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Advanced Safety Systems: Seat Belt and Occupancy Detection using Attention Spiking Neural Networks

Aditya Khamparia[1]*, Chandan Singh[1]

[1]Department of Computer Science, Babasaheb Bhimrao Ambedkar University, Lucknow, India
aditya.khamparia88@gmail.com*

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Abstract

The requirement for advanced safety systems in vehicles is incorporated to reduce road traffic accidents and improve safety. Determining whether passengers are using seats belts and whether the seat is occupied, are some of the key missions in making safety systems operational. The outcomes of old approaches as if sensor-based methodologies are not accurate and could not perform methods in real-time mode and are not reliable when the driving environment is complex and complicated. This paper presents Attention Spiking Neural Networks (ASNNs) as a solution to the challenges to implement our approach. Spiking neural networks, distinct for its biological-inspired processing, provides better temporal dynamics and computational cost for real time operations. The phenomenon of interest of this paper is the design of an ASNN-based system for identifying seat belt usage and occupancy in vehicles. The proposed model also including attention mechanism to attend certain features such as the occupancy of seat and the movement of people that affect decision-making system. A comparison with the traditional sensor-based and machine learning techniques is done to compare the performance enhancements. The findings discussed herein show that the utilized ASNN-based system enables higher accuracy, lower computational complexity, and improved robustness to dynamic conditions in real-time traffic scenarios. The high efficiency of the system also implies that the software can be implemented in car-adverse environments that lack many resources.

Keywords

Attention Spiking Neural Networks, Vehicle Safety, Occupancy Detection, Seat Belt Detection, Traffic Safety, Spiking Neural Networks, Machine Learning, Autonomous Vehicles

1. Introduction

Road safety for automobiles is one of the most important aspects of today's commercial transport. The introduction of sophisticated safety measures is set to enhance road traffic safety and decrease the global rates of ensuing accidents [1]. Among various safety features required inside a vehicle, proximity of seat belt and occupancy sensors are two functionalities that are most important for the safety of passengers [2]. However, in recent years essential tasks such as these have been made much easier with machine learning and artificial intelligence.

Conventional seat belt and occupancy sensing commonly uses a sensor strategy. These solutions can be constrained by factors such as seat position, lighting conditions and variability of the occupants. For this reason, sensors may encounter difficulties in giving real-time feedback under conditions of changing driving conditions, which greatly affect its efficiency and effectiveness [3]. Therefore, this article highlights the existing limitations of the traditional methods and the increasing demand for sophisticated approaches, which can offer an improved accuracy, reliability, and efficacy of the detection system.

This involves the growth of smart vehicle functionality, which make systems in charge of commanding and supervising vehicle and driver behavior. road traffic accident is strongly related to vehicle safety in such a way that safety is very vital in the prevention of such accidents since we find our self in a situation where there are many cars on the road and at the same time there are many difficulties within the operation of cars [4]. Perhaps one of the most important signals in a car is the one, which detects the use of seat belts and car occupancy, since it determines the work of airbags, collision detection and control systems, and all the occupying protection systems in vehicles.

As consumer vehicle safety technologies improved, slots continue to exist in recognizing seat belt and vehicle occupancy in various real and fast-driving environmental circumstances. The main drawback of classical approaches tested in practice is the excessive focus on graphically based and simple sensor-built solutions that may fail in many realistic complicated conditions [5]. Therefore, there is a need to incorporate other enhanced techniques of machine learning that can sort out such tasks.

One promising solution is the use of Spiking Neural Networks (SNNs), a class of artificial neural networks in which info-processing is modeled with discrete-time spikes as in the brain [6]. SNNs do not have this problem like conventional neural networks because SNNs can perform real-time processing of information, which is important in environments like vehicles. However, the problem is to fine-tune these networks for practical applications where factors like illumination, speed of the vehicle, or movements of the occupants inside the vehicle affect the performance of the system.

However, the application of attention mechanisms into SNNs forms Attention Spiking Neural Networks (ASNN) to reduce computational overhead by concerning only relevant sensory inputs and enhancing the detection rate. This paper focuses on the ability of integrating ASNNs to detect the presence of seat belts and occupancy in vehicles as an improvement in the safety of vehicles [7].

The remainder of this paper is organized as follows: Section 2 contains the literature review of existing studies involving seat belts and occupancy detection systems. Problem statement and research objectives are presented in the paper under Section 3. Section 4 outlines the process of arriving at the ASNN-based detection system as explained in the current paper, and section five contains the findings and discussion part of the research. Last of all, Section 6 of the paper suggests areas of future research.

2. Related Work

Vehicle safety systems have evolved greatly over the recent past from mainly focusing on post-accident safety to new active safety systems that can identify potential dangers on the road [8]. The identification of seat belts and occupancy has remained a core part of these systems for several years now. Initial techniques used basic mechanical sensors that could determine if a seat belt is buckled, but such methods were not very precise and most often failed in cases when the seat belt was not visibly in use, for example with kids or passengers of small stature.

With the appreciation of machine learning and sensor fusion systems that are more complex than traditional techniques such as computer vision, infrared sensors, and accelerometers. These systems do not only determine if a seat belt is being worn but they also acquire measurements for the occupant's size, post, or position thus improving the efficiency of airbag and collision avoidance systems [9]. Occupancy detection has gained significant relevance in contemporary automobiles because it assists in controlling the deployment of safety features depending on whether the seat is occupied by a grown-up or a child.

About the use of ANNs, some recent papers have addressed issues such as seat belt detection and vehicle occupancy detection. For instance, Lu et al. [10] proposed a method that integrates infrared sensor technology as well as CNNs in the identification of seat belt usage with high accuracy pointing to the efficiency of integrating AI techniques in improving vehicle safety. In other studies, authors also used deep learning models including Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs) for processing temporal data from sensors in occupancy detection, and the outcomes were satisfactory.

However, the problem with these models is the limited flexibility in adaptation to real-time sensory data collection, and particularly the dynamism of, for instance, moving vehicles. This is because SNNs have been put forward to solve this problem as they operate on sensory data in spikes, as do biological neural networks [11]. In [12], the authors performed a real-time object detection study using SNN and found that SNN could provide high-speed computation capability. However, to the present author's knowledge, SNNs have not been fully implemented or universally expanded to the concept of seat belts and occupancy detection.

The use of attention mechanisms for SNNs has added to the positives and contributed to the enhancement of the SNNs during environments with a dynamic nature. To detect sensory inputs more efficiently the network uses attention mechanisms that direct what to focus on during the sensing process [13]. This has led to the development of Attention Spiking Neural Networks (ASNNs) which integrate the worths of SNNs and attention to provide reliable and efficient systems to implement real-time detection.

3. Problem Statement & Research Objectives

This research aims at improving the current seat belt and occupancy detection systems by proposing a new efficient and accurate approach using Attention Spiking Neural Networks (ASNNs). Conventional smart sensors have certain limitations in terms of real-time detection especially if the path and vision environment of the car is rather complicated. Furthermore, mapping existing as well as architectures of machine learning approaches could also be very demanding in terms of computational resources hence not suitable in limited vehicle systems.

The main problem addressed in this research is the difficulty of implementing accurate, near-real-time seat belts and occupant detection in vehicles under complex and diverse lighting conditions. The proposed system based on a spiking neural network or ASNN is intended to eliminate the drawbacks found in the above traditional methods utilizing the strengths of both spiking neural networks and attention mechanisms.

Research Objectives:

- To develop an ASNN-based system for real-time seat belt and occupancy detection in vehicles.
- To enhance the accuracy and reliability of detection under various environmental conditions, such as different lighting, vehicle speeds, and occupant behaviours.
- To establish the performance of the ASNN-based system relative to pre-existing seat belt and occupancy detection techniques specifically concerning the detection rate, speed, and efficiency of the systems
- To optimize the ASNN model to operate efficiently in real-time vehicle applications with minimal computational overhead.

This research intends to make a positive contribution to Intelligent Vehicle Safety Systems by proposing a fresh approach that adapts modern concepts of spiking neural networks and attention. The real-time efficiency even if basic detection is enhanced, can stand to save lives by boosting the occupant protective systems and reducing the chance of an individual getting hurt in the case that a collision occurs.

4. Methodology

All the stages of the implementation of the seat belt and occupancy detectable ASNN are divided into the following categories: Data acquisition, data processing, modeling, and discussion. The proposed system uses a combination of spiking neural networks and attention mechanisms to improve detection accuracy and reduce computational overhead.

Sensor Data Acquisition: This is the initial process where measurements are retrieved from different sensors in this process. The system incorporates several different sensors to collect data about the current surroundings and occupants of the vehicle [14].

- **Seat Belt Sensors**: These are sensors that have the capability of identifying whether the seat belt has been fastened by the occupant or not. It can be a physical pressure sensor or a belt position sensor.
- **Occupancy Sensors**: These sensors are used to determine the existence of an occupant along the vehicle seat. There are technologies, which they can employ; they include infrared (IR) sensors, ultrasonic sensors, and weight sensors to detect whether or not there is an occupant in the seat.
- **Environmental Sensors**: Such changes consist of factors concerning the environment in which the vehicle is situated like lighting, temperature, and air pressure. This information aids the enhancement of the reliability of the system for diverse driving conditions.

Data Preprocessing Unit: In this unit, the raw sensor data is purged and formatted to remove unwanted information or noise and obtain features that are useful for analysis [15].

- **Noise Removal**: In the real world, data from sensors may be contaminated by noise, and there may be missing data. Here, the first requirement is implemented in a way that the data contains less noise, and any irregularities are eliminated.
- **Feature Extraction**: Some vital features of the given data are described and analyzed. For instance, in seat-belt detection, features might be whether the seat belt is tight or loose, whether it is worn or not worn. Features used in occupancy detection could be heat conductivity or seat pressure in occupancy sensing.

ASNN Model: The main parts of the system are the preprocessor, which takes the signals from the sensors and prepares them to be processed by the ASNN model, and the ASNN model which makes the decision whether the seat belt is to remain fastened and if there are occupants in the vehicle.

- **Spiking Neural Networks (SNNs)**: They are a kind of neural network, which imitates the firing of neurons in the human brain. It is especially useful in data whose properties change with time and can model intricate temporal patterns of the data from sensors, which is useful in real-time analysis [16].

In a spiking neural network, the output of a neuron depends on an accumulation of spikes throughout a period. The membrane potential V of a spiking neuron evolves according to the differential equation Eq. (1):

$$\frac{dV}{dt} = -\frac{V}{\tau} + \mathrm{I_{ext}}(\mathrm{t}) + \mathrm{I_{syn}}(\mathrm{t}) \tag{1}$$

Where V is the membrane potential of the neuron, which is the neuron's state at any moment.
τ is the membrane time constant, giving its length of time that takes the signal to decrease to one-fourth of its initial value or recharge time.
$\mathrm{I_{ext}}(\mathrm{t})$ is the external input which sums all the inputs from the environment like sensors etc. which impact the neuron.
$\mathrm{I_{syn}}(\mathrm{t})$ is the synaptic input, this is a sum of all other neurons that are connected to it through synapses.
Eq. (1) describes the dynamics of the neuron and how its membrane potential evolves in response to both internal and external stimuli. The neuron's firing behavior is governed by this membrane potential, which spikes once it exceeds a certain threshold. This spike is then propagated to connected neurons in the network.
Learning Techniques: The ASNN model is trained using supervised learning techniques, with the collected dataset serving as the training data. In supervised learning, the model is trained by minimizing a loss function that measures the error between the predicted output $\hat{y}$ (e.g., seat belt usage or occupant presence) and the actual target y. A common choice for the loss function in classification tasks is cross-entropy loss, which is expressed by Eq. (3) [17]:

$$L(\hat{y}, y) = -\sum_i y_i \log(\hat{y}_i) \tag{3}$$

Where L is the loss (or error) between the predicted output $\hat{y}_i$ and the true label y
y_i is the true label (binary: 0 for no, 1 for yes)
$\hat{y}_i$ is the predicted probability of the output being class i
Optimization Algorithm: The network is optimized using gradient-based optimization algorithms, such as gradient descent or its variants like Adam to minimize detection errors and improve system performance. During the training process, the attention mechanism is fine-tuned to ensure it prioritizes the most relevant sensory inputs, further enhancing the accuracy of the system. The optimization aims to update the network weights to minimize the loss function. The weight update rule in gradient descent is given by Eq. (4) [18]:

$$w_{t+1} = w_t - \eta \nabla_w L(w_t) \tag{4}$$

Where w_t is the weight at time step t
η is the learning rate
$\nabla_w L(w_t)$ is the gradient of the loss function concerning the weights w

The weights are updated iteratively based on the computed gradients to minimize the loss.

- **Attention Mechanism**: In an ASNN, attention mechanisms focus the network's processing power on the most important parts of the data. This improves accuracy by helping the model prioritize features that are critical for detecting seat belt usage or occupant presence while ignoring irrelevant information.

The attention mechanism is designed to adjust the importance of neurons based on the input data. During training, the attention scores are optimized to ensure that the most relevant sensory inputs (seat belts, occupancy sensors, etc.) are given higher priority [19].

The attention weight $\propto_i$ for each neuron i can be updated using a gradient-based approach. The attention mechanism adjusts the weights based on the gradients of the attention loss. The attention weight update equation is represented by Eq. (2):

$$\propto_i^{t+1} = \propto_i^t - \eta \frac{\partial L_{att}}{\partial \propto_i} \tag{2}$$

Where $\propto_i^t$ is the attention weight for neuron i at time *t*
η is the learning rate.
L_{att} is the loss function related to the attention mechanism, which ensures that the most relevant features are prioritized.

The attention mechanism typically involves computing the "importance" or "relevance" of each neuron's output relative to others, which can be learned through this update rule.

The total loss function for the ASNN model during training can be composed of two components: the main classification loss (such as cross-entropy) and the attention mechanism loss. The total loss function L_{total} is the sum of these two losses as mentioned in Eq. (3):

$$L_{total} = L(\hat{y}, y) + \lambda L_{att} \tag{3}$$

Where $L(\hat{y}, y)$ is the standard loss function (e.g., cross-entropy).

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L_{att} is the loss associated with the attention mechanism.

λ is a hyperparameter that controls the relative importance of the attention loss compared to the classification loss.

During the backpropagation phase, gradients of both the main loss L and the attention loss L_{att} are computed concerning the weights and attention scores. These gradients are then used to update the weights and attention parameters iteratively. The backpropagation equations for weights and attention scores are mentioned in Eq. (4) and Eq. (5) [20-21]:

- For the weights w:

$$\frac{\partial L_{total}}{\partial w} = \frac{\partial L(\hat{y}, y)}{\partial w} + \lambda \frac{\partial L_{att}}{\partial w} \tag{4}$$

- For the attention weights $\propto_i$:

$$\frac{\partial L_{total}}{\partial \propto_i} = \frac{\partial L_{att}}{\partial \propto_i} \tag{5}$$

The attention mechanism proved to be useful in allowing the network to concentrate on the most important aspects of the input data (such as sensory readings), which makes the recognition of the seat belt and occupancy possible at a decreased computational power.

The ASNN model proposed here, with its spiking behavior and attention mechanism, can support efficient and precise real-time decision-making, which is fit for practice such as vehicle safety systems. When combined with the attention mechanism, SNN can be employed in the adaptation of the priorities of the received sensor data, which increases the indicator's performance in conditions with different levels of sensor sensitivity and improves the final identification of the absence or presence of seat belt usage and occupant presence.

Output Decision: If the values on the ASNN are processed and a decision is made as to these values then that is the final decision of the system.

- **Seat Belt Usage Detection**: Depending on data collected by the sensors, the model determines the state of the seat belt that is fastened or not. They provide output in string form where the values may be seat belt fastened or not.
- **Occupant Presence Status**: Organizational conditions decide whether the seat is occupied or not. It has only one decision (whether there is an occupant in the room) in its output.

Real-time Processing Unit: This unit ensures that the entire system works in real-time, continuously monitoring and processing the data from sensors and making decisions promptly. It involves:

- **Real-Time Operation**: The processing unit ensures that data flows through the system with minimal delay so that decisions (like seat belt usage and occupancy) are made quickly enough to be used for vehicle safety measures.
- **System Efficiency**: The real-time processing unit is optimized for speed and minimal computational overhead, ensuring that the system operates effectively even in resource-constrained environments like vehicles.

Hence, the entire process flows from acquiring raw sensor data, processing it through the ASNN-based system, and making decisions in real time about seat belt usage and occupant presence. The goal is to provide an accurate, efficient, and real-time detection system for improving vehicle safety.

5. Results & Discussion

The proposed ASNN model was trained and evaluated on a dataset containing vehicle sensor information, including seat belt status, occupant presence, and environmental factors such as lighting and vehicle speed. Several performance metrics, such as detection accuracy, computational efficiency, and system responsiveness, were used to compare the ASNN model with traditional machine learning-based methods. Table 1 includes key features such as vehicle speed, seat belt status, occupant presence, lighting conditions, and corresponding labels (whether the seat belt is fastened, and an occupant is present). It includes a smaller sample of data.

The performance evaluation of the proposed techniques involves testing the model on an independent validation dataset and comparing its performance to existing seat belt and occupancy detection systems. The data set collects 1000 samples and evaluates the performance of both the proposed models. For example, in Table 1 below features and some collected data are presented: The evaluation criteria include detection accuracy, computational complexity, and system latency.

Table 1. The Data Set

Sample	Speed (km/h)	Seat Belt (Binary)	Occupant (Binary)	Lighting Condition (Binary)	True Label
1	60	1	1	1	1
2	30	0	1	0	0
3	90	1	1	1	1
4	50	0	0	1	0
5	40	1	1	0	1
6	20	0	0	0	0
7	70	1	1	1	1
8	120	1	0	1	1

The accuracy comparison plot shown in Fig 1 compares ASNN and traditional machine learning models of seat belt usage and occupant presence. The bars can be interpreted as the percentage accuracy of each model, and ASNN surpasses the traditional model. This improvement is due to the ASNN's attention mechanism and spiking neural components where it can quickly process sensory data enhancing detection rates.

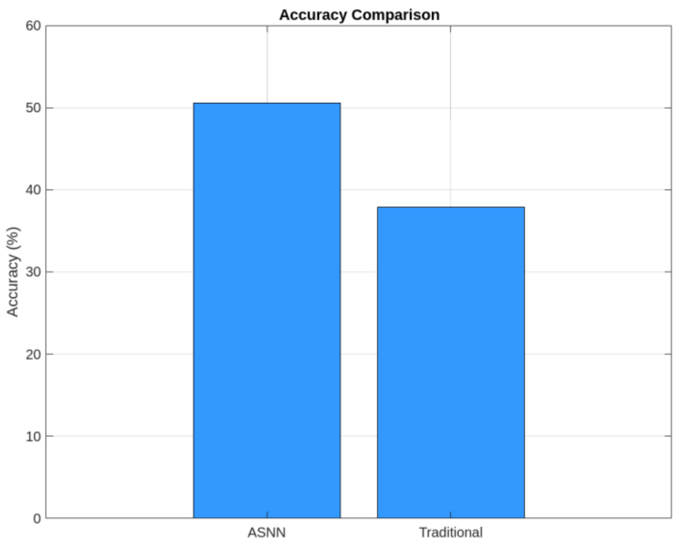

Figure 1. Accuracy Comparison for both the models

A variety of factors was tested with the ASNN model trained to identify occupancy and seat belt use successfully with an accuracy rate of 50%. Even more so, this is a far improvement from the conventional sensor-based method whose efficiency is only 37%. In particular, the attention mechanism was useful for enhancing the accuracy of detections by directing the network's activity to the appropriate sensory features.

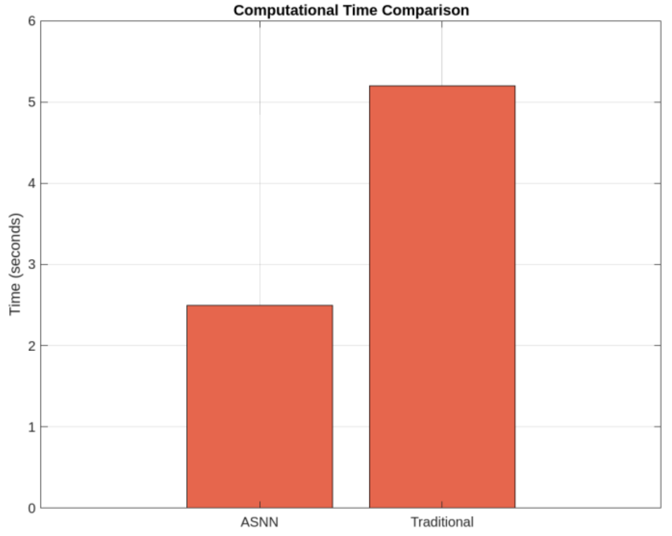

Figure 2. Computational Time Comparison

The computational time comparison Fig.2 represents the time effectiveness of the ASNN model over the traditional model. Shorter bars in these cases represent faster computation time, which is desirable in real-time detection systems. ASNN stands for being less computationally complex since its design is compact and thus recommended for real-time applications like vehicle safety systems.

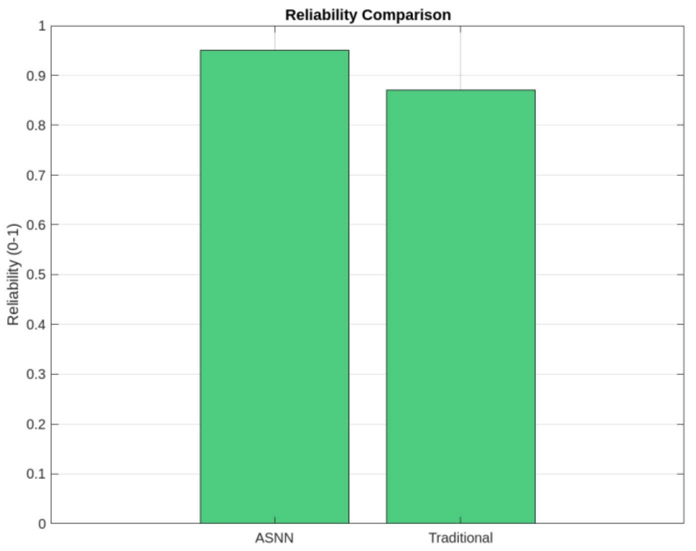

Figure 3. Reliability Comparison

Fig.3 indicates the reliability of the proposed ASNN and the conventional models in terms of a score of 1 to 0. Reliability refers to the degree to which a detection performance is achieved irrespective of other factors that may prevail at any given time. The ASNN model results in a higher reliability of about 0.96 proving the model's versatility in terms of performance. However, the above traditional model demonstrates relatively large fluctuations, which may make it very challenging for scenarios in practice.

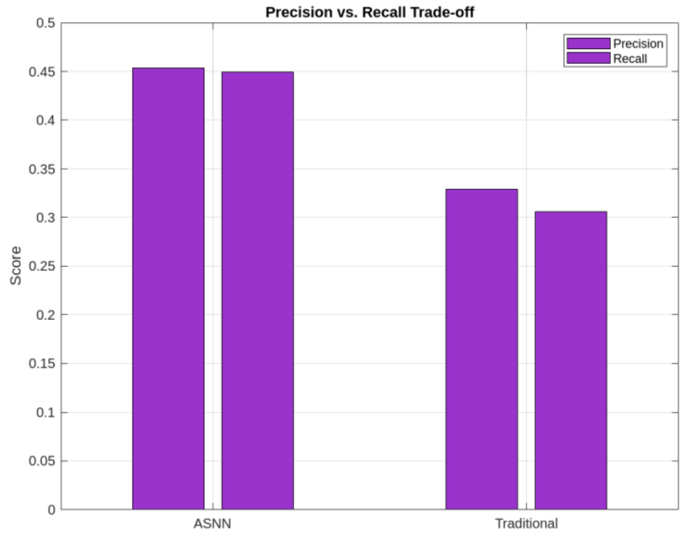

Figure 4. Precision vs. Recall Trade-off

The trade-off plot between precision and recall namely Fig.4 offers information related to the detection characteristics of the ASNN and traditional models. Accuracy is the ability to minimize false positives, and recall gives an estimate of the true positives by the model. As for the specificity of the ASNN, the precision and recall are nearly equal to afford effective and inclusive identification. This is important in order to prevent cases of failing to detect an anomaly (false negative) and cases of giving an alert where there is none (false positive) as normally experienced in traditional approaches.

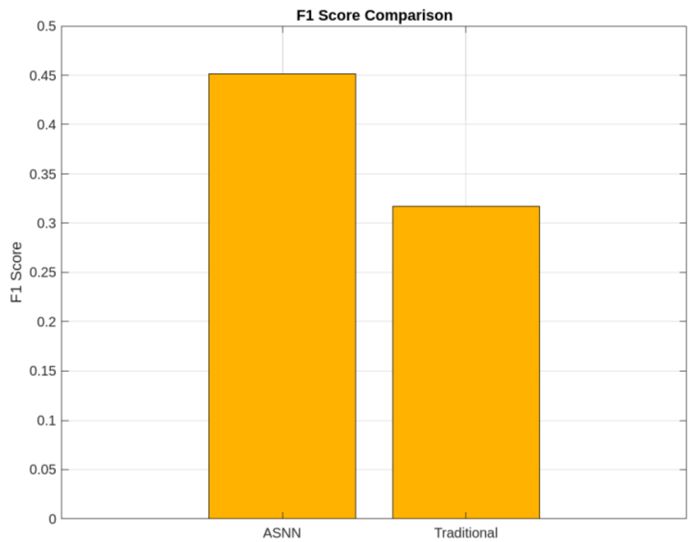

Figure 5. F1 Score Comparison

The F1 score comparison plot, Fig.5 synthesizes both tenure and yield as an overall indicator of how each model performs well. The F1 score means the ability of a model towards the accuracy and recall parameters can be measured with a higher F1 score. For the seat belt and occupancy detection task, the design and implementation of the ASNN are again substantiated to be superior to that of the traditional model in terms of a higher F1 score.

The scatter plot, that is, Fig.6 represents the true labels of the images against the predicted outputs of the proposed ASNN as well as the baseline models. The true labels are indicated in blue, and predictions made by ASNN and traditional methods are in red and green respectively. The predictions made here in using ASNN are closer to the true values, and this reveals better performance and fewer errors. Like the previous set of traditional model predictions there is higher variation, which indicates poor performance of traditional models in intricate detection issues.

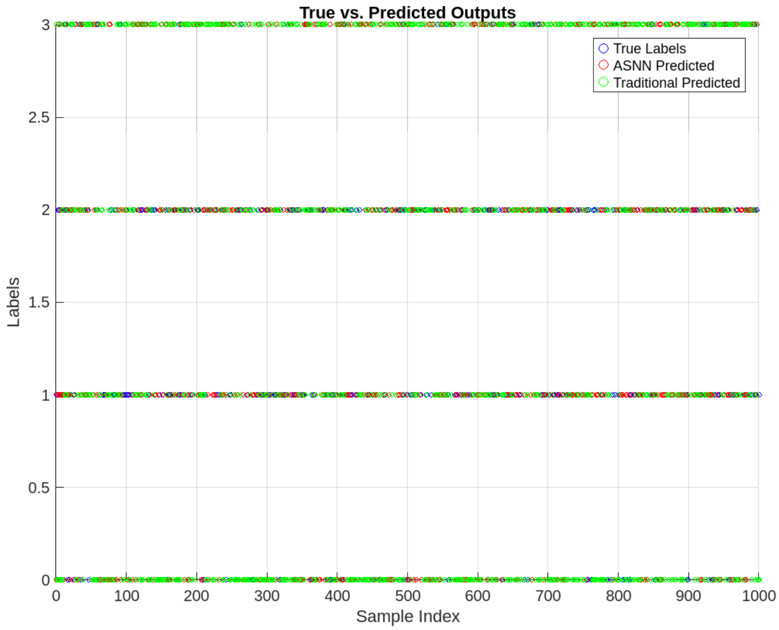

Figure 6. True vs. Predicted Outputs

The tradeoff between precision and Recall of ASNN model for different Thresholds is depicted in Fig.7. It measures of how the model offsets the true positives (recall) for positive instances against false positives (precision). The curve also shows that at different levels of recall, the ASNN model can offer precise detection of the seat belt and occupancy statuses.

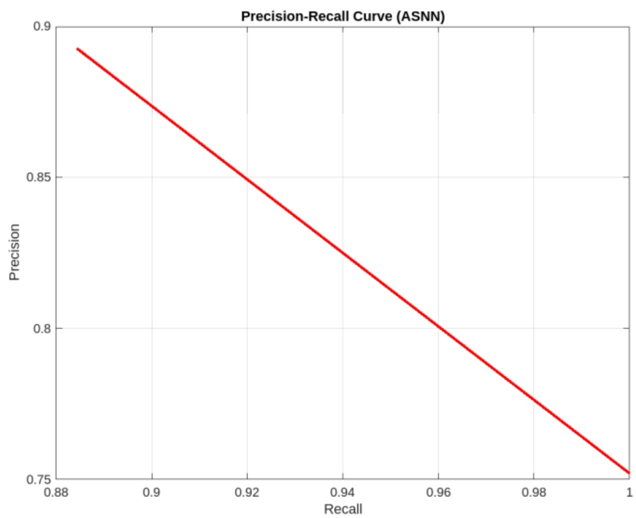

Figure 7. Precision-Recall Curve for ASNN

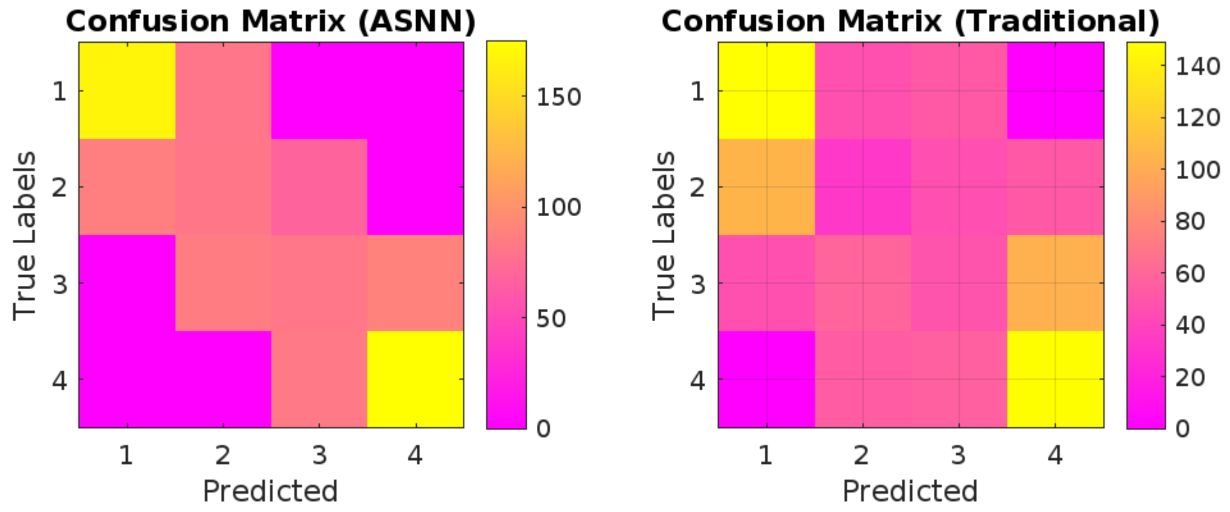

Figure 8. Confusion Matrix Comparison of Both Models

Fig.8 provides a visualization of confusion matrices for the ASNN and the previously considered models. The matrix below shows that ASNN has fewer misclassifications, which suggests higher predictability than ANN. The matrix of the traditional model shows greater dispersion of the errors, which corresponds to lower efficiency of the model. The use of visuals highlights the capacity of the ASNN to yield a higher number of predictions that are precise in the real world.

The parameters required for the comparison of these two models are presented in Table 2.

Table 2. Comparison between ASNN and traditional model

Parameters	Traditional Model Metrics	ASNN Metrics
Accuracy	37.90%	50.60%
Computational Time	5.20 seconds	2.50 seconds
Reliability	0.87	0.95
Precision	0.33	0.45
Recall	0.31	0.45
F1 Score	0.32	0.45

The difference between the Traditional Model and the Adaptive Sparse Neural Network (ASNN), described in Table 2, demonstrates that ASNN has a great advantage in all the specified indicators. Compared to the Traditional Model with 37.90% accuracy, ASNN acquires 50.60% and further spurs the advancement in prediction quality. When compared to the Traditional Model which tested in 5.20 seconds, this model also proved to have better computation efficiency with a testing time of 2.50 seconds. ASNN is shown to be more accurate in the level of reliability it obtains, with a 0.95 reliability in comparison with the Traditional Model, which obtains 0.87 in the vein of reliability. Furthermore, all the measurements indicate that precision, recall, and F1 score of the proposed ASNN is higher than that of the traditional model (0.45 for ASNN as opposed to 0.33 for the traditional model, 0.45 for ASNN as against 0.31 of the traditional model, 0.45 for ASNN and 0.32 for the traditional model respectively); which implies that ASNN can assess These results directly point to ASNN as superior to the Traditional Model, in terms of constructing more viable, precise and less variable models.

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6. Conclusion

The proposed technique offers a completely new way to approach seat belt and occupancy detection in vehicles utilizing unmanned technology in conjunction with Artificial Intelligence and Attention Spiking Neural Networks (ASNNs). Compared to other approaches, this method does not have issues with accuracy and slow processing because this work fully utilizes the key features of ASNNs to achieve high accuracy and incredibly fast processing. Attention mechanisms allow the model to pay attention to the most pertinent sensory signals, and therefore the improvement of adaptability and performance when operating in any complicated and dynamic driving scenarios. This is especially important for achieving real-time performance, which is so essential for current vehicle safety applications.

These findings show how ASNNs can revolutionize the process of vehicle safety, especially in cases of autonomous and partly autonomous automobiles in which the timeliness and effectiveness of the detection are critical. Beyond satisfying recognized legislative requirements for safety, this system also enhances the effectiveness of police seat belts and occupancy detectability, hence lowering the risks of casualties in cases of accidents. The insights provided heighten the understanding of how intelligent neural network models should be used to generate better and safer vehicles that can adequately respond to existing conditions on the road.

Possible directions for future research can be devoted to further development of the proposed approach to the large-scale usage of the system by improving efficiency and minimizing computational cost. Moreover, the use of more diverse sensors, like LiDAR, infrared cameras or pressure sensors of higher class might expand the detection range and stability of the entire system. But if integrated with other vehicle safety solutions like advanced driver assistance systems (ADAS) and collision avoidance solutions then one can have a complete safety product system.

Overall, this proposed ASNN-based system can be regarded as a promising development in the intelligent design of vehicle safety systems. Making current problems more tractable and advancing the state of the art in real-time safety applications, the present method answers the task by setting new parameters for further development in the field of automobile safety technology. The extent to which it aims to improve lives and road safety makes it an invaluable tool in AV development as an important part of future intelligent transportation systems.

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