Article

A Lightweight In-Vehicle Alcohol Detection using Smart Sensing and Supervised Learning

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Abstract: According to the risk investigations of being involved in an accident, alcohol-impaired driving is one of the major causes of motor-vehicles accidents. Preventing highly intoxicated persons from driving would potentially save many lives. This paper proposes a lightweight in-vehicle alcohol detection that processes the data generated from 6-alcohol sensors (MQ-3 Alcohol Sensors) using an optimizable shallow neural network (O-SNN). The experimental evaluation results exhibit a high-performance detection system scoring a 99.8% of detection accuracy with a very short inferencing delay of 2.22 seconds. Hence, the proposed model can be efficiently deployed and used to discover in-vehicle alcohol with high accuracy and low inference overhead as a part of the driver alcohol detection system for safety (DADSS) system aiming at massive deployment of alcohol sensing systems that could potentially save thousands of lives annually.

Keywords: Alcohol Detection; Smart Sensing; MQ-3 Alcohol Sensors; Supervised Learning; Neural Networks.

1. Introduction

Alcohol is a harmful and intoxicating substance that can lead to addiction. According to the World Health Organization (WHO) [1], every year, 3 million people die as a result of alcohol consumption (Figure 1), and millions more suffer from impairments and poor health. Overall, harmful alcohol use accounts for 5.1 percent of the global disease burden. More precisely, harmful alcohol use accounts for 7.1 percent and 2.2 percent of the worldwide burden of illness, respectively, for males and females. Alcohol is the main cause of early death and disability in people aged 15 to 49 years old, accounting for 10 percent of all deaths in this age group. Alcohol-related deaths and hospitalization are more common in disadvantaged and especially vulnerable populations.

In addition, alcohol consumption can lead to driver impairment, which is a major cause of car accidents around the world [1]. Indeed, drinking alcohol before (or even while) driving decreases several of a driver's functional abilities, including tracking power, vision, concentration, reaction time, and proper speed control, all of which increase the risk of a crash [2]. According to [3], Drivers with a Blood Alcohol Concentration (BAC) of 1.5 g/L are judged to be 20 times more dangerous than sober drivers.

Moreover, driving under the influence of alcohol is frequently related to not wearing seat belts, which increases the risk of injury in most cases, as reported in [4]. For instance, a study published in 2014 revealed that Alcohol was involved in around 25 percent of all traffic fatalities in Europe [5].

Between 1995 and 1997, about 40 percent of drivers involved in road accidents in Greece were found to have consumed alcohol [6]. In the United States, alcohol-related car

1 link: https://www.who.int/health-topics/alcohol

check for updates

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Figure 1. Some statistics and critical facts about the dramatic consequences of alcohol consumption.

crashes killed more than 10K people in 2019, accounting for almost 30 percent of all road fatalities [7].

To address this problem, a lot of research, both in industry and in the academy, has been done on smart systems that can identify this type of behavior and help avoid the corresponding risks. The research community has attempted to develop smart systems that may be integrated into modern vehicles [8] to recognize risky behavior and avoid accidents caused by alcohol consumption [9–15].

According to the survey article presented in [16], there exist mainly two categories of drivers behaviors detection techniques, namely:

1. Real-Time Techniques: These methods entail gathering and processing data about the driver's behavior continuously. [17]. The key advantage of these techniques is that they may detect incidents instantaneously, allowing timely decisions to be made and damages to be minimized. Some examples of these techniques are: Vehicle Mounted Cameras [18], Smartphones Built-In Sensors [19,20], Specialized Hardware/Sensors [21], Advanced Driver Assistance Systems (ADAS) [22], etc.
2. Non-Real-Time Techniques: These techniques use offline collected data related to drivers behaviors. They are generally more precise since they use more sophisticated materials and have more available time for computation and analysis. These techniques allow specialized governmental institutions to make future decisions and appropriate measurements for reducing possible risks and accidents. Some examples of these techniques are: Vehicle Mounted Cameras [23], In-Vehicle Data Recorders [24], Simulators [25], Questionnaires [26,27], etc. These techniques may also be used for detecting driving infractions and providing shreds of evidence against drivers when they are issued penalty notices.

In this work, we adopt an approach based on Artificial Intelligence (AI) techniques for analyzing data collected using MQ-3 sensors [28] in order to detect the presence of alcohol inside vehicles. The main characteristic of this type of sensors is that they have a high sensitivity to alcohol with good resistance to disturb gasoline, smoke, and vapor. The sensors are connected via ARM Cortex M4 Microcontroller [29]. The obtained data is stored as a CSV file containing 14,400 samples. The detection problem is then modeled as a supervised machine learning (ML) problem using shallow neural networks (SNN) [30].

The first step for our ML problem is the *preprocessing stage* which consists in importing the data from the CSV file. The second step is the *learning stage* during which the training and testing processes are performed. The next step is the *evaluation stage* which consists of validating our ML model by computing specific performance indicators. Our software module is then uploaded to the microcontroller unit. After this, the device may be installed inside the vehicle to be controlled for detecting alcohol presence. More details about the approach (illustrated in Figure 2) and the obtained results are presented in the next sections.

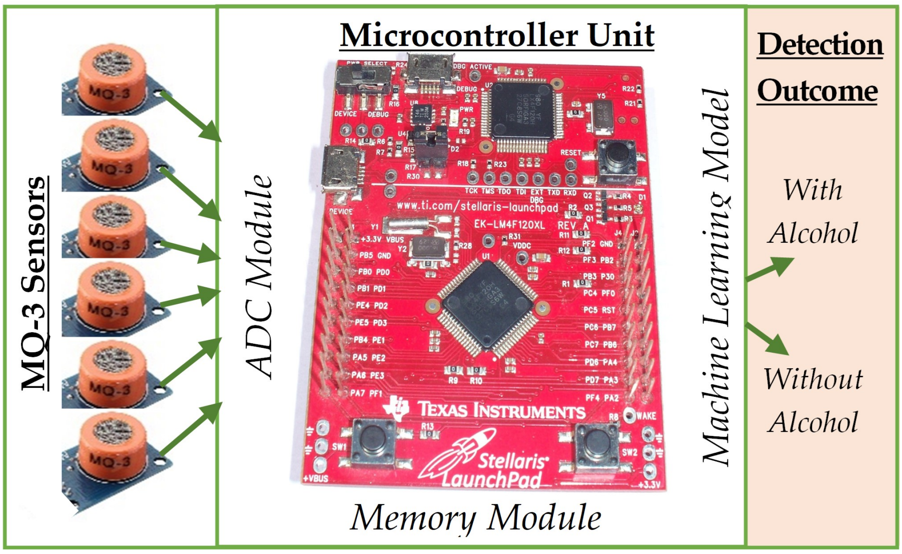

Figure 2. Illustration of the proposed approach.

1.1. Our Contributions

The major contributions of this paper are briefed as follows:

- We develop a new lightweight in-vehicle alcohol detection system using smart sensing and optimizable neural networks. A comprehensive architecture and description are demonstrated to provide the complete view of the computation process.
- We evaluate our intelligent model on dataset instances generated from sensory circuit achieving:
  - High-performance indicators of 99.8%, 99.7%, and 99.5% for accuracy, harmonic mean, and Kappa-index, respectively.
  - Low inferencing overhead equal to 2.22 seconds, making our system appropriate for real-time use in real-life conditions.

1.2. Paper Organization

The remaining part of the paper is outlined as follows. Section 2 reviews related works on similar approaches. In Section 3, the adopted in-vehicle alcohol detection model is presented in details. In Section 4, the main obtained results are presented. Finally, Section 5 concludes the paper.

2. Related work

As formerly stated in the introduction section, several research works in the literature concentrated on the study of alcohol detection for drivers using different instruments and

Table 1. Summary of related works.

Ref	Year	Detection System	Advantages	Limitations
[18]	2020	MQ-3 Alcohol Sensor + Raspberry Pi + Camera	Real-time detection + Blocking vehicle in case of risks	No experimental results provided
[31]	2018	MQ-3 Alcohol Sensor + Buzzer + Breathalyzer + LCD Display + Arduino Uno R3	Real-time detection + Blocking vehicle in case of risks	Maximum error of alcohol concentration estimation reached almost 31 %
[32]	2019	Breath Sensor + Smartphone + Cloud System	Portable solution using a smartphone for collecting data	Decisions are made remotely which may cause problems in case of connection failures
[33]	2018	MQ-3 Alcohol Sensor + STC12C5A60S2 Microcomputer + LCD Display + GU900E GPRS Module	Real-time detection + Triggering Alarms + Blocking Vehicle + Sending SMS to the dirver's Family in case of risks	No experimental results provided
[34]	2020	MQ-3 Alcohol Sensor + RPi Microprocessor + LCD Display + BMP-280 Pressure Sensor + IR-enabled Camera	Real-time detection + Triggering Alarms + Blocking Vehicle in case of risks	Experiences achieved for a very limited number of Drivers (only 3 ones)
[35]	2021	MQ-3 Alcohol Sensor + Machine Learning Techniques + Features Selection	Features Selection Using Genetic Algorithms	Not clear how alcohol detection is achieved once the ML model is constructed
[36]	2018	Machine Learning Techniques + Thayer's scale & NASA-TLX	Link between functional state/alcohol concenration and physiological/vehicle data	Results limited to young drivers
[37]	2019	Machine Learning Techniques + Controller Area Network (CAN) bus + OBD II adapter	Selection of most important features	General approach not not specific to alcohol detection problem
[38]	2021	MQ-3 Alcohol Sensor + Buzzer + Webcam + Raspberry Pi3 + Arduino Uno	Real-time detection + Non-intrusive + Appropriate for usage at night	Only few ML techniques were tested
[39]	2016	Physiological Signals + Case-Based Reasoning (CBR) + KNN algorithm	Using features of individual signals + Combining features from all signals	Only one ML technique was tested

techniques. Below, we consider only **10 Studies** related to this topic. The main findings of these works are summarized in Table 1.

The purpose of the study presented in [18] was to prevent drivers from starting their cars after drinking alcohol and not wearing their seat belts. This system uses an MQ-3 alcohol sensor, which is attached to the driver's seat belt. The Raspberry Pi compares the reading from the sensor unit to the allowable threshold value. The ignition locking mechanism prohibits the drivers from starting the car if they are inebriated. A Raspberry Pi

Camera is also installed on the system to identify the driver's presence. The paper's authors did not provide enough technical details about the adopted solution, and no experimental results were reported.

Similarly, the authors of [31] proposed a breath sample testing-based driver alcohol detection system. The suggested system was developed with the Arduino Compatible Compiler for LabVIEW (ACCL), enabling Arduino boards to be programmed using Labview. The system can analyze the amount of alcohol in a breath sample and control the ignition system's operation to prevent drunk driving. The maximum error of alcohol concentration estimation by the proposed solution reached almost 31 percent.

The authors of [32] proposed a portable alcohol detection system that includes a breath sensor unit, a smartphone that controls the sensor device and communicates various data, and a data cloud system. The detection system can be used to keep an eye on a driver from afar. Four different sensors make up the breath sensor unit. The first is a water vapor sensor, which determines whether the gas being applied is human breath. The others are semiconductor gas sensors that can detect hydrogen, acetaldehyde, and ethanol. The results of the driver's alcohol test are forwarded to a data cloud system for being analyzed automatically, which may cause problems in case of connection failures.

In [33], a vehicle-based alcohol detection system based on IoT technology is presented. The core controller used is a STC12C5A60S2 single-chip microcomputer with an MQ-3 alcohol sensor for collecting data on air alcohol concentration and a GU900E GPRS module for wireless connection. When the driver takes the wheel, the device performs an automated alcohol detection. When the drunk driving threshold is met, the system activates the relay, disables the car, activates the sound and light alert, utilizes the GU900E to execute base station location, and finally sends an SMS to the driver's family the GPS information. The paper's author failed to offer sufficient technical details about the chosen approach, and no experimental data were reported.

The authors of the study [34] developed a driver monitoring and assisting gadget that uses IoT sensors such as an alcohol sensor and an air pressure sensor to check for sobriety and machine learning techniques to capture micro-sleep and frequent yawns to detect drowsiness. The driver is instructed to blow into the mouthpiece when the device is turned on. The driver is authorized to turn the ignition on after a clean and proper blow. Following that, the device employs a camera to monitor the driver for signs of drowsiness constantly and alerts the drowsy driver via the vehicle's sound system or a buzzer. The experimental results reported in this work covered a very limited number of drivers (only three ones).

The authors of the article [35] proposed a non-invasive approach for detecting the presence of alcohol within a vehicle. The proposed technique relies on a set of MQ-3 alcohol sensors installed inside the car. A feature selection technique was carried out utilizing a genetic algorithm. The features obtained through this technique were utilized to build an SVM classification model that detects the presence of alcohol. The proposed methodology is described in detail. However, it is unclear how alcohol detection will be achieved once the ML model is constructed and whether it will be done in a real-time or a non-real-time fashion.

The goal of the study presented in [36] was to check how well different classifications and machine learning techniques could predict alcohol consumption and related functional states. The data was analyzed in 10-second time frames with no superposition or gaps. Two analyses employing classification and machine learning techniques were utilized to test both the algorithms' potential to detect alcohol use and functioning states. The main limitation is that the considered data was limited to young drivers.

The aim of the work presented in [37] was to conduct an empirical study for recognizing driving behavior and to compare the performance of common machine-learning techniques. According to the testing results, many sensor readings acquired from the CAN bus are either highly connected with one another or less relevant related to driving behavior identification. Compared to other approaches, ensemble tree-based algorithms such as

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Decision Trees and Random Forests outperform classic machine learning techniques. The authors adopted a general approach and did not specifically concentrate on the alcohol detection problem.

The authors of the paper [38] proposed a low-cost, non-intrusive real-time driver drowsiness detection system that was coupled with an alcohol detection system. The MQ-3 Sensor is used to detect alcohol in this system. Face detection is then performed using a webcam mounted on the car's dashboard. Drowsiness is recognized, and a warning is issued based on the threshold values of four extracted key face traits. Both systems are connected using a Raspberry Pi3 and an Arduino UNO. In this work, only a few ML Techniques were tested.

A case-based classification method for alcohol detection utilizing physiological indicators was proposed in [39]. Four physiological measures are used in a Case-based reasoning system to detect alcoholic state, including Skin Conductance, Finger Temperature, Respiration Rate, and Heart Rate Variability. The drivers participating in this study are divided into intoxicated and sober. In this work, only one ML technique was tested.

3. In-Vehicle Alcohol Detection Model

The goal of this model is to detect the presence of alcohol inside a vehicle. An intelligent, self-reliant model is proposed for this purpose. The proposed is composed of a hardware module for smart sensing and a software module for the intelligent supervised detection model.

3.1. The Hardware Module

This module is placed inside the vehicle and comprises six MQ-3 sensors and a memory unit connected via ARM Cortex M4 Microcontroller [40]. MQ-3 gas sensor has a high sensitivity to alcohol with good resistance to disturb gasoline, smoke, and vapor [41]. This sensor provides an analog resistive output based on alcohol concentration, and thus it's connected to ARM Cortex M4 Microcontroller via ADC (analog-to-digital convertor) unit. The memory unit is important to keep track of the readings calibrated through the six sensors to provide more comprehensive and accurate detectability of in-vehicle alcohol levels. The readings are captured through the ARM Cortex M4 Microcontroller using a small C language program written for the microcontroller to collect the readings of the six sensors. The hardware part of this model is illustrated in Figure 3. After several experiments, a large number of samples are collected and stored as a CSV file that contains 14,400 samples for the in-vehicle alcohol level experiments. These samples are distributed equally as 7,200 samples for in-vehicle with alcohol and 7,200 samples for in-vehicle without alcohol and finally deployed in a balanced dataset (IVA 2021) [42] to be used for further investigation and modeling.

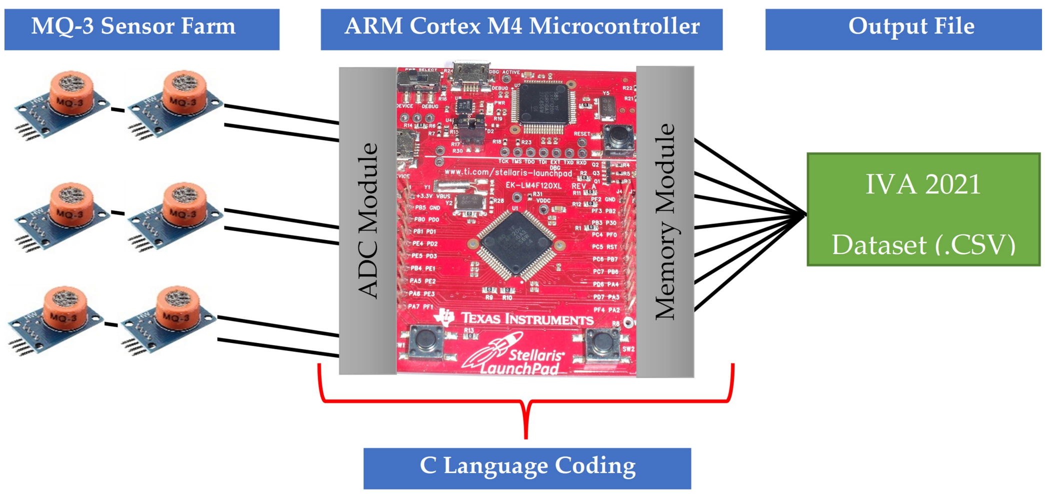

Figure 3. The hardware module for the In-Vehicle Alcohol Detection.

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3.2. The Software Module

This module is developed, coded, and uploaded to the microcontroller unit. The in-vehicle alcohol detection problem is modeled as a supervised machine learning problem developed as a classification system using shallow neural networks (SNN) [43] with its corresponding modules and algorithms. The complete framework for this system is illustrated in Figure 4. Initially, the collected dataset from the hardware module is preprocessed before being fed into the learning operations.

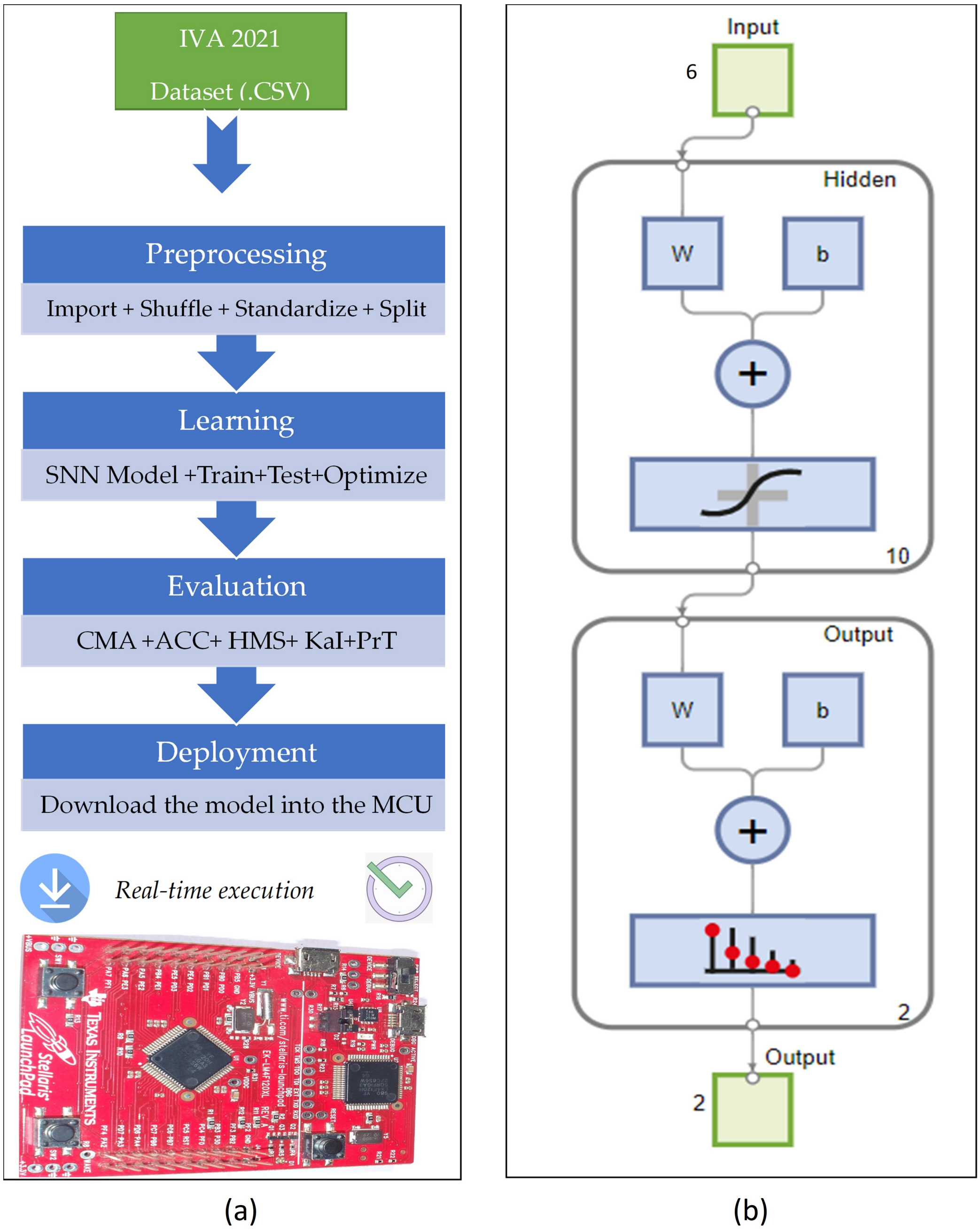

Figure 4. The software module for the In-Vehicle Alcohol Detection: (a) Top view model architecture (b) Structure of ONN model.

- The preprocessing stage starts by importing/localizing the data from the CSV file and making it local into the running model. Several data distortions are fixed at this stage, including removing duplication, handling empty records, fixing data inconsistencies, and others. Then, the data are randomly shuffled to ensure that the dataset has no

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specific sequencing or biasing. Also, to improve the classification process, all data records are standardized (uniformly scaled) using Z-score normalization [44] so that all features are equally important, which eases the supervised learning process of ML approaches. At this point, the data are ready to be fed through the learning phases, and hence the data is split into two subsets; the training dataset to train the model with 70% of the total number of samples and the testing dataset to validate the model effectiveness with the remaining 30% of the total number of samples. Furthermore, to ensure a highly effective validation process, we have used a 5-fold cross-validation [45] that provides five different combination splits of training and testing datasets. The final evaluation metrics are an overall average of the 5-fold cross-validation phases.

- The learning stage is the intelligent part of this module. At this stage, all training and testing (validation) processes are performed. The optimizable neural network (ONN) has been used to train, validate, and test the system. ONN is an optimizable learning model that makes use of different neural network architectures in order to pick up the best architecture that maximizes the performance of the model. In this system, our ONN operates several neural network architectures that have a number of fully connected layers ranging from 1-to-3. The number of neurons at every layer range from 1-to-100 and the number of Iteration is limited to 1000 iterations per model and 30 epochs of training. To sum up, Table 2 below shows the complete configurations and specifications of our proposed ONN. Note that, a shallow neural network (SNN) with 10 neurons at the hidden layer has been selected by the ONN as the optimal learning model for this dedicated problem. The architectural diagram for this optimizable SNN (O-SNN) is depicted in Figure 4 (b). The O-SNN receives 6 inputs (coming from the readings of the six MQ-3 sensors) and processes them at the hidden layer (processor layer) to produce one of the two decisions at the output layer (binary classifier).

Table 2. The brief of system modeling specifications and configurations.

Hyperparameter Search Range	
Number of fully connected layers	1 – to – 3 layers
Activation Functions:	ReLU, Tanh, Sigmoid, None
Standardize data:	Yes or No
Regularization strength (Lambda):	(6.9444e-10) – to – (6.9444)
Hidden layer size:	1 – to – 100
Learning Process Specifications	
Optimizer:	Bayesian optimization [46]
Acquisition function:	Expected improvement per second plus
Training algorithm	Scaled conjugate gradient [47]
Loss/Cost function	Cross entropy error
Feature Selection:	All features used in the model, No PCA
Data Division algorithm	Random Divide Algorithm.
Data distribution	70% training, 5% validation, 25% testing
Validation policy	5-fold cross-validation and 6-validation checks
Optimized Hyperparameters	
Number of fully connected layers	One layer with 10 neurons (O-SNN)
Activation function:	Sigmoid Function
Iteration limit:	30 iterations, 55 epochs, shuffle at every epoch
Regularization strength (Lambda):	1.0887e-09
Standardize data:	Yes (Z-score normalization)

- The evaluation stage is a crucial phase for any ML-based model to figure out whether the model will be the best solution for a given problem. In this research, we will evaluate our system in terms of five vital performance indicators [48] including the binary confusion matrix analysis, the predictive accuracy (%), the harmonic predictive

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		Predicted Class 0	Class 1
Actual	Class 0	True Positives (TP)	False Positives (FP)
	Class 1	False Negatives (FN)	True Negatives (TN)

Performance Indication Metrics

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}(\%) \qquad PrT = \frac{1000,000}{Prediction\ Speed}(\mu Sec)$$

$$HMS = \frac{2 \times \text{Precision x Recall}}{\text{Precision} + \text{Recal}} = \frac{2 \times TP}{2 \times TP + FP + FN}$$

$$\text{KaI} = \frac{\text{Accuracy} - \text{Pe}}{1 - \text{Pe}}(\%) \quad \text{where} \quad Pe = \frac{(TP + FP) \times (TP + FN) + (TN + FP) \times (TN + FN)}{(TP + TN + FP + FN)^2}$$

Figure 5. The five performance indicators used in the evaluation of our proposed system.

average (also called F-measure %), the predictive Kappa index (%), and the predictive time (seconds). The computational formulas for these metrics are shown in Figure 5.

- The deployment stage: once the system is efficiently developed and evaluated. If the developed system meets the requirements, then it can be deployed for online real-time functionality. It can be placed in-vehicle, equipped with a battery (rechargeable), and a small LCD display to read the output decision.

4. Results and Analysis

This paper proposes a computational intelligence model that requires high computational power at both the implementation and experimentation stages. The proposed in-vehicle alcohol detection has been developed and evaluated on a high-performance computing platform comprising fast processing units (Intel Core I.7, Generation-11, central processing unit-CPU) and parallel computation units (4 GB of addition graphical processing unit-GPU). Initially, the ONN model is implemented and operated toward the allocation of the optimal neural network model that maximizes the detection performance and minimizes the inferencing (prediction) delay.

Figure. 6 shows the model optimization using ONN trying the aforementioned hyperparameter search range (stated in Table 2) aiming to determine the best-point hyperparameters that score the minimum classification error within 30 iterations of the learning process. After 7-iterations only, the ONN model was able to reach the minimum classification error (MCE) that belongs to the best-point hyperparameters (optimized hyperparameters) from the hyperparameter search range as follows: the optimal model is the neural network (O-SNN) with one hidden layer composed of 10 neurons (6 features at the input layer and 2 classes at the output layer), the optimal activation function is the sigmoid function with data standardization option using Z-score normalization and regularization strength (λ= 1.0887e-09).

At this point and henceforth, the discussion will focus on the O-SNN model illustrated in Figure.4.(b) as it has been selected as the best neural network architecture to model our problem statement of in-vehicle alcohol detection with high-performance and least delay. For instance, Figure 7 traces the performance trajectories of the O-SNN in terms of cross-entropy loss (CEL) function [49] for 55-epochs of the learning process including training, validation, and testing trajectories. The target value of CEL is to reach the zero value, however, the best validation performance has been recorded after epoch 49 with CEL = 1.0 x 10-3. Along with the figure, the table attached to the figure summarizes the error values obtained for the training, validation, and testing dataset in terms of cross-entropy loss (CEL) and the minimum classification error (MCE). The table reveals the robustness of this model scoring low error rates for all subsets of the dataset (the training, validation, and testing).

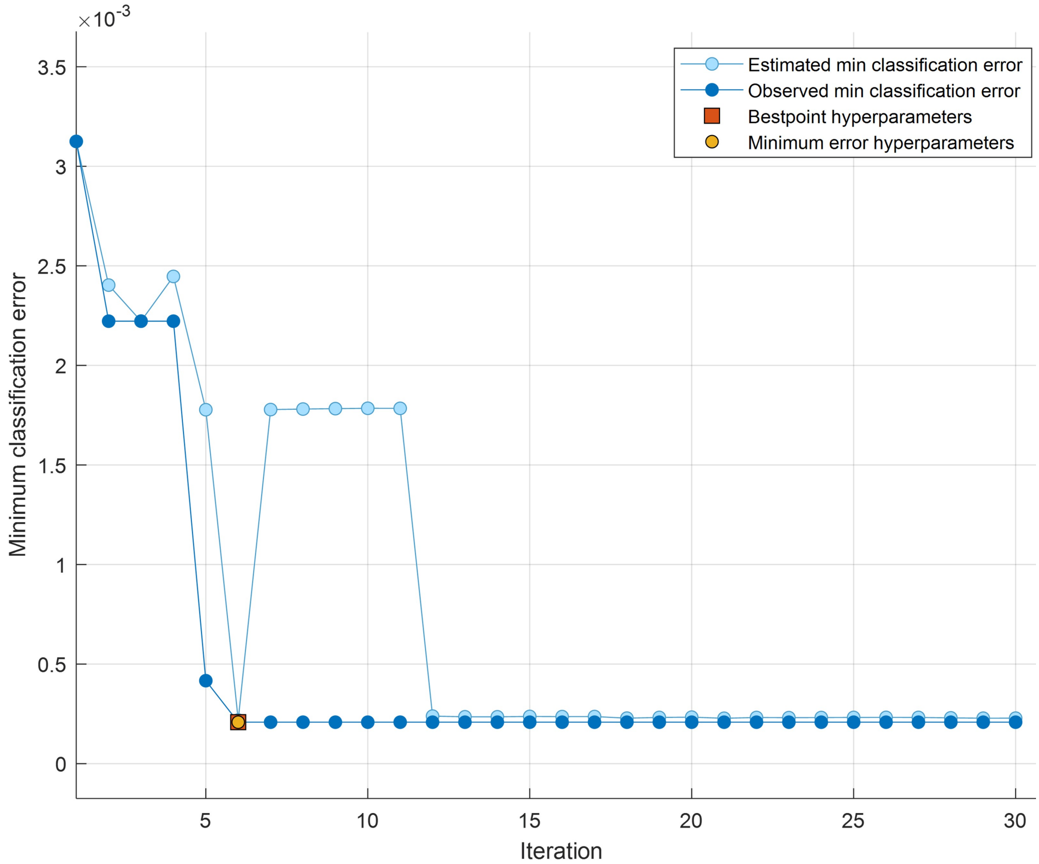
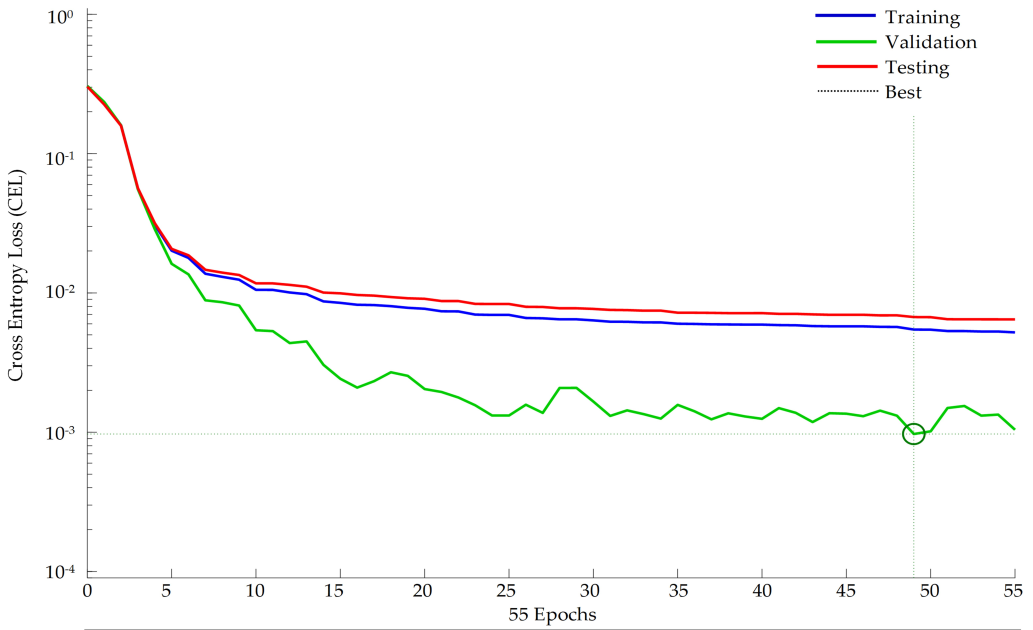


Figure 6. Model optimization for optimizable neural network model using the hyperparameter search range



	# Observations	CEL Value	MCE Value
Training	10,080	0.0055	0.0023
Validation	720	0.0010	0.0
Testing	3,600	0.0067	0.0025

Figure 7. Tracing Performance of the learning process for taring, validation, and testing stages.

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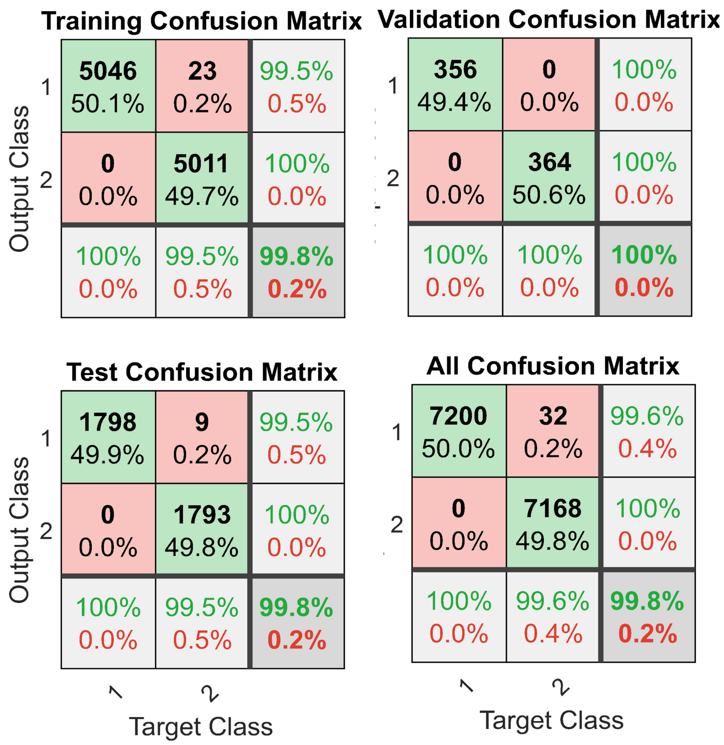
To obtain more perceptions into the proposed model and the solution approach, Figure 8 demonstrates the two-class confusion matrix analysis of the O-SNN model for the training dataset, validation dataset, testing dataset, and the overall dataset. Also, along with the figure, a summary of performance indicators (ACC, HMS, KaI, and PrT) is provided. The employed datasets are balanced comprising a total of 14,400 samples distributed equally between the positive and the negative classes (7,200 samples per class). As can be clearly observed from the figure, overall, the model exhibits a high capability in discriminating positive classes and negative classes having TP = 7200, FP = 32, FN =0, and TN=7168. Accordingly, the overall performance metrics reveals that the system is highly sensitive (sensitivity = 99.6%), highly specific (specificity = 100%), highly accurate (accuracy = 99.8%), and highly precise (precision = 100%). Accordingly, the performance indication metrics for accuracy, harmonic means, kappa-index, and the prediction delay are summarized in Table. 3. In short, the proposed in-vehicle alcohol detection-based O-SNN model is precise, accurate, and lightweight that can provide the inferencing outcome with less than 2.5 sec at least classification error less than 2.5%.



ACC (%)	HMS (%)	KaI (%)	PrT (µsec)
99.8	99.7	99.5	2.2

Figure 8. Two-class confusion matrix analysis of the O-SNN model along with Summary of performance indicators (ACC, HMS, KaI, and PrT).

Eventually, Table 3 provides a performance comparison of our proposed in-vehicle alcohol detection system with other up-to-date state-of-art in-vehicle alcohol detection systems developed via machine learning (ML) or deep learning (DL) models. The table contrasts our best empirical findings recorded for the O-SNN based model with the corresponding findings stated in the existing state-of-art models. In addition to the year of publication, the evaluation in the table compares four comparable design performance scopes including the detection scheme (using ML or DL model), the testing accuracy fractions for the detection systems, the harmonic mean (F-score) fractions for the detection systems, and the kappa-index fractions for the detection systems. Subsequently, the table considers six distinct alcohol detection systems for the in-vehicle ecosystem developed during the last five years (from 2016 to 2021) alongside our proposed in-vehicle alcohol

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detection system which relies on the optimizable shallow neural networks (O-SNN) as the core learning model. The reported detection schemes incorporate the following supervised learning models: genetic algorithm with support vector machine/radial which has been used by [35], Ross-Quinlan decision trees known as (C4.5 DT), used in the development of alcohol detection system in[50], reduced error pruning tree (REPT-DT) decision tree, which has been employed in [36], the random forest classifier (RFC) model used in [37], support vector machine (SVM) utilized by author of [38], and finally, the k-nearest neighbors (kNN) learning model that is used in [39].

According to information provided in the comparison table, one can indisputably conclude that our in-vehicle alcohol detection system is supreme having the highest performance records over the other compared state-of-art schemes. The proposed model has enhanced the validation accuracy by the proportion of 2.2% - 13.8% over the compared models. Besides, the proposed model can be successfully adopted in the real-time ecosystems due to the low prediction delay required by the proposed system (once the data is calibrated by the sensors, only 2.2sec are needed by the intelligent model to provide the detection outcome).

Table 3. Comparison with other existing ML Based in-vehicle alcohol detection systems.

Ref	Year	Learning Scheme	Accuracy	F-Score	Kappa
[35]	2021	GA+ SVM	97.60%	97.5%	97.90%
[50]	2019	C4.5 DT	92.53%	-	-
[36]	2018	REPT DT	87.70%	85.90%	-
[37]	2019	RFC	97.53%	-	-
[38]	2021	SVM	86.00%	98.00%	-
[39]	2016	kNN	92.00%	87.50%	-
Proposed	2022	O-SNN	99.80%	99.70%	99.50%

5. Conclusions

A new lightweight in-vehicle alcohol detection using smart sensing and optimizable neural networks have been developed, implemented, and evaluated in this paper. Specifically, the proposed system is composed of two subsystems 1) The hardware subsystem utilizing a microcontroller, MQ-3 sensors, ADC module, memory unit, battery, and small LCD unit. 2) The software subsystem utilizes a data preprocessing stage, optimizable shallow neural network (O-SNN), and evaluation module. The proposed learning model has been trained using several variants of neural network architectures ranging from 1-3 layers with a variable number of neurons at every layer. The empirical investigation revealed that the best optimizable design is obtained with SNN comprising one hidden layer with 10-neurons and Sigmoid activation function. High-performance indicators have been recorded for the O-SNN model with 99.8%, 99.7%, and 99.5% for accuracy, harmonic mean, and Kappa-index, respectively. Also, the proposed model is lightweight since it can provide the detection decision with only 2.2sec. Hence, we believe that the proposed in-vehicle alcohol detection can be efficiently deployed to provide its functionality in a real-world deployment.

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