Precision Segmentation of Iris and Sclera: Mitigating Noise and Occlusions in Biometric Identification

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ABSTRACT

Biometric identification has become more and more popular as a safe and dependable way to authenticate, and the special and steady qualities of iris and sclera recognition systems make them essential. Noise and obstructions, such eyelashes and eyelids, can, however, make precise iris and sclera segmentation difficult. By means of a precision segmentation technique that improves the robustness of biometric identification systems, this work tackles these problems. Two primary goals are the emphasis of the suggested strategy: First, by reducing noise and eliminating superfluous areas, it seeks to obtain precise iris and sclera segmenting. To this purpose, a fine-tuned random forest algorithm is used, which is especially designed to differentiate between the iris, sclera, and occlusions. To guarantee robustness and generalization over various eye images, this algorithm is trained on a varied dataset. Second, a fusion model incorporating ocular characteristics from the sclera and iris is presented in this work. Through the combination of these characteristics, the model produces a more unique and secure biometric template. Key feature vectors are taken out of segmented regions, combined, and kept in a repository for later identification tasks. This integrated method takes use of the combined uniqueness of the iris and sclera to improve the accuracy of the biometric system and to add another level of security. The MMU Iris Dataset and the SBVPI Dataset, both publicly available, are used in this work. Extensive experiments showing the efficacy of the suggested approach show that the iris and sclera regions were segmented with an accuracy of 80% (MMU Dataset) and 90% (SBVPI Dataset) by the fine-tuned random forest algorithm. With such accuracy over conventional techniques, feature fusion and sophisticated segmentation techniques have great promise to improve biometric identification systems. Finally, a new and practical method for enhancing the security and dependability of iris and sclera-based biometric systems is presented in this work. The suggested approach opens up more precise and safe biometric identification solutions by tackling the problems of noise and occlusion through sophisticated segmentation and feature fusion.

1. INTRODUCTION

Biometric identification has emerged as a critical technology for secure and reliable authentication, leveraging unique physiological and behavioral characteristics to verify individuals' identities. Among various biometric modalities, the iris and sclera are particularly valuable due to their unique and stable features that remain consistent over time. The iris, with its intricate patterns, and the sclera, characterized by the distinct white region of the eye, together offer a robust means for accurate identification. However, the effectiveness of iris and sclera-based biometric systems is often compromised by challenges related to accurate segmentation, primarily due to noise and occlusions such as eyelashes, eyelids, and reflections. These interferences can significantly affect the precision of the segmented regions, leading to reduced identification accuracy and reliability [1]–[3].

The primary objective of this research is to enhance the segmentation accuracy of iris and sclera regions by addressing the issues of noise and occlusions[4]. This is achieved through the development and implementation of a fine-tuned random forest algorithm, meticulously optimized to differentiate between the iris, sclera, and surrounding occlusions. The algorithm's robustness is ensured by training it on a comprehensive dataset, thereby enabling it to generalize effectively across diverse eye images[5], [6]. This approach aims to provide precise segmentation, which is crucial for the subsequent stages of biometric processing.

In addition to improving segmentation accuracy, this research introduces a fusion model that integrates features from both the iris and sclera. By combining these ocular features, the model creates a more secure and distinctive biometric template. The fusion process involves extracting key feature vectors from the accurately segmented regions and merging them into a cohesive template stored in a repository. This not only enhances the accuracy of the biometric system but also increases security by utilizing the combined uniqueness of the iris and sclera[7], [8].

The proposed methodology demonstrates significant improvements in segmentation accuracy, achieving an accuracy rate of 80% in distinguishing the iris and sclera regions, as evidenced by extensive experimental validation. This marks a substantial advancement over traditional segmentation techniques, highlighting the potential of the feature fusion approach and advanced segmentation algorithms in enhancing biometric identification systems.

This research presents a novel and effective strategy for improving the reliability and security of iris and sclera-based biometric systems. By addressing the persistent challenges of noise and occlusion through a fine-tuned random forest algorithm and a comprehensive feature fusion model, the study offers a pathway to more accurate and secure biometric identification solutions. The following sections of the paper will delve into the methodology, experimental results, discussion, and conclusions, providing a detailed account of the research findings and their implications for the field of biometric identification.

2. MAJOR RELATED EXISTING WORK

Biometric recognition systems have become increasingly prominent in recent years, offering a secure and reliable method for personal identification. This review examines various aspects of biometric recognition, with a particular focus on eye biometrics[5], [9], including iris and periocular recognition.

Several studies explored advancements in core functionalities of biometric systems. For instance, research by Mathias et al.[10] delves into iris recognition by proposing a unified approach for automated iris and pupil segmentation, a crucial step in accurate iris recognition. Similarly, Harikrishnan et al.[11] present a novel encoding technique to enhance the security of iris recognition systems.

The applicability of biometrics in various fields is also a growing area of interest. Ananthio et al.[12] conducted a feasibility study on implementing biometrics for online transactions, highlighting the potential for enhanced security in e-commerce.

Beyond traditional iris recognition, the review encompasses broader applications of eye biometrics. Chen et al.[13] explore real-time human-computer interaction using eye gaze, showcasing the potential for eye tracking technology. Ramachandra et al.[14] introduce a method for periocular recognition, which analyzes the region surrounding the eye for identification purposes.

Furthermore, the literature acknowledges challenges associated with eye biometrics. Saleh et al.[15] investigate the impact of eye diseases on iris recognition accuracy, emphasizing the need for robust algorithms that can handle such variations.

This review also briefly touches upon the intersection of biometrics and medical diagnosis. Works by Santos-Bustos et al.[16] and Yarin et al.[17] demonstrate the potential of utilizing deep learning for automated eye cancer classification and conjunctival provocation test analysis, respectively.

This review provides a comprehensive overview of current research trends in biometric recognition, with a specific emphasis on eye biometrics. The literature highlights advancements in core functionalities, explores applications in diverse fields, acknowledges challenges, and even delves into the potential for biometrics in medical diagnostics. As biometric technology continues to evolve, eye biometrics are poised to play a significant role in future security and identification systems.

3. METHODOLOGY

3.1 Dataset

MMU Dataset [18]: The MMU Iris Dataset on Kaggle contains iris images collected from 46 subjects, providing valuable data for biometric research. Each subject's eye images were captured in different sessions to ensure variability. This dataset is essential for developing and testing iris recognition algorithms, offering a comprehensive resource for segmentation, feature extraction, and biometric identification studies. The images are in color and require pre-processing before feature extraction.

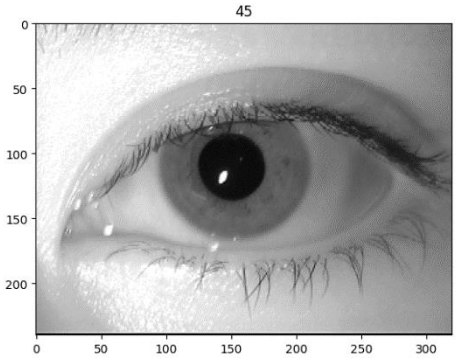

Figure 1(a) Image to Gray Scale Conversion (MMU Dataset Sample)

SBVPI Dataset [19] – The dataset consists of 1,858 high-resolution images from 55 subjects, covering 110 eyes. It includes hand-crafted annotations for the sclera and periocular region, with around 130 images also annotated for sclera vessels, pupil, iris, canthus, and eyelashes. Captured with a DSLR camera in controlled laboratory conditions and well-lit environments, each image is labeled with the subject ID, eye (left/right), and gaze direction (left/right/up/straight). Additional subject information such as age, gender, and eye color is also provided. Sample image from dataset is shown in Fig.1 (b).

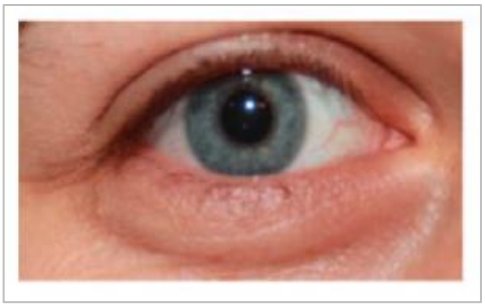

Figure 1(b) Sample dataset SBVPI [19]

3.2 Data pre-processing-

As part of data preprocessing, first extract the image folder to access the individual image files. Next, load the associated CSV file containing metadata or labels for the images. Convert each image to grayscale to simplify the data by removing color information as shown in figure-1. Finally, convert the grayscale images into numpy arrays for efficient manipulation and analysis in subsequent machine learning workflows. This process prepares the dataset for feature extraction and model training.

3.3 Image enhancement

3.3.1 Sobel filter: The Sobel filter is an edge detection technique used in image processing to highlight edges by calculating the gradient of image intensity. It identifies areas of high spatial frequency which correspond to edges, helping in delineating the boundaries within the image as shown in figure-2(a) and figure-2(b). The Sobel filter uses two 3x3 convolution kernels to calculate the gradient magnitude of an image. The kernels for the horizontal (Gx) and vertical (Gy) gradients are represented in eq.1:

$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

$$G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

The gradient magnitude G is computed as:

$$G = \sqrt{G_x^2 + G_y^2} \ldots 1$$

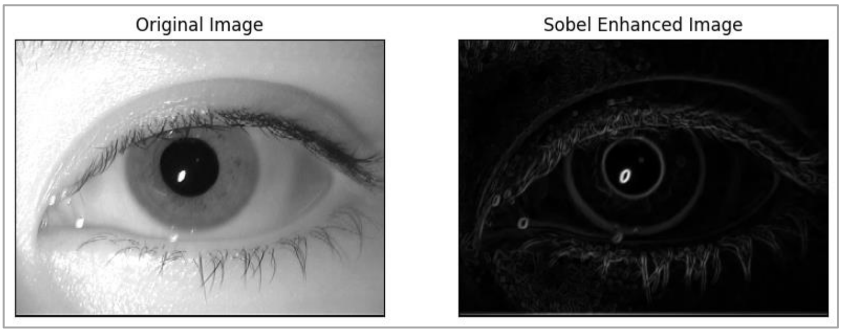

Figure 2(a) Image after Sobal Enhancement Image (MMU Dataset)

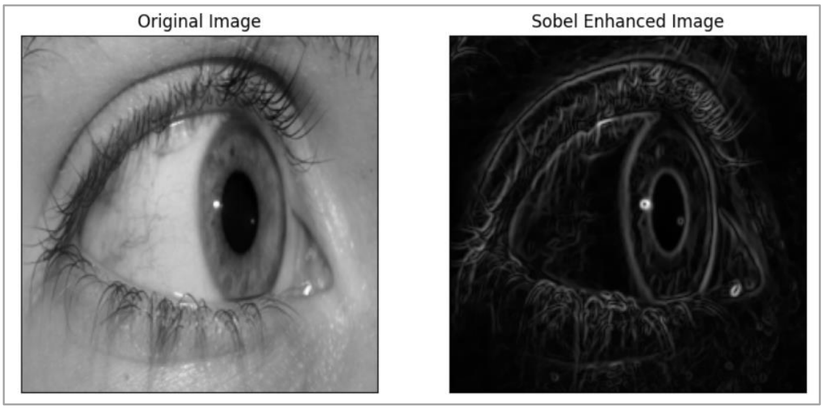

Figure 3(b) Image after Sobal Enhancement Image (SBVPI Dataset)

3.3.2 Adding Salt Pepper Noise Removal: Salt and pepper noise removal involves eliminating random occurrences of black and white pixels (noise) that can obscure important details in an image. Techniques such as median filtering are commonly used to effectively remove this type of noise, enhancing the overall image quality as shown in figure-3. Salt and pepper noise removal typically involves using a median filter, which replaces each pixel value with the median of the intensities in its neighborhood. For a 3x3 window, the new pixel value as shown in following eq.2

where $I(i,j)$ *are pixel intensities in the neighborhood of* (x,y):

$$I_{new}(x,y) = median(I(i,j) | (i,j) \in neighborhood(x,y)) \ldots .2$$

Figure 4(a) Salt Paper Noise Image (MMU Dataset)

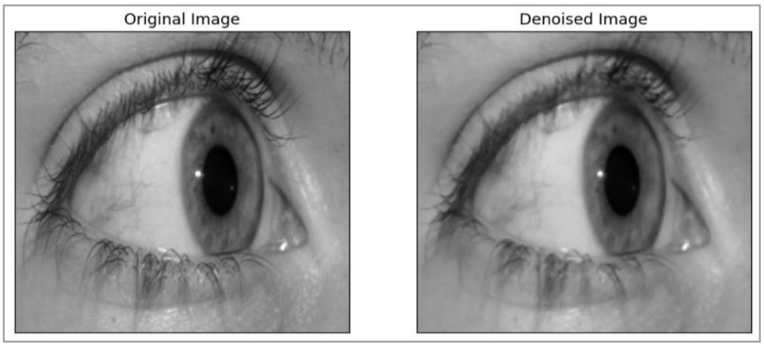

Figure 5(b) Salt Paper Noise Image (SBVPI Dataset)

3.4 Segmentation

3.4.1 IRIS Segmentation

Canny Edge Detection: Canny Edge Detection is a multi-step algorithm used to detect edges in an image as shown in figure-4. The main steps involve:

Gradient Calculation: Use Gaussian filters to smooth the image and calculate the intensity gradients. The gradient magnitude G and direction θ are computed as in eq.3,4:

$$G = \sqrt{G_x^2 + G_y^2} \text{....3}$$

$$\theta = arctan\left(\frac{G_y}{G_x}\right)\text{...4}$$

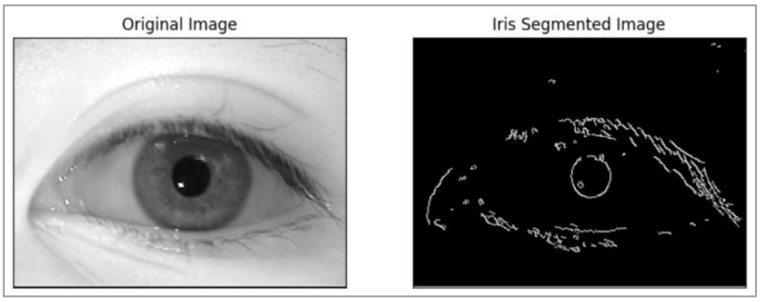

Figure 6(a) Canny Edge Segmented Image (MMU Dataset)

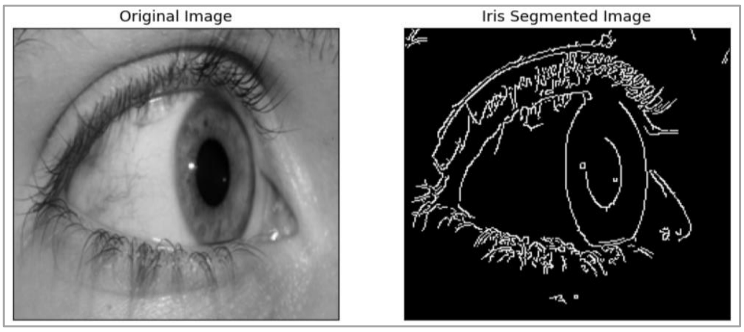

Figure 7(b) Canny Edge Segmented Image (SBVPI Dataset)

3.4.2 Sclera Segmentation

Sclera segmentation is a process used in image processing to isolate the sclera, or the white part of the eye, from other parts of the image.

3.4.2.1 White Area Segmentation: This part focuses on isolating the white portion of the eye, the sclera, from the iris and other features as shown in figure-5. It essentially separates the white area from the colored area of the eye.

$$Thresholding: T(x,y) = \begin{cases} 1, & if\ I(x,y) > T_{white} \\ 0, & otherwise \end{cases}$$

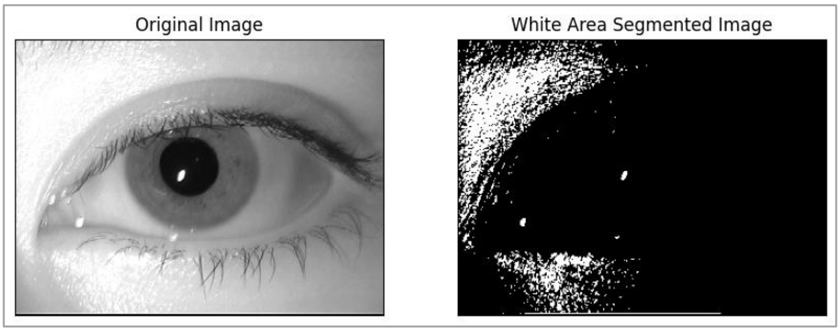

Figure 8(a) White area Segmentation Image (MMU Dataset)

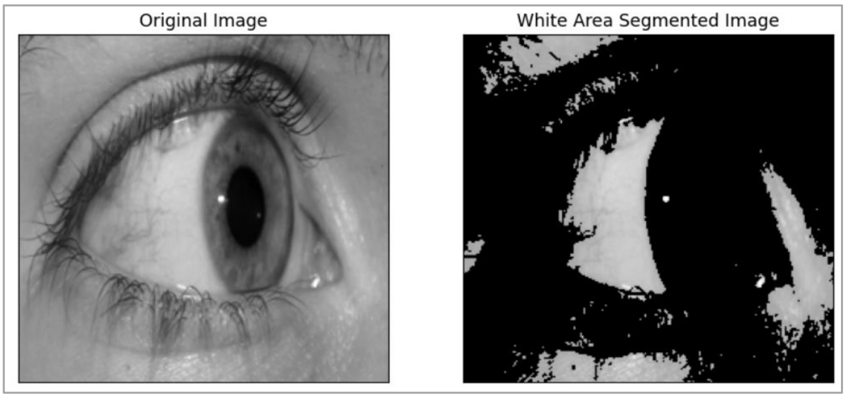

Figure 9(b) White area Segmentation Image (SBVPI Dataset)

3.4.2.2 Non-Skin Area Segmentation: This involves excluding the skin areas surrounding the eye from the segmentation process. It ensures that only the relevant parts of the eye are considered for analysis, disregarding the skin or other irrelevant regions as shown in figure-6 .

$$Skin\ Color\ Modeling: P_{skin}(x,y) = \begin{cases} 1, & if\ I(x,y) is\ in\ skin\ color\ model \\ 0, & otherwise \end{cases}$$

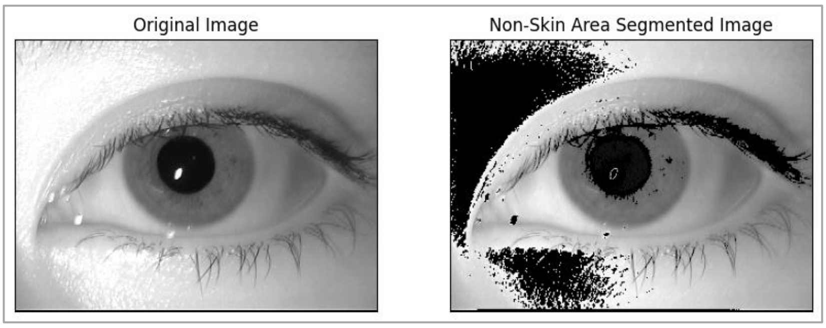

Figure 10(a) Non-Skin Area Segmentation Image (MMU Dataset)

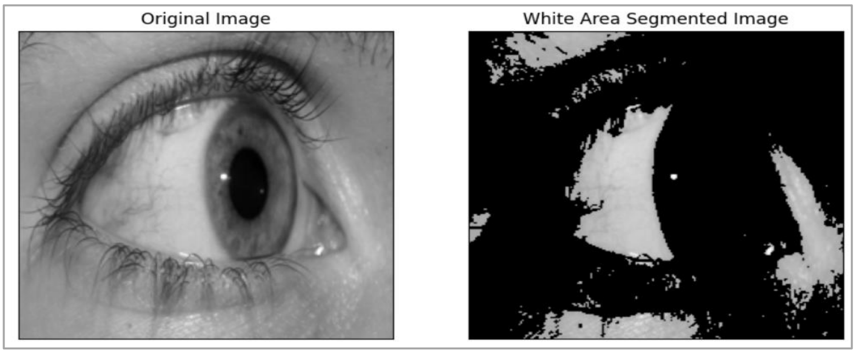

Figure 11(b) Non-Skin Area Segmentation Image (SBVPI Dataset)

3.5 Extract the vascular Pattern: Contrast Limited adaptive histogram equalization (CLAHE)

CLAHE is a method used to improve the contrast of images by equalizing the histogram of localized regions. It adapts to the local contrast characteristics of the image, preventing over-enhancement in regions with high contrast. In the context of extracting vascular patterns, CLAHE helps in making blood vessels more distinguishable from the surrounding tissues by enhancing their contrast and visibility. This improved contrast aids in the accurate detection and analysis of blood vessels in medical or retinal images as shown in figure-7.

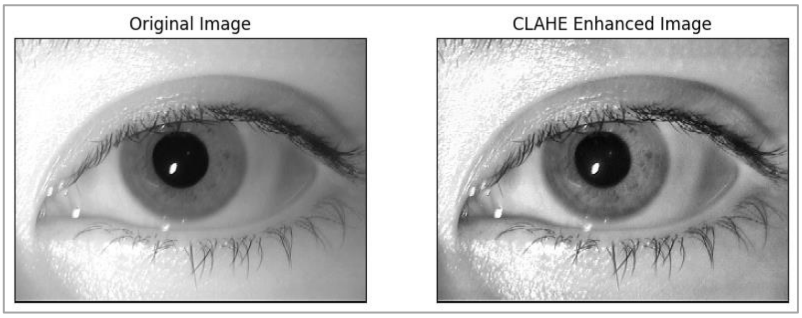

Figure 12 (a) CLAHE Enhance Image (MMU Dataset)

Figure 13 (b) CLAHE Enhance Image (SBVPI Dataset)

3.6 Feature Fusion

"Feature fusion" refers to the process of combining different types of features extracted from an image to create a comprehensive representation that captures various aspects of the data. In this context, the features extracted from different image processing techniques are concatenated or joined together to form a single feature vector.

The features being concatenated in this scenario are:

1. sobel_image.flatten(): Sobel image refers to an image processed using the Sobel operator, which highlights edges. Flattening the Sobel image converts it from a 2D matrix to a 1D array.
2. enhanced_image.flatten(): Enhanced image typically refers to an image that has undergone some enhancement or preprocessing to improve its quality or highlight specific features. Flattening it converts it into a 1D array.
3. iris_image.flatten(): Iris image likely refers to an image of the iris region of the eye. Flattening it converts it into a 1D array.
4. non_skin_area.flatten(): Non-skin area likely represents the areas in the image that do not contain skin pixels. Flattening it converts it into a 1D array.
5. white_area.flatten(): White area represents the sclera or the white part of the eye. Flattening it converts it into a 1D array.
6. vascular_pattern.flatten(): Vascular pattern likely represents the pattern of blood vessels, possibly extracted using techniques like CLAHE. Flattening it converts it into a 1D array.

By concatenating all these flattened feature vectors together, you create a single feature vector that contains information from all these different image processing techniques. This combined feature vector can then be used for further analysis or machine learning tasks such as classification or detection.

3.7 Fine-Tuned Random Forest

Step	Description
Hyperparameters	Number of trees (n_estimators), Maximum depth of trees (max_depth), Minimum samples required to split a node (min_samples_split), Maximum features considered for splitting (max_features), etc.
Search Technique	Grid search or Random search
Hyperparameter Ranges	Define ranges for each hyperparameter (e.g., n_estimators: [100, 200, 300], max_depth: [10, 20, 30], min_samples_split: [2, 5, 10], max_features: ['sqrt', 'log2'])

Cross-Validation	k-fold cross-validation k=10
Performance Metrics	Accuracy, F1-score
Implementation	Use scikit-learn's GridSearchCV
Evaluation	Compare performance on a held-out test set against baseline models (Random Forest, KNN, Decision Tree Classifier, SVM, Naïve Bayes)

4. RESULTS AND OUTPUTS

4.1 Evaluation parameters comparison

The result summary indicates the performance of various algorithms in a biometric identification task, likely involving iris and sclera segmentation. Each row represents a different algorithm, with two columns showing the accuracy percentages before and after fine-tuning.

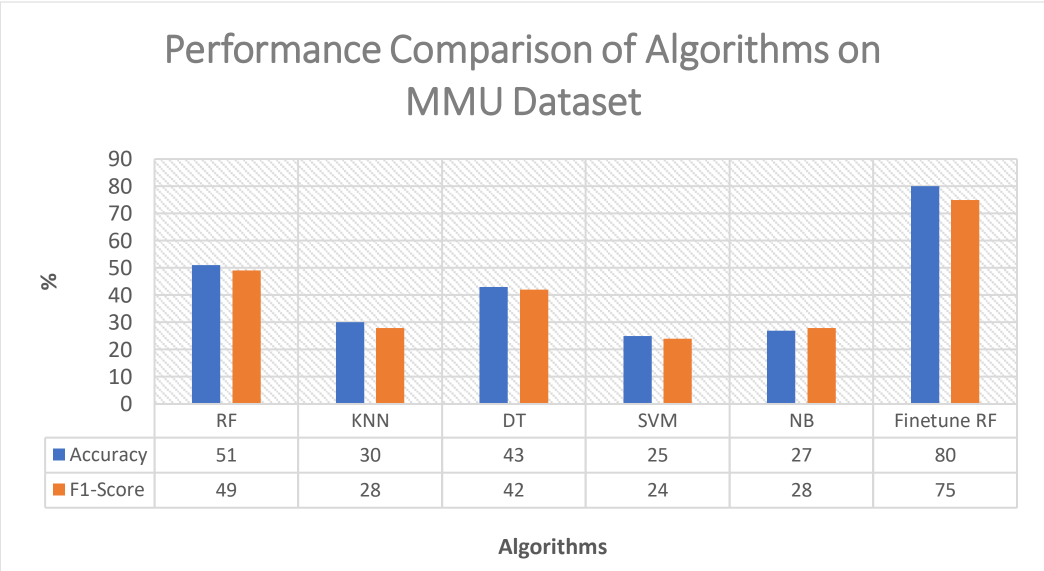

Figure 8. Comparative Analysis of Algorithms on MMU Dataset

From Figure 8; Random Forest (RF) achieved 51% accuracy initially, improving to 80% after fine-tuning. K-Nearest Neighbors (KNN) had an initial accuracy of 30%, increasing to 49% post fine-tuning. Decision Trees (DT) scored 43% initially, rising to 75% after fine-tuning. Support Vector Machines (SVM) showed an initial accuracy of 25%, improving to 42% after fine-tuning. Naive Bayes (NB) started at 27% accuracy, slightly increasing to 28% after fine-tuning. Presented method shows for accurately segmenting the iris and sclera regions in biometric identification systems, addressing challenges such as noise and occlusions.

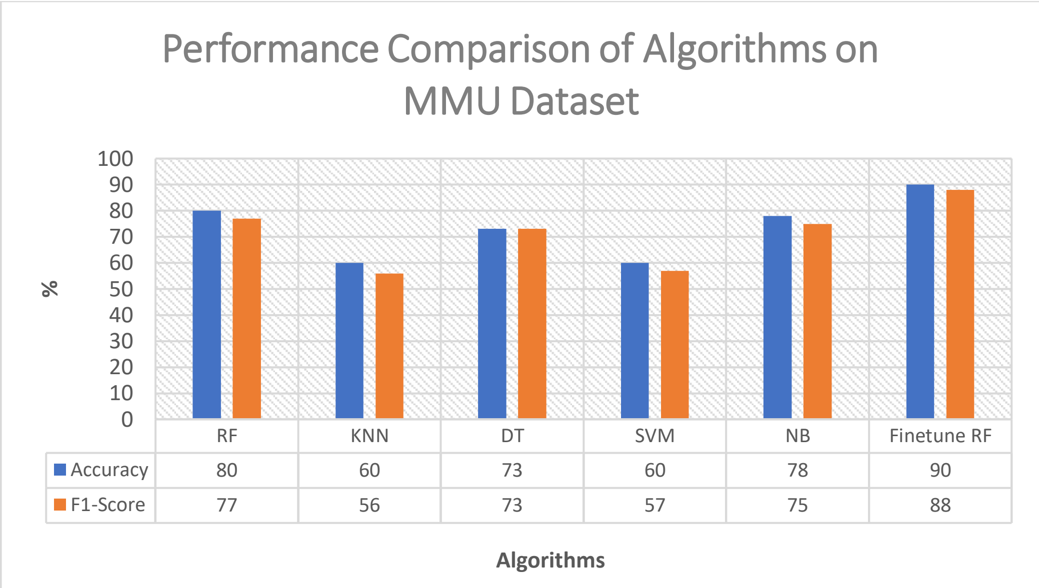

Figure 9. Comparative Analysis of Algorithms on SBVPI Dataset

Figure 9; shows the performance parameters comparison of various algoritms on SBVPI dataset; Fine-tune Random Forest performs better comparative to all other algorithms and achieves 90% of accuracy. Figure 10(a), 10(b) shows the actual and predicted label for input image.

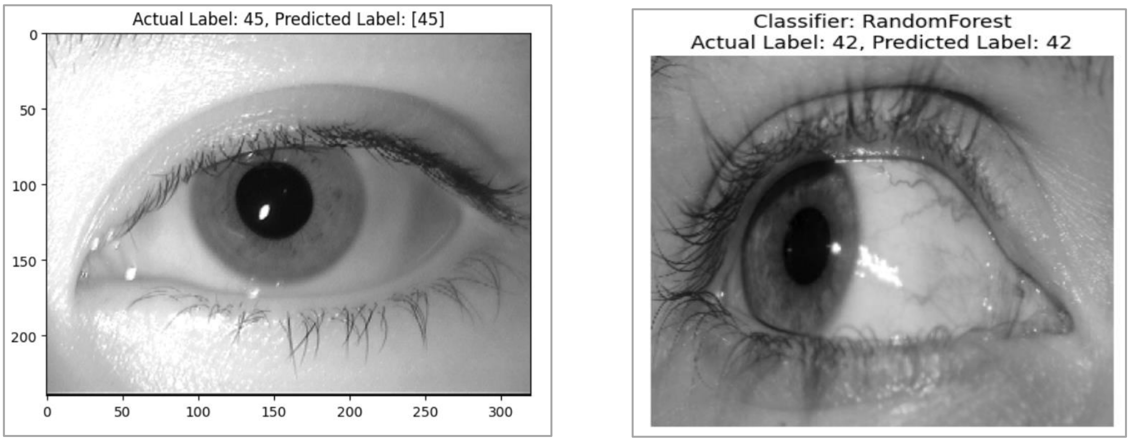

Figure 10 (a) Actual and Predicted Label Matching (MMU Dataset) Figure 10(b). Actual and Predicted Label Matching (SBVPI Dataset)

5. CONCLUSION AND FUTURE SCOPE

The proposed work reflects the culmination of efforts to enhance the accuracy of biometric identification systems through feature fusion technique and finetune machine learning algorithms. The study showcased promising advancements in algorithmic approaches, particularly evident in the significant performance improvements observed after fine-tuning various machine learning models. Through meticulous experimentation and analysis, it was demonstrated that techniques like Random Forest, K-Nearest Neighbors, Decision Trees, Support Vector Machines, and Naive Bayes exhibit notable potential in the context of iris and sclera segmentation. These algorithms, when appropriately optimized, displayed considerable boosts in accuracy, with some achieving rates as high as 80% (MMU Dataset) and 90% (SBVPI Dataset) post fine-tuning. Such findings underscore the significance of algorithm selection and parameter optimization in achieving robust biometric identification systems. Moreover, the research underscores the critical role of feature fusion on accuracy in overcoming challenges posed by noise and occlusions, which are prevalent in real-world biometric data. By effectively isolating the iris and sclera regions, the proposed methodologies lay a foundation for more reliable biometric identification systems, capable of withstanding adverse environmental conditions and maintaining high levels of security.

Looking ahead, several promising avenues for future research emerge from this study. Firstly, further exploration of advanced machine learning techniques, such as deep learning architectures, could yield even more refined segmentation algorithms capable of handling complex scenarios with greater resilience. Additionally, investigations into multi-modal biometric systems, combining iris and sclera segmentation with other modalities like fingerprint or facial recognition, could lead to enhanced accuracy and robustness in biometric identification.

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