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A Novel Machine Learning-Based Multimodal Biometric Human Verification Using Fingerprint and Face Scan Data

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Introduction: The growing use of biometric identification technology in daily life, coupled with a global focus on information security and protection regulations, has led to a surge in multimodal biometrics due to their ability to overcome limitations. This paper introduces the Hybrid Dragonfly Optimized-Weighted K-Nearest Neighbour (HDO-WKNN), a multimodal biometric identification system based on Machine Learning (ML) algorithms for face and fingerprint biometric feature detection.
Methods:The dataset utilized in this study is made of a broad range of fingerprint and facial scan samples. A Gaussian filter minimizes noise during pre-processing and increases the overall signal-to-noise ratio to improve dataset quality. The robust Local Binary Pattern (LBP) method extracts biometric data patterns. The HDO-WKNN algorithm enhances the accuracy and robustness of a multimodal biometric verification system by prioritizing informative features based on their relevance and discriminative power.
Results: To evaluate the usefulness of our suggested strategy, we tested Accuracy, Precision, Recall, F1-score, Net Present Value (NPV), and Specificity and compared the findings to current approaches. This shows that the HDO-WKNN approach may achieve high accuracy and reliability in multimodal biometric human verification settings.

Conclusion: The HDO-WKNN addresses complex multimodal biometric data concerns with power and flexibility to produce more secure and trustworthy identity verification systems.

Keywords: Multimodal Biometric System, Face and Fingerprint recognition, Machine Learning (ML), Multimodal Biometric System, Hybrid Dragonfly Optimized-Weighted K-Nearest Neighbour (HDO-WKNN).

1. Introduction

The exponential growth in mobile users and communication, protecting mobile networks from multiple threats is vital.(1) Mobile data security and preface verification are crucial as sharing expands. Facial recognition is used in authentication systems due to rapid hardware advancement.(2)Encrypted data access is crucial as data and technologies proliferate. Security tokens, USB keys, passwords, and biometrics are needed for most IT-enabled devices. Unique fingerprints, iris, facial emotions, etc., make biometric identification common. (3)Face features and other biometrics are used to recognize and express feelings. It is better at detecting actual people from fakes.(4) Users and designers like multimodal biometrics because they are faster than unimodal solutions. Integrating face and fingerprint modalities may overcome single-modality drawbacks. (5) One-modal biometric systems fail owing to noisy data. Statistically independent biometrics allows this. Use several biometrics for further benefits.(6)

The article (7) presented the several situations that can occur in biometric systems with multiple modalities that use face and fingerprint recognition. It covers possible levels of fusion and combination techniques. The article (8) weighed the self-attention mechanism and the residual structure was used to calculate the fingerprint and face scan biometrics weights. The experiment used the VGG-19 and Alex net network models to extract features from face and fingerprint images. The work (9) combined the biometrics method founded on the profile face and fingerprint that addresses the shortcomings of ear biometrics but also raises the identification rate overall. The study (10)suggested effective multimodal biometric systems that combine the left, right and face palm prints with matching score concatenation fusion. A proposed method for training multimodal biometrics scores to detect and identify people uses a Convolutional Neural Network (CNN) and K-nearest neighbour (KNN) in multifunctional biometric identification systems.

The work of (11) presented techniques of recognition built using the merging of facial and fingerprint modalities, together to reliable multimodal biometric identification. CNN has extensive facial and fingerprint feature extraction. The paper (12) studied does not consider actual applications. Instead, it uses datasets from several sources, including finger vein, fingerprint data, and data from researchers who construct their equipment. The study (13) determined lowering the equal mistake rate by improving the accuracy of fingerprint and face-based multimodal biometric identification. The offered approaches use face scan model and score level fusion to identify users. The paper (14) presented an overview and discussion of the different scenarios that can implemented. It also addresses the various degrees of fusion and integration approaches that can be applied in biometric systems with multiple modalities that combine facial and fingerprint recognition to fuse data and raise the system's overall accuracy. The paper [15] worked on multimodal biometric person identification system based on an algorithm for deep learning for facial, fingerprint, and iris biometric recognition. The study [16] suggested is built on several biometric fusions combining fingerprint and iris biometric features. Several issues in fingerprint feature extraction directly impact the process of extracting minute details, such as feature extraction, binarization and thinning, fingerprint enhancement, normalization of the fingerprint, and scar removal.

The following are the Contributions of the paper:

Multimodal biometrics has gained prominence due to the rising use of biometric identification technology in daily life and global information security and protection requirements.

The research's dataset comprises of a broad range of fingerprint and facial scan samples. The robust Local Binary Pattern (LBP) method extracts biometric data patterns.

This study uses a revolutionary multimodal biometric identification method for humans-based Hybrid Dragonfly Optimized-Weighted K-Nearest Neighbour (HDO-WKNN).

Rest of the paper is organized the paper's body contains section 2 work. Section 3 covers data collection and other processes. Sections 4 and 5 analyze and debate performance. The report concluded in section 6.

2. Methodology

This work suggests a multimodal biometric system based on HDO-WKNN that uses features from the face and fingerprints. The user's face and fingerprint images are first taken. To identify the person, the multimodal system uses two fused HDO-WKNN for facial and finger vein recognition. The model finally generates the user identification. Figure 1 shows the methods for our suggested approach.

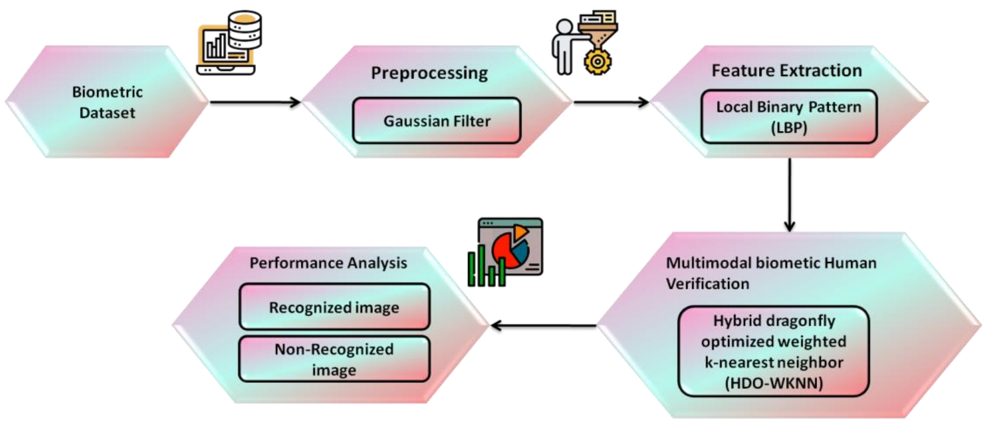

Figure 1. Flow of the suggested method (Source: Author)

Dataset

The fingerprint evaluation process uses Fingerprint Verification Competition (FVC) 2000 DB1 and DB2. A low-cost optical, It uses a sensor to record the FVC 2000 DB1 samples over various time intervals, with an image resolution of 300 × 300. Four models are used for each subject in FVC 2000 DB2, and the images have a resolution of 256 x 364. A low-cost capacitive sensor powers the acquisition system, and the facial image quality is assessed using the YALE and ORL databases.(17) The 400 images in the AT&T standard database, ORL, feature 40 subjects and ten samples each. The resolution of the images is 92 x 112 and there are 15 subjects in the Yale face database, and each person has 11 models.

Data pre-processing using Gaussian filter

Image through Gaussian filter before categorization algorithm chooses a weighted linear filter based on Gaussian function shape. Kernel-centered filtering was determined to refine images. It removes scattered noise. Calculate Gaussian smoothing filter component values.

$$z(y,x) = \frac{1}{v} a^{\frac{y^2+x^2}{2\sigma^2}} \quad (1)$$

The normalization constant is$v$, and the Gaussian kernel standard deviation is represented by σ.

Feature extraction using local binary pattern

LBP, an image-analysis texture describer, has been used for pattern and leaf descriptions. Its strengths include item identification, face and emotion recognition, and demographic classification. The previous LBP operator missed textural details in large structures, so it was expanded to cover a circular neighbourhood. This makes LBP more flexible and cost-effective. The paper determines the center pixels' (yv, xv) LBP codes.

$$LBP_{P.R} = \sum_{b=0}^{B-1} g(s_b - s_v)2^b \text{where} g(y) = \begin{cases} 1, y \geq o \\ 0, y < o \end{cases} \quad (2)$$

Where s_b and s_v represent the gray components of a circle-balanced neighborhood from $B - 1$ to $b = 0$ &$s_b = xP, R, p.$additionally, P represents the number of neighboring pixels in R's circular area. In addition, thresholding function $s(x)$ enables the LBP algorithm to achieve illumination invariance under monotonic variations. The detail of the texture image is 2^bLBP pattern probability distribution. Patterns are calculated for each processed image pixel using LBP algorithm parameters. Image rotation produces different LBP codes.

$$LBP_{B,K}^{kj} = \min\{ROR(LBP_{B.k,}J) | J = 0,1, \dots, b - 1\}, \quad (3)$$

The rotation-invariant LBP is created by rotating the original LBP code in a circle while maintaining distinct patterns. A right shift around ROR $(LBP_{B.k,}\ J)$ shifts P-bit x bits. The dimensionality of attributes plummets. Two uniform bitwise adjustments from 0 to 1 are possible for LBP P and R patterns. Constant descriptor offers $P(P - 1) + 3$ outcome bins for P-bit patterns. Consistent patterns have two compartments $(P(P-1)+1)$, while non-uniform designs have one.

$$LBP_{B,K}^{riu2} = \begin{cases} \sum_{b=0}^{B-1} g(s_b - s_v), \text{if} W(LBP_{B.k,}) \leq 2 \\ B+1, \text{if} W(LBP_{B.k,}) > 2 \end{cases} \quad (4)$$

Combine the remaining patterns into a single value by categorizing them as miscellaneous. There are $(P+2)$ different output patterns for a rotating invariant uniform descriptor when converting from $LBPP, Rto$ $LBP_{B,K}^{riu2}$ P, R. For the operators$LBP_{28,1}^{riu2}$, $LBP_{21,6}^{riu2}$, two and $LBP_{24,4}^{riu2}$, there are bins numbered 10, 18, and 26 in the proper sequence.

Hybrid dragonfly optimized weighted k-nearest neighbour (HDO-WKNN)

HDO-WKNN enhances biometric person verification by combining fingerprint and facial scan data, improving security and accuracy. It employs a hybrid dragonfly algorithm for weighted k-nearest neighbor classification, ensuring reliable human verification.

Weighted K-nearest neighbor (WKNN)

The standard KNN uses distance operations to partition data into new databases based on a similarity metric after storing all relevant data in one database. Non-parametric estimating statistics and pattern detection were used. Using these equations, neighbours are classified by Euclidean distance. The following equation flow of WKNN is shown in Figure 2.

$$Y = [Y_1, Y_2, Y_3, \ldots, Y_m], \quad (5)$$

$$X = [X_1, X_2, X_3, \ldots, X_m] \quad (6)$$

The following formula defines the distance calculated by Euclid between Y and X.

$$T(Y, X) = \sum_{j=1}^{m} \left(Y_j - X_j\right)^2 \quad (7)$$

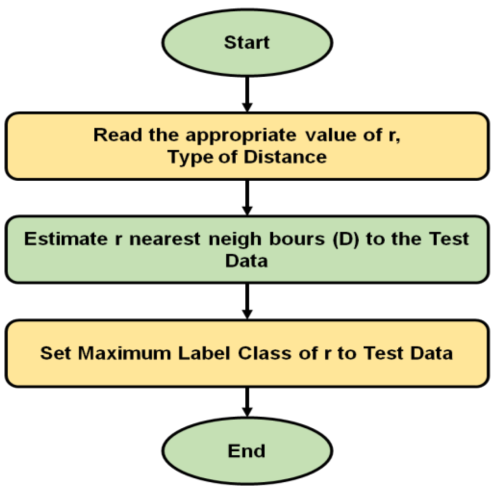

Figure 2.Flow diagram for KNN (Source: Author)

Hybrid Dragonfly optimization

Dragonfly (DF) optimizes search using evolution. Static and moving dragonflies inspired the idea. Fixed-swarm dragonflies search a confined region. An abrupt flying route shift defines fly mobility. Maximizing search space and preventing collisions by separating nearby DF. J neighbours form a cluster. Equation (8) provides an individual's segmentation ($\mathrm{Sep_j}$) inside a group DF's $\mathrm{r^{th}}$ neighbor is $\mathrm{y_r}$.

$$\mathrm{Sep_j} = \sum_{\mathrm{r=1}}^{\mathrm{m}} (\mathrm{y} - \mathrm{y_r}) \tag{8}$$

The alignment term $\mathrm{Alg_j}$ in Equation (9) matches the individual's velocity with nearby DFs. Here, $\mathrm{C_r}$ represents the speed of therth near DF.

$$\mathrm{Alg_j} = \frac{\sum_{\mathrm{r=1}}^{\mathrm{m}} \mathrm{C_r}}{\mathrm{m}} \tag{9}$$

Every DF individual in a cluster travels towards the mass centre of nearby DF equation (10) relates to the cohesion property $\mathrm{Coh_j}$ of DF:

$$\mathrm{Coh_j} = \frac{\sum_{\mathrm{r=1}}^{\mathrm{m}} (\mathrm{C_r})}{\mathrm{m}} \tag{10}$$

Applying equation (11), the $\mathrm{Af_j}$ feature at point $\mathrm{y_{food}}$ is obtained.

$$\mathrm{Af_j} = \mathrm{y_{food}} - \mathrm{y} \tag{11}$$

Equation (12), when applied to the enemy $\mathrm{y_a}$ location, yields the enemy feature $\mathrm{Ee_j}$.

$$\mathrm{Ee_j} = \mathrm{y_a} + \mathrm{y} \tag{12}$$

All five factors combined impact how DF behaves within a cluster. Equation (13) indicates the revised locations of each DF, which are determined by step Δyj.

$$y_j = \Delta y_j + \Delta y_j \tag{13}$$

With inertial weight w, divide, align, and cohesion cause a, b, and c. Dragonfly clusters (Sep_j, Coh_j , Af_j , and Ee_j) represent separation, alignment, cohesiveness, food, and opponents. DF exploitative and inquiring patterns vary by parameter. Modern biometric authentication systems benefit from HDO-WKNN accuracy, durability, and security.

3. Result Analysis

This study relied deeply on Python 3.11. We provide Intel Core i7 laptops with 32GB SSDs and Windows 10. The proposed system's efficacy is evaluated here. Evaluation measures include accuracy, precision, recall, F1-score, NPV, and specificity. Parallel Slap Swarm-Algorithm Based Deep Belief Network (PSSA-DBN) [18], Alex Net-CNN [18], and ResNet50 [18] are used for comparison. Table 1 illustrates the proposed and existing method results.

Table 1.Outcomes of the proposed and existing methods (Source: Author)

Methods	Precision (%)	F1-Score (%)	Accuracy (%)	Recall (%)	NPV (%)	Specificity (%)
PSSA-DBN [18]	96,65	93,55	97,13	98,12	95,62	96,11
ALEX NET-CNN[18]	91,38	90,76	93,93	94,44	90,65	90
RESNET 50[18]	88,57	88,99	92,29	91,22	89,78	86,74
HDO-WKNN (Proposed)	97,8	96,8	98,92	99,4	97,2	98,7

Discrepancies between development and real number originate from inconsistent accuracy. The proportion of true outcomes shows data distribution. Figure 3 shows the accuracy and precision approaches developed and used. PSSA-DBN, Alex Net-CNN, and ResNet50 have obtained accuracy of 97,13 %, 93,93 %, and 92,29 %, respectively, whereas our suggested method has produced HDO-WKNN, which is very accurate at 98,92 %. This strategy outperforms other existing methods. The ratio of correctly categorized cases to all positive data is crucial to accuracy. In terms of precision, current techniques including PSSA-DBN, Alex Net-CNN, and ResNet50 have achieved 96,65 %, 91,38 %, and 88,57 % percent precision, respectively. With 97,8 % of precision, our proposed HDO-WKNN technique surpasses other existing approaches.

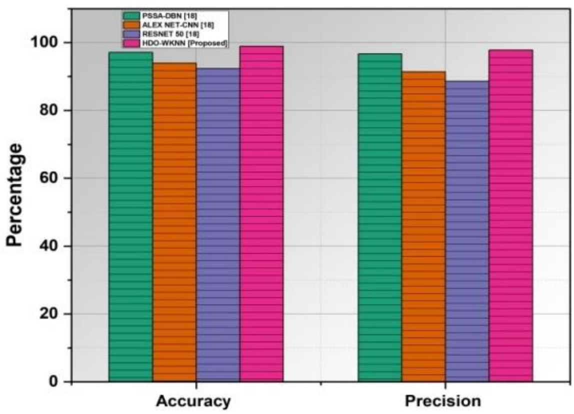

Figure 3.Comparison of Accuracy and Precision (Source: Author)

Recall rates indicate a model locates each higher production in a batch. The study focuses on determining the actual positive to total true benefit ratio and phony negative ratios. Figure 4 depicts the comparison of recall and f1-score of our proposed and other existing approaches. While HDO-WKNN, which we proposed, has achieved 99,4 % of recall, PSSA-DBN, Alex Net-CNN, and ResNet50 have attained recall of 98,12 %, 94,44 %, and 91,22 %, respectively. It performs better than other current approaches. In terms of f1-score other existing methods such as PSSA-DBN, Alex Net-CNN, and ResNet50 have reported f1-score of 93,55 %, 90,76 %, and 88,99 % respectively. Our suggested strategy HDO-WKNN outperforms other current methods with 96,8 % f1-score.

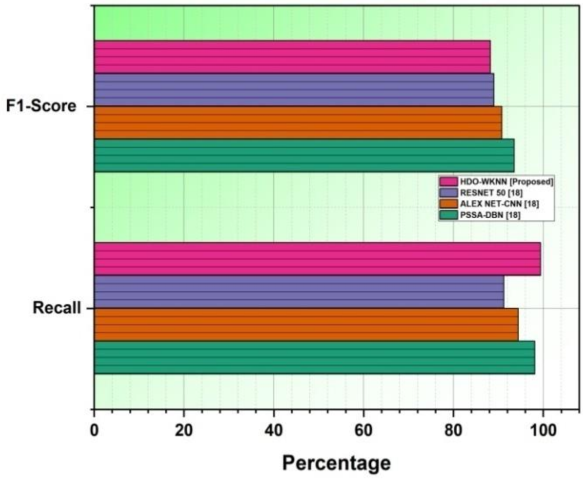

Figure 4.Comparison of F1-score and Recall (Source: Author)

The financial term describing the amount of money that can be made on a project or investment is the net present value or NPV. Over a certain period, it displays the difference between current cash inflows and outflows. The core idea behind NPV is calculating an investment's value while taking the time. In PSSA-DBN, Alex Net-CNN, and ResNet50 have achieved NPV of 95,62 %, 90,65 %, and 89,78 %, respectively, as shown in Figure 5, whereas our proposed technique yielded HDO-WKNN, which is 97,2 % of NPV. And In comparison of Specificity PSSA-DBN, Alex Net-CNN, and ResNet50 have achieved 96,1 %, 90 %, and 86,74 % precision, respectively. Our suggested HDO-WKNN strategy outperforms other current methods with 98,7 % accuracy.

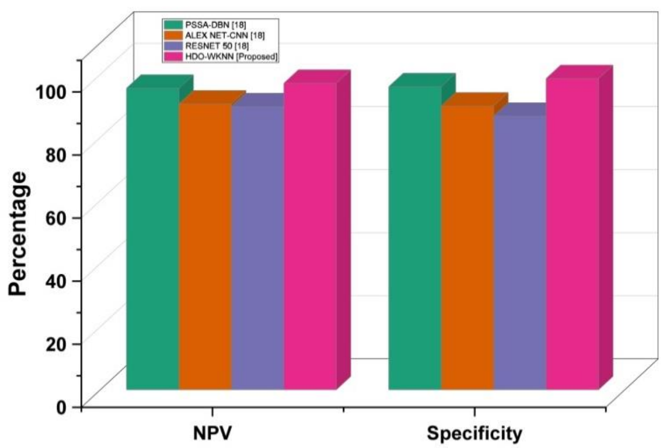

Figure 5.Comparison of NPV and Specificity (Source: Author)

4. Discussion

The fingerprint-facial scan PSSA-DBN multimodal biometric person verification approach needs revision due to limitations such as computer restrictions, privacy concerns, spoofing, and real-time processing [19]. Alex Net-CNN lacks multimodal biometric ID and may over fit small datasets. Fusion of fingerprints and facial scans can require better illumination, posture, and expression [20]. ResNet50 over fit small biometric data and complex calculations will slow real-time verification [21]. HDO-WKNN improves accuracy, robustness, and security by optimizing feature fusion with weighted k-nearest neighbours and hierarchical decision optimization. Real-world use of this strategy overcomes these challenges.

5. Conclusion

This study developed a multimodal biometric user identification system using HDO-WKNN machine learning and two score fusion algorithms. The system uses facial and fingerprint features to identify users. The results showed high accuracy (98, 92 %), precision (97, 8 %), recall (99, 4 %), F1-score (96, 8 %), NPV (97, 2 %), and specificity (98, 7 %). The model can create image-accepting fingerprints. Future research will test the model using diverse multimodal datasets and level fusion techniques. Integrating AI and advanced sensor technologies in multimodal biometric human verification will enhance security and user experience.

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