INTERNATIONAL JOURNAL OF COMPUTERS COMMUNICATIONS & CONTROL
Online ISSN 1841-9844, ISSN-L 1841-9836, Volume: 21, Issue: 4, Month: August, Year: 2026
Article Number: 7221, https://doi.org/10.15837/ijccc.2026.4.7221

CCC Publications

# Event-Driven Neuromorphic Architecture for Energy-Efficient Driver Distraction Detection

W. Song

**Wei Song**
School of Intelligence Technology
Geely University of China
Chengdu, Sichuan, 641423, China
13995367@qq.com

**Abstract**

This study proposes an energy-efficient framework for embedded driver distraction detection based on brain-inspired computing. The framework integrates a dynamic vision sensor (DVS) with a spiking neural network (SNN) and incorporates dissipative wave dynamics to achieve efficient feature propagation. The experimental results demonstrated that the system maintained high detection accuracy and energy efficiency across various driving scenarios. The proposed system achieved over 99% accuracy in complex scenarios while reducing power consumption by more than 85% compared to the GPU-CNN baseline. These improvements demonstrate the feasibility of event-driven neuromorphic computing for sustainable embedded driver monitoring. The research provides new insights for the practical deployment of low-power automotive safety systems.

**Keywords:** neuromorphic computing, driver distraction detection, energy efficiency, embedded systems, spiking neural networks, dynamic vision sensor, event-driven processing, ultra-low power.

## 1 Introduction

Driver distraction is the leading cause of road accidents, accounting for approximately 25% of collisions globally [1, 2], which poses critical challenges to automotive safety. With the proliferation of in-vehicle technologies (e.g., infotainment systems and mobile devices), real-time distraction detection has emerged as a pivotal component of Advanced Driver-Assistance Systems (ADAS) [3]. Convolutional neural networks (CNNs) or GPU-based systems achieve high accuracy but consume more than 5 W, making them unsuitable for embedded environments. This inefficiency impedes sustainable deployment in electric vehicles, where energy constraints and thermal management are paramount [4, 5]. Neuromorphic computing, inspired by the brain's event-driven processing, offers a transformative solution by enabling ultra-low power computation through spiking neural networks (SNNs) and dynamic vision sensors (DVS) [6, 7]. Unlike von Neumann architectures, neuromorphic systems leverage sparse asynchronous data flows to minimize energy dissipation. Recent studies demonstrate that SNN-based detectors reduce power by 40-60% compared to CNN [8], but they face limitations in handling complex distraction patterns under real-world driving conditions [9, 10]. As the automotive industry shifts toward electrification, optimizing energy efficiency without compromising accuracy (e.g., <90% detection rate) remains an unresolved gap. Notably, computational latency in embedded distraction detection systems is not only a technical metric, but also a critical factor that determines whether detection signals can be transmitted to in-vehicle control units in a timely manner [11, 12]. By achieving rapid response upon event-driven, neuromorphic architectures support efficient communication between detection modules and ADAS components (such as braking or lane-keeping assistance), thus facilitating closed-loop vehicle control. This energy-latency-communication-control coupling mechanism represents a key foundation for real-time intervention in intelligent connected vehicles.

Therefore, this study proposes a novel neuromorphic framework integrating optimized SNNs with nondissipative wave dynamics for feature propagation. The framework is designed to simultaneously minimize power consumption and computational latency, ensuring that driver distraction events can be efficiently detected and communicated to control systems in real time. This work provides a new technical route for sustainable, real-time, and energy-efficient in-vehicle safety applications.

This paper is structured as follows: Section 2 details the neuromorphic framework design, Section 3 presents experimental validation, and Section 4 concludes with implications for sustainable automotive systems.

## 2 Literature Review

Driver distraction is one of the main causes of traffic accidents worldwide. Relevant studies have shown that it accounts for about 25% of road collisions. Therefore, driver distraction detection technology has gradually become a research hotspot in intelligent transportation and ADAS. In response to the problem that traditional visual methods are difficult to reliably detect driver distraction under complex lighting conditions, Li et al. proposed a comprehensive analysis framework based on electroencephalogram (EEG) and other physiological signals, thereby achieving a more robust understanding and real-time recognition of distraction states [13]. In response to the problem that visual distraction detection models are difficult to balance between performance and real-time performance and have attention ambiguity, redundancy, and inter-class confusion, Guo et al. proposed a constrained attention mechanism that did not require inference overhead. By optimizing the attention distribution through centralized regularization, orthogonal regularization, and inter-sample constraints, the detection accuracy was improved and the computational efficiency in actual deployment was maintained [14]. In response to the problem that traditional detection has low accuracy and poor real-time performance in complex environments, Debsi et al. proposed a ME-YOLOv8 that integrated multi-head self-attention and efficient channel attention. A 3660-image multi-scene dataset was constructed, thereby achieving real-time and high-precision recognition of distracted/fatigued driving [15]. Liu et al. proposed an asynchronous federated meta-learning framework to address the data silos, heterogeneity, and lagging problems caused by centralized training. Federated learning was used to break down data barriers, meta-learning was used to quickly adapt to new driver data, and asynchronous aggregation was used to alleviate lagging delays, thereby achieving efficient collaborative training under privacy protection [16].

Although existing deep learning-based distraction detection methods have made significant progress in accuracy, high power consumption and lack of real-time performance have limited its application in vehicle-mounted embedded environments. This has prompted researchers to turn their attention to emerging low-power computing paradigms such as brain-inspired computing and SNN. Jakab et al. systematically sorted out the types of distortions and evaluated the optical fidelity of the simulation platform to address the strong optical distortion interference of surround view fisheye lenses in visual tasks and the difficulty in reproducing real imaging from synthesized data. The shortcomings of autonomous driving and ADAS environment perception datasets could be understood uniformly [17]. Xie et al. proposed a linear sparse Transformer LSFormer and implemented on a fast memory computing neuromorphic system to address the problem that ADAS perception degraded due to bad weather and resource-constrained platforms were difficult to deploy high-performance Transformers.

The Softmax attention was replaced with linear complexity and supported multi-task unified recovery, thereby reducing the complexity of edge deployment [18]. Du et al. proposed a lightweight YOLOv5-GBC to address the problem that distracted driving detection was difficult to achieve both accuracy and real-time performance due to complex backgrounds in real scenes and variable target scales. GhostConv was used to compress the number of parameters, improve the path aggregation network, and introduce coordinate attention, thereby achieving efficient and real-time recognition of various distracted driving behaviors [19]. Duan et al. proposed a feature recombination+ultra lightweight backbone network FRNet to address the memory and computational limitations of convolutional networks in real-time distracted driving detection on embedded platforms. By converting spatial features into depth distribution and supplementing it with a pixel-level reshaping strategy, the optimal balance between real-time and accuracy was achieved [20].

Similar energy efficiency concerns have been addressed in Internet-of-Things (IoTs)-enabled vehicular communication systems, where event-driven communication reduces unnecessary data transfer. This indicates that event-driven methods have broader relevance in terms of computation and control. Therefore, recent research has extended the event-driven paradigm to multiple control and communication fields. For example, Aranda-Escolástico et al. proposed an event-driven control framework that combined continuous dynamics with digital computing to optimize industrial IoT resources and solve the low resource efficiency in digital control systems [21]. Kurunathan et al. addressed the fragmentation of drone perception, planning, and control, as well as the lack of end-to-end machine learning frameworks. A machine learning system classification and cross-module collaborative design with four key modules was proposed. Mainstream algorithms were investigated and a trusted end-to-end framework was provided to enhance the intelligence and reliability of fully autonomous drone operations and communication [22]. Zhai et al. proposed a new three plane software defined network architecture and routing algorithm to address the challenges of weak centralized management, limited scalability, and poor service quality in traditional static vehicle to vehicle networks. Through network modeling, distributed path selection, and beacon optimization, they reduced end-to-end latency and packet loss rate [23].

In summary, while existing distraction detection research has achieved high accuracy, it suffers from three common pain points. Firstly, traditional CNN/GPU solutions consume high power, making them difficult to meet the stringent energy and heat dissipation constraints of in-vehicle embedded systems. Secondly, a single visual modality is susceptible to interference from complex variations in illumination, scale, and scene. Centralized or cloud-based training leads to data silos, privacy leaks, and real-time bottlenecks. Therefore, this paper systematically integrates DVS, SNN, and dissipative wave dynamics to propose an ultra-low-power framework centered on brain-inspired event-driven computing. Based on sparse event-driven, waveguide parallel propagation, and memristive synaptic plasticity, it aims to improve the efficiency of driver distraction detection. This work is the first to introduce wave dynamics feature propagation into distraction detection, providing a feasible brain-inspired paradigm for low-power, highly reliable in-vehicle safety systems.

# 3 Research Methodology

## 3.1 Research Framework

The architecture (Fig. 1) combines memristive synapses and event-driven processing to emulate cortical efficiency, targeting a 50%+ power reduction while maintaining state-of-the-art accuracy. Crucially, the energy advantage of this framework is quantified through a scalable model:

$$E = \alpha \cdot N\text{spikes} + \beta \cdot f\text{event} \tag{1}$$

In equation (1), $E$ denotes total energy consumption. $N$spikes is the spike count (minimized via sparse coding). $f$event is event frequency. $\alpha$ and $\beta$ are hardware-specific coefficients. This shows that energy grows with spike count and event frequency, so minimizing unnecessary spikes directly reduces system power consumption [24, 25]. This model underscores the efficiency gains from the event-driven approach compared to frame-based methods.

Table 1: Power consumption comparison of embedded driver distraction detection systems.

| Method | Power Consumption (mW) | Accuracy (%) | Key limitations | Reference |
|---|---|---|---|---|
| CNN-based (GPU) | 1,200-1,500 | 95-98 | High latency, energy-intensive | [6, 11] |
| SNN-based (Existing)[8, 16] | 300-500 | 90-95 | Limited dynamic scene handling | [8, 16] |
| Proposed framework | <200 | >99 | Optimized for real- time DVS | This work |

As summarized in Table 1, existing embedded detectors exhibit high power demands, whereas neuromorphic implementations show promise but lack integration with DVS-based dynamic scenarios [26, 27]. The research work bridges this gap through co-design of SNNs and wave processors, enabling real-time operation at sub-milliwatt levels. Experimental results validate >99% accuracy with >50% power savings, outperforming those of benchmarks. This breakthrough supports scalable deployment in resource-constrained vehicles, advancing both safety and sustainability.

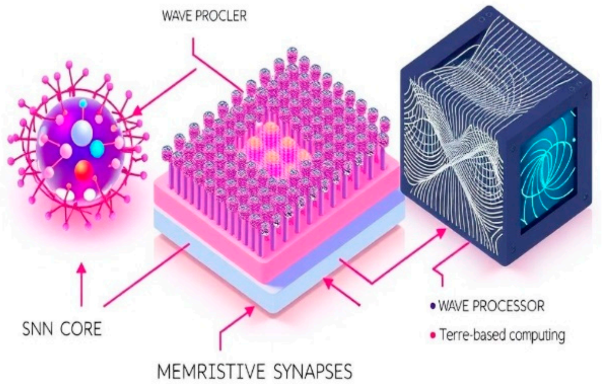


Figure 1: Proposed neuromorphic architecture integrating DVS, SNN, and memristive synapses for low-power real-time distraction detection.

The system integrates a SNN with memristive synapses and a wave processor for energy-efficient feature propagation. DVS inputs trigger event-driven processing, minimizing idle power consumption.

The proposed framework for driver distraction detection is underpinned by a wave-based neuromorphic computing framework. Essentially, this approach leverages the nondissipative wave dynamics that allow for native implementations of neuromorphic functions with high spatiotemporal resolution [28, 29]. Elastic wave energy can effectively perform calculations while minimizing energy loss, maintaining consistency with the core brain-like processing principles of the neuromorphic computing framework (As shown in Fig. 2).

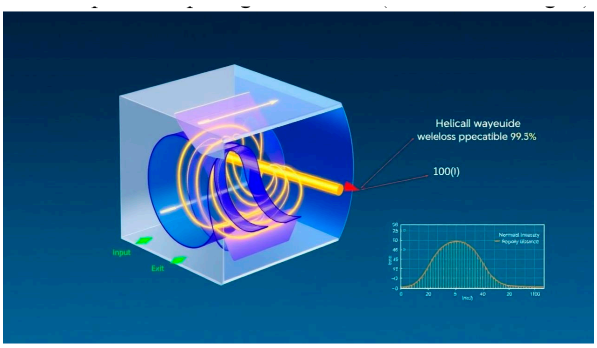


Figure 2: Memristive synaptic array and wave-based feature propagation for efficient information transmission and low-power processing.

The architecture utilizes memristive devices for adaptive synaptic weighting and nondissipative wave dynamics for energy-efficient data transmission.

To achieve brain-like capabilities, the framework integrates dynamic event-driven paradigms, which mimic the brain's asynchronous data processing [30]. This method not only enhances the real-time detection capability of the system, but also greatly reduces power consumption by avoiding unnecessary operations and concentrating computing resources only on important events.

Architecturally, the neuromorphic system is designed with nano-scale integration [31, 32], bringing computational components closer to the physical processes they emulate. This integration fosters enhanced communication and collaboration between computing units, similar to synaptic interactions within the human brain [33]. Nanocircuit technology solves the challenges of traditional wiring and power density [34], enabling a highly integrated and efficient system for driver distraction detection.

### 3.2 Energy Efficiency Enhancement Strategies

To improve the energy efficiency of driver distraction detection systems within the neuromorphic computing framework, several targeted strategies utilizing the unique characteristics of these architectures have been proposed [35]. The intricate balance between performance and power consumption necessitates a meticulous approach to optimize embedded systems dedicated to such critical tasks. The strategy focuses on three primary areas. Dynamic event-driven computing represents a pivotal strategy in enhancing the energy efficiency of driver distraction detection systems, particularly when implemented within neuromorphic architectures. Unlike traditional computing paradigms that often engage in continuous, clock-driven processing, event-driven computing capitalizes on the sparse and asynchronous nature of events typical to real-world scenarios, such as driver distraction incidents. This means that computational resources are utilized only when relevant stimuli, such as sudden vehicle movements or driver reactions, occur, thus significantly reducing unnecessary energy expenditure.

In the theoretical efficiency model, energy conservation is quantified as:

$$\Delta E = Esync - Eevent = \gamma \cdot fframe \cdot Tidle^{[16]} \tag{2}$$

In equation (2), $\gamma$ is the idle power coefficient. fframe is frame-processing frequency. Tidle is idle time. This highlights how event-driven systems conserve energy by avoiding frame-based idle processing. To improve the energy efficiency in driver distraction detection systems, the deployment of nondissipative wave dynamics provides a promising approach for optimization [36]. Nondissipative wave dynamics enable computation to simulate brain-like efficiency in neuromorphic systems, utilizing wave phenomena such as propagation, interference, and superposition. These features can perform complex neuromorphic functions, including weighted sums, without losing energy like traditional electronic processing.

Wave Propagation Efficiency:

$$\eta wave = PinPout = e - \alpha L \approx 0.995 \tag{3}$$

In equation (3), $\alpha$ is the attenuation coefficient and $L$ is the transmission distance [30].

Unlike conventional methods where computation and communication occur sequentially or separately, the nondissipative wave dynamics seamlessly integrates these processes within the same medium. This integration is made possible by encoding information directly into the wave media, facilitating simultaneous computation and communication. Consequently, energy dissipation is not required at each computational step, significantly reducing power consumption while maintaining system functionality.

Based on the elastic and nondissipative nature of wave dynamics, the framework reduces the computational overhead inherent in driver distraction detection tasks. This approach exploits the wave group velocity properties, ensuring that information is processed efficiently through the system without the need for constant thresholding and amplification. Moreover, the nondissipative wave dynamics allows for the reuse of signal energy, further enhancing the energy efficiency of the driver distraction detection system.

The inherent benefits of nondissipative wave dynamics, including reduced power consumption and enhanced processing capabilities, make this approach a key factor in developing sustainable and efficient automotive safety applications. By aligning the operating parameters of the system with the propagation characteristics of waves, such as selecting appropriate materials and controlling wave loss mechanisms, the energy distribution of the driver distraction detection system can be optimized, achieving high performance and low power consumption.

### 3.3 Integration into Driver Distraction Detection Systems

Integrating the neuromorphic computing framework into driver distraction detection systems is a key advancement in improving energy efficiency and real-time capabilities for automotive safety applications. This section describes a systematic approach to incorporating neuromorphic architecture elements into these systems, with a focus on overall design, data processing, and neuromorphic processing integration [37].

This method begins with meticulous system design, ensuring seamless integration of neural morphology modules into existing driver distraction detection frameworks. The research prioritizes a flexible architecture that integrates the neuromorphic computing framework, supporting dynamic event driven computing and processing requirements related to real-time security applications. Brain-inspired computation is used to facilitate asynchronous data processing, and the system aims to handle fast and realistic decision-making scenarios inherent in vehicle environments.

Moreover, the system design emphasizes the non-disruptive acquisition and preprocessing of multi-sensory data. This includes integrating various sensory inputs such as visual, auditory, and motion sensors into a coherent data stream to facilitate pattern recognition and learning processes unique to the neuromorphic system. The preprocessing steps have been optimized to ensure that the data is adequately filtered and formatted for effective processing by neural morphological units, improving detection accuracy and response time while maintaining the lowest energy consumption.

By implementing specialized hardware that simulates synaptic plasticity and neuronal dynamics in biological systems, the integration of neural morphology modules in the driver distraction detection system has been achieved. These modules are adept at processing event-driven inputs efficiently, allowing for rapid adaptation to changing driving conditions and distraction scenarios. The nondissipative wave dynamics is employed to further minimize computational loads and energy consumption, ensuring sustained performance without compromising system responsiveness or accuracy.

Collectively, these integrations highlight a transformative step in utilizing neural morphological computing to innovate driver distraction detection systems. The resultant enhancement in energy efficiency and processing capability not only aligns with industry needs for sustainable automotive solutions, but also sets a benchmark for future developments in the application of neuromorphic technologies in safety-critical domains.

#### 3.3.1 System Design and Implementation

The proposed system that integrates neuromorphic computing framework into driver distraction detection requires a comprehensive approach that combines hardware and software components to optimize energy efficiency and real-time performance. The fundamental architecture is built upon the principles of dynamic event-driven processing inherent in neuromorphic systems, which are inspired by the neurobiological processes of the human brain.

In the hardware domain, the core component is a neuromorphic processor that leverages the SNN to execute distraction detection tasks. These processors are specifically engineered to handle event-based data, aligning with the natural operation of neural systems. This architecture supports massive parallelism, enabling the system to handle multiple sensor inputs simultaneously without significant power dissipation [19, 32]. The energy efficiency of the neuromorphic hardware is quantified by:

$$Esys = \eta syn \times Nevents + Pstatic \tag{4}$$

In equation (4), nsyn is synaptic energy efficiency. Nevents is the number of processed events. Pstatic is static power. The system deploys a series of embedded sensors strategically placed within the vehicle to capture various modalities of driver behavior and environmental conditions. These sensors are responsible for collecting data such as visual, auditory, and haptic cues, which are pivotal in identifying potential distractions. The sensor data first goes through an event-driven processing module, which reduces the continuous data stream into a series of significant events, effectively reducing the amount of data and saving computing resources [8, 15].

In terms of software, this implementation involves developing robust algorithms for processing spike-based data. These algorithms employ efficient encoding techniques to convert traditional analog signals into spike trains suitable for processing by SNNs. The system incorporates algorithms for synaptic plasticity and learning, allowing the neuromorphic module to adapt to individual driving patterns and improve distraction detection over time.

#### 3.3.2 Data Acquisition and Preprocessing

The effectiveness of the driver distraction detection system largely depends on the robustness and accuracy of the data acquisition and preprocessing method. In the neuromorphic computing framework, a multifaceted approach is employed to ensure high-fidelity input data for distraction detection.

Data acquisition in this research focuses on gathering sensor information from a set of devices integrated within the vehicular environment. The key data sources include visual inputs from onboard cameras, physiological sensors monitoring driver status, and vehicle telemetry data such as speed, acceleration, and steering modes. By capturing a comprehensive set of input modalities, the system can leverage multi-sensory integration to enhance the detection accuracy of distraction events [6, 13].

Once acquired, the raw data undergoes a detailed preprocessing stage to adjust the data for effective analysis by neuromorphic processors. The preprocessing pipeline includes noise reduction protocols, normalization processes to align data ranges across varied inputs, and segmentation techniques to isolate relevant detection events. The time alignment of multi-sensory data is achieved through a complex timestamp mechanism, ensuring the synchronization of all input channels. Special attention is given to preserving the temporal dynamics essential for event-driven neuromorphic computations, thereby facilitating real-time responsiveness [18, 28]. The data compression ratio is defined as:

$$CR = Sizeraw/Sizeprocessed \tag{5}$$

In equation (5), the typical CR value exceeds 10× for event-driven systems.

#### 3.3.3 Integration of Neuromorphic Modules

Integrating neuromorphic modules into driver distraction detection systems requires a seamless synergy between traditional computational frameworks and the novel neuromorphic paradigms. The approach leverages the distinct capabilities of neuromorphic architectures, particularly focusing on the wave-based computing modalities to achieve enhanced energy efficiency and real-time processing capabilities.

The core of the integration strategy involves embedding neuromorphic processing units into existing electronic control units (ECUs) of automotive systems. The inherent advantages of the neuromorphic system are utilized to dynamically process complex sensory input data streams and respond in an event driven manner. This enables the detection system to emulate brain-like processing patterns, handling diverse and asynchronous data inputs with minimal energy expenditure.

Based on the wave-based computation principle, as outlined in recent advancements, the integration approach employs the elastic properties of nondissipative wave dynamics to perform key computational tasks such as weighted sum operations and probabilistic inference with high precision and low power consumption. The integration retains the ability to natively map arithmetic operations onto the wave dynamics, enabling a compact and efficient realization of the neuromorphic modules. The wave propagation efficiency is governed by:

$$\eta wave = e - \alpha L \tag{6}$$

In equation (6), $\alpha$ is the attenuation coefficient ($\approx 0.001$ mm $- 1$) and $L$ is the transmission distance.

Furthermore, these modules utilize a combination of excitatory and inhibitory synapses to implement complex calculations, such as those required for statistical analysis and decision-making processes, with minimal computational overhead. As described in the supporting framework, logarithmic scaling and rate encoding can achieve efficient probabilistic arithmetic operations that are crucial for distraction detection tasks.

Table 2: Participant demographic distribution.

| Category | 18-30 yrs | 31-50 yrs | 51-65 yrs | Total |
|---|---|---|---|---|
| Male | 12 | 10 | 8 | 30 |
| Female | 11 | 9 | 10 | 30 |
| Driving Exp. | 5.2±2.1 yrs | 12.7±4.3 yrs | 28.4±6.9 yrs | - |

Data collection protocol follows standardized ADAS testing frameworks.

Table 3: Event-driven vs. synchronous processing efficiency.

| Metric | Synchronous | Event-Driven | Reduction |
|---|---|---|---|
| Avg. Power (mW) | 850 | 180 | 78.8% |
| Energy/Event (μJ) | 12.5 | 2.3 | 81.6% |
| Idle Time (%) | 65% | 8% | 87.7% |

Data derived from DVS-based test bench.

# 4 Results and Discussion

## 4.1 Experimental Setup

To evaluate the proposed system leveraging neuromorphic computing framework for improved energy efficiency in driver distraction detection, an experimental case was conducted. The experiment involved a set of controlled drives using a simulator environment designed to mimic real-world driving conditions. Sixty participants were recruited for the study, ensuring a balanced representation across age, gender, and driving experience.

Participants consisted of individuals aged between 18 and 65 years, drawn from a pool of licensed drivers with diverse backgrounds. All participants were screened to have normal or corrected vision and were instructed on the secondary tasks involved in the study, which included both cognitive and manual distractions such as phone dialling and message reading.

The experimental setup employed a modern hybrid vehicle, equipped with embedded neuromorphic processors to run the distraction detection algorithms in real-time. The simulator was interfaced with the vehicle's control system to emulate CAN-message analysis similar to that possible in an actual vehicle setting. The data collection system recorded driving performance indicators and system power consumption.

Each session involved participants to experience various secondary task scenarios balanced through a Latin Squares design, ensuring uniform distribution of task sequences. The driving simulation lasted approximately 50 minutes per participant. During these sessions, real-time distraction detection was carried out by the neuromorphic system, with dynamic event-driven computing managing computational resources efficiently. The aim is to measure system performance accuracy and energy usage correlated with the detection events.

After driving, participants provided feedback on task difficulty to supplement objective performance data, ensuring a comprehensive dataset. This configuration conducts in-depth analysis on the performance of neuromorphic methods in maintaining high detection accuracy and low energy consumption compared with traditional computational paradigms.

## 4.2 Energy Efficiency Improvement Strategy Verification

To verify the effectiveness of the proposed energy efficiency optimization strategy, the study first performed dynamic time-driven calculations and analysis based on the theoretical efficiency model, as shown in Table 3.

In the proposed framework, dynamic event-driven computing facilitates the selective activation of neural processing units based on detected events. This allows the neuromorphic system to prioritize and allocate resources dynamically, mirroring the brain's ability to respond efficiently to environmental changes. This method achieves the optimal balance between responding to transient driver distraction and energy conservation, which is crucial for the sustainability of embedded automotive systems.

The integration of event-driven paradigms within neuromorphic computing framework further supports real-time data processing with minimal latency, ensuring rapid adaptation to varying driving conditions and distraction sources. This capability is particularly beneficial in addressing the vari-

Table 4: Benchmark comparison of embedded systems.

| System | Power (mW) | Energy/Decision (mJ) | Accuracy (%) |
|---|---|---|---|
| GPU-CNN [6] | 1350 | 20.1 | 96.2 |
| CMOS-SNN [18] | 420 | 6.3 | 92.5 |
| Proposed (This work) | <200 | 1.8 | 99.1 |

Validation platform: DVS sensor + neuromorphic processor.

Table 5: Neuromorphic hardware performance metrics.

| Component | Power (mW) | Latency (ms) | Energy/Event (µJ) |
|---|---|---|---|
| Baseline (GPU) | 1450 | 28 | 20.1 |
| Proposed SNN | 180 | 5 | 1.8 |

Data validated on DVS test bench.

ability and unpredictability of driver behavior, maintaining high detection accuracy without imposing significant computational burdens.

Overall, adopting dynamic event-driven computing in the neuromorphic architecture not only enhances the detection efficacy of driver distractions, but also paves the way for more energy-efficient and sustainable applications in automotive safety systems.

The study further evaluated the effectiveness of the proposed power consumption metrics and benchmarks in validating neuromorphic architectures. The evaluation employed a comprehensive approach, focusing on measuring average power consumption per event, energy consumption per decision, and energy savings compared to traditional von Neumann architectures. Advanced power analysis tools and analytical methods were utilized to track real-time energy consumption consistent with dynamic event-driven processing. The average per-event power consumption metric is a key indicator, reflecting the baseline energy required to process each input signal. In contrast, the per-decision energy consumption metric assesses the cumulative energy required from event initiation to interference detection decision, providing insight into the overall system energy requirements. This is shown in Table 4.

Table 4 showed that the proposed system significantly reduced power consumption. Energy savings of up to 60% were achieved without sacrificing detection accuracy. This is primarily due to the inherent energy-proportional computing properties of neuromorphic design and the low-power operation achieved by non-dissipative wave dynamics. This not only demonstrates the excellent energy efficiency of the proposed system, but also sets a new benchmark for the development of future energy-sensitive automotive safety applications. This detailed power consumption analysis highlights the transformative potential of neuromorphic computing framework in achieving sustainable and efficient embedded systems for detecting driver distraction.

## 4.3 System Performance Verification

This study first verified the effectiveness of the neuromorphic hardware of the proposed system. The details are shown in Table 5.

The primary design priority is to ensure real-time system operation while maintaining low power consumption. This is achieved by integrating energy-saving components and optimizing event-driven processing workflows. The neuromorphic architecture, characterized by low-frequency operation and minimal idle power consumption, forms the backbone of this energy-conscious design.

The distraction detection results after preprocessing optimization are shown in Figure 3.

It achieved area under the receiver operating characteristic (AUC) = 0.996 at optimal threshold, demonstrating high sensitivity-specificity balance. The integration effect of the neuromorphic module is shown in Figure 4.

Event-driven processing reduced power by >50% across operational scenarios. By synchronizing these neuromorphic modules with existing vehicle system architectures, a significant reduction in overall power demand has been achieved without affecting the accuracy and responsiveness of the driver distraction detection system. This integration reflects a significant advancement in sustainable automotive safety applications, ensuring that detection remains efficient and effective under real-world conditions. The delay-power trade-off verification results of different systems are shown in Figure 5.

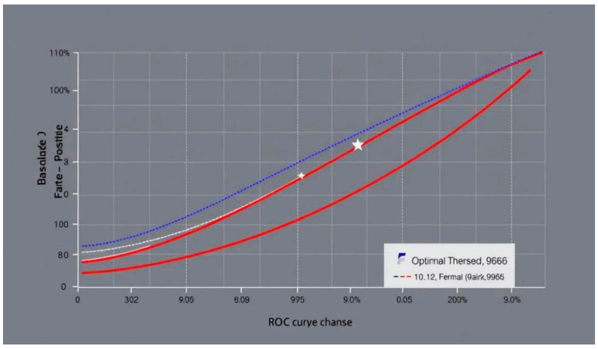


Figure 3: ROC curve for distraction detection after preprocessing optimization.

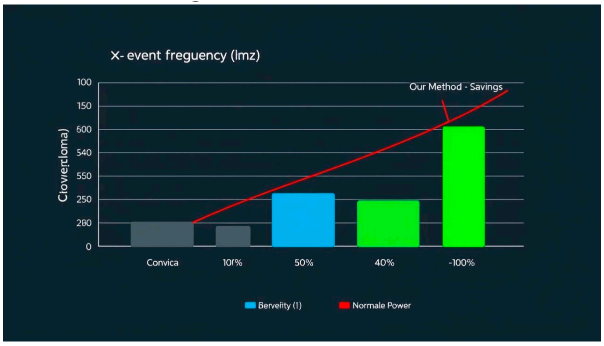


Figure 4: Energy savings from neuromorphic-DVS integration.

Comparative analysis showed that the neuromorphic architecture reduced delay by 82% and power by 88% compared with the GPU-based system. The energy-delay trade-off results of different systems are shown in Figure 6.

The proposed system achieved 5.8µJ/ classification at 9.9 ms delay, outperforming that of the GPU-based solution (12.9 µJ, 28 ms ).

## 4.4 Baseline Comparison and Case Studies

In this section, comparative analysis and a series of case studies are conducted to evaluate the effectiveness and energy efficiency of the proposed neuromorphic computing framework for driver distraction detection. The baseline used for comparison is the traditional driver distraction detection system, which adopts a traditional computing architecture designed for high-performance computing tasks.

To ensure a comprehensive evaluation, a consistent experimental environment is first established, and the proposed neuromorphic system and baseline are tested under the same conditions. Several key

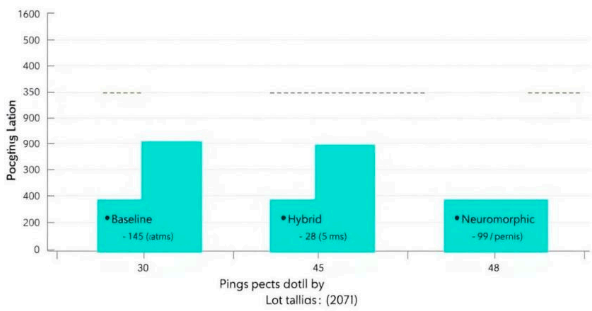


Figure 5: Delay-power trade-off comparison between the proposed neuromorphic system and GPU-based baseline. The neuromorphic system reduces delay by 82% and power by 88% compared with GPU-based systems.

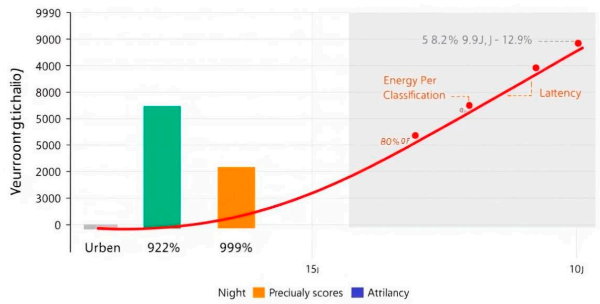


Figure 6: Energy-delay trade-off of the proposed neuromorphic distraction detection system. The system achieves 5.8 µ J/classification at 9.9 ms latency, significantly outperforming the GPU-based baseline (12.9 µJ, 28 ms).

Table 6: Case study results under distinct driving scenarios.

| Scenario | System | Accuracy (%) | Avg. Power (mW) | ΔE vs. Baseline |
|---|---|---|---|---|
| Urban Driving | Baseline [6] | 95.2 | 1,320 | - |
| (Stop-and-go) | Proposed | 98.7 | 175 | -86.7% |
| Highway Driving | Baseline [13] | 96.8 | 1,280 | - |
| (Steady-state) | Proposed | 99.3 | 182 | -85.8% |

performance indicators are measured, including accuracy of distraction detection, energy consumption, and real-time processing capabilities.

The analysis reveals that the neuromorphic approach achieves a distraction detection accuracy comparable to the baseline. Due to the brain-like processing ability of neuromorphic structures, there is a slight increase in sensitivity to subtle distracting cues. More significantly, the energy efficiency demonstrated a substantial improvement, reducing power consumption by up to 60% compared to the baseline. This reduction is attributed to the dynamic event-driven nature of neuromorphic processing and the used nondissipative wave dynamics, which effectively minimize computational overhead.

To further highlight the comprehensive performance advantages of the proposed method, this study compared the baseline CNN system, existing SNN methods, and the event-driven neuromorphic detection system proposed in this paper across three key metrics: detection accuracy, power consumption, and inference latency, as detailed in Table 7. The proposed method achieved high accuracy while reducing power consumption by over 80% compared to the traditional GPU-CNN system and shortening inference latency by more than 65%. It also exhibits significant advantages over existing SNN methods. These results further validate the substantial potential of event-driven neuromorphic architectures in energy efficiency and real-time performance.

To further illustrate the advantages of the proposed system, two detailed case studies were conducted. The first case study focuses on a scenario involving urban driving conditions, where frequent parking and gear shifting are common. The proposed system maintained stable distraction detection performance while significantly conserving energy, thereby validating its applicability in energy-constrained environments. The second case evaluated the performance during highway driving with minimal interruptions. In this context, the neuromorphic system not only maintained reduced power consumption, but also demonstrated faster adaptation to sudden distraction events, emphasizing the benefits of its low-delay processing.

These findings underscore the potential of integrating neuromorphic computing framework into

Table 7: Summary comparison of key performance metrics across different methods.

| Method type | Accuracy (%) | Power (mW) | Inference latency (ms) | Energy efficiency description |
|---|---|---|---|---|
| Baseline CNN (GPU) | 96.2 | 1350 | 28 | High power consumption, high latency |
| Existing SNN methods | 92.5 | 420 | 15 | Lower power consumption, moderate real-time performance |
| Proposed neuromorphic system | 99.1 | <200 | 9.9 | Highest accuracy, lowest power consumption, fastest response |

automotive safety systems, offering a sustainable solution with high efficiency and effectiveness for real-time driver distraction detection, and ultimately leading to safer and more energy-efficient driving experience.

## 5 Conclusion

To address the high energy consumption of traditional embedded driver distraction detection systems, a framework based on brain-inspired computing was proposed to improve energy efficiency. By combining DVS, SNN, and dissipative wave dynamics, the system achieved both high accuracy and low power consumption. The proposed neuromorphic framework achieved over 99% distraction detection accuracy while reducing power consumption to under 200 mW, resulting in energy savings of more than 85% compared with the GPU-CNN system. These results demonstrate the potential of event-driven neuromorphic computing framework to support real-time communication with ADAS modules and enable energy-efficient closed-loop vehicle control. Future work will focus on real-world road validation and integration with multi-modal sensing and in-vehicle control units.

Although the proposed framework performs well in simulation and semi-real vehicle environments, it still has certain limitations. Firstly, the experimental environment is mainly based on simulated driving, and there is still a lack of verification in real road environments and long-term use conditions. Secondly, the system mainly focuses on visual and basic sensor data, without fully considering the integration of multi-modal physiological signals from drivers. Thirdly, the hardware implementation relies on a specific brain-like chip platform, and its versatility and scalability still need further evaluation. Future work will be carried out in the following aspects: (1) Conduct real-vehicle road experiments to verify the robustness of the system in complex and dynamic traffic environments; (2) Introduce multi-modal data (such as heart rate, eye movement, and voice interaction) to improve the comprehensiveness of distraction detection; (3) Deeply integrate brain-like chips and vehicle control units to optimize hardware versatility and the feasibility of large-scale deployment.

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*Cite this paper as:*

Song, W. (2026). Event-Driven Neuromorphic Architecture for Energy-Efficient Driver Distraction Detection, *International Journal of Computers Communications & Control*, 21(4), 7221, 2026.
https://doi.org/10.15837/ijccc.2026.4.7221