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Neuromorphic Computing Model Based on Spiking Neural Network for an Efficient and Resilient Tsunami Early Warning System in Indonesia's Small Islands

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Abstract

This study aims to develop a fault-tolerant neuromorphic computing system for tsunami early detection in Indonesia's small islands, which face significant limitations in energy and network infrastructure. The research was conducted over a three-month period (January–March 2025) using a simulated experimental approach with ocean wave data obtained from BMKG and NOAA. The system model was designed using a Spiking Neural Network (SNN) that mimics biological neuron activity to adaptively recognize ocean wave anomaly patterns. Simulation results show a detection accuracy rate of 94%, maintaining stable performance above 85% even under 25% signal interference. Furthermore, the system's power consumption was recorded at only 0.42 watts—approximately 40–60% more efficient than conventional CNN-based models. The implications of this study include scientific contributions to the development of adaptive and energy-efficient artificial intelligence, as well as practical benefits for agencies such as BMKG and BNPB in designing autonomous and resilient tsunami early warning systems for remote and underdeveloped regions. In the future, this system has the potential to serve as a prototype for edge computing–based disaster mitigation solutions powered by artificial intelligence, particularly relevant for archipelagic nations.

Keywords:

Neuromorphic Computing; Spiking Neural Network (SNN); Fault Tolerance; Edge Computing; Tsunami Early Detection.

INTRODUCTION

Indonesia is the world's largest archipelagic nation, consisting of more than 17,000 islands, most of which lie within the Pacific Ring of Fire. This geographical condition makes the country highly vulnerable to natural disasters, particularly tsunamis. Major events such as the 2004 Aceh tsunami, the 2018 Palu tsunami, and the 2018 Pandeglang tsunami have underscored the critical need for a robust, fast, and reliable early warning system to minimize loss of life and material damage. Although Indonesia has established the Indonesia Tsunami Early Warning System (InaTEWS), its implementation still faces significant challenges, especially in small islands and remote areas lacking adequate infrastructure—such as underwater sensor networks, real-time data communication systems, and stable electricity supply. Consequently, ocean sensor signals are often disrupted or lost during extreme weather, storms, or power failures.

Conventional tsunami detection systems based on digital computing also struggle to handle data noise and signal loss effectively. When sensor data is incomplete or partially corrupted, the system's ability to detect abnormal wave patterns declines substantially. Therefore, a new approach is required—one that can operate autonomously, maintain performance under data interference, and consume minimal energy. Neuromorphic computing emerges as a promising solution, as it mimics the human brain's spike-based neural processing to recognize patterns efficiently and adaptively. Its inherent parallel processing capability and high fault tolerance enable real-time anomaly detection even with imperfect data (Jayaun et al., 2024).

Moreover, neuromorphic systems are highly energy-efficient, making them ideal for edge computing devices deployed in remote islands powered by limited sources such as solar panels or batteries. This approach could significantly enhance Indonesia's tsunami early warning infrastructure, complementing InaTEWS, and providing stronger protection for vulnerable island communities.

The main research problem addressed in this study concerns the vulnerability of current tsunami detection systems to data disruption, hardware limitations, and unstable network conditions. Conventional deep learning models such as CNNs often experience a sharp drop in accuracy when sensor data is incomplete. To address this, the study designs a fault-tolerant neuromorphic computing model based on Spiking Neural Networks (SNN) capable of recognizing ocean wave anomalies in real time, with low energy consumption suitable for low-power hardware. The research also evaluates the system's effectiveness in environments with limited infrastructure, emphasizing autonomous operation and energy efficiency.

The objectives of this study are to develop an SNN-based model for detecting ocean wave anomalies, evaluate its resilience against data noise through simulations, and analyze its energy efficiency and detection accuracy in comparison with conventional models like CNN and RNN.
This research contributes in two major ways: first, by advancing Indonesia's disaster early warning innovation through neuromorphic edge computing for faster and more autonomous alerts; and second, by producing an initial prototype of a resilient and energy-efficient artificial intelligence system, laying the groundwork for neuromorphic and disaster-resilient AI development in Indonesia, and promoting interdisciplinary integration between technology, geophysics, and disaster management toward AI- and IoT-based mitigation transformation (Salima et al., 2024).

Literatur Review

Neuromorphic Computing and Its Fundamental Principles

Neuromorphic computing represents a transformative paradigm in computer technology that emulates the mechanisms of the human brain to achieve efficiency, adaptability, and low energy consumption in information processing. Unlike the traditional von Neumann architecture, which separates memory and computation, neuromorphic systems integrate both components similar to neurons and synapses in biological neural systems. This event-driven and parallel processing architecture allows the system to recognize patterns and adapt to environmental changes without relying on sequential instructions. Mead (2020) emphasizes that the core principle of this technology is "to mimic neurobiological structures so that systems can learn and make decisions like the human brain." These characteristics make neuromorphic computing highly relevant for intelligent applications operating in extreme environments, including disaster early warning systems.

Architecture of Spiking Neural Networks (SNN)

A key component of neuromorphic computing is the Spiking Neural Network (SNN)—the third generation of artificial neural networks that emulate biological neurons transmitting information through electrical impulses (spikes). Unlike conventional Artificial Neural Networks (ANNs) that use continuous values, SNNs send discrete signals representing the timing and frequency of impulses. Their processing involves three essential stages: temporal encoding of input signals into spike trains, neuronal computation through the Leaky Integrate-and-Fire (LIF) model, and adaptive learning via Spike-Timing-Dependent Plasticity (STDP). This approach enables computation to occur only when spikes are generated, making the system highly energy-efficient and resilient to random noise interference. In the context of tsunami early detection, these characteristics are crucial for identifying real-time ocean pressure anomalies under unstable data conditions.

Neuromorphic Chips: Loihi and TrueNorth

The practical implementation of neuromorphic concepts extends beyond software into specialized hardware. Two major developments are Intel's Loihi and IBM's TrueNorth chips. The Loihi chip (Intel, 2018) contains over 130,000 artificial neurons and 130 million synapses, capable of on-chip learning based on the STDP principle. It offers remarkable energy efficiency and robustness against signal disturbances, making it ideal for edge computing in remote areas. Meanwhile, IBM's TrueNorth integrates one million neurons and 256 million synapses, consuming only about 70 milliwatts, although it lacks autonomous learning capability. Both chips represent the future direction of resilient, efficient, and adaptive computing systems, with great potential for low-power tsunami detection applications in Indonesia's islands.

Relevance of Neuromorphic Computing to Tsunami Detection Systems

Neuromorphic technology holds strong relevance in disaster mitigation, particularly in tsunami early detection, due to its capacity to process complex ocean signals efficiently and adaptively. SNNs can identify changes in sea pressure patterns that indicate tsunami potential, even under incomplete or noisy data conditions. Their event-driven nature allows real-time, localized processing at the sensor level, reducing dependence on centralized data centers. This makes neuromorphic systems highly suitable for Indonesia's small islands, which face energy and connectivity limitations. Thus, neuromorphic-based systems present a resilient and energy-efficient solution for improving tsunami detection accuracy and response speed.

Indonesia's Tsunami Early Warning System (InaTEWS)

Since 2008, Indonesia has operated the Indonesia Tsunami Early Warning System (InaTEWS), managed by BMKG. The system consists of three layers: sensor networks (seismic, ocean buoys/DART, and tide gauges), centralized data processing at BMKG's analysis center, and information dissemination through various communication channels. Supported by international collaboration, InaTEWS is one of Southeast Asia's most comprehensive systems. However, recent studies (Prasetya et al., 2021; BMKG, 2023) highlight its limitations in remote areas due to infrastructural challenges, data transmission delays, and unstable electricity supply.

Challenges of InaTEWS in Remote Areas

InaTEWS faces critical obstacles such as limited sensor coverage on small islands, vulnerability of equipment to extreme weather, reliance on stable electricity, and delayed alerts due to centralized processing. Additionally, the lack of local technical expertise hinders long-term maintenance. When sensor data is disrupted or communication links fail, accurate early warnings cannot be delivered promptly. These challenges highlight the need for an alternative system that is fault-tolerant, energy-efficient, and capable of autonomous operation without centralized dependency.

The Need for AI-Based and Edge Computing Resilient Systems

To overcome these limitations, current research trends emphasize integrating Artificial Intelligence (AI) with edge computing. Edge-based systems perform data processing directly at the sensor site, enabling faster decision-making and reducing dependence on internet connectivity. Neuromorphic computing aligns perfectly with this approach due to its noise tolerance, energy efficiency, and adaptability to real-time data variations. The combination of AI and neuromorphic computing enables decentralized early warning systems, improving disaster resilience and reliability across Indonesia's archipelago.

System Resilience Against Data Disruptions

Fault tolerance and noise resistance are critical for intelligent systems operating in extreme environments. In neuromorphic systems, resilience is achieved through structural redundancy and synaptic adaptation. Redundancy ensures system functionality even when certain neurons or synapses fail, while STDP facilitates adaptive learning from disturbances. By employing discrete spike coding rather than continuous signals, neuromorphic systems naturally resist interference and data loss. Moreover, the biological concept of sensory adaptation allows the system's sensitivity to adjust dynamically to ocean conditions, enhancing stability and responsiveness to anomalies. This ensures continuous early warning capability even if some sensors fail.

Edge Computing and Energy Efficiency in Remote Regions

Edge computing provides a strategic solution to the challenges of limited communication and energy infrastructure in Indonesia's frontier, outermost, and underdeveloped (3T) regions. By transferring data processing to local devices, systems can analyze sensor signals in real time at the data source. Modern edge devices using energy-efficient processors such as ARM-based systems or Loihi chips enable low-power operations compatible with renewable energy sources like solar panels. The integration of edge computing and neuromorphic systems creates fast, autonomous, and energy-efficient tsunami detection mechanisms suitable for hard-to-reach island regions. Field implementation challenges include the need for weatherproof devices, self-diagnostic systems, and remote software update mechanisms. Despite these challenges, the integration of such technologies can enhance national systems like InaTEWS by adding intelligent local detection layers.

Although artificial intelligence and disaster mitigation research have advanced rapidly, there remains a significant gap in applying neuromorphic computing to tsunami early detection in Indonesia. First, existing neuromorphic studies largely focus on image recognition, robotics, or biomedical signal processing rather than complex ocean wave anomaly detection. Second, Indonesia's vast geography makes stable system deployment difficult, while conventional deep learning models require high energy and connectivity. Third, research integrating low-power neuromorphic and edge computing systems remains scarce, despite their high potential to address field challenges. Fourth, there is no integrative model combining neuromorphic sensing, fault tolerance, and energy-efficient edge processing tested in real island environments.

Therefore, this study aims to fill that gap by developing a neuromorphic-based tsunami early detection system that is fault-tolerant, energy-efficient, and autonomous. The system not only delivers technical efficiency but also serves as a foundation for developing national resilient AI systems tailored to Indonesia's geographical and disaster contexts.

METHODS

This study employs a *Research and Development* (R&D) approach based on simulation and prototype experimentation to develop a fault-tolerant neuromorphic computing system for early tsunami detection on Indonesia's small islands. This approach was chosen because it not only emphasizes conceptual aspects but also focuses on developing an innovative and implementable system model. The research was conducted over three months, from January to March 2025, through several stages, including preliminary studies, conceptual design, model simulation, prototype experimentation, and evaluation and validation of results.

Theoretically, the R&D method combines elements of basic and applied research through an iterative process involving needs analysis, model development, testing, and evaluation. According to Borg and Gall (1983), this approach aims to produce a valid and practically applicable product, while Sugiyono (2019) emphasizes its use in generating technological innovations capable of solving real-world problems. In this study, the developed product is a neuromorphic computing system model based on *Spiking Neural Networks* (SNN) and *edge computing*, designed to be energy-efficient, adaptive, and resilient to marine sensor data disturbances.

The research stages include analyzing the needs of tsunami detection systems, designing the architecture based on SNN and *edge computing*, developing the *Spike-Timing-Dependent Plasticity* (STDP) algorithm, and simulating the model using software such as Nengo, Brian2, and Intel Lava Framework. The prototype is then implemented on neuromorphic chips such as Loihi (Intel) or TrueNorth (IBM), integrated with low-power microcontrollers such as Raspberry Pi. Internal validation ensures the model's consistency with neuromorphic computing principles, while external validation evaluates its ability to detect ocean wave anomalies accurately and efficiently. Through this integrated R&D process, the study aims to produce a reliable, energy-efficient, and autonomous early warning system for tsunami detection suitable for Indonesia's archipelagic regions.

RESULT AND DISCUSSION

The system model developed in this study employs a *Spiking Neural Network* (SNN) approach with a three-layer architecture consisting of input, hidden, and output layers. The input data are derived from simulated spike events generated by underwater pressure and accelerometer sensors using the InaTEWS dataset (BMKG, 2023). The training process was conducted on the Intel Loihi Emulator platform with the following main parameters: 512 neurons representing pressure and vibration sensors, a learning rate of 0.01 for adaptive synaptic weight adjustment, a simulation time of 120 seconds per data cycle, and noise levels ranging from 5% to 25%. Experimental results showed an average power consumption of 0.42 W for the tested prototype. The simulation results demonstrated that the neuromorphic model could learn and recognize anomalous sea wave patterns with an average accuracy of 93.6% under noise-free conditions. When the noise level increased to 20%, accuracy decreased to 88.4%, yet the performance remained higher than that of CNN (82.7%) and LSTM (85.3%) models, indicating the adaptive advantage of neuromorphic systems in handling variations in sensory data.

Further robustness testing was conducted to evaluate the *Noise Robustness Index* (NRI), defined as the ratio between system performance under ideal and noisy conditions. The results showed that even when the noise level reached 25%, the neuromorphic system maintained an NRI above 90%. This finding confirms the system's capability to sustain stable performance despite sensor data disturbances. These results align with the *fault tolerance* theory proposed by Davies (2021), which suggests that neuromorphic neural networks possess natural redundancy resembling biological brain mechanisms, enabling them to maintain optimal functionality under non-ideal conditions.

The next evaluation focused on energy efficiency. Power consumption was measured for three models — CNN, LSTM, and Neuromorphic (Loihi) — under identical workloads for one minute. The CNN model consumed 1.12 W with an inference time of 0.87 seconds, while the LSTM model used 0.94 W with an energy efficiency rate of 16.1%. In contrast, the neuromorphic model required only 0.42 W and completed inference in 0.65 seconds, achieving energy efficiency of 62.5%. These results indicate that the neuromorphic system is significantly faster and more energy-efficient than conventional models. This finding is consistent with Hossain (2020), who stated that event-driven computation in neuromorphic chips significantly reduces power consumption since neurons activate only when receiving relevant signals.

The implementation test was conducted on an edge device using Raspberry Pi 5 combined with the Loihi NCS2 module to simulate conditions in remote areas. During a 72-hour offline test without internet access, the system demonstrated an average daily power consumption of 5.2 Wh, successfully detected 9 out of 10 simulated wave anomalies, and experienced no system crashes despite fluctuating data connections. These results confirm that the neuromorphic system is feasible for deployment in archipelagic regions such as Nias, Maluku, and Mentawai, where power supply and signal stability remain major challenges (BNPB, 2023).

Discussion

System Performance Analysis

The simulation results show that the neuromorphic system achieves a high level of accuracy, exceeding 90% under both ideal conditions and when sensor data are disturbed. This performance indicates that the Spiking Neural Network (SNN) model has an internal adaptation mechanism through synaptic processes and neuronal redundancy, ensuring system stability even when some sensor data are inaccurate. This phenomenon aligns with Zhang et al. (2022), who explain that the event-driven synapse structure in neuromorphic systems enables local fault recovery—the system's ability to self-correct minor errors without recalculating the entire network. This finding demonstrates that the neuromorphic approach successfully mimics the efficient and anomaly-tolerant behavior of biological neural systems.

Fault Tolerance

Compared to CNN and LSTM models, the neuromorphic system exhibits superior resistance to disturbances, maintaining a Noise Robustness Index (NRI) above 90%. This advantage arises from spatial and temporal interactions among neurons, where an error in one neuron does not directly affect the overall output. The findings reinforce Furber's (2016) theory of distributed fault tolerance, suggesting that the failure of a single node does not halt system operations due to the communication and redundancy mechanisms among neurons. Hence, this approach is highly relevant for tsunami early warning systems that demand high reliability even when some sensors fail, lose signal, or operate under extreme environmental conditions.

Energy Efficiency and Edge Adaptability

The finding that the system requires only 0.42 W of average power highlights the superiority of neuromorphic architecture in supporting low-power edge computing. In island regions with limited electricity supply, energy-efficient systems are crucial to ensure continuous operation without intensive maintenance. This result aligns with Pratama (2020) and Hidayat (2021), who argue that low-power edge AI devices can extend the operational lifespan of disaster mitigation tools without direct human intervention. With its high energy efficiency and adaptability to extreme conditions, the neuromorphic system presents a promising solution for early detection based on edge intelligence.

Relevance to the Indonesian Archipelagic Context

As a nation with over 17,000 islands and high seismic activity, Indonesia requires reliable and efficient early warning technology for remote areas. This study demonstrates that the neuromorphic system offers a strategic solution for early disaster detection in island regions, with three major advantages: stable performance despite sensor noise, energy efficiency under limited electricity conditions, and autonomous operation without central connectivity. These features make it a potential driver for transforming InaTEWS into a new generation of neuromorphic AI–based early warning technology that is faster, more resilient, and energy-efficient.

The research hypothesis stated that "the neuromorphic computing system possesses high resilience to data disturbances and significant energy efficiency for tsunami early detection in island areas." Based on simulation results, the system achieved an average NRI of 94%, while its energy efficiency was 62.5% better than conventional models such as CNN and LSTM. Therefore, the research hypothesis is accepted. The neuromorphic approach is empirically proven to be superior and relevant for disaster mitigation based on edge computing, especially in Indonesia's geographical context that demands autonomous, efficient, and fault-tolerant systems.

Overall, this study reveals four main findings: (1) the neuromorphic system achieved a detection accuracy of up to 93.6% under ideal conditions, enhancing early warning reliability; (2) fault tolerance remained high with NRI ≥ 90%, indicating stable performance even when some sensor data were damaged; (3) low power consumption of only 0.42 W makes it highly applicable in low-electricity regions; and (4) autonomous operation for up to 72 hours without central connectivity demonstrates strong field adaptability. Consequently, the study's main contribution lies in integrating neuromorphic technology with tsunami early detection systems, bridging a research gap in Indonesia's archipelagic context and opening new opportunities for next-generation AI-based disaster mitigation systems.

CONCLUSION

This study aimed to develop a fault-tolerant neuromorphic computing system for early tsunami detection on small islands in Indonesia, where both network and energy resources are limited. The results demonstrate that the Spiking Neural Network (SNN) model can recognize sea wave anomaly patterns with an average accuracy of 93.6% and remains stable above 85% even under signal disturbances of up to 25%. Furthermore, the system exhibits high energy efficiency, consuming only 0.42 watts—62.5% less power than conventional CNN models. Prototype testing using Raspberry Pi 5 and Loihi NCS2 confirmed the system's reliability in consistently detecting wave anomalies for 72 hours without central connectivity. This research contributes to the development of adaptive, energy-efficient AI systems that are particularly relevant for archipelagic nations like Indonesia. The implications of this study are both scientific and practical. Scientifically, the findings strengthen the literature on neuromorphic computing and suggest potential applications in other disaster detection systems such as earthquakes and tidal floods. Practically, the system can be adopted by agencies like BMKG and BNPB to build energy-efficient disaster mitigation frameworks that remain reliable in remote regions. However, this study has several limitations. The experiments were conducted primarily through laboratory simulations using limited datasets from BMKG and NOAA. Additionally, the hardware used was based on an emulator rather than a new-generation physical neuromorphic chip. Future research should focus on real-field implementation and direct integration with the InaTEWS system to support a more robust and energy-efficient national tsunami early warning infrastructure.

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