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Enhancing Women's Safety: Unleashing the Power of EEG Pre-Processing to Decipher Deep Learning Insights into Emotions

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Abstract- In the 21st century, women have made significant strides in contributing to society and participating alongside men in various fields. However, gender-based violence continues to negatively impact women's lives and limit their involvement in decision- making processes. Wearable technologies and mobile applications have emerged as potential solutions for enhancing women's safety, but their effectiveness remains limited due to inadequate social action. This study focuses on the classification of women's emotions using EEG signals, employing a four-stage preprocessing approach. The acquisition of accurate EEG signals necessitates a lengthy observation period and multiple activity processes to capture all brain waves. To improve signal quality, Zero-timeframe windowing (ZTFW) is applied for signal segmentation, Discrete Wavelet Transform (DWT) is utilized for filtering to eliminate erroneous brain activity analysis, Empirical Mode Decomposition (EMD) is employed for noise removal, and Fuzzy Elliptical Filter (FEF) is used to reduce power line noise and electrode interference. The proposed FEF filter demonstrates significant improvements in the denoising process, with a remarkably low mean error rate of 0.03 compared to other filters.

Keywords: Women safety, EEG signal, Zero-time frame windowing (ZTFW), Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD), Fuzzy Elliptical Filter (FEF).

I.INTRODUCTION

In contemporary society, women commonly face various forms of harassment throughout their lives, highlighting the challenges they must overcome to develop confidence and thrive. Additionally, women often encounter safety concerns not only in public spaces but also within their own homes [1]. The right to express oneself freely without the constant worry of personal safety and the need for constant supervision isa fundamental entitlement for women. Remarkably, in the twenty-first century, women have made substantial contributions to society and have achieved notable progress in diverse industries,
alongside their male counterparts. However, rather than diminishing, crimes committed against women, such as harassment, molestation, eve-teasing, rape, kidnapping, and domestic abuse, continue to rise [5]. Despite the implementation of numerous preemptive measures by the government, these misbehaviors persist, and the number of crimes remains largely unaffected.

Presently, an alarming surge in crimes against women is evident, extending beyond the realms of specific times or locations. Harassment of women occurs during the day, both at home and in the workplace, as well as while engaging in routine activities like shopping [6,7]. Consequently, women often experience fear and worry regarding their personal safety. Astonishingly, approximately 80%

of women in our country express concerns about their safety [10]. To address such concerns, women have started using security apps on their smartphones, enabling them to send emergency alerts to chosen individuals and communicate their location in case of emergencies. However, even with these technological advancements, a significant challenge remains. When a woman finds herself in alate-night accident without anyone around to assist her, effectively conveying her predicament becomes problematic.

In a different realm of research, the intersection of neuro science and computer science has given rise to Neuro-Control Interface (NCI), an interdisciplinary field focused on enhancing direct communication and interaction between the human brain and the environment [13]. Notably, NCI approaches encompass two distinct types: invasive methods

involving the implantation of devices for medical purposes [15,16], and non-invasive methods, such as wearable devices like ElectroEncephalography(EEG) [13]. EEG-based Brain-Computer Interface (BCI) has witnessed renewed interest due to advancements in wearable sensors, real-time data streaming, and machine learning techniques, particularly in translational and medical applications [13]. While women aspire to work and pursue employment opportunities [19], concerns over personal safety persist. Although several systems, devices, and techniques have been developed to ensure women's safety, limitations such as low- frequency noise removal, which can result in the loss of information inherent in EEG signals, persist [20].

To address these societal issues, we have developed a device that utilizes deep learning techniques. The primary objective of our research is to preprocess EEG signals for accurate classification of women's emotions. Our proposed preprocessing method includes the use of Zero-time frame windowing (ZTFW) for segmenting EEG signals, Discrete Wavelet Transform (DWT) for filtering out erroneous brain activity, Empirical Mode Decomposition (EMD) for removing background noise and enhancing signal-to-noise ratio (SNR),and Fuzzy Elliptical Filter (FEF) to reduce unauthorized artifacts like power-line noise in EEG brain waves. This study is organized into five sections: Section II provides a comprehensive literature review, Section III presents our proposed preprocessing method for EEG signals, Section IV includes the results and discussion, and finally, Section V concludes the study while outlining potential future enhancements..

II. LITERATURESURVEY

In recent years, there has been a surge in research efforts aimed at advancing women's safety, resulting in the introduction of various tools and techniques.

This section provides a brief overview of some of these noteworthy contributions.

In 2021, Sivachitra et al. [2] proposed a Women Safety Patrolling Robotic system that leverages sound sensors, ultrasonic sensors, ESP cameras, and IoT technology to patrol designated areas with minimal human intervention. This innovative approach holds great potential for enhancing women's safety, particularly during nighttime patrols.

Islam et al. [3] introduced a CNN-based modified model in 2021 for identifying emotions based on the single feature Pearson's correlation coefficient (PCC) of EEG sub-bands. By transforming EEG data into images of EEG sub-band channel correlations, and utilizing a CNN architecture, this approach offers reduced computational cost, lower storage requirements, and faster execution time without compromising performance.

Tayal et al. [4] presented a simple and cost-effective women's safety device in 2021, utilizing hardware implementation based on Node MCU, GPS, and GSM units. When a woman detects any potential risk, she can activate the safety gadget by pressing a button. The device rapidly locates her using GPS and sends an emergency message to saved contacts and the local police control room. Additionally, a bell is used to alert nearby bystanders to provide assistance.

In 2021, Hariharan et al. [8] designed an alert and protection system for women taxi users based on machine learning algorithms. This system incorporates real-time location monitoring and the ability to predict incorrect routes. In emergency situations, an auto mode can be activated. Among the machine learning models tested, a SVM classifier demonstrated the best performance, achieving an accuracy of 89.5 percent.

Gomathy and Geetha [9] developed a wearable safety gadget for women using Arduino in 2021. This device serves to protect women when they are at risk.

It utilizes a wireless sensor for interaction and alarms, while the GPS and GSM components immediately share the woman's location with relevant authorities and stored contacts.

Chen et al. [11] introduced an emotion recognition technique for EEG signals using the AdaBoost method in 2021. Their approach involves extracting emotional components from pre-processed EEG signals in various domains and fusing them into an eigenvector matrix. A linear discriminant feature selection approach is then employed to minimize feature dimensions and classify emotions. The proposed method achieved

an impressive average accuracy rate of 88.70% for the dominance dimensions.

In 2021, Nandi et al. [12] developed a real-time emotion classification system (RECS) based on logistic regression (LR) trained with the SGD algorithm. They employed the widely-used DEAP dataset to evaluate the model's performance. The proposed RECS enables real-time emotion categorization through streaming EEG signals for model training.

Gupta et al.[14] combined techniques such as NLM, DCT, and MBPSO in 2020 for pre-processing, feature extraction, and selection from noisy EEG signals. They utilized the MBPSO method to select the optimal combination of frequency-dependent characteristics. By adjusting the SVM kernel according to WOA, they achieved improved performance in long-term stress classification.

In 2020, Nagabushanam et al. [17] introduced an EEG noise suppression concept using the ID CNN network. They employed an elliptical filter to reduce power line noise, effectively controlling and smoothing the stopband and passband attenuation. With a 6-layer 1D-CNN network featuring various activation and pooling functions, the network's efficiency was evaluated based on accuracy, sensitivity, and specificity metrics. However, one limitation of this system is its relatively low efficiency.

Leske and Dalal [18] developed a novel spectrum interpolation technique in 2019 to eliminate power line noise in EEG and MEG signals. Their approach incorporated three widely used filters: a notch filter, DFT (Discrete Fourier Transform), and Clean line method. By denoising the signals in the amplitude spectrum through curve interpolation in the frequency spectrum, they addressed the powerline noise interference. However, the technique encounters complexity due to the application of the clean-line model.

From a comprehensive analysis of existing EEG signal research and related works, it becomes evident that each study has its limitations. One significant drawback is the challenge of denoising EEG signals due to interference and the overlapping of brain signals. Therefore, the proposed work focuses on addressing this issue by introducing a novel Fuzzy Elliptical Filter (FEF). The complete details of the proposed model are described in the subsequent methodology section.

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III. PROPOSED METHODOLOGY

In this work, we propose a comprehensive pre-processing module designed to address the issue of denoising EEG signals. The recorded EEG brain signal data from women may be contaminated by various types of unwanted noise, including eye movement, electrode interference, power line noise, cortical potential, and electrocardiogram artifacts. The presence of these distortions significantly impacts the Signal-to-Noise Ratio (SNR) and reduces the effectiveness of classification models. To overcome this challenge, we have devised a four- stage pre-processing approach.

In the initial stage, the EEG signals are divided into distinct frames using Zero-time frame windowing (ZTFW) technique. This division facilitates a more accurate analysis of the non-stationary characteristics inherent in the signals. Each frame of the EEG signal is then subjected to the Discrete Wavelet Transform (DWT) to effectively eliminate extrinsic signal artifacts and enhance the signal quality.

Next, the processed signals undergo decomposition as non-stationary signals using Empirical Mode Decomposition (EMD). This decomposition technique enables the separation of the EEG signals into multiple components, thereby facilitating a more refined analysis of the intrinsic brain wave activities.

Finally, we employ the Fuzzy Elliptical Filter (FEF) to target the removal of intrinsic noise artifacts present in the EEG signals. By leveraging this innovative filtering method, we aim to further enhance the signal quality by minimizing the impact of unwanted noise and artifacts associated with brain waves.

Through these four stages of pre-processing, our proposed module aims to effectively denoise the EEG signals, ultimately improving the quality and reliability of the data for subsequent classification and analysis tasks.



Figure.1: Theoverallworkflowoftheproposedmethodology

Data acquisition

The DEAP dataset holds a prominent position in the realm of EEG-based emotion identification research. It encompasses data collected from 32 individuals as their mental states were monitored while watching music videos. Each subject's brain activity was recorded using 40 channels, consisting of 32 EEG electrodes and additional peripheral

channels. The recordings were conducted at a sampling rate of 512 Hz but subsequently down-sampled to 128 Hz. The dataset comprises 40 trials, with each subject being exposed to a different video during each trial.

For each trial, four labels were assigned to capture different aspects of emotional response: valence, arousal, dominance, and liking/disliking. To measure these dimensions, a self-assessment questionnaire was employed. The responses obtained were then mapped to nine distinct emotions associated with the DEAP recordings. These emotions include happiness, sadness, fear, anxiety, thrill, fury, and depression.

The comprehensive nature of the DEAP dataset, encompassing both EEG recordings and corresponding self-assessment measurements, provides researchers with a valuable resource for exploring the intricacies of emotion identification and understanding the relationship between brain activity and **emotional states.**

A. Zero-timeframewindowing(ZTFW)

Zero-time frame windowing (ZTFW) is a technique employed for tracking and preprocessing the spectral properties of EEG data collected from short sample periods. This method involves the evaluation of each electrode by multiplying a brief duration of each trial with a window function that resembles the frequency response of a zero-frequency resonator. The window function, denoted as σ(t), is calculated as follows:

$$\sigma(t)=0.5*(1-\cos((2\pi t)/w_l)), \quad (1)$$

where, w_l is the length of the window.

To eliminate division-by-zero errors and ensure that the average value of the spectrum window signal is 0 without altering the spectral peaks, the initial value of the window, σ(0), is set to 0. Unlike other window functions, the window function σ does not impede signal rapidity in the temporal domain. This characteristic allows for an accurate representation of the EEG signal's spectral properties, facilitating further analysis and interpretation of the underlying neural activity.

The EEG signals acquired during each trial undergo a meticulous process of decomposition into concise segments, with precise determination of the corresponding frame location for each epoch. To simulate real-time categorization effectively, the extensive EEG recording sessions span a duration of 60 seconds. In order to replicate real-time analysis, it becomes imperative to partition the data into smaller time frames. It should be noted that the location of each epoch varies between different subjects. In Figure2, we can observe the delineation of the spectrum denoted as 'S,' representing the length of an epoch frame. Additionally, 'Shift' represents the time interval between consecutive frames within the same EEG trial. During moments of heightened emotional intensity, an epoch aligns with the peak excitation observed in the EEG signal. However, detecting this precise moment can be challenging due to the influence of diverse factors such as auditory stimuli, cognitive tasks, ocular movements, and emotional states. By improving the detection and identification of epochs, the overall quality of features utilized for emotion recognition is significantly enhanced.

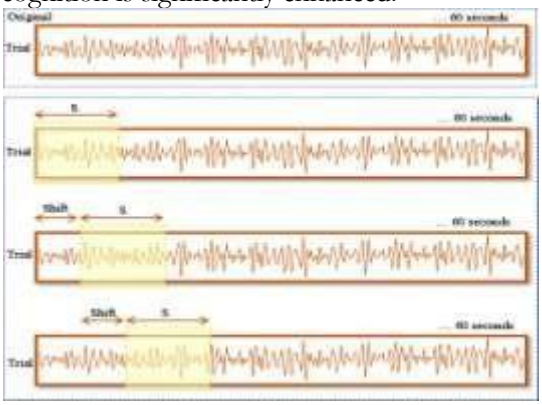


Figure.2:Splittingtheframewindowing

c.Discretewavelettransforms(DWT)

The EEG signals were subjected to a comprehensive frequency analysis using the discretized wavelet transform, enabling the identification of frequency components and their corresponding properties at various decomposition levels. In this discrete wavelet transform, the parameters A and B represent discrete values of dilation and translation, respectively. To establish a relationship between A and B, a logarithmic discretization of the dilation factor A is commonly employed, making B proportional to A. Thus, the normalized wavelet function can be discretized as follows:

$$(t)=reallati[Ax,yB0Ax], \quad (2)$$

where $A = Ax$ and $B = yB0Ax$, with x and y representing integers that control dilation and translation, respectively. A0 denotes the fixed dilation phase, which is greater than 1, while B0 represents the location parameter, which is greater than 0. Empirical Mode Decomposition (EMD)

In the realm of data-driven techniques, a methodology exists for decomposing non-stationary signals into a collection of Intrinsic Mode Functions (IMFs). This technique leverages the time-scale characteristics inherent in EEG signals, eliminating the need for pre- defined fundamental functions, and instead allowing for the decomposition of EEG signals into a predetermined count of IMFs. Each IMF must adhere to two fundamental criteria:

- The count of discrepancies between extreme points and zero-crossings throughout the entire

time domain must be either zero or one.

- The average values of the envelopes, established by the local minimum and maximum intensities, must equate to zero at every point along the time domain.

Algorithm: Empirical Mode Decomposition

1. Recognize the local minima and maxima of *s(t)*.
2. To limit the lower and upper envelope, integrate the local maxima and minima by the cubic spline function.
3. The average value *mv(t)* is determined as,

$$mv(t)=\frac{Emax(t)-Emin(t)}{2} \quad (3)$$

4. Extract *f(t)* from the raw input signal*s(t)*

$$f(t)=s(t)-mv(t) \quad (4)$$

5. If *f (t)* satisfies the norms mentioned above, an IMF module and the residual module z*(t)* is calculated as,

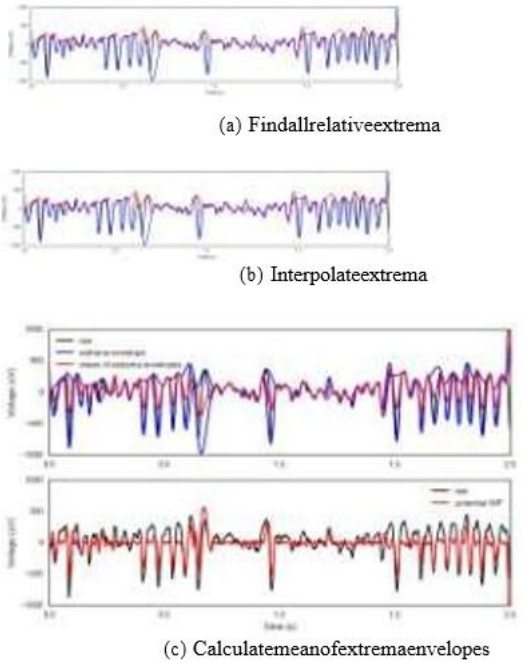
$$IMF_i=f(t) \quad (5)$$

$$z(t)=z(t)-f(t) \quad (6)$$

$$i=i+1 \quad (7)$$

And then goto step7.

6. If not *s(t)=f(t)*and return tostep1.
7. The decomposition is terminated when the residual module z*(t)* attained from (7) is a monotonic function, or else *s(t)=z(t)* and return to step-1.



(a) Findallrelativeextrema

(b) Interpolateextrema

(c) Calculatemeanofextremaenvelopes

Figure.3:Steps involved in the EMD for pre-processing the EEG signals

According to the above-mentioned algorithm, a section of EEG signals is divided into 'n' intrinsic mode functions where n is the extracted IMFs, and z(t) is the residual component.

The EEG signals are processed in this way to reduce their high-frequency components and increase their signal-to- noise ratio. A multi-state classification is also used to classify epileptic seizures in addition to the processed signal.

B. Fuzzyellipticalfilter(FEF)

The fuzzy elliptical filter employs a logic variable with multi-dimensional functional membership to measure the degree of membership for processed data. It analyzes the ripple factor and linearity of the input data, enabling the determination of both the linearity and angle of the network. This elliptical filter incorporates a dedicated adjustment mechanism to equalize ripple behavior, facilitating a faster transition rate between the passband and stopband.

The nth order of magnitude frequency response is expressed as;

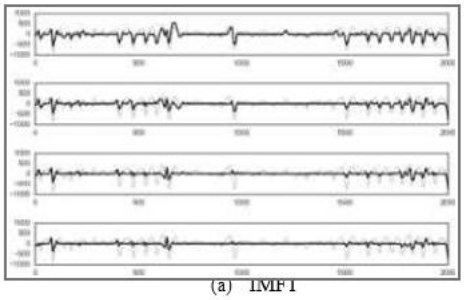
$$|(j\omega)|2 = \frac{1}{1+\varepsilon 2R2(\omega)} \quad (8)$$

Where, (ω) denotes the Chebyshev rational function of ω evaluated from definite ripple characteristics. The evaluation of denoising efficiency relies on utilizing the mean square error (MSE) as a measurement metric. Achieving significant attenuation of frequencies can be accomplished by employing an elliptical filter with

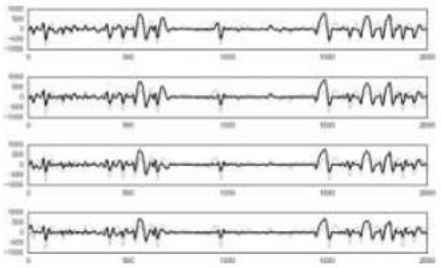
a sharp cut-off frequency. This approach minimizes errors on both sides of the cut-off frequency, resulting in an ideal filtering outcome. By leveraging fuzzy systems, the optimal combination of processed signals is selected, aiming to reduce the MSE of the reconstructed signals. Through this process, the original EEG signal is effectively denoised, eliminating power line noise and electrode interference noise.

IV. RESULTS AND DISCUSSION

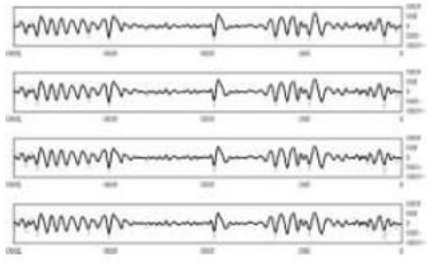
The experimental arrangement of the study was implemented through Spyder, an Anaconda navigator. In this result analysis, DEAP dataset was employed for pre-processing to reduce the distortions from the EEG signals. The EEG signals are divided into a finite number of IMFs using the EMD method without establishing an initial basis function. Figure.4 shows the output of EMD algorithm with various IMFs after pre-processing the EEG signals from low to high orders.



(a) IMF1



(b) IMF2



(c) IMF3

Figure.4: Result of EMD algorithm with various IMFs

EEG signals with power interference have been denoised using the proposed approach. The proposed EMD-based technique is assessed through simulations for a variety of instances. A scan be seen from the first two IMFs in fig. 4, the power interference and other high frequency noise are present. In contrast with the first two IMFs of the raw EEG signal, the first IMF has stronger noise components. Different backdrop rhythms are featured in the second IMF, which also offers some crucial information of the EEG signals from low to high orders.

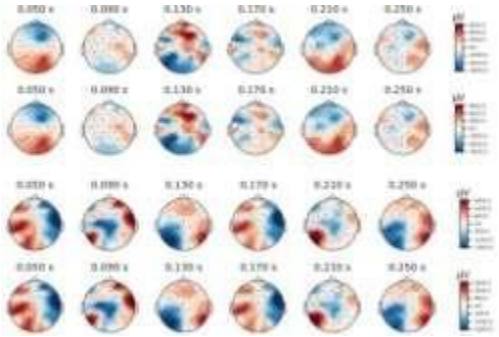


Figure.5: Results of Fuzzy elliptical filter

Figure.5 depicts the results of proposed FEF with the sample of four sets after preprocessing the EEG signals. The signals from the EMD is further processed using the proposed FEF by eliminating the unwanted disortions in the EEEG signals. The process was carried out in several seconds from 0.050 to 0.250 seconds with μV.The output signal of the FEF filter shows the visible reduction of power line noise in the EEG signal from the original database. The pre-processed signal produced has a clear view of filtering the EEG signals.

V. CONCLUSION

This study focused on denoising epileptic brainwaves of women obtained from EEG signals. We proposed a novel denoising filter and employed preprocessing techniques to eliminate noise and improve the accuracy of emotion classification. The approach involved Zero-time frame windowing (ZTFW) for segmentation, Discrete Wavelet Transform (DWT)for filtering, Empirical Mode Decomposition (EMD) for noise removal, and Fuzzy Elliptical Filter (FEF) for reducing power line and electrode interference noise. The experimental results demonstrated the effectiveness of the FEF with a mean error rate of 0.03. Future research can explore alternative filters and robust deep learning approaches to further enhance EEG signal classification.

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