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Enhancing Remote Sensing Image Quality through Data Fusion and Synthetic Aperture Radar (SAR): A Comparative Analysis of CNN, Lightweight ConvNet, and VGG16 Models

Desynike Puspa Anggreyni[1], Indriatmoko[2], Aniati Murni Arymurthy[3], Andie Setiyoko[4]
[1,2,3]Faculty of Computer Science, Universitas Indonesia, Depok, Indonesia
[4]Research Center for Remote Sensing, Indonesia National Research and Innovation Agency, Jakarta, Indonesia

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ABSTRACT

Remote sensing technology benefits many parties, especially for carrying out land surveillance with comprehensive coverage without needing to move the equipment close to photograph the area. However, this technology needs to improve: the image quality depends on natural conditions, so objects such as fog, clouds, and smoke can interfere with the image results. This study uses data fusion techniques to enhance the quality of remote-sensing images affected by natural conditions. The method involves using Synthetic Aperture Radar (SAR) to combine adjacent satellite images from different viewpoints, thereby improving image coverage. Three image classification models were evaluated to process the fused data: Convolutional Neural Network (CNN), Lightweight ConvNet, and Visual Geometry Group 16 (VGG16). The results indicate that all three models achieve similar accuracy and execution speed, namely 0.925, with VGG16 demonstrating a slight superiority over the others, namely 0.90.

Desynike Puspa Anggreyni,
Faculty of Computer Science, Universitas Indonesia, Depok
Jl. Lingkar, Pondok Cina, Kecamatan Beji, Kota Depok, Jawa Barat, Indonesia. 16424
Email: desyanggreynii@gmail.com

1. INTRODUCTION

Remote sensing technology helps process information in a large area quickly. With the ability to measure images in such a way, an expert can obtain information about objects or phenomena on the earth's surface without any direct physical contact [1]. The comprehensive observation area coverage makes technological capabilities diverse, so the output produced also varies according to needs. This capability reduces the time explicitly required for industries with a broad scope, such as mining, agriculture, and weather.

An analyst can use classification techniques when using remote sensing images, primarily to make decisions based on groups of data. Classification works by grouping or labeling pixels in remote sensing images based on specific characteristics [2]. Analysts can identify various features or objects in the observed area with classification. This way, users can understand and interpret the environment more deeply by detecting soil, vegetation, water, or infrastructure.

Synthetic Aperture Radar (SAR) is a technology in remote sensing. SAR works in that each pixel in the radar image represents the energy intensity value of the object reflected to the satellite sensor [3]. SAR data has dimensions of height, width, and polarization. The essential components in SAR are wavelength, polarization, and angle of incidence. SAR imagery has several advantages, such as all-weather acquisition capabilities, day and night, sensitivity to dielectric properties, surface roughness, and the ability to penetrate clouds so that the output from SAR is rich in spectral and spatial information [4]. The most significant advantage of SAR data compared to other optical data in remote sensing is that it is not affected by weather conditions and can see through clouds and, to some extent, vegetation.

In general, remote sensing images can be divided into traditional and deep learning. Conventional methods are proposed to obtain more flexible and general features, such as sparse coding and fisher features [5], to adapt to the universal appropriation of different applications. Although this approach has provided good results for remote sensing scene classification, as remote sensing scene recognition becomes more challenging, the ability to express low-level image features becomes very limited [6]. On the other hand, deep learning methods promote image recognition through classification methods that are much more accurate and faster than traditional methods. Also, classification methods using deep learning can increase image brightness or accuracy.

Data fusion techniques can also help improve image accuracy, complementing deep learning classification techniques. Data fusion is a process dealing with data and information from multiple sources to achieve refined/improved information for decision-making [7], [8]. A general definition of image fusion is `Image fusion, which is the combination of two or more different images to form a new image using a certain algorithm'. Data fusion has become a rapidly growing subject because of its advantages, which facilitate scientists in extracting knowledge and relevant information from the data. Data fusion is an approach oriented to information extraction that has been adopted in several domains. It is based on the synergetic exploitation of data from sources such as [9]. It aims to produce a better result than the one obtained by separately exploiting the same sources [10]. Integration between data is crucial to create continuity of information. Complementary relationships between data create a more comprehensive range of information and increase the value of the analysis results [11]. Data fusion processing is also not a new thing in science. For example, meteorologists predict the weather for several decades.

Remote sensing (Observation of the Earth's surface from an airplane and satellite) has been done for a long time and is relevant to data fusion. Data fusion combines multiple measurements and the quality of information processed during fusion [5]. Data fusion works by taking satellite images from several different sources and integrating them into one part. Usually, data fusion in satellite imagery is needed for in-depth and extensive observations over a large area, such as in earth observation. In addition, the most essential problem in data fusion is the calculation of weight maps that integrate pixel activity information from various sources. This issue can be helped by deep learning techniques for image classification, such as research [12], which successfully overcomes the difficulties of robust activity level and weight assignment strategies using Convolutional Neural Network (CNN) to encode direct mappings from source images to weight maps.

Several previous studies have discussed the classification of remote sensing data using combined datasets. Research [7] utilizes CNN-based for combined and classified SAR and optical data, using Sentinel 1 (VV and VH polarization) and Sentinel 2, which obtains the region near Hisar (India) in a variation of 2D-CNN based on the pyramid fusion method, namely IVF (Infrared and Visible Image Fusion), MEDF (Medical Image Fusion), MFF (Multi Focus Fusion), and ROLP-IVF (Ratio of Laplacian Pyramid – IVF) to compare the results of this study also varied the Sentinel 1 and Sentinel 2 bands. The classification results were analyzed using the Overall Accuracy and Kappa Coefficient, while PSNR, SSIM, ERGAS, SAM, and UIQI were used as fusion parameters.

Study [7] used CNN for feature extraction from Sentinel data fusion, which focuses on estimating the normalized difference vegetation index (NDVI) using Sentinel 1 and Sentinel 2 time series obtained in the Burkina Faso region. The CNN model is trained to estimate missing optical features through data fusion and deep learning by using NDVI at time (t) as feature input as a stacking of Sentinel 1 and Sentinel 2 time series. The results are analyzed using Mean Absolute Error (MAE), Peak Signal Noise Ratio (PSNR), and Structural Similarity Index (SSIM). Research [13] has researched the sentinel 2 area in Semarang, Indonesia; this area was chosen because of its cloud cover and geographical and topographic characteristics. CNN performs sentinel dataset 2 as a land cover classifier. Sentinel 2 is utilized using eCognition to extract several features in several bands of Sentinel 2; each feature is color, hue, texture, and shape and then transformed into NDVI (Normalized Difference Vegetation Index), brightness, GLCM homogeneity, and rectangular suitability.

The author significantly contributed to advancing remote sensing technology by addressing image quality limitations due to natural conditions. The author proposed an innovative solution using data fusion to enhance Synthetic Aperture Radar (SAR) imagery, which combines multiple satellite images from different viewpoints to improve image coverage. Of the previous studies, no research specifically discusses classification using data fusion techniques for SAR data, especially for remote sensing. Therefore, the author developed research using image classification, namely CNN [14], which was also compared with algorithms derived from CNN, namely Lightweight ConvNet and Visual Geometry Group 16 (VGG16) as a comparison [15], [16]. The algorithm developed is then run on the image dataset that has been collected, and the accuracy values and processing speed of the algorithm are compared with each other. The results of this research are expected to provide an alternative methodology for image classification, especially on SAR data obtained from remote sensing.

2. METHOD

The researcher conducted the dataset from Sebastianelli; the dataset was extracted from Google Earth Engine (GEE); the dataset contains 500 pairs of Sentinel-1 and Sentinel-2, which is formed of 100 samples for each class; there are five classes for the CNN fusion classification: River, Lake, Coastline, and City. The dataset is freely open-accessed in (https://github.com/alessandrosebastianelli/S1-S2-DataFusion) [17]. The dimensions of the SAR data images are 64x64x2 for width x height x polarisation type. An example of a dataset processed by the author is in Figure 1. At the same time, the dimensions for multispectral data are 64x64x12 for width x height x number of bands. Both sentinel-1 and sentinel-2 data were obtained from the Google Earth Engine (GEE) catalog through a tool developed by Sebastianelli, which contains the full Sentinel-1 archive of Ground Ranged Detected (GRD) products and the Sentinel-2 archive of Level-2A multi-spectral products.

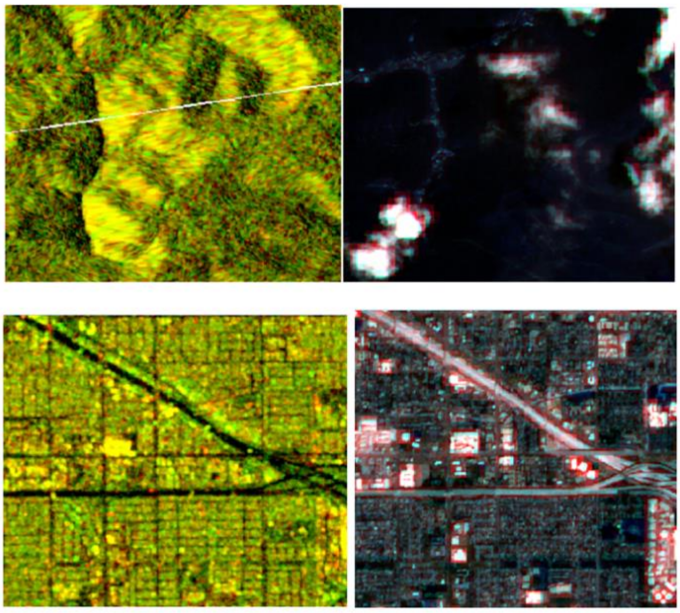

Figure 1. Sentinel 1 and Sentinel 2 Dataset Picture

Image fusion is a tool to combine multisource imagery using advanced image processing techniques. It aims to integrate disparate and complementary data to enhance the information apparent in the images and increase the reliability of the interpretation. This leads to more accurate data [18] and increased utility [19]. It is also stated that fused data provides robust operational performance, i.e., increased confidence, reduced ambiguity, improved reliability and classification.

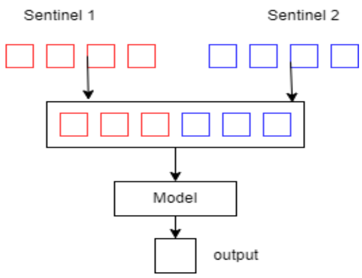

Figure 2. Early Fusion Model Architecture

With the model illustrated in Figure 2, the authors fused Sentinel 1 and Sentinel 2 within the paradigms of fusion methods are (1) Early fusion, (2) Joint Fusion, and (3) Late Fusion; based on this previous study, the early fusion consists in the use of one model that takes the aggregation of Input A and Input B as input and returns. The joint fusion and late fusion combined the result from Sentinel 1 and Sentinel 2 classifiers at the end of the CNN structure, so in this study, authors are using the early fusion method with a variation of CNN algorithms, such as VGG16 and Lightweight ConvNet [20]. The results of [20] showed that Lightweight ConvNet can handle 12 classes of Landsat 8 images, reducing the training times; the modified Lightweight ConvNet uses 30% Gaussian Dropout to reduce overfitting and the training time. So, we adopted this to see the effect of various deep learning structures of fusing Sentinel 1 and Sentinel 2 imagery.

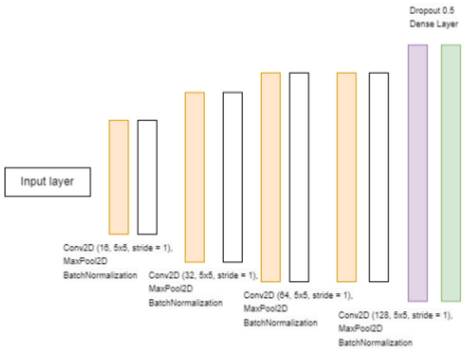

Figure 3. CNN Base Model Architecture

The authors used the same training parameters for the SAR data classifier model as for multispectral data. The values used for the CNN experiment, as depicted in Figure 3, are:

a. Optimizer: RMSprop
b. Learning rate: 0.001
c. Disadvantage: categorical cross-entropy
d. Metrics: accuracy, recall, precision, and omission errors
e. Age: 10
f. Batch size: 16

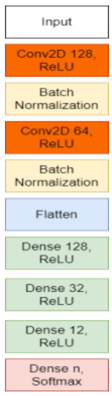

Figure 4. Lightweight ConvNet Architecture

Before combining the Sentinel 1 and Sentinel 2 images, the author performed feature extraction for Sentinel 1 and Sentinel 2, respectively, and then combined them into the initial fusion method. The author extracts these features and then combines them in the convolutional branch of CNN, Lightweight ConvNet (as depicted in Figure 4), and VGG16 (as shown in Figure 5), where the difference between these algorithms lies in the layers and dropout networks.

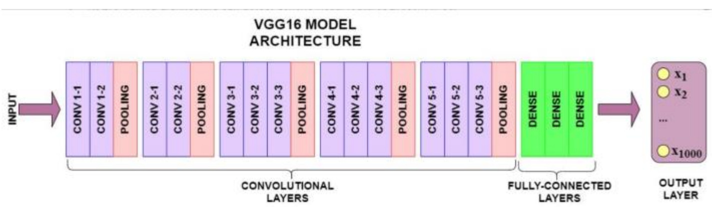

Figure 5. VGG16 Architecture

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In the CNN algorithm, the author uses a dropout layer of 0.5. In contrast, in Light ConvNet, the author uses Gaussian dropout 0.3 as [20] proposed for Land Use and Land Cover (LULC) using Landsat 8 imagery with 13 channels. Additionally, [20] proposed reducing training time, although they did not report training time. Therefore, the author will investigate the training time used in the output. The authors also compared other algorithms, such as VGG16, so we know the effectiveness between different neural network layers for data fusion models, as depicted in Figure 4. The authors also analyzed the results using accuracy metrics and error omissions. Omission error refers to the clearcut area not identified by the algorithm in [21]. In other words, Omission error counts the number of pixels left behind. Class of land use/cover evaluated.

3. RESULT

Table 1 presents the results of image processing from Sentinel-1 and Sentinel-2 and finally merging the two through object fusion. The accuracy results for each dataset per model are obtained by calculating the average accuracy value for each map object, such as City, Coastline, Lake, River, and Vegetation. This calculation shows that the general results are shaped by each specific object [22].

Table 1. Accuracy of CNN, Lightweight ConvNet, and VGG16 on All Datasets

Algorithm	Dataset	City	Coastline	Lake	River	Vegetation	Avg
CNN	**Sentinel-1**	0,9375	0,875	0,9375	0,9375	0,9375	0,925
	Sentinel-2	0,9375	0,9375	0,8125	1	0,9375	0,925
	Early Fusion	1	1	0,8125	1	0,9375	0,925
Lightweight ConvNet	**Sentinel-1**	1	0,875	0,875	1	1	0,95
	Sentinel-2	0,875	0,9375	0,8125	0,9375	0,9375	0,90
	Early Fusion	1	0,875	0,8125	0,875	1	0,925
VGG16	**Sentinel-1**	1	1	0,8125	1	0,9375	0,925
	Sentinel-2	0,9375	1	0,875	0,875	0,9375	0,925
	Early Fusion	0,9375	1	0,8125	0,8125	0,9375	0,90

Table 1 compares the accuracy of three different algorithms—CNN, Lightweight ConvNet, and VGG16—across various datasets and environmental categories. The datasets used include Sentinel-1, Sentinel-2, and an Early Fusion dataset. Each dataset is evaluated for its accuracy in recognizing six categories: City, Coastline, Lake, River, Vegetation, and an overall average accuracy (Avg). The accuracy values are represented as proportions, where 1 denotes 100% accuracy, and 0.9375 denotes 93.75% accuracy.

The CNN algorithm's results in Table 1 show consistent performance across the different datasets, achieving an average accuracy of 0.925. Specifically, it performs best in recognizing features from the Early Fusion dataset with perfect accuracy (1) in the categories of River and Vegetation. CNN's performance is slightly less robust when dealing with the Sentinel-2 dataset, particularly in the Lake category, which drops to 0.8125. However, its performance in other categories remains consistently high, demonstrating its robustness across diverse data sources.

The Lightweight ConvNet and VGG16 algorithms exhibit different strengths and weaknesses. Lightweight ConvNet shows a high average accuracy of 0.95 on the Sentinel-1 dataset but performs slightly less effectively on the Sentinel-2 and Early Fusion datasets, with average accuracies of 0.90 and 0.925, respectively. Notably, VGG16 achieves perfect accuracy in all categories for the Sentinel-1 dataset. Still, it shows a slight decrease in performance in the Early Fusion dataset, particularly in the Lake category, resulting in an average accuracy of 0.90. This comparative analysis highlights the varying strengths of each algorithm depending on the dataset and specific environmental category, indicating that certain algorithms may be better suited for specific types of satellite data or environmental feature detection.

As mentioned in the research methodology, the author also measured the execution speed of each model and dataset in this research.

Table 1. Training time averages between the algorithms

Algorithm	Training Average Time		
	CNN	**Lightweight ConvNet**	**VGG16**
Sentinel 1	1897 s	2164 s	**3737 s**

Sentinel 2	9992 s	3536 s	**2674 s**
Early Fusion	**5000 s**	**5234 s**	**5128 s**

Table 2 displays the average training times (in seconds) for three algorithms—CNN, Lightweight ConvNet, and VGG16—across three datasets: Sentinel-1, Sentinel-2, and an Early Fusion dataset. This comparison provides insight into each algorithm's computational efficiency and resource demands when processing different types of satellite data.

The CNN algorithm demonstrates the shortest training time for the Sentinel-1 dataset at 1897 seconds. However, its training time increases significantly for the Sentinel-2 dataset, reaching 9992 seconds, the highest time recorded in the table for any dataset. For the Early Fusion dataset, CNN's training time is 5000 seconds, indicating a moderate processing demand. This variation suggests that while CNN can be efficient for certain types of data, it may require substantial computational resources for others, particularly when dealing with more complex or larger datasets.

Lightweight ConvNet shows a relatively balanced training time across the datasets, with 2164 seconds for Sentinel-1, 3536 seconds for Sentinel-2, and 5234 seconds for the Early Fusion dataset. Although it has a longer training time than CNN for the Sentinel-1 dataset, it is significantly faster for Sentinel-2. VGG16, on the other hand, has the longest training time for the Sentinel-1 dataset at 3737 seconds but performs more efficiently on Sentinel-2 with a time of 2674 seconds. Its training time for the Early Fusion dataset is 5128 seconds, which is comparable to Lightweight ConvNet. These results indicate that while VGG16 and Lightweight ConvNet may be more consistent in training times across different datasets, VGG16 tends to have higher computational demands overall.

The table highlights the trade-offs between training time and algorithm choice for satellite data processing. CNN may offer faster training times for simpler datasets but could be less efficient for more complex data. Lightweight ConvNet provides a balanced approach with reasonable training times across datasets, making it a versatile choice. VGG16, although more resource-intensive, shows promise in handling complex datasets like Sentinel-2 more efficiently. These insights can guide the selection of algorithms based on the specific requirements of computational resources and dataset complexity in practical applications.

4. DISCUSSION

Based on the final results of the algorithm run in Table 2, the author found that the most extended Early Fusion value was Lightweight ConvNet, which VGG16 followed. The speed disparity between algorithms is more contrasting in the analysis for the Sentinel-2 dataset, where CNN is the slowest with a speed of over 9000 seconds, while VGG16 is only around 2000 seconds. In the Sentinel-1 dataset, the authors did not find significant differences like Sentinel-2 because it still ranged from 1000 to less than 3000 seconds between algorithms.

Based on the results of processing all datasets shown in Table 1, the accuracy obtained is uniform, above 90 percent. Also, several accuracy values are precisely the same between datasets, such as those found in the CNN algorithm. Uniquely, in Early Fusion, only the VGG16 algorithm has a different accuracy value compared to the other two algorithms, namely 90%, which is also the highest among all algorithms. So, the results obtained using the Sentinel 1, Sentinel 2, and Early Fusion datasets are excellent when processed with all the models proposed by the author.

Next, the author explains the measurement results of the running time of each algorithm used and its relationship to algorithm accuracy. On the Sentinel 1 dataset, the CNN algorithm is better at processing the model in terms of speed. However, in terms of accuracy, it still needs to be improved to the Lightweight ConvNet algorithm. The new Lightweight ConvNet algorithm is again superior in Early Fusion data accuracy after the highest accuracy was still held by two other algorithms in Sentinel 2. Sentinel 2 has data types long enough to process by machines. These results are shown in Table 2, where the Sentinel 2 results by CNN reached 9992 seconds. This condition can occur due to CNN, which has more layered data structures and is heavier in model size than the other two models [23]. Uniquely, in Early Fusion data, the algorithm most efficient in carrying out the process is CNN. In this way, the Lightweight ConvNet algorithm is always in the middle of other algorithms regarding processing speed.

In general, from the results of model accuracy and processing speed, with a slight difference, VGG16 is the best algorithm for processing SAR data, especially when processing using Early Fusion. VGG16 was ranked 1st for data processing speed but, on the other hand, was second in Early Fusion data processing. The CNN and Lightweight ConvNet algorithms are by no means foul. The results are close between one algorithm and another regarding model accuracy and execution speed, making these three algorithms suitable for further processing.

The author's method does not include data preprocessing. The values listed in Table 1 and Table 2 may change because the data preprocessing process takes time. However, these results are not very significant because, in principle, the three proposed models have the same basis, namely, the convolution basis. With the same base, the techniques used are the same, but the difference lies in how the layers and matrices are arranged in the layers used.

In short, the data fusion method to improve research results for remote sensing data is very possible. Also, compared to using only one data source for analysis, data fusion is still faster in execution, as shown in Table 2. Data execution speed in Sentinel 2 is still longer on average than data execution in Early Fusion, even the execution speed in Early Fusion only differs by less than 300 points between each algorithm, which is still smaller than the comparison between algorithms on the Sentinel 1 dataset which reaches less than 2000 points.

Previous studies have explored the classification of remote sensing data using fused datasets, focusing on various fusion methods and feature extraction techniques. For example, the study [7] used a CNN-based model to classify SAR and optical data from Sentinel-1 and Sentinel-2 in the Hisar region, India. The authors complement the results of the study [7] with other aspects in the form of the ConvNet algorithm that is able to improve the quality of image processing. In addition, the authors also complement the form of research [13] which only extracts color, hue, texture, and shape features into more detailed points and lines. The authors provide a detailed analysis of the performance of the algorithms on remote sensing data, highlighting the differences in processing speed and accuracy across CNN, Lightweight ConvNet, and VGG16 algorithms. The findings of this study that are novel in the study emphasize the effectiveness of the data fusion method in improving the speed and accuracy of execution, which makes a significant contribution to optimizing remote sensing data processing.

The research contributions include a comprehensive analysis of algorithm performance in processing satellite data, specifically focusing on CNN, Lightweight ConvNet, and VGG16 algorithms. Examining the accuracy and training times across Sentinel-1, Sentinel-2, and Early Fusion datasets, the author demonstrated that while all three algorithms achieve high accuracy above 90%, there are notable differences in their processing speeds. Despite being the fastest on the Sentinel-1 dataset, CNN has significantly higher processing times for Sentinel-2 due to its complex layered data structure. Conversely, VGG16, although slower in some instances, consistently achieves high accuracy and efficient processing times, particularly in Early Fusion data. The findings highlight that data fusion methods enhance execution speed and accuracy, making using multiple data sources advantageous over single data source analysis. This research underscores the nuanced trade-offs between algorithm complexity, accuracy, and computational efficiency, providing valuable insights for optimizing remote sensing data processing.

5. CONCLUSION

Based on the results discussed in Chapter 4, it can be concluded that the three algorithms proposed for this research, namely CNN, Lightweight ConvNet, and VGG16, have good positive results regarding processing speed and model accuracy. Looking more closely, VGG16 is better than the other two models because it has higher accuracy and faster processing speed, even with a number gap below zero point. Therefore, data fusion techniques positively impact research into classifying SAR data from remote sensing. The researcher demonstrated the effectiveness of deep learning models—specifically Convolutional Neural Network (CNN), Lightweight ConvNet, and Visual Geometry Group 16 (VGG16)—in classifying SAR data, showing that VGG16 slightly outperforms the other models in accuracy and execution speed. This research enhances the accuracy and reliability of remote sensing data and opens new avenues for applying deep learning techniques in remote sensing, particularly for SAR datasets.

Not only that, data fusion does not show any significant differences in processing speed either between algorithms or between the datasets that make it up. The data fusion algorithm is more likely to be stable if passed through the three types of algorithms. This shows that the act of data fusion does not change the data structure but, on the other hand, adds value to the data itself due to the addition of new perspectives and new information.

From the results of this research, another thing that can be reviewed in future research is measuring the comparison of accuracy and level of overfit in each algorithm and dataset. That way, the author can determine with greater certainty which algorithms can be used for various types of SAR datasets, especially objects in remote sensing that change very often because they are natural objects.

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