IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 13, No. 1, March 2024, pp. 1022~1029
ISSN: 2252-8938, DOI: 10.11591/ijai.v13.i1.pp1022-1029

Transfer learning 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 of Settat, Morocco
[2]Laboratory of Health Sciences and Technology, Hassan First University of Settat, Morocco

Article Info

Article history:

Received Jul 1, 2023
Revised Oct 9, 2023
Accepted Oct 22, 2023

Keywords:

Alexnet
Convolutional neural network
Epilepsy
ResNet
Visual geometry group

ABSTRACT

Epilepsy stands out as one of the common neurological diseases. The neural activity of the brain is observed using electroencephalography (EEG). Manual inspection of EEG brain signals is a slow and arduous process, which puts heavy load on neurologists and affects their performance. The aim of this study is to find the best result of classification using the transfer learning model that automatically identify the epileptic and the normal activity, to classify EEG signals by using images of spectrogram which represents the percentage of energy for each coefficient of the continuous wavelet. Dataset includes the EEG signals recorded at monitoring unit of epilepsy used in this study to presents an application of transfer learning by comparing three models Alexnet, visual geometry group (VGG19) and residual neural network ResNet using different combinations with seven different classifiers. This study tested the models and reached a different value of accuracy and other metrics used to judge their performances, and as a result the best combination has been achieved with ResNet combined with support vector machine (SVM) classifier that classified EEG signals with a high success rate using multiple performance metrics such as 97.22% accuracy and 2.78% the value of the error rate.

Corresponding Author:

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

1. INTRODUCTION

An epileptic seizure is an abrupt abnormality in the electrical activities of the brain, showing as extreme neuronal network's discharges in the brain that affect the entire body [1]. It is critical to appropriately diagnose epilepsy's patients automatically specially that it has assumed that more than 50 million persons are affected with this illness [2]. In order to detect epilepsy, there are many approaches that have been proposed, and the best approach is related to the specific needs and constraints of the application. Some common approaches include time-series analysis that requires analyzing the electroencephalography (EEG) signal over time to identify patterns or features that are indicative of epilepsy.

This can be performed using techniques such as Fourier transform, wavelet transform, or spectral analysis. the sensitivity of predicting pre-seizure and normal EEG's is about 81% and 88%, respectively. These results confirm our hypothesis that the brain's states are classifiable based on quantitative analyses of EEG [3]. For instance, machine learning this approach involves training a machine learning model on a dataset of EEG signals and labels, and then using the trained model to make predictions on new data. Common machine learning algorithms that have been used for epilepsy detection include support vector machines (SVM), decision trees, and neural networks. Hassan and Subasi [4] decomposed single-channel

EEG signal by using empirical decomposition with adaptive noise, and then implemented an ensemble learning (linear programming boosting) to perform good or else by deep learning. This approach concerns employing algorithms of deep learning for instance recurrent neural networks (RNN) or convolutional neural networks, to investigate EEG signals. Which is capable of learning and extracting the EEG signals features automatically thus successfully detect epilepsy. As an example, to identify epilepsy by using RNN associated with long short-term memory (LSTM) just by analyzing statistical features. Starting with normal, and epileptic channels that has been decomposed into three levels extracting 15 various features, each segment feature was fed into LSTM to classify the EEG signal as a result, this proposed algorithm reached a 96.1% accuracy [5]. Another approach the feature engineering, this approach involves carefully selecting and designing features that are relevant for detecting epilepsy, and then using machine learning algorithms to classify the EEG signals based on these features. This approach requires a good understanding of the characteristics of EEG signals in epilepsy and the patterns that are indicative of the condition.

This study aimed to use different pretrained models, the Alexnet, ResNet50, and VGG19 combined with different classifiers. In the first section, it start by processing raw EEG data and transform those signals to images of spectrogram that represent the power and energy of signal by each frequency, from EEG raw data we extracted spectrogram of each signal to use transfer learning for classification of images, different models Alexnet, ResNet50 and VGG19 that have been associated with classifiers SVM, TREE, discriminant Naïve Bayes kernel k-nearest neighbors (kNN) and linear, beside of what was mentioned before, the architecture of the selected model was represented. In the final part, the result and discussion that shows that the model succeeds in classifying the normal and epileptic images, the performances of pre-trained models were compared and the detection results of 2D-spectrograms were examined; there is a discussion about the success rate metrics of each classifier. the multiple metrics that have been used to evaluate the detection of epilepsy were: accuracy, Error, Recall, Specificity, Precision, false positive rate (FPR), F1_score, matthews correlation coefficient (MCC).

2. METHOD

2.1. Citation and preparation of the dataset

The European Data Format (EDF) EEG file recorded in the unit of monitoring of epilepsy at the American university of Beirut, it contains 6 EEG signals 1 gigabyte size between January 2014 and July 2015. Implementation of 21 scalp electrodes, by 10-20 electrode system, some channels have been eliminated as it was affected with huge artifact, This work was made possible by the Qatar National Research Fund [6]. At the start, the first step is to extract spectrogram images from EDF file of EEG in order to be able to use it as 2D model input, where it has been associated a Convolutional neural network (CNN) model that extracts features with different classifiers. After transforming EDF files to spectrogram images that would be used as our new dataset which we had to split it into training and testing images as shown in Figure 1 with label that identify the two classes the normal and the epileptic one [6].

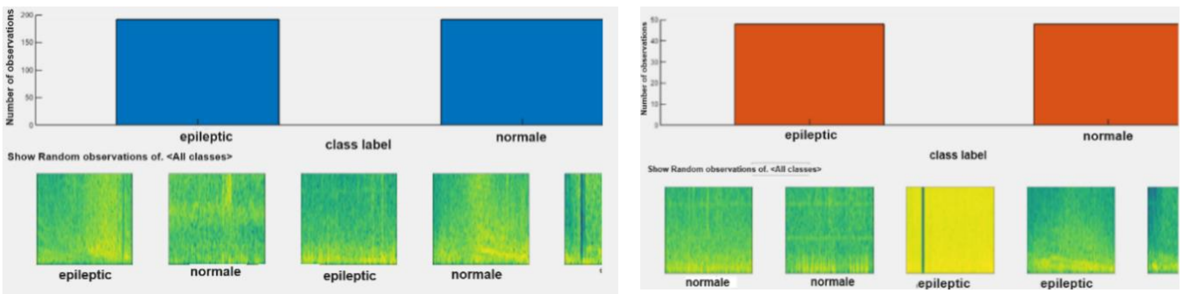

Figure 1. Representation of the result for splitting training and test images

2.2. Preprocessing EEG signal and feature extraction

As is well known that EEG signals are affected by noise and have specific frequency ranges, it is appropriate to study these signals in the frequency domain to be able to eliminate any type of noise in the signal as shown in Figure 2, moreover, to make it easier to extract features. Besides that, we used the notch filter around 50hz to reduce the artifact of the electric supply. After all the stages related to preprocessing and transformation of EDF file to spectrogram images have been conducted and the new dataset has been established. It has been used as an input for our features extractor which is the CNN model.

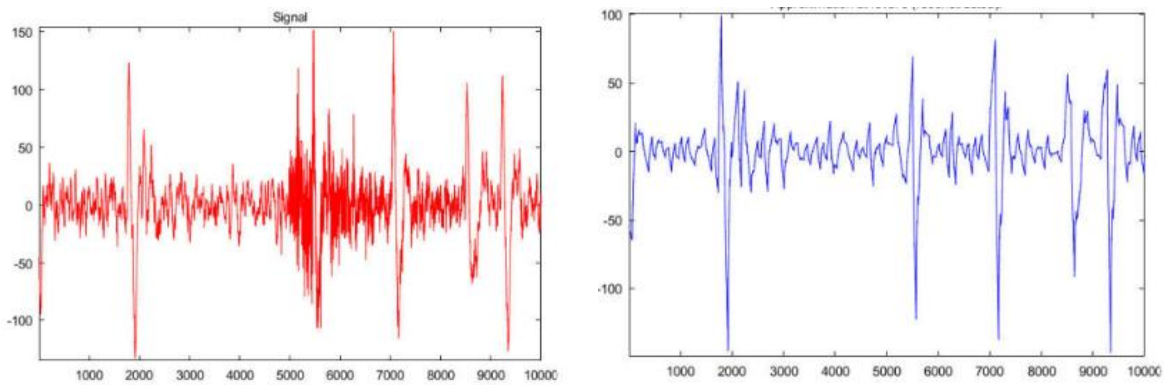

Figure 2. Original EEG signal and the signal after it been denoised

2.3. Pretrained model

Lately, due to the superior overall performance of the several deep learning strategies of CNN network has been widely employed in the different areas of computer vision and image Classification. In the healthcare area, CNN has been actively utilized. they can be applied as a tool that automatically diagnose and support experts in the detection of various diseases. CNN networks have an impressive learning capability for the reason that it has multiple features extractions steps to achieve the correlation and locality of the input data efficiently. For example, ResNet structure in the Figure 3. It represents the CNN structure that implies substitute layers of convolution and pooling that should be associated with at least one fully connected layer in the last layer. This combination of CNN layers plays a crucial role in creating new essential models and accordingly attaining more excellent overall performances [7], [8]. Figure 4 shows how we used transfer learning CNN models to classify a new set of images.

Pretrained image classification networks Figure 4 can classify object categories like keyboard, animals and pencil. Those networks have used over a million training images. Taking advantage of large learning feature representations for a huge number of images. Which had been used as an input to the network, finishing with labeling the object in the image showing the probability related to each class object [9]. Lately the applications of deep learning use more frequently transfer learning. Simply it takes a pretrained network and make it as a beginning to learn new task [10]. Training a network from scratch with randomly initialized weights is absolutely slower than transfer learning that can fine-tuning a network faster and easier and most important using a smaller number of training images [11]. For instance, ResNet composed with 50 layers as shown in Figure 3, the image input layer is the first element of the network. After getting the spectrogram images, we resized it. This step is mandatory since each one of the utilized CNN models has his own input image size resolution, as cited in Table 1. For Alexnet network, it has input images size 227-by-227-by-3. Other networks have different sizes. For instance, the VGG19 network has images of size 224-by-224-by-3 [12].

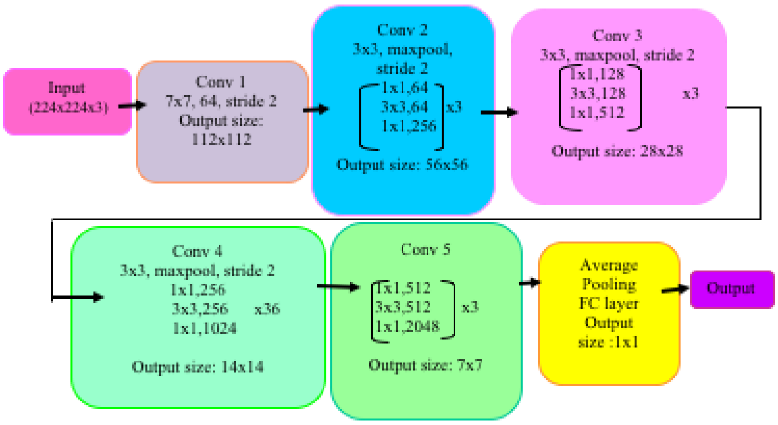

Figure 3. ResNet 50 structure model used as a feature extractor

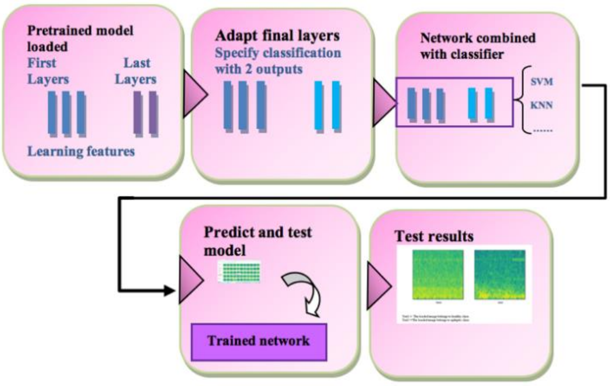

Figure 4. Shows the steps of classification based on pretrained model combined with classifier

Table 1. The specific size of image used as dataset input for each model

Model	Image size
Alexnet	227×227
ResNet50	224×224
VGG19	224×224

2.4. Final steps to classify spectrogram images

In the network, the layer that extracts the image features is the convolutional layer, and layer which is used to classify the input image is the classification layer. fully connected output layer and classification layer which gives the final probabilities for each label, nevertheless the pretrained model used for 1000 output thus this study changes these layers with new ones which are more convenient to the new dataset that has a binary classification. Once this study adapted the size of dataset for each model, test was run using the specific architecture networks for Alexnet, ResNet, and VGG19 CNN model as provided in the MATLAB [13]–[15]. Using a pre-trained model then evaluates the success rate of the network when this study utilized it just as a feature extractor as it is presented in Figure 4. Next step, the pretrained CNN models were employed as a deep feature extractor to extract deep features for spectrogram images. then associated them with classifiers for instance SVM, Naive Bayes, and Discriminant. This study will present the success rate established by each one in the result section.

3. RESULTS AND DISCUSSION

3.1. Confusion matrix

A confusion matrix is an extremely useful tool to observe in which way the model is wrong or right. It can give a clear presentation for correct class prediction and the incorrect one as it is presented in Figure 5. In the confusion matrix, there are 4 numbers to pay attention to.

True-positive: When the model predicted the observation that is positive as positive.
False-positive: When the model predicted the observation that is positive as negative.
True-negative: When the model predicted the observation that is negative as negative.
False-negative: When the model predicted the observation that is negative as positive.

Figure 6 shows the result of classification by a confusion matrix by the classifier which has the best success rate, accordingly it has the following interpretation: The model correctly predicted 70 positive observations but incorrectly predicted 2 as negative. And the model correctly predicted 71 negative samples but incorrectly predicted 1 as positive. From this confusion matrix, it is clear that the data sample is balanced, with the negative and positive class having the same volume of observations which has the value equal to 72.

		Pretrained class	
		P	**N**
Actual class	**P**	**TP**	**FP**
	N	**FN**	**TN**

Figure 5. Representation of confusion matrix for binary classification

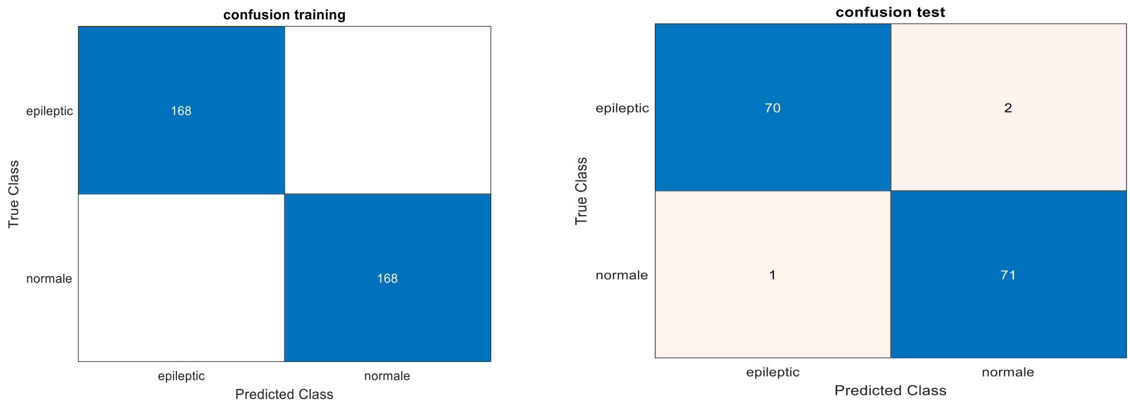

Figure 6. Confusion matrix for training and testing for ResNet model

3.2. Metrics of the classification performance

Metrics based on the binary classification; numerous performance metrics have been proposed [16]–[21]. For our study, the focus is placed on eight of these metrics, which are summarized in Table 2 as expanded in Tables 3-5. This study used seven classifiers, in addition it significantly associated with CNN model. Among them, ResNet50 combined with SVM classifier reached the best success rate with multiple metrics for accuracy 0.9792, error rate 0.0208 while Recall has value 0.9861, obtained specificity of 0.9722.

Table 2. Definition of success rate metrics for classification

Symbol	Metric	Defined as
Acc	Accuracy	$\frac{TP+TN}{TP+FN+TN+FP}$
ERR	Error	$1-ACC$
Rc	Recall	$\frac{TP}{TP+FN}$
SPC	Specificity	$\frac{TN}{TN+FP}$
PRC	Precision	$\frac{TP}{TP+FP}$
FPR	False Positive Rate	1-SPC
F1	F1 score	$\frac{2\times Precision \times Recall}{Precision+Recall}$
MCC	Matthews Correlation Coefficient	$\frac{TP.TN-FP.FN}{\sqrt{(TN+FP)(TN+FN)(TP+FP)(TP+FN)}}$

Table 3. Evaluation metrics for ResNet50 associated with different classifiers

ResNet	Accuracy	Error	Recall	Specificity	Precision	FPR	F1_score	MCC
SVM	0.9792	0.0208	0.9861	0.9722	0.9726	0.0278	0.9793	0.9584
Discriminant	0.9444	0.0556	0.9444	0.9444	0.9444	0.0556	0.9444	0.8889
Kernel	0.4861	0.5139	0.2917	0.6806	0.4773	0.3194	0.3621	0.0302
kNN	0.9653	0.0347	0.9583	0.9722	0.9718	0.0278	0.9650	0.9306
Linear	0.9167	0.0833	0.9583	0.8750	0.8846	0.1250	0.9200	0.8362
Naïve Bayes	0.7361	0.2639	0.6389	0.8333	0.7931	0.1667	0.7077	0.4814
Tree	0.8819	0.1181	0.9028	0.8611	0.8667	0.1389	0.8844	0.7646

Table 4. Evaluation metrics for Alexnet associated with different classifiers

Alexnet	Accuracy	Error	Recall	Specificity	Precision	FPR	F1_score	MCC
SVM	0.9653	0.0347	1.0	0.9306	0.9351	0.0694	0.9664	0.9328
Discriminant	0.9514	0.0486	0.9583	0.9444	0.9452	0.0556	0.9517	0.9029
Kernel	0.5208	0.4792	0.3194	0.7222	0.5349	0.2778	0.4000	0.0455
kNN	0.8889	0.1111	0.8889	0.8889	0.8889	0.1111	0.8889	0.7778
Linear	0.8958	0.1042	0.9306	0.8611	0.8701	0.1389	0.8993	0.7936
Naïve Bayes	0.8194	0.1806	0.7361	0.9028	0.8833	0.0972	0.8030	0.6480
Tree	0.8472	0.1528	0.9306	0.7639	0.7976	0.2361	0.8590	0.7043

Table 5. Evaluation metrics for VGG19 associated with different classifiers

VGG19	Accuracy	Error	Recall	Specificity	Precision	FPR	F1_score	MCC
SVM	0.9028	0.0972	0.8750	0.9306	0.9265	0.0694	0.9000	0.8068
Discriminant	0.9236	0.0764	0.9306	0.9167	0.9178	0.0833	0.9241	0.8473
Kernel	0.5694	0.4306	0.5694	0.5694	0.5694	0.4306	0.5694	0.1389
kNN	0.8472	0.1528	0.8194	0.8750	0.8676	0.1250	0.8429	0.6955
Linear	0.7917	0.2083	0.8194	0.7639	0.7763	0.2361	0.7973	0.5842
Naïve Bayes	0.6042	0.3958	0.3056	0.9028	0.7586	0.0972	0.4356	0.2597
Tree	0.7014	0.2986	0.7222	0.6806	0.6933	0.3194	0.7075	0.4031

3.3. Discussion

Table 6 shows the comparison of different CNN models that have been used in this study which is based on binary classification. In our proposed work, this study utilized for all the models the same dataset, having 140 epileptic images and 140 normal images. This study applied a novel technic by transforming EEG signal to spectrogram images, for Alexnet associated to different types of classifiers, SVM was the best rate with an accuracy, Error, Recall, Specificity, Precision, FPR, F1_score, MCC of 96,53%, 3.47%, 100%, 93.06%, 93.51%, 6.94%, 96.64%, 96.28%, respectively. Thereafter, this study applied the VGG19 model to classify spectrogram images as it is identified normal and epileptic one. it reached 92.36% as an accuracy, error rate of 7.64% when it was combined with the Discriminant classifier. Subsequently, by applying the ResNet50 model to classify the same dataset to achieve an accuracy of 97,92%.

Parvez and Paul [22] the performance of their proposed method is verified using three popular kernels such as Linear, Morlet in the LS-SVM classifier. The results disclose that the prediction accuracies of the proposed method are 89.66%, and 91.95%. Also Gasparini *et al.* [23] They established an approach based on multilayer architecture that includes a time-frequency transformation with feature engineering, and double training associate unsupervised and supervised learning with fine-tuning. This network was successful in discriminating the class with a specificity and sensitivity of 90%. Besides that, Nicolaou and Georgiou [24] in their paper, they used Permutation Entropy (PE) to extract features to detect epilepsy. And SVM used PE values to classify segments of normal and epileptic EEG. The proposed system utilizes the fact that the EEG signal has a higher Pein normal state than epileptic EEG. This approach shows 94.38% of sensitivity and specificity of 93.23%.

Tasci *et al*. [25] in their study, they extracted features of each channel by using feature engineering. In the feature extraction step, they generated two feature vectors by a new hypercube-based feature extractor. they created a feature vector based on various statistical parameters of the signals. To develop a multileveled feature extraction function by applying multilevel discrete wavelet transform (MDWT), and they successfully extracted seven feature vectors, and they maintained the most valuable features selected by using the neighborhood component analysis (NCA) selector. Lastly, these selected features were fed to the k-nearest neighbors (kNN) classifier, this approach attained the highest classification performance which have achieved 87.78% classification accuracy.

Table 6. Comparison of proposed and existing models used for epilepsy classification

Autor	Technique	Accuracy	Accuracy improvement
Parvez and Paul [22]	LS-SVM	91.95%	5.97%
Gasparini *et al.* .[23]	multilayer architecture	90,00%	7.92%
Nicolaou and Georgiou [24]	Permutation Entropy with SVM	94.38%	3.54%
Tasci *et al.* [25]	MDWT with KNN	87.78%	10.14%
This study	VGG19 with DISCRIMINANT	92,36%	5.56%
	Alexnet with SVM	96,53%	1.39%
	ResNet with SVM	97,92%	

4. CONCLUSION

Numerous researches are aiming to combat epilepsy disease by proposing an accurate solution. Yet, the progress in artificial intelligence based on 2D dataset has made hope in the medical field that has proved their efficiency. Consequently, it has been applied to various areas of healthcare, involving EEG analysis for the diagnosis of epilepsy. Thus, a combination of different approaches may be needed to achieve the best results. Therefor this study tried to combine as many classifiers with CNN models and searching for the one which get the best success rate justified with 7 different metrics, as a result to our suggested method that has reached an accuracy of 97.92% with the ResNet model used as a feature extractor with SVM classifier. It is important to note that this study achieved a great result in analyzing EEG data and classifying normal and epileptic signals but what would be more beneficial is to classify seizures in real-time. This can help to identify the presence of seizures and trigger alerts to caregivers, allowing for more timely interventions. Deep learning has also been used to predict the likelihood of future seizures, which can help doctors to develop more personalized treatment plans for patients with epilepsy which will reduce the medical labor force and contribute to the wellness of humanity.

ACKNOWLEDGEMENTS

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

REFERENCES

[1] M. Sazgar and M. G. Young, *Absolute Epilepsy and EEG Rotation Review: Essentials for Trainees*. Springer International Publishing, 2019. doi: 10.1007/978-3-030-03511-2.
[2] "Report by the director-general," 2019.
[3] W. A. Chaovalitwongse, O. A. Prokopyev, and P. M. Pardalos, "Electroencephalogram (EEG) time series classification: Applications in epilepsy," *Annals of Operations Research*, vol. 148, no. 1, pp. 227–250, 2006, doi: 10.1007/s10479-006-0076-x.
[4] A. R. Hassan and A. Subasi, "Automatic identification of epileptic seizures from EEG signals using linear programming boosting," *Computer Methods and Programs in Biomedicine*, vol. 136, pp. 65–77, Nov. 2016, doi: 10.1016/j.cmpb.2016.08.013.
[5] T. Najafi, R. Jaafar, R. Remli, and W. A. Wan Zaidi, "A classification model of EEG signals based on RNN-LSTM for diagnosing focal and generalized epilepsy," *Sensors*, vol. 22, no. 19, p. 7269, Sep. 2022, doi: 10.3390/s22197269.
[6] F. Edderbali, M. Harmouchi, and E. Essoukaki, "Classification of EEG Signal Based on Pre-Trained 2D CNN Model for Epilepsy Detection," in *Lecture Notes in Networks and Systems*, vol. 668 LNNS, Springer Nature Switzerland, 2023, pp. 1008–1016. doi: 10.1007/978-3-031-29857-8_100.
[7] L. Alzubaidi *et al.*, "Review of deep learning: concepts, CNN architectures, challenges, applications, future directions," *Journal of Big Data*, vol. 8, no. 1, 2021, doi: 10.1186/s40537-021-00444-8.
[8] A. Khan, A. Sohail, U. Zahoora, and A. S. Qureshi, "A survey of the recent architectures of deep convolutional neural networks," *Artificial Intelligence Review*, vol. 53, no. 8, pp. 5455–5516, Apr. 2020, doi: 10.1007/s10462-020-09825-6.
[9] B. Kieffer, M. Babaie, S. Kalra, and H. R. Tizhoosh, "Convolutional neural networks for histopathology image classification: training vs. using pre-trained networks," in *Proceedings of the 7th International Conference on Image Processing Theory, Tools and Applications, IPTA 2017*, IEEE, Nov. 2017, pp. 1–6. doi: 10.1109/IPTA.2017.8310149.
[10] R. Ribani and M. Marengoni, "A survey of transfer learning for convolutional neural networks," in *Proceedings - 32nd Conference on Graphics, Patterns and Images Tutorials, SIBGRAPI-T 2019*, IEEE, 2019, pp. 47–57. doi: 10.1109/SIBGRAPI-T.2019.00010.
[11] X. Li *et al.*, "Knowledge distillation with attention for deep transfer learning of convolutional networks," *ACM Transactions on Knowledge Discovery from Data*, vol. 16, no. 3, pp. 1–20, 2021, doi: 10.1145/3473912.
[12] R. Poojary and A. Pai, "Comparative Study of Model Optimization Techniques in Fine-Tuned CNN Models," in *2019 International Conference on Electrical and Computing Technologies and Applications, ICECTA 2019*, IEEE, Nov. 2019. doi: 10.1109/ICECTA48151.2019.8959681.
[13] Matlab Academy, "Machine learning onramp," The MathWorks, Inc. Accessed: Oct. 05, 2023. [Online]. Available: https://matlabacademy.mathworks.com/details/machine-learning-onramp/machinelearning
[14] Matlab Academy, "Deep learning onramp," The MathWorks, Inc. Accessed: Oct. 05, 2023. [Online]. Available: https://matlabacademy.mathworks.com/details/deep-learning-onramp/deeplearning
[15] M. Swamynathan, *Mastering machine learning with python in six steps*. Apress, 2019. doi: 10.1007/978-1-4842-4947-5.
[16] J. Gorodkin, "Comparing two K-category assignments by a K-category correlation coefficient," *Computational Biology and Chemistry*, vol. 28, no. 5–6, pp. 367–374, 2004, doi: 10.1016/j.compbiolchem.2004.09.006.
[17] G. Jurman, S. Riccadonna, and C. Furlanello, "A comparison of MCC and CEN error measures in multi-class prediction," *PLoS ONE*, vol. 7, no. 8, p. e41882, 2012, doi: 10.1371/journal.pone.0041882.
[18] B. W. Matthews, "Comparison of the predicted and observed secondary structure of T4 phage lysozyme," *BBA - Protein Structure*, vol. 405, no. 2, pp. 442–451, 1975, doi: 10.1016/0005-2795(75)90109-9.
[19] D. P. Dirette and M. A. Anderson, "The Relationship between Learning Style Preferences and Memory Strategy use in Adults," *Occupational Therapy in Health Care*, vol. 30, no. 3, pp. 245–254, 2016, doi: 10.3109/07380577.2015.1138015.
[20] M. Sokolova and G. Lapalme, "A systematic analysis of performance measures for classification tasks," *Information Processing and Management*, vol. 45, no. 4, pp. 427–437, 2009, doi: 10.1016/j.ipm.2009.03.002.
[21] G. Canbek, T. Taskaya Temizel, and S. Sagiroglu, "BenchMetrics: a systematic benchmarking method for binary classification performance metrics," *Neural Computing and Applications*, vol. 33, no. 21, pp. 14623–14650, 2021, doi: 10.1007/s00521-021-06103-6.
[22] M. Z. Parvez and M. Paul, "Epileptic seizure prediction by exploiting spatiotemporal relationship of EEG signals using phase correlation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 24, no. 1, pp. 158–168, 2016, doi: 10.1109/TNSRE.2015.2458982.
[23] S. Gasparini *et al.*, "Information theoretic-based interpretation of a deep neural network approach in diagnosing psychogenic non-epileptic seizures," *Entropy*, vol. 20, no. 2, p. 43, 2018, doi: 10.3390/e20020043.
[24] N. Nicolaou and J. Georgiou, "Detection of epileptic electroencephalogram based on Permutation Entropy and Support Vector Machines," *Expert Systems with Applications*, vol. 39, no. 1, pp. 202–209, 2012, doi: 10.1016/j.eswa.2011.07.008.
[25] I. Tasci *et al.*, "Epilepsy detection in 121 patient populations using hypercube pattern from EEG signals," *Information Fusion*, vol. 96, pp. 252–268, 2023, doi: 10.1016/j.inffus.2023.03.022.

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 PHD 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.