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New technic of transfer learning for detecting epilepsy by EfficientNet and DarkNet models

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ABSTRACT

Epileptic seizures are one of the most prevalent brain disorders in the world. Electroencephalography (EEG) signal analysis is used to distinguish between normal and epileptic brain activity. To date, automatic diagnosis remains a highly relevant and significant research topic which can help in this task, especially considering that such diagnosis requires a significant amount of time to be carried out by an expert. As a result, the need for an effective seizure approach capable to classify the normal and epileptic brain signal automatically is crucial. In this perspective, this work proposes a deep neural network approach using transfer learning to classify spectrogram images that have been extracted from EEG signals. Initially, spectrogram images have been extracted and used as input to pre-trained models, and a second refinement is performed on certain feature extraction layers that were previously frozen. The EfficientNet and DarkNet networks are used. To overcome the lack of data, data augmentation was also carried out. The proposed work performed excellently, as assessed by multiple metrics, such as the 0.99 accuracy achieved with EfficientNet combined with a support vector machine (SVM) classifier.

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1. INTRODUCTION

Epilepsy is a major medical problem linked to disorders of cortical excitation. Accurately diagnosing epilepsy in a patient enables selection of the appropriate drug therapy and accurate diagnostic evaluation in the vast majority of situations. Human epilepsy is an intrinsic brain disease in the majority of cases [1]. It can be considered the second most common brain disease worldwide after stroke, with around 700,000 people suffering from epilepsy in Morocco [2]. Over forty million people worldwide (1% of the total human population) currently suffer from epilepsy [2]. Untreated epilepsy represents a major issue for the modern population, due to the associated healthcare costs. Early detection and treatment of epilepsy is further complicated by the disruptive nature of epilepsy, in which seizures are spontaneous and unpredictable due to the chaotic nature of the disorder [3]. Simultaneous hyperactivity of groups of large neurons is the trigger for seizures, which can result in a band of transient changes in cognition and behavior [4]. To understand the triggering system of epilepsy and the evolution of seizures, we need to know how seizures develop and evolve [3].

Electroencephalography (EEG) is an essential clinical diagnostic tool for the assessment, monitoring, and management of neurological disorders related to epilepsy [5]. In the EEG, epileptiform seizures appear as a distinctive feature, usually referred to as rhythmic signals, and often coincide with or even precede the first recognizable conduct changes. The main EEG manifestation is an epileptic seizure, which can involve a discrete part of the brain partially or a whole generalized brain mass [6]. There are some crucial parameters are obtained from these EEG signals, which are highly useful in detecting an epileptic seizure. Despite the over 40 years of investigation in the pathophysiology of it, it remains elusive to explain how clinical transient epileptic spontaneous seizures occur from the comparatively normally brain condition that is noted among seizures [7], [8]. Due to the growing epilepsy patient population and the large workload of detecting seizures by human experts, many attempts at automated seizure detection and analysis have been undertaken [4].

Detecting epilepsy, especially through advancements in machine learning and deep learning, has become a significant area of research. Recent studies have utilized convolutional neural network (CNNs) and reccurent neural network (RNNs) to get a better accuracy of epileptic seizure detection from EEG signals [9]. This study presents a hybrid deep learning model combining CNNs and RNNs to detect epilepsy automatically from brain signal recorded by the EEG. The approach enhances detection accuracy and reduces false positives compared to traditional methods. Hence, it can be computationally intensive and time-consuming to train, requiring substantial hardware resources and optimization. And the increased complexity of hybrid models may lead to overfitting, especially if the training dataset is not sufficiently large or diverse. While attention mechanisms can improve model performance, they can sometimes lead to difficulties in interpreting how attention weights are assigned, complicating the understanding of model decisions. The attention mechanism may increase the computational cost, making real-time implementation challenging. Beside that the deep learning models for epileptic seizure detection. This approach has produced excellent results, but still faces a number of problems in terms of application.
These include the need for a large amount of data.

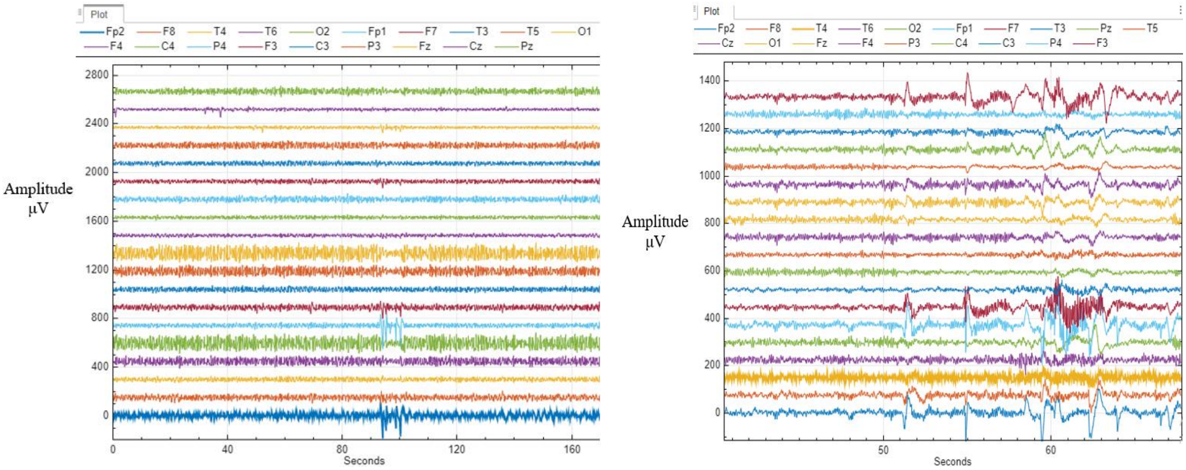
To overcome those limitations, we proposed to base our study on transfer-learning, which is increasingly used to leverage pre-trained models for EEG-based seizure detection, aiming to improve performance with limited training data. Our method involves combining data augmentation, including both transfer-learning and the classifier, as part of the same design. We proposed the use of different models: EfficientNet and Darknet, combined to various classifier, and extracting the spectrogram images which will be an image dataset for the models, the approach resulting in more successful outcomes. The main accomplishments in this research can be summarized as follows: i) a new deep transfer-learning model was proposed with EfficientNet to detect seizure brain signal; ii) employing spectrogram images replaced EEG European data format (EDF); iii) associating model and the previously mentioned classifiers, and iv) achieving significant result. Section 2 gives further information on datasets, pre-processing stages, extracting spectrograms, the proposed CNN architecture and the classifiers. Chapter 3 presents the results of transfer-learning as estimated by multiple metrics. A comparison of the proposed design with the literature is given in this chapter. Lastly, chapter 4 outlines the paper's conclusions and prospective work.

2. METHOD

This chapter discusses in detail the datasets extracted from EEG EDF files, augmentation, preprocessing, transfer-learning and classifiers. In addition, the suggested approach is outlined in detail. implementing pretrained models, Darknet and EfficientNet, in order to determine the most appropriate model for this study's specific problem. These models were each trained on 70% of the dataset. Accordingly, EfficientNet proved to be the best option, and we therefore selected it as our preferred model.

2.1. Datasets

EEG signal analysis is used to address a variety of issues starting by preprocessing, such as data mining, identifing, reducing noise; signal splitting and extract features. The study of these signals is important for not only medical research, but also diagnosis and treatment. Figure 1: illustration of EEG signals EEG data, where the Figure 1(a) represents the normal EEG signal and the Figure 1(b) represents the epileptic one, EEG is a typical signal providing information on electric activity recorded from nerve cells in the cerebral cortex, has been the most commonly used signal for clinical assessment of brain activity and for identifying seizure discharges. The electrical activity model is mainly beneficial to classify epileptic signals and to study of other conditions likely to impair cerebral functionality, and the analyze based on each band can be more appropriate. To be able to reduce noisy characteristic of this signal, in the Figure 1 we present the EEG signal after been extracted from the EDF file which represent the dataset that has been publicly available from the American university of Beirut in the unit of monitoring of epilepsy, the dataset includes 6 EEG epilepstic signals and 20 normal signals with 20 gigabyte size, to overcome the unbalanced data, we used the same amount for each category, the brain signals have been recorded based on 10-20 electrode system [10]. At first, we denoised the signals, extracting each channel and transform it to spectrogram images which will be the input for our model that will be associated to classifiers as illustrated in Figure 2 [11].



(a) (b)

Figure 1. Illustration of EEG signals EEG data (a) representation of normal EEG signals and (b) epileptic brain signal

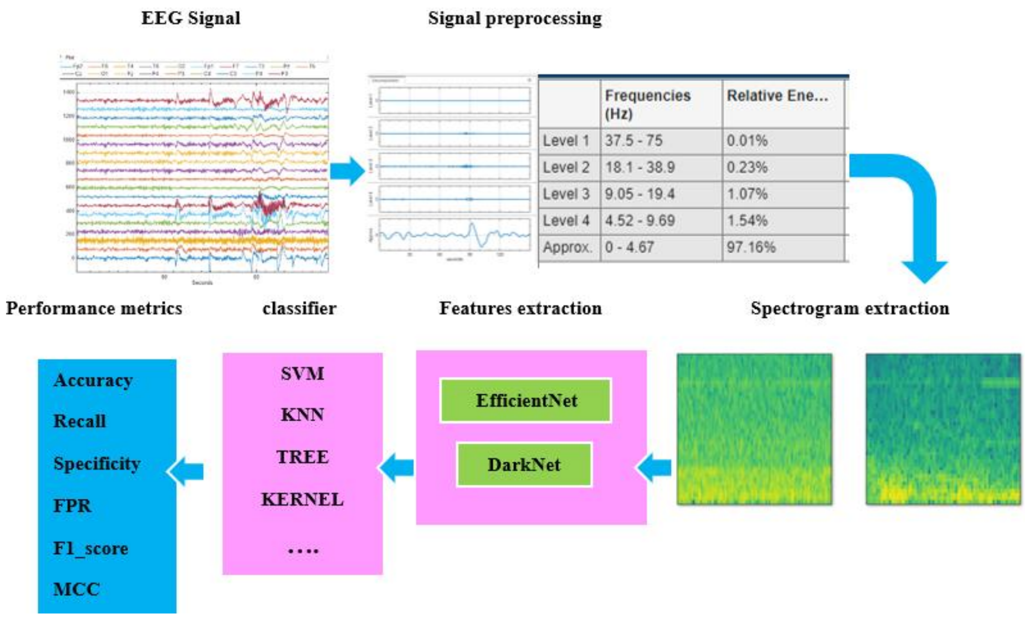
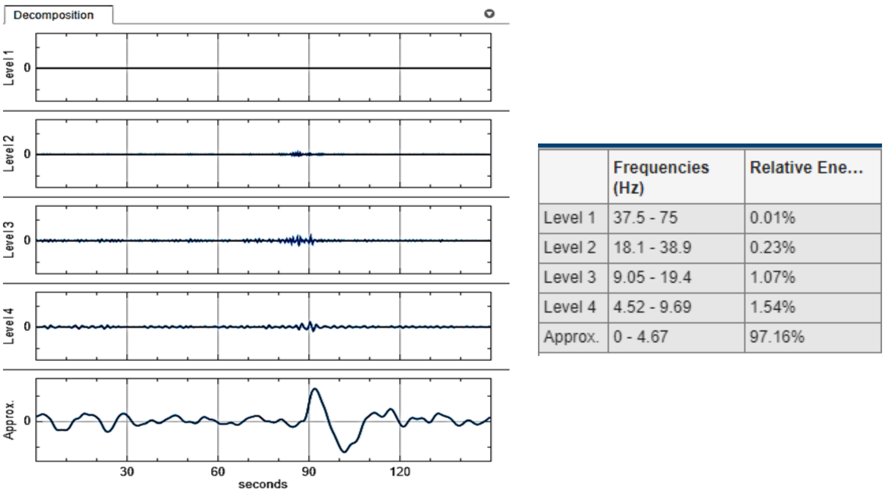


Figure 2. Representation of steps included in the classification approach

2.2. The filtering and data adaptation

Knowing the fact that to select the right mother wavelet transform (WT) can be very crucial that due to each one can give a very big change in the outcomes of this study. That is related to EEG signals of epileptic seizure, for the WT has advantages of giving deeper representation can be very useful hence that demands an important computational time. In the Figure 3 represents wavelet decomposition of the sum mother wavelet of Fp2 channel and the frequency interval, and their energy contribution to the power spectrum after 7 mother wavelets have been used where the resemblance by Sum from levels 4 to 6 was close to the original signal [12].



	Frequencies (Hz)	Relative Ene...
Level 1	37.5 - 75	0.01%
Level 2	18.1 - 38.9	0.23%
Level 3	9.05 - 19.4	1.07%
Level 4	4.52 - 9.69	1.54%
Approx.	0 - 4.67	97.16%

Figure 3. Wavelet decomposition of the sum mother wavelet of Fp2 channel and the frequency interval, and their energy contribution to the power spectrum

2.3. Transfer learning models

This study used some models which considered the most frequent models in deep learning applications [13]. For that reason, this study used more than one model in transfer learning, the first model is DarkNet, which structured as a CNN model architecture, this model has been primarily made to be used in real-time applications in order to detect objects, this model has introduced the method of the you only look once (YOLO) into the main target system. This model is basically structured of convolutional layers, pooling layers, fully connected layers [14]. Where each input during the classification process has the activation values of computational probability is generated by the fully connected layer [15]. Secondly the SoftMax processed the activation value has been given by the previous layer, where every input can be attached to a probability value to relate it to number of classes, that means to be able to associate the input image to the class which reached the highest value among these probability values by the SoftMax layer [16]. Moreover, in order to prevent the problem of overfitting and have a quicker convergence the batch normalization has to be used in DarkNet models [17]. with this model that use image input with size is 224 224 resolutions.

The EfficientNet B0 proposed [18], as shown in Figure 4, is a variant of the EfficientNet architecture. Aiming to deliver top performance with considerably less parameters and FLoating-point operations per second FLOPs, the EfficientNet family of models was created, differentiating it from existing architectures such as ResNet or visual geometry group VGG, EfficientNet B0, was designed to offer a well balanced compromise of model size and performance. An actual architecture diagram includes several layers, notably the input layer, which has to be an image of a size: 224×224 pixels (RGB channels), a typical size for many computer vision applications. To find the best balance between model size and performance, the EfficientNet design adds a breakthrough technology called “compound scaling”, which evenly balances the depth, width and resolution of the network. Network depth is defined by the number of layers, while width is set by the number of channels in each layer.

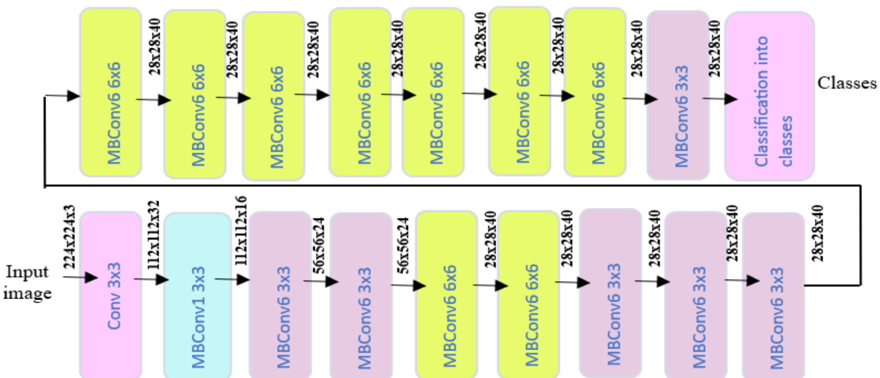


Figure 4. Architecture of EfficientNetb0 network

3. RESULTS AND DISCUSSION

3.1. Evaluation of results

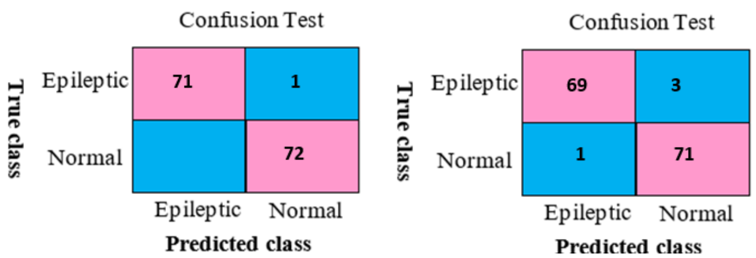
In this section, we introduce the results of the 2 classes model that can identify the normal and the epileptic spectrogram image, in order to judge the performance of the suggested method, multiple metrics have been used [19], [20]. In Tables 1 and 2 we present the two model and the results of the association between each model and various classifiers, as you can see the EfficientNet associated with SVM reached the top outcomes judged by multiple metrics, with 0.9931 accuracy, error rate 0.0069, recall: 0.9861, and specificit:1. After evaluating the models with all these metrics, we present in Figure 5, the matrix of confusion, which is considered a significant tool to judge the incorrectness or correctness of the classification, in Figure 5 that shows the outcome of top model with classifier: EfficientNet with SVM in Figure 5(a) and DarkNet with K-nearest neighbor (KNN) in Figure 5(b).

Table 1. Metrics values for DarkNet model associated with several classifiers

Darknet	Accuracy	Error	Recall	Specificity	Precision	FPR	F1_score	MCC
Discriminant	0.9702	0.0208	0.9583	1.000	1.000	0	0.9787	0.9592
Kernel	0.5000	0.5000	**1.000**	0	0.5000	**1.000**	0.6667	**NaN**
KNN	0.9722	0.0278	0.9583	0.9861	0.9857	0.0139	0.9718	0.9448
Linear	0.9514	0.0486	0.9861	0.9167	0.9221	0.0833	0.9530	0.9050
Naïve Bayes	0.8750	0.1250	0.7778	0.9722	0.9655	0.0278	0.8615	0.7646
Tree	0.8611	0.1389	0.8750	0.8472	0.8514	0.1528	0.8630	0.7225
SVM	0.9653	0.0347	0.9583	0.9722	0.9718	0.0278	0.9650	0.9306

Table 2. Metrics values for EfficientNet model associated with several classifiers

EfficientNet	Accuracy	Error	Recall	Specificity	Precision	FPR	F1_score	MCC
Discriminant	0.9306	0.0694	0.9167	0.9444	0.9429	0.0556	0.9296	0.8614
Kernel	0.5486	0.4514	**0.5139**	0.5833	0.5522	**0.4167**	0.5324	**0.0975**
KNN	0.9306	0.0694	0.9306	0.9306	0.9306	0.0694	0.9306	0.8611
Linear	0.9583	0.0417	0.9722	0.9444	0.9459	0.0556	0.9589	0.9170
Naïve Bayes	0.7292	0.2708	0.5278	0.9306	0.8837	0.0694	0.6609	0.5007
Tree	0.8403	0.1597	0.8472	0.8333	0.8356	0.1667	0.8414	0.6806
SVM	0.9931	0.0069	0.9861	**1.000**	**1.000**	0	0.9930	0.9862



(a) (b)

Figure 5. Confusion matrix of (a) EfficientNet + SVM and (b) DarkNet + Knn

3.2. Discussion

Hossain *et al.* [21] have attained significant findings by CNNs which are used to detect epileptic seizures. They evaluate the CNN solution capability to perform vigorous feature learning from EEG data to identify cerebral epileptic seizures. This approach achieved an accuracy of 98.05%.

Tran *et al.* [22] introduce a new machine-learning-based method for identifying the presence of epilepsy events in recorded EEG signals. Statistically significant features were mined from the raw data by discrete WT processing, followed by selection of pertinent features by means of feature selection on the basis of the binary particle swarm optimizer. This method reduced data dimensionality by 75% and computation time by 47%, ultimately speeding up the process of categorization. After selection, the pertinent features were employed to train a number of models, and hyperparameter tuning was applied to optimize performance even further. The method attained an accuracy of 98.4%.

Raghu *et al.* [23] lused DWT based sigmoid entropy in time and frequency domains for automated detection of epileptic seizures using SVM classifier, five different mother wavelets have been studied. Classification was performed using both segment and event-based approaches. Bio3.1, Rbio3.1, and Haar wavelets were found to be best choice for seizure detection. The Kappa coefficients obtained for all the databases very good result 94.21%.

Liu *et al.* [24] suggest a dual self-attentive residual network (RDANet) associating a spectrum-attentive module embedding global features with local ones, with a channel-attentive module exploiting the interdependency among canal mappings to obtain better prediction efficiencies. The approach suggested reached an accuracy of 92.07%.

Aung and Wongsawat [25] explored the benefits of reliable entropies, fuzzy and distribution entropy, using a modified distribution entropy (mDistEn) to detect seizures. Their findings indicate that the approach achieves the same consistency and better accuracy (92%).

Zheng *et al.* [9] used feature fusion and hybrid deep learning models for epileptic seizure detection based on multi-class feature fusion and the CNN-gated recurrent unit-attention mechanism (CNN-GRU-AM) model. Initially, the EEG signal undergoes wavelet decomposition through the discrete wavelet transform (DWT), resulting in six subband. Subsequently, time-frequency domain and nonlinear features are extracted from each subband. Finally, the CNN-GRU-AM further extracts features and performs classification. The results show that this method achieved a 94.93% accuracy.

Our method based on using WT and extract spectrogram images from each EEG signal to use it as input to model pretrained, to overcome the limited amount of dataset after that we proposed to use the EfficientNet and DarkNet to extract features and use multiple classifiers as a result we achieved 99.31% accuracy Table 3 represent the comparison between all studies have been cited before and ours.

Table 3. Comparing outcomes of the proposed study with recent research related to epilepsy classfication

Author	Method	ACC	Acc improvement
Hossain *et al.* [21]	CNN	98.05%	1.26%
Tran *et al.* [22]	DWT	98.4%	0.91%
Raghu *et al.* [23]	DWT based sigmoid entropy with SVM	94.21%	5.1%
Liu *et al.* [24]	RDANet	92.07%	7.24%
Aung and Wongsawat [25]	Fuzzy entropy mDistEn	92%	7.31%
Zheng *et al.* [9]	CNN-GRU-AM	94.93%	4.38%
This study	DarkNet+Knn	97.22%	2.09%
	EfficientNet+SVM	99.31%	

4. CONCLUSION

This study is based on the transfer learning model approach where, firstly, we extracted the EEG signals from the EDF files; then, we tried to reduce the noise in these signals by a filter and we used the WT to obtain the spectrogram images of each channel, which were used as input for the DarkNet and EfficientNet pre-trained models, which were associated each time with a different classifier, the models chosen are the latest model with the CNN structure, well known for its great involvement in the automated detecting in the domain of medicine, it is considered as a very promising approach that is able to achieve great results when used as a feature extractor where the input is images. Thus, we used as feature extractors, the two models mentioned above, and as classifiers. As a result, for epilepsy classification, the method proposed in this study achieved a remarkable result, which may be a great motivation to go further with the aim of not keeping the search limited to the identification of two classes only but recognizing the affected area and the specific type of epilepsy.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Fatima Edderbali	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓
Hamid El Malali						✓				✓		✓		
Elmaati Essoukaki						✓				✓		✓		
Mohammed Harmouchi		✓				✓				✓		✓	✓	

C	:	**C**onceptualization	I	:	**I**nvestigation	Vi	:	**Vi**sualization
M	:	**M**ethodology	R	:	**R**esources	Su	:	**Su**pervision
So	:	**So**ftware	D	:	**D**ata Curation	P	:	**P**roject administration
Va	:	**Va**lidation	O	:	Writing - **O**riginal Draft	Fu	:	**Fu**nding acquisition
Fo	:	**Fo**rmal analysis	E	:	Writing - Review & **E**diting			

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Mendeley Data at http://doi.org/10.17632/5pc2j46cbc.1

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