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Hyper Spectral Image Classification using Multi Labelled, Multi-Scale and Multi-Angle CNN with MS-MA BT Algorithm

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Abstract*: *For classifying the hyperspectral image (HSI), convolution neural networks are used widely as it gives high performance and better results. For stronger prediction this paper presents new structure that benefit from both MS - MA BT (multi-scale multi-angle breaking ties) and CNN algorithm. We build a new MS - MA BT and CNN architecture. It obtains multiple characteristics from the raw image as an input. This algorithm generates relevant feature maps which are fed into concatenating layer to form combined feature map. The obtained mixed feature map is then placed into the subsequent stages to estimate the final results for each hyperspectral pixel. Not only does the suggested technique benefit from improved extraction of characteristics from CNNs and MS-MA BT, but it also allows complete combined use of visual and temporal data. The performance of the suggested technique is evaluated using SAR data sets, and the results indicate that the MS-MA BT-based multi-functional training algorithm considerably increases identification precision. Recently, convolution neural networks have proved outstanding efficiency on multiple visual activities, including the ranking of common two-dimensional pictures. In this paper, the MS-MA BT multi-scale multi-angle CNN algorithm is used to identify hyperspectral images explicitly in the visual domain. Experimental outcomes based on several SAR image data sets show that the suggested technique can attain greater classification efficiency than some traditional techniques, such as support vector machines and conventional deep learning techniques.

Index Terms*: *Convolution neural networks (CNNs), MS-MA BT (multi-scale multi-angle breaking ties), Hyperspectral image (HSI), Classification, Synthetic aperture radar (SAR)

I. INTRODUCTION

Hyperspectral image (HSI) is commonly used in the remote sensing world to take full benefit of the structure of hundreds of discrete streams over a given image. Hyperspectral image needs precise and robust identification methods to obtain the characteristics from the image. Due to the complicated design of the image scene hyperspectral image has been regarded as a particularly difficult issue (i.e., combined pixels, big amounts of information and restricted practice tests), and therefore many attempts have been made to address this problem in the last few decades. In the initial phase of HSI evaluation, spatial domain classifiers such as support vector machines (SVM) [2], MS-MA BT (multi-scale multi-angle breaking ties) have produce a better achievement in understanding the image scenes. Recent technological progress offers more successful solutions to the ranking of HSI. These techniques aim to distinguish HSI using both spectral and temporal data.

For example, a combined sparse model mixes the data from a few nearby pixels of the test pixel, which is shown to be an efficient way of improving classified efficiency.

Recently, in the field of computer vision, deep learning is of interest to researchers. Specifically, MS - MA BT and convolution neural network (CNN) [21][22] have attracted a lot of attention due to their exceptional results in many fields, such as Synthetic aperture radar [21], image detection [12]. In addition to removal of features, CNNs can discover depictions of features through several convolution sections. MS MA -BT classify in resolution and angles after concatenation feature. Unlike traditional rule-based removal techniques, CNNs can automatically discover characteristics from the initial pictures. In addition, MS-MA BT can be intended as an end-to-end algorithm that can immediately generate classification maps. In particular, multiplicative noise occurs in SAR images like speckle noise. It gives big impact on the training model of deep learning. It is therefore essential to extract the noise in our segmentation model. In addition, the SAR picture contains rich texture structures that are created by distinct land cover such as river, urban area and small objects. The input image patch for the deep model should contain meaningful structures instead of simple pixels. If the quantity of the patch is too small, the patch would not contain image buildings. It means that the picture patch design will not be depicted in the ultimate taught characteristics. If the patch volume is too large, the entry loop will contain redundant buildings. It will improve the network's stress and spend much more time in training and screening.

Many CNN designs and MS-MA BT algorithm have Therefore been introduced to HSI ranking. Usually, neighboring pixels have the same background characteristics in remote sensing pictures. Spectral-spatial multi-functions can be used to efficiently enhance ranking accuracy [5]. This result paper presents a multi-scale MS-MA BT CNN algorithm for semantic segmentation of the SAR picture. The model involves the phase of noise suppression, the phase of concatenation and the

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the phase of ranking.

This paper is arranged as follows. The typical MS-MA BT multi-scale CNN algorithm and the associated training process are described in Section 2. In Section 3, we experimentally evaluate the efficiency of our technique with different parameters. Finally, we will conclude by summarizing our outcomes in Section 4.

This result paper presents a multi-scale multi-angle MS-MA BT CNN algorithm for semantic segmentation of the SAR picture. The system involves the stage of noise suppression, the phase of concatenation function and the phase of ranking in Fig.1.In the noise removal stage, we use the sparse representation technique and design the reconstruction loss feature to obtain the cleared SAR image.

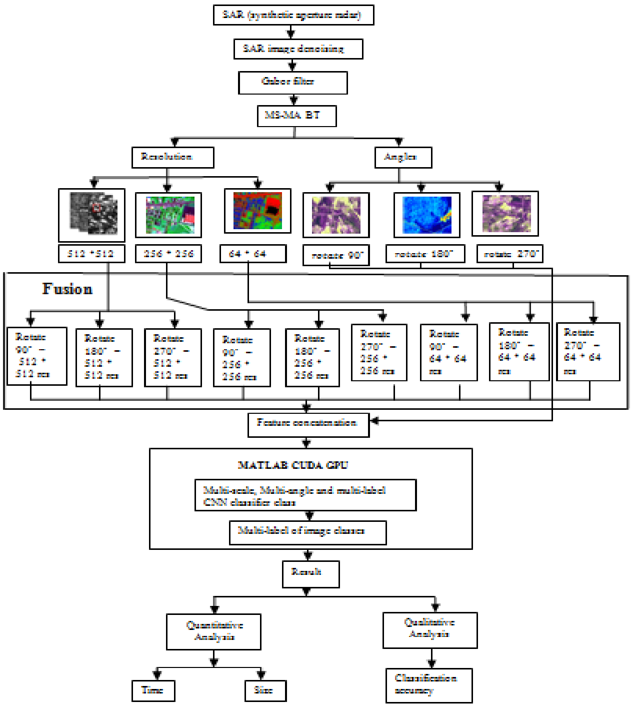

Fig 1: Overview of proposed approach

Our proposed system uses MSMA technique for segmenting the image which is called as multi scale & multi angle. It gives results in resolution as well as angle. The BT algorithm has obtained excellent practical outcome as shown in MS–BT results in resolution and angles [20]. MS-MA BT provides resolution 512* 512, resolution 256 * 256 and resolution 64* 64. It rotates the picture into 90, 180, 270 and provides the highest outcome. All resolution results are conducted in fusion. Fusion provides a combination of angle and resolution. The concatenation layer of the function is used to link the characteristics with different scales, angle and depths. Then the multi-scale multi-angle convolution sections are used to know the multi-scale deep characteristics. Finally, the Multi-scale and multi-angle CNN classifier is used to acquire the SAR/ Hyperspectral image marks. The following observations are given in this paper: (1) We suggest a multi-scale CNN model and MS-MA BT algorithm with noise extraction Convolution phase, concatenation phase and identification phase. This model takes into consideration the multiplicative noise and multi-scale, multi- angle features of the SAR images[21] (2) We decompose the multiplicative noise model into an additional model for extracting the noise. We are using sparse image loss function.(3) Segmentation precision is enhanced in our proposed method compared to state-of - the-art techniques. It results in quantitative and qualitative analysis. Quantitative analysis provides the outcome of time and size whereas the classification accuracy is given by qualitative analysis.

II. MS-MA CNN ALGORITHM

In this result paper we are using MS-MA CNN algorithm.MS-MA CNN gives best result in resolution and angles.

Algorithm: MS-MA CNN Algorithm

Algorithm combines the BT strategy and MS cluster to select the most informative training samples. In order to better represent the MS-MA CNN algorithm, we need to define several variables. q Demonstrates the number of samples to be marked for each iteration. We were using Algorithm to build a vector set X. We take one part of X as training set XT with u initial training samples and for validating the other part of set X, we take set XV with I - u unlabeled samples. After the training set, XT, is labeled, it

is denoted as $B_T = \{(yi_r, xi_r)\}_{r=1}^{u}$. When the validating set is unlabeled, XV = $\{xi_r\}_{r=1}^{I-u}$, In the proposed algorithm, we select q new samples, such as $X_{MS-MA} = \{xi_r\}_{r=1}^{q}$ from the validated set, we label them as $B_{MS-MA} = \{yi_r, xi_r\}_{r=1}^{q}$ and then add B_{MS-MA} into BT[21][22].

Input: Initial classifier parameter, ω ,training set, BT $= (yi_r, xi_r)_{r=1}^{u}$,validating set, $X_v = \{Xi_r\}_{r=1}^{I-u}$, mean-shift parameters, h, candidate samples parameter, .β

1. Train the classifier with MS-MA CNN and achieve the parameter of the classifier $\hat{\omega}$
2. Predict labels for XV using the classifier and obtain $(\hat{yi}_r, xi_r)_{r=1}^{I-u}$
3. For each sample in the prediction $(\hat{yi}_r, xi_r)_{r=1}^{I-u}$, compute its BT value as,

$$\hat{\theta}i_r = max\, p(\hat{yi}_r = k \mid xi_r, \hat{\omega}) - max\, p(\hat{yi}_r = k \mid xi_r, \hat{w}).$$

4. Arrange $\{\theta\}_{r=1}^{I-u}$ in ascending order as $\{\theta_{zr}\}_{r=1}^{I-u}$, and based on the index $\{z_r\}_{r=1}^{I-u}$ take out the first β . q items from XV to be XBT = $\{X_{zr}\}_{r=1}^{\beta . q}$.
5. Discover the q cluster centers for $X_{BT} = \{X_{zr}\}_{r=1}^{\beta \times q}$ by mean shift. Select a sample closest to it for each cluster center and place all chosen q samples qX_{MS-MA} .
$X_{MS-MA} = \{Xi_s\}_{s=1}^{q}$ Label X_{MS-MA} to obtain get

$$X_{MS-MA} = \{(\hat{yi}_s, xi_s)\}_{s=1}^{q}$$

6. Update BT and XV.

$$B_T = B_T \cup B_{MS-MA} ; X_V = X_V - X_{MS-MA}$$

7. If a condition is not satisfied then return to step (1); else, stop the iteration.

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8. Initialize multi-scale CNN for semantic segmentation: set the size of the three scale and angle image patches as $512 \times 512,\ 128 \times 128$ *and* 64×64 and $90^\circ,\ 180^\circ$ and 270° &the no., of the image classes is K;

9. Fusion is done for results obtained from resolution and angle. i.e., Combination of angle and resolution that is $90^\circ,\ 180^\circ, 270^\circ$ and $512 \times 512,\ 128 \times 128,\ 64 \times 64$ resolution;

10: Using a sparse depiction method, remove the SAR image speckle noise;

11: Extract image patches on three scales and angles, normalize image patches;

12: Divide the obtained image patches as test samples and train samples;

13: Using the gradient decent algorithm train the network in Fig. 1 in end to end way;

14: Use of the trained network to obtain the test sample labels;

15: Test sample labels are the semantic segmentation map.

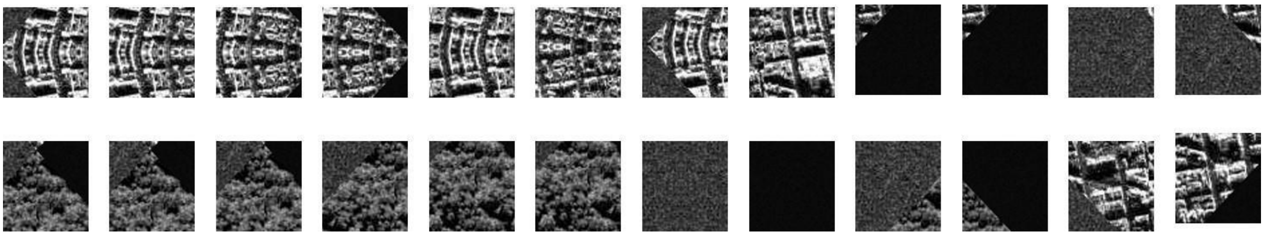


Fig. 2: Few Sample Images from our dataset. The data set contain 1049 samples.

In Table I We have taken dataset of size 1049 sample image with 60% training sample and 40 % testing sample

Table I: Analysis of Angle, Resolution and Fusion of both.

Dataset	S. No	Variant
Dataset A	1	0°
	2	90°
	3	180°
	4	270°
Dataset B	5	64x64
	6	256x256
	7	512x512
Dataset C	8	0° – 64 x 64
	9	0° – 256 x 256
	10	0° – 512x512
	11	90° – 64 x 64
	12	90° – 256 x 256
	13	90° – 512 x 512
	14	180° – 64 x 64
	15	180° – 256 x 256
	16	180° – 512 x 512
	17	270° – 64 x 64
	18	270° – 256 x 256
	19	270° – 512 x 512

It should be observed that we use the image patches to represent the central pixel. We have to record the central pixel locations in the original SAR image. When we understand the image patch tag, the main pixel tag is acquired at the last phase of the network. All central pixel labels represent the SAR image semantic segmentation map.

III. EXPERIMENTALRESULTS

In our analysis, both qualitative and quantitative experiments were used to verify the effectiveness of the proposed multi-scale multi angle model of CNN. The main measures in our approach are shown in above algorithm. In this result paper, we are using the MS-MA BT multi-scale CNN model [21][22]. This chapter concentrates primarily on the texture image segmentation results and the actual SAR pictures.

Implementation details:

We solve the problem of semantic segmentation through a classification framework. We need to construct the data sets. For each pixel, we extract the image patch specifically. We randomly pick some patches as the training samples from the data collection. The rest of the data sets are considered as test samples. Detailed information about the data sets is provided in Table I.

TABLE II: Hyper-parameters of multi-scale CNN.

Initial learning rate	10^{-2}
Epoch	4
Frequency	30
Fully connected layer	10

Furthermore, we contrast our strategy with angle, resolution and fusion. For fair contrast, the test samples, the training samples and the parameters in the comparative strategy are the same with our strategy.

Table III shows the convolution layer details in terms of filter size, no., of parameters and no., of filters. Padding and stride are the parameter of convolution layer. Table IV, V, VI gives comparison of angle, resolution and fusion. We can easily conclude that, the accuracy of fusion is higher compared to accuracy of angle and fusion, because it takes in to account both resolution and angle parameter which an important aspect of SAR images.

Table III: Convolution layer details

Filter size	No. of filter	Parameter
3	8	Padding
2	2	Stride
3	16	Padding
2	2	Stride
3	32	Padding

Table IV: MS-MA BT multi-scale multi-angle CNN by angle

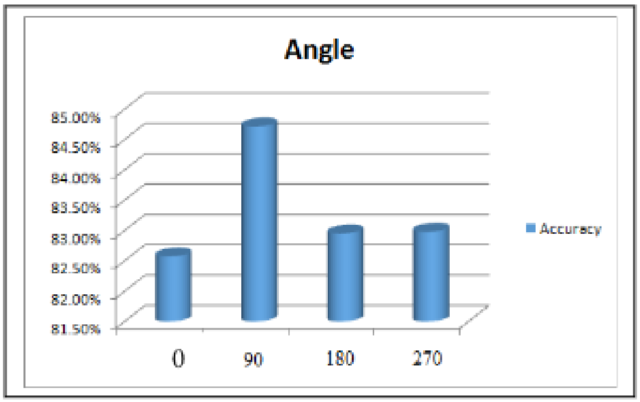
Angle	Accuracy	GPU Time in sec	Non-GPU Time in sec
0°	82.57%	18	36
90°	84.71%	16	37
180°	82.95%	22	38
270°	82.98%	16	36

Table IV represent accuracy, GPU time in sec and Non-GPU time in sec. In which 90∘ angle gives higher accuracy than other angles. It takes 16 sec time, whereas 180∘ and 270∘ angle gives around same accuracy but it takes different time. Non-GPU takes more time than GPU in angle, resolution and fusion as well.

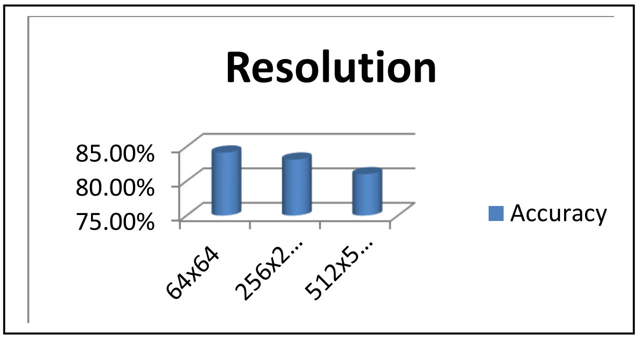
Table V: MS-MA BT multi scale multi angle CNN by resolution

Resolution	Accuracy	GPU Time in sec	Non-GPU Time in sec
64x64	84.14%	17	36
256x256	83.12%	17	36
512x512	81.00%	13	35

Table V shows the MS-MA BT CNN by resolution. As we can see that resolution 64x64 and 256x256 take same time but gives different accuracy, where accuracy of 64x64 is around 84%. 512x512 resolution take 13 sec and it gives 81.00 % accuracy.



Graph 1: Accuracy of MA CNN with angle variant dataset
a) 0° b) 90° c) 180° d)270°



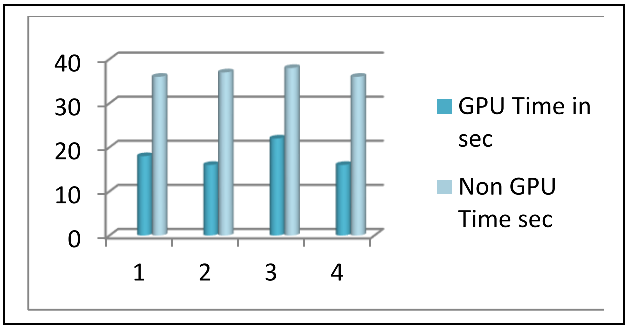
Graph 2: Accuracy of MS CNN with resolution variant dataset
a) 64x64 b) 256x256 c) 512x512

Table VI: Fusion of angle and resolution

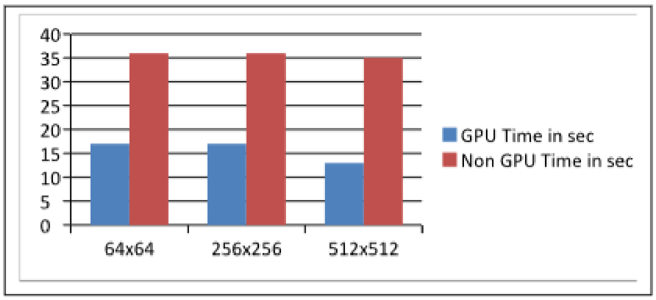
Fusion of Angle and Resolution	Accuray	GPU Time in sec	Non-GPU Time in sec
90°-64x64	84.49%	15	35
90°-256x256	85.73%	14	36
90°-512x512	87.04%	14	36
180°-64x64	84.55%	15	35
180°-256x256	88.99%	19	38
180°-512x512	87.27%	15	35
270°-64x64	85.02%	16	36
270°-256x256	86.14%	16	36
270°-512x512	88.23%	15	35

Above table shows fusion of classification & resolution. In this table we show the classification accuracy, GPU time and Non-GPU time factor of angle and resolution. In fusion table we can clearly see that, it improves the classification accuracy compared to resolution and angle taken individually.

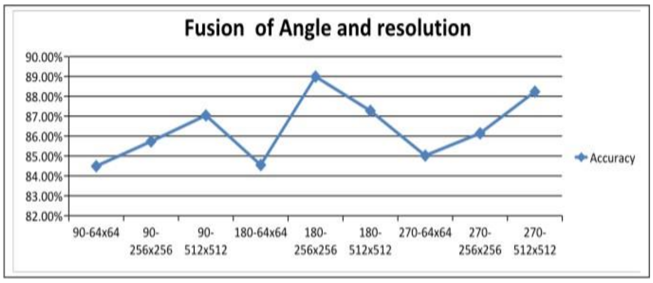
Graph 2 shows the classification accuracy of MS CNN with resolution variant dataset. In this graph 64x64 has higher accuracy than other resolutions.



Graph 3: Time consumption by GPU and Non-GPU with angle variant dataset



Graph 4: Time consumption by GPU and Non-GPU with resolution variant dataset



Graph 5: Classification Accuracy of MS-MA CNN on Fused dataset of Angle variant and Resolution variant

Graph 3 shows, time consumption by GPU and Non-GPU with angle variant dataset. In this time required by Non-GPU is more as compared to GPU.

Graph 4 shows, time consumption by GPU and Non-GPU with resolution variant dataset. In this graph time taken for estimating the classification accuracy increases as resolution of the image increases.

Graph 5 represents accuracy of MS-MA CNN on fusion dataset of angle and resolution variant. In this graph we evaluate total fusion accuracy. We found 180°-256x256 has the highest accuracy compared to other fused datasets.

Graph 6 represents time consumption by GPU and Non-GPU with fused dataset. In this graph time taken for estimating the classification accuracy is around same for resolution and angle variation.

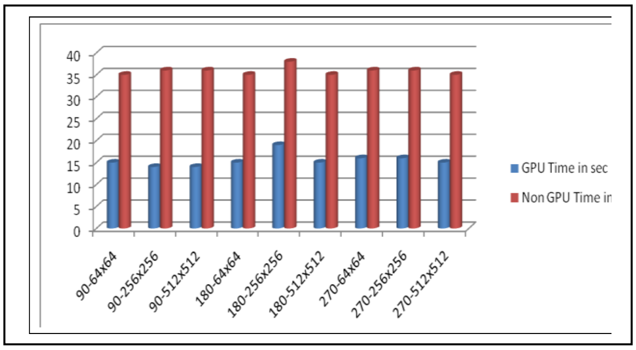
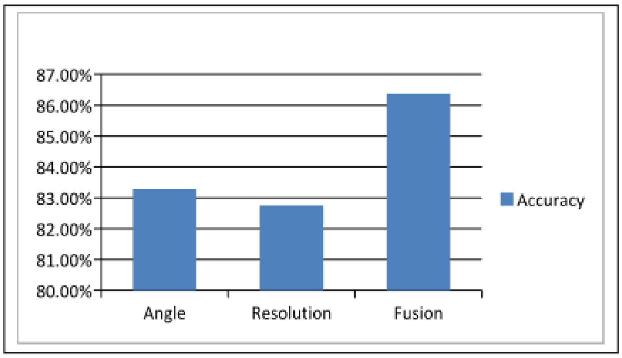


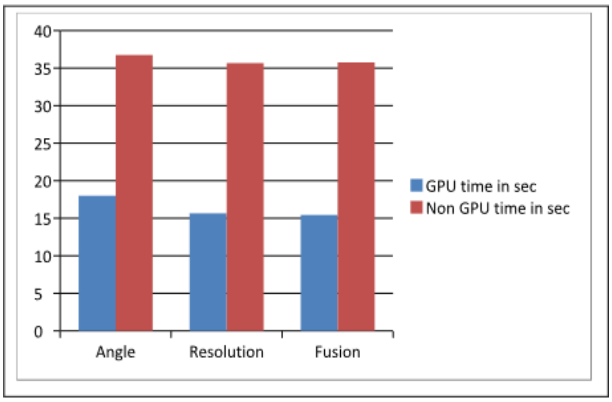
Table VII: Average of Accuracy, GPU time and Non-GPU time analysis with respect to angle, resolution and fusion

	Accuracy	GPU time	Non-GPU time
Angle	83.30%	18	36.75
Resolution	82.75%	15.66	35.67
Fusion	86.38%	15.44	35.77



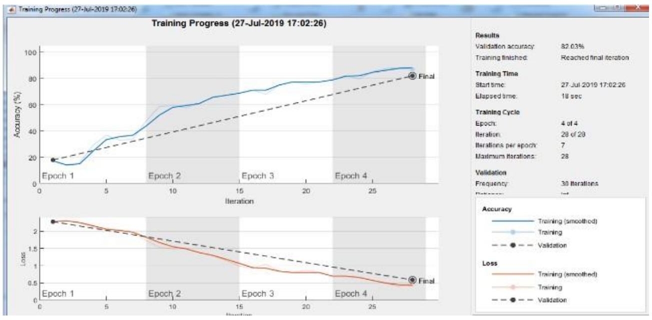
Graph 7: Average of accuracy analysis with respect to angle, resolution and fusion

Graph 7 represent average of accuracy analysis with respect to angle, resolution and fusion. In this graph we found that average of fusion accuracy increases as compared to angle and resolution.



Graph 8: Average of GPU time and Non-GPU time analysis with respect to angle, resolution and fusion

Graph 8 represent GPU time and Non-GPU time analysis with respect to angle, resolution and fusion. In this graph we conclude that GPU time in sec decreases as compared to Non-GPU Time in sec.



Graph 9: Accuracy and Loss obtained by MS-MA CNN on our Dataset in Matlab ANN Toolbox

In graph 9 we can clearly see that, the classification accuracy comes out to be 82.03% with 18 secs required for training data on GPU, as the classification accuracy goes on increasing, loss function goes on decreasing.

IV. CONCLUSION

Our above work represents detailed analysis of hyper spectral SAR image classification using various algorithms. Based on above results it is clear that our newly proposed MS-MA BT CNN algorithm is successfully implemented and tested with highest accuracy of 88.99% as compared to other traditional algorithms. The results improve to a larger extent when along with the resolution, angle is also taken into consideration. Therefore, our algorithm can be also tested for all kind of image datasets available on Internet as well as real-time datasets of satellite or any other media.

In our implementation it is noticed that NVIDIA GPU played a vital role to reduce time complexity compared to regular CPU Processor. Hence it is recommended to use GPU for higher end Image processing Task.

In future the number of training samples and testing samples can be varied. We will try to implement few more feature extraction technique in fusion with our existing work so as it will serve as comprehensive outcome of our research in the domain.

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