iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 9 **Issue:** V **Month of publication:** May 2021

DOI: https://doi.org/10.22214/ijraset.2021.34569

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue V May 2021- Available at www.ijraset.com

Image Analysis of Sauvola and Niblack Thresholding Techniques

M. Chandrakala[1], P. Durga Devi[2]
[1, 2]Department of ECE, Mahatma Gandhi Institute of Technology, Hyderabad, India

Abstract: Image segmentation is a critical problem in computer vision and other image processing applications. Image segmentation has become quite challenging over the years due to its widespread use in a variety of applications. Image thresholding is a popular image segmentation technique. The segmented image quality is determined by the techniques used to determine the threshold value.A locally adaptive thresholding method based on neighborhood processing is presented in this paper. The performance of locally thresholding methods like Niblack and Sauvola was demonstrated using real-world images, printed text, and handwritten text images. Threshold-based segmentation methods were investigated using misclassification error, MSE and PSNR. Experiments have shown that the Sauvola method outperforms real-world images, printed and handwritten text images in terms of misclassification error, PSNR, and MSE.
Keywords: Image thresholding; Misclassification Error (ME); Mean Square Error(MSE);Peak Signal to Noise Ratio(PSNR)

I. INTRODUCTION

Thresholding is a useful technique in image segmentation and machine vision. The main principle behind thresholding is to choose an optimal gray-level threshold value based on the gray-level distribution of items of interest in an image to separate them from the background. Thresholding is a crucial and successful method for image segmentation. Thresholding strategies are classified as global or local based on the number of thresholds that can be detected. Global thresholding selects a single threshold value from the histogram of the entire image whereas local thresholding uses localized gray-level information to choose multiple threshold values; each is optimized for a small region in the image.One of the most used threshold-based techniques is the Otsu method [1]that proposesto obtain an optimum threshold by minimizing the weighted sum of variances of the objects and background pixels.W. Niblack[2] proposed a thresholding method for segmenting the object and its background in an image by calculating mean and standard deviation using the windowing method.

T. R. Singhet al. [3] have done thresholding by considering the integral sum of an image as local mean. For document image binarization, J. Sauvola and M. Pietikäinen[4] have classified the document as background, pictures, and text. Later they applied two different approaches, a soft decision method for background and pictures and a text binarization method for textual and line drawing areas to define a threshold for each pixel. D. Bradley and G. Roth[5] have done binarization of text images by calculating the mean of all the pixel values surrounded the test element horizontally, vertically, and diagonally. If the value of the selected pixel is less than the mean, assigned as black else it is assigned as white. With this adaptive method, they have retrieved the text from the poorly illuminated documents.

B. Lei and J. Fan[6] proposed a new form of square rough entropy to measure the roughness of the object and background in an image by using the homogeneity histogram. The optimal threshold is calculated by computing the square rough entropy.Q. Huang et al. [7] proposed a thresholding method to avoid the effect of non-uniform lighting disturbance and unwanted objects by adaptively selecting image window size based on the pyramid data structure manipulation of Lorentz information measure.S. Aja-Fernándezet al. [8]implemented a multi-region thresholding methodology that is based on relating each pixel in the image to different output centroids via a fuzzy membership function. The centroids can be identified using a clustering method. This method isrobust to noise and artifacts. This paper focuses on Sauvola and Niblack thresholding methods. The paper was arranged as follows.Section 2 discusses data collection and methods. Section 3 explores Niblack and Sauvola's experimental findings. Section 4 explores the paper's conclusion.

II.DATA AND METHODS

A. Data Collection

We collected images for this work from a Berkeley segmentation dataset that contains various types of images with non-uniform illumination, shadows, and occlusion, and each image resolution of 481x 321 pixels.We also used threshold-based segmentation on images from the DIBCO -2009 dataset of print documents with a resolution of 1268x263 pixels and handwritten documents with a resolution of 2025x426 pixels. Each image has been resized to 256x256 pixels to normalize the database.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue V May 2021- Available at www.ijraset.com

B. Methods

We have used the Otsu method, Niblack, and Sauvola's algorithm in this work. The Otsu technique is used to estimate the best image threshold value and is applied only once to the entire image. Because of a single threshold value, certain local characteristics may be lost. The calculation of a threshold at each pixel distinguishes adaptive thresholding methods such as Sauvola and Niblack.

1) *Otsu Method:* Otsu method [1] uses grayscale images and automatically selects the best threshold value from a grayscale histogram. Otsu's method works fairly well if the histogram has a bimodal distribution and a deep and sharp valley between two peaks. The threshold is the system that separates the foreground or object from the background into non-overlapping sets.
2) *Niblack Method:* Niblack [2] is an adaptive thresholding technique that optimizes the threshold value based on the local standard deviation and the mean of each pixel location over a specified window size. The local threshold value at any pixel (s,t) is computed as

$$T(s,t) = m(s,t) + k\sigma(s,t) \qquad (1)$$

Where $\sigma(s,t)$ and $m(s,t)$ are the standard deviation and mean of the sample respectively. The size of the window influences the outcome of binary image segmentation. The window size of document images must change according to the size of the characters. The 'k' is used to adjust and control the standard deviation caused by object features. In this case, 'k' is a constant whose value ranges from 0 to 1. Binarization produces thick and blurry strokes when 'k' is small, slim, and broken strokes when 'k' is large. Niblack is unable to adapt to the large variations in illumination, particularly in document images.

3) *Sauvola Method:* The Sauvola method [4] computes the local threshold value for each pixel individually using the local standard deviation and local mean. The Sauvola method eliminates the background noise issue that occurs in the Niblack method. This algorithm outperforms Niblack's method, particularly when the background contains huge variations, poorly illuminated documents, and irregular illumination. The local threshold at any pixel (s,t)) is computed by sliding window around every pixel location and using the local mean and standard deviation.

$$T(s,t) = m(s,t) * \left[1 + k\left(\frac{\sigma(s,t)}{R} - 1\right)\right] \qquad (2)$$

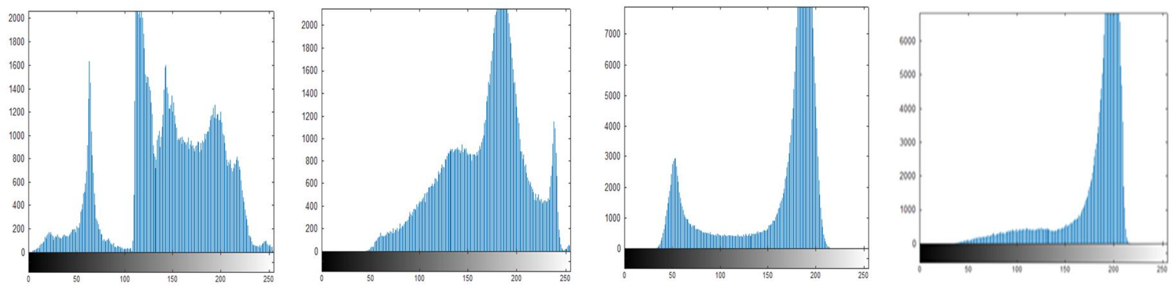
Where $\sigma(s,t)$ and $m(s,t)$ are the standard deviation and mean of the sample respectively. The value of 'k' and the size of the window has a significant impact on image quality. When the grey level values of the background and foreground pixels are proximate to each other, the result of a thresholded image gradually degrades. When compared to the Niblack algorithm, the Sauvola method performs very well on document images, with foreground text pixels having near '0' gray value and background nontext pixels having approximately '255' gray value.

III.EXPERIMENTAL RESULTS OF OTSU,NIBLACK, AND SAUVOLA METHODS

To evaluate the effectiveness of Niblack and Sauvola adaptive thresholding techniques, we used two real-world images, an airplane and a horse image from the Berkeley segmentation data set.And also, two images, a printed text and handwritten text images from the DIBCO -2009 data set. We have conducted experiments on the above four images with irregular illumination conditions, which are depicted in Fig. 1(a) to 1(d).Fig.3(a) depicts the respective ground truth images from the Berkeley segmentation data set and the DIBCO -2009 data set. Fig.2(a) to 2(d) demonstrate that the histograms of the original images are not bimodal, making it difficult to determine threshold value and separate the objects from the background. Multimodalor unimodal histogram problems can be easily solved using local adaptive thresholding methods. In Niblack and Sauvola's adaptive thresholding methods, every pixel in the image will have its threshold value to segment the object from the background. Three thresholding techniques, namely Otsu, Niblack, and Sauvola had been tested on the dataset. Fig.3(b) depicts the experimental result ofthe Otsu thresholding method. Fig.3(c) depicts the experimental result of the Niblack thresholding method. Fig.3(d) depicts the experimental result of the Sauvola thresholding method.

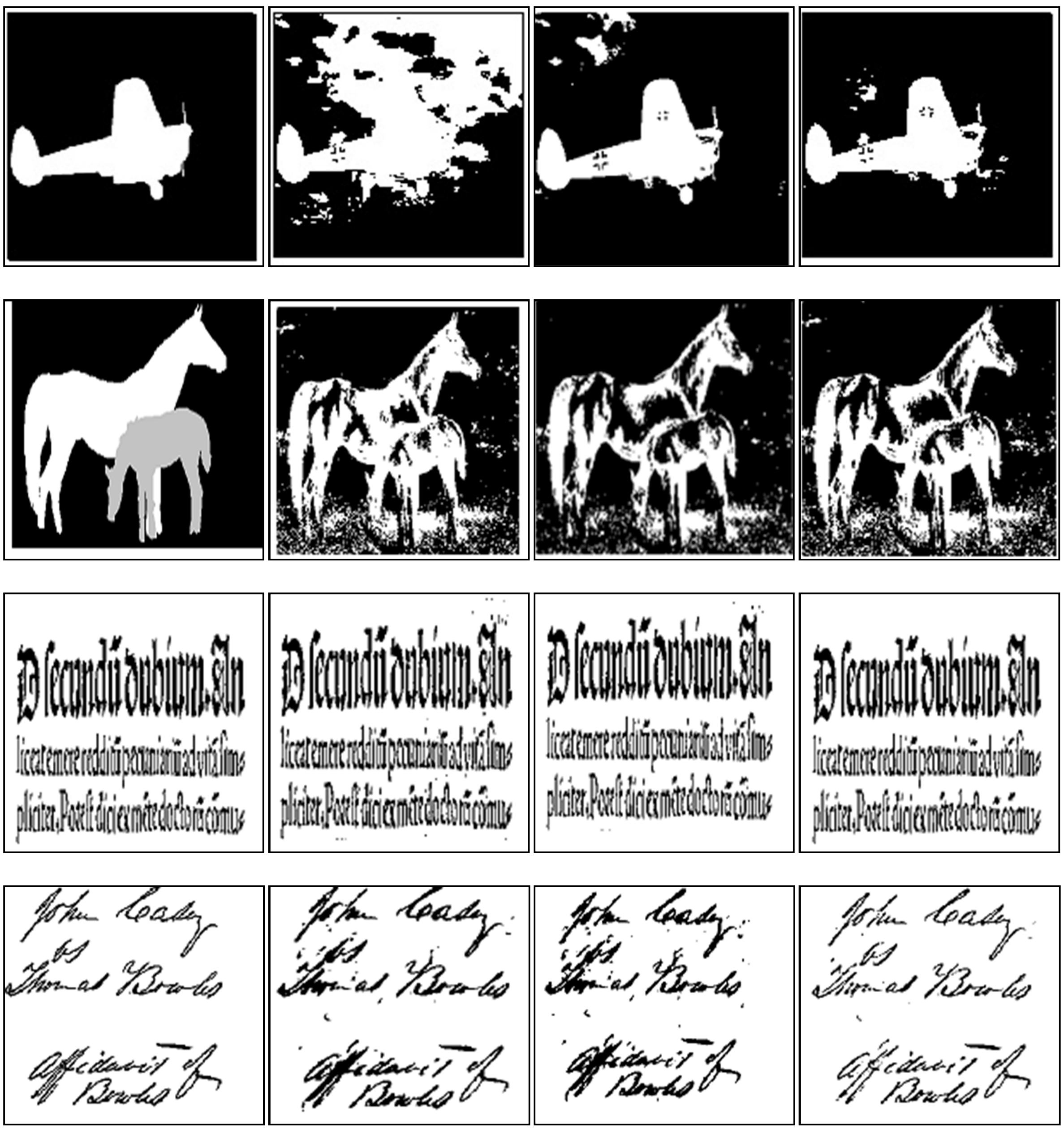
(a) (b) (c) (d)

Fig. 1. Original images: (a) Airplane, (b) Horse, (c) Printed text, (d) Handwritten text



(a) (b) (c) (d)

Fig. 2. Histograms of original images: (a) Airplane, (b) Horse, (c) Printed text, (d) Handwritten text

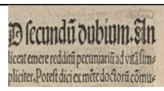
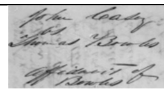


(a) (b) (c) (d)

Fig. 3. Ground truth and segmentation results of different thresholding techniques applied on the images Airplane, Horse, Printed text, Handwritten text: (a) Ground truth (b) Otsu's method (c) Niblack (d) Sauvola.

ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.429
Volume 9 Issue V May 2021- Available at www.ijraset.com

Table I: Misclassification Error for various thresholding techniques

Images	Otsu	Niblack	Sauvola
	0.2982635	0.0321198	0.0230103
	0.1547394	0.1984558	0.1928101
	0.0312042	0.0312042	0.0268250
	0.0381775	0.0585175	0.0228424

The quality of thresholded images was quantitatively analyzed for each experiment using misclassification error (ME). ME calculates the percentage of pixels that are incorrectly classified. Lower the value of ME indicates more accurate segmentation. ME values range from '0' to '1'. ME value ‘0' indicates that the segmentation was done correctly, whereas ME value ‘1' indicates that the segmentation was completely incorrect. Table 1 compares ME with Otsu, Niblack, and Sauvola thresholding techniques for four different images. When compared to the other two methods, the Sauvola technique has a lower misclassification error for all images.

Table II: MSE for various thresholding techniques

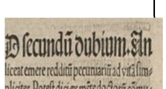
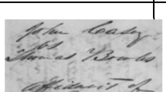
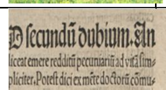
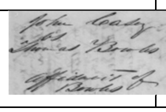
Images	Otsu	Niblack	Sauvola
	0.4549791	0.4453066	0.4421479
	0.4685148	0.4816995	0.4730301
	0.0878390	0.0878390	0.0870518
	0.0773791	0.0829298	0.0760073

Table 2 compares MSE to the thresholding techniques of Otsu, Niblack, and Sauvola for four different images. The presence of a high MSE value indicates that the image is having poor quality. When compared to the other two methods, the Sauvola technique has a lower MSE for all images.

Table III: PSNR (DB) for various thresholding techniques

Images	Otsu	Niblack	Sauvola
	51.5848849	51.6782082	51.7091238
	51.4575664	51.3370373	51.4759114
	58.7279258	58.7279258	58.7670208
	59.2785629	58.9776951	59.3562463

For four different images, Table 3 compares PSNR to the thresholding techniques of Otsu, Niblack, and Sauvola. The higher the PSNR value, the greater the similarity between the thresholded and original image. When compared to the other two methods, the Sauvola technique has a higher value of PSNR for all images.

IV. CONCLUSION

We presented an image analysis using the Otsu, Niblack, and Sauvola thresholding techniques. We have evaluated the performance of various methods using adaptive window size selection, which was tested using images with uneven illumination. In our experiments, the window size and coefficient 'k' in the Sauvola and Niblack thresholding techniques varied from image to image. The window size for text images must be changed depending on the character size. The Sauvola and Niblack algorithms were tested on images with various types of document degradations and uneven lighting conditions. The Sauvola thresholding method outperformed in comparison to Otsu and Niblack on real-world images, printed and handwritten text images in terms of misclassification error, PSNR, and MSE.

REFERENCES

[1] Otsu, N., A threshold selection method from gray-level histograms, IEEE Transactions on Systems Man Cybernet SMC-9 (1), 62–66, 1979

[2] W. Niblack, "An Introduction to Digital Image Processing", pages 115-116. Englewood Cliffs, N.J.:Prenlice Hall, 1956

[3] T. R. Singh, S. Roy, O. I. Singh, T. Sinam, and K. M. Singh, "A New Local Adaptive Thresholding Technique in Binarization," vol. 8, no. 6, pp. 271–277, 2012, [Online]. Available: http://arxiv.org/abs/1201.5227.

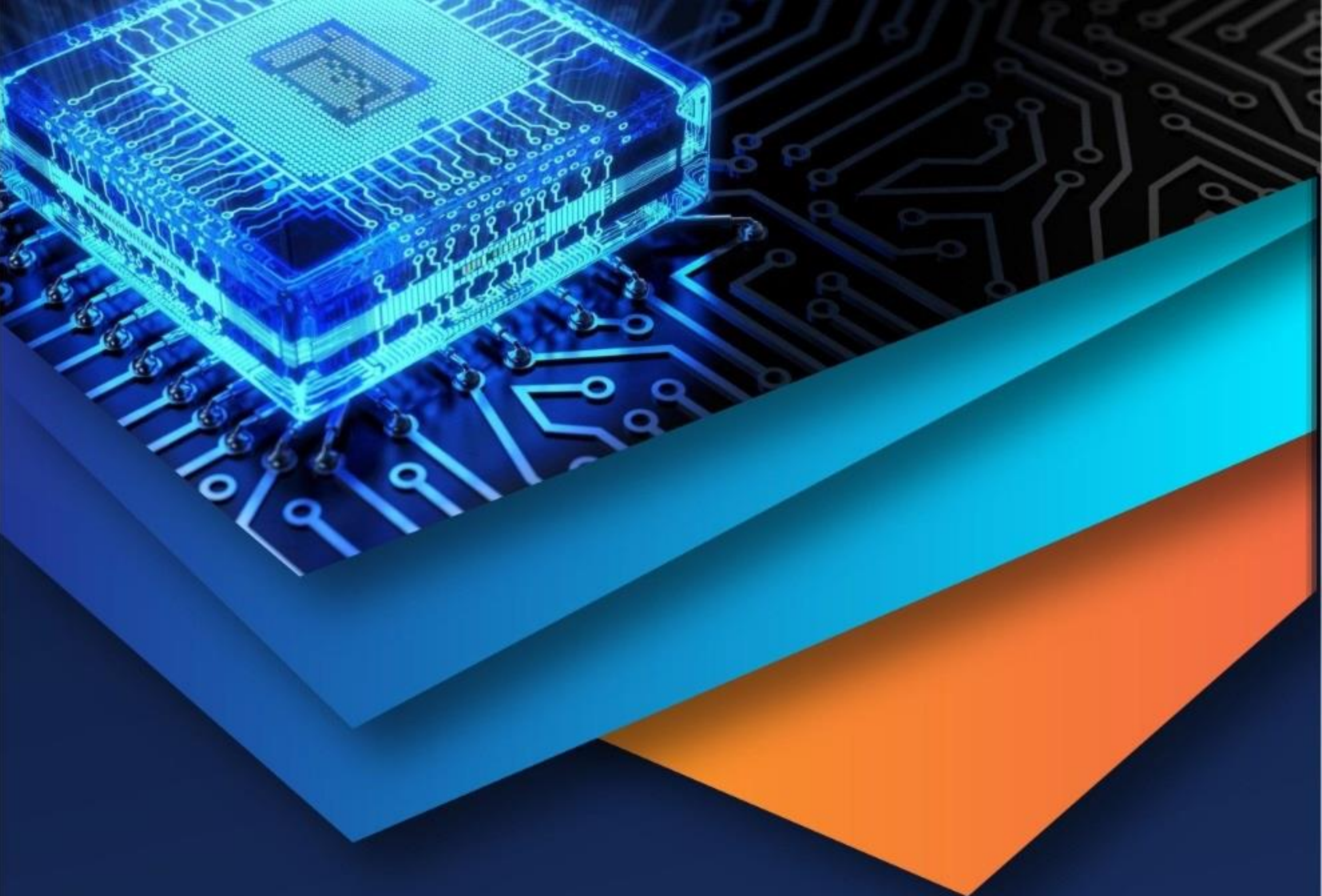
[4] J. Sauvola and M. Pietikäinen, "Adaptive document image binarization," *Pattern Recognit.*, vol. 33, no. 2, pp. 225–236, 2000, doi: 10.1016/S0031-3203(99)00055-2.

[5] D. Bradley and G. Roth, "Adaptive Thresholding Using the Integral Image:Read but to check with sir," *Jgt*, vol. 12, pp. 13–21, 2007.

[6] B. Lei and J. Fan, "Image thresholding segmentation method based on minimum square rough entropy," *Appl. Soft Comput. J.*, vol. 84, p. 105687, 2019, doi: 10.1016/j.asoc.2019.105687.

[7] Q. Huang, W. Gao, and W. Cai, "Thresholding technique with adaptive window selection for uneven lighting image," *Pattern Recognit. Lett.*, vol. 26, no. 6, pp. 801–808, 2005, doi: 10.1016/j.patrec.2004.09.035.

[8] S. Aja-Fernández, A. H. Curiale, and G. Vegas-Sánchez-Ferrero, "A local fuzzy thresholding methodology for multi-region image segmentation," *Knowledge-Based Syst.*, vol. 83, no. 1, pp. 1–12, 2015, doi: 10.1016/j.knosys.2015.02.029.



10.22214/IJRASET

45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY