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Finger Vein Biometric Recognition System using Deep Learning

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***Abstract* - A biometric device called finger-vein recognition utilizes the vein patterns in human fingers to recognize individuals. Finger vein picture recognition technology, which has been successfully applied in a variety of areas, is highly reliant on biometric identification. Because veins are concealed beneath the skin tissue, finger vein image identification has an advantage that cannot be duplicated and is resistant to outside influences. Even though vein-based devices have not yet been fully incorporated into everyday living, they are excellent non-contact options. This research made a deep learning-based finger vein fingerprint recognition suggestion. The deep learning technique used is Convolutional Neural Network (CNN). A public dataset with pictures of the left and right hand's finger veins is used for the application. Python is the tool employed for the execution.**

Keywords: vein identification, biometric technology, convolutional neural network.

I. INTRODUCTION

The goal of biometric identification is to recognize an individual by their bodily characteristics, such as speech, iris, and DNA. In many areas, including online payment, security, and other industries, biometric identification is essential due to the increasing demand for digital security authentication systems. Contactless biometric identification systems are efficient solutions in the security industry for entry control and payments in terms of dependability, durability, comfort, but even more crucially, hygiene. There are numerous non-contact biometric methods, including vascular, motion, iris, and face.

Technology related to artificial intelligence, in particular Deep Learning (DL) technology, has advanced quickly in recent years. DL outperforms transitional image processing techniques in a wide range of computer vision tasks, including biometric identification, biological image analysis, and automated driving. In FVIR duties, DL-based techniques are frequently used. Image capture, image data pre-processing, feature extraction, and classification or other analytic duties are frequently included in the conventional FVIR procedure. Convolutional neural networks (CNNs), in particular, have a significant impact on the human feature extraction procedure when DL-based techniques are used. The use of feature engineering, where the selection of features is based on human subject expertise, has a substantial impact on how well traditional machine learning methods work. CNNs can still derive efficient but abstract characteristics through supervised or semi-supervised learning. By using DL-based techniques, the identification process has been greatly streamlined.

Compared with transitional image processing methods, DL achieves overwhelming performance in many tasks of computer vision, such as biometric recognition, biomedical image analysis, and autonomous driving. DL-based methods are widely used in FVIR tasks.

II. METHODOLOGY

In paper [1] order to enhance finger-vein recognition performance, the writers of this article suggest a deep neural network using bidirectional feature extraction and transfer learning. Finger capillaries have a lot of noise, dark areas, and uneven texture information. Similar information can be found in finger-vein images from the same digit, but there is a big difference between various fingers. In order to recognize useful patterns in finger veins, individuals typically use matching techniques. To adapt the network to our general identification framework, they made a new finger-vein database with the original one's location information reversed and used transfer learning.

The accuracy and generalization of the model are thus improved by using deep CNN to capture finger-vein features and provide more input characteristics for later SVM identification. The finger-vein database of Malaysian Polytechnic University (FV-USM) and that of our lab in the Signal and Information Processing Laboratory are both used in these studies (FV-SIPL). In this research, the contrast-limited adaptive histogram equalization (CLAHE) technique is used to improve the finger-vein pictures. They compare the VGG19 and ResNet50 algorithms to see which works better for the application. According to the performance study, ResNet50 outperforms VGG19 in terms of precision and convergence loss.

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In paper [2], for the goal of identifying finger veins, the authors proposed a four-layer CNN with fused convolutional-subsampling architecture that is simplified. The VeCAD Laboratory of University Technology Malaysia created the database for this study, which contains 50 individuals with 10 samples each for 6 distinct fingers. An improved stochastic diagonal Levenberg-Marquardt learning method is used to teach the NN for quicker convergence performance. The 5-13-50 model suggested a four-layered CNN with the merging of convolution and subsampling layers.

The winner-takes-all principle is used as the classification system in this work. This technique takes the place of the usual biometric approaches' use of similarity measure matching. The benefit of this approach is that each topic is given a real competition during training. the suggested CNN-based approach, which omits the pricey segmentation (local dynamic thresholding) step and instead uses pre-processing. The best normalization and weight starting technique was determined to be the mix of Z-score and uniform weight. The most ideal size was determined to be the original picture at 55 by 67. These choices produced identification rates of 100.00% and 99.38% in tests using samples from 50 and 81 participants, respectively.

In paper [3] a technique for identifying finger veins based on enhanced weighted sparse representation. Each training sample is weighted according to the total of the existing sparse coefficients as a classification foundation in order to lessen the heterogeneity of the samples engaging in sparse reconstruction. The Euclidean distance between each training sample and test sample should be calculated first. A number between 0 and 1 can be acquired by substituting the calculated Euclidean distance into the index of the Gaussian kernel function. This value can then be used. the training sample's weight. Second, the sparse representation classifier's decision-making process is modified. Based on the estimated vector produced by the sparse reconstruction and the amount of the residual between the feature vector and the initial test sample, the initial sparse representation classifier was created.

The FV-USM database and the MMCBNU database, a combined total of two finger vein picture datasets, were utilized in the investigation. The suggested technique has an adequate classification rate when compared to the performance of the current methods. The recognition rate of the classification method based on sparse representation progressively outperforms the conventional classification method based on closest neighbors as the number of training examples rises.

In paper [4], a biometric method based on the identification of human vein patterns is proposed. For that, they make use of image processing technique and machine learning technique. An image contrast intensification method called histogram equalization is first used to extract the area of interest from the original picture. The lower pixel intensity levels are then improved using a gamma compression method. The incoming noise is then removed using a median filtering method. The result should then be converted to double precision maps to boost speed. These all function as picture pre-processing methods to enhance the source image.

Next, canny edge detection algorithm is applied to the pre-processed image. The suggested approach uses the Histogram of Oriented Gradients feature extraction method (HOG). These extracted features are given to the classification algorithm, which is a machine learning technique. The classifier used in this study is Support Vector Machine (SVM). The proposed system results an accuracy of 93.33% while performing evaluation on test data.

In paper [5] using picture processing and machine learning to recognize NIR hand veins. The methods are trained and tested using the CASIA multi-spectral Palm print Image Archive. The ROI is then taken from the 850nm wavelength NIR hand imageries. ROI is linearly bounded with respect to the hand digits. The operator size will be adjusted by the LBP description to the intended information size.

The Naive Bayes method, which works well for binary classification jobs and initializes the model by using the Gaussian NB function, is employed. Using this technique, the computer learned how to take and manipulate the picture in order to identify the NIR Palm Vein. 94.1% of the data can be accurately identified as the NIR palm vein pattern after the suggested system has applied the machine learning classifier and machine learning method.

In this Paper [6] proposes a Finger vein biometric authentication based on Quadrature discriminant analysis. The Vein images captured by the infrared light using CMOS CCD camera. The Infrared rays with 750nm is used. The dark pattern is captured as the vein patten as the blood in the vein absorbs the NIR light. Quadratic Discriminant analysis is used for feature extraction. The minimum distance classification method is used to classify the images. Euclidean distance from pixels to the average vector is calculated. Input images are subjected to pre-processing steps for stabilizing images.

This Paper shows the result of vein recognition with 98.7% accuracy and also shows low False Rejection Rate and False Acceptance Rate in this system. The four levels of Pre-processing steps reduce the data size of the images that make it more comfortable to work with it.

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In paper [7] Discrete Separable Shear let Transformation are used to extract the finger vein features in this paper. Shear let transform is based on composite wavelet theory for 2-dimensional signal. The function used in shear let is band-limited function. A total of 29664 coefficients of finger vein images are used. The information size of the corresponding frequency and direction is described by its amplitude. Coefficient of all sub bands is pulled into vectors.

The recognition rate of a single DSST coefficient sub-band is calculated to measure the contents of information. This paper shows that DSST decomposition can provide an effective and sparse feature description for the finger vein images. It also shows that feature expression sparse performance of the feature vector is lesser than coefficients feature vector before screening.

In paper [8] there has been a lot of interest in vain-based biometric techniques, such as those using the elbow, wrist, palm, finger, and lateral hand veins. This hand vein has a wide range of characteristics and is simple to photograph. NIR sensors are used by palm vein identification systems to take pictures. A CNN-based feature and handmade features make up the palm vein detection system. There are three ways to remove handcrafted features:

Method based on geometry: It primarily employs the vein texture to depict an image's continuous linear structure and gathers data on all lines, curves, and points that are in close proximity to the outline and vein texture.

Statistical-based method: Utilizing statistical data, this technique identifies image traits like local histograms and image invariant moments.

Method based on local invariants: It draws inspiration from the standard scale invariant feature transforms (SIFT) method used in computer vision (CV), and it can immediately derive local invariant palm-vein characteristics.

Through the use of handcrafted features and PVSNet, the training target was chosen. The encoded characteristics were then sent into completely linked layers, where they were then confirmed by a classification network. The handmade features take away DL's ability to decide on the best course of action on its own. Then, in order to acquire pictures of the same quality and demonstrate its efficacy, a CNN structure is suggested for finger-vein. The same pictures were used for both testing and training, which is unacceptable because there is a possibility that actual data will alter unexpectedly during each test.

In paper [9] based on a vein identification method, system suggests a transfer Nonnegative Matrix Factorization (NMF). Since the majority of the current vein identification systems are only efficient for certain data sets, it increases the breadth of the majority of vein recognition characteristics. The following two elements primarily emphasize its contributions: In order to enhance the contrast between the features of various veins and decrease the duplication between feature bases, the model is subject to an orthogonal restriction. And Maximum Mean Difference (MMD) constraint is used to minimize the differences between vein features in various datasets, which means that the information from the source dataset is effectively transmitted to the target dataset and the universality of vein features can be enhanced.

Using bi-linear interpolation, all areas of interest from vein pictures are selected and normalized to M N pixels in this method. Then, by transforming the image matrix to the vector, the initial feature f(MN) can be retrieved.

The testing findings demonstrate that, in terms of transferability, the proposed algorithm outperforms the most recent techniques on two dorsal hand vein data sets and two finger vein data sets. Without creating larger scale data sets, we can create the useful features using just a tiny sample of the pictures the device gathered.

In paper [10] a Deep Dense Net-based composite image-based finger vein identification system. This method fixes many issues with the current CNN-based system. The current systems employ two distinct techniques for network input. The distance between the feature vectors that were extracted from the CNN is measured using a different picture. Because different pictures are produced by different pixel values, noise can affect them. Additionally, the trained network's entire topology cannot be used to calculate the distance between feature vectors, and this technique is less accurate than one that uses different images.

Utilizing a technique less susceptible to noise and able to utilize the complete network, a composite of two finger-vein images was used as the input to a deep, densely-connected CNN to address these issues (Dense Net). For this test, two open datasets were used. Which were the Shandong University homologous multi-modal traits (SDUMLA-HMT) finger-vein database and The Hong Kong Polytechnic University finger picture database (ver. The outcomes demonstrate that the proposed technique performs better than the currently used methods.

The recognition accuracy was verified to be higher when the composite images suggested in the research were input to CNN than when using different images. Additionally, it was found that the composite picture outperformed the difference image in terms of clarity against noise when tested with a noisy image. Additionally, different CNN models were tested

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on the two open databases, and the best recognition accuracy was found when the DenseNet-161 model was tuned and the shift matching technique was applied.

III. CONCLUSION

From this literature survey, we reviewed ten papers for our project Finger vein biometric recognition using deep learning. We got a number of ideas and system requirements such as using of CMOS CCD camera for capturing vein images, Discrete Separable method to extract the finger vein. Usage of weighted sparse representation for finger vein recognition. Studied the four-layer CNN with fused convolutional-subsampling architecture for finger-vein recognition. CNN based feature and handcrafted features for extracting handcrafted features there are three methods: Geometric Based method, Statistical based method, Local invariant-based method is studied.

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