Pragmatic Analysis of Vein Detection and Processing Models from an Empirical Perspective

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Vein detection is a difficult process that can be carried out using context-dependent intrusive & non-intrusive techniques. The models based on image processing, pressure sensing, depth detection, etc. are just a few examples of these techniques. Finding the best vein detection model for a given deployment is challenging, especially when evaluated in terms of their computing complexity, deployment costs, accuracy, precision, and other context-specific criteria. The ambiguity of model selection for various use-cases is further increased by these variances in model performance. Due to this ambiguity, researchers and clinical system designers are required to test & validate different detection models, before using them for their application-specific deployments. To reduce this ambiguity, in identification of an optimum models for This essay contrasts various vein identification techniques in terms of various processing & deployment properties based on distinct use cases. It was discovered that Machine Learning Models (MLMs), including Nave Bayes (NB), Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs), outperformed their competitors. These models use feature augmentation with effective classification in order to optimize Vein detection performance under different clinical scenarios. In order to facilitate decision-making, this paper compares various models' detection accuracy, precision, recall, computational delay, deployment cost, and scalability metrics. Additionally, this paper suggests evaluating a Vein Model Rank Score (VMRS), which integrates various evaluation metrics to identify models with superior all-around performance. Based on VRMS, researchers will be able to identify methods that have better accuracy, lower delay, and higher viability of deployment under clinical use cases.

Keywords: Vein Detection, Machine Learning, Intrusive, Non-Intrusive, Accuracy, Precision, Complexity, Vein Model Rank Score

2023. In Satyasai Jagannath Nanda & Rajendra Prasad Yadav (eds.), *Data Science and Intelligent Computing Techniques*, 381–391. Computing & Intelligent Systems, SCRS, India. https://doi.org/10.56155/978-81-955020-2-8-34

1. Introduction

The multidomain job of vein detection and processing includes the design of sensor interfaces as well as filtering, segmentation, feature extraction, feature selection, classification, and postprocessing procedures. For higher detection performance, it is necessary to build optimized techniques that may be cascaded for each of these models. A number of signal processing techniques, including the selection of the Region of Interest (RoI), image enhancement, localization, dimensionality reduction, minutiae identification, classification, etc., are combined in the typical vein detection methodology shown in Figure. These methods are useful for locating finger veins, but they must be modified for other applications, such calf- or arm-based vein detection.

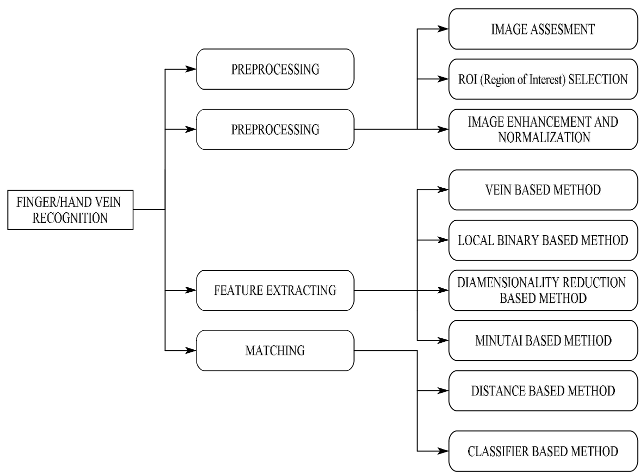

Figure 1. Typical processing components used for identification of finger veins

In terms of how they are applied nuances, advantages, and limitations that are specific to a given environment and functionality, and model-specific future research scopes, a survey of such models[2],[3],[4],[5],[6] that propose vein detection from various body regions is conducted. As a result, finding the best vein detection model for a given deployment is challenging. Furthermore, how well these models perform varies significantly when assessed in section 3 in terms of their processing complexity, deployment costs, accuracy, precision, and other context-specific parameters. According to this comparison, it was shown that machine learning models (MLMs) perform better than linear processing models and that non-intrusive models have a wide improvement scopefor development in terms of real-time usability features. It was also observed that semi-intrusive methods also have high deployment potential, and thus must be used for clinical applications. Finally, this article offers recommendations for ways to further enhance the evaluated models' functionality in a variety of use contexts, as well as some context-specific observations regarding them.

2. Literature Review

Several models are proposed for the identification of veins by invasive and non-invasive techniques. According to the findings of the research in [1], recently, for instance, it is becoming increasingly common to use palm vein biometrics as a pattern for advanced security. There is an unresolved issue that manual vein testing has unacceptable image quality degradation, which can affect the accuracy of testing equipment. However, there are currently two problems with vein segmentation. 1) Label data is difficult to find and collect. 2) Inaccurate labeling information provided by human labeling techniques or computer-aided labeling systems can have a significant impact. Both can affect the validation performance of the network during training. In this paper, we propose an iterative deep belief network (DBN) to extract vein features from initial label data that is automatically constructed using minimal prior information.

This article [2] describes Development of a low-cost single-camera finger vein sensor that can provide clear images of dorsal and ventral finger veins. The device uses a number of near-infrared (NIR) light sources to illuminate the finger from the top, left, and right.

This is particularly true for large datasets that include illustrations of the axial rotation procedure. The [3] work investigation has continued. A few of the deep learning methods that have been created are the principle component analysis network (PCA Net), AlexNet, and Convolutional neural network (CNN). PCA Net is regarded as the most effective approach due to its promising biometric performance when compared to other methods. The proposed method filter was created by comparing the correlation between the initial grayscale image and the venous line image using the canonical correlation analysis (CCA) method.

The idea of using a pre-trained DCNN trained on a large image database as a typical feature map for classifying photos was further explored [4]. As a result, many photo recognition programs have been significantly developed. To provide more representative and fine-grained convolutional features for vein detection, this study proposes semantic feature selection and special multilayer convolutional feature concatenation. The context of low-level convolutional features was removed using a special semantic feature selector. The high-level feature maps of the convolutional layers are combined to create an activation map, and recommended local max pooling is applied to preserve spatial location information (LMP-PSP).

Research provided in [5] indicates that Finger vein recognition is a novel topic of study being investigated in the field of biometric identification at the present. In this paper, an adaptive-learning Gabor filter is suggested as a potential solution to this issue. Using a convolutional neural network and a Gabor filter, To improve the parameters of a convolutional neural network, researchers first calculate the gradient of the Gabor filter parameters based on the objective function.

In the study presented in [6], the vein point method for identifying finger veins divides the image points into vein points and non-vein points, but only after the recognition process is completed, the vein points are separated. shown to be analyzed. The recommended detection strategy considers all image points and divides them into several groups for both feature extraction and similarity evaluation. Point grouping-based approaches: Some methods, such as point grouping-assisted vein extraction and point grouping-assisted Gabor method based on anatomical structure analysis, use the idea of point grouping and It combines two common techniques.

Research conducted in [7] looked deeper into the claim that Initial finger vein images are often of poor quality, which can make it difficult to accurately identify specific finger vein features. To identify finger veins, a Weber local descriptor (WLD) with a Gabor filter of variable curvature was developed in this study. First, providing steering information to the differential excitation operator of the original TLD improves the discrimination between different finger veins and provides a better description of local texture changes within the image. This is followed by different curvatures.

A study conducted in [8] shows that the effectiveness of a device to detect veins on the back of the hand is significantly reduced if part of the back of the hand is obscured by scars, discoloration, or tattoos. A common shape-based feature extraction technique for vein detection is biometric graph matching. The Biometric Graph Matching (BGM) technique, which combines edge characteristics for researchers have improved graph registration and a matching module to extract data that could differentiate between persons.

For the accuracy of feature extraction, a finger vein image's texture edge consistency is crucial. In paper [9] traditional inpainting techniques are prone to causing the in painted image's vein texture to blur and break in the absence of precise texture limitations. Gabor texture constraints provide a method to inpaint finger vein images. The suggested vertical phase difference encoding method may be used to first extract the Gabor texture feature matrix of finger vein pictures from the Gabor filter response. This matrix may be used to precisely characterize texture information. The inpainting procedure follows the local texture continuity of the finger vein picture after known pixels with a different texture orientation than the patch's center pixel are filtered using Gabor's texture limitation approach.

To examine eye issues, fundus photography has grown in popularity among ophthalmologists and computer algorithms, according to study published in [10]. Early diabetes detection relies heavily on retinal vessel-related biomarkers. An accurate classification of the arteries and veins is important to quantify vascular biomarkers. In this study, researcher proposes a new framework that uses graph convolution to enhance global vascular network modeling with local vessel classification.

According to studies found in [11], multimodal biometric systems outperform unimodal systems in terms of security. In this study, a multimodal venous database known by the abbreviation FYO—each letter standing for a separate author—is presented. Wrist veins, dorsal veins, and palm veins of the same person are three biometric features stored in the information system. A medical vein finder was used to take his FYO vein photographs using controlled settings. The usefulness of the vein dataset is demonstrated using dedicated feature extraction tools such as Filters such as the Histogram of Oriented Gradients (HOG), Gabor, and Binarized Statistical Image Feature (BSIF) are also used. Additionally, a deep learning-based dual-model convolutional neural network (CNN) architecture is put forth that, at the decision level, integrates wrist, palm, and back biometric data with vein pictures.
Due to its resistance to presentation attacks and simple acquisition method, the study addressed in reference [12] shows that recently, both academic institutions and the corporate sector have become interested in finger-vein biometric identification technologies. In the present study, this limitation was relaxed and the collection of participants' finger vein patterns was facilitated. The researchers also provide an ad hoc sensing architecture that can capture finger vein morphology using an array of low-cost cameras and a detection framework based on recurrent and convolutional neural networks.

According to a study published in [13], human biometric authentication is becoming increasingly common. Its main purpose is to identify individuals and prevent unwanted access to both physical premises and digital services. In this study, researchers provide a wave atom transform (WAT)-based method for detecting hand veins. Because the WAT domain has a sparser expansion and more possibility for textural information extraction, researchers extract palm-vein features from it. The collected features are then subjected to randomization and quantization to produce a small, privacy-preserving palm-vein template.

Researchers describe a unique active contour-based approach for segmenting pictures of finger veins in the paper cited in reference [14]. The finger-vein images that were collected make it difficult to distinguish between venous and non-venous areas, therefore researchers developed an edge fitting term and a dehazing method to enhance the segmentation process. The researchers also use the kernel fuzzy C-means (KFCM) strategy for initialization, which is able to get around the issue that active contour-based systems are vulnerable to starting contours.

An end-to-end vein texture extraction model that combines a fully convolutional neural network (FCN) with a conditional random field (CRF) is in accordance with findings described in [15]. First, during ROI extraction, the sliding window summation method is used to filter and adjust with special tools to reduce the number of missing pixels. Other weights are also added to the conventional baselines in order to automatically assign labels.By changing the receptive fields to match the veins' sizes and shapes and then substituting the plain equivalents in the regular U-Net mode, the deformable convolution network may capture the delicate venous structural details. The residual network (RNN) and recurrent neural network (RNN) can be combined to further mine and acquire the aforementioned data (ResNet).

The finger vein is a helpful and completely trustworthy form of biometric identification, therefore studies published in [16] claim that is why greater attention has been paid to it. In this study, we build a framework that improves detection performance by combining traditional texture-based approaches with encoded deformation information. Finger vein images must first be represented by pixel-level attributes. Optimized matching is then used to determine the best match for each pixel. The texture attributes of the deformation are then recovered from the displacement matrix, allowing the displacement of each pixel to be determined. Additionally, the results of direct ideal matching on pixel-level features are combined with the encoded deformations using weights learned from a support vector machine (SVM) model.

Researchers have developed a technique called single sample per person (SSPP) palm vein detection [17]. This method utilizes an extensive and comprehensive library of training image samples. This approach, called MSMDGAN CNN, combines a convolutional neural network I'll utilize just one example of each student's work from while training a convolutional neural network (CNN) for hand vein recognition and a multi-scale and multi-directional generative adversarial network (MSMDGAN) for data augmentation.

This paper [18] suggests a unique acquisition method for vein patterns based on the pulsing of the veins to address these problems. To precisely separate the vein patterns, we suggest that the pulsations from vein movies be captured. In addition to being able to recognize the finger vein, the suggested framework contains a built-in method for determining liveness.

This paper [19] proposes the Joint Attendance (JA) module as an attention mechanism, discriminative features can be obtained from low-contrast images by dynamic adjusting and data aggregation in the feature map's spatial and channel dimensions. Vein patterns assist in the extraction of distinctive characteristics through this thorough approach. In order to decrease the dimensionality of the feature map and offer a compact and expressive feature representation, we also add a generalized mean (GeM) pooling layer to the network. The creation of JAFVNet, a cutting-edge shared attention and finger vein network authentication architecture, is the last stage.

According to the work described in [20], a vein identification model based on the multiscale deep representation aggregation (MSDRA) and deep convolutional neural networks (DCNN) was created. A pre-trained DCNN model is extracted in order to provide a multiscale feature map. After removing noisy information from the multiscale feature map using this technique as a first step, the chosen feature map is produced using a local mean threshold approach. To find vein information in particular feature maps and produce a binary vein information mask, the researchers developed an unsupervised vein information mining (UVIM) technique.

According to a study published in [21], to achieve high degrees of recognition security, a finger vein identification framework based on reliable key point correspondence clustering is proposed. Given the simplicity and safety it offers, finger vein identification has shown to be a reliable pattern for personal verification. The base recognizer is built on a descriptor-based scale invariant feature transform (SIFT) methodology.Then, the matching opportunities are improved by designing a multipin put multi-output (MIMO) matching structure in accordance with the diverse physical properties of the finger vein images.

According to the study discussed in the reference [22], a Deep Generalized Label Finger-Vein (DGLFV) model is suggested as a method for obtaining high levels of identification accuracy and feature map extraction. Image semantic segmentation, a brand-new technique for bidirectional traversal, and center diffusion can all be used to extract the largest rectangular finger-vein region. This is done for the predetermined categories. To avoid interference from unregistered users, the researchers will aggressively generalize all of the unknown categories as Class C+1. To further harmonize the classification, recognition, and verification procedures, an adaptive threshold acquisition strategy for Label Receiver Operating Characteristic (LROC) is also recommended.

Due to scale alteration, location translation, and image rotation, according to the study [23] cited. To solve these issues, researchers developed a wavelet denoising ResNet. This ResNet consists of a squeezed and excited ResNet18 model (SER) and a wavelet denoising model (WD). The main purpose of the WD model is to remove optical blur and skin scattering noise from hand vein images. The technology that allows residual learning converts the low-frequency feature of the WD model into a deep learning feature.Rotation, position translation, and scale adjustment are all addressed by the SER model by selectively boosting classification criteria and reducing less helpful qualities.

Palm veins have become a hotbed of biorecognition research due to their inherent advantages of universality, uniqueness, collectability, and stability. In this work in [24], it is suggested to use Neighborhood Preserving Embedding (NPE) and Kernel Extreme Learning Machine (KELM) to detect hand veins. The process begins with a grayscale analysis of vein pictures, produces embedded dimensionality reduction features that preserve the neighborhood, and then use extreme learning machines for detection and classification.

[25] In this paper, To enhance segmentation performance, researchers present a unified framework that accounts for both the change and appearance caused by the vascular flow event. Using this system, 3D HV and PV may be reliably and automatically separated from multi-phase MR pictures. First, background and vein pixels are automatically labeled using a well-known handcrafted vein picture segmentation technique. Based on the patches centered on the named pixels, a training dataset is created. Second, a DBN is trained on the resulting database to forecast the likelihood that, given a patch centered on it, each pixel belongs to be a vein pixel. Then interclass decision making (IDM), which combines neighborhood direction consistency and overlapping region discrimination, is suggested to further the findings on vascular segmentation acquired by both HV and PV clustering.

[26] Intravenous catheterization is regarded as the first and most important stage in the majority of medical treatments. In the past few years, biomedical engineering and the field of health care have paid increasing attention to the localization of subcutaneous veins utilizing NIR. As a result, the suggested research work based on NIR pictures to segment the forearm subcutaneous veins. This study presents Generative Adversarial Networks (GAN), a deep learning-based technique for segmenting and localizing forearm veins. GANs have recently demonstrated promising outcomes in the field of medical imaging.

Because of its convenience and security, the group creating biometric identification technology has focused a lot of emphasis on finger vein recognition. This finding came from a study that was published in [27]. In contrast to the majority of prior works, which focused their attention solely on one aspect of finger vein detection, the authors of this research provide a unified Bayesian framework based on partial least squares discriminant analysis (PLS-DA).

In the study [28], presented to decrease overfitting during the training phase and create a potent deep learning model, large-scale datasets are required. The goal of this study is to validate finger veins using the unique generative adversarial network (GAN) architecture known as the triplet classifier GAN (TC GAN). According to the triplet classifier Contrary to the conventional GAN-based approach, the learning capabilities of triplet loss-based convolutional neural network (CNN) classifiers are improved by GANs by leveraging the generated "fake" data. To increase the amount of training data and improve the CNN's discriminative ability, we collaborate a triplet loss-based CNN classifier with a GAN.

3. System Analysis

It is clear from the thorough examination that internal model properties of existing models differ greatly. This section contrasts various models further according to their qualitative characteristics, such as detection accuracy (A), time to find veins (D), computational complexity (CC), deployment cost (DC), and scalability (S) levels. The best models for performance-specific deployments will be simpler for readers to select as a result. By transforming the values of these metrics into harmonized Low Ranged Scale (LRS), Medium Ranged Scale (MRS), High Ranged Scales (HRS), Very High Ranged Scales (VHRS), and High Scales (H) ranges, they were quantized.This comparison can be seen from the table.1 as follows,

Table 1. Parametric comparison of different Vein detection models

Model	A	CC	D	DC	S
DBN [1]	M	H	L	H	L
NIR [2]	L	L	L	M	L
PCA Net [3]	H	H	H	VH	VH
LMP-PSP [4]	H	H	M	H	H
GF [5]	M	L	M	M	M
HKPUD [6]	M	H	M	H	H
WLD [7]	M	H	M	H	HH
BGM [8]	H	H	H	H	H
GTC [9]	H	M	L	M	H
CNN [10]	H	H	H	H	H
HOGCNN [11]	H	VH	H	H	VH
CRNN [12]	VH	H	VH	H	H
WAT [13]	L	M	H	H	M
KFCM [14]	M	H	H	M	M
FCNN [15]	H	H	VH	H	M
SVM [16]	M	L	M	H	M
MSMDGAN [17]	VH	VH	VH	VH	H
NIR [18]	M	L	L	M	L
JAF VNet [19]	VH	H	H	H	VH
MSDRA [20]	M	M	M	H	M
SIFT [21]	H	H	VH	H	M
DGLFV [22]	H	H	H	H	H
Res Net18 [23]	VH	VH	H	VH	H
NPE KELM [24]	H	H	H	H	H
IDM [25]	M	M	L	H	L
NIR GAN [26]	VH	H	H	VH	L
PLSDA [27]	H	H	H	H	M
TC GAN [28]	VH	VH	H	VH	M

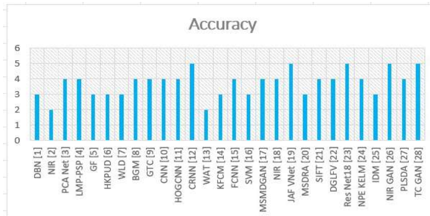

Figure 2. Accuracy levels of different Vein Detection Models

Based on the statistical analysis and figure 2,it may be seen that CRNN [12],JAF VNet [19] ,Res Net[18], NIR GAN [26], TC GAN [28], showcase better accuracy, thus can be used for high-accuracy application deployments.

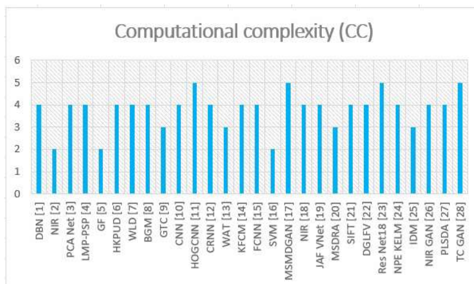

Figure 3. Complexity levels of different Vein Detection Models

Similarly, based on table 1 and figure 3, it is clear from this NIR [2], GF [5], and SVM [16] showcase lower complexity, thus can be used for low-computational power applications.

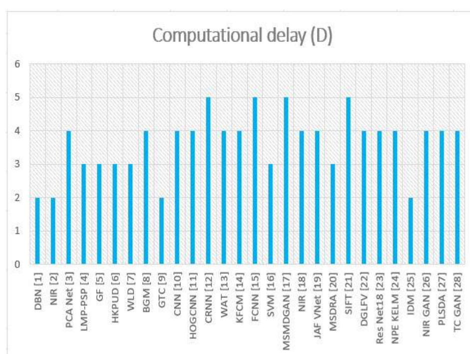

Figure 4. Computational delay levels of different Vein Detection Models

While, based on table 1 and figure 4, this can be seen to be true that IDM [1], NIR [2], GTC [9], and IDM [25] showcase lower delay, thus can be used for high-speed deployments.

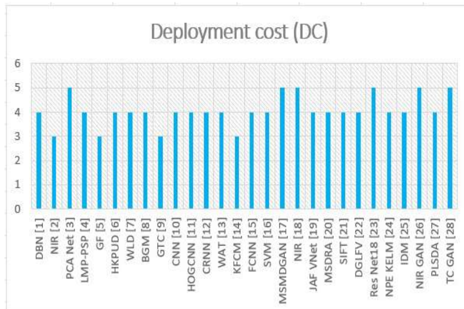

Figure 5. Deployment costs of different Vein Detection Models

Similarly based on the evaluation in table 1 and figure 5, it is clear from this NIR [2], GF [5], GTC[9], and PLS DA [14] showcase lower costs, thus can be used for low cost deployments.

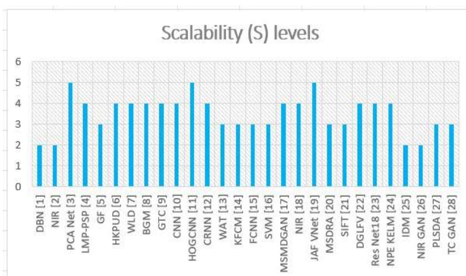

Figure 6. Scalability Levels of different Vein Detection Models

While, based on table 1 and figure 6, it may be seen that PCA Net [3], HOG CNN [11], and JAF VNet [19] showcase higher scalability, thus can be used for large-scale application deployments.

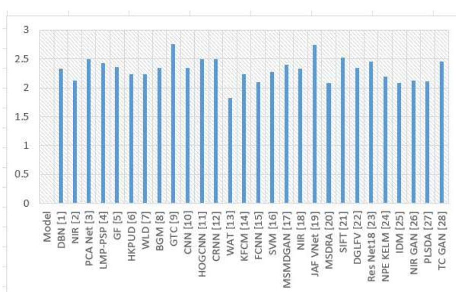

Figure 7. VMRS Levels of different Vein Detection Models

All these metrics are combined to form a novel Vein Model Rank Score (VMRS), evaluated by equation 1,

$$VMRS = \frac{A}{5} + \frac{1}{CC} + \frac{1}{D} + \frac{1}{DC} + \frac{S}{5} \quad (1)$$

From the evaluation, and figure 7, it is clear that from this GTC [9], JAF VNet [19], SIFT [21], PCA Net [3], HOGCNN [11], CRNN [12], TC GAN [28] and Res NET18 [23] showcase improved performance throughout the board evaluation metrics, thus can be used for high-accuracy, low complexity, high speed, low cost, and high scalability deployments.

4. Conclusion and Future Scope

The numerous vein classification models were described in this paper, and they were evaluated in terms of several assessment criteria, such as the accuracy levels, computational complexity, deployment costs, scalability, and latency required for various vein detection scenarios. It was observed that multiple databases are available for use in recognizing veins from different areas of the human body, including those in the finger, palm, and other. Additionally, it was found that deep learning models perform better at accurately detecting veins than linear processing models, making them suitable for a number of clinical applications. The GTC, JAF VNet, SIFT, PCA Net, HOGCNN, CRNN, TC GAN and Res NET18 models improved results in terms of in terms of all evaluation metrics. Thus, these models must be employed for applications requiring higher accuracy and better scalability performance for various use cases. In the future, these models will need to be combined using deep learning techniques, and their validity can be checked using a variety of databases and real-world application scenarios. These models must also be expanded through the use of Q-Learning and Reinforcement Learning techniques, which will help to further optimise performance for various application scenarios.

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