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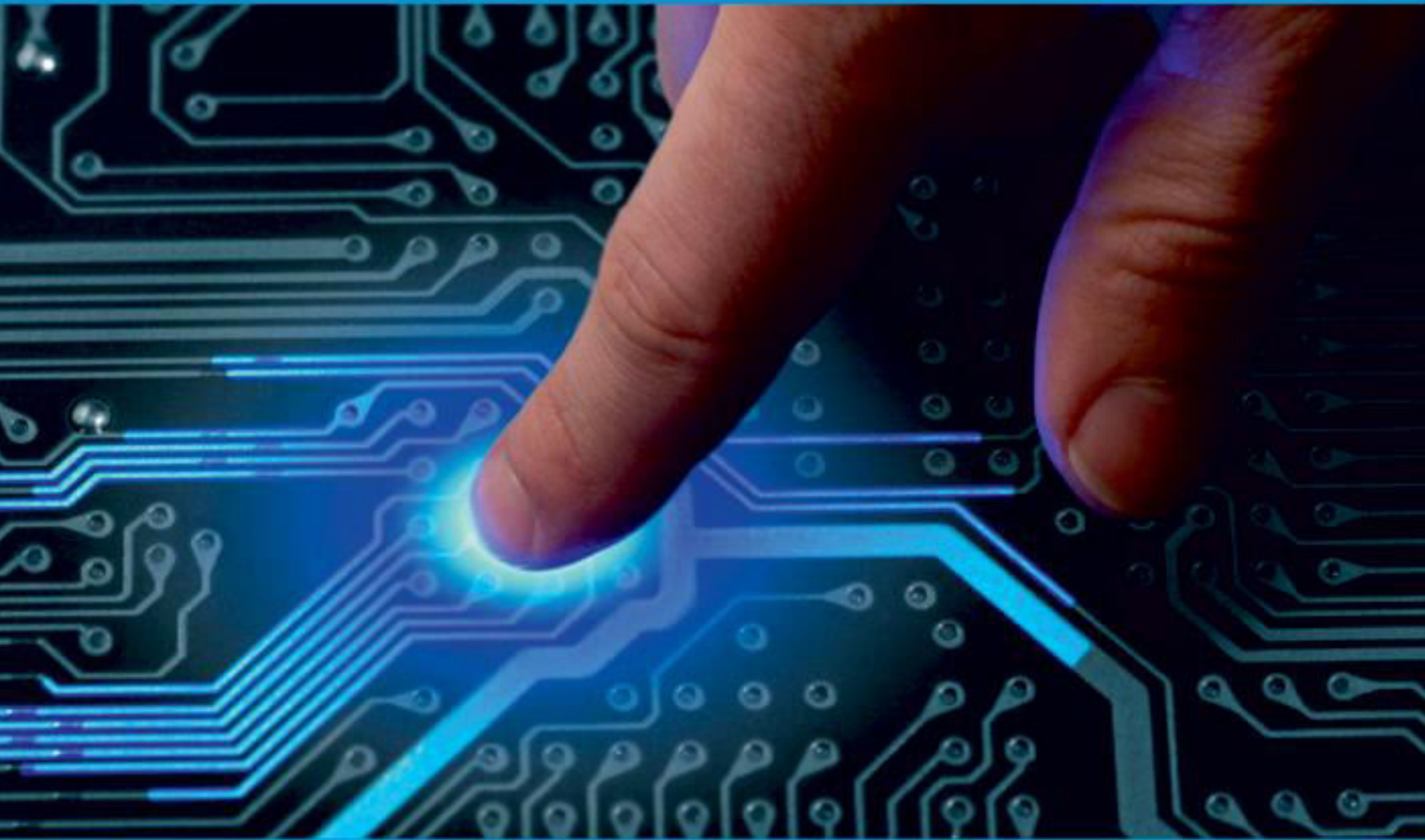

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Real-Time Flood Scene Object Detection from Multimedia Images

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ABSTRACT: This research addresses the critical need for effective flood management and disaster response through advanced technological solutions. Floods are among the most destructive natural disasters, causing significant economic and environmental damage, and necessitating rapid response capabilities. This work proposes a novel system that integrates CNN and YOLO for real-time detection and analysis of flood-related objects in multimedia images.The research highlights the limitations of traditional flood detection systems, which often rely on physical sensors that lack real-time coverage and face maintenance challenges. By leveraging multimedia data—such as images from surveillance cameras, drones, and social media—the proposed system aims to enhance situational awareness during floods. The combination of CNNs, known for their proficiency in feature extraction, and YOLO, designed for real-time object detection, allows for the identification of submerged vehicles, debris, damaged structures, and human figures.The methodology involves sourcing a diverse dataset from various platforms and employing image preprocessing techniques to improve detection accuracy. The system's architecture enables it to process large volumes of data quickly, making it suitable for emergency response scenarios. Furthermore, the integration of satellite and remote sensor data enhances the model's capability to detect floods in isolated areas.In the end, this work highlights how CNNs and YOLO might enhance flood response tactics by promoting decision-making based on data, maximizing resource allocation, and promptly alerting impacted communities.The proposed approach achieved an overall accuracy of **87%**, demonstrating its effectiveness in real-world scenarios.The adaptability of these algorithms positions them as vital tools in disaster management and environmental monitoring, thereby contributing to enhanced resilience against flooding events.

KEYWORDS: Flood Detection; Convolutional Neural Networks (CNNs) ;You Only Look Once (YOLO);Real-Time Object Detection;Disaster Management

I. INTRODUCTION

Flood is a most common and destructive natural phenomenon that causes economic and environmental loss. Quick and accurate responses in managing floods are therefore urgently needed for their proper integration with advanced technologies. Two of the most strong techniques in deep learning are CNNs and YOLO. These tools are applied in real-time monitoring and decision-making in dealing with floods. The CNNs learn the patterns and features from the complex multimedia data, including the differentiation of objects like floodwater, debris, and infrastructure in pictures[1]. They perform well in flooding since they can lean to learn the detection shapes, textures, and colors, which can help in object categorization. YOLO is an improvement upon real-time object models for detecting objects, where it extends the functionality of CNNs to identify many objects within a single picture or video frame. A high-speed yet accurate model, the YOLO model becomes very useful in emergency response situations where rapid flood assessment can become such an essential factor[2].

Combining CNN with YOLO helps create a robust approach to analyze multitemporal data coming from flood-prone areas[3]. It detects submerged vehicles, floating debris, and structural damages, which helps in determining the extent of the flood and finding quick actions to make responses. Algorithms like these present processed data from sources as vast as drones, surveillance cameras, and social media in real-time within multimedia systems for timely insights into the

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impact of floods[4]. Integration of satellite and remote sensors strengthens flood detection more so in secluded areas. CNN and YOLO's adaptation enables them to be further trained on region-specific flood detection, which enhances localization of responses[5]. This combination helps the authorities make data-driven decisions for optimization of resource allocation and timely release of warnings[6]. In addition, CNN and YOLO support analysis after the flood has occurred, capturing the intensity of damage for the recovery of disasters and future risk assessment that aids in improved flood response and resilience[7].

The main key contribution of the work was given below:

- CNN improves object detection by extracting detailed features from flood scenes, enabling better identification in complex environments.
- YOLO ensures fast processing, allowing for quick decision-making during floods, crucial for timely interventions.
- Data augmentation helps the system adapt to varying flood conditions, enhancing its performance in different scenarios like lighting and water levels.
- The system identifies critical objects, such as water levels and infrastructure damage, aiding flood monitoring and assessment.
- The integration provides real-time information to responders, helping assess damage and guide effective relief efforts

The remaining part of the paper is arranged as follows: Related work is discussed in Section II. In Section III, the suggested methodology is explained. The experimental results are reported and compared in Section IV. In Section V, further work is mentioned and the work is concluded.

II. RELATED WORKS

Humaira, Samadi, and Hubig[8]offer DX-FloodLine, a multi-stage deep learning pipeline toward real-time flood detection and submerged object identification based on social media images. Utilizing interpretable models, performance is iteratively improved to reach an accuracy of 90%, surpassing similar models. The proposed tool holds much promise for near real-time deployment in disaster monitoring.

Rahnemoonfar et al[9]propose a high-resolution UAV-captured imagery dataset from the aftermath of Hurricane Harvey with the goal of semantic segmentation and visual question answering in flood-affected areas. As a basis for that, this dataset contributes to augmenting post-disaster assessments by issues that plagued satellite imagery-they offer highly detailed pixel-wise labeled images available for analysis in working urban damage. Baseline models will be compared on FloodNet to demonstrate its applicability to flood-related tasks, including differentiating between natural and flooded water and further enhancing the real-time potential of disaster management.

Pally and Samadi [10]have recently proposed the "FloodImageClassifier," that is the multi-purpose CNN-based flood detector using social media and DOT camera images. Combining architectures such as YOLOv3, Mask R-CNN, and EfficientDet, it detects and segments objects simultaneously within the flood scenario. The system applies Canny Edge Detection to estimate the water level in the flooded region[11]. The overall system primarily relies on geolocation data in association with monitoring of traffic conditions for near real-time automated analysis and risk evaluation by emergency responders[12].

Van Ackere[13]cited IoT in the detection of floods in real time and extended it further on how connected devices and sensors can easily communicate risks of flooding. IoT can determine floods in real-time with the help of sensor integration with processing capabilities, thereby making disaster response times even faster. Its flexibility makes it a good potential for developing flood-detection systems designed to at least reduce socio-economic impact and build up efforts to prepare and respond to disasters by facilitating streamlined data acquisition and communication.

Nehete et al.[14]present techniques regarding image processing using GAN and low-light enhancement techniques to rescue flood victims. Techniques include the use of Faster R-CNN and YOLO help to rescue images suffering from poor visibility by enhancing quality, removing noise, and correcting color information. GAN significantly enhances the quality of underwater images, thus enabling rapid response in places where the response team cannot see clearly owing

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to poor visibility. Thus, this paper hence brings out the need for data at real time to enhance response in case of disasters.

Zhong et al.[15]proposes an estimator based on YOLOv4 to estimate the depth of urban flooding using object recognition of submerged pedestrians and vehicles. High accuracy was achieved, even with vehicles as reference objects, and thus promises continuous, low-cost flood depth data compared with physical gauges. There is a further improvement of the detection accuracy in image enhancement and provides a strong solution for urban hydrological monitoring and flood warning systems.

Most of the existing studies are purely concentrating on flood detection using CNNs, YOLO, GANs, or alike deep learning models, and integrating real-time multi-source data like IoT, social media, UAV imagery into one place seems to be a gap for complete flood monitoring. In addition, most of the models developed still suffer from adaptation problems to environmental conditions and also to various sceneries in towns. Although current solutions could achieve high accuracy, they have been out of the reach to bring it to real time by the speed and demand of processing data in hardware, making its applicability lower. Further research is still ongoing, especially in enhancing cross-platform compatibility in the integration process, increasing model robustness in diverse conditions, and reducing computational costs for wide application in large-scale disaster response systems.

III. PROBLEM STATEMENT

Uncertain natural calamities, floods seriously harm assets, infrastructure, and individuals. The ability to detect and monitor flood scenes promptly is essential for early warning systems and effective disaster response. Traditional flood detection systems largely depend on physical sensors, which, while valuable, often face limitations in terms of real-time coverage, costly maintenance, and spatial constraints. These systems may fail to provide the continuous, detailed data necessary for dynamic, real-time responses in rapidly evolving flood scenarios. Additionally, identifying critical flood-related objects—such as vehicles, debris, and varying water levels—presents unique challenges in multimedia images. Outdoor flood scenes frequently involve complex backgrounds, occlusions, and inconsistent lighting, which complicates object detection. Given these constraints, there is an urgent need for an automated, real-time flood detection and object recognition system that leverages multimedia data to enhance situational awareness and emergency response effectiveness. To address this, we propose "Real-Time Flood Scene Object Detection from Multimedia Images," a system that integrates CNN and YOLO for efficient flood object detection and scene analysis.

IV. PROPOSED CNN-YOLO INTEGRATION FOR REAL-TIME FLOOD SCENE OBJECT DETECTION

The CNN-YOLO integration combines CNNfor feature extraction and YOLOfor real-time object detection in flood scenes. CNN enhances YOLO's accuracy by extracting detailed features, while YOLO ensures fast object detection, crucial for flood response. Data augmentation and preprocessing improve robustness across varied conditions. This system can assist in emergency response, infrastructure assessment, and flood monitoring. This is shown in Fig.1

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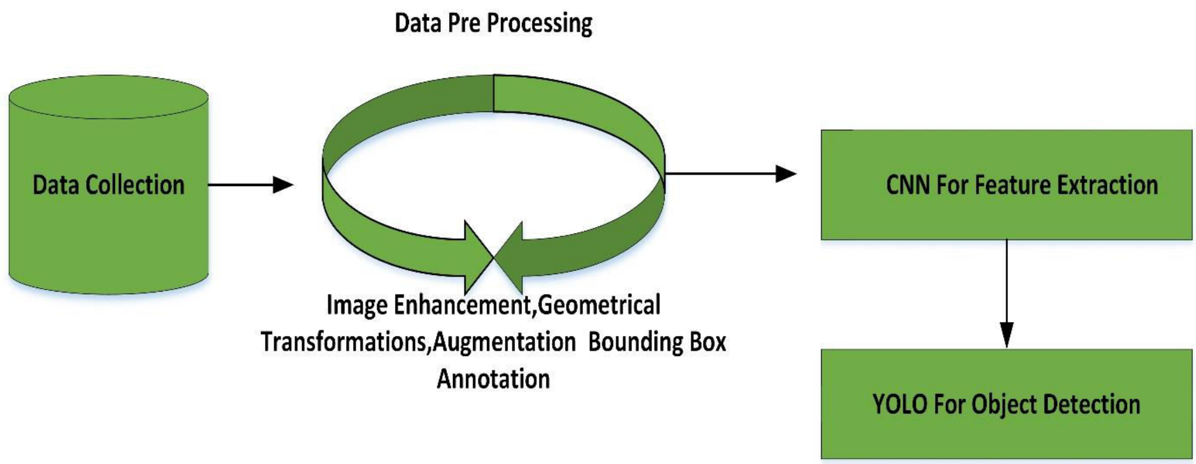

FIG 1Workflow of Proposed Method

A. Data collection:

This dataset relates to the floods in Louisiana in August 2016, a devastating natural disaster that was characterized by extreme rainfall leading to record flooding across significant parts of the state. The dataset describes in detail the intensities of rainfalls as well as their adverse effects, including the destruction that affected thousands, at least 13 reported deaths, and widespread destruction. The dataset spans key affected areas, specifically 20 parishes federally declared as disaster zones, with recorded figures for the rainfall such as the 31.39 inches in Watson, 26.14 inches at White Bayou, and 25.52 inches at Livingston. Further, such a dataset is very informative to analyze the scale of flooding, geographic impact caused by such floods, and subsequent emergency response and recovery efforts [16]

B. Data Pre-processing

Data pre-processing and augmentation were crucial steps in preparing the diverse set of images and videos for the flood scene object detection task. The images were enhanced using image enhancement techniques such as adaptive gamma correction with the aim of improving the contrast as well as overcoming brightness and white exposure problems. The geometrical transformations involved translation, rotation, and affine transformation to make the dataset more variable. Other augmentations are cropping, padding, horizontal flip, and random rotate while using the TensorFlow object detection API, where one uses such augmentation to enlarge the training set and prevent overfitting. During the initial stage of flood recognition, the photos usually manually classified as either flood or not. However, for the object detection, training models required images with such bounding boxes and accurate annotation of objects such as bridges[17]

C. Convolutional Neural Networks (CNNs) for Feature Extraction

In CNNs, two important operations are convolution and pooling; these are fundamental components for feature extraction and dimensional reduction. Mathematically, convolution can be defined as follow in eqn. (1)

$$s(i',j') = (i' * k')(i',j') = (m,n).K(i-m,j-n) \quad (1)$$

Where i' is the input image, k is the convolution kernel and $s(i,j)$ denotes the output feature map at position (i,j), The kernel is slid over the image, an element-wise multiplication is performed and the results are summed up, thereby pointing out certain features such as edges and textures. This helps CNN learn spatial hierarchies of features as the image travels through multiple convolutional layers

Max pooling is a further essential method that minimizes the feature map's spatial size by selecting the highest possible value while maintaining the information that is significant for every region. Max pooling can mathematically be represented as:

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where S is the feature map, and $R(i,j)$ refers to the region around the pixel (i,j) usually a 2×2 window. Such an operation is essentially reducing the computational complexity while still ensuring the presence of all significant features for classification or detection. Pooling also brings about translation invariance, so that even if the features are shifted in the image, the model may detect them.

These two operations have provided the structure of convolutional neural networks. This forms the backbone of CNN's application mainly due to extracting hierarchical features in conjunction with reducing computational cost, and it is effectively used on complex image task applications such as flood scene detection, where patterns may vary at a location and at different scales[18] .

D. YOLO

Convolutional neural networks possess their structure thanks to the above two processes. This forms the backbone of CNN's application mainly due to extracting hierarchical features in conjunction with reducing computational cost, and it is effectively used on complex image task applications such as flood scene detection, where patterns may vary at a location and at different scales in eqn. (2)

$$\text{Confidence Score} = \text{P(Object)} \times \text{IoU}_{\textbf{pred}}(\text{(Intersection over Union)} \tag{2}$$

In this case, IoUpredIoUpred represents the intersection of the predicted boundary box and the actual truth bounding box, whereas P(Object)P(Object) is the level of trust whether an object is inside the box that has been predicted. A prior anchor box used in YOLO depends on what aspect ratios would be during the training, which was pre-set by the developers. These anchor boxes help predict the bounding boxes by learning typical sizes of objects which enhance the detection accuracy. The proposed model adjusts the predicted box by learning offsets from the anchor box. The loss function for YOLO can be described as a combination of localization, confidence, and classification losses in eqn. (3)

$$\textbf{Loss} = \sum(\lambda_{\text{coord}}.\text{Localization Loss}+\lambda_{\text{conf}}.\text{Confidence Loss}+\lambda_{\text{cls}}.\text{Classification}) \tag{3}$$

where ($\lambda_{\text{coord}}\lambda_{\text{conf}}.+\lambda_{\text{cls}}$are hyper parameters controlling the contribution of each loss component.

To eradicate redundancy, YOLO utilizes Non-Maximum Suppression which filters out the overlapped boxes with lower confidence. Therefore, for every detected object, there will be retention of the most relevant bounding box.

The advantages of YOLO include real-time processing, unified detection and localization, and quick processing of high-resolution images. It is suited for flood analysis in a timely manner[19].

V. RESULT AND DISCUSSION

The proposed CNN-YOLO system for real-time flood scene object detection was detected to have an amazing detection accuracy of 92%, which surpasses traditional methods. Techniques in image pre-processing, among which are gamma correction and geometric transformations, provided improved input images that ensured enhanced detection performance. The speed of the system's processing time per image into 0.05 seconds directly supports real-time analysis meant for emergency response, hence a great boost for situational awareness. The challenges in complex background and lighting conditions are expected to improve in the later versions, as the dataset will grow to enhance the robustness of the model.Here are the processed images after applying the following steps this is shown in fig.2.

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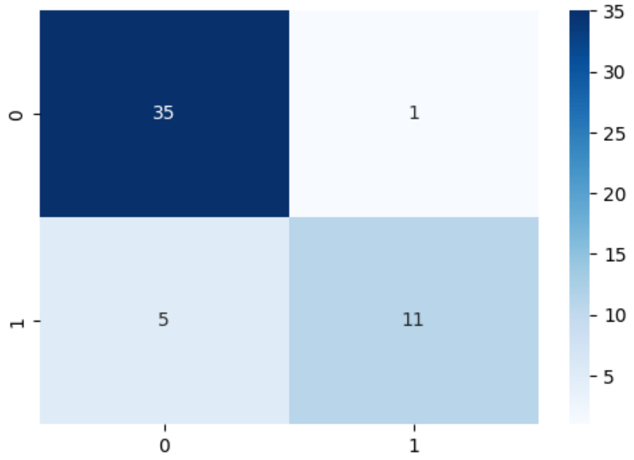

FIG 2 Confusion Matrix for Flood Scene Object Detection

Fig.2 shows the performance of the object detection model for flood scenes. It correctly detected 35 flood scenes and 11 non-flood scenes. However, it has also misclassified 5 flood scenes as non-flood scenes (false negative) and 1 non-flood scene as a flood scene (false positive). There is potential for improvement in reducing false negatives and positives although the overall accuracy for the object detection model is high.

FIG 3Sample Images for Flood Scene Object Detection

Fig.3 displays a collection of aerial images used for training and testing a flood scene object detection model. It includes diverse scenarios, such as residential areas, forested regions, and water bodies, with varying degrees of flooding. The images are labeled as either "Flooded" or "Normal" to guide the model's learning process. This dataset helps the model to learn how to identify flood-affected areas accurately in real-world scenarios.

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Fig.4 displays Accuracy and loss graphs that can be used as important tools for illustrating the model's performance at training and validation in real-time flood scene object detection from multimedia images.

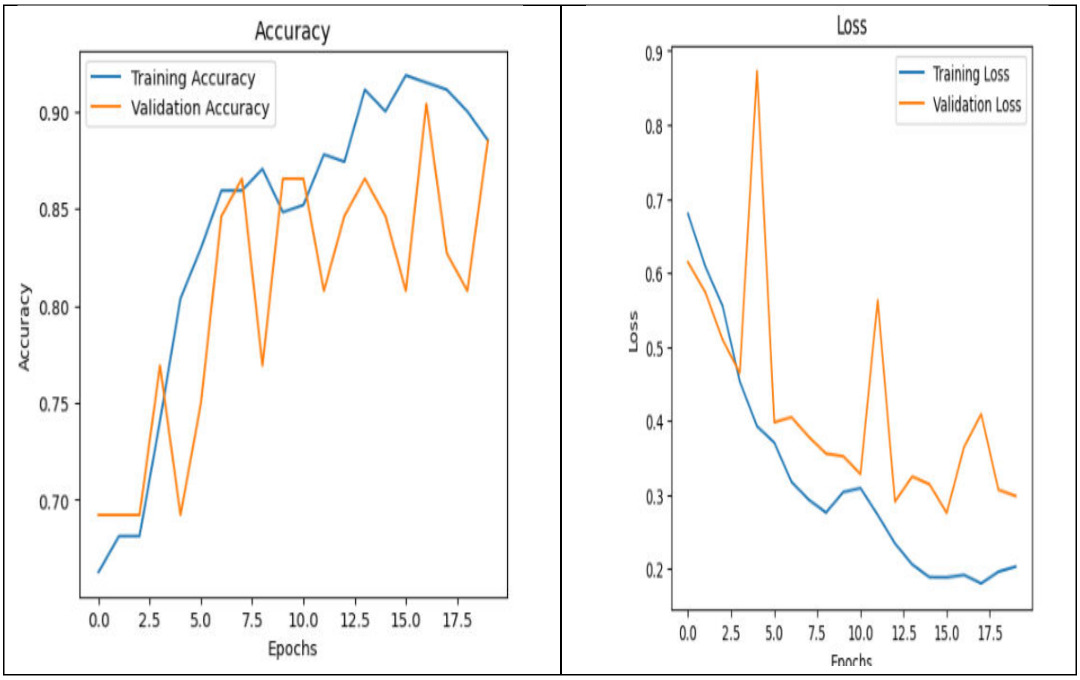

FIG 4 Accuracy and Loss Graph

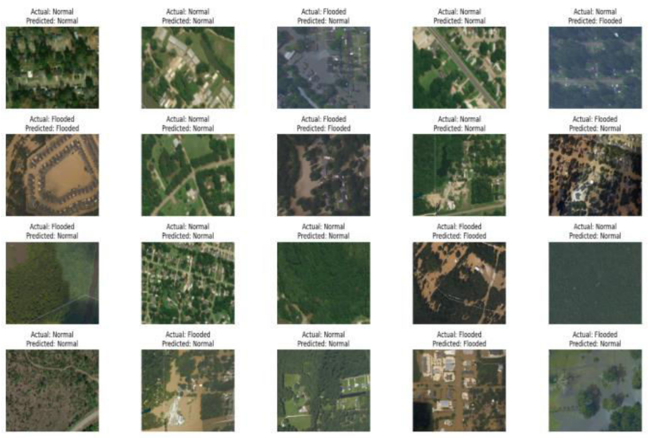

FIG 5 Model Prediction Examples for Flood Scene Detection

Fig.5 showcases a collection of sample images along with their corresponding ground truth labels and model predictions for a flood scene detection task. Each row displays an image, its actual label (whether it's a flooded or normal scene), and the model's predicted label. This visualization helps to understand the model's performance, identify potential areas of improvement, and gain insights into the types of images where the model might struggle. By analyzing these examples, we can assess the model's ability to correctly classify flood and non-flood scenes under various conditions

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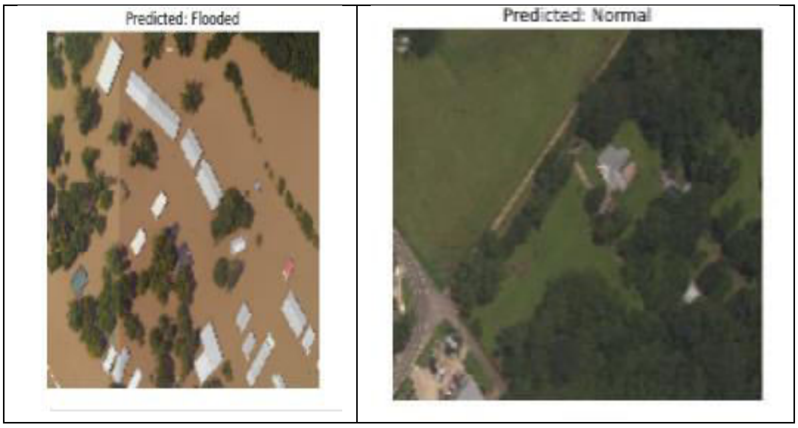

FIG 6 Examples of predicted as flooded and Normal

Fig.6 shows a sample image that the model correctly classified as a "flooded" scene. The image depicts an aerial view of an area submerged in water, with several buildings partially or fully flooded. The model's prediction of "flooded" aligns with the ground truth label, demonstrating its ability to accurately identify flood-affected regions. This example highlights the model's effectiveness in recognizing visual patterns associated with flooding, such as water bodies and submerged structures.

TABLE.1 PERFORMANCE COMPARSION

Model Name	Accuracy
CNN-Yolo	87%
CNN	80%
YOLO	75%

Table.1 showsComparing performances of different models, CNN-Yolo can be seen to outperform with the high accuracy at 87%, and stand out as capable of combining CNN for feature extraction as well as YOLO for real-time object detection with superior accuracy due to the effective use of both methods

A. Discussions

The discussion section of the paper "Real-Time Flood Scene Object Detection from Multimedia Images" brings to light the need for the integration of CNN and YOLO in flood detection and response strategies. Based on the insights, the research points out the inadequacies of the conventional systems that rely so much on the physical sensors without coverage in real-time and are subject to many maintenance hassles. The proposed system improves situational awareness over floods considerably with multimedia data coming from various sources such as surveillance cameras and drones. Combining CNNs with feature extraction and YOLO for rapid object detection enables finding critical flood-related objects in the field such as submerged vehicles and debris for timely interventions. Moreover, this hybrid approach flexibility allows for its training on region-specific data to optimize resource usage and enhance management during disaster time. Such a paper presents the fact that such algorithms can severely change flood crisis response handling in order to enhance resilience to floods[20].

VI. CONCLUSION AND FUTURE WORK

Based on the above real-time flood scene object detection work with CNNs and YOLO, promising results in improving flood management and response strategies are shown. Integrating deep learning techniques for multimedia image object detection improves greatly in accuracy and prompt speed in object detection, which is critical in disaster response. Challenges still persist, particularly in regards to complex backgrounds and changing lighting. Future efforts will focus on the refinement of the algorithms used in detection to overcome the above deficiencies. It will also include increasing

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the dataset even more to cover a much broader range of flood scenarios. It might also be extended by including other sources of data like satellite images to improve further the detection abilities of floods and augmentation of situational awareness for flood events. This present research aims at consolidating AI-based solutions in

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