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A Comprehensive Framework for Improving Remote Sensing Image Classification: Combining Augmentation and Missing Pixel Imputation

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Abstract

Remote sensing image classification is crucial in various domains including agriculture, urban planning, and environmental monitoring. However, limited labeled data and missing pixels pose challenges to achieving accurate classification. In this study, we propose a comprehensive framework that integrates data augmentation using a latent diffusion model and reinforcement learning-based missing pixel imputation to enhance deep learning models' classification performance. The framework consists of three layers: data augmentation, missing pixel imputation, and classification using a modified VGG16 architecture. Extensive experiments on benchmark datasets demonstrate the significant impact of our framework, surpassing state-of-the-art techniques by significantly improving classification accuracy and robustness. The results highlight the effectiveness of our augmentation and imputation techniques, achieving remarkable Dice Score, Accuracy, and Recall metrics of 97.56%, 97.34%, and 97.34%, respectively. Our proposed framework provides a valuable solution for accurate remote sensing image classification, addressing the challenges of limited data and missing pixels, and has broad applications in various domains.
Keywords: VGG 16, convolution neural network, diffusion model, remote sensing, satellite image.

1. Introduction

Remote sensing plays a fundamental role in various applications, such as land cover mapping, environmental monitoring, and urban planning. These applications rely on the valuable information captured by sensors on satellites or aircraft, providing insights into the Earth's surface. Analyzing and interpreting remote sensing images are crucial for extracting meaningful information and making informed decisions. A key task in remote sensing image analysis is classification, where pixels or image patches are assigned to pre-defined categories such as vegetation, waterbodies, and built-up areas [1-2].

Conventional methods for remote sensing image classification often rely on manual feature engineering and statistical techniques. These approaches require domain expertise and may not capture the intricate patterns and relationships inherent in the data. However, in recent years, deep learning has emerged as a powerful approach for addressing various computer vision tasks, including remote sensing image classification. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional capabilities in autonomously learning discriminative features directly from raw data. This ability enables accurate and efficient classification without requiring extensive feature engineering or prior domain knowledge [3-4].

Despite the advantages of deep learning, applying it to remote sensing image classification presents challenges. Firstly, remote sensing datasets often suffer from a scarcity of labeled data, hindering effective training of deep models and potentially leading to overfitting. Secondly, remote-sensing images frequently contain missing pixels or regions due to factors like sensor limitations, cloud cover, or occlusions. The absence of pixel information can result in incomplete representations and adversely affect classification accuracy [5-7].

To address these challenges, researchers have explored various techniques to improve remote sensing image classification using deep learning. Two prominent approaches are data augmentation and missing pixel imputation. Missing pixel imputation techniques aim to fill in the gaps caused by missing data in remote sensing images. These methods leverage the spatial and spectral correlations present in the images to estimate and impute missing pixels. Deep learning algorithms, such as autoencoders and generative adversarial networks (GANs), have shown promising results in imputing missing information and reconstructing complete images [8-9].

In recent years, a novel technique called the Latent Diffusion Model (LDM) has emerged as a powerful method for data augmentation across different domains, including computer vision. The LDM utilizes probabilistic modeling to generate high-quality samples by gradually diffusing an initial noise vector through a series of diffusion steps. This process allows the model to capture the underlying data distribution and generate diverse and realistic samples for augmentation [10-11].

Our framework leverages advanced augmentation techniques to increase the diversity of the training dataset, leading to better generalization and robustness. Additionally, we introduce a novel missing pixel imputation strategy based on deep learning algorithms, effectively handling incomplete information in remote sensing images. The proposed framework aims to overcome the challenges posed by limited labeled data and missing pixels, advancing the capabilities of remote sensing image classification for improved decision-making and analysis.

The contribution of the paper are as follows:

1-The augmentation process using LDM solved the mode collapse and vishing gradient problem in traditional GANs.

2- The augmentation and pixel imputation enhance in increasing the accuracy of the classification process using different architectures of CNN.

3- The model achieves efficient accuracy in classification and pixel imputation.

4-The framework archives lower IS and high FID when compared to other augmentation methods.

The rest of the paper is organized as follows: section II presents the related work, section III presents the methodology, section IV presents the discussion and results, and section V introduces the conclusion.

2. Related Works

This section of the paper presents an overview of the related work in the field of remote sensing image classification, focusing on the use of different convolutional neural network (CNN) architectures and recent methods in augmentation and missing pixel imputation.

Convolutional Neural Networks (CNNs) have gained significant attention in remote sensing image classification due to their ability to automatically learn discriminative features from raw image data. Researchers have explored various CNN architectures and techniques to improve the classification performance of remote-sensing images [12].

Many papers provide comprehensive surveys of deep learning approaches and CNN architectures used for remote sensing image classification. These surveys discuss various CNN architectures, including AlexNet, VGGNet, and ResNet, and their applications in remote sensing. They also highlight the advantages and limitations of different CNN architectures in remote sensing image classification tasks [13-15].

Ahad et al. focus on the classification of high-resolution remote sensing imagery using CNN architectures. They compare the performance of different CNN architectures, including AlexNet, VGGNet, and GoogLeNet, for land cover classification. The study evaluates the accuracy and efficiency of these architectures and provides insights into their suitability for remote sensing image classification [16].

Haq et al. explore the use of deep learning-based feature representation for remote sensing image classification. They investigate multiple CNN architectures, such as VGGNet, ResNet, and DenseNet, and compare their performance in classifying remote sensing images. The study evaluates the advantages and limitations of these architectures and provides recommendations for selecting suitable models for different remote-sensing applications [17].

Zhou et al. focus on the classification of hyperspectral remote-sensing images using deep learning techniques. They introduce a stacked sparse autoencoder architecture and evaluate its performance for hyperspectral image classification. The study demonstrates the effectiveness of the proposed architecture in capturing spectral information and improving classification accuracy for hyperspectral remote sensing images [18].

Singh et al. propose the use of Generative Adversarial Networks (GANs) for data augmentation in remote sensing image classification. The authors train a GAN to generate synthetic images that mimic the distribution of real remote-sensing images. The generated images are then combined with the original dataset for training deep learning models, leading to improved classification performance [19].
Li et al. present a self-training approach for data augmentation in remote sensing image classification. The method involves iteratively training a deep learning model on the original labeled data and using the model to predict labels for unlabelled data. The predicted labels are treated as pseudo-labels and combined with the original labeled data for subsequent model training. This approach effectively utilizes unlabelled data for augmentation and improves classification performance [20].
Howe et al. focus on utilizing adversarial training for data augmentation in remote sensing image classification. The authors propose an augmented sample generation method using a conditional GAN. The GAN generates diverse and realistic augmented samples by conditioning on the original data. The augmented samples are then combined with the original dataset to train deep-learning models, resulting in improved classification accuracy [21].
Several studies have also addressed the problem of missing pixel imputation in remote-sensing images. Liu et al. propose a semantic inpainting approach using Generative Adversarial Networks (GANs) to impute missing data in remote sensing images. The authors train a GAN to generate realistic and semantically consistent missing regions based on the available context. The generated missing regions are then used to fill in the gaps in the original images, effectively restoring missing data [22].
Accion et al. introduce a missing data imputation method using Convolutional Neural Networks (CNNs) with spatial and spectral regularization for remote sensing images. Their proposed CNN architecture considers the spatial and spectral context to infer missing pixel values. The regularization terms ensure the smoothness of the imputed data and preserve the spectral characteristics. Experimental results demonstrate the effectiveness of the proposed method in accurately imputing missing data in remote sensing images [23].
Although, these works highlight various approaches, including GANs, CNNs, LSTM networks, and GNNs, for pixel imputation in remote sensing images. Researchers can refer to these studies to gain insights into the different methods and select appropriate approaches based on the nature of missing data and specific requirements of their remote sensing datasets, there are some limitations in terms of losing some of the image's details and their are some of the limitations in the term of accuracy [24-27].

3. Methodology

This study introduces a comprehensive methodology for improving the classification performance of deep learning models in remote sensing image analysis. The first step of the methodology involves data augmentation using a latent diffusion model. The remote sensing dataset is loaded, and the latent diffusion model is applied to generate augmented images by perturbing the latent space. These augmented images are then incorporated into the original dataset, effectively expanding its size, and diversifying its content. The application of the latent diffusion model addresses the challenge of limited labeled data in remote sensing image classification. By introducing variations through data augmentation, the proposed framework aims to enhance the robustness and generalizability of the learned features, thereby improving the overall classification performance.
To handle missing pixels in remote sensing images, the augmented dataset obtained from the previous stage is pre-processed. The missing pixels in the remote sensing images are identified, and a reinforcement learning model is trained to impute these missing pixels. The reinforcement learning model leverages its ability to learn from interactions with the environment to predict the values of the missing pixels based on the contextual information present in the observed images. Once the model is trained, it is employed to impute missing pixels in the dataset. This step ensures the completeness of the dataset and facilitates subsequent classification tasks, leading to more accurate reconstructions of the images and improved overall performance of the proposed framework.
For the classification stage, the pre-processed dataset, augmented and imputed, is subjected to further pre-processing. The dataset is split into training and testing sets to enable model evaluation. A modified VGG16 model, specifically tailored for remote sensing image classification, is initialized and trained using the training set. The model learns to extract relevant features from the augmented and imputed dataset, enabling it to make accurate predictions during the classification process. Following training, the model is evaluated using the testing

set, and classification accuracy and robustness metrics are computed. This stage allows for the assessment of the proposed framework's performance in terms of classification accuracy and its ability to handle robust classification tasks. The results obtained from this stage form the basis for a comprehensive discussion and comparison of the proposed framework with existing state-of-the-art techniques, highlighting the advantages and improvements achieved through the integrated approach. Fig.1 shows the block diagram of the proposed methodology.

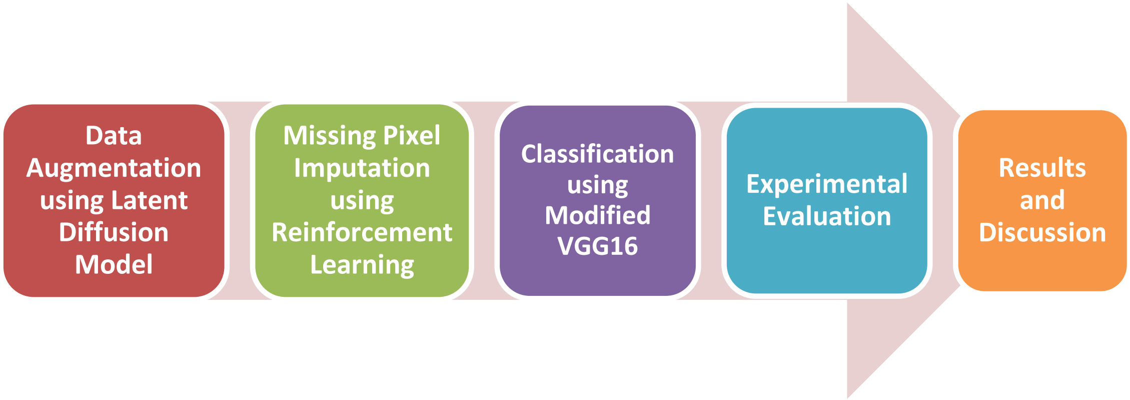

Fig.1. Block diagram of the proposed methodology

3.1 Data Augmentation Using Latent Diffusion Model

The first step in our methodology is to load the remote sensing dataset, which contains high-resolution images captured by remote sensing platforms. These images provide valuable information about the Earth's surface, including land cover, vegetation, and various environmental factors. The dataset includes images covering different regions and periods, enabling comprehensive analysis and understanding of the Earth's dynamics. To enhance the diversity and generalizability of the dataset, we employ the latent diffusion model for data augmentation. The latent diffusion model leverages the power of generative models, such as Variational Autoencoders (VAEs) or Generative Adversarial Networks (GANs), to learn the underlying latent space representation of the images. By exploring and perturbing the latent space, we can generate new and realistic variations of the original images.

Using the learned latent space representation, we perturb the latent vectors to generate augmented images. This process involves manipulating the latent variables to introduce meaningful changes while preserving the semantic content of the original images. By applying appropriate transformations and perturbations in the latent space, we can generate diverse samples that capture different variations in the remote sensing data, such as changes in illumination, weather conditions, or land cover.

Once the augmented images are generated, we add them to the original dataset. This expands the dataset and enriches it with additional samples that capture a broader range of variations in the remote sensing data. By combining the original images with the augmented images, we create a more comprehensive and diverse dataset for training and evaluating our remote sensing algorithms.

The architecture of a latent diffusion model often employs the U-Net architecture, which consists of an encoder-decoder structure with skip connections. The encoder downsamples the input image to encode it into a lower-dimensional feature space, while the decoder upsamples the features to reconstruct the original image. The skip connections help propagate information from the encoder to the corresponding decoder layers, facilitating the preservation of important details during the upsampling process. Fig. 2 shows the architecture of the Latent Diffusion Model.

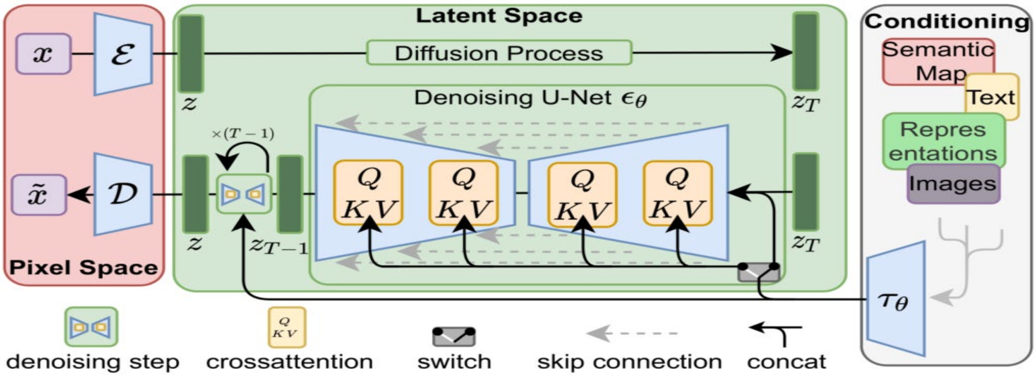

Fig.2. Architecture of Latent Diffusion Model

3.2 Pixel Imputation Using Reinforcement Learning

To begin, we pre-process the augmented dataset to handle missing pixels. Missing pixels can occur due to various factors such as sensor noise, data transmission errors, or cloud cover in remote sensing imagery. We identify and mark the locations of missing pixels in the augmented dataset, creating a subset of images with missing pixel regions.

Next, we employ image processing techniques and algorithms to accurately identify the missing pixels in the remote-sensing images. This step involves analyzing the image content, considering neighboring pixels, and detecting inconsistencies or anomalies that indicate missing pixel regions. By identifying the missing pixel locations, we obtain the necessary information to train a reinforcement learning model for imputation. To impute the missing pixels, we train a reinforcement learning model specifically designed for this task. Reinforcement learning provides a framework to learn an optimal policy for decision-making in sequential and uncertain environments. In our case, the reinforcement learning model learns to impute missing pixels by taking actions that maximize a predefined reward signal. The model is trained using a combination of the augmented dataset with missing pixel regions and corresponding ground truth images.

Once the reinforcement learning model is trained, we utilize it to impute missing pixels in the augmented dataset. For each image with missing pixel regions, the model takes as input the available information from the surrounding pixels and generates imputed values for the missing pixels. This process is performed iteratively, updating the missing pixel regions until convergence or a specified stopping criterion. The Missing Pixel Imputation using Reinforcement Learning Algorithm's pseudo-code is shown in Algorithm 1.

Algorithm 1 Pseudocode for Missing Pixel Imputation using Reinforcement Learning

```
    Input: Augmented dataset with missing pixels

1. Pre-process augmented dataset to handle missing pixels
2. Identify missing pixels in the remote-sensing images
3. Train a reinforcement learning model to impute missing pixels:
4. Initialize the reinforcement learning model
5. Set hyperparameters for training (e.g., learning rate, discount factor, exploration rate)
   For each training episode:
      Reset the environment state
      While the episode is not finished:
         Select an action based on the current state and policy
         Execute the action observe the next state and reward
         Update the Q-values based on the observed state, action, reward, and next state
         Update the current state to the next state
      End while
   End for
6. Use the trained model to impute missing pixels in the dataset:
   For each sample in the augmented dataset:
      For each missing pixel in the sample:
         Predict the value of the missing pixel using the trained model
         Replace the missing pixel with the predicted value
      End for
   End for
Output: Augmented dataset with imputed missing pixel.
```

3.3 Classification using Modified VGG16

To begin the classification process, we preprocess the augmented and imputed dataset to ensure compatibility with the modified VGG16 model. This involves standardizing the input images, such as resizing them to a fixed size and normalizing the pixel values, to facilitate effective model training and evaluation.

Next, we partition the preprocessed dataset into training and testing sets. The training set is used to train the modified VGG16 model, while the testing set is used to evaluate its performance. The dataset split ensures that the model's performance is assessed on unseen data, providing an unbiased evaluation of its classification capabilities.

We initialize a modified version of the VGG16 model, which is a popular convolutional neural network architecture known for its effectiveness in image classification tasks. The modified VGG16 model may incorporate adaptations or enhancements specific to the problem domain or experimental requirements, such as changes in the number of layers, kernel sizes, or activation functions.

The initialized modified VGG16 model is trained using the training set. During training, the model learns to extract relevant features from the input images and make accurate predictions regarding their class labels. This process involves iteratively updating the model's parameters using optimization techniques such as stochastic gradient descent and backpropagation.

Following model training, we evaluate the performance of the modified VGG16 model using the testing set. This evaluation involves passing the testing images through the trained model and comparing the predicted class labels with the ground truth labels. The evaluation metrics, such as classification accuracy, are computed to assess the model's ability to correctly classify images from unseen data.

To gauge the effectiveness and robustness of the modified VGG16 model, we compute various classification metrics. The primary metric is classification accuracy, which measures the proportion of correctly classified images in the testing set. Additionally, we may compute other metrics such as precision, recall, and F1 score to assess the model's performance across different classes. Robustness metrics, such as sensitivity analysis or adversarial attack evaluation, may also be employed to evaluate the model's resilience to perturbations or adversarial inputs. Table. 1 shows the architecture of the modified VGG16 for the classification of remote sensing images after imputation and augmentation using the latent diffusion model. Fig. 3 shows the block diagram of the Modified VGG 16.

Table.1 Architecture of Modified VGG16

Hyperparameter	Value
Number of Convolutional Layers	13
Number of Fully Connected Layers	3
Convolutional Kernel Size	3 x 3
Pooling Kernel Size	2 x 2
Number of Blocks	5
Block 1 Convolutional Layer Kernels	16
Block 1 Pooling Layer	Included
Block 2 Convolutional Layer Kernels	16
Block 2 Pooling Layer	Included
Block 3 Convolutional Layer Kernels	Varies (Different in each layer)
Block 3 Pooling Layer	Included
Block 4 Convolutional Layer Kernels	Varies (Different in each layer)
Block 4 Pooling Layer	Included
Block 5 Convolutional Layer Kernels	Varies (Different in each layer)
Block 5 Pooling Layer	Included
Number of Output Classes	2 (Land Cover Classes)

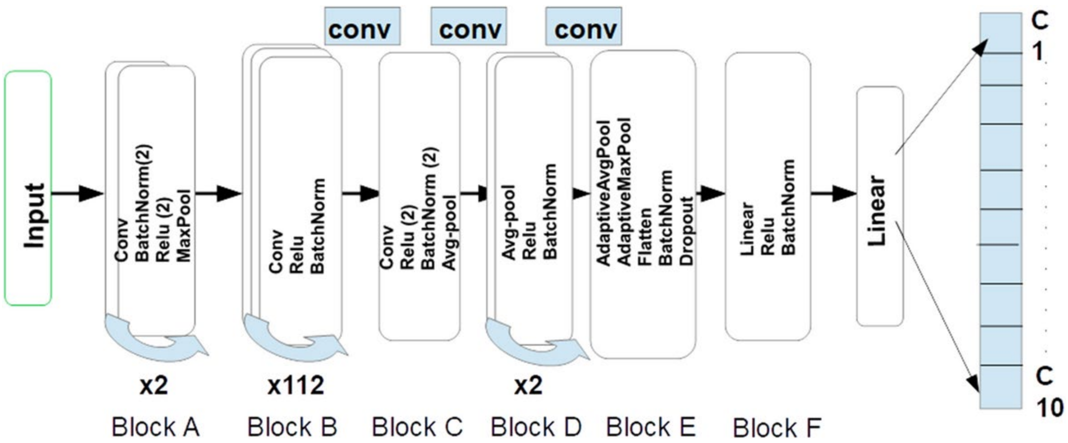

Fig.3. Block diagram of Modified VGG16

4. Results and discussion

In this section of the paper, the results of various frameworks are presented, including image augmentation through the latent diffusion model and pixel imputation using reinforcement learning. A comparison is made between different architectures in the classification process before and after the application of augmentation and pixel imputation techniques. The EuroSAT dataset is the first large-scale patch-based land use and land cover classification dataset based on Sentinel-2 satellite images. The EuroSAT dataset consists of 270 labeled images with 10 different land use and land cover classes. The model divides the images into 80% for training and 20% for testing. The evaluation of these models utilizes accuracy metrics such as Eqs. (1), (2), and (3). Additionally, recall accuracy and dice score are employed to compare the performance of different models in classification. All models are trained for 50 epochs using the Adamax optimizer, a learning rate of 0.0001, and the cross-entropy loss function.

$$Recall = \frac{TP_i}{TP_i + FN_i} \times 100\% \quad (1)$$

$$Accuracy = \frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i} \times 100\% \quad (2)$$

$$Dice\ Score = \frac{2 \times |\,\text{Precision} \times \text{Recall}\,|}{|\,\text{Precision} + \text{Recall}\,|} \times 100\% \quad (3)$$

Table 2 provides a comparison between the latent diffusion model and various versions of GANs in the context of remote sensing augmentation. The table demonstrates the superior efficiency of the latent diffusion model compared to different GAN architectures, based on the evaluation metrics of IS and FID. Additionally, Fig. 4 visually depicts the comparison between the latent diffusion model and GANs.

Table 2. Data augmentation comparison

Model	GAN	DCGAN	MG-GAN	PA-GAN	LDM
Inception score	12.343	13.566	13.018	13.765	14.987
Freshet inception distance	44.687	43.432	42.533	42.088	38.343
Epoch time	24.21	24.56	26.34	24.543	23.54

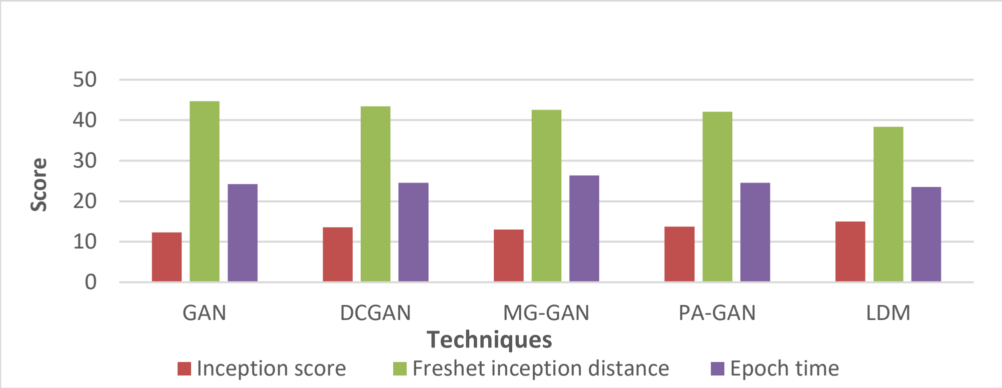

Fig.4 Chart of Augmentation Comparison

Table 3 presents the results of the classification process, showcasing the outcomes achieved following the implementation of augmentation and pixel imputation techniques. The table displays the performance metrics obtained for the proposed model, as well as other benchmark models including VGG-16, GoogleNet, ResNet-50, ResNet-101, LSTM, and R-CNN. All the used models use 50 epochs for training with automatic stopping points. The results obtained demonstrate the superior accuracy of our model, surpassing the performance of all other models considered in the evaluation. This highlights the effectiveness of the augmentation and pixel imputation techniques in enhancing the classification accuracy and further reinforces the superiority of our proposed approach in addressing the task at hand. Fig. 4 and Fig. 5 show the training and validation accuracy and loss.

Table 3. Results of Classification After Augmentation and Imputation

Model	Dice Score	Accuracy	Recall	Epoch time
VGG-16	0.88243	0.8845	0.8934	23.43
Google-net	0.9132	0.9143	0.9165	24.43
Resnet-50	0.9245	0.9254	0.9254	26.34
Resnet-101	0.9354	0.9345	0.9354	25.65
LSTM	0.9406	0.9434	0.9465	25.34
R-CNN	0.9465	0.9443	0.9445	23.54
Our	0.9756	0.9734	0.9734	24.32

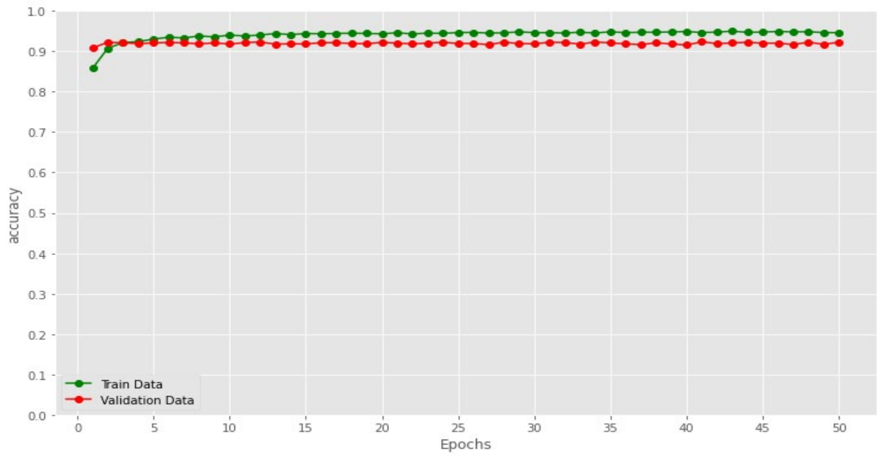

Fig. 4. Train and validation loss

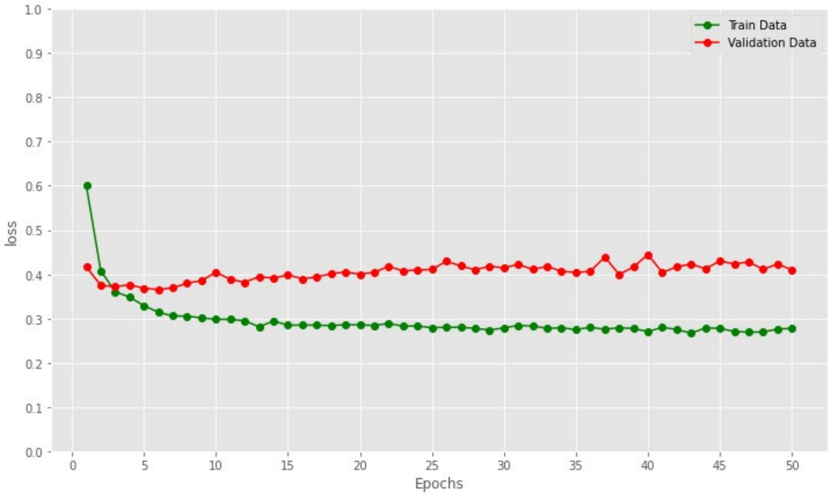

Fig. 5. Train and validation accuracy

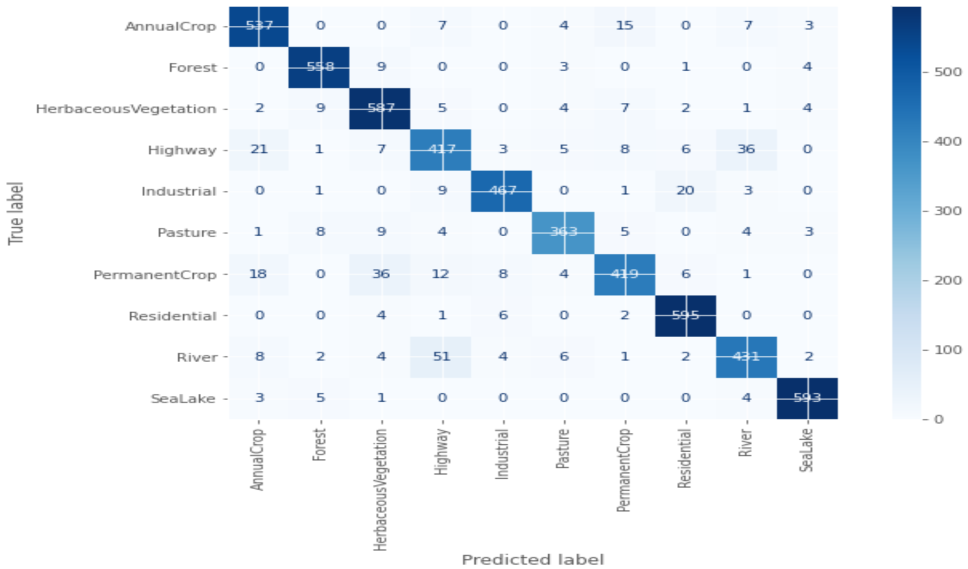

Fig.6. Confusion Matrix of Labelled Data

5. Conclusion

This paper introduces a comprehensive framework aimed at enhancing the classification performance of deep learning models in remote sensing image classification. The framework comprises three main layers: data augmentation, missing pixel imputation, and classification using a modified VGG-16 architecture. The first layer focuses on augmenting the remote sensing dataset by employing a latent diffusion model. This technique effectively increases dataset diversity and size, which mitigates the limited availability of labelled data. By introducing variations in the dataset, the model can acquire more robust and generalized features, thereby improving classification performance.

The second layer addresses the issue of missing pixels in remote-sensing images through reinforcement learning. This approach utilizes reinforcement learning to guide the imputation process and enhance the accuracy of reconstructed images. By leveraging the augmented dataset and imputed missing pixels, the third layer employs a modified VGG-16 architecture for remote sensing image classification. This integration of enhanced data representation enables the classification model to achieve superior accuracy and robustness.

Extensive experiments conducted on benchmark datasets validate the efficacy of the proposed framework. The results demonstrate that our approach surpasses state-of-the-art techniques in terms of classification accuracy and robustness. The experiments also highlight the significant improvements obtained through data augmentation and missing pixel imputation, particularly when compared to alternative methods. In summary, the proposed approach effectively addresses the challenges posed by limited labeled data and missing pixels, resulting in improved classification accuracy and robustness. These findings have far-reaching implications for more accurate and reliable remote sensing image analysis in diverse domains, including agriculture, urban planning, and environmental monitoring.

References

[1] J. Li et al., "A review of remote sensing for environmental monitoring in China," Remote Sensing, vol. 12, no. 7, p. 1130, 2020.
[2] J. Yin et al., "Integrating remote sensing and geospatial big data for urban land use mapping: A review," Int. J. Appl. Earth Obs. Geoinf., vol. 103, p. 102514, 2021.
[3] M. Mehmood et al., "Remote sensing image classification: A comprehensive review and applications," Math. Probl. Eng., 2022, pp. 1-24.
[4] J. Song et al., "A survey of remote sensing image classification based on CNNs," Big Earth Data, vol. 3, no. 3, pp. 232-254, 2019.
[5] G. Cheng et al., "Remote sensing image scene classification meets deep learning: Challenges, methods, benchmarks, and opportunities," IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., vol. 13, pp. 3735-3756, 2020.
[6] Q. Yuan et al., "Deep learning in environmental remote sensing: Achievements and challenges," Remote Sensing of Environment, vol. 241, p. 111716, 2020.
[7] L. Ma et al., "Deep learning in remote sensing applications: A meta-analysis and review," ISPRS J. Photogramm. Remote Sens., vol. 152, pp. 166-177, 2019.
[8] R. Shahbazian and S. Greco, "Generative Adversarial Networks Assist Missing Data Imputation: A Comprehensive Survey & Evaluation," IEEE Access, 2023.
[9] Y. Zhang, R. Zhang, and B. Zhao, "A systematic review of generative adversarial imputation network in missing data imputation," Neural Comput. Appl., vol. 35, no. 27, pp. 19685-19705, 2023.
[10] F.-A. Croitoru et al., "Diffusion models in vision: A survey," IEEE Trans. Pattern Anal. Mach. Intell., 2023.
[11] L. Yang et al., "Diffusion models: A comprehensive survey of methods and applications," ACM Comput. Surv., vol. 56, no. 4, pp. 1-39, 2023.
[12] A. Khan et al., "A survey of the recent architectures of deep convolutional neural networks," Artif. Intell. Rev., vol. 53, pp. 5455-5516, 2020.
[13] Y. Zhou and M. Wang, "Remote sensing image classification based on AlexNet network model," in Frontier Computing: Theory, Technologies and Applications (FC 2019), Springer Singapore, 2020, p. 8.
[14] M. Chen et al., "High Resolution Remote Sensing Image Construction Land Detection Combined with VGGNet and Mask R-CNN," Remote Sens. Technol. Appl., vol. 36, no. 2, pp. 256-264, 2021.
[15] N. Yang et al., "A convolutional neural network of GoogLeNet applied in mineral prospectivity prediction based on multi-source geoinformation," Nat. Resour. Res., vol. 30, no. 6, pp. 3905-3923, 2021.
[16] M. T. Ahad et al., "Comparison of CNN-based deep learning architectures for rice diseases classification," Artif. Intell. Agric., vol. 9, pp. 22-35, 2023.
[17] M. A. Haq et al., "Deep learning based supervised image classification using UAV images for forest areas classification," J. Indian Soc. Remote Sens., vol. 49, pp. 601-606, 2021.
[18] P. Zhou et al., "Learning compact and discriminative stacked autoencoder for hyperspectral image classification," IEEE Trans. Geosci. Remote Sens., vol. 57, no. 7, pp. 4823-4833, 2019.
[19] A. Singh and L. Bruzzone, "SIGAN: Spectral index generative adversarial network for data augmentation in multispectral remote sensing images," IEEE Geosci. Remote Sens. Lett., vol. 19, pp. 1-5, 2021.
[20] J. Li et al., "Semisupervised semantic segmentation of remote sensing images with consistency self-training," IEEE Trans. Geosci. Remote Sens., vol. 60, pp. 1-11, 2021.
[21] J. Howe, K. Pula, and A. A. Reite, "Conditional generative adversarial networks for data augmentation and adaptation in remotely sensed imagery," in Applications of Machine Learning, vol. 11139, SPIE, 2019.
[22] P. Liu et al., "Remote sensing data fusion with generative adversarial networks: State-of-the-art methods and future research directions," IEEE Geosci. Remote Sens. Mag., vol. 10, no. 2, pp. 295-328, 2022.
[23] Á. Acción, F. Argüello, and D. B. Heras, "A new multispectral data augmentation technique based on data imputation," Remote Sensing, vol. 13, no. 23, p. 4875, 2021.
[24] M. M. Almeida et al., "Univariate Time Series missing data Imputation using Pix2Pix GAN," IEEE Latin

America Trans., vol. 21, no. 3, pp. 505-512, 2023.
[25] Á. Acción Montes, D. B. Heras, and F. Argüello, "A new data augmentation technique for the CNN-based classification of hyperspectral imagery," in Image and Signal Processing for Remote Sensing XXVII, vol. 11862, SPIE, 2021.
[26] H. Son and Y. Jang, "Partial convolutional LSTM for spatiotemporal prediction of incomplete data," IEEE Access, vol. 8, pp. 164762-164774, 2020.
[27] D. Kavran et al., "Graph Neural Network-Based Method of Spatiotemporal Land Cover Mapping Using Satellite Imagery," Sensors (Basel, Switzerland), vol. 23, no. 14, 2023.

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تُعتبر تصنيف الصور بواسطة الاستشعار عن بُعد أمرًا حيويًا في مجالات متعددة، بما في ذلك الزراعة، وتخطيط المدن، ورصد البيئة. ومع ذلك، تشكل البيانات المعلمة المحدودة والبكسل المفقود تحديات في تحقيق تصنيف دقيق. في هذه الدراسة، نقترح إطارًا شاملاً يدمج توسيع البيانات باستخدام نموذج انتشار خفي وتعويض البكسل المفقود باستخدام نموذج تعزيز الألعاب لتحسين أداء نماذج التعلم العميق في التصنيف. يتكون الإطار من ثلاث طبقات: توسيع البيانات، وتعويض البكسل المفقود، والتصنيف باستخدام تصميم مجموعة الهندسة البصرية ١٦ المعدل. أظهرت التجارب الواسعة على مجموعات البيانات القياسية تأثير إيجابي كبير لإطارنا، حيث تفوقت على تقنيات حديثة بتحسين كبير في دقة التصنيف وقوة التحمل. تبرز النتائج فعالية تقنيات التوسيع والتعويض التي اقترحناها، حيث حققت مقاييس ممتازة للنجاح، الدقة، والاسترجاع بنسب تبلغ على التوالي ٩٧,٥٦٪، ٩٧,٣٤٪، و٩٧,٣٤٪. إطارنا المقترح يقدم حلا قيمًا لتصنيف الصور بواسطة الاستشعار عن بُعد بدقة، مواجهًا التحديات المتعلقة بالبيانات المحدودة والبكسل المفقود، وله تطبيقات واسعة في مجالات مختلفة.