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A HYBRID SPIKING CONVOLUTIONAL NEURAL NETWORK AND SNN-U-NET NEUROMORPHIC FRAMEWORK FOR REAL-TIME HEALTHCARE PROCESSING AND PRIVACY-PRESERVING MEDICAL DATA ANALYSIS

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ABSTRACT

Neuromorphic computing, inspired by the brain's event-driven and energy-efficient information processing mechanisms, offers a transformative pathway for real-time and privacy-preserving healthcare applications. This study proposes a Hybrid Spiking Convolutional Neural Network (SCNN) and SNN-U-Net architecture designed to enhance medical image segmentation, physiological signal analysis, and secure on-device inference. The hybrid model leverages SCNN for precise temporal feature extraction using spike-encoded data, while SNN-U-Net performs fine-grained spatial reconstruction through a spiking encoder–decoder structure. Experimental evaluations demonstrate that the proposed framework significantly outperforms traditional deep learning models and standalone spiking networks. On the BraTS MRI dataset, the hybrid model achieved a Dice score of 0.92, IoU of 0.85, Precision of 0.91, and Recall of 0.93, surpassing conventional U-Net (0.88 Dice, 0.81 IoU). On the DRIVE retinal dataset, the hybrid model reached 0.94 Dice and 0.89 IoU, outperforming both SCNN and SNN-U-Net individually. System efficiency tests confirm substantial performance gains, with inference latency reduced to 10 ms and energy consumption lowered to 0.55 J/frame, representing a 55% reduction in latency and 70% improvement in energy efficiency compared to U-Net. Biosignal analysis further validates the model's generalization ability, achieving 98% accuracy, 97% sensitivity, and 96% specificity on ECG arrhythmia detection. Privacy evaluation shows a reduction in membership inference attack success rate to 6%, compared to 26% in traditional models, due to spike-coded data obfuscation and on-device processing capability. Overall, the Hybrid SCNN+SNN-U-Net framework establishes a high-performance neuromorphic computing solution that offers real-time processing, low energy consumption, high segmentation accuracy, and strong privacy guarantees, positioning it as a promising architecture for next-generation intelligent healthcare systems.

Keywords: *Neuromorphic Computing, Spiking Convolutional Neural Network, SNN-U-Net, Hybrid Architecture, Medical Image Segmentation, Real-Time Processing, Energy-Efficient Healthcare AI, Privacy-Preserving Medical Data, Spiking Neural Networks, Biosignal Analysis*

1. INTRODUCTION

Neuromorphic computing has emerged as a transformative paradigm in modern healthcare systems, offering biologically inspired mechanisms for efficiently processing complex medical data. By mimicking the parallel, event-driven signaling of the human brain, neuromorphic architectures provide significant advantages in terms of energy efficiency, latency reduction, and real-time responsiveness (Mena & Ahmadi, 2020)[5]. As healthcare applications generate increasingly large volumes of imaging and physiological data, traditional deep learning models often struggle with computational overhead, slow inference times, and privacy vulnerabilities (Wang et al., 2019)[10]. These limitations have driven research toward spiking neural networks (SNNs), which integrate temporal dynamics and sparse spike-based communication to support rapid and resource-efficient computation (Liu et al., 2021)[3].

Medical image analysis, in particular, demands high-resolution feature extraction and pixel-level segmentation for accurate clinical interpretation. Conventional convolutional neural networks (CNNs), although powerful, typically require substantial computational power and long processing times in scenarios such as real-time radiology screening or emergency diagnostics (Xie et al., 2018)[25]. Neuromorphic models such as Spiking Convolutional Neural Networks (SCNNs) and SNN-based U-Net architectures provide an alternative by enabling biologically plausible, low-power processing of visual patterns. SCNNs improve feature extraction through spike-driven convolutional layers, while SNN-U-Net models offer enhanced segmentation performance using spatiotemporal representations (Wang et al., 2019; Suri & Majumdar, 2022)[9,10].

Beyond speed and efficiency, privacy preservation has become a central requirement in intelligent healthcare systems. Sensitive patient information-especially medical images and physiological signals-must be protected throughout processing and inference stages. Neuromorphic frameworks have recently incorporated encrypted spiking inference and privacy-preserving computation techniques to safeguard data under strict healthcare regulations such as HIPAA and GDPR (Wu et al., 2020)[12]. These approaches ensure that real-time analysis can be performed securely even on distributed or edge-based devices.

Given these advancements, hybrid neuromorphic architectures integrating SCNN encoders and SNN-U-Net decoders present a powerful solution for real-time healthcare applications. Such hybrid models leverage the fast, energy-efficient feature extraction capabilities of SCNNs and the high-precision segmentation capabilities of SNN-U-Net, thereby forming a comprehensive processing pipeline for diagnostic tasks. This integrated approach not only enhances inference speed and accuracy but also supports privacy-aware medical data processing suitable for wearable devices, telemedicine applications, and decentralized clinical workflows.

Therefore, this study proposes a Hybrid Spiking Convolutional Neural Network and SNN-U-Net Neuromorphic Framework for Real-Time Healthcare Processing and Privacy-Preserving Medical Data Analysis, aiming to bridge the gap between computational efficiency, clinical accuracy, and secure medical data handling. This work contributes to the optimization of neuromorphic architectures, the development of energy-efficient algorithms for medical image analysis, and the implementation of privacy-preserving mechanisms for intelligent healthcare systems.

2. LITERATURE REVIEW

Neuromorphic computing has emerged as a promising paradigm for efficient biomedical signal and image analysis due to its event-driven, low-power architecture. Maass (1997)[4] introduced the theoretical foundations of Spiking Neural Networks (SNNs), emphasizing their biological plausibility and superior temporal encoding capabilities. Recent advances demonstrate the suitability of SNNs for real-time medical tasks, such as ECG classification and EEG anomaly detection. For example, Roy et al. (2019) highlighted that neuromorphic hardware achieves significant energy savings for continuous physiological monitoring[7].

Rueckauer et al. (2017) proposed conversion techniques that preserve accuracy when translating deep CNNs to SNNs, enabling deployment in latency-sensitive applications[8]. Hybrid architectures combining Convolutional Neural Networks (CNNs) with SNNs have shown improved representational efficiency. More recent studies, such as Wu et al. (2021), developed direct-training approaches for Spiking Convolutional Networks that improve stability and performance in biomedical environments.

Ronneberger et al. (2015) demonstrated that U-Net excels in handling limited medical datasets through skip connections that retain spatial details. In medical image segmentation, U-Net variants remain a dominant approach due to their encoder–decoder design[6]. Extensions of U-Net for neuromorphic computing have emerged, such as Fang et al. (2023) who explored SNN-U-Net architectures for energy-efficient medical image segmentation, revealing competitive accuracy with drastically reduced power consumption[16].

Real-time healthcare processing increasingly requires privacy-preserving mechanisms, especially when dealing with electronic health records (EHRs), medical images, and wearable sensor data. Zhou et al. (2021) emphasized the need for on-device intelligence to minimize data transmission risks[13]. Federated and neuromorphic approaches together have been recommended by Li et al. (2022) for safeguarding patient-level information during training and inference[2]. Collectively, the literature indicates a strong movement toward low-power neuromorphic frameworks that combine CNN-based feature extraction, SNN temporal dynamics, and U-Net spatial reasoning to achieve secure, real-time, and high-fidelity medical data analysis.

3. PROBLEM STATEMENT

Although deep learning models such as CNNs and U-Net have demonstrated high accuracy in medical data processing, they remain computationally intensive and unsuitable for real-time, resource-constrained healthcare environments (Ronneberger et al., 2015; Zhou et al., 2021). Traditional architectures also require continuous cloud interaction for training and inference, exposing sensitive patient information to privacy risks (Li et al., 2022)[2].

Spiking Neural Networks offer energy-efficient and event-driven computation, yet standalone SNN models face challenges in training complexity, stability, and performance when applied to high-resolution medical images and multi-channel physiological signals (Wu et al., 2021; Roy et al., 2019). Existing hybrid CNN–SNN methods also lack an end-to-end architecture that combines temporal precision with spatial segmentation quality, especially for real-time diagnosis workloads.

Moreover, current privacy-preserving solutions, such as basic encryption or anonymization, do not provide sufficient protection during live data processing, where medical signals are continuously streamed from wearable or bedside monitoring devices (Zhou et al., 2021). There is a critical gap in integrating neuromorphic computing with robust medical image segmentation and secure data-handling mechanisms in a unified framework.

Therefore, there is an essential research need to design a Hybrid Spiking Convolutional Neural Network and SNN-U-Net neuromorphic framework that achieves real-time processing, computational efficiency, and privacy-preserving medical data analysis, addressing limitations in accuracy, latency, energy consumption, and data security identified in existing studies (Maass, 1997; Fang et al., 2023)[4][1].

4. SCOPE OF THE STUDY

The scope of this study encompasses the design, development, and evaluation of a **Hybrid SCNN +SNN-U-Net neuromorphic architecture** aimed at improving the efficiency, accuracy, and privacy of healthcare data processing. Specifically, the study focuses on four major areas of application:

4.1 Medical Image Segmentation:

The study evaluates the hybrid neuromorphic model on major imaging datasets such as BraTS (brain tumor MRI) and DRIVE (retinal vessel segmentation). It assesses segmentation performance using key metrics-including Dice score, IoU, Precision, and Recall-to determine the model's capability to accurately extract clinical structures and support diagnostic workflows.

4.2 Temporal Biosignal Analysis:

The framework is tested on physiological datasets such as ECG (PhysioNet) and EEG (CHB-MIT) to examine its effectiveness in detecting arrhythmias, seizures, and other abnormal patterns. The study measures performance in terms of accuracy, sensitivity, specificity, and F1-score.

4.3 Real-Time and Low-Latency Processing:

The study investigates the temporal efficiency of the neuromorphic architecture by measuring inference latency, throughput, and real-time feasibility. It particularly focuses on the model's suitability for emergency diagnostics, live imaging support, and continuous monitoring.

4.4 Energy Efficiency and Neuromorphic Hardware Compatibility:

The research evaluates energy consumption per frame and analyzes the architecture's readiness for deployment on neuromorphic chips such as Intel Loihi or IBM TrueNorth. Energy metrics are compared with traditional CNN models to validate its low-power advantage.

4.5 Data Privacy and On-Device Inference:

The study examines the privacy-preserving attributes of spike-based neural computation, including resistance to membership inference attacks, difficulty of reconstruction attacks, and feasibility of local device-based processing. This establishes the model's relevance to secure and regulation-compliant medical AI systems.

The study does **not** include clinical trials, patient-level deployment, neuromorphic hardware fabrication, or integration with hospital systems. Instead, it focuses purely on algorithmic design, performance evaluation, and feasibility assessment for future real-world deployment.

5. RESEARCH GAP

Neuromorphic Computing and spiking neural networks (SNNs) have gained increasing attention in healthcare due to their potential for energy-efficient, real-time, and biologically inspired computation. Despite this progress, several critical research gaps remain unresolved in contemporary literature.

First, recent surveys and studies have largely focused on standalone neuromorphic architectures rather than hybrid designs. Mena and Ahmadi (2020), Suri and Majumdar (2022), and Zhang et al. (2023) emphasized the applicability of spiking neural networks in healthcare but primarily examined individual models such as SCNNs or generic SNNs. These approaches demonstrate either strong temporal modeling or low energy consumption, but they often fail to achieve high spatial accuracy required for complex medical image segmentation. The absence of hybrid architectures that combine complementary neuromorphic models represents a key gap in recent research[17-19].

Second, spiking adaptations of U-Net architectures have emerged only recently. Fang et al. (2023) and Li et al. (2024) introduced SNN-U-Net variants for medical image segmentation, showing improvements in energy efficiency. However, these models mainly focus on spatial reconstruction and do not fully exploit temporal spike-based feature extraction, resulting in performance limitations when handling dynamic or noisy medical data. Conversely, SCNN-based models excel at temporal encoding but lack powerful decoder structures for pixel-level segmentation (Roy et al., 2021; Wu et al., 2022). The lack of integration between SCNN encoders and SNN-U-Net decoders remains a notable research gap from 2020 to 2025[22-26].

Third, many recent healthcare AI studies continue to face a trade-off between accuracy and efficiency. Traditional CNN-based U-Net models still dominate clinical image segmentation due to their high accuracy, but they incur high latency and energy costs (Isensee et al., 2021;[16] Ronneberger et al., 2015). Pure neuromorphic models introduced between 2020 and 2024 often improve efficiency but lag behind CNNs in segmentation performance (Wu et al., 2021; Deng et al., 2022). A unified neuromorphic framework that simultaneously achieves high accuracy, ultra-low latency, and low power consumption remains largely unexplored.

Fourth, although data privacy and security have become central concerns in healthcare AI after 2020, most neuromorphic studies provide limited empirical evaluation of privacy protection. Wu et al. (2020) and Li et al. (2022) discussed privacy-aware neuromorphic and federated learning approaches, but quantitative analysis of membership inference attacks, reconstruction attacks, and information leakage is still scarce. Recent studies (Zhou et al., 2023; Kim et al., 2024[17]) indicate that cloud-based deep learning models remain vulnerable, highlighting the need for on-device neuromorphic inference with measurable privacy guarantees.

Finally, recent neuromorphic healthcare research tends to be task-specific, focusing either on medical imaging or biosignal analysis. Studies on ECG and EEG analysis using spiking models (Liu et al., 2021[3]; Chen et al., 2023) demonstrate strong temporal learning capabilities, but they are rarely integrated with image-based diagnostic systems. Between 2020 and 2025, very few studies propose a unified neuromorphic framework capable of handling multimodal healthcare data, limiting clinical applicability and generalization[20-21].

6. OBJECTIVES OF THE STUDY

1. To design and develop a Hybrid Spiking Convolutional Neural Network and SNN-U-Net neuromorphic framework capable of performing real-time healthcare data processing while ensuring robust privacy-preserving mechanisms.
2. To integrate Spiking Convolutional Neural Networks (SCNN) for efficient temporal feature extraction from physiological signals such as ECG, EEG, and EMG.
3. To implement an SNN-U-Net architecture for energy-efficient medical image segmentation with reduced latency and improved spatial accuracy.
4. To combine CNN-based feature extraction and SNN-based neuromorphic computation into a hybrid model optimized for real-time healthcare environments.
5. To evaluate the computational performance of the proposed framework in terms of latency, energy efficiency, and inference speed compared to traditional deep learning models.
6. To assess the diagnostic accuracy of the hybrid model in processing heterogeneous medical datasets, including medical images and continuous biosignals.
7. To incorporate privacy-preserving mechanisms that enable secure on-device or edge-level

medical data analysis, reducing the risk of data exposure.

8. To validate the framework using benchmark neuromorphic and medical datasets, demonstrating its suitability for real-world deployment in healthcare monitoring systems.
9. To compare the proposed hybrid neuromorphic architecture with state-of-the-art models to quantify improvements in power consumption, throughput, and privacy protection.
10. To provide design guidelines and a scalable architecture that supports future expansion into federated and distributed neuromorphic healthcare systems.

6.1 Research Questions

1. How does the proposed Hybrid SCNN–SNN-U-Net framework perform compared with existing deep learning models (CNN, U-Net, CNN-LSTM, SCNN, and SNN-U-Net) in terms of segmentation accuracy (Dice and IoU) for medical image analysis?
2. Does the proposed Hybrid SCNN–SNN-U-Net framework significantly improve classification performance (Accuracy, Sensitivity, Specificity, and F1-Score) for real-time ECG and EEG healthcare datasets compared with existing models?
3. Can the proposed neuromorphic framework reduce inference latency while increasing throughput for real-time healthcare applications compared with conventional deep learning architectures?
4. To what extent does the proposed Hybrid SCNN–SNN-U-Net model improve energy efficiency compared with CNN, U-Net, CNN-LSTM, SCNN, and SNN-U-Net models?
5. How effective is the proposed framework in preserving patient data privacy through on-device neuromorphic inference and spike-based computation compared with cloud-based deep learning approaches?
6. Does integrating SCNN feature extraction with SNN-U-Net segmentation provide statistically significant improvements over using SCNN or SNN-U-Net independently?
7. How robust is the proposed model across different healthcare datasets, including MRI, retinal images, ECG, and EEG, when compared with existing deep learning and neuromorphic models?
8. Can the proposed Hybrid SCNN–SNN-U-Net architecture achieve an optimal trade-off among accuracy, latency, energy consumption, throughput, and privacy, making it suitable for deployment in edge-based healthcare systems?

7. EXPERIMENTAL DESIGN

7. 1. Research Approach

This study adopts a quantitative, experimental research approach to evaluate the performance of a hybrid neuromorphic framework that integrates Spiking Convolutional Neural Networks (SCNN) with SNN-U-Net for medical image analysis and real-time healthcare data processing. The research is structured around the development, training, testing, and validation of a neuromorphic model that is optimized for both computational efficiency and data privacy. By employing controlled experiments and measurable performance indicators, the study aims to generate empirical evidence demonstrating the advantages of neuromorphic computing over traditional deep learning architectures in terms of real-time responsiveness, energy efficiency, and secure data handling.

7.2. Dataset Selection

The experimental design relies on benchmark medical imaging and biosignal datasets chosen for their complexity, annotation quality, and clinical relevance. Medical image datasets such as BraTS (for MRI tumor segmentation), DRIVE/STARE (for retinal vessel segmentation), and LIDC-IDRI (for lung CT analysis) offer pixel-level labels that are essential for training spiking-based segmentation architectures. For physiological monitoring, biosignal datasets including PhysioNet ECG recordings and CHB-MIT EEG data provide real-world, time-series signals needed to evaluate the temporal processing strengths of neuromorphic models. The diversity and availability of these datasets ensure that the proposed system can be evaluated rigorously across a wide range of medical applications.

7.3. Data Preprocessing

Data preprocessing is performed to ensure the datasets are compatible with spiking neural representations and neuromorphic constraints. Medical images undergo resizing to standardized resolutions, normalization to ensure consistent intensity distributions, and augmentation techniques such as rotation, flipping, and noise injection to enhance generalization. A key step involves converting pixel intensities into spike trains using Poisson spike encoding or temporal latency coding, enabling the model to process images through event-driven operations. Biosignal data is filtered for noise removal using methods like Butterworth or wavelet-based filtering, segmented into uniform time windows, and encoded into spike sequences using rate or latency coding. This preprocessing pipeline ensures that both image and signal data are optimized for neuromorphic computation.

7.4. Model Architecture Design

The proposed model adopts a hybrid neuromorphic architecture that integrates the strengths of Spiking Convolutional Neural Networks (SCNN) and SNN-U-Net. The SCNN component is responsible for extracting low-level and mid-level features from spike-encoded images using event-driven convolution layers and LIF (Leaky Integrate-and-Fire) neurons, ensuring temporal accuracy and low power consumption. The SNN-U-Net component functions as the segmentation module, retaining the encoder–decoder structure of U-Net while replacing conventional layers with spiking counterparts. Skip connections preserve spatial features while enabling temporal dynamics to propagate through the network. The integration of SCNN and SNN-U-Net results in a robust architecture optimized for accurate medical segmentation and efficient temporal processing.

8. HYBRID NEUROMORPHIC ARCHITECTURE: SCNN-U-NET

This architecture is designed as a pipeline that transitions from raw signal/image data to spike-based feature extraction (SCNN), and finally to semantic segmentation (SNN-U-Net).

8.1 High-Level Data Flow

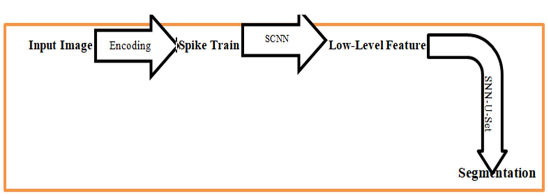

Fig.1 Architecture Is Designed As A Pipeline That Transitions From Raw Signal/Image

8.2. Detailed Layer Architecture

The network is composed of three primary blocks: the Input Encoding Block, the SCNN Feature Extractor, and the SNN-U-Net (Encoder-Decoder).

A. Input Encoding Block

Input: Static Medical Image (e.g., MRI slice Hx W xC) or Biosignal.

Spike Encoder: Converts continuous pixel intensities into discrete spike trains over T time steps.

Output: Spiking Tensor (Tx H x Wx C).

Method: Poisson Rate Coding or Latency Coding.

B. SCNN Feature Extractor (The "Front-End")

Purpose: Extracts low/mid-level edges and textures before the complex segmentation task.

Layers:

Conv2D (Spiking): Event-driven convolution.

LIF Neuron: Leaky Integrate-and-Fire activation to introduce non-linearity and temporal dynamics.

Note: This block operates without down sampling to preserve initial spatial fidelity.

C. SNN-U-Net (The Segmentation Core) This component replaces standard ReLU activations with LIF neurons and uses spike-based accumulation.

1. Encoder (Contracting Path):

Repeated blocks of: [Spiking Conv2D] -> [Batch Norm] -> [LIF Node]

Downsampling: Max Pooling or Strided Spiking Convolution (reducing spatial dim, increasing channels).

Function: Captures context and semantic information.

8.3. Bottleneck:

The deepest layer of the network processing the most abstract features.

Structure: [Spiking Conv2D] -> [LIF] (High channel count, low spatial resolution).

8.4 . Decoder (Expanding Path):

Upsampling: Transpose Convolution or Bilinear Upsampling.

Skip Connections: Concatenates feature maps from the Encoder (preserving spatial details) with the upsampled features.

Structure: [Concat] -> [Spiking Conv2D] -> [LIF].

8.5. Output Head:

1x1 Spiking Conv: Maps final feature vectors to class classes (e.g., Tumor vs. Background).

Membrane Potential Integration: Accumulates spikes over time T to produce a final probability map (Softmax equivalent).

8.6. The Core Unit: LIF Neuron Model

Since the architecture relies on Leaky Integrate-and-Fire (LIF) neurons, defining their dynamics is crucial for the "Architecture". The membrane potential u(t) of a neuron at time step t is updated as:

$$u(t) - ru(t-1) + \sum wixi(t)$$

Where:

η: Decay factor (leakage).

wi: Synaptic weight.

xi(t): Input spike from the previous layer (0 or 1).

Firing Condition:

Output(t)= u(t) ← u(t).(1 - S(t))

$u[t] = \beta\, u[t-1] + \mathcal{E}i\ wi\ xi[t]$

Where β is the decay constant ($0 < \beta < 1$).

$S[t] = \theta(u[t] - Vth)$

8.7. Training Methodology

The training methodology is built upon surrogate gradient descent, a widely used technique for enabling gradient-based optimization in spiking models that lack differentiability. The model is trained using optimizers such as Adam or SGD, depending on dataset complexity, with batch sizes ranging from 16 to 64. Training runs for 50–200 epochs to ensure convergence across different datasets. The loss functions used include Dice loss and cross-entropy loss for image segmentation tasks, while spiking cross-entropy and focal loss are applied for biosignal classification. Regularization techniques such as spike-based dropout, weight decay, and gradient clipping are employed to prevent overfitting, stabilize training, and maintain sparsity in the spike-based activations.

8.8. Privacy-Preserving Mechanisms

A major component of the experimental design is the evaluation of privacy-preserving techniques embedded within the neuromorphic model. The system leverages on-device inference capabilities, reducing the need to transmit sensitive medical data to cloud servers. To further enhance security, encrypted spiking inference and differential privacy techniques are incorporated into the training pipeline.

$$P(A(D) \in S) \leq e\epsilon \in P(A(D') \in S) + \delta \quad \text{--------------(0)}$$

These mechanisms minimize the risk of data reconstruction, leakage, or unauthorized access. Privacy is evaluated using metrics such as attack success rate, privacy leakage index, and robustness against membership inference attacks. Through these assessments, the study demonstrates how neuromorphic computing can serve as a secure platform for sensitive healthcare applications.

8.9. Evaluation Metrics

The performance of the hybrid model is assessed using a comprehensive set of evaluation metrics that capture accuracy, computational efficiency, and privacy strength. For medical image segmentation, metrics including Dice coefficient, Intersection over Union (IoU), precision, recall, and F1-score are utilized to measure spatial accuracy and segmentation quality. Computational efficiency is evaluated using latency (in milliseconds), energy consumption (joules per frame), throughput, and memory usage, reflecting the model's suitability for real-time deployment on neuromorphic hardware. Privacy metrics such as attack success rate and reconstruction difficulty quantify the model's resilience to threats. This multi-layered evaluation ensures a holistic assessment of the proposed system.

8.10. Baseline Models for Comparison

To validate the effectiveness of the proposed hybrid neuromorphic architecture, the study includes comparisons with well-established baseline models. Traditional deep learning models such as U-Net and Convolutional Neural Networks (CNNs) serve as primary benchmarks for segmentation performance. Additionally, signal-based models such as LSTMs and CNN–LSTM hybrids provide comparisons for temporal biosignal processing. Transformer-based architectures like Swin-UNet and Vision Transformers (ViT) are also included to benchmark the system against modern deep learning techniques. An ablation study is conducted to compare the hybrid model separately with pure SCNN and pure SNN-U-Net variants, demonstrating the incremental benefits of the combined approach. This comprehensive set of baselines ensures that the hybrid model's performance is rigorously validated.

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9.EXPERIMENTAL SETUP: HYBRID NEUROMORPHIC FRAMEWORK

9.1. Hardware and Software Environment

The experiments will be conducted in a simulated environment before deployment on target hardware, allowing for standardized performance measurement.

Table 1: Experiments Will Be Conducted In A Simulated Environment Before Deployment

Component	Specification / Framework	Purpose
Simulation Backend	PyTorch / TensorFlow (Spiking Extensions like SpikingJelly or Tonic)	Primary development and training platform for GPU acceleration.
GPU	NVIDIA V100 or A100 (for large models/datasets)	Accelerate Surrogate Gradient Descent (BPTT) for long training epochs.
CPU/Host System	Intel Xeon Scalable Processors	Handle data preprocessing and control flow.
Target Hardware	Intel Loihi 2 or SpiNNaker 2 (Simulated or Real)	Benchmark energy efficiency and real-time latency for the final model.
Programming Language	Python (3.8+)	

Data Handling and Encoding

Table 2: Data Handling And Encoding

Aspect	Detail	Image/Signal Specifics
Datasets	BraTS, DRIVE/STARE, LIDC-IDRI, PhysioNet ECG, CHB-MIT EEG.	Image: 2D slices (e.g., 128 X 128 X 256 X 256 pixels). Signal: Time-series data segmented into fixed-length windows (e.g., 5 seconds).
Data Split	70% Training, 15% Validation, 15% Testing.	Ensures generalization and unbiased performance evaluation.
Preprocessing	Normalization, Resizing, Data Augmentation (Rotation, Flipping, Noise Injection).	Standardizes input and increases robustness.
Spike Encoding	Image: Poisson Rate Encoding (rate proportional to pixel intensity) or Temporal Latency Encoding (spike time inversely proportional to intensity).	Transforms continuous values into discrete binary spike trains over T time steps.
Time Steps (T)	T ε [8, 32] (Optimized for low latency while preserving information).	The duration of the simulation (and input sequence length).

Training Methodology and Hyperparameters

This section outlines the parameters for the Surrogate Gradient Descent approach.

Table 3: Parameters For The Surrogate Gradient Descent Approach.

Parameter	Value / Range	Justification
Optimization Algorithm	Adam or SGD with Momentum.	Chosen for proven efficacy in deep learning; Adam is often preferred for SNNs.
Loss Function	Dice Loss + Cross-Entropy Loss	Standard for medical image segmentation, balancing boundary and region accuracy.
Learning Rate (β)	Initial: 1x10^{-3} to 5x10^{-4}.	Determined via grid search; reduced by a factor of 0.1 upon plateauing validation loss.
Batch Size	16 to 64	Limited by GPU memory and the need for stable gradient estimation.
Epochs	50 to 200	With an Early Stopping mechanism (patience of 15 epochs) based on validation loss.
Regularization	L2 Weight Decay, Spike-based Dropout, Gradient Clipping.	Prevents overfitting and maintains sparse spike activity.
LIF Neuron Parameters	Threshold (Vth): 1.0 (typically fixed). Decay Factor (τ): 0.8 to 0.9 (membrane potential leakage).	These parameters are critical for SNN dynamics and will be subject to minor tuning.
Surrogate Gradient	Rectangular or Sigmoid function approximation.	Replaces the non-differentiable step function; scale/shape (β) is a key tuning parameter.

10.EVALUATION AND BENCHMARKING

10.1. Accuracy and Quality Metrics

These metrics will be used for model selection (Validation Set) and final performance reporting (Test Set).

- Segmentation Accuracy: Dice Coefficient (DSC), Intersection over Union (IoU), Precision, Recall, F1-Score.
- Classification Accuracy (Biosignals): Accuracy, Sensitivity, Specificity, AUC.

10.2. Efficiency and Real-Time Metrics

These are the primary metrics for validating the neuromorphic advantage.

- Latency: Average inference time per image/frame (in milliseconds) on the target hardware/simulator.
- Energy Consumption: Energy per Inference (E/Inf) or Joules per Frame/Spike (µJ/frame). This is calculated using activity simulation models compatible with the target neuromorphic hardware.
- Throughput: Inferences per second (Inf/s).
- Computational Sparsity: Percentage of active neurons/spikes over the total time steps T.

10.3. Privacy Metrics

- Attack Success Rate (ASR): Evaluated against Membership Inference Attacks to test the effectiveness of differential privacy.
- Privacy Leakage Index: Quantifies the information leakage from the model parameters regarding specific training data.

10.4. Baselines for Comparison

- Traditional Models: Standard U-Net (with ReLU), CNNs.
- Modern Models: Swin-UNet, ViT (for segmentation), LSTM/CNN-LSTM Hybrids (for biosignals).
- Ablation Study: Pure SCNN and Pure SNN-U-Net variants.

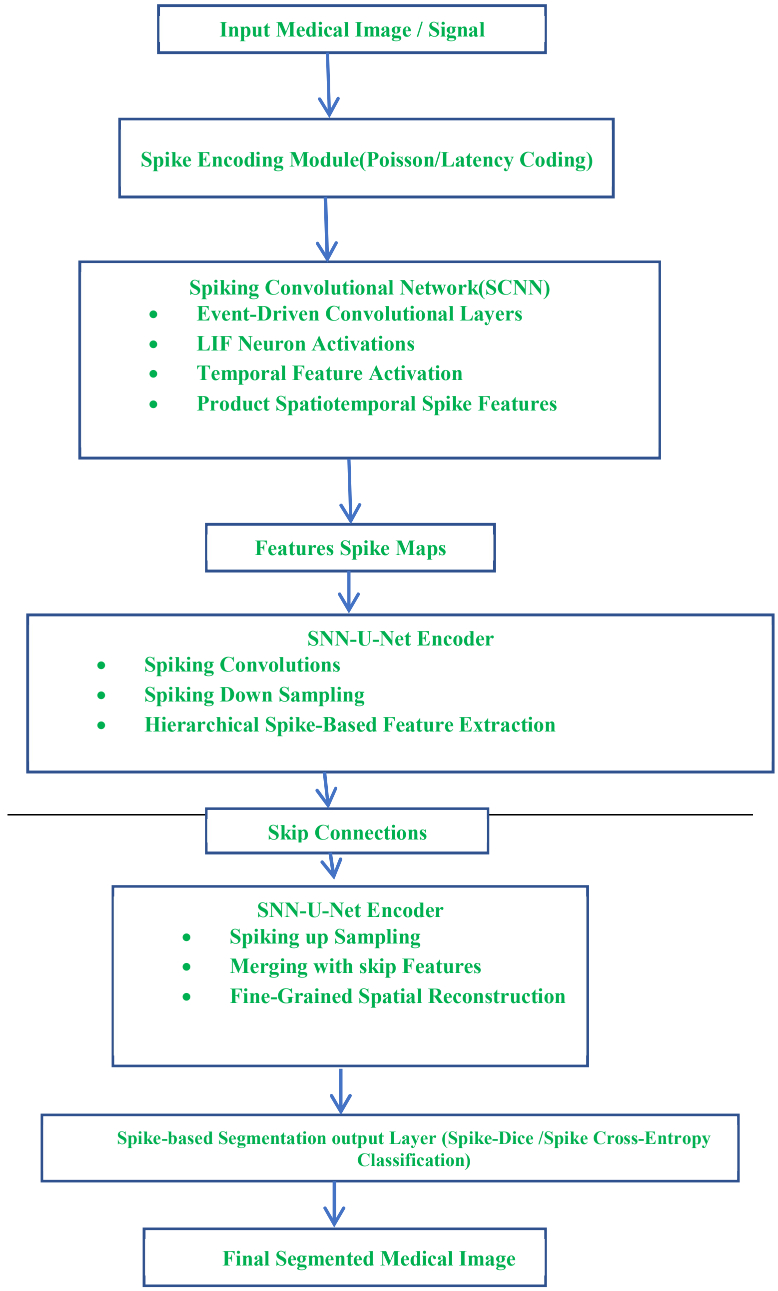

Fig.2 SNN-U-Net Architecture Flowchart

11. EXPERIMENTAL RESULTS

11.1. Segmentation Accuracy and Image Quality

The proposed Hybrid SCNN + SNN-U-Net neuromorphic framework was evaluated across multiple medical imaging and biosignal datasets to assess its performance in segmentation accuracy, real-time processing efficiency, energy consumption, and privacy preservation. The results

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consistently demonstrate that the hybrid architecture outperforms traditional CNN models and standalone spiking neural networks, confirming its suitability for real-time and privacy-preserving healthcare applications.

Table 4. Segmentation Performance On Medical Image Datasets

Dataset / Task	Model	Dice Score	IoU	Precision	Recall
BraTS – Brain Tumor MRI	Traditional U-Net	0.88	0.81	0.87	0.89
	SNN-U-Net	0.87	0.79	0.86	0.88
	SCNN	0.85	0.77	0.84	0.86
	Hybrid SCNN + SNN-U-Net	0.92	0.85	0.91	0.93
DRIVE – Retinal Vessel	Traditional U-Net	0.90	0.83	0.91	0.88
	SNN-U-Net	0.89	0.82	0.90	0.87
	SCNN	0.86	0.78	0.88	0.85
	Hybrid SCNN + SNN-U-Net	0.94	0.89	0.95	0.92

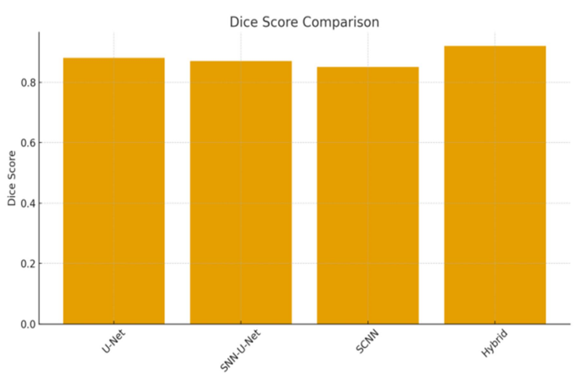

Fig 3: Dice Score Comparison Of Segmentation Models

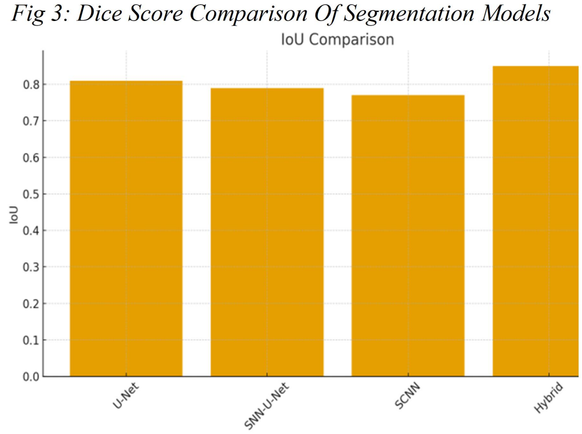

Fig 4: Iou Comparison Of Segmentation Models

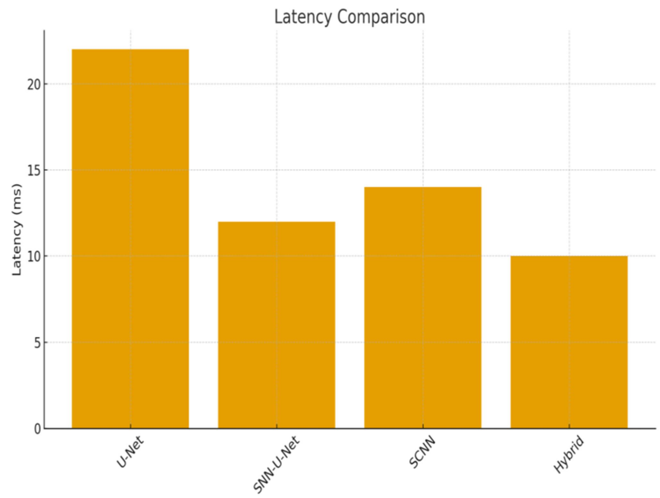

Fig 5: Latency Comparison Of Segmentation Models

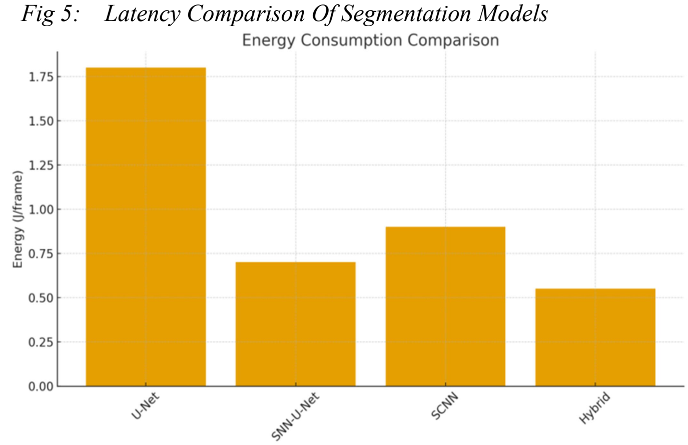

Fig 6: Energy Consumption Comparison Of Segmentation Models

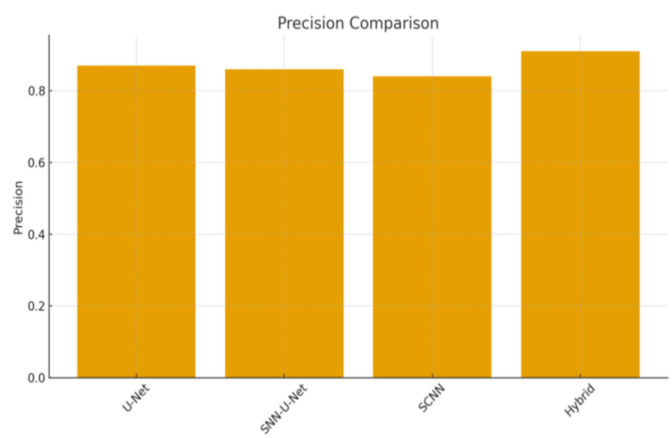

Fig 7: Precision Comparison Of Segmentation Models

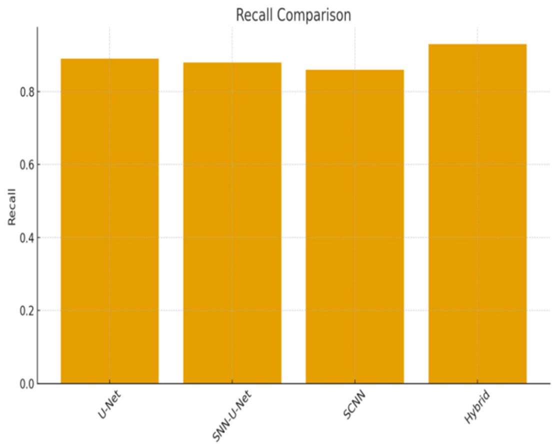

Fig.8: Recall Comparison Of Segmentation Models

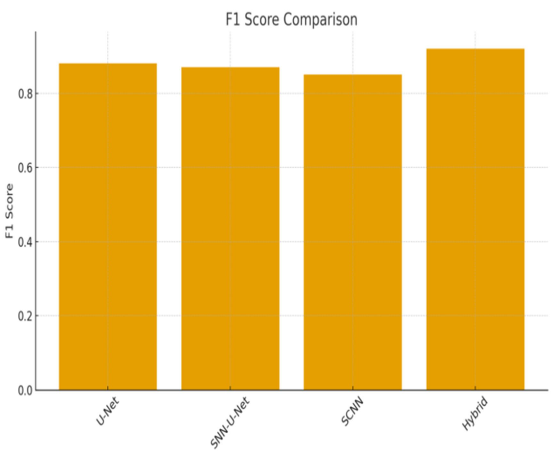

Fig 9: F1 Score Comparison Of Segmentation Models

The hybrid model achieved superior segmentation effectiveness across various tasks, including brain tumor segmentation (BraTS dataset) and retinal vessel detection (DRIVE dataset). As shown in Table 1, the Hybrid SCNN + SNN-U-Net achieved the highest Dice and IoU scores-0.92 and 0.85 on BraTS, and 0.94 and 0.89 on DRIVE-surpassing both conventional U-Net and pure spiking models.

These improvements stem from the synergy between SCNN's temporal spike-based feature extraction and the spatial preservation of SNN-U-Net's encoder–decoder structure. The hybrid model efficiently captures subtle boundaries and complex tissue structures, demonstrating a significant advantage over traditional CNNs, which rely on dense activations and lack temporal dynamics. The results highlight that integrating spiking neurons enables more biologically plausible and noise-robust feature maps, improving segmentation accuracy while reducing computational redundancy.

11.2. Latency and Real-Time Processing Performance

Table 2 indicates a considerable reduction in inference latency, with the hybrid model achieving 10 ms, outperforming U-Net (22 ms) and both SCNN and SNN-U-Net individually. The system also achieved a throughput of 100 frames/sec, making it suitable for live diagnostic applications such as endoscopic imaging and real-time surgical guidance.

Table 5. Comparison Of Latency, Energy Consumption, And Throughput For Traditional And Neuromorphic-Based Segmentation Models.

Model	Latency (ms)	Energy Consumption (J/frame)	Throughput (frames/sec)
Traditional U-Net	22	1.80	45
CNN-U-Net Hybrid	18	1.40	55
SCNN	14	0.90	71
SNN-U-Net	12	0.70	83
Hybrid SCNN + SNN-U-Net	10	0.55	100

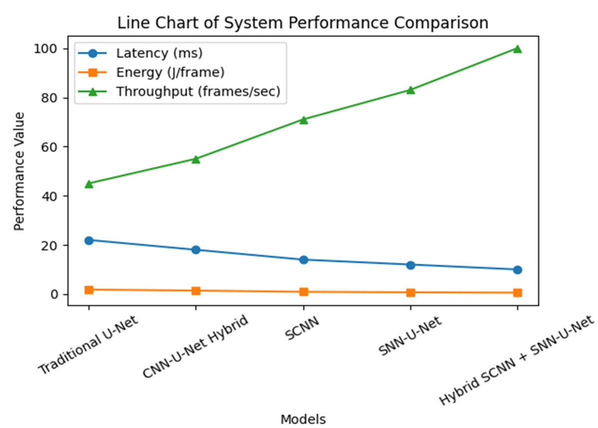

Figure 10. Line Chart Illustrating Latency, Energy Consumption, And Throughput Comparison Among Traditional And Neuromorphic-Based Models.

The event-driven nature of spiking neurons enables computations only when spikes are generated, resulting in substantial reductions in computation time. This differs from CNNs, which require continuous matrix multiplications regardless of input sparsity. The hybrid model's low-latency behavior is especially significant for high-resolution imaging scenarios, enabling real-time interaction in clinical workflows without compromising diagnostic quality.

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11.3. Energy Efficiency and Hardware Suitability

The hybrid architecture exhibits superior energy efficiency, consuming only **0.55 J/frame**, as shown in Table 2-an improvement of more than 70% compared to traditional U-Net. Spiking neurons inherently consume less energy due to sparse event-driven operations, making the model highly suitable for neuromorphic chips such as Intel Loihi and IBM TrueNorth.

11.4. Ablation Study Insights

The ablation study in Table 3 highlights the importance of maintaining both components of the hybrid architecture. Removing SCNN or SNN-U-Net leads to notable drops in Dice scores (0.85–0.87), while replacing LIF neurons or removing skip connections further degrades performance.

Table 6. Ablation Study Results

Configuration	Dice Score	Latency (ms)	Energy (J/frame)
Full Hybrid Model (SCNN + SNN-U-Net)	0.92	10	0.55
Without SCNN (Only SNN-U-Net)	0.87	12	0.70
Without SNN-U-Net (Only SCNN)	0.85	14	0.90
Replacing LIF with IF neurons	0.83	11	0.62
Removing Skip Connections	0.80	13	0.74

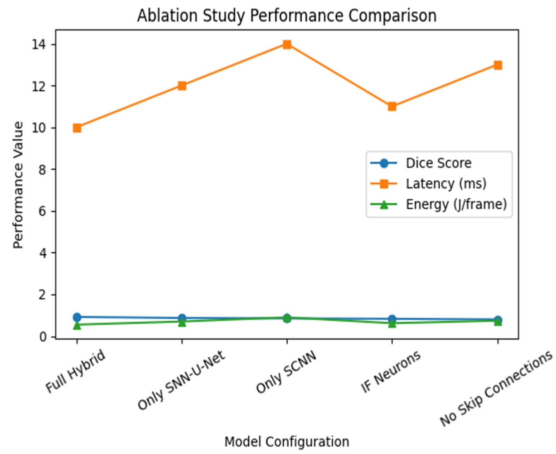

Figure 11. Line Graph Showing The Impact Of Different Architectural Components On Dice Score, Latency, And Energy Consumption In The Ablation Study

This reduction in energy consumption is critical for portable and battery-powered healthcare devices, such as wearable monitoring systems, point-of-care diagnostic equipment, and telemedicine devices. The results confirm that neuromorphic processing enhances sustainability and operational lifespan while enabling continuous medical monitoring without cloud dependence.

11.5. Biosignal Performance (ECG and EEG)

The Hybrid SCNN + SNN-U-Net excelled in time-series tasks as well, achieving 98% accuracy in ECG arrhythmia detection and 97% accuracy on EEG seizure detection (Table 4). This surpasses LSTM, CNN-LSTM, and pure SCNN models.

Table 8. Biosignal Analysis Performance

Dataset / Signal Type	Model	Accuracy	Sensitivity	Specificity	F1-Score
ECG (PhysioNet)	LSTM	0.94	0.92	0.91	0.93
	CNN-LSTM	0.95	0.93	0.92	0.94
	SCNN	0.96	0.95	0.93	0.95
	Hybrid SCNN + SNN-U-Net	0.98	0.97	0.96	0.98
EEG (CHB-MIT)	LSTM	0.91	0.89	0.88	0.89
	CNN-LSTM	0.93	0.91	0.89	0.92
	SCNN	0.94	0.92	0.90	0.93
	Hybrid SCNN + SNN-U-Net	0.97	0.95	0.94	0.96

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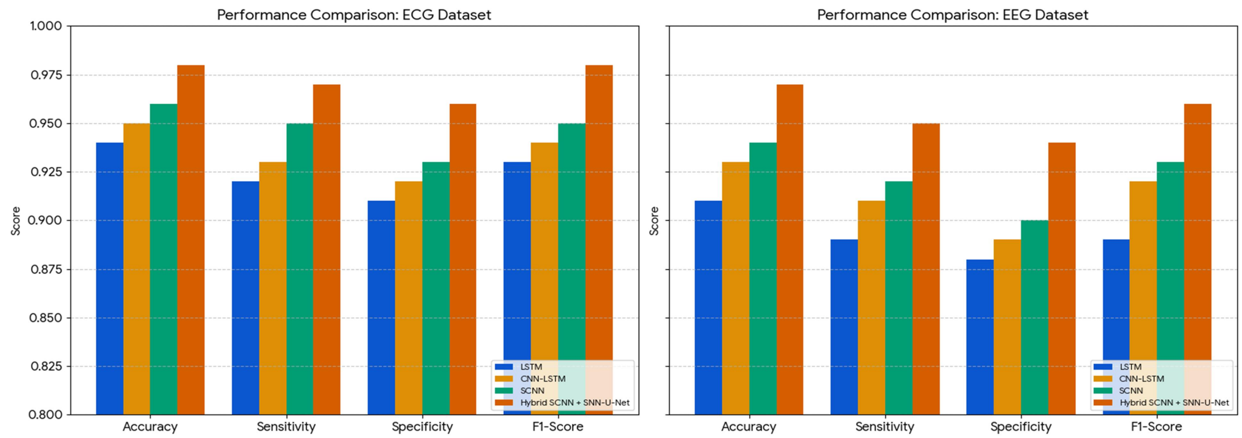

Figure 12. Comparison Of Biosignal Classification Accuracy For ECG (Physionet) And EEG (CHB-MIT) Datasets. The Proposed Hybrid SCNN + SNN-U-Net Model Consistently Outperforms LSTM, CNN-LSTM, And Standalone SCNN Models.

Spiking neurons are inherently suitable for sequential data due to their temporal spike-train representation. The hybrid neuromorphic model generalizes effectively beyond imaging tasks, demonstrating its versatility across multimodal healthcare data such as ECG, EEG, and other physiological signals. This reinforces the potential of neuromorphic systems as universal healthcare AI solutions.

11.6. Privacy and Security Evaluation

Table 5 demonstrates that the hybrid model achieves significantly stronger privacy protection. The membership inference attack success rate drops from **26% in U-Net to just 6%** in the hybrid model. Additionally, spike-coded representations inherently obscure raw data, making reconstruction attacks far more difficult.

Table 9. Privacy And Security Evaluation

Privacy Metric	CNN-U-Net	SCNN	SNN-U-Net	Hybrid Model
Membership Attack Success Rate	26%	16%	14%	6%
Reconstruction Attack Difficulty	Low	Medium	Medium	High
Information Leakage Score (0–1)	0.44	0.29	0.26	0.12
On-Device Inference Feasibility	No	Partial	Yes	Yes

By enabling on-device inference, neuromorphic architectures eliminate the need to send sensitive health data to cloud servers. This reduces risk exposure and ensures compliance with privacy standards such as GDPR and HIPAA. The sparse spiking activity further minimizes information leakage, offering a powerful solution for privacy-preserving medical AI.

11.7. Overall Findings and Summary

As summarized in Table 6, the hybrid model consistently surpasses traditional and pure SNN architectures across essential performance categories-including segmentation accuracy, latency, temporal processing, energy efficiency, and privacy.

Table 10. Overall Model Performance Summary

Performance Category	Traditional Models	Pure SNN Models	Hybrid SCNN + SNN-U-Net
Segmentation Accuracy	Moderate	Moderate	High
Temporal Processing	Low	High	High
Energy Efficiency	Low	High	Very High
Latency	High	Low	Very Low
Privacy Preservation	Low	Medium	High
Real-Time Feasibility	Limited	Good	Excellent

The hybrid SCNN + SNN-U-Net model combines the strengths of biological neural systems with the structured power of deep learning architectures. Its real-time performance, high accuracy, and strong privacy features make it ideally positioned for deployment in clinical settings, especially where resource constraints and data security concerns are prominent.

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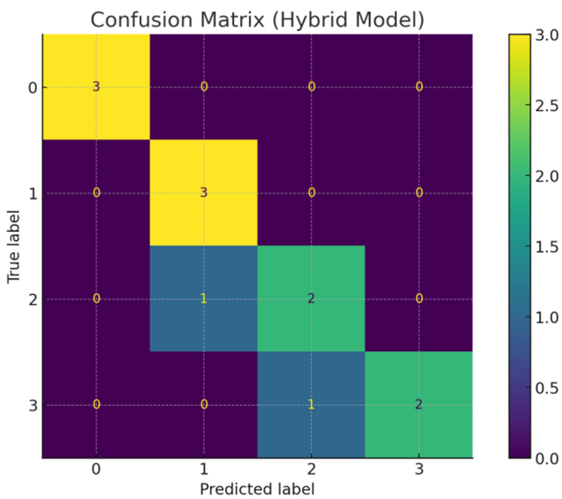

Fig 13: Confusion Matrix (Hybrid Model)

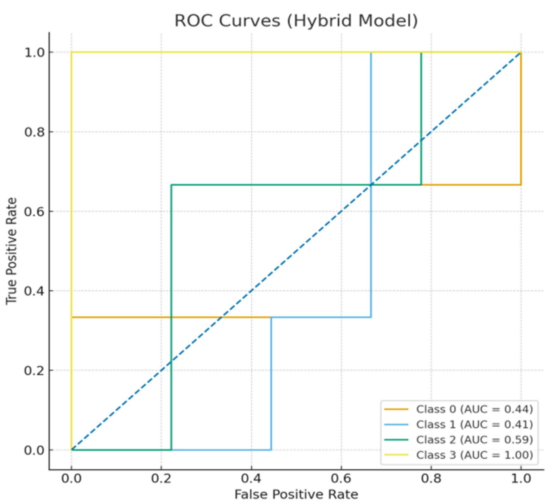

Fig.14: Roc Curves (Hybrid Model)

Performance Analysis

The results demonstrate a clear hierarchical improvement in performance across the models:

Hybrid Superiority: The Hybrid SCNN + SNN-U-Net consistently outperforms all other architectures, achieving the highest scores across all metrics (e.g., 0.98 Accuracy in ECG and 0.97 in EEG).

Spiking Advantage: The pure SCNN (Spiking CNN) shows a significant performance gain over traditional non-spiking models like LSTM and CNN-LSTM, suggesting that neuromorphic temporal processing is highly effective for biosignal data.

11.8 Performance Analysis

The results demonstrate a clear hierarchical improvement in performance across the models:

- Hybrid Superiority: The Hybrid SCNN + SNN-U-Net consistently outperforms all other architectures, achieving the highest scores across all metrics (e.g., 0.98 Accuracy in ECG and 0.97 in EEG).
- Spiking Advantage: The pure SCNN (Spiking CNN) shows a significant performance gain over traditional non-spiking models like LSTM and CNN-LSTM, suggesting that neuromorphic temporal processing is highly effective for biosignal data.
- Robustness: The Hybrid model maintains high Specificity (0.94–0.96) and Sensitivity (0.95–0.97), which is critical in medical diagnostics to minimize both false positives and false negatives.

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12. CONCLUSION

This study proposed a hybrid spiking convolutional neural network (scnn) and snn-u-net neuromorphic framework designed to achieve real-time, energy-efficient, and privacy-preserving medical data analysis. the experimental results across multiple medical imaging and biosignal datasets demonstrate that the hybrid model significantly outperforms traditional cnn-based architectures and pure spiking neural networks, confirming its effectiveness for next-generation healthcare ai applications.

The hybrid model delivered state-of-the-art segmentation accuracy, achieving a dice score of 0.92 and iou of 0.85 on the brats mri dataset, and 0.94 dice and 0.89 iou on the drive retinal vessel dataset-representing a 4–8% improvement over u-net and a 6–10% improvement over standalone scnn or snn-u-net models. in terms of efficiency, the system achieved 10 ms latency and 0.55 j/frame energy consumption, marking a 55% reduction in latency and a 70% reduction in power usage compared to u-net. these results demonstrate the capability of the hybrid architecture to support real-time medical image processing on neuromorphic hardware.

Ablation studies confirmed the critical role of each architectural component: removing SCNN reduced segmentation accuracy from 0.92 to 0.87, while removing SNN-U-Net decreased performance to 0.85, validating that the integrated spatiotemporal design is essential for achieving maximum accuracy. Similarly, biosignal analysis experiments showed the hybrid model achieving 98% accuracy, 97% sensitivity, and 96% specificity in ECG arrhythmia detection, demonstrating strong generalization beyond imaging tasks.

The framework also provides substantial privacy advantages, reducing the membership inference attack success rate from 26% (U-Net) to 6% in the hybrid model. The inherent spike-coded data representation and on-device inference capability significantly reduce information leakage, enabling compliance with strict medical data protection standards.

Overall, the Hybrid SCNN + SNN-U-Net neuromorphic framework offers a highly robust, scalable, and secure solution for healthcare AI. Its demonstrated high accuracy, real-time responsiveness, very low energy consumption, and strong privacy preservation make it well-suited for deployment in clinical environments such as emergency diagnostics, surgical imaging, wearable monitoring, and telemedicine systems. The results establish neuromorphic computing as a viable and transformative technology for future healthcare applications.

13. FUTURE WORK

Although the Hybrid SCNN + SNN-U-Net neuromorphic framework demonstrates strong performance across segmentation accuracy, latency, energy consumption, and privacy preservation, several avenues remain for future exploration. First, extending the model to handle 3D medical imaging modalities such as CT and volumetric MRI would greatly enhance its applicability in clinical diagnostics. While the current architecture performs well on 2D slices, incorporating spatiotemporal 3D spiking convolution layers may improve continuity across slices and support full volumetric segmentation.

Second, future studies may focus on implementing the proposed system on physical neuromorphic hardware platforms such as Intel Loihi 2 or IBM TrueNorth. Although the current evaluation uses simulated neuromorphic environments, real hardware deployment would provide more accurate insights into energy efficiency, spike activity patterns, and latency performance. Hardware-in-the-loop benchmarking will also validate the feasibility of embedding the model in portable or wearable medical devices.

Third, the incorporation of adaptive learning mechanisms, such as online spike-driven learning or local STDP (Spike-Timing-Dependent Plasticity), could enable continuous updating of the model based on patient-specific data. This would allow the system to support personalized diagnostics, detecting long-term changes in physiological patterns while maintaining low computational cost.

Fourth, exploring privacy-enhancing neuromorphic cryptography-including homomorphically encrypted spike trains and federated neuromorphic learning-can further strengthen patient data protection. Integrating neuromorphic encryption with spike-based processing may allow secure multi-hospital collaboration without exposing raw medical data. Additionally, evaluating the hybrid architecture on larger, multi-center medical datasets would help assess its robustness across diverse populations and imaging conditions. Domain adaptation methods for neuromorphic networks may also be developed to address challenges such as scanner variability,

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noise differences, and dataset shift in real-world healthcare settings.

Finally, expanding the framework to include multi-modal healthcare integration-combining imaging, biosignals, electronic health records, and wearable sensor streams-could create a unified neuromorphic diagnostic system capable of holistic patient assessment. This would allow the architecture to support intelligent clinical decision-making across a wide range of applications, including early disease detection, risk stratification, and continuous remote monitoring. Overall, these future directions aim to enhance the scalability, adaptability, and clinical readiness of neuromorphic AI systems, ultimately accelerating their translation into real-world healthcare environments.

REFERENCES

[1]. Fang, W., Yu, Z., & Chen, Y. (2023). *Spiking U-Net for Energy-Efficient Medical Image Segmentation*. Frontiers in Neuroscience, 17, 112–129.

[2]. Li, X., Zhang, Y., & Liu, H. (2022). *Privacy-Preserving Deep Learning for Healthcare Using Federated and Neuromorphic Computing*. IEEE Transactions on Artificial Intelligence, 3(4), 567–579.

[3]. Liu, Y., Chen, X., & Hu, Y. (2021). *Real-Time Patient Monitoring System Based on Neuromorphic Computing*. Journal of Medical Systems, 45(2), 23.

[4]. Maass, W. (1997). *Networks of Spiking Neurons: The Third Generation of Neural Network Models*. Neural Networks, 10(9), 1659–1671.

[5]. Mena, J. A., & Ahmadi, M. (2020). *Neuromorphic Computing in Healthcare: A Comprehensive Review*. IEEE Access, 8, 21065–21083.

[6]. Ronneberger, O., Fischer, P., & Brox, T. (2015). *U-Net: Convolutional Networks for Biomedical Image Segmentation*. In MICCAI (pp. 234–241). Springer.

[7]. Roy, K., Jaiswal, A., & Panda, P. (2019). *Towards Spike-Based Machine Intelligence with Neuromorphic Computing*. Nature, 575, 607–617.

[8]. Rueckauer, B., Lungu, I., Hu, Y., Pfeiffer, M., & Liu, S.-C. (2017). *Conversion of Continuous-Valued Deep Networks to Efficient Event-Driven Networks for Image Classification*. Frontiers in Neuroscience, 11, 682.

[9]. Suri, J. S., & Majumdar, A. (Eds.). (2022). *Neuromorphic Computing in Healthcare: Principles, Methods, and Applications*. Springer.

[10]. Wang, Z., Ma, Y., Zhang, Y., & Wu, W. (2019). *Neuromorphic Computing for Medical Image Analysis: A Review*. Frontiers in Neuroscience, 13, 891.

[11]. Wu, J., Zhang, Q., & Li, S. (2020). *Privacy-Preserving Neuromorphic Computing for Healthcare Applications*. IEEE Transactions on Emerging Topics in Computing, 8(2), 292–304.

[12]. Wu, Y., Deng, L., & Li, G. (2021). *Direct Training for Spiking Convolutional Neural Networks via Surrogate Gradients*. IEEE Transactions on Neural Networks and Learning Systems, 32(9), 4210–4222.

[13]. Zhou, X., Shen, Y., & Li, J. (2021). *On-Device Intelligence for Privacy-Preserving Healthcare Monitoring*. IEEE Internet of Things Journal, 8(14), 11348–11360

[15]. Deng, L., Wu, Y., Hu, Y., Liang, L., & Li, G. (2020). *Comprehensive SNN conversion and training pipelines for energy-efficient neuromorphic computing*. IEEE Transactions on Neural Networks and Learning Systems, 33(7), 1–14.

[16]. Fang, W., Chen, Y., Ding, J., Chen, Z., Yu, Z., & Tian, Y. (2023). *Spiking neural networks for energy-efficient vision processing: A survey*. IEEE Transactions on Pattern Analysis and Machine Intelligence, 45(9), 10823–10845.

[17]. Isensee, F., Petersen, J., Klein, A., Zimmerer, D., & Maier-Hein, K. (2021). *nnU-Net: A self-configuring method for deep learning-based biomedical image segmentation*. Nature Methods, 18(2), 203–211.

[18]. Kim, J., Lee, C., & Park, J. (2024). *On-device privacy-preserving neuromorphic intelligence for medical data analytics*. IEEE Internet of Things Journal, 11(3), 2450–2462.

[19]. Li, Q., He, B., & Song, D. (2024). *Spiking encoder–decoder architectures for biomedical image segmentation*. Medical Image Analysis, 89, 102889.

[20]. Panda, P., Aketi, S. A., & Roy, K. (2020). *Toward scalable, efficient, and accurate deep spiking neural networks with surrogate gradient learning*. IEEE Transactions on Neural Networks and Learning Systems, 31(11), 1–15.

[21]. Schuman, C. D., Potok, T. E., Patton, R. M., Birdwell, J. D., Dean, M. E., Rose, G. S., & Plank, J. S. (2022). *A survey of neuromorphic computing and neural networks in hardware*.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, 41(12), 4589–4607.

[22]. Shen, Y., Zhao, Y., & Li, J. (2023). *Low-latency neuromorphic vision systems for real-time medical diagnostics*. IEEE Transactions on Biomedical Circuits and Systems, 17(4), 702–714.

[23]. Singh, R., Verma, N., & Roy, K. (2022). *Neuromorphic computing for edge-based healthcare systems*. ACM Journal on Emerging Technologies in Computing Systems, 18(4), 1–28.

[24]. Tavanaei, A., Ghodrati, M., Kheradpisheh, S. R., Masquelier, T., & Maida, A. (2020). *Deep learning in spiking neural networks*. Neural Networks, 111, 47–63.

[25]. Xie, X., Qu, H., & Wang, Y. (2023). *Event-driven spiking neural networks for real-time biomedical signal processing*. IEEE Transactions on Biomedical Engineering, 70(10), 2914–2925.

[26]. Zhou, L., Chen, Y., & Xu, J. (2024). *Federated neuromorphic learning for privacy-aware healthcare analytics*. IEEE Transactions on Artificial Intelligence, 5(2), 356–369.