Mobilenet, inception ResNet and GoogleNet for epilepsy detection using spectrogram images

Fatima Edderbali[1], Mohammed Harmouchi[1], Elmaati Essoukaki[2]
[1]Laboratory of Radiance-Mater and Instrumentation, FST, Hassan First University, Settat, Morocco
[2]Laboratory of Health Sciences and Technology, Hassan First University, Settat, Morocco

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ABSTRACT

Epilepsy is considered the most common cerebral disorder, around 1% of the worldwide population suffer from it. Recently, detection of epilepsy has attracted more and more attention. It has become a hastily increasing problem that can worsen their conditions which necessitate a specific and crucial attention where the symptoms can be an impaired awareness or motor symptoms. Besides that, the difficult process of manual inspection of electroencephalography electroencephalogram (EEG). This paper proposes using transfer learning models to detect both normal and epileptic brain activity and auto-classify signals from the brain. The models considered for this study are GoogleNet, MobileNet, and inception residual neural network inception ResNet. These models were associated with seven different classifiers such as discriminant. These classifiers were tested, analyzed and compared with each other. The efficiency of models is comparatively evaluated through result using multiple metrics. We therefore attained an accuracy of 96.53%, a precision of 97.18%, a false positive rate of 2.78% and an F1-score of 96.50%. Finally, comparison of the suggested approach with existing research shows that the performance of epilepsy classification has been markedly enhanced.

Corresponding Author:

Fatima Edderbali
Laboratory of Radiance-Mater and Instrumentation, FST, Hassan First University
Settat, Morocco
Email: f.edderbali@uhp.ac.ma

1. INTRODUCTION

Epilepsy is a sudden abnormality caused by excessive electric discharge of brain activities [1] that distress the entire body that affects 65 million people worldwide [2] and may have a potentially life-threatening impact on affected individuals and their families. Epilepsy disease is twice as severe in low-income countries as in high-income countries, likely due to a high number of risk factors [3]. Identifying epileptic brain signal using electroencephalogram (EEG) that is able to monitor the brain activity and diagnosis of epilepsy in such an effective way however EEG readings must be analyzed by neurologists to detect and classify the patterns of the normal and epilepstic brain signal [4]. This examination put a heavy load on neurologists that can take many hours which can be laborious and reduce their efficiency for those reasons this study aims to develop automatic solution to classify epileptic and non-epileptic EEG brain signals.

Many approaches have been proposed in order to detect epilepsy, several approaches based on time-series analysis that identify patterns in EEG signals that indicate the epileptic or the normal one. Starting with some various traditional detection techniques can extract and classify feature using many types of entropy measures [5] wavelet transforms [6], decomposition by empirical mode [7], empirical data analysis Hilbert–Huang transform method (HHT) [8]. All the next methods that will be cited can be described as handcrafted feature extraction that are time consuming and have a computational complexity to be able to make classification and clustering focal and non-focal epileptic seizures for example: support vector machines (SVM), k-means and fuzzy c-means clustering, neural networks, k-nearest neighbors (KNN), Naive Bayes [9], known as handcrafted feature extraction, offer both time consuming and computational complexity. Thus, implementation of these methods is considered as an orduous process with real-time cases [10].

Recently, machine learning (ML) has been used to detect epileptic and non-epileptic signals [11]. This new approach detected epileptic seizures in longterm human EEG that is a challenging task, especially with small amount of data that has been used for training morever the presence of artifacts and noise in the EEG signals that make learning so difficult which increase depending to type of epilepsy among patients [12]. This automatic approach made a good accuracy when the classification is related to one epilepsy type however it fails in working properly in identifying the normal vs. ictal vs inter-ictal [13]. That can be explained by the fact that models can't be used in general purpose. However, if the classification tends to identify normal and epileptic signal or ictal, inter-ictal and normal one, the labeled data are fewer and accuracy is not enough to assist neurologists, so the only model that is acceptable has to overcome those negative points [14].

Deep learning (DL) has shown promising results in many applications and successfully encodes automatically a hierarchy of features with EEG that has low-frequency with long time-period and high-frequency features with a short time [15]. Moreover, DL has great advantage by giving more robust and discriminate features than hand-designed ones. In order to improve the accuracy in the classification of epileptic and non-epileptic EEG signals. The recent emergence of DL techniques shows significant performance in several applications such as 2D convolutional neural network (CNN) AlexNet [16], visual geometry group (VGG) or 3D networks such as 1D CNN has been successfully used for text understanding, music generation, and other time series data. The end-to-end learning model of DL approach can't select the proper combination of feature extractor and feature subset selector that need suitable classifier. Although DL is slower in training than traditional approach but it is so much faster at test time, the only issue is that the DL needs larger dataset and takes a long time in training, in order to solve this problem, we propose the use of transfer learning which has been already trained with largest data amount and we will select the best classifier that shows best performances.

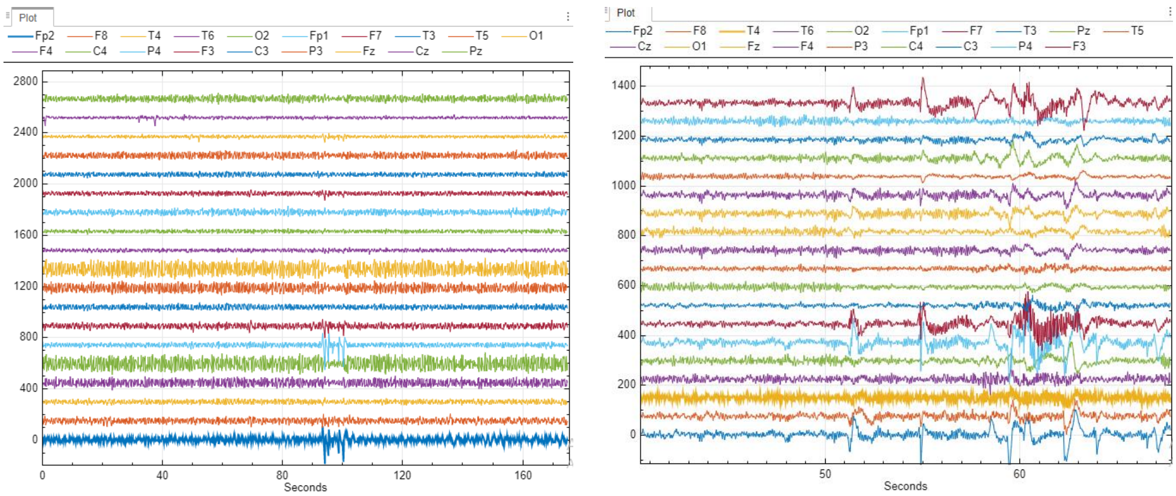
Our method involves combining the training stages of the MobileNetV2 CNN structure, including data augmenting, transfer learning and classifier, within a single solution. We have suggested the use of different transfer learning models: GoogleNet, inception ResNet, and MobileNet which has been associated with different classifiers. We also extracted spectrogram from EEG channels to use them as image dataset for transfer learning models combined with those classifiers: SVM, tree, discriminant Naïve Bayes Kernel KNN and linear the comparison between the associating with different classifiers, leading to more successful results. We carried out trials with models and reported findings. The principal achievements of this study can be summed up as the following: i) a novel deep transfer learning model has been suggested on the basis of MobileNetV2 for detecting epileptic disorder; ii) using spectrogram images instead of European data format (EDF) files of EEG; iii) combining each model with the seven classifiers cited before, with training approaches 30-70% between training and testing; and iv) the results achieved the highest success rate. Section 2 provides details of the datasets, pre-processing steps, spectrogram extraction, suggested CNN structure and classifiers. Section 3 shows transfer learning outcomes as evaluated by several parameters. And a discussion of the suggested design in relation to the literature is included in the same section. Finally, Section 4 presents the findings and forward-looking work of the article.

2. METHOD

This section briefly discusses datasets extracting from EDF files of EEG, enhancement, pre-processing, transfer learning, and classifiers. Furthermore, the proposed DL methods are detailed. We applied pre-trained CNN models, GoogleNet, inception ResNet, and MobileNet, to identify the optimal model for our particular task in this research. The models were all trained on 80% of the data set for 100 epochs. As a result, MobileNetV2 is the best choice, we therefore chose MobileNetV2 as our primary model.

2.1. Datasets

The major challenge in training and validation of the suggested approach lies in the limited availability of publicly labelled datasets. The majority of previous research have relied on limited datasets, thus not guaranteeing that the model will be completely trained. Hence, to improve the generalizability of the suggested model and build a more solid model, it is essential to use a bigger database. The majority of public epilepsy datasets comprise two categories. In this work, since it is generally recognized that EEG signals are noise-sensitive and operate in certain bands of frequency, it is suitable to investigate EEG signals within each band. In such a way to be able to minimize noise, the result of the extracted EEG brain signals in Figure 1 that illustrated in Figure 1(a) normal signals and in Figure 1(b) the epileptic EEG signals of all channels after extracting them from the EDF file, and to ease feature extraction, we additionally used a notch filter set around 50 Hz to minimize electrical power artifact. Following all previous stages, pre-processing and transforming the EDF file into spectrogram images, so the dataset was generated. It was used as an input transfer model that extracts the features. The dataset was obtained from the American University of Beirut in the Epilepsy Monitoring Unit, with EEG signal recording using 21 scalp electrodes arranged in a 10-20 system [17]. We started by obtaining the spectrogram images from the EEG EDF file for using it as input to the 2D model, which has been used to extract features that will benefit the different classifiers to succeed in the classification normal and epileptic spectrogram [18] as it is shown in Figure 2.



(a) (b)

Figure 1. Representation of extracting signal from raw EEG EDF files (a) normal and (b) epileptic one

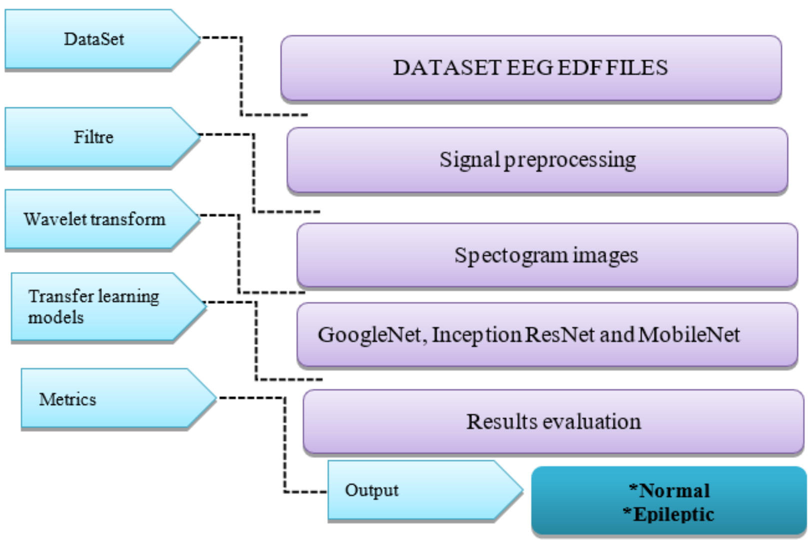


Figure 2. The diagram illustrates the steps involved in classification via a combination of a pre-trained model and a classifier

2.2. Data preprocessing, extracting and augmentation

Deep CNNs have obtained outstanding performance in a variety of image classification problems; nevertheless, such models require big datasets to overcome over-fitting. We require a huge dataset to build a powerful and efficient DL model, and this is not necessarily the case. The methods of data augmentation employed are a range of different techniques that enhance the training dataset size. They allow the classes in the data set to be diversified. Data augmentation has been successfully employed in the proposed model to enhance the data size, prevent over-fitting and generate a more accurate model. These approaches create new images by interactively adjusting various visual characteristics of the image, such as image rotating, flip and zoom. The Dataset includes after extracting from EDF file the spectogram images, they are 1,024×1,007 pixels. We had to downsize the images to match the input form of the models under test. The MobilenetV2 input form is 224×224.

2.3. Transfer learning models

In this paper, those models are chosen because they are frequently used in deep learning applications [19], [20]. Various transfer learning models were used in this article, starting with GoogLeNet: Google has developed a ConvNet model known as GoogLeNet in 2015. The model contains 22 layers and was the winner of 2015 at the ImageNet large scale visual recognition challenge (ILSVRC) with an error rate of 6.7%. While previous ConvNet models included convolution and pooling layers on top of each other, the architecture of GoogLeNet is marginally different. It employs an initialisation module to minimize the number of network parameters. Moving to the inception-ResNet: a new hybrid initialization model using residual connections, similar to ResNet, was introduced in 2017. Known as inception-ResNet, this hybrid model considerably improved the learning speed of the initialization model and outperformed the classic ResNet model slightly. Finally, MobileNetV2 is also a neural network that offers exceptional results when it comes to matching resource constraints with recognition accuracy. It is also one of the most important benefits of being suitable for use on mobile devices and embedded systems. Deep neural network designs encounter a certain number of challenging issues, such as network optimization, vanishing gradient problems and distortion problems [21]. The proposed method explained in Figure 3 started by the spectrogram images from the EEG EDF file as input to the 2D model MobileNet that extracts the features. That will benefit the different classifiers to succeed in the classification normal and epileptic spectrogram.

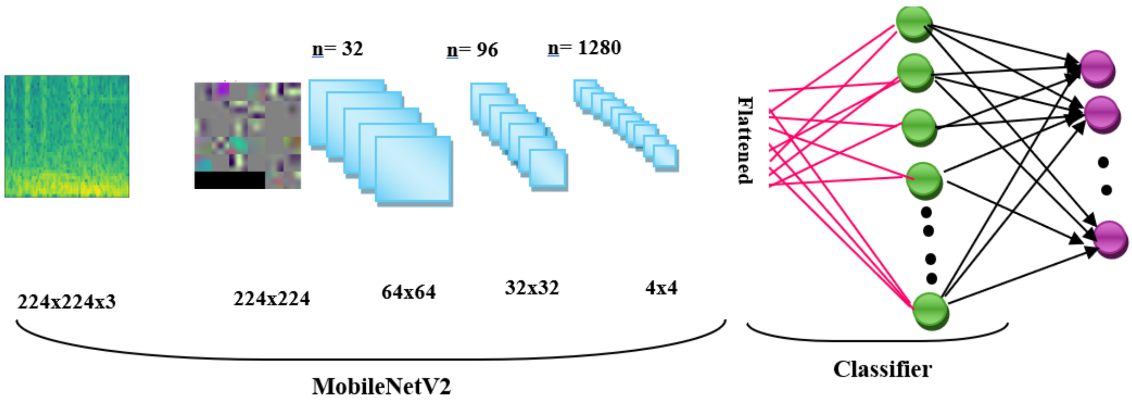


Figure 3. Transfer learning model MobileNet associated with SVM classifier

3. RESULTS AND DISCUSSION

3.1. Metrics of the classification performance and confusion matrix

Performance evaluation through two classes identification: we have decided to evaluate this classification by using several performance metrics [22], [23]. As illustrated in Tables 1 to 3, this paper employed a total of seven classifiers, all of them having a meaningful association with the CNN model. Of them, MobileNet in combination with the SVM classifier made the highest result among several metrics for accuracy 0.9653, error rate 0.0347 while recall was 0.9583, with specificity achieved 0.9722. In addition, the matrix of confusion is an incredibly valuable tool for observing the model's degree of incorrectness or correctness Figure 4. It can provide a clear view of correct and incorrect class model predictions, as can be seen in Figure 4 confusion matrix that illustrates the result of best association of models with classifier in Figure 4(a) GoogleNet with discriminant, Figure 4(b) inception ResNet with KNN, and Figure 4(c) MobileNet with SVM.

Table 1. Classification results for GoogleNet model combined with several classifers

GoogleNet	Accuracy	Error	Recall	Specificity	Precision	FPR	F1-score	MCC
SVM	0.7083	0.2917	0.6667	0.7500	0.7273	0.2500	0.6957	0.4181
Discriminant	0.8264	0.1736	0.8472	0.8056	0.8133	0.1944	0.8299	0.6533
Kernel	0.6319	0.3681	0.5694	0.6944	0.6508	0.3056	0.6074	0.2660
KNN	0.6806	0.3194	0.6944	0.6667	0.6757	0.3333	0.6849	0.3613
Linear	0.5833	0.4167	0.6111	0.5556	0.5789	0.4444	0.5946	0.1669
Naïve Bayes	0.6111	0.3889	0.4306	0.7917	0.6739	0.2083	0.5254	0.2383
Tree	0.7986	0.2014	0.9028	0.6944	0.7471	0.3056	0.8176	0.6106

Table 2. Classification results for inception ResNet model combined with several classifers

Inception ResNet	Accuracy	Error	Recall	Specificity	Precision	FPR	F1-score	MCC
SVM	0.9306	0.0694	0.9167	0.9444	0.9429	0.0556	0.9296	0.8614
Discriminant	0.8819	0.1181	0.8472	0.9167	0.9104	0.0833	0.8777	0.7657
Kernel	0.5417	0.4583	0.6389	0.4444	0.5349	0.5556	0.5823	0.0850
KNN	0.9444	0.0556	0.9444	0.9444	0.9444	0.0556	0.9444	0.8889
Linear	0.9097	0.0903	0.8750	0.9444	0.9403	0.0556	0.9065	0.8214
Naïve Bayes	0.7778	0.2222	0.6250	0.9306	0.9000	0.0694	0.7377	0.5835
Tree	0.8472	0.1528	0.8611	0.8333	0.8378	0.1667	0.8493	0.6947

Table 3. Classification results for MobileNet model combined with several classifers

MobileNet	Accuracy	Error	Recall	Specificity	Precision	FPR	F1-score	MCC
SVM	0.9653	0.0347	0.9583	0.9722	0.9718	0.0278	0.9650	0.9306
Discriminant	0.9306	0.0694	0.9444	0.9167	0.9189	0.0833	0.9315	0.8614
Kernel	0.5556	0.4444	0.3333	0.7778	0.6000	0.2222	0.4286	0.1240
KNN	0.9444	0.0556	0.9583	0.9306	0.9324	0.0694	0.9452	0.8892
Linear	0.9306	0.0694	0.9167	0.9444	0.9429	0.0556	0.9296	0.8614
Naïve Bayes	0.7569	0.2431	0.6667	0.8472	0.8136	0.1528	0.7328	0.5225
Tree	0.8472	0.1528	0.8611	0.8333	0.8378	0.1667	0.8493	0.6947

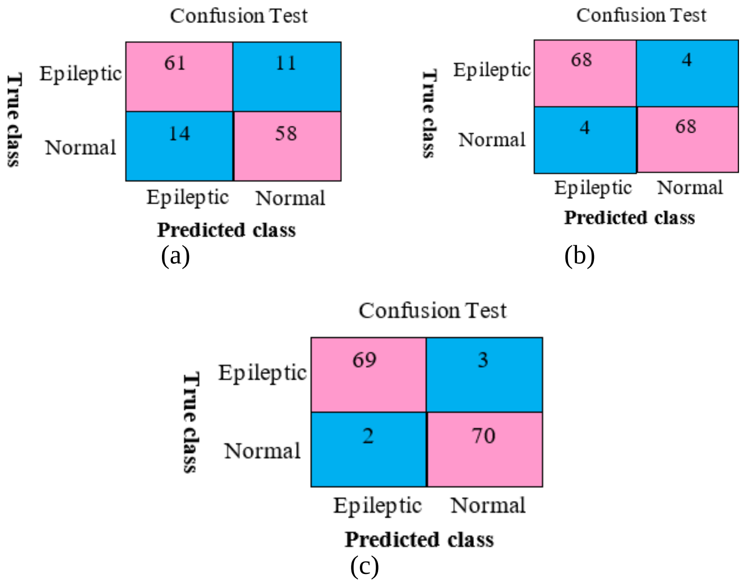


Figure 4. Confusion matrics of the association; (a) GoogleNet with discriminant, (b) inception ResNet with KNN, and (c) MobileNet with SVM

3.2. Discussion

Many people around the world nowadays suffer from epilepsy. The fact that if detection and identification of this cerebral disorder happen in early stage can improve patients' quality of life, to this day, a great amount of research has been conducted to identify abnormalities of brain signals based on artificial intelligence. The objective of these studies is to help doctors make an effective diagnosis of these illness seizures. Artificial intelligent (AI) research entails conventional machine learning [24] and DL [25], [26], nevertheless, they require more data to train, and training is time consuming. Building a powerful model also requires time and lots of data.

In this study, in order to overcome these problems through the use of transfer learning models that have actually already been trained with huge data, so that a large dataset is not needed and results can be given in a short time, Table 4 gives a detailed comparison of the various CNN models that were used in the present study, all of which are binary classification-based. In the work proposed, this study employed for all models the same data set, including normal and epileptic images 140 each class. We implemented a new approach by extracting the spectrogram images from EEG signals, for GoogleNet combined with classifiers, with discriminant having the highest result with precision, error, recall, specificity, accuracy, false positive rate (FPR), F1-score, Matthew's correlation coefficient (MCC) of 82.64%, 17.36%, 84.72%, 80.56%, 81.33%, 19.44%, 82.99%, 65.33%, accordingly. Following this, we applied the inception ResNet model for the classification of normal and epileptic spectrogram images, associated with discriminant which has an accuracy of 94.44% and an error rate of 5.56%. Thereafter, we used MobileNet to categorize this data set, accuracy of 96.53% was achieved.

Table 4. Evaluation of suggested models and others approach related to detection epileptic seizure

Author	Approach	ACC	ACC enhancement
Parvez and Paul [27]	Least square (LS) SVM	91.95%	4.58%
Gasparini *et al.* [28]	Multilayer architecture	90.00%	6.53%
Nicolaou and Georgiou [29]	Permutation entropy with SVM	94.38%	2.15%
Tasci *et al.* [30]	MDWT with KNN	87.78%	8.75%
This study	GooglNet+Discriminant	82.64%	13.89%
	Inception ResNet+KNN	94.44%	2.09%
	MobileNet+SVM	96.53%	

Parvez and Paul [27] have verified the effectiveness of their suggested approach by applying linear and Morlet kernels to the LS-SVM classifier. They reached 89.66% and 91.95% accuracy values. Gasparini *et al.* [28] similarly used multi-layer network approach that includes the transformation from time to frequency domain with feature engineering, and training that associated both unsupervised and supervised learning. So, the model succeeded in distinguishing the different outputs with 90% specificity. Furthermore, Nicolaou and Georgiou [29], in their article, utilized the entropy of permutation (EP) to retrieve features for the detection of epilepsy. Their SVM used the EP to classify EEG segments. The suggested system exploits that EEG signal's higher intensity EP in a normal condition than in an epileptiform EEG. This method offers a sensitivity of 94.38%. In recent work, Tasci *et al.* [30], suggested to extract feature from each channel by feature engineering which was able to achieve great classification result by associating KNN classifier to those features in this work, the accuracy has achieved 87.78%.

4. CONCLUSION

In this paper, we first extract EEG signals from EDF files, followed by filtering the EEG to attenuate the noise that due to the 50 Hz power supply. Afterwards, we applied the wavelet transform to obtain spectrogram images of each signal. We used these images as input for the transfer learning models that we combined with several classifiers, which is well known for its contribution to the automatic detection in medical field nd experimentally, it has been proven that using a pre-trained CNN as a feature extractor for images classification is a very promising approach. So, we used as feature extractors, GoogleNet, inception ResNet, and MobileNet (pre-trained for the large-scale image dataset). As trainable classifiers, SVM, discriminant, kernel, KNN, linear, Naïve Bayes, and tree were employed in combination with these models. As expected, this approach gave excellent results in epilepsy classification, thus motivating us to go further and try to classify the EEG signal in order to not recognize only normal and epileptic activity, but also to identify and specify the type of epilepsy.

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BIOGRAPHIES OF AUTHORS

Fatima Edderbali holds a Master of automatic degree from Hassan First University of Settat in Morocco in 2015. She also received her Bachelor degree on electronic and superior technician in electronic maintenance, respectively. She is currently a teacher of electric engineering at high school since 2012. Her research includes biomedical science and deep learning application in the health field. She has published recently a chapter paper in international conference ICDTA: international conference on digital technologies and applications. From October 2019 until now, she has been Ph.D. student at Laboratory of Radiance-Mater and Instrumentation at Hassan First University of Settat, Morocco. She can be contacted at email: f.edderbali@uhp.ac.ma.

Mohammed Harmouchi born in Sefrou, Morocco, in 1959. He is in charge of the master's degree in biomedical engineering: instrumentation and maintenance. He is the Ex-Director of the Laboratory of Radiation-Matter and Instrumentation, Hassan First University, Settat, Morocco, where he is currently a Professor of Higher Education and the Ex-Head of the Department of Applied Physics, Faculty of Science and Technology. He holds several publications and innovation patents in the fields of biophysics and biomedical engineering. (Based on document published on 9 October 2020). He can be contacted at email: mharmouchi14@gmail.com.

Elmaati Essoukaki born on 1 January 1990. He is currently a Professor of Instrumentation and Biomedical Engineering at Higher Institute of Health Sciences (ISSS), Hassan First University. His research interests include instrumentation and biomedical engineering, biomedical imaging, and signal processing. He holds several publications and innovation patents in the fields of biophysics and biomedical engineering. He can be contacted at email: e.essoukaki@uhp.ac.ma.