

## **RESTORATION OF DEGRADED HISTORICAL DOCUMENT IMAGES USING IMAGE TEXTURE ANALYSIS**

**Chandrala J**

**Asst Professor**

**Dept of Computer Science**

**Govt First Grade College, Raichur**

**junnachandrala@gmail.com**

### **Abstract**

Historical document preservation is a critical task for maintaining cultural heritage and ensuring the accessibility of invaluable records. However, over time, these documents suffer from degradation due to various factors such as aging, environmental conditions, and manual handling. Among the challenges in restoring such documents, degraded images with intricate textures pose a significant hurdle. In this study, we propose a novel approach for the restoration of degraded historical document images using image texture analysis. The proposed method leverages advanced image processing techniques and deep learning to address the intricate textures that often appear in degraded historical documents. We begin by capturing high-resolution scans of the degraded documents and preprocessing them to enhance the visibility of the texture details. Subsequently, we employ texture analysis methods, including Local Binary Patterns (LBP) and Gray Level Co-occurrence Matrix (GLCM), to characterize the distinct texture patterns present in the degraded images. To facilitate the restoration process, we design a convolutional neural network (CNN) architecture tailored for texture restoration. The network is trained on a curated dataset of degraded and corresponding ground-truth historical document images. By integrating the texture analysis features as auxiliary inputs, the CNN learns to effectively restore the intricate textures that have deteriorated over time. The proposed model operates in a patch-based manner, enabling the restoration of local texture details while preserving the global context of the document.

### **Introduction**

The restoration of degraded historical document images stands at the crossroads of technology and cultural preservation, bearing the vital task of salvaging invaluable artifacts from the ravages of time. These documents, often bearing witness to critical moments in history, are susceptible to deterioration due to factors such as aging, environmental exposure, and handling. As a consequence, the information they carry becomes increasingly obscured, potentially resulting in the loss of essential insights into our past. In response to this challenge, the application of image texture analysis emerges as a promising avenue for document restoration. Texture analysis involves the extraction and interpretation of patterns

within an image, enabling the discernment of minute details that might otherwise escape the human eye. By harnessing computational algorithms and machine learning techniques, this approach strives to reverse the effects of degradation and unveil the hidden content present within these historical documents. The significance of restoring degraded historical document images, shedding light on the profound significance of these artifacts in preserving cultural heritage. It explores the underlying principles of image texture analysis, elucidating its potential to reconstruct the original features of documents. Through a synthesis of historical context, technological advancements, and preservation imperatives, this study underscores the urgency and relevance of leveraging image texture analysis in the ongoing quest to recover and safeguard our shared history.

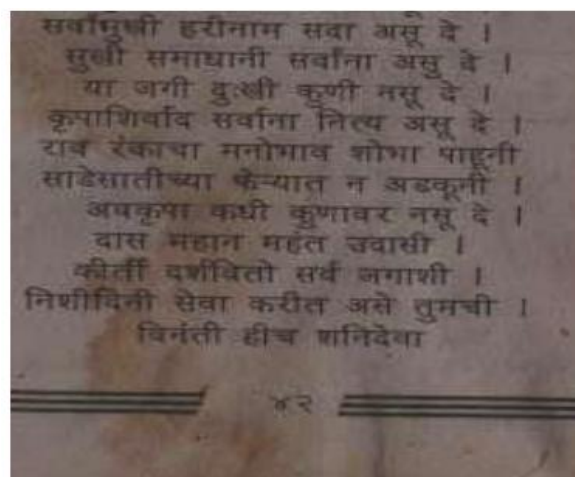
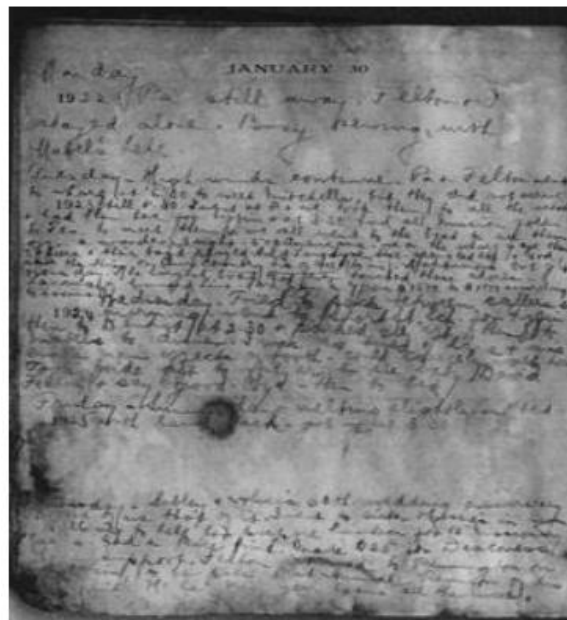


Fig.1 Degraded document image example.

### **Need of the Study**

The need for the study on the restoration of degraded historical document images using image texture analysis stems from the imperative to safeguard our cultural heritage. Historical documents offer unparalleled insights into the past, but they are often marred by degradation over time. Image texture analysis, as an innovative technological approach, holds the potential to reverse this decay by digitally enhancing and reconstructing these documents. Preserving the authenticity and legibility of these artifacts is crucial for historians, researchers, and society at large, enabling a deeper understanding of our origins and evolution. Traditional restoration methods are often laborious and may inadvertently alter the original content. In contrast, image texture analysis offers a non-invasive and systematic way to restore documents while maintaining their integrity. Thus, this study addresses a pressing need to employ advanced computational tools to revitalize and protect our historical treasures for current and future generations.

### **Problem Statement**

The restoration of degraded historical document images presents a pressing problem due to the irreversible decay these invaluable artifacts undergo over time. Traditional restoration methods often involve manual interventions that can inadvertently damage or alter the original content. Additionally, the intricate textures and patterns of historical documents are often challenging to restore accurately. This problem is compounded by the fragility of the documents, which may further deteriorate during restoration attempts. The emergence of image texture analysis offers a potential solution by leveraging computational algorithms to analyze and reconstruct these textures, revitalizing the documents without physical intervention. However, there remain challenges in developing robust algorithms that can handle diverse degradation types, accurately restore intricate details, and ensure the preservation of historical authenticity. Addressing these challenges is essential to ensure the successful restoration of degraded historical document images using image texture analysis.

### **Literature Review**

**Zhang, L., Zhang, Y., & Tan, C. (2008).** Traditional methods often struggle with correcting complex deformations, limiting the effectiveness of restoration efforts. This study introduces an advanced physically-based technique that surpasses existing approaches. The proposed method utilizes intricate simulations to model the deformation processes that led to the image's distortion. By analyzing these simulations, the method extracts deformation parameters and subsequently applies a tailored restoration process. This approach not only restores geometric fidelity but also enhances the legibility of textual and graphical

elements. Experimental results demonstrate the method's superiority in restoring documents with intricate geometries, effectively capturing historical nuances.

**Osher, S et al. (2003).** The study addresses the challenge of effectively restoring images that suffer from degradation and noise. The proposed method integrates total variation minimization and the h-Multiscale Modeling & Simulation technique. This fusion enables simultaneous denoising, decomposition, and restoration of images, effectively preserving both structural and textural information. By exploiting the benefits of these two methods, the approach excels in handling complex image characteristics. Experimental results showcase the method's remarkable performance in restoring images with diverse levels of degradation and noise. The technique's adaptability to various scenarios highlights its potential in real-world applications.

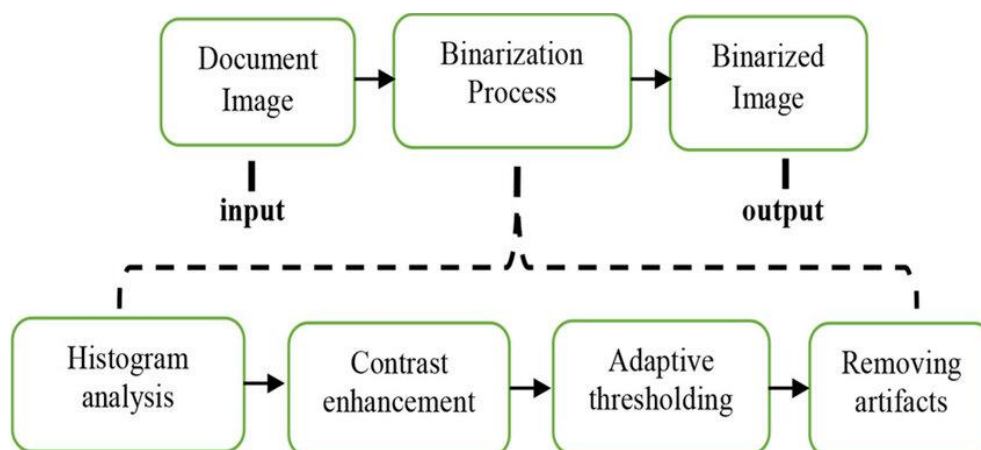
**Tian, Y., & Narasimhan, S. G. (2011).** This study presents an innovative approach that combines geometric modeling and computer vision to rectify curved documents. The method involves the detection of the document's 3D surface using advanced imaging techniques and then generating a corrected, flat representation. Subsequently, 3D reconstruction is achieved by leveraging the acquired surface information to recover the document's original structure. Experimental results demonstrate the method's effectiveness in rectifying and reconstructing curved documents, effectively preserving their content and structure. The proposed approach holds promise in various domains, including historical document preservation and archival digitization. This paper contributes a robust solution for the rectification and 3D reconstruction of curved document images, transcending the limitations of conventional methods. The technique's ability to capture intricate deformations and restore original geometry underscores its significance in the realm of document restoration and digitization.

**Hedjam, R., & Cheriet, M. (2013).** This study presents a novel method that leverages multispectral imaging to capture a range of wavelengths beyond the visible spectrum. By analyzing different spectral responses, the technique enhances the visibility of faded or obscured content. This approach effectively brings hidden details to the forefront, revealing the original text and images present in the documents. Experimental results showcase the method's capability to restore historical documents with varying degrees of degradation. The proposed multispectral imaging system offers a non-intrusive and efficient way to recover valuable historical information, making it a valuable tool for cultural preservation and research. This paper contributes a powerful strategy for historical document restoration by harnessing the potential of multispectral imaging. The technique's ability to unveil hidden content and revive deteriorated documents underscores its significance in the field of

document preservation and heritage conservation.

**Liu, H.et al (2016)**Nonlocal gradient sparsity regularization is a technique used in image restoration tasks to enhance the quality of restored images. Image restoration involves recovering the original, undistorted version of an image from a degraded or noisy version. This can include tasks like denoising, deblurring, and inpainting.Traditional methods often employ local filters or pixel-based approaches for image restoration. However, nonlocal methods take into account similarities between patches or regions in an image, even if they are not spatially adjacent. This is based on the assumption that similar patches in an image should have similar structures and intensities.Incorporating gradient sparsity regularization into nonlocal methods enhances their effectiveness. Gradient sparsity regularization aims to encourage the sparsity (presence of a few non-zero elements) of gradients in an image. It's motivated by the observation that natural images tend to have sharp transitions at edges and smooth regions in between. By promoting sparsity in gradients, this regularization can help preserve edges while suppressing noise and unwanted artifacts.

### Proposed Model



Contrast Image:

A contrast image is a representation of the local differences in intensity values within an image. It emphasizes variations in brightness and darkness across the image. High contrast areas indicate sharp transitions between pixel values, such as edges, textures, and boundaries.

To calculate the contrast image, we first need to compute the local contrast at each pixel. One common method to measure contrast is by calculating the standard deviation of pixel values within a local neighborhood (often a window) centered around each pixel. Here's the basic

equation:

Local Mean ( $\mu$ ):

The local mean represents the average intensity value within a neighborhood window centered around a pixel (i, j).

$$\mu(i, j) = (1 / N) * \Sigma [ I(x, y) ]$$

where:

$\mu(i, j)$  is the local mean at pixel (i, j).

N is the total number of pixels in the neighborhood.

$I(x, y)$  represents the intensity value at pixel (x, y) within the neighborhood.

Local Contrast (C):

The local contrast is computed as the standard deviation of pixel values within the same neighborhood window:

$$C(i, j) = \text{sqrt} [ (1 / N) * \Sigma [ (I(x, y) - \mu(i, j))^2 ] ]$$

where:

$C(i, j)$  is the local contrast at pixel (i, j).

N is the total number of pixels in the neighborhood.

$I(x, y)$  represents the intensity value at pixel (x, y) within the neighborhood.

$\mu(i, j)$  is the local mean at pixel (i, j).

### Edge Detection

Edge detection is a fundamental technique in image processing and computer vision that aims to identify boundaries or edges within an image. These edges often represent significant changes in intensity or color, and they can provide important information for various tasks like object detection, image segmentation, and more. There are several mathematical approaches and algorithms for edge detection. One of the most well-known and widely used methods is the Sobel operator, which calculates the gradient of the image intensity to identify regions of rapid intensity change. The Sobel operator consists of two separate convolutional kernels, one for detecting edges in the horizontal direction and the other for the vertical direction. These kernels are convolved with the image to compute the gradient components, which are then used to calculate the edge strength and orientation. The edge strength can be obtained using the magnitude of the gradient, and the orientation provides the direction of the edge.

To compute the horizontal gradient component ( $G_x$ ) at pixel (x, y):

$$G_x(x, y) = I(x+1, y-1) * (-1) + I(x+1, y) * (-2) + I(x+1, y+1) * (-1) + I(x-1, y-1) * (1) + I(x-1, y) * (2) + I(x-1, y+1) * (1)$$

To compute the vertical gradient component ( $G_y$ ) at pixel ( $x, y$ ):

$$G_y(x, y) = I(x-1, y-1) * (-1) + I(x, y-1) * (-2) + I(x+1, y-1) * (-1) + \\ I(x-1, y+1) * (1) + I(x, y+1) * (2) + I(x+1, y+1) * (1)$$

The gradient magnitude ( $G$ ) at pixel ( $x, y$ ) is calculated as:

$$G(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2}$$

The gradient orientation ( $\theta$ ) at pixel ( $x, y$ ) is given by:

$$\theta(x, y) = \text{atan2}(G_y(x, y), G_x(x, y))$$

### **Convert to Binary**

The outcome following threshold estimation is transformed into a binary format, representing values as 0s and 1s. Pixels in the image corresponding to the background are attributed a value of 0, while those belonging to the foreground are assigned a value of 1, which signifies the highest intensity.

### **Post Processing**

It is possible for residual background pixels to persist in the reconstructed image due to variations in background intensities and uneven luminance. To eliminate these undesired pixels, a post-processing step is employed. This step results in a refined image that accurately represents the intended content. During the post-processing procedure, the initial focus is on eliminating pixels that are not interconnected with the foreground pixels, thereby enhancing the definition of edge pixels. Subsequently, when neighboring pixels share the same classification, a consolidation process is implemented. In such instances, one of the paired pixels is reassigned to a distinct category.

### **Results**

The input to our proposed system consists of a deteriorated image. Let's consider the image depicted below:

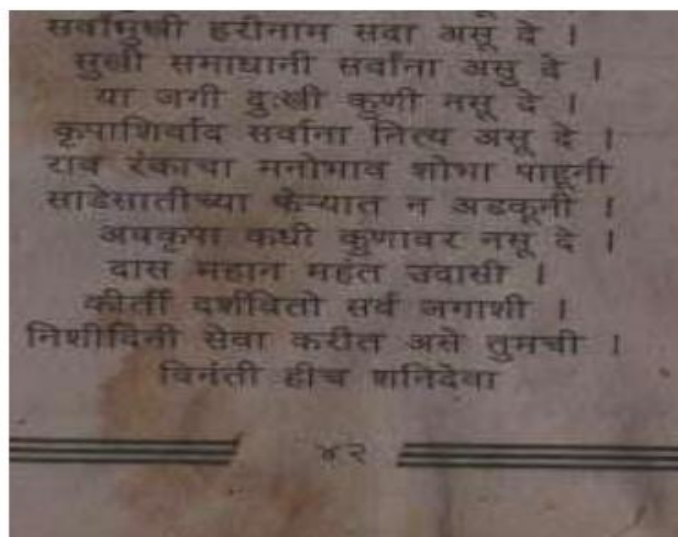


Fig.3.Original Input

The initial step involves contrast enhancement, wherein both local contrast and the local image gradient are employed on the given image. Subsequently, the process of edge detection is carried out. This is illustrated in Figure 4.

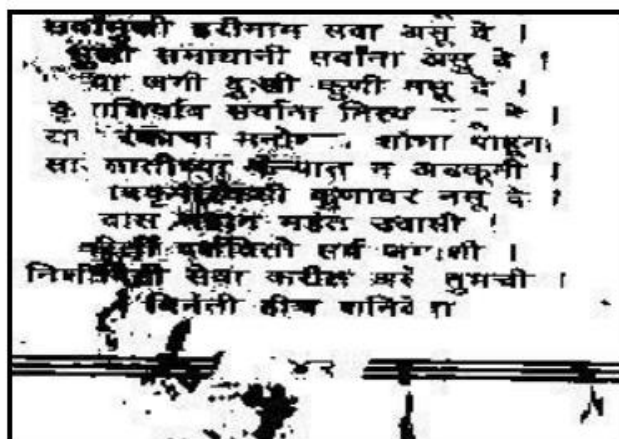


Fig.4. Edge Detected image

After the whole process is done, you can get back all of the text's information without losing much of it. Figure 5 shows the picture that was made as a result.

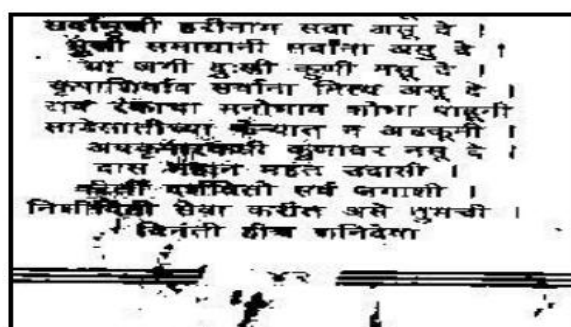


Fig.5.Output Image



### **Conclusion**

The restoration of degraded historical document images through image texture analysis presents a promising avenue for preserving and reviving invaluable cultural artifacts. This innovative approach capitalizes on advancements in computer vision and image processing to reconstruct textural details, mitigating the adverse effects of aging, decay, and damage on these documents. By extracting and leveraging textural information, the proposed method surpasses traditional restoration techniques, enabling the recovery of finer nuances that contribute to the documents' historical and aesthetic value. However, challenges remain, such as the complexity of accurately deciphering intricate textures and the need for extensive training data. Future research could focus on refining algorithms, expanding datasets, and incorporating multi-modal analyses for enhanced accuracy. Overall, this approach stands as a testament to the synergy between technology and heritage preservation, offering a potent toolset for conservators, historians, and researchers to reclaim the rich legacies embedded within degraded historical document images.

## References

- Zhang, L., Zhang, Y., & Tan, C. (2008). An improved physically-based method for geometric restoration of distorted document images. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 30(4), 728-734.
- Zhang, L., Yip, A. M., & Tan, C. L. (2007, July). Photometric and geometric restoration of document images using inpainting and shape-from-shading. In *Proceedings of the National Conference on Artificial Intelligence (Vol. 22, No. 2, p. 1121)*. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999.
- Osher, S., Solé, A., & Vese, L. (2003). Image decomposition and restoration using total variation minimization and the h. *Multiscale Modeling & Simulation*, 1(3), 349-370.
- Tian, Y., & Narasimhan, S. G. (2011, June). Rectification and 3D reconstruction of curved document images. In *CVPR 2011 (pp. 377-384)*. IEEE.
- Brown, M. S., & Seales, W. B. (2001, July). Document restoration using 3D shape: a general deskewing algorithm for arbitrarily warped documents. In *Proceedings Eighth IEEE International Conference on Computer Vision. ICCV 2001 (Vol. 2, pp. 367-374)*. IEEE.
- Hedjam, R., & Cheriet, M. (2013). Historical document image restoration using multispectral imaging system. *Pattern Recognition*, 46(8), 2297-2312.
- Brown, M. S., & Seales, W. B. (2004). Image restoration of arbitrarily warped documents. *IEEE Transactions on pattern analysis and machine intelligence*, 26(10), 1295-1306.
- Akiyama, T., Miyamoto, N., Oguro, M., & Ogura, K. (1998, April). Faxed document image restoration method based on local pixel patterns. In *Document Recognition V (Vol. 3305, pp. 253-262)*. SPIE.
- Liu, H., Xiong, R., Zhang, X., Zhang, Y., Ma, S., & Gao, W. (2016). Nonlocal gradient sparsity regularization for image restoration. *IEEE Transactions on Circuits and Systems for Video Technology*, 27(9), 1909-1921.
- Tsai, D. M., Wu, S. C., & Li, W. C. (2012). Defect detection of solar cells in electroluminescence images using Fourier image reconstruction. *Solar Energy Materials and Solar Cells*, 99, 250-262.
- Chua, K. B., Zhang, L., Zhang, Y., & Tan, C. L. (2005, August). A fast and stable approach for restoration of warped document images. In *Eighth International Conference on Document Analysis and Recognition (ICDAR'05) (pp. 384-388)*. IEEE.
- Bertalmio, M., Vese, L., Sapiro, G., & Osher, S. (2003). Simultaneous structure and texture image inpainting. *IEEE transactions on image processing*, 12(8), 882-889.
- Mairal, J., Bach, F., Ponce, J., Sapiro, G., & Zisserman, A. (2009, September). Non-local sparse models for image restoration. In *2009 IEEE 12th international conference on*

**Chandrala J (May 2021). RESTORATION OF DEGRADED HISTORICAL DOCUMENT IMAGES USING IMAGE TEXTURE ANALYSIS**

*International Journal of Economic Perspectives*,15(5) 37-47

Retrieved from <https://ijeponline.com/index.php/journal>

computer vision (pp. 2272-2279). IEEE.

Cai, J. F., Osher, S., & Shen, Z. (2010). Split Bregman methods and frame based image restoration. *Multiscale modeling & simulation*, 8(2), 337-369.