Land use land cover mapping from Sentinel-1, Sentinel-2 and fused Sentinel images based on machine learning algorithms

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Abstract— **Mapping land use/land cover is a challenge given the diversity of sensors available.**

This paper aims to use and evaluate the contribution of multisensors classification based on machine learning classifiers (neural network and support vector machine) since traditional approaches always suffer from the hand-designed features and misclassification of boundary pixels.

pre-processing of the SAR data(Sentinel 1-A) has been performed. Data have been calibrated, terrain corrected, and filtered by a 5x5 kernel using gamma map approach. Sentinel-2 has been coregistered to Sentinel-1-A. Then principal component analysis PCA fusion was used to fuse multispectral and radar images.

Support Vector Machines (SVM) method and neural network have been implemented as a supervised pixel based image classification to classify Sentinel-1 , Sentinel-2 and fused sentinel images

During the classification, different scenarios(seven) have been applied to find out the performance of Sentinel-1 data. Different combinations of VV and VH polarizations have been analysed and the resulting classified images have been assessed using overall classification accuracy and Kappa coefficient. Results demonstrate that, combining opportunely dual polarization data, the overall accuracy increases up to 93.02% against 73.38% and 70.73% of using individual polarization VV and VH, respectively. Using more than one variable significantly increased the classification accuracy. Especially scenarios5, 6 and 7 has higher accuracies than other scenarios except scenario 4 which is the best.

It was found that adding different types of data(attributes) to the source image gives a classifier more information to consider when assigning pixels to classes and improving classification accuracy.

Keywords— **Sentinel-1A-synthetic aperture radar- neural network- Sentinel-2- support vector machine – Image fusion- machine learning.**

INTRODUCTION

Accurate land cover/land use (LC/LU) is a crucial for various spatial planning, decision making [1].

Within recent years, a variety of new high resolution airborne and spaceborne sensors have been put into place. These sensors are either active (SAR) or passive (optical) [10].

With the Copernicus program and its Sentinel satellites, a growing source of satellite remote sensing data is publicly available at no charge [8]

The goal of image classification is to predict the categories of the input image using its features[16].Image classification problem can be solved by many approaches such as Maximum Likelihood, Mahalanobis, and ANN[16].

Machine learning based classifiers such as Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Decision Tree (DT), and Random forest (RF) are widely used in remote sensing image classification.

The ever increasing computation power and the advanced classification algorithms are making the land use/cover classification more accurate than ever before, where the commonly used algorithms may include the Support Vector Machine (SVM), k-Nearest Neighbors (KNN),Decision Tree (DT), Artificial Neural Networks (ANN), and Random forest (RF)[17].

This research applied different nonparametric, machine learning algorithms for classification, namely support vector machine (SVM), and artificial neural network (ANN).

ANN classifier was originally created, as a mathematical model, for data analysis and pattern recognition in order to mimic the analytical operations and neural storage of the human brain. It is such parallel system of calculation which consists of large number of basic processors with interconnections[14],[23]

The arrangement of the nodes is referred to as the network topology. The first type of layer is the input layer, where the nodes are the element of a feature vector. The second type of layer is the internal or hidden layer since it does not contain output units. The third type of layer is the output layer and this presents the output data. [15].

Many structures of ANN have been developed by the researchers according to the need of their problem[16].

Learning and generalization is the most important in neural network research [18], [19], [20], [21]. Learning is the ability to approximate the underlying behavior adaptively from the training data while generalization is the ability to predict well beyond the training data.

Neural network has been used in remote sensing image classification in these years and gotten a satisfying result. However, there also have several weaknesses in neural network such as slow learning rate, difficult convergence, complex network structure and umbiguous meaning of network [15].

[12] investigated the extraction of urban land use from very fine spatial resolution (VFSR) remotely sensed imagery using convolutional neural networks (CNNs). The CNN depends on fragmented objects as its functional units to

predict linearly shaped objects (e.g. Highway, Canal) and general (other non-linearly shaped) objects. The classification accuracy of CNN was found as follow 89.52% overall accuracy with 0.88 Kappa coefficient.

[22] evaluated how the accuracy of land-cover classification changes along an urban-rural gradient as a function of spatial resolution and the gradient in landscape structure using RapidEye, Sentinel-2A and Landsat 8 images. Land-cover classification was implemented using a deep learning model and landscape metrics were conducted to assess landscape structure. Results revealed that classifications using RapidEye and Sentinel-2A imageries gave more spatial and thematic details in land-cover classification than Landsat 8. Overall accuracy grow up with increasing spatial resolution (30 m, 10 m, 5 m) within the urban and rural areas, however, the 10 m resolution image (Sentinel-2A) produced better results in the transition zone.

Another machine learning classifier is support vector machine. Support vector machine (SVM) is one of the most useful machine learning algorithms. It is based on statistical learning theory. The main advantage of SVM method is the ability to classify high dimensional data with small set of training samples and providing high classification accuracy[26].
SVM works with pixels in the boundary of considered classes which are named support vectors. For the complex data that cannot be separated using linear hyper-planes, optimal hyperplane separating the different classes by nonlinear mapping functions, called kernel functions, can be defined.
Several kernel functions can be used with SVM classifier. However only four of them which are linear, polynomial, radial basis function (RBF), and sigmoid kernels have been commonly used to classify satellite data[14],[1]

One of the limitations of optical sensors is clouds and cloud shadows which lead to gaps in optical imagery and missing information in optical images this disadvantage essentially affects the performance of classification. Multi-sensor combinations is used overcome the disadvantages of clouds and shadows resulted in cloud removal [32].

Image fusion is integrating different images in order to obtain a new image with the best characteristics from both images [9]. Recently, many researchers have been contributed to the image fusion of SAR and optical images with different motivations [27].

The combination of Sentinel-1 and Sentinel-2 have been utilized in various investigations; it has been utilized for wetlands Mapping, moisture mapping [36], as well as for land cover mapping in the lower Magdalena region, Colombia [28]. The blend of both radar and optical imagery empowers the use of complementary information of the same scene and various applications may be thought of [10]. Fewer publications focus on the use of SAR data for Fusion [30]. [29] compared Sentinel -2 with the recent Landsat OLI/TIRS, Sentinel-2 gave better spatial and spectral resolutions in the near infrared region.

In light of merging Sentinel-1 and Landsat-8 information, [31] evaluated the contribution of merging radar/optical imagery for early crop type identification, pointing towards future potential for combining Sentinel-2 imagery. [33] also combined Sentinel-1 and Landsat-8 but concentrated on the detection of winter wheat in China. Recently, [32] used Sentinel-1 to improve the identification of irrigated crops in India.

Another combination strategy was proposed to set the merge of single SAR and MS images for each scene [34]. In order to effectively merge optical and radar imagery, it is important to accomplish an accurate registration of both images [10]. [12] presented an approach for fusing optical and synthetic aperture radar (SAR) data at the pixel level to improve urban land cover (ULC) classification.

PCA has been used for combining sentinel-1 (PAN) and sentinel-2 imageries (Multi-spectral) in order to remove clouds. It is based on statistical parameters. The method is a multi-image orthogonal linear transformation fusion technique based on statistical feature. The technique transforms the multi-spectral image into the principal component. It assumes that the first principal component of the transformation contains all the same spatial information as the full color image. Then the high resolution fusion image is obtained through the principal component inversion [35].

Attributes are unique characteristics that can help distinguish between different objects in an image resulting in improving classification accuracy.

Adoption of texture analysis is the recent trend for classifying remote sensing imagery. Generally, multi-spectral image classification approaches may not be appropriate in classifying PAN imagery(radar image).

Texture is the visual effect caused by spatial variation in tonal quantity over relatively small areas [37]
Three parameters affect texture information extraction, namely window size, displacement vector and quantization level[38]

The research objective was to Compare the latest machine learning algorithms to determine the best option to classify land use/land cover of Al-Qalyobia Governorate, Egypt.

Support Vector Machines (SVMs) and backpropagation have been implemented as a supervised subpixel based image classifications.

Sentinel classification has been implemented using different approaches:

1) A SAR image of the study area using VV
2) A SAR image of the study area using VH.
3) Using original Sentinel-2 image only.
4) A Fused image of SAR image and Sentinel-2 image.
5) A composite image of study area using VV, VH, and difference of two polarimetry (VV-VH) data.
6) A composite image of study area using VV, VH and Mean (VV+VH)/2 data.
7) A composite image of texture measure with SAR image (VV, VH).

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The accuracy of the results is statistically compared using overall accuracy and Kappa index.

Study Area and Data Sources

The study area located at Al-Qalyobia Governorate. The Qalubiya Governorate is located on the eastern side of the River Nile, near the delta head between 30◦06 11and 30◦36’ 36’’ North and 31◦03’ 20’’ and 31◦35’ 32’’ East. The governorate is characterized by a specific location as it is considered the meeting point of the main transport lines between northern governorates. The total area of the governorate is estimated to be 1140.52 km2, of which the cultivated area is 810 km2, representing 71% of its total coverage. The Qalubiya Governorate includes eight districts. The common activity in the governorate is mostly agriculture, in addition to the existence of some industrial parks. The climatic data from the Qalubiya Governorate indicate that the total rainfall does not exceed 7.2 mm/year and the mean minimum and maximum annual temperaturesare16.5◦Cand31.0◦C,respectively.Thee vaporation rates coincide with temperatures, where the lowest evaporation rate (1.9 mm/day) was recorded in January, and the highest value (7.6 mm/day) was recorded in June (EMA 1996). According to the aridity index classes (Hulme and March 1990), the Qalubiya Governorate is located under arid climatic conditions.

- Sentinel – 1A(GRD) (Ground Range Detected) recorded in interferometric wide swath mode were used. Image dated 27 th july 2019. VV and VH polarizations

- Sentinel – 2B Optical Image dated 28th January 2019. Only the bands natively at 10 m/pixel were used in the experiments (blue, green, red and nearinfrared).

  Table 1 (the used bands 2,3,4,8 (The Red, Green, Blue and NIR bands)) contain clouds

Table 1 Bands for Sentinel-2A.

Sentinel-2 Bands	Central Wavelength (µm)	Resolution (m)
Band1 - Coastal Aerosol	0.443	60
Band2 - Blue	0.490	10
Band3 - Green	0.560	10
Band4 - Red	0.665	10
Band5 - Near Infrared	0.705	20
Band6 - Near Infrared	0.740	20
Band7 - Near Infrared	0.783	20
Band8 - Near Infrared	0.842	10
Band 8A - Near Infrared	0.865	20
Band 9 - Water Vapour	0.945	60
Band 10 - Shortwave Infrared (Cirrus)	1.375	60
Band 11 - Shortwave Infrared	1.610	20
Band12 - Shortwave Infrared	2.190	20

I. METHODOLOGY

In this section, the processing chain that has been carried out for LULC was discussed. Fig.1 illustrates the workflow of processing. The processing steps were as follows:

1-Download free images Sentinel-1A - Sentinel-2 imageries was performed.
2-filtering of Radar sentinel 1-A was performed.
3-Rectification of Radar sentinel 1-A was performed.
4- Rectification of MS sentinel 2 was performed .
5-merged images using principal component analysis (PCA) was performed.
6- Senteinel 1 VV alone, VH alone ,senteinel 2 and merged image have been Classified based on deep learning algorithms(SVM and neural network).
7- Classification accuracy has been assessed using overall accuracy and kappa index.
8- Senteinel 1 classification has been improved using a)A composite images of study area using VV, VH, and difference of two polarimetry (VV-VH) data .b) A composite images of study area using VV, VH and (VV+VH)/2 data
c) A composite images of texture measure with SAR image (VV, VH).
The three composite images have been fed to the classification.

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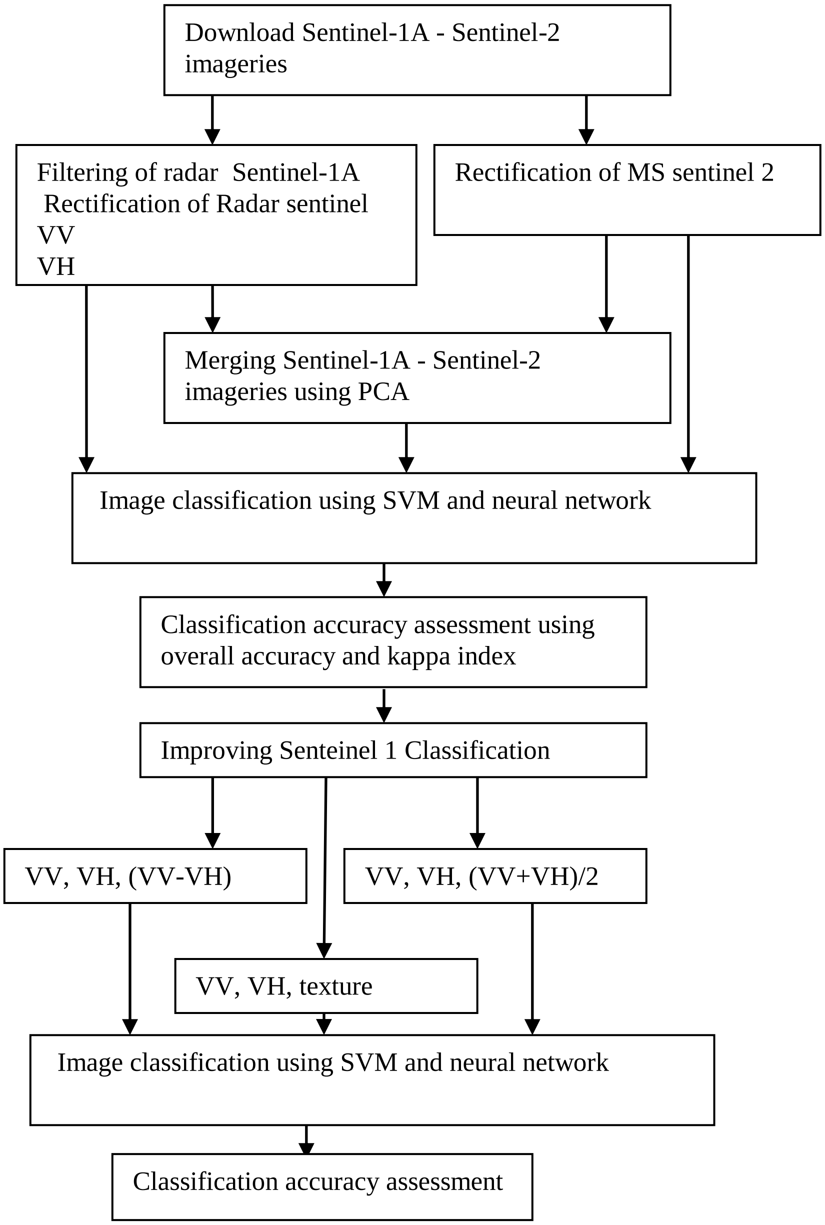

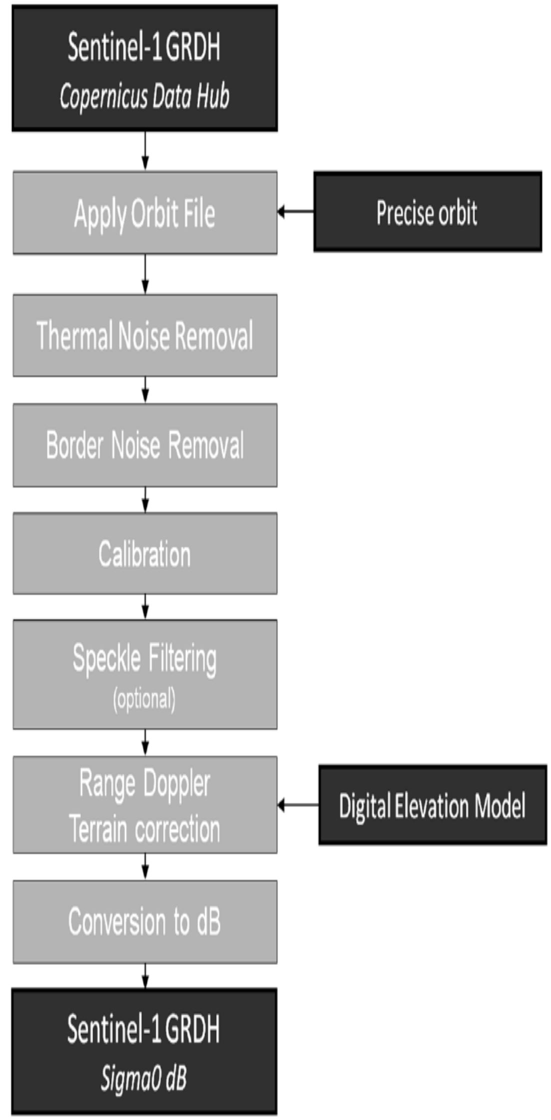

Fig 2. Sentinel-1 Ground Range Detected (GRD) preprocessing workflow.

Fig.1.The workflow of processing.

A.Sentinel 1-A GRD DOWNLOAD

There are two general information on SAR amplitude and phase , phase information will not be used in this research .Therefore the imagery type used in this research is sentinel-1 GRD

The sentinel -1 image was acquired (downloaded)from copernicus in GRDH format. The obtained image was reprojected to UTM zone 36 and WGS84. Fig 2.depicts Sentinel-1 Ground Range Detected (GRD) preprocessing workflow.

B.Preprocessing of radar sentinel -1A GRD

A standard generic workflow to pre-process Copernicus Sentinel-1 GRD data is presented here. The workflow aims to apply a series of standard corrections, and to apply a precise orbit of acquisition, remove thermal and image border noise, perform radiometric calibration, and apply range Doppler and terrain correction. The Sentinel Application Platform (SNAP) version 7.0has been used for processing of Sentinel-1 data. SNAP software is open source software.

A.1.Apply orbit file

The orbit state vectors provided in the metadata of a SAR product are generally not accurate and can be refined with the precise orbital files which are available days to weeks after the generation of the product .

The orbital file provides accurate satellite position and velocity information .Based on this observation, the orbit state vector in the abstract metadata of the product are updated[6];[7]. Fig. 3.a, 3.b. illustrate Applying orbit file to VH ,VV images.

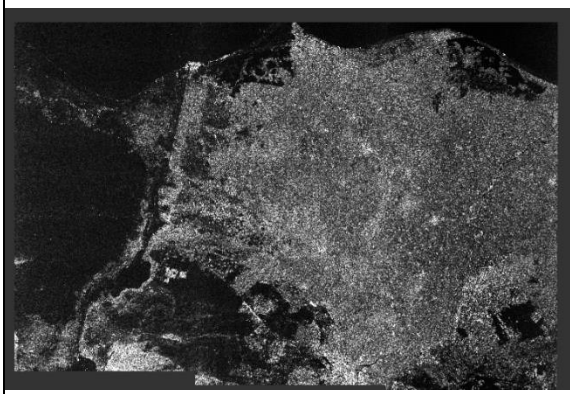

Fig 3 .a Apply orbit file to VH image.

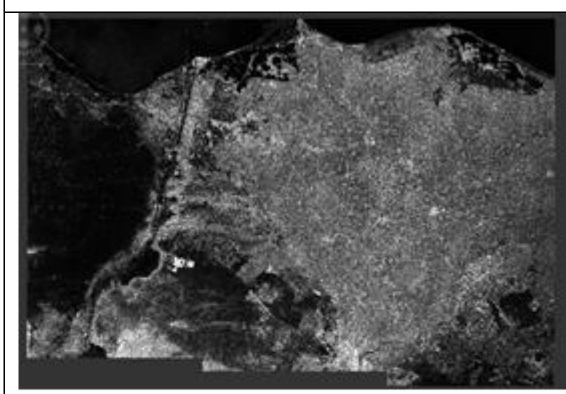

Fig3.b Apply orbit file to VV image.

B.2.Thermal Noise Removal

Sentinel-1 image intensity is disturbed by additive thermal noise, particularly in the cross-polarization channel. Thermal noise removal reduces noise effects in the inter-sub-swath texture, in particular, normalizing the backscatter signal within the entire Sentinel-1 scene and resulting in reduced discontinuities between sub-swaths for scenes in multi-swath acquisition modes. The thermal noise removal operator available in SNAP for Sentinel-1 data can also re-introduce the noise signal that could have been removed during level-1 product generation, and update product annotations to allow for re-application of the correction. Sentinel-1 level-1products provide a noise look-up table (LUT), provided in linear power, for each measurement data set and used to derive calibrated noise profiles matching the calibrated GRD [6];[7]. Figure 4.a,4.b depict thermal noise removal of VH and VV images.

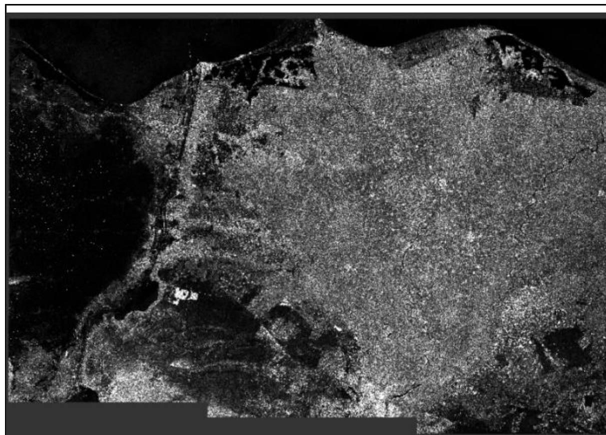

Fig4.a Thermal noise removal of VH image.

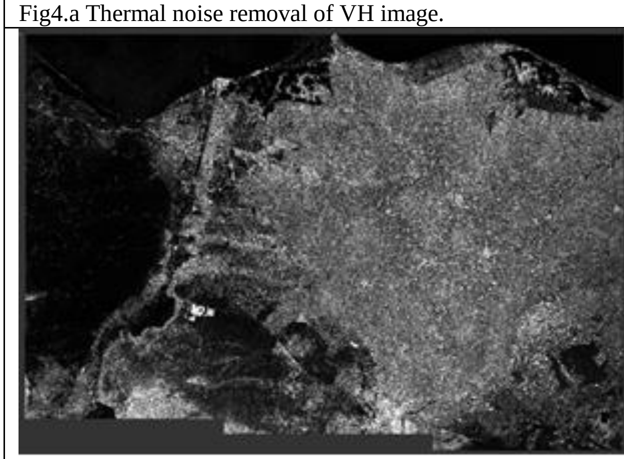

Fig4.b Thermal noise removal of VV image.

B.3.Border Noise Removal

While generating level-1 products, it is necessary to correct the sampling start time in order to compensate for the change of the Earth’s curvature. At the same time, azimuth and range compression leads to radiometric artefacts at the image borders. The border noise removal algorithm, available as an operator in SNAP, was designed in order to remove low intensity noise and invalid data on scene edges[6];[7].

B.4.Calibration

Calibration is the procedure that converts digital pixel values to radiometrically calibrated SAR backscatter. The information required to apply the calibration equation is included within the Sentinel-1 GRD product; specifically, a calibration vector included as an annotation in the product allows simple conversion of image intensity values into sigma nought values. The calibration reverses the scaling factor applied during level-1 product generation, and applies a constant offset and a range-dependent gain, including the absolute calibration constant[6];[7]. Figure 5.a. depicts Sigma -0 vv after calibration of VH image. Figure 5.b depicts Sigma -0 VV after calibration of vv image.

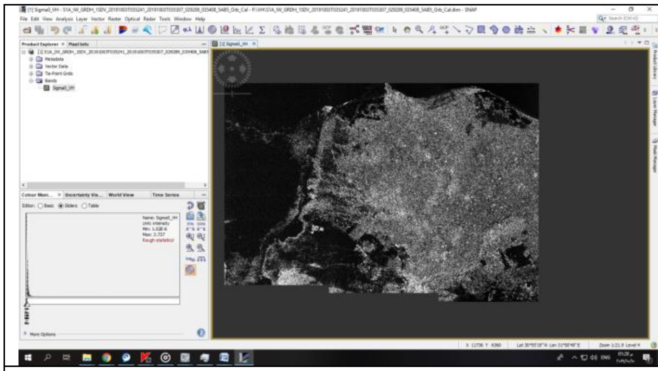

Fig 5. a.Sigma -0 VV after calibration of vh image.

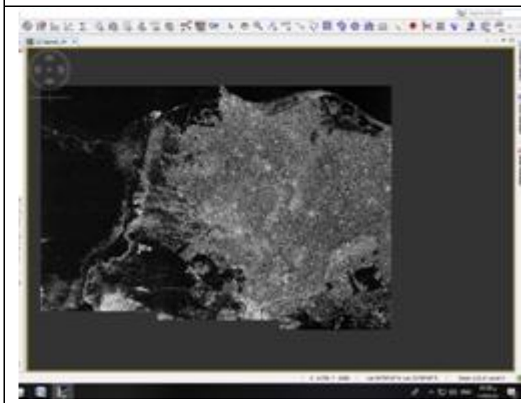

Fig 5. Sigma -0 VV after calibration of vv image.

B.5.Speckle filtering

Speckle, appearing in SAR images as granular noise, is due to the interference of waves reflected from many elementary scatterers. Speckle filtering is a procedure to increase image quality by reducing speckle. When such a procedure is done at an early processing stage of SAR data, speckle is not propagated in ongoing processes (i.e., terrain correction or conversion to dB).

Speckle filtering is not advisable when there is an interest in the identification of small spatial structures or image texture, since it might remove such information. The refined Lee filter has been found to be superior, with respect to other single product speckle filters, for visual interpretation, because of its ability to preserve edges, linear features, and point target and texture information.

More recently, multitemporal speckle filters have been developed to reduce speckle, taking advantages from multiple SAR observations in time. The proposed preprocessing workflow includes a speckle filtering step, which could be skipped by selecting 'None' as the filter type.

Currently, one of the following filters is available in the SNAP single product speckle filter operator: 'Boxcar', 'Median', 'Frost', 'Gamma Map', 'Lee', 'Refined Lee', 'Lee Sigma', 'IDAN'[6];[7]. Figure 6.a, 6.b illustrate Gamma filter of VH and VV images.

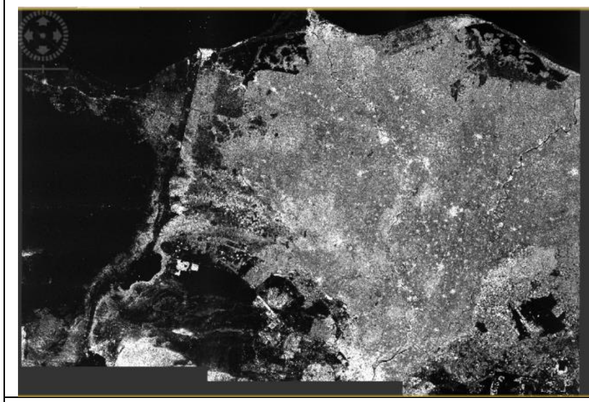

Fig 6.a Gamma filter of VH image.

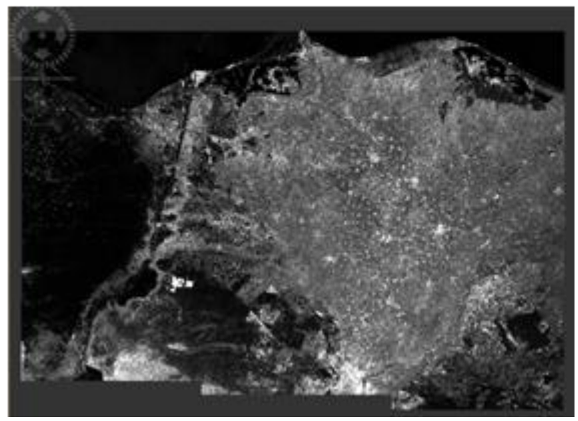

Fig5.6 Gamma filter of VV image.

B.6.Terrain correction

SAR data are generally sensed with a varying viewing angle greater than 0 degrees, resulting in images with some distortion related to side-looking geometry. Terrain corrections are intended to compensate for these distortions so that the geometric representation of the image will be as close as possible to the real world. Range Doppler terrain correction is a correction of geometric distortions caused by topography, such as foreshortening and shadows, using a digital elevation model to correct the location of each pixel. The range Doppler terrain correction operator available in SNAP implements the Range Doppler orthorectification method. For geocoding SAR scenes from images in radar geometry, It makes use of available orbit state vector information in the metadata, the radar timing annotations, and the slant to ground range conversion parameters together with the reference digital elevation model data to derive the precise geolocation information. The target Coordinate Reference System (CRS) can be selected and optionally set to match the UTM zone of the overlaying Sentinel-2 granules. The operator allows the selection of the image resampling method and the target pixel spacing in the target CRS. This processing step allows the spatial snapping of Sentinel-1 GRD products to Sentinel-2 MSI data grids, in order to geolocate data to a common spatial grid and promote the use of satellite virtual constellations

[6];[7]. Figure 7.a,7.b. depict Terrain corrected of VH and VV images .

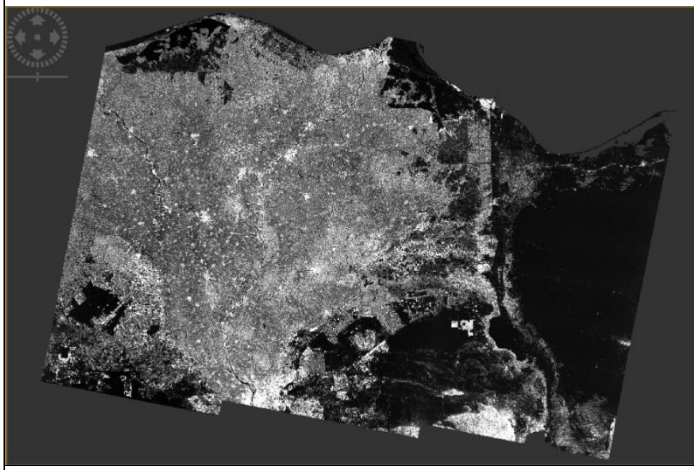

Fig7.a Terrain corrected of VH image.

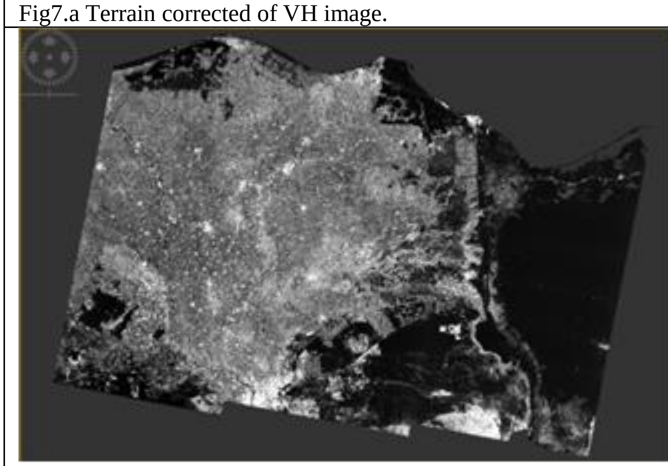

Fig 7.b Terrain corrected of VV image.

B.7.Conversion to dB

As a last step of the preprocessing workflow, the unitless backscatter coefficient is converted to dB using a logarithmic transformation[6];[7]. Figure 8.a, 8.b illustrate conversion to DB for VH and VV images.

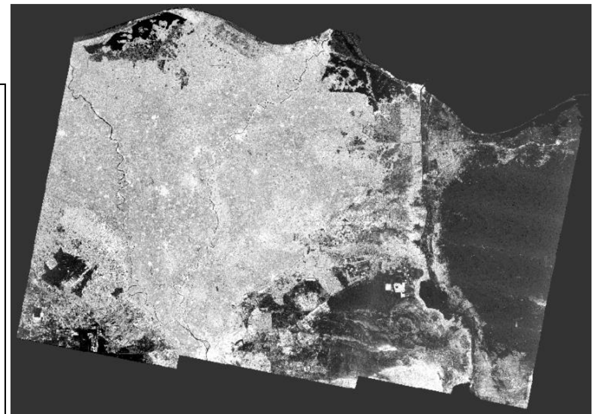

Fig 8.a Conversion to DB of VH image.

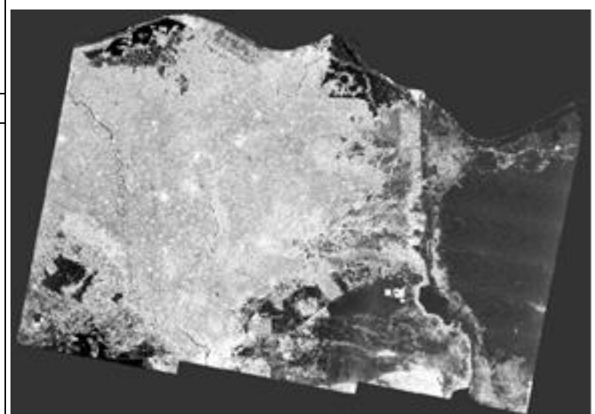

Fig8.b Conversion to DB of VV image.

C.Download Optical Sentinel 2 image

The sentinel -2 image was acquired (downloaded)from Copernicus. The obtained image was reprojected to UTM zone 36 and WGS84.

Snap software was used to export the bands(2,3,4,8) of sentinel 2 to geotiff format then the bands were layerstacked. Image to image registration was performed using Erdas imagine between the radar image and the optical image the optical images with resolution 10 m was resampled to 5 m (resolution of radar image). The radar image is the base and sentinel 2 is the slave then the radar image was subsetted.

Resampling, Atmospheric Correction and Subset selection are necessary in pre-processing satellite images.

Resampling ensures that images of each band have the same resolution and number of pixels. Subset selection allows re-choosing specific areas of interests.

Atmospheric Correction algorithms are based on the Atmospheric/Topographic Correction for Satellite Imagery[5]. Atmospheric Correction is not required for Sentinel-2B
Figure9 a depicts sentinel -1 image. Figure 9 b illustrates sentinel -2 image.

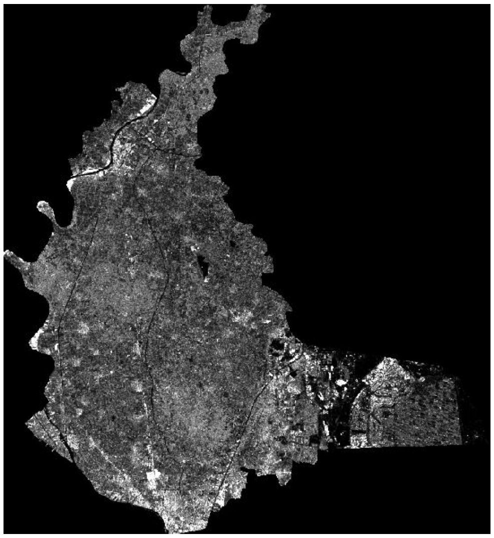

Fig 9 a sentinel -1 image.

Fig9 b sentinel -2 image.

D.Image fusion

The objective of image fusion is to take advantage of the synergy between multispectral images that are of lower spatial resolution, and a single broad (panchromatic) band covering the whole of the visible spectrum that has higher spatial resolution (Va°gen ,2006). The fusion of multispectral image with the panchromatic radar image was performed using PCA. ERDAS Imagine 2014 was used for performing the task. Figure 10 illustrates fused image resulted from PCA.

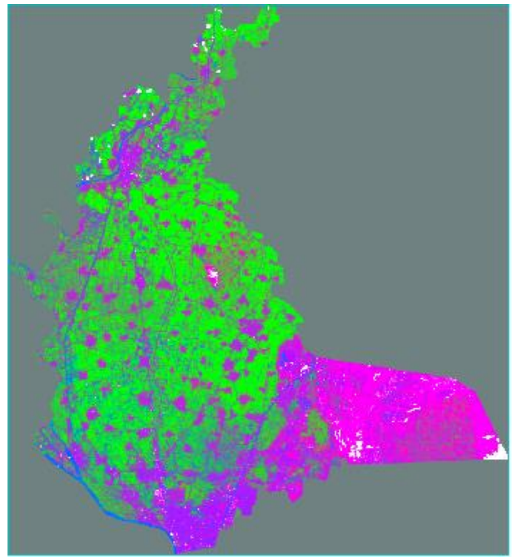

Fig 10 Fused image resulted from PCA.

E. Texture extraction

Texture can be defined as "the spatial distribution of tonal variations" [39]
For GLCM construction and texture calculation, a small window of 3 x 3 pixels was used.
Textures were extracted using ENVI 5.1 Software

$$\text{Mean}=\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} iP_{i,j} \qquad \text{Equation 1}$$

[40]

F.Deep learning

Deep learning has had an enormous impact on the field of remote sensing in the past few years [12]
This is mainly due to the fact that deep neural networks can model highly non-linear relationships between remote sensing observations and the eventually desired geographical parameters, which could not be represented by physically-interpretable models before. One of the most promising directions of deep learning in remote sensing certainly is its pairing with data fusion which combine SAR with optical et image [2]

H.Classification

Classification is a way of classifying land cover contents into different classes using well defined classifiers. It is defined as the ordering or arrangement of pixels into groups or sets on the basis of their relationships.
A number of different image processing, analysis and classification methods are available in order to generate land cover maps from high resolution optical remote sensing data[11]

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Traditional pixel-based classification techniques are often not capable to resolve mixed pixel problem. Since the traditional hard classifier can label each pixel only with one class, urban can only be recorded as either present or absent.
The existence of mixed pixels led to the development of numerous methods of subpixel classifiers in which each pixel is allocated to all classes in varying proportions. Among the most popular techniques for subpixel classification are artificial neural networks and support vector machines (SVM)[25].

The neural network and support vector machine classification methods were conducted.
The training and test data are manually extracted and labeled from the high-resolution images of Google Earth.
Signatures collection: is the first step in the classification process. Four classes were selected to represent the land use/land cover classes of the study area: Urban, roads,desert and vegetation. Thirty signatures (polygons) have been collected in each class for different dataset.
Signatures evaluation: The objective of signatures evaluation is to ensure that they represent unique land covers and that they will produce the most accurate classification.
The collected signatures were evaluated, and the result is accepted before the classification process.
The Classification was implemented in ENVI 5.1.. Afterward, post-classification refinements were used to reduce classification errors. Table 2. Shows classification results

F.1Artificial neural networks (ANN)

Artificial neural networks (ANN), is an interconnected group of simple processing elements (called artificial neurons or nodes) that uses a mathematical or computational model and are capable of performing massively parallel computations for data processing based on connectionist approach to computation [3]. The arrangement of the nodes is referred to as the network topology. The first type of layer is the input layer, where the nodes are the element of a feature vector. The second type of layer is the internal or hidden layer since it does not contain output units. The third type of layer is the output layer and this presents the output data. Neural network has been used in remote sensing image classification in these years and gotten a satisfying result [3].

F.2Support Vector Machine (SVM)

In this study , SVMs is chosen as the classifier since in comparison with other approaches SVMs generalizes well even with small training samples [5].
The principle of SVM is to define an optimal hyperplane to maximize margin width by using training subset [4]. In the present study, the Radial Basis Function (RBF) is used. optimum parameters were determined as 0.333 and 100 for kernel width and penalty parameter, respectively.

Figure 11 a. depicts PCA classified with SVM. Figure 10 b. depicts PCA classified with Neural network

H.Classification accuracy assessment

Results of the two used supervised machine learning classifiers were evaluated in terms of the Overall accuracy (OA) statistical index.

OA= number of correct classified pixels/total number of pixels [32]

Seventy randomly selected points were used to evaluate the accuracy of classification.

Kappa coefficient of agreement
The kappa coefficient of agreement is a discrete multivariate analysis technique used to evaluate the accuracy of classification maps created with remotely sensed imagery.
The kappa coefficient is calculated from the error matrix and measures how the classification performs compared with the reference data. Kappa is used to determine if a classification produced from remotely sensed imagery is better than random.
The kappa coefficient of agreement is the difference between the actual agreement (major diagonal total) and the chance agreement (row or column totals) of the matrix. The kappa coefficient was recommended because it considers all elements of the confusion matrix.
The kappa can be defined as:

$$K = \frac{\text{observed accuracy} - \text{chance agreement}}{1 - \quad \text{chance agreement}}$$

and it is computed as:

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{it} \,.\, X_{ti})}{N^2 - \sum_{i=1}^{r}(X_{it} \,.\, X_{ti})}$$

where
r Number of rows in error matrix
Xii Number of observations in row (i) and column (i) on the major diagonal
Xit Total of observations in row i shown as marginal total of the matrix
Xit Total of observations in column i shown as marginal total at the bottom of the matrix
N Total number of observations, included in the matrix[24]

A morphological opening filter using kernel size 3 x 3 was applied to the classified imageries followed by morphological closing filter in order to remove small elongated objects such as fences and to separate regions just bridged by a thin line of pixels.

Table 2. Classification results

Description of variables	Overall accuracy% SVM	KAPPA INDEX SVM	Overall accuracy% NEURAL NETWORK	KAPPA INDEX NEURAL NETWORK
vv	73.38	0.75	71.59	0.70
vh	70.73	0.72	68.31	0.69
senteinel 2	86.2	0.82	83.1	0.735
merged image usingPCA	96.81	0.95	95.22	0.93
VV, VH, (VV-VH)	92.66	0.9	90.26	0.89
VV, VH, (VV+VH)/2	90.22	0.88	89.91	0.85
VV, VH, Texture	93.02	0.92	92.27	0.91

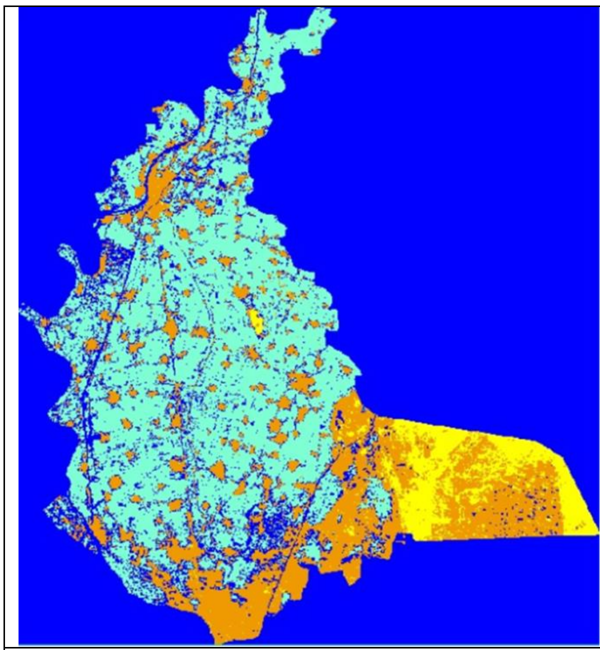

Fig 11 a.PCA SVM.

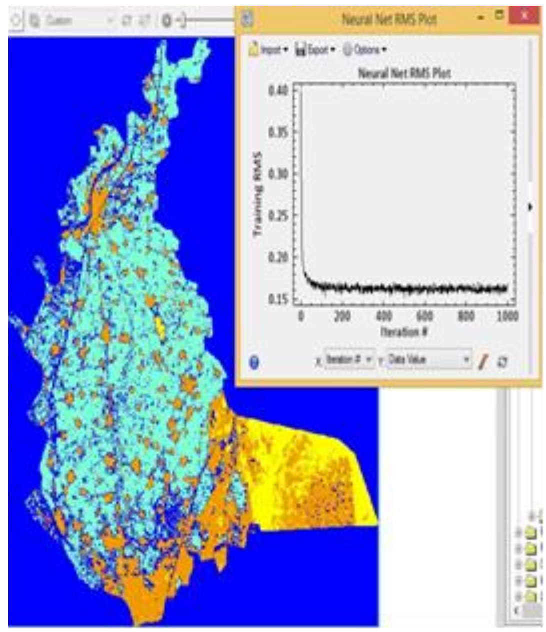

Fig 11 b.PCA Neural network.

II. Results and Discussion

Sentinel-1A images were acquired through the Copernicus Open Access Hub. The scenes were acquired as Ground Range Detected (GRD) Level-1 products in the Interferometric Wide (IW) swath mode, therefore multi-looked and projected to ground range using an Earth ellipsoid model. Preprocessing was performed using the Sentinel Application Platform (SNAP). Firstly, orbit state vectors were refined with precise orbit files and GRD data was radiometrically calibrated to sigma 0 (σ nought). Then, thermal noise removal was performed before applying a speckle noise reduction based on a 5 * 5 gamma filter, in order to reduce the speckle noise while preserving the textural information. Finally, Range-Doppler terrain correction were applied based on the 25m SRTM 1-sec Digital Elevation Model(DEM) and conversion from linear to decibel scale.

Multispectral image (sentinel-2)has been coregisterd to the orthorectified PAN image(sentinel-1). Nearest neighbour resampling technique is used for resampling the multispectral image to the pixel size of (5 m).

The RMST error of radar image and sentinel-2 image were found 0.42 and 0.45 m respectively.

The result reveals that the fused image has higher spatial frequency information than the original images.

The fusion of multispectral image with the panchromatic radar image using PCA yields better high spectral and spatial resolution image. In this research image fusion has been performed to remove cloud, enhance the information apparent in the images as well as to increase the reliability of the interpretation. Classification was performed using SVM and neural network.

In the experimental analysis seven scenario was defined for image classification, and impact of variables was evaluated. First, each polarization was classified as single variable and the results show that VV polarization has slightly higher accuracy than VH polarization (Using more than one variable significantly increased the classification accuracy. Especially scenarios5, 6 and 7 has higher accuracies than other scenarios except scenario 4 which is the best.

Experimental results indicated that different scenarios provided different results according to corresponding variables. Using difference imagery (VV-VH) as a third variable into the classification resulted in higher accuracy than mean and Using texture as a third variable into the classification resulted in higher accuracy(VV-VH)

V.CONCLUSION

This paper investigates the problem of urban land cover classification by using Sentinel-1 , Sentinel-2 and fused sentinel imageries and machine learning based classifiers. Automatic supervised classification of imagery is required to extract land use / land cover data. Machine learning algorithms are the most promising techniques to reach this goal.
Support Vector Machines (SVM) and neural network methods have been implemented as a supervised pixel based image classification to classify the dataset.
It was found that SVM classification results is better than neural network classification results for urban impervious surfaces extraction. During the classification, different scenarios have been applied it was found that the best classification resulted from fused PCA then multispectral image then radar image

Different combinations of VV and VH polarizations have been analysed and the resulting classified images have been assessed using overall classification accuracy and Kappa coefficient. Results demonstrate that, combining opportunely dual polarization data, the overall accuracy increases up to 93.02% against 73.38% and 70.73% of using individual polarization VV and VH, respectively. Using more than one variable significantly increased the classification accuracy. Especially scenarios5, 6 and 7 has higher accuracies than other scenarios except scenario 4 which is the best.

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