SAR IMAGE CLASSIFICATION USING DEEP LEARNING

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ABSTRACT

This paper tackles the complex problems of low contrast and speckle noise in synthetic aperture radar (SAR) image categorization. We suggest a unique method that makes use of Generative Adversarial Networks (GANs) to create synthetic SAR images for training deep learning (DL) models, namely Convolutional Neural Networks (CNNs), by utilizing the power of DL. The CNN performs better when it comes to classifying SAR photos because the GAN is trained to produce a variety of synthetic images for various classifications. Using the MSTAR dataset, a thorough analysis shows an astounding 98.5% accuracy, proving the state-of-the-art status of our method. This shows that GANs may be used to enhance DL models in an efficient manner, opening the door to useful SAR image categorization systems that have a great deal of potential for real-world use. The frameworks TensorFlow and Keras are used in the implementation.

Keyword: - *GAN-Generative Adversarial Network, CNN-Convolution Neural Network, DL-Deep Learning, MSTAR dataset, Keras, TensorFlow.*

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1. INTRODUCTION

Due to intrinsic features such speckle noise and low contrast, characterizing SAR pictures is particularly challenging. neural networks with convolutions in recent years, CNNs—a subset of deep learning technology—have shown a great deal of promise for enhancing picture classification. However, the vast and varied training datasets needed for deep learning algorithms might not be easily accessible in most applications. To overcome the lack of labeled training data, our proposed method uses generative adversarial networks (gans) to generate produced SAR images, which are subsequently utilized to train CNNs. This innovative strategy aims to deliver state-of-the-art performance to CNN.

Training a GAN to generate synthetic SAR images that fall into many classifications is the primary phase in our procedure. The CNN model is then trained using these artificial images and the Keras and TensorFlow frameworks. The stability of our method is demonstrated with an outstanding 98.5% accuracy on the demanding MSTAR dataset. The efficacy of this GAN-enhanced DL model demonstrates how useful and successful it may be in advancing the field of SAR picture categorization and points to its potential for real-world applications.

2. EXISTING SYSTEM CLASSIFICATION METHODS

For classifying SAR images, other classification models have been investigated in addition to our suggested GAN-enhanced CNN method. Customized feature extraction approaches are sometimes combined with machine learning algorithms like Random Forests and Support Vector Machines (SVMs) in traditional ways. Even though these techniques are effective, they might not be able to handle the complexity and unpredictable nature of SAR images, particularly in difficult datasets such as MSTAR.

Deep learning models, especially CNNs, have been more popular in SAR image categorization recently because of their capacity to automatically learn hierarchical features. SAR data has been processed using standard CNN architectures such as VGG, ResNet, and Inception, with some instances yielding competitive results. Another method to use information from other datasets is transfer learning, which involves optimizing models that have already been trained on optical pictures for SAR tasks.

2.1 LIMITATIONS OF EXISTING SYSTEMS

The inherent difficulties of SAR imaging are frequently too much for the current SAR image classification systems to handle, especially those that depend on conventional deep learning models or classical approaches. Adapting to the diversity found in SAR photos, reducing speckle noise, and dealing with poor contrast are some of these issues. SAR data contains complex and hierarchical patterns that may be difficult for traditional approaches that rely on created characteristics to capture. Furthermore, the optimal performance of many deep learning models depends on large and diverse labelled datasets, which is often a restriction in SAR applications due to data scarcity. The models' overall efficacy in obtaining high accuracy and robust performance may be limited by their reliance on pre-existing structures and techniques, which may make them less flexible to the distinctive features of SAR imagery.

3. PROPOSED SYSTEM

Generative Adversarial Networks (GANs) are utilized in our proposed system to enhance data, hence introducing a novel approach to SAR image categorization. To create synthetic SAR images that mimic the various classes found in the target dataset, a GAN is trained in this system. Convolutional neural networks (CNNs) are trained on this artificial dataset for SAR image classification, after it has been enhanced using GAN.GANs are essential for mitigating the drawbacks of conventional SAR datasets, which include low contrast, few labeled samples, and speckle noise. The CNN receives a more comprehensive and diversified dataset from the GAN's diverse synthetic picture generation, which improves the CNN's capacity to effectively categorize and generalize real-world SAR images.The CNN is then trained using this enhanced dataset, where it picks up hierarchical patterns and characteristics from both artificial and real-world samples. The CNN's robustness and performance in difficult situations are enhanced by the addition of GAN-generated data, which helps it better adapt to the special properties of SAR imaging.

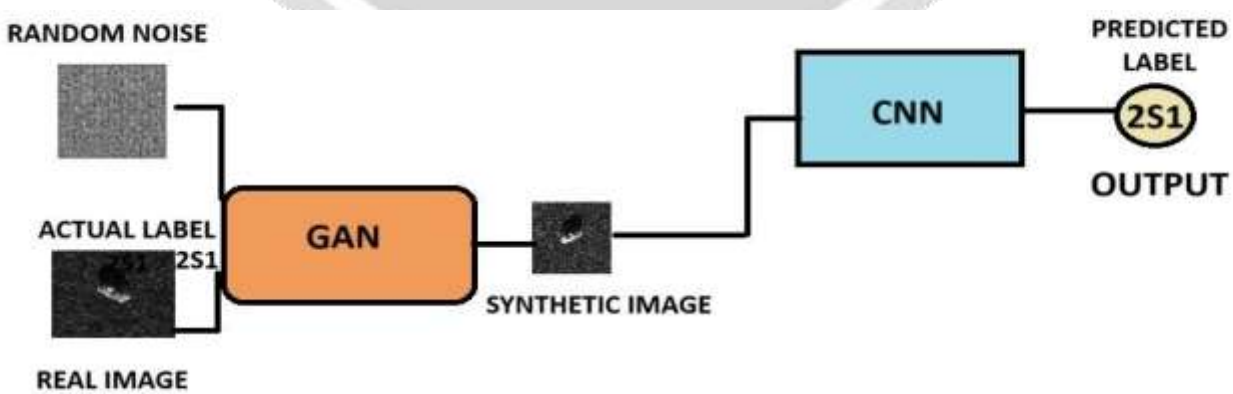

Fig -1: Flow Chart of project

3.1 REQUIREMENTS

- **Google co-lab:** Google Colab is a free cloud-based platform by Google for collaborative Python coding. It offers a Jupyter notebook interface, runs entirely in the cloud, and provides access to powerful computing resources like GPUs and TPUs. Users can seamlessly save and share their work via integration with Google Drive.

- **MSTAR DATASET:** A popular set of synthetic aperture radar (SAR) pictures for target detection and classification studies is the MSTAR (Moving and Stationary Target Acquisition and detection) dataset. Images of military vehicles and targets are commonly included in the MSTAR collection. The MSTAR dataset comprises 11 classifications that correspond to various kinds of military vehicles and equipment.

- **TENSORFLOW AND KERAS:** SAR image classification project is centered around TensorFlow and Keras, which facilitate the creation and training of both Generative Adversarial Network and Convolutional Neural Network models. As the open-source deep learning framework of choice, TensorFlow offers versatility in terms of neural network design implementation, computation optimization, and model deployment across a range of hardware. With its high-level API that is integrated with TensorFlow, Keras makes the process of generating models simpler by providing an intuitive interface and complexity abstraction to facilitate effective prototyping and experimentation. When used in tandem, these resources give our project access to cutting-edge deep learning capabilities, guaranteeing scalable and reliable SAR picture classification.

- **numpy:** It is a powerful Python library for numerical computing, providing support for arrays, matrices, and mathematical functions. It offers efficient operations on large datasets, making it essential for scientific computing, data analysis, and machine learning tasks. NumPy's array-oriented computing capabilities enable faster execution of mathematical operations compared to traditional Python lists, making it a cornerstone library in the Python ecosystem for numerical computing tasks.

3.2 CGAN IMPLEMENTATION:

1. Our proposed Generative Adversarial Network (GAN) architecture for image generation comprises a generator and a discriminator in an adversarial training framework.

2. The generator network employs densely connected layers with Leaky ReLU activations and reshaping operations to transform random noise, along with class information, into synthetic images.

3. Conversely, the discriminator is a Convolutional Neural Network (CNN) designed to distinguish between real and generated images, utilizing convolutional layers with Leaky ReLU activations and a final sigmoid activation for binary classification.

4. During training, the generator strives to produce images indistinguishable from real ones, while the discriminator aims to accurately classify between real and synthetic samples.

5. This adversarial process iteratively refines both networks, leading to a generator capable of producing realistic images that closely resemble real ones.

6. The combined GAN model integrates the generator and discriminator, with the discriminator's weights frozen to prevent further updates during joint training.

7. Trained end-to-end, the generator seeks to deceive the discriminator, while the discriminator learns to make more accurate distinctions.

8. Through this adversarial interplay, the GAN converges to a point where the generator generates authentic-looking images.

9. Loss functions and optimizers are configured to guide this adversarial learning process, ensuring the enhancement of the generator's ability to create synthetic images closely resembling real ones.

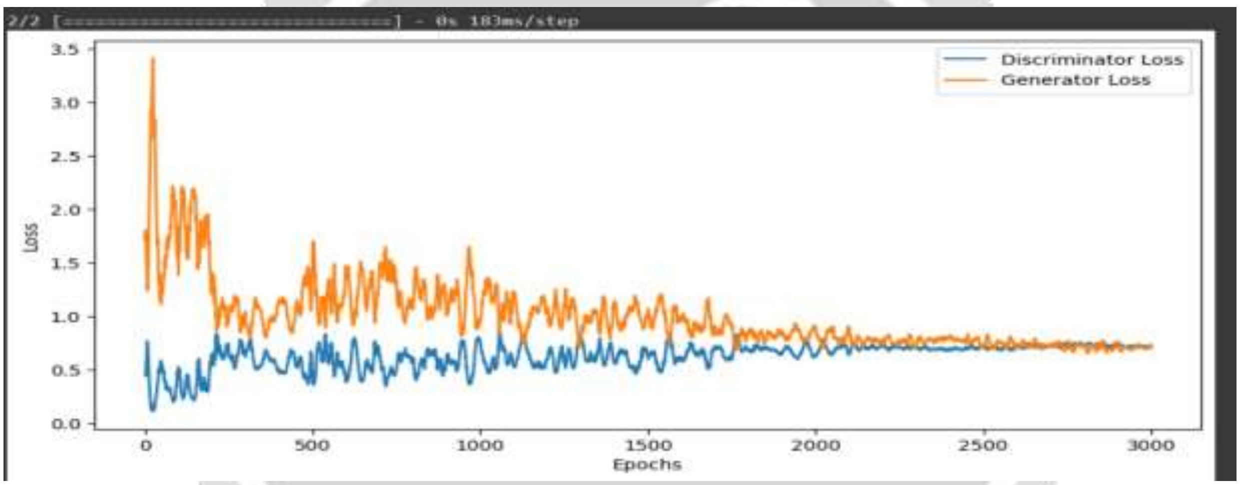

Fig -3: Losses plot of cGAN

Fig -4: Generated synthetic images of GAN

3.3 CNN IMPLEMENTATION:

1. Our convolutional neural network (CNN) model is structured as follows:

- Convolutional layers, starting with 32 filters of size (3, 3) and ReLU activation, followed by max-pooling.

- Subsequent reduction of complexity with additional convolutional layers (64 filters of size 3x3) and max-pooling.

2. The model further incorporates a flatten layer to prepare the data for dense layers.

3. Dense layers follow, including a layer with 128 neurons and ReLU activation, along with dropout regularization to prevent overfitting.

4. The output layer consists of 11 neurons with a softmax activation function, assuming 11 classes for classification.

5. The model is compiled using the Adam optimizer, categorical cross-entropy loss function, and accuracy as the evaluation metric.

6. The model summary is printed, providing an overview of the architecture, layer configurations, and parameters.

7. The GAN-generated synthetic images, enriched through adversarial training, serve as input to this CNN. These images, mimicking real data characteristics, enhance the dataset size and contribute to the CNN's ability to learn intricate patterns.

8. During training, the CNN aims to classify MSTAR dataset images based on the features learned from the GAN-generated synthetic data, improving the model's ability to handle SAR image classification challenges.

9. The CNN iteratively refines its parameters through backpropagation, optimizing its performance in discerning patterns in both real and synthetic data.

10. The end-to-end system, combining GAN-generated data augmentation and CNN classification, aims to achieve state-of-the-art performance on the MSTAR dataset, demonstrating the effectiveness of our proposed approach in SAR image classification.

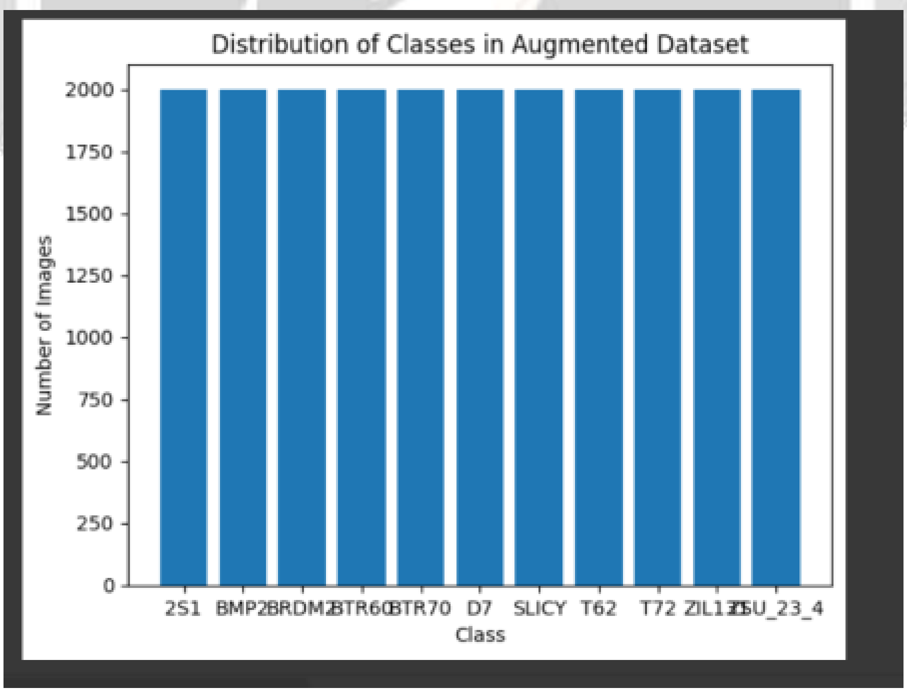

Fig -5: Input of CNN (augmented dataset generated by GAN)

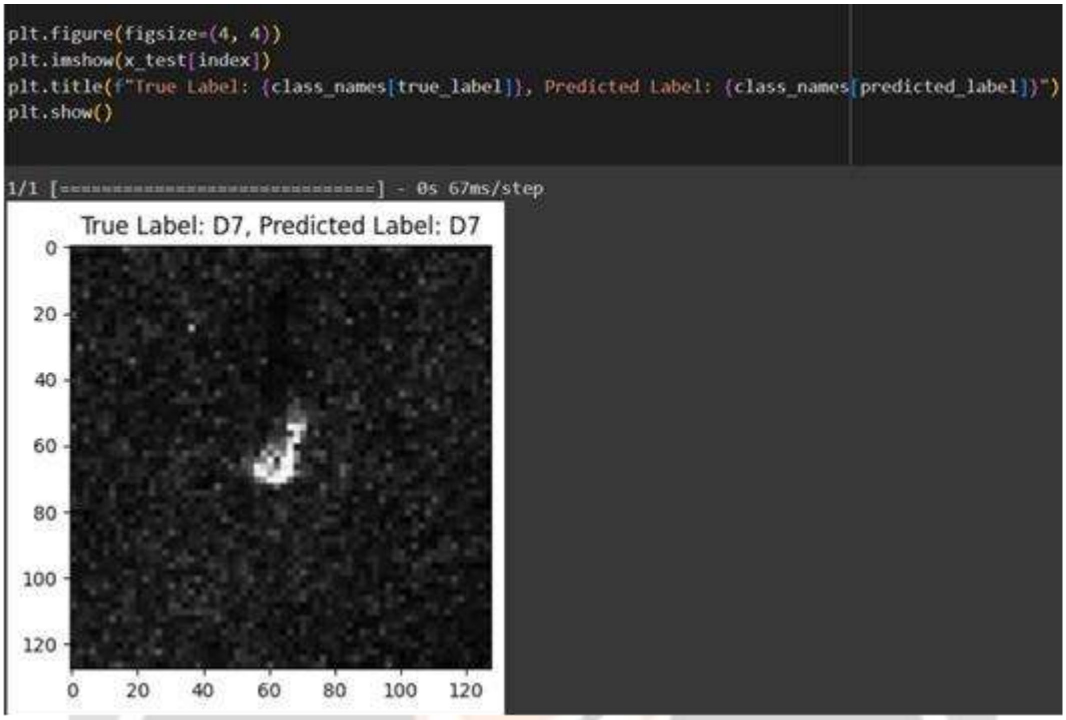

Fig -6: output of CNN

4. CONCLUSION

In conclusion, by utilizing a Generative Adversarial Network (GAN) for data augmentation, our study successfully addresses data shortage in SAR image categorization. The GAN significantly increases the original 242 picture dataset over 11 classes, producing an augmented dataset with 2000 photos per class. The capacity of the Convolutional Neural Network (CNN) model to recognize complex patterns in SAR images is greatly enhanced by augmentation.

Performance metrics demonstrate the effect of data augmentation: the poor accuracy of the original dataset significantly improves to an amazing 98% when using the GAN-generated augmented dataset. This demonstrates how well our method works to improve the CNN's learning ability, resulting in cutting-edge results on the difficult MSTAR dataset.

To sum up, the integration of CNN classification with GAN-generated synthetic data proves to be a powerful approach for SAR image classification. This highlights the ability of novel data augmentation methods to surmount constraints brought about by a scarcity of labelled data. This indicates the usefulness and efficacy of developing SAR image categorization systems.

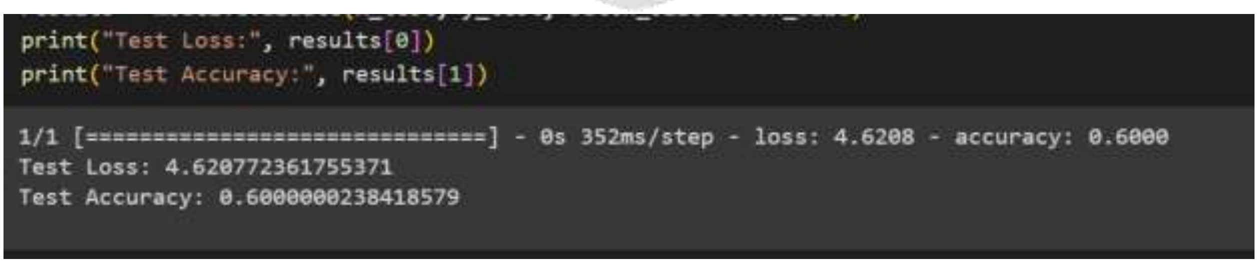

Fig -7: Test Accuracy(CNN) before using augmented dataset

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2/2 [==============================] - 1s 232ms/step - loss: 0.0362 - accuracy: 0.9833
Test Accuracy: 98.33%
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Fig -7: Test Accuracy(CNN) after using augmented dataset

5. REFERENCES

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