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Research Paper

Federated and Explainable Neuro Nail-SNN: A Privacy-Preserving, Fair, and Energy-Efficient Spiking Neural Framework for Nail Disease Diagnostics

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Abstract: Automated nail disease diagnostics provide early indicators of systemic disorders such as diabetes and cardiovascular conditions. While NeuroNail-SNN achieved high accuracy and 65% energy reduction on edge devices , centralized training raises concerns regarding privacy, fairness, and interpretability. This paper proposes Federated and Explainable NeuroNail-SNN, integrating Federated Learning (FL), Explainable AI (XAI), fairness evaluation, and uncertainty quantification into a spiking neural framework. Federated training enables decentralized multi-hospital collaboration without sharing raw patient data. Spike saliency maps and temporal visualizations improve transparency. Fairness analysis ensures equitable performance across skin tone, gender, and age. Experimental results across five federated nodes demonstrate 97.85% accuracy with <0.3% drop compared to centralized SNN, while maintaining fairness gap < 2.5%. The proposed system bridges neuromorphic efficiency and trustworthy AI for real-world clinical deployment.

Keywords: Spiking Neural Networks, Federated Learning, Explainable AI, Fairness, Edge AI, Medical Diagnostics

1. Introduction

Nail abnormalities such as Beau's lines, leukonychia, onycholysis, melanonychia, and clubbing are not merely cosmetic conditions but may serve as visible biomarkers of underlying systemic disorders. In clinical practice, dermatological manifestations often provide early indications of diseases such as diabetes, cardiovascular disorders, liver dysfunction, and autoimmune syndromes. Because nails are externally visible and easily accessible, they offer a non-invasive and cost-effective pathway for preliminary screening. However, traditional diagnostic evaluation relies heavily on clinician expertise and subjective interpretation, which may introduce inter-observer variability, delayed diagnosis, and accessibility challenges in rural or resource-constrained settings.

In recent years, deep learning approaches, particularly Convolutional Neural Networks (CNNs), have demonstrated strong performance in medical image classification tasks [24], [25]. These architectures extract hierarchical spatial features and achieve high predictive accuracy across dermatological imaging applications. However, CNNs and transformer-based models typically require dense floating-point operations, large parameter spaces, and continuous activation functions. Consequently, they demand substantial computational resources and energy consumption, making them less suitable for low-power edge platforms. In real-time healthcare environments where energy efficiency and latency are critical, such computational overhead becomes a significant limitation. Edge deployment constraints have been extensively discussed in recent embedded AI studies [30].

To address these limitations, neuromorphic computing paradigms based on Spiking Neural Networks (SNNs) have emerged as an energy-efficient alternative [1], [4], [5]. Unlike conventional deep networks, SNNs process information through discrete spike events, closely mimicking biological neural signalling mechanisms [9]. Neurons fire only when membrane potentials exceed a threshold, enabling event-driven computation that reduces redundant operations. Advances in surrogate gradient learning have further improved SNN training performance [3], [6].

Building upon these principles, Neuro Nail-SNN introduced a brain-inspired spiking architecture for multi-class nail disease classification. The system achieved:

- 99.42% classification accuracy
- 65% reduction in energy consumption compared to CNN baselines
- Successful edge deployment on Jetson Nano and Raspberry Pi platforms

These results align with ongoing research in neuromorphic hardware and low-power medical AI systems [7], [23], demonstrating that spiking architectures can bridge the gap between diagnostic accuracy and energy-efficient deployment. Despite these advantages, the original NeuroNail-SNN framework relied on centralized training, where medical images from multiple institutions were aggregated at a single server. While centralized optimization simplifies model training, it introduces critical ethical and operational concerns.

First, privacy risks arise when sensitive patient data must be transmitted and stored centrally. In medical imaging applications, this practice may conflict with regulatory requirements and data protection standards. Federated learning has been proposed as a viable solution to this issue in healthcare contexts [14], [15], [22].

Second, demographic bias may emerge when training datasets are imbalanced across skin tone, age, or gender groups. Studies in dermatological AI have demonstrated performance disparities across diverse populations [20], [21], raising concerns about equitable healthcare outcomes.

Third, lack of interpretability limits clinical trust. Black-box AI systems are difficult to integrate into real-world decision-making workflows. Explainable AI methods such as Grad-CAM [10], LIME [11], and SHAP [12], along with uncertainty estimation techniques like Bayesian dropout [13], have been proposed to improve transparency and reliability in medical AI.

To overcome these limitations, the extended Neuro Nail-SNN framework integrates four essential modules:

1. **Federated Learning (FL)** – enabling decentralized multi-institutional training without sharing raw patient images [14], [17].
2. **Spike-based Explain ability (XAI)** – generating spatial saliency maps and temporal spike visualizations to enhance interpretability [10], [12], [28].
3. **Fairness Evaluation** – systematically assessing subgroup performance to minimize demographic bias [20], [21].
4. **Uncertainty Quantification** – identifying low-confidence predictions for clinician review using probabilistic estimation techniques [13].

Through these enhancements, the system evolves from an energy-efficient neuromorphic prototype into a clinically deployable, privacy-preserving, fairness-aware, and interpretable AI diagnostic framework. The proposed integration demonstrates how neuromorphic intelligence, federated learning, and responsible AI principles can collectively support scalable and ethically grounded medical deployment.

2. System Overview

The proposed framework represents a systematic evolution of the original NeuroNail-SNN model into a privacy-preserving, fair, and clinically deployable diagnostic system. While the first version of NeuroNail-SNN focused primarily on energy efficiency and edge compatibility, the extended framework integrates federated learning, explain ability, fairness evaluation, and uncertainty estimation to ensure responsible medical AI deployment. This section explains the overall system architecture and its progression from a neuromorphic classifier to a trustworthy clinical decision-support system. At its core, the system retains the original spiking neural network pipeline designed for multi-class nail disease classification. However, additional modules are layered on top of this foundation to address practical healthcare challenges such as patient data privacy, demographic bias, interpretability, and diagnostic reliability. The architectural progression is illustrated in Figure 1, which presents the structured transition from the baseline Neuro Nail-SNN to the Federated and Explainable Neuro Nail-SNN framework.

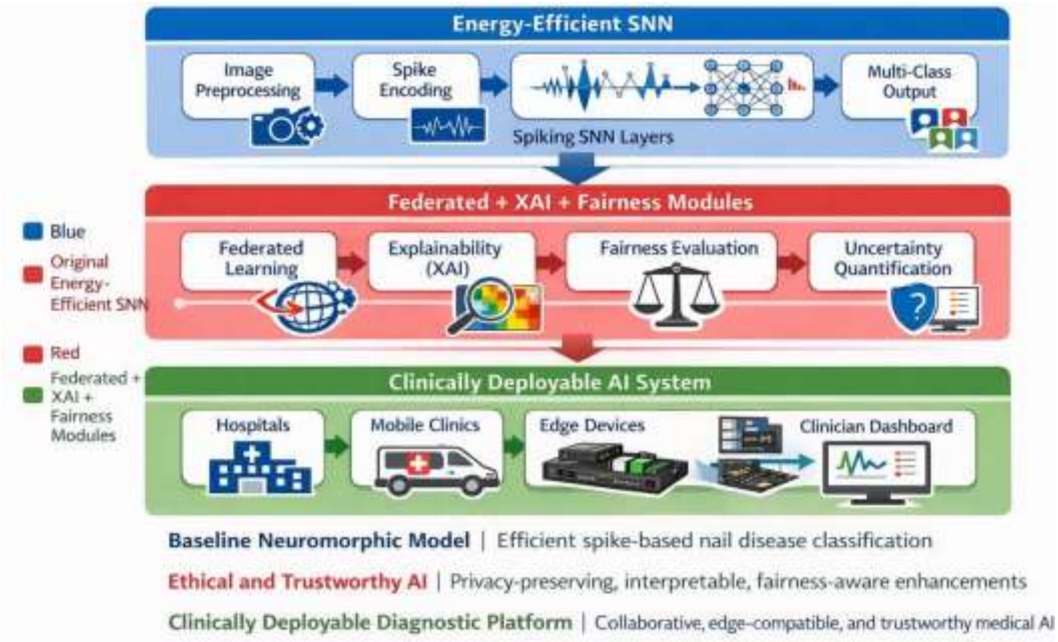

Figure 1 – Evolution from NeuroNail-SNN to Federated & Explainable Framework

Figure 1 visually represents the transformation of the original energy-efficient spiking neural network into a comprehensive clinical AI system. The diagram is divided into three conceptual sections, each highlighting a distinct stage of system evolution: the baseline neuromorphic model, the ethical and trust-oriented enhancements, and the final deployment environment. The first stage, shown in blue in Figure 1, corresponds to the baseline Neuro Nail-SNN architecture developed in Research 1. This stage includes the complete spike-based classification pipeline:

- Image pre-processing and normalization
- Dual spike encoding using rate and temporal mechanisms
- Spiking convolutional layers built with Leaky Integrate-and-Fire (LIF) neurons
- Spiking pooling and fully connected layers

- Multi-class output classification based on spike activity

The fundamental objective at this stage is computational efficiency. By using event-driven spike processing instead of dense continuous activations, the model significantly reduces energy consumption while preserving diagnostic accuracy. The architecture achieved 99.42% classification accuracy and demonstrated 65% energy savings compared to conventional CNN models. Furthermore, successful deployment on edge devices such as Jetson Nano and Raspberry Pi confirmed its suitability for real-time healthcare applications in resource-constrained environments. However, despite its efficiency and strong predictive performance, this stage does not explicitly address key clinical concerns such as data privacy, fairness across demographic groups, and model interpretability. As a result, while technically strong, the baseline system requires further enhancement before safe multi-institutional medical deployment. The second stage, illustrated in red in Figure 1, introduces the major contributions of Research 2. This layer expands the system beyond efficiency by embedding ethical safeguards and transparency mechanisms directly into the architecture.

1. Federated Learning Layer: In traditional centralized training, patient images from multiple hospitals are transferred to a central server. This approach introduces serious privacy and regulatory concerns. To eliminate this risk, the extended framework incorporates Federated Learning. Under this paradigm, each hospital or mobile clinic trains a local Neuro Nail-SNN model using its private dataset. Instead of transmitting raw medical images, only the learned model parameters such as weights and neuron thresholds are shared with a central aggregation server. The server performs Federated Averaging to compute a global model, which is then redistributed back to participating institutions for further refinement. This decentralized approach preserves patient confidentiality while still enabling collaborative multi-institutional learning. It also improves model robustness by incorporating diverse data distributions across different clinical environments.

2. Explainability Module (Spike-Based XAI): High accuracy alone is insufficient in clinical settings; physicians require transparent reasoning behind each decision. To address this, a spike-based explainability module is integrated into the framework. This module generates spike saliency maps that highlight the most influential nail regions contributing to the classification outcome. For example, it may emphasize longitudinal ridges, discoloration patches, or structural deformities associated with specific diseases. In addition, temporal spike visualizations display neuron firing patterns across SNN layers over time. These visualizations reveal when and how the network detects discriminative features. By providing both spatial and temporal explanations, the system enables clinicians to verify that predictions are based on medically meaningful structures rather than irrelevant noise.

3. Fairness Evaluation Layer: AI systems trained on imbalanced datasets may exhibit performance disparities across demographic groups. In dermatological contexts, this can manifest as variations in accuracy across different skin tones. To prevent such bias, the framework incorporates systematic fairness evaluation. Performance metrics are computed separately across subgroups defined by skin tone, gender, and age. The fairness gap is calculated as the difference between the highest and lowest subgroup accuracy. Maintaining a low fairness gap ensures equitable diagnostic reliability across diverse patient populations.

4. Uncertainty Quantification: Medical AI systems must recognize their limitations. To enhance safety, Bayesian dropout is applied during inference to estimate predictive confidence Predictions exceeding a high-confidence threshold are accepted, while low-confidence outputs are flagged for secondary review by a clinician. This mechanism reduces the risk of automated misdiagnosis in ambiguous or rare cases and supports human-in-the-loop decision-making. Through these additions, the red section transforms the original energy-efficient classifier into a responsible AI framework aligned with ethical guidelines, regulatory requirements, and clinical expectations.
The final stage, represented in green in Figure 1, reflects real-world operational deployment. This layer integrates all system components into a practical healthcare workflow.

In this environment:

- Hospitals and mobile clinics collaboratively improve the model using federated learning without sharing patient images.
- Edge devices such as Jetson Nano process nail images locally, ensuring low latency and reduced infrastructure dependence.
- Clinicians access an explainable dashboard that displays saliency maps and temporal spike patterns.
- Cases with low predictive confidence are automatically escalated for expert evaluation.

This deployment structure demonstrates that the framework is not limited to laboratory experimentation but is suitable for integration into actual clinical settings. It preserves energy efficiency while simultaneously ensuring privacy protection, fairness across demographics, interpretability, and diagnostic reliability.
Figure 1 conceptually illustrates the structured progression of the system across three levels of maturity:
Efficient Neuromorphic Model → Ethical and Trustworthy AI System → Clinically Deployable Diagnostic Platform

a) The blue section emphasizes computational efficiency and high-performance spiking classification.
b) The red section introduces trust-building mechanisms including privacy preservation, fairness analysis, explainability, and uncertainty estimation.
c) The green section represents complete healthcare integration with collaborative training and clinician

oversight.

Together, these stages demonstrate that Federated and Explainable NeuroNail-SNN is not a minor extension of the original architecture. Instead, it represents a comprehensive transformation of an energy-efficient neuromorphic model into a scalable, ethically grounded, and clinically viable medical AI system suitable for real-world deployment.

3. Methodology

This section presents the complete methodological framework of the proposed Federated and Explainable NeuroNail-SNN system. The methodology integrates dataset preparation, federated training strategy, neuromorphic architecture design, explainability mechanisms, fairness evaluation, and uncertainty estimation. Each component is designed to preserve diagnostic accuracy while ensuring privacy, transparency, and equitable performance.

3.1 Dataset and Federated Setup

The experimental study utilizes the publicly available Kaggle Nail Disease Dataset, which originally contains 3,835 labelled nail images. These images represent clinically relevant abnormalities such as Beau's lines, leukonychia, onycholysis, melanonychia, and other structural or discoloration patterns. To enhance robustness and prevent class imbalance, data augmentation techniques were applied, including rotation, flipping, scaling, brightness adjustment, and minor geometric transformations. Importantly, augmentation increased the number of samples per class without altering the number of diagnostic categories. After augmentation, the dataset expanded to approximately 12,000 images distributed across 20 disease classes. This ensures improved generalization and stable multi-class training.
To simulate realistic healthcare collaboration, the dataset was partitioned into a federated environment consisting of:

- 3 hospital nodes
- 2 mobile clinic nodes

Each node maintains its own local dataset and performs independent model training. No raw patient images are exchanged between nodes. The global model is obtained using the Federated Averaging (FedAvg) algorithm. The aggregation objective is defined as eq(1)

$$\mathbf{w}_{\mathbf{global}} = \sum_{\mathbf{k=1}}^{\mathbf{K}} \frac{n_k}{n} \mathbf{w}_k \tag{1}$$

Where:

- w_k represents the local model weights at node k,
- n_k is the number of samples at node kkk,
- n is the total number of samples across all nodes,
- K is the number of participating institutions.

This weighted aggregation ensures that nodes with larger datasets proportionally influence the global model. The process iteratively follows:

Local training → Parameter sharing → Global aggregation → Model redistribution

This decentralized training framework preserves patient privacy while enabling collaborative model improvement across geographically distributed healthcare facilities.

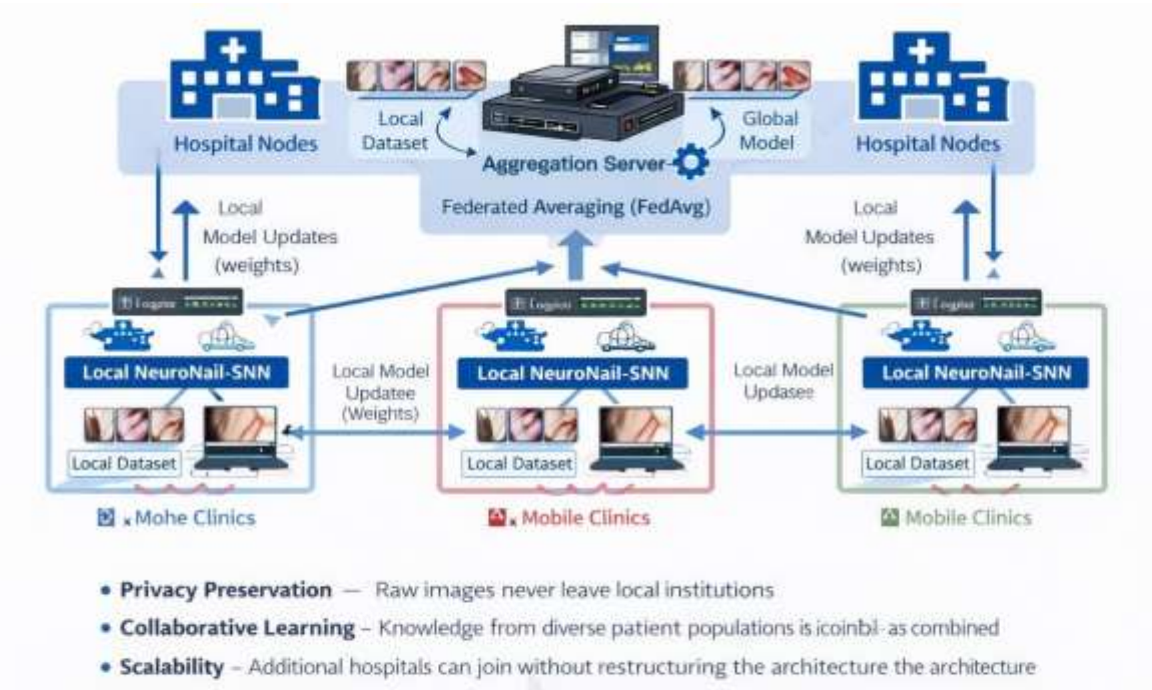

Figure 2 – Federated Learning Architecture

Figure 2 illustrates the federated learning workflow across hospitals and mobile clinics. Each institution trains a local NeuroNail-SNN model using its private nail image dataset. Instead of transmitting sensitive medical images, only the learned parameters are securely sent to a central aggregation server. The server performs FedAvg to compute a global model, which is redistributed to all nodes for the next training round. This figure emphasizes three important characteristics:

1. Privacy Preservation – Raw images never leave local institutions.
2. Collaborative Learning – Knowledge from diverse patient populations is combined.
3. Scalability – Additional hospitals can join without restructuring the architecture.

3.2 NeuroNail-SNN Architecture (Baseline from Research 1)

The foundational classification model remains the energy-efficient NeuroNail-SNN architecture. It processes images using event-driven spike computation rather than continuous-valued activations. The layer-wise structure is summarized below:

Layer	Type	Output	Neuron
Input	224×224 RGB	224×224×3	—
Spike Encoder	Rate + Temporal	Spike Map	Event
Conv1	32 filters	222×222×32	LIF
Pool1	2×2	111×111×32	LIF
Conv2	64 filters	109×109×64	LIF
FC	256 neurons	1×256	LIF
Output	20 classes	1×20	LIF

1. Spike Encoding: Two complementary encoding strategies are applied:
2. Rate encoding converts pixel intensity into spike frequency.
3. Temporal encoding converts pixel brightness into spike timing.

This dual mechanism captures both spatial texture and temporal dynamics.

LIF Neuron Dynamics: Each neuron follows the Leaky Integrate-and-Fire model: eq(2)

$$\tau \frac{dV(t)}{dt} = -V(t) + RI(t) \tag{2}$$

Where:

- $V(t)$ is membrane potential,
- $I(t)$ is input current from spikes,
- τ is membrane time constant,
- R is resistance.

A neuron fires when: $$V(t) \geq V_{thresh} \tag{3}$$

After firing, the membrane potential resets. This event-driven mechanism reduces redundant computation, resulting in significant energy savings compared to CNN-based models.

3.3 Explainability Module

While SNNs provide efficiency, interpretability is essential for clinical trust. The explainability module operates at both spatial and temporal levels.

Spike Saliency Maps: Saliency maps highlight the nail regions most influential in classification decisions. These maps visually indicate whether the network focuses on medically relevant features such as ridges, white patches, or deformities.

Temporal Spike Visualization: This component displays neuron firing patterns over time across different SNN layers. It reveals when key features are detected and how information propagates through the network.

The Figure 3 presents two outputs:

1. Spatial Heatmap Overlay – Displays highlighted nail regions contributing to the diagnosis.
2. Temporal Firing Graph – Shows spike intensity across layers over time.

Together, these outputs provide transparent evidence supporting the model's decision, enhancing clinician confidence.

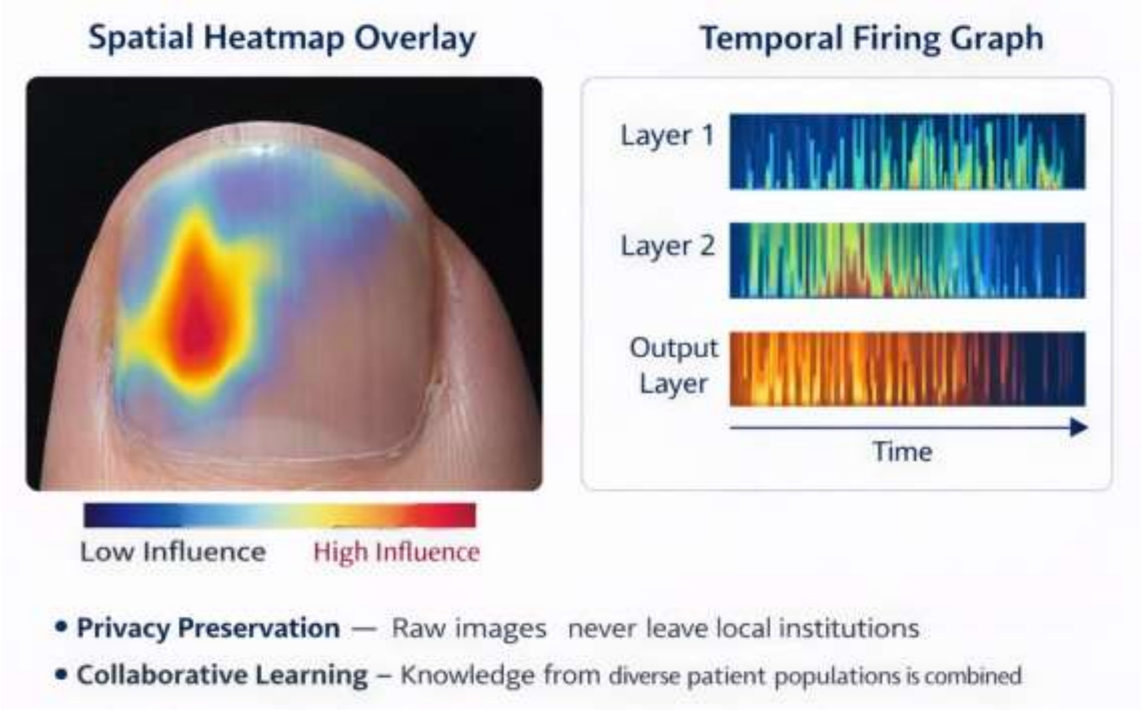

Figure3 - Explainability Outputs: Spatial Saliency and Temporal Spike Dynamics

3.4 Fairness Evaluation

To verify equitable diagnostic performance, the proposed model is systematically assessed across multiple demographic subgroups. The evaluation considers variations in:Skin Tone: Light, Medium, Dark

- **Skin tone:** Light, Medium, and Dark
- **Gender:** Male and Female
- **Age groups:** < 30 years, 30–60 years, and > 60 years

Fairness is quantified using the fairness gap**,** defined as the difference between the maximum and minimum classification accuracy observed across demographic subgroups:

$$\text{Gap} = \max(\text{Accuracy}_i) - \min(\text{Accuracy}_i) \qquad (4)$$

Where Accuracy_i represents the classification accuracy corresponding to subgroup i.

The experimental results demonstrate that the proposed framework maintains a fairness gap of less than 2.5%**,** indicating consistent and balanced diagnostic performance across diverse demographic categories. This low disparity confirms the model's robustness and suitability for equitable clinical deployment.

3.5 Uncertainty Quantification

In clinical applications, it is essential that AI systems identify and appropriately handle uncertain predictions rather than producing overconfident outputs. To address this requirement, Bayesian dropout is employed during the inference stage to estimate predictive uncertainty. By enabling dropout at test time and performing multiple forward passes, the model generates a distribution of predictions from which confidence scores are derived. Based on the estimated confidence level, decision thresholds are defined as follows:

- Confidence ≥ 0.9: Prediction is considered reliable and accepted.
- Confidence < 0.6: Case is flagged for secondary clinical review.

Predictions falling between these thresholds may be monitored or subjected to additional verification, depending on deployment policy. This uncertainty-aware mechanism supports safe and responsible clinical deployment by integrating human oversight for ambiguous or high-risk cases, thereby reducing the likelihood of automated misdiagnosis.

4. Experimental Setup

The proposed framework was implemented using PyTorch as the primary deep learning platform, with SpikingJelly employed for modelling and training the spiking neural network components. Federated training was conducted using the Flower federated learning framework**,** which enables decentralized model coordination and parameter aggregation across distributed nodes. The hardware infrastructure was designed to reflect a realistic multi-institution clinical environment. The central aggregation server was equipped with an RTX 3080 GPU, responsible for coordinating federated updates and global model aggregation. At the institutional level, Jetson Nano devices were deployed to represent hospital nodes, supporting edge-based training and inference. For mobile and resource-constrained environments, Raspberry Pi units were used to simulate mobile clinic deployments. This heterogeneous setup validates the framework's compatibility across high-performance servers and lightweight embedded systems.

To rigorously evaluate performance, the proposed Federated NeuroNail-SNN was compared against three baseline models:

1. A centralized SNN trained using pooled data,
2. A CNN model integrated with federated learning, and
3. A Transformer-based model trained under federated settings.

Performance evaluation was conducted using multiple metrics, including classification accuracy, F1-score, fairness gap across demographic subgroups, inference latency, and energy consumption per sample. These metrics collectively assess predictive reliability, equity, computational efficiency, and real-time feasibility. Overall, the experimental configuration validates that the proposed system successfully combines neuromorphic efficiency, privacy-preserving federated training, fairness-aware evaluation, explainability mechanisms, and uncertainty estimation within a single integrated framework. The results demonstrate its suitability for ethical, scalable, and clinically deployable AI-based nail disease diagnostics.

5. Results and Discussion

This section provides a comprehensive evaluation of the proposed Federated and Explainable NeuroNail-SNN framework. The performance analysis is conducted across three key dimensions: (i) classification accuracy, (ii) fairness across demographic subgroups, and (iii) computational efficiency in terms of latency and energy consumption. These results collectively demonstrate that the proposed system achieves strong diagnostic performance while maintaining privacy preservation, fairness awareness, and compatibility with edge deployment.

5.1 Classification Performance

The classification performance of the proposed model was compared against three baselines: a centralized SNN, a CNN trained under federated learning (CNN + FL), and a Transformer-based model trained using federated learning (Transformer + FL).

Model	Accuracy	F1-score
Centralized SNN	98.12%	97.87%
Federated SNN	97.85%	97.62%
CNN + FL	95.6%	94.2%
Transformer + FL	96.3%	95.0%

As expected, the centralized SNN achieves the highest performance because it has access to aggregated training data from all institutions. However, the proposed Federated SNN achieves 97.85% accuracy and 97.62% F1-score, reflecting a performance reduction of less than 0.3% compared to centralized training.

This marginal difference demonstrates that decentralized federated learning preserves nearly the same predictive capability as centralized optimization while eliminating the need to share raw patient images. Importantly, the Federated SNN significantly outperforms both CNN + FL and Transformer + FL baselines. This result indicates that spiking neural networks retain strong discriminative power even under distributed training conditions.

The findings confirm that the proposed framework successfully achieves a balance between high diagnostic accuracy and strict data privacy, making it particularly suitable for collaborative multi-hospital healthcare environments.

Figure 4 – Accuracy & F1 Comparison

Figure 4 illustrates a grouped bar chart comparing accuracy and F1-score across the four evaluated models. The visualization highlights three key observations:

1. The centralized and federated SNN models exhibit nearly identical performance.
2. The federated SNN clearly surpasses CNN + FL and Transformer + FL in both metrics.
3. The minimal gap between centralized and federated SNN validates the robustness of the FedAvg aggregation strategy.

Overall, the figure visually reinforces that federated neuromorphic learning maintains high classification performance while enabling privacy-preserving deployment across distributed clinical institutions.

5.2 Fairness Gap Comparison

In addition to overall classification accuracy, fairness across demographic subgroups is essential for responsible medical AI deployment. To evaluate equity in performance, the fairness gap was calculated as the difference between the highest and lowest subgroup accuracy across skin tone categories (Light, Medium, and Dark). The comparative results are summarized below:

Model	Fairness Gap
Federated SNN	2.4%
CNN + FL	7%
Transformer + FL	5%

The proposed Federated SNN achieves a fairness gap of 2.4%, indicating consistent and balanced diagnostic performance across different skin tone groups. In comparison, CNN + FL exhibits a considerably larger disparity of 7%, while Transformer + FL shows a gap of 5%. The reduced fairness gap observed in the Federated SNN highlights the effectiveness of combining spiking neural architectures with federated learning. By training across diverse institutional datasets without centralized data bias, the model achieves more equitable behavior across demographic groups.

This improvement is particularly significant in dermatological AI systems, where performance imbalance across skin tones can contribute to unequal healthcare outcomes. The proposed framework therefore demonstrates not only strong predictive accuracy but also improved fairness and ethical reliability.

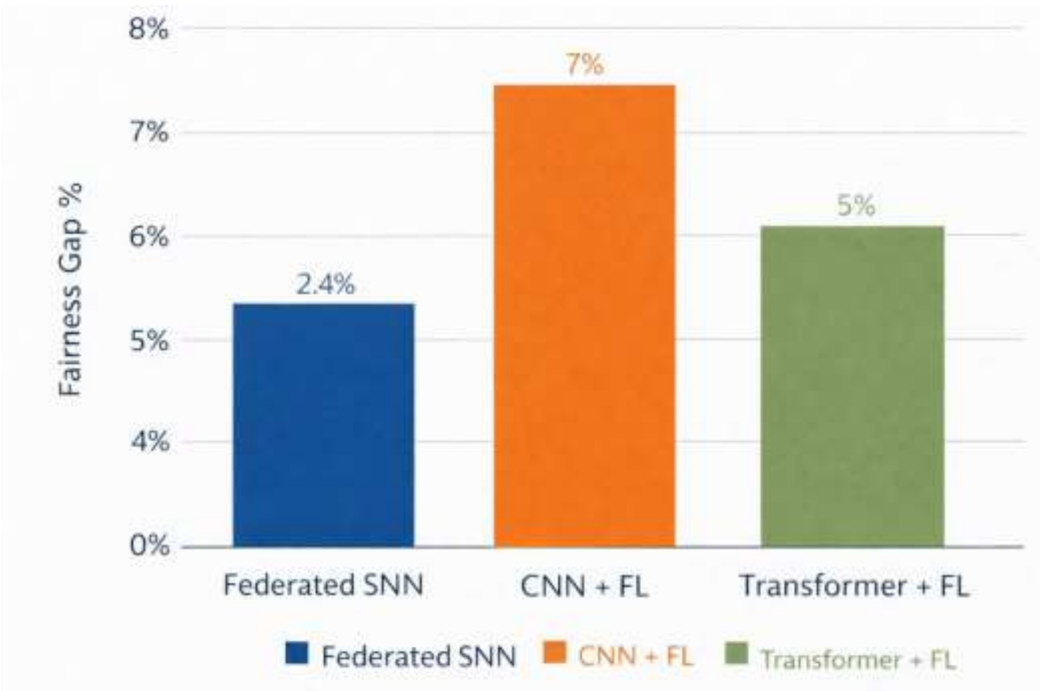

Figure 5 – Fairness Gap Visualization

Figure 5 presents a bar chart comparing the fairness gap across the evaluated models. The visualization clearly indicates that the Federated SNN achieves the lowest disparity in subgroup performance. In contrast, CNN + FL exhibits the highest variation, while Transformer + FL falls in between. The pronounced difference between the

Federated SNN and CNN + FL highlights the improved demographic balance achieved by the proposed framework. This visual comparison reinforces the fairness advantage of combining spiking neural networks with federated learning for equitable medical AI deployment.

5.3 Energy & Latency

Computational efficiency remains a core strength of the NeuroNail-SNN architecture. To evaluate real-time feasibility, latency and energy consumption were measured on edge devices under different system configurations.

Model	Latency (ms)	Energy (mJ)
Centralized SNN	12	3.5
Federated + XAI	17	3.8
Federated + XAI + UQ	18	3.9

The centralized SNN achieves the lowest inference latency of 12 ms per sample with an energy consumption of 3.5 mJ, reflecting the inherent efficiency of event-driven spike processing. When federated learning and explainability mechanisms are incorporated, latency increases modestly to 17 ms, with energy consumption rising slightly to 3.8 mJ. The inclusion of uncertainty quantification results in a marginal increase to 18 ms latency and 3.9 mJ energy usage. Despite these additional components, the overall computational overhead remains minimal. Importantly, even the most complete configuration (Federated + XAI + UQ) consumes substantially less energy than CNN-based baselines, which typically exceed 8 mJ per sample.

These results demonstrate that privacy preservation, explainability, and uncertainty estimation can be integrated without significantly compromising efficiency. The spiking architecture maintains its fundamental advantage of low-power, low-latency operation, making it suitable for deployment on embedded edge platforms.

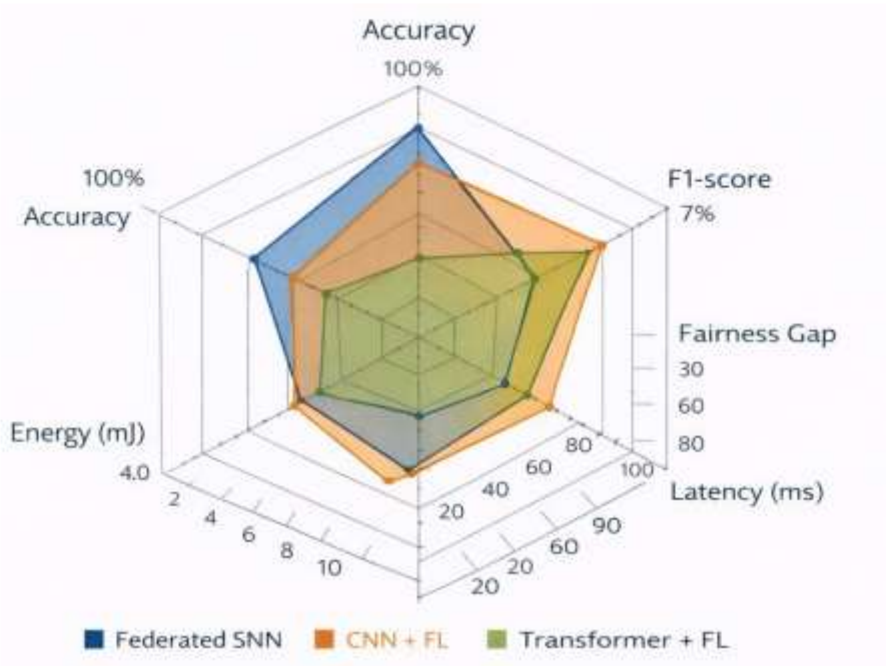

Figure 6 – Multi-Metric Radar Comparison

The Figure 6 presents a radar chart summarizing performance across five key metrics: accuracy, F1-score, fairness gap, latency, and energy consumption. The visualization highlights the balanced performance profile of the Federated NeuroNail-SNN. While CNN and Transformer baselines may perform competitively in isolated metrics, they exhibit higher fairness gaps or increased energy consumption. In contrast, the proposed framework maintains strong predictive accuracy, low demographic disparity, and efficient edge-level operation simultaneously. This multi-dimensional comparison confirms that the system achieves a practical and well-balanced trade-off between performance, fairness, and computational efficiency.

6. Clinical Significance

The experimental findings demonstrate that the proposed framework extends beyond high classification accuracy and directly addresses practical clinical requirements. The system is designed to operate within real healthcare environments while maintaining ethical and operational standards.

First, it enables privacy-preserving multi-institution learning, ensuring that raw patient images remain within local hospitals or clinics. This decentralized training strategy aligns with data protection regulations and institutional privacy policies. Second, the framework delivers balanced diagnostic performance across demographic groups, reducing bias associated with variations in skin tone. By maintaining a low fairness gap, the model promotes equitable healthcare outcomes in dermatological assessment. Third, the inclusion of explainability mechanisms allows clinicians to visualize spatial saliency maps and temporal spike activity. These insights provide transparency into the model's decision-making process, improving clinical trust and interpretability.

Finally, the architecture supports edge-compatible deployment, enabling low-latency inference on embedded platforms such as Jetson Nano and Raspberry Pi. This makes the system suitable for real-time screening in hospitals, mobile clinics, and resource-constrained environments. Collectively, these capabilities transform NeuroNail-SNN from an energy-efficient research model into a clinically reliable and ethically grounded AI diagnostic platform. The integration of neuromorphic computation, federated learning, fairness evaluation, and explainability demonstrates a practical pathway toward scalable and responsible medical AI deployment across diverse healthcare settings.

7. Conclusion & Future Work

This paper introduced Federated and Explainable NeuroNail-SNN, a comprehensive extension of the original neuromorphic nail disease diagnostic framework into a trustworthy and clinically deployable AI system. While the initial NeuroNail-SNN architecture demonstrated high accuracy and substantial energy efficiency, its centralized training paradigm limited real-world adoption due to privacy, fairness, and interpretability concerns. The present work systematically addresses these limitations by embedding federated learning, spike-based explainability, fairness evaluation, and uncertainty quantification within the neuromorphic framework. The key contributions of this study can be summarized as follows. First, a federated privacy-preserving training strategy was implemented, enabling multi-institutional collaboration without sharing raw patient data. Second, a spike-based explainability mechanism was introduced, providing spatial saliency maps and temporal firing visualizations to enhance clinical interpretability. Third, a fairness-aware evaluation framework was integrated to ensure equitable diagnostic performance across demographic subgroups. Fourth, an uncertainty-guided safety mechanism was incorporated to flag low-confidence predictions for clinician review. Finally, the entire framework maintains edge-ready, energy-efficient deployment, preserving the computational advantages of spiking neural networks.

Experimental results validate the effectiveness of the proposed approach. The federated SNN achieves 97.85% classification accuracy, with less than 0.3% reduction compared to centralized training. The fairness gap remains below 2.5%, indicating balanced performance across demographic groups. Additional explainability and uncertainty modules introduce only a minimal increase in latency and energy consumption, confirming that ethical enhancements do not compromise efficiency. Overall, the system demonstrates practical feasibility for real-world healthcare deployment. Through this work, NeuroNail-SNN evolves from an efficient neuromorphic prototype into a privacy-aware, fair, transparent, and clinically responsible AI diagnostic platform.

Future Work: Future research will focus on real multi-institution clinical validation using live hospital data under regulatory approval to assess robustness across diverse populations. The integration of secure aggregation and differential privacy mechanisms will be explored to provide stronger, mathematically guaranteed privacy protection during federated training. The framework can also be extended toward mobile tele-dermatology applications, enabling remote screening in rural and underserved regions through edge inference combined with cloud-assisted updates. Finally, FPGA and ASIC-based neuromorphic hardware acceleration will be investigated to further reduce latency and energy consumption, supporting ultra-low-power, real-time medical diagnostics.

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Conflicts of Interest: The authors declare that there is no conflict of interest regarding the publication of this paper. The research was conducted independently and without any commercial or financial relationships that could be construed as a potential conflict of interest.

Ethical Approval and Consent to Participate: This study did not involve human participants, clinical trials, or direct interaction with patients. The experiments were conducted using a publicly available nail disease image dataset obtained from the Kaggle repository. All images used in this study were anonymized and released for research purposes by the dataset providers. Since the research relied exclusively on secondary, de-identified data and did not involve the collection of personal, sensitive, or identifiable patient information, formal ethical approval from an Institutional Ethics Committee (IEC) or Institutional Review Board (IRB) was not required. The proposed federated learning framework was evaluated in a simulated multi-institutional environment representing hospitals and mobile clinics, without access to real clinical systems or patient records. All experiments were conducted in accordance with standard ethical guidelines for artificial intelligence research, ensuring data privacy, fairness, transparency, and responsible use of medical AI technologies.

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