



DenseNet-based ensemble network for land cover and land use classification of patch-based denoised SAR images

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Received: 2 March 2023 / Accepted: 24 September 2023 / Published online: 11 October 2023
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Abstract

Classification of synthetic aperture radar (SAR) images is very important for analyzing these images. The developing remote sensing allows many high-dimensional SAR images to be recorded and interpreted. However, due to the growth in data sizes, the features increase, and analyzing becomes difficult. Therefore, deep learning algorithms capable of automatic feature extraction are needed. This study proposes SAR DenseNet-based Ensemble Network (SARDE-Net), an ensemble deep learning network based on DenseNet architectures, for the classification task. The high-dimensional real-world SAR image was taken from the TerraSAR-X image archive. Before the SAR image is transferred to our model, it is split into 100 x 100 patches and categorized into five classes. In addition, Sparsity-Driven Despeckling (SDD) filter is applied for denoising to increase the capability of proposed method on patch classification. Our method classifies denoised-SAR images obtained with a patch-based approach with its state-of-the-art components. SARDE-Net was compared to other deep learning classifiers in recent literature and achieved the highest results with 98.77% accuracy, 98.81% precision, 98.64% recall, and 98.72% f1-score metrics. It has been confirmed that our model can also be applied to large datasets containing complex images.

Keywords Synthetic aperture radar (SAR) · Remote sensing · Deep learning · Land classification · Image processing · Despeckling

Introduction

Synthetic aperture radar (SAR) is a commonly preferred system for imaging landforms because it is not affected by factors such as weather conditions compared to optical data (Wu et al. 2020). SAR combines the images collected with its multiple radar units in the electronic environment. This combination provides a higher resolution in SAR images than large images obtained by one radar unit at a time. In addition, SAR can perform imaging in day and night time zones without being affected by light. Although SAR provides many advantages by adapting to all these conditions in the imaging process, the analysis process is more challenging than images obtained from other remote sensing devices (Chen et al.

2020). Objects captured by SAR in large areas on the earth are reflected by the intensity of the backscattering electromagnetic wave. Although SAR, which can provide imaging over wide areas, increases the number of detectable objects, reflected objects are more challenging to distinguish than their actual appearance. Therefore, the detection process is also complex, and experts are needed at this stage. In remote sensing applications, it is difficult and error-prone for classes of interest to have large amounts of labeled data (Digra et al. 2022). On the other hand, it is very time-consuming to perform object detection and analysis with the human eye in SAR images covering wide areas. In such cases, it creates the need for deep learning methods that provide time efficiency by automating the analysis process.

Deep learning algorithms are highly preferred compared to classical machine learning methods for the classification of images and object detection in recent studies, thanks to automatic feature extraction (Huang et al. 2022; Zhao et al. 2022; Sannapu et al. 2022). DNNs (deep neural networks) (Miikkulainen et al. 2019), created by deepening layers in artificial neural networks, allow complex data to be processed by mathematical modeling. CNNs (convolutional neural

Responsible Editor: Biswajeet Pradhan

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networks) (Xiao et al. 2021) within DNNs achieve success in the image analysis process by applying the convolution function to the mathematical data of the images. CNNs, a feed-forward network, can provide solutions to computational complexity and high-dimensionality problems in model architectures that receive inputs of different sizes, thanks to its pooling layer. In other words, CNNs can successfully perform image classification using less training and parameters than other deep neural networks (Passah et al. 2022). Thanks to these advantages, CNNs are also used in classifying SAR images and detecting objects on SAR images. In this context, El Housseini et al. (2017) proposed an automatic target recognition system using deep learning architecture to recognize military vehicles in SAR images. They suggested using a convolutional autoencoder for the optimization of the system. Furukawa (2017) proposed an automatic target recognition system in SAR images, studied CNN translation invariance, and emphasized the importance of data augmentation. This study is of great importance in analyzing spatial-temporal synthetic aperture radar images. Wu et al. (2021) proposed a ship detection system in SAR images using a global reasoning module and a mask-assisted ship detection module. Bianchi et al. (2020) developed a deep learning method to detect and classify oil spills worldwide. They proposed a segmentation architecture named Oil Free ConvNet based on U-Net for this system. Li et al. (2022) proposed a semantic segmentation framework for land use classification on optical and SAR images. Chen et al. (2020) proposed a new deep learning approach called Multi-resolution Attention and Balance Network with Region Proposal Network (RPN) for feature mapping and a bridge detection system in SAR images. Pradhan et al. (2020) used a Zero-Shot Learning approach using class attributes learnt from the Word2Vec model, both the features extracted by the single-layer CNN used in the first stage, and a second CNN model that predicts class assignment using class attributes during training and only features during prediction.

Land use and land cover classification is important for obtaining the necessary information in areas such as urban planning, agricultural land management, natural disaster management, and road planning. Due to the uniqueness of its application in remote sensing, classification applications in particular need further development and research (Ma et al. 2019). Due to the presence of various types of obstacles with similar transparency and spectral values to the classes considered in the images obtained by remote sensing methods, it is still difficult to obtain accurate extraction of classes using classification and segmentation methods (Abdollahi and Pradhan 2021). Moreover, the similarity between land cover and land use classes and the heterogeneity within classes, the characteristics of land use have not yet been resolved (Digra et al. 2022). In line with all these

considerations, this proposed study provides a solution to an important research gap in the literature.

The aim of this paper is to propose an SAR Ensemble DenseNet (SARDE-Net) based on deep learning algorithms for the classification task of different land use and land cover belonging to 5 classes which are water, building, vegetation, road, and coast landforms on SAR images. The analysis system (Ozcan et al. 2020), which was previously proposed using classical machine learning methods for classification, has been extended with deep learning methods, and higher accuracy has been achieved in this study. Also, more images were included in the dataset compared to the previous study. The SAR image with the dimensions of 22,000 x 19,000 used in the study was taken from public TerraSAR-X spotlight image archive. Afterward, the high-dimensional and wide-area SAR image was divided into 100 x 100 patches with discriminative and independent features. Cropped images are separated into 5 classes with the patch-based approach. Before the patch-based split images were transferred to the deep learning network, speckle noise filtering was applied with the Sparsity-Driven Despeckling (SDD) (Ozcan et al. 2015). The SDD filter removes noise on SAR images caused by natural factors such as light. A system for recognizing denoised images belonging to water, building, vegetation, road, and coast classes has been developed. The objective of the method proposed in this study is to develop an improved ensemble learning model by analyzing the performance of deep learning models, which are widely used in the literature, on SAR images. The main contribution and novelty of our study can be summarized as follows:

- In this study, images were divided into small patches, and classification was performed using images with a larger number and more detail. The patch-based approach is a solution to the spatial resolution problem caused by the remote acquisition of the images.
- In addition, studies in the literature have shown that speckle noise caused by scattering on SAR images has a negative effect on classifier performance. In this study, an SDD filter is applied to remove speckle noise, and performance is improved.
- Also, it has been observed that there is no study in the literature that performs classification on SAR images using multiple deep learning models. The project includes a comparison of deep learning models, and an ensemble learning model has been created using high-performing models.
- Besides the application of hyper-parameter settings and fine-tuning of the deep learning networks used, the model structure has been modified to improve performance.
- Also, the running time of the models was optimized. The number of parameters has been significantly decreased

while creating the ensemble model. In this way, computational complexity and cost are reduced.

Materials and methods

Study area and dataset

The high-dimensional SAR image used in the study was taken from the open source access TerraSar-X archive. The SAR image obtained using single polarized (VV channel) and spot light mode has 1 m image resolutions. In addition, the obtained image is 16 bit and 22,000 x 19,000 in size. Visakhapatnam Port in India, located at latitude 17°44'05.6"N and longitude 83°19'12.0"E, was used as the study area. The study area includes areas with water, coast, building, road, and vegetation (Fig. 1).

The SAR image covering large areas was divided into 100 x 100 patches using the sliding window method. The amount of sliding was adjusted so that each patch had different features. The patches were automatically categorized according to their coordinates using Google ground truths. Our dataset was divided into training, validation, and test sets, corresponding to a 70% - 15% - 15% split, respectively. Figure 2 shows examples of images belonging to each class. In addition, the data were augmented after the dataset was splitted. Thus, the number of images belonging to each class was increased.

The dataset contains 2208 water, 2324 building, 2344 vegetation, 1860 road, and 2024 coast class images. Patch images of roads referred to as land use include intersections,

highways, and railways. The building class, which is defined as another land use, has structures such as workplaces, construction sites, and factories. The vegetation class, specified as land cover, includes green areas such as woodlands, forests, and farm areas. The patch images, which belong to the class of coast, represent areas with waterfront where water and land coexist.

Despeckling SAR images

Despeckling was performed on the images used in the study. In this way, the quality of SAR images has increased significantly, and the analysis process has become much easier with deep learning models. Preprocessing was performed using the SDD (Ozcan et al. 2015) filter for despeckling. SDD, which optimizes the despeckling process performed on the images using different norm values, is shown in Eq. 1.

$$\hat{F} = \operatorname{argmin}_F \left[\sum_p (F_p - G_p)^2 + \lambda \wedge (|(\partial F)_p|, f) \right] \quad (1)$$

where the cost is minimized, and G denotes the speckled image. In addition, F regards the despeckle image, p shows the pixel indices, and λ indicates the smoothing level. In this formulation, the norm value depends on the variable f . When the f variable takes 0, it is expressed as l_0 -norm, and when it takes the value of 1, it is expressed as l_1 -norm. This way, a fractional norm value is obtained by providing a sparse solution.

Fig. 1 Visakhapatnam Port in India



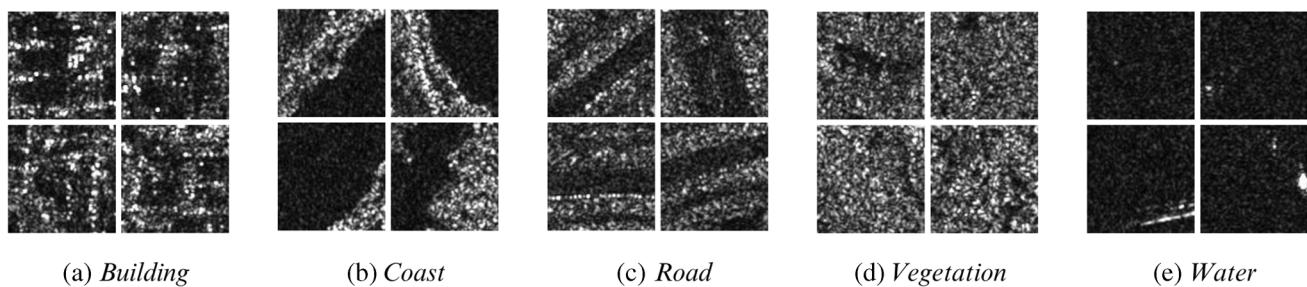


Fig. 2 This overview shows sample image patches for all 5 classes in the generated dataset. The images are 100x100 pixels in size. Each class contains around 2000 images, in total 10,760 images

Ensemble deep learning architecture

We propose the SARDE-Net architecture to achieve high performance on images where objects are difficult to distinguish, such as on SAR images. In the proposed architecture, a high-performance ensemble model was created with dense connections of the DenseNet architecture, which consists of a series of dense blocks and contains a convolution operation between each block. The loss of information in the layers can be encountered as the number of layers and processes increases in deep learning models (Huang et al. 2017). The DenseNet architecture combines feature maps at each layer in a feed-forward and iterative pattern, resulting in a higher information flow than other architectures (Yaohua and Xudong 2019; Gui et al. 2018). This architecture, which has robust feature propagation, reduces the number of parameters while solving the vanishing gradient problem.

The ensemble method, frequently used in machine learning, is a technique that generalizes by using more than one model or model output to solve a problem. While creating the model, DenseNet-121, DenseNet-169, and DenseNet-201 classifiers were ensembled. During the training of deep learning models, the weights are optimized at each iteration. Therefore, training the models requires a lot of time. In this case, a pre-trained model with fine-tuning provides better accuracy (Novelli et al. 2017). Fine-tuning is a way to apply or utilize transfer learning. DenseNet architectures that are pre-trained on the ImageNet dataset are configured to be used with the transfer learning approach. The use of

these pre-trained models allows for iteration and information transfer between layers. In addition, each model was fine-tuned to reduce the computational complexity of the ensemble learning method. For fine-tuning purposes, some layers of the models are frozen. Freezing the layers means that the weights of the pre-trained model are maintained during training, so that they are not updated. The weights were only updated in the last or added layer of each classifier. Thus, the weights in all layers are prevented from being updated, and the number of trained parameters and the training time are significantly reduced. In addition, a pooling layer was added after each model of SARDE-Net. In this way, while reducing the computational load by reducing the size of the feature maps, important information is protected by preserving the most prominent features. Each combination was examined for the selection of the added pooling layer, and the combination with the highest performance was used. This combination is obtained by transmitting the DenseNet-121 and DenseNet-169 model to the GlobalAveragePooling layer, and the DenseNet-201 model to the GlobalMaxPooling layer. In addition, various combinations have been examined to adjust the hyperparameters, and the parameters providing the highest performance are shown in Table 1. In summary, the developed model can be summarized as follows:

In the ensemble model, inputs are passed to a lambda layer, as shown in Fig. 3. Through the lambda layer, non-portable and sequential functions are layered. The size of the input features is transferred to this layer. Lambda layer imposes the output features to DenseNet-121, DenseNet-169,

Table 1 Details of the ensemble model

	DenseNet-121	DenseNet-169	DenseNet-201	SARDE-Net
Kernel size	3x3	3x3	3x3	3x3
Activation function	ReLU	ReLU	ReLU	Softmax
Drop out	None	None	None	None
Dense layers	121	169	201	495
Pooling layers	GlobalAverage	GlobalAverage	GlobalMax	
Optimiser	Adam	Adam	Adam	Adam
Batch size	32	32	32	32

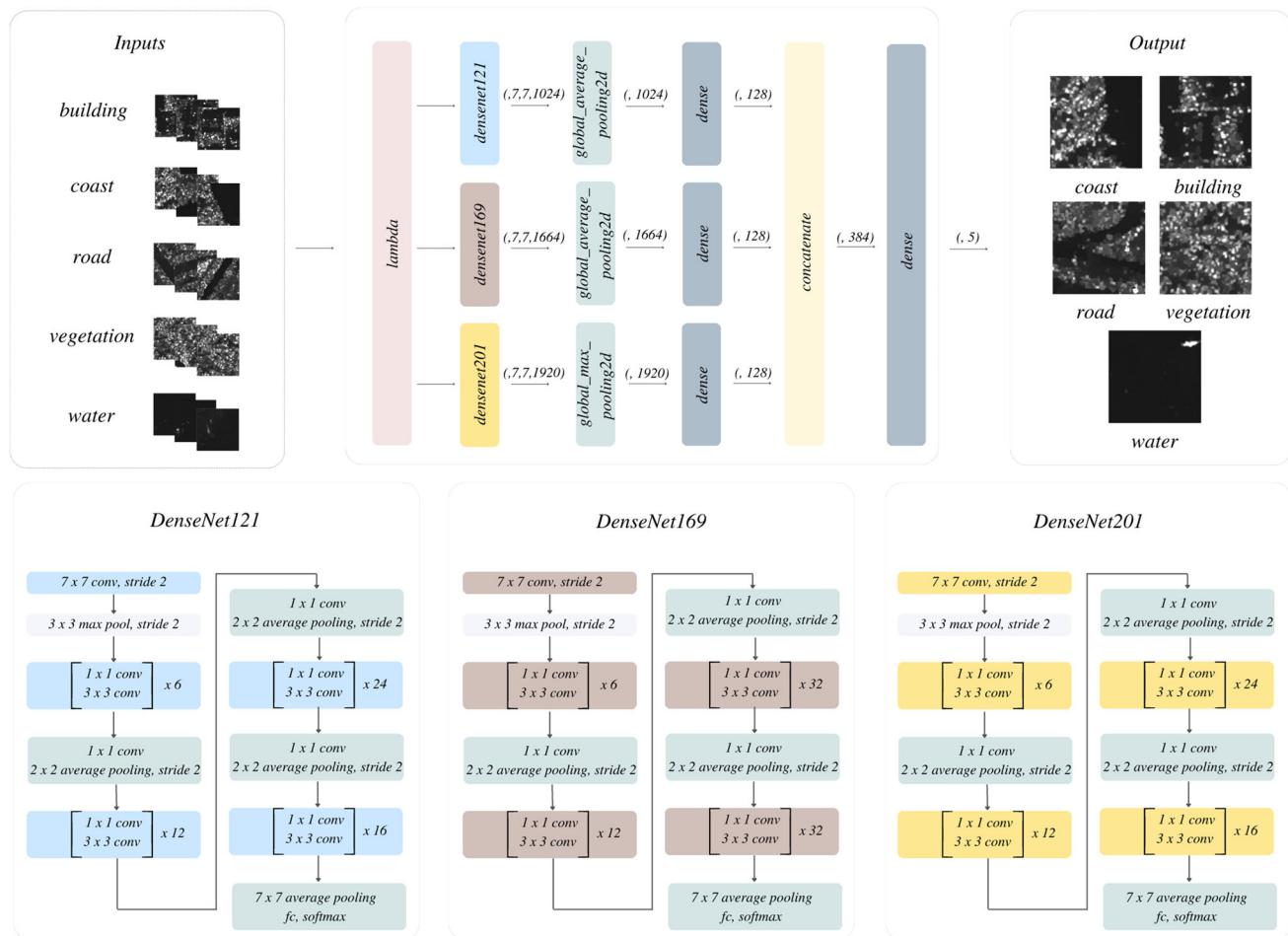


Fig. 3 Workflow pipeline of the ensemble method proposed in the study

and DenseNet-201 architectures separately as inputs. In this way, fine-tuning is simplified with fewer parameters. The transferred outputs are passed through an appropriate pooling layer and then through the dense layer. The matrices of the dense layers are combined through the concatenate layer. This layer takes a feature matrix of the same size and returns the concatenated form of the matrices. Thus, outputs from the ensemble model are obtained without loss of information. Finally, the size of the feature matrix passing through the concatenate layer is matched to the sizes of the output classes with the dense layer.

Results

SAR image used in the study was obtained as 16 bits and has a size of 22,000x19,000. SAR images covering wide areas were divided into 100x100 patches to avoid redundant

features for efficient use of deep learning and allow the network to focus on classes. Patches were automatically divided into classes based on their coordinates using Google ground truths. Speckle noise filtering was performed by applying an SDD filter to SAR images divided into patches. Figure 4 shows original and SDD-filtered examples of images belonging to different classes in the dataset. Different pixel-shifting ratios are applied in the patch-based approach to prevent the similarity of the images.

Models to be ensembled using transfer learning have been configurated for the classification task on SAR images. Configuration was made since it takes time to train all parameters in each epoch and the parameters of the pre-trained network are specific to the dataset from which it was trained. The update of the weights is prevented by making particular layers of the models used non-trainable. This process provides faster training by reducing the number of parameters in the model. Through this process, known as fine-tuning, pre-trained

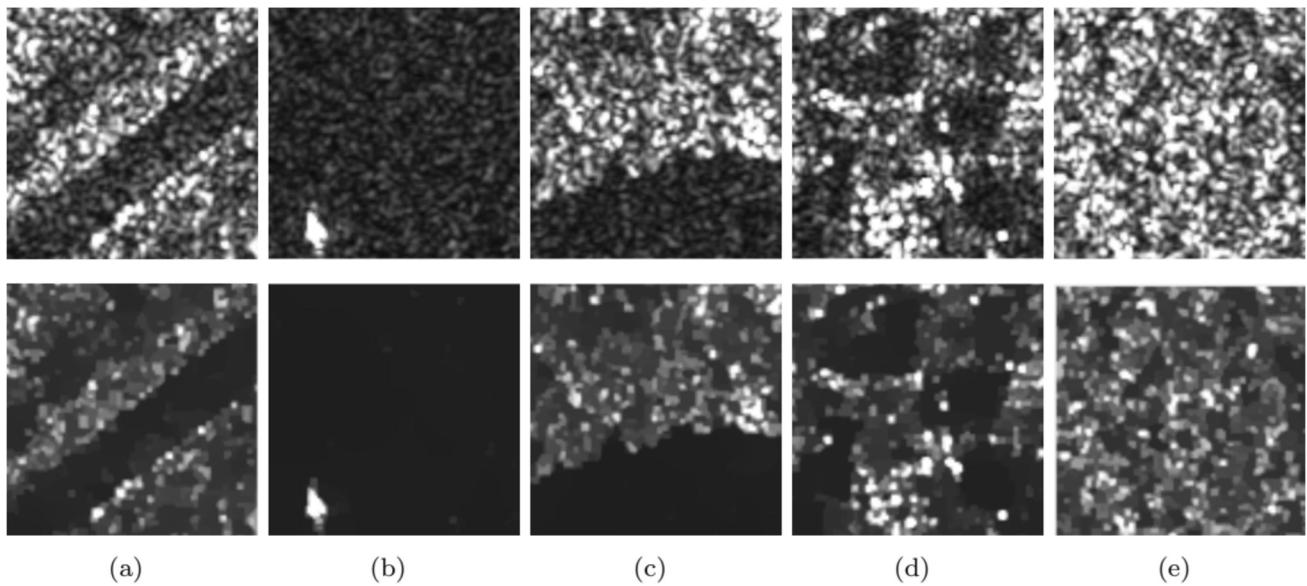


Fig. 4 Unfiltered and SDD-filtered dataset images belonging to different classes. **(a)** Road; **(b)** water; **(c)** coast; **(d)** building; **(e)** vegetation

features are gradually adapted to the data, providing meaningful improvements and making layers more relevant.

Networks frequently used in image classification problems and the proposed SARDE-Net are trained on the same dataset, and their performances are compared in Table 2. In addition, the individual performance of DenseNet-121, DenseNet-169, and DenseNet-201 architectures used in the SARDE-Net architecture are also included in the comparison table. Accuracy, precision, recall, and f1-score metrics were used for performance measurement. The three architectures with the highest accuracy were used as the base model while creating the ensemble model. The results of each network show that these three architectures perform better than other

classification architectures, and the proposed SARDE-Net, which concatenates the three architecture outputs, provides the best performance.

The outputs of the SARDE-Net model are shown graphically in Fig. 5. The correct and incorrect predictions are shown in tabular form. Here, TP represents the correct predictions, and FP represents the incorrect predictions. The class names in the upper part of the figure as column names are the predicted class, and the class names in the lower part are the true labels. Analysis of this visualization may reveal the confusing elements of the model. For example, an image in the road class is confused with the building class because of the dark regions on the roadside. An image in the coast

Table 2 Results of performance evaluation metrics on test dataset

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
AlexNet	95.44	95.60	95.19	95.39
VGG-16	95.12	95.13	95.12	95.05
EfficientNet	96.42	96.42	96.09	96.22
GoogleNet	95.59	95.52	95.45	95.49
ResNet-50	95.44	95.28	95.28	95.28
ResNet-101	94.12	94.39	93.41	93.90
ResNet-152	93.78	94.19	93.13	93.65
MobileNet-v2	93.62	93.49	93.53	93.51
ViT	96.91	97.12	96.92	97.01
DenseNet-121	97.09	97.08	96.88	96.98
DenseNet-169	96.18	96.21	95.92	96.07
DenseNet-201	97.18	97.37	96.81	97.09
SARDE-Net	98.77	98.78	98.77	98.76

	<i>building</i>	<i>coast</i>	<i>road</i>	<i>vegetation</i>	<i>water</i>
TP					
FP					
true label	<i>road</i>	<i>water</i>	<i>coast</i>	<i>building</i>	<i>coast</i>

Fig. 5 Example outputs of SARDE-Net

class has bright spots, probably due to the effect of backscattered signals from a ship or object in the port, and has been assigned to the water class.

Discussion

Labeling and classification of remote sensing images is a challenging task. One of these challenges is that the number of remote sensing images is increasing every day as the technology develops, but it is almost impossible to label all this data. Another issue is speckle noise in SAR images, which is caused by natural factors such as light. Speckle noise is small areas of brightness where random differences in brightness are observed in the image. SAR data are affected by the presence of speckle, which can make the interpretation of images difficult (Silveira and Heleno 2009). This makes it difficult to determine the distinctive features of the images and negatively affects the classification process. In particular, small objects can be confused with regions of speckle noise. Many speckle noise removal methods have been developed to solve this problem.

Molini et al. (2020) used a customized version of blind spot convolutional networks where noise is constrained by excluding a variable amount of pixels to account for the

correlation structure. This work was one of the first deep learning-based despeckling methods entirely on real single-view complex SAR images. Another CNN-based approach was the method that incorporated residual networks and used time-averaged cumulative smoothing of sample area images as a multiplicative noise-free image (Sebastianelli et al. 2022). Meraoumia et al. (2022) proposed a semi-supervised deep learning algorithm. Their proposed SAR2SAR algorithm utilizes multi-temporal time series, and the neural network learns to restore SAR images by looking only at noisy acquisitions. In addition, the noise2noise framework proposed by Jaakko Lehtinen et al. (2018) is used in their study. However, SAR images with and without speckle noise are required to train the deep learning algorithms (Dalsasso et al. 2020). There is an inherent limitation of speckle-free references for matching a SAR image to a speckle-free image. Although such images can be obtained indirectly through some form of averaging by spatial or temporal integration, they are imperfect (Meraoumia et al. 2022).

The pre-processing of SAR images for speckle reduction or removal is of crucial importance for many applications (Argenti et al. 2013). Previous studies have shown that image enhancement significantly improves classification performance. In this study, the SDD filter is used, which exploits the texture preservation property of the non-local averaging

Table 3 Classification results of performance evaluation metrics

Class	Precision(%)		Recall (%)		F1-score (%)	
	Original	Filtered	Original	Filtered	Original	Filtered
Building	95.04	96.95	97.02	99.43	96.02	98.18
Coast	96.43	99.66	96.74	98.02	96.59	98.83
Road	96.98	98.89	91.78	96.07	94.31	97.46
Vegetation	98.04	99.43	99.72	99.72	98.87	99.57
Water	99.09	99.1	99.39	100	99.25	99.55
Weighted avr	97.14	98.78	97.14	98.77	97.12	98.76

filter. One of the main reasons for using this method is that it provides successful smoothing of homogeneous regions by preventing the distortion of edge and point scatterers. In addition, this image filtering step, which is used as a pre-processing step, has a high performance in terms of time and accuracy. In order to investigate the contribution of the pre-processing of the images by applying the SDD filter, the classification was performed on the original SAR images without filtering. Table 3 shows the performance results obtained by classifying the original SAR images and the SAR images preprocessed with the SDD filter using SARDE-Net for each class. According to the table, it is seen that there is a significant difference in the precision, recall, and f1-score metrics for each class. For example, for the coast class, while the precision was 96.43% when training with the original image, this value reached 99.66% when the SDD filter was applied. The experimental study revealed that the SDD filter significantly improved the classification performance.

In this study, to investigate the effect of different deep learning methods on classification accuracy, they were compared using widely used models. The results of this comparison are shown in Table 2. The table shows that DenseNet architectures achieve higher accuracy values than other networks. Owing to the information flow provided by its dense connections, the DenseNet architecture has come to the forefront by performing a more effective training. Therefore, it

was decided to use these networks for the ensemble model construction. In this context, three different versions of the DenseNet architecture were combined in different combinations using pooling and dense layers. In order to maximize the performance of the ensemble learning model, different combinations of output and post-activation functions were used in all three models. The highest performance was achieved by using the ReLU activation function in all models and the Softmax activation function in the output layer. In the training of the SARDE-Net model, different batch sizes were used, and although there was not much difference between the accuracy results, the best performance was achieved when 32 batch sizes were used. Since 224 x 224 is used as the input size in deep learning models, the data with a size of 100 x 100 was updated during training to be suitable for the models.

The number of epochs that deep learning architectures need to be trained on for each dataset varies. In order to decide how much to train the network, the loss and accuracy values of the network should be analyzed during training. The success of the training can be measured when the loss value decreases to the lowest possible value and the accuracy value reaches the highest possible value. At this point, training should be stopped to prevent the network from overfitting. For this purpose, an early stopping function is used in the study by the usage of the callback object. The callback object was used to monitor the metrics at every batch of training

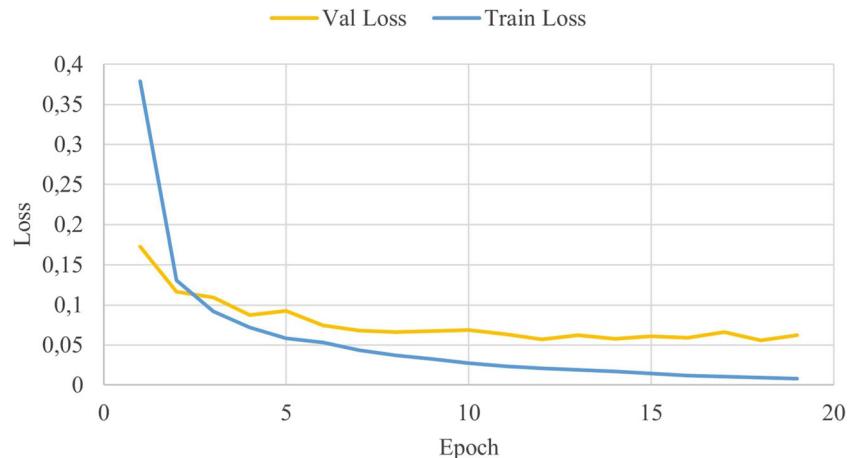
Fig. 6 Training and validation loss values per epoch

Table 4 Cross-validation results of performance evaluation metrics

Fold	Accuracy (%)	Recall (%)	F1-Score (%)
Fold 1	92.62	92.74	92.53
Fold 2	90.92	91.39	90.78
Fold 3	91.87	92.03	91.82
Fold 4	93.44	93.71	93.40
Fold 5	91.94	92.09	91.74
Avr	92.16	92.39	92.05

and to save the model periodically. After each training batch, logs are maintained with callback that provide statistical data on the model. In addition, early stopping was applied with callback to prevent overfitting of the model during training. The early stopping function interrupts the training when there is no improvement in the tracked metric of the model. In the study, the training is stopped by monitoring validation accuracy and determining the epoch in which the model performs best and cannot provide better performance. The training and validation loss graph of SARDE-Net architecture is given in Fig. 6. It is seen in the graph that the loss values decrease as the number of epochs increases.

In addition, the patch-based approach, which allows us to generate the dataset efficiently, is one of the reasons for the high performance of the study. Another issue is the appropriate distribution of the data. In this context, the cross-validation method was used to examine the distribution of the dataset and the reliability of the model. Cross-validation allows to analyze the generalization ability of the model by observing its performance on different data subsets. Table 4 shows the results obtained with 5 folds. The analysis of these results indicates that there is no outlier difference between the accuracy values. Therefore, the reliability of the model is clearly demonstrated.

Conclusion

We proposed a deep learning-based ensemble model for classifying SAR images covering different regional features. The proposed model concatenates DenseNet models as the base architecture. When performing concatenation, parameter and computational complexity are reduced. In this way, our model reaches 98.77% accuracy, 98.81% precision, 98.64% recall, and 98.72% f1-score and performs better on SAR images than other state-of-the-art deep learning methods presented in the literature. The classification performance of the model was improved with 10,760 images obtained by following a patch-based approach in the SAR image. Although the dataset was obtained using a patch-based approach and then augmented, the small amount of labeled data can be

considered a limitation of the study. To overcome this limitation, self-supervised methods applied to less labeled data may be effective. Also, despeckling images as a preprocessing step increased the success rate of the classifier. It has been confirmed that our model, which classifies images obtained by patch-based approach, can also work on large datasets containing images such as SAR, thanks to its classification capability.

Funding This work was supported by the Scientific Research Projects Unit of Karabuk University with the project number KBUBAP-23-YL-027. The authors appreciate the financial and scientific support.

Declarations

Conflict of interest The authors declare no competing interests.

References

- Abdollahi A, Pradhan B (2021) Integrated technique of segmentation and classification methods with connected components analysis for road extraction from orthophoto images. *Expert Syst Appl* 176:114908. <https://doi.org/10.1016/j.eswa.2021.114908>
- Argenti F, Lapini A, Bianchi T, Alparone L (2013) A tutorial on speckle reduction in synthetic aperture radar images. *IEEE Geosci Remote S* 1(3):6–35. <https://doi.org/10.1109/MGRS.2013.2277512>
- Bianchi FM, Espeseth MM, Borch N (2020) Large-scale detection and categorization of oil spills from SAR images with deep learning. *Remote Sens-basel* 12(14):2260
- Chen L, Weng T, Xing J, Pan Z, Yuan Z, Xing X, Zhang P (2020) A new deep learning network for automatic bridge detection from SAR images based on balanced and attention mechanism. *Remote Sens-basel* 12(3):441
- Dalsasso E, Denis L, Tupin F (2020) SAR2SAR: a semi-supervised despeckling algorithm for SAR images. *IEEE J Sel Top Appl* 14:4321–4329
- Digra M, Dhir R, Sharma N (2022) Land use land cover classification of remote sensing images based on the deep learning approaches: a statistical analysis and review. *AJGS* 15(10):1003. <https://doi.org/10.1007/s12517-022-10246-8>
- El Housseini A, Toumi A, Khenchaf A (2017) Deep learning for target recognition from SAR images. In: IEEE Seminar on Detection Syst Arch and Tech (DAT), pp 1–5
- Frurukawa H (2017) Deep learning for target classification from SAR imagery: data augmentation and translation invariance. [arXiv:1708.07920](https://arxiv.org/abs/1708.07920)
- Gui Y, Xue L, Li X (2018) Sar image despeckling using a dilated densely connected network. *Remote Sens Lett* 9(9):857–866
- Huang X, Zhang B, Perrie W, Lu Y, Wang C (2022) A novel deep learning method for marine oil spill detection from satellite synthetic aperture radar imagery. *Mar Pollut Bull* 179:113666
- Huang G, Liu Z, Van Der Maaten L, Weinberger KQ (2017) Densely connected convolutional networks. In: Proc CVPR IEEE, pp 4700–4708
- Jaakkola Lehtinen JHS, LTKMA, Jacob Munkberg, Aila, T (2018) Noise2noise: learning image restoration without clean data. [arXiv:1803.04189](https://arxiv.org/abs/1803.04189)
- Li X, Zhang G, Cui H, Hou S, Wang S, Li X, Chen Y, Li Z, Zhang L (2022) MCANet: a joint semantic segmentation framework of

- optical and SAR images for land use classification. *INT J Appl Earth Obs* 106:102638
- Ma L, Liu Y, Zhang X, Ye Y, Yin G, Johnson BA (2019) Deep learning in remote sensing applications: a meta-analysis and review. *ISPRS Int Soc Photogramme* 152:166–177
- Meraoumia I, Dalsasso E, Denis L, Abergel R, Tupin F (2022) Multitemporal speckle reduction with self-supervised deep neural networks. *IEEE T Geosci Remote S* 61:1–14
- Miikkulainen R, Liang J, Meyerson E, Rawal A, Fink D, Francon O, Raju B, Shahrzad H, Navruzyan A, Duffy N et al (2019) Evolving deep neural networks. In: Artificial intelligence in the age of neural networks and brain computing, pp 293–312
- Molini AB, Valsesia D, Fracastoro G, Magli E (2020) Speckle2Void: deep self-supervised SAR despeckling with blind-spot convolutional neural networks. *IEEE T Geosci Remote S* 60:1–17
- Ozcan C, Sen B, Nar F (2015) Sparsity-driven despeckling for SAR images. *IEEE Geosci Remote S* 13(1):115–119
- Ozcan C, Ersoy KO, Ogul IU (2020) Fast texture classification of denoised SAR image patches using GLCM on spark. *Turk J Electr Eng Co* 28(1):182–195
- Passah A, Sur SN, Paul B, Kandar D (2022) SAR image classification: a comprehensive study and analysis. *IEEE Access* 10:20385–20399
- Pradhan B, Al-Najjar HA, Sameen MI, Tsang I, Alamri AM (2020) Unseen land cover classification from high-resolution orthophotos using integration of zero-shot learning and convolutional neural networks. *Remote Sens-basel* 12(10):1676
- Sannapu AR, Nayak P, Charan UR et al (2022) Classification of marine vessels using deep learning models based on SAR images. In: 2022 International conference on inventive computation technologies (ICICT). IEEE, pp 123–129
- Sebastianelli A, Rosso MPD, Ullo SL, Gamba P (2022) A speckle filter for Sentinel-1 SAR ground range detected data based on residual convolutional neural networks. *IEEE J Sel Top Appl* 15:5086–5101. <https://doi.org/10.1109/JSTARS.2022.3184355>
- Silveira M, Heleno S (2009) Separation between water and land in SAR images using region-based level sets. *IEEE Geosci Remote S* 6(3):471–475. <https://doi.org/10.1109/LGRS.2009.2017283>
- Wu Z, Hou B, Jiao L (2020) Multiscale CNN with autoencoder regularization joint contextual attention network for SAR image classification. *IEEE T Geosci Remote* 59(2):1200–1213
- Wu Z, Hou B, Ren B, Ren Z, Wang S, Jiao L (2021) A deep detection network based on interaction of instance segmentation and object detection for SAR images. *Remote Sens-basel* 13(13):2582
- Xiao X, Wei G, Zhou L, Pan Y, Jing H, Zhao E, Yuan Y (2021) Treatment initiation prediction by EHR mapped PPD tensor based convolutional neural networks boosting algorithm. *J Biomed Inform* 120:103840
- Yaohua X, Xudong M (2019) A SAR oil spill image recognition method based on DenseNet convolutional neural network. In: 2019 IEEE Int Conf Robot (ICRIS), pp 78–81. <https://doi.org/10.1109/ICRIS.2019.900028>
- Zhao S, Luo Y, Zhang T, Guo W, Zhang Z (2022) Active learning SAR image classification method crossing different imaging platforms. *IEEE Geosci Remote S*

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