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## Synthetic Aperture Radar Image Classification: a Survey

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### Abstract

In this review paper, several studies and researches were surveyed for assisting future researchers to identify available techniques in the field of classification of Synthetic Aperture Radar (SAR) images. SAR images are becoming increasingly important in a variety of remote sensing applications due to the ability of SAR sensors to operate in all types of weather conditions, including day and night remote sensing for long ranges and coverage areas. Its properties of vast planning, search, rescue, mine detection, and target identification make it very attractive for surveillance and observation missions of Earth resources. With the increasing popularity and availability of these images, the need for machines has emerged to enhance the ability to identify and interpret these images effectively. This is due to the fact that SAR image processing requires the formation of an image from the measured radar scatter returns, followed by a treatment to discover and define the image's composition. After reviewing several previous studies that succeeded in achieving a classification of SAR images for specific goals, it became obvious that they could be generalized to all types of SAR images. The most prominent use of Convolutional Neural Networks (CNN) was successful in extracting features from the images and training the neural network to analyze and classify them into classes according to these features. The dataset used in this model was obtained from the Moving and Stationary Target Acquisition and Recognition (MSTAR) database, which consists of a set of SAR images of military vehicles, for which the application of the CNN approach achieved a final accuracy of 97.91% on ten different classes.

**Keywords:** Synthetic Aperture Radar (SAR), Classification, SAR images, Segmentation, Convolutional Neural Networks (CNN), Moving and Stationary Target Acquisition and Recognition (MSTAR).

### تصنيف صور الرادار ذي الفجوة المركبة: مراجعة لدراسة سابقة

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### الخلاصة

في ورقة المراجعة هذه ، تم مسح العديد من الدراسات والأبحاث ، لمساعدة الباحثين في المستقبل ، لتحديد التقنيات المتاحة في مجال تصنيف صور الرادار ذي الفجوة المركبة (SAR) . تزداد أهمية صور الرادار (SAR) في مجموعة متنوعة من تطبيقات الاستشعار عن بُعد نظراً لقدرة أجهزة استشعار الرادار (SAR) على العمل في جميع أنواع الظروف الجوية ، والاستشعار عن بعد نهائياً ولبداً للنطاقات الطويلة ومناطق

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التغطية. إن التخطيط الواسع والبحث والإنقاذ واكتشاف الألغام وتحديد الأهداف يجعلها جذابة جدًا لموارد الأرض في مهام المراقبة. مع تزايد شعبية هذه الصور وتوافرها ظهرت بالمقابل الحاجة إلى الآلات توفر القدرة على تحديد وتفسير تلك الصور بشكل فعال، حيث تتطلب معالجة صور الرادار (SAR) تكوين صورة من عوائد مبعثر الرادار المقاسة، تليها معالجة لاكتشاف وتحديد الأهداف المتكونة من الصورة. وبعد الاطلاع على عدد من الدراسات السابقة التي نجحت في انجاز تصنيف صور الرادار (SAR) لاهداف محددة ولكن لا يمكن تعميمها على جميع انواع صور الرادار (SAR) وكان استخدام الشبكات العصبية الالتفافية (CNN) الابرز نجاحاً وذلك باستخراج الميزات من الصور وتدريب الشبكة العصبية عليها وتصنيفها الى فئات وفقاً للميزات المستخرجة من تلك الصور، إن مجموعة البيانات المستخدمة هي للتعرف على الأهداف الثابتة والمتحركة (MSTAR)، والتي تتكون من مجموعة من صور الرادار (SAR) حول المركبات العسكرية؛ لقد وصلوا إلى الدقة النهائية البالغة 97.91% على عشرة فئات مختلفة.

## Introduction

Airborne radar imaging frameworks have been used for a considerable length of time in numerous significant frameworks and applications. With the advancement of innovations, commercial radar imaging satellites have been launched over the past two decades and SAR is presented on the European Remote-Sensing Satellite (ERS-1/2 satellites), the data of which are widely distributed and generally available. But radar images require positional image processing to exploit the potential of the important modern SAR sensors in environmental and civil protection applications. The real requirements for effective tools for automated analysis have increased with the vast amount of radar images acquired by satellites through space missions [1].

A SAR image is a 2-D map of the image scene's microwave reflectivity at 0.2 to 100 m resolution. The SAR sensor has some interesting properties that were not experienced during the use of the optical sensors, which are:

- SAR is an active imaging system. For example it provides lighting and is therefore independent of sunlight.
- SAR uses microwaves that penetrate clouds, vegetation, soil and snow.
- SAR uses polarized radiation and can therefore use the image scatterer's polarization signatures to gain more information about the structure of the scatterer.
- SAR is a coherent imaging method. This is the prerequisite for SAR interferometry. On the other hand, this makes the radiometric interpretation of SAR images difficult due to the appearance of speckles [2].

SAR imaging method uses signal processing to improve precision beyond the aperture limits of the actual antenna. Specific absorption rate permits the use of longer wavelengths and still achieves good resolution with antenna structures. SAR data processing requires the image of measured radar scatter yields to be formed, followed by the detection and identification process of formatted image targets. The current SAR processing process indicates that image composition is separated from the decision task.

Two types of SAR simulation systems are available, which are:

1. Systems simulating the image of the SAR.
2. Systems simulating the SAR imaging system that generates raw data on the qualitative rate of absorption, which must then be processed as an image [3].

SAR imaging has a high precision capacity and is extremely useful in many applications, including mine detection, rain, sea, oceanography, and snow [4]. It is also efficiently used in the monitoring of oil pollution on the ocean surface [5], as well as terrain classification [6]; discovering hidden objects in the forest, plant planning, crop type, landscape identification, hydrology, volcanism monitoring, climate meteorology, and natural risk management. This review aims to organize the approaches that concentrate on the SAR images classification and identify the suggested methods in related fields of research.

## Literature Review

The importance of the classification of SAR images has resulted in several survey papers. A comprehensive survey of the previously published works related to the classification of SAR image, as well as years of publication and topics, is described in Table-1.

**Table 1-** Survey Papers in Synthetic Aperture Radar (SAR) Image Classification

Year	Paper	Topic
1998	[7]	Synthetic Aperture Radar Image Coding.
1998	[8]	Genetic Programming for Automatic Target Classification and Recognition in Synthetic Aperture Radar Imagery Radar.
2000	[9]	Model-Based Classification of Radar Images.
2003	[10]	Unsupervised Classification of Radar Images Using Hidden Markov Chains and Hidden Markov Random Fields.
2006	[11]	Texture-Based classification of Ground-Penetrating Radar Images.
2008	[12]	A Rotation-Invariant Transform for Target Detection in SAR Images.
2010	[13]	Double Polarization SAR Image Classification Based on Object-Oriented Technology.
2011	[14]	Multilevel Local Pattern Histogram for SAR Image Classification.
2011	[15]	Target Image Enhancement in Radar Imaging Using Fractional Fourier Transform.
2011	[16]	Synthetic Aperture Radar Image Classification via Mixture Approaches.
2018	[17]	Superpixel Segmentation of Polarimetric Synthetic Aperture Radar (SAR) Images Based on Generalized Mean Shift.
2018	[18]	A Hierarchical Fully Convolutional Network Integrated with Sparse and Low-Rank Subspace Representations for PolSAR Imagery Classification.
2020	[19]	A Proposed Approach to Determine the Edges in SAR images.
2020	[20]	Deep Learning for SAR Image Classification.

Baxter and Seibert [7] clarify the applications that need human interpretation of SAR images for image archiving. They well acquainted 2 complete transformations, namely Dennis Gabor transformation and Gabor-like wavelet transformation. Each of these transformations has individual strengths and weaknesses. The Dennis Gabor conversion tends to maintain good textures, while Gabor-like wavelet conversion tends to keep both textures and shadows well. To get the best SAR image quality, the researchers came up with the best compression system, which consists of a wavelet switching that uses a Gabor-like tree structure with smooth biorthogonal wavelet filters.

Stanhope and Daida [8] illustrate the Genetic Programming (GP) model to gain insights into the use of the GP as a choice algorithm in the experiments performed to solve the application problem. The first task in the application of GP is the creation of rules to classify a set of military objectives depicted by SAR, where in the first experiment GP was used to produce a logical language with a collection of predefined features and to construct logical expressions to describe the target with an expanded set of features.

The second task was performed through the second experiment to obtain a new set of military objectives generated from SAR images in the first experiment by using SAR sensor to built bases to classify tanks.

Chiang et al. [9] illustrate a Bayesian-model-based imaging and decision approach for the classification of radar images. In this model-based image processing framework, the processing objective is to categorize objects where model-based classification or pattern matching combines uncertainty in both sensor data and object class models to calculate hypothesis probability instead of using a large catalog of image templates. Model matching permits the user to estimate the performance of the trace table and provide durability against environments that has not been measured before. Therefore, the approach provides the means to manage complexity in specific hypotheses where SAR image pixels are structured to become executable and scalable.

Fjørtoft *et al.* [10] explain the combination of approaches under hidden Markov models between unsupervised radar object identification and generalized mixture estimation. Where parameter estimation and classification processes are used, Markov random fields are used to enforce spatial order constraints by distributing families and parameters of the fixed or hermetic radar surface. The

goal of using this approach is to achieve optimal results in most situations, so the final evaluation can achieve quick and robust mix and well-organized classification results, but the disadvantages of this method suggest that estimating the uniformity coefficient is a difficult problem.

Moyseyet al. [11] introduce a test to assess whether various measures to capture Ground-Penetrating Radar (GPR) data features, when combined with an atomic neural network, can introduce a human interpretation. Quantitative tissue measurements are an important step in the successful advanced development of "Ground-Penetrating Radar pictures" analysis techniques. Thus, the researchers focused on the texture of the image, which is one of the main characteristics used to interpret radars in GPR data. Through the experiments and results, they found that the computers were capable to produce human explanations with an accuracy of more than 93%, through measures that describe the structure of the local spatial GPR image.

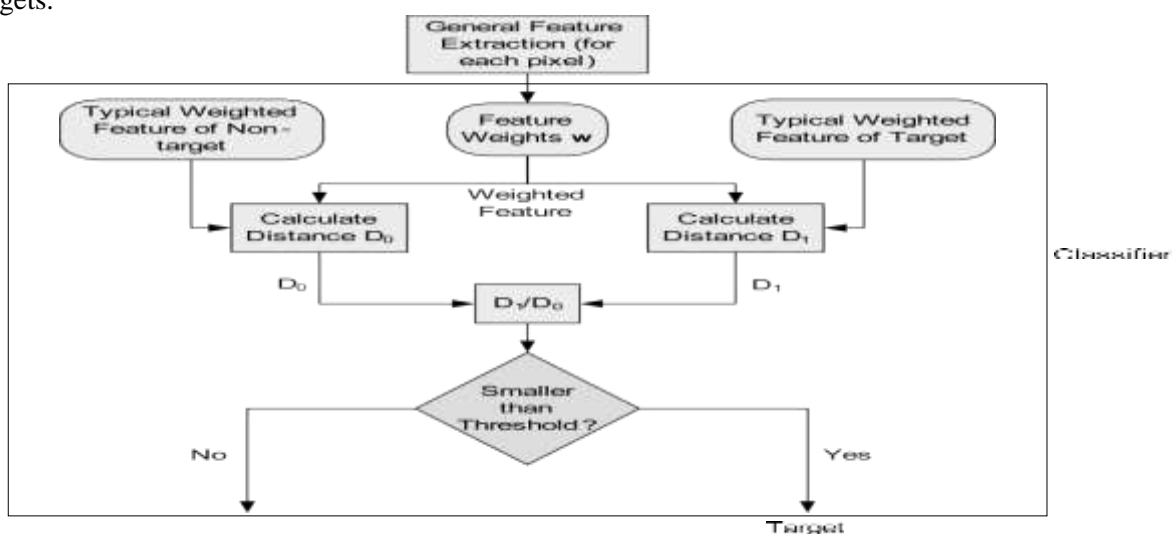
Ye et al. [12] propose a powerful algorithm to design an automatic target discovering system of rotating targets. The aim of this system is to identify all Automatic Target Detection (ATD) vehicles hidden in the woods. One thing to take into account is the forest thickness that is immediately commensurate with the picture's noise. Therefore, when analyzing images, the essential assumptions made are that the background noise is fixed and targets are moving. The important idea of the proposed algorithm is described below.

(1) Initially, the test image is defined as an image in which the algorithm attempts to identify the surrounding targets. The reference image is an image from the same location as the test image, but it is captured when the targets move to another location. The algorithm takes the difference between the two images to detect the moving targets in the test image, and the effect is mostly a collection of moving targets.

(2) The detection algorithm of this paper consists of supervised learning, balance, and combining diversity, as well as a more advanced local fixed descriptor where the function of the local descriptor is to extract local characteristics from the area of interest identified in the image. Their success in image data analysis applications makes the static local descriptors of the spin a powerful target discovery algorithm against spin targets.

(3) The weighting feature increases the distinction between target and non-target groups. The processing step is the step of noise reduction that removes the clear context. The main advantages of the processing stage are that, in the learning phase, it can improve the play of the algorithm and the pace of the competition.

(4) Finally, the post-processing combines nearby pixels, removes small discoveries, and produces the location of each discovery. The results of the experimental analysis of high-resolution SAR images showed a high potential that was used for blend-based models in the SAR image classification problem. Figure-1 shows the diagram of classification that used in the algorithm of discovering rotating targets.

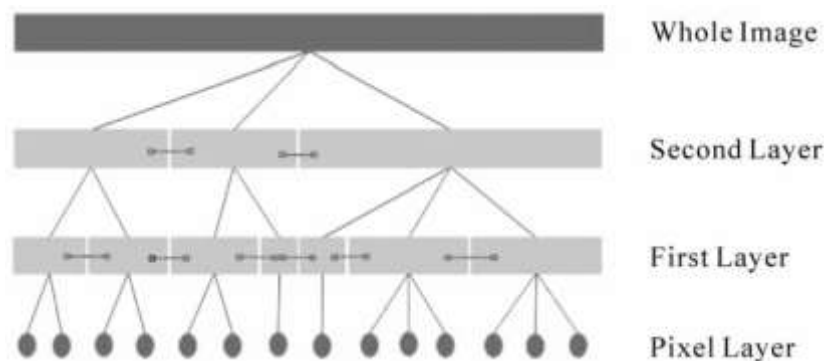


**Figure 1-**The diagram of classification used in the algorithm of discovering rotating targets.

Liu *et al.* [13] aim to classify object-oriented polarized SAR objects. The authors showed the following: (1) because the smallest object-oriented identification unit in the extraction of information is the object containing more semiconductor information from neighboring pixels, they are therefore distinguished by a high degree of perception accuracy. (2) Object-oriented engineering identification benefits not only from the diffuse image information but also from the size and shape data as well as the additional external object information. (3) The accuracy of the score is improved from 73.7% to 91.84%. The result shows that the object-oriented classification software is ideal for high-precision, double-polarization classification compared to the traditional pixel-based classification.

Object-oriented classification has two primary methods, including the closest method of neighboring distance, where members can separate peaks, hills, and plains based on the pattern of terrain. Using the ground

Object area, statistical information may make additional classification depending on the location, as shown in Figure-2.



**Figure 2-**Image object's network structure hierarchy graph.

The multi-scale segmentation of a SAR image included multiple small areas of the image that have several elements. At first, considered each pixel is an object; also, an image object has several forms, such as color, width, shape, uniformity, etc. The process involves combining similar objects with closed objects.

If the area is cut individually, it will create some damaged areas and the analysis of the data will not be helpful.

There is a scale for each layer object. Remote sensing images can be represented from multiple object layers, rather than a single scale, by a variety of the same process of scales. After several hashes, it will form a multi-layered scheme of artifacts. Image artifacts are created at different levels, while the neighboring relationship and heritage level establish the relationship that influences the objects.

Similar hash image metrics calculate and accelerate the number of data units to be processed in the category.

It is possible to extract the characteristics of a larger spatial surface from a broad split layer such as lakes, forests, etc. Likewise, the proposal includes the creation of smaller layers to separate small size or complex feature areas.

The nearest classification range is equivalent to the classification supervised, which the specimen must decide. The user function method is used to organize the method of classification by representing the spectrum, shape, and texture properties along with other information of the object. Other auxiliary data such as maps are known as taxonomy of terrestrial objects and may also be used by object-oriented taxonomy.

Uncensored classification recognizes only 4 features, while hills and bare lands are not classified correctly, because hills are assigned to the farmland category. Since the overall dispersion properties are similar in the form of fields and hills, it is not possible to separate two types of surface features.

Dai *et al.* [14] propose a simple theoretical and mathematical feature known as the Multi-Level Local Pattern Scheme (MLPH) for the classification of SAR images in different forms. The study showed the following:

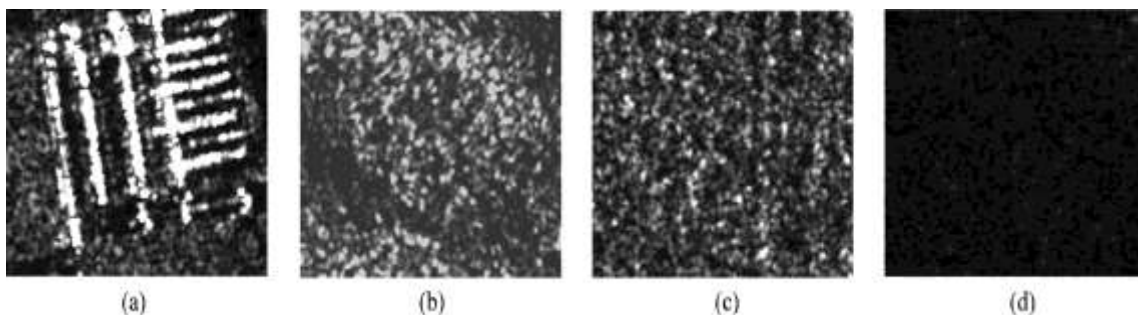
1. Since MLPH captures local and global structural information, it is a very strong SAR photo definition.
2. It is good for noise production.
3. The dominant factor in SAR dispersion is surface roughness, for example:
  - The local style is characterized by large, bright and dark areas coexisting with the SAR of the structurally controlled area. (i.e. buildings).
  - The local pattern is characterized by splashes of magnificent "spots", which are often formed by large tissues, for the area controlled by the fabric such as forests or farmland.
  - The regional pattern for a very flat area is a homogeneous dark area such as road surface or water. The distinguishing between the four styles (A) construction, (b) forest, (c) farmland, (d) water) is shown in Figure-3, while extracting an LPH from a pixel's neighborhood is shown in Figure-4.
  - MLPH is based on the idea that two key factors for local patterns are sufficient to determine the terrain category in SAR images. These factors are:
    - 1) Size (bright / dark areas, spots, etc.)
    - 2) Level (contrast level in the local model).

The results in Table-2 below include the analytical methods discussed in the results of previous studies for comparison with the classification accuracy developed by SVM with various features on the data TERRASAR-X DATA. The results showed that the MLPH method resulted in the highest accuracy.

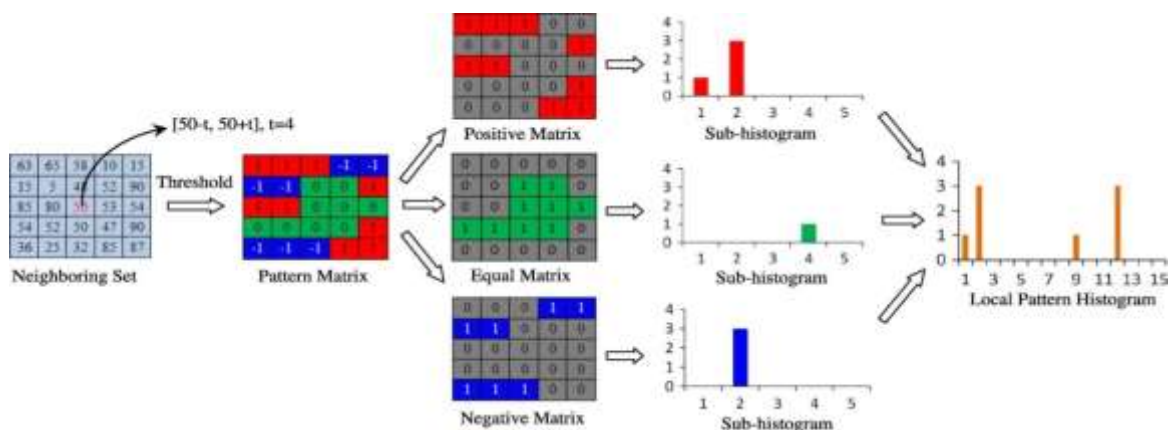
**Table 2-** Classification of the accuracies set by the SVM with different features on the TERRASAR-X

	Hist	GLCM	Gabor	GMRF	MLPH
Buildings	85.01	87.72	86.47	87.41	<b>88.08</b>
Farmland	68.11	79.71	64.62	65.56	<b>82.77</b>
Woodland	73.84	61.86	57.01	59.13	<b>76.52</b>
Water	90.69	88.74	79.09	87.15	<b>90.16</b>
Average	78.73	79.66	71.97	74.52	<b>84.08</b>

DATA



**Figure 3-**Example of images of four types of areas (a) Construction, (b) Forest, (c) Farmland, (d) Water.



**Figure 4-** Extracting an LPH from a pixel's neighbourhood.

El-Mashed *et al.* [15] introduce a new Doppler algorithm to obtain high-resolution photos of Doppler-based Objectives of radar imagery (RDA-FrFT). The FrFT attracted a lot of interest and opened up possibilities for useful applications in radar imaging, due to its sensor potential, signal processing and pattern recognition identification.

Using FrFT in SAR imaging, the reflection coil generated by this proposed algorithm indicates that the signal is higher than noise performance. Thus in the direction and azimuth distance of the target image, we can obtain high-resolution and low-side lobes.

Krylov and Zerubia [16] produce a supervised identification method incorporating PDF mixture and "random field Markov" approach for regulation. This method is specialized with basic SAR in solving the problem of processing SAR images, using different categories of distributions chosen as the basis for approaching the mixture. This enables a total likelihood score, which is then optimized through a random Markov field method and enhanced by diagram reduction.

Lang *et al.* [17] develop a Grid-Based Motion Statistic (GMS) algorithm to divide the PolSAR image. The authors reached the following:

(1) Pre-screening strategy and post-processing steps are embedded in this algorithm. (2) This algorithm has good noise control and can retain detailed information by producing superpixels that correspond to the actual scene. (3) GMS filtering time consumption is longer than other algorithms and thus fragmentation quality may decrease.

Wang *et al.* [18] Present a new idea which inspired the tremendous success of FCN in semantic division and the similarity between semantic classification and Polar Aperture Radar image classification (PolSAR). The authors implemented the idea as follows:

(1) They created a full merge hierarchy that automatically combines deep spatial patterns that FCN learns with scattered sub-features and low-level scatter representation, capturing high-dimensional polarization data from local and global systems. (2) To extract non-linear deep spatial information for PolSAR, the previously trained deep FCN-8s model is transferred. (3) Shallow features and low-grade sub-space features are combined to enhance the distinction between deep spatial features. (4) The success of this method depends mainly on FCN's powerful capabilities to automatically learn multi-scale, non-linear deep spatial information. The study explores, in a close to the ground dimensional subspace, the basic local and global structures of PolSAR data.

Abbas[19] present a new method inspired by the setting edges process, which is one of the essential methods used in many fields, including radar images, which helps to display objects such as mobile vehicles, ships, aircraft and meteorological and terrain forms. To recognize these objects accurately, it is important to detect their edges. In this research, the proposed method (Ridgelet transform, Bezier curve, and Sobel operator) with Ridgelet transform was used and showed better results than wavelet transform because it eliminates noise by using Ridgelet transform soft thresholding before the edge detection step.

The results revealed that, in both subjective and objective experiments, the favored approach has superior effects over Sobel edge detection and the wavelet method. The values for the Peak Signal to Noise Ratio(PSNR) were 9.3812, 9.8918, 9.6521, and 9.0743 using the Sobel operator method and 10.2564, 10.7927, 10.5612, and 10.8633 using the wavelet method. In the proposed method the values were increased to 12.6542, 12.9514, 12.8574, and 12.3013, respectively.

Image classification can be defined as one of the most important tasks in the area of machine learning. Recently, deep neural networks, especially deep convolution networks, participated greatly in end-to-end learning which reduces the need for human designed features in the image recognition, like the Convolution Neural Network. It offers the computation models which are made up of several processing layers for learning data representations with several abstraction levels.

Ahmed and Mahmoud.[21]explain a previously trained model of convolutional neural networks based on certain parameters and hundreds of images to train and predict gender images using probability measures. Precision accuracy was equal to 0.68 and 0.3225 respectively. They used deep learning, especially CNN, to classify images after predicting image objects and classifying them into groups. We also note that CNN and pre-trained models with SAR images were implemented, as shown in the following study.

[20] clarify using a deep learning algorithm, particularly in the field of computer vision which has recently achieved a lot of success. This paper aimed to explain a new method of classification applied to SAR images using transfer learning accompanied by fine-tuning methods in such a classification

schematic. The ImageNet database which employed the pertained architectures Visual Geometry Group (VGG16) was used as a feature extractor and a new classifier was trained based on the extracted features. The data used was SAR images of Moving and Stationary Target Acquisition and Recognition (MSTAR) data. A final accuracy of 97.91 percent for ten different classes was achieved.

### Comparison

The comparison of methods that were used to classify SAR images and the findings obtained are shown in Table-3 after reviewing the survey papers in Table-1 above in the field of Synthetic Aperture Radar Image Classification.

**Table 3-** Comparison of survey papers listed in Table 1- above.

Research No.	Results of methods used
[7]	<ul style="list-style-type: none"> <li>Providing the best way of viewing SAR images, human interpretation in applications for image compression, and archiving.               <ul style="list-style-type: none"> <li>Successful SAR image compression with best quality image and saved time and space in storage.</li> </ul> </li> </ul>
[8]	The genetic algorithm was used to create new bases for a group of pictured military targets using the SAR sensor. It succeeded in increasing the targets from fewer targets.
[9]	Classifying the objects by comparing radar sensor data to environments, by providing this complexity management approach in some assumptions and SAR image pixels that are designed to be applicable and capable of development.
[10]	Providing quick, immediate, and optimum ratings for most cases.
[11]	Ground texture was used to classify SAR images the structures of the earth was described. It produced a high accuracy of 93% in describing the structures of the earth.
[12]	It succeeded in detecting moving targets based on the detection algorithm for rotating targets due to the thickness of the forest that matches the noise in the image.
[13]	<ul style="list-style-type: none"> <li>Provided the best way to get more accurate information from pixel methods.</li> <li>This approach was effective in classifying structures and objects on Earth.</li> </ul>
[14]	<ul style="list-style-type: none"> <li>A very strong description of SAR images.</li> <li>Powerful noise projection.</li> <li>MLPH succeeded in distinguishing between four styles.</li> </ul>
[15]	<ul style="list-style-type: none"> <li>The resulting reflection coil shows that the signal is higher than the noise level, so high-resolution subject images are obtained.</li> <li>They introduced a Doppler-based Doppler algorithm (RDA-FrFT) which uses FrFT because of its optics, signal processing, and pattern recognition ability.</li> </ul>
[16]	Its use is restricted to connecting to spatially defined Markov fields.
[17]	<ul style="list-style-type: none"> <li>The GMS algorithm was developed to split the PolSAR image.</li> <li>It has good noise control and can retain detailed information by producing superpixels.</li> <li>GMS filtering time consumption is longer than other algorithms, so fragmentation quality may decrease.</li> </ul>
[18]	<ul style="list-style-type: none"> <li>The effectiveness of this approach depends primarily on the FCN's powerful ability to learn multiscale, nonlinear, deep spatial information automatically.</li> <li>This approach witnessed the tremendous success of FCN in the semantic division and the similarity between semantic classification and classification of PolSAR images.</li> </ul>
[19]	<ul style="list-style-type: none"> <li>The proposed method manages the edges better than the methods of Sobel and Wavelet.</li> <li>The performance of the edged image is increased, and the consistency of the edge image becomes very good when used with Sobel operator.</li> <li>The RMSE is reduced, and the proposed approach raises PSNR.</li> </ul>
[20]	<ul style="list-style-type: none"> <li>It gives high precision.</li> <li>Since SAR data has speckle noise and is slightly less intuitive than optical data, the proper classification of features can be a challenge for human labelers and models.</li> </ul>



## Conclusions

This paper provides an overview of the SAR images classification. The primary function of the classification algorithm for SAR images is to transform the SAR images into a collection of objects or pixels and interpret the SAR images. Even with a lot of research efforts in the design of systems, the quality of SAR images classification systems is still inadequate. The main challenge of the SAR images scaling method is the exploration and application of the theory and the conceptual know-how for the identification of the objects in SAR images. No standard frame can be used for extracting features on all forms of radar frames. Knowledge is used by the proposed systems to improve the efficiency for specific purposes of classifying SAR images, but these systems cannot be extended to SAR images from other fields. The following several findings are derived from the results of the tests found in the review papers included in this survey:

- In previous papers, SAR processing suggests that image production is distinct from the decision-making function, since the method of detecting and identifying targets from the problem object varies depending on the need for a device designed to serve a specific purpose.
- Classification models can have a major impact on the search result, as the combination of a rational multi-approach and multi-concept training technique exploits their respective strengths and improves the efficiency of the SAR object classification system.
- As researchers, we suggest the use of Convolutional Neural Networks (CNN) in the classification of SAR images after they managed to improve the performance of object recognition models for a variety of targets in 2020, given that CNN, as compared with the other approaches, showed an accurate classification of 97.91 percent on ten different classes of MSTAR dataset applications.

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