Impact Of Data Augmentation On Identifying Water Bodies In Satellite Images

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Abstract. Recognizing surface water is helpful in an assortment of remote sensing applications, the applications such as assessing the accessibility of water, estimating its adjustment of time, and anticipating dry seasons and floods. However, identifying surface water with old-style techniques is certainly not an essential endeavour. Instead, distant identifying with expansive consideration and distinctive passing noticing is the most intelligent response for surface water checking. To Identify surface water efficiently, we developed a deep learning model that can process full Landsat Image inside a single shot without separating the contribution to tiles and increasing the model accuracy by applying data augmentation resulting in the model coming over a modified version of the original data in every case by using the data augmentation to the images and their identical masks.

INTRODUCTION

Detailed surface water maps are required for many portions of Earth science, for example, checking changes in wetlands and waterways because of environmental variation and organic evolution modifications [4]. In acknowledging these needs, we have developed a deep learning model to detect water bodies from satellite images and optimised the model using data augmentation. When training the neural systems, data augmentation is the commonly used preprocessing approach. The term augmentation, which means the operation or method of performing or becoming more significant in size or amount, compiles the result of this method. However, another notable effect is that it improves or extends the heterogeneity of the data. The enhanced heterogeneity of the information implies that the model comes over an alternate variant of the first information at each preparation stage. Still, they endure from high variance, which indicates that these models over fit the training data and exhibit poor performance on test data, or the data they have not seen before would prompt higher prediction disappointments. Subsequently, the expanded assortment from information expansion diminishes the change of the model by improving it at summing up.

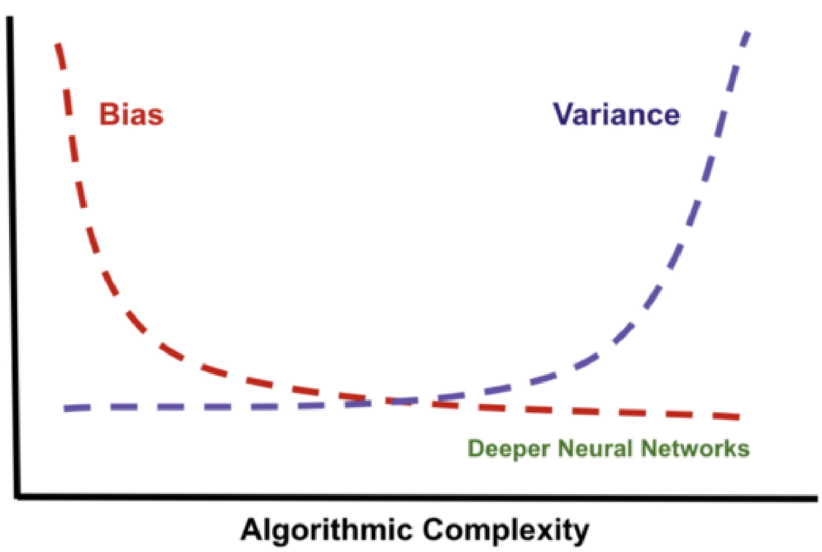
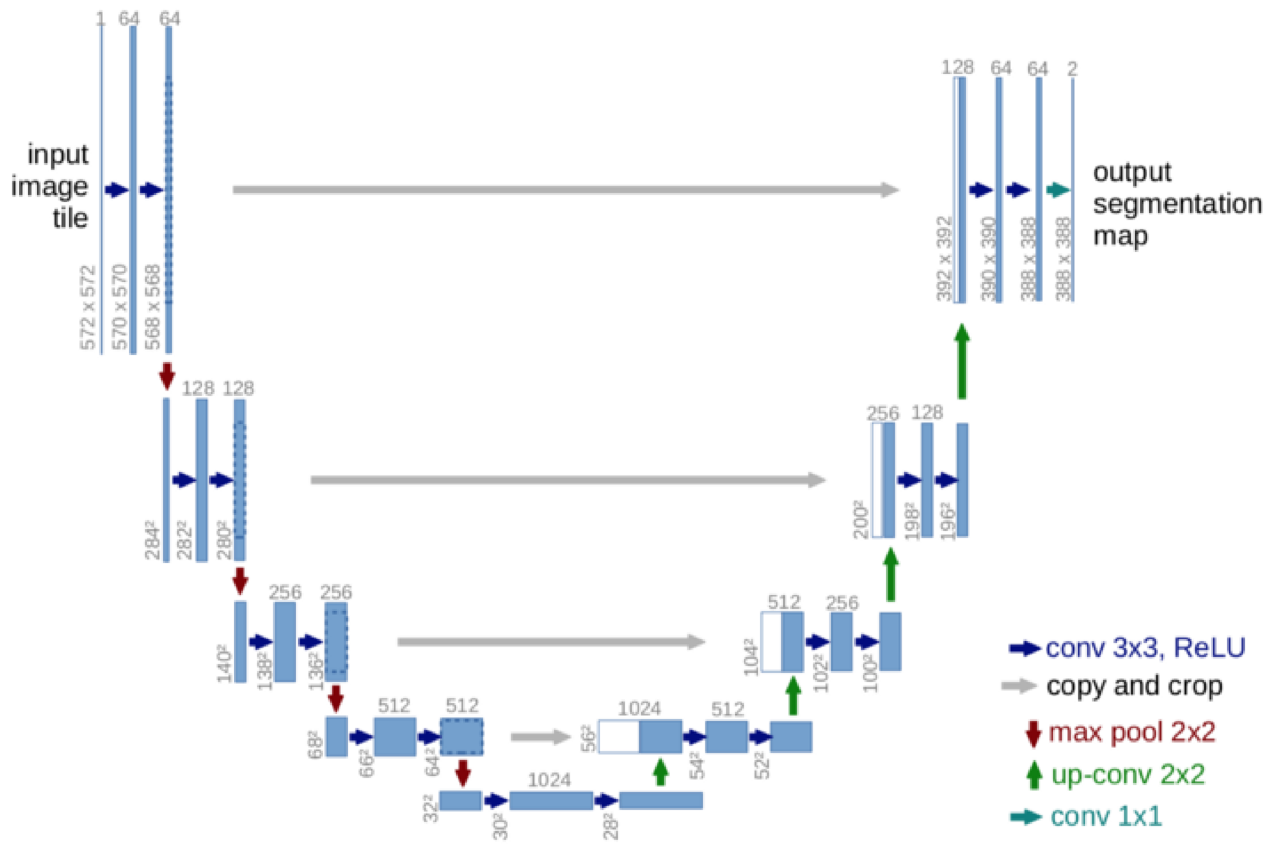


FIGURE 1. Algorithmic Complexity

Complex models like profound neural networks have low bias however experience the ill effects of high variance. Segmentation is a methodology that partitions an image into segments. It is an image processing methodology that allows us to classify objects and characters in images. Segmentation is mainly used in applications such as remote sensing or tumour detection in bio medicine.



[12] **FIGURE 2**. U-Net architecture

U-Net is a U-shape symmetric architecture consisting of two major parts. The left part is called the contracting path and the right path is called the expansive path. From the name itself, we can observe that the model has a "U" shape. The architecture is symmetric and comprises of two significant parts — the left part is known as the contracting path, which is established by the general convolutional measure; the right part is the expansive path, which is comprised of translated 2d convolutional layers. The U-Net architecture can process fast and accurate image segmentation; U-Net is a convolutional neural network developed for image segmentation. U-Net is advanced from the customary CNN was first applied in 2015 to deal with biomedical pictures. Convolutional Neural Networks gave respectable outcomes in simpler picture division issues yet it hasn't gained any great headway on complex ones. That is the place where UNet comes into the picture. UNet was first planned particularly for clinical picture division. It showed such great outcomes that are utilized in numerous different fields.

EXPERIMENTS

We look at two explicit instances of information expansion with the assistance of Keras Image Data Generator. We investigate the aftereffects of both experiments that lead to overfitting and underfitting during the preparation. Accordingly, for examining both the experiments, the measurements we considered are 'Precision and Loss' during preparing and approval, where binary cross-entropy was assumed as the misfortune work.

Experiment 1: This case is also called the base case, where rescaled just the pixel worth of pictures and their masks. Augmentation is not applied to this situation.

Experiment 2: In this case addition to rescaling, both the images and masks were flipped vertically or horizontally randomly

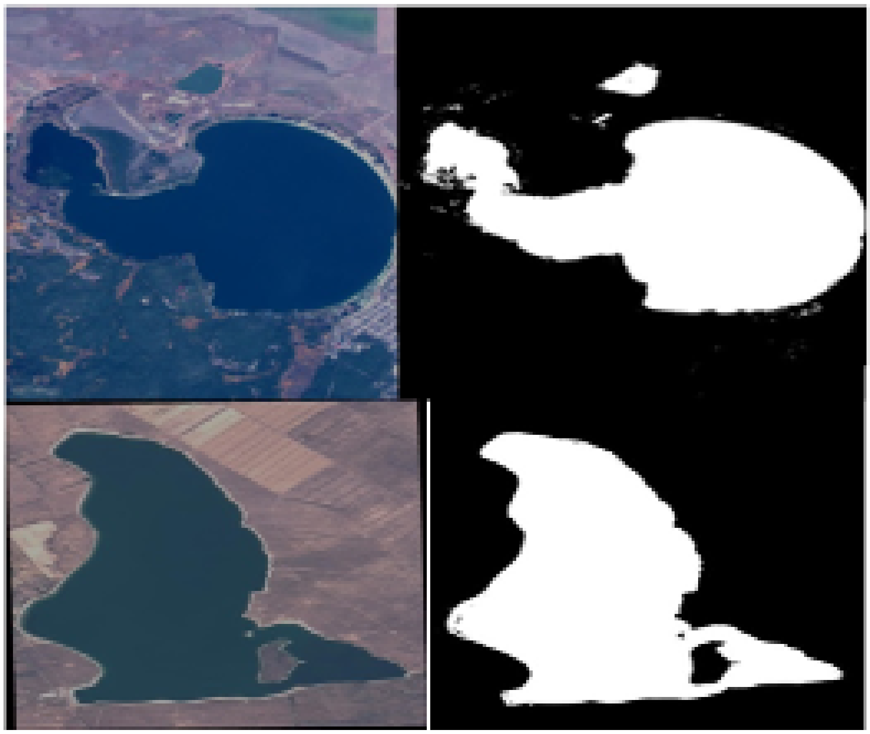


FIGURE 3. Images and Masks. Various types of Augmentations on the same image and its mask.

LITERATURE REVIEW

Charan, DL Rama, D. Sai Siva Teja, R. Subhashini, Y. Bevish Jinila, and G. Meera Gandhi. (2020) conducted a study on CNN-based water resources using satellite images. They are targeting and estimating the space of a water body utilizing GIS using GIS which is a geographic data framework that is a conceptualized system that can catch and investigate spatial and geographic information. They are using The Geospatial Data Abstraction Library, a PC programming library for perusing and composing raster and vector geospatial information designs, and using machine learning algorithms to extract water bodies from the Resources at-2 satellite Images. In addition, they have collected a dataset from ISRO39;s geoportal known as BHUVAN.

Isikdogan, Leo F., Alan Bovik, and Paola Passalacqua. (2019) conducted a study on seeing through the clouds with deepwatermap. They focused on designing a robust DeepWaterMapV2 that can detect water bodies passing through the clouds without depending on any sensors in situations where the mists don39;t completely block the scene. They have utilized the fundamental U-Net design for their model without any adjustments to the U-Net engineering. They have planned the DeepWaterMapV2 to have a uniform element map size all through the organization. They have collected the Landsat-8 dataset from the google earth engine platform.

Reddy, K. Rithin Paul, Suda Sai Srija, R. Karthi, and P. Geetha. (2020) The authors directed an examination on Evaluation of water body extraction from satellite pictures utilizing open-source apparatuses.quot; In Intelligent Systems, Technologies, and Applications. The creators have taken Satellite pictures of Chennai city in India and have surveyed water body extraction from those satellite pictures. The principal place of their assessment was to consider the train and break down the eventual outcomes of various AI computations, for instance, Decision tree, Naïve Bayes, Multilayer Perceptron, K-closest neighbour, Random woodland for removing the water bodies. They used the dataset from Landsat 5 and used the Weka instrument for portrayal and R to visualize the results. They found that the Naïve Bayes classifier computation could perceive lake regions better than the broad scope of different measures during assessments of the development.

Wei, Xufeng, Wenbo Xu, Kuanle Bao, Weimin Hou, Jia Su, Haining Li, and Zhuang Miao. (2020) The creators led an examination on A Water Body Extraction Methods Comparison Based on FengYun Satellite Data. In this investigation, creators have used Remote recognizing advancement for removing water bodies. The makers used the Fengyun satellite pictures, which have the advantage of high time objective and multispectral gatherings. Totally seven methodologies were applied in the examination, including single-band edge, water body filed, information choice tree regulated and solo grouping, ghostly coordinating with dependent on discrete molecule swarm streamlining with natural element enhancement(SMDPSO+LFE). These were used to isolate the water surface of Poyang Lake. The results showed that the overall gathering precision of SMDPSO+LFE was significantly higher stood out from any excess procedures, and the kappa co-successful was in like manner more elevated than the other. Eight sights were taken to analyze the consistent quality and found that SDMPSO+LFE is, for the most part, suitable than any excess estimations.

Mishra, Kshitij, and P. Prasad. (2015) The authors investigated the Automatic extraction of water bodies from Landsat symbolism utilizing the perceptron model. The creators proposed pondering water elements from images taken from Landsat and implementing the perceptron model on the images dataset, and the expulsion of waterbodies segments from satellite illustration is by and large examined in the tireless viewpoint. The perceptron model is a machine learning model. It includes sanctioning subject on a direct pointer work that joins scarcely any brand name properties of the substance regularly regular as the feature vector. Moreover, the survey adds to the yield work and a double intricate isolating point exertion when gotten along with totals.

METHODOLOGY

Data augmentations on satellite images are performed by deep learning algorithms, where the u-net, CNN architecture, processes the satellite images.

Segmentation is a cycle that segments a picture into areas. It's anything but a picture preparing approach that permits us to isolate items and surfaces in pictures. It is a process in computer vision where the picture is sectioned into various portions addressing each different class in the picture. The division is particularly liked in applications, for example, remote sensing or tumour identification in biomedicine.

U-Net is a convolutional neural organization engineering that extended with not many changes in the CNN design. The architecture is symmetric and comprises two significant parts —the contracting path and the expansive path. The presented design had two primary parts that were encoder and decoder. The encoder is about the covenant layers followed by pooling activity. It is utilized to remove the components in the picture. The second part decoder utilizes translated convolution to allow restriction.

The below figure shows the proposed architecture.

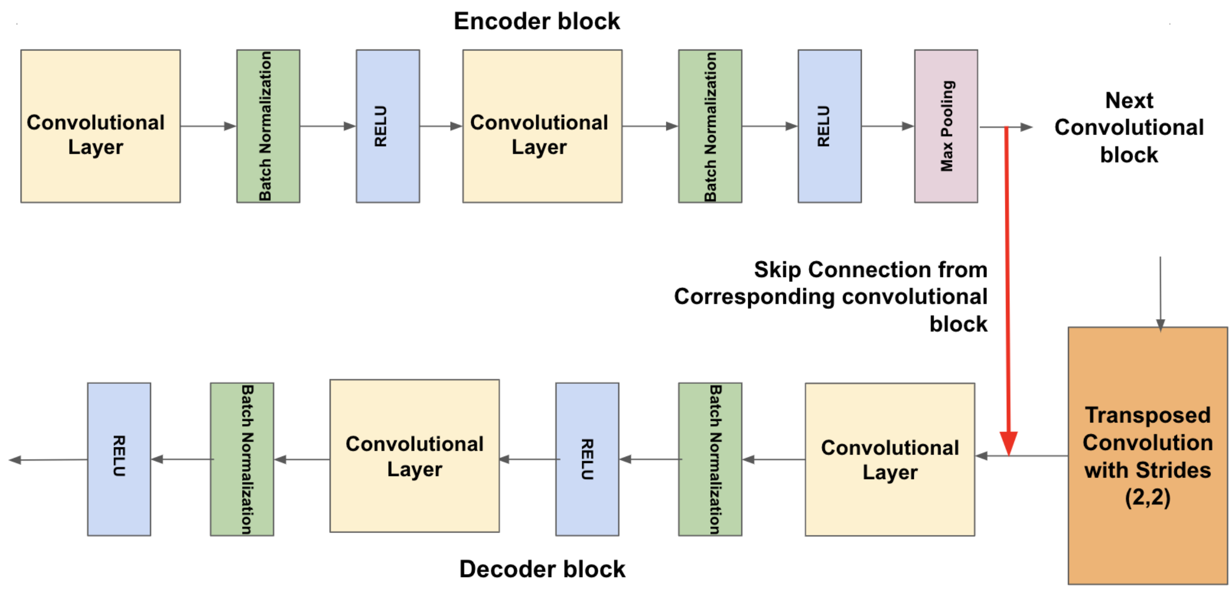


FIGURE 4. Modified Version Of U-Net Model.

We have carefully modified the U-Net network architecture. A U-NET is an autoencoder with leftover or skips associations from each convolutional block in the encoder to its partner in the decoder. This outcome is in a topsy-turvy 'U' like construction. We look at two explicit instances of information expansion with the assistance of Keras Image Data Generator. We investigate the aftereffects of both experiments that lead to overfitting and underfitting during the preparation. Accordingly, for examining both the experiments, the measurements we considered are 'Precision and Loss' during preparing and approval, where binary cross-entropy was assumed as the misfortune work.

When managing semantic division, we applied similar augmentation to the images and their particular masks. In both experiments, the pixel upsides of both the pictures and covers are rescaled by a factor of 1/255.

ABOUT THE DATASET

The dataset we have collected is from Kaggle. It is the world's biggest information science local area with integral assets and assets to assist you with accomplishing your information science objectives. We have used the satellite images from sentinel2 and their corresponding masks, which segment the water bodies. Normalized has calculated the masks difference and water index. The dataset consisted of a total of 2841 images and their corresponding masks out of which 2560 images were selected for the training of the model and hence were considered under the train set, and range of step count 256 of the images and corresponding masks were used for validating the model hence taken under the validation set, and range of step count 25 of the final images were used for testing and hence considered under the test set.

RESULT AND DISCUSSION

Data Pre-Processing

Data Pre-processing is that progression wherein the information gets changed, or Encoded, to carry it's anything but an expression that now the machine can without much of a stretch parse the data. As such, the highlights of the information would now be able to be effectively interpreted by the algorithm. The principal point of data pre-processing is to perceive and empty goofs and duplicate data, to make a trustworthy dataset. This improves the idea of the arrangement of data for examination and engages identical elements.

Training Result

We trained the model for eight epochs for both the experiments with a batch size of 16 for each epoch and 160 steps per epoch and compared the outcome of both the experiments.

Experiment 1:

In this experiment pixel worth of images and their corresponding masks are rescaled. Augmentation is not applied to this situation.

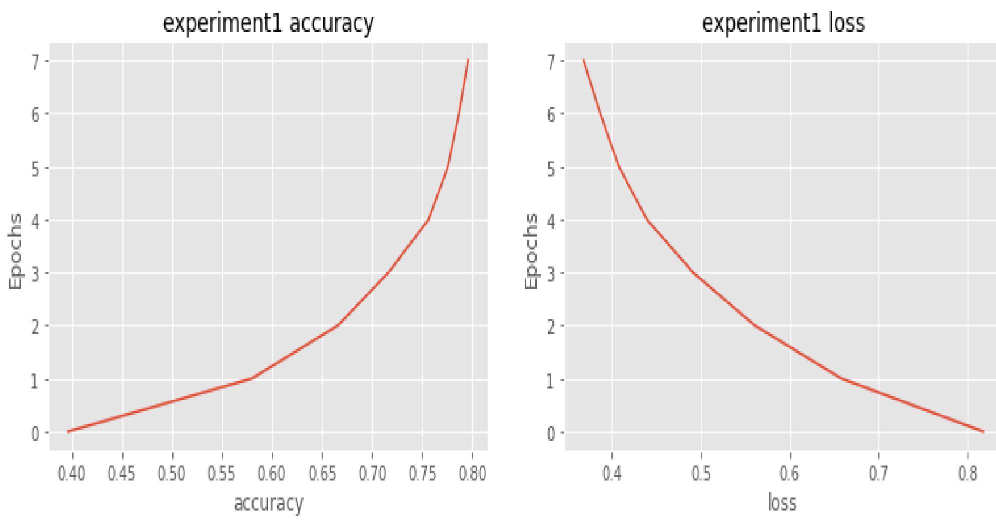


FIGURE 5. Plots Of Experiment1 Training History The graph which shows the increasing accuracy with increase in number of epochs and the graph which shows the decreasing loss with increase in number of epochs during the training of the model1 where augmentation is not applied.

From the above graph, we can see the training history of experiment1, which is the base case in this experiment. The model was trained without applying any kind of data augmentation technique and we only rescaled the pixel worth of pictures and their corresponding masks. We can see the gradual increase in the accuracy and decrease of the training loss with each epoch and each step within epochs. At the end of the 8th epoch, the model achieved an accuracy of 0.7812(78.12%).

Experiment 2:

In this experiment addition to rescaling, data augmentation technique is applied. Both the images and their corresponding masks are rescaled and then are flipped vertically or horizontally.

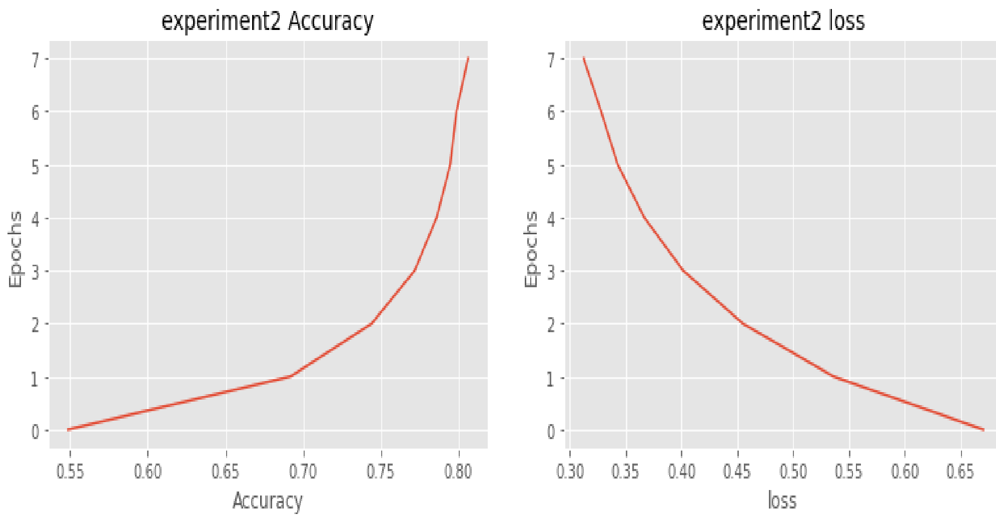


FIGURE 6. Plots Of Experiment2 Training History The graph which shows the increasing accuracy with increase in number of epochs and the graph which shows the decreasing loss with increase in number of epochs during the training of the model2 where augmentation is applied.

From the above graph, we can see the training history of experiment2. In this expermient2, we have applied data augmentation by flipping the axis in addition to the rescaling. The model showed a gradual increase in accuracy with an increase in the epoch. At the end of the 8th epoch, the model achieved an accuracy of 0.8234(82.34As we can see in the graph, the accuracy has crossed 0.80, whereas, in experiment1, the accuracy was not reached 0.80, where both experiments are conducted with the same no of epochs and steps. In these experiments, the same model is trained, one with augmentation and one without augmentation.

Test Result

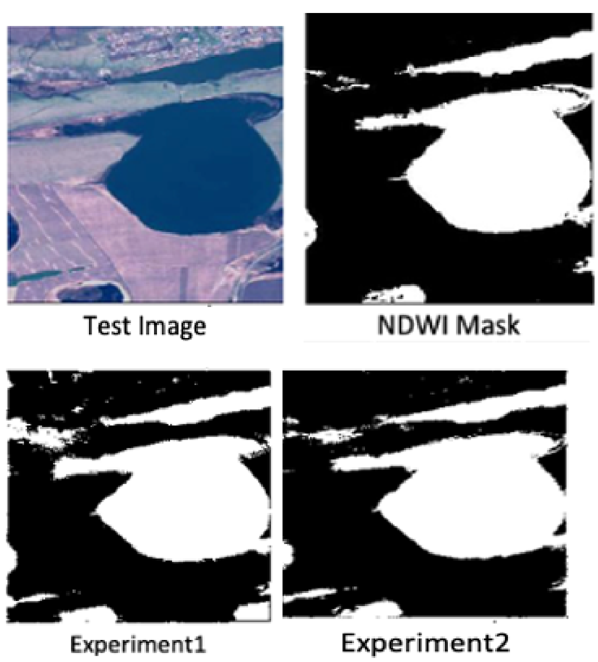


FIGURE 7. Output Result1 Of The Prediction Images showing the input test image and its corresponding mask also containing the prediction result obtained from experiment1 and experiment2.

From the above fig, we can see predicted images of water bodies in satellite images. We can make out the difference between the result of experiment1 and experiment2. The result of the experiment failed to detect the edges of the water region and the boundary is not very accurate. The model also failed to detect smaller water areas around the larger water region. The case of experiment2 where the data augmentation technique has been applied showed significantly better results when compared to that of experiment1. The model was able to detect edges of larger water regions more clearly and created a more accurate boundary around the water region when compared to that of experiment1.

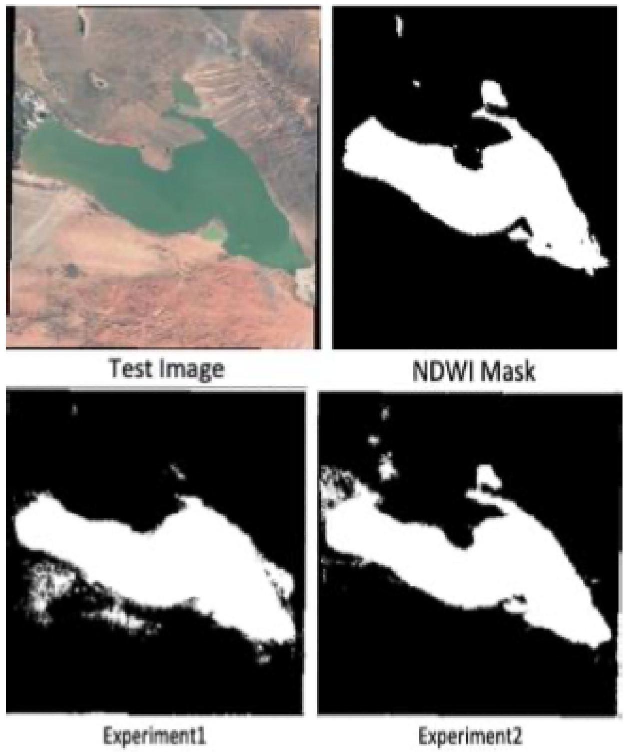


FIGURE 8. Output Result2 Of The Prediction Images showing the input test image and its corresponding mask also containing the prediction result obtained from experiment1 and experiment2.

From the above images, we can observe that result2 is also showing the same results when compared with result1. As explained in Test1, model2 where we applied the data augmentation showed significantly better performance and was able to detect edge cases more accurately when compared with model1. Hence we concluded that the same mode1, when trained with augmented data, shows greater accuracy and better performance than the model when trained in the old-style approach. Applying data augmentation on the dataset before training the model will result in improving the accuracy and performance significantly.

CONCLUSION

We depicted an optimized convolutional neural network model custom-made for partitioning the water from high-resolution satellite images. We inferred a worldwide scale surface water informational collection from openly accessible informational indexes to prepare an exact water division model. Our model opens up additional opportunities for an assortment of hydrography applications. It is conceivable to make a high-goal surface water guide of the whole Earth. Those surface guides made by our model can be utilized as contributions to the errand specific models for additional investigation. For instance, it can be used as a drop-in rade for a water list in RivaMap [4] to get stream networks from the given surface water maps naturally

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