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Pol-SAR Image Feature Selection using Episodical Proximity Stratagem in Machine Learning

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Abstract: Utilizing polarimetric synthetic aperture radar (Pol-SAR) for image classification is increasingly significant in machine learning applications. However, the complex spatial structural patterns present challenges in extracting features, resulting in prolonged time requirements for Pol-SAR image classification. Thus, identifying intrinsic features for target recognition through feature selection becomes a daunting task in this study. To overcome this challenge, we introduce a novel approach termed Episodical Proximity Selection. This method employs principal component analysis to choose optimal features from the extracted set, thereby simplifying the complexities associated with feature selection. These selected features are then inputted into a classifier for classification. Our findings demonstrate that this method effectively identifies the most relevant features in Pol-SAR images, thereby improving the accuracy of the proposed system.
Keywords: Classification Pol-SAR images, PCA analysis.

1.Introduction

Pol-SAR (Synthetic Aperture Radar) image classification finds applications in various domains such as map updating, urban area classification, classification of highly randomized clustering forests, and Automatic Target Recognition (ATR), among others. Principal Component Analysis (PCA) is employed for dimensionality reduction. The utilization of Polarimetric Synthetic Aperture Radar (Pol-SAR) imaging has garnered considerable interest in remote sensing applications due to its capability to offer detailed insights into the scattering properties of Earth's surface targets. This paper introduces an approach to Pol-SAR image feature selection through extraction techniques. Specifically, we investigate the effectiveness of diverse machine learning algorithms in Pol-SAR image classification post feature selection, with the aim of enhancing accuracy and efficiency in land cover classification tasks. Our exploration encompasses preprocessing steps essential for Pol-SAR data, suitable feature extraction methods for Pol-SAR imagery, and the selection of apt machine learning algorithms for classification. Experimental findings illustrate the performance of various classifiers on Pol-SAR datasets, offering valuable insights into the most effective strategies for accurate land cover classification in Pol-SAR imagery. With the widespread use of PolSAR in civil applications like topographic mapping, resource discovery, and disaster monitoring, as well as military applications like battlefield reconnaissance, situation surveillance, and precise guidance, PolSAR image interpretation research has gotten a lot of attention in recent decades, ranging from supervised to unsupervised approaches [1].

The following two challenges remain in high-resolution SAR picture classification: Spatial structural patterns that are complex, because of the coherent imaging system and Object shadow occlusion, pixels of the same object can have a lot of variation, which is called speckle [2]. Hand-crafted feature-based methods can perform fairly well for some particular categories with limited training data and have excellent low-level feature representation capabilities of SAR images [3]. Manually annotating SAR data in real-world applications is time-consuming and labor-intensive. Given the scarcity of SAR-labelled data, several schemes, such as domain adaptation, have been proposed [4]. Previously, for SAR feature learning, a deep supervised and contractive neural network (DSCNN) was used [5].

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Then the discriminant deep belief network (DisDBN) is then proposed for high-resolution SAR image classification [6]. Manifold learning is used in optical images to enhance semantic segmentation efficiency [7]. Then, using LPP, a multi-alignment fusion algorithm for hyperspectral and polarimetric SAR is proposed [8].

Algorithms for PolSAR image classification abound in the remote sensing community [9]. As one of the most important aspects of classification algorithms, feature extraction has had a lot of success and is still being developed [10]. The polarization characteristics of the ground goal are described in PolSAR data [11]. Some classifiers with training–a testing format that functions directly on the PolSAR co-variance data have recently become a hot topic of study [12]. Then, for optical remote sensing scene classification, a system that combines multi-layer CNN feature maps and covariance pooling was implemented [13].

Other techniques, on the other hand, use image patches or super pixels as classification units, which may result in classification errors in certain areas and may not maintain the contours of certain ground targets as well [14]. Since the coherency or covariance matrix can be used to define the scattering characteristics of distributed targets in PolSAR images, it is rational to make classification algorithms function directly on these covariance matrices [15]. The Neighbourhood Preserving Embedding (NPE) algorithm is similar to the Linear Programming Problems (LPP) algorithm in that it aims to keep the local structure of the data manifold while still optimizing the objective function. The NPE algorithm is commonly used in chemical processes or computer fault detection and diagnosis, facial recognition and facial clustering, image indexing, and image classification [16]. Because of the uneven distribution of data, the neighbourhood of the sample point is changed. The main contributions of this paper are as follows.

The problem of feature selection reduced via episodical proximity selection, in which principal component analysis is utilize to choose the best features from the retrieved features.

The paper's structure is outlined as follows: Section 1 introduces the topic; Section 2 delves into related work; Section 3 introduces innovative solutions; Section 4 discusses implementation results and comparisons; and Section 5 offers concluding remarks.

2. Literature survey

Ren et al. [17] proposed and tested a sparse subspace clustering-based feature extraction method for PolSAR image classification. Even though the feature extraction approaches work well, there are some disadvantages. The extracted features no longer contain the original data, and some vital data may have been corrupted or omitted.

Pham et al [18] found to provide Semantic segmentation networks, such as SegNet promising classification results on VHR polarimetric SAR data and incorporating structural gradient tensors with polarimetric features at inputs to had better guide, the network to concentrate on highly geometric and structural details from their results and the accuracy of classification has improved. However, the sample point's neighbourhood altered because of the uneven distribution of data.
Moham et al [19] proposed a new end-to-end completely convolutional neural network with an encoder-decoder paradigm for classification of PolSAR imagery, specifically for distinguishing wetland groups. There are two key components to the proposed architecture: (1) the high-level abstract features are extracted using an encoder a convolutional filter stack; and a decoder, in which the encoder stage's output feature map is progressively up-sampled to the input volume's spatial resolution using a stack of transposed convolutional filters. However, there is a lack of discriminative features and the appearance of speckles.

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Liu et al. [20] proposed a statistical CNN (SCNN) for land-cover classification from SAR images, which uses first- and second-order statistics to classify the distributions of CNN features (including mean and variance). The variance, on the other hand, just considers the statistical properties of independent feature maps and ignores the relationship between them.

Ni et al. [21] proposed a multimodal bilinear fusion network for land cover classification that used the covariance matrix to fuse optical and SAR features. In general, the above methods use the matrix logarithm operation to map the covariance directly to Euclidean space for classification. They do not, however, expand the covariance matrix to the deep network to mine the possible discriminant features of second-order statistics in greater detail.

The extracted features no longer contain the original data, and some vital data may have been corrupted or omitted [17]. However, the sample point's neighbourhood is altered as a result of the uneven distribution of data [18]. However, there is a lack of discriminative features and the appearance of speckles [19]. The variance, on the other hand, just considers the statistical properties of independent feature maps and ignores the relationship between them [20]. They do not, however, expand the covariance matrix to the deep network to mine the possible discriminant features of second-order statistics in greater detail [21]. Thus, a novel technique is recommended for solving the aforementioned issue to achieve a more discriminative representation and resolve the effects of speckles, maintaining image boundaries and smoothing classification results.

3. Pol-SAR Image Feature Extraction using Episodical Proximity Selection
Polarimetric SAR represents an advanced form of imaging radar employed in radar remote sensing applications. Within existing systems, the extraction of features from single-polarized Pol-SAR images is significantly affected by the shape and orientation of scatterers, leading to a time-intensive process due to the intricate statistical nature and complex three-dimensional structural patterns involved in Pol-SAR image classification. To tackle this challenge, a novel method called Episodical Proximity Selection has been introduced. This method selects features by computing a proximity parameter through principal component analysis (PCA), which reduces high-dimensional data to a lower dimensionality without sacrificing crucial features. Consequently, the proposed system identifies valuable features from Pol-SAR images while filtering out undesired ones, resulting in a reduced-dimensional projection. Consequently, the proposed system effectively extracts and selects features from Pol-SAR images, enhancing the overall performance of the system. The architecture of the proposed system is depicted in Figure 1.

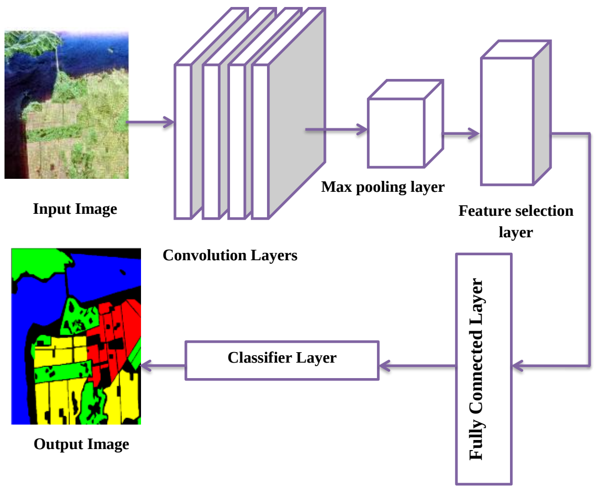

Fig. 1: Architecture of the proposed system.

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In figure 1, the input pol-SAR image first sent to the convolution layer in which the convolution layer extracts the features using convolution operation from the input Pol-SAR image then the max-pooling layer takes the input from the convolution layers; the max-pooling layer maps the extracted features based on maximum value from the input image. After that, feature selection layer selects the best features from the extraction features of max pooling layer. Then fully connected layer connects all the best features of the input image and the classification layer accurately classifies the input image.

4.Methodology

In this paper, the problem of feature selection reduced via episodical proximity selection, in which principal component analysis is utilize to choose the best features from the retrieved features

4.1. Episodical Proximity Selections

In the process of episodically proximal selection, optimal features are chosen from the extracted ones via Principal Component Analysis (PCA), mitigating issues encountered in image classification. PCA serves as an unsupervised method for feature reduction, transforming high-dimensional data into a lower-dimensional representation that retains maximum variance with minimal reconstruction error. Consequently, PCA is employed to identify the most suitable features within episodically proximal selection. By converting the original data, PCA eliminates correlations between bands. Episodic Proximity Selection detects data patterns among features, utilizing statistical features of the bands to assess their correlation or dependence. This approach enhances classification accuracy while streamlining feature selection. Furthermore, PCA diminishes the dimensionality of Pol-SAR image data while preserving underlying trends and patterns, facilitating the effective identification of intrinsic features from extracted ones without reconstruction challenges. The resultant feature set from principal component analysis effectively reduces dimensions. Below, the process of dimensionality reduction through PCA algorithm is elucidated.

Principal Component Analysis (PCA) is a commonly used technique for dimensionality reduction and feature extraction in various fields, including remote sensing and image processing. When applied to polarimetric synthetic aperture radar (SAR) images for classification purposes, PCA can help in reducing the dimensionality of the data while preserving most of its important information. Here's a general overview of how PCA can be applied to polarimetric SAR images classification: Data Preparation: Polarimetric SAR images consist of multi-channel data representing different polarization states. Each pixel in the image is characterized by its intensity values across these polarization channels. Before applying PCA, the data needs to be organized into a suitable format. Typically, each pixel's intensity values across all polarization channels are arranged as a vector. Covariance Matrix Calculation: PCA starts by calculating the covariance matrix of the data. The covariance matrix provides information about the relationships between different features (polarization channels in this case). It's calculated by taking the dot product of the data matrix and its transpose. Eigenvalue Decomposition: Once the covariance matrix is calculated, PCA finds its eigenvectors and eigenvalues. Eigenvectors represent the directions in the feature space where the data varies the most, while eigenvalues indicate the amount of variance explained by each eigenvector. Selecting Principal Components: The eigenvectors are sorted based on their corresponding eigenvalues in descending order. This sorting allows us to select the principal components (eigenvectors) that capture the most variance in the data. Typically, a certain percentage of the total variance is chosen to retain most of the information while reducing the dimensionality. Projection: Finally, the original data is projected onto the selected principal components. This projection transforms the data into a lower-dimensional space while retaining most of the relevant information. The reduced-dimensional data can then be used for classification using various machine learning algorithms. Classification: After reducing the dimensionality using PCA, the resulting features can be fed into a classifier for polarimetric SAR image classification. Common classifiers used in remote sensing applications include Support Vector Machines (SVM), Random Forests, and Neural Networks. Benefits of using PCA for polarimetric SAR image classification include: •

Dimensionality reduction, which can lead to improved computational efficiency and reduced storage requirements. • Removal of redundant or irrelevant features, which can enhance classification accuracy by focusing on the most informative features. • Visualization of data in a reduced-dimensional space, which may aid in understanding the underlying structure of the data. However, it's important to note that PCA assumes linear relationships between features and may not capture complex nonlinear relationships present in the data. In some cases, nonlinear dimensionality reduction techniques like t-Distributed Stochastic Neighbour Embedding (t-SNE) may be more appropriate. Additionally, the effectiveness of PCA depends on the specific characteristics of the polarimetric SAR data and the classification task at hand. Therefore, it's often beneficial to experiment with different dimensionality reduction techniques and classifiers to find the most suitable approach for a given application.

Principal Component Analysis (PCA) is a widely employed method for reducing dimensionality and extracting features across various domains, such as remote sensing and image processing. In the context of polarimetric synthetic aperture radar (SAR) images, PCA offers a means of dimensionality reduction while retaining significant information crucial for classification tasks.

Outlined below is a general procedure for applying PCA to polarimetric SAR image classification:

Data Preparation: Polarimetric SAR images comprise multi-channel data representing distinct polarization states. Prior to PCA application, the data necessitates organization into a suitable format, typically involving arranging intensity values for each pixel across polarization channels into vectors.

Covariance Matrix Computation: PCA commences by computing the covariance matrix of the data, which elucidates relationships among different features (i.e., polarization channels). This matrix is derived through the dot product of the data matrix and its transpose.

Eigenvalue Decomposition: Following covariance matrix computation, PCA identifies eigenvectors and eigenvalues. Eigenvectors delineate directions within the feature space where data variation is most pronounced, while eigenvalues signify the variance extent explained by each eigenvector.

Principal Component Selection: Eigenvectors are sorted based on corresponding eigenvalues in descending order, facilitating the selection of principal components capturing maximum data variance. Typically, a predetermined percentage of total variance is retained to preserve critical information while reducing dimensionality.

Projection: Subsequently, original data is projected onto selected principal components, effecting transformation into a lower-dimensional space while conserving pertinent information. The resultant reduced-dimensional data can be utilized for classification employing diverse machine learning algorithms.

Classification: Post-PCA dimensionality reduction, resultant features are inputted into classifiers for polarimetric SAR image classification. Common classifiers in remote sensing applications include Support Vector Machines (SVM), Random Forests, and Neural Networks.

Advantages of PCA for polarimetric SAR image classification encompass:

- Dimensionality reduction, enhancing computational efficiency and diminishing storage requirements.
- Elimination of redundant or irrelevant features, augmenting classification accuracy by focusing on informative features.

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- Visualization of data in a reduced-dimensional space, potentially facilitating comprehension of underlying data structure.

Nevertheless, it's imperative to acknowledge that PCA assumes linear feature relationships and might not capture complex nonlinear relationships. In such scenarios, nonlinear dimensionality reduction techniques like t-Distributed Stochastic Neighbor Embedding (t-SNE) might be more suitable. Additionally, PCA efficacy hinges on specific polarimetric SAR data characteristics and classification objectives, warranting experimentation with diverse dimensionality reduction techniques and classifiers to identify optimal approaches for specific applications.

Algorithm1: Principal Component Based Feature Selection Algorithm

Input: $extractedfeatures\ (di - di')$
Output: $bestfeatures\ B_{fea}$
// Get the principal components
To compute the size of the features
$[m, n] = size((di - di'))$
To compute the mean for each dimension,
$$(d) = {}^{1}/_{N} \sum_{i=1}^{N} (di)$$
$(di - di') = (di - di') - repmat(d, 1, N)$
To find the covariance matrix,
$cov(d) = {}^{1}/_{N} \sum_{i=1}^{N} (di - di')(di - di')T$
To find the Eigen vectors and Eigen values
$[\varepsilon\ v] = eig(\varphi)$
To extract the diagonal matrix,
$V = diag(v)$
To compute the sort of the variance,
$[\alpha\beta] = sortvar(-1 \times v) \times ({}^{1}/_{N-1} \times \varphi)$
$\alpha = v(\delta)$
$\beta = \beta(:, \delta)$
$\delta = rindicies$
To compute the best data,
$B_{fea} = {}^{\beta}/_{\alpha} \times (di - di')$

The first step is to use the given formula to get the mean of X.

$$(d) = {}^{1}/_{N} \sum_{i=1}^{N} (di) \quad (1)$$

Equation (1) aids in both data normalization and covariance computation. Then the covariance matrix is computed in the second step as.

$$cov(d) = {}^{1}/_{N} \sum_{i=1}^{N} (di - di')(di - di')T (2)$$

Here, the covariance matrix is used to identify the correlation and dependencies among features. Then the last step of the principal component analysis is the spectral decomposition of the covariance matrix using Eigenvectors $\mathcal{E}_1, \mathcal{E}_2, \ldots, \mathcal{E}_D$ and Eigenvalues $v_1, v_2, \ldots, v_D$. The Eigenvalues are sorted as $v_1 \geq v_2 \geq \cdots \geq v_D$. From the covariance matrix, the Eigenvectors and the Eigenvalues are calculated and it is given as,

$$[\varepsilon\ v] = eig(\varphi) \quad (3)$$

Then the diagonal matrix is extracted by using,

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$$V = diag(v) \quad (4)$$

then the variance is computed and the best features are selected from the bands. The episodical proximity selections flowchart is show in figure 2.

The covariance matrix identifies the relationship among features of the input Pol-SAR image, and then through the eigen-decomposition of the covariance matrix, eigenvectors and eigenvalues are getting from the Pol-SAR image. Next, extract the diagonal matrix from the decomposition matrix. Finally, episodical proximity selections compute the best data from the input Pol-SAR image. In this way the episodical proximity selections efficiently selects the best features from the extracted features without losing information from any features. After selecting the best features from the max-polling layer, the proposed system must classify the best features efficiently. For that reason, the proposed system uses multifarious stratification stratagem for classify the image without classification errors.

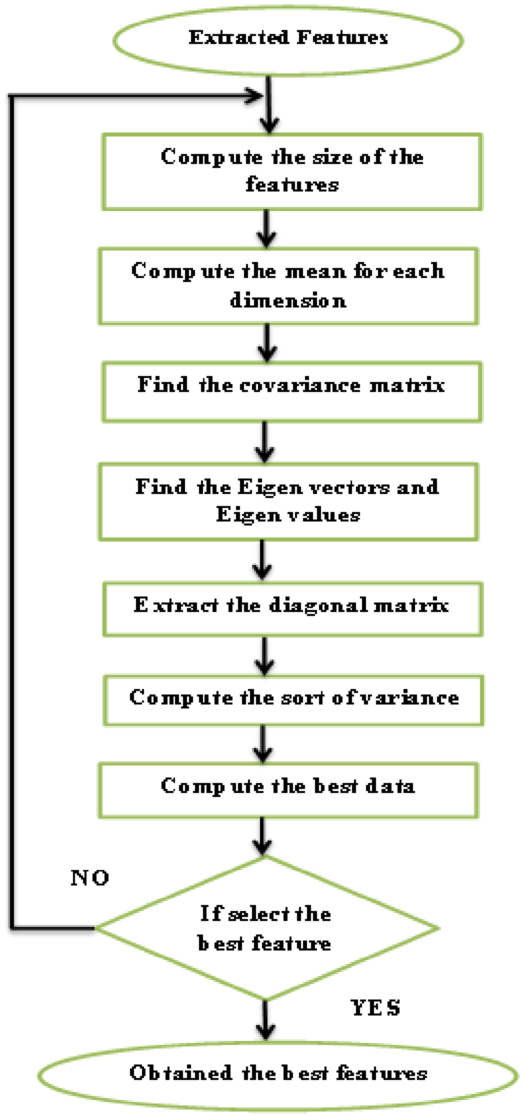

Fig. 2: Flowchart of Episodical Proximity Selections.

5. Results and Discussion

This section offers a thorough account of the implementation outcomes, along with an evaluation of the performance of the proposed system. Additionally, it includes a comparative analysis to verify the valuable performance of the proposed system.

5.1 Experimental Setup

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The implementation of this work has been carried out using the Python programming language with the following system specification and the simulation results are discussed below.

Platform : Python
OS : Windows 10
Processor : 64-bit Intel processor
RAM : 8 GB RAM

5.2 Dataset Description

The proposed system utilized the Indian Pines dataset for analysis, which represents a segment of a larger scene captured by the AVIRIS sensor above the Indian Pines test site in northwestern Indiana. The scene comprises 145x145 pixels and encompasses 224 spectral reflectance bands spanning the wavelength range of 0.4–2.5 x 10^(-6) meters. Approximately two-thirds of the Indian Pines scene consists of farmland, while the remaining one-third comprises forests or other natural permanent flora. Additionally, the scene features two major dual-lane highways, a rail line, as well as scattered low-density residences, other man-made structures, and minor roadways. Notably, the image was captured in June, revealing that some crops such as maize and soybeans are still in the early stages of growth, covering less than 5% of the area. The ground truth data is categorized into sixteen distinct classes, all of which are not mutually exclusive. The sixteen categories of the ground truth figure are outlined below.

Groundtruth classes for the Indian Pines scene and their respective samples number

#	Class	Samples
1	Alfalfa	46
2	Corn-notill	1428
3	Corn-mintill	830
4	Corn	237
5	Grass-pasture	483
6	Grass-trees	730
7	Grass-pasture-mowed	28
8	Hay-windrowed	478
9	Oats	20
10	Soybean-notill	972
11	Soybean-mintill	2455
12	Soybean-clean	593
13	Wheat	205
14	Woods	1265
15	Buildings-Grass-Trees-Drives	386
16	Stone-Steel-Towers	93

Fig. 3: Category of ground truth.

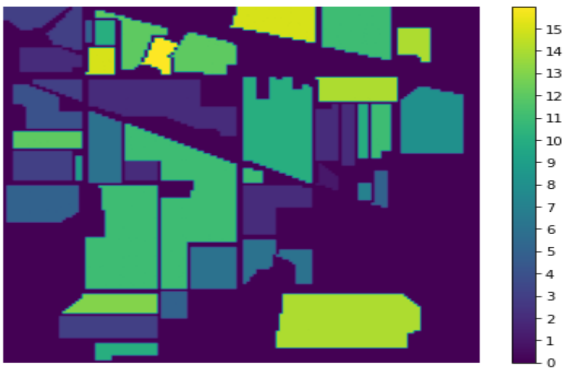

Fig.4: Simulation result of classification Pol-SAR image.

The figure 4 shows the simulation output of the classified Pol-SAR image. In scrumptious integrant wrenching, the features are extracted from the Pol-SAR images by using the convolution layer in which it extracts all the features from the input Pol-SAR image at the same time it increases the variety of intra-layers features and makes full use of a large number of training sets by convoluting

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the Pol-SAR images with convolution filters in all layers. In figure 3 shows the ground truth classes for the Indian pines scene and their respective sample number. Then the proposed system must find out the suitable features from the extracted features so, a novel episodical proximity selection approach used to select the best features from the extracted features in which the principal component analysis used to select the best features. Afterward, the proposed system used a multifarious stratification stratagem for efficiently classify the essential features in which the composite kernel is integrated with an elastic net classifier to achieve better classification accuracy. As a result, the proposed system efficiently extracted, selected the features from the input Pol-SAR images, and classified the features more precisely. The different categories of the ground truth of the output Pol-SAR image are given below table.

Table 1
Ground truth values of the input Pol-SAR image

Numbers	Classes
0	Alfalfa
1	Corn-notill
2	Corn-mintill
3	Corn
4	Grass-pasture
5	Grass-trees
6	Grass-pasture-mowed
7	Hay-windrowed
8	Oats
9	Soybean-notill
10	Soybean-mintill
11	Soybean-clean
12	Wheat
13	Woods
14	Buildings-Grass-Trees-Drives
15	Stone-Steel-Towers

5.3 Performance metrics of the proposed system
5.3.1 Accuracy
The accuracy of the input data is calculated using,

$$\text{Accuracy} = \left[\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}}\right] \qquad (5)$$

TP- True Positive Value
TN- True Negative Value
FP- False Positive Value
FN- False Negative Value

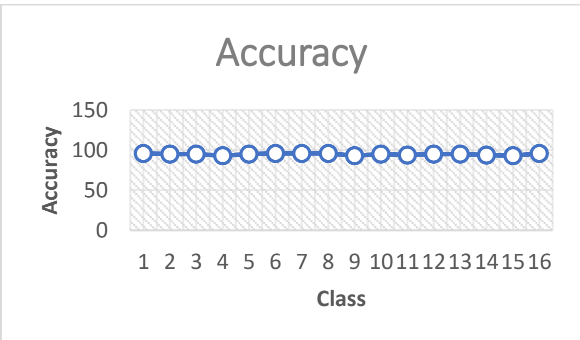

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Fig. 5: Accuracy of the proposed system.

The accuracy of the proposed system is shows in figure 5. It clearly shows the precision of the proposed system is increased when the number of classes is increasing. The proposed episodical proximity selection improves the accuracy of the proposed system by reducing the number of input features. Because a large number of input features degrade system performance, the principal component analysis is used for dimensionality reduction and selecting the best features from the extracted features in which the PCA increase the classification accuracy and reduces the processing time, thereby improving the precision of the proposed system.

5.3.2 Precision

The precision of the input data is calculated using,

$$\text{Precision} = \frac{TP}{TP+FP} \qquad (6)$$

TP- True Positive Value
FP- False Positive Value

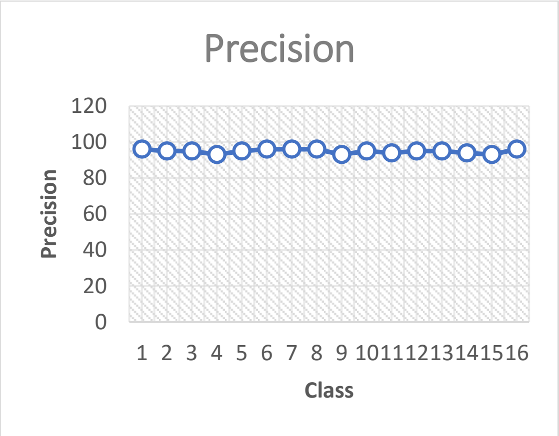

Fig. 6: Precision of the proposed system.

The precision of the proposed system is shows in figure 6. It clearly shows the precision of the proposed system is increased when the number of classes is increasing.

5.3.3 Recall

The recall of the input data is calculated using,

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (7)$$

TP- True Positive Value
TN- True Negative Value

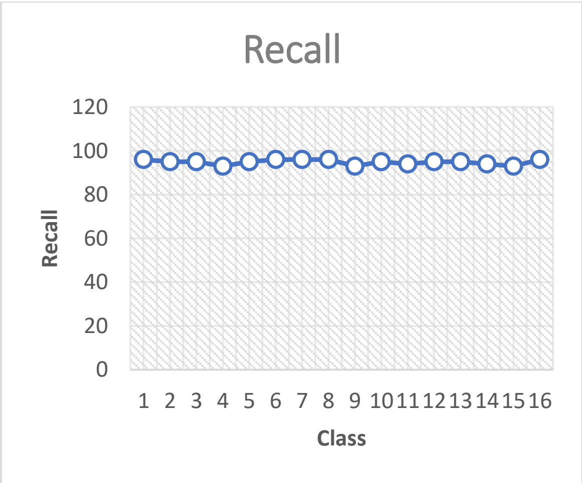

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Fig. 7: Recall of the proposed system.

Figure 7, clearly explains the recall of the proposed system. The number of classes is increasing from 0 to 15 as well as the recall of the proposed system of is also increasing.

5.3.4 F1-Score

The F1-Score of the input data is calculated using,

$$F1=2*\frac{Precision*Recall}{Precision+Recall} \quad (8)$$

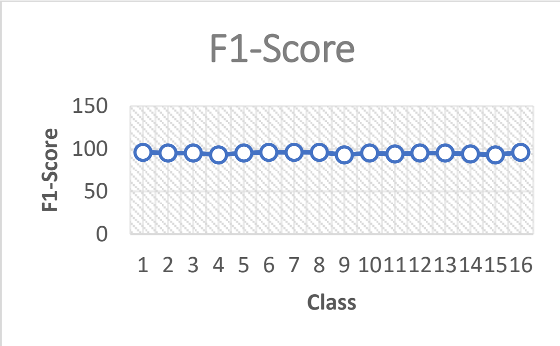

Fig. 8: F1 score of the proposed system.

Figure 8, clearly shows the f1 score of the proposed system is increased when the number of classes is increasing. From the graph, the number of classes increased as well as the proposed system f1 score is also increased.

5.4 Performance comparison of the proposed method

This section describes various performances of the proposed method comparing with the results of previous methodologies and depicting their results based on various metrics.

Accuracy comparison of the proposed system.

The accuracy of the proposed system is high that is 95.69% when compared with the existing output accuracy of two-layer NN [24] which is 86.33%, RBF-SVM [22] is 87.95%, three-layer NN [24] is 88%, LeNet-5 [23] which is 88.12%, shallower CNN [25] is 90%, D-DBN [25] is 91%, and contextual CNN [25] is 94.12%, and from the conclusion, it is noted that two-layer NN has the lowest accuracy whereas our proposed system has the highest accuracy.

Recall comparison of the proposed system.

The proposed recall is 95.99%, the existing system recall of two-layer NN [24] which is 85%, RBF-SVM [22] is 86.12%, three-layer NN [24] is 86.95%, LeNet-5 [23] which is 87%, shallower CNN [25] is 89%, D-DBN [25] is 89%, and contextual CNN [25] which is 92% and from the conclusion, it is noted that two-layer NN has the lowest recall whereas our proposed system has the highest recall. When a recall compared to the existing systems such as two-layer NN, RBF-SVM, three-layer NN, LeNet-5, shallower CNN, D-DBN, and contextual CNN the proposed system recall is higher than the existing systems.

Precision comparison of the proposed system.

The precision of the proposed system is 95.99%. In figure 13, the precision of two-layer NN [24] which is 86.12%, RBF-SVM [22] is 87.88%, three-layer NN [24] is 87.97%, LeNet-5 [23] which is 88%, shallower CNN [25] is 90%, D-DBN [25] is 90%, and contextual CNN [25] which is 93.88%

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and from the conclusion, it is noted that two-layer NN has the lowest precision whereas our proposed system has the highest precision.

F1 score comparison of the proposed system.

The proposed f1 score is 94.98 percent, compared to the existing recall of two-layer NN [24] which is 85 percent, RBF-SVM [22] which is 86.12 percent, three-layer NN [24] which is 86.34 percent, LeNet-5 [23] which is 87 percent, shallower CNN [25] which is 89 percent, D-DBN [25] which is 89 percent, and contextual CNN [25] which is 92 percent. When comparing the proposed system's f1 score to existing systems like two-layer NN, RBF-SVM, three-layer NN, LeNet-5, shallower CNN, D-DBN, and contextual CNN, the proposed system's f1 score is higher.

6. Conclusion

In this work, Pol-SAR classification achieved by using a novel Episodical Proximity Selection in which principal component analysis is used to dimensionality reduction therefore the proposed system is efficiently extracting the best features from the extracted features and it makes the classification process easy. As a result, the proposed system has a more discriminative representation and maintains the image boundaries and smooth classification results are carried out and the performance metrics of the proposed system shows that the accuracy is increased by 95.69%, precision is increased by 95.99%, recall is increased by 95.99%, sensitivity is increased by 98.99%, and F1-score is increased by 94.98%.

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