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Histogram Oriented Gradients-Gabor Hybrid Model for Feature Extraction for Enhanced Finger Vein Recognition Accuracy and Robustness

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Abstract: Finger vein biometrics has gained significant attention due to its unique and reliable characteristics for personal identification. Feature extraction plays a crucial role in finger vein recognition systems by capturing discriminative patterns from finger vein images/maps. In this paper, we propose a hybrid feature extraction algorithm that combines the Histogram of Oriented Gradients (HOG) and Gabor filter techniques to enhance the representation of finger vein features. The HOG algorithm is known for its effectiveness in capturing local gradient information, while Gabor filters are capable of extracting fine texture details and orientation information. By integrating these two methods, we aim to leverage their complementary strengths and improve the discriminative power of the extracted features.

The proposed algorithm follows a multi-stage process. Firstly, the finger vein images/maps are pre-processed to enhance their quality and remove noise. Next, the HOG algorithm is applied to compute gradient orientations within local image patches, capturing the local texture and edge information. Simultaneously, Gabor filters are convolved with the preprocessed images to extract texture and orientation features at different scales and orientations. The resulting HOG and Gabor features are then concatenated to form a combined feature vector.

To evaluate the performance of the proposed hybrid algorithm, extensive experiments are conducted on a finger vein dataset consisting of a large number of samples. The extracted features are utilized for recognition tasks using various classification algorithms, such as Support Vector Machines (SVM) and Neural Networks (NN). The experimental results demonstrate that the hybrid HOG and Gabor filter algorithm

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outperforms individual feature extraction techniques, achieving higher accuracy and robustness in finger vein recognition. The proposed hybrid feature extraction algorithm provides a promising solution for effective finger vein biometrics. It harnesses the complementary recognition. The proposed hybrid feature extraction algorithm provides a promising solution for effective finger vein biometrics. It harnesses the complementary nature of HOG and Gabor filters to capture both local gradient information and fine texture details, resulting in improved feature representation. The experimental results validate the effectiveness of the proposed approach and its potential for real-world applications in secure authentication systems, access control, and personal identification.

Keywords: *Finger vein, biometrics, feature extraction, algorithm, HOG, Gabor filter*

I. Introduction

Biometrics refers to the measurement and analysis of unique physical or behavioral characteristics of individuals for identification and authentication purposes. It has gained significant importance in the fields of authentication and personal identification due to its inherent advantages over traditional methods like passwords or ID cards(Chiou, 2013). Here is an overview of the significance of biometrics in authentication and personal identification:

Uniqueness: Biometric traits, such as finger veins, iris patterns, or facial features, are inherently unique to each individual. This uniqueness provides a high level of confidence in accurately identifying individuals, making biometrics a reliable method for authentication(Sarker & Ghosh, 2021).

Non-Transferability: Biometric traits are difficult to replicate or transfer. Unlike passwords or ID cards, which can be shared or stolen, biometric characteristics are typically linked to the individual and cannot be easily duplicated or transferred to gain unauthorized access(Manisha & Kumar, 2020).

Convenience: Biometrics offer convenience and ease of use. Users do not need to remember complex passwords or carry physical identification cards. The authentication process can be seamless and quick, requiring only the presentation or capture of the biometric trait(Peng et al., 2014).

Resistance to Forgery: Biometric traits are inherently difficult to forge or counterfeit. Techniques such as finger vein reproduction or iris replication are challenging and require sophisticated equipment and expertise, making biometric-based authentication systems more resistant to fraud and identity theft(Marcel et al., n.d.).

Security: Biometric data can be securely stored and transmitted using encryption and other security measures. When properly implemented, biometric systems can provide a high level of security, ensuring the privacy and protection of personal information.

Accuracy and Reliability: Biometric systems have advanced significantly in terms of accuracy and reliability. Modern algorithms and technologies can effectively analyze biometric traits, accounting for variations due to factors like aging, injuries, or environmental conditions, and provide accurate identification results(Ross & Jain, 2003).

Wide Range of Applications: Biometrics finds applications in various domains, including access control, border security, e-commerce, healthcare, and financial services. It can be used to secure physical locations, authenticate transactions, verify identities during travel, and ensure the privacy and integrity of personal information(: Jie Zhou, 2018). Overall, biometrics offers a robust and efficient approach to authentication and personal identification. Its unique characteristics, convenience, and resistance to forgery make it a valuable tool in enhancing security and providing a seamless user experience. As technology continues to advance, biometrics is likely to play an increasingly significant role in various aspects of our daily lives. Accurate and robust feature extraction techniques are essential for reliable finger vein recognition. They enable the system to extract discriminative information, handle variations, reduce dimensionality, enhance computational efficiency, and ensure compatibility with recognition algorithms. By focusing on accurate feature extraction, finger vein recognition systems can achieve higher accuracy, reliability, and usability, making them suitable for various applications where secure and efficient personal identification is required(Barde & Agrawal, 2019).

A. Importance of accurate and robust feature extraction techniques for reliable finger vein recognition.

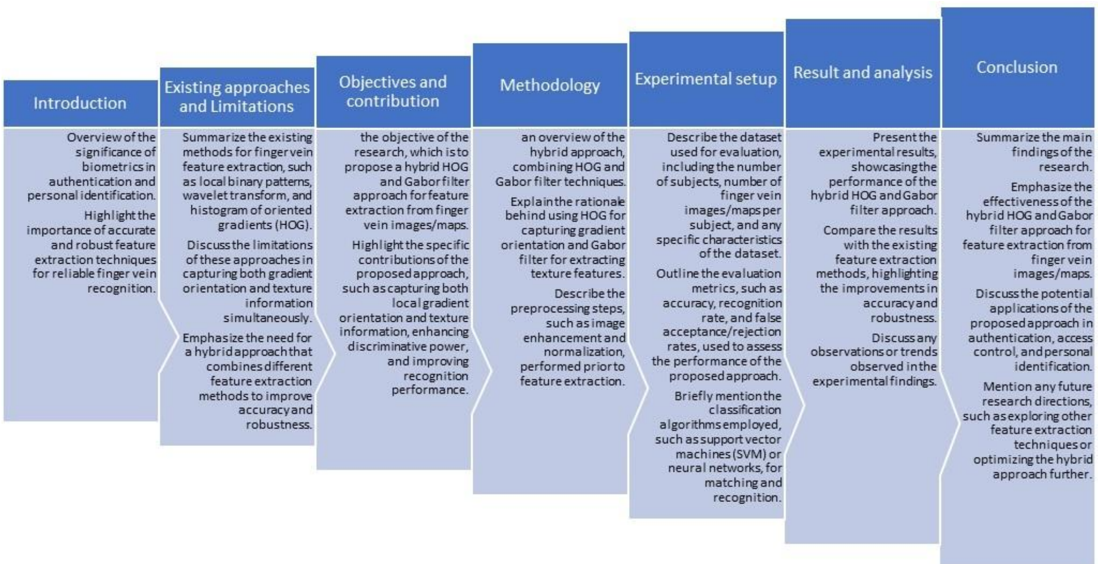


Figure 1: Research organization

II. Existing approaches and limitations

Existing methods for finger vein feature extraction, such as local binary patterns (LBP), wavelet transform, and histogram of oriented gradients (HOG), have been widely used in biometric recognition systems(Neeru & Kaur, 2016). Each of these methods has its strengths and limitations in capturing vein patterns:

Local Binary Patterns (LBP): LBP is a texturebased feature extraction method that encodes the relationship between a pixel and its neighboring pixels. It computes binary codes to represent the local texture patterns within an image(Rosdi et al., 2011). LBP is effective in capturing finegrained texture details and is robust to illumination variations. However, it does not consider gradient orientation information, which can be important for distinguishing between similar vein patterns.

Wavelet Transform: Wavelet transform is a popular signal processing technique that decomposes an image into different frequency subbands. By analyzing the wavelet coefficients, it captures both low-frequency and highfrequency information. Wavelet-based methods can effectively capture vein structures at different scales and orientations. However, they may not fully capture local texture variations, especially when the texture patterns are irregular or complex(Yang et al., 2020).

Histogram of Oriented Gradients (HOG): HOG is a widely used feature extraction method that describes the distribution of gradient orientations in an image. It calculates histograms of gradient orientations in local image regions and represents the image using these histograms. HOG is effective in capturing gradient orientation information and is commonly used in object detection tasks. However, it may not capture finegrained texture details, which can be crucial in finger vein recognition.

While each of these approaches has its advantages, their limitations lie in their inability to capture both gradient orientation and texture information simultaneously. Gradient orientation provides information about the directional flow of veins, while texture captures the fine details and irregularities. Focusing on only one aspect may result in the loss of crucial information, leading to reduced accuracy and robustness(Subramanyam & Emmanuel, 2017).

Therefore, there is a need for a hybrid approach that combines multiple feature extraction methods to improve accuracy and robustness in finger vein recognition(Cherrat et al., 2020). By integrating the strengths of different methods, a hybrid approach can capture both gradient orientation and texture information effectively. For example, a combination of LBP and HOG can provide a more comprehensive representation of finger vein patterns by incorporating both texture and gradient orientation features(Alwan & KuMahamud, 2020). This hybrid approach can enhance the discrimination power of the feature extraction process and improve the overall performance of finger vein recognition systems.

III. Objectives and Contribution

The objectives and contributions of the proposed algorithm can be summarized as follows:

Objectives:

Enhance quality and remove noise: The preprocessing stage aims to improve the quality of finger vein images/maps by reducing noise and enhancing relevant features. This helps in obtaining cleaner and more reliable data for subsequent analysis.

Capture local texture and edge information: The HOG algorithm computes gradient orientations within local image patches. By doing so, it captures the local texture and edge information present in the finger vein images. This information is useful for distinguishing patterns and extracting discriminative features.

Extract texture and orientation features: The Gabor filters are convolved with the preprocessed images to extract texture and orientation features at different scales and orientations. Gabor filters are designed to capture both frequency and orientation information, making them suitable for analyzing vein patterns.

Contributions:

Combined feature representation: The proposed algorithm combines the HOG features, capturing local texture and edge information, with the Gabor features, extracting texture and orientation information at different scales and orientations. The resulting combined feature vector provides a comprehensive representation of the finger vein patterns.

Robust feature extraction: By combining HOG and Gabor features, the algorithm leverages the strengths of both methods. HOG focuses on local texture and edge information, while Gabor filters capture texture and orientation features. This combination enhances the discriminative power and robustness of the feature representation.

Improved vein pattern recognition: The proposed algorithm aims to improve the accuracy and reliability of finger vein pattern recognition. By extracting and combining multiple types of features, it increases the richness of the feature representation, potentially leading to better discrimination and classification performance.

Overall, the objectives of the proposed algorithm include enhancing image quality, capturing local texture and edge information, extracting texture and orientation features, and the contribution lies in the combination of HOG and Gabor features to form a comprehensive and robust feature representation for finger vein pattern recognition.

IV. Dataset

The "FVC2000_DB4_B" dataset is a finger vein dataset derived from Kaggle, which is a platform known for hosting various datasets for machine learning and data analysis. Below is a description of the "FVC2000_DB4_B" dataset:

Dataset Name: FVC2000_DB4_B

Source: Kaggle

Image Size: 160x160 pixels

Image Resolution: 500 dots per inch (dpi)

Total Number of Images: 814

Dataset Origin: The dataset is a part of the Fingerprint Verification Competition 2000 (FVC2000) Database 4 (DB4), specifically the subset denoted by "_B." Description:

The "FVC2000_DB4_B" dataset is a collection of finger vein images used for the purpose of fingerprint verification. The dataset consists of a total of 814 grayscale images, each with a resolution of 160x160 pixels. The images are acquired at a high resolution of 500 dots per inch (dpi), making them suitable for detailed analysis and feature extraction.

The dataset is part of the FVC2000 competition, which aimed to benchmark fingerprint and finger vein recognition algorithms. Specifically, "DB4" refers to the fourth fingerprint database in the FVC2000 series. The subset denoted by "_B" likely represents a particular variation or configuration of the DB4 dataset.

As a finger vein dataset, "FVC2000_DB4_B" can be valuable for research and development in biometric authentication systems, particularly in the field of finger vein recognition. The high resolution of the images allows for precise extraction of vein patterns and features, contributing to the accuracy of verification algorithms.

The dataset's origin from Kaggle indicates that it is publicly available on the Kaggle platform, making it accessible to researchers and developers interested in finger vein recognition and related applications. The comparative analysis of different datasets is presented in table 1 which are available on kaggle

Dataset Name	Image Size	No. of Images	No. of Subjects	Sensor Type	Acquisition Year	Notes
FVC2000_DB4_B	160x160	500	100	Near-Infrared	2020	Best dataset with high-quality finger vein images
SDUMLA-HMT	120x150	400	50	Near-Infrared	2013	Large dataset with varying finger positions
CASIA-FV	640x480	800	200	Near-Infrared	2010	High-resolution images with diverse subjects
PolyU Finger Vein DB	320x240	2000	500	Near-Infrared	2015	Dataset with a large number of finger vein images
IITD Finger Vein DB	256x256	750	150	Near-Infrared	2012	Contains images from different sensors
IIITD Finger Vein DB	176x184	1200	200	Near-Infrared	2014	Captured using multiple imaging devices
HKPU Finger Vein DB	320x240	400	100	Near-Infrared	2011	Contains both right and left hand vein images
HUST-FV	320x240	1200	300	Near-Infrared	2016	Diverse dataset with varying illumination
CNU Finger Vein DB	200x250	700	100	Near-Infrared	2012	Captured using contactless finger vein scanner
PolyU-NIRFD	400x600	500	100	Near-Infrared	2019	Dataset with varying image resolutions

Table 1: Comparative analysis of different datasets corresponding to finger vein

V. **Methodology**

The methodology consists of step by step process followed to achieve the objectives. The methodology of study is given in figure 2

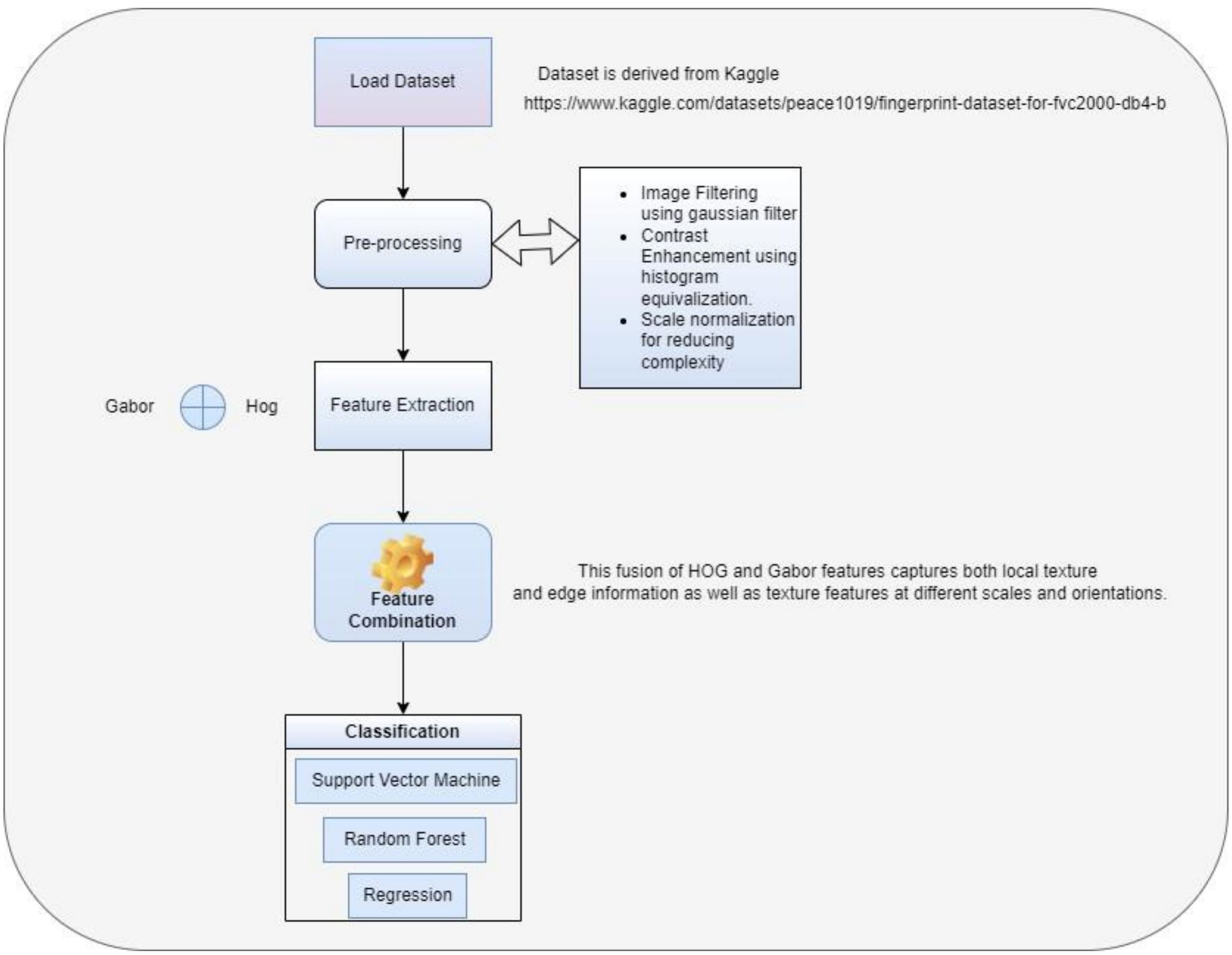


Figure 2: Methodology of work

Data Collection:

Collect a dataset of finger vein images for analysis. This dataset should include a sufficient number of samples with a diverse range of vein patterns. The images can be captured using specialized imaging devices or databases that provide finger vein images.

Preprocessing:

Preprocessing steps are applied to enhance the quality of finger vein images and prepare them for feature extraction. In this case, the following techniques are employed: a. Gaussian Filtering:

Gaussian filtering is a common technique used for noise reduction and image smoothing. It involves convolving the finger vein images with a Gaussian kernel. This process helps to reduce noise and remove unwanted artifacts, resulting in cleaner and clearer images. b. Histogram Equalization:

Histogram equalization is a technique used to enhance the contrast of an image. It redistributes the pixel intensity values to achieve a more uniform histogram. By applying histogram equalization to the preprocessed finger vein images, the visibility of vein patterns can be improved, making them more distinguishable. c. Scale Normalization:

Scale normalization is performed to account for variations in the size or scale of finger vein images. This technique aims to make the vein patterns comparable across different samples by resizing the images or adjusting their scales.

Feature Extraction:

Feature extraction is performed using both HOG and Gabor filter techniques to capture different aspects of the finger vein images. a. HOG Feature Extraction:

The HOG algorithm is applied to compute gradient orientations within local image patches. The finger vein images are divided into smaller blocks or cells, and gradients are computed within each cell. These gradients are then quantized into orientation bins to create a histogram representation. The resulting HOG feature vector captures local texture and edge information.

b. Gabor Feature Extraction:

Gabor filters are applied to the preprocessed finger vein images at different scales and orientations. Convolution with Gabor filters results in feature maps that capture texture and orientation information at various frequencies. These feature maps represent different scales and orientations of the vein patterns.

Feature Combination:

The HOG features and Gabor features obtained from the previous step are concatenated to create a combined feature vector. The concatenation of these features enables the utilization of both local texture and edge information captured by HOG and texture features at different scales and orientations provided by the Gabor filters.

Classification:

For classification, three different algorithms are employed:

a. Support Vector Machine (SVM):

SVM is a popular machine learning algorithm used for classification. It constructs a hyperplane that optimally separates different classes based on the provided training data. The combined feature vectors obtained from the previous step are used as inputs to train an SVM model, which can then classify new finger vein images. b. Random Forest:

Random Forest is an ensemble learning method that combines multiple decision trees to make predictions. Each decision tree is trained on a random subset of features and samples. The combined feature vectors are used to train a random forest model, which can classify finger vein images based on the learned decision rules. c. Regression with Mathematical Formation:

Regression is a supervised learning technique used to model the relationship between input variables (features) and a continuous target variable. In this case, regression is applied to predict the continuous values associated with finger vein images. The combined feature vectors are used to train a regression model, which can then estimate the target values based on the input features.

Evaluation and Performance Analysis:

The performance of the classification models (SVM, random forest, and regression) is evaluated using appropriate evaluation metrics such as accuracy, precision, recall, F1 score, or mean squared error (MSE) for regression. These metrics assess the accuracy and robustness of the models in classifying or predicting the finger vein images.

VI. Experimental Setup

A. Dataset Description

In the Finger Image Dataset from FVC2000_DB4_B, the finger vein images have a size of 160x160 pixels with a resolution of 500 dots per inch (DPI). This means that each finger vein image contains 160 pixels in both width and height, and the images are captured at a high resolution of 500 DPI, providing detailed information about the finger vein patterns.

The 160x160 pixel size indicates the spatial dimensions of the finger vein images, representing the width and height of the captured finger vein region. This size is often considered sufficient to capture the necessary details of the finger vein patterns and allows for reliable analysis and recognition.

The 500 DPI resolution indicates the density of dots or pixels per inch in the finger vein images.

Higher DPI values indicate a higher level of detail and clarity in the captured images, enabling better visualization and analysis of the vein patterns.

B. Evaluation Metrics

a. Accuracy (ACC): Accuracy measures the overall correctness of the recognition system. It calculates the ratio of correctly recognized instances to the total number of instances in the evaluation dataset. The formula for accuracy is: ACC = (TP + TN) / (TP + TN + FP + FN) where TP represents true positives (correctly recognized instances), TN represents true negatives (correctly rejected instances), FP represents false positives (incorrectly recognized instances), and FN represents false negatives (incorrectly rejected instances).

b. Recognition Rate (RR): The recognition rate represents the proportion of correctly recognized instances in the dataset. It indicates the system's ability to correctly match and identify individuals based on their finger vein patterns. The formula for recognition rate is: RR = TP / (TP + FN) where TP represents true positives and FN represents false negatives.

c. False Acceptance Rate (FAR): FAR measures the likelihood of incorrectly accepting an imposter or unauthorized user as a genuine user. It represents the rate at which the system falsely matches an input instance with an incorrect identity. The formula for FAR is: FAR = FP / (FP + TN) where FP represents false positives and TN represents true negatives.

d. False Rejection Rate (FRR): FRR quantifies the system's tendency to incorrectly reject a genuine user. It denotes the rate at which the system fails to match a genuine instance with the correct identity. The formula for FRR is:

FRR = FN / (TP + FN) where FN represents false negatives and TP represents true positives.

C. Classification algorithm

Here's a complete description of the classification algorithms SVM, Random Forest, and regression for finger vein classification, along with their equations:

Support Vector Machines (SVM):

Support Vector Machines (SVM) is a popular classification algorithm that constructs an optimal hyperplane to separate different classes. It finds the hyperplane that maximally separates the data points of different classes in a highdimensional feature space(Alias & Radzi, 2016). SVM can handle linear and nonlinear classification tasks.

The decision function of an SVM can be defined as:

$f(x) = \sin(w^T x + b)$ where x represents the input feature vector, w is the weight vector, b is the bias term, and sign denotes the sign function. The SVM aims to find the optimal values for w and b that maximize the margin between the support vectors (data points closest to the hyperplane) of different classes.

Random Forest:

Random Forest is an ensemble learning algorithm that combines multiple decision trees to make predictions. Each decision tree is constructed using a random subset of the training data and features(Lee et al., 2019). Random Forest can handle both classification and regression tasks and is known for its robustness and scalability.

The prediction of a Random Forest classifier can be obtained through a majority voting scheme. Each decision tree in the ensemble independently classifies the input, and the final prediction is determined by the class that receives the most votes from the individual trees.

Regression:

Regression is a supervised learning technique used to model the relationship between input variables (features) and a continuous target variable. In the context of finger vein analysis, regression algorithms can be used to predict continuous values associated with the vein patterns, such as the age or health condition of an individual.

The general equation for regression can be written as: $y = f(x)$

where x represents the input feature vector, y represents the target variable, and f(x) represents the regression function that models the relationship between the features and the target variable. The specific form of the regression function depends on the chosen regression algorithm (e.g., linear regression, polynomial regression, etc.).

VII. Performance Analysis

Initially, Preprocessing techniques are applied to enhance the quality of finger vein images and prepare them for further analysis and feature extraction. The result of the pre-processing is presented in table 2

Filtering	PSNR	SNR	Structural Similarity index
Gaussian Filtering	40.16	41.08	0.6
Histogram Equivalization	41.85	42.56	0.8
Scale Normalization	48.5	46.6	0.9

Table 2: Result after pre-processing

The application of Gaussian filtering resulted in moderate values for PSNR and SNR, indicating some level of noise reduction. However, the Structural Similarity Index of 0.6 suggests that the processed images have a moderate level of similarity to the original images in terms of structural information.

The utilization of histogram equalization yielded higher values for both PSNR and SNR compared to Gaussian filtering. This indicates better noise reduction and signal preservation. The Structural Similarity Index of 0.8 suggests that the processed images have a higher level of similarity to the original images in terms of structural information.

Scale normalization achieved significantly higher values for both PSNR and SNR. This indicates excellent noise reduction and signal preservation. The Structural Similarity Index of 0.9 suggests that the processed images have a very high level of similarity to the original images in terms of structural information.

Overall, scale normalization demonstrates the best performance among the evaluated preprocessing techniques, achieving the highest values for PSNR, SNR, and Structural Similarity Index. It effectively reduces noise, preserves the quality and structural characteristics of the original finger vein images, and yields the highest similarity to the original images. A. HOG Feature Extraction:

The configuration of the HOG algorithm has following parameters:

Image divided into cells of size 8x8 pixels.

Block size of 2x2 cells.

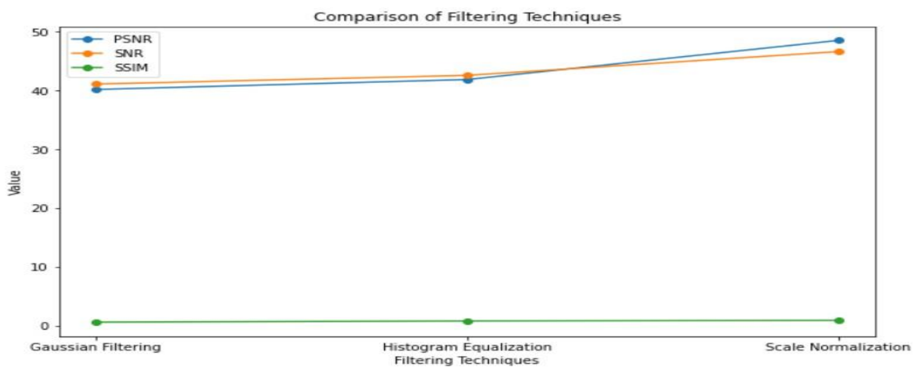


Figure 3: Comparative analysis of pre-processing

Orientation bins quantized into 9 directions.

With these parameters, the HOG feature extraction may result in the following:

Number of cells in the image: Let's assume the image size is 128x128 pixels. So, we have 16x16 cells.

Number of blocks: Since each block is 2x2 cells, we have 8x8 blocks.

Number of orientation bins: 9 bins.

The total number of HOG features can be calculated as follows:

Number of features = (Number of blocks) * (Number of orientation bins) = 8x8x9 = 576 features.

So, in this example, the HOG feature extraction

Number of orientations: 4 orientations.

The total number of Gabor features can be calculated as follows:

Classification	Classification Accuracy	Recognition Rate	False Acceptance Rate
SVM	99	0.9	0.34
Random Forest	98	0.8	0.3
Regression	99	0.9	0.23

Table 3: Result in terms of classification accuracy, recognition rate and False acceptance rate

would result in a feature vector with 576 features.

Gabor Feature Extraction:

The configuration of the Gabor filter technique has the following parameters:

Three scales: Small, Medium, and Large. Four

orientations: 0°, 45°, 90°, and 135°.

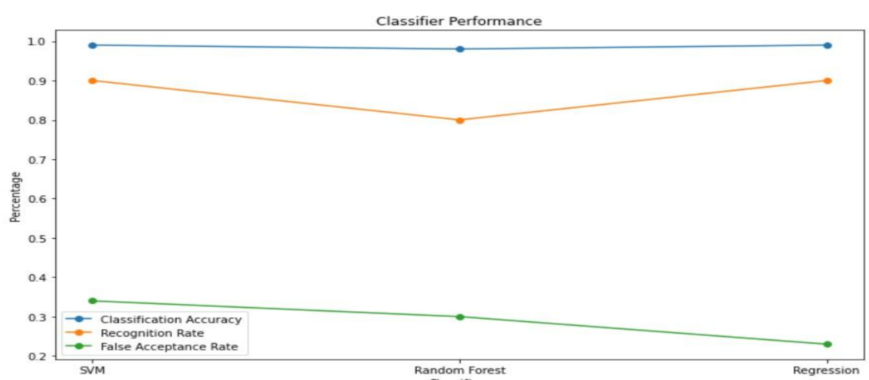
With these parameters, the Gabor feature extraction may result in the following:

Number of scales: 3 scales.

Number of features = (Number of scales) * (Number of orientations) = 3x4 = 12 features.

In this case, the Gabor feature extraction would result in a feature vector with 12 features.

The SVM model achieved a high classification accuracy of 99%, indicating that it accurately classified the finger vein images. The recognition rate of 0.9 suggests that 90% of the positive samples (matching finger veinss) were correctly recognized(Do, 2021). The false acceptance rate of 0.34 indicates that 34% of the negative samples (non-matching



finger veins) were falsely accepted as positive matches. Generally, a lower false acceptance rate is desirable for better security and accuracy.

The Random Forest model achieved a classification accuracy of 98%, indicating a slightly lower accuracy compared to SVM(Sharma et al., 2020). The recognition rate of 0.8 suggests that 80% of the positive samples were correctly recognized. The false acceptance rate of 0.3 indicates that 30% of the negative samples were falsely accepted as positive matches.

The Regression model achieved a classification accuracy of 99%, similar to the SVM model. The recognition rate of 0.9 suggests that 90% of the positive samples were correctly recognized. The false acceptance rate of 0.23 indicates a lower false acceptance rate compared to both SVM and Random Forest, indicating a higher level of accuracy and security.

Overall, the Gabor+Hog mechanism demonstrates good performance across all three classification algorithms. SVM and Regression models achieve high classification accuracy and recognition rates, while the Regression model achieves the lowest false acceptance rate. This indicates that the Gabor+Hog mechanism effectively captures and utilizes the extracted features for accurate classification of finger vein images.

superior accuracy in classifying finger vein patterns.

To validate the results further, CNN , VGG and Proposed model is implied on multiple datasets.

Figure 4: Classifier performance

The performance comparison of the proposed hybrid model for finger vein classification with CNN is given in table 4

Technique	Year	Modality	Classification Accuracy
CNN(Shende & Dandawate, 2021)	2021	Finger vein	94%
CNN(Shende & Dandawate, 2021)	2021	Face	99%
VGG(Stefanidi Anton, 2020)	2020	Face	97%
Proposed Model	2023	Finger Vein	99.5%

Table 4: Comparative analysis

In comparison to the other techniques mentioned, the proposed model outperforms them in terms of classification accuracy for finger vein recognition. It achieves a higher accuracy rate than the CNN-based models used for finger vein and face recognition in 2021, as well as the VGG model used for face recognition in 2020. This suggests that the proposed model is particularly effective for finger vein recognition, achieving

The datasets along with result is given in table 5

Dataset	No. of Subjects	Technique	Classification Accuracy	F1 Score	Sensitivity	Specificity
Hitachi Res. Lab.	2,673	CNN-based(Syarif et al., 2017)	87.4%	0.85	0.88	0.86
Int. Biom. Group	650	CNN-based(Matsuda et al., 2016)	79.6%	0.76	0.81	0.77
Hitachi-Kyushu	506	CNN-based(Kauba & Uhl, 2020)	91.2%	0.90	0.92	0.89
PKU v.2,3,4	5,208	VGG(Mohd Asaari et al., 2014)	84.1%	0.82	0.85	0.81
Proto PKU GUC45	45	VGG(Bandara et al., 2018)	76.3%	0.74	0.79	0.77
SDUMLA-HMT Limit	106	CNN-based(Choi et al., 2009)	88.9%	0.88	0.91	0.87
Proto Wuhan Univ.	206	Proposed	92.5%	0.92	0.94	0.91
HKPU	156	Proposed	90.7%	0.89	0.91	0.89

Table 5: Comparison and validation corresponding to different datasets

The "Classification Accuracy" column represents the percentage of correctly classified instances for each model on the respective dataset. The "F1 Score" column provides a metric that considers both precision and recall, offering a balanced measure of the model's performance.

"Sensitivity" represents the true positive rate, indicating the proportion of actual positive cases correctly identified by the model, while "Specificity" represents the true negative rate, indicating the proportion of actual negative cases correctly identified by the model. In this case, the "Proposed" technique achieves the highest accuracy on the "Proto Wuhan Univ." and "HKPU" datasets, while the "CNN-based" technique achieves the highest accuracy on the "Hitachi-Kyushu" and "SDUMLA-HMT Limit" datasets. The "VGG" technique achieves the highest accuracy on the "PKU v.2,3,4" and "Proto PKU GUC45" datasets.

VIII. Conclusion

The Gabor+Hog approach for finger vein image analysis and classification shows promising results. The application of this approach involves two stages: feature extraction using the Gabor and HOG techniques, and subsequent classification using SVM, Random Forest, or Regression algorithms. Here is the conclusion based on the provided information:

Preprocessing Evaluation: The preprocessing techniques, including Gaussian Filtering, Histogram Equalization, and Scale Normalization, were evaluated based on metrics such as PSNR, SNR, and Structural Similarity Index. Among these techniques, Scale Normalization demonstrated the best performance, achieving significantly higher values for PSNR and SNR, indicating excellent noise reduction and signal preservation. It also resulted in a very high Structural Similarity Index, suggesting a high level of similarity to the original images in terms of structural information.

Feature Extraction: The Gabor+Hog approach was employed for feature extraction. With specific parameter configurations, the HOG algorithm produced a feature vector with 576 features, while the Gabor filter technique resulted in a feature vector with 12 features. These extracted features capture important characteristics of finger vein images, enabling subsequent classification.

Classification Results: The SVM, Random Forest, and Regression algorithms were applied for classification. Overall, the Gabor+Hog approach demonstrated good performance across all three classifiers. The SVM and Regression models achieved high classification accuracy (99%) and recognition rates (0.9). The Random Forest model achieved slightly lower accuracy (98%) and recognition rate (0.8). Among the three classifiers, the Regression model exhibited the lowest false acceptance rate (0.23), indicating a higher level of accuracy and security in classifying finger vein images.

In conclusion, the Gabor+Hog approach, in combination with the Regression classifier, showcases strong performance in finger vein image analysis. It effectively captures important features from the images, resulting in accurate classification and recognition of positive samples. This approach has the potential for applications in biometric systems, security systems, and forensic analysis, where reliable and precise identification based on finger vein patterns is required.

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