Project Notes:

Project Title:
Name:

Note Well: There are NO SHORT-cuts to reading journal articles and taking notes from them. Comprehension is paramount. You will most likely need to read it several times, so set aside enough time in your schedule.

Contents:

Knowledge Gaps:

This list provides a brief overview of the major knowledge gaps for this project, how they were resolved and where to find the information.

Knowledge Gap	Resolved By	Information is located	Date resolved
Types of seizures and symptoms	Online source	Types of Seizures: How to Tell Them Apart and Giving First Aid (healthline.com)	9/23/24
DNN vs CNN and other DL techniques	Online source	Understanding Deep Learning: DNN, RNN, LSTM, CNN and R-CNN | by SPRH LABS | Medium	10/3/24

Overfitting	Ashwin	MAMS	10/9/24

Literature Search Parameters:

These searches were performed between (Start Date of reading) and XX/XX/2019.
List of keywords and databases used during this project.

Database/search engine	**Keywords**	**Summary of search**
Science Direct	Epilepsy	Epileptic seizures, causes, different types
Science direct	Seizure	Different kinds, how to predict future ones, how to associate different seizure types with different epilepsy
Scientific Report	Deep learning	Different DL techniques, the benefits and pitfalls of each, how they're used in different scenarios, how they can be used to predict seizures

Tags:

Tag Name	
#CNN	#CBD
#EEG	#seizure

Article #1 Notes: Title

KEEP THIS BLANK AND USE AS A TEMPLATE

Source Title	
Source citation (APA Format)	
Original URL	
Source type	
Keywords	
#Tags	
Summary of key points + notes (include methodology)	
Research Question/Problem/ Need	
Important Figures	
VOCAB: (w/definition)	
Cited references to follow up on	
Follow up Questions	

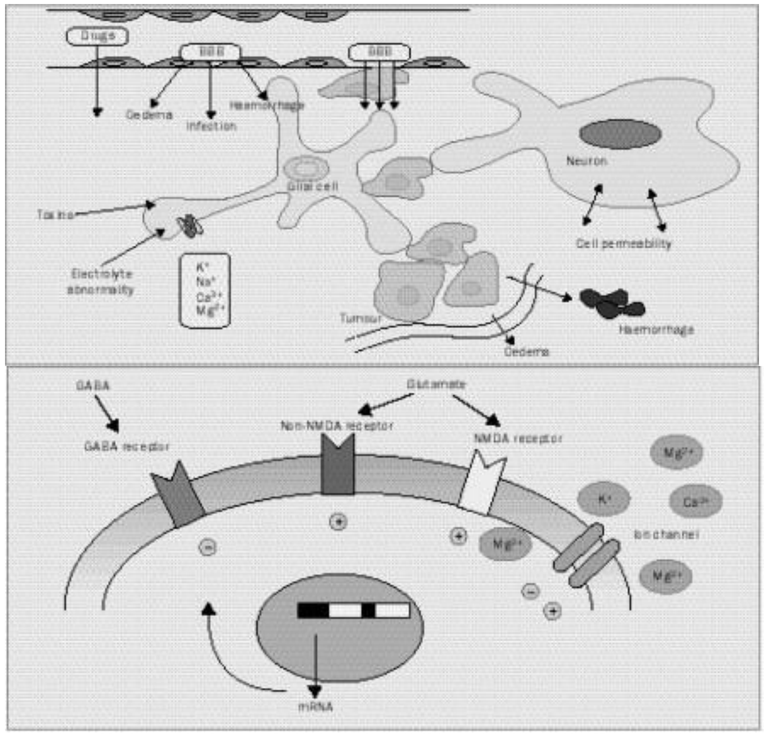
Article #1 Notes: Physics pushes peak performance

Source Title	Physics pushes peak performance
Source citation (APA Format)	nature physics. (2024). Physics pushes Peak Performance. *Nature Physics*, *20*(8), 1219–1219. https://doi.org/10.1038/s41567-

	024-02625-7
Original URL	Physics pushes peak performance | Nature Physics
Source type	Journal Article
Keywords	Athletes, performance, improve
#Tags	#performance #athlete
Summary of key points + notes (include methodology)	This article examines how the study of physics is used to help enhance athletic performance, focusing on movement, equipment, and technique. It shows the advancements that have been made like advanced footwear and prosthetics, along with the respective applications of physics principles to refine technique. I looked for key words, the title, looked for knowledge gaps.
Research Question/Problem/ Need	What role does the physical material of their equipment play in injury prevention and effectiveness?
Important Figures	
VOCAB: (w/definition)	Hydraulic effects – Hydraulic effect refers to the amplification of moderate pressure exerted over a longer distance into powerful energy for a shorter distance
Cited references to follow up on	Shankar, S., & Mahadevan, L. (2024). Active hydraulics and odd elasticity of muscle fibres. *Nature Physics*, *20*(9), 1501–1508. https://doi.org/10.1038/s41567-024-02540-x
Follow up Questions	What other research could be done to enhance athletic performance? What could be engineered to back up this research? How could it be further applied?

Article #2 Notes : Medical Causes of Seizures

Source Title	Medical Causes of Seizures
Source citation (APA Format)	Delanty, N., Vaughan, C. J., & French, J. A. (1998). Medical causes of seizures. *The Lancet*, *352*(9125), 383–390. https://doi.org/10.1016/s0140-6736(98)02158-8
Original URL	10.1016/S0140-6736(98)02158-8
Source type	Journal Article
Keywords	Epilepsy, gene therapy, EEG, focal epilepsy, neuronal discharge. hyperexcitability
#Tags	#GABA #causes #systemic
Summary of key points + notes (include methodology)	Seizure treatment for medically ill patients is targeted at the correction of underlying causes with short-term medication. Seizures are common in patients with systemic illnesses (affecting the entire body rather than a single body part or organ). Seizures can be convulsive as well as non-convulsive. They can be focal, generalized, or initially focal with secondary generalization Causes can include: Medication-related (eg, pethidine) Narcotic and other drug withdrawal Organ failure and ischaemic-hypoxic encephalopathy Metabolic disturbance Sleep deprivation and multifactorial causes Other infection (eg, HIV, malaria) After cardiorespiratory arrest Toxin exposure (eg, carbon monoxide poisoning) electrolyte and glucose abnormalities, ischaemic-hypoxic encephalopathy, medications, and medication withdrawal. Many biochemical abnormalities, which affect excitability of neurons, occur in patients with systemic illness and can lead to seizure. Any event or combination of events that disturbs the delicate balance between

	neuronal excitation and inhibition can produce a seizure. A relative imbalance of brain neurotransmitters may predispose to seizure activity
Research Question/Problem/ Need	Identifying causes of seizures and explaining knowledge gaps that could further research in this area.
Important Figures	
VOCAB: (w/definition)	GABA, medicine that helps control seizures
Cited references to follow up on	Young, B. G., Jordan, K. G., & Doig, G. S. (1996). An assessment of nonconvulsive seizures in the intensive care unit using continuous EEG monitoring. *Neurology*, *47*(1), 83–89. https://doi.org/10.1212/wnl.47.1.83 Traynelis, S. F., & Dingledine, R. (1988). Potassium-induced spontaneous electrographic seizures in the rat hippocampal slice. *Journal of Neurophysiology*, *59*(1), 259–276. https://doi.org/10.1152/jn.1988.59.1.259
Follow up Questions	How could one go about measuring these factors that can cause seizures? Are some factors more likely to lead to a seizure than others, and if so, which?

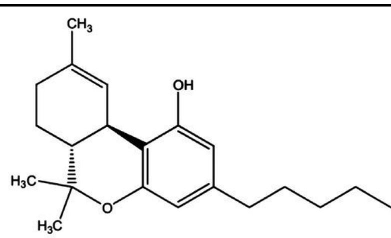
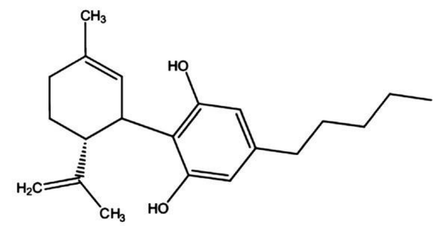
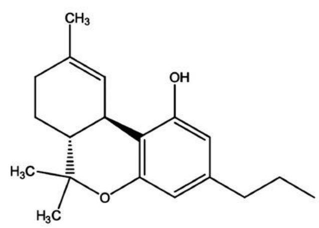
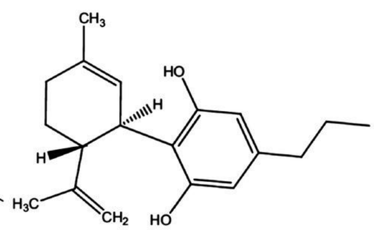
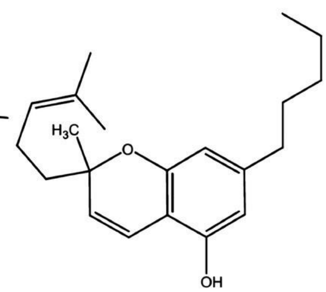
Article #3 Notes: Idiopathic epilepsy seizures: Types, causes, treatment, and outlook

Source Title	Cannabidiol: Pharmacology and potential therapeutic role in epilepsy and other neuropsychiatric disorders Idiopathic epilepsy seizures: Types, causes, treatment, and outlook
Source citation (APA Format)	Yetman, D. (2024, June 17). *Idiopathic epilepsy seizures: Types, causes, treatment, and outlook*. Healthline. https://www.healthline.com/health/idiopathic-epilepsy-seizures
Original URL	Idiopathic Epilepsy Seizures: Types, Causes, Treatment, and Outlook (healthline.com)
Source type	Online sources
Keywords	Epilepsy, gene therapy, EEG, focal epilepsy, neuronal discharge. hyperexcitability
#Tags	#seizures #tonic #clonic
Summary of key points + notes (include methodology)	Tonic- muscle stiffness Clonic- muscle jerking Tonic-clonic: both
Research Question/Problem/ Need	Many people have seizures and it is important to know the difference between different types of seizures

<table>
<tr><td>Important Figures</td><td>
<table>
<tr><th>Type of IGE</th><th>Gene</th></tr>
<tr><td>Juvenile absence epilepsy</td><td>• CACNA1A
• EFHC1
• SLC2A1</td></tr>
<tr><td>Childhood absence epilepsy</td><td>• CACNA1G
• CACNA1H
• CACNG3
• GABRA1
• GABRG2
• GABRB3
• SLC2A1</td></tr>
<tr><td>Juvenile myoclonic epilepsy</td><td>• CACNA1H
• CACNB4
• CASR
• EFHC1
• GABRD
• GABRA1</td></tr>
</table>
</td></tr>
<tr><td>VOCAB: (w/definition)</td><td>GABA, medicine that helps control seizures</td></tr>
<tr><td>Cited references to follow up on</td><td>Devinsky, O., Cilio, M. R., Cross, H., Fernandez-Ruiz, J., French, J., Hill, C., Katz, R., Di Marzo, V., Jutras-Aswad, D., Notcutt, W. G., Martinez-Orgado, J., Robson, P. J., Rohrback, B. G., Thiele, E., Whalley, B., & Friedman, D. (2014). Cannabidiol: Pharmacology and potential therapeutic role in epilepsy and other neuropsychiatric disorders. Epilepsia, 55(6), 791–802. https://doi.org/10.1111/epi.12631</td></tr>
<tr><td>Follow up Questions</td><td>Do different parts of the brain trigger different seizures?</td></tr>
</table>

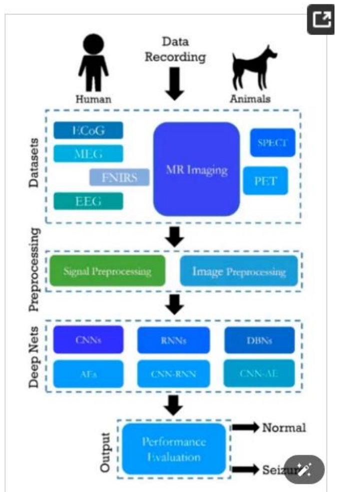
Article #4 Notes: Cannabidiol: Pharmacology and potential therapeutic role in epilepsy and other neuropsychiatric disorders

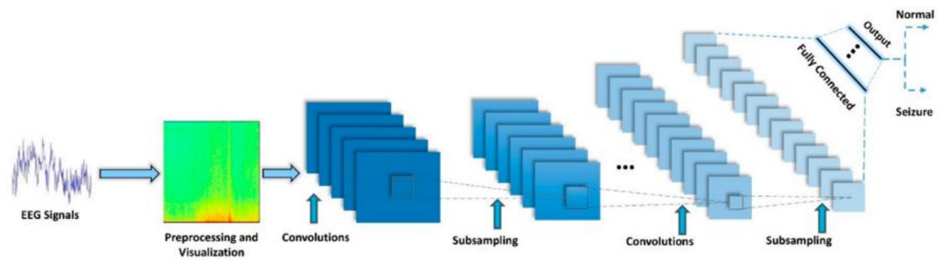
Source Title	Cannabidiol: Pharmacology and potential therapeutic role in epilepsy and other neuropsychiatric disorders
Source citation (APA Format)	Devinsky, O., Cilio, M. R., Cross, H., Fernandez-Ruiz, J., French, J., Hill, C., Katz, R., Di Marzo, V., Jutras-Aswad, D., Notcutt, W. G., Martinez-Orgado, J., Robson, P. J., Rohrback, B. G., Thiele, E., Whalley, B., & Friedman, D. (2014, May 22). *Cannabidiol: Pharmacology and potential therapeutic role in epilepsy and other neuropsychiatric disorders - devinsky - 2014 - epilepsia - wiley online library*. Cannabidiol: Pharmacology and potential therapeutic role in epilepsy and other neuropsychiatric disorders. https://onlinelibrary.wiley.com/doi/full/10.1111/epi.12631
Original URL	Cannabidiol: Pharmacology and potential therapeutic role in epilepsy and other neuropsychiatric disorders - Devinsky - 2014 - Epilepsia - Wiley Online Library
Source type	Journal Article
Keywords	Cannibioid, CBD,
#Tags	#CBD
Summary of key	Δ9-Tetrahydrocannabinol (Δ9-THC) is the primary psychoactive component of

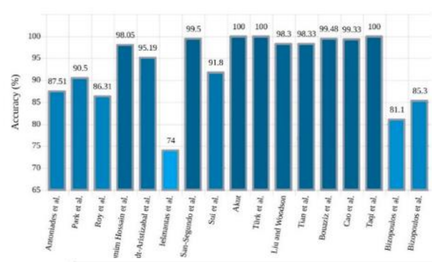
points + notes (include methodology)	cannabis, while cannabidiol (CBD) is the main nonpsychoactive ingredient. Both cannabis and Δ9-THC have demonstrated anticonvulsant effects in most animal studies, but they can also act as proconvulsants in some healthy animals. Small and methodologically limited human studies on CBD for epilepsy have produced inconclusive results. There is a lack of data from well-designed, double-blind, randomized controlled trials assessing the efficacy of pure CBD for any condition. This article explores the history of cannabis and its derivatives in treating epilepsy from ancient times to today, reviews the clinical pharmacology of cannabis's neuroactive components, summarizes research on the potential of cannabinoids for other neurological and psychiatric disorders, and discusses future directions for clinical trials.
Research Question/Problem/ Need	Can CBD be used to help treat neurological disorders?
Important Figures	 Δ^9-Tetrahydrocannabinol (Δ^9-THC)  Cannabidiol (CBD)  Δ^9-tetrahydrocannabivarin (Δ^9-THCV)  Cannabidivarin (CBDV)  Cannabichromene (CBC)
VOCAB: (w/definition)	Tetrahydrocannabinol - Primary psychoactive compound in cannabis CBD - Crystalline, nonintoxicating cannabinoid
Cited references to follow up on	Fusar-Poli, P., Crippa, J. A., Bhattacharyya, S., Borgwardt, S. J., Allen, P., Martin-Santos, R., Seal, M., Surguladze, S. A., O'Carrol, C., Atakan, Z., Zuardi, A. W., & McGuire, P. K. (2009). Distinct effects of Δ9-tetrahydrocannabinol and cannabidiol on neural activation during emotional processing. *Archives of General Psychiatry*, *66*(1), 95. https://doi.org/10.1001/archgenpsychiatry.2008.519
Follow up Questions	Do the positives outweigh the negatives? Who decides that?

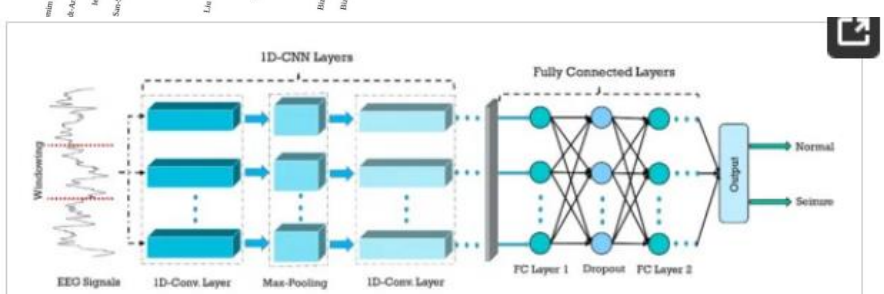
Article #5 Notes: Epileptic seizures detection in EEG signals using TQWT and ensemble learning

Source Title	**Epileptic Seizures Detection Using Deep Learning Techniques: A Review**
Source citation (APA Format)	Shoeibi, A., Khodatars, M., Ghassemi, N., Jafari, M., Moridian, P., Alizadehsani, R., Panahiazar, M., Khozeimeh, F., Zare, A., Hosseini-Nejad, H., Khosravi, A., Atiya, A. F., Aminshahidi, D., Hussain, S., Rouhani, M., Nahavandi, S., & Acharya, U. R. (2021, May 27). *Epileptic seizures detection using Deep Learning Techniques: A Review*. MDPI. https://www.mdpi.com/1660-4601/18/11/5780
Original URL	Epileptic Seizures Detection Using Deep Learning Techniques: A Review (mdpi.com)
Source type	Journal Article
Keywords	RNN
#Tags	#CNN #DNN
Summary of key points + notes (include methodology)	Using deep learning technology (DL) it is easier to identify epilepsy at an earlier stage and also allows for the detection of an oncoming seizure. Some of these technologies are CNNs (Convolutional neural network), RNNs (Recurrent neural networks), DNNs (Deep neural networks), and AEs (Autoencoders). These all have their own upsides as well as downsides. There are several public databases out there that provide people with the data they would need to carry out their research. This data is acquired via fMRIs, MRIs, and/or EEGs. This data is used to make CAD models that can accurately predict oncoming seizures. This has been used to make handheld models and wearable devices.
Research Question/Problem/ Need	It is important to detect epilepsy early on and detect oncoming seizures. How is using DL techniques the best way to go about this?

<table>
<tr>
<td>Important Figures</td>
<td>






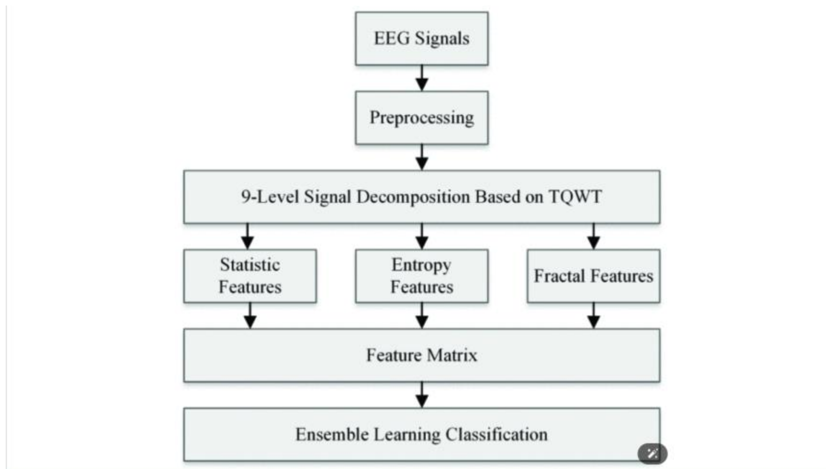
Sketch of accuracy (%) obtained by various authors using 2D-CNN models for seizure detection.


</td>
</tr>
<tr>
<td>VOCAB: (w/definition)</td>
<td>RNN- recurrent neural network
LSTM – Long Short-term memory
GRU – Gated Recurrent unit</td>
</tr>
<tr>
<td>Cited references to follow up on</td>
<td>Shoeibi, A., Ghassemi, N., Alizadehsani, R., Rouhani, M., Hosseini-Nejad, H., Khosravi, A., Panahiazar, M., & Nahavandi, S. (2021b). A comprehensive</td>
</tr>
</table>

	comparison of handcrafted features and convolutional autoencoders for epileptic seizures detection in EEG signals. *Expert Systems with Applications*, *163*, 113788. https://doi.org/10.1016/j.eswa.2020.113788
Follow up Questions	Can I objectively choose which DL technique is the best to identify seizures?

Article #6 Notes: Epileptic seizures detection in EEG signals using TQWT and ensemble learning

Source Title	Epileptic seizures detection in EEG signals using TQWT and ensemble learning
Source citation (APA Format)	Ghassemi, N., Shoeibi, A., Rouhani, M., & Hosseini-Nejad, H. (2019). Epileptic seizures detection in EEG signals using TQWT and Ensemble Learning. *2019 9th International Conference on Computer and Knowledge Engineering (ICCKE)*, 403–408. https://doi.org/10.1109/iccke48569.2019.8964826
Original URL	[Epileptic seizures detection in EEG signals using TQWT and ensemble learning | IEEE Conference Publication | IEEE Xplore]
Source type	Journal article
Keywords	Subband
#Tags	#EEG
Summary of key points + notes (include methodology)	In this paper, they proposed a method for seizure detection, which can be used as the core of a CAD to help epileptic patients. This approach has a few stages: preprocessing, feature extraction, and classification. First, low-frequency noises are removed from signals using a high-pass Butterworth filter. Next, each signal is decomposed into nine subbands using a TQWT wavelet, then statistical, entropy-based, and fractal features are extracted from these subbands. Finally, a classification

<table>
<tr><td></td><td>algorithm is used to distinguish a seizure from normal signals.</td></tr>
<tr><td>Research Question/Problem/ Need</td><td>Using ensemble learning, how can we create a CAD to help in the detection of seizures?</td></tr>
<tr><td>Important Figures</td><td>


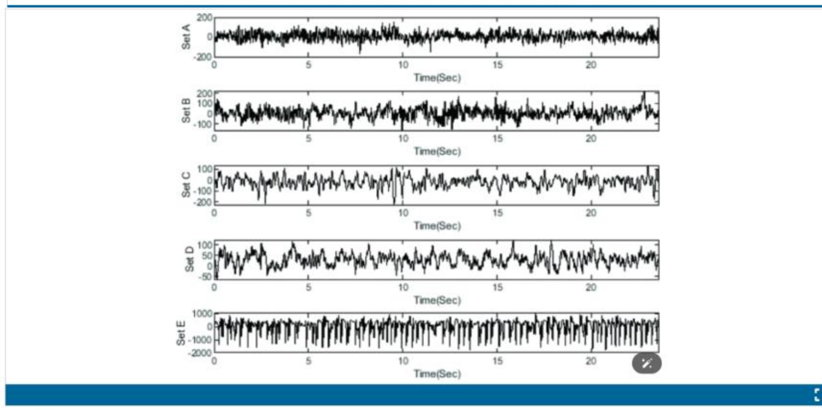


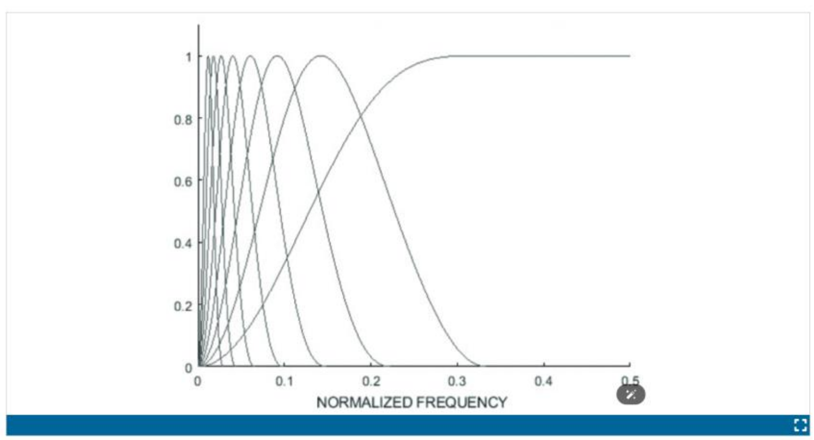
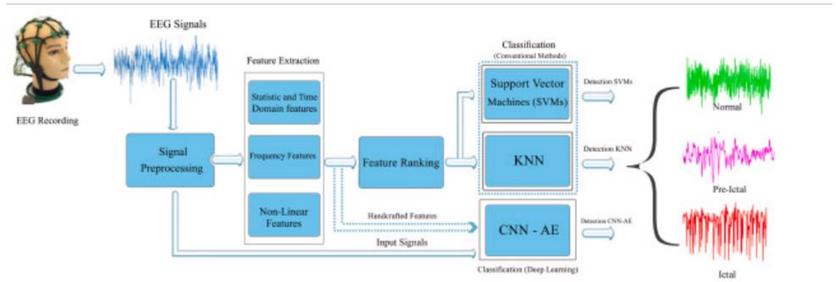
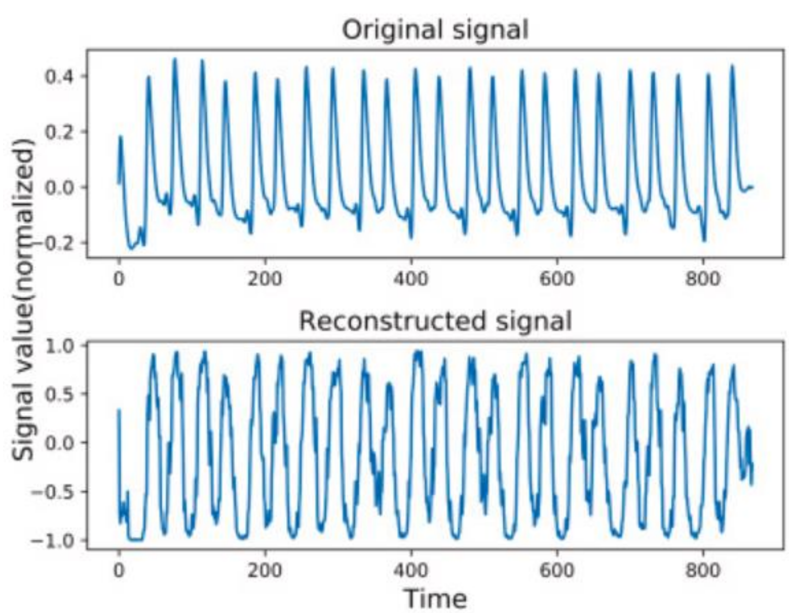
Fig. 2.
Bonn EEG dataset.


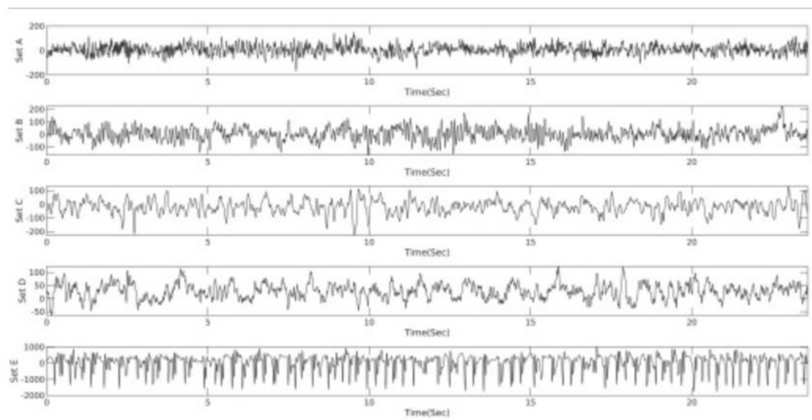
Fig. 4.
TQWT frequency response with Q=1, r=3, J=8.
</td></tr>
<tr><td>VOCAB: (w/definition)</td><td>Overfitted- the model is too specific to the data and can’t be</td></tr>
</table>

	generalized Sub-bands - In signal processing, sub-band coding (SBC) is any form of transform coding that breaks a signal into a number of different frequency bands, typically by using a fast Fourier transform, and encodes each one independently
Cited references to follow up on	Li, M., Chen, W., & Zhang, T. (2017). Automatic epileptic EEG detection using DT-cwt-based non-linear features. *Biomedical Signal Processing and Control*, *34*, 114–125. https://doi.org/10.1016/j.bspc.2017.01.010 Faust, O., Acharya, U. R., Adeli, H., & Adeli, A. (2015). Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis. *Seizure*, *26*, 56–64. https://doi.org/10.1016/j.seizure.2015.01.012
Follow up Questions	Could this be used to determine different types of epilepsy? Do the frequencies change drastically with different types of epilepsy?

Article #7 Notes: A comprehensive comparison of handcrafted features and convolutional autoencoders for epileptic seizures detection in EEG signals

Source Title	A comprehensive comparison of handcrafted features and convolutional autoencoders for epileptic seizures detection in EEG signals
Source citation (APA Format)	Shoeibi, A., Ghassemi, N., Alizadehsani, R., Rouhani, M., Hosseini-Nejad, H., Khosravi, A., Panahiazar, M., & Nahavandi, S. (2021). A comprehensive comparison of handcrafted features and convolutional autoencoders for epileptic seizures detection in EEG signals. *Expert Systems with Applications*, *163*, 113788. https://doi.org/10.1016/j.eswa.2020.113788
Original URL	A comprehensive comparison of handcrafted features and convolutional autoencoders for epileptic seizures detection in EEG signals - ScienceDirect
Source type	Journal Article

Keywords	Fractal Dimension
#Tags	#EEG #CNN-AE #CNN #AE #more
Summary of key points + notes (include methodology)	An algorithm was evaluated based off of the Bonn dataset which is often regarded as the benchmark for epileptic seizure diagnosis studies. It has 5 subsets, A-E. Each of them have 100 single-channel EEG segments with t=23.6s and 4097 signals. **DO MORE RESEARCH ON BONN DATASET.** Then, the features were extracted. These were the time domain and statistical, frequency, and non-linear features. They used Fractal Dimensions. Other authors works and methods were used to find the fractal dimension.
Research Question/Problem/ Need	Using current DL technology, how can a hybrid method be made for detecting oncoming epileptic seizures?
Important Figures	 

	
VOCAB: (w/definition)	Fractal Dimension- A useful metric defined on a fractal is the measure on how the detail in the fractal changes with scale, known as its fractal dimension, D. Another view is, when projected onto a grid, how many elements the fractal covers as the number of elements increases. The fractal dimension need not be an integer. Using the gathered data, they developed an efficient CAD capable of diagnosing seizures
Cited references to follow up on	Acharya, U. R., Hagiwara, Y., Deshpande, S. N., Suren, S., Koh, J. E., Oh, S. L., Arunkumar, N., Ciaccio, E. J., & Lim, C. M. (2019a). Characterization of focal EEG signals: A Review. *Future Generation Computer Systems*, *91*, 290–299. https://doi.org/10.1016/j.future.2018.08.044 Acharya, Udyavara Rajendra, Hagiwara, Y., Koh, J. E., Oh, S. L., Tan, J. H., Adam, M., & Tan, R. S. (2018). Entropies for automated detection of coronary artery disease using ECG signals: A Review. *Biocybernetics and Biomedical Engineering*, *38*(2), 373–384. https://doi.org/10.1016/j.bbe.2018.03.001
Follow up Questions	Is this plausible using other DL techniques other than CNN-AEs?

Article #8 Notes: Characterization of focal EEG signals: A review

Source Title	Characterization of focal EEG signals: A review
Source citation (APA Format)	Acharya, U. R., Hagiwara, Y., Deshpande, S. N., Suren, S., Koh, J. E., Oh, S. L., Arunkumar, N., Ciaccio, E. J., & Lim, C. M. (2019). Characterization of focal EEG signals: A Review. *Future Generation Computer Systems*, *91*, 290–299. https://doi.org/10.1016/j.future.2018.08.044
Original URL	https://doi.org/10.1016/j.future.2018.08.044

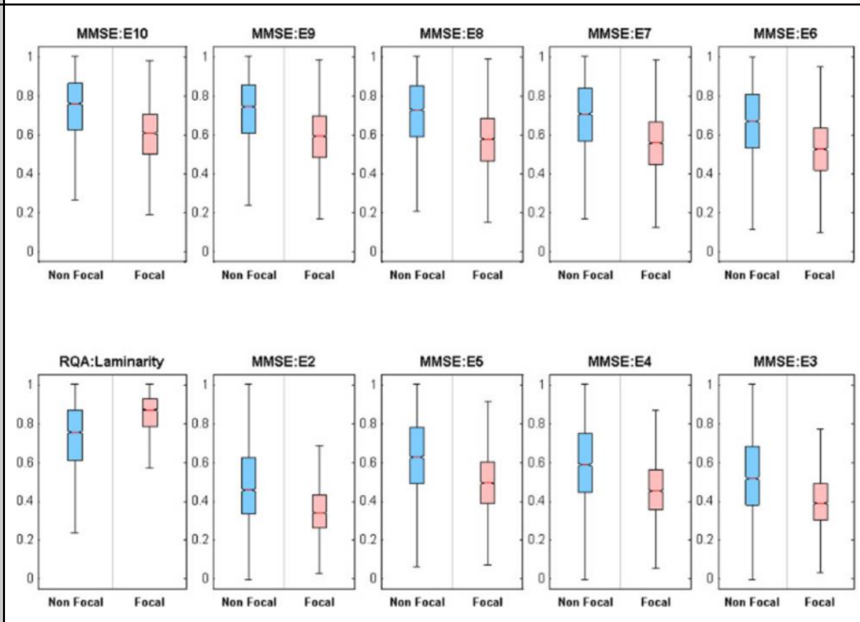
Source type	Journal article
Keywords	Focal and nonfocal EEG signals
#Tags	#EEG
Summary of key points + notes (include methodology)	The study highlights the development of a computer-aided detection (CAD) system that utilizes nonlinear features to enhance the differentiation between F and NF signals. Nonlinear analysis has shown promise in revealing hidden patterns within EEG data, which can aid clinicians in identifying the epileptogenic zones. Research indicates that various feature extraction techniques, particularly those involving signal decomposition methods like empirical mode decomposition (EMD) and discrete wavelet transform (DWT), have led to high classification accuracy rates in distinguishing between F and NF signals. The review concludes that the CAD system can serve as a valuable tool in clinical settings, facilitating objective analysis and supporting epilepsy diagnosis and treatment decisions. Future work is suggested to integrate deep learning techniques into the CAD system to further improve its effectiveness in identifying EEG signal characteristics.
Research Question/Problem/ Need	How can nonlinear feature extraction techniques effectively differentiate between focal (F) and non-focal (NF) EEG signals to aid in the localization of epileptogenic areas in epilepsy patients?
Important Figures	

Fig. 4. A sample of (a) F and (b) NF X–Y difference recurrence plots.

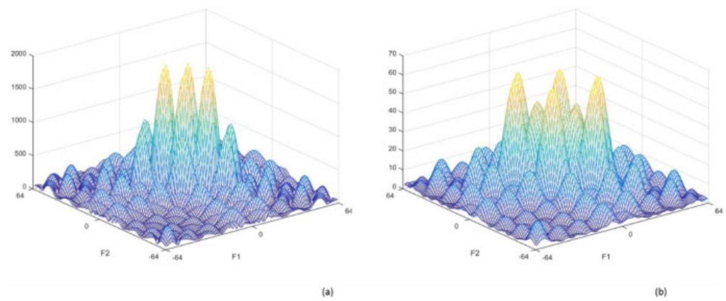
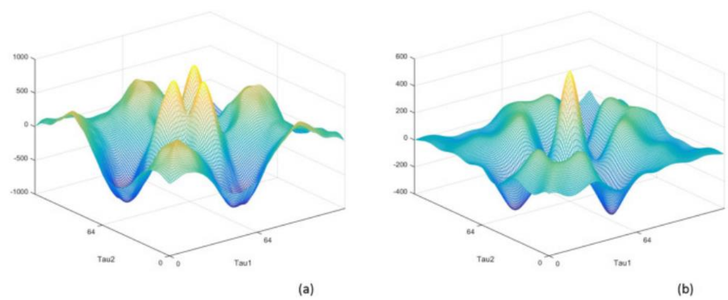


Fig. 5. A sample of (a) F and (b) NF X–Y difference bispectrum plots.



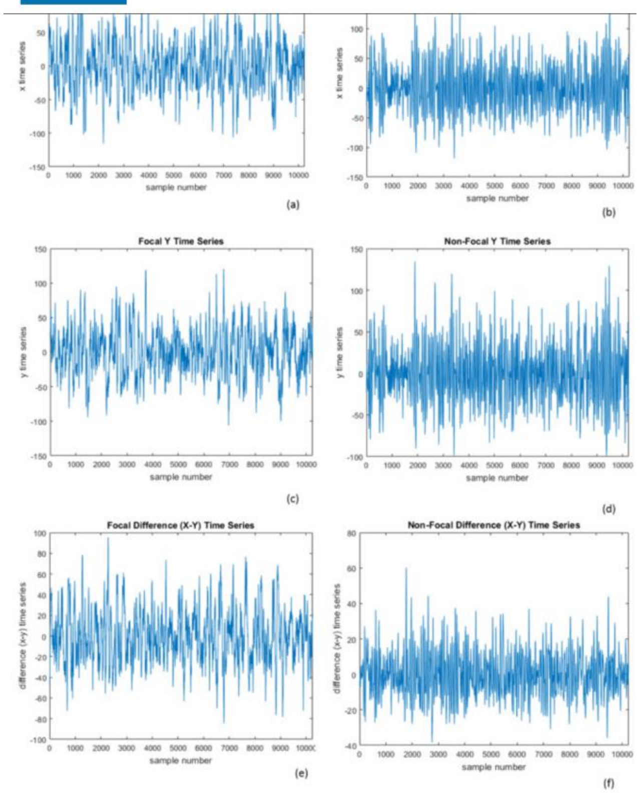
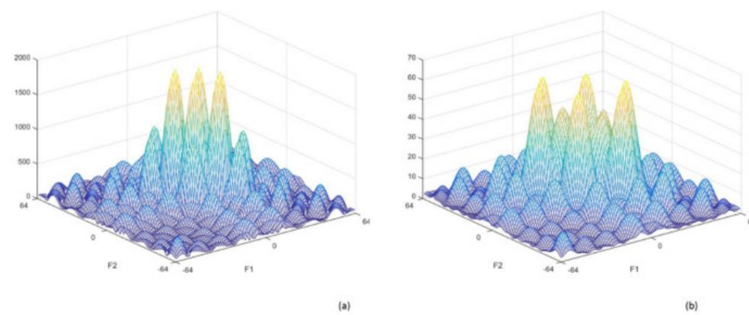
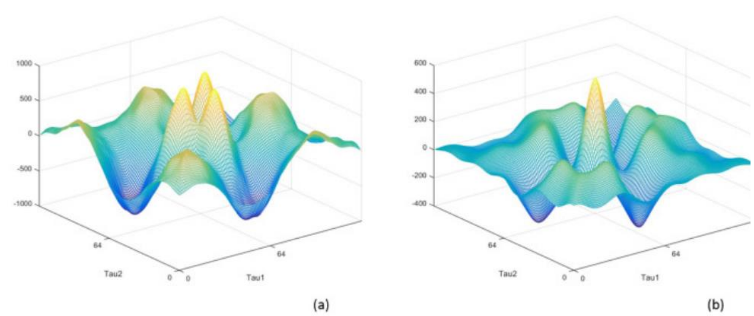
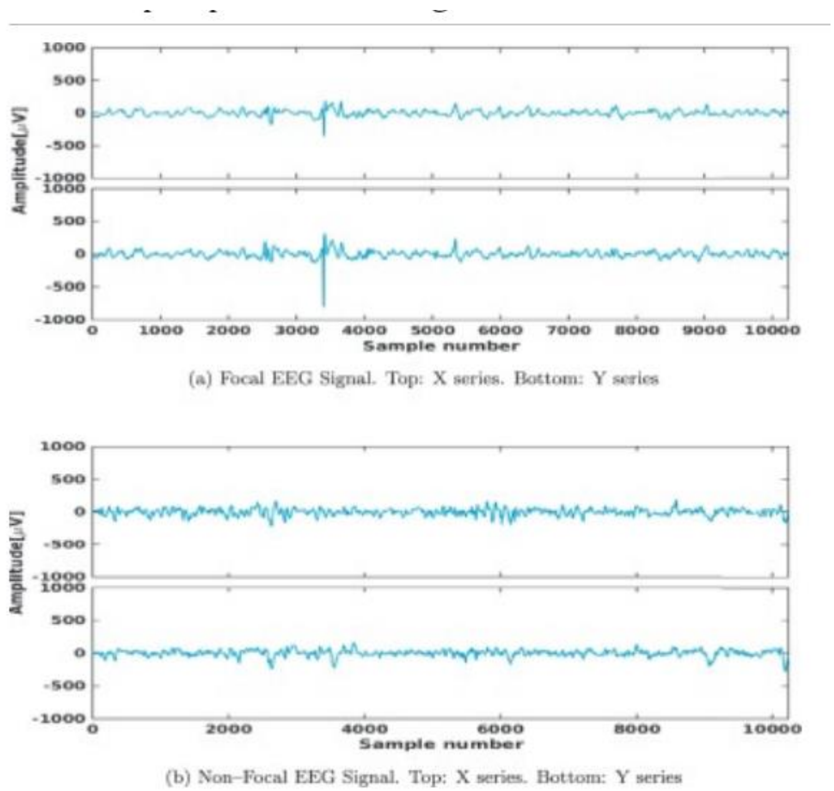
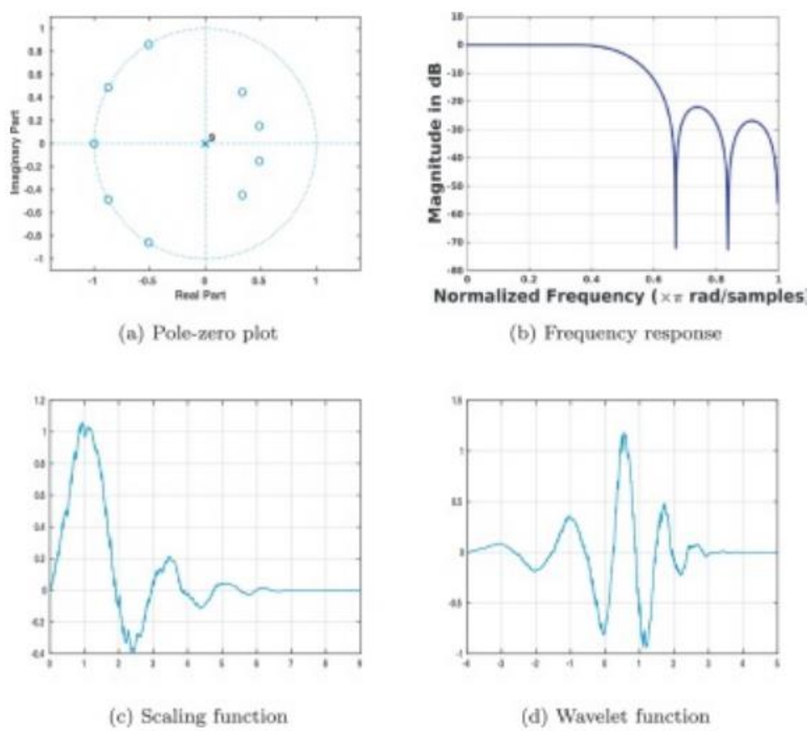


	Fig. 4. A sample of (a) F and (b) NF X–Y difference recurrence plots.  Download: Download high-res image (619KB) Download: Download full-size image Fig. 5. A sample of (a) F and (b) NF X–Y difference bispectrum plots. 
VOCAB: (w/definition)	Non-focal (NF)- Focal (F)- Electroencephalogram (EEG) signals acquired from the epileptogenic areas (affected region) are called the focal EEG signal. In contrast, those obtained from the non-affected regions are termed non-focal EEG signals
Cited references to follow up on	Sharma, M., Dhere, A., Pachori, R. B., & Acharya, U. R. (2017a). An automatic detection of focal EEG signals using new class of time–frequency localized orthogonal wavelet filter banks. *Knowledge-Based Systems*, *118*, 217–227. https://doi.org/10.1016/j.knosys.2016.11.024
Follow up Questions	How does the performance of the CAD system compare to traditional methods of EEG analysis? What challenges did the researchers encounter when implementing the CAD system? How might deep learning techniques enhance the capabilities of the CAD system in future research?

Article #9 Notes: An automatic detection of focal EEG signals using new class of time–frequency localized orthogonal wavelet filter banks

Source Title	An automatic detection of focal EEG signals using new class of time–frequency localized orthogonal wavelet filter banks
Source citation (APA Format)	Sharma, M., Dhere, A., Pachori, R. B., & Acharya, U. R. (2017). An automatic detection of focal EEG signals using new class of time–frequency localized orthogonal wavelet filter banks. *Knowledge-Based Systems*, *118*, 217–227. https://doi.org/10.1016/j.knosys.2016.11.024
Original URL	https://doi.org/10.1016/j.knosys.2016.11.024
Source type	Journal article
Keywords	Focal EEG signals Non-focal EEG signals Time-frequency localization Wavelet filter banks LS-SVM (Least Squares-Support Vector Machine) Wavelet entropies
#Tags	#focal, #nonfocal, #EEG, #wavelet, #LS-SVM
Summary of key points + notes (include methodology)	The study presents an automatic detection system for differentiating focal (FC) and non-focal (NFC) EEG signals using a novel class of time-frequency localized orthogonal wavelet filter banks. The methodology involves several key steps: first, EEG signals are filtered using a Butterworth filter to eliminate noise; then, the signals are decomposed into subbands using the new wavelet filter banks. Various entropy measures, including Shannon and Tsallis entropies, are extracted from the wavelet coefficients as features for classification. These features are ranked using a Student's t-test ranking algorithm and subsequently

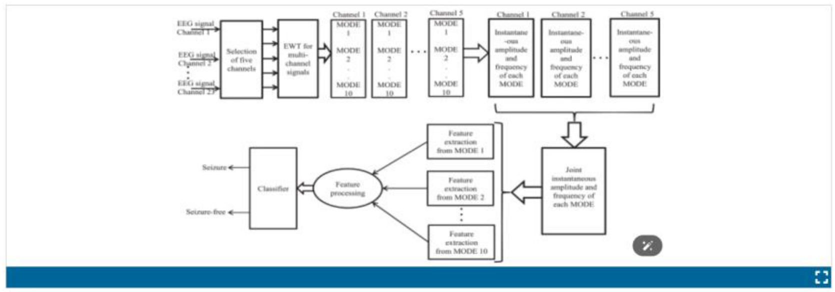
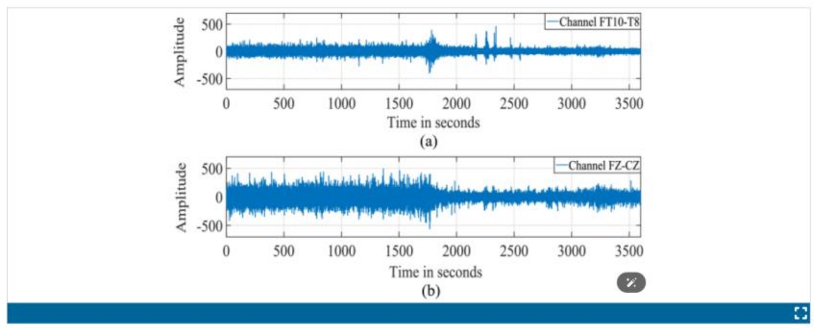
	classified using a Least Squares-Support Vector Machine (LS-SVM). The proposed method achieved a classification accuracy of 94.25%, with sensitivity at 91.95% and specificity at 96.56%, demonstrating its effectiveness in aiding the localization of epileptic foci for surgical intervention.
Research Question/Problem/ Need	How to automatically and accurately detect and classify focal (FC) and non-focal (NFC) EEG signals in patients with pharmacoresistant focal epilepsy?
Important Figures	 (a) Focal EEG Signal. Top: X series. Bottom: Y series (b) Non–Focal EEG Signal. Top: X series. Bottom: Y series

	 (a) Pole-zero plot (b) Frequency response (c) Scaling function (d) Wavelet function
VOCAB: (w/definition)	Focal Epilepsy: A type of epilepsy where seizures originate in a specific area of the brain, known as an epileptic focus. This condition can lead to localized symptoms depending on the area affected. Wavelet Transform (WT): A mathematical technique used to analyze signals by breaking them down into components at different frequencies, allowing for better time-frequency localization compared to traditional methods like the Fourier transform. Least Squares-Support Vector Machine (LS-SVM): A type of machine learning algorithm used for classification tasks that minimizes the least squares error between predicted and actual outcomes, enhancing predictive accuracy. Entropy: A measure of disorder or randomness in a system; in the context of signal processing, it quantifies the complexity or unpredictability of a signal, which can be useful for feature extraction in classification tasks.
Cited references to follow up on	Menon, V., & Crottaz-Herbette, S. (2005). Combined EEG and fmri studies of Human Brain Function. *International Review of*

	Neurobiology, 291–321. https://doi.org/10.1016/s0074-7742(05)66010-2
Follow up Questions	What specific advantages does the new class of time-frequency localized orthogonal wavelet filter banks offer over traditional wavelet transforms for EEG signal analysis? How does the classification accuracy of 94.25% compare to other methods in the literature for distinguishing focal and non-focal EEG signals? What are the clinical implications of achieving high accuracy in automatically detecting focal EEG signals?

Article #10 Notes: A Multivariate Approach for Patient-Specific EEG Seizure Detection Using Empirical Wavelet Transform

Source Title	A Multivariate Approach for Patient-Specific EEG Seizure Detection Using Empirical Wavelet Transform
Source citation (APA Format)	Bhattacharyya, A., & Pachori, R. B. (2017). A multivariate approach for patient-specific EEG seizure detection using empirical wavelet transform. *IEEE Transactions on Biomedical Engineering*, *64*(9), 2003–2015. https://doi.org/10.1109/tbme.2017.2650259
Original URL	A Multivariate Approach for Patient-Specific EEG Seizure Detection Using Empirical Wavelet Transform | IEEE Journals & Magazine | IEEE Xplore
Source type	Journal article
Keywords	EWT, multivariate analysis, feature extraction
#Tags	#EWT
Summary of key points + notes (include methodology)	The article investigates a multivariate approach for detecting epileptic seizures using the Empirical Wavelet Transform (EWT), focusing on the oscillatory nature of EEG signals across adaptive frequency scales. The methodology involves applying EWT to multivariate EEG data from the CHB-MIT scalp EEG database, where 2-second epochs are analyzed using five automatically selected channels. Features are extracted from the joint instantaneous amplitudes of these signals, and a novel feature processing step enhances discrimination between seizure and non-seizure epochs. The proposed method achieves impressive results, with average sensitivity of 97.91%, specificity of 99.57%, and accuracy of 99.41% across 177 hours of EEG records, surpassing existing techniques. This approach not only facilitates real-time monitoring but also builds patient-specific models for improved seizure detection, addressing the challenges posed by long-duration EEG recordings contaminated with noise and artifacts.
Research Question/Problem/ Need	How to develop an efficient automatic seizure detection system for long-duration EEG recordings using a multivariate approach that

	analyzes the oscillatory nature of EEG signals across adaptive frequency scales?
Important Figures	 Fig. 1. Proposed multivariate EWT based method for patient-specific EEG seizure detection.  Fig. 2. EEG signals corresponding to two different channels of patient 1.
VOCAB: (w/definition)	Empirical Wavelet Transform (EWT): A mathematical technique used for analyzing nonstationary signals by creating adaptive wavelet-based filters that can capture the signal's frequency characteristics. Multivariate Analysis: An analytical approach that considers multiple variables or channels simultaneously, allowing for a more comprehensive understanding of complex data like EEG signals. Feature Extraction: The process of identifying and isolating relevant information from raw data (in this case, EEG signals) to improve the performance of classification algorithms. Sensitivity and Specificity: Metrics used to evaluate the performance of a diagnostic test; sensitivity measures the proportion of true positives identified, while specificity measures the proportion of true negatives. Channel Selection: The method of choosing specific EEG channels for analysis based on statistical measures to reduce computational complexity while maintaining detection accuracy. Moving-Window Analysis: A technique used in signal processing where a fixed-size window moves across the data to analyze segments sequentially, often used for real-time monitoring.

Cited references to follow up on	Witte, H., Iasemidis, L. D., & Litt, B. (2003). Special issue on epileptic seizure prediction. *IEEE Transactions on Biomedical Engineering*, *50*(5), 537–539. https://doi.org/10.1109/tbme.2003.810708 Osorio, I., Frei, M. G., & Wilkinson, S. B. (1998). Real-time Automated Detection and quantitative analysis of seizures and short-term prediction of clinical onset. *Epilepsia*, *39*(6), 615–627. https://doi.org/10.1111/j.1528-1157.1998.tb01430.x
Follow up Questions	How does the performance of this multivariate EWT approach compare to univariate methods for EEG seizure detection? What are the advantages of using adaptive frequency scales from EWT compared to fixed frequency bands for analyzing EEG signals?

Patent #1 Notes: Algorithm for detecting a seizure from cardiac data

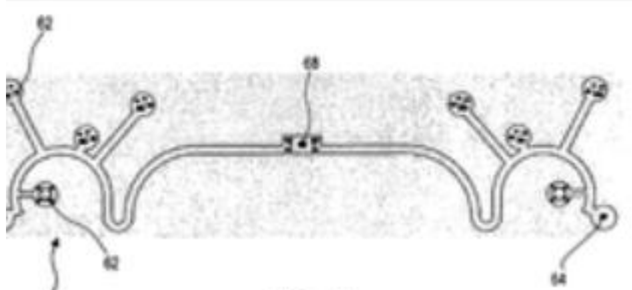
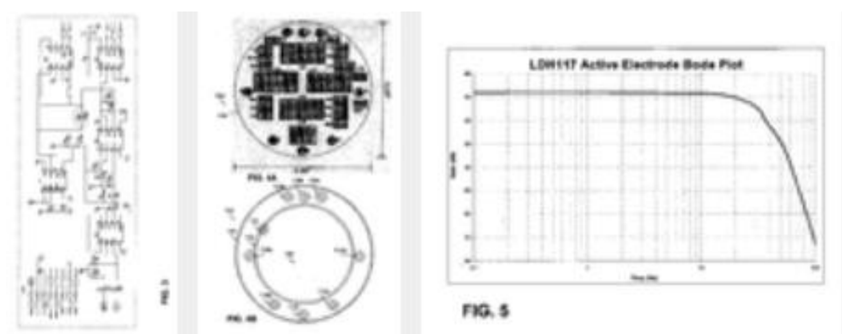
Source Title	Algorithm for detecting a seizure from cardiac data
Source citation (APA Format)	Osorio, I., & Frei, M. (2011, November 3). ALGORITHM FOR DETECTING A SEIZURE FROM CARDIAC DATA.
Original URL	[ALGORITHM FOR DETECTING A SEIZURE FROM CARDIAC DATA (freepatentsonline.com)]
Source type	Patent
Keywords	Blood pressure Pulse transit time (PTT) Non-invasive measurement Optical sensor Accelerometer
#Tags	#patent #seizure #cardiac
Summary of key points + notes (include methodology)	This patent introduces a method for non-invasive blood pressure measurement using pulse transit time (PTT). The invention combines an optical sensor and an accelerometer, managed by a processing unit, to estimate blood pressure without traditional cuff methods. The optical sensor detects a pulse at one body location, while the accelerometer captures heartbeat data at another, allowing the processing unit to calculate PTT and derive blood pressure estimates. This approach offers several advantages, including continuous monitoring capability, improved comfort, and potential integration into wearable devices. The technology has wide-ranging applications in personal health monitoring, clinical settings, and sports and fitness tracking. By providing a more convenient and less invasive solution for blood pressure monitoring, this invention could significantly impact long-term health management and revolutionize how we track this crucial vital sign.
Research Question/Problem/ Need	How to develop a non-invasive, continuous method for measuring blood pressure that is more convenient and comfortable than

	traditional cuff-based methods?
Important Figures	*dont know why screenshots aren't working, go back on phone and scan it in* FIGURES 1A 3C and 3D
VOCAB: (w/definition)	Pulse Transit Time (PTT): Definition: The time it takes for a pulse wave to travel between two arterial sites in the body. PTT is used as an indicator of blood pressure and cardiovascular health. Non-invasive: Definition: A medical procedure or measurement that does not require entering the body or breaking the skin. Non-invasive techniques are generally more comfortable for patients and carry fewer risks.
Cited references to follow up on	Zijlmans, M., Flanagan, D., & Gotman, J. (2002). Heart rate changes and ECG abnormalities during epileptic seizures: Prevalence and definition of an objective clinical sign. *Epilepsia*, *43*(8), 847–854. https://doi.org/10.1046/j.1528-1157.2002.37801.x van Elmpt, W. J. C., Nijsen, T. M. E., Griep, P. A. M., & Arends, J. B. A. M. (2006). A model of heart rate changes to detect seizures in severe epilepsy. *Seizure*, *15*(6), 366–375.

	https://doi.org/10.1016/j.seizure.2006.03.005 Haas, S. M., Frei, M. G., & Osorio, I. (2007). Strategies for adapting automated seizure detection algorithms. *Medical Engineering & Physics*, *29*(8), 895–909. https://doi.org/10.1016/j.medengphy.2006.10.003
Follow up Questions	How accurate is the blood pressure estimation using PTT compared to traditional cuff-based methods? What are the potential limitations or challenges in implementing this technology in real-world applications? How does the device account for individual variations in physiology that might affect PTT measurements?

Patent #2 Notes: Active, multiplexed digital electrodes for EEG, ECG and EMG applications

Source Title	Active, multiplexed digital electrodes for EEG, ECG and EMG applications
Source citation (APA Format)	Fadem, K., & Schnitz, B. (2005). Active, multiplexed digital electrodes for EEG, ECG and EMG applications (U.S. Patent Application No. 11/092,395). U.S. Patent and Trademark Office.
Original URL	[US20050215916A1 - Active, multiplexed digital electrodes for EEG, ECG and EMG applications - Google Patents]
Source type	Patent
Keywords	Biopotential Measurement Active Electrodes Digital Conversion Electrocardiogram (ECG) Electromyogram (EMG) Signal-to-Noise Ratio (SNR) Amplification Filtering Analog-to-Digital Converter (A/D) Multiplexing Instrumentation Amplifier High Input Impedance Butterworth Filter Variable Gain Amplification Serial Peripheral Interface (SPI) Conductive Materials (Ag/AgCl) Noise Reduction Signal Integrity
#Tags	#patent #EEG

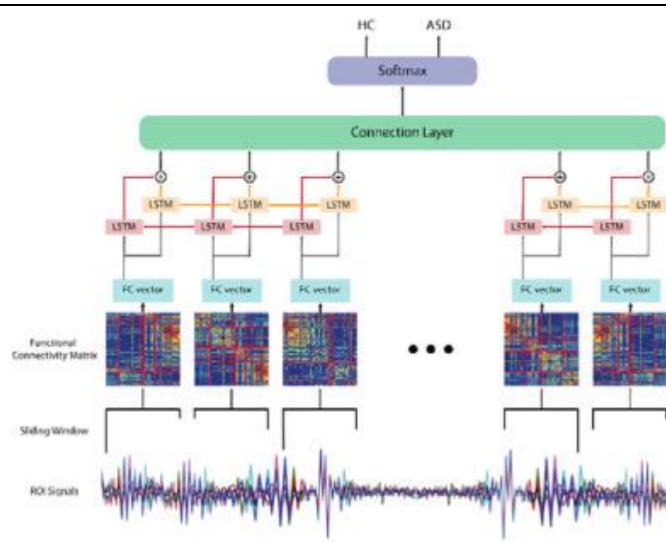
Summary of key points + notes (include methodology)	This patent describes an advanced biopotential measurement system that uses active, digital electrodes for applications like EEG, ECG, and EMG. The system incorporates amplification, filtering, and analog-to-digital conversion directly within each electrode, located less than 15 mm from the conductive contact. This design significantly improves signal-to-noise ratio by minimizing signal degradation and noise pickup. The electrodes feature a multi-stage signal processing chain, including an instrumentation amplifier, low-pass and high-pass filters, and variable gain amplification. Each electrode contains a 16-bit A/D converter and operates on a Serial Peripheral Interface (SPI) bus, allowing for multiplexing of multiple electrodes through a single digital output connection. This approach reduces the number of wires needed between the measurement device (e.g., headset) and the control box, while providing high-quality, digitized biopotential measurements directly at the source
Research Question/Problem/ Need	How can we improve the signal quality and reduce noise in biopotential measurements (particularly EEG, ECG, and EMG) by addressing the limitations of traditional electrode systems?
Important Figures	 FIG. 6 
VOCAB: (w/definition)	Biopotential: Refers to the electrical potential difference that arises from the activity of living cells, commonly measured in physiological studies to assess functions such as brain, heart, and muscle activity. Signal-to-Noise Ratio (SNR): A measure that compares the level of a desired signal to the level of background noise. A higher SNR indicates a clearer signal with less interference.

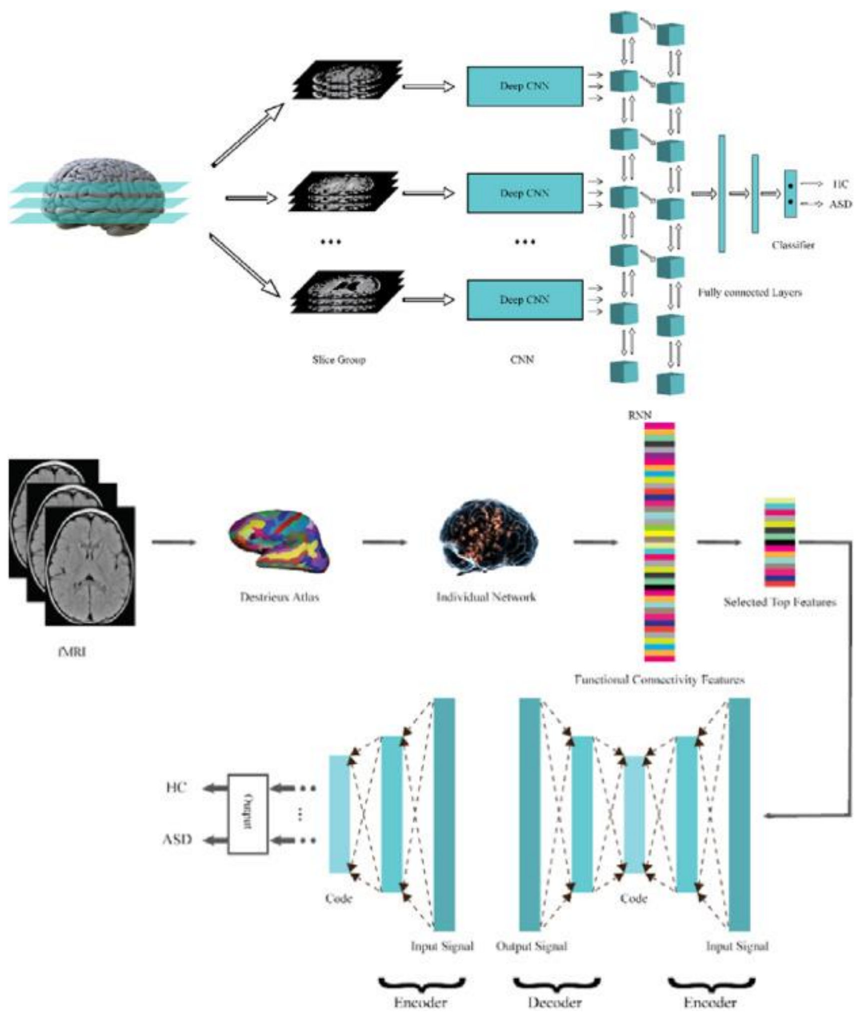
	Amplification: The process of increasing the amplitude or strength of a signal. In biopotential measurements, amplification is crucial for detecting small electrical signals generated by physiological processes. Analog-to-Digital Converter (A/D Converter): An electronic device that converts an analog signal (continuous signal) into a digital signal (discrete values), allowing for digital processing and analysis of the data. Multiplexing: A method that combines multiple signals into one signal over a shared medium. In this context, it allows multiple electrodes to send their signals through a single output connection. Filtering: The process of removing unwanted components from a signal, such as noise or interference, to isolate the desired information. Instrumentation Amplifier: A type of amplifier designed specifically for precise low-level signal amplification.
Cited references to follow up on	Zoth, P., Giebel, A., & Fischer, F. (2002, September 25). Portable handheld hearing screening device and method with internet access and link to hearing screening database.
Follow up Questions	How does the signal quality of this active electrode system compare to traditional passive electrode systems in real-world clinical settings? What are the power requirements for these active electrodes, and how does this affect battery life in portable applications?

Article #11 Notes: Deep learning for neuroimaging-based diagnosis and rehabilitation of Autism Spectrum Disorder: A review

Source Title	Deep learning for neuroimaging-based diagnosis and rehabilitation of Autism Spectrum Disorder: A review
Source citation (APA Format)	Khodatars, M., Shoeibi, A., Sadeghi, D., Ghaasemi, N., Jafari, M., Moridian, P., Khadem, A., Alizadehsani, R., Zare, A., Kong, Y., Khosravi, A., Nahavandi, S., Hussain, S., Acharya, U. R., & Berk, M. (2021). Deep learning for neuroimaging-based diagnosis and rehabilitation of autism spectrum disorder: A Review. *Computers in Biology and Medicine*, *139*, 104949. https://doi.org/10.1016/j.compbiomed.2021.104949
Original URL	Deep learning for neuroimaging-based diagnosis and rehabilitation of Autism Spectrum Disorder: A review - ScienceDirect
Source type	Journal Article
Keywords	Autism Spectrum Disorder (ASD) Deep Learning (DL) Neuroimaging Diagnosis Rehabilitation
#Tags	#DL #ASD #CNN #neuroimaging
Summary of key points + notes (include methodology)	Autism Spectrum Disorder (ASD) is a developmental condition that affects how individuals communicate, behave, and interact with others. Because it manifests differently in each person, early and accurate diagnosis is vital to ensure appropriate support and intervention. Neuroimaging techniques, like structural MRI (sMRI) and

<table>
<tr><td></td><td>functional MRI (fMRI), allow researchers to study the brain's structure and activity, offering new ways to understand ASD. With the help of deep learning (DL), a form of artificial intelligence, scientists can analyze these images more effectively. DL models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), automatically detect patterns in the brain that traditional methods might miss. These tools have significantly improved diagnostic accuracy and are now being used to create personalized treatment plans, giving individuals care tailored to their specific needs.

Despite its promise, the use of deep learning in ASD research faces some challenges. Large, diverse datasets are needed to train DL models, but these are often difficult to collect due to differences in brain scans across populations. Additionally, DL models are sometimes seen as “black boxes” because they make decisions in ways that are not easy to explain, making it harder for doctors to trust and use them in real-world settings. To overcome these obstacles, researchers are working to create models that are easier to interpret and to combine multiple types of data—like neuroimaging, behavioral assessments, and clinical records—for a more comprehensive understanding of ASD. These advancements could lead to faster diagnoses and treatments that address each person’s unique brain and behavior, offering hope for more effective support in the future.</td></tr>
<tr><td>Research Question/Problem/ Need</td><td>The central research problem revolves around improving the accuracy and effectiveness of diagnosing and treating Autism Spectrum Disorder (ASD) using advanced computational techniques.</td></tr>
<tr><td>Important Figures</td><td>
</td></tr>
</table>

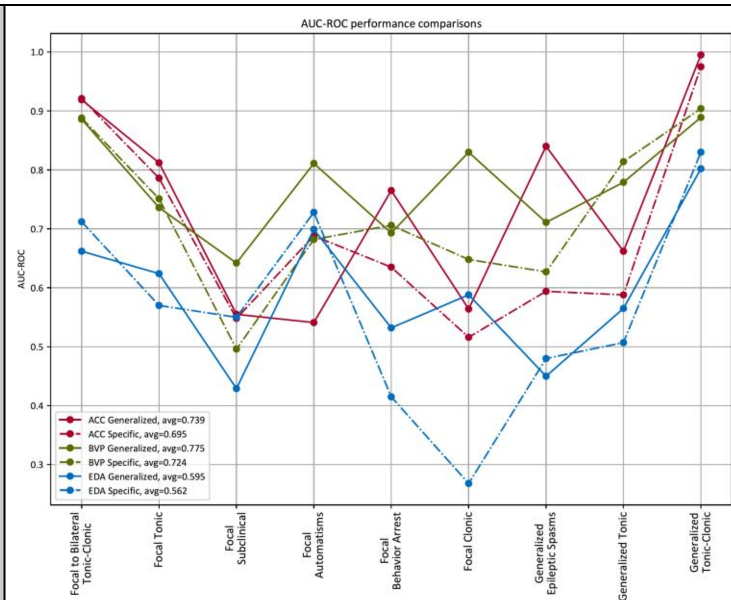
	
VOCAB: (w/definition)	Structural MRI (sMRI)- A neuroimaging technique that provides detailed information about the physical structure of the brain, such as the size and shape of different regions. Functional MRI (fMRI)- A neuroimaging technique that measures brain activity by detecting changes in blood flow, providing insights into functional connectivity between brain regions. Feature Extraction The process of identifying relevant characteristics or patterns in data. In deep learning, this is done automatically by the model, unlike traditional methods that require manual selection. Multimodal Data- The integration of different types of data, such as combining sMRI, fMRI, and behavioral assessments, to provide a more comprehensive analysis. Interpretability- The degree to which the outputs of a machine learning or deep learning model can be understood and explained by

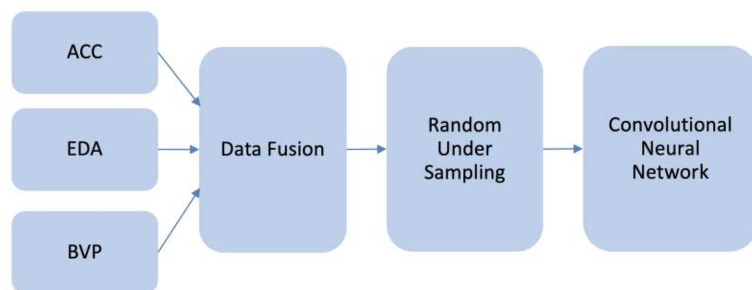
	humans, particularly critical in clinical settings. Personalized Intervention- Tailored therapeutic strategies designed to meet the unique needs of an individual, often based on specific neural or behavioral profiles. Black Box Model- A machine learning model whose decision-making process is not easily interpretable or transparent, creating challenges for trust and clinical adoption.
Cited references to follow up on	Shoeibi, A., Sadeghi, D., Moridian, P., Ghassemi, N., Heras, J., Alizadehsani, R., Khadem, A., Kong, Y., Nahavandi, S., Zhang, Y.-D., & Gorriz, J. M. (2021). Automatic diagnosis of schizophrenia in EEG signals using CNN-LSTM models. *Frontiers in Neuroinformatics*, *15*. https://doi.org/10.3389/fninf.2021.777977
Follow up Questions	How does multimodal data integration improve the accuracy of diagnosing ASD using neuroimaging techniques? What are the challenges in applying "black box" models in clinical settings, and how can improving model interpretability address these issues?

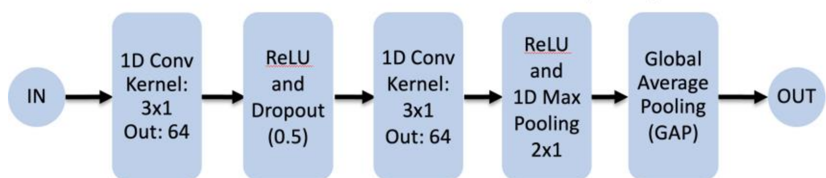
Article #12 Notes: Seizure detection using wearable sensors and machine learning: Setting a benchmark

Source Title	Seizure detection using wearable sensors and machine learning: Setting a benchmark
Source citation (APA Format)	Tang, J., El Atrache, R., Yu, S., Asif, U., Jackson, M., Roy, S., Mirmomeni, M., Cantley, S., Sheehan, T., Schubach, S., Ufongene, C., Vieluf, S., Meisel, C., Harrer, S., & Loddenkemper, T. (2021). Seizure

	detection using wearable sensors and Machine Learning: Setting a benchmark. *Epilepsia*, *62*(8), 1807–1819. https://doi.org/10.1111/epi.16967
Original URL	https://doi.org/10.1111/epi.16967
Source type	Journal Article
Keywords	Seizure Detection Wearable Sensors Machine Learning Electrodermal Activity (EDA) Accelerometry (ACC)
#Tags	#DL #CNN #epilepsy #seizures
Summary of key points + notes (include methodology)	This study looks at the efficacy of wearable devices combined with some machine learning algorithms for detecting a variety of epileptic seizures. The study, conducted with 94 patients, researched utilized wrist and ankle-worn sensors to collect data on body temperature, electrodermal activity (EDA), accelerometry (ACC), and photoplethysmography (BVP). The data was analyzed using two distinct machine learning algorithms: one focused on specific seizure types and the other on a generalized approach that combined all seizure types. The results indicated that the algorithms could detect seizures better than just chance, with the best performance, through a fusion of ACC and BVP data, yielding an area under the receiver operating characteristic curve (AUC-ROC) of 0.752. Methodologically, the study involved enrolling patients into an epilepsy monitoring unit where they wore the sensors for extensive periods. The researchers ensured synchronization between the wearable device and EEG recordings to maintain accuracy in seizure detection. They used CNNs to make time series data from the sensors. They used random under sampling to balance the datasets. It highlights the potential of wearable technology and machine learning in improving seizure detection. This emphasizes the need for further validation with larger datasets.
Research Question/Problem/ Need	The critical need for reliable, automatic, and nonintrusive methods to detect a broad range of epileptic seizure types using wearable devices. The study aims to evaluate seizure detection performance across various epileptic seizures using wrist- and ankle-worn multisignal biosensors combined with machine learning algorithms.

<table>
<tr>
<td>Important Figures</td>
<td>


(A) Machine learning framework


(B) Convolutional neural network (CNN)


</td>
</tr>
<tr>
<td>VOCAB: (w/definition)</td>
<td>EDA (Electrodermal Activity)- Reflects changes in skin conductance, which can be associated with seizure activity

BVP (Photoplethysmography)- An optical technique used to measure blood volume changes in microvascular tissues.

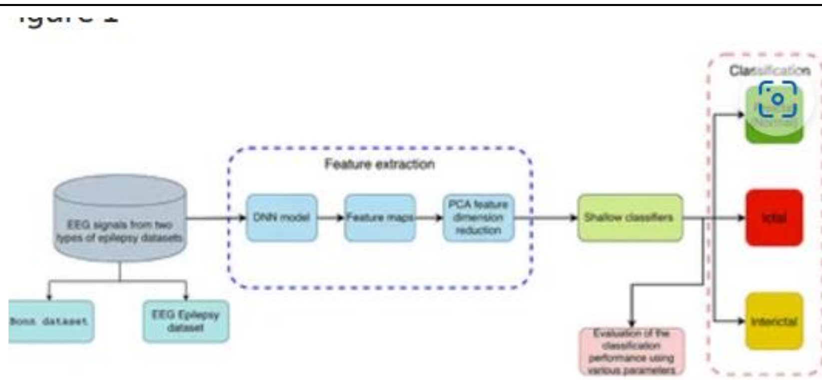
AUC-ROC (Area Under the Receiver Operating Characteristic Curve)- A statistical measure used to evaluate performance

Cross-Validation- A statistical method used to assess how the results of a statistical analysis will generalize to an independent dataset.</td>
</tr>
<tr>
<td>Cited references to follow up on</td>
<td>Leijten, F. S. (2018a). Multimodal seizure detection: A Review.</td>
</tr>
</table>

	Epilepsia, *59*(S1), 42–47. https://doi.org/10.1111/epi.14047
Follow up Questions	What strategies could be employed to improve the detection accuracy for seizure types that were less successfully identified by the current algorithms? How could the integration of additional clinical information enhance the performance of the machine learning models for seizure detection?

Article #13 Notes: Epileptic seizure detection with deep EEG features by convolutional neural network and shallow classifiers

Source Title	Epileptic seizure detection with deep EEG features by convolutional neural network and shallow classifiers
Source citation (APA Format)	Zeng, W., Shan, L., Su, B., & Du, S. (2023). Epileptic seizure detection with deep EEG features by convolutional neural network and shallow classifiers. *Frontiers in Neuroscience*, *17*. https://doi.org/10.3389/fnins.2023.1145526
Original URL	Frontiers | Epileptic seizure detection with deep EEG features by convolutional neural network and shallow classifiers
Source type	Journal Article
Keywords	Deep EEG Features, Shallow classifiers, ML in neuroscience
#Tags	#DL #CNN

<table>
<tr>
<td>Summary of key points + notes (include methodology)</td>
<td>The article discusses the use of deep learning, specifically convolutional neural networks (CNNs), for detecting epileptic seizures from electroencephalogram (EEG) data. The researchers emphasize how deep CNNs can automatically extract complex features from EEG signals, which are often difficult to interpret manually. These features represent high-level patterns in the brain’s electrical activity that are crucial for identifying seizure events. By combining deep learning with shallow classifiers—simpler machine learning models like support vector machines—the study improves the accuracy of seizure detection. This hybrid approach leverages the strengths of both deep learning and traditional classifiers, making the model efficient and robust enough for real-time detection in clinical settings.
In terms of methodology, the study starts with EEG data collection from patients, which is preprocessed to remove noise and normalize the signals. CNNs are then used to extract deep features from the raw EEG data, which are followed by shallow classifiers for final seizure classification. The model is evaluated based on accuracy, sensitivity, and specificity to ensure reliable detection of seizures. This approach has significant clinical implications, offering a potential tool for continuous monitoring and early seizure warning systems. However, challenges such as ensuring model robustness in diverse clinical settings and enhancing model interpretability for healthcare providers remain important areas for further development.</td>
</tr>
<tr>
<td>Research Question/Problem/ Need</td>
<td>How can deep learning techniques, specifically convolutional neural networks (CNNs), be utilized to improve the detection of epileptic seizures from electroencephalogram (EEG) signals?</td>
</tr>
<tr>
<td>Important Figures</td>
<td>
</td>
</tr>
</table>

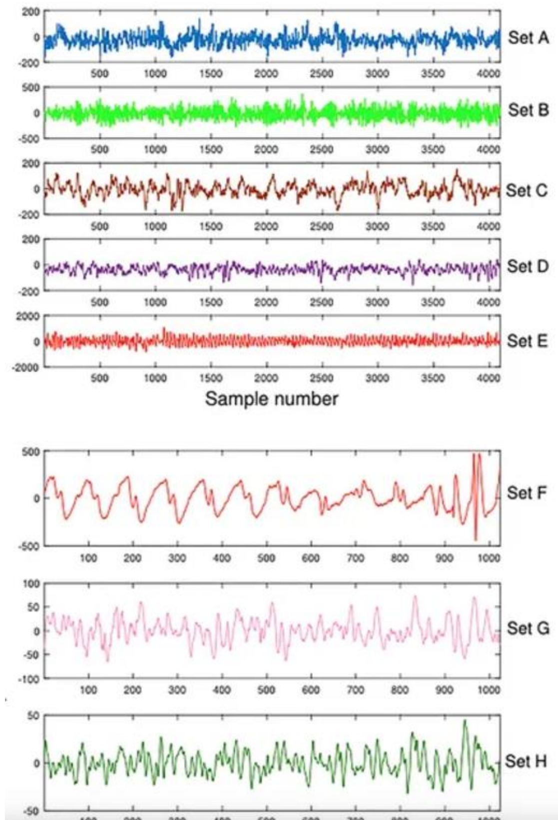
<table>
<tr>
<td></td>
<td>


Figure 3

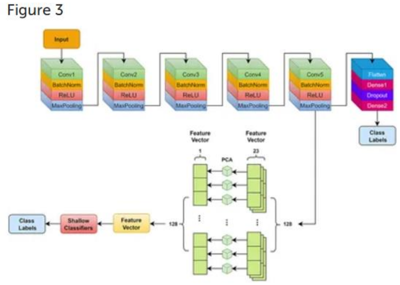


Figure 3. Deep neural network model and feature extraction used in this study. Conv, convolution.
</td>
</tr>
<tr>
<td>VOCAB: (w/definition)</td>
<td>
Shallow Classifiers- Simplified machine learning models that are used for classification tasks based on less complex algorithms. While they are faster and less computationally expensive compared to deep learning models, they are less capable of handling complex data patterns, such as those found in EEG signals.

Sensitivity- A performance metric that measures the proportion of actual positive cases (e.g., seizures) correctly identified by a model. In the context of seizure detection, high sensitivity means the model effectively detects most seizure events, minimizing false negatives.

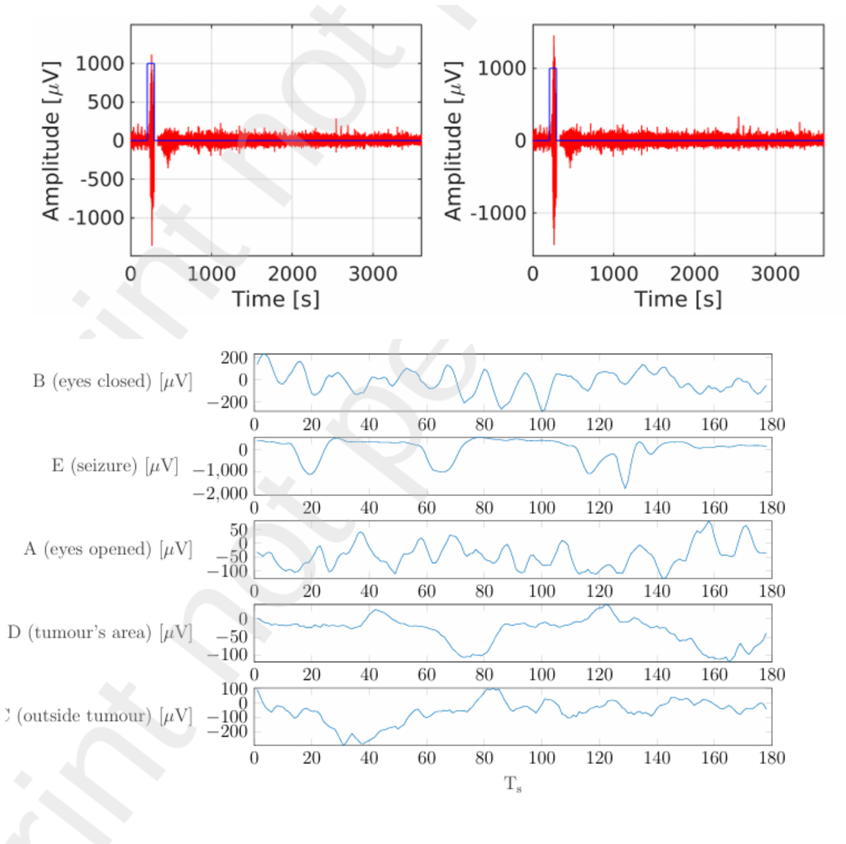
Specificity- A performance metric that measures the proportion of actual negative cases (e.g., non-seizure periods) correctly identified by
</td>
</tr>
</table>

	the model. High specificity means the model accurately distinguishes between seizure and non-seizure periods, minimizing false positives. Hybrid Approach- The combination of different methods or techniques to solve a problem. In this study, the hybrid approach refers to combining deep learning (for feature extraction) with shallow classifiers (for classification) to create a more effective and computationally efficient seizure detection system.
Cited references to follow up on	Gupta, V., & Pachori, R. B. (2019). Epileptic seizure identification using entropy of FBSE based EEG rhythms. *Biomedical Signal Processing and Control*, *53*, 101569. https://doi.org/10.1016/j.bspc.2019.101569
Follow up Questions	How does the combination of shallow classifiers and deep learning models enhance the efficiency and accuracy of seizure detection systems in clinical settings? What are the potential challenges in achieving high sensitivity and specificity in real-time seizure detection, and how can these challenges be addressed?

Article #14 Notes: Epileptic Seizure Detection Using FPGA-Accelerated Neural Networks and EEG Signals

Source Title	Epileptic Seizure Detection Using FPGA-Accelerated Neural Networks

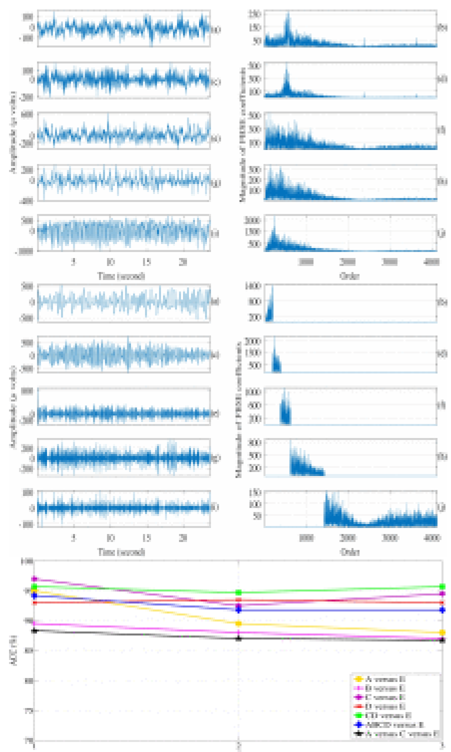
	and EEG Signals
Source citation (APA Format)	Wieczorek, J., Zabolotny, W., & Schmid, A. (2023). *Epileptic Seizure Detection Using FPGA-Accelerated Neural Networks and EEG Signals*. https://doi.org/10.2139/ssrn.4414752
Original URL	Epileptic seizure detection using FPGA-accelerated neural networks and EEG signals
Source type	Journal Article
Keywords	FPGA, HLS, AR, SoC, Zynq SoC
#Tags	#epilepsy
Summary of key points + notes (include methodology)	The study explores epileptic seizure detection using FPGA-accelerated neural networks and EEG signals, focusing on developing an efficient method for identifying seizure events. Utilizing two datasets—the University of Bonn and SWEC-ETH—the researchers implemented a feed-forward neural network synthesized using High-Level Synthesis (HLS) and deployed on a Zynq System on Chip (SoC). The preprocessing techniques included autoregressive modeling, local binary patterns, and approximate entropy, with the final implementation achieving a remarkable 96% classification accuracy and a classification time of approximately 7µs per sample.The research addresses a critical need in epilepsy management, highlighting that around 50 million people suffer from epilepsy globally, with 80% of cases reported in developing countries. By developing an automated seizure detection method, the study aims to support neurologists and reduce the time-consuming and error-prone process of manual EEG analysis. The proposed design is particularly suitable for low-delay applications in clinical environments, offering a potential breakthrough in real-time seizure detection and monitoring technologies.
Research Question/Problem/ Need	There's a need for efficient and automated epileptic seizure detection using EEG signals
Important Figures	

	 Figure 1: Examples of the Bonn University dataset signals.
VOCAB: (w/definition)	Field Programmable Gate Array (FPGA): A type of integrated circuit that can be configured by the user after manufacturing, allowing for the implementation of custom hardware designs. High-Level Synthesis (HLS): A design process that converts high-level programming languages (like C or C++) into hardware description languages (like VHDL or Verilog) for FPGA implementation. HLS simplifies the design of complex hardware systems by allowing developers to work at a higher abstraction level. Autoregressive Modelling (AR): A statistical analysis technique used to model and predict future values based on past data points. System on Chip (SoC): An integrated circuit that consolidates all components of a computer or electronic system onto a single chip, including a processor, memory, and input/output interfaces. Zynq SoC- A specific type of System on Chip developed by Xilinx that integrates a dual-core ARM Cortex-A9 processor with FPGA fabric.
Cited references to follow up on	Akter, Most. S., Islam, Md. R., Tanaka, T. T., Fukumori, K. F., Iimura, Y.

	I., & Sugano, H. S. (2019). Automatic identification of epileptic focus on high-frequency components in interictal ieeg. *2019 8th International Congress on Advanced Applied Informatics (IIAI-AAI)*, 1075–1076. https://doi.org/10.1109/iiai-aai.2019.00233
Follow up Questions	How does the implementation of High-Level Synthesis (HLS) on FPGA improve the efficiency and speed of epileptic seizure detection compared to traditional methods? What are the potential limitations and challenges of using the SWEC-ETH dataset for training neural networks in seizure detection, and how might these affect the generalizability of the model?

Article #15 Notes: Epileptic seizure identification using entropy of FBSE based EEG rhythms

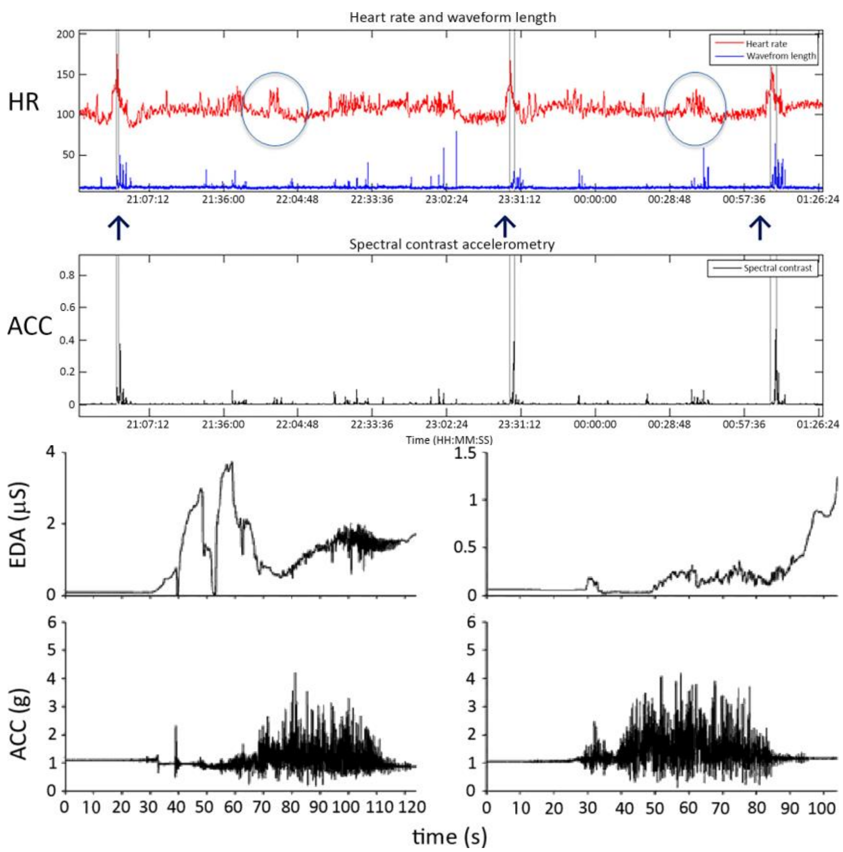
Source Title	Epileptic seizure identification using entropy of FBSE based EEG rhythms
Source citation (APA Format)	Gupta, V., & Pachori, R. B. (2019). Epileptic seizure identification using entropy of FBSE based EEG rhythms. *Biomedical Signal Processing and Control*, *53*, 101569. https://doi.org/10.1016/j.bspc.2019.101569
Original URL	https://doi.org/10.1016/j.bspc.2019.101569
Source type	Journal Article
Keywords	Weighted Multiscale Renyi Permutation Entropy (WMRPE) Classification Accuracy Additive White Gaussian Noise (AWGN) Signal-to-Noise Ratio (SNR) Random Forest (RF) Least Squares Support Vector Machine (LS-SVM) Feature Extraction
#Tags	#epilepsy #EEG #seizures
Summary of key points + notes (include methodology)	The study offers a new method for detecting epileptic seizures by analyzing electroencephalogram (EEG) signals using rhythms gathered from Fourier-Bessel series expansion (FBSE) and weighted multiscale Renyi permutation entropy (WMRPE). By separating both healthy people and those who have epilepsy, this approach seeks to improve the classification accuracy of EEG signals. Delta, theta, alpha, beta, and gamma are among the different brain rhythms that are identified by first using FBSE on EEG signals in order to extract coefficients. The main feature used for categorization is WMRPE, which records amplitude information and allows multi-scale analysis of the EEG data. The study employs a variety of classifiers, including random forest and least squares support vector machine, to classify the EEG data. Using a strong validation technique that uses 10-fold cross-validation, the classification performance gets evaluated on seven separate classification tasks. These contain both two-class and three-class classification situations and effectively differentiate between different

	levels of seizure activity and normal brain function. Notably, the recommended method shows robustness against noise by maintaining performance at different signal-to-noise ratio levels. Overall, the results suggest that, when compared with current techniques, the combination of WMRPE and FBSE significantly improves classification accuracy. By enabling fast and precise identification of seizures in clinical settings, this development in automated seizure detection systems may reduce the strain for neurologists.
Research Question/Problem/ Need	The research addresses the need for an improved automated system to identify epileptic seizures using electroencephalogram (EEG) signals
Important Figures	
VOCAB: (w/definition)	Weighted Multiscale Renyi Permutation Entropy (WMRPE)- A statistical measure used to quantify the complexity of time series data, particularly in EEG signals, by analyzing the order of values and their distribution across multiple scales. Fourier–Bessel Series Expansion (FBSE)- A mathematical technique used to decompose signals into a series of basis functions, allowing for the analysis of different frequency components within EEG signals. Classification Accuracy- A metric used to evaluate the performance of a classification model, defined as the ratio of correctly predicted instances to the total instances in a dataset. Signal-to-Noise Ratio (SNR)- A measure used in science and

	engineering that compares the level of a desired signal to the level of background noise. A higher SNR indicates a clearer signal. Additive White Gaussian Noise (AWGN)- A basic noise model used in information theory to mimic the effect of random processes that add noise to a signal, characterized by its Gaussian distribution and constant power spectral density. Random Forest (RF)- An ensemble learning method for classification and regression that constructs multiple decision trees during training and outputs the mode of their predictions. Least Squares Support Vector Machine (LS-SVM)- A type of support vector machine that uses a least squares loss function for training, often employed for regression and classification tasks in machine learning.
Cited references to follow up on	Janjarasjitt, S. (2015). Spectral exponent characteristics of intracranial eegs for epileptic seizure classification. *IRBM*, *36*(1), 33–39. https://doi.org/10.1016/j.irbm.2014.07.005
Follow up Questions	How exactly does Fourier–Bessel series expansion (FBSE) separate EEG signal rhythms? What makes weighted multiscale Renyi permutation entropy (WMRPE) unique in analyzing EEG signals?

Article #16 Notes: Multimodal seizure detection: A review

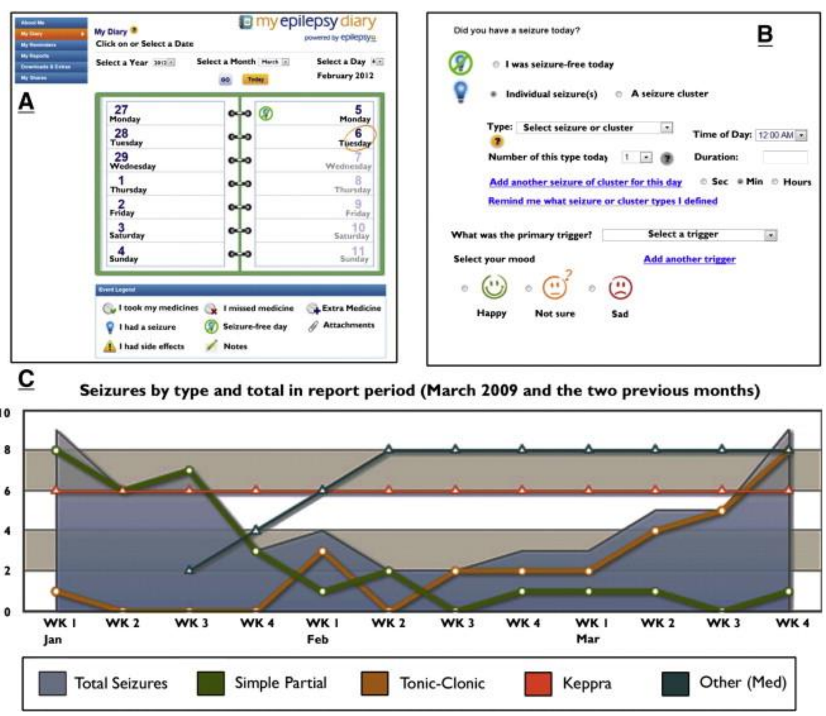
Source Title	Multimodal seizure detection: A review
Source citation (APA Format)	Leijten, F. S. (2018). Multimodal seizure detection: A Review. *Epilepsia*, *59*(S1), 42–47. https://doi.org/10.1111/epi.14047
Original URL	**https://doi.org/10.1111/epi.14047**
Source type	Journal Article
Keywords	Electrodermal activity (EDA) Oximetry Tonic-clonic seizures Remote sensing Video detection Radar sensing Movement detectors Sound detection Sensor fusion False detection rate (FDR) Sensitivity
#Tags	#seizure #EEG #epilepsy
Summary of key points + notes (include methodology)	The article "Multimodal Seizure Detection: A Review" by Frans S.S. Leijten and the Dutch TeleEpilepsy Consortium examines the efficacy of combining various non-EEG-based modalities to detect motor seizures in both children and adults. The review analyzes studies conducted between 2010 and 2017 that utilized contact sensors such as accelerometers, electromyography (EMG), heart rate monitors,

	electrodermal activity sensors, and oximetry, as well as remote sensors including video, radar, movement, and sound detectors. Findings indicate that combining multiple sensors can enhance sensitivity in detecting tonic-clonic seizures, though results regarding the impact on false detection rates are inconsistent. The authors emphasize the necessity for larger, rigorously designed field studies to validate these preliminary findings and to develop generic algorithms that could be effective for the majority of patients.
Research Question/Problem/ Need	improving the detection of motor seizures, particularly tonic-clonic seizures, using non-EEG-based modalities
Important Figures	
VOCAB: (w/definition)	Multimodal Sensors - Devices that combine data from multiple sensing modalities (e.g., motion, sound, heart rate) to enhance the accuracy and reliability of detecting specific events or conditions, such as seizures. Tonic-Clonic Seizures - A type of seizure characterized by sudden loss of consciousness, stiffening of the muscles (tonic phase), and rhythmic muscle contractions (clonic phase). These are often associated with significant motor activity and are among the most detectable seizure types. Electromyography (EMG) - A technique used to measure and record

	the electrical activity of muscles. It is often used in seizure detection to monitor involuntary muscle activity during a seizure. False Detection Rate (FDR) - The proportion of incorrect or false-positive detections made by a system compared to the total number of detections. Lowering the FDR is a key challenge in developing reliable seizure detection tools. Sensitivity - A metric that quantifies a system's ability to correctly identify true positive cases (e.g., actual seizures). High sensitivity indicates a lower likelihood of missed detections.
Cited references to follow up on	Fisher, R. S., Blum, D. E., DiVentura, B., Vannest, J., Hixson, J. D., Moss, R., Herman, S. T., Fureman, B. E., & French, J. A. (2012). Seizure diaries for clinical research and practice: Limitations and Future Prospects. *Epilepsy & Behavior*, *24*(3), 304–310. https://doi.org/10.1016/j.yebeh.2012.04.128
Follow up Questions	What specific combinations of sensors (e.g., accelerometers, EMG, heart rate monitors) have shown the most promise in improving sensitivity and reducing false detection rates for seizure detection? What challenges or limitations exist in developing generic algorithms that can work effectively across diverse patient populations for multimodal seizure detection?

Article #17 Notes: Seizure diaries for clinical research and practice: Limitations and future prospects

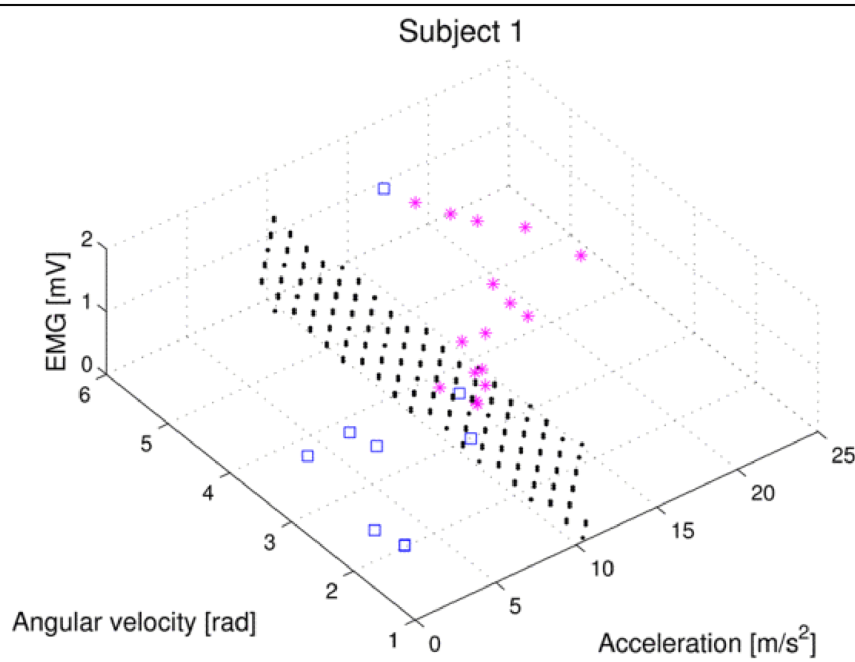
Source Title	Seizure diaries for clinical research and practice: Limitations and future prospects
Source citation (APA Format)	Fisher, R. S., Blum, D. E., DiVentura, B., Vannest, J., Hixson, J. D., Moss, R., Herman, S. T., Fureman, B. E., & French, J. A. (2012). Seizure diaries for clinical research and practice: Limitations and Future Prospects. *Epilepsy & Behavior*, *24*(3), 304–310. https://doi.org/10.1016/j.yebeh.2012.04.128
Original URL	https://doi.org/10.1016/j.yebeh.2012.04.128
Source type	Journal Article
Keywords	Integration with electronic medical records (EMRs) Validation studies Privacy concerns Pediatric epilepsy Regulatory guidelines Anti-seizure medication trials Standardized data sets Underreporting Digital literacy
#Tags	#seizure #epilepsy
Summary of key points + notes (include methodology)	The article "Seizure Diaries for Clinical Research and Practice: Limitations and Future Prospects" by Robert S. Fisher et al. examines the role of seizure diaries in tracking epilepsy outcomes in clinical and research settings. Seizure diaries are essential tools for documenting seizure frequency, types, and triggers, aiding in treatment evaluation and understanding seizure patterns. However, traditional paper-based diaries are limited by underreporting due to patients' inability to recognize all seizures, as well as issues like misplacement, delayed

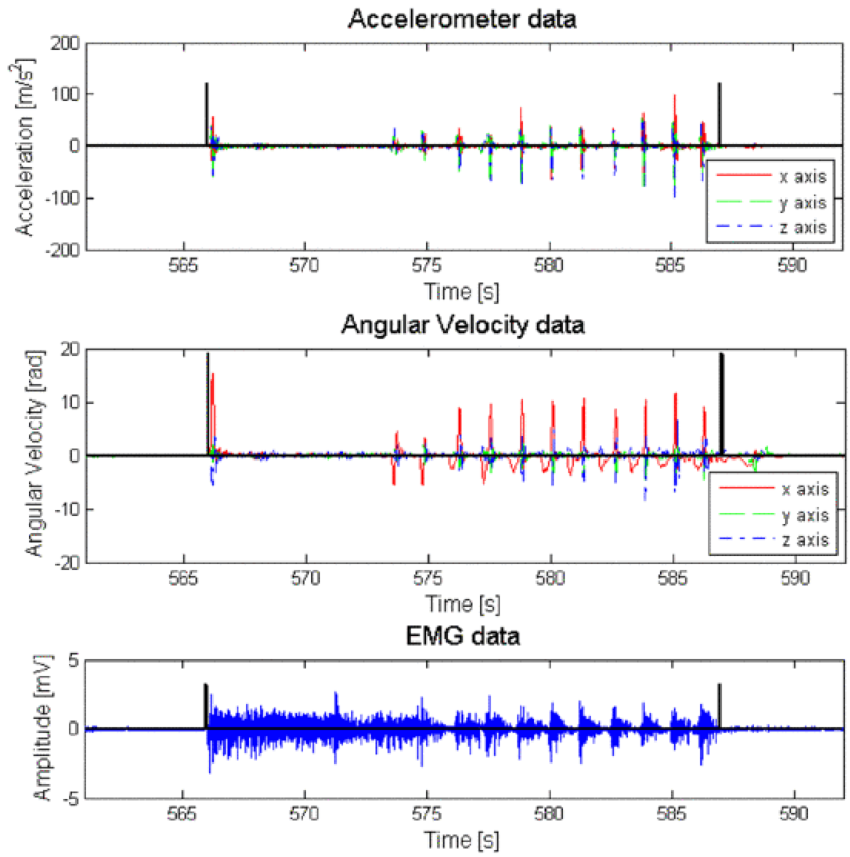
	entries, and inconsistent usage. In contrast, electronic seizure diaries offer significant advantages, including improved accuracy through time-stamping, enhanced accessibility, real-time feedback, and the ability to integrate with electronic medical records and other digital health tools. Despite these benefits, electronic diaries come with challenges such as digital literacy requirements, higher costs, and privacy concerns. Pediatric use is particularly complex due to multiple caregivers and varied seizure presentations. Platforms like the Epilepsy Diary by epilepsy.com and SeizureTracker are gaining popularity, showing a preference for electronic over paper diaries among patients. However, their adoption in clinical trials remains limited due to the need for validation as reliable research tools and clear regulatory guidelines. The authors recommend conducting validation studies to assess the accuracy of both paper and electronic diaries, developing standardized data sets, and integrating diaries with electronic sensors to improve seizure detection. Addressing privacy concerns, regulatory collaboration, and specific challenges in pediatric populations is also emphasized. In conclusion, while seizure diaries are valuable in epilepsy management and research, ongoing efforts to enhance their reliability, usability, and integration into clinical workflows are necessary to maximize their potential.
Research Question/Problem/ Need	challenges and limitations associated with using seizure diaries for tracking epilepsy, both in clinical practice and research
Important Figures	
VOCAB: (w/definition)	Seizure Diaries - Tools used by patients to record the frequency, type,

	duration, and triggers of seizures. These diaries help in tracking epilepsy and evaluating the effectiveness of treatments. Underreporting - The failure to report or record all occurrences of seizures, often due to patients not recognizing or forgetting seizures, leading to incomplete or inaccurate data. Digital Literacy - The ability to use digital technologies effectively. In the context of electronic seizure diaries, it refers to a patient's ability to understand and interact with digital tools such as smartphones or computer-based systems. Integration with Electronic Medical Records (EMRs) - The process of linking seizure diaries (electronic or paper) with a patient's electronic health records to ensure seamless access and sharing of data between patients and healthcare providers. Real-time Feedback - Immediate feedback provided by electronic systems, such as reminders or validation of data, which can help improve data accuracy and ensure timely entries in seizure diaries.
Cited references to follow up on	Conradsen, I., Beniczky, S., Wolf, P., Terney, D., Sams, T., & Sorensen, H. B. D. (2009). Multi-modal Intelligent seizure acquisition (MISA) system -- a new approach towards seizure detection based on full body motion measures. *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2591–2595. https://doi.org/10.1109/iembs.2009.5335334
Follow up Questions	What are the specific challenges in validating electronic seizure diaries as reliable tools for both clinical practice and research, and how can these be addressed? How can the integration of seizure diaries with wearable sensors or other digital health tools improve the accuracy of seizure tracking and monitoring?

Article #18 Notes: Multi-modal intelligent seizure acquisition (MISA) system--a new approach towards seizure detection based on full body motion measures

Source Title	Multi-modal intelligent seizure acquisition (MISA) system--a new approach towards seizure detection based on full body motion measures
Source citation (APA Format)	Conradsen, I., Beniczky, S., Wolf, P., Terney, D., Sams, T., & Sorensen, H. B. D. (2009). Multi-modal Intelligent seizure acquisition (MISA) system -- a new approach towards seizure detection based on full body motion measures. *2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2591–2595. https://doi.org/10.1109/iembs.2009.5335334
Original URL	https://doi.org/10.1109/iembs.2009.5335334
Source type	Journal Article
Keywords	Full-body motion analysis Real-time monitoring Electromyography (EMG) Accelerometers Gyroscopes Multi-sensor integration
#Tags	#EEG #seizure #epilepsy
Summary of key points + notes (include methodology)	This article introduces something called the MISA system, which is a novel approach to detecting epileptic seizures through comprehensive body motion analysis. This system is designed for real-time seizure detection to allow for timely assistance for patients who may be

	unconscious or unable to seek help during seizures. The methodology involved a pilot study with three subjects who simulated 15 seizures each and performed predefined normal activities over a four-hour monitoring period. Data were collected using multiple sensors, including electromyography (EMG), accelerometers, magnetometers, gyroscopes (collectively referred to as AMG), electrocardiography (ECG), electroencephalography (EEG), as well as audio-video recordings. The study found that the non-subject-specific MISA system, relying on accelerometer, gyroscope, and EMG data, successfully detected 98% of simulated seizures, with only four normal movements misclassified as seizures. When customized for individual subjects, the system achieved 100% detection accuracy, with a maximum of one false positive. These results highlight the MISA system's potential as a reliable tool for seizure detection, leveraging full-body motion analysis to enhance patient safety and support timely interventions.
Research Question/Problem/ Need	Can a multi-modal seizure detection system, using a combination of body motion measures, improve the accuracy and reliability of detecting seizures in real time?
Important Figures	

	
VOCAB: (w/definition)	MISA (Multi-modal Intelligent Seizure Acquisition) System - A seizure detection system that uses data from multiple sensors, such as accelerometers, gyroscopes, and electromyography (EMG), to analyze full-body motion and detect seizures in real time. Electromyography (EMG) - A diagnostic technique that measures and records the electrical activity of muscles, often used in seizure detection to monitor involuntary muscle activity. Accelerometers - Sensors that measure changes in velocity or acceleration, commonly used in wearable devices to detect motion patterns indicative of seizures. False Positives - Instances where a system incorrectly identifies normal activities or events as seizures, a common challenge in seizure detection technologies. Non-subject-specific Detection - A detection approach that applies generalized algorithms across different users rather than customizing them for each individual, aiming for broader applicability but sometimes facing accuracy trade-offs.

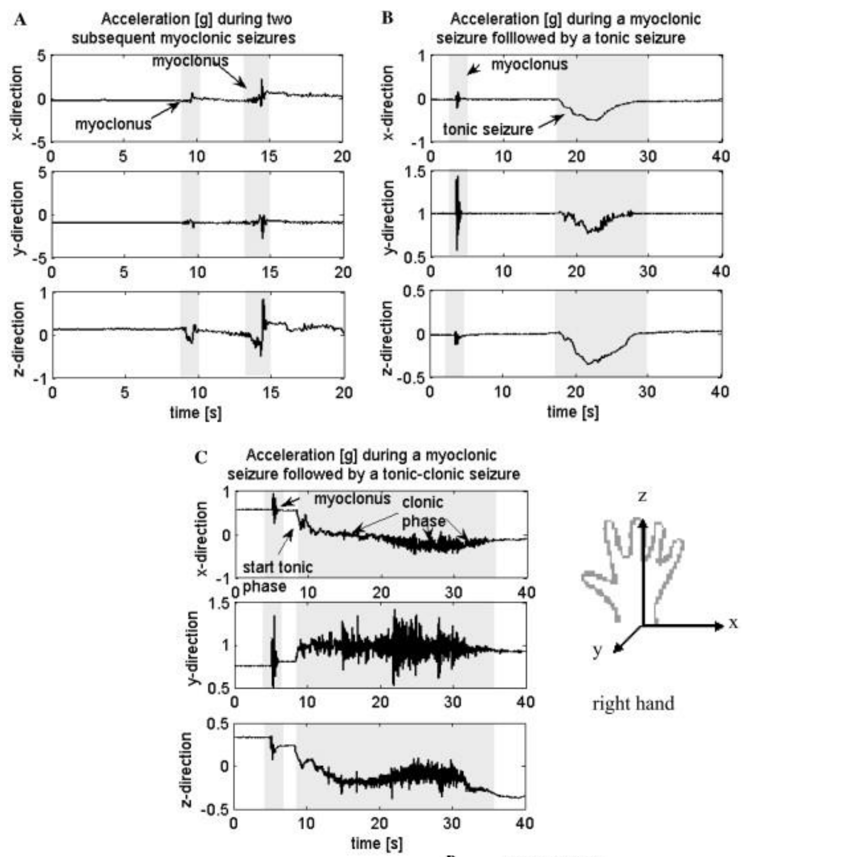
Cited references to follow up on	Nijsen, T. M. E., Arends, J. B. A. M., Griep, P. A. M., & Cluitmans, P. J. M. (2005). The potential value of three-dimensional accelerometry for detection of motor seizures in severe epilepsy. *Epilepsy & Behavior*, *7*(1), 74–84. https://doi.org/10.1016/j.yebeh.2005.04.011
Follow up Questions	How can the MISA system's algorithms be further optimized to reduce false positives while maintaining high seizure detection accuracy across diverse populations?

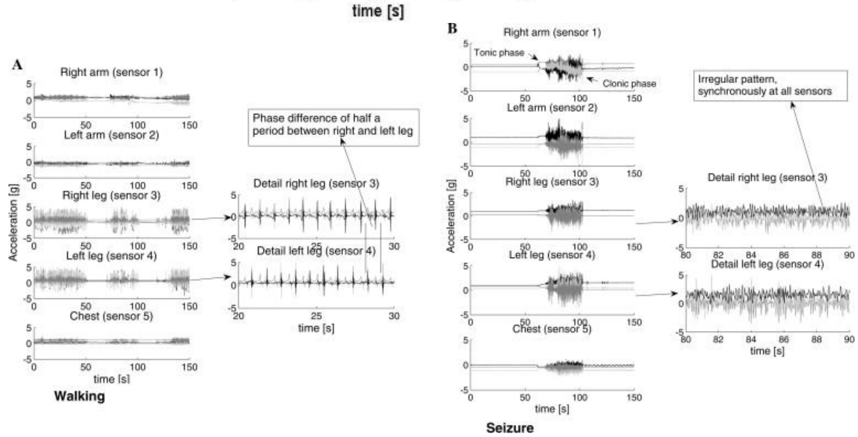
Article #19 Notes: The potential value of three-dimensional accelerometry for detection of motor seizures in severe epilepsy

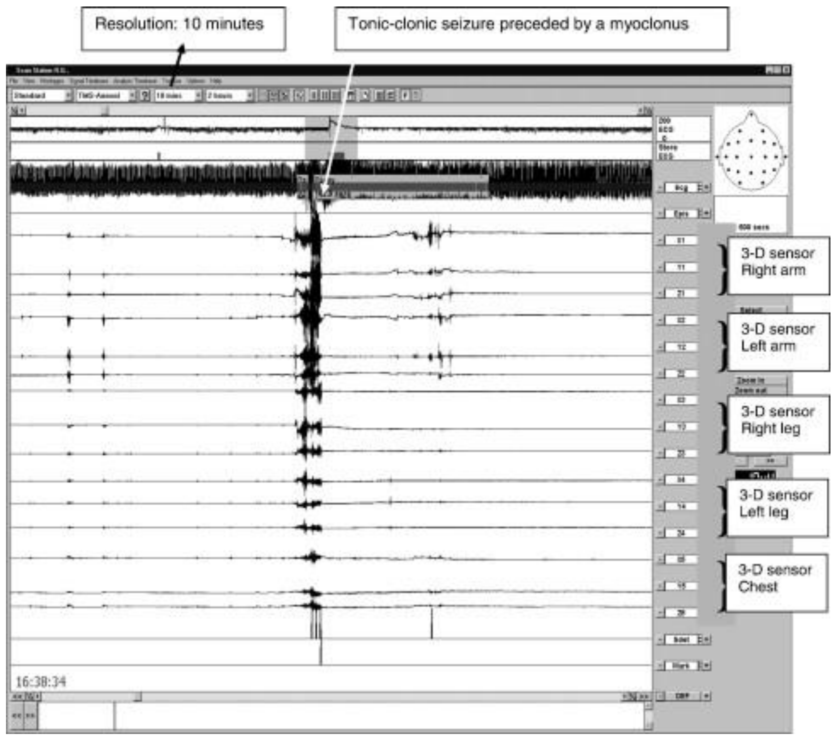
Source Title	The potential value of three-dimensional accelerometry for detection of motor seizures in severe epilepsy
Source citation (APA Format)	Nijsen, T. M. E., Arends, J. B. A. M., Griep, P. A. M., & Cluitmans, P. J. M. (2005). The potential value of three-dimensional accelerometry for detection of motor seizures in severe epilepsy. *Epilepsy & Behavior*, *7*(1), 74–84. https://doi.org/10.1016/j.yebeh.2005.04.011

Original URL	https://doi.org/10.1016/j.yebeh.2005.04.011
Source type	Journal Article
Keywords	Epilepsy Seizure Detection Motor Seizures Three-dimensional accelerometry
#Tags	#CNN #EEG #seizure #epilepsy
Summary of key points + notes (include methodology)	This article explores the use of three-dimensional (3D) accelerometry (ACM) as a tool for detecting motor seizures in patients with severe epilepsy. The study involved monitoring 18 patients over a 36-hour period using 3D ACM alongside video/EEG recordings. During this time, 897 seizures were identified—seven times more than what was reported by nursing staff—highlighting the issue of underreporting in clinical settings. The findings revealed that 48% of seizures were detected through ACM data alone, and in 10 of the 18 patients, all seizures were exclusively identified using ACM. This demonstrates the system's potential effectiveness, particularly for detecting seizures in individuals where other methods may fall short. Additionally, the study observed that 95% of motor seizures displayed stereotypical movement patterns detectable by ACM, suggesting its suitability for developing automated detection algorithms. The research concludes that 3D accelerometry can serve as a valuable complement to EEG in seizure detection, offering an innovative method to improve patient monitoring and care.
Research Question/Problem/ Need	Three-dimensional accelerometry (3D ACM) Motor seizures Seizure detection Stereotypical movement patterns

Important Figures



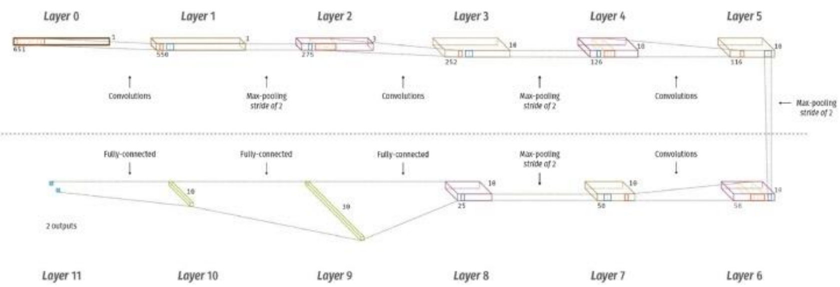


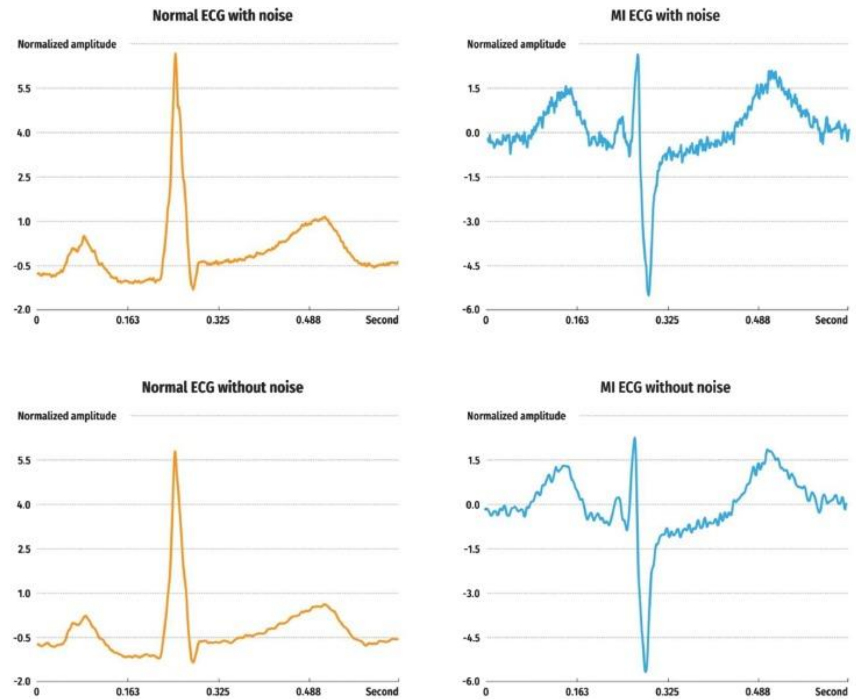
	
VOCAB: (w/definition)	Three-dimensional accelerometry (3D ACM) - A method of measuring and recording movement in three dimensions using accelerometers, typically used to detect body movements, including seizures. Motor seizures - Seizures characterized by involuntary muscle movements, such as jerking or convulsions, that can be observed through physical motion. Seizure detection - The process of identifying and recognizing a seizure event using various monitoring techniques, such as accelerometry, EEG, or video recording. Stereotypical movement patterns - Repetitive and predictable physical movements that occur during seizures, which can be detected and analyzed to identify seizure events. Automated detection algorithms - Computerized methods designed to automatically recognize seizure events by analyzing data (e.g., movement patterns from accelerometers) without human intervention.
Cited references to follow up on	Amano, K., Takamatsu, J., Ogata, A., Miyazaki, C., Kaneyama, H., Katsuragi, S., Deshimaru, M., Sumiyoshi, S., & Miyakawa, T. (2000). Characteristics of epilepsy in severely mentally retarded

	individuals. *Psychiatry and Clinical Neurosciences*, *54*(1), 17–22. https://doi.org/10.1046/j.1440-1819.2000.00630.x
Follow up Questions	How can the integration of 3D accelerometry with other monitoring tools, like EEG or video surveillance, improve the overall accuracy and reliability of seizure detection in clinical settings?

Article #20 Notes: Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals

Source Title	Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals
Source citation (APA Format)	Acharya, U. R., Fujita, H., Oh, S. L., Hagiwara, Y., Tan, J. H., & Adam, M. (2017). Application of deep convolutional neural network for automated detection of myocardial infarction using ECG signals. *Information Sciences*, *415–416*, 190–198. https://doi.org/10.1016/j.ins.2017.06.027
Original URL	https://doi.org/10.1016/j.ins.2017.06.027
Source type	Journal Article

Keywords	Convolutional Neural Network Electrocardiogram Myocardial Infarction Deep Learning Noise Removal
#Tags	#CNN #EEG #seizures #epilepsy #DL
Summary of key points + notes (include methodology)	The research focuses on the automated detection of myocardial infarction (MI) using electrocardiogram (ECG) signals through a deep convolutional neural network (CNN). Myocardial infarction, often resulting from blocked coronary arteries, poses significant health risks, with many cases going undetected until a heart attack occurs. The study proposes a novel CNN-based approach that does not require prior noise removal or feature extraction, allowing it to accurately classify ECG beats as normal or indicative of MI, achieving accuracies of 93.53% and 95.22% for noisy and denoised signals, respectively. The dataset utilized includes ECG data from 200 subjects, comprising both MI and healthy individuals, with each ECG beat segmented and normalized for training the CNN. The architecture consists of multiple convolutional and pooling layers designed to extract relevant features from the ECG signals efficiently. The model was trained using a standard backpropagation algorithm and validated through 10-fold cross-validation to ensure robustness. Results indicate that the proposed system can effectively aid clinicians in diagnosing MI, potentially improving early detection rates and patient outcomes in clinical settings.
Research Question/Problem/ Need	The need for an automated and accurate method to detect myocardial infarction (MI) using electrocardiogram (ECG) signals
Important Figures	

	
VOCAB: (w/definition)	Myocardial Infarction (MI): A medical condition commonly referred to as a heart attack, occurring when blood flow to a part of the heart is blocked, leading to damage or death of heart muscle tissue. Electrocardiogram (ECG): A diagnostic test that records the electrical activity of the heart over time, providing essential information for diagnosing various cardiovascular diseases, including myocardial infarction. Computer-Aided Diagnosis (CAD): A technology that uses computer systems to, in this case, assist healthcare professionals in interpreting medical data, improving the speed and accuracy of diagnoses by providing objective analysis of signals such as ECGs.
Cited references to follow up on	Acharya, U. R., Fujita, H., Adam, M., Lih, O. S., Sudarshan, V. K., Hong, T. J., Koh, J. E., Hagiwara, Y., Chua, C. K., Poo, C. K., & San, T. R. (2017). Automated characterization and classification of coronary artery disease and myocardial infarction by decomposition of ECG Signals: A Comparative Study. *Information Sciences*, *377*, 17–29. https://doi.org/10.1016/j.ins.2016.10.013
Follow up Questions	What are the implications of using deep learning techniques for the automated detection of myocardial infarction in clinical practice, particularly regarding the accuracy and efficiency of ECG analysis?