



شبكة المعلومات الجامعية  
التوثيق الإلكتروني والميكرو فيلم

# بسم الله الرحمن الرحيم



**MONA MAGHRABY**



شبكة المعلومات الجامعية  
التوثيق الإلكتروني والميكرو فيلم



## شبكة المعلومات الجامعية التوثيق الإلكتروني والميكرو فيلم



**MONA MAGHRABY**



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التوثيق الإلكتروني والميكروفيلم

# جامعة عين شمس

## التوثيق الإلكتروني والميكروفيلم

### قسم

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### يجب أن

تحفظ هذه الأقراص المدمجة بعيدا عن الغبار



**MONA MAGHRABY**



# **A DEEP LEARNING IDENTIFICATION SYSTEM FOR DIFFERENT EPILEPTIC SEIZURE DISEASE STAGES**

By

**Reeham Hussein Mahrous Ahmed Gabr**

A Thesis Submitted to the  
Faculty of Engineering at Cairo University  
in Partial Fulfillment of the  
Requirements for the Degree of  
**DOCTOR OF PHILOSOPHY**  
in  
**Biomedical Engineering & Systems**

FACULTY OF ENGINEERING, CAIRO UNIVERSITY  
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**Title of Thesis:**

**A Deep Learning Identification System for Different Epileptic Seizure Disease Stages**

**Key Words:** Deep learning, CNN, EEG, Epilepsy

**Summary:**

Epilepsy is a neurological disorder caused by abnormal discharge in the brain. The electroencephalogram plays an important role in monitoring brain activity in epilepsy diagnostic tasks. The EEG recording of epileptic patients shows abnormal activities including inter-ictal, pre-ictal, and ictal activity. Automatic detection of these abnormal activities aids the neurologists rather than using visual scanning. The selection of discriminative features from different EEG activities is the basis of the seizure detection method. Deep learning is introduced as an efficient approach in computer-aided medical diagnosis systems; it learns features automatically. In this study, a convolutional neural network (CNN) is employed to identify different epileptic seizure stages. We investigate CNN performance with different signal forms. First, time-domain signal is used as input to one dimensional 1-D CNN network. Second, the EEG signal is transformed to images using two different time-frequency domain transformation methods (Short-Time Fourier Transform (STFT) and the Continuous Wavelet Transform (CWT)), then the spectrogram and scalogram images produced for different epilepsy stages used as input to two dimensional CNN (Alexnet). The experiments are performed using CHB-MIT dataset which contains long time epilepsy recordings for different patients, the EEG signal from scalp left frontal-parietal bipolar channel (FP1-F7) only used. The performances of CNN using time domain signals and time-frequency domain images were compared. As the appearance of preictal activity is unknown, the experiment was done using a preictal labeled as 10 minutes before ictal onset once, then the experiment was repeated by using a preictal as 5 minutes before ictal. Experimental results suggest that the scalogram of the EEG signal increased the CNN classification accuracy to 97%. However, the spectrogram images achieved an accuracy of 73%, while the time domain signals achieved the lowest performance with an accuracy of 64%.

# **Disclaimer**

I hereby declare that this thesis is my own original work and that no part of it has been submitted for a degree qualification at any other university or institute.

I further declare that I have appropriately acknowledged all sources used and have cited them in the references section.

Name:      Reeham Hussein Mahrous      Date: 28/9/2020

Signature:



## **Dedication**

I dedicate my dissertation work to my husband (Dr. Ahmed Abdelhamid Torki) and my son (Asser) for their support, patience, encouragement and help to finish my study.

I also dedicate this dissertation to my mother in law (Dr. Samia Mohamed Fathy) for her great support, effort, and concern during the period of doctoral study and my father in law (Dr. Abdelhamid Mohamed Torki) for his encouragement and continuous guidance to finish this study.

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