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Flood Disaster Estimation Using Images and Machine Learning

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Abstract: Pakistan is exposed to heavy floods every year, which can cause significant damage to property, infrastructure and loss of life. To minimize the loss, an estimation of the post flood disaster using images of inundated areas and Machine learning is a better solution for improving the efficiency and accuracy of disaster response efforts in the country. The research aims to enhance flood disaster management by utilizing real-time data to measure flood water levels in inundated areas.Estimating floodwater levels is challenging due to different levels and moderate visibility of objects. Building precise flood level maps is crucial for assisting emergency plan activities in the case of a flood. It's crucial to gather data from the disaster region in order to create these maps. In this circumstance, National disaster management authorithy (NDMA) platforms might be helpful information source. In this article, we provide a technique for measuring floodwater using images from (NDMA) sites. If there is no previous experience or understanding of the area where the image was taken, determining how much the items in the image are immersed in water might be one method of estimating the flood level. Several things contribute to the difficulty of this endeavor, including: The size of the items in the photograph may not be understood with certainty; Different areas of the photographic scene's flood-water may appear at varying heights, and objects may only be just partially apparent since they may be submerged in the water. We provide an approach to address these issues that first identifies classes of items whose sizes are roughly known before using this feature to calculate the water level. We first create a dataset of flood-water images to test the viability of this method, and then we train a deep learning model on it. Finally, we demonstrate how our trained model can accurately estimate flood levels while also recognizing objects. Flood Disaster Estimation using images and machine learning has the potential to make a policy based decision on flood disaster estimation in the country. With the use of this proposed solution one can save the lives and property on bigger scale.
Keywords: Estimation Flood Disaster, Images, Machine Learning, Pakistan.

1. Introduction

Floods are considered to account for 84% of all natural disaster-related deaths globally. There has been a significant rise in the previous 20 years in the recorded number of flood occurrences, resulting in impacted persons and economic damage, and this trend does not seem to be slowing down [1]. Annually, frequent flood catastrophes in several countries result in indirect economic losses of $60 billion[2] and hundreds of lives[3]. In addition, urban areas are home to more than half of the world's population, with over 500 cities providing homes for over a million people [4]. Inadequate drainage systems in metropolitan areas have made the prevention of floods from unexpected, intense rainstorms a top priority [5]. Therefore, governments are under pressure to develop reliable and accurate maps of urban flood risk zones and to maintain planning for flood risk management that priorities prevention, protection, and preparedness [6]. Rapid and dependable flood forecasting models are essential for predicting future urban flooding, minimizing risks enhancing water resource management, policy recommendations, data analysis, and evacuation planning [7].

During a flood, the water that is present in an area can rise to an abnormal height. Floods are usually caused by excessive rain or heavy snowmelt, but they can also be caused by powerful storms that produce very heavy rain. Flooding can also occur as a result of the leakage of water from a nearby river or a lake, drained by a drought or a construction project. Where flooding occurs, the water can rise so quickly that it can damage property and affect the operation of transportation facilities[8].

Flood disasters can be devastating, leaving death and destruction in their wake. For many years, attempts to accurately estimate the extent of a flooding disaster and its potential damage have been hampered by the lack of reliable data. However, with the development of machine learning and image processing, it is now possible to collect a huge amount of data that can be used to precisely estimate the extent of flooding disasters. By combining the data collected with machine learning and image processing, an accurate estimate of the damage a flooding disaster can cause can be generated, enabling governments and emergency responders to better prepare and respond to the disaster. This article will discuss how machine learning and image processing can help to estimate the extent of a flooding disaster and its potential damage.

This research introduces a new method for identifying floods based on automated picture analysis. This model combines machine learning and image processing techniques in a comprehensive manner for efficient post-flood management. The resulting model has shown to be more accurate and require less training time than earlier methods. The objective of this research is to create a computationally efficient model that can categories flooded and non-flooded photos more accurately and quickly, allowing for quick rescue efforts in flood-affected areas. A comprehensive sequential multi-step approach based on image processing and training the model for picture examination has been created for this aim. The classifier uses the updated images to train the model and machine on detections and update the fundamental methods. Results revealed a decrease in training time and an increase in accuracy. The proposed approach is discussed after a discussion of several techniques employed in both image processing and machine learning for flood management over the previous ten years.

In this research convolutional neural network (CNN) is used for object detection. We use again neural network architecture to identify how much they are submerged in water. We take dataset from National disaster management authority (NDMA) and also we use MS-COCO pretrained model to predict the water level estimation.

2. Literature Review

Previous research has shown the outstanding capacity of physically-based models to mimic various flood events. In [9] a article suggests a way for employing a convolutional neural network (CNN) to forecast the long-term temporal two-dimensional range and depth of flooding in all grid points. Using a significant rainfall dataset gathered from actual flooding occurrences, the deep learning model was trained, and the related raster flood statistics were generated using a physical model. When comparing the performance of two CNNs, a simple CNN and Inception CNN, different rainfall distributions (at various times or over various development periods), the network of the simulated area, and the simulated area's topography were taken into account. When the coordinate data was absent from the input data, neither CNN architecture could converge. The accuracy of flood predictions was improved by including topography elevation information to the rainfall data that already contained coordinates. The outcomes of this study showed that the suggested technique does not require real-time flooding observation data for adjustments, and we came to the conclusion that the system may be applied to long-term flood forecasting. When the water level changes from rising to falling, our model can precisely predict the change. Within seconds of obtaining meteorologically predicted rainfall data, a long-term forecast of the two-dimensional flooding range and depth may be made.In [10] explains a water level detection system that leverages aerial drones and image recognition technology. The system employs the R-CNN learning model in conjunction with a novel labeling method for reference objects, including houses and cars. By utilizing data augmentation and transfer learning techniques, and address the challenges associated with the limited and diverse data set of flood images captured from a top-down perspective. We enhance the object recognition model by overlaying Mask R-CNN, and for water level detection, we employ the VGG16 network. To evaluate the effectiveness of our proposed system, we conducted assessments using realistic images captured during the disaster. Preliminary results indicate that our system achieves a detection accuracy of 73.42% for submerged objects, with a remarkably low error of only 21.43 cm in estimating the water level As mentioned in [11], it has been shown that 1D, 2D, and 3D (dimensional) models of floods are all conceivable. One-dimensional models (or 1D model) depict the flood flow as a straight line parallel to the main channel of the river [12]. 2D models compress the flood field into two dimensions because they presume with the intention of the third dimension, water depth, is insignificant relative to the further two [13]. The 3D models can solve the horizontal flow using the 2D shallow water equations, and they can replicate the vertical characteristics using the quasi-3D extension [13].To achieve state-of-the-art performance in physically-based flood simulation, a multitude of original algorithms, approaches, and concepts have been developed. A mound of textual content comparing and contrasting several ways. Regarding mathematical modeling of flood propagation, Alcrudo et al. [14] supplied the Impact Project with a comprehensive reference. Pender et al. [16] examined the hydraulic models used in research on flood risk management and categorized them based on their maximum flood size. Woodhead et al. [17] conducted an in-depth analysis of flood inundation models for the FLOOD site project. However, its utility for short-term forecasting was hindered by the complexity of floods and the substantial processing required [18].By decreasing the hydraulic concepts, physically reduced approaches [19] may minimize the computational cost of calculations required to provide predictions. The simplicity with which the cellular-automata flood model [20] may be implemented has contributed to its rising popularity. Floods pose a significant threat to people's lives, property, and urban infrastructure. Effective flood control can be improved by utilizing advanced methods like image identification and machine learning. This research introduces a three-step method for identifying flood-affected areas using photos, classifying them as flooded or not, and training a machine learning system, achieving an accuracy level of 90%. [21], Leitao et al. [22] built flood-simulation-specific Self-Organizing Maps to rapidly predict the flood magnitude and water depth.

Not only have physically based approaches been explored and used for flood estimation, but also various ML techniques. The dataset used by Kim et al. [23] includes hourly precipitation from 160 rain gauges around the region, enabling the researchers to improve flood predictions by including atmospheric parameters into an ANN model. Using daily rainfall-runoff data from 1986 to 2003, Aichouri et al. [24] created an MLP and a traditional MLR model for flood prediction. According to the results, it seems that MLP is more productive than MLR in terms of rainfall-runoff yields. Mahdi et al.[25] explores the use of convolutional neural networks (CNN) and recurrent neural networks (RNN) for spatially specific flash flood probability prediction and mapping in Golestan Province, Iran. The study uses a geographic database, SWARA, and ROC analysis to understand the interaction between floods and contributing variables.Chang et al[26] .'s hybrid ANN model can forecast regional flooding in a metropolitan area in real time. Due to its high R2 and low RMSE, the hybrid model seemed more precise. Using a model based on a mix of ANN and WNN models, Partal et al. [27] predicted daily precipitation. The research indicates that the hybrid model performed much better than the other variations at several test locations. Kan et al. [28] created an innovative hybrid machine learning (HML) hydrological model for flood forecasting using ANN and KNN.DL models have shown their applicability for flood forecasting over the last many years by routinely outperforming the standard ML technique at an acceptable rate [29]. Compared to MLP and SVM, the predictive accuracy of a Deep Learning Neural Network created by Bui et al. [30] for mapping flash flood hazard is much higher. By applying deep convolutional neural networks to the issue of flood detection in surveillance video, Moy de Vitry et al. [31] shown that this method might serve as a low-cost, scalable alternative to existing methods. Gebrehiwot et al. [32] used a VGG-based fully convolutional network to recover flooded areas from UAV images more precisely than traditional classifiers such as SVM (FCN-16s).RNN, a neural network structure that can maintain temporal information, may show to be more effective for spatial flood forecasting tasks when applied to time series flood data. Chang et al. [33] trained an RNN to estimate the stream flow of a river two days into the future using data from several gauge stations. This method was used to multiple-step-ahead prediction using a neural network architecture that permits growth [34]. Comparing RNN to physical and statistical models, Gude et al. [35] revealed that RNN predicted water gauge height with greater precision.

However, Many Research Papers used deep learning models, machine learning and image processing models to detect flood water estimation using different methods but they have used post-processing technique that can't be implemented easily in real-time application. Real-time field data collecting, however, is sometimes costly, risky, and challenging to get. Stream gauges can offer real-time data, but only for sites that are being watched. High cost sensors have been used previously Like Radar ranger and sonar ranger and many others. We plan to propose image Dataset from National Disaster management authority (NDMA) to detect or estimate the flood water parameters (water level and depth).

3. Research Methodology

The research methodology entails the systematic collection of data, specifically images depicting flood-affected regions, sourced from the repositories of the National Disaster Management Authority (NDMA) websites and various associated reports. Subsequently, a comprehensive data pre-processing phase is executed to enhance the quality of the images and render them amenable for analysis. This pre-processing stage may encompass activities such as labeling and image enhancement to ensure optimal data readiness. Following data pre-processing, the dataset is partitioned into distinct segments for the purpose of training and testing machine learning models. This division sets the stage for selecting a machine learning model that best aligns with the research objectives. Finally, the chosen machine learning model is diligently developed, enhance in its deployment for real-world applications in the context of flood disaster estimation. Figure 1 demonstrates the comprehensive methodology used in the research study.

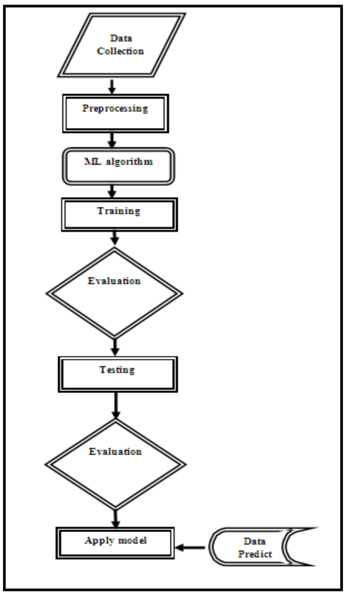

Figure 1. Proposed Methodology of Flood Disaster Estimation.

For object detection, convolutional neural networks (CNN) are utilized. Then, for the items falling under specific classifications, we assess their degree of submersion in water once more using a Neural Network design. After developing the network design, we locate photos that include data on flood-water levels and utilize that dataset to train our network. To train a neural network, the pictures in our training dataset need to be labeled. The first stage in determining which things we should examine for the classification task—in this case, it is human—based on things that are partially immersed in water, to determine the flood-water level.

The deep learning method for estimating flood-water levels is described in this section. We build our architecture on Mask R-CNN[36], a cutting-edge method for, say, segmentation. Figure.2 demostrates the primary feature extractor functions as the architecture's skeleton. Any conventional convolutional neural network will work. The goal is to run a single image through a number of layers to extract distinct elements from it. Low-level characteristics like blobs and edges are picked up by the lower layers. They begin identifying entire things like automobiles, people, and buses as we advance through the levels. In this module, the input picture is transformed to feature maps for simpler handling in the other modules.[37] The Region Proposal Network (RPN), a neural network, scans the picture and assigns scores based on whether or not there is an item in the scanned regions. They are essentially boxes that cover the image, and they are referred to as anchors. Numerous anchors of various sizes and aspect ratios are around the image. Depending on how well they perform, these anchors are categorized as positive, neutral, or negative. The next level of categorization is then applied to the anchors with high scores (positive anchors).RPN also scans the feature maps produced by the backbone rather than the picture to avoid performing additional calculations. Positive anchors might not entirely enclose an object in their protection. The non-maximal suppression approach is used to suppress bounding boxes per class due to their overlap and proximity. The method computes the intersection of anchors, maintaining only the box with a higher object score.[37]

In this research study the deep learning method is used for estimating the flood-water level. The architecture uses Mask R-CNN for segmentation and features extraction. It runs through layers, detecting low-level characteristics and identifying objects like automobile, people, and buses. The input image is transformed into feature maps, and Feature Pyramid Network (FPN) can be used to enhance the backbone. The Region Proposal Network (RPN) is a neural network that analyzes pictures and rates them according to the presence of anchors—boxes that surround the image

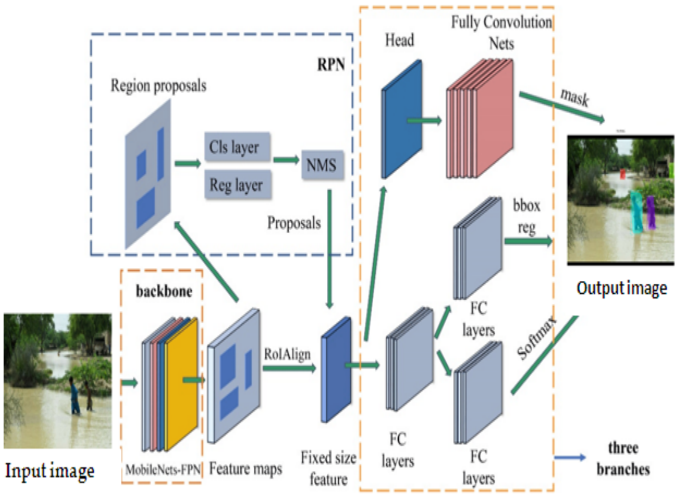

Figure 2. The architecture diagram of Mask RCNN

3.1 Dataset

In this research study we collect image dataset from National disaster management authority (NDMA) reports. For this research study we collect 1000 images from the NDMA reports we use 650 images for training purpose and 350 images for the validation purpose. We have taken actions to improve our model's performance because the quantity of the dataset we acquired for training is quite little. We have decided to use a pre-trained model to get around this constraint. We have specifically included our unique class information to the Ms-COCO pre-trained model as a basis. The objective of this strategy is to increase our model's accuracy while it is being trained. [38][39]

3.2 Reference average Height Values used to Estimate water depth

Estimating water depth is a crucial aspect of various industries and scientific studies. Whether it's for navigation, hydrographic surveys, flood forecasting, or environmental monitoring, accurate knowledge of water depth is essential. One common approach to estimate water depth is by using reference average height values, which play a fundamental role in this process. For estimating the depth of flood water reference height values are required for this purpose Table.1 indicates the average references height values which are used to find out the depth of flood water.

Table 1. Average reference values used to estimate the water level and depth

Objects:	Reference Average Value (cms)	Reference Average Value (feet)
Man	175cm	5.74147ft
child	120cm	3.93701ft
car	17cm	0.557743ft
House	240cm	7.87402ft

4. Evaluation strategy and Results

The proposed work is to automate the estimation of flood water level from the images. The proposed Mask RCNN model is trained on the flood water level datasets.

To accomplish the experimental research, we used the free and open-source Mask R-CNN package. All experiments were carried out using Kaggle notebook, CUDA 9.0, and CUDNN 9.0 implemented on machines with an Intel Hp Elite Book 830 G6v4@3.40G Hz CPU and a Quadro M5000 graphics processing unit. A total of 70 epochs with 200 steps each were trained. We trained the model using a mini-batch size of 1 image per GPU for 11k iterations, starting with a learning rate of 0.001.

We utilized a momentum of 0.9 and a weight decay of 0.0001. In this configuration, training on a single 1-GPU computer took four hours. The performance of the object detector is often assessed using the average precision (AP), and the precision/recall curve is summarized by computing the area under the curve. Recall is used to show the proportion of positive samples that the classifier judges to be true, and precision is used to account for the proportion of positive samples that are considered to be true for a specific category.

The mAP, which stands for "multiple APs," is a performance statistic for algorithms that forecast the positions and types of objects. The common COCO [40] measures, including AP, AP50, and AP75, were employed in this study.

We used the COCO [36] weight file to train the upgraded network in Mask R-CNN, and the testing set to assess its correctness. The training took four hours in GPU mode. A 744 x 992 pixel image took 1.8 seconds to analyses in GPU mode. Four different kinds of electronic components' APs were captured. Figure 3 shows that the AP of tantalum was greatest, at 97.32%, and that the APs of the electrolytic capacitor, resistor, and potentiometer were, respectively, 86.55%, 92.23%, and 96.36%.

Figure 3 shows the precision value of the flood level estimation using the as the threshold dividing point, sample-by-sample methodology. This is because when the threshold points are shifted to the left, more positive samples are discovered to be positive and more negative samples are discovered to be positive as well.

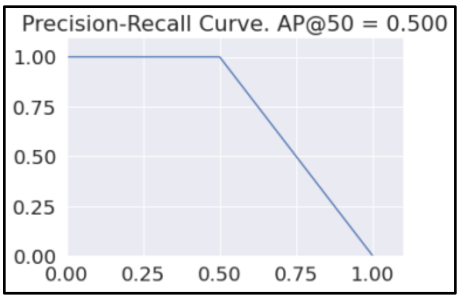

Figure 3. precision value of the flood level estimation

4.1 Testing New Images

In order to evaluate the upgraded Mask R-CNN's performance in instance segmenting flood level estimate, we used 650 new images. When building the training dataset, we make sure that the MS COCO dataset and the Flood dataset are represented fairly. This dataset is used to train the model (standard), and k-fold cross-validation is used to further confirm its accuracy. To lessen the bias and the amount of computations needed for training, a 5-fold cross validation approach is employed. The analysis of some of the test photos on a qualitative level are shown in Figures 4 and 5. We have labeled the ground-truth level in the black boxes of the images for easy examination and comparison. Also note that the colors of the masks in the following figures have no particular meaning. It is common to observe that objects are likely to be partially hidden and dispersed in images of flood catastrophes. Therefore, the model must perform as intended under these conditions.

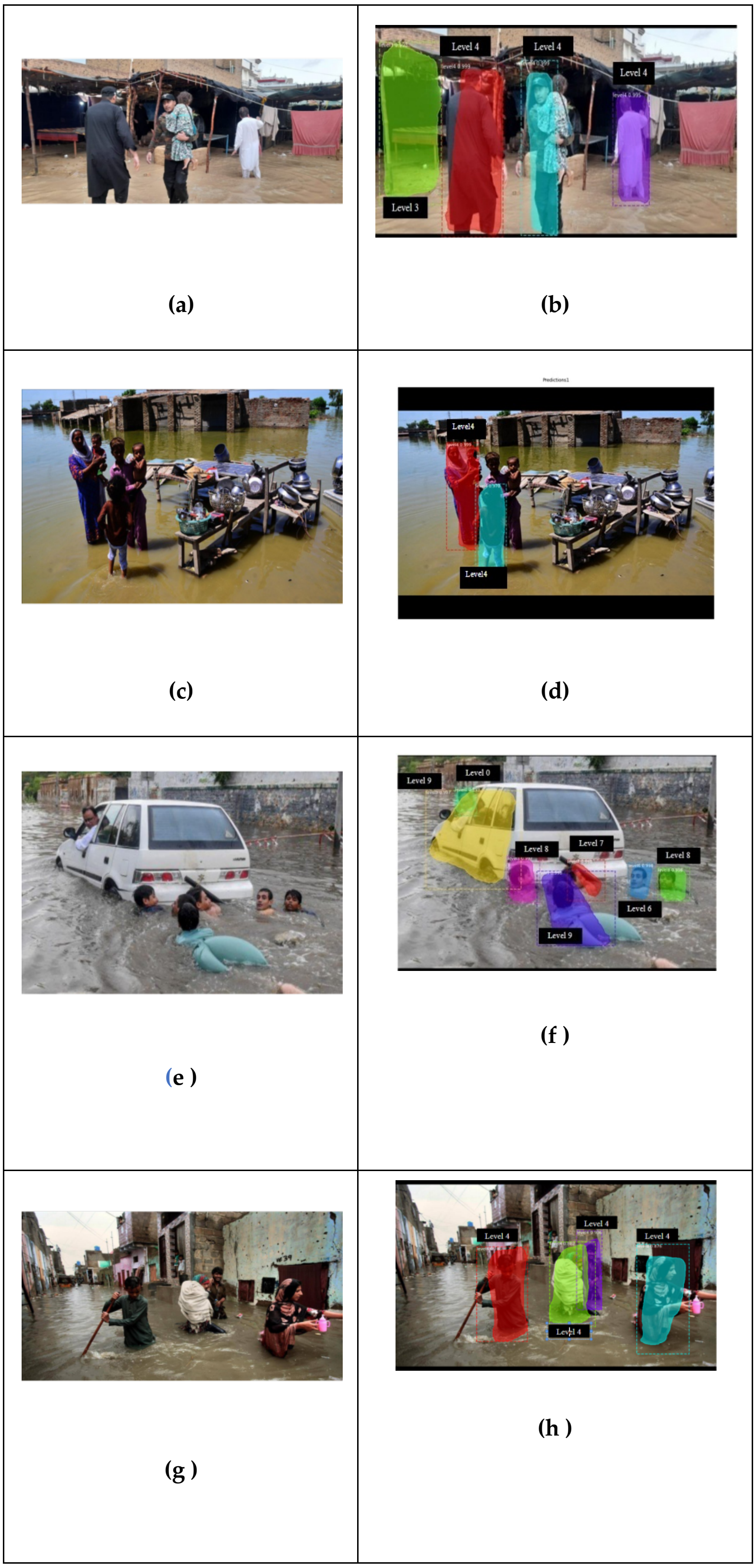

Figure 4. Displays a qualitative analysis of test photos.

Figure 4(b) depicts one example of such a picture. The fact that just a tiny portion of the items in 4(b) are visible and that they are standing close to one another demonstrate how strongly obscured they are.

This makes the detecting procedure more difficult. As can be seen from the prediction, two persons are detected in this case as a single person, while a third person is not detected at all. Despite the fact that this is not the best detection outcome, it is not crucial for our objectives to recognize every instance of an item in the image since we are more interested with accurately calculating the water level.

It's also typical to see individuals sitting or standing on high objects or surfaces during floods. In order to protect themselves against flooding, individuals often try to move to higher locations when the low-lying areas get inundated first. The flood-water level might not be seen throughout the entirety of the photograph. Figure 4(d) depicts this type of event in detail, thus it is important to identify and precisely locate them there. Since certain objects in a picture of a flood event are partially submerged, the model performs significantly better when the events are properly predicted.

Figure 4(d) shows two individuals on higher ground who are correctly classified, while several of the automobiles are categorized as level 6 rather than level 5, and the opposite is true. Level 0 was correctly predicted in Figure 4(f), when a human being may be seen standing within the backseat. However, the car doesn't always make the right predictions. It is anticipated that level 4 will exist when level 3 of the actual world exists, but the other car will experience level 4 when level 3. With the exception of one object that was mistakenly assigned to level 6 rather than level 7, the flood event image in Figure 4(h) contains three objects, two of which are appropriately predicted.

Figure 5 shows two examples of the model functioning badly. In Figure 5(b), the automobile is mistaken for a house because of its windows and entryway. Furthermore, despite the fact that flood water can be seen in the picture, no class disaster flood has been identified. This could be the case since flood water is unique for a body of water in that it is brown in shade and also motionless. Figure 5(d), the second picture, displays simply one individual who was incorrectly thought to be two persons.

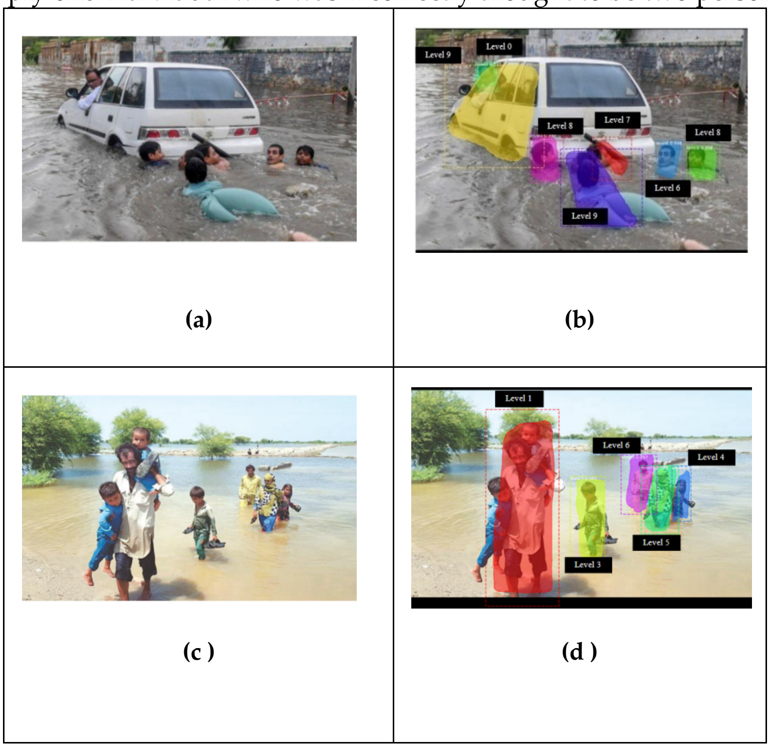

Figure 1. Displays two instances

Output Values of Floodwater Level and Depth Estimations from Images

The provided data in Table 1 consists of output values corresponding to various images. These images are used to estimate the levels and depths of floodwater. The data likely represents the results of some predictive or analytical process that takes images as input and calculates the associated floodwater levels and depths as output.

In the context of floodwater estimation, these output values are likely numerical measurements that quantify the extent of flooding in terms of water levels and depths. These measurements could be represented in units like meters or feet, indicating how high the water has risen in a particular area or how deep the water is at different points within the flooded region.

This kind of data is essential for understanding the severity and scope of flooding in an area. It can be used for various purposes, such as disaster management, risk assessment, urban planning, and emergency response coordination. Analyzing these output values can provide valuable insights into the potential impact of flooding and help authorities make informed decisions to mitigate its effects.

Table 2. Output values of Flood water level and watet depth

Level Name	Water level	Water depth
Level 0	No water	0
Level 1	0.995	174.005cm
Level 2	0.988	174.012cm
Level 3	0.961	151.039cm
Level 4	0.962	174.038cm
Level 5	0.985	174.015cm
Level 6	0.973	174.027cm
Level 7	0.976	174.024cm
Level 8	0.981	174.019cm
Level 9	0.991	174.009cm
Level 10	0.998	16.002cm

4.2 Model Specifications

For achieving optimal accuracy, different hyper parameters were used during the implementation of flood water level prediction. Categorical cross entropy function chosen as the loss function to measure the model performance during training. The number of epochs used in the training was set to 70.An epoch represents a complete iteration through the entire training dataset. A learning rate of 0.001 was utilized during training to determine the step size at each iteration while adjusting the model's weights and biases.

Table 3. The model Hyper training parameters

Parameters	Values
Optimizer	Accuracy
Learning rate	0.001
Loss	Categorical cross entropy loss
Metrics	accuracy
Epochs	70
Verbose	1

4.3 Confusion Matrix

A confusion matrix is a table that is frequently used to assess how well a machine learning classification model is performing. Comparing the model's predictions to the data's real ground truth labels aids in determining the model's accuracy. When it comes to challenges involving binary or many classes of categorization, the matrix is extremely helpful.

Useful measures including accuracy, recall (sensitivity), specificity, and F1-score are provided by the confusion matrix, which aid in analyzing the model's performance and pointing out potential improvement areas.

The model's precision recall and F1 score values are 1.00 and average precision is 0.50, respectively.

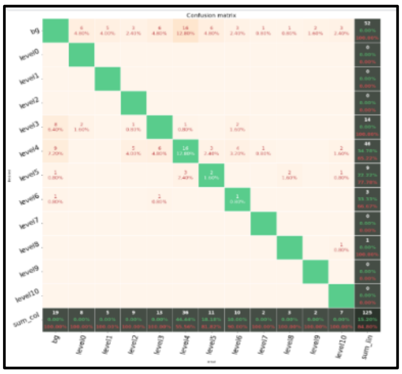

Figure 6. Attained results of the Flood water level in form of the confusion matrix

5. Conclusion and Future Work

In this research study, we introduce a fully automated methodology designed to predict floodwater levels with a high degree of accuracy. Our approach revolves around analyzing images sourced from reports of the National Disaster Management Authority (NDMA). The primary aim of our study is to establish a robust framework for estimating water levels associated with instances of flooding. The prediction is accomplished through the utilization of a deep learning framework.. We have built this algorithm particularly on top of the Mask R-CNN architecture. When an instance of a certain item is discovered, the suggested model conducts instance segmentation while also forecasting flood level. We also offer a technique for combining the level forecasts for several object instances to get a single water level estimate for the whole image. The trained model effectively estimate water level from images within an acceptable accuracy i.e 74.5% and water depth acceptable accuracy i.e 78%

As technology continues to evolve, the combination of images and machine learning holds immense potential for revolutionizing how we anticipate, prepare for, and respond to flood disasters. This study opens avenues for further research, collaboration, and implementation of image-based machine learning solutions in real-world scenarios, ultimately contributing to more resilient and adaptive strategies in the face of increasing flood challenges.

As part of our future endeavors, we envisage an expansion of our framework to incorporate textual information. Frequently, images are accompanied by relevant text describing the content. Our intuition is that by synergizing these two interlinked sources of information, we can potentially enhance the accuracy of predictions even further.

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Conflicts of Interest: The authors have no conflicts of interest to declare.

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