolutional neural networks as a network framework for deep learning, where these networks take images as inputs and avoid the laborious creation of features present in traditional detection algorithms.

The use of CNNs with less preprocessing reduces algorithm complexity and increases effectiveness, approaching biological neural networks. These networks employ mathematical operations, particularly convolution, from which they derive their name.

CNNs can be defined as neural networks that use convolution in at least one of their layers instead of performing a general matrix multiplication. Convolution is a concept that significantly contributes to constructing a feature space based on a signal. Through convolution, CNNs achieve their goal of learning high-level features in information. CNNs are especially advantageous for inputs that possess structure, repetitive patterns, and spatially distributed values, such as image and audio data. These networks mimic the functioning of the human brain [9].

Neural Network Model The neural network model is the heart of the image-based river recognition process. Generally, a convolutional neural network (CNN) architecture is used due to its ability to learn local patterns and features in images, making it especially suitable for computer vision tasks such as segmentation and river classification [9].

A typical CNN structure includes several components, generally involving a combination of convolutional layers and pooling layers, which tend to enhance effectiveness [9].

Reference [10] explains object detection as the process of employing suitable approaches to determine whether an analyzed image contains a predefined specific object and, if so, identifying the location of that object in the image.

Several researchers have analyzed rain prediction using machine learning techniques. In Banyuwangi, the Adaptive Neuro-Fuzzy Inference System has been employed to forecast rainfall. Studies have focused on predicting monthly rainfall rates using two neural network models. The accuracy of the first model is notably higher than that of the second, reaching an average of 98% compared to 75% for the second model. Both models perform better when fluctuations in precipitation are minimal. Further research is suggested using more extensive datasets, such as daily or weekly rainfall rates, to enhance the accuracy and effectiveness of the proposed models [11].

Reference [11] explain that machine learning can explicitly learn and improve systems, offering computer programs that can handle data without requiring specific programming for each task. This technology can work with large datasets. Artificial Intelligence systems are used to train data and enhance flood prediction systems, enabling the creation of early warning systems in the early stages of development.

The flood prediction technique is effectively organized based on available data and an evaluation of qualifying criteria, demonstrating inspiring performance. By estimating floods in real-time, flood values can be visually obtained in a user interface [11].

Real-time flood estimation through machine learning can rapidly process large volumes of data. Compared to stochastic methods like the Muskingum method, flood modeling with machine learning proves to be accurate, straightforward, and adaptable for multiple calculations. Using the predicted flow, the timing of gate operation can be determined based on the inflow in the reservoir [11].

Reference [12] mention that a CNN is structured with a multilayer neural network. These layers are:

- Convolutional Layer: Input images undergo a convolution stage with filters that weigh values depending on training, and the features that should appear in the output are extracted.
- Pooling Layer: Information is reduced, and necessary information is retained.
- Fully Connected Layer: Neural networks are formed to display the output after flattening the data coming from the convolution and pooling layers.

Reference [12] subsequently add that prediction accuracy depends on the CNN structure. Therefore, the combination of layers is meticulously analyzed and tested. To obtain necessary information from image input, CNNs require training using a dataset that combines images with correct corresponding values, requiring a repetitive training process.

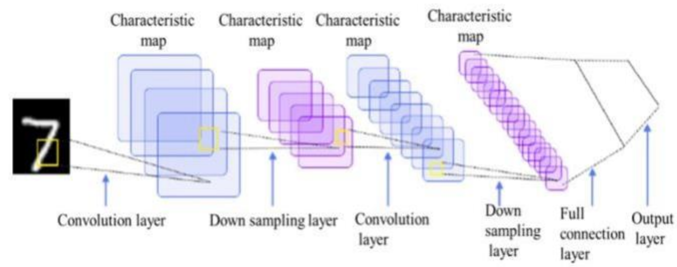

Fig. 1 The architecture of a convolutional neural network [19].

The proper selection of inputs is a crucial factor for the success of an Artificial Neural Network (ANN) model. An excess of redundant inputs can cause issues with local minima. By understanding the physical system being modeled, a more informed choice of inputs can be made. For instance, in a river system, upstream river levels can effectively predict downstream river levels. Reference [13] mentioned that datasets ranging between 0.1-0.9 or 0.2-0.8 can enhance the generalization ability of an Artificial Neural Network architecture [14].

Recent developments in Intelligent Machine technology and high-speed data analysis algorithms have displaced conventional forecasting methods. Initially, an intelligent model was created to predict river flow based on Artificial Neural Networks (ANN). Unlike mathematical models that require precise knowledge of all contributing variables, a trained ANN can estimate process behavior even with incomplete information. It's a proven fact that neural networks possess robust generalization capabilities, meaning that once properly trained, ANNs can provide accurate results even for cases they have never encountered before [15].

B. Image Preprocessing

Before images can be used by a machine learning model, comprehensive preprocessing is essential. This includes:

- Geometric and Atmospheric Correction: Aligning and correcting images to remove geometric distortions and adjustments for atmospheric factors that may affect image quality.
- Noise Removal: Reducing artifacts and noise in images to improve quality and coherence.
- Contrast Enhancement: Adjusting contrast to highlight

relevant features, such as bodies of water.

As Ref [16] mentions, after gathering the image dataset through web scraping and automated downloading, image preprocessing is conducted to prepare the data for training the AI-based log detection system.

This involves resizing all images to a consistent dimension, normalizing pixel values to a common scale, and optionally applying data augmentation techniques like rotation, flipping, and scaling to diversify the dataset. Additionally, cropping and padding may be used to focus on relevant regions of interest, while color space conversion, filtering, and noise removal help enhance image quality and feature extraction [16].

Histogram equalization enhances image contrast, and edge detection algorithms highlight object boundaries. These preprocessing steps ensure that the AI model receives well-prepared data, enabling it to effectively detect and track logs and their fragments on river surfaces for accurate flood alert systems [16].

Moreover, adjustments to hue, saturation, contrast, and enhancements are mentioned within these processes. Most studies used manual laboratory analysis and failed to meet the water quality index standard, besides employing an excessive number of parameters. It has been observed that machine learning can yield positive results in detecting irregularities in water quality, and these works are based on similar previous research. Machine learning algorithms have the potential to significantly reduce the number of erroneous predictions. It's crucial to highlight that, especially in river detection and flood prevention, algorithms must accurately distinguish the river and its course, avoiding confusion with elements like rocks or trees surrounding the river environment. This distinction is fundamental to ensure legitimate and accurate results, preventing errors stemming from confusion with the surrounding environment [16].

C. River Segmentation

The availability of a segmented dataset is especially valuable in tasks requiring precise object localization. The meticulous segmentation in this dataset allows the algorithm to gain a refined understanding of the visual characteristics of objects, leading to increased accuracy and performance in detection [17].

Segmentation is a fundamental step involving the identification and delineation of water bodies, i.e., extracting rivers from general images of the Earth's surface. Image processing techniques like thresholding, region-based segmentation, or the use of convolutional neural networks (CNNs) are employed for this task. Precise segmentation is essential to isolate rivers from other elements in the images, such as roads or buildings.

Semantic segmentation is a form of pixel-level classification. Pixels belonging to the same category must be classified in that same category. In other words, semantic segmentation seeks to understand the image at the pixel level. Before the popularity of deep learning methods, semantic segmentation methods such as the texton forest and random forest were widely used. However, with the development of convolutional neural networks, deep learning methods show much better performance than traditional methods [17].

D. Feature Extraction

Relevant features are extracted from regions identified as rivers. These features may include water texture, shape of riverbeds, river width, temporal changes, characteristics of surrounding vegetation, among others.

A neural network, typically a convolutional neural network (CNN), is used to automatically learn patterns and discriminative features in the images. The CNN is trained using a labeled dataset containing examples of rivers and non-river-related areas.

Once rivers have been segmented, relevant features are extracted from these identified river regions. Features may include:

Water Texture: Analysis of water texture, which may vary depending on flow speed and turbulence.

- Riverbed Shape: Measurement of the shape and contour of rivers to distinguish between different types of rivers and water bodies.
- River Width: Determination of the river's width at various points along its length.
- Temporal Changes: Tracking temporal changes in the location or shape of rivers over time.

III. Methodology

This chapter provides a detailed overview of the strategic approach, techniques, instruments applied, and the methodology employed in this study. The relevance of a robust and precise methodology becomes fundamental to ensure the validity and reliability of the obtained results.

Firstly, the adopted approach will be discussed, outlining the guiding principles and conceptual structure that have directed this research. Subsequently, the specific techniques and instruments used for data collection, analysis, and processing will be addressed, detailing their application in the study context.

A. Approach

The ongoing project focuses on river overflow prevention through a qualitative approach that combines computer vision and automated learning techniques, specifically using convolutional neural networks. This qualitative approach seeks not only model accuracy but also aims to comprehend the complexities and contexts of the river environment to enhance predictive capability.

Convolutional neural networks will be employed to detect and predict potential overflows. This qualitative approach will concentrate on the detailed analysis of preselected field images, emphasizing the identification of subtle yet significant changes in river behavior. Visual detection of early signs of overflow will be prioritized, such as unusual fluctuations in water levels, movements in surrounding topography, and other crucial visual markers in flood prediction.

In addition to visual detection, a neural network structure will be implemented that, in conjunction with image analysis, will allow for a qualitative assessment of overflow possibilities. This approach seeks to understand beyond quantitative metrics, exploring the subtleties and context of the river environment to improve the model's predictive capacity and ultimately mitigate flood risks in riverside areas.

B. Applied Techniques and Instruments

Image Processing with RoboFlow and YOLO:

• Use of RoboFlow for data preprocessing, image labelling, and dataset generation for training.

• Implementation of YOLO (You Only Look Once) as an object detection model in images, leveraging its efficiency and accuracy in identifying specific areas in the images.

Deep Learning with PyTorch in Python:

• Employment of the PyTorch library in Python for the development, training, and evaluation of convolutional neural network models.

• Utilization of PyTorch functionalities in Python for implementing and adjusting specific models for river overflowdetection.

Python Programming and Development:

• Python as the primary language for algorithm implementation, data manipulation, and overall project development.

• Possibility of using Jupyter Notebook in Python for experimentation and exploratory analysis.

Model Validation and Evaluation:

• Implementation of evaluation metrics in PyTorch (Python) to measure the accuracy, recall, F1-score, and otherrelevant metrics of the overflow detection model.

Collaboration and Project Management:

• Integration with version control platforms like Git for collaboration and tracking changes in the code.

• Use of a GitHub repository to store Python code, collaborate with other developers, and maintain a historical record of the project.

These Python tools and techniques, including RoboFlow, YOLO, and PyTorch, will be essential for the project's success in river overflow prevention through computer vision and deep learning.

C. Study Methodology

In the quest to enhance efficiency and flexibility in the research process, elements of the agile Scrum methodology have been integrated. The Agile Scrum method is an iterative and incremental approach to project development and can be applied to development. A table in Trello was used to create the list of tasks to be divided into each work cycle necessary for the development of the project.

Originating from a rugby play, Scrum is presented as an agile method for software development conceived by Jeff Sutherland and his team in the early 1990s. This methodology has evolved with significant contributions from Schwaber and Beedle, expanding its scope and application [18].

The fundamental principles of Scrum align with the agile manifesto and have been adapted to guide research activities within a structured process. This process encompasses crucial stages such as requirement definition, analysis, design, evolution, and delivery, each approached with a specific focus within the Scrum framework.

Fig. 2 Trello board showing the progress of project tasks.

Within each of these stages, tasks are carried out through a process pattern called a "sprint." The flexibility of Scrum allows the team to adapt and define, in real-time, the work to be performed within each sprint, adjusting it according to the demands and complexities inherent in the researched problem. Figure 3 illustrates the general flow of the Scrum process applied to research [18].

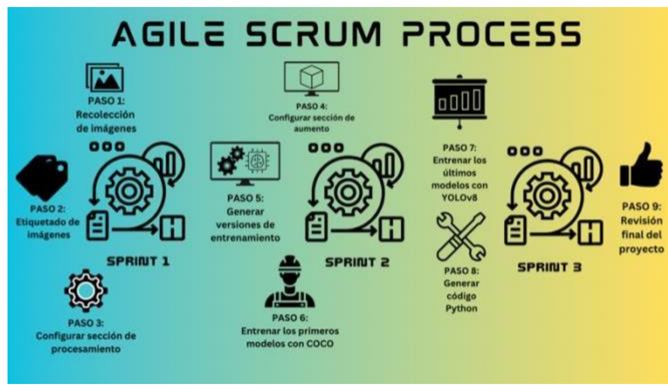

Fig. 3 Agile scrum process implemented in the investigation.

This approach not only emphasizes agility and flexibility in task execution but also underscores the application of software process patterns, as indicated by Noy02, which have proven effective in projects with tight deadlines, changingrequirements, and critical business scenarios. Each of these patterns defines specific development actions integrated into the research process, providing a solid structure for task execution and activities [18].

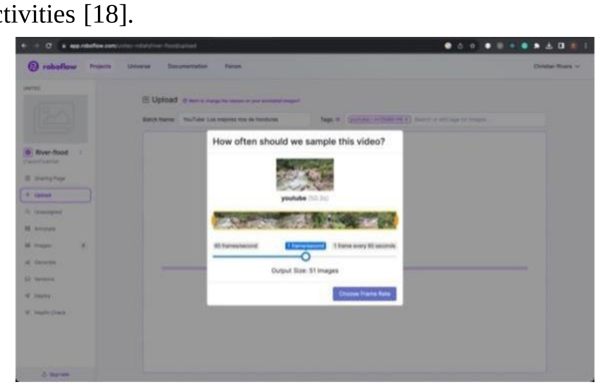

Fig. 4 Fragmentation of Honduran river video for image generation.

The integration of Scrum into the research process aims not only to improve efficiency but also to foster adaptability and responsiveness of the team to challenges and changes that may

For this project, RoboFlow, YOLO and PyTorch are used to train a model capable of identifying rivers and predicting floods, focusing on multiple aspects. It begins with extensive data collection representing a diversity of riverine scenarios, ensuring the inclusion of variables such as water levels, flow patterns, and riparian characteristics. Validation is carried out by partitioning the data set into training, validation, and testing subsets.

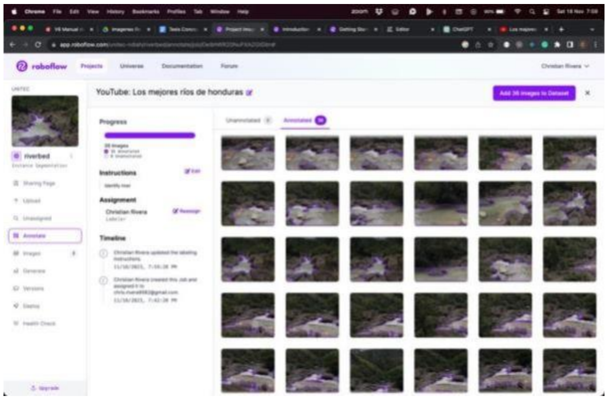

Fig. 5 labelling river frame in Roboflow for class classification.

This process was very useful to collect a greater number of images. By dividing the video into frames, the algorithm learns to detect variations in the shape of the river and detect different types of textures, properties that a single static image cannot provide.

During the training phase, a constant evaluation of the accuracy and effectiveness of the model on the validation set is carried out. This process is not limited to passive observation alone but involves active hyperparameter tuning and the application of various training techniques within the PyTorch environment.

Continuous evaluation on the validation set acts as a vital feedback mechanism. It allows you to identify areas of improvement and opportunities to optimize the performance of the model. Adjustments to hyperparameters such as learning rates, batch size, loss functions, and network architecture are made strategically to maximize model accuracy and generalization.

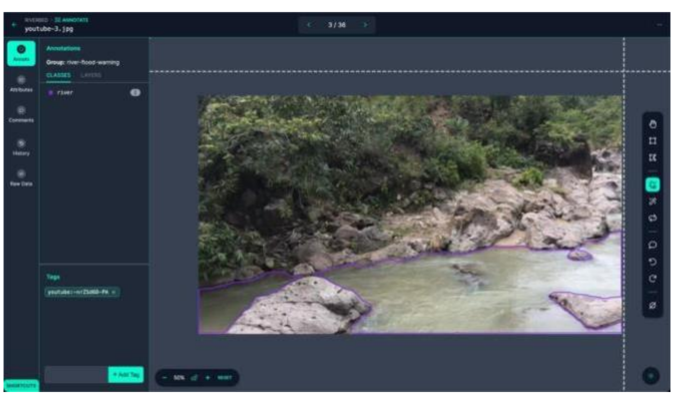

Fig. 6 labelling river frame in Roboflow for class classification.

PyTorch, as a development environment, offers a wide range of techniques and tools for optimizing the training of artificial intelligence models. The flexibility it provides allows you to experiment with different approaches, such as regularization techniques, advanced optimizers, and weight initialization methods, with the goal of boosting model performance. This iterative and adaptive approach to the training process not only seeks to improve the current results, but also ensure that the model can effectively generalize to unseendata. The combination of precise adjustments and the intelligent use of the tools available in PyTorch contribute significantly to the evolution and constant improvement of the model, increasing its ability to make accurate and consistent predictions.

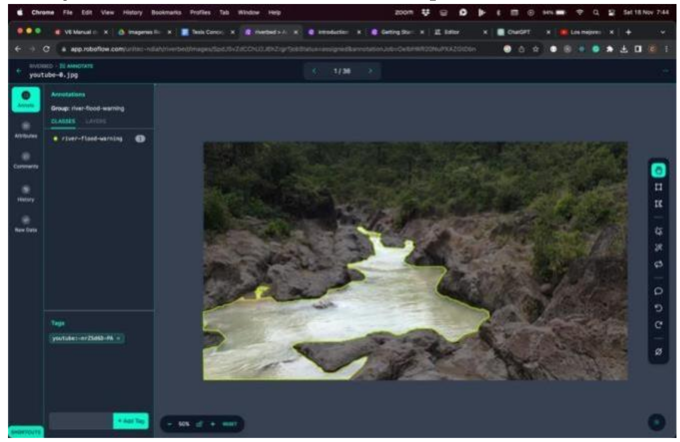

Fig. 7 Label from another angle of the river.

Labelling different angles of the same river is importantas it helps the algorithm to be resistant to changes in movement of the camera that is capturing the images in real time.

The more angles that are captured and labelled, the more shapes, angles and perspectives can be recognized and processed in training.

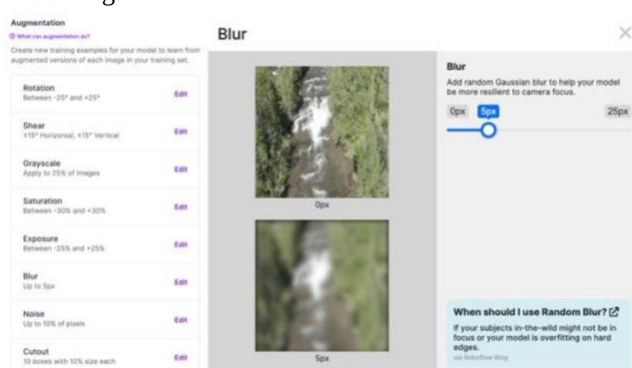

Fig. 8 Labelled images available to the model to train.

In the image augmentation section, parameters such as grey scale, blur, noise, cut-out, and contrast can be added to add difficulty and increase the number of images to train. Illustration 8 – Augmentation module to calibrate computer vision model. Source: self-made.

Once the training process is completed, it is time to export the optimal version of the algorithm. This phase generates code in Python; however, its successful execution requires the prior installation of several crucial libraries and packages such as Roboflow, Supervision, Ultralytics and YOLO. These components are essential to ensure the smooth and efficient operation of the algorithm in its operating environment.

IV. RESULTS AND DISCUSSION

The present study focused on the detection and segmentation of rivers using advanced computer vision techniques, specifically using Roboflow and YOLOv8. A total of 1017 diverse images were collected and labeled to form a representative dataset covering multiple river types in varied environments and conditions.

A. Dataset and Labelling

The dataset used in this project was built with a large and diverse set of images spanning different types of rivers, addressing variations in landscapes, lighting, capture angles and weather conditions. Each image was meticulously labeled to accurately identify the presence of the river in the scene and its shape, allowing for effective training and validation of the models.

Annotation heatmap is a useful tool in object detection using computer vision and neural networks. In the context of river detection, it can be valuable for accurately identifying and delineating waterways in images or videos.

The process of detecting objects, such as rivers, typically involves the use of deep learning algorithms such as convolutional neural networks (CNN). These networks may require large, labeled data sets to train effectively.

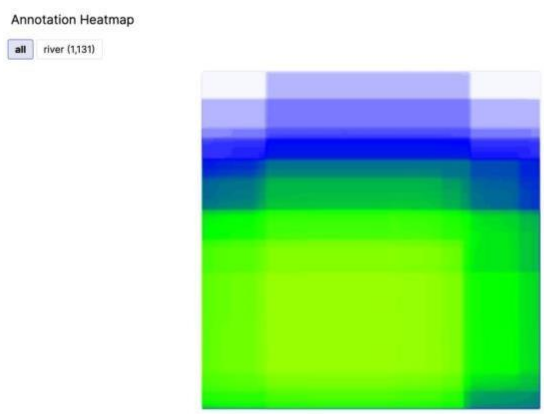

Fig. 9 Annotation heatmap.

It is a visual representation that highlights the areas of an image that are relevant to the detected object. In the case of river detection, this could mean that the heat map shows the sections where the algorithm identifies the presence of a river. This visual information is valuable for understanding how the model interprets and locates rivers in the images. Using it in river detection with neural networks can help by displaying regions relevant to river detection, the network can focus on specific features, such as the shape, flow pattern, or structure of the water, reducing the likelihood of confusion with similar visual elements, such as the sky or colored areas. and comparable textures.

This ability of the network to focus on specific areas relevant to river detection thanks to the heat annotation map can significantly improve its accuracy by avoiding confusion with similar visual elements, but not related to the object of interest.

B. Training and Evaluation of the Model

Multiple training iterations were implemented using YOLOv8, taking advantage of its ability to detect and segment instances with high accuracy. During the training process, hyperparameters were adjusted and configurations were optimized to improve the model's ability in river detection.

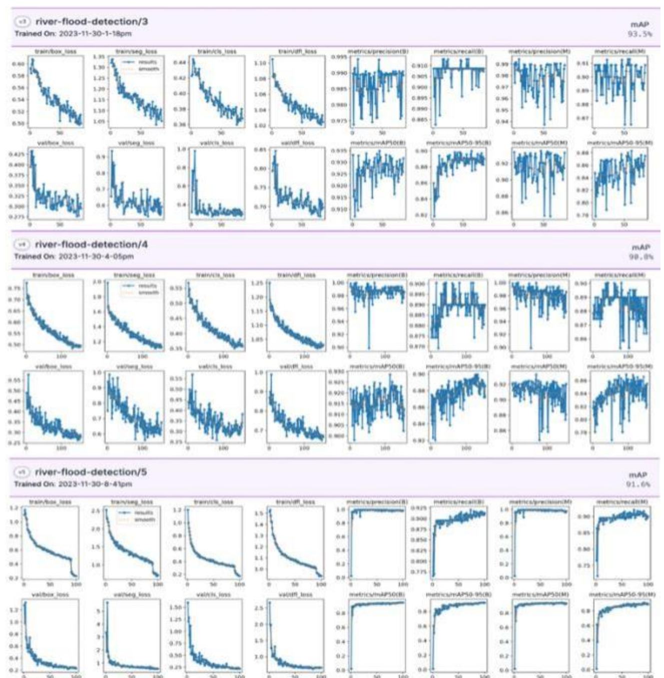

Fig. 10 YOLOv8 average precision metric in neural network version 5.

Within a computer vision project and convolutional neural networks, multiple training runs were executed. Initially, a COCO database was used as a starting point, then transitioning to specific training with YOLOv8. While evaluating the results, significant fluctuations in metrics were observed, indicating notable losses in the model's validation.

It was noted that by increasing the number of training instances and iterations, the learning curve exhibited a smoother and more stable progression. This pattern suggests a decrease in the algorithm's error rate, indicating an improvement in the model's accuracy and reliability in prediction.

The results obtained demonstrated outstanding performance of the trained algorithm. The model achieved an average precision rate of 91.6% in river detection, both in static images and video sequences. This precision remained consistent even when facing different capture angles and variations in environmental conditions.

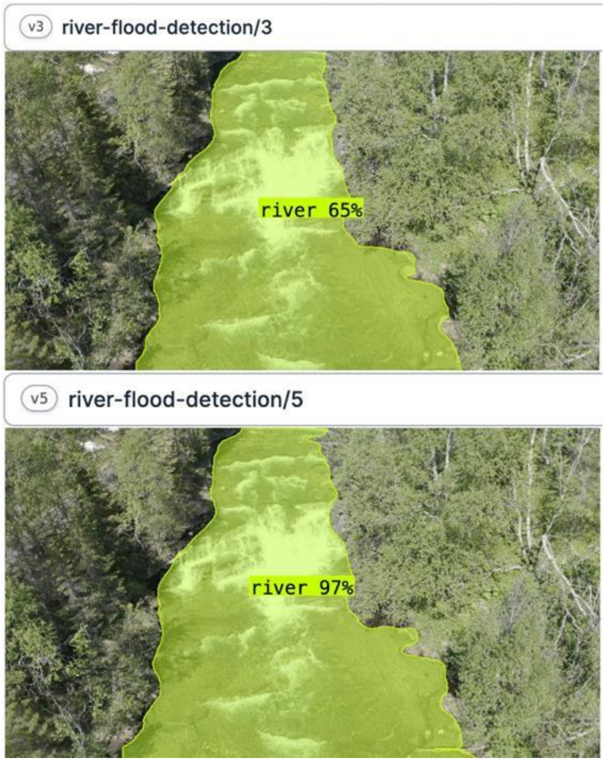

Fig. 11 Comparison of Confidence Level in the Latest Training Version.

In its initial stage, the algorithm showed a certainty of 65% in delineating the river's morphology, presenting difficulties in distinguishing it from other elements with similar visual characteristics, such as flooded streets, the sky, or dunes, which share wavy features resembling the riverbed. After an extensive training period, the latest version has experienced a significant advancement, reaching a certainty level of 97%. This refinement has allowed maintaining effectiveness in accurately identifying the river configuration, avoiding confusion with the mentioned contextual elements.

Whether in images or video, the algorithm marks in a red box the section where a river is detected and analyzes its height and width. Similarly, it detects the exact shape of the river through nodes and groups them into X/Y coordinates within the detected box, which serves to analyze the riverbed and detect anomalies in growth or direction. This information is saved in JSON format, which can be analyzedin Python.

C. Detection and Generalization Capability

The trained algorithm demonstrated its ability to identify various types of rivers in diverse environments, including urban and rural areas, as well as different shapes and sizes of water bodies.

Fig. 11 Detecting different rivers at numerous angles and shapes with YOLOv8.

Furthermore, its ability to detect rivers from multiple angles and lighting conditions provides significant robustness in its practical application.

Having completed the training of the latest version with the YOLOv8 model, the learning curve of the algorithm has improved significantly. In the training segment it is seen how the learning curvature is improving, but there is an incredible improvement in iteration 90 to 100 in frame loss, segmentation loss and class loss. This being the reason why 100 cycles were crucial to improve the accuracy of the algorithm. The precision metrics show that it consistently exceeds 90%.

The validation section also presents a curvature quite closeto 0.2 precision loss and finally the average precision metric section we notice that it still exceeds 91% constantly at early stages of the training cycles.

D. Overflow Prediction

One of the key applications of this model is its potential ability to predict overflow situations. Although this phase of the project is in development, the foundations established in

V. Conclusions

The conclusions of this project reflect the fulfillment of the objectives set in the implementation of an advanced river recognition system through images, supported by artificial intelligence technologies. The combination of the computer vision algorithm for river identification and convolutional neural networks for overflow prediction has demonstrated significant effectiveness. The system has achieved a certaintyof 91% in the precise identification of the area where theriver is located and the exact delimitation of its shape in the analyzed images. This precision translates into a valuable tool for measuring river channels and evaluating the risk of overflows, thus supporting the management of water resources and the prevention of natural disasters in the region.

The development and integration of artificial intelligence, especially using convolutional neural networks, has been crucial in achieving this precision in the detection and analysis of critical features in river images. In addition, the continuous adjustment and evaluation of the models has contributed to improving the accuracy and detection capacity of the system, focusing on compliance with the general objective of the project.

The exhaustive documentation of the design, development, and implementation of the system, together with the results obtained and lessons learned, constitutes a valuable resource for future research and similar projects. Together, these achievements position the system as a solid and effective tool to improve water resources management, prevent natural disasters, and safeguard the safety of the population and infrastructure in the region.

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