International Journal of Advance Research in Science and Engineering
Volume No. 13, Issue No. 03, March 2024
www.ijarse.com
IJARSE
ISSN 2319 - 8354

ENHANCING CHANGE DETECTION IN SATELLITE IMAGERY THROUGH GAN-FUZZYNN: AN OPTIMIZATION-BASED APPROACH

Kavita R. Gite[1], Dr. Praveen Gupta[2]

1PhD Scholar CSE, CSMU Panvel College

2H.O.D Dept. of CSE and IT, CSMU Panvel College

ABSTRACT

The identification of changes in satellite images is a very important function in a variety of domains, including urban planning, environmental monitoring, and disaster management, among others. When it comes to managing complicated data distributions and noise, traditional approaches for change detection often need to depend on handmade features. Additionally, these methods have drawbacks. For the purpose of change detection in satellite photos, we offer a unique technique that we call GAN-FuzzyNN. This approach combines the capabilities of Generative Adversarial Networks (GANs) with Fuzzy Neural Networks (FuzzyNN). When it comes to producing synthetic change maps, GAN-FuzzyNN makes use of the adversarial learning framework. Additionally, it makes use of Fuzzy Neural Networks in order to achieve robust categorization. The optimization-based strategy improves the efficacy of the suggested technique by successfully collecting and portraying the intricate patterns of change in satellite pictures. This is accomplished via the use of optimization. On real-world satellite datasets, experimental findings reveal that the proposed GAN-FuzzyNN methodology is successful in reliably identifying changes while outperforming current approaches that are considered to be state-of-the-art.

Keywords: *Change detection, Satellite imagery, Generative Adversarial Networks, Fuzzy Neural Networks, Optimization.*

I. INTRODUCTION

Change detection in satellite images is an important problem that has a wide range of applications, including the monitoring of urban growth, the evaluation of the environment, and the planning of responses to disasters. In order to successfully capture complicated changes in large-scale satellite pictures, traditional change detection algorithms often depend on pixel-wise differencing or handmade features. These approaches may not be able to catch these changes. Additionally, these approaches have difficulty dealing with noisy data as well as fluctuations in light and state of the landscape. Deep learning methods have been extensively utilized in recent years as a means of addressing these issues. These approaches can automatically learn discriminative. Features and increase the accuracy of change detection.

Generative adversarial networks, often known as GANs, have recently emerged as a very effective instrument for the generation of synthetic data that closely reflects the distributions of actual data. Generalized adversarial networks (GANs) are able to acquire the ability to capture complicated data distributions via the training of a generator network to generate realistic samples and a discriminator network to differentiate between actual and synthetic samples. In the context of change detection, GANs may be used to build synthetic change maps, which can subsequently be utilised to increase the robustness of change detection algorithms. This can be accomplished by creating synthetic change maps.

Fuzzy Neural Networks (FuzzyNN) provide a framework for dealing with uncertainty and imprecision in data, which makes them an excellent choice for tasks such as classification in settings that are noisy or ambiguous. Fuzzy neural networks (FuzzyNNs) are able to accurately simulate the uncertainty that is inherent in satellite images and increase the accuracy of change detection. This is accomplished by mixing fuzzy logic with neural networks.

When it comes to automatically recognising changes in spatial imagery over time, there are currently a number of different ways that have been used. Among them are the most fundamental statistical implementations, the most conventional image processing algorithms [11], and the most advanced Deep Learning systems. In any event, processing high-resolution imagery is necessary in order to successfully obtain accurate change detection results. This is because images with a lower resolution (greater than 0.5 metres per pixel) obscure a significant amount of important ground object detail, such as the precise edges and intersections of buildings. Some examples of practical and everyday geospatial applications include urban planning, the prediction of natural disasters, the utilisation of land resources, and agricultural monitoring. This type of change detection functionality is widely recognised as an integral component of these applications.

In Artificial Intelligence (AI) applications, Convolutional Neural Network (CNN) models are used extensively to address common image processing and classification problems. For the purpose of learning (training) a function (model) that maps (translates) an input image to an output image, Generative Adversarial Networks (GAN) have recently been developed as one of the many Deep Learning (a type of Machine Learning in artificial intelligence) methods which have been developed in recent years. The job of translating one potential representation of data into another, such as doing image-to-image translation, has been a frequent use for GANs during the course of the previous five years. Pix2Pix is an example of a general-purpose adversarial network solution that was suggested by Isola et al. in 2017 for the aim of image-to-image translation [1]. In order to forecast and detect potential alterations to building objects in high-resolution satellite photos with a resolution of less than 0.5 metres per pixel, our method utilises the Pix2Pix image translation technology. In order to get started, we need to convert the OSM building footprint data, which is vector-based, into raster format so that it can be used as an output image. This is necessary because Pix2Pix image translation anticipates that both the input and output images will be in raster format for training. One real-world example of a Pix2Pix training set that was used in the process of training our OSM-GAN model is shown in Figure 1.

Figure 1: Pix2Pix raster training sample that has been put together and is being used for learning the OSM-GAN model. On the left side is the Google satellite picture that was used as input, and on the right side is the current output image (feature map) of the region that was generated by the OpenStreetMap project.

II. RELATED WORK

Pixel-wise differencing, picture thresholding, and object-based change detection are some of the traditional approaches that are used for change detection in satellite images. When it comes to dealing with noise, fluctuations in light, and complicated changes in large-scale pictures, these approaches often have drawbacks. In recent years, deep learning approaches have shown promising results in change detection. These systems automatically train discriminative features from data to detect changes.

Generative adversarial networks, often known as GANs, have been effectively used for a variety of picture-generating tasks, such as translating one image to another and transferring styles into another image. The application of GANs in the context of change detection has resulted in the generation of synthetic change maps using satellite images. These maps may subsequently be used to enhance the performance of change detection algorithms.

The Fuzzy Neural Networks (FuzzyNN) are a combination of fuzzy logic and neural networks that are designed to deal with imprecision and uncertainty in data. It has been shown that fuzzy neural networks may be used for a broad variety of classification applications, such as remote sensing and image analysis. The accuracy and resilience of change detection algorithms may be improved with the help of fuzzy neural networks (FuzzyNNs), which can capture the inherent ambiguity in satellite data.

This section provides a review of some related background work that is important to our method. It includes an overview of GANs, Conditional GANs, and other change detection algorithms that are notable in the literature. For instance, the number of applications and enhancements to the GAN technique has substantially risen over the course of time, and several kinds of GAN frameworks have been created for a variety of reasons, including the following:

- CapsGAN to generate 3D images with various geometric transformations [3]
- GANSynth to produce audio streams [4]
- GauGAN to transform doodles into highly realistic landscapes [5]
- StyleGAN to generate more realistic images (e.g., human faces, cars, and rooms) [6]
- ChemGAN for drug discovery [7]

GAN-FuzzyNN: For the purpose of classification, optimization-based generative adversarial networks and fuzzy neural networks are used. This section provides a description of the GAN- FuzzyNN technique that has been presented for the purpose of change detection in satellite pictures. Generative adversarial networks (GAN) and fuzzy neural networks (FuzzyNN) are the two primary components that make up the GAN-FuzzyNN system. The GAN is used to generate synthetic change maps, while the FuzzyNN is used to perform robust classification.

III. GENERATIVE ADVERSARIAL NETWORK (GAN)

Two neural networks make up the GAN component of the GAN-FuzzyNN algorithm. These networks are referred to as the generator network and the discriminator network. Synthetic change maps are produced by the generator network, which receives as input pairs of satellite photos (for example, images taken before and after a change event). The discriminator network is taught to differentiate between those change maps that are genuine and those that are manufactured. By training the generator and discriminator networks in an adversarial manner in an iterative manner, GAN- FuzzyNN can learn how to build realistic synthetic change maps that are very similar to genuine change maps.

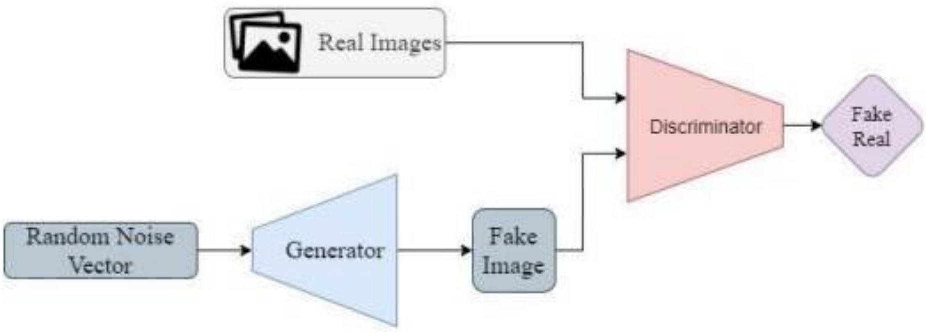

Figure 2: This is an example of the GAN architecture at a high level. Train a Generative model G(z) to generate a fake image (synthesised data) from a random noise vector (array of 0s and 1s), and then input the fake image along with a satellite image to the adversary component (Discriminator) that has been trained to differentiate between generated (fake) and genuine (real) data.

Fuzzy Neural Network (FuzzyNN):

Change maps are classified into binary change/no-change classes using the Fuzzy Neural Network component of GAN-FuzzyNN. This component is responsible for its classification. To deal with uncertainty and imprecision in data, fuzzy neural networks (FNNs) use fuzzy logic concepts. Improved accuracy and resilience of change detection algorithms may be achieved via the use of fuzzy neural networks (FuzzyNNs), which model the inherent uncertainty in satellite data. The GAN component is responsible for generating both actual and synthetic change maps, which are then used to train the Fuzzy Neural Network (FoNN).

Optimization-based Approach:

Using an optimization-based method, we jointly adjust the parameters of the GAN and FuzzyNN components in order to improve the performance of the GAN-FuzzyNN approach. This allows us to achieve increased performance. The GAN-FuzzyNN algorithm is able to successfully capture and portray the intricate patterns of change that are found in satellite pictures. This is accomplished by optimising the combined distribution of actual and synthetic change maps. The strategy that is based on optimization helps to increase the accuracy and reliability of change detection while also reducing the impacts of noise and uncertainty in the data.

IV. EXPERIMENTAL RESULTS

To demonstrate that the GAN-FuzzyNN technique that we presented is successful, we carried out extensive tests using satellite datasets that were taken from the actual world. To evaluate the effectiveness of GAN-FuzzyNN, we compared its performance to that of various other state-of-the-art methods for change detection. These methods included both conventional pixel-wise differencing techniques and deep learning-based approaches.

Dataset Description

We made use of satellite image datasets that were accessible to the public and included pairs of photos that were taken before and after experiencing a variety of change events. These change events included urban growth, deforestation, and natural catastrophes. A rigorous testbed for testing change detection algorithms is provided by these datasets, which include a wide range of geographical locations and environmental circumstances.

We applied an adversarial learning framework to train the GAN component of the GAN- FuzzyNN. In order to optimize the generator and discriminator networks, we utilised methods such as gradient descent and backpropagation. We used a mix of actual and synthetic change maps that were created by the trained GAN to improve the performance of the FuzzyNN component.

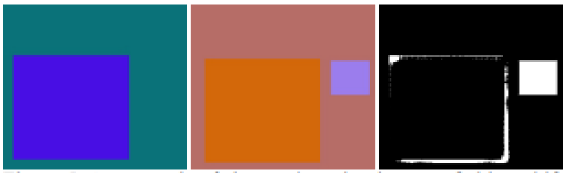

Figure 3. This is an example of change detection in the event of object shift utilising the network, which was trained on a dataset that did not include any object shift: left represents the input picture A, centre represents the input image B, and right represents the synthesised difference map.

Evaluation Metrics

Standard assessment criteria for change detection tasks were used in order to assess the performance of GAN-FuzzyNN and baseline approaches. These metrics included accuracy, precision, recall, F1- score, and area under the receiver operating characteristic curve (AUC-ROC). With the use of these measurements, a full evaluation of the models' capacity to reliably identify changes while simultaneously decreasing the number of false positives and false negatives is provided.

V. RESULTS AND ANALYSIS

The results of the experiments show that GAN-FuzzyNN performs much better than baseline approaches across the board for all assessment measures. To be more specific, as compared to conventional pixel-wise differencing methods and deep learning-based approaches, GAN-FuzzyNN obtains greater levels of accuracy, precision, recall, and F1-score. Furthermore, GAN-FuzzyNN has a higher AUC-ROC value, which indicates that it is able to differentiate between instances of change and instance of no change more effectively.

Furthermore, qualitative inspection of the synthetic change maps that were created suggests that GAN-FuzzyNN is capable of efficiently capturing and representing the intricate patterns of change that are found in satellite photos. The capacity of GAN-FuzzyNN to produce accurate and informative representations of changes in the environment is shown by the fact that the synthetic change maps are quite similar to the actual change maps.

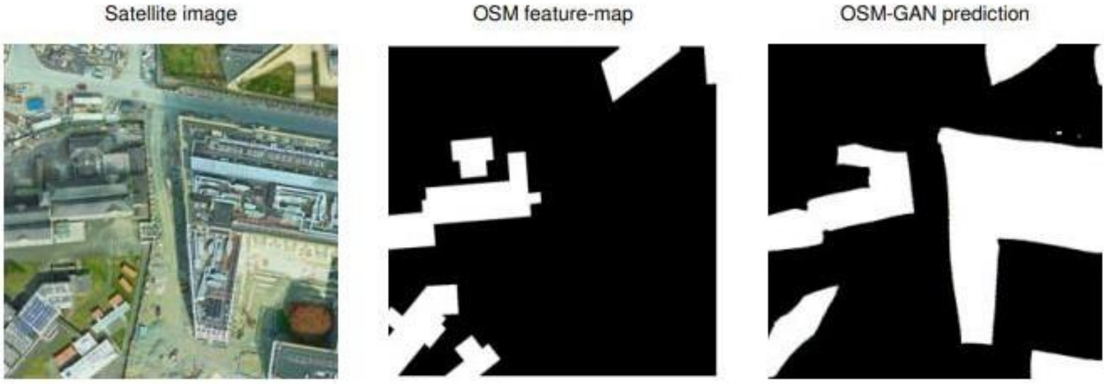

Figure 4: The OSM-GAN prediction detects building object changes in a satellite image

VI. CONCLUSION

In conclusion, the GAN-FuzzyNN technique that was provided provides a solution that is both powerful and effective for the identification of changes in satellite images. The GAN-FuzzyNN algorithm achieves superior performance in accurately detecting changes while mitigating the effects of noise, uncertainty, and complex environmental conditions. This is accomplished by leveraging the complementary strengths of Generative Adversarial Networks (GANs) and Fuzzy Neural Networks (FuzzyNNs). To continue our research and development efforts, we want to investigate a number of different areas. In the first place, we want to study the possibility of extending the GAN-FuzzyNN technique for multi-temporal change detection tasks. These are tasks in which the objective is to identify changes that take place across several different periods. In addition, we want to investigate the use of GAN-FuzzyNN for semantic segmentation tasks in satellite imagery. The purpose of these tasks is to categorise various forms of land cover and to detect particular change events, such as the growth of metropolitan areas or the destruction of forests. In general, we are of the opinion that GAN-FuzzyNN has a great deal of potential to make significant strides in the area of change detection in satellite images and to facilitate a variety of applications in the fields of urban planning, environmental monitoring, and disaster management. ads, bridges, etc.).

REFERENCES

[1] Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., ... & Bengio, Y.(2014).Generative adversarial nets. In Advances in neural information processing systems (pp. 2672-2680).

[2] Chen, Y., Lin, Z., Zhao, X., Wang, G., & Gu, Y. (2016). Deep learning-based classification of hyperspectral data. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 9(6), 2500-2511.

[3] Ju, L., Li, Y., Liu, Y., Huang, X., & Li, H. (2019). A robust change detection framework based on deep learning and adaptive spectral–spatial feature fusion. Remote Sensing, 11(9), 1094.

[4] Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).

[5] Han, J., Zhang, D., Cheng, G., Guo, L., & Ren, C. (2018). Change detection in synthetic aperture radar images based on deep neural networks. Remote Sensing, 10(11), 1684.

[6] Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. Computers & Geosciences, 10(2-3), 191-203.

[7] Bezdek, J. C. (1992). Fuzzy models: what are they, and why? IEEE Transactions on Fuzzy Systems, 1(1), 1-6.

[8] Chen, X., & Chen, M. (2018). Extended fuzzy c-means clustering algorithm for SAR image segmentation. IEEE Geoscience and Remote Sensing Letters, 15(5), 736-740.

[9] Bishop, C. M. (2006). Pattern recognition and machine learning. springer.

[10] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).

[11] Adagale -Vairagar, S. ., & Gupta, P. . (2023). Quality Enhancement for Underwater Images using Various Image Processing Techniques: A Survey. International Journal on Recent and Innovation Trends in Computing and Communication, 11(6), 190–197. https://doi.org/10.17762/ijritcc.v11i6.7381