Neuromorphic Fingerprint Recognition via Dense Attention Enhancement and Spiking Neural Networks

Aditya Goyal, Dr. Mangal Das

Department of Computer Science and Engineering,
Gautam Buddha University, Greater Noida, Uttar Pradesh, India.
Corresponding Author: mangal.das@gbu.ac.in

ABSTRACT

Degraded fingerprints caused by dry skin, dirt, or weak sensors remain a significant problem in biometric authentication. To improve the efficiency of neuromorphic recognition, this paper proposes a two-stage framework that integrates fingerprint enhancement with neuromorphic recognition. A Dense Attention U-Net (DenseAttUNet), guided by ORRAM, is used to restore damaged ridge patterns. The restored output is subsequently injected into an EfficientNet-B2 backbone, where ERRAM bridges spatial characteristics with a Spiking Neural Network (SNN) for energy-efficient classification. The entire system was trained and tested on 4,695 degraded fingerprints. The enhancement module achieved a PSNR of 18.04 dB and SSIM of 0.7380. Recognition achieved 85.12% accuracy and an F1 score of 85.74%. These findings verify that combining brain-inspired computing with intelligent image restoration provides a robust, scalable fingerprint recognition system under real-world degradation.

Keywords: Fingerprint Enhancement, Spiking Neural Network (SNN), Dense Attention U-Net, EfficientNet-B2, Biometric Recognition, Neuromorphic Computing.

I. INTRODUCTION

Fingerprint identification is one of the most reliable ways of identity verification — it is being implemented in smartphones, ATMs, border security, and even in forensic investigation. Its accuracy can be explained by the biological fact that the ridge pattern of any given person is unique and does not change during their lifetime. Nevertheless, in practice fingerprint systems fail more often than expected. In the real world, conditions such as dry, scarred skin, wetness, and dust and poor-quality sensors result in blurry, incomplete images, causing the important ridge structure to completely disintegrate. Once these degraded images are introduced into a recognition system the outcome is a False Rejection — a failure that is inconvenient in normal practice, and may be disastrous in high-security applications. This disparity between theory and practice is one of the most pressing open challenges in biometric security. Classical methods like Gabor filters and histogram equalization had limited enhancement and did not cope with unpredictable and complicated degradation. Deep CNNs made great progress in the field but are computationally intensive and fail badly with extreme noise A smarter alternative lies in Neuromorphic Computing - a system based on the human brain and which works on discrete electrical spikes, only, when necessary. The resulting Spiking Neural Networks (SNNs) are both energy efficient and noise resistant, and thus they are highly suitable in low-power edge biometric devices [11], [26]. Neuromorphic methods have been applied to content-based image retrieval problems as well [15].

A. Novelty and Contributions

In this paper, we propose a two-stage neuromorphic scheme that repairs damaged fingerprints and recognize the individual in one jointly trained system. The essential innovation is a dual-attention bridge (ORRAM and ERRAM) that transfers structural ridge information of the enhancement phase to the recognition phase. We make three contributions:

- DenseAttention U-Net (DenseAttUNet) is presented that employs Sobel-derived gradient magnitude and orientation priors to restore severely damaged fingerprint ridges.
- An EfficientNet-B2-based hybrid neuromorphic classifier working within an ERRAM-based framework inside a Leaky Integrate-and-Fire (LIF) SNN is proposed to perform accurate, energy-efficient identity recognition through event-driven spike processing.
- It is shown that joint end-to-end training of both phases works better than traditional decoupled algorithms, and the spatial and temporal goals support and complement each other to achieve the best results.

II. RELATED WORK

The suggested framework is at the intersection of deep visual learning, neuromorphic computing, and

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biometricse curity. In this section, three of the most pertinent research threads are reviewed which inform its design directly.

A. *Deep CNN Architectures for Feature Extraction.*

Deep learning has revolutionized visual recognition through the ability of models to learn high-level, hierarchical features in an automatic and unsupervised manner. Basic architectures like ResNet/skip connections, DenseNet/dense feature reuse, and Efficient Net/compound scaling have continued to increase accuracy and efficiency [2], [4], [5]. In spatial restoration tasks, symmetric encoder-decoder architecture of U-Net with skip connections is still popular [1]. Spatial and channel-level feature selection is even more refined by the addition of attention mechanisms such as CBAM [3]. All these advances form the architectural foundation of the suggested enhancement phase.

B. *Spiking Neural Network Learning Algorithms.*

SNNs are not easily trained due to the non-differentiable nature of spike generation, where standard backpropagation cannot be used. This was tackled by Neftci et al. [23] using surrogate gradient learning — replacing a smooth approximation in the backward pass — later confirmed by Zenke and Vogels on more complex tasks [24]. Complementary training techniques, such as STBP, STDP, and SLAYER, have expanded the training space of both supervised and unsupervised neuromorphic models [11], [12]. The spiking classifier in this work builds upon the computational foundations established by these techniques [26]. Conversion of conventional deep neural networks to efficient event-driven spiking neural networks has also been explored [14].

C. *Neuromorphic Hardware and Spike-Based Intelligence*

Neuromorphic hardware is designed to perform event-driven computation, becoming active only upon event occurrence, and thus, consuming very little power when idle [13]. The Loihi processor used by Intel has scale efficiency of microjoule level [10], and small-scale designs, such as the processor by Frenkel et al., and SpiNNaker, confirm the viability of deployment [21]. According to Roy et al., SNNs substitute the energy-intensive multiply-accumulate operations with sparse accumulate-only updates [25]— a key benefit of always-on, low-power biometric authentication at the edge.

III. METHODOLOGY

This paper introduces a two-stage end-to-end pipeline of degraded fingerprint recognition that is jointly trained. Stage 1 restores damaged fingerprint images via a DenseAttUNet guided by ORRAM. Stage 2 identifies the person with the help of EfficientNet-B2 backbone [4], an ERRAM attention bridge, and an LIF Spiking Neural Network classifier. Having a single computational graph enables both stages to reinforce each other in the course of optimization.

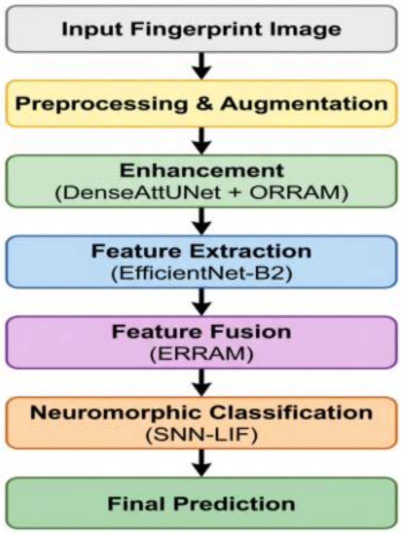

Fig. 1. Proposed end-to-end neuromorphic fingerprint recognition pipeline

A. *Dataset and Preprocessing*

The data includes 4,695 degraded fingerprint images across 5 identities (divided into training (3,496), validation (699), and testing (500) sets). All pictures are resized to 256×256 and normalized to [-1, 1]. Online stochastic augmentation, using Augmentations, i.e. horizontal flips, 90-degree rotations, coarse dropout, brightness/contrast shifts, and Gaussian blur, is used at training time to simulate real-world sensor variability.

B. *Stage 1 — Fingerprint Enhancement*

1) **DenseAttUNet Architecture:** The restoration network has a symmetric encoder-decoder design with four encoding stages at channel dimensions [32, 64, 128, 256]. Every step uses convolution, batch normalization, LeakyReLU, a Residual Dense Block (RDB) [2], [5], and max-pooling. The decoder consists of transposed convolutions with Attention Gates on skip connections to selectively keep informative encoder features. RDBs apply dense feature concatenation, which is compressed with a 1 × 1 convolution and recalibrated by CBAM, and a learnable residual scalar to stabilize the gradients. The result is a Tanh-scaled single-channel restored map in the range [−1,1].

2) **ORRAM —** Orientation-Ridge Residual Attention Map: ORRAM feeds the Sobel-computed ridge structure to the attention process. Magnitude M and orientation θ are calculated as:

The mathematical model of ORRAM has the following definition:

$$\text{Gradient Magnitude: } M = \sqrt{G_x^2 + G_y^2}$$

$$\text{Orientation: } \theta = \frac{arctanarctan\ 2\ (G_y, G_x)}{\pi}$$

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The contrast-enhancement of the input image x is defined as $E = \tanh\tanh(contrast \cdot x)$. A two-layer convolutional network then yields a spatial attention map A out of the concatenation of x, M and θ. The residual output is: $out = x + A \odot (E - x)$. This makes sure that enhancements are applied only where there is ridge structure.

C. Enhancement Loss Function

A well-designed composite loss function (including five different penalty terms) is used to optimize the enhancement pipeline: it guarantees pixel-level fidelity and structural coherence.

$$L_{enh} = 1.0L_{L1} + 0.8L_{SSIM} + 0.1L_{Perceptual} + 0.3L_{Edge} + 0.1L_{Frequency} \quad (1)$$

Where the constituent terms are defined as: Additionally, focal loss can be used to address class imbalance in classification tasks [19].

L1 Loss: Penalizes absolute pixel differences between the target and predicted image.

SSIM Loss: Measures the structural dissimilarity with an 11 ×11 Gaussian kernel (calculated as 1 − SSIM).

Perceptual Loss: Computes the L1 distance between high level VGG-16 feature maps of the prediction and target [8].

Edge Loss: Reduces the L1 difference between the Sobel gradient magnitude of the prediction and the ground truth.

Frequency Loss: Calculates the L1 distance between the magnitudes of their respective discrete Fourier transforms.

Multi-scale deep supervision of decoder stages 2 and 3 is used to enable the deeper gradient penetration, which results in the final training goal:

$$L_{total} = L_{enh} + 0.3(0.4L_{DS2} + 0.16L_{DS3}) \quad (2)$$

D. Stage 2 — Neuromorphic Recognition

1) ***EfficientNet-B2 Backbone:*** To extract biometric features, an EfficientNet-B2 backbone (trained on ImageNet) is used. The pre-trained weights of the RGB channels of the first convolutional layer are averaged to form a single-channel to fit the single-channel grayscale output of Stage 1. The backbone then reduces the spatial hierarchies to a 1408-dimensional feature vector through global average pooling, which is then regularized using Batch Normalization and Dropout (p=0.4).

2) ***ERRAM—Embedding-Ridge Relational Attention Map:*** The ERRAM module is particularly developed to calculate cross-attention between the global CNN features and the localized structural ridge features. The important observation is that with the alignment of these modalities, the network becomes very resistant to spatial translation. Spatial output of ORRAM (1×256×256) is fed into a 4-layer CNN to obtain a 256-dimensional structural ridge vector. The 1408-dimensional CNN feature is linearly projected into Query matrix (Q) and ridge feature (256) is projected into Key (K) and Value (V) matrices. Scaled dot-product attention is applied to model their relational dependencies [7]. The original CNN feature is then concatenated with the output context vector and run through a fully connected layer to reduce the 1664-dimensional tensor to a powerful 512-dimensional embedding.

The attention dynamics can be defined as:

Attention Score: $att = softmax\left(\frac{QK^T}{\sqrt{256}}\right)$

Context Vector: $context = att \cdot V$

3) ***LIF Spiking Neural Network Head :*** In order to realize a classification with a high level of energy efficiency, the 512-dimensional ERRAM embedding is fed into a 3-layer Leaky Integrate-and-Fire (LIF) SNN [11], [26], which is trained using snnTorch [22]. The network topology and the membrane decay parameters (β) have the following form:

- ***LIF Layer 1:*** 512 → 256 neurons (β = 0.90, learnable)
- ***LIF Layer 2:*** 256 → 128 neurons (β = 0.85, learnable)
- ***LIF Output:*** 128 → 5 neurons (β = 0.80, learnable)

The SNN is a model of temporal dynamics with rate-coding scheme across T = 10 discrete time steps. In training, the non-differentiable spike generation is estimated with a fast sigmoid surrogate gradient (slope parameter of 25).

The neuronal dynamics are dictated by:

Rate-coded output: $\hat{y} = \sum_{t=1}^{10} S_{output}(t)$

Membrane Update:

$$U(t) = \beta U(t-1) + Wx(t) - S(t-1)V_{th} \quad (3)$$

Spike Emission:

$$S(t) = \{1, U(t) \geq V_{th}\ 0, otherwise$$

4) **ArcFace Auxiliary Head** : In order to enforce intra class compactness and inter-class separation, an ArcFace loss head [6] is added to the 512-dimensional embedding as a regularizer:

$$L_{arc} = -\log\log\left(\frac{e^{s\cos\cos(\theta_y+m)}}{e^{s\cos\cos(\theta_y+m)} + \sum_{j\neq y} e^{s\cos\cos(\theta_j)}}\right) \quad (4)$$

Where θ is the angle between the embedding and the target class weight, m = 0.3 is the additive angular margin and s = 32 is the feature scale. 5) Total Recognition Loss: The downstream neuromorphic classifier is trained through a

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linearly weighted loss combination of four loss functions:

$$L_{recog} = L_{spike} + 0.5L_{ArcFace} + 0.3L_{triplet} + 0.003L_{center} \quad (5)$$

Here, L_{spike} represents the primary cross-entropy loss over the rate-coded SNN logits. $L_{triplet}$[17] (With a margin of 0.5) is used to cluster together embedding's of the same identities, and separate those that differ, and L_{center} [18] reduces the intra-class variance of the features relative to their dynamically updated class centroids.

E. *Training Configuration*

Both enhancement and recognition are optimized together in an end-to-end manner for 60 epochs. The empirical setting uses a batch size of 16, input resolution of 256 × 256. The Adam W optimizer uses a weight decay of 3×10^{-4}. To balance learning, a different learning rate policy is used: the pre-trained backbone uses the rate 2×10^{-5} and the newly initialized heads use the rate 2×10^{-4}. The One Cycle LR scheduler is used, with pct start = 0.3, and div factor = 10. Clipping of gradients is set at a norm of 1.0. All computational processes use Automatic Mixed Precision (AMP) on an NVIDIA Tesla T4 GPU (15 GB VRAM) to optimize memory usage.

IV. EXPERIMENTAL SETUP AND RESULTS

A. *Experimental Setup and Hyper Parameter Configuration*

All the computational experiments to empirically validate the proposed architecture were run on an NVIDIA Tesla T4 with 15 GB of VRAM. The hybrid network comprising a total of 16.71 million learnable parameters (5,309,437 in the DenseAttUNet enhancement stage and 11,407,787 in the EfficientNet+ERRAM+LIF recognition stage) was trained in an end-to-end fashion with a mini-batch size of 16 for 60 epochs.

The Adam W algorithm was used to perform optimization with a coefficient of weight decay of 3×10^{-4}. A One Cycle LR scheduling policy was used, where the neuromorphic recognition head and the pre-trained EfficientNet-B2 backbone had a peak learning rate of 2×10^{-4} and 2×10^{-5} respectively. The Leaky Integrate-and-Fire (LIF) spiking neurons were simulated over T = 10 discrete time steps with a firing threshold of 0.8. The 4,695 samples dataset was divided into training (3,496), validation (699) and testing (500) sets as shown in Figure 2, and a stochastic augmentation pipeline was used to model sensor variability in the real world.

B. *Evaluation Metrics*

The architectural performance is measured by conventional performance standards. The assessment of the enhancement module is done using Peak Signal-to-Noise Ratio (PSNR, in dB) and Structural Similarity Index (SSIM). Macro Accuracy, Precision, Recall and F1-Score on the validation subset are used to evaluate the downstream recognition performance. Additionally, t-SNE dimensionality reduction is applied to visually confirm the inter-class separability of 512-dimensional latent embedding's. Experiments with this protocol yielded peak validation scores of 18.04 dB PSNR and 0.7380 SSIM on structural restoration, which resulted in an effective recognition rate of 85.12% (Precision: 85.99%, Recall: 85.63%, F1 Score: 85.74%).

C. *Fingerprint Enhancement Results*

Quantitative measurement of the enhancement stage was done using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). Table 1 records the performance trend at the key training milestones.

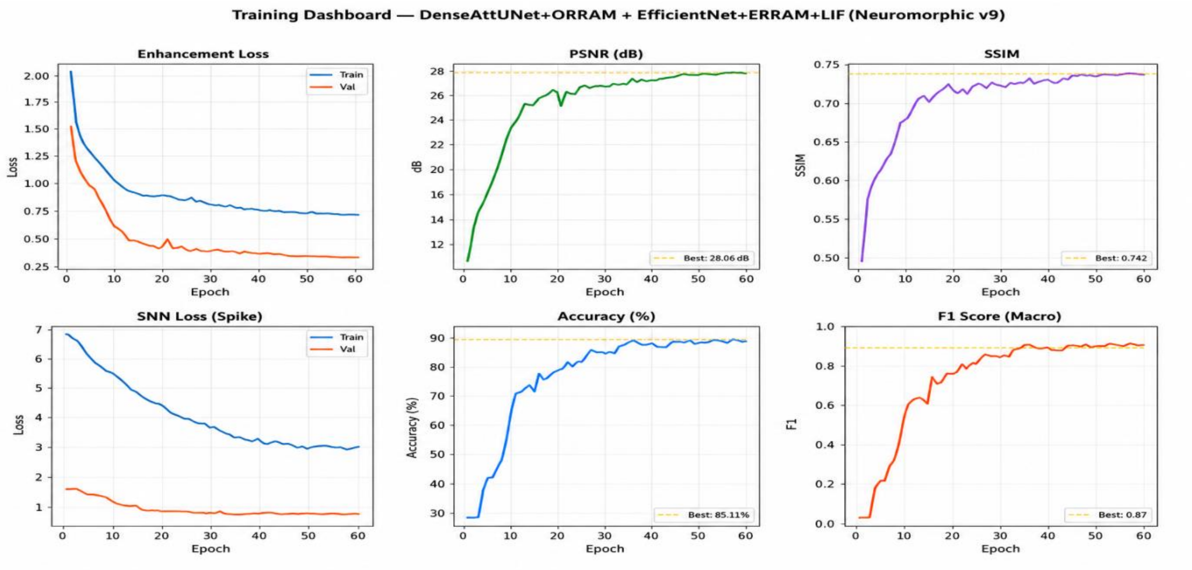

Fig. 2. Experimental framework detailing the dataset distribution, stochastic augmentation pipeline, and primary system hyper parameters.

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TABLE I
METRICS EVOLUTION OF ENHANCEMENT DURING TRAINING.

Epoch	Enhancement Loss	PSNR (dB)	SSIM
1	2.043	11.34	0.4904
10	1.049	16.05	0.6774
36	0.806	17.84	0.7316
57	0.743	18.04	0.7380

Figure 3 reflects the training dynamics indicating a coordinated enhancement and recognition metrics improvement. The high-fidelity ridge reconstruction in Stage 1 directly provides optimal spatial priors for downstream identity discrimination.

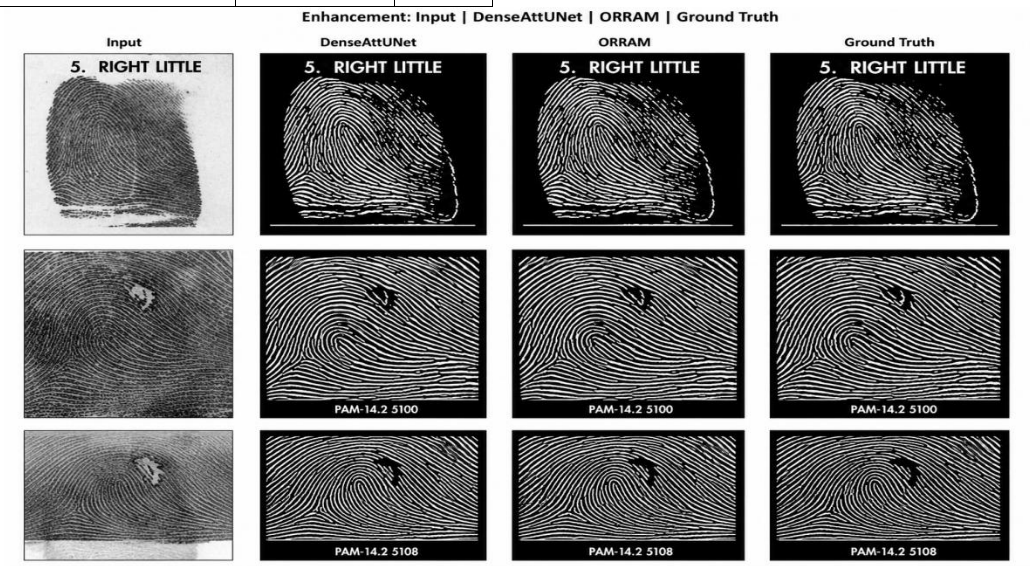

Fig. 3. Training Dashboard — Visualizing the convergence of Enhancement Loss, PSNR, SSIM, and SNN Accuracy across 60 epochs..

D. Neuromorphic Recognition Results

On the validation set, identity classification was assessed based on rate-coded output logits over T = 10 time steps. The accuracy reached a peak of 85.12% at epoch 57. The entire analysis of recognition, the per-class performance, and confusion boundaries are shown in Figure 4.

TABLE II
FINAL VALIDATION SET RESULTS.

Metric	Value
Accuracy	85.12%
Precision (Macro)	85.99%
Recall (Macro)	85.63%
F1-Score (Macro)	85.74%

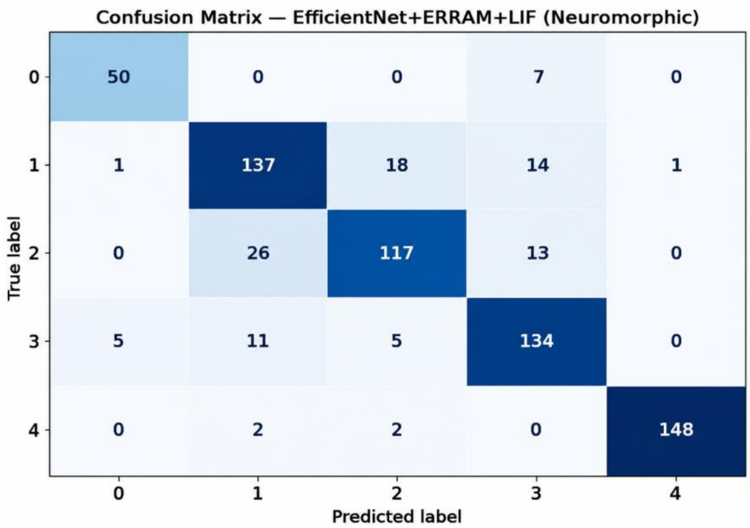

Fig. 4. Neuromorphic SNN Recognition Performance — Aggregate validation metrics and the 5-class confusion matrix analysis

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E. Joint Training Convergence

The concomitant improvement of spatial (PSNR) and temporal (spiking accuracy) metrics is an indication of the architectural soundness of the joint optimization. The attention mechanisms (ORRAM and ERRAM) serve as a key communicative intermediary, whereby excellent ridge-enhancement is transformed into a strong identity feature extraction.

V. DISCUSSION

The key strength of this framework lies in its joint end-to-end training approach. The model attains very rapid convergence by sharing intermediate representations between the two stages; with recognition accuracy increasing to well above 55% in only 10 epochs, something that isolated, independently trained models consistently fail to match. ORRAM has two functions in this pipeline: it not only reconstructs ridge topologies when enhancement is performed, but also provides structural priors directly to the ERRAM cross-attention mechanism. The increase in SSIM from 0.49 to 0.74 validates the claim that structural preservation is the primary factor rather than pixel-sharpness. The LIF spiking head had an accuracy of 85.12% and F1-score of 85.74% at T = 10 time steps. When deployed on neuromorphic hardware such as Intel Loihi, the change to sparse accumulate-only operations instead of multiply-accumulate can yield significant energy savings — which is highly important to always-on edge biometric systems. The confusion matrix displays an almost perfect classification of Class 4, and the major error group between Class 1 and 2 is inherent to the similarity between ridges and not a weak point of the model, which can be remedied by a larger ArcFace margin or increased-resolution inputs. The current shortcomings are a closed 5-class scope of evaluation and a hybrid (partial) SNN architecture. The next research priorities are scaling to open-set protocols, then to public benchmarks, like FVC2002 and NIST SD302, and a full spiking end-to-end topology.

VI. CONCLUSION

This paper introduces a new end-to-end neuromorphic architecture that provides fingerprint enhancement and biometric recognition as a single and unified computation graph. Coupling DenseAttUNet with ORRAM for spatial restoration and EfficientNet-B2 for identity recognition, the system manages to do something that cannot be achieved by decoupled pipelines: the two stages mutually enhance each other. This design is supported by the results. The enhancement module achieved the highest PSNR of 18.04 dB and the highest SSIM of 0.7380, and was able to restore degraded ridge topologies. The downstream neuromorphic classifier achieved an accuracy of 85.12% and a macro precision of 85.99%, recall of 85.63% and F1-score of 85.74%. These numbers not only represent the raw performance, but also the quality of the embedding space, which was defined by a four-loss objective with spike cross-entropy, ArcFace, triplet, and center losses, that ensured that the representation of classes remained compact, well-separated, and unbiased. ORRAM was not just an enhancement module. It acts as a structural bridge, which uses Sobel-derived ridge priors as feed-forward guidance to the ERRAM cross-attention mechanism and guarantees that what is visually rebuilt also is discriminative for identity recognition. This dual functionality is one of the key architectural concepts of this work. The LIF spiking head, which was trained using the fast sigmoid surrogate gradient over T = 10 time steps, illustrates that event-driven, brain-inspired computation is not only a theoretical option, but a viable option, in biometric classification. Deployed on neuromorphic hardware like Intel Loihi, its sparse accumulate-only operations have large energy benefits over traditional deep networks, and it is highly suitable for always-on low-power edge authentication.

Future directions will focus on three priorities: scaling the framework to open-set verification with larger identity pools, transforming the EfficientNet-B2 backbone to a fully spiking architecture, and scaling to well-known public datasets such as FVC2002, FVC2004, and NIST SD302.

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