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A Gaussian Mixture Model Approach for Robust Watermark Text Detection in Documents

Maheshwari S Hiremath
Department of Studies in Computer Science,
Davangere University, Davangere, India

Basavanna Mahadevappa
Department of Studies in Computer Science,
Davangere University, Davangere, India

Shivanand Sharanappa Gornale
School of Mathematics and Computing Sciences.
Rani Channamma University, Belagavi, India

ABSTRACT
Watermark text detection is a crucial process in image processing and digital forensics, particularly for ensuring content authenticity and preventing unauthorized use of digital media. Watermarks, often embedded in images, serve as a visible or invisible form of protection, and their detection is essential for verifying the integrity and ownership of digital assets. Detecting watermark text which is often subtle, semi-transparent, or integrated into the background presents significant challenges. In this paper, we propose an effective approach for watermark text detection using a Gaussian Mixture Model (GMM), an edge detection technique, and morphological functions. A Gaussian Mixture Model (GMM) with four cluster components is applied to model the distribution of pixel intensities. The GMM represents the intensity histogram as a mixture of Gaussian distributions, each parameterized by its mean, variance, and weight. Canny edge detection is applied to the grayscale image to retain the actual edge information. The resulting image is then refined using morphological closing a process that involves dilation followed by erosion to fill small gaps and smooth edge contours. To further isolate meaningful edges, Otsu's thresholding method is applied, selecting an optimal threshold that minimizes intra-class variance between the foreground and background. Finally, the watermark text is embedded into the image by modifying the pixel values in a predefined region, resulting in a watermarked output image.

Keywords: Watermark text, Gaussian Mixture Model, Canny edge, Morphological operation, Otsu Thresholding.

INTRODUCTION
Copyright protection of digital data has become an increasingly important task in the big data era, owing to the rapid development of data acquisition techniques. With the growing digitalization of the world economy and trade, cross-border data flow has become a significant trend. Such data flow can be viewed as a form of data trade, which profoundly impacts commodity production and international trade [1]. Since cross-border data is so vital,

protecting data ownership has become an urgent necessity. A digital watermarking system provides an effective solution to this issue and has made great progress in the watermarking of image, video, and audio data. Early research on text watermarking proposed three main approaches: linguistic-based watermarking, image-based watermarking, and structural-based watermarking. The linguistic-based approach relies on natural language theory and includes two subtypes the semantic approach and the syntactic approach. In the semantic approach, the watermark is embedded based on the semantic structure of the text. In the syntactic approach, elements such as nouns, verbs, and pronouns are used to conceal watermark information. The image-based approaches treat text data as images. Modifying word spacing, letter spacing, or baseline shifting are common methods in this category. The structural-based watermarking algorithms depend on the specific characteristics of a language.

Due to the requirements of daily operations, legal documents are often scanned and stored digitally as document images [2]. These documents are used in government agencies, banks, schools, military institutions, and other sectors where document security is of utmost importance. Protecting such documents is not only a matter of authorized access but also a challenge that continues to attract research interest, particularly in the field of document analysis and recognition. To address these challenges, digital watermarking can be used as an effective solution, enabling the concealment of a signal or secret information within a digital medium. In this paper, the digital medium refers to a document image or host document. The embedded signal or secret information is called a watermark. After embedding the watermark, the host document becomes a watermarked document. The watermark is embedded in such a way that any distortions introduced are imperceptible, while maintaining robustness against common forms of degradation.

In previous studies, various watermarking techniques have been proposed for both document and natural images, using methods in spatial and transform domains. The advent and widespread use of the Internet have greatly increased the utilization of digital media. Digital images including pictures and text are widely used in applications such as digital libraries, which provide access to vast collections of stored data, and for transmission over the Internet or other communication networks. Many of the world's major libraries have also begun digitizing their collections and storing them digitally, as digital storage has proven to be more economical than producing and maintaining paper-based documents.

The watermark text extraction process is an important and challenging area of research in computer vision and machine learning. Watermarked text pixels typically differ from other text and background pixels. This article presents a novel model for detecting and extracting watermark content from documents. Figure 1 illustrates sample watermarked document images.

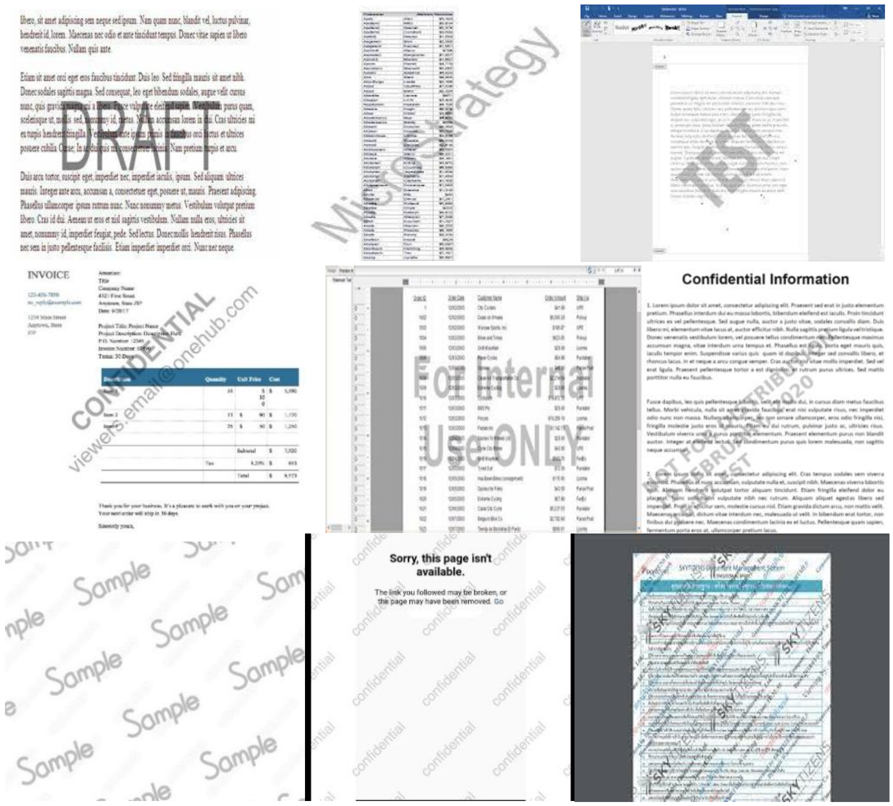


Figure 1: Sample images of watermark documents.

RELATED WORK

Although text watermarking is a crucial field for research, the existing literature on digital text watermarking is woefully deficient. Various text watermarking methods have been put out in the past. These include text watermarking with text images, methods based on synonyms, presuppositions, syntactic trees, noun-verb agreements, words and sentences, acronyms, and typographical errors.

Gong et al. [1] developed an adaptive visible watermarking method based on a two-phase Mamdani fuzzy inference system for watermarking text extraction in PDF documents. The grayscale uniform distribution and binary removal attack were used to remove watermarking. The method has higher performance in visible watermarking with less distortion and better visual effects. Singh and Sharma [2] applied zero watermarking for tamper detection in document images. The lifting wavelet transform is applied to transform the document image to obtain these sub-bands. The developed method combines watermarks with the key watermark method. The method is also used to localize the watermark area. Laouamer and Tayan [3] implemented a linear interpolation and non-blind watermark method for recovery, localization, and tamper detection. Stirmark-based attacks and random point-based attacks are used for sensitive documents. The method is able to localize and correct the tampered region with high accuracy. Tan et al. [4] developed a feature-based text image watermarking method for documents. The geometric invariant feature is evaluated based on a multiplicative transformation model. The invariant features of parity check to connect soft authentication were used to extract watermarking. Zenati et al. [5] used Binary Robust Invariant Scalable Key points of potential features for embedding position. The method combines cryptography and steganography for grayscale and color image watermarking. Brassil et al. [6,7] implemented a line-shift algorithm that moves a line upward or downward (left or right) based on watermark bit values. The method is able to withstand attacks in watermarking. Maxemchuk et al. [8–10] developed a word-shift algorithm that modifies the inter-word spaces to embed the watermark. The method combines cryptography and steganography for grayscale images.

Low et al. [11] proposed a feature coding algorithm in which certain text features are altered to encode watermark bits in the text. The method is able to correct the tampered region with high accuracy. Huang and Yan [12] developed an algorithm based on the average inter-word distance in each line. The distances are adjusted according to the sine wave of a specific phase and frequency. Amano and Misaki [13] used the feature and pixel-level algorithm for watermark text extraction. The method marks the documents by modifying the stroke features such as width or serif. Gamal Fahmy [14] introduced non-blind and quasi-blind methods for watermark text or logo extraction from images. This method does not require more information about host samples to extract the complete watermark information. READ coding is used by Palit and Garain [15] to compress the prototype library, and arithmetic coding is used to compress location (positional) information. Partial decompression of the document is required to get prototype information and the prototype library. TamilSelvan et al. [16] used an eigenvalue-based watermark generation concept for the validation and righteousness confirmation of watermark text documents. Tang and Wang [17] extracted the watermark text information by applying the inverse process of the watermark embedding technique. The method computes the binary information of the nearest Chinese characters by applying the eight-stroke concept. Barlaskar et al. [18] developed the watermark embedding and extraction method based on DWT and DCT approaches. The distortion correction methods are incorporated to overcome unauthorized attacks. Kim et al. [19] introduced a novel learning-based method for retrieving watermark synchronization based on CNN. Through the estimated watermark matrix, the watermark can be decoded. The cross-validation extraction technique is employed by Fang et al. [20] for a multiple watermark extraction process. The analysis of the method shows the robustness of the screen-shooting process.

Karki et al. [21] proposed a unique deep learning-based approach to embedding and extracting textual information from images utilizing Transformer-based architectures. This strategy improves data security and integrity by making the model more adaptable to individual image properties and potential threats. Krubinski et al. [22] introduced a novel benchmark, K-Watermark, containing 65,447 data samples generated using a watermark text pattern rendering procedure. They also developed an end-to-end solution (Wextract) for detecting bounding box instances of watermark text, introducing a variance minimization loss and a hierarchical self-attention mechanism. Lu et al. [23] developed an entropy-based detection method (EWD) that customizes the weight of each token during watermark detection according to its entropy. The approach is training-free and fully automated, achieving better detection performance in low-entropy scenarios. Munyer et al. [24] introduced a deep learning-driven text watermarking methodology for text source identification, particularly focusing on distinguishing between human-written and LLM-generated text. The approach demonstrates high imperceptibility, robustness, and detection accuracy. Liu et al. [25] presented a watermark recognition method for PDF documents utilizing NLP techniques. By collecting many PDF documents and employing an improved N-gram language model based on forward and reverse matching algorithms, the authors established a KenLM language model to identify watermarks in PDF documents. The proposed method effectively improves the accuracy of watermark recognition. Li et al. [26] proposed a method for modifying the edge pixels of text strokes in PDF documents to embed watermarks. This approach ensures that the watermark remains detectable even after the document is printed and scanned, addressing challenges in document authentication and copyright protection. Arabi et al. [27] presented SEAL, which embeds semantic information into watermarks, enabling distortion-free verification without a database of key patterns. It improves robustness against forgery attacks by conditioning watermark detection on the original image content. Zhuang Li [28] introduced a bipolar watermarking technique that splits generated text into positive and negative poles, enhancing detection without requiring additional computational resources or knowledge of the prompt. The method demonstrates effectiveness and compatibility with existing optimization techniques.

Singh et al. [29] developed a rule-based technique that utilizes the iText library to parse PDF files. Their method effectively extracts metadata and analyzes object structures, making it suitable for well-formatted digital documents. However, it is limited to detecting visible watermark text and does not perform well on scanned or image-based documents. To overcome these drawbacks, Chen et al. [30] applied Convolutional Neural Networks (CNNs) for watermark detection in image-rendered pages. This approach proved resilient to rotation, font variations, and other distortions, although it required a large set of labelled training data. In the pursuit of faster and more adaptable solutions, Liu et al. [31] adopted the YOLOv5 model for real-time watermark detection. Their system demonstrated strong accuracy and speed across a variety of document types and watermark styles. Shifting the focus from visual to textual watermarking, Munyer et al. [32] introduced DeepTextMark, a framework that embeds and detects invisible watermarks in LLM-generated text using Word2Vec representations, sentence encoding, and transformer-based classifiers.

Recent advancements have continued in this direction. Lu et al. [33] proposed an Entropy-based Watermark Detection (EWD) method that identifies AI-generated content without any model training, relying instead on entropy scores to detect low-entropy watermark patterns. Building upon this concept, Tianle Gu et al. [34] designed Invisible Entropy (IE), a compact yet highly accurate framework that significantly reduces model size while maintaining strong detection performance. Text watermarking has progressed from simple rule-based and geometric methods to advanced deep learning approaches. Modern models like CNN, Transformer, and YOLO achieve robust, real-time detection, while recent entropy- and semantic-based methods enhance accuracy and adaptability. However, developing a unified, lightweight framework for both visible and invisible watermarking remains a key future challenge. Hence, this article proposes a watermark text detection method using GMM, edge detection, and morphological processing. A four-component GMM models pixel intensities, followed by Canny edge detection, morphological closing, and Otsu's thresholding to isolate edges. The watermark is then embedded by modifying pixel values in a defined region.

PROPOSED METHODOLOGY

The watermark text extraction process is an important task due to its wide variety of applications in the field of image processing. It helps to identify forged documents and provides information about the owner of the documents. Hence, the watermark text extraction process is a demanding research area. In this research work, the watermark text image is taken as input and then converted into 2D gray-level information. The Gaussian Mixture Model helps to distinguish the watermark text information from other regions of the image and predicts the cluster labels for each pixel in the gray-level information. To retain the boundary region of the actual watermark text, the canny edge detector is applied, and morphological functions are performed to obtain accurate edge information. Finally, Otsu's thresholding is used to obtain the binarized information of the watermark text regions in the image. The algorithm of the proposed method is represented below, and the flow diagram is depicted in Figure 2.

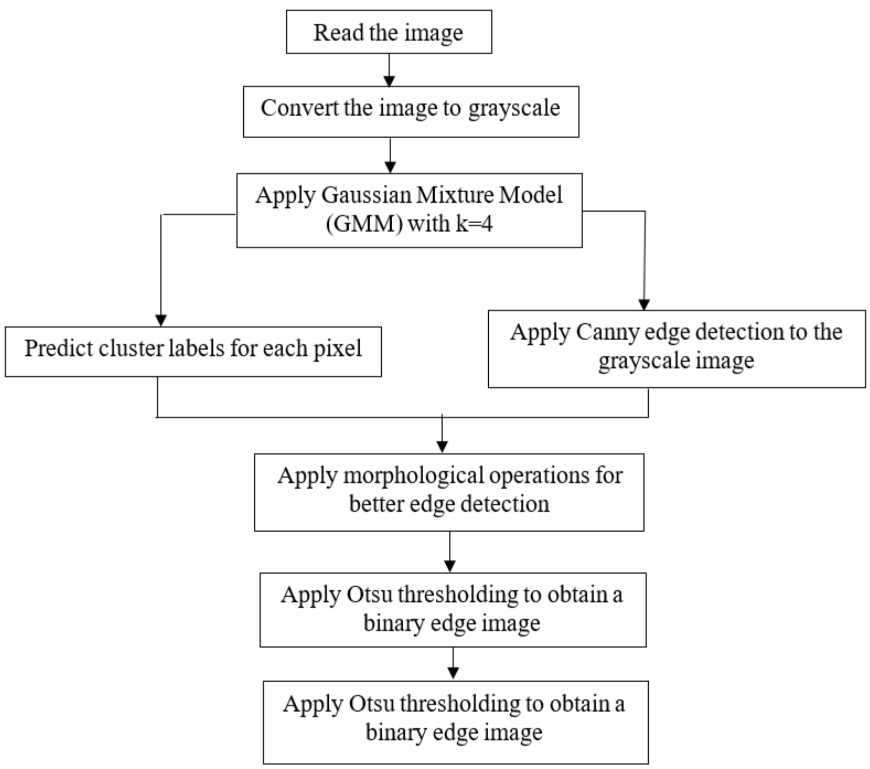


Figure 2: Flow diagram of the proposed methodology

Workflow of the Proposed Methodology

The input image I(x, y) is a color image represented by its red, green, and blue channels. To reduce computational complexity and emphasize intensity-based features, the color image is first converted into a grayscale image G(x, y) using a weighted sum. A Gaussian Mixture Model (GMM) is applied to the grayscale intensities, modelling the pixel distribution as a mixture of k = 4 Gaussian components, where ω_i are the component weights, and μ_i and σ_i^2 are the mean and variance of the ***i***th Gaussian. Each pixel is assigned to a cluster by computing the posterior probability of each component and selecting the one with the highest value. After clustering, edge detection is performed on the grayscale image using the Canny method. The image gradients Gx and Gy are computed with magnitude and direction. Edges are thinned via non-maximum suppression, and the final edge pixels are determined using double thresholding with edge tracking by hysteresis, resulting in a binary edge map C(x, y). The cleaned edge image C(x, y) is then binarized using Otsu's thresholding, which selects an optimal threshold T to minimize intra-class variance. Finally, the watermark text Iout(x, y) is separated from the given document image by modifying pixel values within a predefined text region.

Gaussian Mixture Model

A Gaussian Mixture Model (GMM) [38] is a parametric probability density function represented as a weighted sum of Gaussian component densities. GMMs are commonly used as a parametric model of the probability distribution of continuous measurements or features. Watermark text extraction from images using a Gaussian Mixture Model (GMM) relies on modelling the pixel intensity distribution of the image as a mixture of multiple Gaussian components. Typically, in a grayscale document image, text regions and background regions have distinct intensity characteristics. The GMM models the overall intensity histogram as a weighted sum of Gaussian distributions. The pixel is then assigned to the class with the highest posterior probability. In the context of watermark text extraction, pixels assigned to the Gaussian component with the lower mean are typically considered part of the watermark text. The resulting binary mask can be refined using morphological operations and connected component analysis to remove noise and isolate watermark textual regions.

$$P(G) = (x + a)^n = \sum_{i=1}^{4} w_i \, N(G \mid \mu_i, \sigma_i^2) \tag{1}$$

Equation 1 represents a Gaussian Mixture Model (GMM) applied to the grayscale pixel intensities G of an image, using 4 clusters. It models the overall probability distribution of pixel intensities as a weighted sum of 4 Gaussian distributions. Where $P(G)$ is the overall probability density function for a given grayscale. w_i represents the weights of the component. N is the Normal distribution. μ_iIndicated as mean and σ depicted the variance.

Canny Edge Detector for Text Edge Components

The Canny edge detector is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges in images. Canny edge detection is a technique to extract useful structural information from different vision objects and dramatically reduce the amount of data to be processed. Canny has found that the requirements for the application of edge detection on diverse vision systems are relatively similar. Thus, an edge detection solution to address these requirements can be implemented in a wide range of situations. Edge detection is a process that involves mathematical methods to find points in an image where the brightness of pixel intensities clearly changes, or we can say that it is an image processing technique for finding the boundaries of objects within images.

Canny edge detection can be a useful tool in the process of watermark detection, particularly when the watermark introduces visible changes in the structure of an image. This method works by identifying areas of rapid intensity change, which often correspond to the edges of text or logos used in watermarks. The process begins by smoothing the input image I(x,y) using a Gaussian filter. This step minimizes the influence of noise, making the actual edges such as those formed by watermark text more prominent. The image gradients in horizontal and vertical directions $G_{x(x,y)}$ and $G_{y(x,y)}$ [Equation 2] are computed to capture changes in intensity. These gradients are then used to calculate the gradient magnitude $M(x, y)$ [Equation 3] representing edge strength, and the gradient direction $\theta(x, y)$ [Equation 4] indicating the orientation of the edge.

$$G_{x(x,y)} = \frac{\delta G}{\delta x}, G_{y(x,y)} = \frac{\delta G}{\delta y} \quad (2)$$

$$M(x, y) = \sqrt{\left\{G_x^{2(x,y)} + G_y^{2(x,y)}\right\}} \quad (3)$$

$$\theta(x, y) = tan^{-1}\left(\frac{G_{y(x,y)}}{G_{x(x,y)}}\right) \quad (4)$$

Morphological operations and Otsu Thresholding

Morphological Operations is a broad set of image processing operations that process digital images based on their shapes. In a morphological operation, each image pixel corresponds to the value of other pixels in its neighborhood. By choosing the shape and size of the neighborhood pixel. Morphological operations apply a structuring element to an input image, creating an output image of the same size.

$$C(x, y) = (E \oplus B) \ominus B \quad (5)$$

The equation 5 represents a morphological closing operation, commonly used in image processing to refine edge maps, especially when dealing with faint or broken edges like those in watermark text. The operation begins with dilation ($E \oplus B$), where the edge map E is expanded using a structuring element B. This step helps to fill in small gaps or breaks in the detected edges, which can occur when the watermark text is semi-transparent or faint. After dilation, erosion ($(E \oplus B) \ominus B$) is applied to shrink the edges back to their original size but ensures that any gaps between them remain filled. The result is a cleaner, more continuous edge representation, which is especially useful for detecting watermark text. By connecting fragmented edges and smoothing irregularities, morphological closing helps make the watermark text more recognizable and easier to isolate from the rest of the image.

Algorithm:

1 Read the input image I(x, y).

$$I(x, y) = \left[I_{R(x,y)}, I_{G(x,y)}, I_{B(x,y)}\right]$$

2 Convert the color image to grayscale G(x, y).

$$G(x,y) = 0.2989 \cdot I_{R(x,y)} + 0.5870 \cdot I_{G(x,y)} + 0.1140 \cdot I_{B(x,y)}$$

3 Apply Gaussian Mixture Model (GMM) clustering with a specified number of clusters (k=4).

$$P(G) = (x+a)^n = \sum_{i=1}^{4} w_i N(G \mid \mu_i, \sigma_i^2)$$

4 Predict cluster labels for each pixel in the grayscale image with posterior probability for each pixel.

$$\gamma_{i(G(x,y))} = \frac{w_i . N(G(x,y)/\mu_i, \sigma_i^2}{\sum_{j=1}^{4} w_i N(G \mid \mu_i, \sigma_i^2)}$$

$$Cluster_{labels}(x,y) = argmax \gamma_i G(x,y))$$

5 Apply Canny edge detection to the grayscale image.

$$G_{x(x,y)} = \frac{\delta G}{\delta x}, G_{y(x,y)} = \frac{\delta G}{\delta y}$$

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

$$\theta(x,y) = tan^{-1}\left(\frac{G_{y(x,y)}}{G_{x(x,y)}}\right)$$

6 Perform morphological closing to the detected edges.

$$C(x,y)=(E \oplus B) \ominus B$$

7 Otsu thresholding to obtain a binary edge image.

$$\sigma_w^2(T) = \omega_1(T) \cdot \sigma_1^2(T) + \omega_2(T) \cdot \sigma_2^2(T)$$

8 Output of watermark text.

$$I_{out}(x,y) = \begin{cases} WatermarkTextIfC(x,y) > T \\ NonWatermarkOtherwise \end{cases}$$

EXPERIMENTAL ANALYSIS

An experiment has been conducted on watermarked document images to analyze the performance of the presented watermark text extraction model. The dataset was collected by capturing watermarked PDF documents, and some watermark text samples were gathered from Google. The collected dataset contains several challenges, such as variations in color, size, contrast, and orientation. The max-min clustering approach helps to increase the gap between watermark text pixels and background pixels. Finally, heuristic rules are employed to identify the actual watermark text pixels from the given input samples, and intermediate results are shown in Figure 3.

A Gaussian Mixture Model (GMM) is then applied to segment different regions in the grayscale image, helping isolate potential watermark patterns based on pixel intensity distribution. Next, Canny edge detection is performed to capture fine edges and outlines that may belong to embedded watermarks. The resulting edges are refined using morphological closing, which fills small gaps and connects broken watermark structures. This cleaned edge map is then used to generate a masked image that highlights the potential watermark areas. The output images are shown in Figures 4 and 5, respectively.

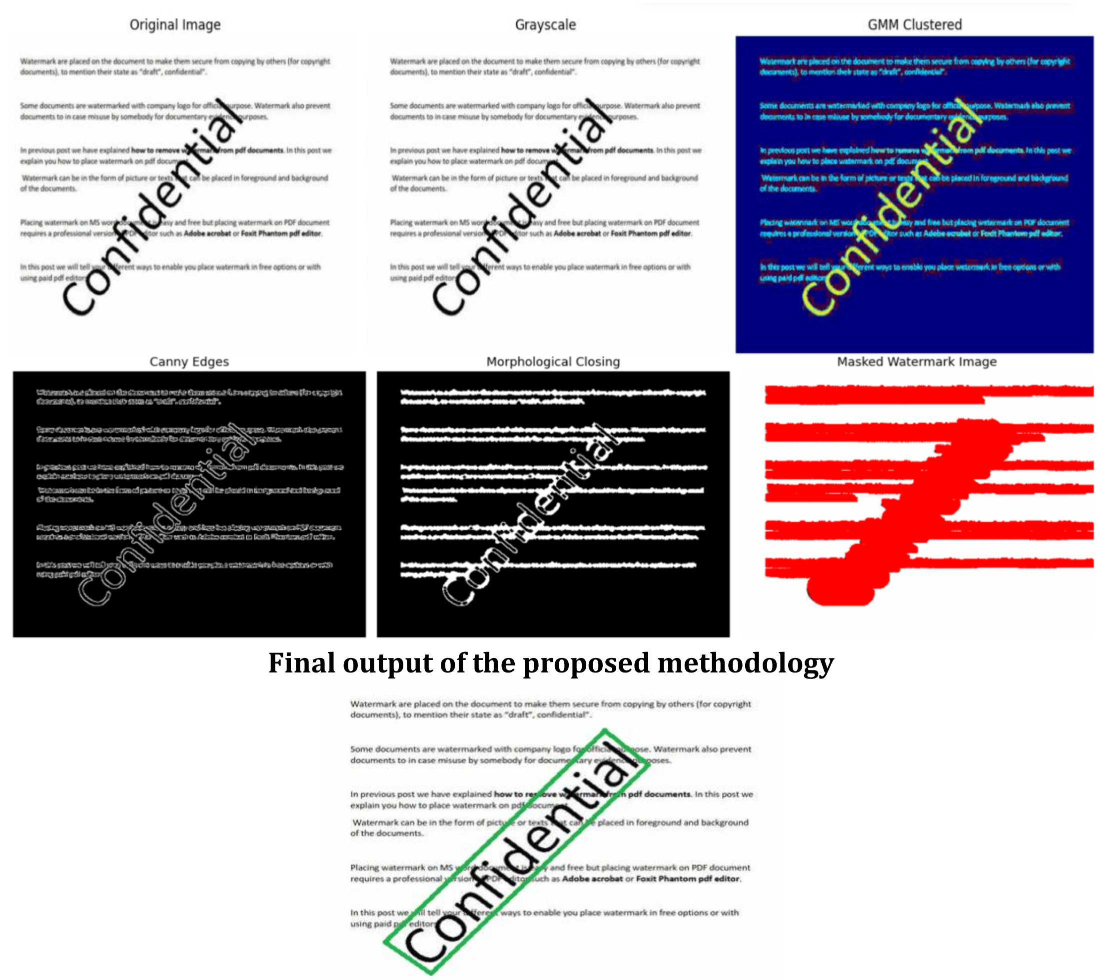
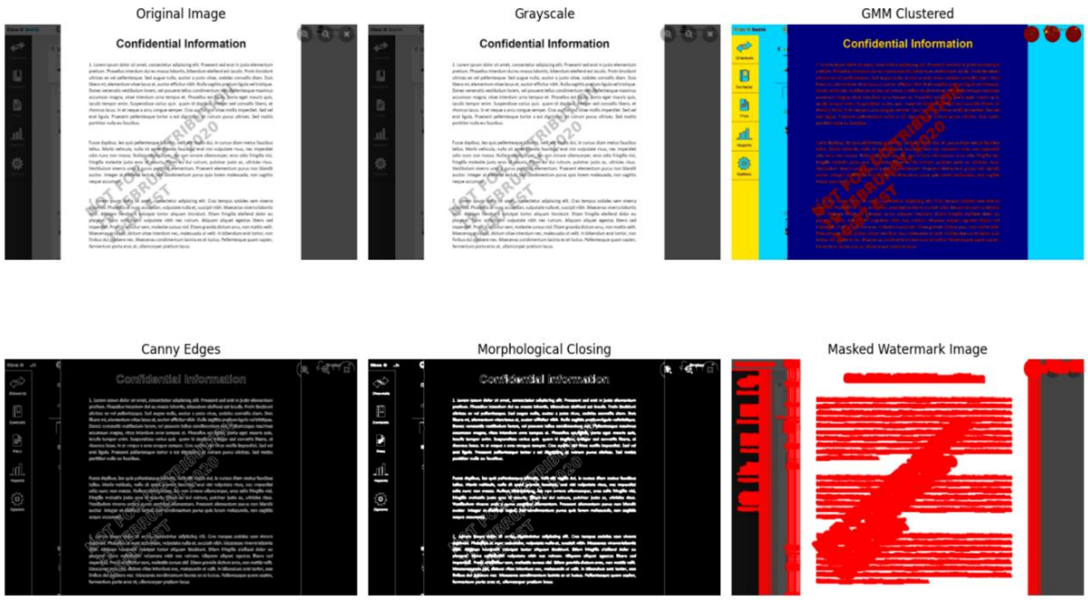


Figure 3: Stepwise intermediate results of the proposed methodology for single oriented text



Final output of the proposed methodology

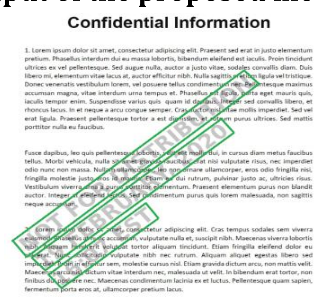
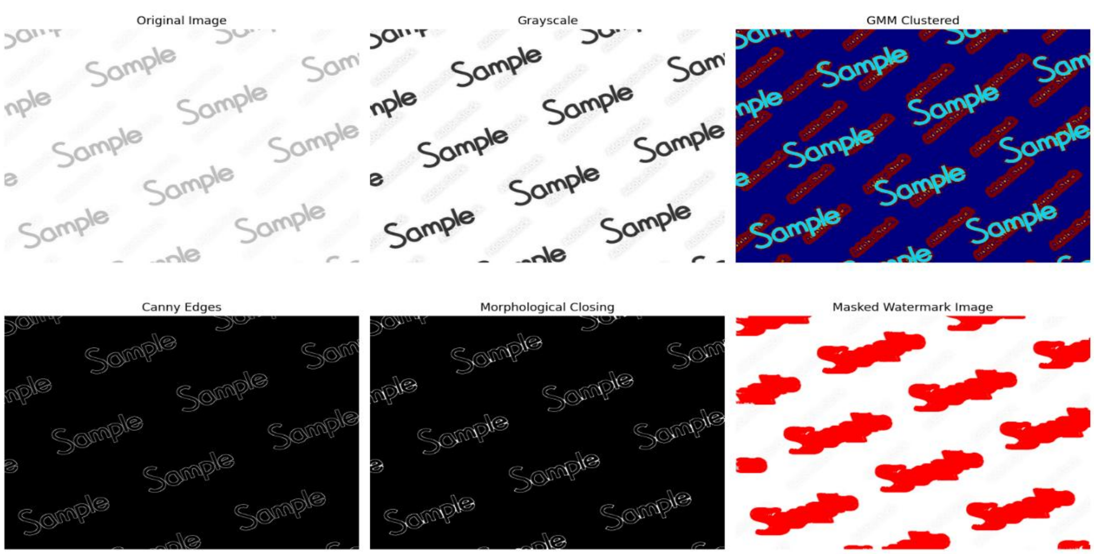


Figure 4: Stepwise intermediate results of the proposed methodology for multiple line oriented text



Final output of the proposed methodology

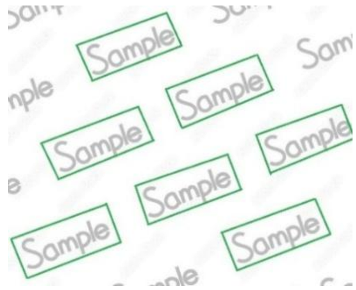


Figure 5: Stepwise intermediate results of the proposed methodology for multiple watermark texts

Metrics Used for Evaluation of the Proposed Model

The efficiency of the suggested method is evaluated by considering measurements such as precision, recall, and F1-score. The main factors that need to be analyzed to calculate these measurements are as follows:

- **Actual Watermark Text Information (AWTI):** It considers all watermark text information present in the given input.
- **Truly Detected Watermark Text Information (TDWTI):** It includes only the watermark text information identified by the proposed algorithm.
- **Falsely Detected Watermark Text Information (FDWTI):** It represents non-watermark text information that is incorrectly identified as watermark text information.

From the above parameters, namely AWTI, TDWTI, and FDWTI, precision is calculated as shown in Equation 1, recall is calculated as in Equation 2, and F1-score is calculated as represented in Equation 3. The max-min cluster effectively separates the watermark text pixel region from the background pixel region. The proposed model achieves 84.21% precision, 91% recall, and 87.47% F1-score. A sample output of the proposed model is shown in Figure 6.

$$Precision = \frac{TDWTI + FDWTI}{AWTI} \tag{1}$$

$$Recall = \frac{TDWTI}{AWTI} \tag{2}$$

$$f1 - Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{3}$$

Sample Outcomes of the Proposed Model

The proposed watermark text detection model effectively identifies and locates watermark text embedded within digital images. The model successfully detects the presence of the watermark and outputs the coordinates of the bounding box surrounding the watermark text. The proposed watermark text detection model demonstrates strong potential in accurately identifying and localizing watermark text within digital images. By leveraging deep learning techniques and OCR integration, the model is capable of detecting subtle, low-contrast watermark texts with high precision. Figure 4 represents some of the sample outcomes of the proposed model.

Figure 6: Sample outcomes of the watermark text detection model

Comparative Analysis with Proposed Model

The comparative analysis of watermark text detection methods reveals a clear progression in technique sophistication, tailored to meet the increasing complexity of digital document formats. The comparative analysis is shown in Table 1.

Table 1: Comparative analysis of the proposed methodology with existing methods

Methods	Precision	Recall	f1-score
Otsu + Morphology [35]	65.3	78.9	71.4
Canny + Hough Transform [36]	59.2	72.4	65.0
OCR + Heuristics [37]	70.5	62.1	66.0
Proposed Methodology	**84.21**	**91**	**87.47**

Table 1 represents a comparative analysis, which demonstrates that the proposed methodology achieves the best overall performance in watermark detection, with the highest levels of precision, recall, and F1-score among the evaluated methods. Otsu combined with morphological operations [35] shows strong recall, indicating that it detects most watermarks, but its precision is moderate due to a higher rate of false positives. Canny with Hough Transform [36] performs less effectively overall, struggling to accurately differentiate watermarks from background features. The OCR with heuristic filtering method provides better precision, correctly identifying watermark regions more selectively, but it often misses subtler instances, resulting in lower recall. In contrast, the proposed approach maintains both high accuracy and consistency, making it the most reliable and robust technique for watermark text detection.

CONCLUSION AND FUTURE WORK

The extraction of watermark text is an important task due to the vast range of applications in the field of image processing. Watermark text detection was effectively achieved by integrating Gaussian Mixture Models (GMM), canny edge detection, and morphological operations. The GMM technique allowed for robust segmentation of image regions based on pixel intensity distribution, which proved essential in distinguishing watermark areas from the background. The Canny edge detection algorithm contributed by accurately capturing the contours and edges of watermark text, even in low-contrast scenarios. Morphological operations further refined the output by eliminating noise and enhancing the structure of the detected watermark, facilitating clearer separation and detection. Finally, Otsu thresholding is utilized to obtain binarized information from the image's watermark text sections. Overall, this hybrid approach provides a reliable and computationally efficient framework for watermark text detection, with potential applications in document authentication, copyright protection, and digital forensics. In future work, the extraction technique needs to be robust for degraded watermark text images. Probabilistic-based models and adaptive thresholding methods may also be explored to make the system more resilient to varying lighting conditions and image quality.

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