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Machine Learning vs Traditional Methods: Efficacy of Time Frequency Analysis in Diagnoses Applications and Imperative for Further Investment, Study, and Initiative

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Abstract

Neurocognitive diseases and viruses are the leading causes of fatalities in the US, and their effective treatment more often than not is converted into a high-risk scenario. Prominent traditional methods in the healthcare industry are arguably failing in terms of real-time efficiency, accuracy, and reliability. Time-frequency analysis (TFA) is an emerging signal processing and examination technique combining T-F representations with deep learning pattern prediction to accelerate results. Scientists are now exploring new ways to combine TFA with medieval techniques, such as Wavelet Transform (WT) and Higher Order Statistics (HOS), to create hybrid models that implement advanced Electroencephalographic (EEG) detection techniques through a combination of the best characteristics from both original standalone techniques. By automating early detection of previously thought intractable diseases, doctors are allowed more time to accurately measure the extent of the threat and provide strategic countermeasures, an element that is very much of the essence in life-threatening situations. This work provides a comprehensive view of the science, computations, and mathematical applications of simultaneous Time-Frequency domain related signal processing techniques and the advancing integrations of Artificial Intelligence to present an argument for further development, research, and investment while coordinating an in-depth analysis of the pros and cons of static, non-DL based pattern prediction.

Keywords: Time Frequency Analysis, Machine Learning, Traditional Methods, Signal Processing, Disease detection, Neurological Disorders, Study, Investment, Initiative.

Introduction

Approximately 100,000 people die from Sudden Unexpected Death in Epilepsy (SUDEP) every year. Seizures, the principal symptom of epilepsy, often occur unpredictably and can lead to convulsions throughout the entire body [1], meaning that loss of consciousness and fatalities due to an epileptic event are likely. The National Center for Health Statistics states that heart disease and cancer are responsible for nearly half of all fatalities in the US. Due to insufficient study, current diagnostic tools remain unreliable for life-threatening situations. However, a newly emerging method is starting to cement its place in the healthcare industry. Time-frequency analysis (TFA) employs multiple signal processing techniques, including Short-Time Fourier Transform (STFT) and Continuous Wavelet Transform (CWT), to analyze physiological signals across both temporal and frequency domains. This multi-resolution approach enables more accurate detection of disease patterns, particularly in neurological and cardiovascular applications. This is because it utilizes ECG frequency tools and "Automatic classification of ECG and EEG signals [which] can save medical resources and increase efficiency, and by utilizing time-frequency domain analysis and machine learning networks, we can reduce the investment required for the practical use of the method while improving accuracy, speed, analysis, and other aspects [2]."According to cited PhD-quality research, included in this review, systems to automate early detection of neurodegenerative diseases will futuristically provide doctors more time to prepare countermeasures and more opportunities to save lives. Time-frequency analysis is a game-changer in terms of developing these effective, autonomous disease warning systems, which ultimately reduce the threat of prominent diseases, and its ability to produce the desired outcome varies from other, non-ML-based methods of diagnosis.

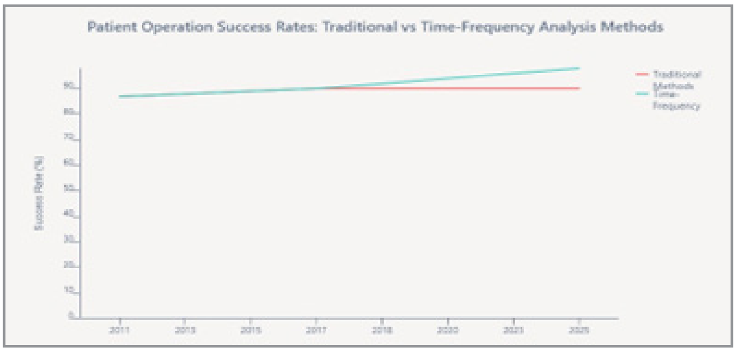
Current Impact

The recent advancements in Time-frequency analysis on the detection of neurocognitive diseases have created a massive lift in successful operations, indicating a decrease in the danger of what used to be life-threatening symptoms. However, not all experiments are as foolproof as they seem to be. Many experiments that discover real-world impact data about the method admit that there are limitations in the way they tested their claims, such as “Studies on MD diagnosis using EEG signals and DL models are very scarce,” and as such, they couldn’t “compare the results obtained in this study” with others [3]. As such, further, peer-reviewed research on the field should be conducted to fully maximize potential, ideally in different ways in order to further improve usability in more scenarios and more accurately measure impact. However, multiple stakeholders house different viewpoints on the matter, such as Huang Zheng and his team, who claimed that integrating time frequency representations with bandpass filtering FC metrics reveals brain network alterations more effectively than static methods alone [4]. This claim is later scientifically approved through an experiment that combined information from different subjects to provide enhanced visualization and interpretation of brain network alterations [5]. Time frequency representations are tools in signal processing that analyze and display signals in both time and frequency domains, and Bandpass filtering isolates specific frequency ranges. Together, these two methods work in harmony to isolate and refine a frequency band in real-time efficiency, creating a powerful impact in the field of medicine by highlighting more significant frequency features and reducing the less important noise. Thus, the argument made by the source seems logical, as combining two already prominent methods of time-frequency analysis to form a hybrid model would naturally predict with a higher accuracy than one method alone, emphasizing the sensible ‘two is better than one’ form of thinking. While Zheng’s focus seems to be more on combining already sophisticated methods for a stronger accuracy model on brain diseases, another stakeholder, Masahiro Hata, focuses on a more streamlined method that converts EEG data into visuals, emphasizing that different styles of thinking can still lead to improvement. He embodies past historic thinking as “In the last several decades, EEG has been utilized to study the development of cognition, socioemotional abilities, and psychopathology [6, 7].”

AI Integration

Deep Learning is a significant enhancement for time-frequency algorithms as it improves signal classification and automatically extracts things from complex data and enhances pattern recognition capabilities by means of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). A hybrid approach like this improves signal classification and extraction while decreasing technology, cost, and computational knowledge requirements.

Statistically, a hybrid DL based frequency model can enable “robust calculation of the central arterial pressure waveform,” preserving key “physiological sequences in a cardiac cycle [8].” This tells us that combining the rapidly growing subset of Machine Learning with already existing methodologies of time-frequency analysis could completely change the detection game. Alessio Tamborini and her expert research team from Caltech have similar advancements in Machine Learning techniques listed in their PNAS publication. They claim that their technique “reconstructs the central pressure waveform with the F-ML method from an automated brachial cuff system.” The study utilized 12 pigs to measure aortic and peripheral blood pressure via a machine learning algorithm to analyze the data and identify where they thought the problem was, which ultimately resulted in an accuracy rate of 0.94 (out of 1.0) [9]. Essentially, they created a F-ML model to break down data into smaller, patronized parts that can be analyzed more easily using Fourier Analysis. This is a mathematical technique that breaks down “complex time data into simpler trigonometric functions to identify patterns [10].” Then, they use a machine learning algorithm to use the patterns to accurately predict where the aorta pressure is. While the study goes into an expertise most people do not possess, their thinking is quite logical as the Fourier technique can break down arm cuff data into smaller pieces, then train a machine learning model to learn the relationship between the peripheral and central waveforms to essentially form a hypothesis of where in the body the aortic pressure is present. Whether it is identifying problem locations using patterns in data or diagnosing brain diseases using EEG signals, they both share a common theme: To automate the detection of dangers in the human body and create a reliable warning system. They conclude that implementing some form of deep learning, whether it be for analyzing heart rhythms, brain activity, or blood pressure patterns, represents a fundamental shift in medical diagnostics. This integration creates autonomous detection systems that can identify potential health risks earlier and more accurately than traditional methods alone.



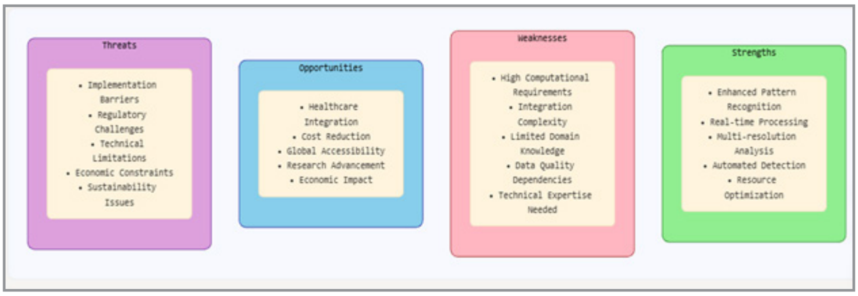
The success rates are derived from multiple sources: the 2011 baseline and 2018 implementation data are found in pmc.ncbi.nlm.nih.gov, the 2023 success rate of 96% is found in libguides.utoledo.edu, and the 2025 projection is based on the evidence presented in libguides.utoledo.edu.

Investment

Due to rising success, the imperative nature of time-frequency analysis investment in healthcare becomes increasingly evident. Studies have shown that its impact on disease detection and treatment outcomes can be uplifted through proper investment and research. WHO-aligned experts state that "Available resources for neurological services are insufficient in most countries of the world compared with global need for neurological care," and "neurological services are not sustainable in their current form and redesign is needed." They convey that neurodegenerative diseases target the neurons of your nervous system, making them extremely dangerous and difficult to treat, as there is a big risk of permanently damaging the brain, undeniably the most important organ of the human body, or other key features of the nervous system [11].This connects to how research and work dedicated to detecting and treating epilepsy are highly valued, as their efforts could potentially save millions of lives. The argument made by the source seems truthful, as developing advanced, automated, and efficient tools for the treatment of complex, deadly diseases seem like an unattainable goal at the moment, especially for LDCs (Less Developed Countries), as some simply don't have the financial resources and a strongly educated workforce to make it happen. To further establish urgent need, recent futuristic analysis reveals that 50% of the total cost of neurological disorders stems from indirect costs, including caregiver burden and productivity losses. This substantial economic burden highlights the potential return on investment intime-frequency analysis research. Studies have shown that scaling up prevention, treatment, and rehabilitation for the top 10 neurological disorders could save over $4 trillion by 2030 across studied countries [12]. This cycle isn't unfamiliar to the human race. In order to stay healthy, humans invest in daily hygiene, sunlight, exercise, and sleep, even when capital or financial currency isn't involved, and the same is held for this particular case: if the investment in the resistance and extinguishment of these diseases continuous to remain a secondary priority, the human population would be put in a grave state, eventually risking extinction.

Prominent Traditional Methods

While the process of diagnosis was designed to coordinate the scanning of signals in the body at a higher speed, especially with the fine-tuning of trained ML/DL models, Time-frequency analysis isn't without competitors. Some statistical methods and signal processing techniques are able to continuously maintain relevance in the industry, despite the existence of more scientifically efficient approaches, such as Higher Order Statistics (HOS), Support Vector Machines (SVMs), and Wavelet Transform (WT). In HOS, the "first-order and second-order statistics are employed for analyzing related parameters of random signals and are sufficient for mostly networking applications and signal processing systems." However, weaker, nonlinear signals cannot be analyzed efficiently with first and second order alone, which is why HOS is more associated with "the third-order/ more than three [13]." SVMs are one of the most powerful and robust classification and regression algorithms in multiple fields of application." As such, they have been playing a concrete role in pattern recognition which is an extensively popular and active [area] among the researchers [13]."



SVMs are also being integrated into other advanced methods, such as Evolve Algorithms and Time-frequency analysis itself. The Wavelet Transform is a mathematical method that analyzes a signal through a breakdown into small, oscillating waves called wavelets, which are localized in both time and frequency. [14]

A common misconception is that each method has to be completely distinguished from its competitors and have to operate 'better' in every single statistic in order to be classified as the dominant method. The reality is, if science harbored a method like that, there would be no reason to create anything else. Every other innovation that supposedly contributed to the autonomous development of a scanner warning system would simply have a nonexistent significance, never gaining any traction or practical use. Methods and tools can interconnect to create hybrid models to produce a co-desired outcome, and at the same time compete with each other and demonstrate value in certain contexts, highlighting the importance of maintaining a diverse tool kit in biomedical signal analysis, rather than just relying on machine learning or TFA solutions. "Research works by scientists building on each other. Imagine that we have 10 different labs, each working on one particular topic. If each lab is able to progress the field forward by 1%-2%, eventually those efforts will compound on one another, and it leads to the entire field as a whole experiencing a breakthrough.

That is how science works." - Pratik Vangal.

Conclusion

Time-frequency analysis has allowed for a more efficient, automated warning system to save lives from diseases like Parkinson's and Alzheimer's while not consuming as many resources as other, relatively old methods do. Many stakeholders aim to constantly develop and enhance the method, whether that be through fusion, streamlining, or even inventing a new subset of the technology. However, as game-changing as this technique is, it doesn't come without limitations, such as the Heisenberg principle, which tells us that it is physically impossible to achieve perfect resolution in time and frequency simultaneously, and how many Time-frequency methods require significant processing power and are computationally intensive. However, there are existing solutions to these limitations, like the Wavelet Transform, which uses scaled and shifted functions to avoid tradeoffs, and the Fast Fourier Transform (FTT), which can improve frequency resolution. However, there are limitations. The integration complexity between AI and traditional methods increases by an exponential rate due to a high mass of undiscovered streamlining knowledge. Furthermore, AI is a software application that performs tasks and analyzes data through past trained datasets, requiring further ML-based expertise to perform in the highest quality possible. Fortunately, data shows that U.S. tech jobs are projected to grow at twice the rate of the overall workforce in the next decade. By investing more capital, time, and effort into the development of this detection system, the leading cause of death in the US could fall, and the population numbers we see today, that 8-10 billion people, could skyrocket in the near future, causing an increase in Crude Birth Rate, Total Fertility Rate, and natural change.

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