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Advancements in Binarization and Noise Reduction Techniques for Ancient Script Preservation on Stone, Palm Leaves, and Copper Plates

Ayyoob M. P.*[1], P. Muhamed Ilyas

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Abstract: This study specifically examines the methods used to protect and improve the condition of ancient texts that are engraved on three different types of materials: stone inscriptions, palm leaves, and copper plates. Every material poses distinct difficulties because of its texture, surface properties, and vulnerability to degradation over time. In order to minimize the negative impacts of noise, various noise reduction techniques such as median filtering, despeckle filtering, and Gaussian smoothing are utilized. Following that, well-established binarization methods such as Otsu, Niblack, and Sauvola are utilized to enhance the binarization process for different types of script materials. The effectiveness of these strategies is assessed using measures such as Mean Square Error (MSE), Structural Similarity Index Measure (SSIM), and Peak Signal-to-Noise Ratio (PSNR). The results indicate that the unique technique surpasses other methods in improving the quality of binarized text on all three types of script materials. This offers great opportunities for preserving and extracting vital textual information from these diverse and historically important mediums.

Keywords: *Ancient Writings, Noise Reduction, Binarization Techniques, Stone Inscriptions, Palm Leaves, Copper Plates, Preservation, Enhancement.*

1. Introduction

The quality of text extracted through Optical Character Recognition (OCR) is influenced by various factors, encompassing the nature of the imaging device employed (such as scanners or cameras), the script's age, the materials used for recording, preservation methods, exposure to extreme temperatures, and inappropriate cleaning methods. Notably, camera-based capture, due to its lower resolution compared to scanners, may lead to more frequent errors in text recognition.

Within the realm of the literary domain, numerous approaches aim to enhance degraded script images. Among these techniques, binarization stands out as a crucial step. Prior to binarization, images undergo various denoising techniques to eliminate unwanted noise types like speckle noise, Gaussian noise, salt and pepper noise, and others. This background noise tends to obscure the original textual data.

To address these issues, a gamut of filtering techniques, including median filtering, Gaussian blurring, and despeckling, are deployed. These techniques aim to refine the script images by reducing noise interference. Subsequently, thresholding, or binarization, is employed after these filtering steps to create a binary representation of the script.

Thresholding exists in two primary categories: global and local (adaptive). In addition to the proposed approach, three renowned binarization techniques—Otsu [1], Niblack [2], and Sauvola et al. [3]—are utilized to process ancient script etched on copper plates, palm leaves, and stone surfaces.

The evaluation of the effectiveness of these techniques relies on three well-known metrics: the Structural Similarity Index Measure (SSIM), Mean Square Error (MSE), and Peak Signal-to-Noise Ratio (PSNR). These metrics serve as benchmarks to assess the performance of the proposed strategy in comparison to established binarization techniques.

Through the analysis of outcomes derived from these metrics, the effectiveness and superiority of the suggested strategy in enhancing the OCR quality of ancient scripts on varied surfaces, such as copper plates, palm leaves, and stone surfaces, become evident.

The subsequent sections of this work are structured in the following manner: Section 2 provides a description of the associated work. Section 3 offers an elaborate explanation of the suggested methodology, encompassing the techniques used for reducing noise and converting data into binary form. Section 4 showcases the experimental findings and performance assessment, illustrating the superiority of our groundbreaking approach in improving the quality of binarized text across all three script sources. Section 5 serves as the final part of the report and provides an overview of prospective areas for further research.

2. Related Work

Ancient handwritten writings contain noise in a variety of forms [4], which can be reduced using a variety of denoising techniques. Numerous methods have been established in the

[1,2] *Sullamussalam Science College, Areacode*
Kerala-India
** Corresponding Author Email: mpayyoobmp@gmail.com*

literature for different document denoising jobs, such as palm leaf [5,6,7,8,9], copper plate [10] and stone inscriptions [11].

One of the most difficult tasks in degraded ancient script binarization is choosing the optimal value for the thresholding parameter after the image enhancement operations. Different binarization techniques are employed in the literature. It can be broadly divided into two categories: global and local (adaptive) approaches. For ancient script binarization that has degenerated, global binarization techniques are insufficient.

Seven different approaches were explored by Mustafa et al. [12] for binarization on H-DIBCO 2012 data sets. They discovered that the gradient-based approach yielded the best results.

For optimal outcomes, Omar Boudraa et al. [13] also examined a variety of thresholding techniques. Based on the uniform hue of the copper plate inscription, Rasmana et al. [14] describe a novel method of integrating Otsu thresholding with the feature of Gray Level Cooccurrence Matrix (GLCM). They achieve an F-measure of 95.4%, a pseudo-F-measure of 94.44%, and a PSNR of 11.15.

The linear regression method is utilized to normalize the pictures, and S. Das et al.[15] use the Fast ICA (Independent Component Analysis) methodology to minimize noise in stone inscriptions. Cumulative residual entropy yields the threshold value.

In Tamizhi script on stone inscriptions, a multi-level improvised binarization approach [16] is employed.

A quicker and more accurate method for extracting Tamil sounds from stone inscriptions is presented by S. Raja Kumar et al. [17]: Bhuvaneswari et al [18] present new methods for image acquisition and thinning for ancient stone inscriptions.

[19,20,21,22,23,24] explain various image enhancement and binarization methods with high accuracy rate on palm leaf documents.

3. Methodology

3.1. Image Acquisition

In image processing, image acquisition is an action of retrieving an image from an external source for further processing. This vital step employs a variety of capture devices, such as scanners, cameras, and mobile phones, all of which significantly impact the quality of the acquired images. The specifications of the image captured device is summarized in Table 1.

Table.1. Specifications of the image captured device.

Property	**Value**
Horizontal Resolution	72 dpi
Vertical Resolution	72 dpi
Camera Model	i Phone 12
Flash Mode	No Flash
35mm Focal Length	26

The sample copper plate and stone data are collected from the Hill Palace archaeological museum and palace located in the Tripunithura neighborhood of Kochi, Kerala, India.

The palm leaf data are collected from the state archives department, Thiruvananthapuram, Kerala, India.

3.2. Gray Scale

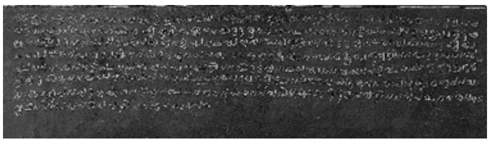
For images that contain colors that are represented in RGB (Red, Green, Blue). This means that the computations are made three times, once for each color. In a grayscale image, each pixel is assigned a single value that corresponds to its brightness, with darker areas represented by darker shades of gray and lighter areas represented by lighter shades of gray.

Figure 1 Shows the original images and its corresponding gray scaled images.

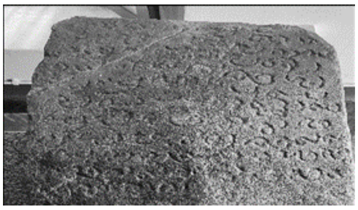
a) Copper plate

b) Stone inscription

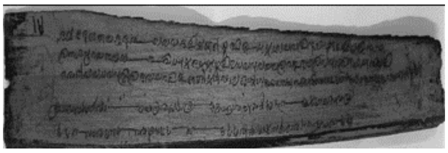
c) Palm leaf



d) Gray scaled image of (a)



d) Gray scaled image of (b)



d) Gray scaled image of (c)

Fig. 1. Original images and its corresponding gray scaled images.

3.3. Super Resolution (SR)

Pixel expansion becomes necessary to achieve a higher resolution of an image that originates from its lower resolution state. The decrease in image quality is primarily caused by processes such as down sampling, blurring, and noise interference. In this context, the approach involves duplicating both the height and width. dimensions of each pixel in the image.

3.4. Speckle Noise

Speckle noise is a multiplicative noise which reduces the image resolution and contrast. Speckle noise can be modelled as follows [4]:

$$I(i,j) = M(i,j) * N(i.j) \quad (1)$$

Where I (i,j) is observed image, M(i,j) is noise free image and N(i,j) is speckle noise.

The despeckle filter removes noise from images without blurring edges. The filter replaces each pixel with the median value of the pixels within the specified radius.

3.5 Salt and Pepper Noise

The image is corrupted by impulse (maximum and minimum) noise, which is called salt and pepper noise.

When dealing with impulse noise like salt and pepper, our preference lies in utilizing spatial-domain non- linear filtering. The median filter effectively eliminates noise while preserving fine lines and maintaining image sharpness.

In median filter, the center value in the kernel window is replaced by the middle (median) value of the corresponding window with P x P. Here we used the value 3 for P to minimize the noise. The equation is shown in 2.

$$D(m, n) = \text{median Blur } \{S(p, q)\}, \text{ where } (p, q) \in K_{pq} \quad (2)$$

Here S(p, q) refers to the value of the pixel at coordinates (p, q) in image S. D(m, n) represents the resulting value after applying the median blur operation to the set of pixels. We collect all the pixel values within the kernel K_{pq}.

3.6 Gaussian Noise

Gaussian Noise is a statistical noise having a probability density function equal to normal distribution. Gaussian noise can be modelled as follows:

$$P(G) = \sqrt{1/2\pi\sigma^2}\, e^{-(g-\mu)2/2\sigma2} \quad (3)$$

where g is the pixel value, σ is the standard deviation and μ is the mean.

The Gaussian smoothing operator performs a weighted average of surrounding pixels based on the Gaussian distribution.

3.7 Binarization

The technique of binarization is critical in the broad field of document image processing since it is the foundation for distinguishing text from background in photographs. By producing a binary representation, this crucial stage helps to simplify a complicated visual document—which is frequently made up of different intensities, colors, and textures.

The key of binarization is its capacity to separate and isolate text areas from their background with accuracy. In this segmentation procedure, a multi-tone or colored image is converted to a binary format in which pixels are classified into two classes: background (the non-textual, contextual portions) and foreground (usually text, graphics, or relevant content).

The effectiveness of binarization methods influences the tasks that follow in terms of document processing. Its main objective is to effectively separate text elements from the surrounding image so that text may be read, extracted, and interpreted more easily.

A variety of techniques are used by binarization algorithms to accomplish this discrimination. To differentiate text from background, they examine pixel intensity, color, texture, and spatial properties. Complex layouts, noise, aging or handling-related document deterioration, and lighting fluctuations are some of the factors that make advanced algorithms necessary for accurate text extraction.

The quality and precision of the binarization process play a major role in the success of OCR, information retrieval, text analysis, indexing, and document archiving. Accurately interpreting and processing textual information included in document images is made possible by reliable binarization, which guarantees the success of next stages in document analysis and comprehension.

3.7.1 Local Otsu

Local Otsu binarization, a variant of the Otsu method, introduces an adaptive and localized thresholding approach within the domain of image processing. In contrast to the global thresholding technique that calculates a single threshold value for the entire image, Local Otsu divides the image into smaller, non-overlapping regions or windows. For each of these distinct regions, it computes an optimal threshold independently.

This adaptive methodology enables a more nuanced and contextually appropriate threshold determination process. It addresses scenarios where the illumination, contrast, texture, or characteristics of different parts within an image vary significantly. By computing individual thresholds for localized regions, Local Otsu allows for a finer level of granularity in the binarization process.

The segmentation and extraction of objects or features from complex backgrounds are notably improved through Local Otsu binarization. It is particularly beneficial in scenarios where lighting conditions fluctuate, causing uneven illumination across the image. Moreover, images with varying textures, contrasts, or regions of different densities benefit greatly from this approach. The adaptive nature of Local Otsu allows for enhanced precision in identifying and isolating specific objects or features within the image. It facilitates the extraction of details, contours, and fine structures by optimizing the thresholding process based on the characteristics of each local region. As a result, this technique significantly contributes to more accurate object segmentation and background suppression.

3.7.2 Niblack

The Niblack algorithm calculates the threshold value for a pixel by considering the mean and standard deviation of pixel intensities within a small window or neighborhood around that pixel. If the pixel's intensity is greater than this threshold, it is assigned to the foreground. Otherwise, it is considered part of the background.

Niblack thresholding is particularly useful when dealing with images with non-uniform illumination or varying background intensity. It helps to handle variations in lighting and contrast.

3.7.3 Sauvola

The Sauvola algorithm is a dynamic and adaptive method used in image processing for local thresholding and binarization. Its functionality involves computing thresholds for individual pixels by considering statistical parameters derived from the surrounding neighborhood of each pixel within the image.

At its core, the Sauvola algorithm utilizes the mean and standard deviation of pixel intensities within a small, predefined sliding window or neighborhood centered around each pixel. This window moves across the entire image, analyzing local pixel information within its vicinity. The mean value characterizes the average intensity level, while the standard deviation measures the variability or spread of pixel intensities within that neighborhood.

The threshold for binarization is then computed based on these statistical parameters using the Sauvola formula:

$$\text{Threshold} = \text{Mean} * (1 + k * ((\text{Standard Deviation} / R) - 1)) \quad (4)$$

Here, 'k' represents a parameter known as the Sauvola coefficient, which acts as a sensitivity control parameter for the binarization process. It adjusts the threshold value computed from the mean and standard deviation, affecting the algorithm's adaptability to different image conditions and textures.

The 'R' term in the formula denotes the maximum pixel intensity range within the image.

The k-value essentially governs the sensitivity of the binarization process. A higher k-value results in a more adaptive threshold that is sensitive to smaller local variations in pixel intensity, potentially capturing finer details but also increasing the likelihood of including noise or artifacts in the binary output. Conversely, a lower k-value produces a less sensitive threshold, which might overlook subtle variations but provides a smoother binary output with reduced noise sensitivity.

3.8 Proposed Method

The proposed approach involves a sequence of sequential steps to enhance the quality of captured text images. Initially, color images of written content obtained via the camera are converted into grayscale photos. This conversion is essential as it simplifies the subsequent processing steps and focuses solely on the intensity variations within the image. Furthermore, the grayscale transformation serves as a fundamental step for the subsequent enhancement processes.

Subsequently, to ameliorate the image resolution, a super-resolution technique is employed. Super-resolution methods aim to enhance image quality by generating high-resolution images from one or multiple low-resolution images. This process involves extrapolating additional pixel information to improve the overall clarity and detail of the text captured in the images.

Following the resolution enhancement step, a series of noise reduction techniques are implemented to refine the image further. Gaussian smoothing, median filtering, and despeckle filtering are applied to diminish various types of unwanted noise present in the image. Gaussian smoothing helps in reducing high-frequency noise by convolving the image with a Gaussian kernel. Median filtering, on the other hand, replaces each pixel's value with the median value within its neighborhood, effectively reducing salt-and-pepper noise. Despeckle filtering aims to eliminate speckle noise, a form of granular interference commonly found in images.

Subsequent to these preprocessing stages, the adaptive thresholding approach is utilized. In this method, the determination of the threshold value is based on a weighted sum of neighboring pixel values, with the weights assigned through a Gaussian window. This adaptive thresholding technique ensures a more flexible and nuanced approach to binarization, considering local variations in image intensity.

Continuing with the process, the Prewitt operator, a type of edge detection filter, is utilized to identify horizontal (X-axis) and vertical (Y-axis) edges within the image. This step is crucial for delineating the edges of textual elements, allowing for better identification and extraction of textual content.

Finally, to enhance the visual representation and the structural aspects of the text, a dilation procedure is applied. Dilation enlarges the shapes within the image, emphasizing the textual elements and improving their overall clarity and legibility from their initial form. This dilation process aids in the refinement and enhancement of the text's visual appearance after the preceding series of image processing steps.

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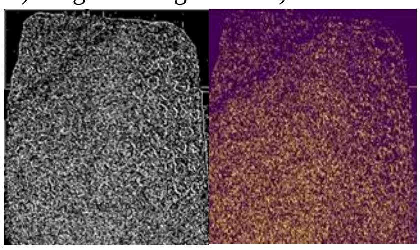
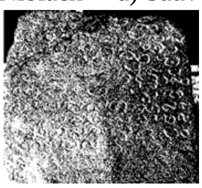
Figures 2, 3 and 4 show the binarized stone inceptions, copper plate and palm leaf of the above methods.

a) Original Image b) Local Otsu

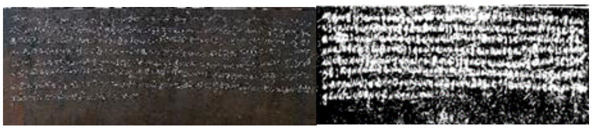


c) Niblack d) Sauvola

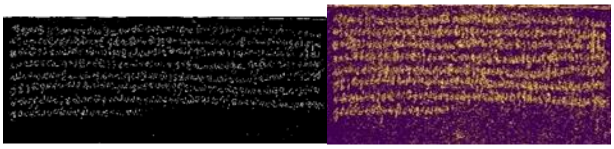


e) Proposed method

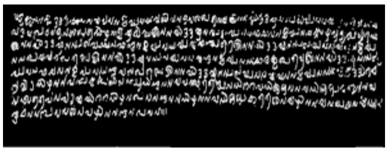
Fig. 2. Binarized stone inceptions of the above methods.



a) Original Image b) Local Otsu



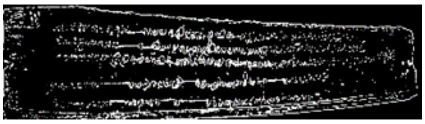
c) Niblack d) Sauvola



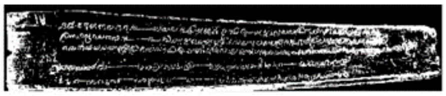
e) Proposed method

Fig. 3. Binarized copper plate of the above methods.

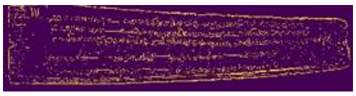
a) Original Image



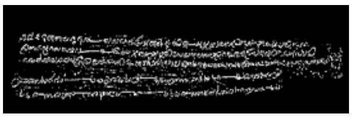
b) Local Otsu



c) Niblack



d) Sauvola



e) Proposed method

Fig. 4. Binarized palm leaf of the above methods.

4.Experimental result and performance evaluation

We employ three metrics to assess the acquired results: the structural similarity index measure (SSIM), mean squared error (MSE), and peak signal-to-noise ratio (PSNR) of the binarized images of a copper plate, stone, and palm leaf. Superior enhancement quality is indicated by a high peak signal-to-noise ratio (PSNR) value, whereas substandard enhancement quality is indicated by a low PSNR value. On the other hand, mean squared error, or MSE, is a measure of the differences between two similar images, like the original and the improved image.

Lower MSE values indicate higher quality enhancement, while elevated MSE values indicate lower quality.

$$\text{PSNR} = -10 \log \left[\frac{\sum_{i=0}^{m-1} \sum_{J=0}^{n-1} [G(i,j) - s(i,j)]^2}{m \times n \times 255^2} \right] \quad (5)$$

$$\text{MSE} = \left[\frac{\sum_{i=0}^{m-1} \sum_{J=0}^{n-1} [G(i,j) - s(i,j)]^2}{m \times n} \right] \quad (6)$$

SSIM [25] serves as a metric for assessing structural information, encompassing aspects like luminance, contrast and structure. It is formally defined as:

$$\text{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1) + (2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (7)$$

Where μ_x is the pixel sample mean of x

μ_y is the pixel sample mean of y,

σ^2_x is the variance of x,

σ^2_y is the variance of y,

σ_{xy} is the covariance of x and y, c1 and c2 are two variables to stabilize the division with weak denominator.

Table 2 shows the comparison results.

Table 2. PSNR, MSE and SSIM values of the copper plate, stone and palm leaf images binarized by various techniques.

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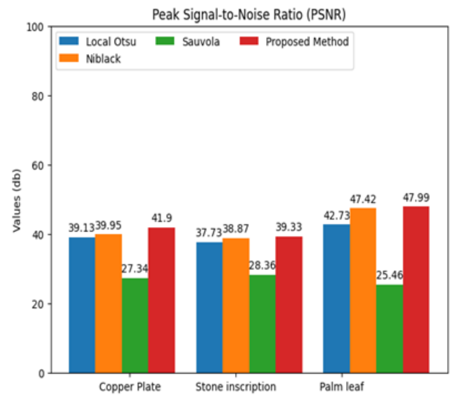
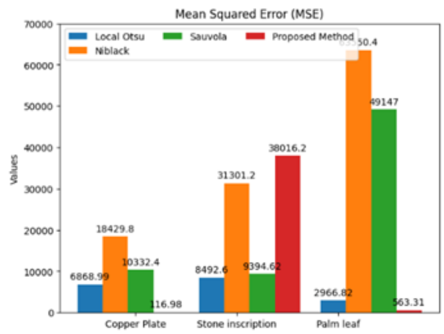
palm leaf images binarized by various techniques.

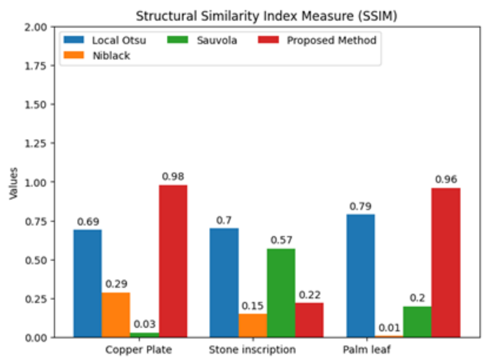
Material	Binarization methods	Performance Evaluation metrics		
		PSNR	MSE	SSIM
Copper Plate	Local Otsu	39.13	6868.99	0.69
	Niblack	39.95	18429.76	0.29
	Sauvola	27.34	10332.44	0.03
	Proposed Method	**41.9**	**116.98**	**0.98**
Stone inscription	Local Otsu	37.73	8492.6	0.7
	Niblack	38.87	31301.17	0.15
	Sauvola	28.36	9394.62	0.57
	Proposed Method	**39.33**	**38016.19**	**0.22**
Palm leaf	Local Otsu	45.38	5301.38	0.86
	Niblack	47.42	63550.44	0.01
	Sauvola	25.46	49146.98	0.2
	Proposed Method	**47.99**	**563.31**	**0.96**



a) PSNR comparison of local Otsu, Niblack, Sauvola and proposed method on copper plate, stone inscription and palm leaf.



b) MSE comparison of local Otsu, Niblack, Sauvola and proposed.



c) SSIM comparison of local Otsu, Niblack, and proposed method on copper plate, stone inscription and palm leaf.

Fig. 5. PSNR, MSE and SSIM values of the copper plate, stone and palm leaf images binarized by Otsu, Niblack, Sauvola and proposed method.

5. Conclusion

Binarizing historical manuscripts is a difficult undertaking since it involves dealing with different types of noise and the distinct features of the materials employed for preservation. The scope of our research was cantered on three separate mediums: stone inscriptions, palm leaves, and copper plates, each of which posed unique difficulties. In order to tackle these difficulties, we utilized various noise reduction approaches and examined well-established binarization methods in conjunction with our novel methodology.

Our investigation, employing criteria such as Mean Square Error, Structural Similarity Index Measure, and Peak Signal-to-Noise Ratio, showed that our method consistently surpassed the established techniques in improving the quality of binarized text across all three sources. These findings highlight the efficacy of our method in safeguarding and collecting useful written data from historically important sources.

Our study enhances binarization procedures for ancient scripts, providing a viable approach for scholars and practitioners who aim to digitize and conserve textual heritage found in various historical sources with precision.

Conflicts of interest

The authors declare no conflicts of interest.

References

[1] N. Otsu, "A Threshold Selection Method from Gray-Level Histograms," in *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62-66, Jan. 1979, doi: 10.1109/TSMC.1979.4310076.

[2] Niblack, Wayne. 1985 “An Introduction to Digital Image Processing”, Strandberg Publishing Company, DNK, 8787200554, 10.5555/4901.

[3] Sauvola, J. and Pietaksinen, M. 2000. “Adaptive document image binarization”, Pattern Recognition, 33, pp. 225–336.

[4] ARULPANDY, P.; PRICILLA, M. Trinita. Speckle Noise Reduction and Image Segmentation Based on a Modified Mean Filter. **Computer Assisted Methods in Engineering and Science,** [S.l.], v. 27, n. 4, p. 221–239, sep. 2020. ISSN 2956-5839.

[5] B J Bipin Nair, KV Aadith Raj, M Kedar, S Pai Vaishak, EV Sreejil, Ancient Epic Manuscript Binarization and Classification Using False Color Spectralization and VGG-16 Model, Procedia Computer Science, Volume 218, 2023, Pages 631-643, ISSN 1877-0509, https://doi.org/10.1016/j.procs.2023.01.045.

[6] Bannigidad, Parashuram & Sajjan, S.. (2023). Restoration of Ancient Kannada Handwritten Palm Leaf Manuscripts Using Image Enhancement Techniques. 10.1007/978-3-031-28324-6_9.

[7] Sudarsan, Dhanya & Sankar, Deepa. (2019). A Novel approach for Denoising palm leaf manuscripts using Image Gradient approximations. 506-511. 10.1109/ICECA.2019.8822224.

[8] Rege, Priti. (2008). Enhancement of Palm Leaf Manuscript and Color Document Images with Synthetic Background Generation. Journal of Advances in Engineering Science. 25-34.

[9] Singh, Mayank & Sreedevi, Indu. (2023). Denoising of palm leaf manuscripts using Gaussian filter and conservative smoothing. 050005. 10.1063/5.0142237.

[10] Sachin Bhat, Seshikala G (2019). Restoration of Characters in Degraded Inscriptions using Phase Based Binarization and Geodesic Morphology . International Journal of Recent Technology and Engineering (IJRTE) ISSN: 2277-3878, Volume-7, Issue-6, March 2019.

[11] Sukanthi, S. Sakthivel Murugan and S. Hanis Binarization of Stone Inscription Images by Modified Bi-level Entropy Thresholding. Fluctuation and Noise Letters 2021 20:06.

[12] Mustafa, Wan & Kader, Mohamed. (2018). Binarization of Document Images: A Comprehensive Review. Journal of Physics: Conference Series. 1019. 012023. 10.1088/1742-6596/1019/1/012023.

[13] Omar Boudraa and Walid Khaled Hidouci and Dominique Michelucci (2019). Degraded Historical Documents Images Binarization Using a Combination of Enhanced Techniques. Computer Vision and Pattern Recognition.

[14] Rasmana, S. T., Suprapto, Y. K., & Purnama, I. K. E. (2016). The new otsu thresholding for binarization of the ancient copper inscriptions. *International Review on Computers and Software*, *11*(10), 907-914. https://doi.org/10.15866/irecos.v11i10.10359.

[15] S. Das, S. Mandal and A. K. Das, "Binarization of stone inscripted documents," *2015 IEEE International Conference on Computer Graphics, Vision and Information Security (CGVIS)*, Bhubaneswar, India, 2015, pp. 11-16, doi: 10.1109/CGVIS.2015.7449883.

[16] Monisha Munivel, V.S. Felix Enigo, MLIBT: A multi-level improvised binarization technique for Tamizhi inscriptions, Expert Systems with Applications, Volume 236, 2024, 121320, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2023.121320.

[17] S. RajaKumar and V. Subbiah Bharathi, "Eighth century tamil consonants recognition from stone inscriptions," *2012 International Conference on Recent Trends in Information Technology*, Chennai, India, 2012, pp. 40-43, doi: 10.1109/ICRTIT.2012.6206766.

[18] Bhuvaneswari, G., and V. Subbiah Bharathi. “An Efficient Method for Digital Imaging of Ancient Stone Inscriptions.” *Current Science*, vol. 110, no. 2, 2016, pp. 245–50. *JSTOR*, http://www.jstor.org/stable/24906752. Accessed 2 Nov. 2023.

[19] B. N. B J and N. S. Rani, "An Optimal Thresholder for Ancient Degraded Palm leaf Document Binarization," 2021 5th International Conference on Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, 2021, pp. 1737-1744, doi: 10.1109/ICECA52323.2021.9676095.

[20] S. Cherala and P. P. Rege, "Palm Leaf Manuscript/Color Document image Enhancement by Using Improved Adaptive Binarization Method," *2008 Sixth Indian Conference on Computer Vision, Graphics & Image Processing*, Bhubaneswar, India, 2008, pp. 687-692, doi: 10.1109/ICVGIP.2008.64.

[21] M. W. A. Kesiman, S. Prum, J. -C. Burie and J. -M. Ogier, "An initial study on the construction of ground truth binarized images of ancient palm leaf manuscripts," 2015 13th International Conference on Document Analysis and Recognition (ICDAR), Tunis, Tunisia, 2015, pp. 656-660, doi: 10.1109/ICDAR.2015.7333843.

[22] R. Chamchong and C. C. Fung, "Optimal selection of binarization techniques for the processing of ancient palm leaf manuscripts," 2010 IEEE International Conference on Systems, Man and Cybernetics, Istanbul, Turkey, 2010, pp. 3796-3800, doi: 10.1109/ICSMC.2010.5642008.

[23] Sabeenian R S, Paramasivam M E and Dinesh P M, "Appraisal of localized binarization methods on Tamil palm-leaf manuscripts," 2016 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET), Chennai, India, 2016, pp. 793-797, doi: 10.1109/WiSPNET.2016.7566242.

[24] K. Subramani and S. Murugavalli, "A novel binarization method for degraded tamil palm leaf images," 2016 Eighth International Conference on Advanced Computing (ICoAC), Chennai, India, 2017, pp. 176-181, doi: 10.1109/ICoAC.2017.7951765.

[25] Huang, J. & Yang, X. Fast reduction of speckle noise in real ultrasound images. *Signal Processing* **93**, 684–694 (2013).