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Flood Detection Based on UNet++ Segmentation Method Using Sentinel-1 Satellite Imagery

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ABSTRACT

As one of the natural hazards that occur in some parts of the world, floods have devastating effects on people, the environment, and infrastructure. The management of this crisis can be effective in reducing severe financial and life losses. A critical aspect of managing this natural disaster is the accurate identification of flooded areas and their trends. The article presents a method for the identification and segmentation of flooded areas using the UNET++ neural network and Sentinel-1 satellite images in c-band and single-polarized (HH and VV) and double-polarized (HH+HV and VV+VH) forms. These images were provided by NASA from Nebraska, Alabama, Bangladesh, Red River North, and Florence. The labeling process for all these images was done by the NASA implementation team and the IEEE GRSS Earth Science Informatics Technical Committee. In this network, EfficientNet-B7 is used as an encoder for feature extraction. Based on evaluation criteria such as IoU, F1-score, Recall, Accuracy, and Precision, the efficiency of the model has been evaluated. This model has demonstrated a high potential for detecting and segmenting flooded areas. Using this method, 84.77% IoU is obtained, which is higher than other methods such as UNet and FPN neural networks which participated in the ETCI (the maximum IoU obtained by these methods is 76.81%)

KEYWORDS

Flood segmentation, UNet++, SAR images, deep neural networks

1. Introduction

Floods are one of the natural disasters that occur frequently and widely and cause extensive financial losses and casualties(Abdulaal et al., 2014). The NCDR announced in 2019 that over 47% of natural disasters were caused by floods, which led to the deaths of over 5100 people. In addition, according to the United Nations announcement, floods have the highest number of casualties among all-natural disasters. As a result, it is necessary to manage this phenomenon by predicting the occurrence and accurate assessment of the flooded areas(Guha-Sapir et al., 2016). There are different floods(Iqbal et al., 2021):

1. Rain or Pluvial floods, which occur because of heavy rains in a short period. In these floods, the amount of surface runoff exceeds the infiltration rate and drainage capacity.
2. Fluvial flooding, which occurs because of overflowing rivers at the peak of the rainy season.
3. Flash flood, which occurs because of heavy rain in a short period and has a high speed.
4. Coastal floods are caused by coastal hurricanes and tornadoes.

According to different floods, natural factors (climate changes) and human factors (urbanization) can be considered as the main causes of floods. It is expected that climate change and global warming increase the occurrence and destructive power of floods in the coming years(Iqbal et al., 2021). In this way, with the increase in temperature, the atmosphere holds more water vapor, which causes an increase in heavy rains and the risk of flooding(Zhou et al., 2018). Also, urbanization and the growth of construction of buildings and roads and as a result the expansion of impervious surfaces causes a decrease in the penetration of

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runoff caused by rainfall and the water storage capacity, which increases urban floods (Ferreira et al., 2018; Kalantari et al., 2017). Urban floods destroy infrastructures such as power transmission lines, communication lines, and transportation networks, and because of the high population density in these areas, they cause widespread damages and casualties (Anni et al., 2020; Cherqui et al., 2015; Zhao et al., 2020).

Because of the importance of identifying flood-affected areas to improve the crisis management process, accurate methods should identify these areas. Today, with the improvement of satellite images and the development of deep learning methods, the accuracy of identifying flooded areas can be improved. One of the improvements in satellite images is that it is now possible to shoot day and night regardless of weather, with the help of SAR satellites. Optical images and SAR data are also used to determine the chemical and physical characteristics and of the earth's surface, respectively. In recent years, with the increase in the number of SAR satellites in orbit, the revisit time of Sentinel-1 has improved to 6 days (or less).

This study identifies and segments the flooded areas using satellite images and deep learning algorithms. Based on Sentinel-1 SAR images of different areas, a UNet++ model was used to identify flooded areas in this study. The network training process was conducted by selecting and using a subset of images belonging to three different regions, rather than using all the images in the dataset. Therefore, a part of the existing data was used as input to the neural network rather than a large amount of data. In this way, the training time of the network was reduced and a model with high accuracy was obtained.

2. The Related Work

In 2017, Tanguy et al.(Tanguy et al., 2017) combined SAR images of RADARSAT-2 satellite with high resolution (3 meters resolution and HH polarization) and hydraulic data of a specific period in flooded areas, using the classification method with the help of fuzzy rules segmented flood areas with 87% accuracy.

In 2019, Li et al.(Li et al., 2019) introduced a self-learning convolutional neural network (A-SLCNN) using TerraSAR-X satellite images. They solved the problem of training data limitations and showed that the use of images at different time intervals plays a key role in flood identification.

Abdirahman Osman Hashi et al.(Hashi et al., 2021) published a paper that proposed a real-time flood detection system based on machine learning algorithms and deep learning 2021. In this study, the economic inefficiencies of current flood prevention strategies are highlighted, and a hybrid model based on Arduino and GSM modems is proposed to detect water levels and assess flood risk before it occurs, which can have significant humanitarian implications. Different machine learning algorithms were used to analyse the results, including Random Forest, Naive Bayes, J48, and Convolutional Neural Networks. The Random Forest algorithm outperformed the other models by 98.7% with an accuracy rate of 98.7%.

In 2022, Tanim et al.(Tanim et al., 2022) used various supervised and unsupervised machine learning algorithms to detect floods in sentinel images. The proposed unsupervised method for classifying and detecting flood images achieved precision measures ranging from 0.53 to 0.85, recall values ranging from 0.85 to 0.9, and accuracy measures ranging from 0.69 to 0.87. In this study, Random Forest, Support Vector Machines, and Maximum Likelihood Classifiers were used as supervised algorithms. The new unsupervised framework integrates the Otsu algorithm with fuzzy rules and iso-clustering methods to detect urban floods. The proposed method might be used in other cities that are at risk of urban flooding and may be useful for the design of transportation networks and the construction of urban infrastructure to reduce flood risk.

A flood detection method using a MS-Deeplab model was proposed by Han Wu et al. in 2022(Wu et al., 2022). In the proposed method, a lightweight MobileNetV2 backbone is used with a DeeplabV3+ architecture to construct the model and a joint loss function based on cross-entropy and dice coefficient to address the imbalanced categorical distribution of the dataset.

Several of these studies were conducted using data available in the study area. As an example, Tanguy et al.(Tanguy et al., 2017) carried out flood mapping using satellite images and hydraulic data for the target area. Therefore, the results may differ based on the hydraulic data of other areas. Traditional thresholding and statistical methods frequently fall short of achieving high accuracy levels. Moreover, machine learning techniques like Random Forest tend to exhibit lower accuracy when compared to their deep learning counterparts. The selection between deep learning and conventional methods should be contingent upon the unique characteristics of the problem at hand, the availability of data, and the computational resources at your disposal. In certain instances, hybrid approaches that harness the complementary strengths of both deep learning and traditional methods can prove to be particularly effective.

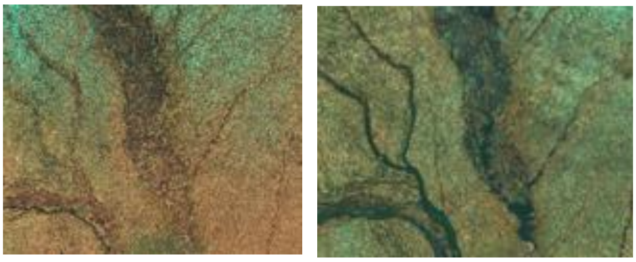
There have been various data sources employed in previous flood identification studies. The collection of such data is often both costly and time-consuming. Therefore, to identify and determine flood extents and obtain the necessary data, machine learning methods and satellite imagery gradually replaced traditional approaches. However, these images have only been recently used for this purpose. The IoU (Intersection over Union) evaluation criterion should also be used when using machine learning methods to identify flood-affected areas, as it provides a better understanding of how a method performs. Therefore, while many existing studies in flood detection using machine learning methods may have achieved high accuracy, it is essential to take other criteria into account when evaluating these methods.

3. Materials and Methods

3.1. Case study

In this research, Sentinel-1 satellite images were used to identify and segment the flood. These images were taken from five different locations around the world including Nebraska, North Alabama, Bangladesh, Red River North, and Florence.

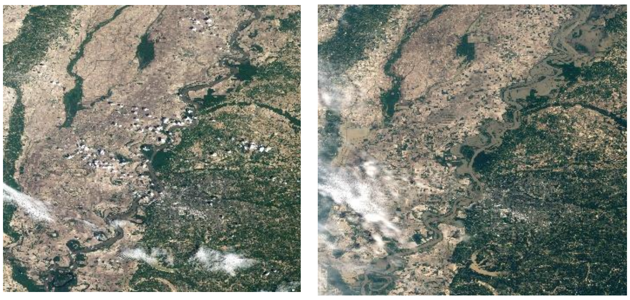
The state of Nebraska is in the western part of the United States. It is on large plains and is therefore vulnerable to floods, particularly sudden floods. In recent years, because of global warming and changing urbanization patterns, the number of floods in Nebraska has increased, so the 2011 Missouri River flood and the 2019 flood affected large parts of the state and caused a lot of financial losses (Figure 1).



(a) (b)

Figure 1. a) Before and b) after the flood in Nebraska

Because of the wet weather and the large Tennessee, Coosa, and Finette rivers in the northern part of Alabama, many floods have occurred. In this area, there have been many major floods, including the 1929 flood of the Tennessee River, the great flood of 1974, and the flood of 2019, which have caused a great deal of damage to infrastructure, properties, and agricultural lands (Figure 2).



(a) (b)

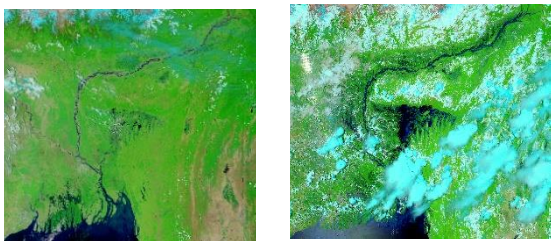
Figure 2. a) Before and b) after the flood in Alabama

The Red River North region is in both the United States and Canada. Since this area is flat and close to the Red River, it has suffered from many floods over the years (Figure 3). There are frequent floods along the banks of this river in the cities of Fargo in North Dakota and Morehead in Minnesota. Besides these floods, the floods of 1997, 2009, and 2011 can be mentioned.

(a) (b)

Figure 3. a) Before and b) after the flood in Red River

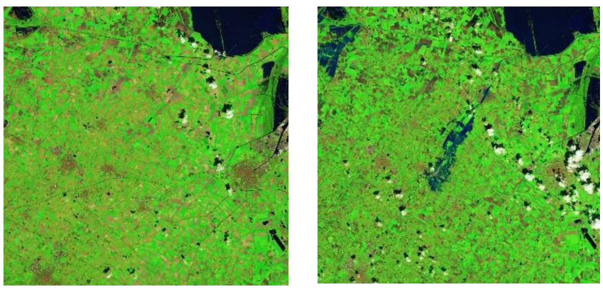
Bangladesh is in South Asia in the delta of three rivers: The Ganges, Brahmaputra, and Meghna. As a result, it is always at risk of flooding, and approximately one-third of the country is affected by flooding (Figure 4). Floods in this country are also caused by tropical storms and sea storms. Floods have intensified in recent years because of global warming and human factors, including deforestation and unplanned urbanization.



(a) (b)

Figure 4. a) Before and b) after the flood in Bangladesh

Florence is on the banks of the Arno River in the center of Italy. As a result, many floods occur in this region during the rainy seasons. A significant flood occurred in this area in 1966, due to heavy rain and flooding of the river, the height of the flood reached six meters in some areas of the city and caused extensive damage to infrastructure (Figure 5).



(a) (b)

Figure 5. a) Before and b) after the flood in Florence

The location of these areas is shown in Figure 6.

Figure 6. Location of the study areas

The total area covered by each region is presented in Table 1.

Table 1. Study areas and total area of them

Region	Total area covered
Nebraska	1. 1741
North Alabama	13789
Bangladesh	7150
Red River North	6746
Florence	7197

In this research, with the help of 66810 sentinel-1 satellite images in two polarizations VV and VH, and in dimensions of 256 × 256 pixels, the network training process has been done. The labeling process has been done for all these images and the water bodies and flooded areas have been identified separately for the images belonging to each region at different times. In this process, water bodies and the flooded areas are assigned the number 1 and the other areas are assigned the number 0. This dataset is related to the ETCI 2021 NASA competition and was obtained through the website of this competition[1]. An example of labeled data can be seen in Figure 7.

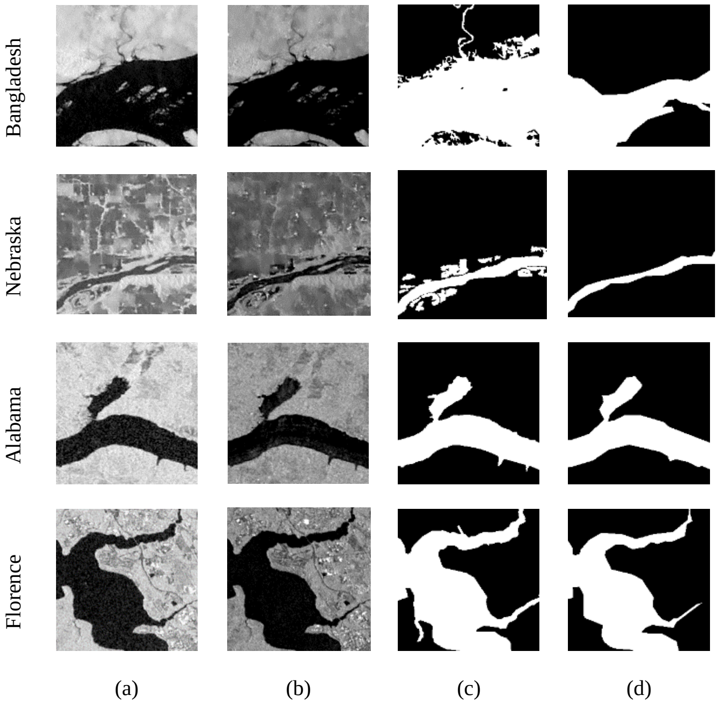


Figure 7. a) SAR image in VH polarization, b) SAR image in VV polarization, c) flood label, d) water body label

3.2. Methodology

The UNET++ model or nested UNET is an image segmentation model designed based on the UNET model. The difference between the UNET++ model and the UNET model is in the different designs of skip connections and deep monitoring(Bousias Alexakis & Armenakis, 2020). The UNET++ network consists of an encoder subnetwork or backbone, followed by a decoder subnetwork. As opposed to UNET, UNET++ incorporates redesigned skip pathways that connect the two sub-networks and utilize deep supervision(Zhou et al., 2018). In the UNET model, the feature maps obtained from the encoder network are directly transferred to the decoder network at the same level(Mesvari & Shah-Hosseini, 2023). But in the UNET++ model, nested convolution blocks are used in the connection between encoder and decoder networks, and the number of skip connections between convolution blocks has increased. Increasing the number of skip connections between convolution blocks enhances the training and performance of deep neural networks by addressing gradient-related challenges, preserving features, and enabling the network to handle information at different scales. This is particularly valuable in tasks requiring complex representations, such as image analysis and segmentation. The dense convolutional block makes the feature maps of the encoder network and the corresponding feature maps of the decoder network to be conceptually similar to each other, and the network optimization problem is less difficult, and the results are more accurate. Nested convolutional blocks in UNET++ models consist of interconnected convolutional layers with skip connections and may include attention mechanisms, enabling the model to capture multi-scale information for

1 https://nasa-impact.github.io/etci2021/

precise image segmentation. Different UNET++ variants may introduce variations in the architecture to adapt to specific tasks and datasets.

UNet++ introduces a nested skip connection structure, which means it has multiple skip connections at different scales and depths in the network. This helps capture features at various levels of abstraction and improves the network's ability to capture both fine and coarse details in the images.

UNet++ promotes feature reuse by connecting the skip connections from different levels to multiple decoder blocks. This allows the network to make better use of features extracted at different stages of the encoder and helps in preserving spatial information.

The nested skip connections in UNet++ can act as a form of regularization, reducing the risk of overfitting. By fusing information from multiple levels, the network can make more informed decisions about segmentation boundaries.

UNET++ is derived from the original U-Net

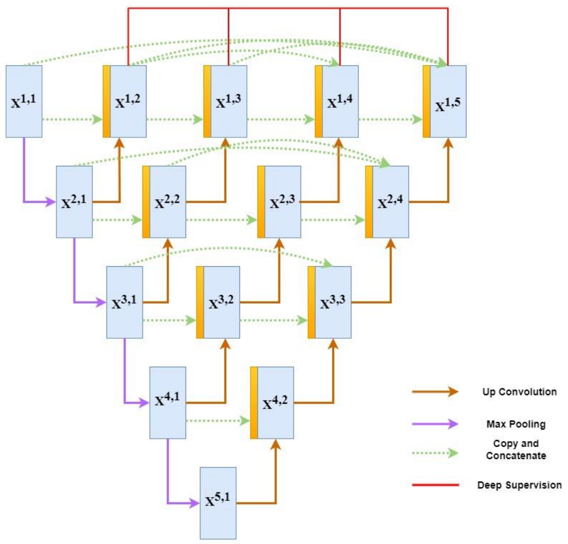


Figure 8. Segmentation model used in the study

4. Validation criteria

Several evaluation metrics have been determined because of the approach used in this paper and these metrics are as follows: Precision, Recall, Internal Validity, F1Score, and accuracy.

Recall is the percentage of relevant instances among the retrieved instances, whereas precision is the frequency of relevant instances among the retrieved instances. So precision, as well as recall, depends on relevance. To calculate these metrics, the following formula is used:

$$\text{precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (1)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (2)$$

TP and TN correspond to pixels that the model correctly

architecture. In a skip pathway, all convolutional layers are composed of k 3×3 kernels. For deep supervision, each target node is assigned a 1×1 convolutional layer with a sigmoid activation function. The final segmentation map is generated by averaging four segmentation maps produced by UNET++. Also, in this type of model, deep monitoring is used to improve the efficiency of the network training process.

Deep monitoring allows the model to operate in two modes: 1) accurate mode, in which all branches of the segmentation of a general average are taken from the outputs; 2) Fast mode, in which the final segmentation map is selected through one of the segmentation branches (Figure8). In this network, efficientnet-b7 was used as an encoder that can recognize unseen new images of skin disorders more accurately than other systems (Hridoy et al., 2021). Adam optimizer was applied with a learning rate of 0.001 and the loss function used in the training process was the MSE loss function.

$$\text{IoU} = \frac{|A \cap B|}{|A \cup B|} \quad (3)$$

identified and rejected, respectively. Furthermore, FP and FN represent pixels that the model incorrectly identified or rejected.

The F1-score represents the harmonic mean of precision and recall, and it includes both precision and recall measurements. The F1score can be described as follows:

$$\text{F1Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{(\text{Precision} + \text{Recall})} \quad (4)$$

IoU (Intersection - Over - Union) statistic, which represents the ratio between intersections and unions of two sets, is used to analyse the similarity between samples. In image semantic segmentation, these two sets represent prediction and reference. IoU is calculated using this equation:

The prediction is represented by A and the ground truth is represented by B. The accuracy of a model can be described as the metric that describes how it performs across all classes. This is calculated as the percentage of correct predictions to total predictions.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (5)$$

5. Results and Discussion

This article describes a method for identifying and segmenting flood-affected areas using Sentinel-1 satellite imagery and a deep learning algorithm. During this process, the pixels that belong to the flood areas should be identified in the images with high accuracy and well-defined in the final map. In this study, a UNET++ neural network was used to segment flooded areas. Due to increasing the learning speed, a portion of the satellite images has been used in the training process. Although this method can detect floods with high accuracy, the results can be generalized to flood detection in other environments because testing the model was conducted using images that were not present during network training.

After the completion of the training process, the evaluation of the model was done based on evaluation criteria including IoU, F1-score, Recall, Accuracy, and Precision. Table 2 presents the values of the network evaluation criteria. According to these results, the model had significant performance in identifying and segmenting flood areas.

Table 2. Metrics of the models on the test data

Metrics	Value
IoU	84.77
F1-score	89.03
Recall	90.32
Accuracy	99.5
Precision	94.44

Various methods have been applied with the dataset to identify floods. These methods were compared based on IoU values and the most efficient method was introduced at the ETCI 2021 NASA competition. While information about the research methodology chosen for this competition is not currently available, it is worth noting that the methodologies employed by the second and third-place teams can be found within their respective articles(GHOSH et al., 2022; Paul & Ganju, 2021). (Paul & Ganju, 2021) describes a semi-supervised learning approach that enhances accuracy through a cyclical process involving multiple stages. In (GHOSH et al., 2022), the authors introduce two deep learning methods. The first method utilizes a UNet architecture, while the second one employs a Feature Pyramid Network (FPN). Both methods leverage the publicly available Sentinel-1 dataset for their applications. Table 3 compares the IoU values obtained by these methods with the method implemented in this article(GHOSH et al., 2022).

Table 3. Comparison IoU values of models

Participants	Methods	IoU
Team Arren (Xidian University)	Not found	76.81
Siddha Ganju (NVIDIA) & Sayak Paul (Carted)	Pseudo labeling + Ensembles with CRF post processing	76.54
Shagun Garg (GFZ Postdam)	FPN + UNet	75.06
Proposed method	**UNet++**	**84.77**

A comparison between the model's detection and the ground truth map is shown in Figure 9. This figure shows that the flooded areas are well-identified and segmented in SAR images.

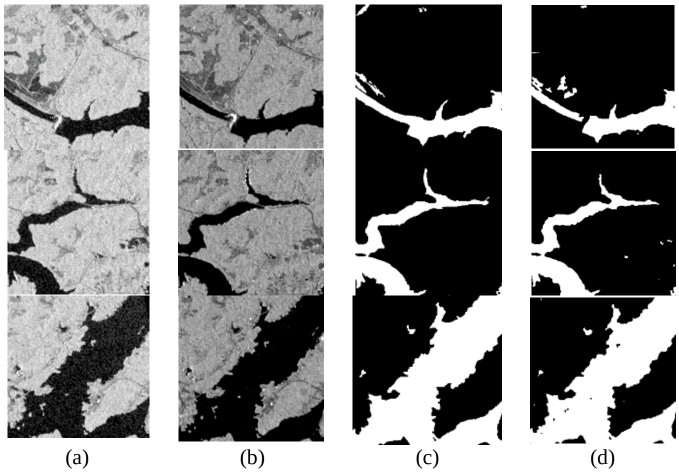


Figure 9. a) SAR images in VH polarization, b) SAR images in VV polarization, c) ground truth, d) predicted image

6. Conclusion

In this study, a UNET++ neural network is used to detect and segment flooded areas in SAR images. In this neural network, EfficientNet-B7 is used as an encoder backbone. During the training process of this deep learning network, SAR images from Bangladesh, Nebraska, and Florence were used. Finally, the network was tested using images from Alabama. In conclusion, an IoU value of 84.77% was obtained using this model on this dataset which is higher than the IoU values obtained by the winners of the ETCI 2021 competition which are equal to 76.81, 76.54 and 75.06%. UNet++ presents numerous advantages, notably improved feature aggregation and accuracy, making it a robust selection for semantic segmentation tasks, particularly when demanding requirements for precise boundary detection and feature integration across multiple scales exist. Other evaluation criteria indicate that the model performs well in segmenting and identifying flooded areas. The values of these criteria, including F1-score, Recall, Accuracy and Precision, are equal to 89.03, 90.32, 99.5 and 94.44%, respectively. In this research, the IoU criterion examines the performance of the model better than other evaluation criteria. Using a more accurate dataset that includes different types of floods, such as urban floods and open floods, the model will improve. If a more reliable and comprehensive dataset was used, which included the floods, such as urban flood and open flood, the model would be more accurate and would identify the types of flood classes. As a result, using this dataset can enhance the model and improve the results. Deep learning methods may also be effective in refining the model. A flood-prone area should be identified and segmented in order to estimate the probability of flooding in each region and design models in urban planning and preventative efforts to reduce losses caused by flooding. It has been showed in this article that the model can identify flooded areas that were not used in the network training process with high accuracy. Therefore, the model can be generalized to identify floods in other regions of the world as well. By entering a portion of the data into the network, the training time has been reduced. Because of the differences in architecture between the two networks, this model achieved higher accuracy than the UNet model, which is one of the most well-known models in image segmentation. Thus, these differences can be valuable in image segmentation.

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