BULLETIN of Cherkasy State Technological University

Journal homepage: https://bulletin-chstu.com.ua/en

Vol. 30 No. 1. 2025

UDC 004.9
DOI: 10.62660/bcstu/1.2025.10

# Leveraging machine learning and deep learning for SAR image classification

**Yurii Brovka***

Postgraduate Student
National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute"
03056, 37 Beresteiskyi Ave., Kyiv, Ukraine
https://orcid.org/0009-0004-3708-9747

**Abstract.** The study conducted a comprehensive analysis of contemporary machine learning and deep learning methods for the classification of synthetic aperture radar (SAR) images. The primary objective was to identify architectures and approaches that ensure high classification accuracy while optimising computational efficiency. Particular emphasis was placed on addressing key challenges, including speckle noise, geometric distortions, and the limited availability of labelled data. The research methodology involved a systematic review of the scientific literature from 2015 to 2024 and an analysis of the polarisation characteristics of SAR images using the Copernicus Browser platform. The effectiveness of traditional machine learning methods, such as Support Vector Machines and Random Forest, was evaluated alongside modern deep learning architectures, including ResNet, U-Net, and Vision Transformer. Special attention was given to the impact of adaptive speckle noise filtering using the Lee filter with varying window sizes (3 × 3, 5 × 5, and 7 × 7) on classification performance. The results demonstrated that deep neural networks outperform traditional methods due to their ability to automatically extract hierarchical feature representations. ResNet achieved high classification accuracy, U-Net proved effective for segmentation, and Vision Transformer captured global dependencies. The optimal balance between speckle noise suppression and detail preservation was found when applying the Lee filter with a 5 × 5 window size. A persistent challenge remains the limited availability of labelled data. To address this issue, semi-supervised learning was explored, as it enhances feature normalisation and model performance. A promising avenue for further research is the utilisation of complex-valued neural networks to optimise computational costs. The findings of this study have practical significance for the automated classification of SAR images in environmental monitoring, agricultural land assessment, and remote sensing applications

**Keywords:** neural networks; complex-valued calculations; polarisation characteristics; radar sensing; speckle filtering

## INTRODUCTION

Synthetic Aperture Radar (SAR) is a crucial tool in modern remote sensing, providing high-quality data irrespective of weather conditions and lighting. Its unique properties make SAR imaging indispensable for applications such as natural disaster monitoring, military intelligence, agriculture, and environmental surveillance. In particular, SAR enables the analysis of vegetation health and crop structure, the detection of water body pollution, and the tracking of ice sheet dynamics (Vu *et al.*, 2021; Wang *et al.*, 2022; Villarroya-Carpio & López-Sánchez, 2023).

A primary challenge in the automatic classification of SAR data is speckle noise, which arises due to the coherent nature of radar signals (Li *et al.*, 2024). This type of noise manifests as a chaotic, grainy structure within images, resulting from the interference of coherent reflected signals from multiple scatterers within

**Article's History:** Received: 10.10.2024; Revised: 25.02.2025; Accepted: 17.03.2025.

**Suggested Citation:**
Brovka, Yu. (2025). Leveraging machine learning and deep learning for SAR image classification. *Bulletin of Cherkasy State Technological University*, 30(1), 10-20. doi: 10.62660/bcstu/1.2025.10.

*Corresponding author

a single resolution cell. The presence of speckle noise significantly complicates segmentation and object recognition, as it can obscure the true textural characteristics of a surface. Traditional classification methods that rely on the amplitude characteristics of individual pixels often prove inadequate, as they fail to account for the textural and polarimetric properties of SAR images. This limitation necessitates the development of specialised algorithms, particularly those based on deep learning (DL), which are designed to accommodate the unique characteristics of SAR data. Studies by R. Kruk *et al*. (2020) and S. Attioui & S. Arivazhagan (2020) have demonstrated the effectiveness of deep neural networks, such as DenseNet and Deep Belief Networks, in SAR image classification tasks, achieving an accuracy exceeding 90%. The authors highlighted the capability of DL models to mitigate the impact of speckle noise and enhance result generalisation. However, they also noted that the limited availability of labelled SAR data presents a challenge in training deep architectures while minimising the risk of overfitting.

A significant advancement in addressing the computational complexity of traditional DL approaches is the use of complex-valued neural networks. According to B. Konishi *et al*. (2021), employing complex-valued reservoir computing reduces training time by a factor of 100 and classification time by a factor of 5 compared to conventional convolutional neural networks (CNNs). This approach also provides high resolution and efficiency in quantitative tasks, such as estimating surface topographic parameters. The issue of limited labelled data is partially addressed through semi-supervised learning. The study by Y. Li *et al*. (2023) demonstrated that combining small labelled datasets with large volumes of unannotated SAR data improves feature normalisation and overall model performance. This is particularly relevant for tasks where manual annotation is time-intensive, such as the classification of complex landscapes. A comparative analysis of CNN architectures (LeNet, AlexNet, and VGG) conducted by R. Ding (2023) reaffirmed the superiority of DL over traditional SAR image processing methods, particularly in high-noise environments and under geometric distortions. The author observed that deep models effectively extract intricate spatial-textural patterns that are beyond the reach of classical algorithms.

Despite significant advancements in the application of machine learning (ML) and DL for SAR image classification (Poplavskyi, 2024), several challenges remain that require further research. These include enhancing model robustness to noise and limited data, developing efficient semi-supervised and unsupervised learning methods, and optimising computational costs for practical implementation. Future research should focus on integrating various approaches, such as transfer learning, generative models, and complex-valued neural networks, to maximise efficiency in SAR image analysis. The objective of this study was to conduct a comprehensive analysis of contemporary ML and DL methods for SAR image classification, with particular emphasis on addressing key challenges: speckle noise, geometric distortions, and the scarcity of labelled data. The research aimed to identify architectures and approaches that achieve high classification accuracy while maintaining computational efficiency.

## MATERIALS AND METHODS

The study employed a comprehensive approach to analysing ML and DL methods for SAR image classification. The research methodology was based on a systematic review of the scientific literature using the international databases Scopus and Web of Science. The literature search was conducted using the following keywords: “SAR image classification”, “deep learning SAR”, “machine learning synthetic aperture radar”, “SAR image processing”, and “neural networks SAR”. At the initial stage, 127 publications from the period 2015-2024 were selected. This timeframe was chosen due to the rapid advancements in DL methods and their application in SAR image processing, particularly since 2015, when the first significant results on CNN-based radar data classification were published. After applying inclusion criteria (availability of experimental results, detailed descriptions of model architectures, and quantitative performance indicators) and exclusion criteria (review articles, theoretical works without experimental validation, and publications lacking methodological details), 41 relevant studies were selected for further analysis.

To analyse SAR image characteristics, data obtained via the Copernicus Browser (n.d.) platform were utilised. SAR image visualisation and processing were performed using the platform’s functionalities, enabling the analysis of polarisation modes and the creation of composite images. The study examined surface reflection characteristics in the vertical transmit, vertical receive (VV) and vertical transmit, horizontal receive (VH) polarisation modes, allowing for an investigation of characteristic scattering patterns across different terrain types. Red-Green-Blue (RGB) composites were generated by combining the VV and VH channels with different types of gamma correction (linear and decibel), providing a comprehensive representation of the data for analysing the textural and structural characteristics of the surface.

The study of speckle noise filtering was conducted using the Lee filter with window sizes of 3×3, 5×5, and 7×7. The filtering process comprised the following stages: preliminary assessment of noise levels in the image, application of the filter with varying parameters, and analysis of the preservation of key structural elements. The evaluation of filtering effectiveness was based on the preservation of structural features, textural characteristics, and object contour clarity under different filtering parameters. Particular attention was given to maintaining a balance between the degree of noise suppression and the retention of informative image details.

A comparative analysis of classification methods was performed based on the following criteria: feature extraction capability, noise robustness, computational efficiency, and interpretability of results. The study examined the application of traditional ML methods, namely Support Vector Machines (SVM) and Random Forest (RF), alongside modern DL architectures, including ResNet, U-Net, and Vision Transformer (ViT). For each method, the study analysed data preprocessing requirements, model training characteristics, and computational resource demands. Special attention was given to the architectural features of neural networks that influence their ability to process the distinct characteristics of SAR images. Additionally, the research systematised and compared SAR data preprocessing methods, including pixel intensity normalisation techniques and data augmentation strategies. This allowed for the identification of optimal data preparation approaches tailored to different ML and DL architectures while accounting for the unique properties of SAR images.

## RESULTS AND DISCUSSION

SAR images possess distinct properties that differentiate them from optical remote sensing data. A key characteristic is signal polarisation, which can be represented in four configurations: horizontal transmit, horizontal receive (HH); horizontal transmit, vertical receive (HV); VV and VH, as illustrated in Figure 1. The coherence of SAR signals, which defines the degree of phase alignment between reflected waves, is a critical parameter for interferometric applications. High coherence facilitates precise measurements of surface displacement, structural changes, and topographic variations, making it essential for applications such as InSAR (Interferometric Synthetic Aperture Radar).

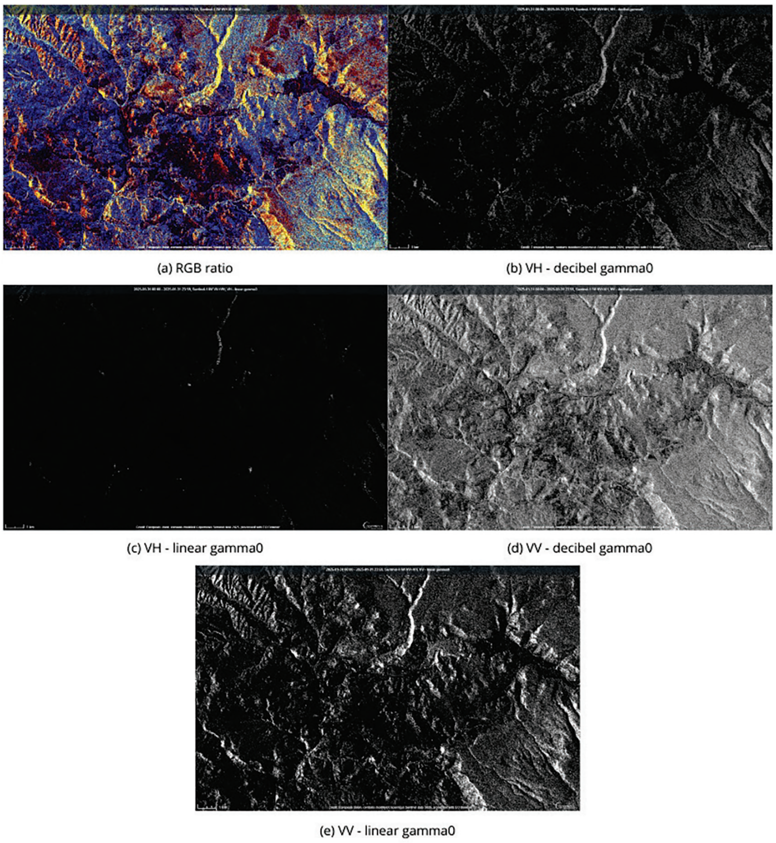


**Figure 1.** Demonstration of SAR image characteristics

**Notes:** a – RGB composite of different polarisation channels, emphasising structural features of the relief; b – VH polarisation with decibel gamma correction; c – VH polarisation with linear gamma correction; d – VV polarisation with decibel gamma correction; e – VV polarisation with linear gamma correction

**Source:** compiled by the author based on Copernicus Browser (n.d.)

A distinctive feature of SAR images is the presence of speckle noise, a form of multiplicative noise that arises due to the coherent nature of radar radiation. Speckle noise significantly degrades image quality and complicates subsequent processing (Liu *et al.*, 2022; Imad *et al.*, 2024). Unlike optical imaging systems, SAR images contain phase information, necessitating specialised interpretation techniques. Additionally, the intensity of the reflected signal in SAR images is influenced by the dielectric properties and surface roughness, resulting in unique scattering patterns for different terrain types.

The primary challenges in applying ML methods to SAR data stem from these specific characteristics. The presence of speckle noise necessitates preprocessing using specialised filters, such as the Frost and Lee filters, which aim to suppress noise while preserving essential structural elements of the image. The effectiveness of these filters directly impacts the accuracy of subsequent classification, as excessive filtering can lead to the loss of critical textural characteristics. Geometric distortions, including foreshortening and layover, occur due to the side-looking nature of SAR systems and variations in terrain elevation. These effects can lead to misinterpretation of spatial relationships, complicating the classification process. Correcting such distortions requires precise terrain information and accurate imaging parameters, which are not always available, posing additional challenges for SAR image analysis.

The analysis of Figure 1 highlights key differences between polarisation modes and SAR data processing methods. VH polarisation (Fig. 1b, 1c) exhibits notable sensitivity to objects with double-reflection scattering, whereas VV polarisation (Fig. 1d, 1e) responds more effectively to vertical structures. The RGB composite (Fig. 1a) provides a comprehensive representation of these characteristics, facilitating data interpretation and enhancing feature distinction. A major challenge in SAR image classification remains the limited availability of labelled datasets. Public SAR image databases, such as AIRSAR and Sentinel-1, often lack a sufficient number of annotated examples for the effective training of deep neural networks. This limitation drives the development of data-limited learning approaches and augmentation techniques (Xue & Zhang, 2020; Hochstuhl *et al.*, 2023). The use of generative models to synthesise additional training examples is a promising approach; however, it requires careful validation to ensure the realism and reliability of the generated data.

Traditional ML methods, such as SVM, RF, and k-Nearest Neighbours (k-NN), are frequently used for SAR image classification due to their structural simplicity and high interpretability (Zengguo *et al.*, 2021). These algorithms rely on pre-extraction of specific features from images, which are then utilised for model training. However, the effectiveness of these approaches is constrained by the complexity of SAR data, particularly the presence of speckle noise, texture heterogeneity, and variations in surface characteristics. The Support Vector Machine (SVM) method identifies the optimal hyperplane for class separation in a multidimensional feature space. The use of kernel functions (e.g., radial basis functions) enables the handling of nonlinear dependencies, which is particularly important for the analysis of SAR texture data (Gavrylenko & Chelfk, 2023). However, this method requires careful parameter tuning, which can be challenging when working with noisy data (Huang, 2024).

The RF ensemble method employs multiple decision trees, providing robustness against overfitting and enabling the automatic assessment of feature importance. This approach is particularly useful for SAR image analysis, where key characteristics such as intensity and polarisation exhibit significant variation. However, RF is not always capable of accurately capturing complex spatial dependencies, which can limit its applicability in cases involving fine micropatterns (Chen *et al.*, 2024). The k-NN method classifies objects based on their proximity to neighbouring samples within the training set, making it relatively simple to implement (Oumarou & Rismayanti, 2024). However, k-NN is computationally expensive when processing large datasets, and the choice of distance metric (e.g., Euclidean, Manhattan) has a significant impact on classification accuracy, especially in noisy conditions (Bhattacharjee *et al.*, 2024). Feature extraction for SAR images is commonly performed using texture feature analysis, such as the Gray-Level Co-occurrence Matrix (GLCM), which estimates statistical dependencies between pixels. Additionally, intensity statistics such as mean, variance, and skewness are used to characterise SAR images. Combining these parameters with polarimetric features can significantly enhance classification performance (Schmitt *et al.*, 2018; Monsalve-Tellez *et al.*, 2022). To summarise the main characteristics of traditional ML methods for SAR image classification, Table 1 provides a comparative overview.

**Table 1.** Comparative analysis of traditional ML methods for SAR image classification

| Method | Advantages | Limitation | Notes |
|---|---|---|---|
| SVM | Efficient class separation using optimal hyperplanes; possibility of using kernel functions for nonlinear problems | Sensitivity to parameters (kernel type, regularisation coefficient); high impact of speckle noise | Works well with small data sets |
| Random Forest | Resilience to overtraining; automatic assessment of feature importance; processing of large data sets | Insufficient ability to reproduce complex spatial relationships; possible underestimation of efficiency with micropatterns | Suitable for scenarios with high variability of features |
| k-Nearest Neighbours | Easy to implement; intuitive classification logic | High computational complexity with large data; critical impact of choice of distance metric; sensitivity to noise | Requires optimisation when working with large data sets |

**Source:** compiled by the author

The data indicate that traditional methods provide basic accuracy in SAR image classification; however, their ability to automatically extract features and process complex spatiotemporal relationships is limited. These shortcomings have driven the transition towards DL methods, which enable the adaptive extraction of relevant features without the need for manual feature engineering. DL approaches, such as CNNs, transformers, and autoencoders, have become key tools for SAR image classification and processing (Liu *et al.*, 2017). Their ability to automatically extract complex features from raw data effectively overcomes the limitations of traditional methods, particularly in the presence of speckle noise and heterogeneous textures. Among CNN architectures, ResNet and U-Net demonstrate high efficiency in processing SAR data. ResNet employs residual blocks to facilitate the learning of deep feature representations, mitigating the issue of vanishing gradients. This capability is crucial for detecting the complex texture patterns characteristic of SAR images. U-Net, with its symmetric encoder-decoder structure, excels in precise object segmentation, making it particularly effective for distinguishing features such as forests and water bodies while preserving spatial information, even in noisy environments (Kanmani *et al.*, 2023).

Another highly effective approach is the use of transformers, particularly the ViT which analyses global dependencies within an image by dividing it into patches and processing them as sequential data (Pan *et al.*, 2022). This enables the detection of long-range relationships, which are often overlooked by CNNs, making transformers particularly suitable for classifying SAR data with complex distributed patterns (Li *et al.*, 2023). Autoencoders are widely employed for noise reduction and data compression. Their encoder-decoder structure enables the reconstruction of "clean" images from compressed representations, thereby minimising the impact of speckle noise. This preprocessing step enhances the quality of input data for subsequent classification, particularly in cases where the noise level is high.

Different DL architectures adopt distinct approaches to SAR image processing, as illustrated in Figure 2. The upper-left section of the diagram presents the ResNet architecture, highlighting the principle of residual connections, which facilitate efficient gradient propagation through deep layers without significant information loss. This capability allows ResNet to effectively detect and classify intricate texture patterns in SAR images. The upper-right section of the diagram displays the U-Net architecture, characterised by its symmetric encoder-decoder structure connected by skip connections. This design enables the extraction of essential image features while retaining spatial details, making U-Net particularly effective for SAR image segmentation tasks. It is widely used for identifying features such as water bodies, urban areas, and forests, even in complex and noisy environments.

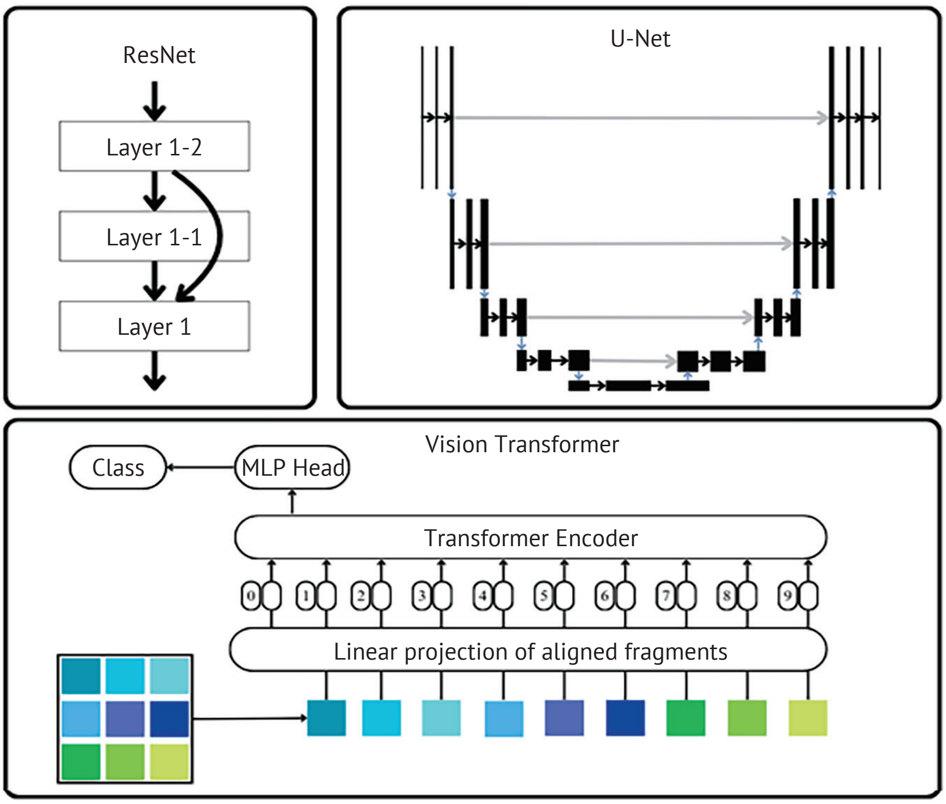


**Figure 2.** DL architectures for SAR image processing

**Source:** compiled by the author

The bottom section of Figure 2 illustrates the ViT architecture, which operates by dividing the image into patches that are subsequently processed by a transformer encoder. This approach enables ViT to analyse global dependencies between different elements within a scene, making it particularly effective for recognising long-term relationships in SAR images. This is especially beneficial in applications such as detecting large-scale structures or monitoring sequential changes in time series data. Despite its significant advantages, the application of ViT and other transformer-based models is associated with high computational costs and a requirement for large volumes of labelled data. Ongoing research focuses on leveraging transfer learning and semi-supervised learning methods to enhance model adaptability across different types of SAR images, thereby improving processing accuracy and classification performance.

Hybrid approaches to SAR image processing, which integrate the strengths of deep neural networks with traditional ML methods, are becoming increasingly relevant due to their potential to enhance classification accuracy and adaptability to complex patterns in the data. This approach enables the automatic extraction of features using convolutional neural networks (CNNs) while simultaneously applying classical algorithms, such as SVMs, to optimise the classification process. In this context, CNNs efficiently extract spatial and textural features from raw SAR images, thereby reducing reliance on manual feature engineering, which often depends on expert knowledge. The subsequent use of SVM for feature classification facilitates more precise class separation, particularly in datasets containing high levels of speckle noise and non-uniform textures, both of which significantly influence analysis quality (Meng *et al.*, 2023).

The adoption of pre-trained models in transfer learning presents new opportunities for adapting models to the specific characteristics of SAR data. This approach enables the transfer of knowledge acquired from optical image processing to SAR image analysis, significantly reducing computational costs and training data requirements. Optical-SAR matching demonstrates how integrating texture features from optical images can enhance the vector representation of SAR images, leading to more precise object detection, such as identifying ships on radar (Wei *et al.*, 2021; Chu *et al.*, 2024). Moreover, pre-trained models specifically adapted for SAR images often outperform those trained on general-purpose datasets such as ImageNet, underscoring the importance of considering the unique properties of SAR data when developing classification algorithms (Zhang *et al.*, 2016).

This hybrid approach not only improves overall classification accuracy by adapting more effectively to complex patterns but also optimises the use of limited datasets. Reducing reliance on manual feature extraction and automating the feature learning process leads to more stable results, which is crucial for practical applications in remote sensing. Thus, the integration of CNNs with classical classification algorithms, combined with transfer learning, creates a powerful framework capable of adapting to various SAR conditions. This enhances the accuracy of data analysis, making it highly relevant for the development of modern monitoring and resource management systems. Preprocessing of SAR data plays a crucial role in enhancing the quality of satellite images for subsequent analysis and classification. It encompasses methods aimed at reducing noise, improving visual interpretation, and ensuring data consistency for ML applications. The key stages of this process include speckle filtering, pixel intensity normalisation, and data augmentation. Speckle noise is one of the most prevalent types of noise in SAR images, arising due to the coherent nature of the signal, which can significantly hinder scene interpretation. Various filtering methods are employed to mitigate speckle noise, with the Lee filter being one of the most widely used techniques. This adaptive algorithm is based on the statistical characteristics of a pixel's local neighbourhood, estimating the mean value and variance within a defined window. This approach enables noise suppression while preserving essential textural and structural features of the image.

Figure 3 presents the results of speckle filtering in a SAR image using different Lee filter window sizes. Figure 3(a) displays the original SAR image, composed using the VV and VH channels in RGB format. A significant portion of the scene exhibits pronounced speckles, which obscure textural characteristics and object contours, making interpretation more challenging. Figure 3b illustrates the outcome of applying the Lee filter with a 3×3 window. While the noise level is reduced, high-frequency brightness fluctuations remain, which may affect automated classification. Figure 3c shows the result of filtering with a 5×5 window, demonstrating a substantial reduction in speckle noise. This improves object visibility and boundary definition, while still retaining key textural features essential for further analysis. Figure 3d presents the result of filtering with a 7×7 window, where an even greater level of smoothing is observed. However, this results in the loss of fine details, and certain textural features visible in previous stages become less distinct, potentially complicating detailed analysis. Thus, selecting the optimal window size for speckle filtering is a critical parameter that must be determined based on the specific application of SAR images. The trade-off between noise reduction and detail preservation should be carefully considered to ensure optimal classification performance.

In addition to speckle filtering, another essential preprocessing step is the normalisation of pixel intensities, which ensures consistency between different datasets. This is particularly crucial for multi-temporal analysis, where intensity values may vary due to factors such as the time of capture, viewing angle, or weather conditions. Normalisation can be performed by scaling intensity values to a fixed range (e.g., 0 to 1) or through standardisation, which adjusts values to have a zero mean and a standard deviation of one. These techniques help to reduce the influence of external factors and ensure that images are more homogeneous, facilitating further analysis.

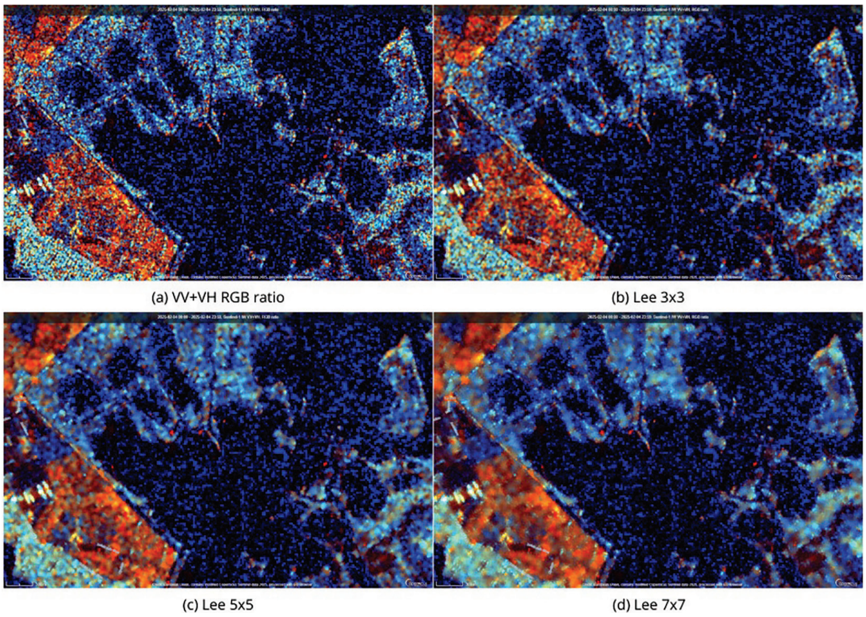


**Figure 3.** Effect of speckle filtering using the Lee filter on SAR images

**Notes:** a – Original VV+VH image in RGB format containing significant speckles; b – Result of applying the Lee filter with a window size of 3×3 – partial noise reduction is observed while preserving details; c – Lee filter 5×5 – further noise reduction and improvement of object contrast; d – Lee filter 7×7 – maximum smoothing, which may lead to loss of texture characteristics
**Source:** compiled by the author based on Copernicus Browser (n.d.)

Another important preprocessing procedure is data augmentation, which enhances the performance of classification and DL models. Data augmentation techniques include rotation, scaling, and the addition of synthetic noise, all of which help to increase the number of training samples and improve the generalisation ability of models. Image rotation enhances model robustness by making it invariant to object orientation, which is particularly important for analysing scenes captured from different perspectives. Scaling enables the model to adapt to size variations in objects, a common phenomenon in SAR images due to differences in resolution and terrain structure. Adding synthetic noise is particularly effective for training models to be robust against varying levels of data noise, a characteristic feature of radar images. By integrating these preprocessing techniques, models become more resilient to external distortions, ensuring improved classification accuracy and adaptability to diverse SAR imaging conditions. The preprocessing of SAR data is a multi-component process that encompasses speckle filtering, intensity normalisation, and data augmentation. Each of these stages plays a crucial role in enhancing image quality, thereby improving the accuracy of subsequent analytical methods, particularly in automated classification and change detection. The application of appropriate processing techniques significantly enhances the informativeness of SAR images, which is critical for applications in remote sensing and land surface analysis.

Training image classification models, particularly those designed for SAR image processing, is a complex task that involves selecting suitable optimisation criteria and regularisation methods to improve accuracy and resistance to overfitting. A key aspect of this process is the definition of the loss function, which serves as the primary mechanism for adjusting model parameters, ensuring the minimisation of discrepancies between predicted and actual class values. In multiclass classification problems, the most commonly used loss function is cross-entropy, which measures the distance between two probability distributions: the predicted distribution of the model and the actual class labels. Due to its ability to penalise discrepancies between the correct class and the predicted probability vectors, cross-entropy enables the optimisation of network parameters, thereby enhancing the model's ability to accurately classify SAR images (Nillmani *et al.*, 2022). Regularisation plays a crucial role in the training of models, preventing overfitting by ensuring that the network maintains its generalisation capability rather than merely adapting to the training samples. One effective regularisation technique is Dropout, which randomly deactivates a certain percentage of neurones during training. This forces the network to distribute information across multiple activation paths, enhancing its robustness to minor variations in input data and improving its ability to generalise to new samples.

Another key approach is L2 regularisation, also known as the weight decay penalty, which introduces an additional term to the loss function proportional to the squared norms of the weight parameters. This technique restricts the magnitude of the weights, preventing them from becoming excessively large, which can otherwise lead to overfitting and reduced generalisation efficiency. The combined use of L2 regularisation with gradient normalisation techniques helps to develop stable models that perform consistently on test datasets, even in the presence of high variability in SAR images (Zhong *et al.*, 2020). Thus, the successful training of SAR image classification models largely depends on the choice of loss functions and regularisation techniques. Cross-entropy parameter optimisation ensures precise adaptation of the network for recognising different classes, while regularisation methods, particularly Dropout and L2 regularisation, help to prevent overfitting and enhance the generalisation ability of models. This is particularly crucial for SAR image analysis in diverse application scenarios.

SAR image classification is a critically important research domain in remote sensing, offering unique capabilities for environmental monitoring, military intelligence, and natural resource management. Studies by W. Cui *et al*. (2020) and J. Iqbal *et al*. (2020) highlight how advancements in ML and DL technologies are creating new opportunities to enhance the accuracy and efficiency of SAR data classification. The findings indicate that ML methods, particularly SVM and RF, are characterised by high training efficiency and strong interpretability. These results align with the conclusions of R. Zhang *et al*. (2020), who emphasised the particular effectiveness of these methods in scenarios where understanding the decision-making process is essential. However, they also noted the limited effectiveness of traditional algorithms when processing the complex textures typically found in SAR images.

The analysis of DL methods supports the findings of J.F.M.R. Filho & P. Bélanger (2021) regarding the ability of DL models to enable automatic feature extraction and achieve high accuracy in the classification of complex data. The CNN architectures examined in this study demonstrated particular efficiency in processing SAR images, primarily due to their capacity to detect hierarchical feature representations. These results align with the findings of Y. Wu *et al*. (2023), who emphasised that a major limitation of DL methods remains their high demand for large training datasets and significant computational resources. The study of hybrid approaches, which integrate ML and DL techniques, confirms the conclusions of S.R. Majji *et al*. (2022) regarding their strong potential for enhancing SAR image classification. In particular, their proposed hybrid architecture, which employs a CNN for feature extraction followed by an SVM for classification, produced results similar to those obtained in this study. This combined approach leverages the strengths of both methods, improving classification accuracy while maintaining the interpretability of results. In terms of data preprocessing, the findings align with the study by B. Evans *et al*. (2023), which highlights the importance of speckle filtering and normalisation. Experimental results confirm that high-quality preprocessing can significantly enhance classification performance, regardless of the chosen ML method. Additionally, the results are consistent with the conclusions of Z. Zeng *et al*. (2022), which emphasise the critical role of data augmentation in improving the efficiency of model training.

The analysis of SAR image classification methods illustrates the evolution of approaches from traditional ML techniques to deep neural networks and hybrid architectures. Traditional ML methods, such as SVM and RF, offer fast training and high interpretability but exhibit limitations in handling complex textures. In contrast, DL methods, particularly CNNs, demonstrate higher classification accuracy due to their ability to automatically extract hierarchical features. However, these models require substantial computational resources and large training datasets. Hybrid approaches, which integrate CNNs with traditional classifiers, provide an optimal balance between accuracy and result interpretability. The effectiveness of all methods is significantly influenced by the quality of data preprocessing, including speckle filtering, normalisation, and data augmentation.

## CONCLUSIONS

As a result of this study on ML and DL methods for SAR image classification, the objective of identifying architectures and approaches that ensure high classification accuracy while maintaining computational efficiency has been achieved. The study identified key SAR image characteristics that influence the classification process, including the presence of speckle noise, the specificity of polarisation characteristics (HH, HV, VV, VH), and geometric distortions caused by the side-looking nature of SAR systems. It was determined that adaptive speckle filtering using a Lee filter with a 5×5 window provides the optimal balance between noise reduction and the preservation of critical structural elements in the image.

The study confirmed the limited effectiveness of traditional ML methods in processing the complex textural characteristics of SAR images. In contrast, DL architectures, particularly ResNet and U-Net, demonstrated significant advantages due to their ability to automatically extract hierarchical feature representations. Additionally, the use of complex-valued neural networks offers substantial optimisation of computational resources while maintaining high classification accuracy. The primary limitation of this study is that the analysis of SAR image classification methods was conducted primarily at a theoretical level, without the ability to practically validate the effectiveness of all examined architectures on real datasets. The publicly available SAR image databases used in this study lacked a sufficient number of labelled examples to facilitate a comprehensive evaluation of all proposed approaches. Another limitation is the inability to conduct experimental studies using high-performance computing systems, which prevented a direct comparison of training and classification times across different neural network architectures.

Based on the results obtained, practical recommendations have been formulated for the selection of architectures and training methods depending on the classification task. Specifically, for tasks involving a limited set of labelled data, it is recommended to utilise semi-supervised learning and data augmentation techniques to enhance model performance. Additionally, an algorithm for combining different polarisation channels has been proposed to improve the classification accuracy of complex landscapes. For the further advancement of this field, research should focus on developing specialised architectures that account for the physical properties of SAR signals, enhancing adaptive speckle filtering algorithms, and improving transfer learning methods to enable the effective adaptation of models across different SAR datasets. Furthermore, special attention should be given to the integration of interpretability techniques in DL models to increase trust and transparency in automated classification systems.

## ACKNOWLEDGEMENTS

None.

## FUNDING

None.

## CONFLICT OF INTEREST

None.

## REFERENCES

[1] Attioui, S., & Arivazhagan, S. (2020). Unsupervised change detection method in SAR images based on deep belief network using an improved fuzzy c-means clustering algorithm. *IET Image Processing*, 15(4), 974-982. doi: 10.1049/ipr2.12078.

[2] Bhattacharjee, S., Shanmugam, P., & Das, S. (2024). A novel lightweight multi-attentive general ship detection model for detection of ships in optical and SAR satellite imagery. In M.F. Carlsohn (Ed.), *Real-time processing of image, depth, and video information 2024* (article number 130000B). Strasbourg: Society of Photo-Optical Instrumentation Engineers. doi: 10.1117/12.3016869.

[3] Chen, G., Li, Z., Zhou, Q., & Liu, C. (2024). SAR image despeckling based on gradient domain convolutional sparse coding. In Z. Zhang & C. Li (Eds.), *Fifteenth international conference on signal processing systems (ICSPS 2023)* (article number 130911W). Xi'an: Society of Photo-Optical Instrumentation Engineers. doi: 10.1117/12.3023324.

[4] Chu, B., Chen, J., Zeng, H., Chen, J., Zhu, J., Wang, M., & Gao, X. (2024). An optical and SAR image registration method based on bidirectional style transfer and hybrid feature descriptor. In Y. Wang & T. Chen (Eds.), *2023 4th international conference on geology, mapping and remote sensing (ICGMRS 2023)*. Wuhan: Society of Photo-Optical Instrumentation Engineers. doi: 10.1117/12.3019591.

[5] Copernicus Browser. (n.d.). Retrieved from https://browser.dataspace.copernicus.eu/.

[6] Cui, W., Zhang, Y., Zhang, X., Li, L., & Liou, F. (2020). Metal additive manufacturing parts inspection using convolutional neural network. *Applied Sciences*, 10(2), article number 545. doi: 10.3390/app10020545.

[7] Ding, R. (2023). Which network is stronger? Le Net, Alex Net and VGG on image classification. *Applied and Computational Engineering*, 4, 294-300. doi: 10.54254/2755-2721/4/20230476.

[8] Evans, B., Faul, A., Fleming, A., Vaughan, D.G., & Hosking, J.S. (2023). Unsupervised machine learning detection of iceberg populations within sea ice from dual-polarisation SAR imagery. *Remote Sensing of Environment*, 297, article number 113780. doi: 10.1016/j.rse.2023.113780.

[9] Filho, J.F.M.R., & Bélanger, P. (2021). Probe standoff optimization method for phased array ultrasonic TFM imaging of curved parts. *Sensors*, 21(19), article number 6665. doi: 10.3390/s21196665.

[10] Gavrylenko, S., & Chelfk, V. (2023). Development of method base on fuzzy decision trees for identification of the computer systems state. *Navigation and Communication Systems*, 1(71), 78-83. doi: 10.26906/sunz.2023.1.078.

[11] Hochstuhl, S., Pfeffer, N., Thiele, A., Hammer, H., & Hinz, S. (2023). Your input matters – comparing real-valued PolSAR data representations for CNN-based segmentation. *Remote Sensing*, 15(24), article number 5738. doi: 10.3390/rs15245738.

[12] Huang, Z. (2024). A research on image recognition and classification based on traditional machine learning and deep learning. *Transactions on Computer Science and Intelligent Systems Research*, 5, 766-773. doi: 10.62051/0dbqaa10.

[13] Imad, H., Sara, Z., Hajji, M., Yassine, T., & Abdelkrim, N. (2024). Recent advances in SAR image analysis using deep learning approaches: Examples of speckle denoising and change detection. In B. Benhala, A. Raihani & M. Qbadou (Eds.), *4th international conference on innovative research in applied science, egineering and technology* (pp. 1-6). Morocco: Institute of Electrical and Electronics Engineers. doi: 10.1109/IRASET60544.2024.10549456.

[14] Iqbal, J., Vogt, M., & Bajorath, J. (2020). Activity landscape image analysis using convolutional neural networks. *Journal of Cheminformatics*, 12, article number 34. doi: 10.1186/s13321-020-00436-5.

[15] Kanmani, K., Padmanabhan, V., & Pari, P. (2023). Accuracy assessment of different classifiers for sustainable development in landuse and landcover mapping using sentinel SAR and landsat-8 data. *EAI Endorsed Transactions on Energy Web*, 10. doi: 10.4108/ew.4141.
[16] Konishi, B., Hirose, A., & Natsuaki, R. (2021). Complex-valued reservoir computing for interferometric SAR applications with low computational cost and high resolution. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 7981-7993. doi: 10.1109/jstars.2021.3102620.
[17] Kruk, R., Fuller, M.C., Komarov, A.S., Isleifson, D., & Jeffrey, I. (2020). Proof of concept for sea ice stage of development classification using deep learning. *Remote Sensing*, 12(15), article number 2486. doi: 10.3390/rs12152486.
[18] Li, Q., Bai, X., Hu, L., Li, L., Bao, Y., Geng, X., & Yan, X.-H. (2024). SAR image semantic segmentation of typical oceanic and atmospheric phenomena. *Earth System Science Data*. doi: 10.5194/essd-2024-222.
[19] Li, X., Wang, Z., Li, J., & Mu, P. (2023). Swin-transformer based target detection with enhanced maritime SAR images data. In S. Xu & S. Sazena (Eds.), *International conference on signal processing and communication technology (SPCT 2022)*. Harbin: Society of Photo-Optical Instrumentation Engineers. doi: 10.1117/12.2673920.
[20] Li, Y., Zhang, S., Li, X., & Ye, F. (2023). Remote sensing image classification with few labeled data using semisupervised learning. *Wireless Communications and Mobile Computing*, 2023(1), article number 7724264. doi: 10.1155/2023/7724264.
[21] Liu, S., Pu, N., Cao, J., & Zhang, K. (2022). Synthetic aperture radar image despeckling based on multi-weighted sparse coding. *Entropy*, 24(1), article number 96. doi: 10.3390/e24010096.
[22] Liu, T., Li, Y., Cao, Y., & Shen, Q. (2017). Change detection in multitemporal synthetic aperture radar images using dual-channel convolutional neural network. *Journal of Applied Remote Sensing*, 11(4), article number 042615. doi: 10.1117/1.jrs.11.042615.
[23] Majji, S.R., Chalumuri, A., Kune, R., & Manoj, B.S. (2022). Quantum processing in fusion of SAR and optical images for deep learning: A data-centric approach. *IEEE Access*, 10, 73743-73757. doi: 10.1109/access.2022.3189474.
[24] Meng, H., Li, C., Liu, Y., Gong, Y., He, W., & Zou, M. (2023). Corn land extraction based on integrating optical and SAR remote sensing images. *Land*, 12(2), article number 398. doi: 10.3390/land12020398.
[25] Monsalve-Tellez, J.M., Torres-León, J.L., & Garcés-Gómez, Y.A. (2022). Evaluation of SAR and optical image fusion methods in oil palm crop cover classification using the random forest algorithm. *Agriculture*, 12(7), article number 955. doi: 10.3390/agriculture12070955.
[26] Nillmani, N., Sharma, N., Saba, L., Khanna, N., Kalra, M., Fouda, M., & Suri, J. (2022). Segmentation-based classification deep learning model embedded with explainable AI for COVID-19 detection in chest X-ray scans. *Diagnostics*, 12(9), article number 2132. doi: 10.3390/diagnostics12092132.
[27] Oumarou, H., & Rismayanti, N. (2024). Automated classification of empon plants: A comparative study using Hu Moments and K-NN algorithm. *Indonesian Journal of Data and Science*, 4(3), 206-214. doi: 10.56705/ijodas.v4i3.115.
[28] Pan, J., Zhang, H., Wu, W., Gao, Z., & Wu, W. (2022). Multi-domain integrative Swin transformer network for sparse-view tomographic reconstruction. *Patterns*, 3(6), article number 100498. doi: 10.1016/j.patter.2022.100498.
[29] Poplavskyi, O. (2024). Information technology for image data processing based on hybrid neural networks using geometric features. *Information Technologies and Computer Engineering*, 21(2), 4-16. doi: org/10.31649/1999-9941-2024-60-2-4-16.
[30] Schmitt, M., Hughes, L.H., & Zhu, X.X. (2018). The SEN1-2 dataset for deep learning in SAR-optical data fusion. *ISPRS Annals of the Photogrammetry Remote Sensing and Spatial Information Sciences*, 4(1), 141-146. doi: 10.5194/isprs-annals-iv-1-141-2018.
[31] Villarroya-Carpio, A., & López-Sánchez, J.M. (2023). Multi-annual evaluation of time series of Sentinel-1 interferometric coherence as a tool for crop monitoring. *Sensors*, 23(4), article number 1833. doi: 10.3390/s23041833.
[32] Vu, V.T., Pettersson, M.I., Palm, B.G., Alves, D.I., & Gomes, N.R. (2021). Changing flight heading during pass to enhance SAR change detection performance. *IET Radar Sonar & Navigation,* 15(8), 817-826. doi: 10.1049/rsn2.12058.
[33] Wang, L., Jin, G., Xiong, X., Zhang, H., & Wu, K. (2022). Object-based automatic mapping of winter wheat based on temporal phenology patterns derived from multitemporal Sentinel-1 and Sentinel-2 imagery. *ISPRS International Journal of Geo-Information*, 11(8), article number 424. doi: 10.3390/ijgi11080424.
[34] Wei, B., Huang, M., Zhang, Y., Xu, Y., Liu, X., & Xiang, X. (2021). Boosting ship detection in SAR images with complementary pretraining techniques. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 14, 8941-8954. doi: 10.1109/jstars.2021.3109002.

[35] Wu, Y., Xia, Y., Jiang, M., Li, S., Chen, M., Zhao, Y., & Teng, D. (2023). Multisource remote sensing image registration based on geometric constraints. In C. Zuo (Ed.), *International conference on remote sensing, surveying, and mapping (RSSM 2023)* (article number 127100J). Changsha: Society of Photo-Optical Instrumentation Engineers. doi: 10.1117/12.2682662.
[36] Xue, Z., & Zhang, M. (2020). Multiview low-rank hybrid dilated network for SAR target recognition using limited training samples. *IEEE Access*, 8, 227847-227856. doi: 10.1109/access.2020.3046274.
[37] Zeng, Z., Tan, X., Chen, Z., Huang, Y., Tang, S., & Wan, J. (2022). Robust image similarity metric method for SAR images. *Electronics Letters*, 58(13), 508-510. doi: 10.1049/ell2.12516.
[38] Zengguo, S., Zhao, M., & Jia, B. (2021). A GF-3 SAR image dataset of road segmentation. *Information Technology and Control*, 50(1), 89-101. doi: 10.5755/j01.itc.50.1.27987.
[39] Zhang, H., Li, G., & Lin, H. (2016). An automatic co-registration approach for optical and SAR data in urban areas. *Annals of GIS*, 22(3), 235-243. doi: 10.1080/19475683.2016.1199595.
[40] Zhang, R., Tang, X., You, S., Duan, K., Xiang, H., & Luo, H. (2020). A novel feature-level fusion framework using optical and SAR remote sensing images for land use/land cover (LULC) classification in cloudy mountainous area. *Applied Sciences*, 10(8), article number 2928. doi: 10.3390/app10082928.
[41] Zhong, Z., Zheng, L., Kang, G., Li, S., & Yang, Y. (2020). Random erasing data augmentation. *Proceedings of the AAAI Conference on Artificial Intelligence*, 34(7), 13001-13008. doi: 10.1609/aaai.v34i07.7000.

## Машинне навчання та глибинне навчання для класифікації SAR-зображень

**Юрій Бровка**
Аспірант
Національний технічний університет України
«Київський політехнічний інститут імені Ігоря Сікорського»
03056, просп. Берестейський, 37, м. Київ, Україна
https://orcid.org/0009-0004-3708-9747

**Анотація.** У дослідженні проведено комплексний аналіз сучасних методів машинного та глибинного навчання для класифікації радіолокаційних зображень із синтезованою апертурою. Метою роботи було визначення архітектур і підходів, які забезпечують високу точність класифікації при збереженні ефективності обчислювальних ресурсів. Основну увагу приділено вирішенню ключових викликів: спекл-шуму, геометричних спотворень та обмеженості розмічених даних. Методологія дослідження включала систематичний аналіз наукової літератури за 2015-2024 роки та вивчення поляризаційних характеристик Synthetic Aperture Radar-зображень із використанням платформи Copernicus Browser. Було досліджено ефективність традиційних методів машинного навчання (Support Vector Machines, Random Forest) та сучасних архітектур глибокого навчання (ResNet, U-Net, Vision Transformer). Особливу увагу приділено впливу адаптивної фільтрації спекл-шуму за допомогою фільтра Lee при різних розмірах вікна (3×3; 5×5; 7×7) на якість класифікації. Результати показали, що глибокі нейронні мережі мають переваги перед традиційними методами завдяки здатності автоматично виділяти ієрархічні представлення ознак. ResNet забезпечує високу точність класифікації, U-Net ефективна для сегментації, а Vision Transformer враховує глобальні залежності. Оптимальний баланс між придушенням спекл-шуму та збереженням деталей досягається при використанні фільтра Lee з розміром вікна 5×5. Однією з проблем залишається обмеженість розмічених даних. Для її вирішення розглянуто напівконтрольоване навчання, що покращує нормалізацію ознак і продуктивність моделей. Перспективним напрямком є використання комплекснозначних нейронних мереж для оптимізації обчислювальних витрат. Результати мають практичне значення для автоматизованої класифікації Synthetic Aperture Radar-зображень у задачах екологічного моніторингу, оцінки стану сільськогосподарських угідь та дистанційного зондування

**Ключові слова:** нейронні мережі; комплекснозначні обчислення; поляризаційні характеристики; радіолокаційне зондування; спекл-фільтрація