Deep Bio-Sensing Embedded System for a Robust Car-Driving Safety Assessment

Francesco Rundo
ADG, Central R&D
STMicroelectronics
Catania, Italy
francesco.rundo@st.com

Concetto Spampinato
Perceive Lab
University of Catania
Catania, Italy
cspampinato@dieii.unict.it

Sabrina Conoci
University of Messina
Messina, Italy
sabrina.conoci@unime.it

Francesca Trenta
IPLAB
University of Catania
Catania, Italy
francesca.trenta@unict.it

Sebastiano Battiato
IPLAB
University of Catania
Catania, Italy
battiato@dmi.unict.it

***Abstract*—Recent statistics confirmed that the car driver drowsiness monitoring reduces drastically the road accidents. In scientific literature, several advanced approaches have been proposed to monitor the driver's level of attention, providing a real-time warning to increase driving safety. With this aim, we propose an innovative method which consists of ad-hoc designed bio-sensing system to assess the car driver's physiological state. The designed bio-sensing system includes a probe which detects a physiological signal of the subject i.e. the PhotoPlethysmoGraphy (PPG). The physio-probe device has been embedded on several points of the car's steering wheel in order to sample the PPG signal from the driver's hand. Furthermore, ad-hoc motion magnification algorithm was developed to reconstruct PPG from visual car driver face motions when physical PPG signal is unavailable. An innovative deep learning system completes the proposed pipeline in order to classify the driver drowsiness from the so collected PPG signal. The drowsiness detection performance (average accuracy of around 90%) confirmed the effectiveness of the proposed approach.**

***Index Terms*—ADAS. Deep learning, Bio-signals**

I. Introduction

In the last few years, various techniques have been implemented to measure the car driver drowsiness. The Drowsiness status denotes a physiological state that leads to a reduction of the level of awareness and a tendency to fall asleep [1]. This fact motivates the need to develop an effective solution to detect drowsiness in the early stages. Specifically, there is an increasing growth of studies that focus on analyzing correlation between car driver drowsiness and such electrical bio-signals of the subject i.e. EEG (Electroencephalography) or ECG (Electrocardiography). However, the mentioned techniques are impracticals, since they require that the driver wears a range of bio-sensors. Nevertheless, driver monitoring based on physiological signals has been used in various applications spanning cardiology to the automotive field [1]. In order to overcome the mentioned limitations, PhotoPlethysmoGraphic (PPG) signal has been used to assess a subject's physiological status [1], [2]. Researchers have become increasingly interested in the PPG signal because it does not require the driver to wear any sensors and it is very simple to sample. [1]. The PPG signal formation is regulated by the subject's bloodstream directly connected to cardiac activity which in turn is regulated by Autonomic Nervous System (ANS) that characterizes the subject's awareness level [3]. Furthermore, several studies confirmed the correlation between blood pressure estimation and physiological attention, becoming an important aspect of determining the drowsiness state [4], [5]. Despite being an effective tool, the PPG signal is very susceptible to Motion Artifacts (MA) generated by body movements, and it also requires the use of specific sensing devices with ad-hoc post-processing pipeline [1], [6]. Therefore, developing a robust and non-invasive system to monitor the PPG signal alongside assessing the subject's blood pressure could represents an advance in automotive monitoring systems. The authors propose an innovative pipeline to assess the driver's drowsiness level by extracting features of the PPG signal without requiring invasive devices. The remainder of the paper is structured as follows. In Section II, we introduce the PPG signal specifying the underlying physical principle that characterizes its formation. In Section III, the main scientific contributions reported in literature are discussed. In Section IV the authors reported the proposed pipeline. In Section V, the experiments and validation results are analyzed. Finally, in Section VI, conclusions and future developments are analyzed.

II. The PPG: Underlying Physical Phenomena

Photoplethysmography (PPG) is a non-invasive estimation of blood volume changes in tissue by measuring characteristics of light either absorbed or reflected from tissue [1].More specifically, PPG is a physiological signal generally acquired using an optical sensing system which monitores the blood flow dynamic related to the cardiac phases [1], [2], [7]. We collect the PPG signal by illuminating the region of interest

978-8-8872-3749-8 ©2020 AEIT

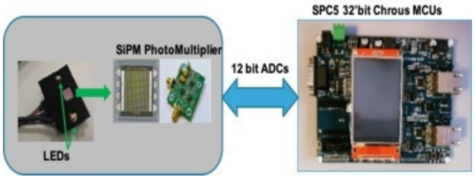

Fig. 1. The overall architecture of the proposed PPG Sensing Device.

of the subject's skin using a Light Emitting Diode (LED). By coupling the LED with a photo-sensing device, we are able to sample the part of back-scattered light (photons), which is not absorbed by the blood flow (Back-Scattered signal) of the subject on which the optical sensing system is placed [8]. An electrical transduction circuit of the optical signal completes the PPG signal sampling pipeline. As reported, ANS regulates the heart rate of the subject, generating an impact in the arterial blood flow. The so collected data will be properly processed.

A. The PPG Sensing System

Recently, several hardware architectures have been proposed to acquire the PPG signal [8], [9]. In this section, we describe the proposed hardware pipeline based on the use of a photo-multiplier silicon device, called Silicon PhotoMultiplier (SiPM) [10]–[12]. Our proposed sensing device is therefore composed of two OSRAM LED emitters (SMD package) emitting at 850 nm and used as optical light sources with a SiPM detector. The total area of the proposed SiPM device is $4.0 \times 4.5\ mm^2$. Furthermore, the detector consists of 4871 square microcells with 60 µm of the pitch, a geometrical fill factor of 67.4%. It is also packaged in a surface mount housing (SMD) having a $5.1 \times 5.1\ mm^2$ total area. In [8]–[10], we reported further details about the proposed hardware system. In Fig. 1, we reported the implemented PPG sensing device. The designed hardware board includes an SPC5 32-bit Chorus microcontroller device employed to sample the PPG optical signal (trough the embedded 12-bit Analogic to Digital Converter (ADC)) and perform the required signal filtering and stabilization [11]–[13]. The sampling PPG signal introduces various types of noise (e.g., motion artifacts, micro - breathing movements, etc.) [11], which compromises the robustness. This issue requires the usage of such filtering layer of the raw PPG. To this aim, we implemented a raw PPG signal filtering pipeline using a Butterworth band-pass filter in the 0.5 - 8 Hz range. In particular, we proposed an innovative, robust, and de-noising pipeline signal, called PPG-PRS [13]–[15]. The resulting signal contains PPG standard compliant waveforms [11], [12]. . In Fig. 2, we reported a detail of the compliant filtered PPG waveform.

III. Related Works

In this section, we summarize previous approaches on evaluating car-driver status using physiological signals. Generally, existing approaches propose invasive and computationally expensive solutions [16] alongside using high-performance systems to ensure high levels of safety while driving [14], [16].

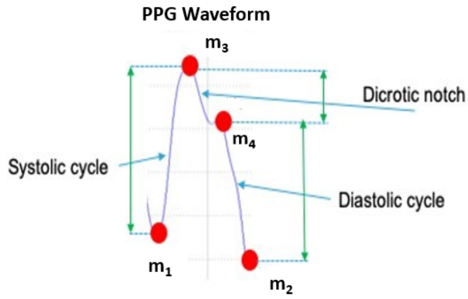

Fig. 2. Filtered compliant PPG waveform with details about extreme points m1, m2, m3, m4.

In this context, the PPG signal is the easiest to sample among all the physiological signals [16]. On this basis, promising approaches on drowsiness detection are listed, followed by the latest approaches using deep learning. In the automotive field, the use of PPG signals is preferred to monitor drowsiness instead of acquiring other electronic signals, such as the ECG. Indeed, the ECG requires contact with at least three points of the car driver (Einthoven triangle) [14], reducing comfort and robustness. In addition to detect physiological signals, researchers have adopted such visual information (i.e., facial expressions, eye blinks, etc.) to analyze the driver's level of attention [17]. Several studies have pointed out the correlation between a subject's attention level and the dynamic of related Heart Rate Variability (HRV) [18]. In this context, many efforts have been made to design and implement efficient, reliable, and sustainable solutions for fatigue and drowsiness monitoring based on usage of physiological data. In [18], the authors used three types of recurrence plots (RPs) derived from the R-R intervals of the heartbeats to feed a Convolutional Neural Network for the classification of drowsy/awake status. Specifically, the authors investigated the pattern of Heart Rate Variability (HRV) to monitor the car driver's drowsiness [18]. In this work, the HRV is collected by using ECG and PPG sensors, which inevitably introduce some artifacts. Over the last years, researchers have investigated the use of blood pressure to determine the level of attention, alongside analyzing physiological signals. For example, Monte-Moreno et al. [19] proposed a non-invasive approach to estimate the systolic and diastolic blood pressure by acquiring PPG signal. In order to estimate the blood glucose level (BGL), systolic (SBP), and diastolic (DBP) blood pressure, in [19] a signal processing module is designed to extract features from the PPG waveform to be used as input data for a different machine learning algorithms. In [13], the authors described an innovative approach to estimate BP from PPG signal. The experimental results confirmed the effectiveness of the proposed approach.

IV. Methods and Materials

This section presents the overall pipeline. The Visio2PPG pipeline architecture is described first. Afterwards, we introduced a Deep Long Short-Term Memory (D-LSTM) framework .Moreover, a pipeline to estimate blood pressure is described. Finally, we provide details about our implemented ad-hoc Deep Convolutional Neural Network (D-CNN).

A. The proposed Visio2PPG Reconstruction Pipeline

In this section, we describe the Visio2PPG architecture that comprises a PPG sensing device for preliminary system calibration coupled with a Computer Vision camera module to sample subject's face from whom extracting facial descriptors. A Machine Learning algorithm that correlates the aforementioned subject's face descriptors with the corresponding PPG waveforms, completes the proposed pipeline. In the training-calibration stage, the proposed pipeline correlates the time-dynamic (in all sampled video frames) of the selected face descriptors with the corresponding PPG features to evaluate the car driver's drowsiness and the corresponding blood pressure level. During the calibration phase, the PPG signal is collected using the previously described coupled LED-SiPM sensing device, embedded in the vehicle steering wheel [12], [13]. After acquiring the PPG signal, the PPG-PRS algorithm produces a compliant PPG time-series [13], [14], filtering the raw PPG signal. Therefore, we stabilize the PPG time-series by removing motion and noise artifacts. In addition, the PPG-PRS algorithm provides a study of the first and second derivatives of the filtered PPG signal to detect the minimum and maximum extreme points of each selected compliant PPG waveform. When collecting the PPG signal, we recorded a video sequence of the subject's frontal face with a camera device having a low framerate, under high light condition. Recently, a significant amount of works focused on the correlation between facial micro-movements and the cardiac pumping activity [20], confirming that these micro-movements are strongly correlated to the PPG signal. In order to amplify these micro-movements, some authors have formulated several approaches based on Motion Magnification. This process is particularly hardware-demanding requiring high frame-rate acquisition devices (on average, framerate ranging from 10 Kfps up) [21]. Inspired by the work of Wu et al. [22], where the authors used Video Magnification to reveal the bloodstream, we proposed an approach to elaborate video sequences of the car driver's face. The purpose is to preliminarly identify significant landmarks or descriptors on the driver's face. To detect the mentioned landmarks, we used the approach proposed by Kazemi and Sullivan in [23]. It estimates the location of 68 coordinates that map the facial structures or structure-landmarks (i.e., eyes, noise, mouth, etc.) on a subject's face image.. We analytically formalize the reconstruction of landmark dynamics by using Kazemi and Sullivan algorithm $\psi_{KS}(.)$. Formally, let be $I_t(x, y)$ the captured M gray-level (or luminance channel in case of colour camera device) driver face video frames at the instant t_k , the *i-th* landmark dynamic time-serie $l_i\left(t_k, x_l, y_l\right)$ is reconstructed using the following equation:

$$\ell_i\left(t_k, x_l, y_l\right) = \psi_{KS}\left(I_{t_k}\left(x, y\right)\right);\ k = 1..N_f; i = 1..N_L \quad (1)$$

where $\ell_i\left(t_k, x_l, y_l\right)$ represents the pixel intensity dynamic of the *i-th* landmark identified at the frame position (x_l, y_l) while *Nf* represents the number of captured frames and *NL* represents the number of 68 identified landmarks (Eq. 1). Once detecting landmarks dynamics, we analyzed the descriptors time-series $\ell_i\left(t_k, x_l, y_l\right)$ in order to correlate their temporal intensity with the underlying cardiac activity. The main advantage of the proposed method consists in not requiring the use of high-frame rate camera devices.

B. The Deep LSTM architecture

As introduced, we propose ad-hoc Deep Long Short-Term Memory (D-LSTM) framework to correlate the driver's facial landmarks and the corresponding cardiac activity. In particular, our D-LSTM network is based on Vanilla architecture initially proposed by Hochreiter and Schmidhuber in [24]. In this contribution, we significantly improved the approach previously described in [25] based on employing a D-LSTM architecture to reconstruct some features of the PPG signal to characterize the driver's drowsiness level. The proposed D-LSTM architecture is composed of 1 input layer, 2 hidden layers, and 1 output layer. Specifically, we designed the input layer with 64 units and the two hidden layers with 64 and 128 cells, respectively. The output layer comprises 1 cell providing the predicted PPG sample. Each LSTM layer is followed by a batch normalization and a dropout layer appointed to boost the overall performance. We trained our model with an initial learning rate of 10^3. We also set the batch size to 512, and the maximum number of training epochs to 200. In training-calibration phase, the proposed Deep LSTM learns the correlation between the selected facial landmark time-series $\ell_i\left(t_k, x_l, y_l\right)$ with the corresponding sampled PPG signal, for each subject. The output of the so designed Deep LSTM pipeline represents predicted extreme points of PPG signal. We carried out several tests that reported acceptable performances related to reconstruction of the features of the PPG signal. Our findings suggest that it is not required to use all the landmark time-series but thanks to the D-LSTM architecture, the computing of a composite signal as a function of all the sampled landmarks signals is enough for the designed application. Specifically, we perform the following computation:

$$\mu_\ell(t_k) = \frac{1}{N_L}\sum_{j=1}^{N_L} \ell_j(t_k, x_l, y_l) \quad (2)$$

Using Eq. 2, the so computed signal $\mu_\ell(t_k)$ will be fed as input of the D-LSTM. The deep architecture will be trained to correlate the input signal $\mu_\ell(t_k)$ with such features of the corresponding PPG signal of the analyzed subject i.e. with the extreme points *m1,m2,m3,m4* as reported in Fig.2. Once collecting PPG signal, the extreme points *m1,m2,m3,m4* are computed by the PPG-PRS algorithm through first and second derivative-based approach [13]. Otherwise, when the Vision2PPG reconstruction system takes over the pipeline (in the absence of real PPG signal because the driver does not have the hand in contact with the sensor in the steering wheel), the extreme points are predicted by D-LSTM previously trained on the sampled PPG signal. After the Deep LSTM framework has learned the correlation between the driver's facial landmarks and the extreme points of the corresponding PPG signal, the training-calibration phase will be dropped. The calibration phase requires $15/20$ seconds of PPG signal (our sensing device performs acquisition at 1 kHz) and corresponding visual frames (at 40 fps). Finally, the underlying trained model provides a feed-forward estimation of the PPG extreme points as per Fig. 2. An HRV block closes the pipeline providing a corresponding attention measurement based on classical frequency analysis of the so determined extreme points of PPG [13].

C. The Blood pressure estimation pipeline

In this section, we describe the pipeline used to monitor the driver blood pressure since it is strongly correlated to the driving safety. We propose a novel solution to measure blood pressure level of the subject by simply acquiring the corresponding facial video frames and then processing it with the proposed Vision2PPG reconstruction pipeline. As described, we retrieved the extremal points of the subject's PPG signal. These points are fed as input of a properly configured Shallow Neural Network that classifies the normal-blood pressure subjects from those who report pressure values beyond the norm. Once collecting the set of extremal points of the PPG waveforms, we characterized the subject's cardiac activity depending on the blood pressure. Formally, for each pair of PPG waveforms PPG^j, PPG^{j+1} , we define the following indicators:

$$\varphi = \left[m_1^j, m_2^j,\ m_3^j,\ m_4^j, dx_i^j, dy_i^j, mAI^J\right] \tag{3}$$

$$m_i^j = \left(x_{m_i^j}, y_{m_i^j}\right) \tag{4}$$

$$dx_i^j = x_{m_i^{j+1}} - x_{m_i^j}, \tag{5}$$

$$dy_i^j = y_{m_i^{j+1}} - y_{m_i^j} \tag{6}$$

$$mAI^j = ((y_{m_3^j} - y_{m_1^j}) - y_{m_4^j})/(y_{m_3^j} - y_{m_1^j}) \tag{7}$$

$\forall\ j = 1..(N^{PPG} - 1)$, $i = 1, 2, 3, 4$, where mAI^J is a modified version of the so-called Augmentation Index, usually computed for measuring the arterial stiffness while N^{PPG} represents the number of estimated extremal points (Eq. 7). The other indicators reported in the Eqs. (3)-(6) characterize cardiac cycles and, therefore, the corresponding blood pressure level. The elements of the vector φ represent the input of the aforementioned Shallow Neural Network (SNN) designed to learn the correlation between the computed input of elements and the corresponding value of the systolic and diastolic blood pressure. The designed SNN (with an hidden layer of 500 neurons) is trained with the Scaled Conjugate Gradient backpropagation (SCG) algorithm [14]. The output of the SNN framework is a binary value which is a discriminating flag denoting if the subject shows normal pressure values (0) or not (1). The set $120/80$ indicates 120 mmHg for systolic pressure and 80 mmHg for diastolic pressure. Under the supervision of a team of physiologists, we setup $120/80$ mmHg as acceptable blood pressure whereas higher/lower values are considered anomalous.

D. The Deep CNN Pipeline

To assess the level of car driver drowsiness, the authors propose an innovative pipeline based on ad-hoc Deep Convolutional Neural Network (D-CNN). The proposed D-CNN network is composed of three convolutional layers. Except for the last convolutional layer, each layer is followed by a ReLU activation layer (with batch-normalization) and 2×2 max-pooling layers. The first convolutional layer performs 32 operations with 3×3 kernel filters, where the second and the third ones show 64 and 128 kernel filters of 3×3, respectively. A Softmax layer completes the D-CNN pipeline performing binary classification of the visual input data i.e., drowsy/wakeful status of the analyzed driver. We performed fine-tuning for 100 epochs using Adam optimizer and cross-entropy as the loss function. To conduct our experiments, we also set the learning rate to 0.001 and the batch size to 32. The input visual frame of the D-CNN is a segmented car driver eye (77×77 resolution) obtained through Haarcascade classifier [26]. We designed the proposed D-CNN in order to be hosted in the STA1295 Accordo5 embedded automotive-grade platform, which includes a 3D-GFX accelerator cell [1].

E. The driving safety monitoring

In this work, we proposed a pipeline that combines the driver's physiological and visual data, sampled by specific sensors placed in the car. On this basis, we implemented a pipeline which reconstructs the features of the driver's PPG signal from visual information when the steering embedded sensors will do not provide real PPG data. The extracted features allow us to reconstruct the driver's level of attention through the analysis of HRV and evaluating the blood pressure dynamics providing a robust measure of the driving safety level. We increased the robustness of the proposed approach by processing the video frames of the driver's face through a D-CNN model, performing a further classification of the driver's attention level. In Fig.3, the overall scheme of the proposed driving safety estimation architecture is shown. We have implemented a block called Driving Safety Decision System (DSDS) to analyze the outputs produced by the previous pipelines (i.e., HRV analysis from PPG or Visual landmarks based reconstructed signal, SNN output related to blood pressure estimation from PPG or Visual reconstructed PPG, D-CNN classification of the facial expression of the driver). In detail, DSDS generates an acoustic signal, whether at least one safety control block estimates a significant level of risk. The acoustic signal is managed by the STA1295 Accordo5 system, which hosts the DSDS software implementation. To sum up, the Vision2PPG pipeline reconstructs

[1]STMicroelectronics Accordo5 Automotive Microcontroller: https://www.st.com/en/automotive-infotainment-and-telematics/automotive-infotainment-socs.html?icmp=tt4379_gl_pron_nov2016

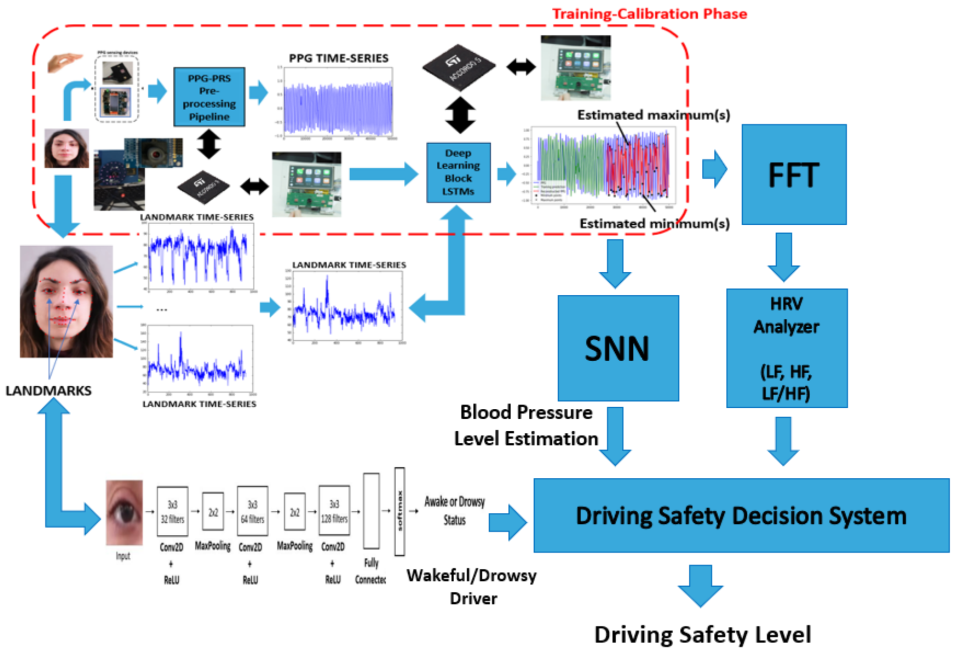

Fig. 3. The overall scheme of the proposed pipeline.

the extreme points of the PPG signal of a monitored car-driver. Therefore, the distribution in the frequency domain of the reconstructed PPG extreme points $(m1, m2, m3, m4)$ from the proposed pipeline is robust and allows to obtain a frequency spectrum (FFT) very close with the real one (i.e., determined by the driver's real PPG signal). Through this reconstructed PPG data, we obtained a robust HFT suitable to characterize the driver's drowsiness level [17]. Moreover, a PPG based blood pressure analysis will be perfomed by SNN sub-system which is correlated to driver drowsiness. A further DCNN architecture works simultaneously with the Deep LSTM framework, providing a further assessment of the driver's attention level based on the analysis of facial features as illustrated in [25]. The system provides a measure of the overall driver's attention level by analyzing the rankings of the three mentioned sub-systems.

V. Experimental Results

In this section, we describe the experimental setup. Seventy both healthy (45 subjects having a blood pressure less or equal to $120/80$ mmHg), and hypertensive (25 subjects having a blood pressure higher than $120/80$ mmHg) took part in the data collection. The minimum age of the subjects was 20 years, while the maximum age was 75 years. After signing the consent form[2], subjects were recorded (frontal face) using a color camera device having a max resolution of 2.3 Mpx and 40 fps as framerate. The collected dataset includes systolic and diastolic pressure and PPG signal measurements, plus video sequences of the subject's face. Moreover, subjects performed different drowsiness states under the supervision of a team of physiologists. Simultaneously, we collected the EEG signal from subjects determining the real level of attention. Each measurement session is around 10 minutes long, 5 of which in a state of full attention and 5 in a state of low attention. The PPG was acquired by using the described sensing device with sampling frequency at 1 kHz. In order to collect the blood pressure measurements, we used a classic certified sphygmomanometer. In the collected dataset, the minimum pressure value is around $105/70$, while the maximum pressure value is $160/95$. The collected dataset was split into 70% for training, 15% for validation and 15% for testing. In our experiments, a NVIDIA GeForce RTX 2080 GPU as used for training and testing. Moreover, MATLAB full toolboxes rel. 2019b environment for Deep Learning framework were employed. We compare our proposed method with another similar pipelines [2]. Table I shows the accuracy benchmark comparisons both regarding to the early recognition of the low-attention driver (Drowsy Driver) and to the early detection of the high-attention driver (Wakeful Driver). A measure of the average performances is reported (overall accuracy). This comparison highlights the effectiveness of the proposed method, showing a 2% increase in accuracy with respect to [2]. We also validated the performance of SNN network used to estimate the blood pressure level by comparing our method with other approaches in literature [27]. Table II shows the BP values measured both to normal-pressure subjects (Class 1) and to those with an abnormal BP (Class 2). As confirmed by the metrics in Table II, the margin of error for the implemented pipeline is also considerably low. The results for SSN network suggest that our model provides reliable classification results as confirmed by the overall accuracy of 88.73%.

[2]Ethical Committee CT1 (authorization n.113 / 2018 / PO)

TABLE I
CAR DRIVER DROWSINESS PERFORMANCE COMPARISON

Method	**Drowsiness Estimation**		
	Overall Accuracy	***Drowsy Driver***	***Wakeful Driver***
Proposed	95.07%	$95,77\%$	$94,36\%$
[2]	$94,38\%$	95.83%	92.95%

TABLE II
BLOOD PRESSURE PERFORMANCE COMPARISON

Method	**Blood Pressure (BP) Estimation**		
	Overall Accuracy	***Class 1 Normal BP***	***Class 2 Abnormal BP***
Proposed	88.73%	88.88%	92.30%
[27]	88.73%	91.11%	84.61%

VI. CONCLUSIONS AND FUTURE WORK

In this paper, we introduced a multi-modal approach that combines visual and physiological data to evaluate the driver's drowsiness. The obtained results confirmed the robustness of the proposed approach. Future work aims to collect more data to further improve the performance of the safety monitoring [27]–[30].

ACKNOWLEDGMENT

This research was funded by from the National Funded Program 2014-2020 under grant agreement n. 1733, (ADAS + Project).

REFERENCES

[1] F. Rundo, S. Petralia, G. Fallica, and S. Conoci, "A nonlinear pattern recognition pipeline for ppg/ecg medical assessments," in *Convegno Nazionale Sensori*. Springer, 2018, pp. 473–480.

[2] F. Rundo, C. Spampinato, and S. Conoci, "Ad-hoc shallow neural network to learn hyper filtered photoplethysmographic (ppg) signal for efficient car-driver drowsiness monitoring," *Electronics*, vol. 8, no. 8, p. 890, 2019.

[3] G. Schmidt, A; Thews, *Autonomic Nervous System*, 1989.

[4] A. Y. Husodo, I. Hermawan, W. Jatmiko, B. Wiweko, A. Boediman, and B. K. Pradekso, "Multi-parameter measurement tool of heart rate and blood pressure to detect indonesian car drivers drowsiness," in *2018 3rd International Seminar on Sensors, Instrumentation, Measurement and Metrology (ISSIMM)*. IEEE, 2018, pp. 68–73.

[5] M. I. Mamun, A. Rahman, M. A. Khaleque, M. F. Mridha, and M. A. Hamid, "Healthcare monitoring system inside self-driving smart car in 5g cellular network," in *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)*, vol. 1. IEEE, 2019, pp. 1515–1520.

[6] A. E. Dastjerdi, M. Kachuee, and M. Shabany, "Non-invasive blood pressure estimation using phonocardiogram," in *2017 IEEE International Symposium on Circuits and Systems (ISCAS)*. IEEE, 2017, pp. 1–4.

[7] V. Vinciguerra, E. Ambra, L. Maddiona, M. Romeo, M. Mazzillo, F. Rundo, G. Fallica, F. di Pompeo, A. M. Chiarelli, F. Zappasodi *et al.*, "Ppg/ecg multisite combo system based on sipm technology," in *Convegno Nazionale Sensori*. Springer, 2018, pp. 353–360.

[8] S. Conoci, F. Rundo, G. Fallica, D. Lena, I. Buraioli, and D. Demarchi, "Live demonstration of portable systems based on silicon sensors for the monitoring of physiological parameters of driver drowsiness and pulse wave velocity," in *2018 IEEE Biomedical Circuits and Systems Conference (BioCAS)*. IEEE, 2018, pp. 1–3.

[9] D. Agrò, R. Canicattì, A. Tomasino, A. Giordano, G. Adamo, A. Parisi, R. Pernice, S. Stivala, C. Giaconia, A. Busacca *et al.*, "Ppg embedded system for blood pressure monitoring," in *2014 AEIT Annual Conference-From Research to Industry: The Need for a More Effective Technology Transfer (AEIT)*. IEEE, 2014, pp. 1–6.

[10] M. Mazzillo, G. Condorelli, D. Sanfilippo, G. Valvo, B. Carbone, G. Fallica, S. Billotta, M. Belluso, G. Bonanno, L. Cosentino *et al.*, "Silicon photomultiplier technology at stmicroelectronics," *IEEE Transactions on Nuclear Science*, vol. 56, no. 4, pp. 2434–2442, 2009.

[11] V. Vinciguerra, E. Ambra, L. Maddiona, S. Oliveri, M. F. Romeo, M. Mazzillo, F. Rundo, and G. Fallica, "Progresses towards a processing pipeline in photoplethysmogram (ppg) based on sipms," in *2017 European Conference on Circuit Theory and Design (ECCTD)*. IEEE, 2017, pp. 1–5.

[12] M. Mazzillo, L. Maddiona, F. Rundo, A. Sciuto, S. Libertino, S. Lombardo, and G. Fallica, "Characterization of sipms with nir long-pass interferential and plastic filters," *IEEE Photonics Journal*, vol. 10, no. 3, pp. 1–12, 2018.

[13] F. Rundo, S. Conoci, A. Ortis, and S. Battiato, "An advanced bio-inspired photoplethysmography (ppg) and ecg pattern recognition system for medical assessment," *Sensors*, vol. 18, no. 2, p. 405, 2018.

[14] P. F. S. P. F. Rundo, S. Conoci, "Processing of electrophysiological signals," Patent IT Patent Nr. 102 017 000 081 018, 2017.

[15] Y. Choi, S. I. Han, S.-H. Kong, and H. Ko, "Driver status monitoring systems for smart vehicles using physiological sensors: A safety enhancement system from automobile manufacturers," *IEEE Signal Processing Magazine*, vol. 33, no. 6, pp. 22–34, 2016.

[16] E. Vavrinskỳ, V. Tvarožek, V. Stopjaková, P. Soláriková, and I. Brezina, "Monitoring of car driver physiological parameters," in *The Eighth International Conference on Advanced Semiconductor Devices and Microsystems*. IEEE, 2010, pp. 227–230.

[17] E. Vural, M. Cetin, A. Ercil, G. Littlewort, M. Bartlett, and J. Movellan, "Drowsy driver detection through facial movement analysis," in *International Workshop on Human-Computer Interaction*. Springer, 2007, pp. 6–18.

[18] H. Lee, J. Lee, and M. Shin, "Using wearable ecg/ppg sensors for driver drowsiness detection based on distinguishable pattern of recurrence plots," *Electronics*, vol. 8, no. 2, p. 192, 2019.

[19] E. Monte-Moreno, "Non-invasive estimate of blood glucose and blood pressure from a photoplethysmograph by means of machine learning techniques," *Artificial intelligence in medicine*, vol. 53, no. 2, pp. 127–138, 2011.

[20] T.-H. Oh, R. Jaroensri, C. Kim, M. Elgharib, F. Durand, W. T. Freeman, and W. Matusik, "Learning-based video motion magnification," in *Proceedings of the European Conference on Computer Vision (ECCV)*, 2018, pp. 633–648.

[21] M. Rubinstein, N. Wadhwa, F. Durand, W. T. Freeman, and H.-Y. Wu, "Revealing invisible changes in the world," *Science*, vol. 339, no. 6119, pp. 519–519, 2013.

[22] H.-Y. Wu, M. Rubinstein, E. Shih, J. Guttag, F. Durand, and W. Freeman, "Eulerian video magnification for revealing subtle changes in the world," *ACM transactions on graphics (TOG)*, vol. 31, no. 4, pp. 1–8, 2012.

[23] V. Kazemi and J. Sullivan, "One millisecond face alignment with an ensemble of regression trees," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2014, pp. 1867–1874.

[24] J. Schmidhuber and S. Hochreiter, "Long short-term memory," *Neural Comput*, vol. 9, no. 8, pp. 1735–1780, 1997.

[25] F. Trenta, S. Conoci, F. Rundo, and S. Battiato, "Advanced motion-tracking system with multi-layers deep learning framework for innovative car-driver drowsiness monitoring," in *2019 14th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2019)*. IEEE, 2019, pp. 1–5.

[26] P. Viola and M. Jones, "Rapid object detection using a boosted cascade of simple features," in *Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001*, vol. 1. IEEE, 2001, pp. I–I.

[27] F. Rundo, A. Ortis, S. Battiato, and S. Conoci, "Advanced multi-neural system for cuff-less blood pressure estimation through nonlinear hc-features." in *ICETE (1)*, 2019, pp. 327–331.

[28] F. Rundo, S. Rinella, S. Massimino, M. Coco, G. Fallica, R. Parenti, S. Conoci, and V. Perciavalle, "An innovative deep learning algorithm for drowsiness detection from eeg signal," *Computation*, vol. 7, no. 1, p. 13, 2019.

[29] F. Rundo, F. Trenta, A. L. di Stallo, and S. Battiato, "Grid trading system robot (gtsbot): A novel mathematical algorithm for trading fx market," *Applied Sciences*, vol. 9, no. 9, p. 1796, 2019.

[30] F. Rundo, F. Trenta, A. L. Di Stallo, and S. Battiato, "Advanced markov-based machine learning framework for making adaptive trading system," *Computation*, vol. 7, no. 1, p. 4, 2019.