

Bachelor of Science in Computer Science & Engineering



**Detection of Floodwater on Roadways, Using Mask  
R-CNN by Image Processing**

by

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**Thesis Proposal**

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# 1 Introduction

Natural disasters, such as floods, pose significant threats to human lives, infrastructure, and the environment. Among the many consequences of flooding, water accumulation on roadways disrupts transportation, hinders rescue operations, and exacerbates the impact on affected communities. Hence, the timely and accurate detection of floodwater on roadways is of utmost importance for efficient disaster management and mitigation.

Advancements in computer vision and deep learning techniques have opened new possibilities for automating flood detection and analysis. One such powerful tool is the Mask R-CNN (Region-based Convolutional Neural Network), which combines object detection and instance segmentation to accurately identify and delineate objects within images.

This thesis aims to leverage the capabilities of Mask R-CNN and apply image processing techniques to detect and delineate floodwater on roadways from aerial or ground-level images. By training the model on a diverse dataset containing flooded and non-flooded roadway scenarios, the system can learn to distinguish between the two and produce precise floodwater masks, thus enabling the identification of flooded areas.

The proposed research will explore various challenges related to floodwater detection, including variations in water levels, lighting conditions, and the presence of occlusions, debris, or shadows on roadways. Moreover, the study will investigate the potential for real-time flood monitoring by deploying the trained model on edge devices or utilizing cloud-based solutions.

The successful development and implementation of a robust floodwater detection system can significantly enhance disaster response strategies and aid decision-makers in deploying resources more effectively during flooding events. Furthermore, the integration of such technology into existing monitoring systems and emergency response frameworks can contribute to a more resilient and adaptive approach to combatting the impact of floods on road networks and communities at large.

Over the last five years, object detection and segmentation have been evolving rapidly where new approaches are being invented, and new application areas are emerging. Previous studies for the detection and segmentation of floodwater focused on remote sensing methods, which leverage aerial photographs and radar data. The main goal in this paper is to contribute to the development of such a system by showing how image-based sensing and detection techniques could be utilized to detect floodwater present on the roadways.

## 2 Background and Present State

Reviewing several studies on Detecting floodwater on roadways from Image data using Mask-R-CNN, will be the main objective of this part.

In [1], The author proposes novel flood image classification methods using VGG-16 and logistic regression, achieving high performance. Flood area segmentation methods were compared, showing promising results for both superpixel-based and FCN approaches. FCN has room for improvement with more labeled data. Future work includes testing more advanced segmentation networks, extracting floodwater information like severity and depth, and enhancing the model for water reflection cases.

In [2], The study proposes an image-based method using passive monitoring cameras for early flood warning. It detects abnormal water level fluctuations, providing accurate monitoring images and water level data for disaster prevention in small urban areas. This approach supplements the current methods relying on in situ and remote sensing data, enhancing timely decision-making for reducing flood disasters.

In [3], The study focuses on robust water detection for UGV autonomous navigation, as traversing through deep water can damage UGV electronics and disrupt military missions. Previous work detected water bodies at mid to far range using sky reflections but faced challenges at close range. The study explores detecting water based on color variations from leading to trailing edges, using saturation and brightness changes. Software was developed to identify candidate water regions with low texture, evaluate color changes, and apply ellipse fitting for final

water detection. This approach effectively identifies water bodies, aiding UGV navigation and mission safety.

In [4], The study presents an image segmentation method for aerial images, demonstrating its effectiveness in hydrological modeling. Although there are some errors, the results are comparable to hand-labeled data. The approach is general and can be improved further by considering shadows and increasing the number of classes for peak flow estimation.

In [5], The article introduces an Artificial Neural Network (ANN) approach for flash flood sensing using a custom-designed sensor with ultrasonic rangefinder and infrared temperature sensors. ANNs accurately estimate temperature deviations affecting sound speed, outperforming other models. The method enables real-time water level monitoring in streets with high precision and robustness. Future work will explore rain detection using ultrasonic reflections and water presence detection for fault identification purposes. The approach significantly reduces power usage and bandwidth in wireless sensor networks.

In [6], The paper introduces a novel approach for flood detection, focusing on visual features not previously explored in the literature. The method uses a probabilistic model to determine the flood region's position in images by analyzing color, contrast, entropy, and their dynamic changes across frames. Unlike complex feature extraction methods, this approach allows for fast processing, suitable for real-time flood detection and video retrieval in news content. Experimental results demonstrate the method's applicability.

In [7], The paper applies the Mask-RCNN algorithm to detect and segment floodwater in urban, suburban, and natural scenes with high accuracy. The model achieves 99 percent accuracy in floodwater detection and 93 percent accuracy in segmentation. However, the coarse pixel resolution of the segmentation results is noted as an artifact. Future studies will explore floodwater depth prediction, improve detection speed, and address water reflection challenges to enhance segmentation accuracy.

In [8], The paper presents a model for water detection based on dynamic texture,

enabling safe robot navigation in natural environments. The method utilizes entropy measurements from optical flow trajectories to detect water regions, even in less rippled areas. Future work will explore probabilistic models, spatio-temporal smoothing, and tracker stabilization techniques to enhance accuracy and robustness.

In [9], the study estimates flood extent using simple color segmentation and depth analysis on crowd-sourced random images. This method provides valuable information for providing help to flood-affected areas by approximating the percentage of submerged area and floodwater volume from the images. Future work aims to enhance accuracy by considering additional factors such as vehicles and human body parts relative to the water level to calculate the flood extent.

## 3 Specific Objectives and Possible Outcomes

The main objectives of this work are as follows:

1. To achieve high accuracy and precision in floodwater detection and segmentation to support reliable decision-making during flood events.
2. To create an automated system that can detect floodwater presence on roadways without the need for manual intervention.
3. To develop image processing techniques to accurately segment and delineate floodwater regions on roadways.
4. To ensure that the system can handle large-scale image datasets and adapt to different geographic locations.



# 4 Impact Identification

## 4.1 Improved Flood Disaster Response

The automated floodwater detection and segmentation system can significantly improve flood disaster response efforts. By providing real-time monitoring and accurate flood extent information, emergency responders and authorities can make informed decisions and deploy resources more efficiently.

## 4.2 Minimized Infrastructure Damage

Early detection of floodwater on roadways can help minimize the damage caused to critical infrastructure such as roads and bridges. Timely actions can be taken to divert traffic, close affected areas, or reinforce vulnerable structures, reducing repair costs and ensuring public safety.

## 4.3 Potential Societal Benefits

Accurate flood monitoring can potentially save lives and protect communities from the devastating impact of floods. The system's effectiveness in providing timely and reliable flood information can enhance public safety and reduce human casualties.

# 5 Outline of Methodology

## 5.1 Dataset Collection & Preprocessing

The gathering of data has proven to be the most difficult aspect of our research. We have to acquire a diverse dataset of aerial or ground-level images containing both flooded and non-flooded roadway scenes. The dataset should cover various lighting conditions, water levels, and road types. Now We Prepare the dataset by resizing, normalizing, and augmenting the images to enhance the model's robustness and generalization capabilities. We Ensure that the dataset is properly labeled with ground truth floodwater regions described in figure 1.

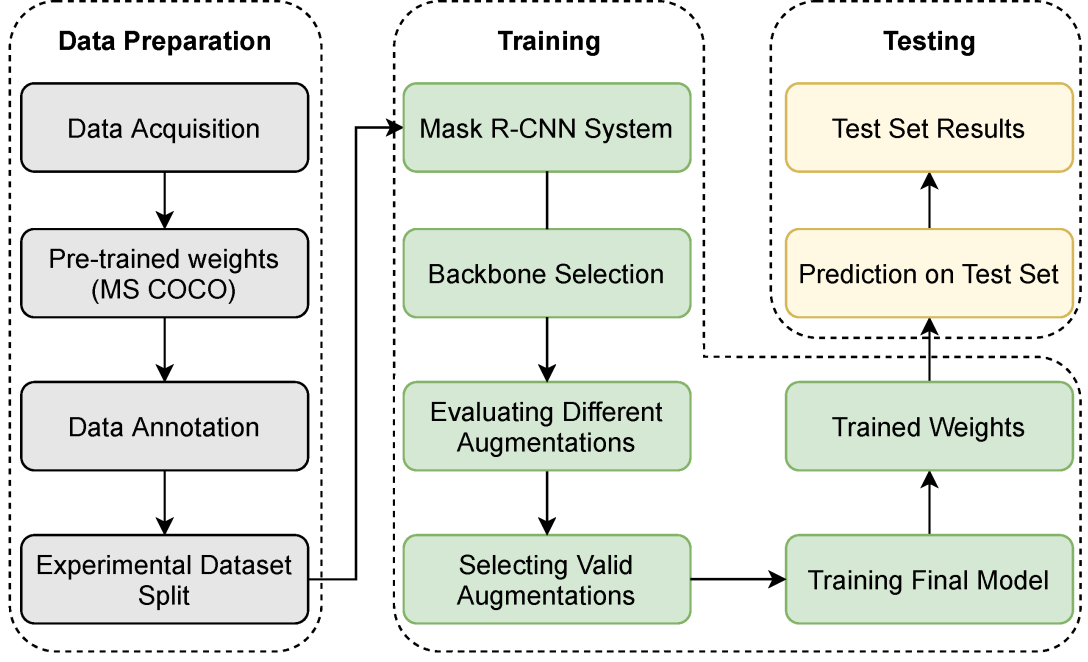


Figure 1: Process flow diagram of the proposed methodology

## 5.2 Feature Extraction

The feature extraction process involves the following steps:

**Convolutional Layers:** The input images are passed through multiple convolutional layers, where each layer learns to detect various low-level features such as edges, textures, and colors.

**Region Proposal Network (RPN):** The RPN generates candidate object proposals in the image by predicting bounding box coordinates and objectness scores for potential regions of interest.

**Region of Interest (RoI) Align:** RoI Align is used to extract fixed-size feature maps from the convolutional layers for each proposal, preserving spatial information and enabling precise localization.

**Classification Branch:** The extracted RoI features are fed into the classification branch to classify whether each RoI contains floodwater or not.

**Mask Branch:** The RoI features are also passed through the mask prediction branch, which predicts the binary masks for floodwater regions, pixel by pixel, within each RoI.

### 5.3 System Overview

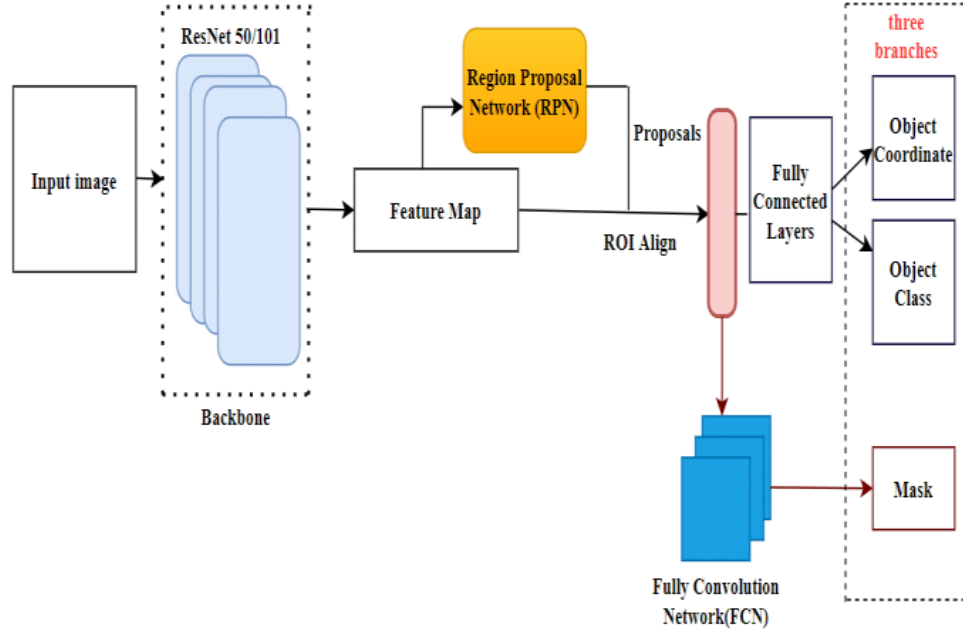


Figure 2: Process flow diagram of the proposed methodology

Figure 2 represents our suggested methodology graphically. Following the feature extraction stage, each machine learning model, deep learning model, will be trained independently. In order to obtain more accurate findings, we shall mix a few models.

## 6 Applications

1. **Disaster Management and Response:** The accurate detection and segmentation of floodwater on roadways can aid disaster management agencies in assessing the extent of flooding, identifying affected areas, and allocating resources for rescue and relief operations.
2. **Urban Planning and Infrastructure Design:** Understanding the extent and frequency of flooding on roadways can inform urban planners and engineers in designing resilient infrastructure to mitigate flood risks and minimize damage to roads and bridges.
3. **Transportation and Traffic Management:** Detecting floodwater on roadways in real-time can assist transportation authorities in rerouting

traffic, implementing road closures, and managing traffic flow during flood events.

4. **Flood Monitoring and Early Warning Systems:** The developed image processing approach can be integrated into flood monitoring systems to provide real-time detection and early warning of floodwater on roadways. This can help in alerting authorities and communities about potential flood risks and enable timely evacuation and disaster preparedness.
5. **Smart City Integration:** The floodwater detection system can be integrated into smart city frameworks to create more adaptive and resilient cities that can respond effectively to environmental hazards.

## 7 Required Resources

A computer with a potent CPU and GPU will be needed to carry out this study. To predict the floodwater on roadways, large datasets will be employed.

### 7.1 Required Tools

- A highly configured Desktop or Laptop
- Operating systems: Windows
- IDE: Jupyter Notebook
- Some Python Libraries:
  - Tensorflow
  - Keras
  - Numpy, Pandas, Matplotlib and Seaborn

## 8 Cost Estimation

The cost estimation of this research work is given below. This cost estimation may need to be changed to the requirements.

a. Cost of Data Collection : Tk. 5000

b. Cost of Materials :

- |                       |           |
|-----------------------|-----------|
| • Hardware Equipments | Tk 100000 |
| • Softwares           | Tk 5000   |

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Total	Tk. 105000
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c. Drafting & Binding :

- |            |         |
|------------|---------|
| • Paper    | Tk 500  |
| • Drafting | Tk 1000 |
| • Printing | Tk 500  |
| • Binding  | Tk 500  |

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Total	Tk. 2500
Miscellaneous	Tk. 500

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Grand Total	Tk. 112500
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## 8.1 Time Management

Gantt Chart for the entire timeline from the beginning of the thesis:

**CSE-400 (Proposal)**

	Weeks/Cycles												
	1	2	3	4	5	6	7	8	9	10	11	12	13
<b>Supervisor and Topic Selection</b>	↔												
<b>Background Reading</b>		↔											
<b>Literature Review</b>				↔									
<b>Research Methods Planning</b>							↔						
<b>Proposal</b>										↔			

Figure 3: Gantt chart of time management.

# CSE Undergraduate Studies (CUGS) Committee

Reference :

Meeting No :

Resolution No :

Date :

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Signature of the Student

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Signature of the Supervisor

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Signature of the Head of the Department

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