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An Automatic ANFIS System for Classifying Features from Remotely Sensed Images Using a Novel Technique for Correcting Training and Test Data

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Abstract: The pattern data is collected by sampling the remotely sensing images, the training and test data for each feature could have wrong data belongs to the other features. This affected the performance of the trained nets. To enhance the proposed classifier efficiency, train it on corrected training data. So, a novel technique is applied to correct the training and test data, started by removing the noise pixels for all features. After that the training and test data are improved by excluding all repeated pixels that having the same colour values. This article presents the Adaptive Neuro-Fuzzy Inference System (ANFIS) working in an automatic way. It is designed to classify environmental features which have occurred from the Colorado wildfire. They are fires, dark fires, ash fires, clouds, ground and vegetation. These features are recorded by remotely sensed images. The system can rebuild the architecture of the ANFIS net according to three parameters. They are the kind of Membership Function (MSF), the number of MSF, and number of epochs. The proposed system is trained on the three groups. With each group, the system is designed having the ability to do many trials until get the best ANFIS net and find the best classification on test data and images. The system is applied on four different images, in order to check the performance of the trained ANFIS nets. The trained system provides an excellent classification of test data sets and the performance is 99.9%. Our study demonstrated the proposed classifier efficiency is improved; it is trained on corrected training data. Due to all specified features are correctly classified from the provided images. In addition to, the processing time for all experiments is reduced by about 50%.

Keywords: ANFIS, correcting training data, correcting test data, feature classification, image processing

1 Introduction

Remote sensing is a technique that is used to observe and monitor the earth surface or the atmosphere from out of space using satellites or aircrafts. It is obtained information about objects on the Earth's surface without direct contact with these objects, therefore, it also called earth observation [1-3]. Accurate extraction for the land use/land cover changes of the Earth's surface is extremely important tasks of remote sensing technology [4-6]. Land use maps are produced from remotely sensed images, pattern recognition and detection techniques like classification and clustering can be applied in many problems, for example [7-9]. These remotely sensed images can be used in many applications e.g. for monitoring objects on ground cover [10,11], extraction of features on ground cover [12,13], change detection in ground cover [14,15], and many others [16,17]. The classified features can be used in geographic information systems databases [18,19]. ANFIS is a powerful processing tool and a multi-layer network model, it is produced from Fuzzy Logic. ANFIS uses an artificial neural network learning algorithm to assign fuzzy rule with the appropriate MSFs that is simulated according to the behaviour of input and output data [20,21]. This technique is designed to produce an appropriate solution for function approximation using hybrid learning algorithm depending on the shape and the location of MSF [22,23]. The ANFIS architecture which gives the best result for a particular problem can only be determined experimentally [24]. The following MSFs are chosen as classifiers in the proposed system. They are

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difference of two sigmoid (dsigmf) [25], two-sided Gaussian curve (gauss2mf) [26], Gaussian curve (gaussmf) [27], generalized bell curve (gbellmf) [28], Pi-shaped curve (pimf) [29], product of two sigmoidal (psigmf) [30], trapezoidal (trapmf) [31], and triangular (trimf) [32]. Other most related works are presented as follows. Maheswari K. Uma and Rajesh S. [33] applied a system using ANFIS to classify features from remotely sensed images using ANFIS, the performance was 99.49%. Behery G.M. [34] designed a system using ANFIS to classify dust, clouds, water and vegetation features from studied images that were obtained by NASA's Aqua satellite. The proposed system is trained on the features of the provided images to find the best ANFIS net that has the ability to have the best classification. The performances of the best three trained nets were 98.95%, 98.72% and 98.62%. In the remotely sensing image retrieval methods, the images are extracted from the remote sensing image database by means of three characteristic models they are visual features, object features and the scene feature. Kiran A.B. and Manthalkar R.R. [35] applied the ANFIS system using MATLAB to extract object features. The performance is measured by utilizing a compilation of remote sensing images taken from the database. The obtained performance was 94.7%. Texture features play a predominant role in land cover classification of remotely sensed images. So, Jenicka S. and Suruliandi A. [36] built a system to classify land cover patterns in the remotely sensed image. Moreover, land cover classification of remotely sensed image has been performed using Gabor wavelet and ANFIS classifier. The classification accuracy of the classified image obtained was found to be 92.8%. Comparing with the previous systems, the current research tries to improve the performance by adding a novel technique to correct the training and test data that are used to train and test the best ANFIS nets. In this research study, ANFIS system is proposed which automatically adjusts the parameters. The inputs are three sets of data, they are represented the training data that are collected from the three RGB bands of the studied remotely sensed image. This system is carried out to classify fires, dark fires, ash fires, clouds, ground and vegetation features from Colorado images by applying ANFIS system using a set of MSFs. The rest of paper is structured as follows; Section 2 describes the pattern data and how it collected. In Section 3, the description, architecture and whole training process of ANFIS system are presented. In addition to, the correction of training and test data is carried out. The obtained results and comparison are shown in Section 4. The discussion is introduced in the Section 5. The last section concludes the work and presents a future work.

2 Pattern Data

This study is applied on a big remotely sensed image that was obtained by NASA using the Operational Land Imager on Landsat 8. This image was acquired on July 6, 2018. It is false color to better differentiate burned areas (red) from the surrounding landscape. The fire is located five miles northeast of Fort Garland and spanned on both sides of Highway 160. The fire affected 107,967 acres of land on 12 July 2018, making it almost the second largest fire in Colorado. This fire was one of 14 fires burning in Colorado [37-38]. The state experienced hot summer days, high winds, and extreme to exceptional drought conditions for the past three months. The image type is RGB and its information is presented in Table 1. The studied image contains multiple features. These features are fires, dark fires, ash fires, clouds, ground and vegetation. Each feature has a big difference in its color pixels; see Figure 1. This study aims to classify the above-mentioned features from the studied images. The pattern data is randomly collected from the proposed image for each feature by drawing a set of lines over the feature's areas. All located pixels on these lines are considered a data for this feature. This process is repeated until collect enough pattern data from all areas having different color for that feature. These pixels may contain invisible pixels related to other features. All data is represented by three-pixel grey levels, one for each band. These bands are red, green and blue. The grey levels values are ranged from 0 to 255 and coded as eight bits binary numbers. During the collection process, each feature must be represented by all its colors. After the collection, each feature is considered as a class. So, all features have six classes. Each class is divided into two partitions: one for training and the other for test. After that, all training partitions are merged as one group and stored in a single file for training. By the same way, the test partitions are also merged as another group and stored in other file for test.

3 ANFIS System

The ANFIS systems are more efficient methods for classifying features from images [39]. Figure 2 shows the general architecture of the proposed ANFIS system. This architecture is created using a Tokagi Sugeno FIS, the structure contains five layers. Fuzzy MSFs are implemented in Layer-1. The following two layers nodes are constructed to create the antecedent parts for all rules. Layer-4 represents the first-order Takagi-Sugeno rules for every fuzzy rule. Finally, Layer-5 is used to calculate the trained system output. ANFIS system is assessed by two statistical criteria, namely, the root mean squared error and the coefficient of determination. This system is designed to identify a probability density function ? (R, G, B). The values of R, G and B represent the three inputs of the proposed system. Each input has n of MSFs and contains n2 base rules. The proposed system is designed to build the architecture of ANFIS automatically on the training and test data groups, each experiment is applied in many tries without any help from the users. The system

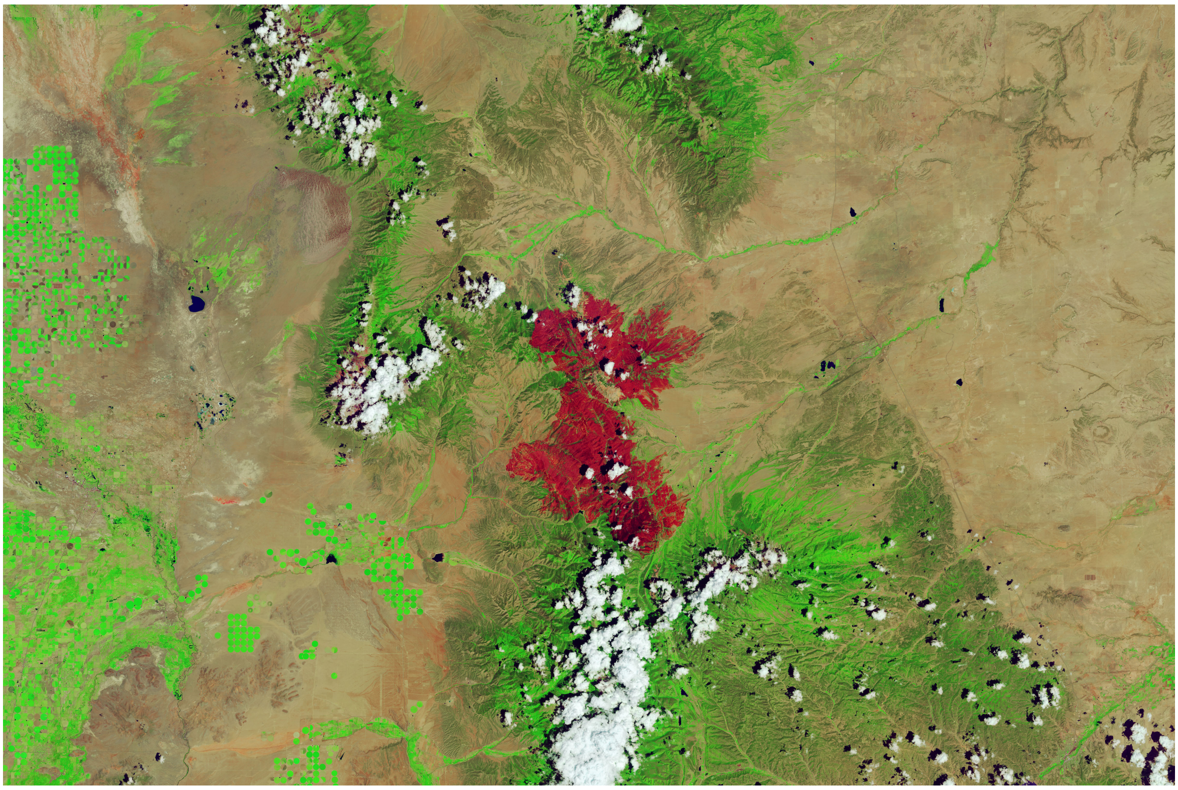


Fig. 1: The original image was achieved by NASA Satellite [37].

is firstly started to assign values of three parameters. They are MSFs names, number of MSFs for the three inputs and Number of Epochs (NOEs). The proposed MSFs names are dsigmf, gauss2mf, gaussmf, gbellmf, pimf, psigmf, trapmf and trimf. They are stored in a list. In the first try, the system is applied on the first group of training and test data using 100 epochs, two MSFs and the first MSF name is chosen. In the next trials, the NOEs are incremented by 100 up to 3000 epochs. The number of MSFs is incremented by one up to seven and the next MSF name is chosen. The training and test processes are continued until having the required best training performance, the resulted ANFIS net is used for classifying the specified features. Then, the obtained training, test performances, best ANFIS net and the workspace are stored. It is found that the obtained best ANFIS net is reached the optimal solution using 1000 epochs and the performance is not improved by extending the training up to 3000 epochs; see Figure 3. Therefore, all experiments are applied with 1000 epochs as a maximum. This system is firstly applied to correct the training and test data, and to classify all specified features as given in the following two sections.

3.1 Correcting Training and Test Data

As mentioned above, the collected pattern data for each feature could have wrong data belongs to the other features. This data effects on the performance of the trained nets. So, misclassified pixels are produced for all features. Therefore, a novel technique is proposed to correct the pattern data due to a corrected training and test data. This correction process is accomplished through two stages. In the first one, all noise pixels are removed from training and test data. The second stage is used to exclude all repeated colour-pixels having the same values from the training and test data. Six experiments are designed to remove the noise pixels. Moreover, the proposed ANFIS system is applied on the pattern data of the six features as training data, one feature is selected to represent one class and the other five features represent other class. This selection is done in a linear combination as shown in Figure 4. In the first experiment, the cloud feature is selected to represent the cloud class, the other features are considered as non-cloud. Figure 4 shows this selection process for all six experiments. The cloud and non-cloud files are used as training data with ANFIS system in the first experiment. After training, the trained net is used to remove any noise-cloud pixels from the data of other five features, as shown in Figure 5. These processes are shown in more detail for removing the noise cloud pixels from

Table 1: The studied image information

Image type	Taken date	Length	Width	Size /MB
Landsat 8	July 6, 2018	4830	3220	3.64

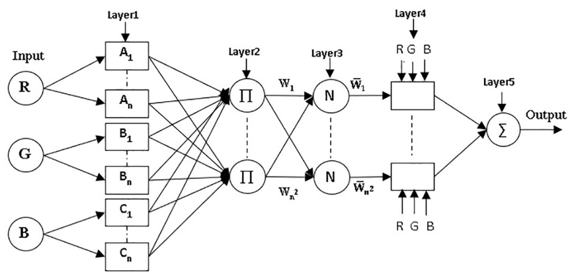


Fig. 2: ANFIS net architecture.

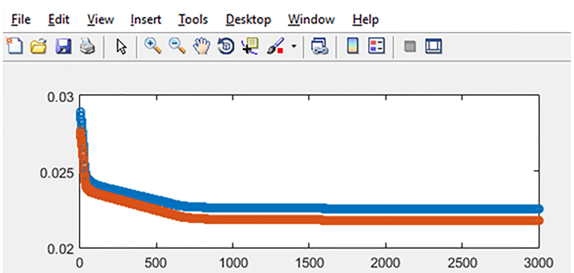


Fig. 3: The ANFIS performance at 3000 epochs.

pattern data as given in Figure 6. In the proposed system, similar processes are applied for other features. Each experiment is designed for removing the noise pixels for one feature from the pattern data. In the second experiment, the fire feature is selected, the other features are considered as non-fire. After training, the trained net is used to remove any noise-fire pixels from the data of other five features, as shown in Figure 5. In the next four experiments, the noise pixels of dark fires, ash fires, ground and vegetation are removed from the pattern data respectively as shown in Figures 4-5. At the end of these processes, most of noise pixels for all features are removed from the pattern data due to an improvement in the training and test data. For instance, the number of removed noise pixels from training and test data of *Group*1_1 experiment is 4842 and 1103 respectively; see Table 2 for other groups. In the second stage, all repeated colour-pixels having the same values are excluded from the training and test data. For instance, the number of removed repeated colour-pixels from training and test data of *Group*1_1 experiment is 1689 and 1585 respectively; see Table 2 for other groups. The description of the corrected training and test data groups is shown in Table 2. Each training data group is used in an experiment to train an ANFIS net and the corresponding test data is used to compute the performance of trained net.

Training Data

Experiments		
1	Clouds	Non-Clouds: Fires, dark fires, ash fires, ground and vegetation
2	Fires	Non- Fires: Clouds, dark fires, ash fires, ground and vegetation
3	Dark fires	Non-Dark fires: Clouds, Fires, ash fires, ground and vegetation
4	Ash fires	Non-Ash fires: Clouds, Fires, dark fires, ground and vegetation
5	Ground	Non-Ground: Clouds, Fires, dark fires, ash fires and vegetation
6	Vegetation	Non-Vegetation: Fires, dark fires, ash fires and ground

Fig. 4: The training data of the correction technique.

Experiments	Test Data	Action
1	Fires, dark fires, ash fires, ground and vegetation	Remove clouds
2	Clouds, dark fires, ash fires, ground and vegetation	Remove fires
3	Clouds, Fires, ash fires, ground and vegetation	Remove dark fires
4	Clouds, Fires, dark fires, ground and vegetation	Remove ash fires
5	Clouds, Fires, dark fires, ash fires and vegetation	Remove ground
6	Fires, dark fires, ash fires and ground	Remove vegetation

Fig. 5: Removing the noise pixels for six features using trained nets respectively.

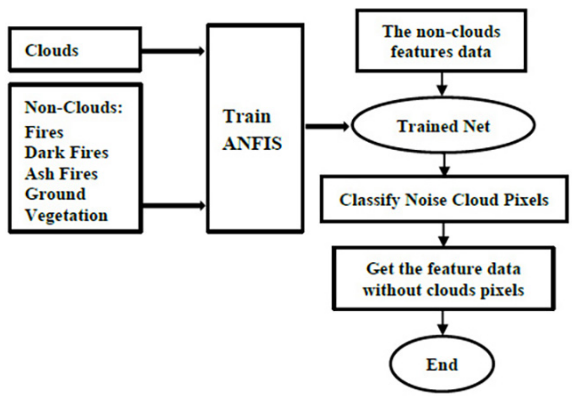


Fig. 6: The complete process for removing the noise cloud pixels.

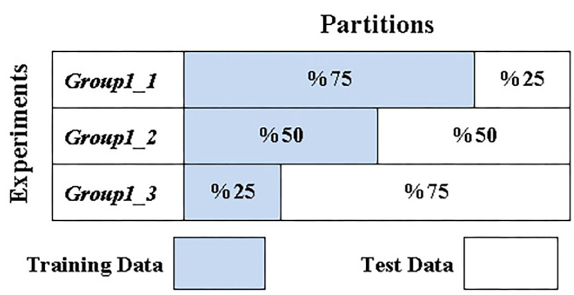


Fig. 7: The corrected training and test data division groups.

Table 2: Training and test data groups after applying the correction technique

Experiments	Training data (Size/pixel)				Test data (Size/pixel)			
	Original	Corrected after		Percentage	Original	Corrected after		Percentage
		Remove Noise	Remove Repeat			Remove Noise	Remove Repeat	
Group1_1	11373	6531	4842	%57	3791	2688	1103	%71
Group1_2	7582	4752	2830	%63	7582	4690	2892	%62
Group1_3	3791	2688	1103	%71	11373	6531	4842	%57

3.2 Best Trained ANFIS Nets

The proposed system is applied on the corrected training and test data using the above settings. This data is produced from dividing the corrected pattern data according to each feature as three situations. These situations are (three-quarters for training and one quarter for test), (half for training and the other for test) and (one quarter for training and two- quarters for test). These divisions are divided in a systematic way. Moreover, all features are fully represented in the training data; see Figure 7. After that, the training partitions of all features are merged as one group and stored in a single file for training. By the same way, the test partitions are also merged as another group and stored in other file for test. For example, the number of corrected training and test data in the Group1_1 are reduced by 4842 and 1103 respectively; see Table 2 for other groups. The whole system is illustrated in more details as shown in the Figure 8. The system is applied on three training and test data groups using eight kinds of MSFs, to choose the best. In each experiment, many trials are done by changing the architecture of the ANFIS system through the training and test processes until get the required performance. When training is completed, three trained ANFIS nets are produced. Each ANFIS net is the best one in the corresponding experiment. These ANFIS nets are used to classify the features data from the specified sections. Figures 9-14 show the behaviour of the best MSFs before and after training using two, three and four MSFs respectively. The performances of the obtained three ANFIS nets using the best functions are shown in Figure 15. The architectures of the best obtained ANFIS nets are shown in Figure 16. The obtained performance of these ANFIS nets on the training and test data sets are presented on the Table 3. It is found that the best ANFIS nets of these functions are reached the optimal solution using 1000 epochs with two, three and four MSFs. It is found that, the best performances of ANFIS nets using function on training and test data are 99.98%, 99.82%, 99.96% and 99.31% respectively. The specified colours of classified features are given in the Figure 17.

Table 3: The obtained performances of ANFIS nets

Groups	**MSF name**	**No. of MSF**	**No. epochs**	**Training Perf.**	**Test Perf.**
ANFIS1_1	gbellmf	2	1000	99.98%	99.96%
ANFIS1_2	gbellmf	3	1000	99.82%	99.31%
ANFIS1_3	gauss2mf	4	1000	99.55%	99.11%

Table 4: The first two test images Information

Image Name	**Start Coordinates**	**Size / Pixels**
image1	'1850x975'	'1000x1000x3'
image2	'2200x1975'	'1000x1000x3'

Table 5: The second two test images information

Image Name	**Start Coordinates**	**Size / Pixels**
image3	'1850x975'	'50x50x3'
image4	'2200x1975'	'50x50x3'

4 Results

Two sections are chosen from the studied image for classifying all specified features. These images are called image1 and image2 respectively; the information of these images is given in Table 4. Figures 18-20 show the selected two images and the ANFIS nets classification results of these images respectively. It is found that all features are precisely classified. In order to compare the actual performances of the trained ANFIS nets for classifying features data correctly or mis-classifying, two other small images are chosen from contiguous areas, the first one has cloud feature only and the other has fire and dark fire. The images are called image3 and image4 respectively; the information is introduced in Table 5. The best nets are applied on the two small images and correctly classified the three features; see Figure 21. From the comparison results, it is found that the proposed system obtained on the highest performance comparing with others [33-36], the classification accuracy is 99.96%; see table 6 for more details. Thus, the proposed system is correctly classified the specified features more accurately. Moreover, correcting the training and test data, due to an improvement in the training and test processes. In addition to, the processing time is reduced to about the half.

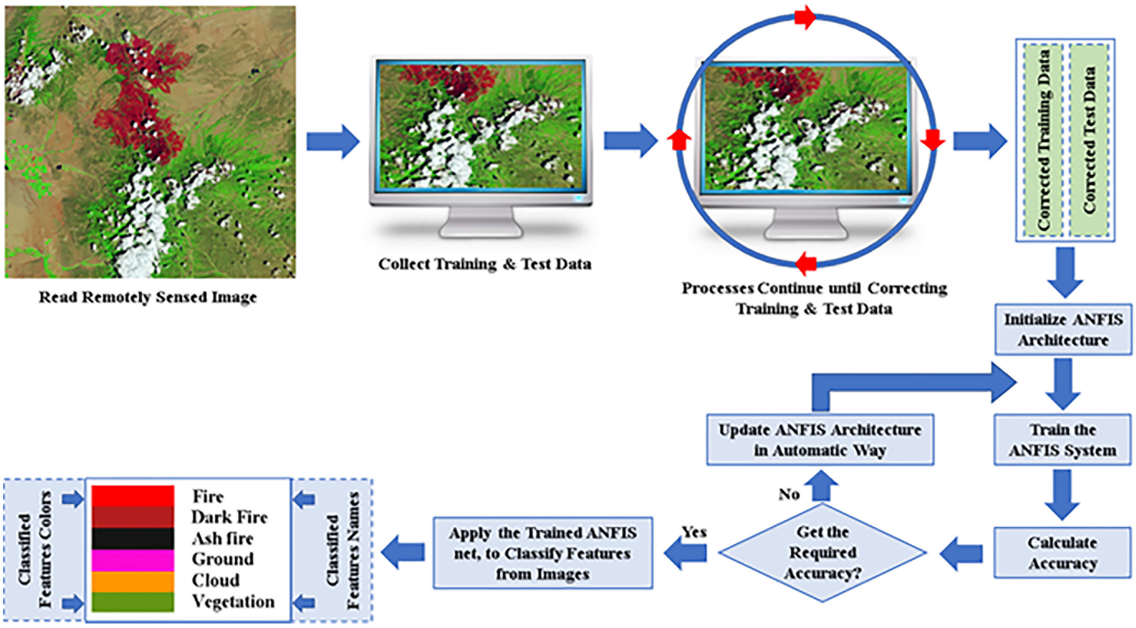


Fig. 8: Whole processes of the proposed system.

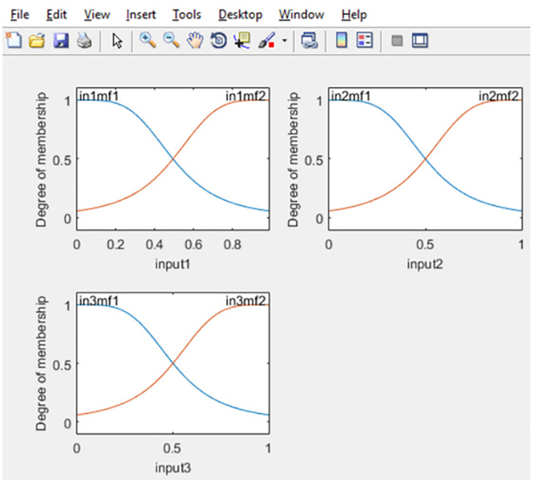


Fig. 9: Two MSFs structure before training.

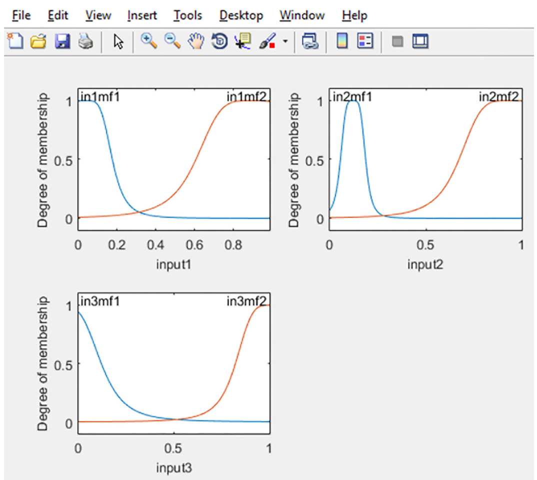


Fig. 10: Two MSFs structure after training.

Table 6: Comparison with other systems

Systems	Classification accuracy
Proposed System	99,96%
Maheswari and Rajesh [33]	99.49%
Behery [34]	98.95%
Kiran and Manthalkar [35]	94.7%
Jenicka and Suruliandi [36]	92.8%

5 Discussions

This article presents ANFIS system that has designed to apply many experiments automatically without any help from the users to classify fires, dark fires, ash fires, clouds, ground and vegetation features from remotely sensed images. As mentioned above, the training and test data for each feature could have wrong data belongs to the other features. This wrong data could affect the performance of the trained nets. So, misclassified pixels are produced for all features. The proposed system has a novel technique to correct the pattern data due to a

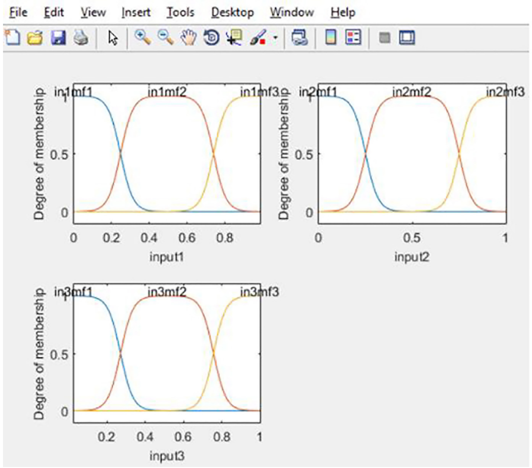


Fig. 11: Three MSFs structure before training.

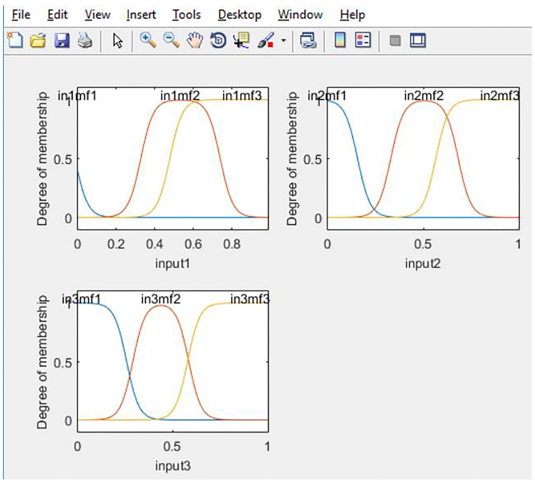


Fig. 12: Three MSFs structure after training.

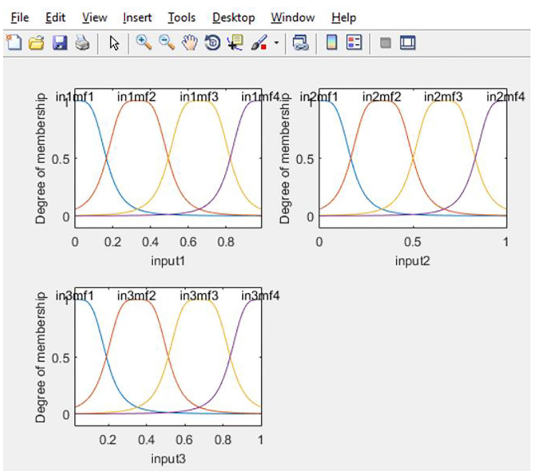


Fig. 13: Four MSFs structure before training.

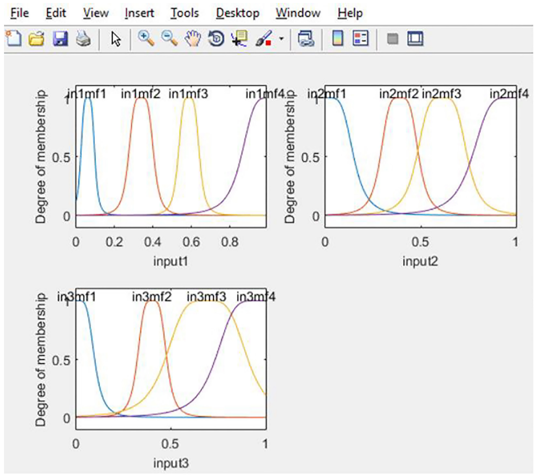
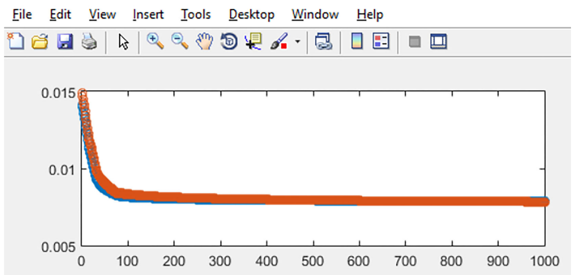
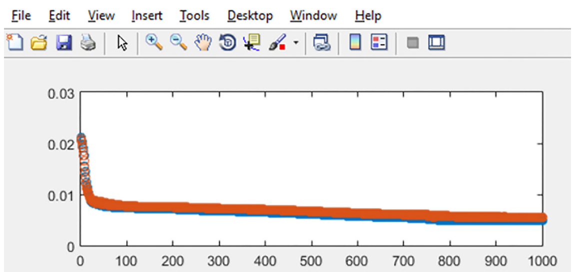


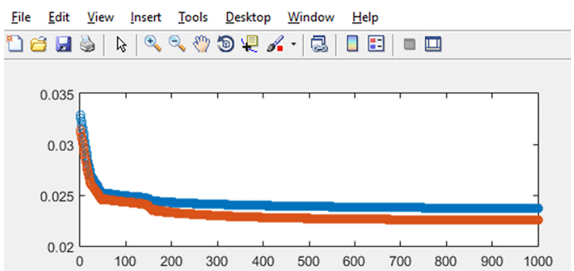
Fig. 14: Four MSFs structure after training.



(a)

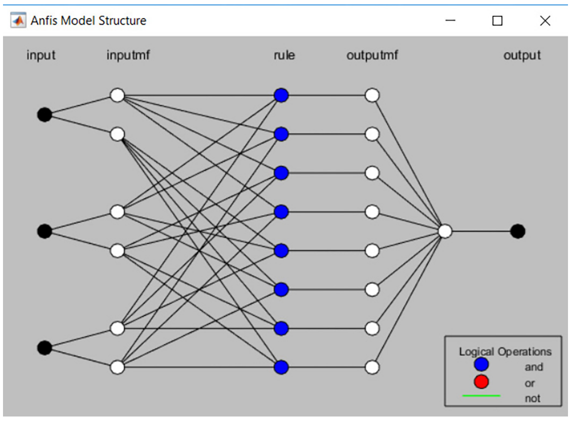


(b)

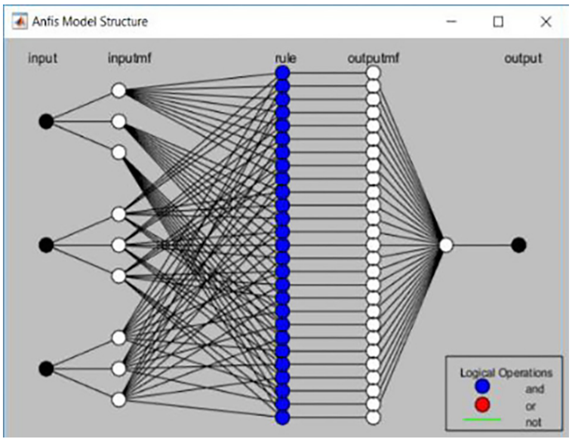


(c)

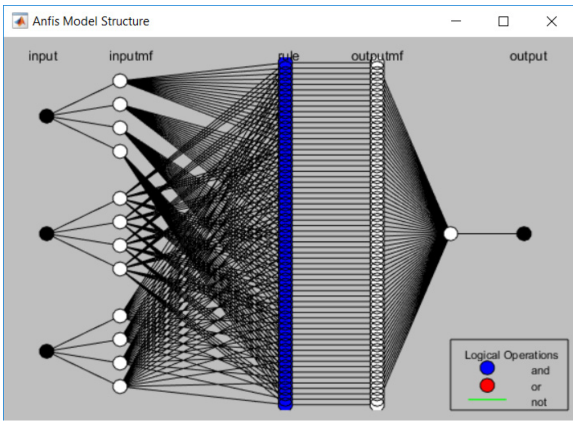
Fig. 15: The ANFIS Performances for: (a) Group1_1; (b) Group1_2; (c) Group1_3.



(a)



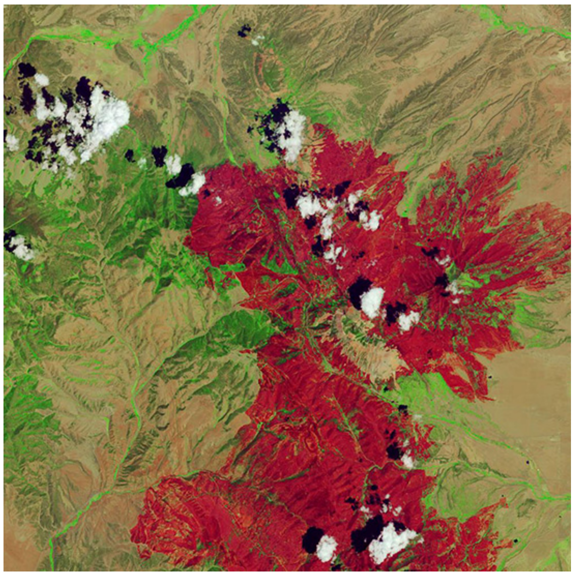
(b)



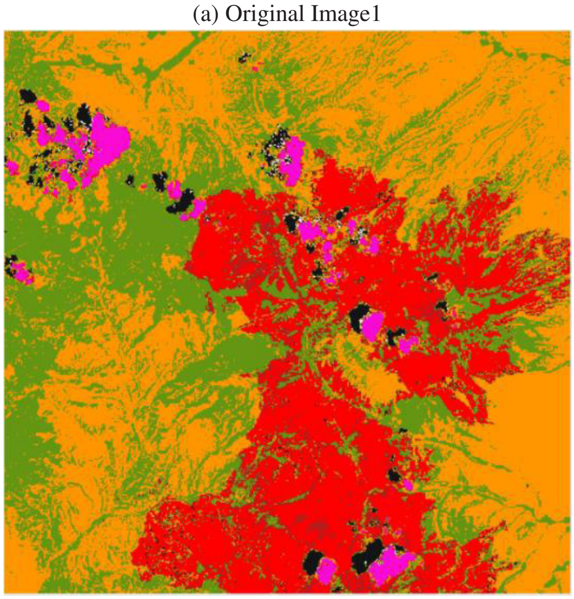
(c)

Fig. 16: The best ANFIS architecture for: (a) Group1_1; (b) Group1_2; (c) Group1_3.

Fig. 17: The specified colors of classified features.

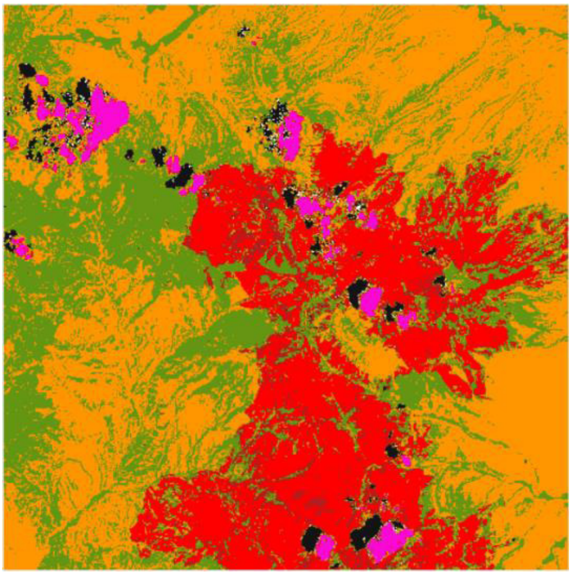


(a) Original Image1

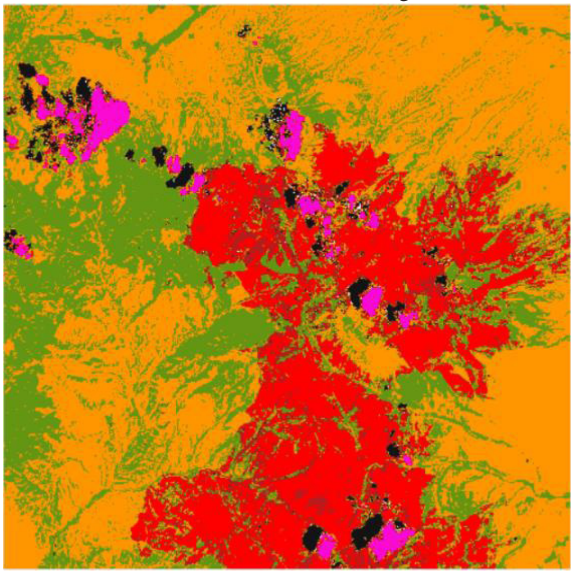


(b) First Classified Image

Fig. 18: The ANFIS classification results of image1 using the best trained ANFIS1_1 net.

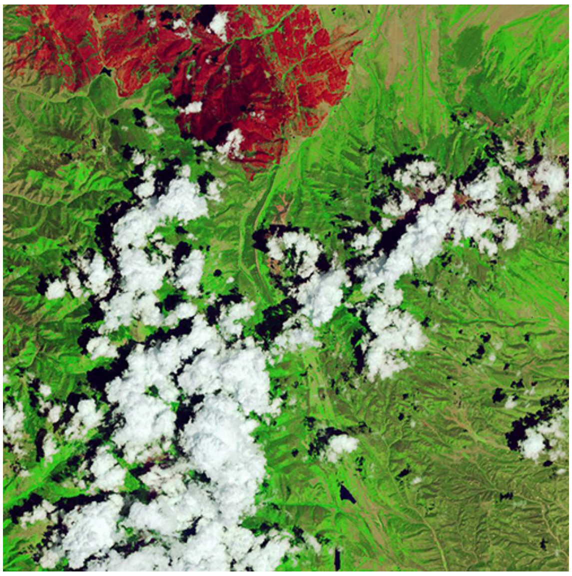


(a) Second Classified Image

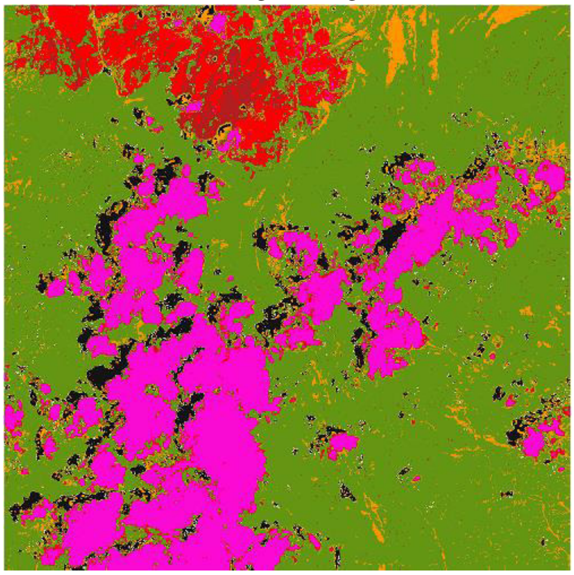


(b) Third Classified Image

Fig. 19: The ANFIS classification results of image1 using the best trained ANFIS1_2 and ANFIS1_3 nets.



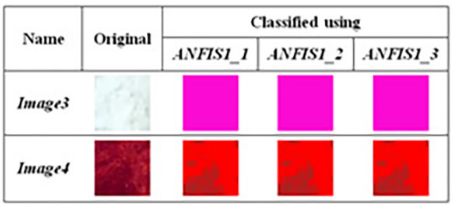
(a) Original Image2



(b) Classified Image

Fig. 20: The ANFIS classification results of image2 using the best trained ANFIS net.

corrected training and test data. This correction process is executed through two stages. In the first one, most of noise pixels are removed from training and test data. The second stage is used to exclude all repeated color-pixels having the same values from the training and test data. From the results, big reduction in the training and test data for the three groups after applying the proposed correction technique. For example, the training and test data in the Group1_1 are reduced by 57% and 71% respectively. Thus, due to an improvement in the training and test processes and the processing time in all experiments is reduced to about 50%. The system is



Name	Original	Classified using		
		ANFIS1_1	ANFIS1_2	ANFIS1_3
Image3				
Image4				

Fig. 21: The ANFIS classification results.

trained on three training data groups, the pattern data are collected and divided into three groups for the training and test data. If extra numbers of MSFs and NOEs are used, more computations are required, but difficult problems may be solved. Moreover, the proposed system is built having the ability to do many trials until get the best ANFIS nets using a low number of NOEs and MSFs. This system is applied using eight kinds of MSFs, in order to find the best. In each experiment, one kind of MSFs is chosen, the number of MSFs is determined, and the number of epochs is specified in a linear combination way as described in the Section 3. The system can rebuild the architecture in automatic way. It is found that, two and three MSFs using "gbellmf' with 1000 epochs and four MSFs using "gauss2mf "with 1000 epochs are enough for reaching the optimal performance. The best nets performances on training and test data are 99.98%, 99.82%, 99.96% and 99.31% respectively. The proposed system is compared with other four systems [33-36], it is found that this system is the best obtained the highest performance and get more accurately classified features. The main reason for getting this performance is the training and test data are corrected, also due to the processing time is reduced to about the half.

6 Conclusions

This work presented ANFIS system to work in automatic way by rebuilding the architecture using some parameters. They are the number of NOEs, MSFs and eight kinds of MSFs. This system has a novel technique to correct the training and test data by removing the noise pixels and all repeated colour-pixels having the same values. Moreover, big reduction is happened in the number training and test data due to the trained ANFIS nets having high performances. Thus, these nets are correctly classified the six specified features from the four test images and test data, although each feature has a big difference in the corresponding colour pixels. In addition to, the training and test processes is quickly executed due to a low. In future, the correction of training and test data technique will be merged with the ANFIS system to work in automatic way.

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