Stream-based Identification of Gender using Noninvasive Electroencephalographic Technology

Original Scientific Paper

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Abstract *– Numerous studies on EEG signals have revealed differences in brain activity patterns between males and females. However, these differences aren't always consistent or significant, as they can be affected by factors like age, task engagement, and specifics of EEG measurements. In our research, we introduce a new approach to detect gender called 'Stream-based Identification of Gender using Noninvasive Electroencephalographic Technology. We employed this technique to investigate how male and female brains respond differently during video streaming tasks with the aim of exploring functional disparities between them. This study aims to advance our understanding of gender-specific brain responses. We used data collected in our previous research from 122 volunteers (85 male, 37 female). Utilizing a deep learning (DL) approach allowed us to achieve 99% accuracy in gender identification. The applications of our model extend to various fields, including advertisements, multi-level security systems, and healthcare, showcasing the potential of advanced machine learning techniques in neuroscientific research.*

Keywords: *EEG, sex, gender difference, machine learning, deep learning*

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1. INTRODUCTION

Exploring gender differences can yield crucial insights across diverse fields, including healthcare, cognitive science, education, and sociology. Here are several reasons why identifying and understanding gender differences is important.

Health and Medicine - Men and women respond differently to medications due to their unique biology [1]. Understanding these differences helps doctors provide better treatments, improving results and reducing side effects. Diseases like heart disease may show different symptoms in men and women, so research helps doctors diagnose and treat them more effectively for each sex.

Technology and AI - Biometric technologies like facial recognition and voice ID work by analyzing physical traits that vary between sexes [2]. Understanding these differences makes the systems more secure and user-friendly. Designing technology that considers gender differences can improve user satisfaction by accounting for physical and behavioral preferences.

Education and Workplace - Males and females often have different learning styles [3]. Adapting teaching to these differences can improve learning. In workplaces, men and women may face unequal opportunities for career growth and pay. Research helps address these issues by promoting policies like diversity training and flexible work option.

Social Understanding and Policy - Studying gender differences helps challenge stereotypes and shows how gender influences behavior and roles in society [4]. This leads to greater respect and acceptance of diverse gender identities.

Understanding these differences helps create more inclusive and effective practices that benefit all individuals, regardless of gender. There are three main approaches to identifying gender or sex differences:

Biological Methods: Genetic Testing, analyzing DNA to determine sex chromosomes or genetic variations related to biological sex. Hormonal Analysis, measuring hormone levels to understand physiological differences between sexes. Physical Examination, assessing anatomical features and secondary sexual characteristics to determine biological sex.

Behavioral and Psychological Methods: Self-Report, individuals self-identifying their gender through surveys, interviews, or questionnaires based on their internal sense of identity. Psychological Assessment, evaluating gender identity, expression, and related behaviors through psychological tests or clinical evaluations.

Technological and Computational Methods: Biometric Analysis, using biometric data (e.g., facial recognition, voice patterns) to infer gender based on physical characteristics. Machine Learning Algorithms, training algorithms on datasets containing biometric or behavioral data to predict or classify gender.

Biometric data that can identify sex or gender differences typically include physiological, anatomical, and sometimes behavioral characteristics that differ between males and females. Here are some common types of biometric data used for sex or gender identification. Differences in facial structure, such as jawline, cheekbones, and distance between eyes, can be analyzed using facial recognition technology [5, 6]. Acoustic properties of speech, including pitch, frequency, and resonance, are used in voice analysis to distinguish between male and female voices [7, 8]. While fingerprints themselves are not inherently gender-specific, certain patterns or ridge densities may correlate with biological sex [9]. Measurements of hand size, finger length ratios, and palm characteristics can be analyzed to infer sex differences [10]. Unique patterns of blood vessels in the retina can be scanned and compared for differences between males and females [11]. Like retinal patterns, unique iris patterns can be scanned and compared for sex-related differences [12]. Genetic markers, including those found on sex chromosomes can definitively determine biological sex [13]. Differences in walking patterns and movements can sometimes indicate gender-specific characteristics, though this is less commonly used compared to other biometric methods [14]. The shape and size of the ear, including the earlobe and inner ear structures, can be analyzed for gender identification [15].

Brain Structure: While not typically used in everyday biometric applications, differences in brain structure and function have been studied to understand gender differences in cognition and behavior. Research has identified several differences in brain structure between genders, although these differences exist on a spectrum and can vary widely among individuals. Here are some key findings.

On average, male brains are larger than female brains, with 8% to 13% more total volume [16]. Males generally have bigger cerebrum, cerebellum, amygdala, and hippocampus. However, brain size doesn't determine intelligence or cognitive abilities.

Females tend to have more grey matter compared to white matter than males [17]. Grey matter processes information, while white matter connects different brain regions.

There may be slight differences in the thickness and surface area of the cerebral cortex between males and females, which could affect cognitive abilities and emotional processing [18].

The hippocampus, key for memory, and the amygdala, linked to emotions, can differ in size and connectivity between males and females, possibly impacting learning and emotional regulation [19].

The corpus callosum, which connects the brain's two halves, tends to be larger in females [20]. Both genders show neuroplasticity, but this adaptability is influenced by hormones and life experiences.

Functional imaging shows differences in brain activity during tasks between males and females, reflecting different cognitive strategies. While there are average differences in brain structure, individual variation is significant. Genetics, hormones, and experiences all contribute to these differences. Ongoing research aims to better understand these complexities.

In our study, we use Electroencephalograph (EEG) signals to identify gender differences, but there are many studies based on EEG data for various types of classification, such as emotion recognition [21], cognitive load [22], sleep stages [23], mental disorders [24], motor imagery [25], attention level, fatigue detection [26], seizure detection [27], speech imagery [28], drug effect [29], learning disabilities [30], pain detection [31], and more. Determining gender from

EEG signals alone is not straightforward and generally not highly accurate. EEG records the electrical activity of the brain and reflects complex neural patterns associated with cognitive and physiological activities. While there are broad generalizations about gender differences in brain structure and function, EEG signals are typically used to study brain states, neural disorders, or cognitive function rather than to identify biological characteristics like gender.

Research into gender differences in EEG has shown some variance between males and females in aspects such as amplitude and frequency of the brain waves. For instance, studies have suggested differences in the alpha wave frequency (a type of brain wave commonly associated with relaxation and lack of visual stimuli), with women generally showing higher frequencies than men. However, these differences are often subtle and influenced by a range of factors including age, hormonal status, and health conditions. In Table 1, a research review is shown on gender classification based on EEG signals using various methods.

The first section of this paper introduces the importance of gender classification and the different types of classification. Section 2 covers the data collection process, preprocessing, and presents some classification techniques based on EEG characteristics. Section 3 details our proposed deep learning method for gender classification using video streaming data. Finally, Section 4 provides the conclusion.

Table 1. Methods and Findings of similar studies

Ref.	Device	Number of Electrodes and electrode placement	Participants	Age	Hand preference, eyes open, eyes close	Stimuli	Preprocess
32	EEG-4418, Nihon Kohden	18, (10-20)	40 (20 males)	19-26	Right-handed, EC	Rest and During Photic Stimulation	Bandpass filter 0.3-60 Hz
33	Brain-tronics	30, (15% extending, distance to 5% anterior of Fz)	20 (10 males)	mean 24.5	Right-handed, EO	Visual based anagram and mental arithmetic tasks	Bandpass filter 1–30 Hz
34	Nihon Kohden	19, (10-20)	30 (15 males)	20-30	Right-handed, EO	Mental rotation task Shepard-figures.	Bandpass filter
35	EEG-16 S, Medikor, Hungary	16, (10-20)	30 (15 males)	19-23	Right-handed, EC	Listening test tapes and memorize words	Bandpass filter between 0.3-30 Hz
36	Quick-Cap	19, (10-20)	76 (38 males)	mean 21	Right-handed, EO	Emotional intelligence test WAIS-R and MSCEIT	Bandpass filter 0.15–50.0 Hz
37	Electrical Geodesics	128, (geodesic sensor net)	114 (54 males)	18-30	Right-handed, EO	Eriksen Flanker Task with arrow stimuli presented	Low-pass filtered at 30 Hz
38	BrainAmp Standard	37, (10-20)	27 (13 males)	mean 24.6	Right-handed	Spatial navigation in virtual environments	0.5 -50 Hz filter.
39	PSYLAB	6, (Pseudo-unipolar recordings were acquired)	42 (21 males)	20-29	EO, EC	Visual and motion-onset stimulation	Frequency band of 0.3-100
40	Australian EEG Database	23, (10-20)	40 (20 males)	19-69	EO, EC	Resting state	1 -30 Hz filter.
41	Emotiv Epoc	14, (10-20)	60 (35 males)	6-55	EC	Resting position	DWT
42	Neuroscan	30, (10-20)	28 (13 males)	18-30	EO, EC	Resting conditions	Bandpass filter 0.15–45 Hz
43	Emotiv Epoc	14, (10-20)	60 (35 males)	6-55	EC	Resting position	DWT
44	Biosemi ActiveTwo system	32, (10-20)	32 (16 males)	19-37	EO	Watching the audiovisual clips,	Bandpass filter 4-45 Hz
45	EEGLab MATLAB	19, (10-20)	134 (41 males)	mean 46	EC	The patients received 4 weeks of antidepressant treatment. Acoustic stimuli	PREP pipeline
46	Geodesics system	64, (Geodesics system)	61 (30 males)	mean 12.48	EC	Sleep condition	Bandpass filtered signal from the Hilbert transform
47	Emotiv Epoc	14, (10-20)	10 (6 males)	22.6 ± 2.75	EO	Short video clips with audio	Bandpass filter 0.5–64 Hz
48	Neuroscan Synamps2	30, (10-20)	80 (40 males)	18-26	Right-handed, EO, EC	Resting conditions	DFT
49	USBamp, Austria	16, (10-20)	20 (10 males)	22-30	Right-handed, EO	Color and black/white stimuli	Bandpass filter 0.1-50 Hz
50	Nicolet One EEG System	21, (10-20)	1140 (504 males)	18-88	EC, EO	From clinical recordings and exhibited a mix of paradigms with resting states, stimuli, and so forth.	Bandpass filter 1-40 Hz
51	BioSemi ActiveTwo	64, (10-20)	227 (145 males)	20-77	EC, EO	Resting state	Bandpass filter 2-20 Hz

2. DATA COLLECTION AND PREPROCESSING

In our study, we included students and teachers from the Mongolian University of Science and Technology as participants, with a total of 122 individuals comprising 85 men and 37 women. Among them, 112 participants were aged between 17 and 23 years, while the remaining 10 were aged between 25 and 54 years. This age distribution was considered when analyzing gender differences in EEG signals, as age related variations in brain activity could potentially influence the results. We controlled for age related variability by ensuring that the majority of participants were within a relatively narrow age range (17–23 years), reducing the impact of age on the observed gender differences. This approach allowed us to focus on the primary objective of investigating gender specific EEG patterns while accounting for potential confounding effects of age. Furthermore, we ensured that age groups were balanced across genders to further minimize any potential bias in the results.

We acknowledge that the gender imbalance in our sample may affect the generalizability of our findings and that a more balanced gender representation could provide additional insights. The gender distribution in our study was primarily influenced by the availability and recruitment process of participants. Despite efforts to recruit a diverse sample, logistical constraints, such as the availability of volunteers and their willingness to participate, resulted in an unequal representation.

Although there was a gender imbalance, we implemented measures to minimize bias in the analysis. For instance, data preprocessing, feature extraction, and modeling were conducted without gender based disparities. Separate analyses were performed for male and female participants, revealing consistent trends in EEG features across both groups. These trends suggest that our findings reflect generalizable patterns. However, we recognize that the smaller female sample size may limit the detection of certain subtle gender specific differences.

To address this limitation, we plan to conduct follow up studies with a more balanced gender representation to validate and extend our findings. This will enable us to assess whether the observed patterns remain consistent across a more representative population.

Before starting brain signal measurements, they filled out a questionnaire, and their psychological status was rated on a scale of 1 to 10. Psychological status will be used in further research to determine the individual's condition. Participants are allowed to move their heads, facial muscles, eyes, blink, mouth, hands, and make slight body movements. In this measurement, the participant sits in front of a screen and watches a 120-second silent video featuring nature, cars, animals, and male and female actors, as shown in Figure 1 below. The video has no sound and features a very colorful nature, with land and sea animals, and includes very famous male and female actors. In some scenes, such as those involving cars and motorcycles, rapid changes occur, including with female actors. The nature and animal scenes are relaxing.

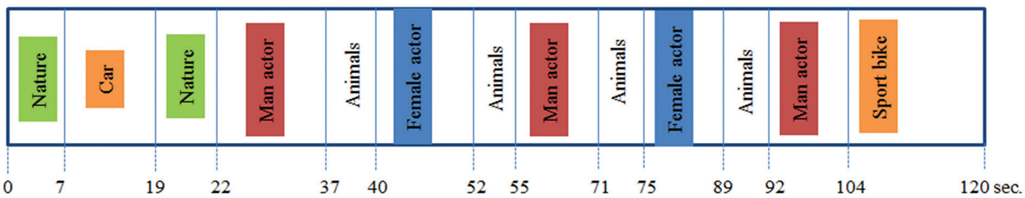

Fig. 1. Processes in the video

Testing was conducted using the Emotiv EpocX 14-channel headset, where data was recorded at a resolution of 16 bits and a sampling rate of 128 samples per second. In this study, electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4, plus two additional CMS/DRL and P3/P4 electrodes) were placed according to the 10-20 international standard on the scalp. All channels were retained for analysis without exclusion. Due to the unequal number of male and female participants, we balanced the groups with 37 women and 37 randomly selected men. The training set consisted of 31 women and 31 men, while the test set included the remaining 6 women and 19 men.

In all subsequent experiments, a bandpass filter ranging from 0.1 Hz to 40 Hz was applied to remove inherent noise from the EEG signal recordings, ensuring improved signal clarity. Inconsistencies in gender differences in EEG signals were addressed through rigorous preprocessing, task standardization, and balanced sampling. Participants performed a standardized video streaming task under controlled conditions to minimize external influences such as noise and light. Data collection was conducted at similar times of day to account for circadian rhythms, and participants were screened for neurological conditions, fatigue, and medication use.

To ensure consistent task engagement, participants were provided with clear instructions and regular breaks to prevent fatigue during the EEG recording sessions. Additionally, task engagement was monitored through behavioral observations and self-reports collected after each session. While task engagement was not directly quantified, the experimental design was structured to maintain high and consistent levels of attention among participants.

Epochs containing artifacts were excluded from the analysis, and only high-quality EEG recordings with minimal artifacts were included. Equal sampling was ensured during training to mitigate gender imbalances in the dataset.

We recorded brain signals from a 120-second video clip, and the total recording length was trimmed to 117 seconds to standardize the data. Therefore, the size of one person's brain recording is 14 x 14976 data points (channels by 117 seconds * sampling rate). Afterwards, we computed the mean of brain recordings from all male participants and separately computed the mean of brain recordings from all female participants. This means that the resulting evoked object contains the averaged signal for each of the 14 channels over the specified time window. Based on previous studies, we employed Independent Component Analysis (ICA) to remove eye-related noise from each participant's brain signal recordings. This method allows for the separation of eye movement artifacts from the desired brain signals, improving the quality of data analysis and interpretation.

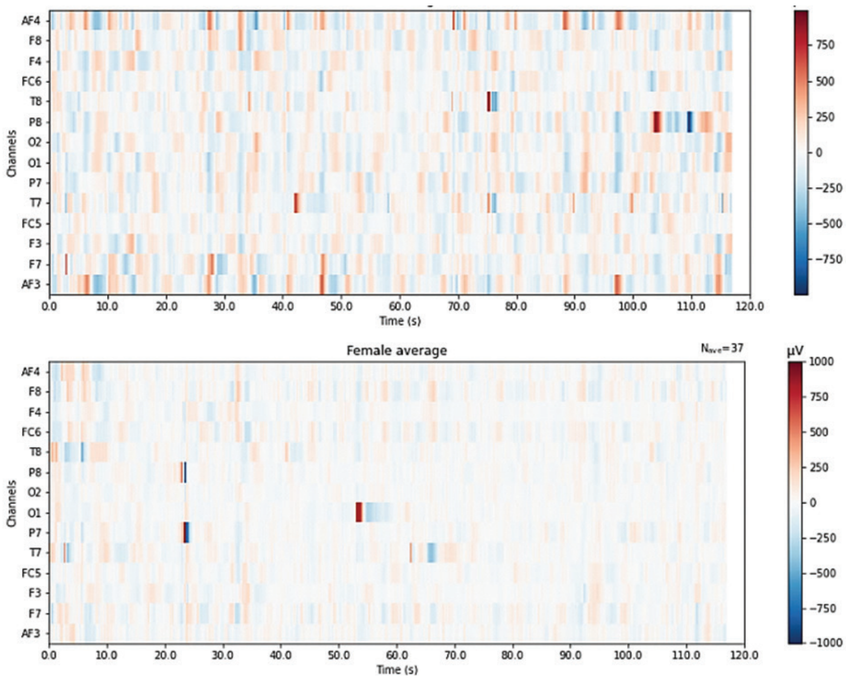

Fig. 2. Average EEG recordings of men's and women's brains

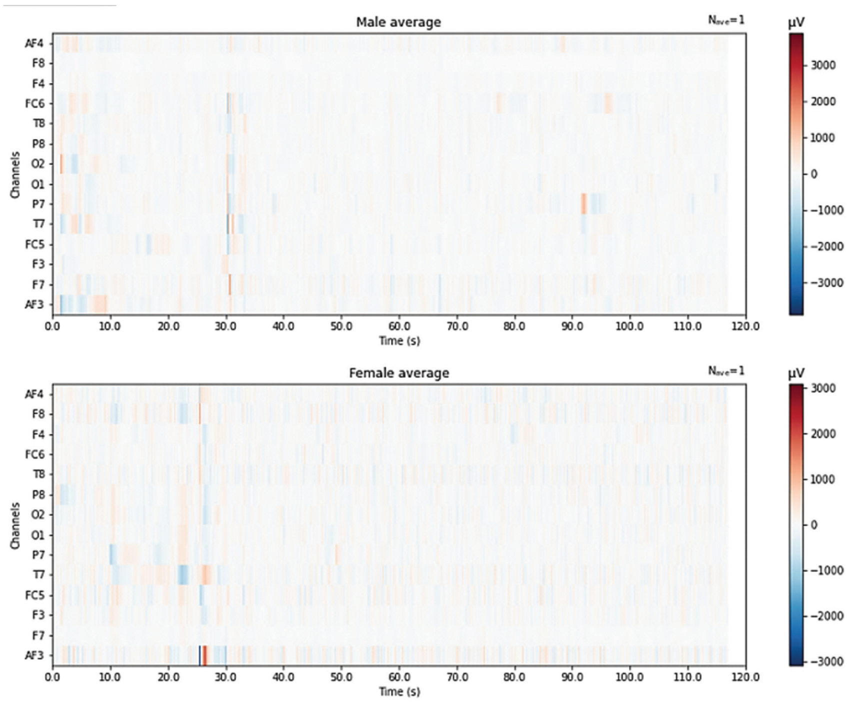

Fig. 3. Average EEG recordings of men's and women's after applying ICA

As the last step in data preparation, we performed gender-specific signal normalization. This involved subtracting the average EEG signal of females (used to create a 'common pattern' for female-EEG) from each male participant's EEG data and subtracting the average EEG signal of males (used to create a 'common pattern' for male-EEG) from each female participant's EEG data. This procedure ensured that gender-specific differences in baseline EEG activity were minimized before further analysis.

When we subtract the average female EEG data from the first male participant's EEG data, the result highlights the differences between this specific male's EEG signals and the typical female EEG signals. For each channel and each time point, this difference signal shows how the first male's EEG data deviates from the average female EEG data. Positive values in the difference signal indicate that the first male's EEG activity at those points is higher than the average female EEG activity. Negative values indicate that the first male's EEG activity at those points is lower than the average female EEG activity. This result provides a relative comparison between the first male's EEG and the average female EEG. It can be used to study gender-related differences in brain activity or to identify specific features that distinguish the first male's EEG pattern from the average pattern observed in females. By examining the difference signal, we can identify unique patterns or anomalies in the first male's EEG data compared to the average female EEG data. Our dataset comprises EEG data from male participants (37 subjects, 14 channels, 14,976 time points) and female participants (37 subjects, 14 channels, and 14,976 time points).

Before proceeding with classification, we performed wavelet transformation on the average EEG data separately for male and female participants. This transformation was conducted to analyze EEG signals in both time and frequency domains, allowing us to detect and extract specific temporal and spectral features that might distinguish between genders. By applying wavelet transformation, we aimed to uncover nuanced variations in brain activity patterns across different frequency bands and time intervals, thereby enhancing our ability to discern gender-specific neural signatures in the EEG recordings.

AF3 and AF4 electrodes are located on the left and right sides of the forehead, near the front, and are typically used to monitor activity in the prefrontal cortex, which is associated with higher cognitive functions and emotional regulation. EEG studies involving AF3 often focus on attention, executive function, and emotional processing.

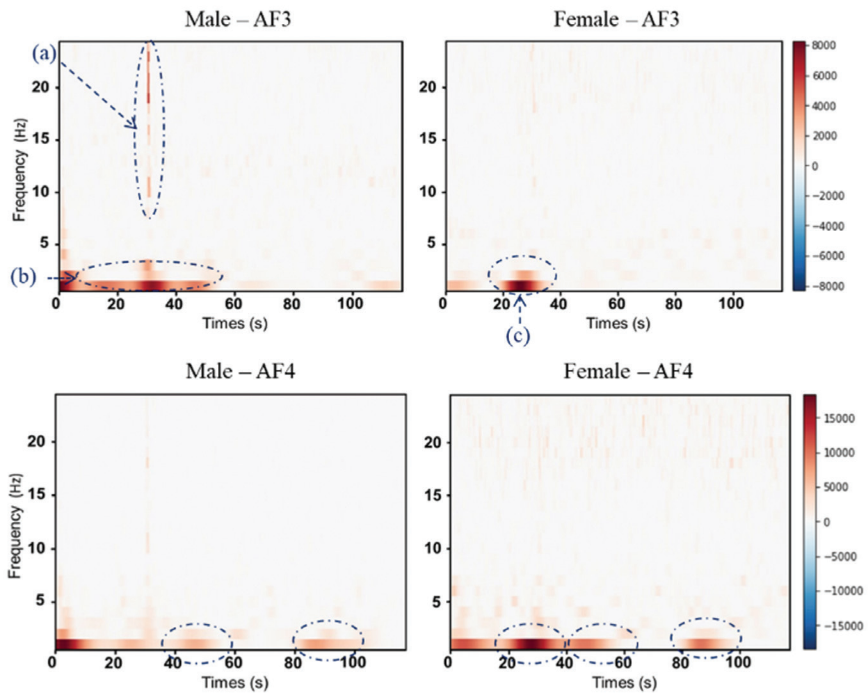

Fig. 4. AF3 and AF4 electrodes in males and females

(a) - between 27 and 30 seconds, high frequencies become active at the AF3 electrode on the man's head. This coincides with the "text" appearing in the video we showed, which the participants may have focused on. (b) - car, nature and man and female actor was shown. (c) - in the video between 22 and 37 seconds, a male actor was shown, and there was activity observed at the female AF3 point. In AF4, there was activity in low frequencies observed when both male and female actors were shown during the video stream.

F7 and F8 are located on the left and right sides of the head, in front of the ears, and are used to study brain activity related to language processing, emotional responses, and other cognitive functions.

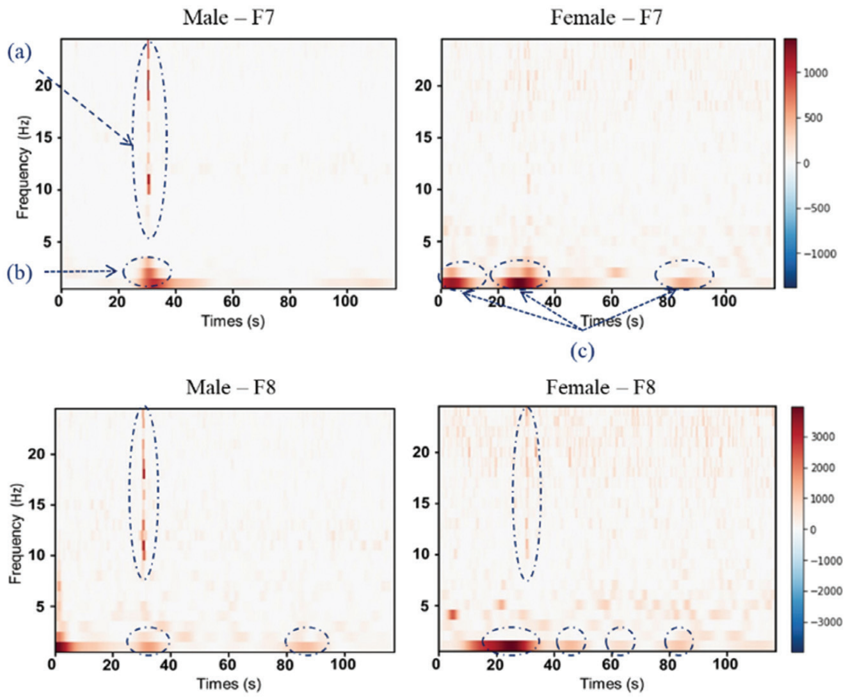

Fig. 5. F7 and F8 electrodes in males and females

(a) – The same high-frequency activity was observed in F7 when the "text" appeared in the video. (b) – a male actor was shown. (c) - male and female actors were shown in the video. In male F8, low-frequency activity was observed when the female actor was shown in the video. In female F8, low-frequency activity was observed when the male actor was shown in the video.

F3 and F4 are located on the left side of the head, in the frontal lobe, and they are used to study brain activity related to cognitive functions such as attention, problem-solving, and motor control, as well as emotional processing.

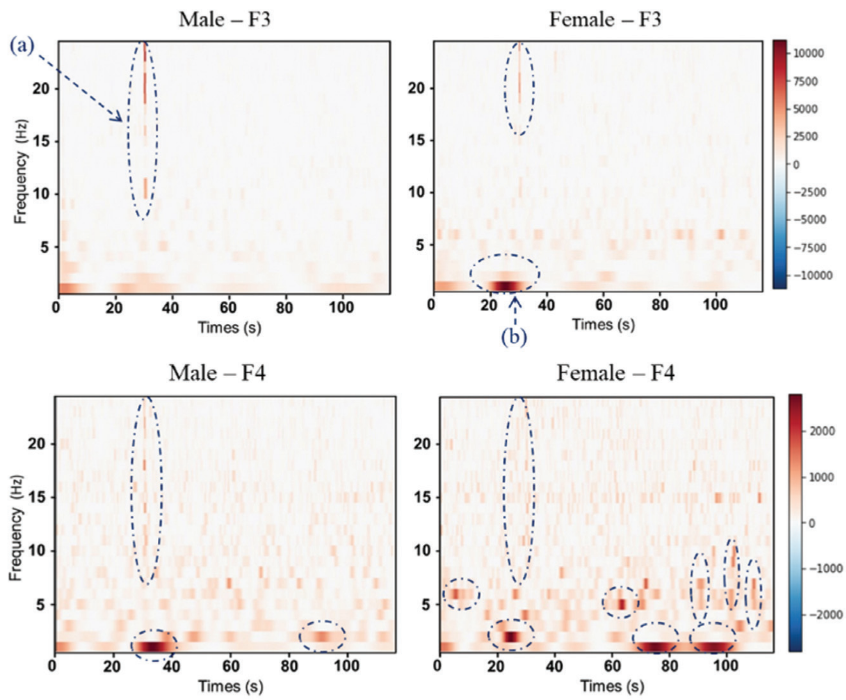

Fig. 5.F3 and F4 electrodes in males and females

In both male and female F3 and F4, high frequencies were still observed when text appeared in the video. In low frequencies, there were activities shown in actors of the opposite gender. In female F4, activities were observed in the frequency range between 4-12 Hz when the opposite gender appeared in the video.

FC5 and FC6 are located on the left side of the head, in the frontal-central region, and are used to study brain activity related to cognitive processes such as working memory, decision-making, and language production.

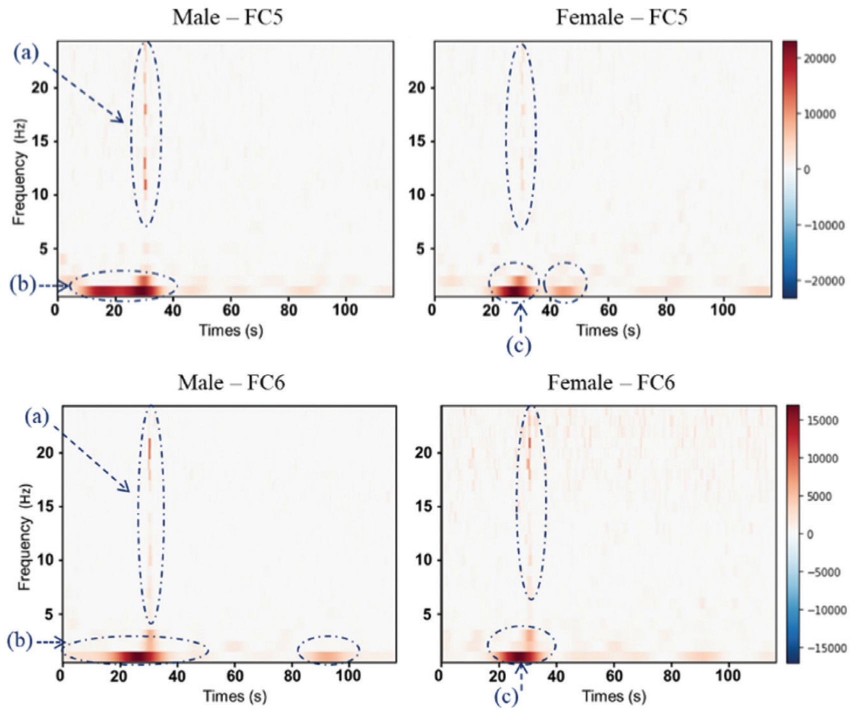

Fig. 7. FC5 and FC6 electrodes in males and females

In FC5 and FC6, elevated high-frequency activity was detected when text appeared in the video, whereas increased low-frequency activity was noted when actors were shown in the video. T7 and T8 are actually located on the left and right sides of the head, respectively, in the temporal lobe. They are used to study brain activity related to auditory processing, language comprehension, and memory functions.

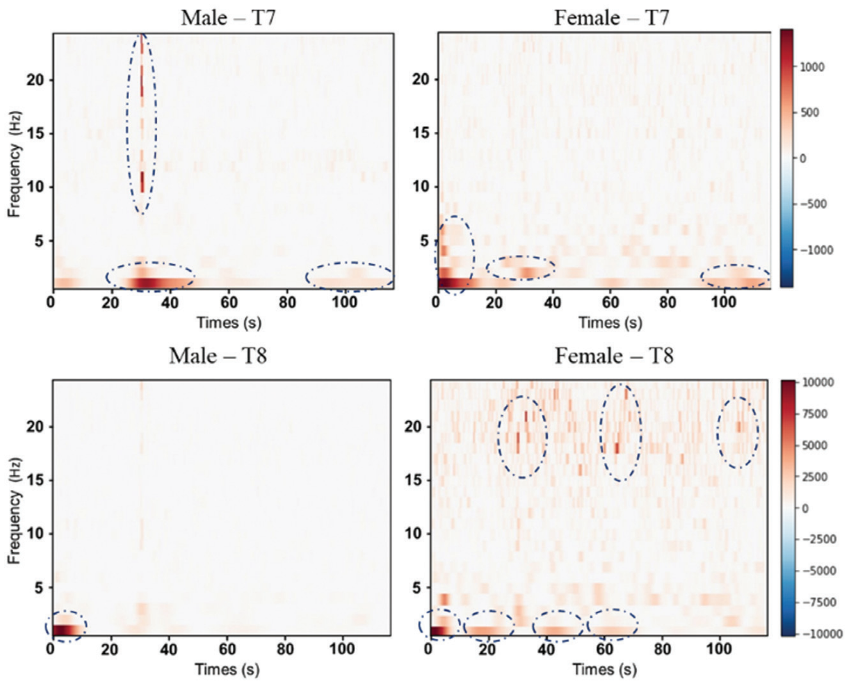

Fig. 8. T7 and T8 electrodes in males and females

In male T7, high-frequency activity can be observed when text appears in the video, whereas low-frequency activity is present at the start of the video. In female T8, there are also instances of high-frequency activity.

P7 and P8 are located on the left side of the head, in the parietal lobe, and are used to study brain activity related to sensory processing, spatial awareness, and attentional processes.

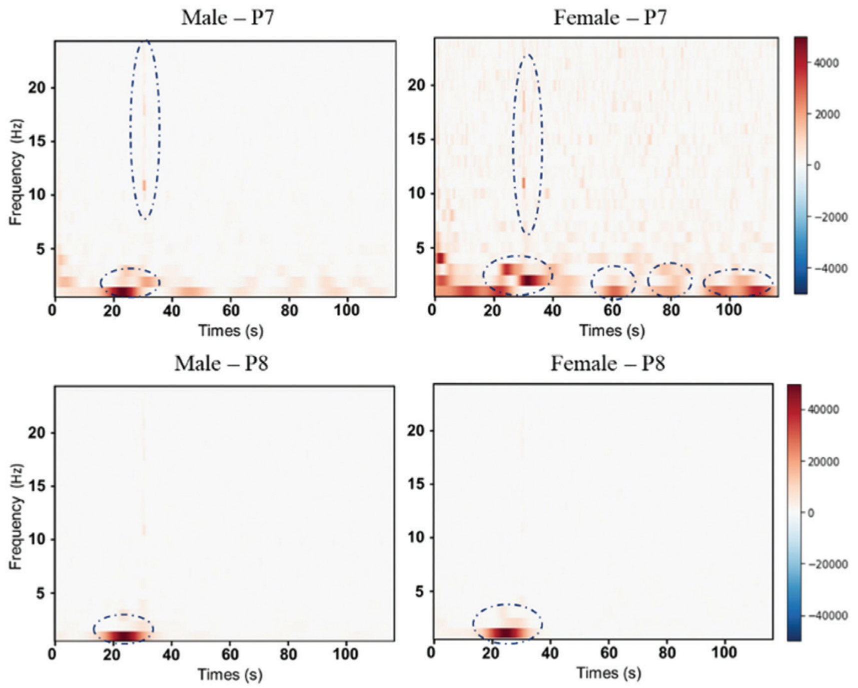

Fig. 9. P7 and P8 electrodes in males and females

In female P7, high-frequency activities are observed along with some lower frequency activities when actors are shown in the video. In both male and female P8, only one instance of low-frequency activity is observed during the same time period.

O1 and O2 are actually located on the left and right sides of the head, respectively, in the occipital lobe. They are indeed used to study brain activity related to visual processing, including visual perception, attention to visual stimuli, and various aspects of visual cognition.

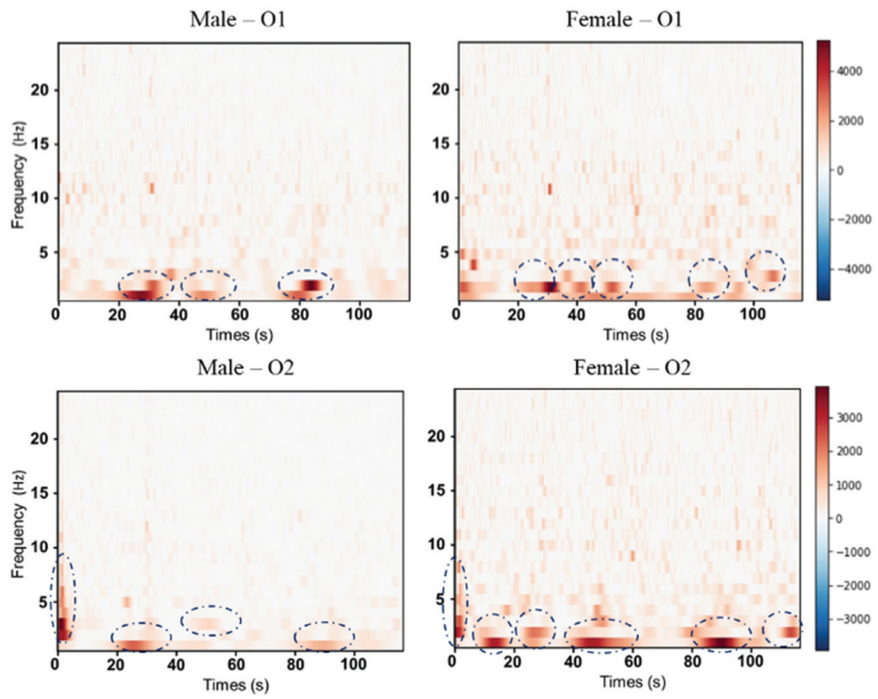

Fig. 10. O1 and O2 electrodes in males and females

In both male and female O1 and O2, there are numerous instances of high-frequency activities. Additionally, when actors appear, there are also occurrences of low-frequency activities. In this experiment, when a 2-second text appeared in a video, participants focused on reading it. As a result, high-frequency harmonics were observed on some channels at that moment. Additionally, female participants exhibited low-frequency activation each time a male actor appeared, a phenomenon also observed by male participants. Women may notice higher frequencies appearing more prominently in certain channels compared to men.

3. DEEP LEARNING METHOD FOR CLASSIFICATION

Before incorporating DL methods, we initially utilized the Power Spectral Density (PSD) analysis and the Common Spatial Pattern (CSP) algorithm in our research aimed at classifying gender based on EEG data. These methods were employed to extract pertinent features from EEG signals [52], which are crucial for accurate gender classification. Since the features we are interested in are related to frequency, our approach involves analyzing the power spectrum density of EEG signals. This method allows us to examine the distribution of signal power across different frequency bands, which is essential for extracting relevant features for gender classification. The figure below illustrates the power spectral changes of the AF3, AF4, and T7 channels respectively for males and females.

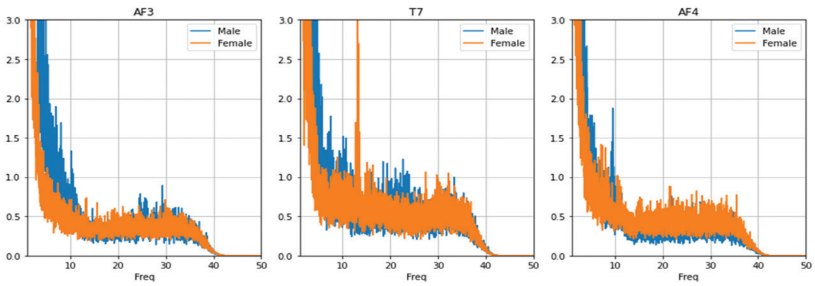

Fig. 11. AF3, AF4 and T7 channels PSD

First, we need to find a way to quantify the level of activity. We use the logarithm of variance of the signal within certain frequency bands as a feature for the classifier. The feature for the classifier will be the logarithm of the variance of each channel. This will yield a single variable for each trial. The figure below shows a bar chart of the logarithm of variance for males and females.

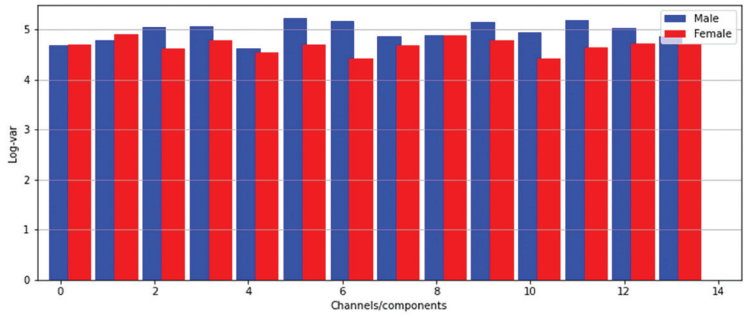

Fig. 12. Logarithm of variance for males and females

There are differences between the two classes that we can observe here. However, we need to maximize the difference between the male and female classes. We will use the CSP algorithm, which is designed to maximize the difference in variation between the two classes. We will find spatial filters that maximize the variance for one class and minimize the variance for the other class. The figure below shows the effect after applying this spatial filtering. Those are logarithm of variance features or components.

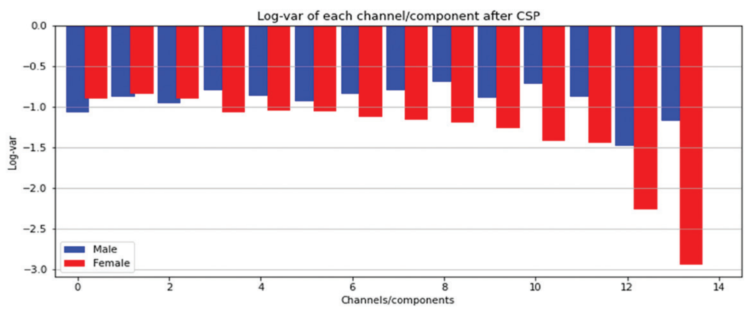

Fig. 13. Logarithm of variance for males and females after applying spatial filtering

These changes can be visualized as part of the power spectral density. The figure below visualizes the PSD after common spatial filtering. We can see a significant difference.

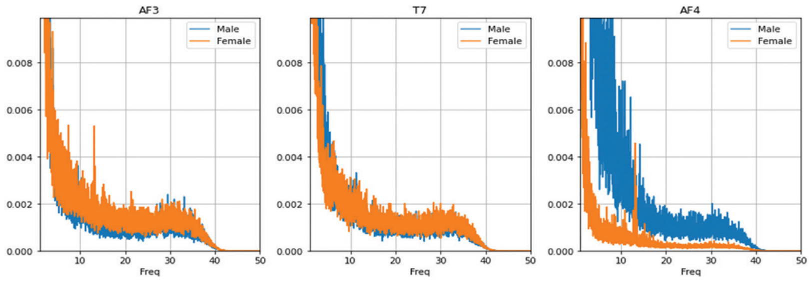

Fig. 14. PSD after common spatial filtering

We can now use these features to train a classifier and achieve good accuracy. We can discriminate between two classes as shown in the scatter plot on the two-dimensional plane below.

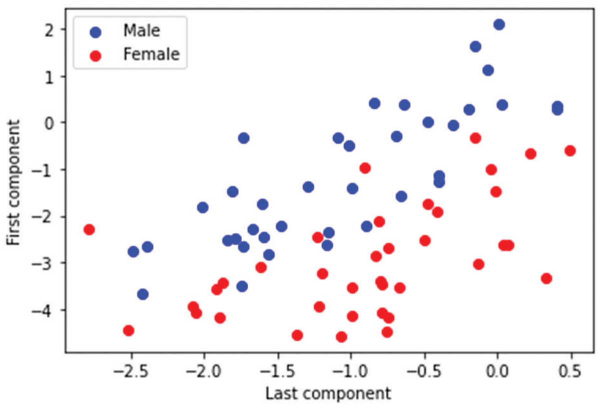

Fig. 15. CSP components between males and females

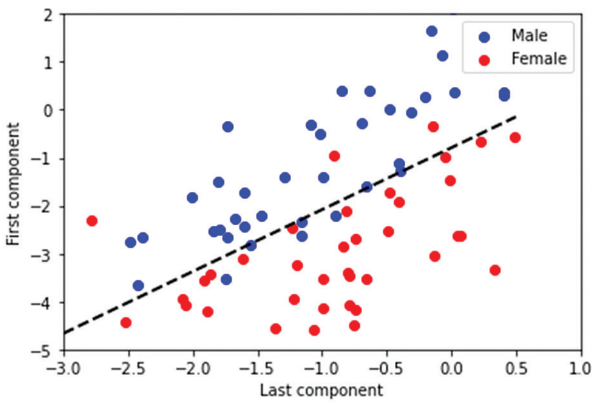

Fig. 16. Linear classification between two classes

Our decision boundary parameters have the following coefficients: W: [2.57161 -1.9911], b: 1.57859. Using this method, we can classify males and females with 89.2% accuracy.

After that, we developed a DL model and tested it. Preprocessing was performed using a bandpass filter and we excluded 4 components using ICA basing on multiple tests and evaluations. The data was divided into 70% for training, 10% for validation, and 20% for testing. The figure below shows our developed model for gender classification.

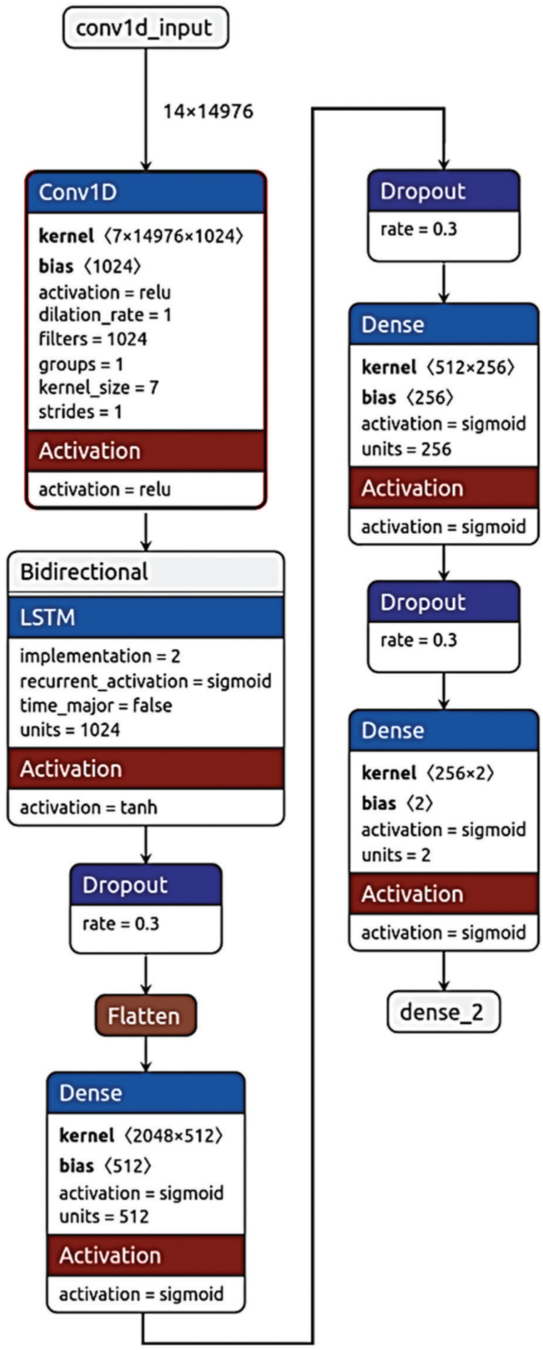

Fig. 17. Stream-based gender classification DL model

This model achieves 92% accuracy when using only preprocessed data.

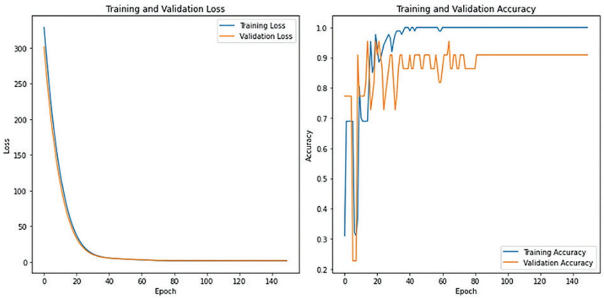

Fig. 18. Model results using preprocessed data

We added an additional step in data preparation. As previously discussed, the 'common pattern' of male/female EEG is subtracted from each participant's female/male EEG data alternately.

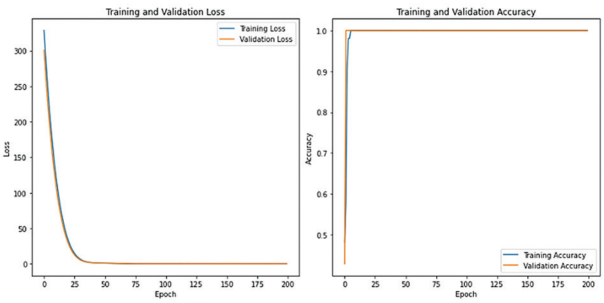

Fig. 19. Model results after average subtraction

With the assistance of this processed data, our DL model achieved remarkably high accuracy in accurately distinguishing between male and female genders. The data preprocessing, which involved subtracting the average EEG signal of females from each male participant's data and vice versa, significantly enhanced the model's ability to discern gender based on EEG patterns. In this case, using this processed data allows us to explore ways to make our model more efficient by potentially reducing its complexity. The confusion matrix is shown below the figure.

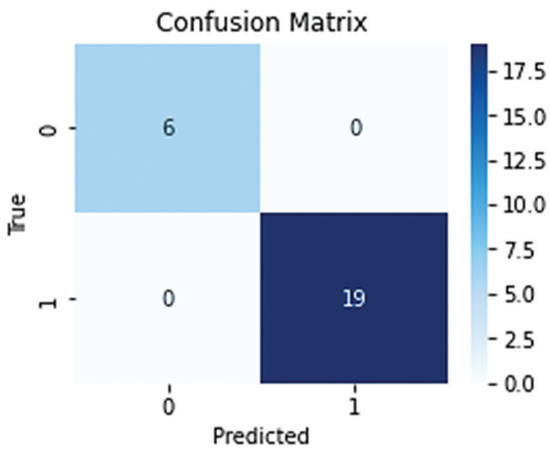

Fig. 20. Confusion matrix of our model

We correctly classified 6 females and 19 males based on our model's predictions.

4. CONCLUSION

This study presents a novel approach, the Stream-based Identification of Gender using Noninvasive Electroencephalographic Technology (SIGNET) method, by combining a deep learning model with spatiotemporal feature extraction for gender classification using EEG signals during video-streaming tasks, LSTM networks. Our method achieved 99% accuracy, highlighting its efficacy in distinguishing male and female brain activity during complex, dynamic tasks. These results demonstrate the potential of this framework in personalized medicine, neurotechnology, and gender-specific applications within AI.

Limitations of the method. While our study achieved promising results, several limitations must be acknowledged. The gender imbalance in our dataset (85 males and 37 females) presents challenges to the generalizability of our findings. Although equal sampling was ensured during training, future studies should aim for more balanced gender representation to validate these findings across a broader population. Additionally, our age distribution was concentrated between 17 and 23 years, which limits the generalizability of the results to older populations. Overfitting, due to the relatively small sample size, was a potential concern. To address this, we employed various strategies, including robust data preprocessing (e.g., ICA), gender-specific normalization and dropout regularization in the LSTM network to ensure generalization. These methods effectively mitigated overfitting and improved the model's robustness. Another limitation is the computational cost of deep learning models, particularly for real time applications. While the LSTM-based model demonstrated excellent performance in controlled environments, its scalability to real time systems or mobile platforms remains a challenge. Future research should focus on model optimization and edge computing to address this issue.

Key Findings. Our findings confirm that gender-based differences in EEG patterns are significant, particularly during tasks involving cognitive and emotional processes. Previous studies [33, 35] reported gender differences in cognitive tasks such as mental arithmetic and verbal memory. Similarly, our study highlights significant gender-related activity in the prefrontal cortex and occipital lobes regions critical for sensory processing and cognitive functions with more pronounced differences observed during the video-streaming task, which engaged both cognitive and emotional processing. Unlike traditional machine learning models, such as SVMs or Random Forests, which focus on static features, our use of LSTM networks allowed for the capture of temporal EEG patterns. This temporal sensitivity enabled the detection of subtle gender specific neural differences that static models might overlook. Furthermore, our application of wavelet transformations to analyze time-frequency features enhanced the model's ability to capture variations in frequency bands associated with gender differences.

Future Research and Application. Our future work aims to extend this study by incorporating larger and more diverse datasets to improve generalizability and explore additional factors such as age, cognitive state, and environmental influences that may affect EEG based gender classification. Addressing these factors will enhance the robustness and applicability of SIGNET in real world settings, opening new possibilities for personalized education systems and neuropsychological research. By leveraging deep learning models to analyze gender-specific EEG patterns, adaptive learning environments can be developed to cater to gender specific cognitive and emotional dynamics. Similarly, understanding gender differences in brain activity can contribute to more personalized therapeutic interventions for conditions such as ADHD and depression. In the realm of neurotechnology, this study has implications for improving the accuracy and security of biometric systems and BCIs by incorporating gender sensitive models. Future research can further explore how these findings might be extended to other demographic factors, such as age, cognitive states, and mental health conditions, potentially leading to more personalized and adaptive neurotechnology solutions. In addition, developing the SIGNET method for real time applications holds significant promise. The results of this study can be applied to personalized medicine, neurotechnology, AI applications, BCIs, and adaptive learning systems, providing a foundation for more advanced, gender-sensitive AI models designed for gender analysis.

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