International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Target Detection of Sar Image using Modified Markov Random Fields Ayed Model Segmentation Along With Google Net Classification

A.Glory Sujitha, P.Vasuki, S. Md. Mansoor Roomi

Abstract*: *In the modern world the mechanism of target detection in the SAR images have huge assistance for humans to deal with complex visual signals of satellite images effectively. However, the ultimate aim of the paper was to segment the region of interest precisely from despeckling SAR images. This paper proposes a novel modified Markov random fields ayed model segmentation along with Google NET classification target detection. In the initial stage, the image gets despeckled for removing the unwanted noise. The boundaries of the images were calculated for checking the discontinuity using the canny edge detector. Then in the data reduction step by grouping the similar data items. Then the target region was segmented using the modified Markov random fields ayed model methods then the segmented output can undergo the classification process by using the Google NET CNN architecture. The proposed technique was capable of getting better results under risky conditions . Thus, the results validate the target detection of detection rate in different complexity over the existing methodology

Keywords: Despecking SAR image, Synthetic Aperture Radar (SAR), Canny edge detector, modified Markov random fields ayed model, Google NET CNN classification, and Target Detection.

I. INTRODUCTION

The SAR images and the inaccessible sensing systems can serve an huge amount of the information that can be utilized in many areas of the research which is useful for the analysis purpose. The acquired information can be used for mapping process, analysis of the traffic, geographical analysis etc. Nowadays the satellite images are easily available to the public so researchers and scholars can easily get that from the source. The process of the despeckling in the SAR images was assumed to be a conclusive job for the purpose of the target detection because generally the SAR images are loaded with heavy noises. Visual consideration significantly improves the capacity of the social visual framework to manage images under a refined domain. A beneficial outcome can be picked up by acquainting visual consideration with target location in despeckling SAR pictures. With the Persistent advancement in military innovation, target location in
a SAR picture turns out to be more and more troublesome. The earth around targets turns out to be increasingly entangled, and data on targets decreases.

Figure 1: Despeckling of SAR image

Figure 1 shows the despeckling of the SAR image. Airborne or Spaceborne is a category of two-dimensional imaging radar. As SAR can have the information about the heavy environmental conditions but it is of high enticement in military and common applications. For deep understanding of the SAR images needs experts since not at all like normal images, SAR images mirror the backscattering force of the electromagnetic waves. The SAR images are obtained in the form of the microwave pulses via antennas in the surface of the earth. The microwave pulses are generated due to the scattering of the energy from the space craft. The SAR utilizes the radar guideline to shape a images by using the time postponement of the backscattered signals.

The SAR images are obtained by the release of the microwave rays from the antenna but the images obtained have the less resolution when compared to the ordinary image. Progressively flawless subtleties on the ground can be settled by utilizing a smaller shaft. The beam width is contrarily relative to the size of the antenna , i.e.

Manuscript published on November 30, 2019.
* Correspondence Author
A.Glory Sujitha , Research Scholar, Department of CSE, SSM Institute of Engineering and Technology Dindigul, Ind **ssmglory@gmail.com**
DR.P.Vasuki , Professor, Department of ECE, KLN College of Information Technology, Pottapalayam Sivagangai District, India
Dr. S. Md. Mansoor Roomi ,Associate Professor/ECE department, Thiagarajar College of Engineering ,smmroomi@tce.edu

larger the size of the antenna but the release of the beam is less Hence for despeckling of the SAR image by a human is tedious and incredibly troublesome, which legitimizes the requirement for effective despeckling method for SAR image target location by implementing the modified Markov random fields ayed model along with the Google NET CNN classification.

II. RELATED WORKS

Zhang et al. (2011) [1] proposed a powerful despeckling procedure to enhance the targets apart from the edges and spots of the SAR images. Both despeckling effects of reciprocal sifting and an improved INL Means algorithm are used for identifying the targets. After the implementation of the algorithm targets can gets enhanced. **Liu et al. (2014) [2]** proposed a novel objective discovery calculation for SAR images dependent on an improved visual consideration strategy. With the advancement of SAR innovation, target discovery calculations are stood up to with numerous troubles in a confounded condition and shortage of target data**. Xie et al. (2019) [3]** proposed a novel profound convolutional neural system design called umbrella. The implemented structure comprises of two substitute CNN-layer squares. One square is a combination of the six 3-layer ways, which is utilized to extricate different level highlights from various convolution layers. The other square is made out of convolution layers, and pooling layers are for the most part used to diminish measurements and concentrate various leveled include data. The mix of these two squares could extricate rich highlights from various spatial scale and all the while lighten overfitting. **Han B et al. (2010) [4]** proposed a HMAX, for extracting the features. Base up or saliency-based visual consideration enables primates to distinguish vague unobvious objects or unfocused in a jumbled scenes. Straightforward multi-scale feature was mapped that can recognize neighborhood spatial discontinuities in power, shading, direction, and are joined into a "saliency" map. **Kaihua Zhang et al. (2010) [5]** proposed a new area based marked weight power (SPF) work, which can effectively stop the forms at feeble or obscured edges. Besides, the outside and inside limits can be consequently distinguished with the underlying shape being anyplace in the images. The proposed ACM with SBGFRLS has the property of particular neighborhood or worldwide division. It can section the ideal item as well as different articles. Then the level set capacity can be effectively introduced with a twofold capacity, which is more productive to develop than the broadly utilized the distance function. The computational expense for conventional re-introduction can likewise be diminished. At last, the proposed calculation can be productively executed by the basic limited distinction plot**. Bisceglie et al. (2005) [6]** proposed a novel method for the detection of the false alarm rate in the SAR images. Here the **SAR images are obtained via air borne sensor. X. Xu et al. (2013) [7]** proposed a novel method for the detection of the robustness in the contour. The combined method of local and global intensity fitting new active contour model that can be used for measuring the robustness . Hence the proposed methods shows precise results when compared to the all the other existing methods. **Boahua Zhang et al. (2018) [8]** proposed a novel statistical method for reconstruction of the image and to point out the target effectively. **Haiyi Yang et al. (2017) [9]** proposed a novel algorithm to improve the detection of the targets effectively. **Wang et al. (2008) [10]** proposed a improved method for detecting the false alarm rate in the SAR images by using the Gaussian distribution function**. Erfanian S et al. (2010) [11]** proposed a novel method for detecting the false alarm rate by using the integrated technology. The performance of the novel integrated method with other existing methods to prove the effectiveness of the methods**.** . **Zhaocheng Wang et al. (2018) [12]** implement the single shot multibox detector for the purpose of detecting the targets from the SAR images. **Jen King Jao et al. (2000) [13]** analyze a process that can be taken place in the development of the SAR images**. Han et al. (2015) [14]** proposed a deep learning method for identifying the structural information about the object. **Schleher et al. (1976) [15]** proposed a novel weibull clutter method for measuring the clutter parameters. **Y. Chen et al. (2008) [16]** make a survey on the different classification technique, feature extraction technique and feature selection technique for characterizing its performance quality. **Gao et al. (2009) [17]** proposed an adaptive CFAR algorithm for detecting the targets in the SAR images.**Smith M. E et al. (1997) [18]** analyzed the VI-CFAR method and declared that the VI-CFAR method was very effective in the analysis of the clutter . **Fei Gao et al. (2018) [19]** proposed a novel visualization technique for detecting the targets in the SAR and in the optical images. To prove the effectiveness of the method the proposed method was compared with the other recent existing methodologies**. Çetin et al. (2001) [20]** proposed about the created images with expanded goals, decreased side flaps, diminished spot, and simpler to-fragment areas. Our strategy viably manages the complex-esteemed, irregular stage nature of the fundamental SAR reflectivity.

III. PROBLEM STATEMENT

The main challenges are not only capturing the images but also process the captured information faster and disseminate them instantly in the desired target detection with accuracy. The primary approach for any target detection problem is to segregate different components from a scene and find the one that is of interest from the rest. Segmentation is still a difficult task and a valid problem for the robust target detection system. There is a difficulty in finding the guards and clutter region. Thus, the target detection for the SAR image is to be most accurate.

IV. PROPOSED METHODOLOGY

In this proposed methodology, there is a given input SAR image that can be despeckled by implementing the padding matrix and the window suppression methods. Then, it is analyzed by two stages of approaches for detecting the targets in the SAR image. The first stage of the proposal deals with the modified Markov random fields ayed model segmentation method for target detection in the SAR images precisely **,** whereas in the second stage of the proposal deals with the process of the classification using the Google NET CNN. Design flow of the proposed technique steps are represented below,

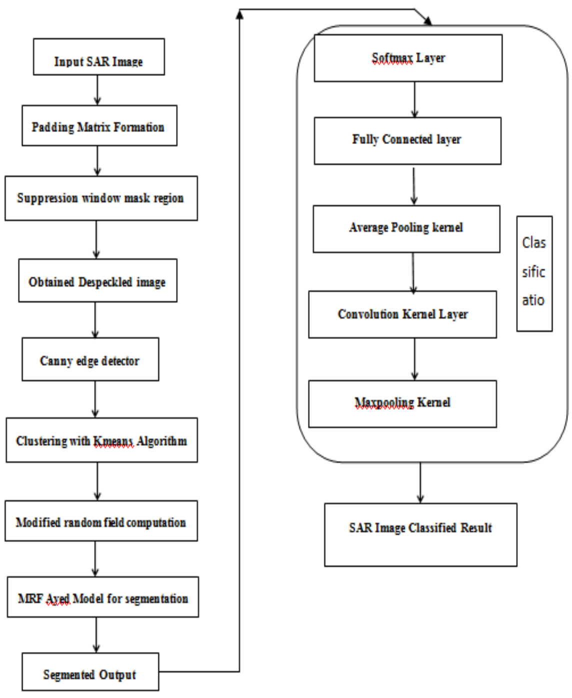


Figure: 2 Schematic representation of the proposed methodology.

Figure 2 represents the schematic representation of the proposed methodology. By giving the input SAR image, the analysis expresses that the large amount of the disturbances are there in the input in the form of the noise. The method of the pre-processing paddling matrix method was used.Here in which the space inside the border and outside the border also the contents of the image can be boxed in. Here in this method, there is a need to calculate the padding array and the paddle size. To identify the outsider elements, the padding was used. Here the padding matrix in which from the input source the important pointed areas can be sorted out to make the segmentation process easy. As with any distance or size declaration, the distance can be given. The padding vector method is just a simple method by clicking the padding option; the process of sorting can be done where the pad size represents the non-negative integers, which will explain the amount of padding with its dimension — the padding process in which the image can be thoroughly monitored. Here first, the images are separated into a pixel matrix, and then the center point can be fixed. Then depend upon the abnormal appearance or color in the images from the central position, the area can be pointed and sort out. This can make the segmentation step very easy. Then the surrounding area can get masked to make the area of interest highly notable. The masking effect can be produced the distinguish the area of interest and the unwanted regions. Then after the masking effect, most of the unwanted areas and the noises get reduced as a result of it, the image should be converted into a despeckled image. The edges can be detected in the despeckled image for the purpose of extracting the useful information about the object. Here the edge detection was somewhat simple because already denoising and suppression were done; hence, by leaving the weak edge pixels, the pointed edges found out. The clustering k-means algorithm was applied to cluster the sharp edge features. The main goal of this process is to prevent the loss of valuable information; also, it's a time-saving process when compared to the other clustering techniques. Depend upon the size shape or else color, and the clustering process can be undergone. This algorithm can easily group the required standard information into groups, which can be very useful for the process of the segmentation.

Target Segmentation

Target Segmentation is done using MRF with the Ayed model thrash out by the binary target region and multi-threshold with low time consumption. It considers the Ayed model for MRF to achieve the better segmentation process of the SAR image. An image might be in the form of 2-D grid point set of M= {(I,j)|1} where T and S are considered as width and height of an image. Score field Y= {Y_1, Y_2 … Y_T} is an arbitrary field corresponding to the two-dimensional grid points set S, Y=y where y= {y_1, y_2 … y_T}, there is a configured to the random field. Each element of M symbolizes the mutual association through a neighborhood system of M is defined as follows:

$$S = \{S_i | \forall i \in M\} \qquad (1)$$

For a common grid position set M, neighborhood position of i defines as location set whose distance to i is less than $\sqrt{c}$:

$$S_j = \left\{ j \in M \left[distance\left(PX_i, PX_j\right)\right]^{2} \le r, i \neq j \right\} \qquad (2)$$

Where, dist (K, D) represents the Euclidean distance of K and D, and c is an integer. It would be noted that the pixels in the border location or locations near the border had less.

Therefore the conventional potential function is defined as:

$$V(y_i, y_j) = \begin{cases} \beta, & y_i = y_j \\ 0, & y_i \neq y_j \end{cases} \qquad (3)$$

Where, R is a normalized constant,

$$R = \sum_{y \in \alpha} e^{-O(y)} \qquad (4)$$

So far, the relative intensity of the veins, which is the potential sums of all groups in a group set Q.

$$O(y) = \sum_{\{i,j\} \in Q_2} V_2(y_i, y_j) \qquad (5)$$

Segmentation with above function is not ideal as it introduces the potential role of Ayed Modeled by a gamma distribution of mean intensity c_i and number A of looks, i.e.

$$P_{c_i,A}(I(y)) = \frac{A^A}{c_i(A)} \left(\frac{I(y)}{c_i}\right)^{A-1} e^{\frac{-AI(y)}{c_i}} \qquad (6)$$

Capitalize on likelihood PA (M|I) is equivalent to minimizing –log PA (M|I). Then, combining the equation (4), it becomes;

$$-\log PA(M|I) = A\left(\sum_{i=1}^{S} m_i . log_{c_i}\right) + \alpha \qquad (7)$$

Where α is a constant. c_i is the average mean intensity of I(y) is independent of I(z) for y!=z to the area of a region can be transformed to minimize the following two – a region of segmentation

$$W^{\text{MRF with Ayed model}} = \sum_{\{i,j\} \in Q_2}^{S} V_2(y_i, y_j). m_i . log_{c_i} + \gamma \int c_i \, dx \quad (8)$$

The effect of boundary leakage to solve the addition of updation process by using a Laplacian operator into the segmentation of the target boundary at smaller values.

$$\frac{\partial\gamma}{\partial t} = R\Delta\gamma + \frac{1}{R}\nabla(\gamma) \qquad (7)$$

Pseudo code for Modified MRF Ayed Model Segmentation:

```
Input:  cluster values φ_cl , Gaussian_val ω_gl , edge val ψ_el ,
mu_val δ_ml , sigma_val δ_ev , inner_iter τ_1i , outer_iter τ_oi
                Output: Segemented valued γ_s
Step1 : initialize the parameters,
        u_dc=[Inner iteration outer iteration]
Let to MRF computation,
 for ii=1 : τ_1i        // Inner iteration
  for j=1 : ψ_el      //edge value
 yi=φ_cl-ψ_el
 temp=yi*yi/δ_ev^2
temp1=temp+log(δ_ev)

for jj=1 : φ_cl * ω_gl    //all labels
  t1 = 1 / (√(2*π)*δ_ev^2 *exp(ψ_el−1)^2 δ_ev^2)
t2=t1*0;
for ind=1 : τ_1i *τ_oi    // all pixels
        k=mode (indices-1, τ_1i)+2;
        l=base ((indices-1)/ τ_1i)+2;
        m=0;
        if k-2>=2 && R(k-2,l)==0
          v=v+(l~=p(k-2,j))/3;
        end
        if k+2<=m && R(k+1,l)==0
          v=v+(l~=P(k+1,l))/3;
        end
        if l-2>=1 && R(kl-2)==0
          v=v+(l~=P(k,l-2))/3;
        end
        if l+1<=m && Z(k,l+1)==0
          v=v+(l~=P(k,l+1))/3;
        end
        temperature3(indices)=v;
      end
      M_(l,:)=temperature1.*exp(-temperature2);
γ_s=imdilate(o_)
```

Classification using Google NET CNN:

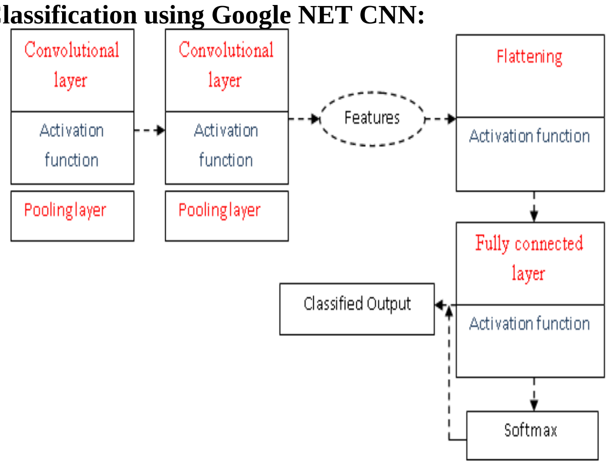


Figure:3 Classification using Google NET CNN

Figure 3 represents the classification of Google NET CNN. The Google NET convolutional neural network is one of the deep learning neural networks. Google NET CNN represents a massive breakthrough in image recognition and in the classification process. They're most normally used to break down visual symbolism and are regularly working off optics in images characterization and classification.

A Google NET CNN has been arranged in the form of the layers.

- ReLU layers
- Convolutional layers
- Pooling layers
- a Fully connected layer

While comparing other image classification algorithms, Google NET CNNs have very less pre-processing steps. This CNN has to be used in various fields for several different purposes.

Convolution

The main role of this convolution step is to concentrate highlights from the info picture. The convolutional layer is consistently the initial phase in Google NET CNN . In this process from the input image, the features are detected, and the feature map was created.

A. *ReLU layer*

The redressed straight unit layer is the next stage to the convolution layer. Here the enactment function was applied on the feature maps for increasing the non-linearity in the network. Here the negative values can be simply removed.

Pooling:

The pooling process can gradually reduce the input size. The pooling step can reduce overfitting. This can quickly point out the required parameters rapidly by reducing the number of the required parameter.

Flattening

It is somewhat a simple step in which the polled feature map should be flattened into the sequential column of numbers.

B. *Fully connected layer*

C. *Here in which the features that can be combined with the attributes. This can complete the classification process with the high percentile of accuracy. Mainly the error can be calculated, and it can be backpropagated.*

Softmax:

D. *The **Softmax** was implemented in various research areas for several problems. Those decimal probabilities must mean 1.0. Consider the accompanying variations of Softmax:*

E. *•Full Softmax is the Softmax, which can compute a likelihood for each conceivable class.*

F. *•Softmax computes a likelihood for all the positive names however just for an arbitrary example of negative names.*

V. RESULT AND DISCUSSION

The performance analysis of the proposed methodology is verified by the SAR images, and various target detection was assessed. The contrasts in the center of the image of our methods are high accuracy of the target detection result.The overall accuracy of target detection is defined as:

$$\text{Accuracy} = \frac{\#\text{detected}_{\text{TARGETS}}}{\#\text{total}\ \text{TARGETS}}$$

Retrieval Number: D9442118419/2019©BEIESP
DOI:10.35940/ijrte.D9442.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

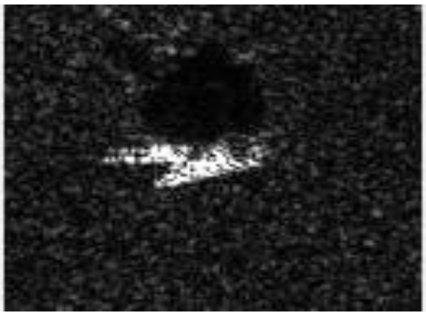


Figure:4 Input image

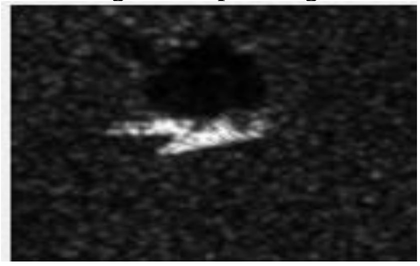


Figure 5 Despeckled image

Figure 5 represents the process of the noise reduction using the matrix formation and window suppression process

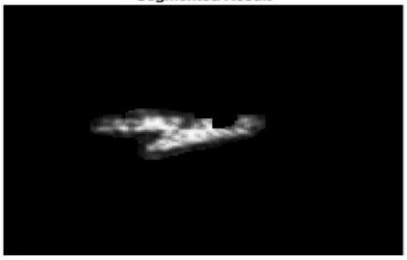


Figure 6 Segmented output

Figure 6 represents the segmented output using Markov random fields ayed model.

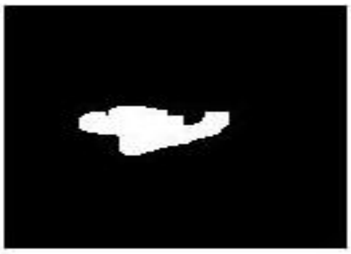
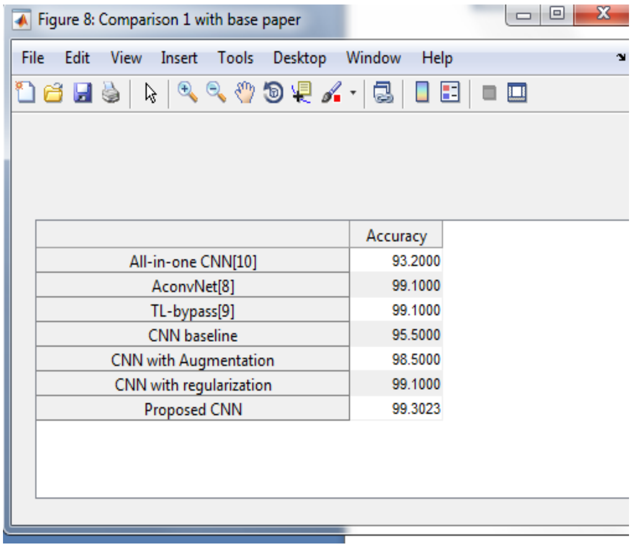


Figure 7 Target detection

Figure 7 represents the target detection using Google NET CNN

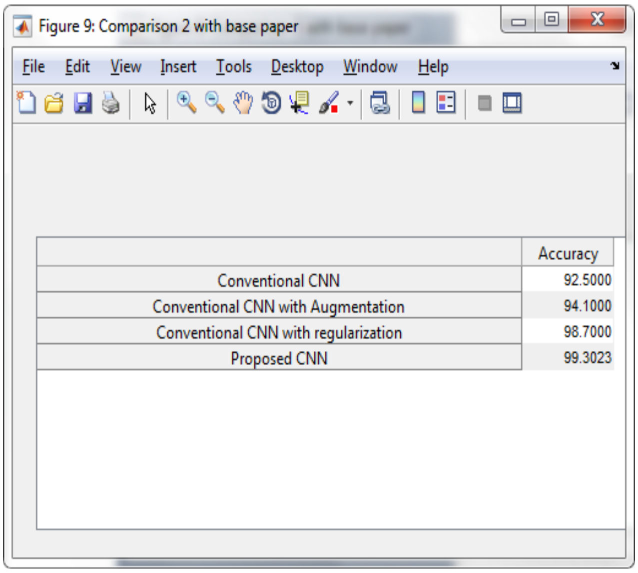
Accuracy	99.3023
Sensitivity	100
Specificity	99.2306
Precision	93.0233
Recall	100
F-measure	0.9639

Table 1 Overall performance of the proposed Google NET CNN classifier



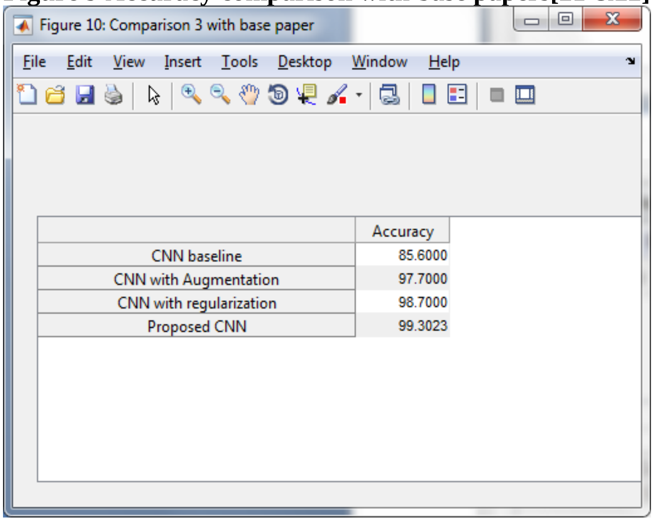
	Accuracy
All-in-one CNN[10]	93.2000
AconvNet[8]	99.1000
TL-bypass[9]	99.1000
CNN baseline	95.5000
CNN with Augmentation	98.5000
CNN with regularization	99.1000
Proposed CNN	99.3023

Figure 8 Accuracy comparison with base papers[21 &22]



	Accuracy
Conventional CNN	92.5000
Conventional CNN with Augmentation	94.1000
Conventional CNN with regularization	98.7000
Proposed CNN	99.3023

Figure 9 Accuracy comparison with base papers[21 &22]



	Accuracy
CNN baseline	85.6000
CNN with Augmentation	97.7000
CNN with regularization	98.7000
Proposed CNN	99.3023

Figure 10 Accuracy comparison with base papers [21 &22]

Retrieval Number: D9442118419/2019©BEIESP
DOI:10.35940/ijrte.D9442.118419
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

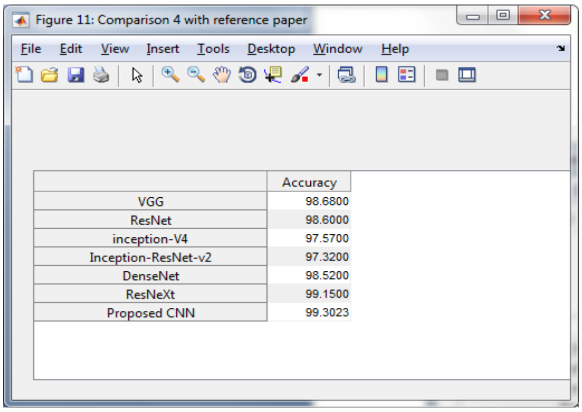


Figure 11: Comparison 4 with reference paper

	Accuracy
VGG	98.6800
ResNet	98.6000
inception-V4	97.5700
Inception-ResNet-v2	97.3200
DenseNet	98.5200
ResNeXt	99.1500
Proposed CNN	99.3023

Figure 11 Accuracy comparison with base papers [21 &22]

The figure 8,9,10 and 11 represents the comparison of the performance of the proposed method with the existing method.

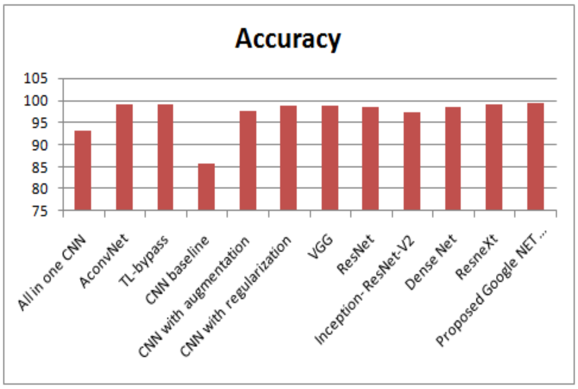


Figure:12 proposed Vs. existing methods

Figure 12 represents that the proposed Google NET CNN acquired the higher accuracy percentile of 99.30 in terms of accuracy when compared to the other existing methods.

VI. CONCLUSION

This paper has presented a modified Markov random fields ayed model segmentation along with Google NET CNN classification for target detection in despeckled SAR image. The result shows that the noise refining process was precise in the Canny edge detection. Hence the proposed novel modified Markov random fields ayed model can undergo segmentation in an complicated environment. The overall approach of the target detection levels was very high when compared to other existing methodologies. The performance of the proposed method validates the best results as focusing on target with highly constructed as effective.

REFERENCES

1. Zhang, W. G., & Zhang, Q. “SAR image despeckling combining target detection with improved nonlocal means." Electronics Letters, 47(12), 724.doi:10.1049/el.2010.3474 (2011).
2. Liu, S., & Cao, Z. “SAR image target detection in complex environments based on improved visual attention algorithm." EURASIP Journal on Wireless Communications and Networking, 2014.
3. Xie, Y., Dai, W., Hu, Z., Liu, Y., Li, C., & Pu, X. "A Novel Convolutional Neural Network Architecture for SAR Target Recognition." Journal of Sensors, 2019, 1–9. doi:10.1155/2019/1246548, (2019).
4. Han B, Xinbo G, Walsh V, Tcheang LA. "A saliency map method with cortex-like mechanisms and sparse representation." ACM international conference on image & video retrieval; 2010 Jul 5–7; Xi'an: China. New York: ACM; 2010.
5. Kaihua Zhang, Lei Zhang, Huihui Song, Wengang Zhou, "Active contours with selective local or global segmentation: A new formulation and level set method." Image and Vision Computing 28, 668–676. 2010.
6. Bisceglie M., Galdi, C., "CFAR Detection of Extended Objects in high-resolution SAR images," IEEE Transactions on Geoscience and Remote Sensing, vol. 43, pp. 833-843, (2005).
7. X. Xu and C. He, "Implicit active contour model with local and global intensity fitting energies," Math. Probl. Eng. 2013, Article ID 367086, 13 (2013).
8. Zhang, B., Jiao, D., & Lv, X. “A target detection algorithm for SAR images based on regional probability statistics and saliency analysis." International Journal of Remote Sensing, 1–17 (2018).
9. Haiyi Yang, Zongjie Cao, Yiming Pi, and Shuo Liu “Target Detection in High-Resolution SAR Images via Searching for Part Models." IEEE Geoscience and Remote Sensing Letters, 14(5), 664–668 (2017).
10. Wang, C., Liao, M., Li, X., "Ship detection in SAR Image Based on the Alpha-stable Distribution," Sensors, vol. 8, pp. 4948-4960, (2008).
11. Erfanian S., Vakili, V.T., "Introducing Excision Switching-CFAR in K distributed Sea Clutter" Signal Processing, Vol. 89, pp. 1023-1031, (2009).
12. Wang, Z., Du, L., Mao, J., Liu, B., & Yang, D. “SAR Target Detection Based on SSD with Data Augmentation and Transfer Learning." IEEE Geoscience and Remote Sensing Letters, 1–5 (2018).
13. Jao, J.K.; Lee, C.E.; Ayasli, S. "Coherent Spatial Filtering for SAR Detection of Stationary Targets." IEEE Trans. AES, 35, 378–384, 2000.
14. Han, J.; Zhang, D.; Cheng, G.; Guo, L.; Ren, J. "Object detection in optical remote sensing images based on weakly supervised learning and high-level feature learning." IEEE Trans. Geosci. Remote Sens., 53, 3325–3337, 2015.
15. Schleicher, D. "Radar Detection in Weibull Clutter." IEEE Trans. Aerosp. Electron. Syst., 6, 736–743, 1976.
16. Chu He, Mingxia Tu, Xinlong Liu, Dehui Xiong, Mingsheng Liao "Mixture Statistical Distribution Based Multiple Component Model for Target Detection in High-Resolution SAR Imagery," International Journal of Geo-Information (ISRPS), 2017.
17. Gao, G., Liu, L., Zhao, L., Shi, G., Kuang, G., "An Adaptive and Fast CFAR Algorithm Based on Automatic Censoring for Target Detection in High-Resolution SAR Images," IEEE Trans. on Geoscience and Remote Sensing, vol. 47, pp. 1685-1697, (2009).
18. Smith M. E., Varshney, P. K. "VI-CFAR: A novel CFAR algorithm was developed based on data variability," Proceedings of the 1997 IEEE National Radar Conference, pp. 263-268, (1997).
19. Fei Gao, Aidong Liu, Kai Liu, Erfu Yang, Amir Hussain "A novel visual attention method for detecting the targets from the SAR images" Chinese journal of Aeronautics (CSAA) 2018.
20. Çetin, M., Karl, W., C., "Feature Enhanced Synthetic Aperture Radar Image Formation Based on Nonquadratic Regularization," IEEE Transactions on Image Process, Vol. 10, No. 4, pp. 623-631, (2001).
21. Kwak, Y., Song, W.-J., & Kim, S.-E. (2018). Speckle-Noise-Invariant Convolutional Neural Network for SAR Target Recognition. IEEE Geoscience and Remote Sensing Letters, 15.doi:10.1109/lgrs.2018.2877599
22. Gao, F., Shi, W., Wang, J., Hussain, A., & Zhou, H. (2019). A Semi-Supervised Synthetic Aperture Radar (SAR) Image Recognition Algorithm Based on an Attention Mechanism and Bias-Variance Decomposition. IEEE Access, 7, 108617-108632.

AUTHORS PROFILE

A.Glory Sujitha , Research Scholar, Department of CSE, SSM Institute of Engineering and Technology Dindigul, Ind ssmglory@gmail.com

DR.P.Vasuki , Professor, Department of ECE, KLN College of Information Technology, Pottapalayam Sivagangai District, India

Dr. S. Md. Mansoor Roomi ,Associate Professor/ECE department, Thiagarajar College of Engineering ,smmroomi@tce.edu