Detection of Schizophrenia using Machine Learning

Team: **CSE_I_27**

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[IJECE] Submission Acknowledgement "Using EEG Scalograms and Convolution Neural Networks for Schizophrenia Detection in Adolescents" Inbox ×

Lech M. Grzesiak <ijece@iaescore.com>
to me

Wed, May 25, 11:12 PM (13 days ago)

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Problem Statement

Studying existing solutions based on different techniques (sMRI, fMRI, EEG) with **adolescent** data points to facilitate early detection.

Converting the raw EEG signals to a well defined dataset using Continuous Wavelet **Transform** technique.

Proposing a novel methodology using Convolution Neural Network (**CNN**) that outperforms existing solutions based on previous metric study.

Abstract

- Schizophrenia is a serious mental illness that interferes with a person's ability to think clearly, manage emotions, make decisions and relate to others.
- This project proposes a convolution neural network-based schizophrenia detection technique that makes use of biomedical signals to classify patient groups.
- The use of electroencephalogram (EEG) data from an adolescent control group is done to tailor the model to facilitate accurate early detection.
- To prepare the EEG impulses, the Morlet Wavelet Transform is used to obtain RGB scalograms in image format. These are fed into the 7 layers deep CNN. In the end, the model is shown to have F1 score of 0.945.

INTRODUCTION

Scope

Accurate + **Cost-friendly** detection of Schizophrenia

at an early stage

Motivation

Treatment is **much more effective** if Schizophrenia is detected early. Initial signs are **very subtle** and can’t be detected by humans

Challenges

Present research and datasets focused on Adult patients

Current models use fMRI heavily

Objectives

- To **use Electroencephalography (EEG)** neuroimaging technique **to diagnose Schizophrenia** in patients in comparison to fMRI and sMRI techniques.
- To **create a model using Deep Learning** which **outperforms existing techniques** and is more optimised.
- To do a **performance evaluation of proposed model** based on the different parameters which are:

1. **Sensitivity**
2. **Specificity**
3. **F1-score**
4. **Accuracy**
5. **Negative predictive value**
6. **Positive predictive value**

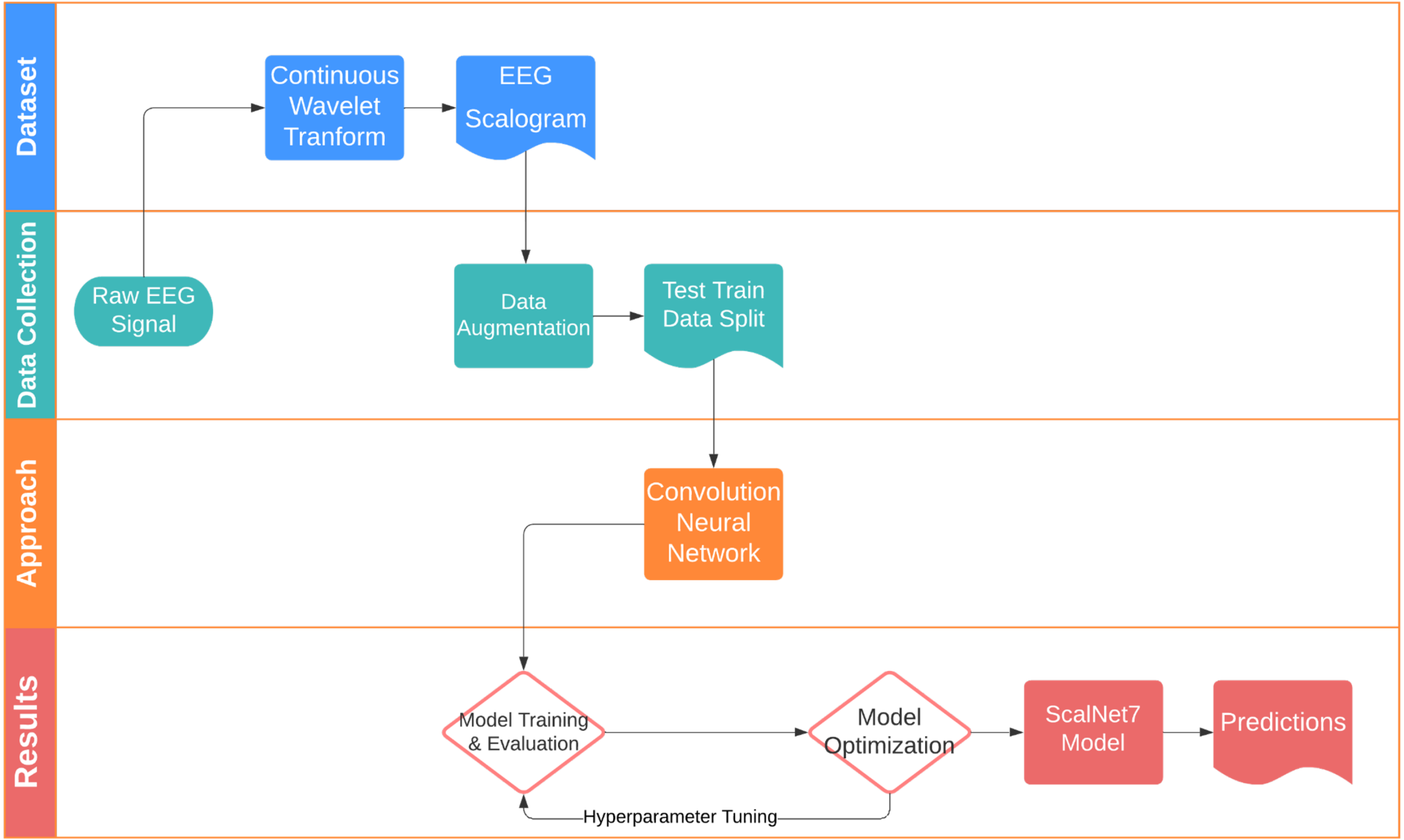
Research Gaps

- Method to extract useful features and then feeding into the classifier for standard class mapping operations has lot of human intervention required and the computational complexity involved.

ScalNet 7 model make uses Morlet Wavelets and Convolution Neural Networks for creating a deep learning classification pipeline.

All model specifications are chosen so as to limit the time and computation complexity of the detection operation.

Data Flow Diagram



Technology Stack

01 **Python**

For signal processing.

02 **Tensorflow + Keras**

ML Models

03 **Google Colab**

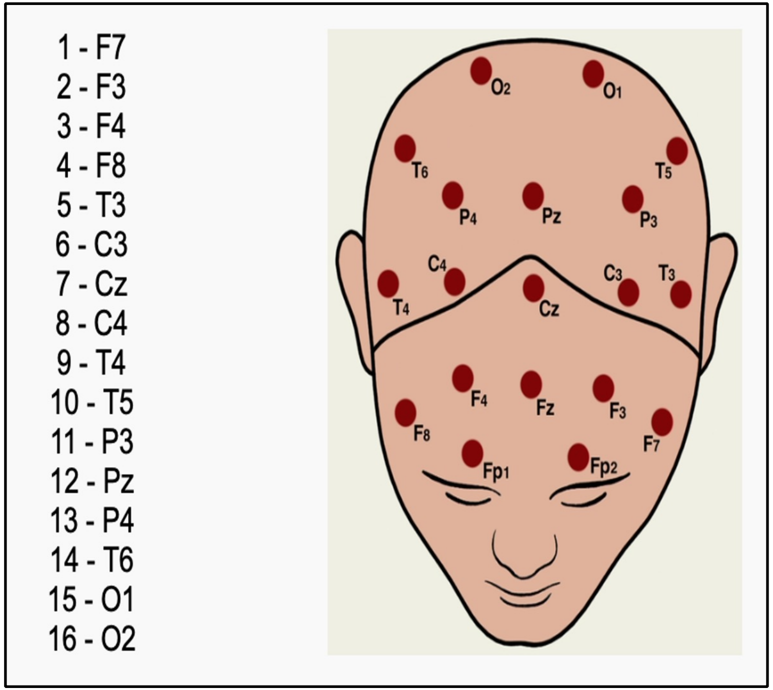
Modelling Approach

04 **Visualisation Libraries**

Numpy, Pandas, Matplotlib

DATASET USED

- For the present project's purpose, the EEG data used was obtained from an archive of the Faculty of Biology, M.V. Lomonosov Moscow State University.
- There are two EEG data archives for two groups of subjects.
- The subjects were adolescents who had been screened by a psychiatrist and divided into two groups: healthy (n = 39) and with symptoms of schizophrenia (n = 45).
- EEG records from each of the 16 channels were obtained. The topographical positions of channel numbers are shown in figure



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122853  -292.57
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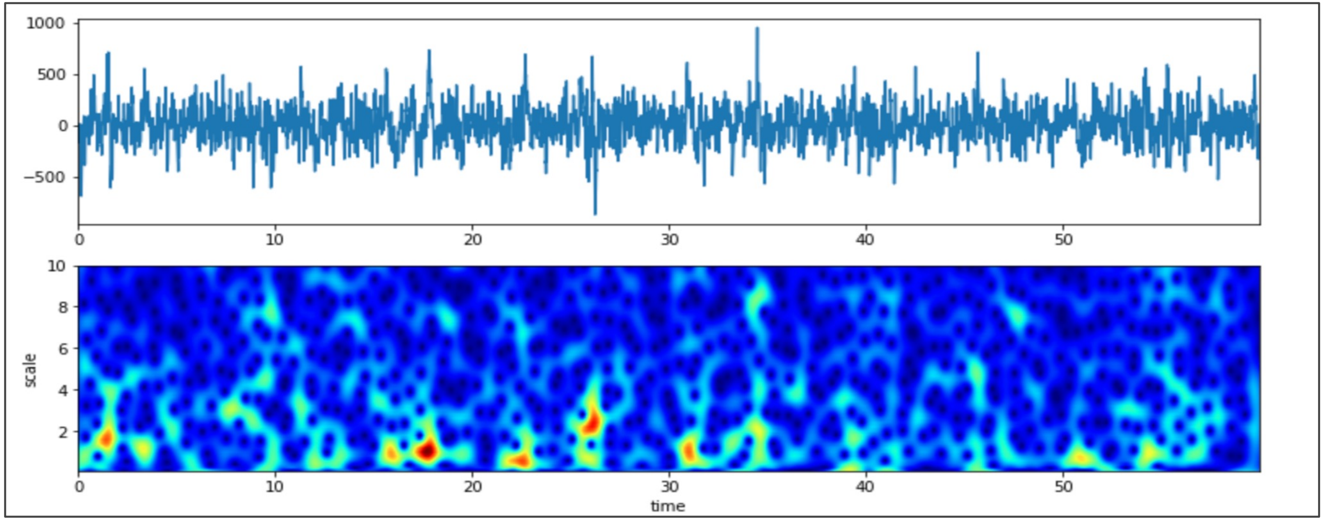
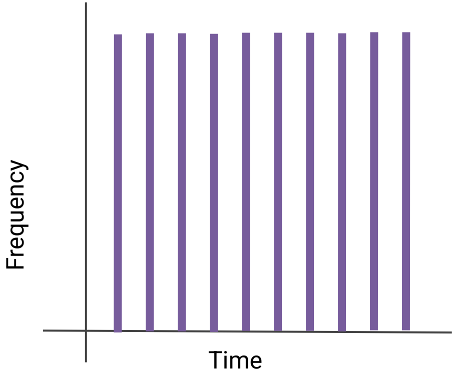
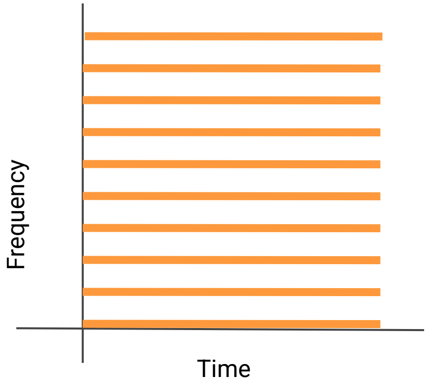
0	347.78	507.87	488.54	369.86	347.78	408.50	488.54	449.90	369.86	427.82	...	278.77	347.78	309.14	27.60	-110.41	-430.58	-571.35	-632.07	-521.67
1	-30.06	-70.74	-90.19	29.18	229.90	249.35	9.73	-110.53	-390.83	-430.62	...	-560.60	-430.62	-340.43	-350.15	-270.57	79.58	279.41	439.46	399.67
2	89.53	129.06	269.74	309.27	309.27	209.28	-70.92	-251.14	-370.89	-290.67	...	119.76	-10.46	-60.46	-201.14	-190.68	-730.16	-570.87	-30.23	219.75
3	228.97	69.32	-170.15	-191.16	-210.06	-151.25	-111.33	-151.25	-331.90	-350.81	...	-1390.62	-691.11	-430.63	-191.16	-81.92	199.56	388.62	258.38	-21.01
4	148.97	109.99	48.73	29.24	69.61	109.99	189.35	208.84	169.86	29.24	...	318.83	79.36	-11.14	-190.74	-270.10	-391.23	-410.72	-370.35	-270.10

5 rows x 122881 columns

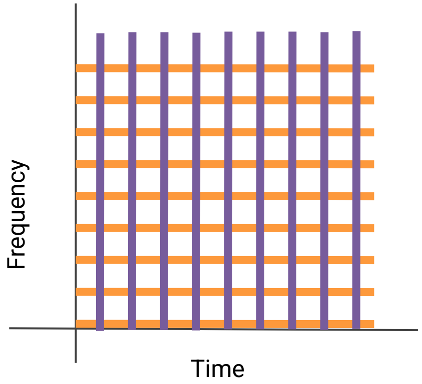




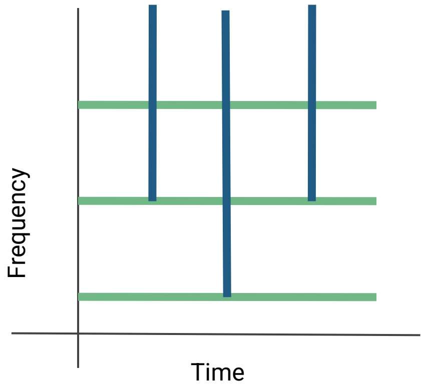
Time Series



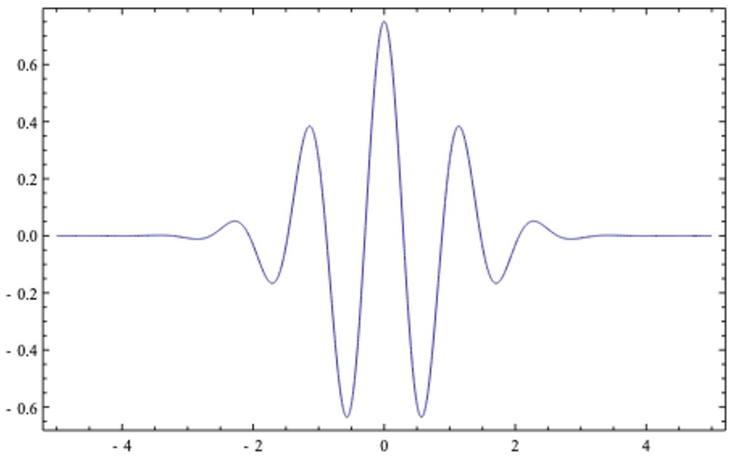
Fourier Transform



Spectrogram



Wavelet Analysis

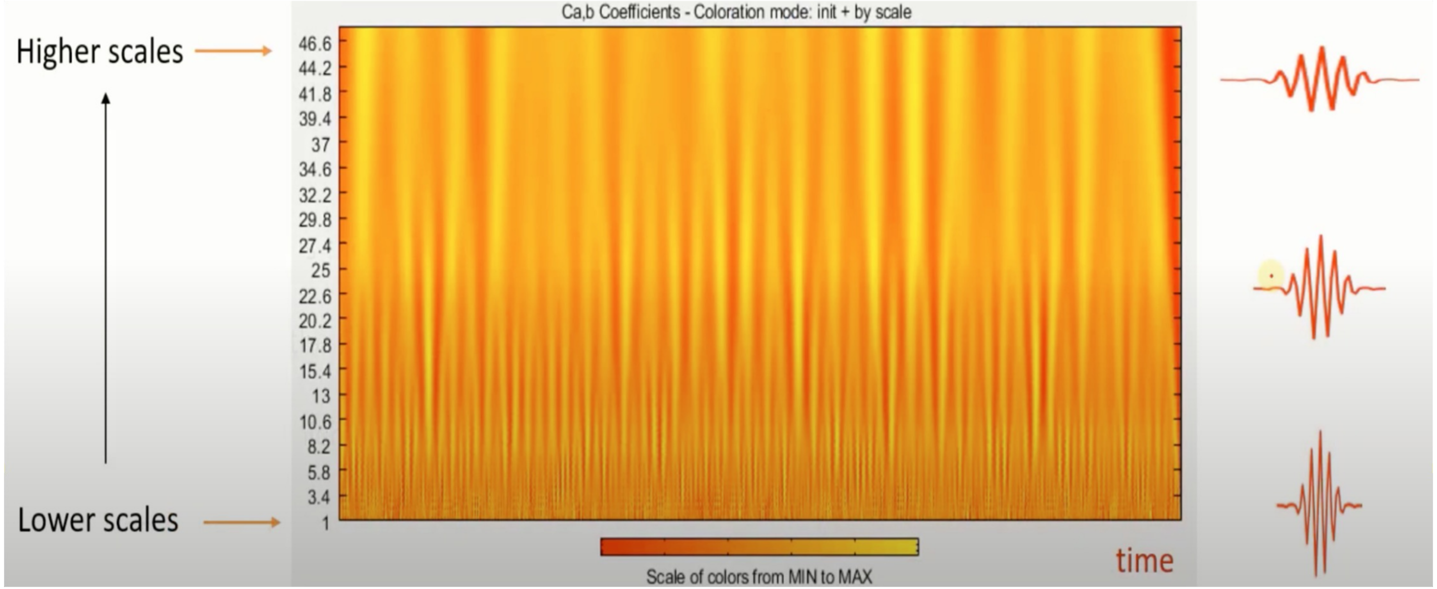


Morlet Wavelet

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-b}{a}\right) \quad a, b \in \mathrm{R} \qquad \ldots(1)$$

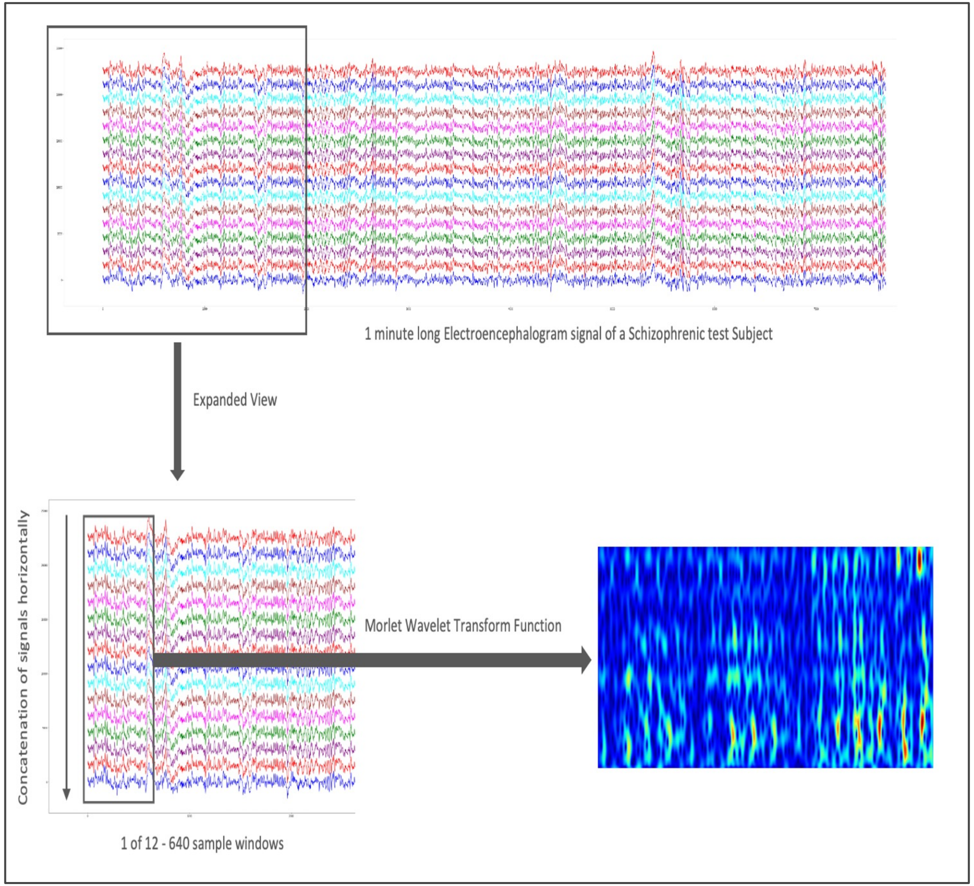
$$\psi(t) = e^{jw_0 t} e^{\frac{-t^2}{2}} \qquad \ldots(2)$$

$$CWT(a,b) = \langle f, \psi_{a,b} \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t).\ \psi^*\left(\frac{t-b}{a}\right) \mathrm{dt} \qquad \ldots(3)$$

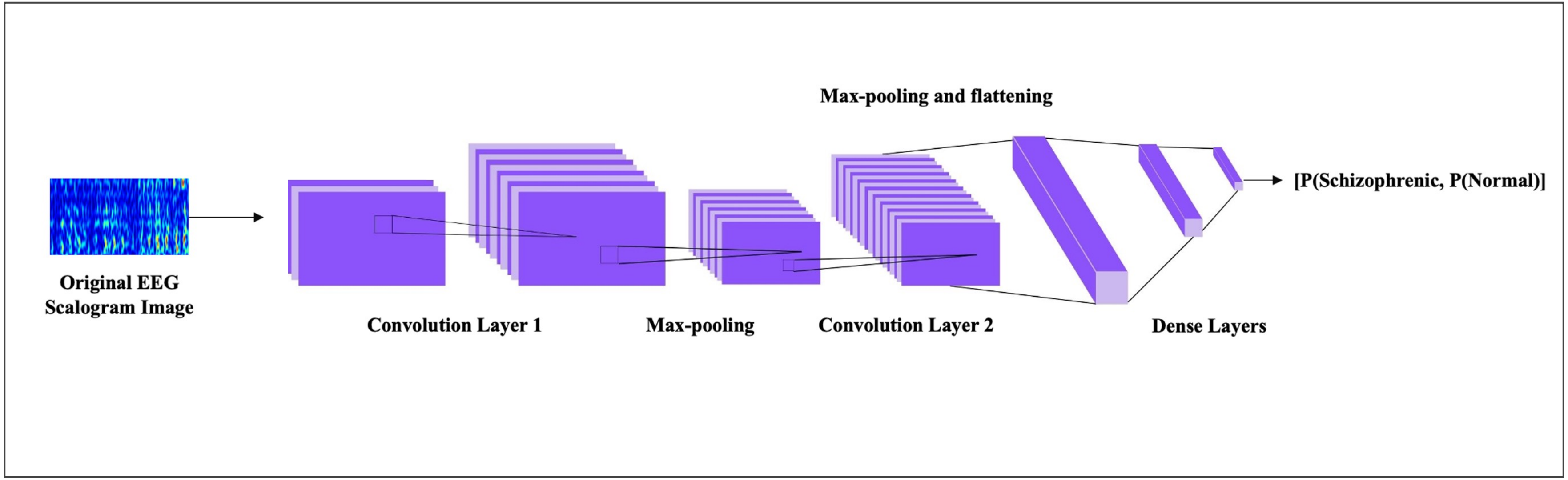


Proposed model

- The proposed model is titled **ScalNet7** and it is a **7 layer deep convolution** neural network.
- Scalograms are prepared using **Morlet wavelet transform.**
- For each test subject, **640 samples per each electrodes** are combined to get a single scalogram.
- **Input :** Scalograms of EEG signals
- **Output :** Class probability prediction.



The ScalNet7 Model



7 Layers in Total

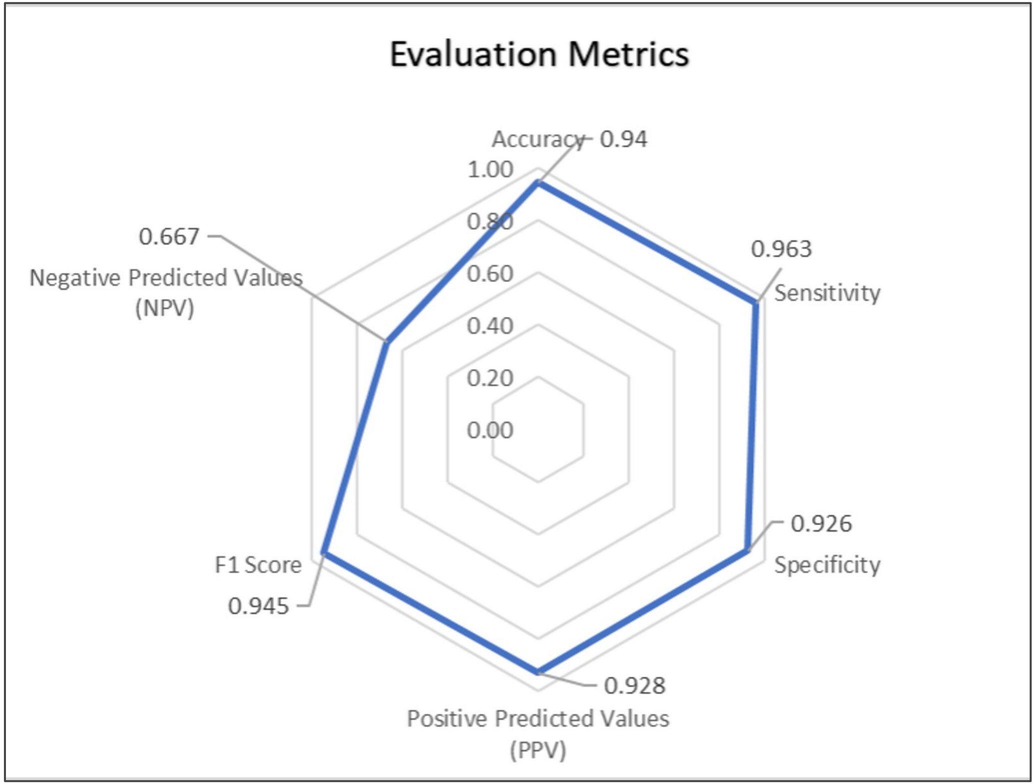
2 Max-pooling layers of

2 Convolution layers of kernel size 3X3

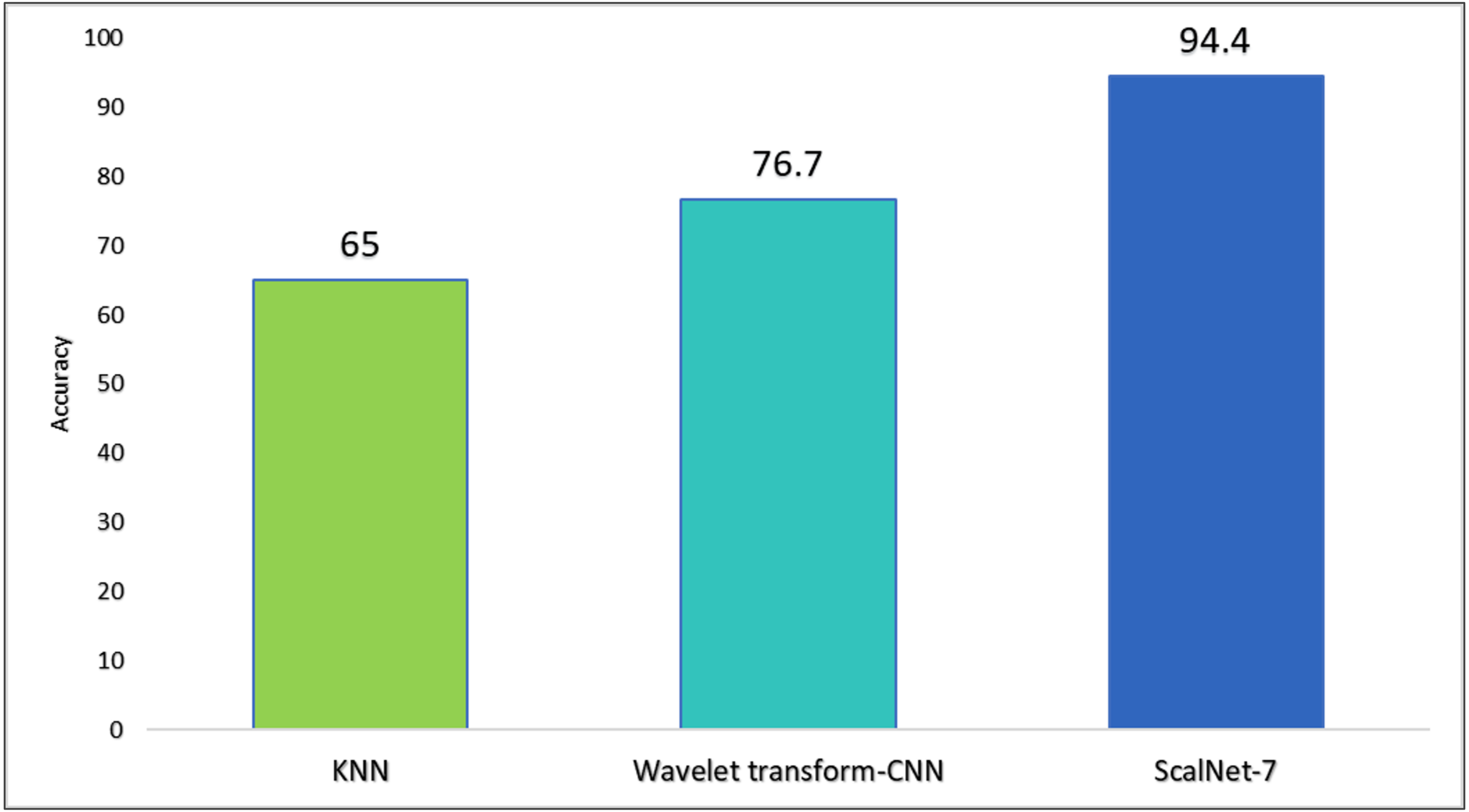
One flattening layer and 2 dense layers with Re-Lu and softmax activations respectively

RESULTS

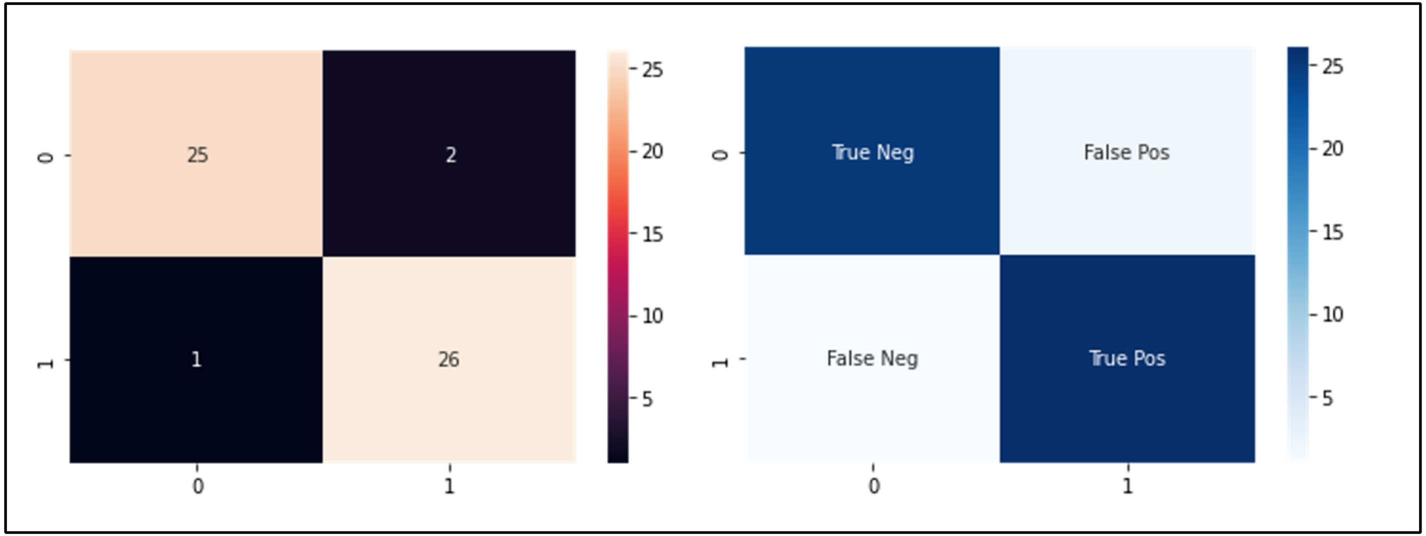
Parameter	Value
Accuracy	94.44%
Sensitivity	0.963
Specificity	0.926
Positive Predicted Values (PPV)	0.928
F1 Score	0.945
Negative Predicted Values (NPV)	0.667



Comparison between our models

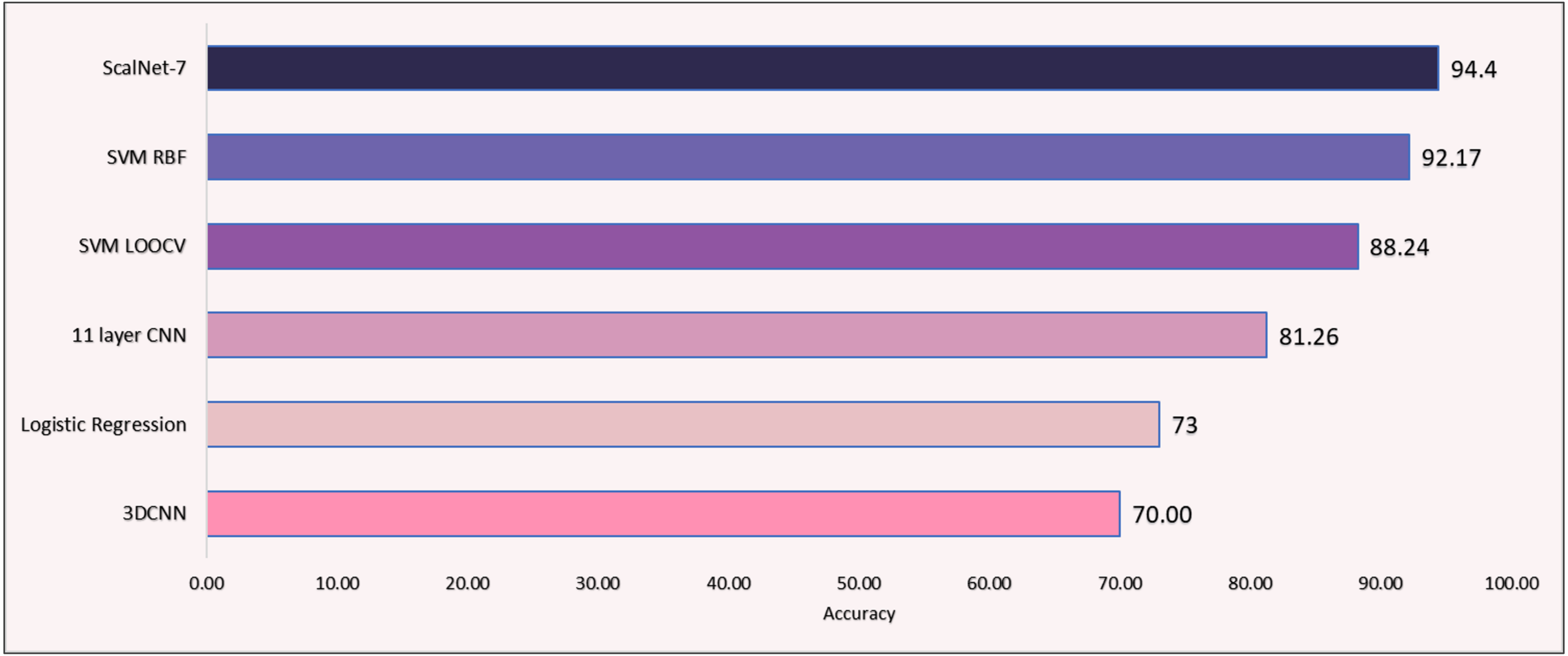


Confusion Matrix



True Negative	25
False Negative	1
True Positive	26
False Positive	2

Comparison with existing solution



Feasibility Study for Engineering Significance

Need: Help diagnose people who may seem healthy now but are at a risk of developing mental health diseases at a later stage.

	EEG Electroencephalogram	MRI Magnetic Resonance Imaging	fMRI Functional MRI
Measures brain activity?	Directly	Only structure	Indirectly (BOLD response)
Level of expertise needed	Some training	Extensive training	Extensive training
Cost	Accessible to many researchers	Requires extensive funding	Requires extensive funding
Portability	Both fully portable and semi-portable devices available	Not portable	Not portable

Conclusion

Project Conclusions

- Our study was focused on utilizing data from adolescent test subjects so as to work towards bridging the gap that exists in the early detection of this disease
- The presented model uses convolution neural networks and Morlet wavelet analysis for the detection of schizophrenia using EEG scalograms. The model converged at a training accuracy of 100% and testing accuracy of 94.4%.
- The lightweight framework and computationally inexpensive nature of the model also make it highly feasible for field implementation.

Future Scope

In the future, the performance of the model can be enhanced by making the model deeper and training on a more expansive, balanced and inclusive dataset. Further, efforts to enhance the negative predicted value (NPV) parameter may also be made.

Thank You!

Team: **CSE_I_27**

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Project Guide: Dr. Neelam Sharma

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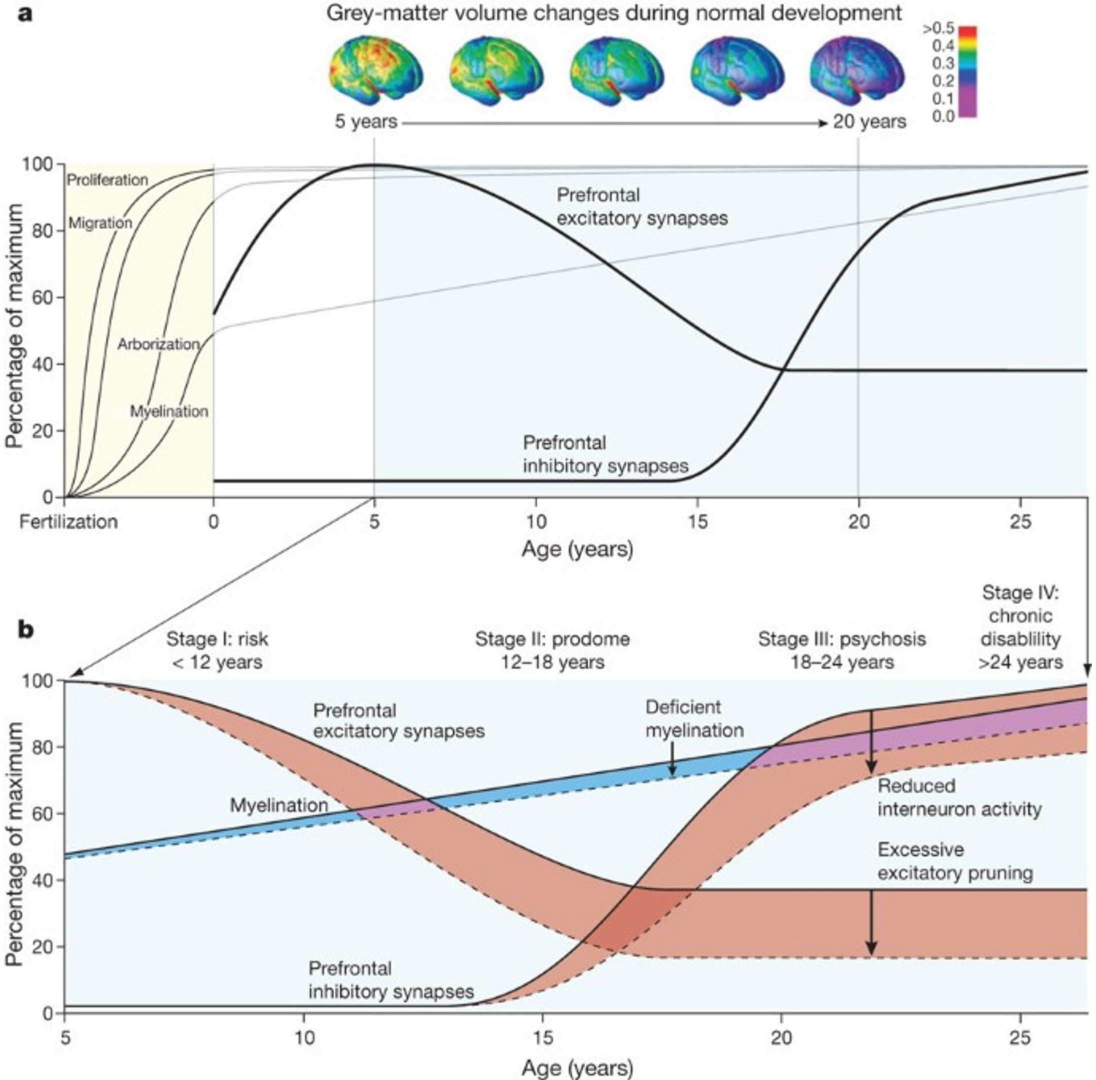
Early Stage Detection



A Wavelet is a waveform of effectively limited duration that has an average value of zero. It is defined as,

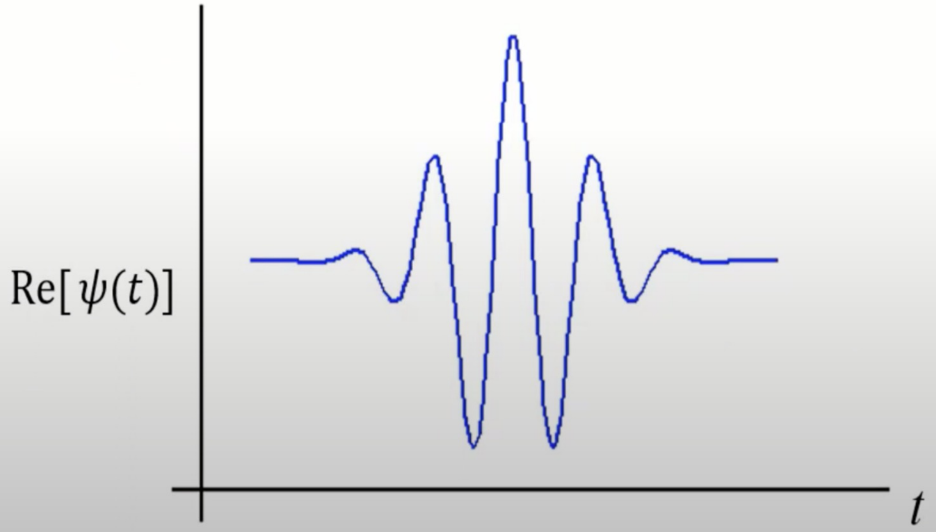
$$\boxed{\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\,\psi\left(\frac{t-b}{a}\right) \quad a,b \in \mathbb{R}}$$

Here a and b are called Dilation (Scale) and Translation (Position) parameters respectively.

An example wavelet is shown below.

$$\boxed{\psi(t) = e^{j\omega_0 t} e^{-\frac{t^2}{2}}}$$

Morlet Wavelet

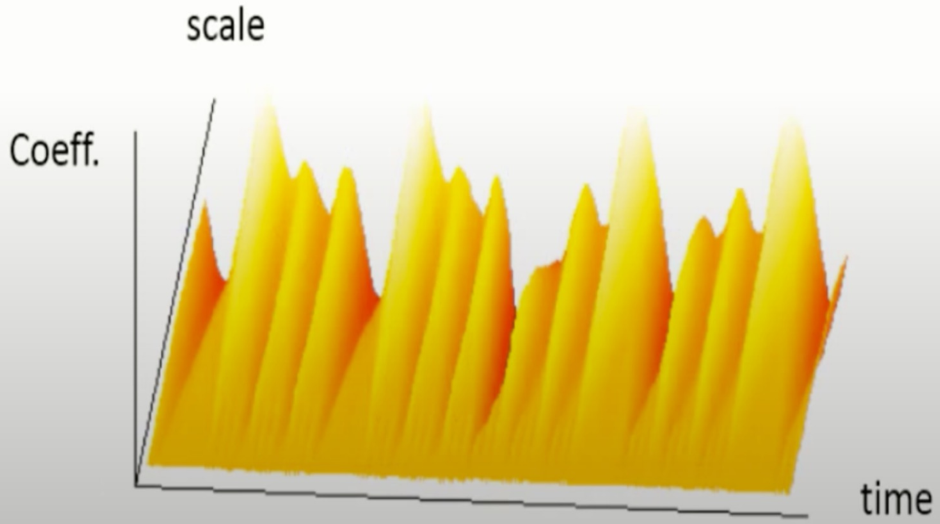


The Continuous Wavelet Transform (CWT) of a signal $f(t)$ is then given by the equation,

$$\boxed{CWT(a,b) = \langle f,\, \psi_{a,b} \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} f(t).\, \psi^{*}\left(\frac{t-b}{a}\right) dt}$$

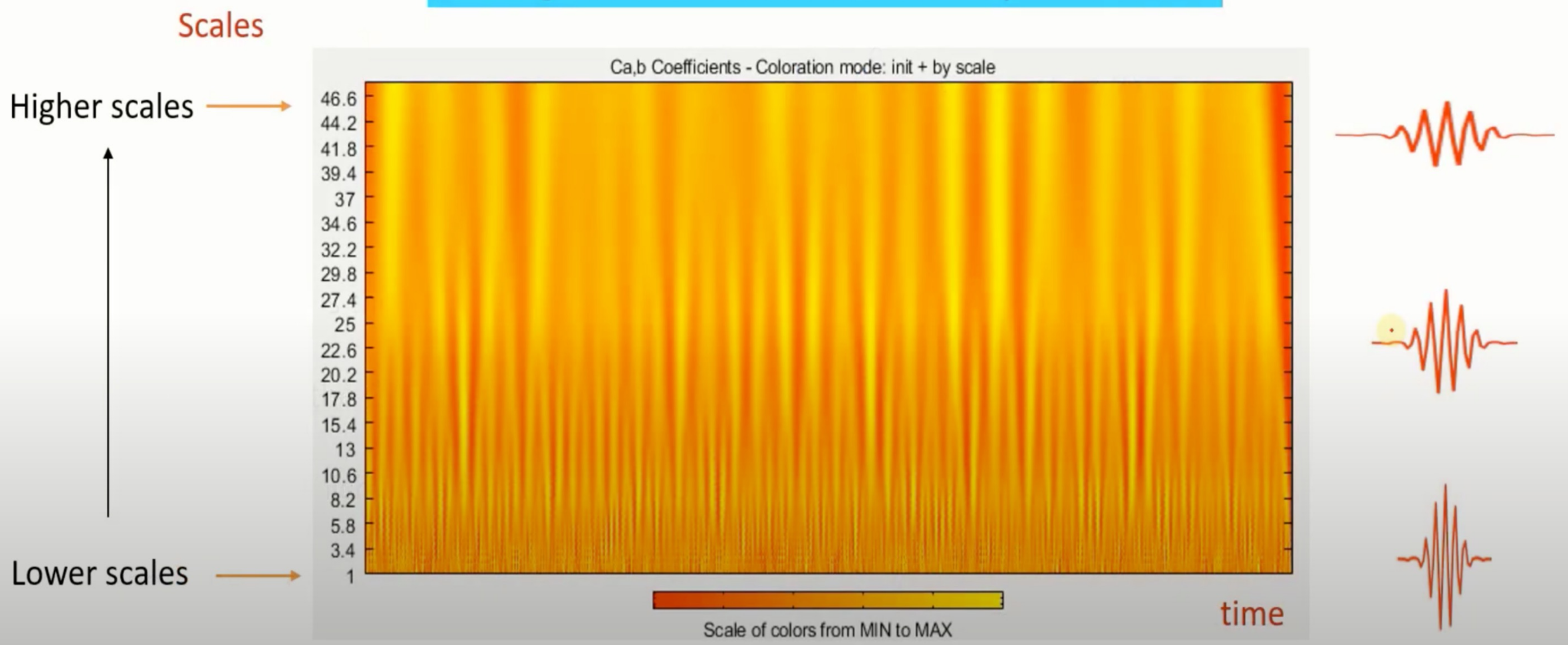
Here, $\langle f, \psi_{a,b} \rangle$ is the $\mathbb{L}^2$ inner product.

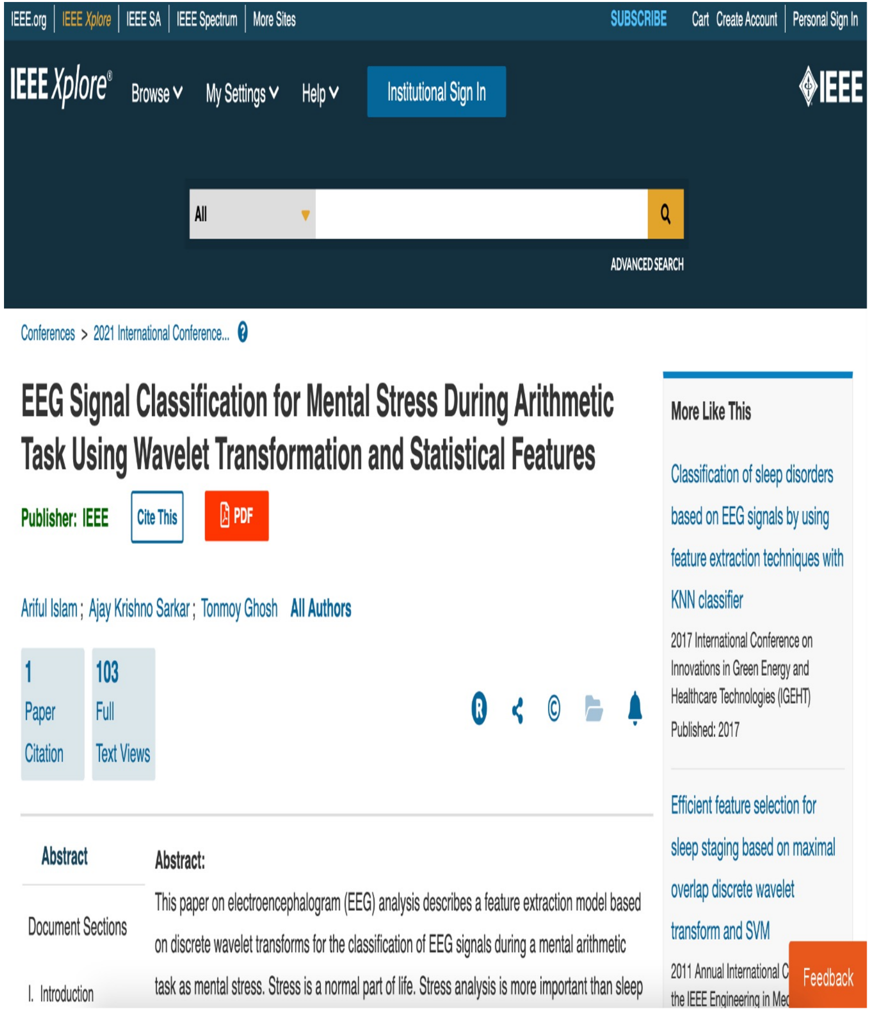
The results of the CWT are many wavelet coefficients, which are a function of a (scale) and b (position).



Continuous Wavelet Transform (CWT)

Scalogram: Wavelet Coefficients Representation

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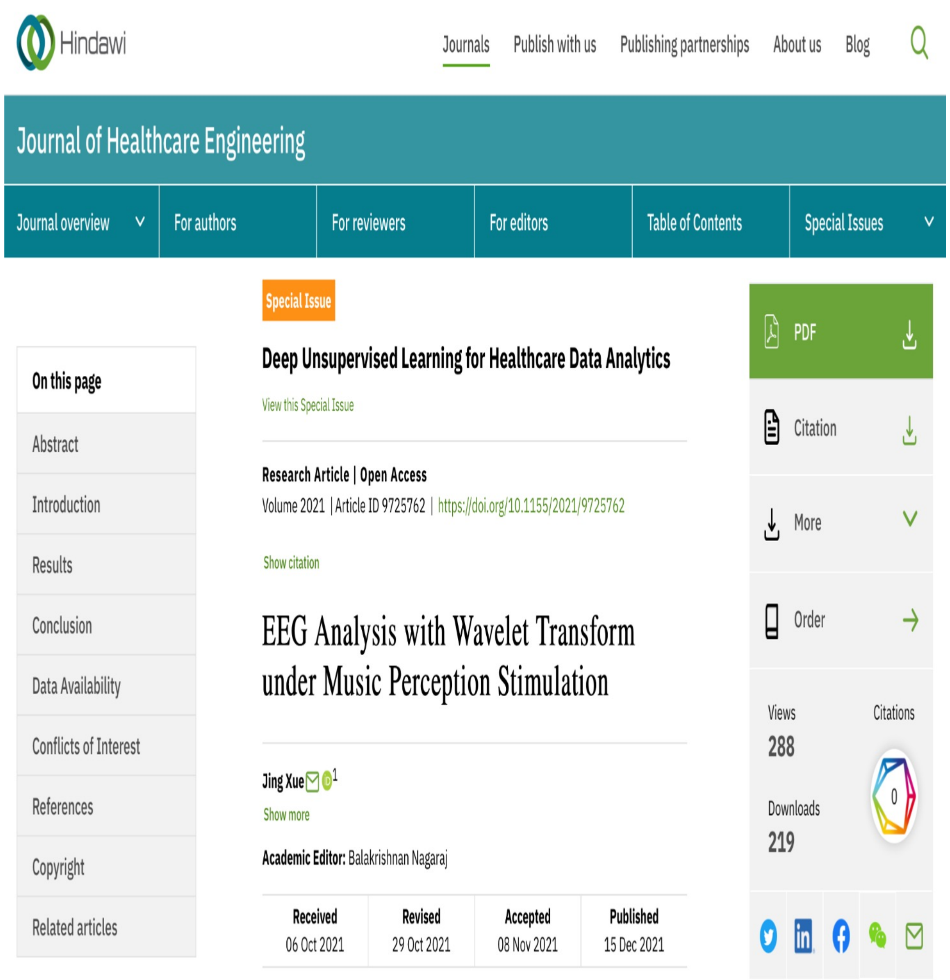
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