



# Accurate Segmentation for Low Resolution Satellite images by Discriminative Generative Adversarial Network for Identifying Agriculture Fields

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## Abstract

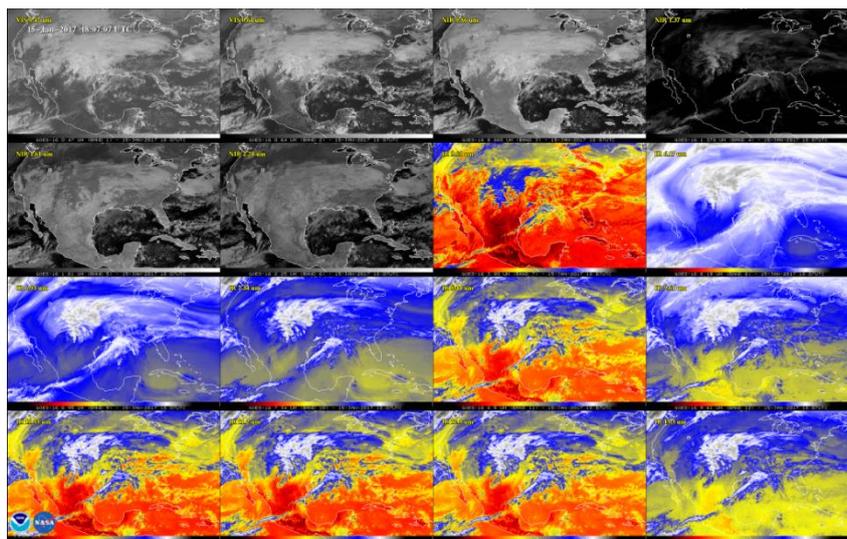
Agricultural field identification is still a difficult issue because of the poor resolution of satellite imagery. Monitoring remote harvest and determining the condition of farmlands rely on the digital approach agricultural applications. Therefore, high-resolution photographs have obtained much more attention since they are more efficient in detecting land cover components. In contrast, because of low-resolution repositories of past satellite images used for time series analysis, wavelet decomposition filter-based analysis, free availability, and economic concerns, low-resolution images are still essential. Using low-resolution Synthetic Aperture Radar (SAR) satellite photos, this study proposes a GAN strategy for locating agricultural regions and determining the crop's cultivation state, linked to the initial or harvesting time. An object detector is used in the preprocessing step of training, followed by a transformation technique for extracting feature information and then the GAN strategy for classifying the crop segmented picture. After testing, the suggested algorithm is applied to the database's SAR images, which are further processed and categorized based on the training results. Using this information, the density between the crops is calculated. After zooming in on SAR photos, the crop condition may be categorized based on crop density and crop distance. The Euclidean distance formula is used to calculate the distance. Finally, the findings are compared to other existing approaches to determine the proposed technique's performance using reliable measures.

**Keywords:** Satellite images, agriculture fields monitoring, GAN, image segmentation, object detection

## 1. INTRODUCTION

Precision agriculture relies heavily on satellite pictures to monitor agricultural areas. Satellite farming depends upon the discovery of intra-field changes to maximize output. Therefore, a satellite picture must be segmented and classified before any additional work can begin. To accurately estimate crop acreage, structure, and geographic distribution and to provide crucial input parameters for crop yield models, categorization of crops is a must-have need. This system uses a variety of approaches that improve the level of automation. When demand for agricultural goods grew in the second half of the 20th century, farmers either expanded their acreage or increased the productivity. Environmental hazards may arise from both. Increased agricultural productivity was accompanied by increased emissions, harmful impacts on soil and groundwater, and changes in land-use patterns that reduced farmland development owing to limited accessible areas and improved technologies [1–5].

These systems may include essential and accurate information. However, they are generally based on past administrative maps, human field delineations based on satellite or aerial images, and in-the-field mappings using Global Positioning Systems (GPS). Rather than extracting specific polygons, many earlier efforts to field extraction focused on determining the position and breadth of the fields within a picture. For example, Landsat images may be segmented using edge detection and morphological decomposition, or random forest classifiers can be trained using picture attributes such as mean reflectance values [6-8].



**Figure 1.** NOAA Dataset [31]

Land use monitoring of agricultural landscapes and production systems is critical, particularly in highly fragmented landscapes with significant spatial and temporal variability

owing to a wide range of crop types, sizes, forms, and management approaches, as well as crop rotations. On smallholder farms, automatic field delineation is difficult since the borders aren't always well defined by visible lines. Instead, they must be retrieved by identifying differences in the textural and spectral patterns of various cultivars. Standard edge detection methods often fall short of the desired level of precision in such situations [9].

There has also been an increase in the number and distribution of remote sensing applications. A distant satellite age and an open-supply attitude have made it easier to obtain, compare, and utilise agricultural data at the farm size.

However, since these methods rely on exact or set scale parameters, they are unable to fulfil the need for scale dependency and are responsible for problems such as extraction error or extraction leakage. According to the spatial dependency theory, comparable things tend to cluster together in a small region, so photos may be separated into a few locations where identical devices are concentrated. New techniques of research that aim at the adjacent department, have emerged in recent years. When this partition divides the picture into local areas, they did so by using the cutline to establish a set of rules and two alternative regular grid development methodologies [10-15]. This research article contains several sections: past research work of SAR image segmentation process for identifying a crop field in section 2. Then, section 3 delivers the proposed research work for agricultural field identification, and section 4 discusses the experimental results by the GAN approach with several metrics. Finally, it concludes the research work in the final section.

## **2. Past Research Work**

According to Begue et al., croplands and rangelands have distinct differences in the timing of the start of growing season. These occurrences may be utilized to obtain satellite imagery's topic bounds [16]. Farmland is managed using hierarchical rule sets and spatial information-based suggestive-shift segmentation, as described by Ming et al. Because they were tested in sparsely populated areas with little agriculture, the above-mentioned methods had limited applicability and thus were not universally applicable [17].

Xu et al. in a study published in 2019, shows that the Multi-Temporal (MT) SAR backscattering responses may be used only to classify crops. Using K-mean clustering, the temporal intensity designs were clearly shown. Averages of intensity and cluster center intensity vectors were used as inputs [18].

Expert knowledge and SAR image-centered phonological information were both examined in the study by Benson Kipkemboi et al. (2017), which focused on crop sequence-centered ensemble classification approach. Perceived boundaries may be detected using a canny edge detector. It has recently been shown that algorithms that mimic an expert's delineation through monitored category strategies may be used for accurate picture segmentation in the computer vision sector [19].

Cognitive type was employed by Turker and Kok for computerised statistics on far-flung sensing and the removal of colourful sub-barriers in modern agricultural settings. For the sector-based examination, satellite photos and discipline boundary information were used [20].

Multiscale local signals, such as colour, brightness and texture, are combined with global picture information to estimate boundary probabilities in a "globalised probability of boundary" approach. Connecting and smoothing out edge pieces are possible using a globalisation framework based on spectral clustering. An affinity matrix indicating the similarity between pixels is generated using the local cues obtained by oriented gradient operators [21].

### **3. Proposed Architecture**

#### **3.1 Construction of Framework**

The original GAN, which has two networks, is suggested. Generational and discrimination are two separate networks. Using GAN's adversarial training, the generation network's samples follow an accurate data distribution. To detect agricultural lands, the suggested GAN uses a deep-learning model. Figure 2 depicts the model's general structure for proposed work with GAN approach. The GAN is similar to the original generative adversarial networks that has an interaction matrix generator, a prediction generator, and a time-series discriminator [22-25].

#### **3.2 Generative Models**

Generative models, on the other hand, learn the underlying distribution of individual types, whereas discriminative models learn the decision boundaries between classes. Separate models for conditional and joint probabilities are used in discriminative modelling, with the former accounting for the joint probability when labels are not present. Generative models aim to produce fresh samples from the same distribution giving some training data. Creating a

model that is comparable to the dataset is the goal of the training process. This is accomplished by estimating a density function from the input data, either directly (through VAEs) or implicitly (through GANs). Rather than focusing on a single result, generative models are frequently used in agricultural field area video prediction using low-resolution SAR pictures to deal with future uncertainty.

### 3.3 Prediction Generator

Previously, there have been explanations of the requirement to cope with two dependencies in many linked time series prediction problems:

- Time series are highly dependent on one another.
- There are temporal dependencies in each time series.

An interaction matrix generator was used to generate the interdependency. In building a prediction generator, the goal is to address both types of dependence. A time series interaction graph is created by combining the adjacency matrix of the interaction with the feature matrix of time series data. A convolutional chart and long-term memory networks make up the prediction generator ( $G_p$ ). An interaction matrix and a time series feature matrix are used to characterise the graph's input. An intermediate feature representation that integrates the interactional relationships between time series is obtained by performing graph convolution operations on the interaction graph. Later, these intermediate feature representations are processed by long-term memory networks, which then store the temporal relationships they imply. In this method, the prediction generator can forecast the value of each time series.

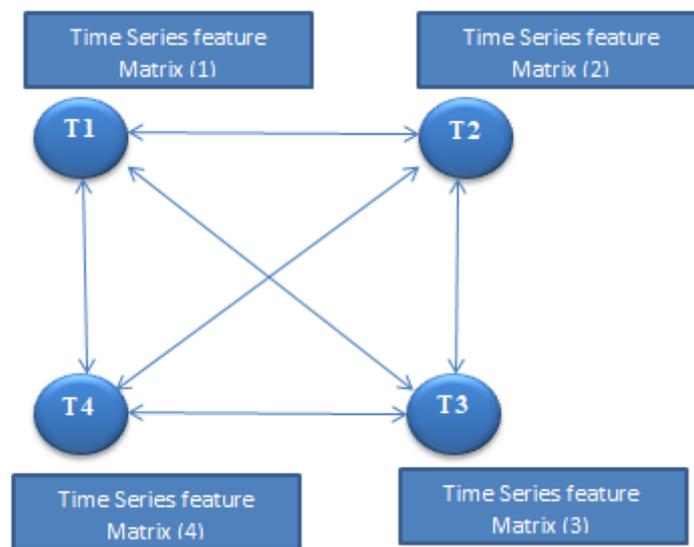
### 3.4 Interaction Matrix Generator

Transposed convolutional networks are used to provide a mapping function for SAR image field identification in the interaction matrix generator ( $G_i$ ). It maps a high-dimensional random noise vector from the Gaussian distribution to an interaction matrix in the first step. Then, using this interaction matrix as the adjacency matrix of the time series interaction graph, it detects agricultural land.

### 3.5 Time Series Discriminator

A picture created by the prediction generator is evaluated using the time series discriminator. To determine the likelihood that an input sample is accurate, it uses real-time series samples and false-time series samples as input [26]. Using the gradient information, the

interaction matrix and prediction generators may fine-tune their parameters once the discriminator has been well-trained as an estimator of the two generators. Simple 4 time series feature matrix has been shown in figure 1.



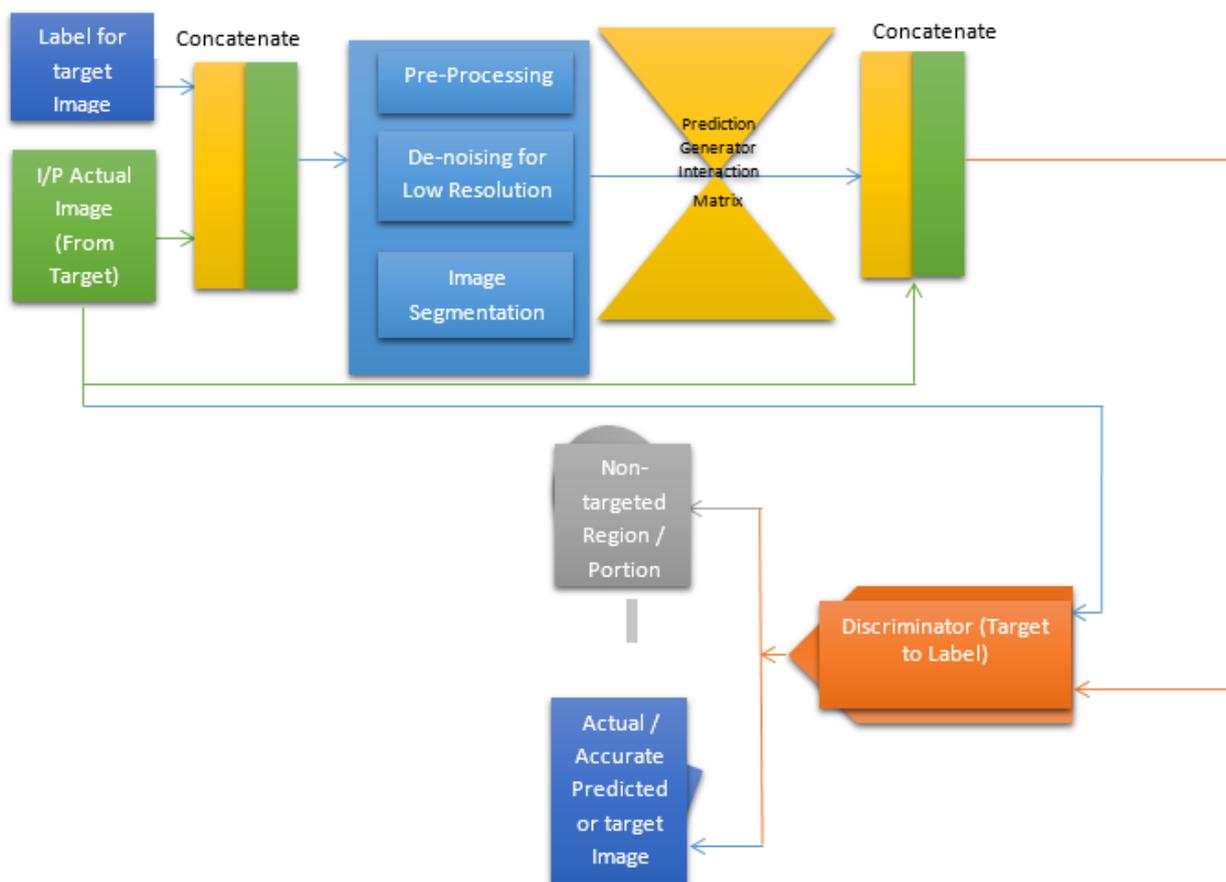
**Figure 1.** Flow of time series feature matrix

### 3.6 Proposed Workflow

A generation process, a discrimination process, and an adversarial process make up the entire workflow of this research's proposed framework technique. The interaction matrix generator generates an interaction matrix by first transforming a random noise vector. It then constructs a time series interaction graph using the interaction matrix and the time series feature matrix to properly forecast agricultural land. SAR pictures with low-resolution pixels were taken with the interactional dependencies between time series and the temporal dependencies within each time series to obtain the predicted value for each time series [27-30]. Creating real low-resolution samples and false samples is the initial step in the discriminating process.

The matrix concatenation is used to extract real-time series samples from the time series feature matrix and genuine targets, and to construct false time series samples from the right data and fake marks provided by the prediction generator. After that, the discriminator is trained on real and fake samples. When the discriminator can discern between real and low-resolution images, it has finished its training. Adversarial processes have a well-trained discriminator fixed as the evaluator of the generators' outputs. Two generators' network settings

are changed to optimize the likelihood that the false samples created by the two generators being accepted as real samples by the discriminator.



**Figure 2.** Proposed workflow for identifying accurate predicted region by GAN

#### 4. Results and Discussion

The best results were at 50K epochs for the suggested generative adversarial network evaluation and hyperparameters when tested in the Python programming paradigm. Using this method, it is possible to make predictions in the dataset of NOAA for the next one, two, and five days in the future. The "Adam optimizer" with the best evaluation value is used in the optimization method. The best results were obtained using 50k epochs and a one-day forecast. The GAN deep learning model is implemented using the Pytorch (<https://pytorch.org/>) deep learning toolkit. The random noise vector has 512 dimensions and is sampled from a Gaussian distribution in the interaction matrix generator. Figure 3 shows density based agricultural land categorization.



**Figure 3.** Density based Agricultural land categorization

It can be observed from the table that the proposed GAN model has the best prediction results on the three datasets under the two-assessment metrics of MAE and RMSE. In Figure 3, 'A' indicates dense Agri-land and 'B' indicates initial condition of the crop assumption. The ARIMA is a single-time series prediction approach among different comparison methods. The experiments with many connected time-series prediction issues showed poor results when this technique didn't account for inter-series interactional connections. As part of the inquiry, the VAR (Vector Auto-Regression) model is used to solve many time series prediction issues at once. The correlation between time series may be captured to some degree using this approach. As a linear model with limited capacity to fit data with complicated patterns, it is marginally better than the ARIMA model at predicting outcomes. In terms of accuracy, both SVR and LGB are strong machine learning models. The following two performance metrics are measured in this work.

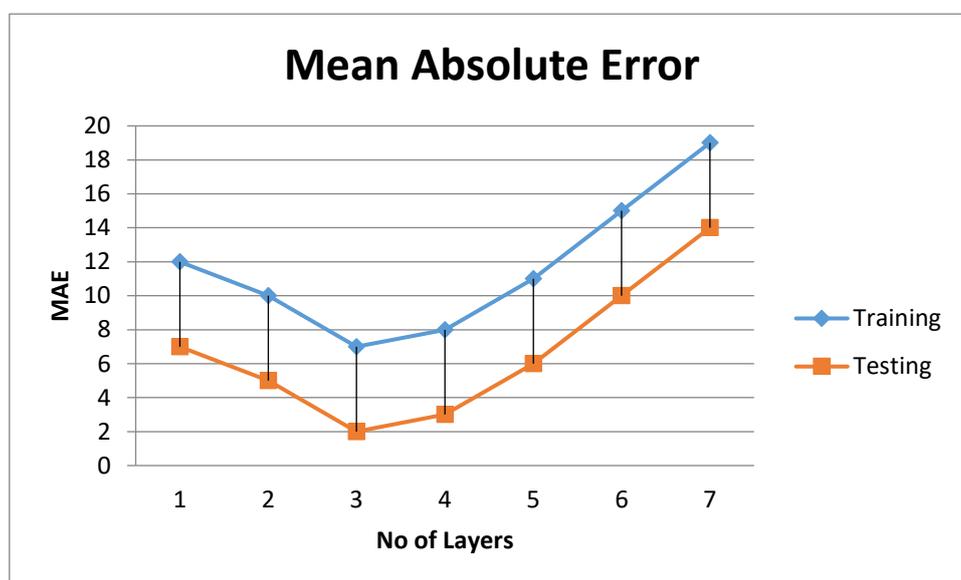
$$MAE = \frac{|(output_i - Output_p)|}{n}$$

$$RMSE = \sqrt{\frac{\sum (Output_i - Output_p)^2}{n}}$$

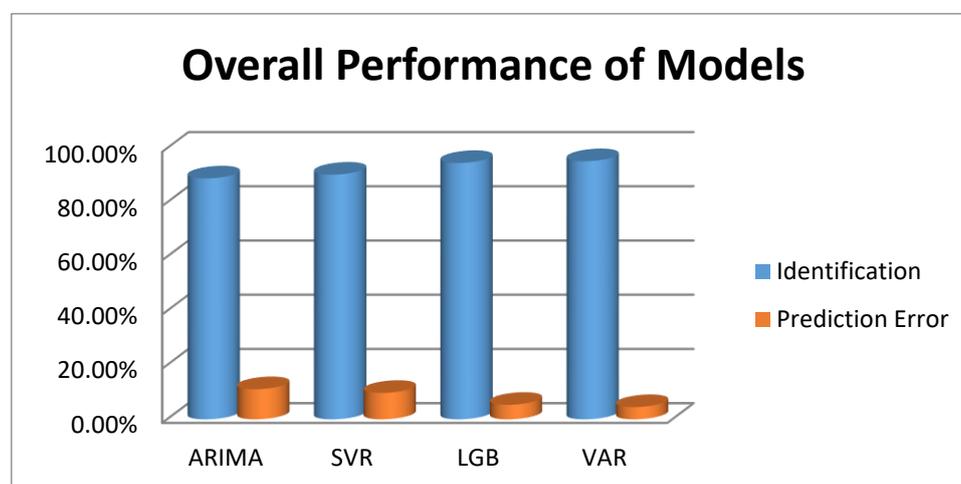
Regarding the Store Item and NOAA datasets, SVR performs better than VAR, but VAR performs better than SVR on the Web Traffic dataset. The proposed GAN clearly outperforms the other six approaches in predicting the three datasets, indicating that this model has clear advantages in several related time series prediction issues. Figure 4 & 5 shows overall performance charts. In this figure a, x axis indicates no. of layers for MAE. In the third layer, MAE gets diminished than other layers.

**Table 1.** Performance metrics of proposed GAN model

S.No	Deep Learning Model	Identification Accuracy	Mean Absolute Error	RMSE	Prediction Error (%)
1	ARIMA	88.87%	23.24	41.23	11.12
2	SVR	90.27%	18.04	30.82	9.75
3	LGB	94.58%	17.49	31.76	5.35
4	VAR	95.23%	20.01	38.24	4.52



**Figure 4.** Mean Absolute Error Vs. Number of layers



**Figure 5.** Overall performance metrics

## 5. Conclusion

Thus in this research study, an agricultural field is identified in low-resolution SAR picture accurately by using a unique deep learning model GAN technique is proposed. Two generators and a discriminator make up the model's generative adversarial network design. As part of the adversarial training process, the discriminator assists the two generators in fine-tuning their parameters, resulting in results that are as precise as possible for determining the state of a crop field. For future crop type mapping investigations, researchers will investigate ways to include hierarchical segmentation into the overall framework. Additionally, multi-temporal data and multispectral band fusion within a multi-scale contour detection approach need to be studied further.

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