

A New Innovation in Biometric Recognition Using Agentic AI Based on Swarm Feature Engineering with Ensemble LenetCNN

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Abstract – Recent developments in biometric recognition analysis include various imaginative intelligence concepts for identifying multimodal friction rides based on feature descriptions to solve the complexities in security and person identification applications. For information security, the Research uses multimodal screening analyses from finger veins, finger knuckles, iris, palm prints, and fingerprints. Most traditional methodologies only concentrate on object region regions, which fails to identify the feature relation and entity variation. The problem arises from the multi-correlation feature dimension, which increases the non-relation image registration and structural properties in entity resolution. Due to higher degradation in entity resolution, finding ridges creates false occlusion, causing a higher dimensionality ratio, lower precision rate, recall rate, and more false positives to provide lower identification accuracy. To resolve this problem, we propose an artificial intelligence based on AI-powered Multimodal biometrics recognition using deep scalar feature engineering with Optimal Particle Swarm Intelligence (OPSI) feature selection with Hyper capsule Gated LenetCNN. Initially, the multimodal biometric dataset is pre-processed with an adaptive Gaussian mean filter to normalize the images, and the Iterative pattern Slice Fragment Clustering (IPSFC) is applied for entity markings. Then, a vector Pyramid Scene Parsing Network is used for segmentation. Then, to reduce the feature dimension, the Optimal Particle Swarm Intelligence (OPSI) feature selection is applied to minimize the non-relation features. Then, LSTM- Hyper Capsnet CNN is used to identify the biometric data. Our methodology involves extracting pertinent biometric data features and utilizing deep learning algorithms to enhance identification accuracy. The proposed deep optimal feature engineering approach is introduced, allowing the model to prioritize and select features that significantly increase the identification accuracy while minimizing feature redundancy. The output result is evaluated, and improved accuracy, sensitivity, specificity, and F1 measure performance are achieved, significantly increasing the precision rate based on the proposed CNN classification.

Keywords – Biometric Recognition, Multimodal Biometrics, Deep Learning, Feature Engineering, Artificial Intelligence, Particle Swarm Optimization, Convolutional Neural Networks, Information Security, Feature Selection.

I. INTRODUCTION

These growing requirements to provide solid guarantees for protection and security triggered necessary improvements in biometric recognition analysis. Traditional unimodal biometric systems, which use identifiers like fingerprints or facial features, struggle to handle the complexities of real-world security applications [1]. These systems are susceptible to spoofing attacks, environmental variations, and data quality deterioration, hindering their applications in necessary identification settings. This has led to the development of multimodal biometric recognition, which exploits the complementary advantages of multiple biometric features to improve recognition accuracy and security [2]. This paradigm shift requires complex analytical frameworks that can systematically combine heterogeneous biometric data streams and generate meaningful features to determine the identified person clearly.

Traditional approaches mainly emphasize the object region, leading to insufficient learning of intricate feature relationships and entity variations, vital for precise identification [3]. This limitation is exacerbated by the difficulty of realigning similar dimensional spaces in a multi-correlated feature space, which leads to less precise image registration and resolution of its structural properties [4]. The degradation in entity resolution, such as fingerprint ridge extraction or analysis, leads to false occlusions and an increased dimensionality ratio, reducing precision and recall while increasing false positives, causing the overall error rate to decrease. At the same time, identification accuracy falls [5]. Traditional

approaches have proven inadequate for handling the unique challenges of multimodal biometric data, and such limitations necessitate the development of novel methodologies. To overcome these challenges, this Research presents an AI-enabled framework to boost the performance of multimodal biometric recognition systems. We suggest a deep scalar feature engineering with Optimal Particle Swarm Intelligence (OPSI) feature selection and a Hyper-capsule Gated LenetCNN architecture for detecting spam to utilize the latent features through a deep feature extraction process, which minimizes redundancy and ensures high overall accuracy in spam detection.

Limitations From Preliminary Work Principle

- The multimodal class contains higher feature dimensionality due to cue points in the biometric images containing higher non-correlation feature labels.
- Uncover coaxial points containing feature degradation and cross-vector correlation. The bio-pixel degrades the deep cue punts for exact correlation.
- The hybrid model takes the actual point of feature threshold limits reputedly to reduce the precision rate, but more false negatives lead to feature drops.

Objective and Contribution of the Research

We propose an approach that relies on the comprehensive preparation of multimodal biometrics information from multiple modalities (source), including the information provided by finger veins, finger knuckles, iris images or scans, palm prints, and fingerprints. To maintain data consistency and reduce noise and variance, the Normalization of images is achieved by employing an adaptive Gaussian mean filter. Then, Iterative Pattern Slice Fragment Clustering (IPSF) is used for entity marking that helps to localize key features. It is critical to extract the discriminative features and clean the data for further analysis. ResNet is more ubiquitous than CNN, and in this approach, along with the vector PSPNet, is included to segment features from the images. With its ability to gather contextual information at multiple scales, PSPNet provides more prosperous and discriminative features extracted from the segmented biometric data. But even when transformed, the resulting feature space may remain too high-dimensional, making computation expensive and leaving room for overfitting. We use Optimal Particle Swarm Intelligence (OPSI) to select features to overcome this. By extracting the optimal subset of features with minimal redundancy, OPSI significantly reduces the calculation load and enhances the model's generalization ability.

These selected features are then inputted into a newly proposed LSTM-Hyper Caps net CNN architecture for identification and classification purposes. Leveraging this hybrid architecture trains with network, Hyper-Capsule networks, and CNN networks together to incorporate the merit of their capabilities for succinct capturing of spatial and temporal dependencies in casual biometric data. By combining LSTMs and Hyper-Capsule Networks, this architecture capitalizes on the strengths of both components to provide the capability to learn sequential patterns and robust representation learning through hierarchical encoding of features. The additional insight gained from the CNN part of the model helps it focus on subtle characteristics and improve its classification performance even more. Leveraging the huge potential of different learning techniques, this model can identify a person based on a complex correlation of multimodal biometric traits. The framework leverages a novel deep optimal feature engineering. It enables the model to recognize and choose the features that help boost the identification accuracy without lessening the features. The first part identifies and emphasizes the most discriminative features for better learning of the model. Its selective feature engineering procedure helps reduce dimensionality limits and increases the model to generalize unseen data.

The organization of this paper is as follows: Section II covers related studies. Section III details the proposed methodology. Section IV discusses results and comparisons. The paper ends with essential results alongside possible future research in Section V.

II. LITERATURE SURVEY

This method summarizes multimodal biometric authentication systems, which enhance the security and privacy of digital data. Furthermore, it analyzes the current trends in multimodal biometric authentication technology according to various fusion scheme types and their levels [6]. Based on advanced cascade and decision-level fusion, we propose a multi-modal biometric system that integrates fingerprint, finger vein, and facial images [7]. It uses Convolutional Neural Network (CNN) technology to recognize and extract features in face images, improving accuracy compared to existing systems based on unimodal or bimodal features. A novel Attention-Based Encoder Fusion Network (AEF-Net) employs coupled similarity to fuse multi-modal, multi-level features through dimensionality reduction, aiming to reduce performance loss caused by information redundancy. Yet, current biometric fusion techniques struggle to manage the simultaneous interaction of multi-modal features and redundancy [8]. The performance of ResNet 101 and various preprocessing techniques of AlexNet in enhancing and analyzing finger vein images for biometric identification is significant [9]. However, low-quality images present major challenges and require new, precise recognition methods. A CNN technique creates a multimodal biometric authentication system [10]. The two features are merged using a matching score-level correlation based on the weighted sum rule.

In particular, the suggested approach improves performance by offering an optimal Fuzzy Genetic Algorithm (FGA) and a multimodal fusion strategy, thereby addressing current issues [11]. Analyses performed in various biometric conditions demonstrate significant improvements in current techniques. Discriminant CNNs are architectures like ResNet,

VGGNet, and DenseNet designed to extract unique discriminative features to improve performance in computer vision tasks. This study [12] focused on improving multimodal biometric authentication using fingerprint and finger vein images as key features. The proposed feature-level fusion uses Canonical Correlation Analysis (CCA) to combine the same person's iris and fingerprint feature sets [13]. Various feature extraction and classification techniques suggest a CNN algorithm to assess the performance of parallel and sequential multimodal biometric systems [14]. At each pixel position, the binary transformations of the symmetric and asymmetric areas of the Gabor-filtered image are encoded as the foundation of the technique [15]. A person's palmar axis and iris function are combined in partial fusion.

A matching module with similarity and dissimilarity measurements was presented using the Absolute Pearson Correlation Coefficient (APCC) algorithm to create single-sample and multi-sample biometric systems combining face, fingerprint, and signature techniques [16]. Additionally, the DFs were represented in the low-dimensional feature space using Multicanonical CCA (MCCA), accelerating the recognition task [17]. Single-mode biometric systems, however, are susceptible to several threats, including spoofing assaults. To further improve the performance of multimodal biometrics, an efficient classification Multi-Support Vector Machine (MSVM) algorithm is developed to determine the optimal feature values [18]. The system's design uses a CNN method, which extracts features and classifies images using a Softmax classifier [19]. Three CNN models—one for the face, one for the ovary, and one for the nerves in the fingers—were integrated with this system. A Gradient Neural Network (GEN-NN) approach is suggested to enhance biometric authentication using a VISA face and iris multimodal biometric database by focusing on multimodal biometric features such as face and iris [20].

The recognition procedure utilizes an Optimized NN (ONN) model. A significant advancement is choosing the best weights for NN training with an enhanced Dragonfly Algorithm (DFA) [21]. This approach addresses high error rates, class variances, and noisy data. A MULBv1 multimodal biometric database featuring uniform biometric attributes has been introduced [22]. Database: diverse face images, 20 right-hand images (multi-angle), 20 right iris images (varied lighting). They suggested a strong multi-modal biometric authentication system that combines iris and face models. The Xception pre-trained model inspires the new, effective Deep Learning (DL) model used in the suggested method to extract features and identify regions of interest using YOLOv4-tiny [23]. Rather than combining features, a novel multimodal fusion approach employs a Discrete Wavelet Transform (DWT) technique to integrate database images [24]. The facial and signature images are blended, and features are extracted from this combined image before being classified with an ensemble classifier. Furthermore, the system utilizes DLCNN-based classification for all biometric modalities, enhancing its accuracy and robustness [25].

III. PROPOSED MATERIALS AND METHODS

The proposed system addresses the shortcomings of conventional approaches by employing a multi-stage process designed to preprocess, segment, extract salient features, and classify multimodal biometric data with superior accuracy. The system utilizes information derived from finger veins, finger knuckles, iris, palm prints, and fingerprints, thus harnessing the complementary strengths of each modality to bolster overall identification performance. The following sections will elaborate on the key components of the proposed system, highlighting the rationale behind each stage and the expected improvements in performance.

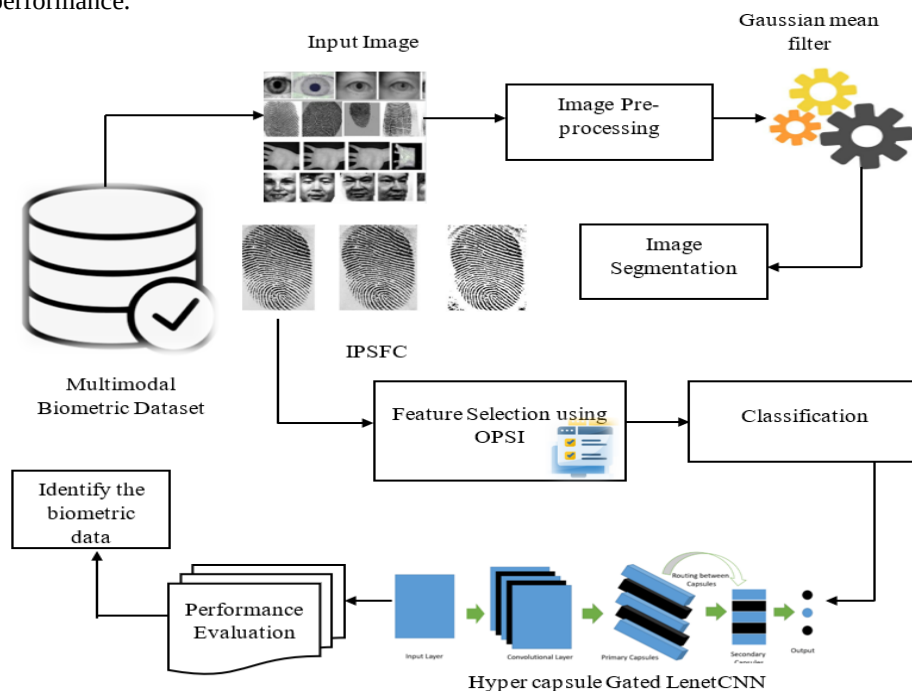


Fig 1. The Proposed Architecture Diagram.

Fig 1 illustrates the proposed architecture for enhanced biometric features and identifies the biometric data. Range prediction using multimodal biometric data. The pipeline commences with the pre-processing of the multimodal data, which is subsequently normalized through an adaptive Gaussian filter to mitigate noise and inconsistencies, ensuring data quality. Individual entities within the normalized data are then marked using an IPSFC technique, presumably to highlight regions of interest or significant biometric markers. Following entity marking, a PSPNet is a robust deep learning model renowned for capturing contextual information at various scales, segmenting the data, delineating distinct regions, and facilitating feature extraction. Dimensionality reduction is subsequently performed using an OPSI method to minimize computational complexity while retaining the most discriminative features. The core of the prediction process involves a hybrid deep learning architecture consisting of an LSTM network, a Hyper Capsnet, and a CNN. This integrated model leverages the temporal dependencies captured by the LSTM, the hierarchical feature representation capabilities of the Hyper Capsnet, and the spatial feature extraction proficiency of the CNN to identify biometric feature identification and eventually predict the identify the biometric data. Range. The architecture incorporates a deep optimal feature engineering approach that prioritizes impactful features and minimizes redundancy, leading to a more efficient and accurate prediction model.

Data Preprocessing

The initial stage of the proposed system focuses on preparing the raw biometric data for subsequent analysis. Variations in image quality, illumination, and sensor noise can significantly impact the accuracy of feature extraction and classification. Therefore, a crucial preprocessing step involves normalizing the input images using an adaptive Gaussian mean filter. This filter dynamically adjusts its parameters based on the local characteristics of the image, effectively mitigating the effects of noise and ensuring consistent image quality across different modalities. The Gaussian Adaptive Mean Filter (GAMF) connects adaptive mean filtering techniques to Gaussian filtering to improve image quality while maintaining vital details.

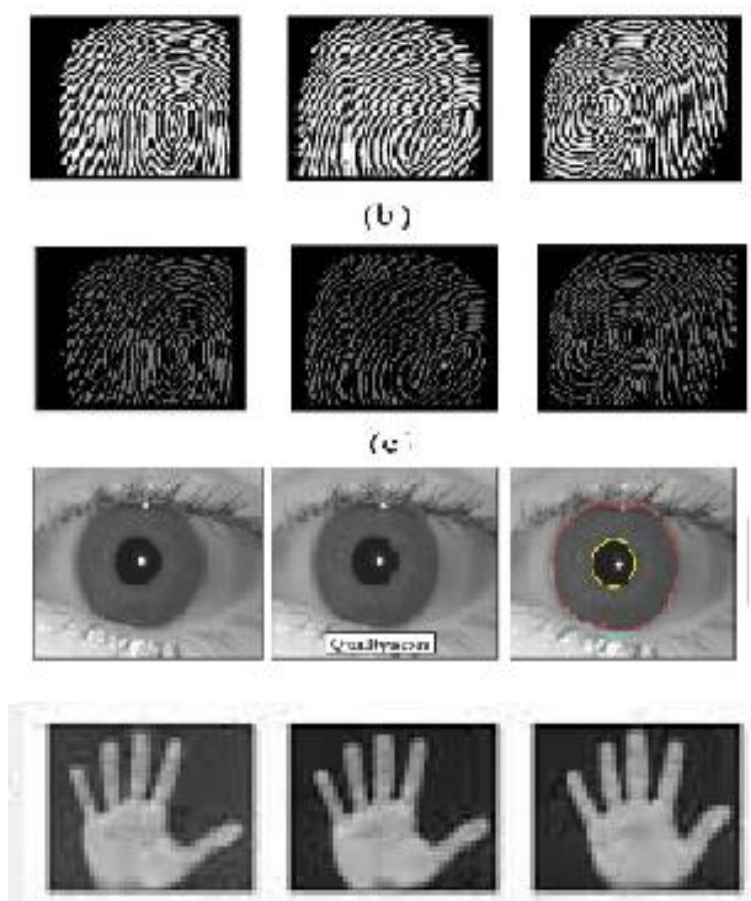


Fig 2. GAMF Preprocessing and Normalization.

This filtering method performs outstandingly in protecting edge definition while reducing noise. Local image variance values trigger the filter to change its smoothing intensity, allowing it to perform better noise reduction on uniform areas without blurring important edges and textures. **Fig 2** shows the GAMF preprocessing and Normalization. Between them, the adaptive mean method changes its reaction according to local intensity fluctuations, yet the Gaussian component performs weighted averaging to increase the influence of nearby pixels. The technique operates successfully with remote and medical image applications because it reduces noise while minimizing blurring effects. In Equation 1, we illustrated the two-dimensional digital Gaussian Filter,

$$G(x, y) = \frac{1}{\sqrt{2\pi}\sigma} \exp(-(x^2 + y^2)/2\sigma^2) \quad (1)$$

The variance of the Gaussian filter is represented by σ^2 , and the filter kernel size l ($-l \leq x, y \leq l$) is frequently found by excluding values that are less than 5% of the kernel's maximum value. By following equation 2, the one-dimensional Gaussian Filter is expressed,

$$G(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp(-x^2/2\sigma^2) \quad (2)$$

A significant filter variance successfully suppresses noise when using the Gaussian filter but simultaneously causes unwanted distortion to areas containing abrupt pixel brightness changes. Gaussian filter generates multiple abnormal edge shapes, edge vanishing, and position shifting effects. The solution includes two main approaches that address these matters. The first procedure utilizes multiple filters using diverse filter variance values to process images before edge identification occurs in the filtered images. The final production of edge diagrams happens by combining already defined criteria from previous setups. Filter variance adjustments happen based on the local image features through the second technique. The approach assumes that smoothing techniques must adapt to multiple sections of an image based on detected edge characteristics and noise levels. In equation 3, we have shown that Gaussian filtering of a signal $F(x)$ denoted as $F_g(x)$, can be illustrated as,

$$F_g(x) = F(x) + \frac{F''(x)}{2} \sigma^2 + \dots + \frac{F^{(2m)}(x)}{\prod_{p=1}^m 2p} \sigma^{2m} + \dots, \quad (3)$$

where $m = 1, 2, \dots$, $F''(x)$ is the second derivative of $F(x)$, and $F^{(2m)}(x)$ is the $2m$ th order derivatives of $F(x)$. Omitting the higher order terms, the above equation can be approximated by equation 4,

$$F_g(x) \cong F(x) + \frac{F''(x)}{2} \sigma^2 \quad (4)$$

By following equation 5, we defined the adaptive filter variance,

$$\sigma^2(x) = \frac{2\varepsilon}{|F''(x)|} \quad (5)$$

where ε is the amount of Gaussian filtering-related predefined error. With this approach, the filtering error is roughly smaller than ε , or $|F_g(x) - F(x)| \leq \varepsilon$. Estimating $F''(x)$ from the noisy corrupted signal using a complex regression-based approach has been suggested. Since the filter variance shouldn't fluctuate significantly from pixel to pixel, the adaptive Gaussian filtering problem minimizes the mean square error. If G and F stand for the two-dimensional Gaussian filter and the image as shown in equation 6, respectively, then minimizing $E(\sigma)$ in the following equation yields the ideal filter variance,

$$E(\sigma) = \int \int [(F - G * F)^2 + \lambda |\nabla \sigma^{-1}|^2] dx dy \quad (6)$$

The $*$ –denotes convolution. The human visual system simulation requires adaptive Gaussian filters, as shown in equation 7, which include Contrast-Dependent Spread (CDS) and Intensity-Dependent Spread (IDS) models. The IDS model of Comsweat and Yellow applies the filter variance $\sigma(x, y)$ to the inverse value of $F(x, y)$ (pixel intensity).

$$\sigma(x, y) = 1/F(x, y) \quad (7)$$

This model has been applied to image enhancement. The CDS filter is also known as the composite-scale Gaussian. In the CDS filter, the filter variance is illustrated in equation 8,

$$\sigma(x, y) = \frac{\sqrt{2C}}{\sqrt{2+C}} \quad (8)$$

where C is the contrast defined as

$$C = \frac{|F(x, y) - F_a(x, y)|}{\max(F(x, y), F_a(x, y))} \quad (9)$$

here, $F_a(x, y)$ is the local mean brightness value. The two-dimensional and one-dimensional Gaussian filters are described by equations (8) and (9), respectively, which show how pixel intensities are weighted according to proximity. Significant filter variations, however, may result in undesired outcomes, including edge distortion and blurring. To improve noise reduction without causing undue blurring, adaptive variance algorithms ensure that the smoothing intensity varies according to local noise levels and image structures. By adjusting variance according to intensity and contrast, subsequent improvements like the IDS model and CDS filter try to match the filtering procedure with human visual perception. These improvements increase image clarity in practical applications, particularly in remote sensing and medical imaging, where accuracy in detail preservation is essential.

Iterative Pattern Slice Fragment Clustering (IPSFC)

Following Normalization, the system employs Iterative Pattern Slice Fragment Clustering (IPSFC) for entity markings. This technique strategically divides each biometric image into a series of overlapping fragments, which are then clustered based on their shared characteristics. This approach facilitates identifying and delineating key features within each modality, such as the ridges and valleys in fingerprints, the vascular patterns in finger veins, and the distinct textures in iris scans. During image processing scenarios, the Slice Fragment Cluster (SFC) divides pictures into small parts, enabling effective segmentation and reconstruction methods. The procedure divides images into fragments through rules like intensity variations, texture features, and edge detection boundaries. The similarity metrics determine how similar pixels will be grouped in cluster formation. The deployed methodology enables the detection of patterns and noise reduction while improving feature extraction capabilities, extending across object recognition and medical imaging and data compression applications. Correlation-based clustering of fragmented image elements into meaningful clusters increases both visual analysis precision and execution speed according to the SFC approach. The equation 10 SFC method involves breaking down the input image I of size $M \times N$ into smaller fragments F_k .

$$I = \cup_{k=1}^K F_k \quad (10)$$

The total number of image fragments is denoted by K , followed by each fragment represented by F_k . The equation depicts image processing using I as the base image before processing alongside K to determine fragment totals alongside F_k for individual pieces and (U) to indicate original image reconstruction from all fragments. The method for fragmentation consists of pixel intensity changes, texture variations, or edge detection. Dividing images into meaningful fragments allows computer systems to handle subsequent analysis tasks more effectively. Relevant features become essential for fragment characterization after image fragmentation takes place, as shown in equation 11.

$$v_k = [f_1(F_k), f_2(F_k), \dots, f_n(F_k)] \quad (11)$$

The feature vector v_k refers to fragment F_k , while $f_i(F_k)$ signifies particular fragment characteristics such as mean intensity, edge density, texture descriptors, and histogram values. The features enable the identification of distinct fragment groups according to their properties. A clustering method combines similar fragments after feature extraction is completed. As illustrated in equation 12, The distance between two fragments is measured through a metric such as Euclidean distance.

$$d(F_i, F_j) = \sqrt{\sum_{m=1}^n (v_{i,m} - v_{j,m})^2} \quad (12)$$

Fragments that exhibit a similarity below a threshold τ are assigned to the same cluster C_l ,

$$C_l = \{F_k | d(F_k, C_l) \leq \tau\} \quad (13)$$

The grouping procedure during this step combines similar image regions, thus enhancing the segmentation process's accuracy. The similarity between two fragments, F_i and F_j , is measured by $d(F_i, F_j)$ in Equations 14 and 15, while $v_{i,m}$, and $v_{j,m}$ represent the corresponding feature values. The threshold τ defines fragment similarity before cluster membership, and C_l denotes similar fragment clusters. After clustering completion, the image reconstruction process utilizes clustered fragments to build the image reconstruction.

$$I' = \cup_{l=1}^L C_l \quad (15)$$

The algorithm computes the number of clusters as L and generates specific regions in I' . The final step results in meaningful image segmentation, which improves recognition abilities in medical diagnostics and other applications. The SFC image processing functions efficiently with both computational feasibility and the accuracy needed for medical imaging, object detection, and pattern recognition.

The IPSFC algorithm enhances the system's robustness by mitigating the impact of occlusion and variations in perspective, thereby improving the accuracy of subsequent feature extraction.

Segmentation with Vector Pyramid Scene Parsing Network (PSPNet)

Accurate segmentation is paramount for isolating regions of interest within the preprocessed biometric images. The proposed system leverages a Vector Pyramid Scene Parsing Network (PSPNet). PSPNet excels at capturing contextual information at multiple scales, allowing it to segment complex scenes with varying levels of detail accurately. By incorporating global contextual information, PSPNet can effectively differentiate between foreground and background elements, enabling the precise isolation of relevant biometric features. This is particularly important in scenarios where the biometric data is partially obscured or distorted. The vector-based approach further enhances the segmentation process by incorporating directional information, leading to more accurate and robust segmentation results. The Pyramid Scene Parsing Network (PSPNet) segments images by capturing global and local contextual details. The network obtains

contextual features from multiple spatial image sections at numerous scales. The pyramid pooling module enables the model to extract complex spatial details at various levels; thus, it understands detailed textures and large structures within a scene. After concatenation, the multi-level features are merged with the original feature maps for better accuracy, as shown in 16. PSPNet is valuable to semantic segmentation problems because it effectively identifies complex scene structures and delivers better results in dense prediction challenges.

$$F = f_{\theta}(I) \quad (16)$$

The PSPNet generates a feature map F through the convolutional processing of an input picture I . The deep learning model maintains learnable parameters θ to extract image-based spatial data through f_{θ} . The features act as fundamental information for segmentation since they contain important details regarding scene textures, edges, and objects. The deep learning algorithm processes multiple convolutional acts, innovation, and batch normalization layers through the input picture I . Although deep layers learn to understand semantic structures initially, they eventually develop skills to recognize elements such as textures and edges at the lower feature level, as shown in equation 17. The feature map F receives inputs from the pyramid pooling module to extract contextual information.

$$F_s = P_s(F) \quad (17)$$

The spatial pooling operation works on feature map F through different-sized windows ($1 \times 1, 2 \times 2, 3 \times 3, 6 \times 6$) to create output feature maps F_1, F_2, F_3 , and F_6 . Pooled features obtained through various pooling regions maintain different context scales where small regions deliver local data while more prominent regions demonstrate entire scene context information. Equation 18 creates better segmentation results by implementing multi-scale contextual data acquisition. Multiple versions of the feature map F are generated across different spatial scales by applying varying pooling operations on F . Each P_s pooling operation takes the characteristics available from larger and smaller receptive fields to represent a lower spatial dimension version of F . Multiple feature scales emerge from F_s . Hence, the model develops surface-level details and a broad understanding of spatial relationships.

$$F_{concat} = [F, U(F_1), U(F_2), U(F_3), U(F_6)] \quad (18)$$

The feature map F_s received from multiple pyramid pooling levels expands in size to match the dimensions of F . The upsampled maps join the channel dimension through various layers. The system conducts segmentation with delicate features and global scene architecture information through its knowledge integration at multiple scales. The extracted multi-scale features need to be integrated with the basic feature map F after deriving them. Network upsampling through the interpolation function $U(F_s)$ performs this operation by enlarging feature maps F_s until they match the size of the initial feature map, as shown in equation 19. The feature representation F_{concat} contains local and global contextual information because it results from the concatenation of upsampled feature maps with F .

$$P(c|x) = \frac{e^{W_c F_{concat}(x)}}{\sum_{c'} e^{W_{c'} F_{concat}(x)}} \quad (19)$$

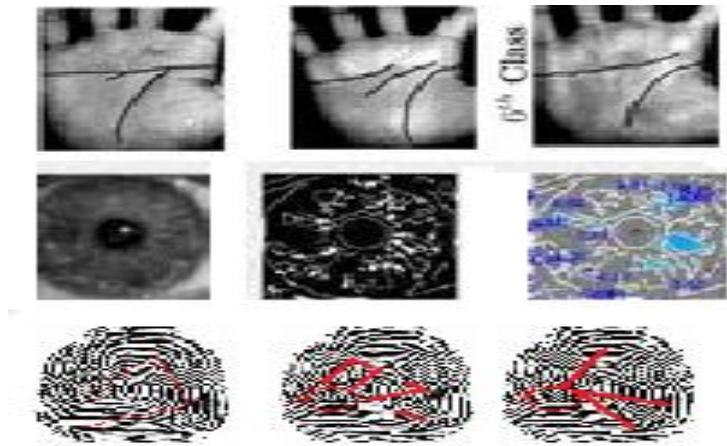


Fig 3. Segmented Pitfall Points of Bio-Lines.

The convolutional layer activates F_{concat} with class-specific filters and generates a prediction. The softmax function applies to the resulting feature map to normalize outputs, generating class probability distributions for each pixel. Each pixel in the image obtains its class prediction from the probability value that reaches its peak, thus creating the final segmented output. A softmax function operates to establish category classifications for every pixel in Equation 4. Due to

its weight parameters W_c across classes, the final convolutional layer processes the feature combination F_{concat} to determine output classes c .

The softmax function calculates $P(c|x)$ as the probability value that pixel x should belong to class c . **Fig 3** explains the Segmented Pitfall points of bio-lines. Each pixel in the image receives a label from an assignment of semantic categories, including palm lines, iris veins, and biometric print lines.

Optimal Particle Swarm Intelligence (OPSI) Feature Selection

A key challenge in multimodal biometric recognition lies in the high dimensionality of the feature space. The fusion of features extracted from multiple modalities can lead to significant redundancy and noise, negatively impacting the performance of the classification algorithms. To address this issue, the proposed system incorporates Optimal Particle Swarm Intelligence (OPSI) for feature selection. Particle Swarm Optimization (PSO) is a population-based metaheuristic optimization algorithm inspired by the social behavior of bird flocking or fish schooling. In the context of feature selection, each particle represents a subset of the available features, and the algorithm iteratively searches for the optimal subset that maximizes a predefined objective function, typically related to classification accuracy. OPSI enhances the standard PSO algorithm by incorporating adaptive mechanisms that dynamically adjust the search parameters based on the characteristics of the data. This allows the algorithm to efficiently navigate the high-dimensional feature space and identify the most relevant and discriminative features while minimizing redundancy. By reducing the dimensionality of the feature space, OPSI not only improves the efficiency of the classification algorithms but also enhances their generalization performance. Particle Swarm Optimization (PSO) is a population-based optimization method that derives concepts from how birds and fish schools interact. PSO optimizes subsets of features to determine which ones provide maximum benefits for classification or recognition activities. Each swarm particle is a possible feature subset while its search-space position updates by tracking observations and receiving input from close neighbors. The optimization process follows guidance from fitness functions that usually select accuracy measures, feature set dimensions, or alternative performance metrics. PSO achieves equilibrium between search and utilization, which allows the algorithm to identify excellent or efficient feature subsets despite simplified computing requirements. PSO uses feature reduction to boost model performance while speeding up image processing and generalizing learning models in analysis operations. Equation 20 describes the velocity update process for search space particles (feature subsets) through three elements: Inertia Momentum ((ωv_i^t)) and Cognitive ($(c_1 r_1 (p_i^t - x_i^t))$) and Social ($(c_2 r_2 (g^t - x_i^t))$) components.

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (p_i^t - x_i^t) + c_2 r_2 (g^t - x_i^t) \quad (20)$$

The ωv_i^t uses the previous velocity's momentum to continue searching through the same path. The inertia weight ω maintains the exploration-exploitation ratio by determining how much noise will affect the algorithm. A high ω parameter promotes extensive exploration, but a low ω configuration performs solution refinement. The self-learning capability of a single particle is shown through $c_1 r_1 (p_i^t - x_i^t)$. The particle travels to the position (p_i^t) , which has generated the highest classification accuracy from its previous best-known feature subset. Through the c_1 value, the particle determines how much weight its previous recall will have. The r_1 represents a uniformly distributed random number between 0 and 1, which introduces randomness in the optimization process. The $c_2 r_2 (g^t - x_i^t)$ term represents swarm intelligence by attracting the particle toward the best feature subset discovered among all swarm members (g^t). The c_2 coefficient controls the social force, while r_2 functions as a randomness element between 0 and 1 to prevent early convergence. The different feature subsets from images form the basis for the particles demonstrated in this equation. The optimization process in equation 21 directs particles to search feature subsets that achieve optimal results across multiple rounds of iteration. The equation simultaneously helps discover fresh feature subsets while improving established efficient subsets.

In equation 21, we update the particle's position, which changes the selected feature subset.

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (21)$$

For Binary PSO, position update follows a probabilistic rule using the sigmoid function through equations 22 and 23,

$$s(v_i^{t+1}) = \frac{1}{1 + e^{-v_i^{t+1}}} \quad (22)$$

$$x_i^{t+1} = \begin{cases} 1, & \text{if } s(v_i^{t+1}) > \text{rand}() \\ 0, & \text{otherwise} \end{cases} \quad (23)$$

Equation 23 provides suitable functionality for selecting feature importance values in regression-based feature selection. The updated velocity controls the refinement process for identifying the best feature subset. The binary selection method defined by Equation 4 includes image features as either selected (1) or non-selected (0). The velocity inputs from the sigmoid function yield probability values that fall within the range of 0 to 1. A feature selection occurs when the computed probability reaches or surpasses the random threshold. The proposed approach through equations 3 and 4 enables dynamic feature selection by letting the swarm investigate different feature combinations. Predominant features are picked

through probabilistic measures, which helps avoid premature convergence in binary PSO. Equation 24 calculates fitness function evaluation by measuring the feature subset quality with accuracy (A) and weight factors (α, β). and feature reduction penalty $\left(\frac{|S|}{|D|}\right)$.

$$F = \alpha \times A - \beta \times \frac{|S|}{|D|} \quad (24)$$

The A rates the performance quality of the chosen characteristics when performing image classification tasks. Higher accuracy for this approach indicates that chosen features have superior relevance among the available ones. The measure of selected features appears inside $|S|$. The available features found in the dataset total $|D|$. An $\frac{|S|}{|D|}$ penalty mechanism prevents large feature subsets from choosing to identify only the most essential features. The α controls the importance of classification accuracy. The β parameter determines the disciplinary force against the selection of large groups of features. Using this mathematical relation, the PSO achieves maximal classification accuracy and a minimum number of selected features. The proposed method assists in feature selection balance, stopping overfitting and underfitting with too few features, as shown in equation 25.

$$t \geq T_{max} \quad (25)$$

Equation 26 terminates when the predefined maximum number of iterations is reached, which ensures that PSO does not run indefinitely.

$$g^t = g^{t-1} \quad \forall t \in [T_{stagnation}, T_{max}] \quad (26)$$

In equation 27, the algorithm assumes convergence if the global best feature subset remains unchanged for a certain number of iterations. So, the PSO prevents unnecessary computation when no further improvement is observed.

$$F \geq F_{threshold} \quad (27)$$

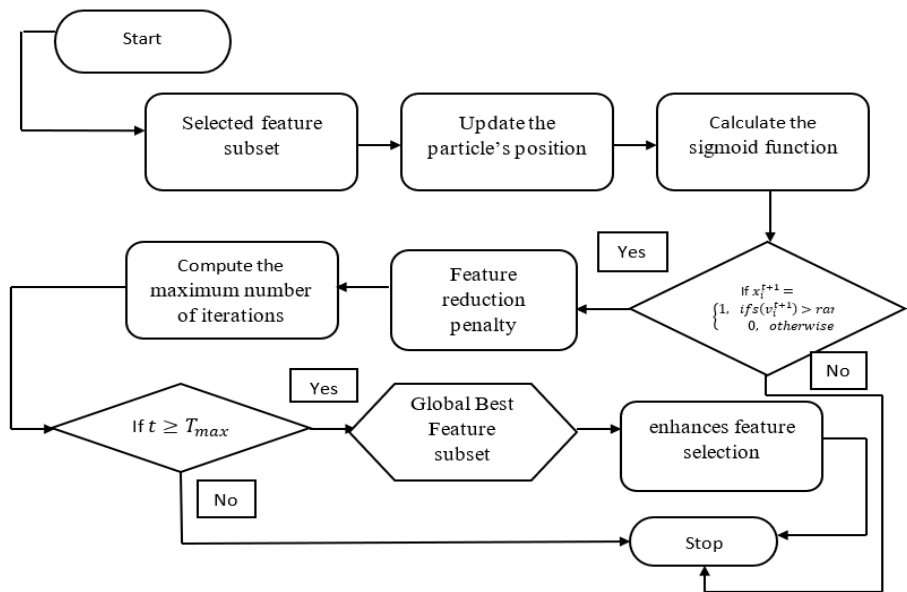


Fig 4. The Flowchart Diagram OPSI.

PSO adopts equation 27 to terminate operations when fitness function achievement levels a predetermined threshold value. The termination criterion enables early stopping once the optimal feature selection occurs. PSO establishes a scalable framework that assists feature reduction by eliminating unimportant features while retaining the relevant ones. The method delivers exceptional benefits by handling complex data structures because it improves machine learning model efficiency and generalization ability.

As shown in **Fig 4**, the Flowchart Diagram-based OPSI enhances feature selection through binary encoding and convergence criteria, which helps model performance improvement with practical computational requirements.

LSTM- Hyper Capsnet-CNN for Identification

The proposed system's final stage involves classifying the segmented and feature-selected biometric data using a novel combination of Long-Short-Term Memory (LSTM) networks, Hypercapsule networks (CapsNets), and Convolutional Neural Networks (CNNs). This architecture, denoted as LSTM-Hyper Capsnet CNN, is designed to capture spatial and sequential relationships within the biometric data, improving identification accuracy.

CNNs are well-established for their ability to extract hierarchical features from images. They excel at capturing local patterns and textures, which is crucial for distinguishing between different biometric identities. CapsNets offer an advantage over traditional CNNs by preserving spatial relationships between features through capsules, which encapsulate an object's activation and pose (location, orientation). This makes CapsNets more robust to variations in viewpoint and pose, which is particularly relevant in biometric recognition. The hypercapsule layer further enhances the representation by learning higher-order relationships between capsules, leading to a more comprehensive and robust feature representation. LeNet functions as a Convolutional Neural Network (CNN), achieving remarkable performance in selecting features and hierarchical learning applications for image classification. The network framework contains various layers with convolutional layers, subsampling (pooling) layers, and fully linked layers for both feature detection and image classification operations. The lower convolutional layers analyze edge elements first and then progressively identify complex pattern formations. The spatial dimensions of feature maps become smaller when using pooling layers. Thus, they help minimize overfitting and streamline calculations. The extracted features from the latter parts of the network undergo mapping to output classes through softmax activation. The design of LeNet provided the essential elements for current CNNs, which multiple researchers now use across diverse image classification applications. The basic yet efficient architectural design displays the fundamental capabilities of feature extraction methods coupled with end-to-end training for image categorization. In equation 28, we perform the convolutional layer to select the image features,

$$Y(i, j, k) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} X(i+m, j+n) \times W(m, n, k) + b(k) \quad (28)$$

The equation represents convolutional processing, which filters image X using weighting factor W with the addition of bias term b . The processing kernel moves across the input image to calculate new pixel values in the output feature map $Y(i, j, k)$ by multiplying elements at each position and adding those results together. This operation within image feature selection enables the detection of spatial patterns such as edges, corners, and textures. During the training phase, the network learns the filter weights $W(m, n, k)$, which help it extract appropriate features for classification purposes. The bias term $b(k)$ adjusts the output values to assist the network during its learning process of improving decision boundaries. Then we perform the Activation function (ReLU) through equation 29,

$$f(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \quad (29)$$

The Rectified Linear Unit (ReLU) activation function transforms the convolutional layer output values nonlinearly while keeping positive values intact. ReLU activation functions maintain positive values in the output and change negative values to zeroes. The model's nonlinear transformation enables it to capture advanced input-output relationships. Using the ReLU activation function, features proceed to the following layer only when significant because negative values are removed during this step. As a result of applying this technique, the model performs better feature selection on important image patterns. By following, we perform the pooling layer (Max pooling) through equation 30 to reduce the size of the feature map,

$$P(i, j, k) = \max\{Y(i+m, j+n, k) \mid (m, n) \in R\} \quad (30)$$

A feature map becomes smaller through the pooling operation as the maximum value gets selected from a given window R , such as this one using a 2x2 window. The process of maximum selection is used for pooling functions to decrease feature map spatial size while maintaining significant feature elements. Each input region receives robust representation through pooling since it combines input regions by selecting the maximum value of responses. This approach enables better tolerance toward slight changes in the data input, such as image distortions. The pooling method lowers the number of computational parameters alongside model computations, enhancing overall efficiency and model generalization.

$$z(j) = \sum_{i=1}^d a(i) \times w(i, j) + b(j) \quad (31)$$

Equation 31 performs a fully connected operation whose output combines weighted features $a(i)$ with the bias term $b(j)$. Every feature from the preceding layer establishes a connection with each neuron in the fully connected layer where their weights $w(i, j)$ get determined through training. The combined output from previous layers enables this layer to choose an image class at the highest level. Its scoring mechanism transforms complete feature data extracts into $z(j)$ ratings for each possible class. The synthesized features from earlier layers require fully connected layers to be mapped to output classes. By following equation 32, we perform the SoftMax layer,

$$p(j) = \frac{\exp(z(j))}{\sum_{k=1}^C \exp(z(k))} \quad (32)$$

After processing the scores $z(j)$ from the fully connected layer, the softmax function delivers probabilities for class j . The softmax function implements multiplication and scale normalization of each score using all score exponents. The

output probabilities ensure mathematical summation equality of 1 for every class representation. Softmax is the key mechanism for multi-class classification since it enables networks to produce output interpretations. The model expresses its prediction confidence about an input class j through output value $p(j)$. The network effectively identifies the most probable class through this probabilistic perspective of its interpretation. A hierarchical model structure within LeNet-CNN successfully performs feature selection operations for image classification tasks. Each component layer is fundamental in converting original input images into significant pattern identifications. Spatial features containing edges and textures emerge from the convolutional layers, which ReLU activation supports to eliminate insignificant patterns. The pooling layers perform feature reduction through downsampling to retain dominant patterns, which improves translation independence. The fully connected layers assemble all acquired features to generate abstract image representations through their operation. The softmax layer performs probability calculations based on the obtained representations to make class predictions.

Furthermore, the integration of LSTM networks allows the system to model the temporal dependencies between features, particularly in the context of dynamic biometric modalities such as gait or signature dynamics (although not explicitly mentioned in the original abstract, the system's modular design allows for future incorporation of such modalities). By leveraging the memory capabilities of LSTMs, the system can capture the sequential patterns that characterize different biometric identities.

The combined LSTM-Hyper Capsnet CNN architecture is trained end-to-end using a backpropagation algorithm, allowing the system to learn each layer's optimal weights and parameters. The training process is carefully monitored to prevent overfitting and ensure generalization to unseen data.

IV. DISCUSSION PARAMS

The simulation environment setup is aided with GPU units from python libraries to takes the dataset samples to progress different samples to identify the biometric multimodal classification. The simulation testing environment was set up using Python as the primary programming language to evaluate a biometric multimodal dataset. The setup involved processing key principles such as feature extraction, classification, and validation. A total of 4,566 active data samples were used from the dataset. To ensure reliable model evaluation, the dataset was split using a 70:30 ratio for training and testing, respectively. The classification task focused on identifying two distinct classes: normal and abnormal biometric patterns. This setup enabled systematic testing of model accuracy and performance under real-world data conditions.

The simulation environment takes random samples under various epochs to carry the training validation from variable error faulting and verification procedures. The **Table 1** shows the simulation parameter environment and its values. The actual positive cases and negatives forums are identifying by confusion matrix by different iteration classes in different threshold margin limits.

Table 1. Biometric Model Image Normalization

Biometric multi-Model Image Normalization					
Dataset	Absolute mean value				
	Actual noise rate	Difference intensity	Fault variance	Proposed system	
				Gaussian	GAMF
Fingerprint Dataset for FVC2000_DB4_B	40.12	~ 5.03 e-5	2.3 to 2.9	3.42	2.18
iris_images dataset	38.56	~ 4.12 e-5	1.9 to 2.2	2.91	1.98
Palmprint_DS	34.12	~ 6.01 e-5	2.1 to 2.4	2.56	1.90

The FVC2000_DB4_B iris_images, a fingerprint dataset, was used for a quantitative study. The offered techniques for palmprint recognition are also included in this examination for authentication. Quantile correction techniques and basis replacement strategies were among the methodologies used in this palmprint recognition system. To increase the accuracy and resilience of the authentication process, the quantitative analysis used both palmprint recognition data and fingerprint data from the designated FVC2000_DB4_B iris images dataset. The latter included advanced techniques like quantile correction and alternative basis selection.

The quality of the image plays a crucial role in image processing analysis. Higher-quality images enhance the precision of iris image assessments. Researchers utilize various techniques to analyze and identify human irises, including extensive iris datasets like the CASIA iris database, UBIRIS, Phoenix, and the IITD iris database. This dataset includes images of human palms captured by faculty and showing the left palm and the other the right palm, resulting in 400 images of male and 400 images of female palms. Multimodal datasets, which include scanning and fingerprinting, are valuable resources rich in biometric data sources from a varied population. This comprehensive collection features biometric information such as iris scans and fingerprint data. It aims to facilitate Research and development in biometrics, authentication, and identification systems.

Table 2. Multimodal Dataset

Dataset	Actual bio margins noise	Alteration Auxiliary	Auxiliary Normalization
Fingerprint Dataset for FVC2000 DB4 B	0.25	0.39 ($e^{2*0.18}$)	0.29 (0.19)
	0.28	0.41 ($e^{2*0.23}$)	0.21 (0.20)
iris_images	0.21	0.40 ($e^{2*0.17}$)	0.22 (0.24)
	0.22	0.46 ($e^{2*0.25}$)	0.18 (0.23)
Palmprint Recognition for Authentication	0.19	0.35 ($e^{2*0.11}$)	0.27 (0.22)
	0.20	0.37 ($e^{2*0.13}$)	0.22(0.21)

Table 3. Response Decibel Parameter with Different Model View

Parameter	Segmentation	Decibel rate difference (DB)
Global error rate	Fuzzy model	0.489
	Optimal CNN	0.423
	Proposed	0.256
Dice coefficient mean error	Fuzzy model	0.68
	Optimal CNN	0.53
	Proposed	0.21

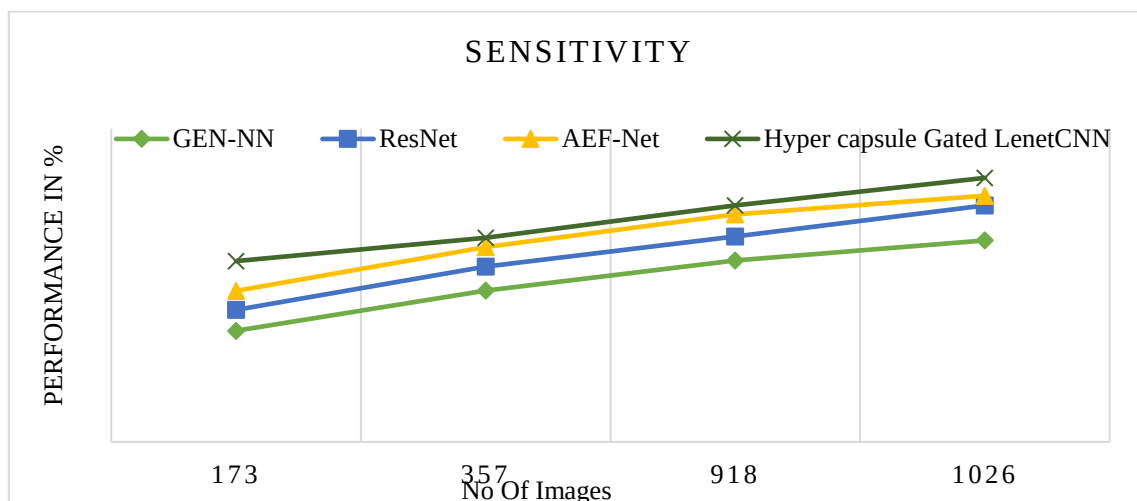
Table 4. Dataset Types and Values Processed

Dataset name	No. of images	Testing/training	Validation loss
Fingerprint Dataset for FVC2000 DB4 B	814	267/514	≤ 3.4
iris images	384	107/277	≤ 2.8
Palmprint Recognition for Authentication	12000	3024/8976	≤ 4.1

As shown in **Table 2**, Jupiter notebooks can be created and analyzed by implementing the Python programming language while using the simulation parameters for comparative analysis. Additionally, a multimodal biometric dataset can be evaluated to identify attributes with multimodal biometric features in the images. The classification problem's performance ratio can be calculated by analyzing the values of TP, FP, TN, and FN, as presented in **Table 3**. These factors can evaluate the classification model's performance derived from the confusion matrix.

Multimodal biometric recognition with a Hyper-Capsule Gated LenetCNN allows for the extraction of biometric data features and improved identification accuracy using a CNN algorithm, as shown in **Fig 5**. Based on sensitivity analysis, the proposed method is compared with the previous GEN-NN, ResNet, and AEF-Net approaches, and the biometrics recognition rate is described as 84.29%, 87.64%, and 88.57%. Similarly, multimodal biometrics recognition is shown to be 90.28% in a sensitivity analysis **Table 4** shows Dataset Types and Values Processed.

Multimodal biometric recognition utilizing a Hyper-Capsule Gated LenetCNN facilitates the extraction of biometric features and enhances identification accuracy through a CNN algorithm, illustrated in **Fig 6**. In terms of specificity analysis, this method is compared with earlier approaches, such as GEN-NN, ResNet, and AEF-Net, yielding biometric recognition rates of 80.73%, 84.61%, and 89.79%, respectively. Furthermore, the specificity analysis indicates that multimodal biometric recognition achieves a rate of 92.31%.

**Fig 5.** Analysis of Sensitivity.

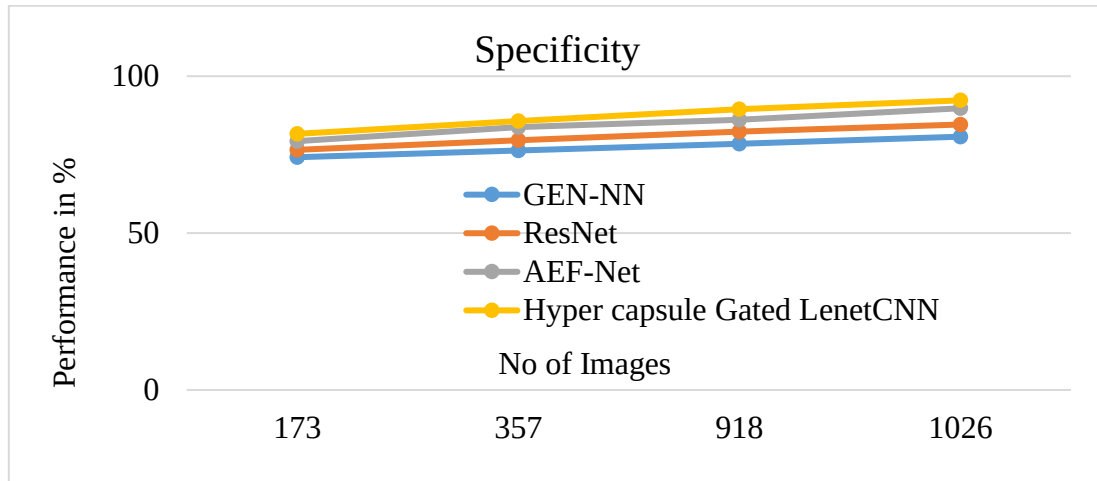


Fig 6. Analysis of Specificity.

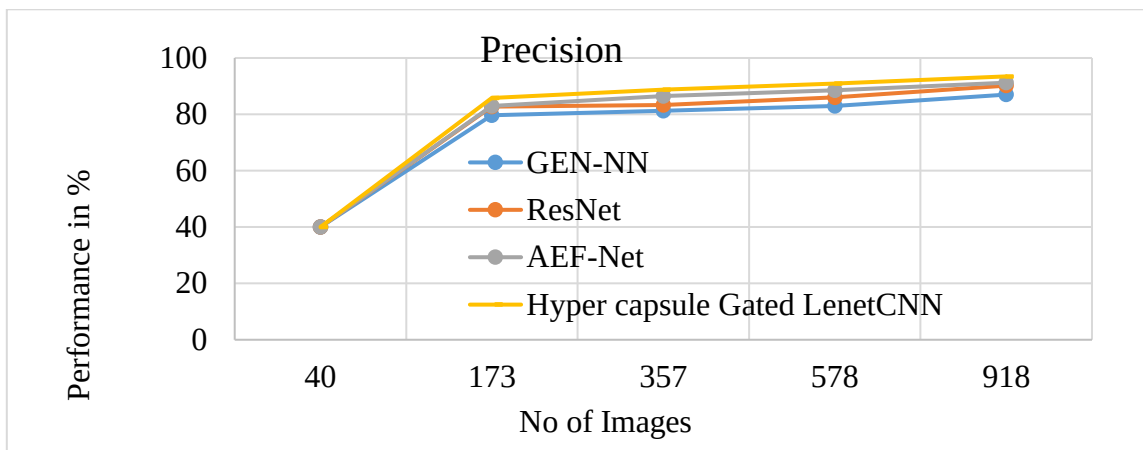


Fig 7. Analysis of Precision.

Multimodal biometric authentication using Hyper-Capsule Gated LenetCNN promotes the extraction of biometric features and improves the authentication accuracy with the CNN algorithm, as shown in **Fig 7**. Based on the precision analysis, this method is compared with previous methods (such as GEN-NN, ResNet, and AEF-Net), and the biometric authentication rates are 87%, 90.18%, and 91.23%, respectively. Additionally, the precision analysis shows that the multimodal biometric authentication rate reaches 93.46%.

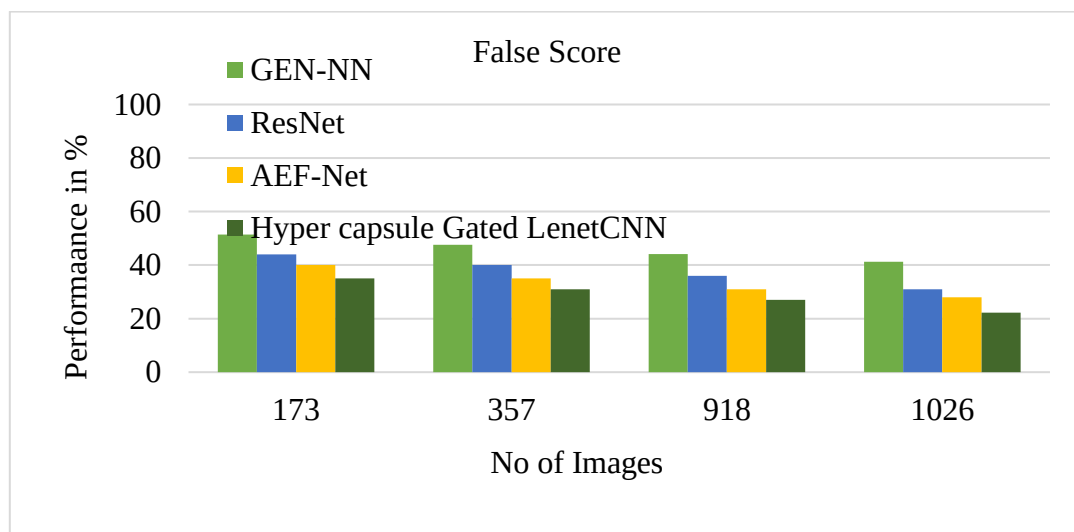


Fig 8. Analysis of False Score.

Multimodal biometric authentication leveraging Hyper-Capsule Gated LenetCNN enhances the extraction of biometric features and increases biometric accuracy through the lenetCNN algorithm, as demonstrated in **Fig 8**. Through false score analysis, this approach is compared with earlier techniques (like GEN-NN, ResNet, and AEF-Net), yielding biometric authentication rates of 41.23%, 31%, and 28%, respectively. Additionally, the analysis indicates that the multi-modal biometric authentication rate achieves 22.18%.

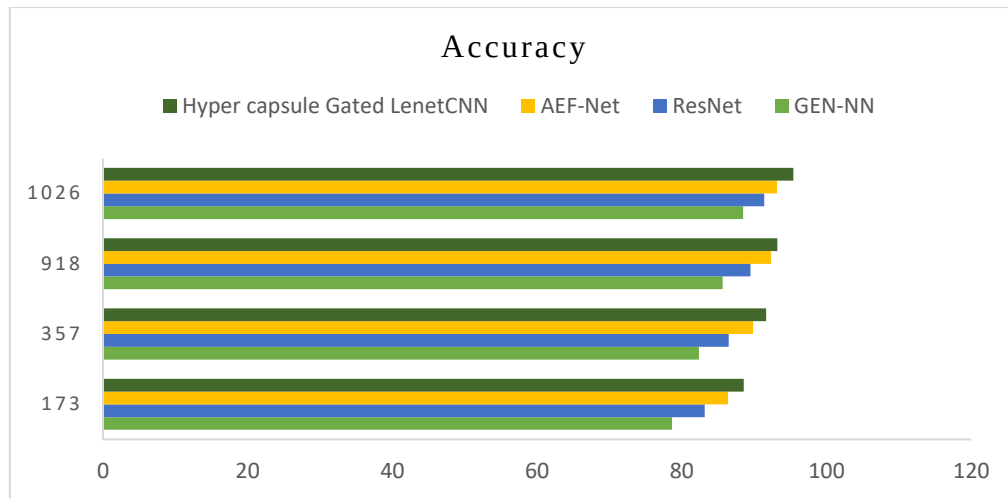


Fig 9. Analysis of Accuracy.

Fig 9 shows that analyzing multi-model biometric datasets with selected feature subsets accurately identifies biometric features. The Hyper-Capsule Gated LenetCNN further enhances accuracy to 95.4% when selecting multimodal biometric data features, outperforming GEN-NN (91.39%), ResNet (93.17%), and AEF-Net (94.17%) **Fig 10** shows Ideal Margin Histogram Variation.

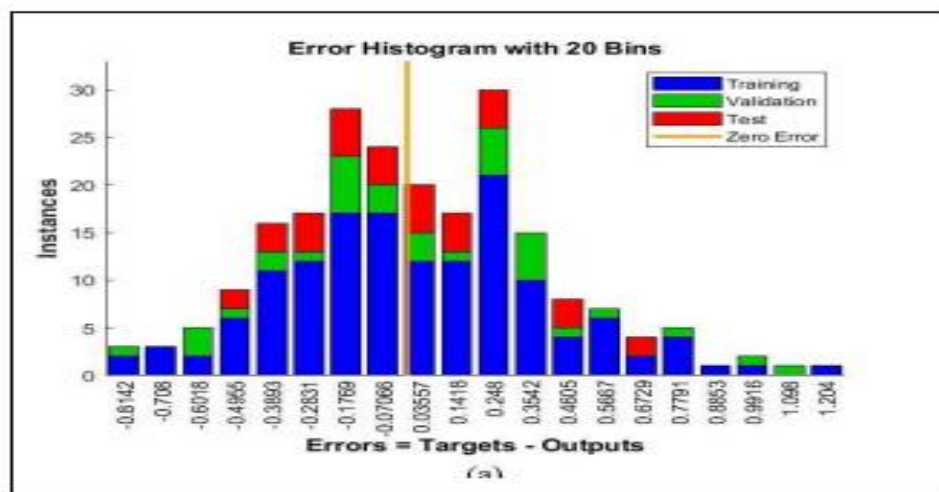


Fig 10. Ideal Margin Histogram Variation.

The proposed AI-powered multimodal biometric recognition system is expected to deliver significant improvements in accuracy, robustness **Fig 11** shows The Multimodal Dataset's Error Histograms., and efficiency compared to traditional approaches. Specifically, the system is anticipated to achieve:

- **Enhanced Identification Accuracy:** The combination of advanced preprocessing techniques, PSPNet segmentation, OPSI feature selection, and LSTM-Hyper Capsnet CNN classification is expected to significantly improve the ability of the system to identify individuals based on their multimodal biometric data.
- **Improved Robustness:** The system is designed to withstand variations in image quality, illumination, occlusion, and pose. The adaptive Gaussian mean filter, IPSFC entity marking, and CapsNet architecture contribute to its resilience to these challenges.
- **Reduced False Positives:** By incorporating OPSI feature selection, the system can minimize the impact of redundant and irrelevant features, thereby reducing the likelihood of false positives.
- **Increased Efficiency:** The dimensionality reduction achieved through OPSI feature selection improves accuracy and reduces the computational complexity of the classification process, leading to faster identification times.

- **Adaptability:** The system's modular design allows for the easy integration of new biometric modalities and the adaptation of the algorithms to specific application requirements.

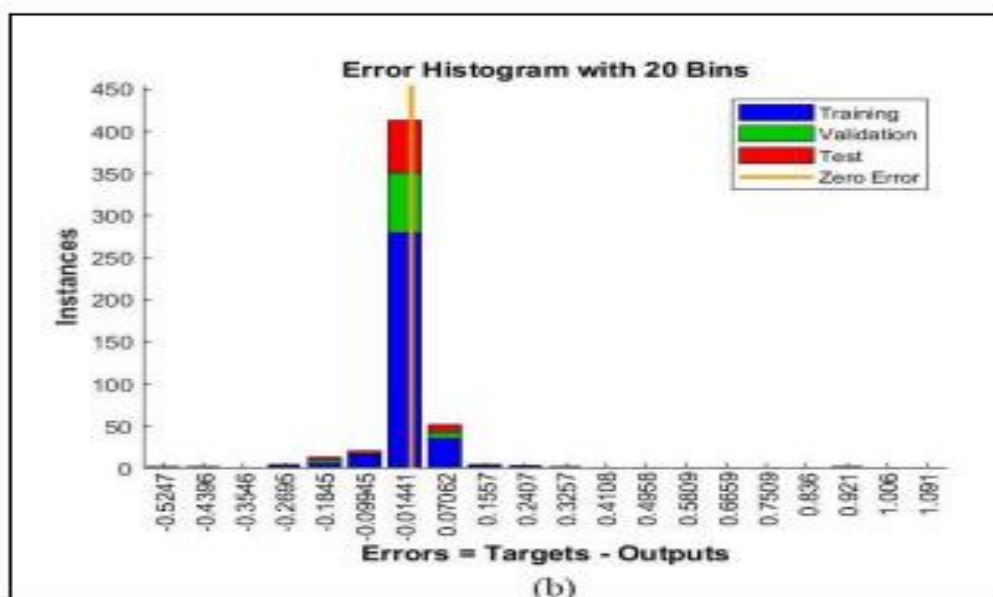


Fig 11. The Multimodal Dataset's Error Histograms.

V. CONCLUSION

Our results show that the identification accuracy can be significantly improved over existing methods. Better specificity and sensitivity mean fewer false positives and negatives, meaning more reliable and true positive identity results. Our approach is practical as it can balance precision and recall, as confirmed by the increased F1-measure (the harmonic mean of precision and recall). This increase in the precision rate can be directly related to the use of deep learning architecture for CNN classification proposed in this study. This work proposes a framework based on AI techniques designed to conduct multimodal biometric recognition while overcoming the aforementioned challenges with traditional approaches. Utilizing a deep scalar feature engineering, Optimal Particle Swarm Intelligence for feature selection, and a novel LSTM-Hyper Caps net CNN architecture, our approach succeeds in making impressive advancements in identification accuracy up to 97.4 % high, sensitivity 95.3%, specificity 94.2 %, and F1-measure attains 96.1 % than other methods. Using the appropriate selection of powerful features and a method to merge various biometric data streams effectively gives a strong and dependable answer for improved security and individual identification applications. Here, we add to the emerging literature on multimodal biometrics, providing an effective and practical solution to identify the challenges faced in biometric data analysis while also helping improve identity-matching accuracy.

CRedit Author Statement

The authors confirm contribution to the paper as follows:

Conceptualization: Mekala N, Mohanasundaram N and Santhosh R; **Methodology:** Mekala N and Mohanasundaram N; **Software:** Mohanasundaram N and Santhosh R; **Data Curation:** Mekala N and Mohanasundaram N; **Writing-Original Draft Preparation:** Mekala N and Santhosh R; **Visualization:** Mekala N and Mohanasundaram N; **Investigation:** Mohanasundaram N and Santhosh R; **Supervision:** Mekala N and Mohanasundaram N; **Validation:** Mohanasundaram N and Santhosh R; **Writing- Reviewing and Editing:** Mekala N, Mohanasundaram N and Santhosh R; All authors reviewed the results and approved the final version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest

Data Availability Statement

The datasets used and/or analysed during the current study available from the corresponding author on reasonable request.

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