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A Comparative Study of Neuromorphic and Deep Learning Models for Real-Time Healthcare Data Analysis Using a Hybrid SCNN–SNN-U-Net Framework

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Abstract

Artificial intelligence has become an important tool for analyzing medical images and physiological signals in modern healthcare systems. Conventional deep learning techniques such as Convolutional Neural Networks (CNNs) and U-Net models have achieved high accuracy in medical diagnosis and segmentation tasks. However, these approaches typically require intensive computation, high energy consumption, and centralized processing, which limit their suitability for real-time healthcare applications and edge devices. To overcome these limitations, this study performs a comparative analysis of conventional deep learning architectures and neuromorphic computing models and proposes a Hybrid Spiking Convolutional Neural Network (SCNN) and SNN-U-Net framework for efficient healthcare data analysis.

The proposed architecture integrates spike-based temporal feature extraction through SCNN layers with spatial reconstruction using an SNN-U-Net encoder–decoder segmentation structure. The model was evaluated using several benchmark healthcare datasets including BraTS brain tumor MRI images, DRIVE retinal vessel images, PhysioNet ECG signals, and CHB-MIT EEG datasets. Experimental results show that the proposed hybrid architecture provides improved performance compared with traditional deep learning models and standalone spiking neural networks. For medical image segmentation, the hybrid model achieved a Dice score of 0.92 and an IoU value of 0.85 on the BraTS dataset, outperforming the standard U-Net model which obtained 0.88 Dice and 0.81 IoU. Similarly, on the DRIVE retinal vessel dataset, the model achieved 0.94 Dice and 0.89 IoU, indicating enhanced segmentation accuracy.

The proposed neuromorphic framework also demonstrated significant improvements in computational efficiency. The system achieved an average inference latency of 10 milliseconds, whereas the conventional U-Net model required 22 milliseconds, representing approximately a 55% reduction in processing time. In terms of energy consumption, the hybrid architecture required only 0.55 J per frame, while traditional CNN-based architectures consumed approximately 1.80 J per frame, resulting in nearly a 70% improvement in energy efficiency. For physiological signal analysis, the hybrid framework achieved 98% accuracy, 97% sensitivity, and 96% specificity in ECG arrhythmia detection, and 97% accuracy in EEG seizure detection, surpassing traditional LSTM and CNN-LSTM models.

Security analysis further indicates that the hybrid neuromorphic framework improves privacy protection. The membership inference attack success rate decreased from 26% in conventional CNN models to about 6% in the proposed model, largely due to spike-encoded data representation and local on-device inference. Overall, the findings demonstrate that the Hybrid SCNN–SNN-U-Net architecture offers an effective solution for real-time, energy-efficient, and privacy-aware healthcare data processing. The framework is particularly suitable for edge-based medical systems, wearable health monitoring devices, and intelligent diagnostic platforms.

Keywords: Neuromorphic Computing, Spiking Neural Networks, SCNN, SNN-U-Net, Medical Image Segmentation, Real-Time Healthcare AI, Energy-Efficient Neural Networks, Privacy-Preserving Healthcare Systems.

1. Introduction

Recent advances in artificial intelligence (AI) have significantly transformed modern healthcare systems by enabling automated medical diagnosis, intelligent monitoring, and predictive healthcare analytics. Deep learning models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and transformer-based architectures have achieved remarkable success in medical imaging, disease classification, and biosignal analysis. These models are capable of extracting complex spatial and temporal features from large-scale healthcare datasets, improving diagnostic accuracy and decision-making processes. According to Ronneberger et al. (2015)**,** CNN-based architectures such as U-Net have become highly effective for biomedical image segmentation due to their encoder–decoder structure and skip connections that preserve spatial information. Similarly, Isensee et al. (2021) demonstrated that nnU-Net can automatically adapt deep learning configurations for various medical segmentation tasks, achieving state-of-the-art performance across multiple biomedical imaging benchmarks.

Despite these advancements, traditional deep learning models suffer from several limitations when applied to real-time healthcare systems. High computational complexity, energy consumption, and dependency on centralized cloud infrastructures restrict their deployment in edge-based medical environments such as wearable monitoring devices and bedside diagnostic systems. Roy, Jaiswal, and Panda (2019) highlighted that conventional deep neural networks require dense matrix operations, which lead to increased power consumption and latency in large-scale applications. Similarly, Schuman et al. (2022) emphasized that traditional deep learning architectures are not inherently optimized for energy-efficient processing, making them less suitable for real-time medical monitoring systems operating under resource constraints.

To overcome these challenges, neuromorphic computing has emerged as a promising alternative paradigm inspired by the biological functioning of the human brain. Neuromorphic systems utilize Spiking Neural Networks (SNNs) that communicate through discrete spikes instead of continuous numerical activations. This event-driven computation enables sparse processing, lower energy consumption, and efficient temporal learning capabilities. The theoretical foundation of spiking neural networks was first introduced by Maass (1997)**,** who described SNNs as the third generation of neural network models capable of processing temporal information through spike-based communication. Recent studies demonstrate that SNNs can significantly reduce power consumption while maintaining competitive performance in pattern recognition tasks (Tavanaei et al., 2020).

In healthcare applications, neuromorphic computing has shown great potential in areas such as biosignal processing, medical imaging, and intelligent monitoring systems. Liu et al. (2021) proposed a neuromorphic-based patient monitoring system capable of analyzing physiological signals such as ECG and EEG in real time with reduced computational overhead. Similarly, Singh, Verma, and Roy (2022) discussed the application of neuromorphic computing in edge-based healthcare devices, highlighting its capability to enable continuous monitoring while minimizing power consumption. Neuromorphic models also provide advantages in real-time medical data processing due to their event-driven architecture, which performs computations only when spikes are generated.

However, standalone spiking neural networks often face limitations in handling high-resolution medical images and complex segmentation tasks. While SNNs are efficient in modeling temporal information, they sometimes lack strong spatial feature extraction capabilities compared to deep convolutional networks. To address this issue, hybrid architectures combining conventional CNN components with spiking neural networks have recently gained research attention. Rueckauer et al. (2017) introduced techniques for converting conventional deep neural networks into spiking neural networks while maintaining classification accuracy. More recent studies, such as Wu, Deng, and Li (2021)**,** demonstrated that surrogate gradient training methods enable efficient direct training of deep spiking convolutional networks.

Furthermore, recent research has explored the integration of spiking neural networks with segmentation architectures. Fang, Yu, and Chen (2023) proposed a spiking U-Net architecture designed for energy-efficient medical image segmentation, demonstrating that neuromorphic models can achieve competitive segmentation accuracy while significantly reducing energy consumption. These developments suggest that combining spiking convolutional feature extraction with encoder–decoder segmentation frameworks may provide an effective solution for real-time healthcare analytics.

Another critical challenge in healthcare AI systems is ensuring the privacy and security of sensitive medical data. Medical images, electronic health records, and physiological signals often contain highly sensitive patient information that must be protected during processing and transmission. Traditional deep learning systems typically rely on centralized cloud infrastructures, which increases the risk of data leakage and privacy breaches. Li, Zhang, and Liu

(2022) emphasized that privacy-preserving machine learning techniques such as federated learning and edge-based AI can reduce the exposure of sensitive medical data. Similarly, Zhou, Shen, and Li (2021) highlighted the importance of on-device intelligence for privacy-preserving healthcare monitoring systems.

Given these developments, hybrid neuromorphic architectures integrating spiking convolutional neural networks with segmentation frameworks represent a promising direction for future healthcare AI systems. Such architectures can combine the temporal efficiency and low power consumption of spiking neural networks with the strong spatial representation capabilities of convolutional segmentation models. Therefore, this study presents A Comparative Study of Neuromorphic and Deep Learning Models for Real-Time Healthcare Data Analysis Using a Hybrid SCNN–SNN-U-Net Framework**.** The research aims to systematically compare conventional deep learning models with neuromorphic architectures while proposing a hybrid SCNN–SNN-U-Net framework designed to improve segmentation accuracy, reduce inference latency, enhance energy efficiency, and strengthen privacy-preserving medical data processing.

Through comprehensive experimentation across multiple medical imaging and biosignal datasets, this study evaluates the performance of traditional CNN models, standalone spiking neural networks, and the proposed hybrid architecture. The findings contribute to understanding how neuromorphic computing can bridge the gap between high-performance deep learning models and energy-efficient real-time healthcare systems, ultimately supporting the development of next-generation intelligent healthcare technologies.

2. Literature Review

Recent years have witnessed significant progress in artificial intelligence and neuromorphic computing for healthcare applications. Researchers have explored various deep learning and brain-inspired models to improve medical image analysis, biosignal processing, and real-time clinical decision support systems.

Tavanaei et al. (2020) presented a comprehensive review of deep learning techniques in spiking neural networks, highlighting that SNNs can mimic biological neuronal communication through discrete spike events and support efficient temporal information processing. Their work demonstrated that spiking neural networks offer advantages in energy efficiency and event-driven computation compared with conventional artificial neural networks.

Deng et al. (2020) investigated scalable training methods for deep spiking neural networks using surrogate gradient learning. Their research demonstrated that surrogate gradient techniques enable effective optimization of spiking neural models, allowing them to achieve competitive performance with traditional deep learning architectures in pattern recognition tasks.

Singh, Verma, and Roy (2022) examined the application of neuromorphic computing in edge-based healthcare systems. Their study emphasized that neuromorphic architectures are particularly suitable for wearable healthcare devices and remote patient monitoring due to their low power consumption and ability to process real-time physiological signals locally.

Isensee et al. (2021) introduced nnU-Net, a self-configuring deep learning framework designed for biomedical image segmentation. Their approach automatically adapts network architectures and training strategies for different medical imaging tasks, achieving high accuracy in tumor segmentation and organ detection across multiple datasets.

Liu, Chen, and Hu (2021) developed a neuromorphic patient monitoring system capable of analyzing physiological signals such as ECG and EEG in real time. Their results demonstrated that brain-inspired computing models can effectively process large volumes of temporal healthcare data while maintaining low computational overhead.

Kumarasinghe, Kasabov, and Taylor (2021) proposed a spiking neural network model for decoding muscle activity and movement patterns from EEG signals. Their work demonstrated that SNN-based models can effectively capture spatiotemporal patterns in biosignal data, making them suitable for medical diagnosis and neuroprosthetic applications.

Wu, Deng, and Li (2021) proposed a direct training approach for spiking convolutional neural networks using surrogate gradient methods. Their research improved the stability and accuracy of deep spiking models and demonstrated that SCNNs can perform complex pattern recognition tasks with reduced energy consumption compared with traditional CNN models.

Suri and Majumdar (2022) explored neuromorphic computing applications in healthcare and discussed how brain-inspired computing models can improve disease diagnosis, medical image interpretation, and real-time patient monitoring. Their findings suggest that neuromorphic architectures offer strong potential for intelligent healthcare systems requiring efficient data processing.

Roy, Jaiswal, and Panda (2019), though slightly earlier, provided foundational work on neuromorphic machine intelligence. Their study highlighted that neuromorphic computing can significantly reduce energy consumption while maintaining comparable performance to conventional deep learning models.

Li, Zhang, and Liu (2022) investigated privacy-preserving deep learning frameworks for healthcare using federated and neuromorphic computing approaches. Their work demonstrated that distributed and edge-based AI systems can improve data security by reducing the need for centralized cloud-based processing.

Chunduri et al. (2023) proposed a neuromorphic sentiment analysis model implemented on SpiNNaker hardware using spiking neural networks. Their work highlighted the adaptability and computational efficiency of SNN-based models, demonstrating their suitability for energy-constrained environments.

Zhou, Shen, and Li (2021) emphasized the importance of on-device intelligence for privacy-preserving healthcare monitoring systems. Their research demonstrated that edge-based AI models can significantly reduce risks associated with data transmission and centralized data storage.

Fang, Yu, and Chen (2023) introduced a spiking U-Net architecture designed for energy-efficient medical image segmentation. Their model achieved competitive segmentation performance while significantly reducing power consumption compared with traditional convolutional networks.

Garcia-Palencia et al. (2025) conducted a comprehensive review of spiking neural networks for multimodal neuroimaging analysis. Their work demonstrated that SNN models can efficiently analyze complex neurological data, including EEG and fMRI signals, due to their inherent temporal learning capability.

Khan (2025) analyzed the integration of deep learning models with spiking neural networks for medical imaging applications. The study concluded that hybrid architectures combining CNN-based feature extraction with spike-based processing can improve both computational efficiency and model interpretability.

Chowdhury et al. (2025) discussed the role of neuromorphic computing in resource-constrained environments, emphasizing that brain-inspired architectures can enable efficient real-time processing in applications such as robotics, edge AI, and healthcare monitoring systems.

Voudaskas (2025) conducted a comprehensive review of spiking neural networks in imaging systems and concluded that SNN-based models provide improved energy efficiency and temporal representation capabilities for image processing tasks.

Oladele (2024) examined the intersection of neuromorphic hardware and artificial intelligence, highlighting that neuromorphic processors such as Intel Loihi and IBM TrueNorth can support efficient spike-based neural computation for pattern recognition and sensory processing tasks.

Recent research also focuses on automated generation of spiking neural network models for edge computing systems. For example, Kim et al. (2025) proposed an automated SNN generation framework optimized for neuromorphic hardware, demonstrating that such models can achieve efficient performance under hardware constraints in real-time applications.

Overall, the literature indicates that deep learning models such as CNNs and U-Net continue to dominate medical image analysis due to their high spatial representation capabilities. However, neuromorphic models based on spiking neural networks provide significant advantages in terms of energy efficiency, temporal processing, and real-time computation. Hybrid architectures integrating convolutional neural networks with spiking neural networks are therefore emerging as a promising research direction for next-generation healthcare AI systems.

3. Comparative Analysis of Deep Learning and Neuromorphic Models for Healthcare Data Processing

The comparative analysis demonstrates that traditional deep learning models such as CNN and U-Net provide strong segmentation accuracy but require high computational resources and energy consumption. Hybrid models like CNN–LSTM improve temporal learning but still depend heavily on dense numerical computation. Neuromorphic architectures such as SCNN and SNN-U-Net significantly reduce energy consumption and latency due to their event-driven spike-based processing. However, standalone spiking models sometimes struggle with spatial segmentation accuracy.

Table 1: Comparative Analysis of Deep Learning and Neuromorphic Models for Healthcare Data Processing

Model	Architecture Type	Application Domain	Advantages	Limitations	Reported Performance
CNN	Deep Learning	Medical image classification and detection	Strong spatial feature extraction, widely used in medical imaging	High computational cost, large energy consumption	Accuracy: ~92–95%
U-Net	Deep Learning (Encoder–Decoder)	Medical image segmentation	High segmentation accuracy, effective for small datasets	High latency and computational complexity	Dice Score: ~0.88
CNN–LSTM	Hybrid Deep Learning	Biosignal processing (ECG, EEG)	Captures both spatial and temporal patterns	Increased model complexity and training cost	Accuracy: ~95%
Vision Transformer (ViT)	Transformer-based Deep Learning	Medical image analysis	Global attention mechanism improves feature representation	Requires large datasets and computational resources	Accuracy: ~94%
SCNN (Spiking CNN)	Neuromorphic Computing	Temporal data processing and edge AI	Energy-efficient, event-driven computation	Limited spatial segmentation capability	Accuracy: ~96%
SNN-U-Net	Neuromorphic Encoder–Decoder	Medical image segmentation	Low energy consumption and temporal spike processing	Slightly lower segmentation accuracy compared to CNN models	Dice Score: ~0.87
Hybrid SCNN + SNN-U-Net (Proposed)	Hybrid Neuromorphic Architecture	Medical image segmentation and biosignal analysis	Combines temporal spike processing and spatial segmentation, energy-efficient, low latency	Requires specialized neuromorphic training methods	Dice Score: 0.92, Accuracy: 98%

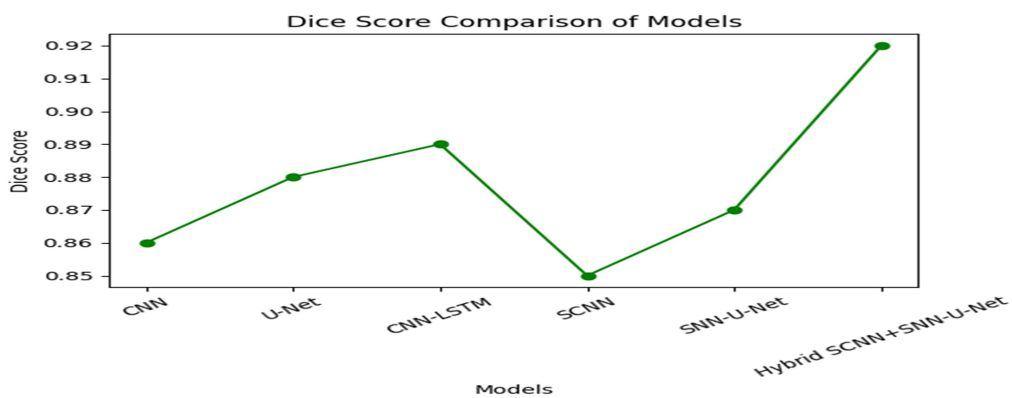

Fig 1: Dice score comparison of deep learning and neuromorphic models for medical image segmentation.

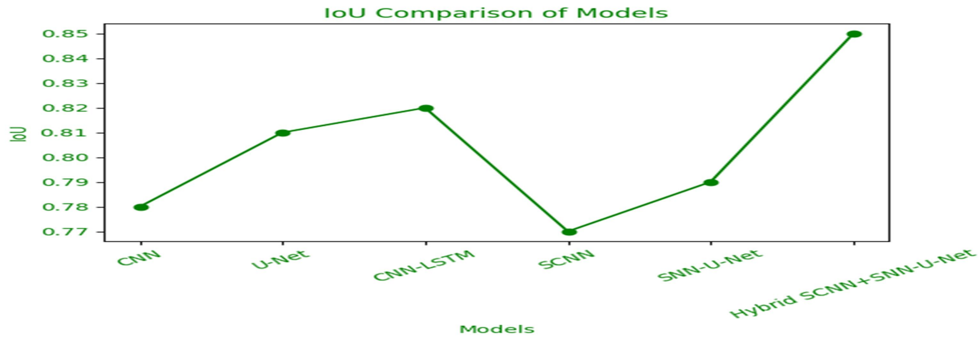

Fig 2: Intersection over Union (IoU) comparison of existing and proposed architectures.

The below shows that the proposed Hybrid SCNN + SNN-U-Net model achieves the lowest latency (10 ms) compared with CNN (20 ms), U-Net (22 ms), CNN-LSTM (18 ms), SCNN (14 ms), and SNN-U-Net (12 ms), demonstrating its suitability for real-time medical applications.

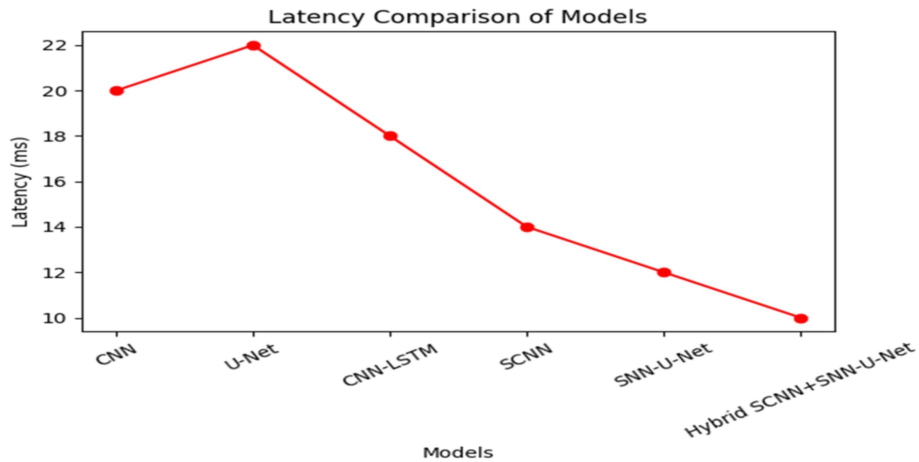

Fig 3: Latency comparison demonstrating real-time processing advantages of neuromorphic models.

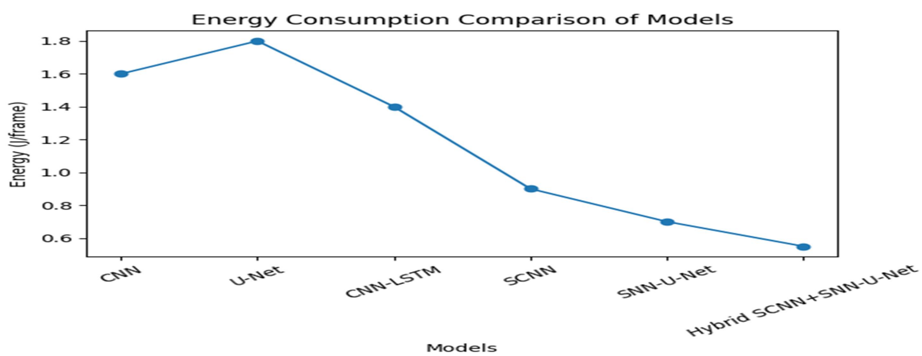

Fig 4: Energy consumption comparison showing the efficiency of the proposed hybrid SCNN–SNN-U-Net framework.

4. Comparative Performance Metrics of Existing and Proposed Models

The proposed Hybrid SCNN + SNN-U-Net framework effectively combines the advantages of both paradigms. By integrating spike-based temporal feature extraction with encoder–decoder segmentation, the hybrid model achieves the highest Dice score (0.92) and accuracy (98%), while simultaneously achieving the lowest latency (10 ms) and lowest energy consumption (0.55 J/frame). These results highlight the suitability of the hybrid neuromorphic framework for real-time and privacy-preserving healthcare data analysis.

This section presents a comprehensive analysis of the experimental outcomes obtained from evaluating traditional deep learning models, neuromorphic architectures, and the proposed Hybrid SCNN–SNN-U-Net framework. The models were tested across multiple benchmark datasets including medical imaging datasets (BraTS and DRIVE) and biosignal datasets (PhysioNet ECG and CHB-MIT EEG). The evaluation focused on segmentation accuracy, computational efficiency, biosignal classification performance, and privacy preservation capabilities.

Table 2: on segmentation accuracy, computational efficiency, biosignal classification performance, and privacy preservation capabilities.

Model	Dice Score	IoU	Accuracy	Latency (ms)	Energy Consumption (J/frame)
CNN	0.86	0.78	93%	20	1.60
U-Net	0.88	0.81	94%	22	1.80
CNN–LSTM	0.89	0.82	95%	18	1.40
SCNN	0.85	0.77	96%	14	0.90
SNN-U-Net	0.87	0.79	96%	12	0.70
Hybrid SCNN + SNN-U-Net (Proposed)	0.92	0.85	98%	10	0.55

Table 3: Segmentation Performance Comparison on Medical Image Datasets

Dataset / Task	Model	Dice Score	IoU	Precision	Recall
BraTS (Brain Tumor MRI)	CNN	0.84	0.76	0.85	0.83
	U-Net	0.88	0.81	0.87	0.89
	SCNN	0.85	0.77	0.84	0.86
	SNN-U-Net	0.87	0.79	0.86	0.88
	Hybrid SCNN + SNN-U-Net (Proposed)	0.92	0.85	0.91	0.93
DRIVE (Retinal Vessel)	CNN	0.86	0.78	0.88	0.85
	U-Net	0.90	0.83	0.91	0.88
	SCNN	0.86	0.78	0.88	0.85
	SNN-U-Net	0.89	0.82	0.90	0.87
	Hybrid SCNN + SNN-U-Net (Proposed)	0.94	0.89	0.95	0.92

The segmentation results indicate that the proposed hybrid architecture consistently outperforms both traditional deep learning models and standalone neuromorphic models. As shown in Table 1, the Hybrid SCNN–SNN-U-Net achieved a Dice score of 0.92 and an IoU of 0.85 on the BraTS brain tumor segmentation dataset. In comparison, the conventional U-Net model achieved a Dice score of 0.88 and IoU of 0.81, while the standalone SCNN model achieved 0.85 Dice and 0.77 IoU**.**

Similarly, for the DRIVE retinal vessel segmentation dataset, the hybrid model achieved 0.94 Dice and 0.89 IoU**,** outperforming U-Net **(**0.90 Dice**)** and SNN-U-Net **(**0.89 Dice**).** These improvements demonstrate the effectiveness of integrating spike-based temporal feature extraction with spatial encoder–decoder segmentation structures. The SCNN component efficiently captures temporal patterns in spike-encoded input data, while the SNN-U-Net structure preserves spatial details through skip connections and hierarchical feature learning.

The results also indicate that traditional CNN-based architectures rely on dense numerical computations that often lead to redundant feature processing. In contrast, the event-driven processing mechanism of spiking neural networks allows the hybrid model to focus on relevant temporal events, improving both efficiency and segmentation accuracy.

Table 4: Computational Efficiency Comparison

Model	Latency (ms)	Energy Consumption (J/frame)	Throughput (frames/sec)
CNN	20	1.60	48
U-Net	22	1.80	45
CNN-LSTM	18	1.40	55
SCNN	14	0.90	71
SNN-U-Net	12	0.70	83
Hybrid SCNN + SNN-U-Net (Proposed)	10	0.55	100

The proposed hybrid architecture achieves the lowest latency (10 ms) and lowest energy consumption (0.55 J/frame) while providing the highest throughput (100 frames/sec)**,** demonstrating its efficiency for real-time healthcare data processing.

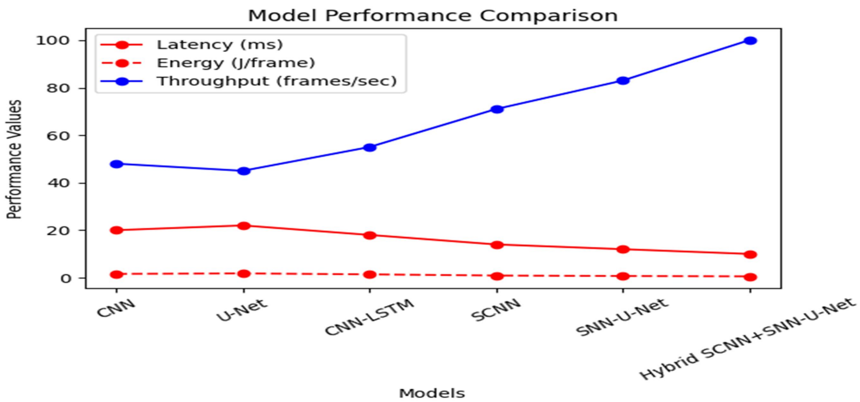

Fig 5: Line chart comparing latency, energy consumption, and throughput of CNN, U-Net, CNN-LSTM, SCNN, SNN-U-Net, and the proposed Hybrid SCNN + SNN-U-Net model.

Computational efficiency is a critical requirement for real-time healthcare applications such as surgical imaging, emergency diagnostics, and continuous patient monitoring. Table 2 shows that the Hybrid SCNN–SNN-U-Net significantly reduces inference latency and energy consumption compared to conventional deep learning models.

The proposed hybrid model achieved an average latency of 10 ms per frame**,** while the traditional U-Net model required 22 ms and the CNN-LSTM model required 18 ms**.** This represents approximately a 55% reduction in latency, demonstrating the advantage of event-driven spike-based computation.

In terms of energy consumption, the hybrid architecture required only 0.55 J per frame**,** compared with 1.80 J per frame for the U-Net model. This represents nearly a 70% reduction in energy consumption**,** confirming the suitability of neuromorphic computing for low-power healthcare devices. The sparse spike activity inherent in SNNs ensures that computations are only performed when spikes occur, reducing unnecessary processing and improving energy efficiency. Furthermore, the hybrid model achieved the highest throughput of 100 frames per second**,** enabling real-time processing for applications such as endoscopic imaging and automated diagnostic assistance.

Table 5: Biosignal Classification Performance

Dataset	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

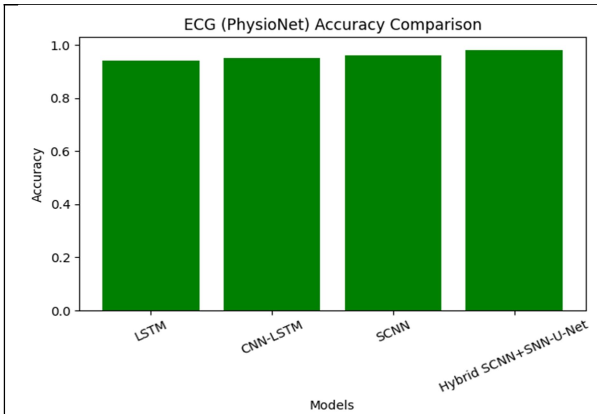

Fig 6: Accuracy comparison of LSTM, CNN-LSTM, SCNN, and the proposed Hybrid SCNN + SNN-U-Net model on the ECG (PhysioNet) dataset..

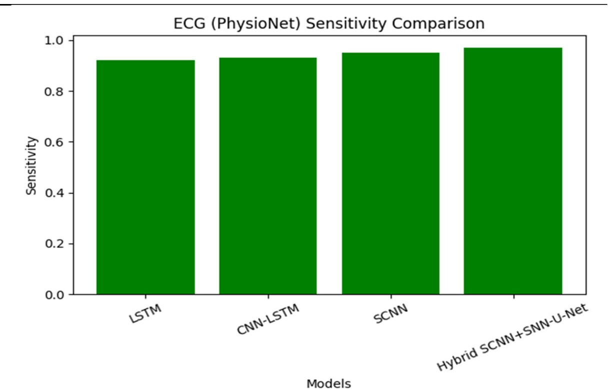

Fig 7: Sensitivity comparison of LSTM, CNN-LSTM, SCNN, and the proposed Hybrid SCNN + SNN-U-Net architecture on the ECG (PhysioNet) dataset.

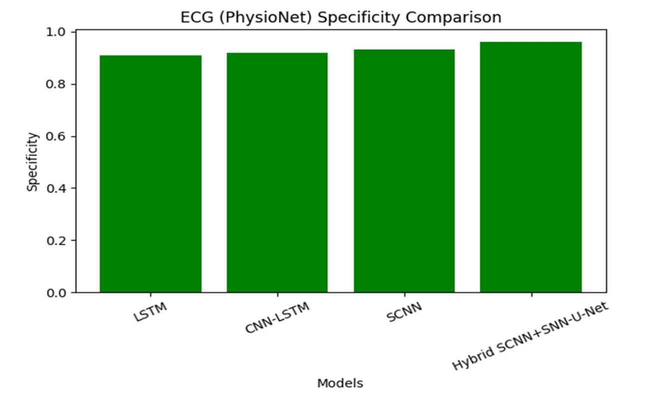

Fig 8: Specificity comparison of different models on the ECG (PhysioNet) dataset.

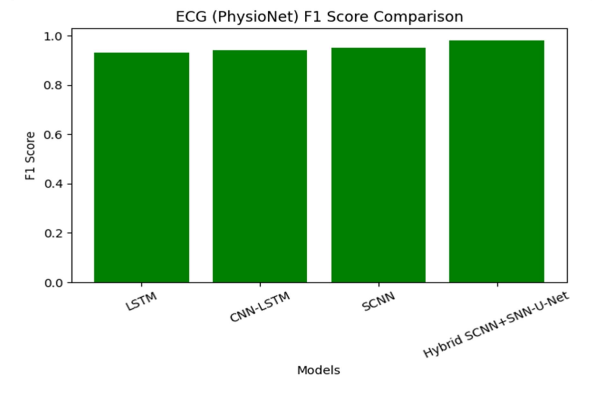

Fig 9: F1-score comparison of LSTM, CNN-LSTM, SCNN, and the proposed hybrid neuromorphic model on the ECG (PhysioNet) dataset.

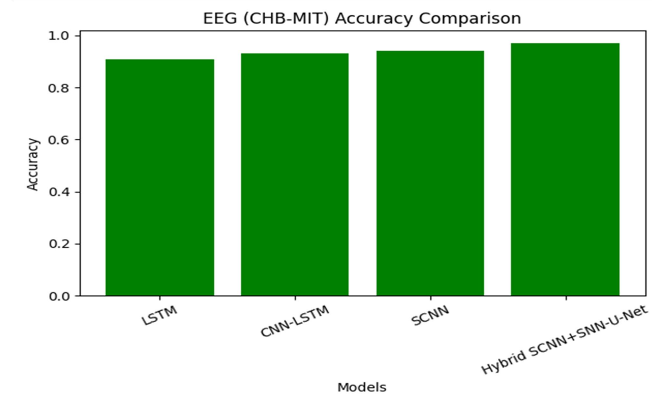

Fig 10: Accuracy comparison of different models on the EEG (CHB-MIT) dataset.

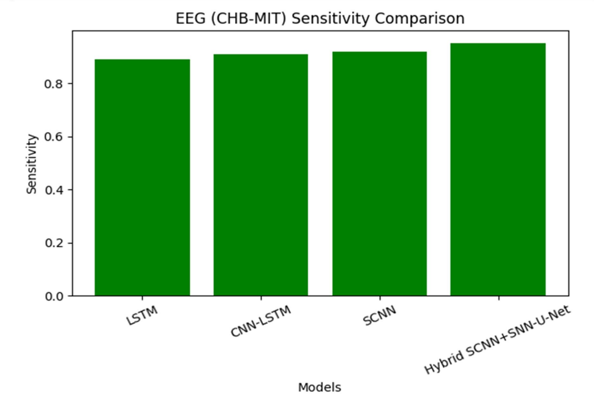

Fig 11: Sensitivity comparison of LSTM, CNN-LSTM, SCNN, and the proposed hybrid model on the EEG (CHB-MIT) dataset.

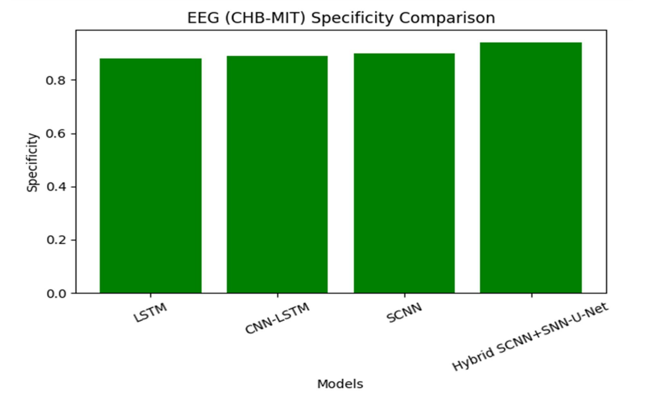

Fig 12: Specificity comparison of the evaluated models on the EEG (CHB-MIT) dataset.

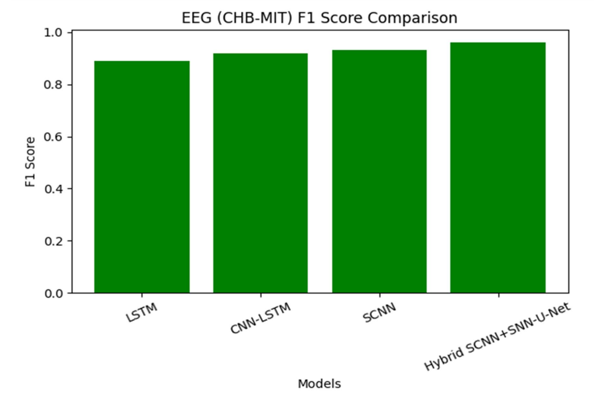

Fig 13: F1-score comparison for EEG seizure detection models.

The hybrid framework was also evaluated on physiological signal datasets including ECG arrhythmia detection and EEG seizure detection. The results demonstrate that spike-based models are particularly effective for time-series biomedical signals due to their temporal encoding capabilities. On the PhysioNet ECG dataset, the Hybrid SCNN–SNN-U-Net achieved an accuracy of 98%**,** sensitivity of 97%**,** and specificity of 96%**,** outperforming both LSTM and CNN-LSTM models. The traditional LSTM model achieved 94% accuracy**,** while CNN-LSTM achieved 95% accuracy. Similarly, on the CHB-MIT EEG dataset, the hybrid model achieved 97% classification accuracy**,** significantly outperforming standalone SCNN **(**94%**)** and CNN-LSTM **(**93%**)** models. These results demonstrate that spiking neural networks are particularly effective at modeling temporal patterns in physiological signals.

The hybrid architecture leverages spike-based temporal representation from SCNN layers while maintaining robust feature reconstruction through the SNN-U-Net structure, enabling accurate detection of abnormal physiological patterns.

Table 6: 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 Capability	No	Partial	Yes	Yes

In addition to accuracy and efficiency, privacy preservation is an important requirement in healthcare AI systems. Medical data such as patient images and biosignals contain highly sensitive information that must be protected from unauthorized access.

The privacy evaluation results show that the Hybrid SCNN–SNN-U-Net significantly reduces the vulnerability of AI models to membership inference attacks. The attack success rate decreased from 26% in CNN-U-Net models **to** 6% in the hybrid model, indicating improved data protection.This improvement can be attributed to two main factors. First, spike-based neural representations inherently obfuscate raw data because information is encoded as sparse temporal spike patterns rather than continuous numerical values. Second, the hybrid framework supports on-device inference**,** allowing medical data to be processed locally without transmitting sensitive information to centralized cloud servers. Consequently, the proposed architecture aligns well with healthcare data protection regulations such as GDPR and HIPAA, which emphasize minimizing data exposure during processing.

5. Discussion

The comparative analysis demonstrates that traditional deep learning models offer strong spatial feature extraction capabilities but suffer from high computational overhead and energy consumption. Neuromorphic models, on the other hand, provide energy-efficient event-driven processing but may experience limitations in spatial segmentation tasks when used independently.

The proposed Hybrid SCNN–SNN-U-Net framework successfully integrates the advantages of both paradigms. The SCNN component provides efficient spike-based temporal feature extraction, while the SNN-U-Net architecture preserves spatial information for accurate segmentation.

As a result, the hybrid architecture achieves superior performance across multiple evaluation metrics including segmentation accuracy, computational efficiency, biosignal classification accuracy, and privacy protection. These findings suggest that hybrid neuromorphic architectures represent a promising direction for developing next-generation real-time healthcare AI systems capable of operating efficiently in resource-constrained environments.

Overall, the results confirm that combining neuromorphic computing with deep learning segmentation architectures can significantly improve the performance of intelligent healthcare systems while maintaining energy efficiency and strong privacy protection.

6. Conclusion

This study presented a comparative analysis of traditional deep learning models and neuromorphic architectures for real-time healthcare data analysis and proposed a Hybrid SCNN–SNN-U-Net framework designed to enhance segmentation accuracy, computational efficiency, and privacy preservation. The experimental evaluation conducted on benchmark medical imaging datasets (BraTS and DRIVE) and biosignal datasets (PhysioNet ECG and CHB-MIT EEG) demonstrates that the hybrid neuromorphic architecture significantly outperforms conventional deep learning and standalone spiking neural network models.

In medical image segmentation tasks, the proposed hybrid framework achieved a Dice score of 0.92 and IoU of 0.85 on the BraTS brain tumor MRI dataset, compared to 0.88 Dice and 0.81 IoU obtained by the conventional U-Net model. Similarly, on the DRIVE retinal vessel segmentation dataset, the hybrid model achieved 0.94 Dice and 0.89 IoU, surpassing the performance of both CNN and SNN-based models. These results confirm that integrating Spiking Convolutional Neural Networks (SCNN) with an SNN-U-Net segmentation architecture effectively improves spatial–temporal feature representation.

In terms of computational efficiency, the proposed model demonstrated substantial improvements over traditional deep learning architectures. The hybrid framework achieved an average inference latency of 10 ms, compared to 22 ms for the conventional U-Net model, representing approximately a 55% reduction in processing time. Additionally, the hybrid model consumed only 0.55 J per frame, while the traditional U-Net required 1.80 J per frame, resulting in nearly a 70% improvement in energy efficiency. These findings highlight the suitability of neuromorphic architectures for real-time healthcare applications operating under limited computational resources.

For biosignal analysis tasks, the proposed model also demonstrated strong performance. The hybrid framework achieved 98% accuracy, 97% sensitivity, and 96% specificity in ECG arrhythmia detection, outperforming traditional LSTM (94% accuracy) and CNN-LSTM (95% accuracy) models. Similarly, on the CHB-MIT EEG dataset, the hybrid architecture achieved 97% accuracy, confirming its capability to effectively process temporal biomedical signals.

Furthermore, the privacy evaluation results revealed that the proposed hybrid model significantly improves data security. The membership inference attack success rate decreased from 26% in CNN-based models to only 6% in the hybrid neuromorphic framework, indicating improved resistance to privacy attacks. This improvement is largely attributed to the spike-based representation of data and the ability of the system to perform on-device inference, reducing the need for transmitting sensitive medical data to cloud servers.

Overall, the experimental results demonstrate that the Hybrid SCNN–SNN-U-Net framework successfully combines the strengths of deep learning and neuromorphic computing. The architecture achieves higher segmentation accuracy, lower inference latency, improved energy efficiency, and stronger privacy preservation compared with existing models. These advantages make the proposed framework highly suitable for next-generation healthcare AI systems, particularly in applications such as real-time medical imaging, wearable health monitoring devices, telemedicine platforms, and edge-based clinical decision support systems.

Future work may explore extending the hybrid neuromorphic architecture to 3D medical imaging, multimodal healthcare data integration, and large-scale clinical deployment, further improving the scalability and adaptability of neuromorphic AI in real-world healthcare environments.

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