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Robust 3D finger knuckles biometric identification with hierarchical featureNet architecture

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ABSTRACT

A novel biometric identifier known as the 3D finger knuckle pattern provides highly discriminative characteristics for the finger knuckle-based personal identification. This paper addresses the challenge of 3D finger knuckle recognition, aiming to enhance precision and overcome limitations in existing approaches. Leveraging neural network technology, it introduces a novel neural network framework for this purpose. Recent research has made significant progress in 3D finger knuckle recognition, particularly in the areas of matching schemes, feature representations, and specialized deep neural networks. Challenges such as limited training data and dataset heterogeneity are discussed. The proposed 3D hierarchical featureNet (HFN) methodology involves a multi-stage pre-processing process for 3D images, encompassing detection, cropping, smoothing, and hole-filling. Feature similarity is evaluated with nearest neighbor distance ratios, enabling precise recognition. The key contribution of this work is the introduction of a new feature vector that incorporates curvature data, improving the state-of-the-art. The methodology employs statistical distribution analysis for feature similarity and 3D geometry for accurate curvature representation. Overall, this research offers a comprehensive solution for 3D finger knuckle recognition, enhancing accuracy and efficiency through innovative pre-processing, feature extraction, and similarity evaluation methods.

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1. INTRODUCTION

Biometric technology has the capacity to efficiently accomplish various security requirements through its rapid and precise identification of individuals. Physical biometrics, such as the face, iris, ear, palmprint, fingerprint, and vein patterns, have been proven to be reliable and practical for automated human identity recognition in various real-world scenarios [1]. The applications mentioned above include features such as authentication for border checks, unlocking personal devices, and approving financial transactions. The fingerprint biometric identifier is commonly acknowledged as the most commonly used among various biometric identifiers for applications such as e-governance, e-business, and law enforcement [2]. Several applications have demonstrated the utilization of supplementary biometric identifiers, such as facial features, iris patterns, fingernail characteristics, palm prints, or vascular patterns [3], [4]. The evaluation of the effectiveness of biometric identifiers is performed by assessing their accuracy, efficiency, and, importantly, their capacity to fulfill application requirements in a user-friendly manner. Biometric recognition installations utilizing fingerprint technology have faced numerous challenges due to recurring skin deformations, persistent dirt, perspiration, moisture, and marks. Furthermore, it has been noted that a specific proportion of individuals demonstrate non-usable fingerprints, whereas iris recognition necessitates utilizing images of higher quality [5]. Additionally, recent research has demonstrated that face recognition systems are vulnerable to presentation attacks, including the use of advanced makeup techniques. The utilization of finger knuckle recognition offers an alternative solution that presents several advantages in these situations: the acquisition of finger knuckle images can be feasibly carried out in conjunction with fingerprinting, enabling both procedures to be performed simultaneously [6], [7]. The utilization of finger knuckle biometrics in isolation yields consistent and distinct data, ensuring reliable identification. The incorporation of this supplementary data alongside other biometric identifiers has the potential to enhance recognition accuracy. Finger knuckle images have become increasingly popular for biometric identification due to their exceptional accuracy, efficient performance, and the ease with which finger dorsal images can be generated [8].

Within the domain of fingerprint recognition, the acquisition of finger knuckle pattern images offers significant advantages. This characteristic is primarily attributed to their inherent resistance to damage that may occur during routine activities [9]. Long-range photography is capable of easily capturing the patterns of finger knuckles. This is primarily due to the distinct creases and curved patterns present on the knuckles, which are prominent when compared to fingerprints. The utilization of finger knuckle patterns in biometric recognition has demonstrated the ability to address certain limitations associated with relying solely on fingerprints [10]. The knuckle pattern is commonly acknowledged as a significant factor in personality identification within the domain of hand traits. The human eye has the ability to perceive curved patterns and prominent creases, allowing for visualization even when observed from a significant distance. The knuckle patterns yield primary data pertaining to the distinct characteristics of knuckle curves and folds. The extraction of knuckle curves and wrinkles from 2D images poses a significant challenge [11]. The observed outcome can be attributed to fluctuations in lighting conditions caused by multiple factors, such as uneven reflections originating from adjacent 3D knuckle surfaces. The modifications can have a significant impact on the intensity of the data. The integration of 3D information for the analysis of knuckle patterns can result in more accurate results, as it remains unaffected by variations in lighting conditions [12].

Moreover, it has been observed that 2D image biometric systems demonstrate an increased susceptibility to spoofing attacks. The integrity of the biometric system is compromised to a significant extent when an individual attempt to impersonate another person by presenting printed images [13]. The utilization of 3D data in biometric recognition has gained significant traction due to advancements in 3D reconstruction methodologies. The integration of 3D data obtained from finger knuckle patterns offers additional and reliable information, enhancing the reliability and accuracy of biometric recognition [14]. Spoofing attack detection capability is readily accessible in 3D knuckle imaging systems. The process of generating 3D knuckle pattern reproductions is known to pose significant challenges due to the need for deliberate finger exposure in difficult imaging conditions. The current circumstances differ from the typical scenarios encountered when capturing covertly acquired two-dimensional knuckle images [15]. In conclusion, the utilization of 3D knuckle patterns shows significant potential in addressing specific limitations related to alternative hand characteristics within the field of biometrics. The limitations imposed by conventional methodologies have restricted the current state of 3D knuckle recognition. The Figure 1 shows the three stages 3D image reconstruction process of finger knuckle wherein segmentation is performed on a raw image and converted into a 3D reconstructed Image.

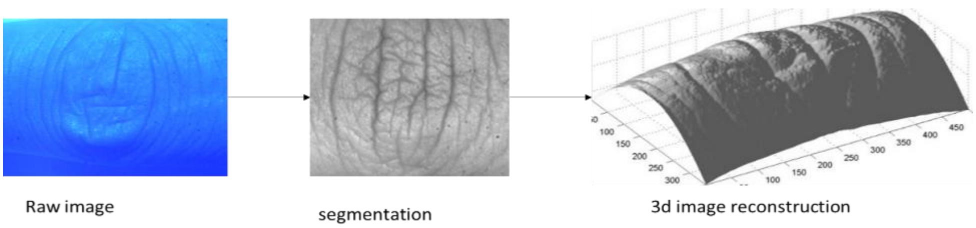

Figure 1. 3D image reconstruction process

Extensive research has been undertaken to investigate deep learning systems in various computer vision applications, such as biometrics. The development of advanced 3D finger knuckle identification involved in the utilization of deep learning techniques. The parameters employed in traditional finger knuckle identification methods need to be accustomed to suit various imaging scenarios and are specific to the database being utilized. Parameter tuning is an essential aspect of the detection process. The deep neural network designs are widely acknowledged for their high generalization capabilities. However, it is expected that the limited performance will be a concern of directly implementing designs such as [16]. Difficulties may arise during the integration process of fully contactless finger knuckle images. The issue pertaining to intrinsic rotational and translational shifts in contactless imaging has not been adequately resolved in previous studies. Additionally, it is essential to recognize that requires a predetermined number of output classes during the training process. This indicates that the introduction of a new topic requires retraining each time. The finger knuckle recognition and segmentation method described in [10] is considered inappropriate for contactless imaging in the presence of a complex background. The knuckle recognition and segmentation technique is implemented using the Mask R-CNN approach. It is important to note that the Mask R-CNN method is known for its complexity and is not considered ideal for real-time identification systems. At present, conventional deep neural network-based object identification and segmentation algorithms do not have the capability to simultaneously recover the orientation angle of the finger knuckle and accurately segment the knuckle region. Accurate assessment of the provided finger knuckle is essential to ensure optimal performance for online finger knuckle recognition [17].

The incorporation of 3D data has resulted in an improvement in the recognition precision of finger knuckle images. The existing constraint in 3D finger knuckle recognition arises from the obstruction introduced by the handcrafted approach. The effectiveness of neural network technology has been demonstrated in addressing two computer vision challenges, namely object segmentation and object identification [12]. A comprehensive examination has been undertaken to analyses the methodology used in different biometric applications, including face, iris, and fingerprint recognition.

- A novel approach known as hierarchical featureNet (HFN)+is designed to improve the characteristics of 3D images and the degree of identification of 3D images in low light.
- Enhanced 3D image recognition: this methodology improves the quality and accuracy of 3D finger and knuckle image recognition through advanced pre-processing and efficient feature similarity evaluation.
- Novel feature vector: the methodology introduces a unique feature vector that captures local-global features, enhancing the detailed representation of 3D finger knuckles for improved recognition.

2. RELATED WORK

The main focus of the thorough study on 3D finger knuckle recognition [18], whereas further research has been conducted to improve the construction of matching schemes, refine feature representations using similarity functions, and design specialized deep neural networks. In the image recognition, recognizing 3D finger knuckles is a significant difficulty. The limited availability of training data, which impairs the effectiveness of general deep neural networks, is a serious problem. The high heterogeneity found in the distributions of both the training and test datasets further augments the issue.

There have been several attempts to align contactless finger knuckle images using different approaches. In this work, key points, binary representations of local spatial characteristics, and the use of subspace algorithms are all used to encode the local 3D curvature of knuckle creases. The mentioned strategies have performed well; this provides an in-depth analysis. The use of cellphones for contactless finger knuckle detection has been studied in the past [19]. The correct segmentation of the finger knuckle presents one of the difficulties. The finger must be properly positioned in the image's center for this technique to work. The mentioned restriction is a major barrier to the widespread application of this technology. According to Cheng and Kumar [20], the traditional approach for contactless finger knuckle detection involves taking images of the finger knuckles against a simple background rather than a complicated one. After correcting the finger knuckle position in the provided image, the proposed approach moves on to detect the finger's edges in order to extract the areas that match to the finger knuckle creases. This method used for identifying and segmenting finger knuckles turns into severe problems, leaving it unable to detect and segment these knuckles with sufficient accuracy. The limitations of the current approach are a result of these difficulties. Intricate backdrops, several fingers knuckle visible in the same field of vision, concealed or partially veiled finger knuckles, and changes in position and scale are just a few of the difficulties that are included. In terms of object detection, deep neural network models have made substantial progress.

These models include the anchor-free based object detection method, the sliding window detection algorithm, the 2-stage series of R-CNN models [21], the 1-stage YOLO series the SSD models, and the R-CNN models with two stages, these models display specific benefits and drawbacks. The 1-stage concept is shown primarily to increase processing efficiency while maintaining a high standard of accuracy. A further boost in detection speed is produced by using the anchor-free strategy [22]. The 2-stage methodology, in contrast, ensures a high level of object detection accuracy. This work used the YOLOv5 model, a modern version of the

YOLO model, to accomplish accurate and effective finger knuckle area recognition. Kumar and Xu [17] present the comparative experimental results on numerous minor and major knuckle patterns. The study makes use of information from over 700 different people that was taken from a publicly accessible database. The use of this methodology as a standard for performance assessment using 2D knuckle images is justified by the improved results obtained when local feature descriptors are used in comparison to other methods [23].

The user made no contributions the state-of-the-art technique is improved upon in this work by the addition of a new feature descriptor that incorporates curvature data. Additionally, this study presents a technique for computing similarity functions that makes use of the statistical distribution of the feature space that has been encoded. This suggested feature representation takes advantage of a 3D geometry viewpoint to ensure accurate storing of curvature information. The probability mass distributions of the encoded feature space are analyzed during the comparison of two templates to derive the similarity function. By simultaneously encoding and combining deep features of varied sizes, the proposed technique seeks to increase the dependability of the deep feature representation. During contactless imaging, the issue of unintentional finger motions is addressed via a collaborative feature representation technique. To achieve exact matching, the proposed method uses an effective alignment mechanism with a fully convolutional architecture [24], [25].

3. PROPOSED METHODOLOGY

The proposed methodology begins with pre-processing to enhance 3D finger and knuckle images by detecting, cropping, normalizing surfaces, and filling holes. Feature extraction follows, designing feature vectors that capture local information. The architecture involves multi-level feature extraction, emphasizing local-global feature extraction and key-point identification. These key points facilitate image embedding and similarity calculations for accurate recognition, resulting in enhanced 3D image analysis for finger and knuckle identification.

3.1. Pre-processing

The finger and knuckle image obtained is pre-processed prior to enhance the local characteristics of the finger and knuckle and reduce the impact of the original 3D scanning surface acquisition. The procedure consists of three distinct stages. Detection and cropping, surface normal, smoothening the image and fill holes.

3.1.1. Detection and cropping

The primary goal of the initial scan is to precisely identify the position of the tip and ignore any regions that exceed the 3D boundaries of the image. The first step in the process involves the segmentation of the 3D image. The procedure involves the utilization of a series of horizontal scans of the image. Following this, a collection of horizontal contours of the image is produced. The process of interpolating points along the contour is performed uniformly to ensure that the gap is filled for each horizontal contour. In order to establish two intersections with the horizontal section, a series of strategically positioned probe points are employed on each respective section. Following this, a circle is accurately positioned at each of the specified points. The probe point produces a triangular shape with two intersecting points. The procedure for determining the target point for the involves placing the analysis point on the segment that corresponds to the highest point of the connected triangle, denoted as variable h. To ensure a comprehensive record of potential targets for the image, it is essential to repeat this procedure for each horizontal plane. The target sites are subjected to examination using the random sample consensus (RANSAC) procedure. The remaining options can be conceptualized as a set of points that are situated on the finger image. In the process of generating a 3D representation through image scanning, it is essential to exclude any data points that surpass a 90-millimeter distance.

3.1.2. Smoothening the image and fill holes

The median filter is employed to remove spikes that occur at the vertices of 3D images. Before calculating the median and replacing the original coordinates, the filter organizes the coordinates within a designated neighborhood. The elimination of the spikes results in the development of undesired voids on the surface in three dimensions. The presence of these holes can also be attributed to various additional factors, including occlusion, light absorption in shaded areas, specular reflection from different surfaces. Cubic interpolation is a method that can be employed to interpolate missing data points in 3D surfaces.

3.1.3. Surface normalization

When compared to a basic point in a cloud image, the traditional image often shows more information. As a result, the distinctive local features are given more attention, making it easier to extract and identify different characteristics of the image. By using an optimization-based method, it is possible to estimate the normal components of the image. To align the plane with a particular point's local neighbors, the cost function is minimized. The matrix is given as in (1).

$$R = [r_1, r_2, \dots\dots.., r_p]^V, r_k \in T^3 \quad (1)$$

The coordinates are represented as $r_k = [r_{kz,} r_{ka,} r_{kb}]^V$. The vector is represented as $p_k = [p_{kz,} p_{ka,} p_{kb}]^V$ which is further evaluated by the parallel point S_k around s_k. This is computed by solving the optimization problem given by (2). C is represented here as the cost function, within a neighbourhood of a 5×5 matrix. Each 3D point consists of its normal component as the Z, A and B channels as shown in (3).

$$minC(r_k, S_k, p_k) \quad (2)$$

$$P(R) = Pz(l,m), Pa(l,m), Pb(l,m) \quad (3)$$
$$1 \le l \le o, 1 \le m \le p$$

The normalization of the cloud point images in the database is estimated as normal image component. This image consists of more feature information in accordance with its corresponding cloud image, and this specific image looks improper. In the normal images the details are generalized and highlighted through other colors.

3.2. Hierarchical feature extraction

The image feature depicts the local expression of for image features, reflect the features of the image. Upon obtaining the key features identification from 3D image, the feature description shows the local information with each key aspect in form of matrix. The projection of statistical descriptor is encoded by geometric information for corresponding surface. A protection mechanism is rolled out for a statistic 3D image recognition. A key aspect represented as S through its supporting radius t, the parallel points around S through the distance is less than t are removed from the surface to generate a set of points as $S = \{s_1, s_2, \dots, sO\}$. The descriptor here is generated by the following steps.

In the first step, the cloud points are rotated and measured through S by a set of angles through the x-axis $\{\vartheta_m\}, m = 1,2,3 \dots\dots M$. The cloud point is depicted as $S'(\vartheta_m)$, the cloud point denoted after rotating $S'(\vartheta_m)$, is projected as the x-axis YZ, ZB, AB that results in three cloud points as $S'_k(\vartheta_m)$, $k = 1,2,3$. The 2D projection is described through the 3D local surface in a concise way. Retaining its significant dimensional reduction for the purpose of achieving the geometrical information of various points set to S as measured. In the second step the extraction of geometrical information involves dividing each point into $P_\mu^{seg} \times P_\mu^{seg}$ that mesh outs the average. To evaluate the number of points in each grid for $P_\mu^{seg} \times P_\mu^{seg}$ distribution for this matrix is obtained. The matrix M is further obtained to normalize the invariance to change the resolution of the grid. The information is further compressed onto the distribution matrix F. The matrix F can enhance the efficiency to evaluate the storage. The projection is rotated through the connection established as Shannon entropy for a feature vector as $h_z(\vartheta_m)$ rotating around the x-axis. To encode more information through the local surface the point-set S is rotated and projected around the y and z axis in a similar way to generate sub-feature vectors as $h_a(\vartheta_m), h_b(\vartheta_m)$ which rotates around y-axis and z-axis. The sub-feature vectors are connected to a vector form through an overall feature vector, shown as in (4).

$$h = \{h_z(\vartheta_m), h_a(\vartheta_m), h_b(\vartheta_m)\} m = 1,2, \dots\dots., V \quad (4)$$

The feature vector is further compressed to choose a set of training parameters and compute the covariance matrix as E. This is further decomposed into Eigen values that obtains the Eigen vector. The eigenvectors are arranged in the descending order fashion. The first P_{uh} eigenvector to form the matrix V_{uh}. P_{uh} is determined to fetch the training parameter of the feature is compressed via ϑ ratio. ϑ determines a positive number close to 1.

3.3. Architecture

A hierarchical featureNet (HFN) structure is used to extract local-global features on point clouds in an iterative manner by improving the sample layer making it effective to capture local information source of 3D finger images. The three ensemble extraction modules consisting of sampling with the multilayer perceptron (MLP) layers that extracts local-global features. The first two-layer focus on the local features of different view fields by identifying the center of mass within the local area to find the neighboring points to build the local area set, whereas the MLP layer focuses on the global features. The data collection is sampled and grouped to extract local features on the image. Figure 2 shows the proposed architecture of 3D finger knuckle HFN.

The local feature selection used for μ 3D keypoint detection to extract vectors with essential recognition through the local surface by the key points since μ which crops a circular region with the local region for an information around a single point consisting of a geometric shape in comparison with the global information. The local features are extracted after sampling the key points and covering the global region to terminate the process. These key feature points that gets the final global features. The global features are used as the image embedding. This algorithm is used to calculate the cosine similarity in between the images. The distance between the scans is considered within a given threshold, these scans belong to the similar equation.

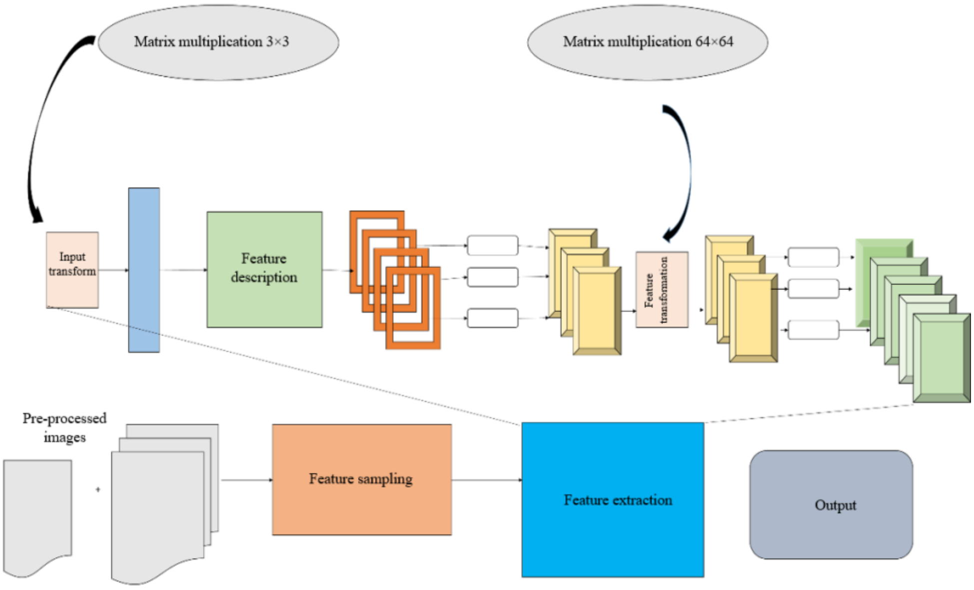

Figure 2. Proposed architecture of 3D finger knuckle HFN

3.4. Hierarchical featureNet feature matching

Assume $\beta^k = \{h_p^k\}$ and $\beta^l = \{h_o^l\}$ are µ feature sets extracted from 3D image as R^k and R^l. The nearest neighbour distance method is used for the purpose of feature extraction. Each feature here depicts the h_p^k in β^k that matches the features in β^k to obtain its closest feature $h_{o'}^l$ the second closest feature is $h_{o''}^l$ shown in (5) and (6). However, $\beta^{l\backslash h_{o''}^l}$ is the feature set β^l discarding features $h_{o''}^l$. The nearest neighbour-distance ratio is evaluated as shown in (7).

$$h_k = X_{uh}^V\, h_k \tag{5}$$

$$h_{o''}^l = arg\ arg h_o^l \in \beta^{l\backslash h_{o''}^l} min||h_p^k - h_o^l||_2 \tag{6}$$

$$t_d = \frac{||h_p^k - h_{o'}^l||_2}{||h_p^k - h_{o''}^l||_2} \tag{7}$$

The ratio t_d is less in comparison with the threshold α_h, $(h_p^k, h_{o'}^l)$ is evaluated as the potential for feature similarity. To achieve robust feature similarity, $h_{o'}^l$ matches the features in β^k. If h_p^k is the most nearby feature in β^k to $h_{o'}^l$ and satisfies the nearest neighbour distance criterion as (h_p^k, h_o^l) which is considered as feature similarity. The threshold α_h determines the number and accuracy of feature similarity. The feature similarity is generated by a smaller threshold which is not efficient to achieve estimation of transformation. A large threshold leads to a large number of false positives that reduces the performance of transforming the estimation. For 3D cloud point images, the same spot is analyzed at different angles for relevant features and matched accurately, wherein the 3D point cloud images from different individuals that do not match with the parallel features. The features in β^k are matched against features β^l resulting in a set of key-points as $E^{kl} = \{e_1^{kl}, e_2^{kl} \dots\dots e_p^{kl}\}$ here $e_p^{kl} = \{s_p^k, s_p^l\}$ consist of a pair of matched key points s_p^k.

4. PERFORMANCE EVALUATION

The performance evaluation of the proposed methodology is conducted using key metrics for the Hong Kong Polytechnic University (HKPolyU) 3D finger knuckle images database [26]. Accuracy metric is utilized to measure the overall correctness of the classification model, indicating its ability to predict the majority of cases effectively. The equal error rate (EER) assesses the performance of binary classification systems, such as finger and knuckle recognition, by finding the threshold where false acceptance and rejection rates are equal. Additionally, the cumulative match characteristic (CMC) metric evaluates the rank-based accuracy of the system, especially relevant in biometric identification. This comprehensive evaluation, involving a diverse set of metrics, ensures the robustness and effectiveness of the methodology in 3D finger and knuckle image recognition. In order to prove the HFN model efficiency it is compared with methodologies like squeeze and-excitation based ResNet (SE-ResNet) [27], DensNet [28], stochastic gradient descent (SGD) [29], finger knuckle network (FKNet) [19], and existing model [30].

4.1. Dataset details

The HKPolyU 3D finger knuckle images database [26] is a publicly available database that specifically comprises 3D finger knuckle images. The library provides an extensive compilation of 2,508 3D images showcasing the forefinger, accompanied by an additional selection of 2,508 3D images specifically emphasizing the middle finger. The images mentioned above are obtained from a sample of 228 individuals. The study incorporated a cohort comprising of 190 individuals. Throughout the duration of the study, a series of images are captured from the participants during two separate sessions. A subset comprising 89 participants is selected from a total sample size of 190 patients to partake in a photography session. Two separate lenses are utilized during the session. The procedure resulted in the generation of complex visuals that span multiple domains. In the initial session, the training set consists exclusively of the initial image acquired from each of the 190 participants. The test set consists of six images for each subject. Data augmentation is a commonly used technique in the training process to improve the quality and quantity of the dataset. The technique employs training images that have been rotated by a specific degree. The copies are subjected to a rotation of approximately 10 degrees. The evaluation process generates a total of 215,460 simulated comparison scores (1,901,896) and 1,140 actual comparison scores (1,906), which are summed up together. The data obtained during the initial session is commonly referred to as the training/gallery set, analogous to biometric enrollment or registration. The data acquired during the subsequent session is commonly known as the test or probe set, resembling biometric evaluation.

4.2. Metrics evaluation

The metrics used for analyses here are used in a wide range of scenarios and can be utilized for diverse evaluation purposes. Accuracy is a widely used metric for evaluating classification models, as it provides a measure of how well the model correctly predicts the class labels. On the other hand, EER is mainly employed in binary classification tasks, where the goal is to distinguish between two classes. Ranking-based retrieval or recognition systems are typically evaluated using the CMC metric.

- EER: is a quantitative metric used to evaluate the performance of binary classification systems. It is commonly applied in biometric systems; such as face recognition or fingerprint identification. The EER is defined as the specific threshold value at which the false acceptance rate (FAR) and the false rejection rate (FRR) are equal to each other. The EER is a significant metric in receiver operating characteristic (ROC) analysis. It represents the point of intersection between the ROC curve and the line of equality. At this specific point, the FAR is equal to the FRR.
- Accuracy: is a commonly employed performance metric utilized to assess the overall correctness of a classification model. The metric is quantified as a percentage and evaluates the proportion of accurately predicted events relative to the total number of instances in a dataset. A high level of accuracy in a model signifies its ability to effectively predict the majority of cases within the dataset.
- CMC: is a commonly used performance statistic in the domains of face recognition and biometric identification. The purpose of this evaluation is to assess the rank-based accuracy of a retrieval or recognition system. The likelihood of accurately matching a query sample to the genuine match is displayed by CMC in the top N ranked results. In scenarios where the significance of a ranked list of potential matches is paramount, it is common practice to employ such a list for the purpose of evaluating the performance of a system in situations where multiple matches are possible.

4.3. Results

The ROC curve of the image illustrates the performance comparison of various algorithms. The x-axis of the curve represents the FAR, while the y-axis represents the genuine acceptance rate (GAR). The metric used to quantify the rate at which false images are erroneously identified as real is referred to as the FAR. Conversely, the rate at which the original images are accurately recognized is denoted as the GAR. The performance of the model is enhanced as the ROC curve approaches the upper-left corner of the graph. Consequently, the model would exhibit a 100% GAR and a 0% FAR. Based on the analysis of the ROC curve depicted in the accompanying image, it can be observed that the proposed model exhibits the highest level of performance. Following the proposed model, the FKNet [8], SGD, DensNet, and SE-ResNet models demonstrate progressively decreasing levels of performance. The proposed model demonstrates an EER of 0.7%, significantly lower than the EER observed in the other models. The EER of the ROC curve corresponds to the point where the FAR and the FRR are equal. The statistic is valuable for evaluating the efficacy of different models as it takes into account both the FAR and the GAR. The ROC curve illustrates that the proposed model consistently exhibits a higher GAR compared to the other models, across all FAR values. The aforementioned observation suggests that, even in scenarios where the FAR is low, the proposed model exhibits better performance in accurately identifying original images. In comparison to the other models, this particular model exhibits a lower EER and a higher GAR. Figure 3 shows the comparison of the existing state-of-art-techniques with the proposed system for ROC comparison.

The CMC curve in the image shows the performance of a finger and knuckle image recognition system on a test set of images. The x-axis of the curve is the rank, and the y-axis is the recognition rate. The rank is the position of the correct match in the list of all matches returned by the system. The recognition rate is the percentage of test images for which the correct match is ranked in the top positions. A higher CMC curve indicates better performance. The CMC curve in the image shows that the proposed finger knuckle image recognition system showcases good performance. The recognition rate for rank 1 is over 90%, and the recognition rate for rank 10 is over 98%. This means that the system is able to correctly identify the target image in the top 10 results for over 98% of the test images. The CMC curve also shows that the proposed system outperforms the existing system [27]. The recognition rate for rank 1 is over 10% higher for the proposed system than for the existing system. This means that the proposed system is more likely to correctly identify the target finger knuckle as the top result. Figure 4 shows the comparison of existing state-of-art-techniques with the proposed system for CMC.

The accuracy graph is plotted here by comparing FKNet [26] methodology with the proposed system wherein the FKNet [26] model depicts an accuracy of 90.8 and the accuracy of the proposed model is 93.5. In comparison with the FKNet [26] model the proposed model ensures better performance. Figure 5 shows the Accuracy comparison of FKNet network with the proposed model.

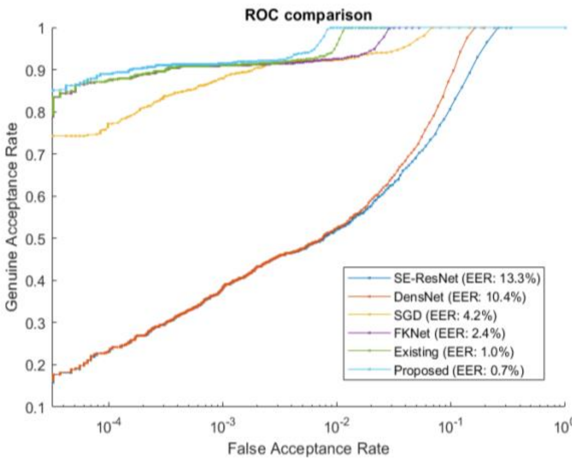

Figure 3. Comparison of existing state-of-art-techniques with proposed system for ROC comparison

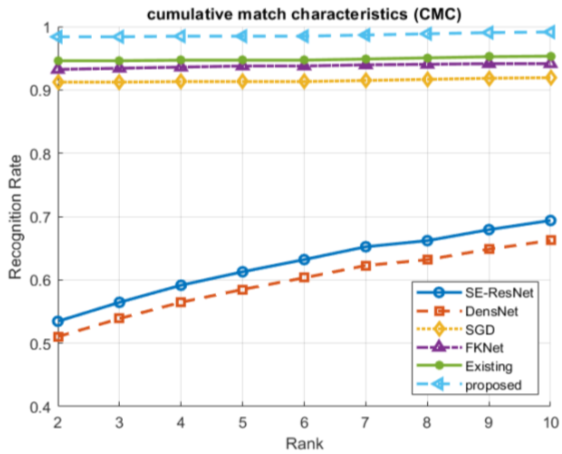

Figure 4. Comparison of the existing state-of-art-techniques with the proposed system for CMC

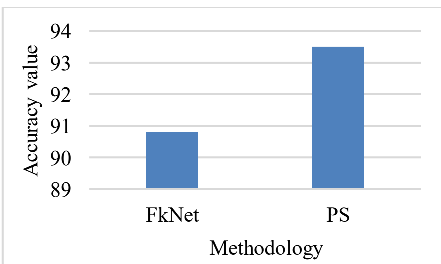

Figure 5. Accuracy comparison

4.4. Comparative analysis

In the comparative analysis of the existing system and the proposed system, several key performance metrics were evaluated. In terms of the ROC metric, the proposed system performs efficiently in comparison with the existing system [27], indicating its ability to distinguish between positive and negative cases. The CMC metric, which measures ranking-based recognition performance, also it depicts that the proposed system obtains a higher value of 0.98 compared to the existing system. Furthermore, the proposed system significantly excels in overall accuracy, achieving 93.5% accuracy, while the FKNet [26] reached 90.8%. These findings collectively indicate that the proposed system offers improved performance and accuracy.

5. CONCLUSION

The proposed methodology, named HFN, for enhanced 3D finger and knuckle image analysis, this paper presents a comprehensive methodology for improving the analysis of 3D finger and knuckle images. The system utilizes a multi-stage process that initiates with pre-processing steps aimed at enhancing image quality and refining local characteristics. The phase of feature descriptor extraction efficiently captures local information and important features. Feature vectors are generated for accurate recognition by rotating and projecting points from various angles, in conjunction with grid-based geometrical information. Performance evaluation using various metrics shows that PointNRD outperforms existing methods, offering higher accuracy and lower EER. The aforementioned methodology exhibits potential applications in the fields of biometrics, security, authentication, and object recognition, indicating a notable progression in the realm of 3D image analysis.

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AUTHOR CONTRIBUTIONS STATEMENT

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Mamatha Aruvanalli Shivaraj	✓	✓		✓	✓	✓		✓	✓	✓	✓	✓		✓
Honganur Chandrasekharaiah Nagaraj	✓	✓			✓			✓	✓	✓	✓	✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors would like to declare that there is no conflict of interest pertaining to financial, personal, or professional in connection with the manuscripts.

INFORMED CONSENT

The authors would like to inform you that the data sets have been taken with prior consent from Hong Kong Polytechnic university.

DATA AVAILABILITY

The authors would like to inform that the data set for carrying out the research is publicly available in https://www4.comp.polyu.edu.hk/~csajaykr/3DKnuckle.htm. Official consent for using the database was obtained from the Hong Kong Polytechnic university.

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