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Use of SVM for Fault Detection in a LED Light Control Unit

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ABSTRACT
Machine Learning algorithms are used to solve classification and prediction problems in the automotive industry. In the development of lighting systems for automobiles, such as LED Light Controller Units, it is common to develop algorithms to detect failures of their sensors and/or internal devices; so, its detection depends on a correct characterization of the algorithm. Therefore, the present experiment uses Support Vector Machines and Logistic Regression classification algorithms to model open circuit-type fault detection algorithms in an LED matrix. Among the results obtained, the more related variables to detect the fault are identified, as well as their accuracy and precision in light-dimming scenarios where the algorithm presents vulnerability.

***Keywords* -** LED Controller, Logistic Regression, Open Circuit Failure, SVM, Machine Learning

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I. INTRODUCTION

The automotive industry is creating increasingly complex electrical and electronic systems, which must comply with standards to ensure their operation and the safety of people [1]. In addition, it focuses on efficiency and cost reduction by integrating solutions with the Internet of Things (IoT) and artificial intelligence [2]. Since the 1970s, there has been an exponential increase in the number of electronic systems that have gradually replaced those that are purely mechanical or hydraulic. The increasing performance and reliability of hardware components and the possibilities offered by software technologies have made it possible to implement complex functions that improve the comfort and safety of vehicle occupants.

Among the purposes of electronic systems is to help the driver control the vehicle through functions related to steering, traction, braking, or lighting, such as the anti-lock braking system (ABS), the electronic stability program (ESP), the electric power steering (EPS), the lighting control unit (LCU), active suspensions or engine control [3]. Each of the above functions is implemented in an electronic control unit, known as ECU. ECUs are embedded systems that run the software that controls one or more electronic systems or subsystems of a vehicle. It is considered a high-complexity unit. They are composed of a microcontroller and a set of sensors and actuators [4]. Since then, the complexity of cars has increased at an accelerated rate. Modern vehicles can contain 150 ECUs or more, and their programming sophistication varies depending on their task. It can range from simple sensor signal processing to an infotainment system with multiple applications [5].

The headlights and taillights of a vehicle are considered critical devices to provide safety, especially when driving at night or in dark conditions due to environmental conditions [6]. Such devices are regulated by the ISO 26262 standard, where the International Organization for Standardization (ISO) published the functional safety standard for road vehicles ISO 26262 in 2011 [7]. Later, in 2018, ISO published a second edition to strengthen security development [8]. Such standards ensure that software and hardware developers in the automotive industry follow the same security development principles [9].

Devices based on LED (Light Emitting Diode) technology have benefits such as high brightness, reliability, low energy consumption, and long life. These advantages have made their use feasible in many applications within the automotive industry [10]. However, LEDs are p-n junction semiconductor devices, where electrical and optical properties depend on temperature.

Only 30% of the energy in systems based on LEDs is used to emit light [6], causing eventual degradation in its useful life and lighting performance. The increase in temperature results in a forward voltage drop due to the decrease in the energy gap of the active region of the LEDs [11]. The voltage fluctuation can be directly reflected in the automotive LED lamp as flickering [12]. For the above reasons, faults are presented in ECUs that control LED devices frequently. Therefore, the implementation of diagnostics is relevant not only to avoid further degradation of the LED but also to warn that the brightness level of the light module is no longer within policy and regulations and must undergo maintenance [13].

II. PROBLEM STATEMENT

This research work arises from the need to guarantee security from the software perspective in the ECU in charge of controlling the lighting of the automotive, ensuring the correct detection of diagnostics in it, and focusing on open circuit failure. Incorrect diagnostic detection may incur penalties from customers on automotive companies since they are part of the requested functional requirements. Therefore, these units must be able to correctly diagnose faults in the LED matrix connected to the UCLED (Unit Controller of LED). The most common faults to detect, among others, are short-to-ground faults, short-to-battery faults, and open circuit faults.

Detecting the above faults is carried out through the internal circuitry of a DC/DC converter called Buck controller, which is interconnected to the UCLED microcontroller. It can control the current passing through the LED matrix and adjust the PWM to achieve dimming of the LED matrix. Incorrectly configuring or setting low current or PWM levels to the buck controllers can cause unexpected behavior, affecting the fault detection in the UCLEDs. To resolve some of these problems, it is enough to adjust the internal configuration registers of the Buck controller if the hardware configuration allows it. In cases where it is not possible to update the internal registers of the buck controller or make modifications to the electronic components, it becomes necessary to look for software alternatives to satisfy this need and avoid dangerous faults.

III. METHODOLOGY

The general procedure of the present experiment is defined as follows:

1. Building a minimal system.
2. Buck controller variable selection.
3. Dataset creation.
4. Preprocessing and dataset reduction.
5. Create logistic regression (LR) and SVM models.
6. Validate model performance.

A minimum UCLED system is created, where the test object is the DC/DC converter – Buck controller. The components of the minimum UCLED system are shown in Fig. 1 and are the following:

• Power supplies (5V and 12V).
• Microcontroller.
• DC/DC Converter – Boost Controller.
• DC/DC Converter – Buck Controller.
• LED Matrix.

The DC/DC converter – Buck controller is the test object for this experiment. This converter has read registers, which the microcontroller accesses through the SPI communication protocol. The information from registers is stored in RAM within the microcontroller application program. The variables selected are shown in Table 1.

The variables that were selected for this experiment are shown in Table 1. These variables were chosen because they can be accessed through the microcontroller when communicating with the DC/DC converter – Buck controller. Fig. 2 illustrates the components of the experimentation for the dataset creation process, together with the iSYSTEMS daqIDEAS tool.

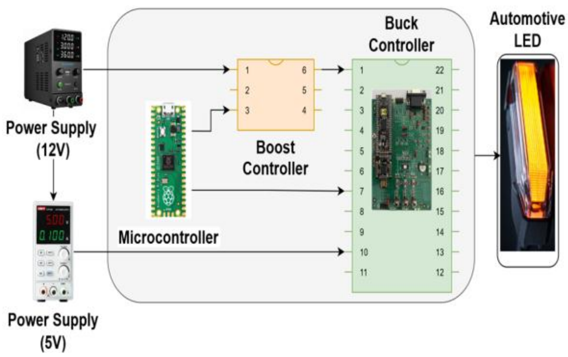

Figure 1: Minimum UCLED system.

Table 1: Variables Selected.

Variable	Type	Range
RohmInfo.Vin	IN	12V
RohmInfo.V5ext	IN	4.5V - 5V
RohmInfo.pwm	IN	5% - 100%
RohmInfo.current	IN	100 mA - 1.5A
RohmInfo.Vpin	IN	5V - 65V
RohmInfo.Thermal	IN	-40 °C - 150 °C
RohmInfo.Vsnsn1	IN	2.5V - 60V
OL_Detect	OUT	Normal - Open Circuit

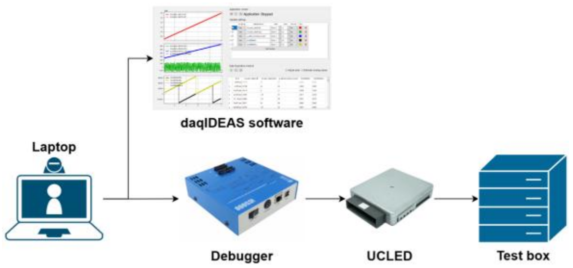

Figure 2: Experimentation and dataset creation process.

Once the datasets have been created, the information obtained is analyzed. The analysis is split into two, one for 5% and another for 100% PWM, according to the minimum and maximum value of the “RohmInfo.pwm” variable, where 6,450 and 11,400 samples were obtained respectively.

With previously processed information, SVM and LR machine learning algorithms for classification are used. SVM was selected because it has been used as a powerful tool for solving practical binary classification problems. Furthermore, SVMs have been preferred due to being superior to other supervised learning methods [14]. Another classification method selected is LR, a well-known statistical solution for modeling binary data. LR will only be used as a result comparator against SVM in the present experiment. Together with SVM are two widely used classification methods [15].

Finally, once the models are created, the algorithm is evaluated using a confusion matrix that is utilized for the algorithm's performance measurements. The confusion matrix counts true positive (TP), true negative (TN), false positive (FP), and false negative (FN) forecasts. Cross-validation is also used to calculate performance estimates.

The process randomly splits the training dataset into k iterations, where k-1 iterations are used for training and one for model evaluation. This cross-validation process is more robust for best results.

IV. RESULTS

The results obtained during the experimentation are shown and described in this section. A scatter matrix is created to visualize the pairwise relationships of the values between the different columns of the dataset. The dataset selected is 100 % PWM scenarios since it detects the open circuit fault, Fig. 3.

Fig. 3 illustrates the pair values to be analyzed, those related to detecting the open circuit fault, column OL_Detect_True. It is observed that the pair values RohmInfo.Vsnsn1 and OL_Detect_True, the open circuit fault is presented at a certain LED voltage level (around 50V). This behavior can be seen in more detail in Fig. 4. In the rest of the pair values, there is no clear relationship with the fault.

A correlation matrix is created to measure the linear dependence between pairs of features (columns). It is to know the value or values relationship to detect the open circuit fault. Fig. 5 presents the correlation of the values of the columns of the dataset. The correlation matrix indicates that the values in the RohmInfo.Vsnsn1 column exhibits a high relation with the open circuit fault detection OL_Detect_True column since its correlation coefficient is 0.83.

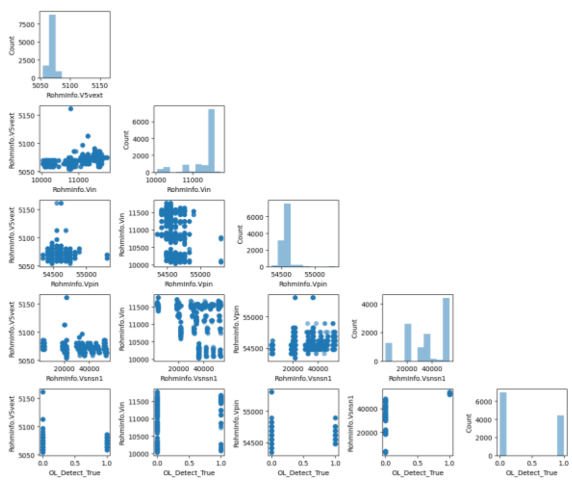

Figure 3: Resulting scattering matrix.

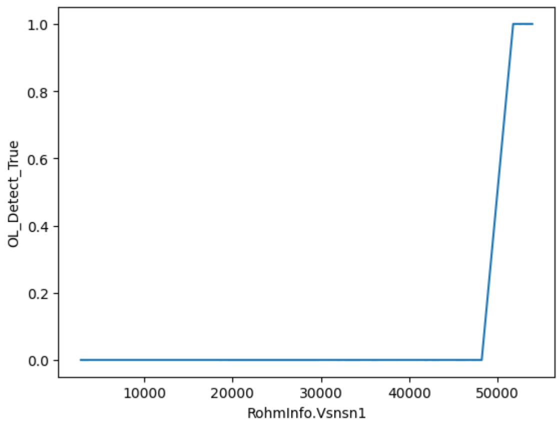

Figure 4: Relation between RohmInfo.Vsnsn1 and OL_Detect_True.

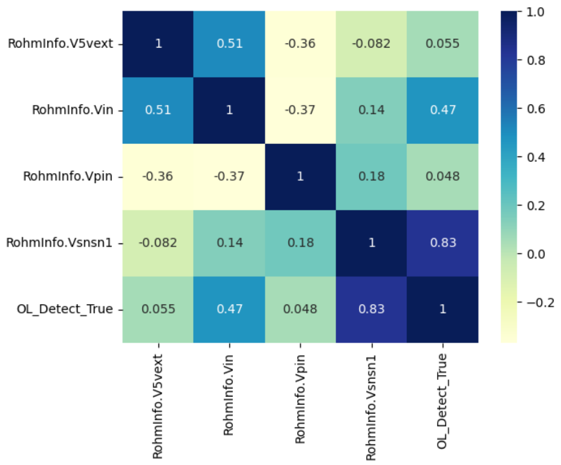

Figure 5: Correlation of selected variables.

From the above results of the scattering matrix and correlation matrix, it can be observed that the voltage level of RohmInfo.Vsnsn1 tends to the voltage levels of RohmInfo.Vpin when the value of OL_Detect_True is true.

Fig. 6 shows that the voltage in the RohmInfo.Vpin column remains constant since it belongs to the voltage that the Boost controller supplies to the Buck controller. When the voltage level of RohmInfo.Vsnsn1 increases to a level close to RohmInfo.Vpin, the value of OL_Detect_True changes from 0 to 1.

With the relation obtained between RohmInfo.Vpin and RohmInfo.Vsnsn1, with the value of these variables, a threshold for detecting the open circuit fault is obtained. This threshold is obtained using (1).

Threshold = RohmInfo.Vpin max value - RohmInfo.Vsnsn1 max value. (1)

A threshold value for open circuit fault detection in 5% PWM_scenarios is 5.861V ≈ 6V. This value also can be used in 100% PWM scenarios. Now, the obtained models are evaluated with the obtained threshold value.

Table 2 shows a summary of the comparison of the results obtained with SVM and LR. It shows similar results for the classification of results when the detection voltage threshold is not adjusted, and the same result is reached when the detection voltage threshold is already adjusted.

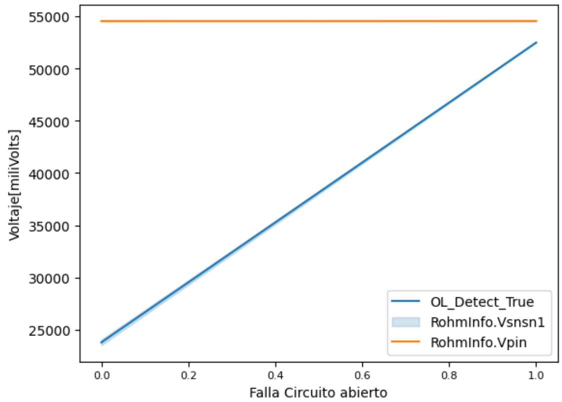

Figure 6: Relation between voltages and open circuit fault.

Table 2: Summary of Algorithm Results.

Model	Accuracy	Recall	Precision	F1
SVM No Adjust	57%	23%	38%	29%
SVM With Adjust	90%	100%	71%	83%
LR No Adjust	54%	26%	36%	30%
LR With Adjust	90%	100%	71%	83%

V. CONCLUSION

This work successfully addressed the objective of finding patterns in the data set and thus being able to propose a software solution for the detection of open circuit faults. The following can be concluded:

- From information analysis, patterns were found in the independent variables, which correctly describe the behavior of an open circuit fault with the voltage level information of the Buck controller.
- It is concluded that if the result of the subtraction between RohmInfo.Vpin and RohmInfo.Vsnsn1 is less than or equal to 6V. An open circuit fault is present in the device. Therefore, a formula based on voltage levels can be implemented.
- Using well-known machine learning algorithms, we built and tuned models to ensure detection when PWM values were close to 5%.
- The methodology presented can be used to detect other types of faults, such as shorts to ground and shorts to battery since both have different behaviors based on voltages.

To implement the voltage strategy, it must be considered that the maximum voltage consumed by the LED matrix is not close to the voltage supplied by the Boost controller. That is, if the Boost controller is feeding the Buck controller with 56V, it is recommended that the LED array voltage is set to a maximum of 49V. This ensures that there are no false open circuit detections.

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