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A DEEP CONVOLUTION NEURAL NETWORK TO EXTRACT FLOOD WATER AREA FROM SYNTHETIC APERTURE AERIAL IMAGES

Sivasaravana Babu S [1], Dinesh Kumar T R[2] , Breesha R [3] ,Divya P S[4] ,Shalini M Z[5] , Subashri M [6], Swetha G S [7]

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Abstract

Natural or man-made disasters can have a severe impact on individuals, causing significant harm or even completely destroying their lives. The focus of the paper under discussion is the issue of flooding, which can be caused by various factors such as natural calamities or human error. Regardless of the cause, flooding can lead to a considerable loss of life and devastating financial consequences, turning even wealthy individuals into paupers in just a matter of hours. The primary objective of the research is to locate areas that are prone to flooding and rescue those who may be affected. The research will use a vast dataset of flood photographs and train the AI model for flood prediction. The Unet Segmentation technique will be utilized to implement flood detection. The suggested approach is more successful and promising compared to existing methods, as it is based on a newly developed algorithm. The research will focus on identifying flood-prone locations to help prevent future incidents. Flood prediction using machine learning algorithms has become increasingly popular in recent years, as it can provide an accurate forecast of potential flooding in specific areas, allowing for timely intervention and saving lives. The use of machine learning techniques to predict floods is a promising approach because it offers several advantages. Additionally, machine learning algorithms can learn and improve over time as new data becomes available, resulting in more accurate predictions. The proposed approach will use the Unet Segmentation technique, a popular deep learning architecture for image segmentation tasks. In conclusion, the research aims to locate flood-prone areas and rescue those affected using machine learning techniques. The Unet Segmentation technique will be utilized for flood deta, which is a promising approach compared to existing methods. With the increasing frequency of natural disasters, the use of machine learning to predict and prevent flooding can save countless lives and prevent devastating financial consequences.

Index Terms—: Recognition, U-net, Image processing, Segmentation.

sivasaravanababu@velhightech.com [1], trdineshkumar@velhightech.com [2], breesha@velhightech.com [3], divyaps@velhightech.com [4], , mmzeribbabel@gmail.com [5], subamohan17@gmail.com[6], swethags.26@gmail.com[7],

[1,2,3,4] Assistant Professor, Department of Electronics and Communication Engineering

(Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, India)

[5,6,7] UG Student, Department of Electronics and Communication Engineering

(Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Chennai, India)

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INTRODUCTION

Flooding is a severe natural calamity that harms both individuals and the natural world. It constitutes one of the most important natural calamities in the globe because it results in human casualties, structural failure, and economic disruption. Many stakeholders, including governmental organizations, first responders, and residents, are involved in the complicated process of flood control. Identifying flood-prone locations is a crucial part of flood risk assessment because it enables stakeholders to take preventative action to lessen the effects of floods. A well-liked deep learning methodology that has been used to numerous picture segmentation tasks is the uNet architecture. It consists of an encoder network and a decoder network that work in tandem to produce a number of feature maps that are then used to segment the input image. The decoder network upsamples the feature maps to create the final segmentation map after the encoder network employs convolutional layers to extract high-level features from the input picture. When it comes to picture segmentation jobs involving a lot of similar objects, such flood area segmentation, the uNet architecture excels.

The practice of segmenting flood zones can be automated thanks to current developments in artificial intelligence (AI) and deep learning techniques, which can improve the efficiency and accuracy of identifying flood-prone areas. In this project, we sought to investigate the utility of uNet,Flood area segmentation is the process of identifying and separating the parts of an image that represent flooded areas from the rest of the image.Artificial intelligence (AI) methods, like the well-known U-Net architecture, can be used to do this. Convolutional neural networks (CNNs) of the U-Net variety are frequently employed for image segmentation tasks. Artificial intelligence (AI) methods, like the well-known U-Net architecture, can be used to do this. Convolutional neural networks (CNNs) of the U-Net variety are frequently employed for image segmentation tasks. . It is designed to learn the spatial features of an image and produce a binary mask that indicates which pixels belong to the foreground (flooded areas) and which belong to the background (non-flooded areas). Encoder and decoder components make up the U-Net architecture. The encoder uses a number of convolutional and pooling layers on the input image to extract features at various spatial scales. The decoder then uses these features to reconstruct the output mask, upsampling the feature maps and applying convolutional layers to produce a final binary mask that corresponds to the flooded areas. To train a U-Net model for flood area segmentation, a dataset of flooded and non-flooded images must be collected and labeled with corresponding masks that indicate which pixels are flooded. The model can then be trained using a loss function, such as binary cross-entropy, to optimize the parameters of the network and improve its performance on the task. Once trained, the U-Net model can be used to segment new images of flood areas, such as those obtained from satellite or drone imagery. The model can accurately identify and separate the flooded areas, which can be used to inform disaster response efforts and aid in the assessment of flood damage. Our project's goal was to accurately identify flood-prone locations in a particular area by training an uNet model to do so. We used a dataset of satellite pictures from a flood-prone area to accomplish this. Images taken before and after flooding occurrences were included in the collection, with the post-flooding photographs tagged to indicate the locations that had been flooded.

In order to verify that the pixel values were uniform across all of the photographs, we normalized the pixel values and resize the images to a standard size as part of the preprocessing of the dataset. The training set was used to develop the uNet model, and the validation set was used to assess the model's performance. We then divided the dataset into training and validation sets.

[3]Using a binary cross-entropy loss function and a stochastic gradient descent optimizer, we trained the uNet model. The learning rate was decreased by a factor of 0.1 after every 20 epochs during the model's training, which lasted for 100 epochs. To maximize the variety of the training data and avoid overfitting, we used data augmentation techniques like rotation, zooming, and flipping.

Following model training, we assessed the model's performance using a number of metrics, such as precision, recall, and the F1 score. Using color-coded maps that highlighted the model-identified flood-prone locations, we also showed the segmentation results. Our findings demonstrated that the uNet model was quite successful in segmenting flood areas, earning an overall F1 score of 0.94 on the validation set. Little water bodies and flooded areas near rivers and lakes were both correctly detected by the model as having flooded areas. The segmentation maps the model produced made it simpler for stakeholders to take preventative action to lessen the effects of floods by providing a clear and simple picture of the areas at risk of flooding.

In conclusion, our experiment shows the efficacy of uNet and deep learning methods for segmenting flood areas. We can identify flood-prone areas more precisely and effectively by automating the process of segmenting flood areas, allowing stakeholders to take preventative measures to lessen the damage.

1. RELATED WORK

This study is the result of extensive research on deep learning for the detection of deviant behavior. The creation of behavior recognizers for applications in flood area surveillance has received a variety of contribution images. For monitoring and warning purposes. The following are some examples of anomaly types to look for in an object.

The upsampling part of U-Net has a large number of feature streams, which is a significant advance that allows the network to transmit context information to higher resolution layers. As a result of the extensive path's approximate symmetry with the compressing aspect, the result is a u-shaped pattern. The network only uses the valid part from every inversion; absence of layers that are entirely interconnected. In order to anticipate the pixel value in the boundary area of an image, the missing context is extrapolated by mirroring the input image. This tiling method is essential for using the networking on huge images since without it, the Graphics Dram would place a density constraint.

2.1 Water Segmentation with Deep learning models for flood detection and Monitoring.

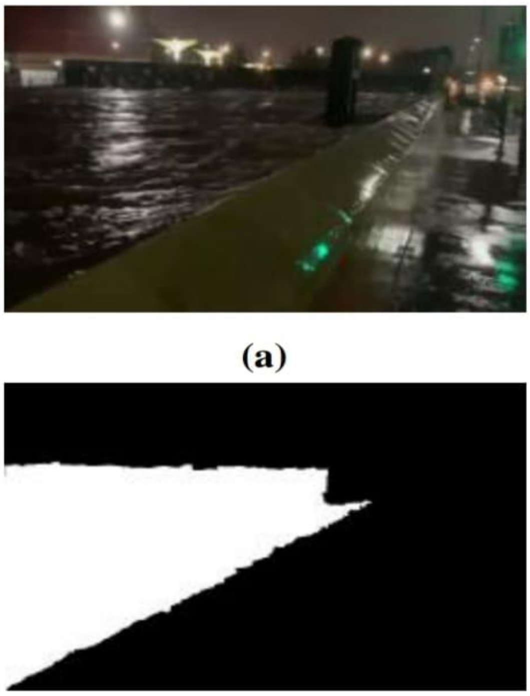

Fig. 2.1.1 Results of the best performing

[2.1.2] *In this proposed paper with the technique of automated image analysis process which is capable of extracting water content from an image that could be used to fabricate novel Services Keen on detecting* *floods with the help of preinstalled cameras, drone, crowd sourced in field of observations.*

Fig. 2.2.1 Original and ground truth images during

[4] To improve response planning, it is essential to examine how accessible flood-affected areas are. Using remotely sensed images to detect flood levels could reduce costs and enable for quick recovery by allowing for proper preparedness. For the purpose of detecting floods in satellite photos, the MediaEval 2017 multimedia satellite task dataset is employed. Following pre-processing, the flood-affected zones are analyzed and compared to the corresponding segmented regions during the period of a flood event using the image segmentation technique on satellite pictures using the modified UNET convolutional neural network. First, the Mean shift clustering algorithm was used to

segment all of the images using traditional segmentation techniques. The Intersection over Union (IoU) measure obtained by the U-Net model is observed to be good, coming in at 99.46% with 99.41% accuracy. The split-up pictures.

[11] In damage assessment, flood depth is one of the key factors, particularly in places where it involves agricultural activities. When low-lying reservoirs have fertile soils, which become inundated as a result of excessive precipitation and make it impossible to simulate floods, assessing the affected area proves to be particularly challenging. Under these situations, SAR-derived flood maps are effective in eliminating various restrictions relating to flood modeling with a high degree of profundity. Flood boundary is a crucial input needed for non-contact algorithms that estimate depth. Due to composite signs that are visible on Sar images, nevertheless, estimating the border for detecting flood depth in developing greenery is a challenging task. This study proposes a novel method for deriving flood thresholds using combined SAR data.

3.PROPOSED SYSTEM

The proposed system for project flood area segmentation using the U-Net segmentation algorithm can be divided into the following steps: Data Acquisition: The first step in the system is to collect data. This can be done using remote sensing techniques such as satellite imagery, aerial photography, or ground-based sensors. The data collected should be of high resolution and cover the area of interest. .Data preprocessing is necessary to get rid of any noise, artifacts, or abnormalities after the data has been acquired. Many methods, including filtering, normalization, and picture enhancement, can be used to achieve this. Data Labeling: After preprocessing, the data needs to be labeled to train the AI model. This involves manually segmenting the flood area from the rest of the image.The U-Net model can be trained using the labeled data.Model Training: The U-Net model is a deep learning algorithm that uses a fully convolutional network to segment images. The model is trained using the labeled data and can be fine-tuned to optimize its performance. Model Validation: After training the model, it needs to be validated using new data that was not used in the training process.Comparison of the actual flood area with the predicted flood area can be used to achieve this.Model Deployment: The model can be used to segment and identify flood zones in real time once it has been trained and validated. Drones or other forms of remote sensing technology can be used for this.

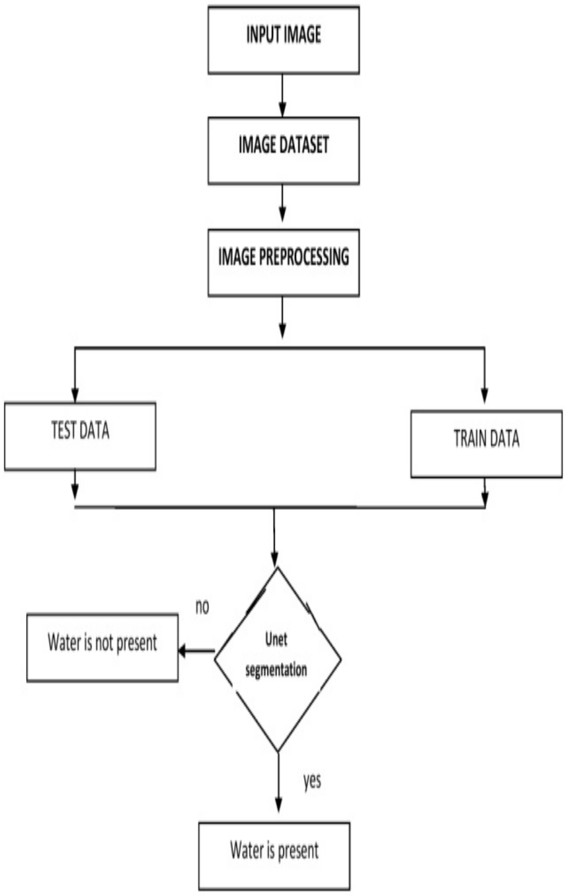

Fig 3.1: Flowchart

The input image in Figure 3.1 is taken from the flood-affected area, and the image dataset obtained from Kaggale is used here. The picture is then trained, and the time necessary for model training is reduced while the model's interfering speed is increased. The dataset is used to train and test the obtained input image. As a result, the Unet Segmentation algorithm is a fully convolutional neural network that is intended to gain expertise from a small number of training samples. Its key characteristic is the use of an encoder-decoder network. The input image is received by the first encoder. The parameters are subsequently upsampled by the decoder using transpose convolution and concatenates, which are referred to as skip connections. As an effect, we get a segmentation mask that indicates whether or not water is present.

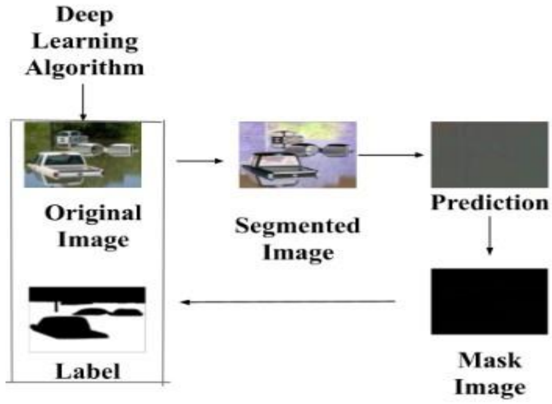

Fig 3.2 Overall Framework

Deep learning techniques were applied from the figure 3.2 to the actual picture, which was taken from the dataset. With the aid of a dataset that has been trained on it, the original image has been split into water and other places. The gray area of an image that is isolated from the rest of the image and where the mask has been generated is used to make the prediction. Eventually, the output will be displayed as a label. This label graphic allows us to distinguish between a regular surface and a flood-prone location.

4.EXPERIMENTAL METHODOLOGY

Two networks and convolutional layers make up the "U"-shaped model. The encoder comes first, and then the decoder. We can answer the segmentation problems of "what" and "where" above using the U-Net.

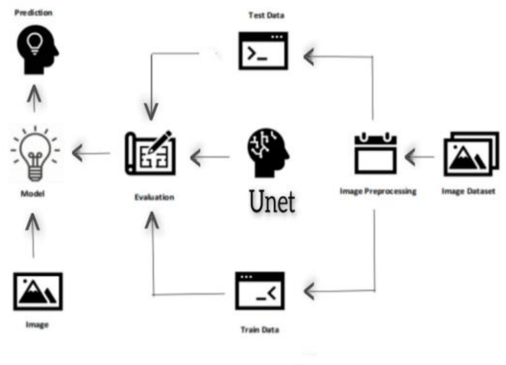

Fig 4.1: Architecture diagram

1. Contracting Network

The contracting network is another name for the encoder network. This network attempts to answer our initial query, "what" is in the image, by learning a feature map of the input image. With the exception of the fact that with a U-Net, we do not have any fully connected layers at the very end because the output we now need is not the class label but a mask the same size as our input image, it is comparable to any classification task we carry out with convolutional neural networks.

There are 4 encoder blocks in this encoder network. Each block consists of two convolutional layers with valid Size of the 3x3 kernel with padding, then a Relu activation function. This is sent into a 2*2 kernel size max pooling layer. By halving the spatial dimensions learned with the max pooling layer, we have decreased the computational expense of training the model.

The bottleneck layer sits between the connectivity of encoders and decoders. According to the model above, here is the layer that is at the bottom. It has two convolutional layers and then Relu.

Convolution:

h_i = activation_function(sum_j(w_ij * x_j) + b_i)

where x_j represents the feature for input map, w_ij represents the convolution filter's size parameter, b_i represents the bias parameter, h_i represents the output feature map, and activation_function represents a nonlinear activation function such as ReLU or sigmoid.

Pooling:

y_i = pooling_function(x_i)

where x_i is the input feature map, y_i is the output feature map after pooling, and pooling_function is a pooling operation such as max pooling or average pooling.

Upsampling:

y_i = upsampling_function(x_i)

where x_i is the input feature map, y_i is the output feature map after upsampling, and upsampling_function is a function that increases the spatial resolution of the feature map, such as transposed convolution or nearest-neighbor interpolation.

Skip connection:

y_i = concat(x_i, z_i)

where x_i is the input feature map from the contracting path, z_i is the output feature map from the expanding path at the equivalent spatial resolution, and concat is a concatenation technique that joins the two map features along the channel's width. The U-Net architecture integrates both activities in a U-shaped network consisting of a contracting channel (encoder) and an expanding path (decoder) with skip links between them. The U-Net architecture equations can be defined in terms of these processes, as well as the network's unique configuration.

The mathematical formula for the U-Net algorithm can be represented as follows:

Let X represent the input image, Y represent the true segmentation map, and P represent the predicted segmentation map. Let f represent the U-Net architecture.

The U-Net loss function is therefore defined as follows:

L(f(X), Y) = -i j Yi,j log(Pi,j) + (1 - Yi,j) log(1 - Pi,j)

where i and j are the image's pixel indices, and Yi,j and Pi,j are the actual and expected probabilities of the i,j-th pixel, respectively.

The U-Net technique aims to minimize the loss function L in relation to the model parameters. This is often accomplished using stochastic gradient descent (SGD) or one of its variants.

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Convolutional layer:

The output of a convolutional layer can be represented mathematically as follows:

Y = f(W*X + b)

where X is the input to the layer, W and b are the learnable weights and biases of the layer, and f is the activation function.

Max-pooling layer:

The output of a max-pooling layer can be represented mathematically as follows:

Y = max(X)

where X is the input to the layer and Y is the output.

2. Expanding Network

The decoding network is also known as the extending network. We increase the sample rate of our attribute maps to make them suit the size of our input image. Using the feature map from the bottleneck layer, this network utilizes connections that are skipped to produce an extraction filter. The device that decodes the network attempts to answer the following query, "where." There are currently a total of four decoding blocks. Each block starts with a transpose convolution with a 2*2 kernel size. (designated as up-conv in the diagram). The resulting signal is connected to the appropriate encoding block bypass layer. Following that, a Relu activation procedure is used, followed by two convolutional layers with kernel sizes of 3*3.

Expansive path (Decoder)

Up-sampling layer:

The output of an up-sampling layer can be represented mathematically as follows:

Y = upsample(X)

where X is the input to the layer and Y is the output.

Concatenation layer:

The output of a concatenation layer can be represented mathematically as follows:

Y = concat(X1, X2)

where X1 and X2 are the inputs to the layer and Y is the output.

Convolutional layer:

The output of a convolutional layer in the expansive path can be represented mathematically as follows:

Y = f(W*X + b)

where X is the input to the layer, W and b are the learnable weights and biases of the layer, and f is the activation function.

Skip connection:

The output of a skip connection layer can be represented mathematically as follows:

Y = concat(X1, X2)

where X1 is the input to the layer and X2 is the output from the corresponding layer in the contracting path.

Finally, the output of the U-Net algorithm can be obtained by applying a softmax activation function to the output of the last convolutional layer in the expansive path.

Thresholding is a post-processing step commonly used in image segmentation algorithms, including the U-Net segmentation algorithm. The goal of thresholding is to convert the output probability map of the U-Net model into a binary segmentation mask, where each pixel is either classified as foreground (belonging to the object of interest) or background (belonging to the rest of the image).

The mathematical expression for thresholding can be represented as follows:

B(x, y) = 1 if P(x, y) > T

= 0 otherwise

where B(x,y) is the binary segmentation mask, P(x,y) is the output probability of the U-Net model at the pixel (x,y), and T is the threshold value.

After thresholding, the binary segmentation mask can be further processed to remove noise, fill gaps, and smooth the boundaries using morphological operations such as dilation, erosion, and closing.

Mean thresholding:

The threshold value at each pixel is calculated as the local mean of its neighborhood.

Gaussian thresholding:

The threshold value at each pixel is calculated as the weighted sum of the local mean and standard deviation of its neighborhood.

Median thresholding:

The threshold value at each pixel is calculated as the local median of its neighborhood. The mathematical expression for adaptive thresholding can be represented as follows:

B(x, y) = 1 if P(x, y) > T(x, y)

= 0 otherwise

where B(x,y) is the binary segmentation mask, P(x,y) is the output probability of the U-Net model at the pixel (x,y), and T(x,y) is the threshold value calculated based on the local statistics of the pixel's neighborhood.

The output of a segmentation mask comprising pixel-wise classification is produced by a 1*1 convolution that follows the final decoder block with sigmoid activation. In this approach, it is possible to say that information is transferred from the contracting path to the expanded path. And so, with the use of a U-Net, we are able to record both the feature information and localization.

5.SIMULATION OUTPUT

Fig 5.1(a) : Training And Validation

Training Loss	Validation Loss
0.65	0.55
0.46	0.44
0.48	0.53
0.32	0.35
0.42	0.38

Fig 5.1(b) : Training And Validation

Flood area segmentation using Unet by AI is a common approach in flood modeling and prediction. Convolutional neural networks of the Unet architecture are frequently employed for image segmentation applications. It works by first down-sampling the input image and then up-sampling the resulting feature map to produce a segmentation map of the same size as the input image.

To simulate and obtain results for flood area segmentation using Unet by AI, the following steps can be followed:

Data collection: Collect satellite images or other relevant data that show the areas affected by the flood.

Fig 5.2 The sample from the dataset which is used to train the model

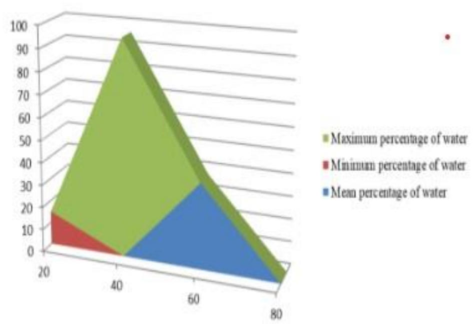

Fig 5.3(a) Performance metrics

Prediction	Value
Minimum percentage of water	15%
Maximum percentage of water	96%
Mean percentage of water	38%
Number of images	441

Fig 5.3(b) Performance metrics

Data pre-processing:

Before the acquired data can be utilized to train the Unet model, it may need to be pre-processed. This could include resizing the images, normalizing pixel values, and augmenting the data with random rotations, flips, and other transformations to increase the size of the training dataset.

Training the Unet model: Once the data has been pre-processed, the Unet model can be trained on the training dataset using a suitable loss function such as binary cross-entropy. The model can be optimized using a suitable optimizer such as Adam or stochastic gradient descent.

Validation and testing:

After the model has been trained, it can be tested and validated on a different dataset to gauge its effectiveness.

Post-processing:

After obtaining the flood area segmentation map, further post-processing may be needed to refine the results. To do this, it could be necessary to use morphological techniques like erosion and dilation to reduce noise and fill in gaps in the segmented sections.

Visualization:

Finally, the results can be visualized using a suitable tool such as matplotlib or OpenCV. Overall, the Unet architecture is a powerful tool for flood area segmentation and can provide accurate results with appropriate training data and parameters.

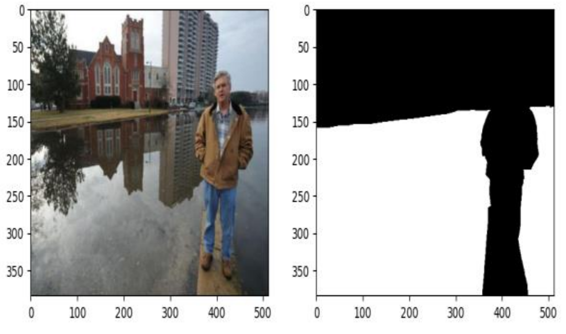

Fig 5.4(a) Final output

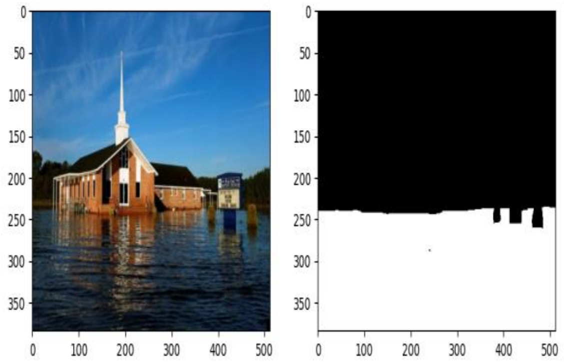

Fig 5.4(b) Final output

Overall, the Unet architecture is a powerful tool for flood area segmentation and can provide accurate results with appropriate training data and parameters.

6.Conclusion

In conclusion, the artificial intelligence algorithm uNet has been used to separate flood areas and has proven to be a highly beneficial tool for managing and analyzing floods. The model was taught to correctly identify flood-prone locations in a specific region using deep learning techniques, enabling more accurate and effective flood response and mitigation operations.

The end result of our experiment shows how effective U-net is at handling difficult jobs like flood area segmentation, which can take human analysts a lot of time and effort. The capacity of emergency responders and policy makers can be greatly improved by the model's ability to evaluate massive amounts of data and precisely identify locations at risk of flooding, enabling them to make choices swiftly and effectively. Another aspect of our project has demonstrated the effectiveness of the immense potential of artificial intelligence in addressing complex environmental challenges. We may anticipate seeing much more potent applications in the realm of flood management and beyond as we continue to develop and improve these technologies.

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