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Research Paper

Integrated Land Atmosphere Monitoring in Rivers State Nigeria with UAV

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Abstract
Automatic data analysis systems in the IoT were crucial to our investigation. A major use of drones was monitoring land atmosphere, especially in cities. Analysing metropolitan areas with pollutants and animal habitats required this monitoring. Data analysis helped identify river irregularities, lowering the likelihood of ecological disasters and floods. Continuous monitoring allowed urbanisation impact assessments and environmental conservation. This study presented an end-to-end system where drone users measured and the U-Net network segmentation mask was augmented by image processing techniques. The system segmented with a neural network and overlaid the mask over edge-detected images. All pixels under the mask were clustered to establish river or bank affiliation. Additionally, several measurements from the same location were compared and analysed for variations. The system architecture automated activities using graphics processing algorithms, resulting in more accurate segmentation. We used VGG16 to encode data from southern Polish rivers and achieved a Dice coefficient of 0.8524. This strategy was especially useful in Rivers State, Nigeria, where oil bunkering and unlawful refining caused widespread black soot. These activities substantially harmed air quality and public health, necessitating accurate and regular environmental monitoring. The UAV-based integrated land-atmosphere monitoring system detected and analysed these environmental issues, showing the major impact of industrial activity on the local environment and helping design appropriate mitigation methods.
Keywords*: River State Monitoring, Remote Sensing, Image Processing, Drones, VGG16, End-To-End System*

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I. Introduction

A competence that is crucial for recognising temporal changes and differences has been made possible by technological breakthroughs, which have enabled the development of systems that automatically analyse data that has been acquired. The environment is being greatly impacted by climate change, which is making the effects of natural occurrences like rainfall and rising water levels in rivers even more catastrophic. It is of the utmost importance to perform continuous monitoring of river conditions, particularly in urban regions where rivers flow through towns and pose dangers to human habitats. Continuous environmental monitoring is made easier through the integration of autonomous systems with sensors, notably drones that are equipped with the capability to record video (Prokop et al., 2023). According to Diaconu et al. (2023), conducting an analysis of water conditions permits the development of flood protection systems and offers alerts regarding changes at rivers and in the surrounding area.

The need of continuous data collecting is demonstrated by Internet of Things (IoT) solutions, such as the system built by Rusdi et al. (2023) to monitor water levels in Binjai City using an Arduino microcontroller and ultrasonic sensors. This system demonstrates the importance of reducing error rates and improving accuracy. Even though many of the systems that are now in place concentrate on water quality analysis, there is an increasing demand for methods that can notify authorities of changes in the environment. Systems such as the supervisory framework developed by Jiang et al. (2023) combine equipment, models, and experience to monitor and manage the state of municipal waterways. This highlights the relevance of the Internet of Things (IoT) in automating data processing and enabling prompt interventions (Kumarapu et al., 2022). When it comes to unmanned aerial vehicles (UAVs), the information obtained from cameras is frequently in conjunction with geolocation, altitude, and lens information in order to precisely georeference measurement data.

Applications that do real-time analysis have an emphasis on the identification and classification of objects (Singh et al., 2022). The utility of unmanned aerial vehicles (UAVs) in environmental monitoring is highlighted by studies such as those conducted by Tur et al. (2020) on coastline development in Turkey and Yin et al. (2023) on Lake Urmia. These studies highlight the capabilities of UAVs to capture photometric pictures, point clouds, and segmented network models for reliable data interpretation. It is clear that environmental monitoring using unmanned aerial vehicles (UAVs) is both relevant and necessary. However, in order to increase data quality, many systems rely on huge datasets and additional sensors. This results in a gap in the availability of solutions that can work directly with measurement data without the need for classification training beforehand. In order to address this issue, we proposed a comprehensive system that automatically processes data obtained from drones in order to analyse the current health of rivers and generate mosaic visualisations of the region that has been analysed. The entirety of the study is carried out within a single application by this system that is based on mobile technology. The data is processed and analysed by the system through the determination of picture coordinates, the segmentation of rivers on simplified images through the use of a dedicated network with learning transfer, and the utilisation of image processing and clustering methods for more accurate segmentation all of which are utilised. Users are able to visualise the area that has been analysed, overlay segmentation images, and compare current data with previous records that have been saved. Additionally, it enables for comparison with archival data in order to analyse temporal variations.

The application of this technology is especially pertinent in Rivers State, Nigeria, where environmental contamination caused by continued oil bunkering and illegal refining activities has resulted in widespread black soot. The significant impact on both the quality of the air and the health of the general population highlights the fundamental requirement for precise and ongoing environmental monitoring. A powerful instrument for identifying and analysing these environmental concerns is provided by the integrated land-atmosphere monitoring system that makes use of unmanned aerial vehicles (UAVs). This system also helps to highlight the considerable impact that industrial activities have and contributes to the development of effective mitigation solutions.

II. Literature Review

The development of new technologies has made it possible to create devices that are fitted with a variety of sensors, which has improved the ways of data processing that may be achieved for analytical reasons. An example that is particularly noteworthy is a water quality evaluation system that makes use of sensors to collect values of temperature, carbon monoxide, and pH (Kumar et al., 2023). During the processing phase, the data that have been collected are sent to a computer using a wireless network. The results of the processing are then saved either in the cloud or on a server. Tasks are efficiently compartmentalised into discrete phases or pieces of equipment by this technique, which results in improvements in both efficiency and accuracy. The analysis of data from a variety of sensors is the primary focus of other systems. For instance, the dynamics of arsenic in water were modelled by using data from water analyses, which were then processed by clustering and regression models for further study (Marcheva et al., 2023). In a similar manner, a river water quality management system utilised qualitative data that was then subjected to multiple regression analysis (Seo et al., 2023). When it comes to precisely analysing measurement data and noticing specific changes in sites that are inaccessible, such as deep or high-altitude regions, monitoring systems are absolutely necessary.

In addition, monitoring systems are utilised in a variety of environmental scenarios, such as volcanoes (Budi-Santoso et al., 2023). In order to enable real-time data analysis, these systems have progressed from visual to automatic analyses employing a variety of sensors, as well as from offline to online modes on their modes of operation. According to Sreedevi et al. (2023), modern monitoring systems continue to have limits that require newly developed changes or solutions. This is despite the substantial progress that has been made. In order to conduct a complete analysis and make use of distributed systems and models, it is crucial to integrate diverse methodologies. This is evident in the many Internet of Things (IoT) solutions that utilise machine learning, specifically neural networks (Połap and Srivastava, 2021). To give an example, segmentation networks with LSTM layers that have been trained on several years' worth of data can forecast changes based on past data (Yin et al., 2023). This is very useful in lake state assessments. Because it makes use of a large amount of training data, this method enables a high level of accuracy. Finding ways to forecast changes in lake boundaries can provide insight into upcoming environmental disruptions. The development of point clouds that offer exact location data for analysed items is made possible by models that are based on LiDAR laser data (Włodarczyk-Sielicka et al., 2023; Zhou et al., 2023). In a practical sense, this technique provides datasets that are both larger and more precise.

The supervision and evaluation of water resources are becoming increasingly important as a result of the growth of metropolitan areas. In their presentation, Liu et al. (2023) emphasised the emerging trend of utilising geostatic solutions and remote sensing in order to improve the quality of water resource monitoring. The precision that deep learning provides is a crucial factor in the applications that are being discussed here. Numerous Internet of Things (IoT) solutions, such as drones that are fitted with sensors for the purpose of data gathering and analysis, make extensive use of machine learning algorithms. Convolutional neural networks, also known as CNNs, are particularly interesting due to its ability to automatically detect features in images that are just two dimensions in size (Li et al., 2019). When CNNs were first being developed, the primary focus was on developing modelling frameworks that could identify driver weariness and analyse seismic anomalies based on graphical data.

Due to the significant pollution caused by ongoing oil bunkering and illegal refining activities, environmental monitoring in Rivers State, Nigeria, presents a unique set of obstacles. This has led to widespread black soot, which has had a considerable negative impact on both the quality of the air and the health of the general populace. The implementation of strong monitoring systems that are able to provide accurate and continuous data is necessary in order to address these difficulties. When applied in such circumstances, unmanned aerial vehicle (UAV)-based systems that are coupled with Internet of Things (IoT) and advanced machine learning algorithms present a promising solution for real-time environmental monitoring and analysis.

Figure 1: Visualization of the use of the drone when taking recordings by the camera that is positioned towards the ground. The drawing also overlays the data used to perform georeferencing, such as: width w and height h of the image, the height of the drone H and the field of view as the α angle.

The use of neural networks requires extensive databases for high accuracy. However, transfer learning minimizes the time needed for training by using pre-trained networks or their fragments for new databases. This approach is exemplified by models like Inception (Szegedy et al., 2015) and VGG16 (Simonyan and Zisserman, 2014). Transfer learning allows trained network fragments to be adapted to various other network concepts, such as segmentation. U-Net, a neural network architecture with an encoder to extract image features and a decoder to generate segmented images, is particularly effective (Raza et al., 2023). For example, U-Net was used to segment MRI images to detect brain tumors, with input images from CT scanners processed to highlight any tumors (Candan and Kalkan, 2023). Similarly, networks analyzing point clouds created with LiDAR can enable road segmentation, detecting roads or obstacles (SaiNikhil, 2023). These examples of recent advancements focus on single elements like classification or segmentation, but they can be integrated into larger information technology systems (Połap, 2023).

III. Methodology

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$$d = 2H \cdot \tan\alpha /2 \quad (1)$$

Offset can be calculated according to:

$$\text{offset} = (W/H) \quad (2)$$

where W and H are, respectively, the width and height of the image recorded by the camera. Using these values, we determine the location of two points on the edges of the image by determining their values with the help of the real value using a rhumb line. Each of the remaining image points is determined with the values calculated according to the above formulas, but each time determining the distance and angle relative to the center of the image, i.e., the projection of the gimbal point.

In the next step, each frame is processed by a trained U-Net. Learning transfer was used to create a dedicated solution. The VGG16 model was used, which allowed for creating part of the encoder. VGG16 is a pretrained

Convolutional Neural Network (CNN) model, consisting of 16 convolutional layers and max-pooling layers in between (presented visually in Figure 2). The model was trained on an ImageNet subset, consisting of over a dozen million samples of 22,000 different classes. CNNs are based on how the human eye perceives the world around. Rather than paying attention to every single pixel, we can extract information from what is called a perception field. These perception fields are created by convolutional layers. Each convolutional layer has a set of channels, each one assigned its own weight matrix. With this matrix, feature maps are obtained by processing an input image through each individual channel. Max-pooling layers help to reduce the amount of input data even further, shrinking obtained feature maps by passing further only the strongest signals (in the case of VGG16, the strongest signal among 3 × 3 matrices). The output of each convolutional layer can be described by:

$z_{i,j,k} = b_k \sum_{u=0}^{f_h-1} \sum_{v=0}^{f_w-1} \sum_{k'=0}^{f_{n'}-1} x_{i',j',k'} \cdot w_{u,v,k',k}$

where $i' \; i \times s_h + u$, $j' \; j \times s_w + v$ (3)

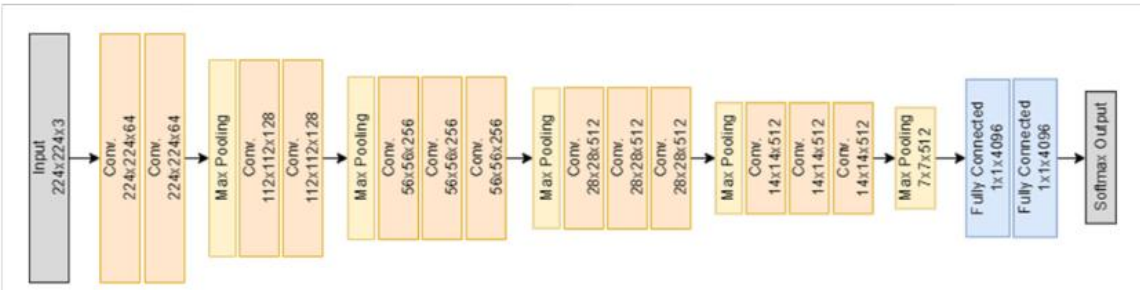

FIGURE 2 : VGG16 network architecture. Each convolutional layer has 3 × 3 kernel and each max pooling layer has 2 × 2

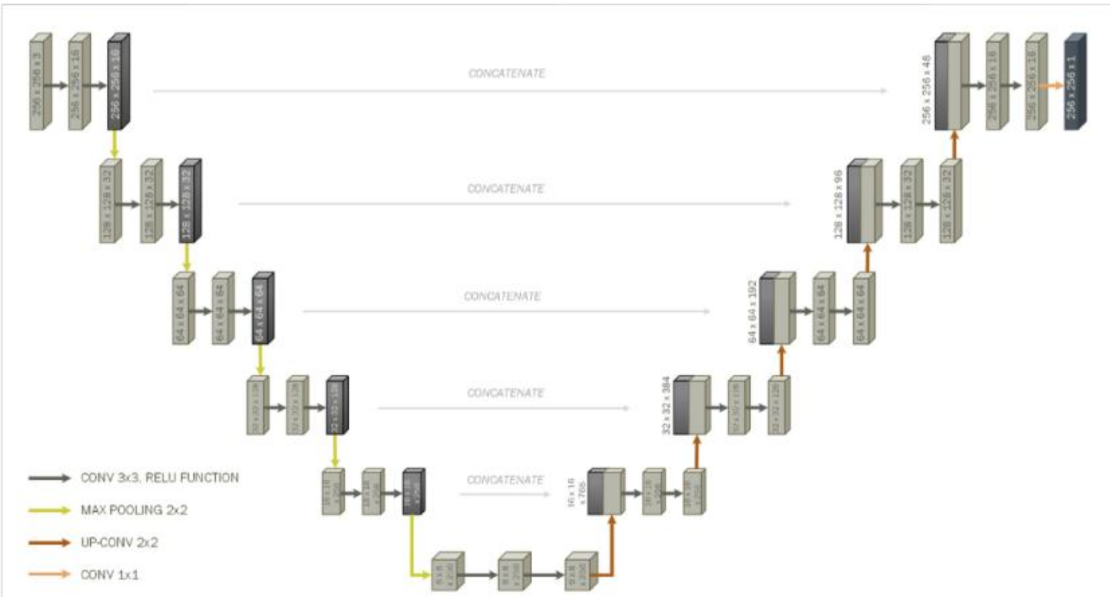

Figure 3 : Used U-NET architecture for river segmentation. The model was based on VGG16 learning transfer.

Having described VGG16, the pretrained model provides a set of weights able to extract useful and abstract features from an image. A network model was selected to reduce the number of learning parameters due to its use in mobile/server applications. The architecture of such a network is shown in Figure 3. The name U-Net is derived from the shape in which the network is most often presented. It can be divided into two segments, encoding and decoding. Both are connected via concatenation paths, which provide information about feature maps from the encoder's convolutional layers to the decoder's upsampling convolutional layer. This process greatly reduces the time required for such encoding/decoding structures to converge, making the U-Net architecture so successful, especially with the use of learning transfer.

At this stage of data processing, it should be noted that the frame is much larger than the network input. To properly process the image, the frame is resized. The neural network returns a segmented image of the river, which allows quick location of the water as well as the shore. However, the image size is smaller than the image frame, so the segmentation result is extended to the full image, allowing it to be resized to its original size. This results in a loss of edge accuracy. Achieving very accurate segmentation with U-net (even for the original frame size) is possible but requires a huge amount of training data. Training on large amounts of data means that the training process will require a lot of computing power. Assuming that the framework should ultimately work as a mobile application with server access, the amount of required computing power is minimized (for instance due to internet transfer).

Obtaining the location of the land on the frame using the segmentation performed by the network allows its localization. Then the edge is analyzed to detect the boundaries as accurately as possible. This is accomplished through the use of the Sobel-Feldman edge detection algorithm (Lubna et al., 2016), which allows marking the appropriate pixels. Such an image is combined with the result of segmentation, which allows focusing on the edges to be taken into account. This is done by matching the segmented area of the river on the image with edges. If there are some pixels under the segmented area, then these will be analyzed. Point analysis is based on the idea of clustering against two classes: the river or the rest of the area. We only focus on the black pixels (representing the edges) within the river segmentation area. If a given pixel has enough neighbors in a small area, it will point to an area that is not a river. For this purpose, a single black pixel is distanced from the other ones. Pixels whose distance is less than θ\thetaθ relative to the analyzed one are counted. If the number of pixels is greater than γ\gammaγ% of the analyzed area, then a given pixel together with all its neighbors defines an area that is not a river. At the end of processing all pixels, if any of them is not covered by the area defined by the neighborhood of any point, it is automatically changed to the background color. Visualization of this operation is presented in Figure 4. Segmentation areas processed in this way enable a much more accurate segmentation of the river. Given that each frame is previously georeferenced, we automatically have coordinates that cover the river area. The georeferenced image, mask, measurement date, and flight parameters are saved in the database.

Using the location, it is possible to compare the state of the lands with archival data. If there are records in the database about previous flights of the drone in this area, then the information from the database and the appropriate frames assigned to these coordinates are downloaded. If there is more than one record associated with this location, the last one is ultimately returned for change comparison. However, the possibility of selecting other archival data allows for the analysis of the state of the river over a longer period of time. The comparison is done by analysing two segmentation masks in exactly the same areas. In practice, this comparison can be made by comparing the coordinate values of the river (to minimize the number of calculations). If any area has been reduced, it will mean that the water in the river has decreased. Otherwise, the water has increased, and attention should be paid to the potential flooding of the river into neighboring areas. Alerting can be done by visualizing the overlapping of areas and marking where changes are suspected. A general framework is shown as pseudocode for re-implementation purposes in Figure 5.

IV. Experiments

4.1 Case Study and Used Equipment

Test basic measurements were made on 17 March 2024. A DJI Mavic 2 Pro drone, with a field of view of 60° and a height of 90 m above the surface, was used to perform the measurement operation. The drone moved along both banks, recording the area with the camera facing vertically downward. As a result, 12 short measurements were made, each averaging 20 seconds with a frame size set to 1920 × 1080 pixels. An example area combination from the obtained drone frames is shown in Figure 6, where the connection was made using the SIFT algorithm. The implementation of the solution was based on Python 3.9.7 with the OpenCV and TensorFlow libraries, running on a dedicated server equipped with an Intel Core i9-10850K 3.60 GHz processor, 32 GB RAM, and an NVIDIA GeForce RTX 3060 12 GB graphics card. A simple mobile application for data visualization processed on the server was also constructed in Java.

4.2 Tests and Analyses of the Proposed Method

The first stage of the research involved analysing the number of samples needed to obtain correct results. This was done by creating a merged measurement image, as seen in Figure 6. Images were merged using frames spaced 1, 2, 3, and 4 seconds apart. The amount of connected area was verified using the SIFT algorithm and evaluated against the largest amount of space coverage. This process involved georeferencing and checking the difference on the y-axis relative to the shore. This method can be described as evaluating the number of connected frames representing the river's bank. The coverage results are shown in Figure 7.

Next, a segmentation database was manually created for all 4,300 frames, where manual segmentation was performed to obtain a mask. Pairs of images (frame and mask) were used to train the U-Net neural classifier with VGG16 coders. The database was divided into training and test sets in a 70:30 ratio, with 3,010 samples in the training set and 1,290 in the test set. The training process used the ADAM algorithm for 30 epochs. ADAM, known for its adaptive learning rate, is widely used due to its swift convergence towards optimal solutions. The training process was set to automatically interrupt in cases of overfitting or stagnant evaluation metrics. However, the performance consistently improved, and the training was not interrupted. Dice coefficient, precision, and recall were chosen as evaluation metrics. The Dice coefficient measures twice the cardinality of the union of two sets divided by the sum of their cardinalities (see Eq. 4). It was also used as the loss function (see Eq. 5). Changes in these coefficients over each epoch are plotted in Figure 8.

Dice Coefficient = (2 A ∩ B| |/A| | + B| |) (4)

loss 1 −Dice Coefficient (5)

Subsequent tests focused on analyzing the γ and θ coefficients. Tests were conducted for γ values of 0.2, 0.3, and 0.4, and θ values of 10, 15, 20, 25, and 30. The gamma parameter indicated the acceptance value of the analyzed area as not water (likely the shore or flora). Each pixel in the processed image was evaluated by detecting edges under the segmentation mask from the U-Net network, based on the number of neighboring edges within the θ radius measured by the Euclidean metric. For each parameter set, the number of correctly classified pixels relative to the original image was checked. The results of the γ and θ parameters are shown in Figure 9.

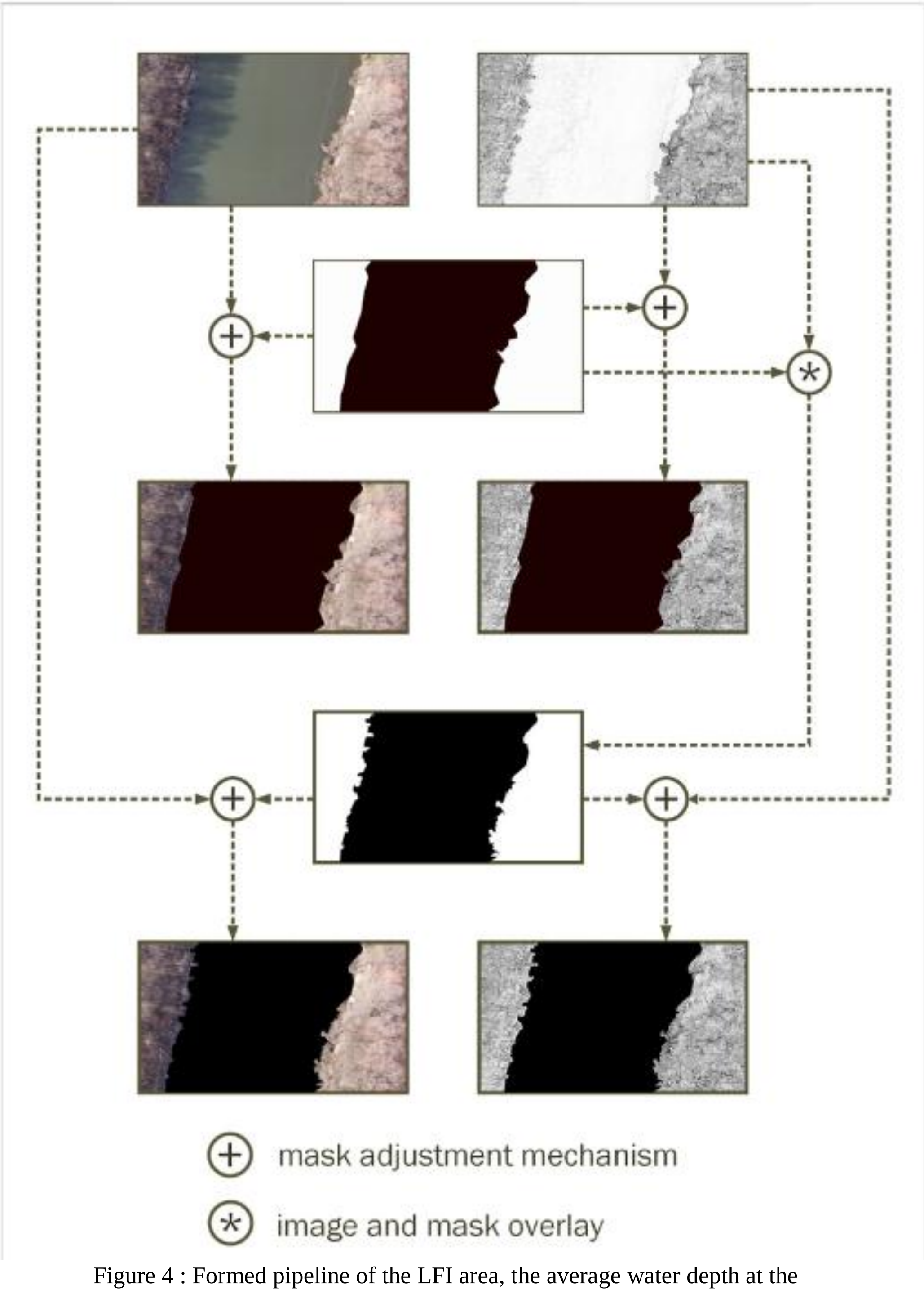

Figure 4 : Formed pipeline of the LFI area, the average water depth at the outer seaward LFI edge, the average distance from the coast to the outer seaward LFI edge.

To validate the solution and its ability to detect differences, an additional drone flight was conducted over the same area on 28 March 2023, using the same drone parameters. Frames were extracted every 2 seconds with $\gamma = 0.3$ and $\theta = 25$. Changes in mask positions indicated small changes in the river's banks, as shown in Figure 10. Validation involved automated drone data recording, processing on the server, and placement in a database, using deep neural networks and image processing methods. Each system element was tested for quality and potential to build automatic data analysis systems for drone data, especially important in built-up areas along the river.

```
Algorithm 1: Proposed framework
  Input: Drone flight data; trained neural network, drone data
  Output: Information on changes in the state of rivers
  Save the video recorded by the drone;
  Download the drone's flight path and geographic coordinates;
  Download flight altitude;
  for each two seconds do
      Cut one frame from the video;
  for each frame do
      Calculate georeference;
      Use u-net to perform river segmentation;
      Perform edge detection;
      Improve river segmentation by clustering edge pixels under network
        segmentation;
      Save georeferenced segmentation result to database;
  Create an image of combined photos;
  if there are data from the same coordinates then
      Compare the location of the river in relation to the determined
        segmentation and its location from georeference;
      if the river is wider then
          Send a notification about an increase in the water level;
      if the river is narrower then
          Send notification about water level reduction;
```

Figure 5 : Algorithm with detailed step by step of the proposed framework.

Initial experiments adjusted the number of extracted frames from video recordings, analyzing extraction intervals of 1, 2, 3, or 4 seconds. The SIFT algorithm detected key points in individual images and connected them. Frames were considered sufficient if they could be combined into one area representing the entire measurement area. Results showed smaller coverage areas with longer intervals due to fewer common points between consecutive frames. Extracting frames every 1 or 2 seconds covered the entire test area, but 1-second intervals required twice as many frames, increasing computational load (see Figure 7).

With frame extraction intervals determined, the focus shifted to the neural network for segmentation. A manually created database of segmented images was necessary for network training. Results from 30 epochs showed high coefficients, including a Dice coefficient of 0.8524 and a loss of 0.1476. Plotted curves in Figure 8 showed decreasing loss on the training set and stable but fluctuating loss on the test set. Better results would require a significantly expanded database. Precision and recall also showed high values, but precision increased while recall decreased, indicating the model's tendency to classify uncertain pixels as part of the river. Monitoring multiple metrics highlighted the model's strengths and weaknesses, especially its challenges with edge pixels.

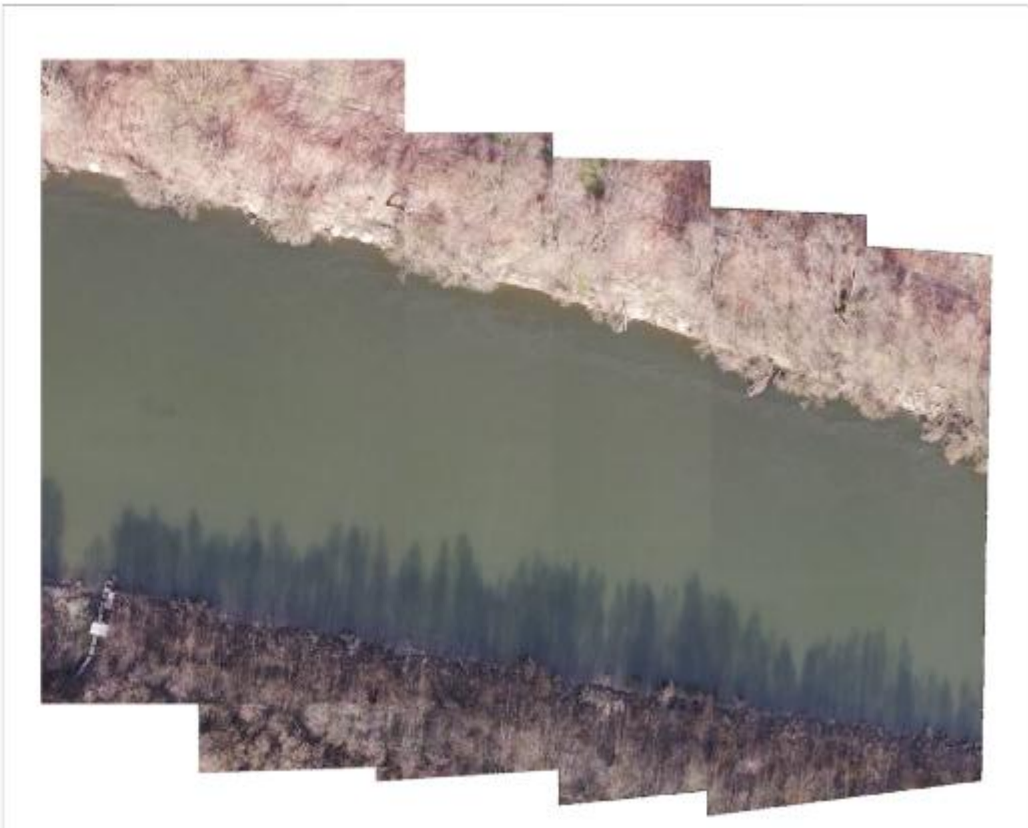

Figure 6 : An example of a measurement sample made using a drone.

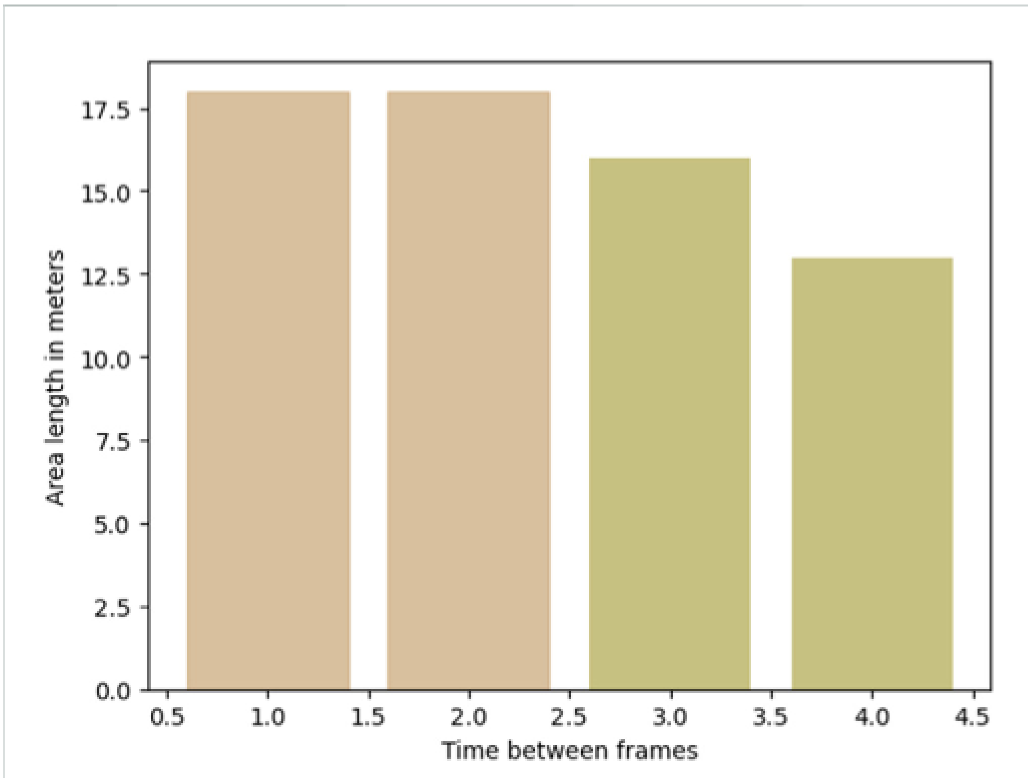

Figure 7 : An example of a measurement sample made using a drone.

The final tests analyzed the segmentation mask improvement parameters γ and θ. The best results for various γ values were obtained with θ = 25 pixels. The coverage parameter showed the best value at θ = 20 and γ = 0.3. Analysis indicated a 65% coverage threshold as the upper limit for correctly assigned points. Parameters selected through these tests enabled an additional drone flight for validation. Differences in coverage results indicated changes, such as grown bushes on the shore (see Figure 10).

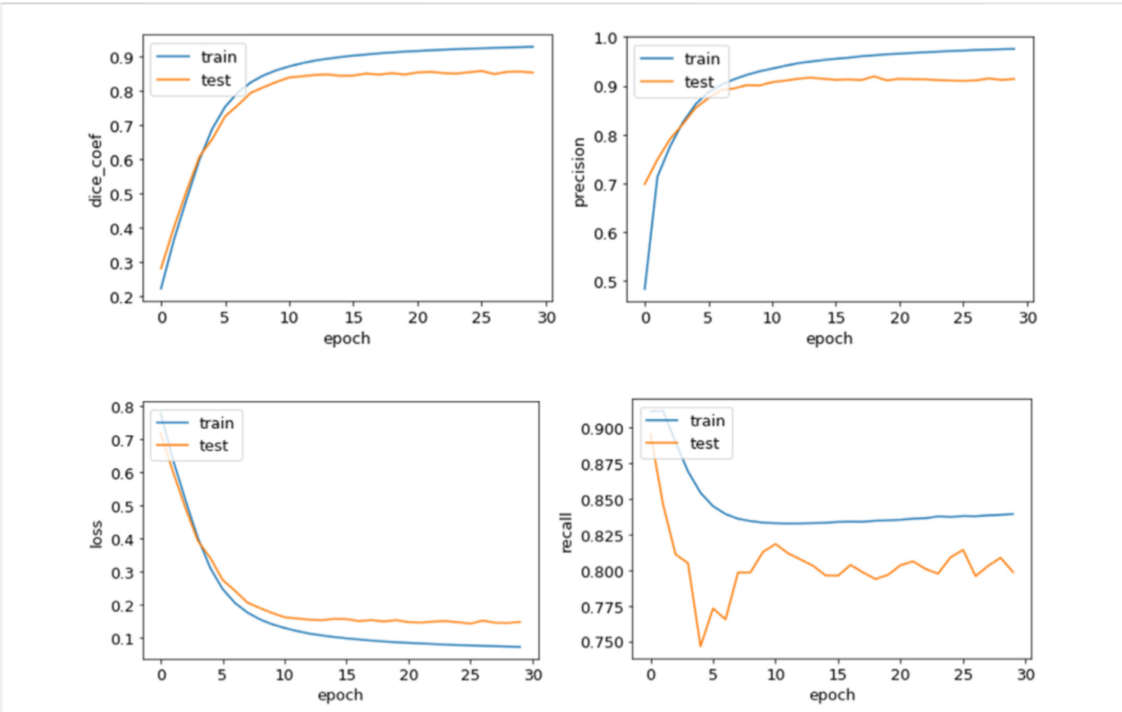

Figure 8 : Algorithm with detailed step by step of the proposed framework.

4.3 Discussion

The proposed solution aims to analyze rivers and potentially use it in monitoring or warning systems. Real-time access to results, provided the network is already trained, makes the end-to-end system architecture highly beneficial. Automation and data manipulation prevention enhance practicality and safety. However, the solution's metrics were limited by the small data set. Transfer learning, using VGG16 as an encoder, mitigated data limitations.

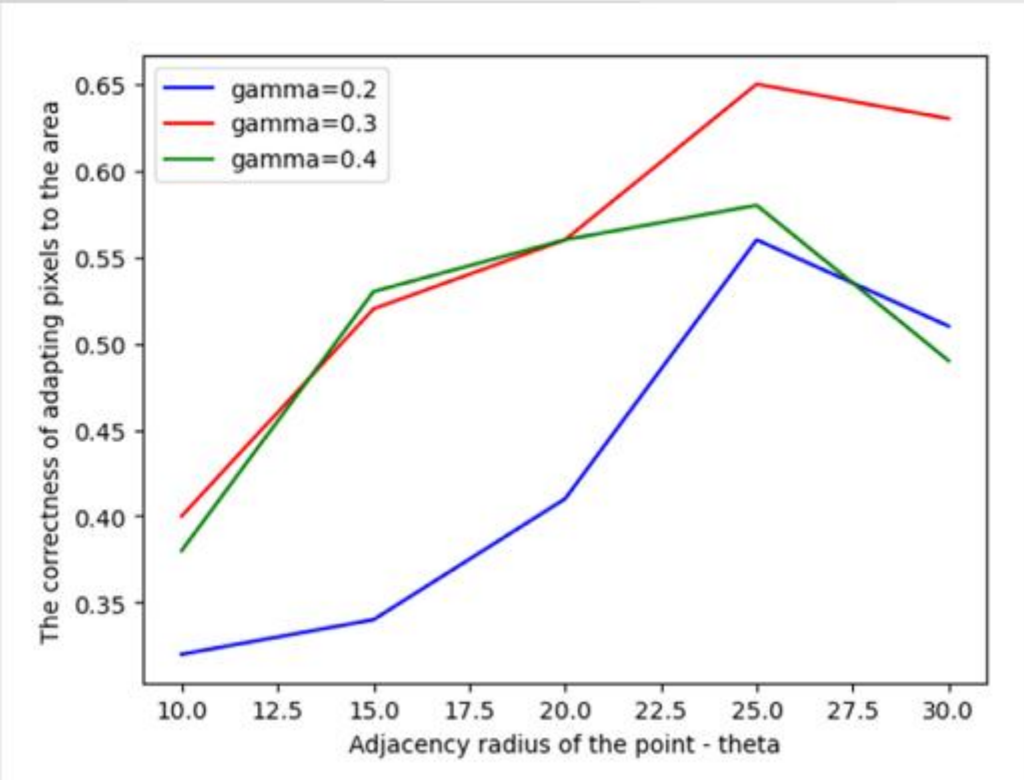

Figure 9 : Measured dependence of individual parameters during the segmentation mask improvement.

Figure 10: Measured dependence of individual parameters during the segmentation mask improvement

The end-to-end architecture automates methodology, allowing for initial analysis with a small data set, unlike most methods requiring specific databases or single areas. Literature review highlights advancements in the field, such as the U-Net-LSTM prediction model using long-term data and STN integration into U-NET networks (Yin et al., 2023). Another approach used point cloud data (Tur et al., 2020). Current research explores various water body boundaries analysis methods. Compared to others, this system's end-to-end architecture and initial stage methodology enable analysis with minimal data, though it may be part of a larger water reservoir analysis system (Włodarczyk-Sielicka et al., 2023).

V. Conclusion

In order to address the major environmental concerns that are caused by oil bunkering and illicit refining activities, this study demonstrated the effectiveness of an integrated land-atmosphere monitoring system in Rivers State, Nigeria. The system included the utilisation of unmanned aerial vehicle technology. Our methodology placed an emphasis on an end-to-end model, which made use of deep learning and image processing techniques in order to automatically analyse data acquired by drones. For the purpose of monitoring river conditions and identifying pollution patterns, the proposed system, which was constructed around the U-Net neural network with transfer learning and supplemented with traditional image processing techniques, produced high segmentation accuracy to achieve the desired results. One of the most important advantages of our method is that it eliminates the requirement for human participation by reducing the necessity for data processing and analysis to be automated.

Real-time analysis that is both quick and precise is ensured by this, which is essential for ensuring fast responses to changes in the environment. The capability of the system to georeference and process photos at a variety of intervals makes it possible to conduct extensive monitoring of river statuses as well as the impact that urbanisation and industrial operations have on the environment. In spite of the great level of accuracy that was reached, there were several difficulties that were observed, such as the small size of the training dataset. However, the utilisation of VGG16 learning transfer was able to alleviate these constraints, which resulted in an improvement in the neural network's initial performance. The outcomes that we have obtained highlight the usefulness and efficiency of combining deep learning with image processing for the purpose of environmental monitoring. The segmentation masks that are generated by the system make it possible to do comparative analysis with historical data. This makes it possible to identify changes in the state of the river as well as points of pollution that are particularly prevalent. The expansion of the dataset and the incorporation of autonomous data supervision will be the primary focusses of future work in order to enhance the robustness of the system.

Additionally, resolving issues regarding privacy through the use of federated learning will be a priority. This will allow for the distribution of computational requirements among users while simultaneously improving data security. Our objective is to improve the system's overall functionality, with the goal of ensuring that it continues to serve as an indispensable instrument for environmental management and policy-making in areas that are experiencing severe pollution and ecological degradation. Taking this approach has the potential to provide solutions that are both scalable and efficient for real-time environmental monitoring. This will contribute to improved management of natural resources and will help mitigate the effects of environmental risks through mitigation.

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