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Automatic Segmentation of Flood Region in Otsu's/Kapur's Threshold Enhanced Images using Deep-Learning Scheme

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Abstract

Artificial Intelligence (AI) supported data analytics is adopted in variety of domains to process the data with a guaranteed accuracy. The application of the AI-schemes, like Machine-Learning (ML) and Deep-Learning (DL) are commonly considered when a faster and accurate image examination is necessary. Hence, AI techniques are frequently utilized to process gray/RGB images. This research aims to propose a DL-supported segmentation tool to examine the Flood Monitoring Image (FMI) data. The developed system encompasses the following phases: (i) image collection and resizing, (ii) image pre-processing utilizing the Butterfly Algorithm (BA) and Otsu's/Kapur's based multi-threshold, (iii) executing DL-segmentation to extract the flood region from the selected image, and (iv) comparing segmented area with the binary mask (BM), and calculating the essential image metrics to validate tool's efficacy. This study validates the merit of DL-tool on the unprocessed and pre-processed images. The experimental results of this study demonstrate that the VGG-UNet yields superior segmentation outcomes, with better mean value of Jaccard-index (>93%), Dice-coefficient (>95%), and accuracy (>95%) in comparison to other DL-schemes employed in this research.

Keywords: Disaster management, Flood monitoring, Image processing, VGG-UNet, Detection.

1. INTRODUCTION

In recent years, data handling based on a chosen Artificial Intelligence (AI) techniques are gradually raising due to its accuracy and significance in handling simple and complex data. The AI-techniques, like Machine-Learning (ML) and Deep-Learning (DL) are commonly adopted in various data handling tasks, including the image and video processing applications. Image examination is considered

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to be one of the prime tasks compared to video in most of the real-time cases. Further, the outcome of image examination helps to achieve the necessary solution for a chosen problem [1].

This research aims to develop an AI assisted approach to detect the flood and its severity using the RGB-scaled digital images collected from the data repository. Implementing the automatic flood detection scheme plays a critical role in; flood prediction, development of early warning system, and damage assessment. The prompt and precise identification of floods will support in building the early warning systems, which are vital for preserving lives, property, and vital infrastructure. These systems help to provide necessary information to the authorities with up-to-date information regarding the commencement and advancement of floods, enabling them to promptly notify the public and facilitate evacuations and other preventive measures [2].

During the heavy rain condition, automatic alerting systems are essential for; issuing the necessary warning to reduce death, and property damage due to the flood. The computerized flood forecasting system supports timely warnings and evacuations, which considerably reduce the casualties. Further, the essential methods, like building flood defenses, installing drainage systems, and allocating emergency resources also will reduce damage due to the flood during the heavy rain condition [3].

Flood warning systems facilitate focused relief operations in addition to prompt responses. These technologies give crucial data for organizing rescue efforts and distributing relief to the most impacted areas by precisely charting the severity of flood. By ensuring that aid reaches people in immediate need, this focused strategy increases the overall effectiveness of disaster management operations [4]. Additionally, it aids in setting priorities for the distribution of resources, preventing wastage and ensuring that vital supplies get to the places where they are most needed.

Precise flood detection aids in post-disaster rehabilitation and reconstruction. For determining the extent of damage and organizing the reconstruction process, comprehensive flood maps and information on water levels and impacted areas are important. This data promotes resilience in impacted communities by assisting international organizations, non-governmental organizations, and government agencies in developing and putting into practice efficient recovery plans. It also assists in locating weak points in the infrastructure, directing future building initiatives to be more flood-resistant, and lowering the likelihood of calamities in the future [5].

The goal of this study is to develop an AI-assisted image examination tool to analyze the flood region in RGB-scaled digital image. The proposed DL-tool based approach consists following phases: (i) collection and resizing flood image data; (ii) RGB-image pre-processing based on tri-level threshold based pixel grouping utilizing the Butterfly Algorithm (BA) and Otsu/Kapur function; (iii) implementing the chosen DL-segmentation scheme to extract the flood region; and (iv) performing a pixel-level comparison between the extracted Flood Region (FR) and binary-mask (BM) to compute the required image metrics. These values are used to confirm the efficacy of the implemented scheme.

This study considered the FR segmentation based on VGG-UNet, and in order to simplify the architecture, VGG16 is assigned as the backbone. The relevant details about this technique can be obtained from [6, 7]. The experimental results of the suggested method validate that; VGG-UNet based segmentation along with the Kapur's entropy pre-processed image provides improved result than the Otsu's enhanced images. The VGG-UNet along with Kapur's pre-processed image helps to achieve better values of Jaccard-index (>93%), Dice-coefficient (>95%), and Accuracy (>95%).

The experimental results of this study validate that, VGG-UNet combined with pre-processed image provides a better outcome compared to the unprocessed image based examination.

The contribution of this research includes;

(i) Enhancing the chosen RGB-scaled image using BA and Otsu/Kapur function,

(ii) Implementing the VGG-UNet to segment the FR with better accuracy,

(iii) Verifying the merit of the proposed tool using the unprocessed and pre-processed images.

2. LITERATURE REVIEW

One of the most essential practices during the disaster management is; keeping an appropriate practice to monitor the change in weather, and issuing a warning when the weather level exceeds above the manageable value. One of the severe conditions in weather is a heavy flood during the downpour, which requires careful monitoring in order to enable the necessary warnings and evacuations to reduce the damage on people and property.

Even though several monitoring methods are available, digital image-supported technique is a widely executed procedure for the flood monitoring. Unmanned aerial vehicle (UAV) collected images and videos are essential for locating the necessary areas affected by significant flooding [8]. After the images are acquired, a selected image evaluation approach is applied to detect flood severity and enable necessary warning.

The availability of the high-performance camera helped the environmental monitoring tasks to shift towards the digital imagery supported schemes. The images help to provide necessary information needed to analyze the flood area using a chosen AI-scheme. The presence and intensity of the flood were determined by digital image supported studies confirmed that, pre-processed image based methods offers better outcome compared to the unprocessed based techniques; even the AI-approaches are used. Earlier studies executed in flood monitoring task suggest that, deep-learning (DL) based monitoring is useful for organizing and executing the necessary procedures, and it also yields a significant improvement in flood forecasting.

TABLE 1 shows details about few selected flood image examination using AI-based techniques;

The major research gaps in DL-based flood monitoring are as follows; the unprocessed image based flood monitoring discussed in earlier research provides a lesser segmentation result when traditional and DL-based segmentation is executed. Further, the pixel complexity in the unprocessed RGB images are large, which may result in a poor result during the training and validation process. Further, the test results also have lesser segmentation accuracy.

To overcome the above discussed issue, this research aims to employ an image pre-processing scheme based on Otsu's/Kapur's function. To execute the chosen tri-level threshold selection process using the Otsu's/Kapur's based scheme, this work employed the heuristic algorithm based practice. After the enhancement of RGB-image pixels based on tri-level threshold, the FR from this image is effectively extracted using the DL-scheme, which has an encoder-decoder section. In

Table 1: Summary of DL-supported flood monitoring scheme

Reference	Methodology
Jaisakthi et al. [9]	In this study, a novel modified UNet is proposed as a means of segmenting the FR from the RGB-scale image that was selected. The results of this research prove to be superior to those obtained by other approaches that are already in use.
Li et al. [10]	This work discusses a novel approach to determining the flood submerged range. This approach is based on the combination of attention mechanism and UNet.
Ghosh et al. [11]	A comprehensive analysis on the segmentation and evaluation of the FR from sentinel-1 data was proposed in this work. The DL-tool was used for the analytical project.
Safavi et al. [12]	Detailed estimation of automatic FR recognition in non-real and actual image instances is presented in this paper, which also serves to authenticate the effectiveness of proposed system.
Rambhad et al. [13]	The automatic detection of FR from satellite photos using DL-tool is discussed as an implementation of the process.
Zaffaroni and Rossi [14]	The reason of this presentation and discussion is to provide a comprehensive analysis of the FR detection from flood photos using the DL-tool. The utilization of this method contributed to the achievement of a superior result on the selected image database.
Wu et al. [15]	The DL-tool is used to give a real-time evaluation of the FR data obtained from the SAR flooded photos.
Mesvari et al. [16]	Within the context of Sentinel-1 satellite photography, an innovative UNet++ technique is provided for the purpose of automatically detecting the FR.
Ghosh et al. [17]	As part of this work, a hierarchical UNet scheme was provided in order to segment the FR from the Sentinel-1 data. This scheme was then evaluated against the NASA benchmark dataset in order to validate the relevance of the technique that was implemented.
Nemni et al. [18]	This study suggests a method that utilizes a convolutional neural-network for the purpose of detecting FR in synthetic aperture radar pictures in a quick and efficient manner.

comparison to previous literature discussed in TABLE 1, the proposed technique yields superior results on the FR examination database.

Proposed work implemented the VGG-UNet, by considering the VGG16-as the backbone and it helps to segment the FR from Otsu's/Kapur's function enhanced image. This tool also considered the BA based optimal threshold selection process to enhance the RGB-images using pixel grouping concept. The performance of the developed DL-tool is verified using the unprocessed and pre-processed images and the results are presented and discussed.

3. METHODOLOGY

Implementation of appropriate DL-tool for the image examination task relies mainly on the image complexity, work to be executed, and the expected accuracy for the considered problem. To achieve the overall performance for the FR extraction and evaluation task, this research proposed the VGG-UNet approach based on VGG16 and this technique is tested and verified using the unprocessed and pre-processed images.

For this study, the chosen RGB-scaled pictures were put through a new pre-processing method based on the BA with Otsu/Kapur function. FIGURE 1 shows the different stages that can be used with the newly created DL-tool. These pictures, such as original-image and BM, are taken from the data repository [19] and resized to 512x512 pixels. The chosen threshold selection method is then considered to pre-process the image database, which is then used to train and test the VGG-UNet. After taking the FR from the chosen image and comparing it to the BM, the required image metrics are calculated, as shown in the figure. This process is done again and again for 100 test images. The final result is written down as the mean± standard deviation. The attained image metrics confirms that the proposed DL-tool works well on the RGB-image database.

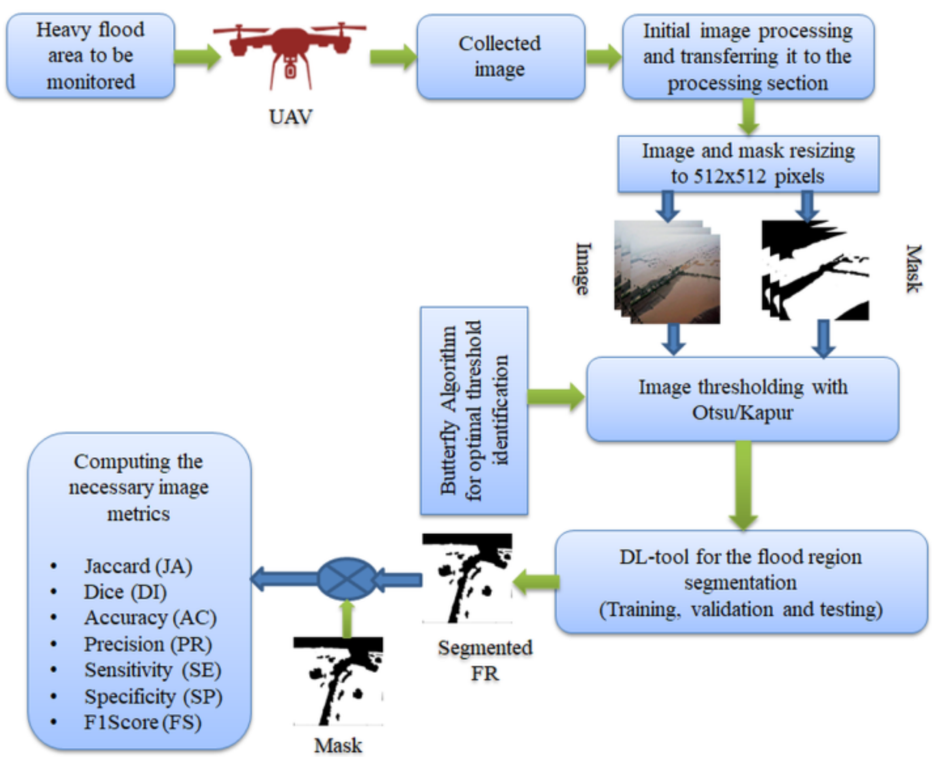


Figure 1: Automatic tool and carries detection using UDL-model

3.1 Data Collection

The necessary images for this research were collected from [19]. This database consist 290 images along with the BM. After collecting these images, necessary data augmentation (horizontal-flip and vertical-flip) is executed to increase the number of images to 870 images. Before the augmentation, each image is modified to 512x512 pixels and these are used to train and validate the performance of VGG-UNet. FIGURE 2 presents the sample image and the BM from the collected database. The proposed VGG-UNet segments the water section from these images and then the extracted FR is then considered to get the required metrics to confirm the advantage of the developed tool.

(a) Image (b) Mask

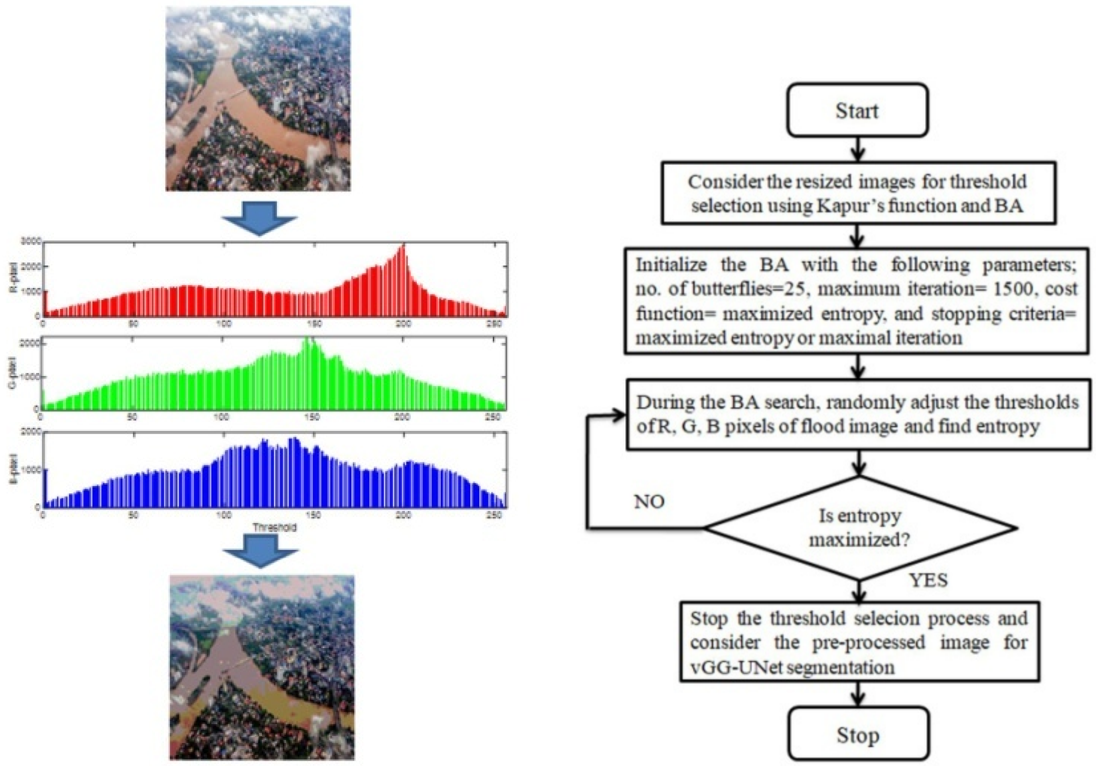
Figure 2: Sample image and mask from database

3.2 Image Pre-processing

Data pre-processing is one of the common practices in the image segmentation tasks and in the literature, a number of imaging schemes are available to enhance the visibility of the required image region. Threshold based image enhancement is one of the common pre-processing practice and tri-level threshold (Th=3) selection using the Otsu's/Kapur's based methods are some common practice to improve the pixel visibility [20, 21]. Identification of the optimal threshold from the chosen approach is quite complex when it is identified manually. Hence, this work considered the BA to find the optimal threshold.

The BA is a recent heuristic techniques invented by [22] to discover the optimal result for chosen numerical optimization problem. The major merit of the BA is, it is similar to other heuristic schemes, which aims to find the finest solution with a faster convergence rate. This work considered the BA discussed in Rajinikanth et al. (2024) [23]. The employed BA is then allowed to find the finest threshold (Th=3) from the chosen image. This work in the literature implemented this scheme on the grey-scale image and this research executes this task on the RGB-image. The improved image is then used for verifying the performance of the DL-segmentation methods considered in this study. The following works presents the necessary information regarding the Otsu's and Kapur's image threshold tasks.

The implementation of the proposed work is depicted in FIGURE 3. FIGURE 3(a) presents the RGB-image threshold selection process and FIGURE 3(b) presents the flow-chart which demonstrate the whole process, which executed the BA-based image threshold selection. The initial BA parameters are assigned as in [23] and this algorithm is allowed to adjust the R,G,B thresholds till the entropy is maximized. This process is repeated for all the images and the improved images are considered for segmentation with VGG-UNet and other models of this research.



(a) Threshold selection in RGB image (b) Flowchart

Figure 3

FIGURE 4 presents the outcome obtained with the proposed task; FIGURE 4(a) shows the unprocessed image, FIGURE 4(b) and (c) shows the Otsu's and Kapur's based threshold selection to enhance the flood section from the chosen images. In Otsu's and Kapur's threshold image, the visibility of the FR is better compared to the unprocessed image.

3.3 DL-segmentation

Due to its merit and practical significance, a number of digital image segmentation works adopted the DL-methods to achieve a better result. Traditional DL-segmentation includes an encoder (image to feature conversion) and decoder (features to image reconstruction) assembly to identify and extract the necessary region from the image. It needs a supervised training process and hence, it is trained using the image and the corresponding binary mask. This research employed the VGG-UNet with VGG16 as backbone and essential information regarding this can be found in [24].

(a) Unprocessed image (b) Otsu (c) Kapur

Figure 4: Unprocessed and pre-processed images

The initial parameters for the DL-segmentation schemes are assigned as follows; learning rate= 1e-4, optimizer= Adam, pooling= max, initial activation= ReLU, final activation= SoftMax, epochs= 125, and monitoring metrics= accuracy and loss. These parameters are assigned for all the chosen DL-models to achieve a better segmentation result.

3.4 Prime Metrics for the Performance Evaluation

The proposed DL-tool's usefulness is checked by comparing the initial and final metrics from the FR and BM job. True-positive (TP), false-positive (FP), true-negative (TN), and false-negative (FN) are some of the first metrics that are calculated during the pixel level comparative job. These numbers are then used to figure out the necessary measures, such as JA, DI, AC, PR, SE, and SP and its mathematical expressions are depicted in Eqns. (1) to (6). The segmentation performance is verified using 100 images, and the performance of the proposed DL-model is checked and confirmed against unprocessed and pre-processed images.

Mathematical expression for image metrics;

$$\text{Jaccard-index (JI)} = \frac{TP}{TP + FP + FN} * 100 \tag{1}$$

$$\text{Dice-coefficient (DC)} = \frac{2TP}{2TP + FP + FN} * 100 \tag{2}$$

$$\text{Accuracy (AC)} = \frac{TP + TN}{TP\_TN + FP + FN} * 100 \tag{3}$$

$$\text{Precision (PR)} = \frac{TP}{TP + FP} * 100 \tag{4}$$

$$\text{Sensitivity (SE)} = \frac{TP}{TP + FN} * 100 \tag{5}$$

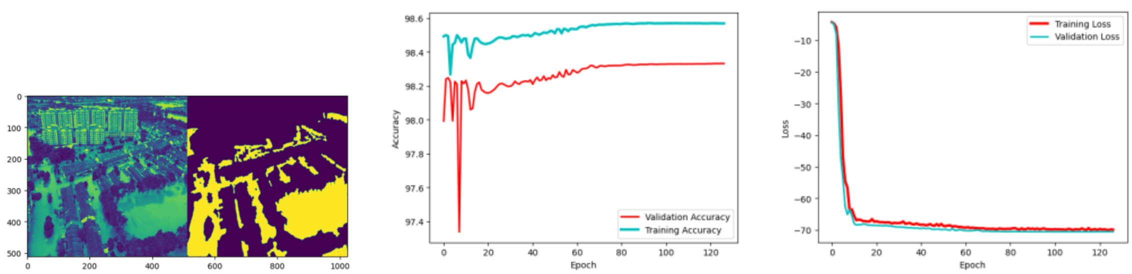
$$\text{Specificity (SP)} = \frac{TN}{TN + FP} * 100 \tag{6}$$

where TP, TN, FP , and FN are the values of true-positive, true-negative, false-positive, and false-negative achieved during the comparison of segmented FR and BM.

4. RESULT AND DISCUSSION

This part of the work presents the investigational outcome. The pre-processing task is implemented using Matlab software, and Python software is considered to execute the developed DL-tool. The following specifications describe the computer that is used for this work: processor: AMD Ryzen5, 16 GB RAM, and 4 GB VRAM. The DL-tool is trained on 670 images and then tested on 100 images to confirm its significance. The final 100 images are considered to test the performance of the DL-model.

FIGURE 4 shows what the first training result for VGG-UNet looked like. The training results for a chosen image and the BM are shown in Fig. 5(a). Accuracy vs. epochs is shown in Fig. 5(b), and loss vs. epochs is shown in Fig. 5(c). These results show that the VGG-UNet gives better training accuracy (about 98%) on the chosen image database. The same job is done again with different models, and the outcomes are written down.



(a) Training (b) Accuracy (c) Loss

Figure 5: Experimental investigation with VGG-UNet

The testing result obtained with the VGG-UNet is presented in FIGURE 6 and it confirms its efficiency. Similar results are achieved with other methods, like UNet, UNet+, and UNet++.

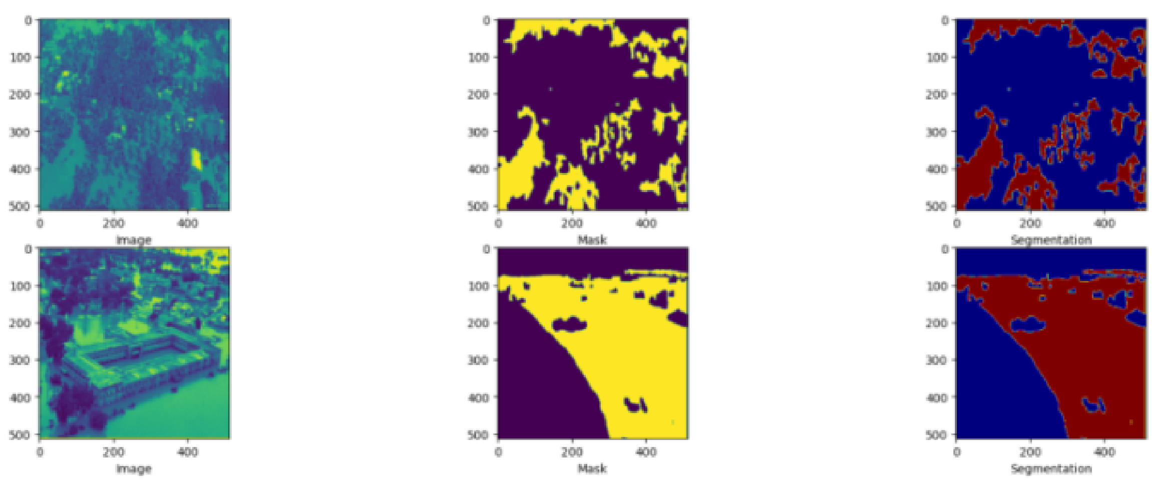


Figure 6: Training outcome of VGG-UNet form Kapur enhanced image

Similar practice is repeated for all other images (100 numbers) and other DL-models. A sample segmentation result obtained with the Kapur enhanced images with the chosen DL-models are depicted in FIGURE 7. FIGURE 7(a) and (b) presents image and the BM, FIGURE 7(c) to (f) shows the experimental outcomes achieved with the chosen DL-schemes. Finally, the mean of these images are recorded to confirm the merit of the developed system.

(a) Image (b) BM (c) VGG-UNet (d) UNet (e) UNet+ (f) UNet++

Figure 7: Segmentation result with different DL-models on a chosen image data

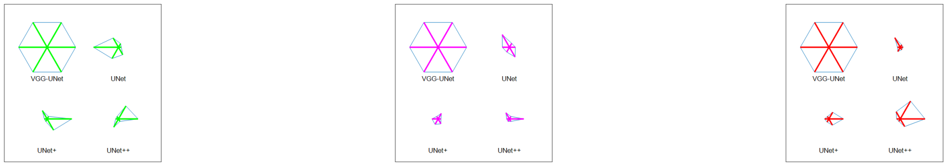
The comparison of the segmented FR and the BM gives the necessary metrics as shown in TABLE 2. In this table, only the average results of 100 images are considered for the evaluation for both the unprocessed and the threshold images. The experimental outcome confirms merit of VGG-UNet on the chosen images compared to other DL-schemes. Further, the overall result achieved with the Kapur's threshold image is better compared to unprocessed and Otsu. This confirms that the proposed DL-tool provides a better outcome when the Kapur's processed image is examined using the VGG-UNet.

Table 2: Overall performance achieved using the test DTP database

Image	Model	JI	DC	AC	PR	SE	SP
Raw	**VGG-UNet**	84.25 ± 1.16	87.31 ± 2.07	87.47 ± 1.82	87.03 ± 2.04	86.03 ± 2.20	86.63 ± 1.18
	UNet	84.05 ± 2.16	86.42 ± 2.27	86.81 ± 2.02	86.94 ± 1.45	85.58 ± 2.16	86.35 ± 2.13
	UNet+	84.22 ± 1.63	86.37 ± 1.94	86.77 ± 1.63	86.38 ± 2.04	85.29 ± 1.04	86.41 ± 2.72
	UNet++	84.18 ± 2.22	86.81 ± 1.08	86.52 ± 2.74	86.38 ± 1.27	85.48 ± 1.32	86.27 ± 1.08
Otsu	**VGG-UNet**	92.14 ± 0.17	94.73 ± 0.28	97.05 ± 0.04	97.46 ± 0.11	96.94 ± 0.14	97.05 ± 0.03
	UNet	91.47 ± 1.05	93.15 ± 1.14	96.32 ± 1.18	94.72 ± 0.26	95.36 ± 1.04	95.77 ± 0.28
	UNet+	91.38 ± 0.53	93.27 ± 0.27	95.71 ± 0.57	94.59 ± 0.40	95.41 ± 0.56	95.35 ± 0.08
	UNet++	91.72 ± 0.63	93.04 ± 0.56	95.93 ± 0.23	94.17 ± 0.04	95.18 ± 0.16	95.15 ± 0.49
Kapur	**VGG-UNet**	93.09 ± 1.04	94.95 ± 0.33	97.68 ± 0.29	97.93 ± 0.05	97.76 ± 0.28	97.92 ± 0.12
	UNet	92.21 ± 0.34	93.67 ± 0.24	96.47 ± 0.37	95.18 ± 0.19	95.83 ± 0.37	95.83 ± 0.19
	UNet+	92.61 ± 0.17	93.91 ± 0.18	95.91 ± 0.19	95.33 ± 0.11	95.72 ± 0.22	96.18 ± 0.11
	UNet++	92.96 ± 0.26	94.55 ± 0.32	96.28 ± 0.04	95.27 ± 0.06	95.66 ± 0.09	96.31 ± 0.17

FIGURE 8 presents the overall performance of the implemented FR segmentation task. FIGURE 8(a) presents the results of unprocessed image, FIGURE 8(b) shoes the outcome of Otsu image and FIGURE 8(c) depicts the outcome achieved with the Kapur's pre-processed image. These images also substantiate that the performance of the VGG-UNet is superior in all the image cases.

This work used the DL-tool to examine FR from an RGB-scaled image. This work executed VGG16 based VGG-UNet and in the future, VGG16 can e replaced with VGG19 model to enhance the



(a) Unprocessed image (b) Otsu’s (c) Kapur’s

Figure 8: Overall evaluation with Glyph-plot

outcome of the VGG-UNet model. Further, in the future, ResNet18 model can also be considered to generate the ResUNet model to achieve a better outcome during the FR detection task.

The merit of proposed study is that it examines the FR using a simple and effective method to process digital images. The main limitation of the proposed approach in the real-time flood monitoring includes, collection of the flood images with digital camera, sending the collected image to the pre-processing and segmentation algorithm and decision making. The practical difficulty in real-time image collection can be overcome with Unmanned Aerial Vehicle (UAV) supported image collection and remote computer based processing and decision making. The current research was implemented on the existing image database and in the future, it can be considered to analyse the real flood images collected from the digital camera.

5. CONCLUSION

The goal of this study is to create a DL-tool that can help in analysing the RGB-scaled digital images and segment the FR with better accuracy. The earlier research, that were already executed on a chosen database used complicated image examination methods to find the FR. Further, the detection accuracy in the earlier works is also less, since these methods considered the unprocessed images. For faster and more accurate FR identification, proposed research considered the Otsu’s/Kapur’s threshold selection, and to enhance this work, it considered the BA. After the images have been pre-processed, the FR from these images is evaluated. The DL-tool considered the VGG16 as the backbone to construct the VGG-UNet model which offered a better result. The merit of VGG-UNet is confirmed against the conventional models, UNet, UNet, and UNet++. The experimental outcome confirmed that the VGG-UNet outperforms these DL-models for unprocessed and pre-processed image cases. This confirms the merit of the developed scheme in FR detection task and in future, this technique can be considered to examine the real-time images collected using digital camera.

5.1 Conflicts of Interest

The authors declare that there is no conflict of interest.

5.2 Data Availability Statement

The data considered in this research can be accessed from https://www.kaggle.com/datasets/faizalkarim/flood-area-segmentation/

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