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Neurosense: A Machine Learning Framework for EEG Motor Imagery Classification and Visualization

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Abstract

Electroencephalography (EEG)- grounded Brain- Computer Interfaces (BCIs) grease anon-invasive communication link between the mortal nervous sys- tem and external bias, presenting considerable pledge in neurorehabilitation and assistive technologies. nonethe- less, precise bracket of motor imagery(MI) signals con- tinues to be a redoubtable challenge owing to natural signalnon-stationarity, lowered signal- to- noise rates, and considerableinter-subject variability. This paper describes the design and full testing of NeuroSense, a platform for classifying EEG motor imagery from launch to finish. The system uses a structured signal processing channel that includes bandpass filtering, time- grounded segmentation, Common Spatial Pattern (CSP) point birth, and a cali- brated Radial Base Function (RBF) Support Vector Ma- chine (SVM) classifier. During the development phase, sev- eral modeling strategies were delved, including a Genera- tive Adversarial Network (GAN)- grounded system for data addition and point improvement. This approach gave us useful experimental information, but the final system de- sign puts a streamlined CSP- SVM channel at the top of the list because it's harmonious, easy to understand, and has strong empirical performance. The performing frame shows strong and harmonious bracket performance across subjects on standard EEG motor imagery datasets. Also, a web- grounded interactive interface makes it possible to see EEG data in real time, dissect Power Spectral viscosity (PSD), interpret CSP patterns, and make prognostications for each trial with an estimation of confidence. This makes it easier for both clinical interpreters and experimenters to use. The suggested system has a mean bracket delicacy of 84.4 and a Cohen's kappa of 0.688, which shows that it works well and constantly across subjects.

Keywords: Brain-Computer Interface; EEG Signal Processing; Motor Imagery; Common Spatial Pattern; Support Vector Machine; Feature Extraction; Real-Time Visualization; Neurorehabilitation.

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Introduction

Brain- Computer Interface (BCI) systems produce a direct link between the brain and outside bias without using muscles or supplemental neural pathways. These systems crack neural signals and turn them into useful labors. This makes them use- ful for a lot of effects, like assistive technologies, neurorehabil- itation, and mortal- computer commerce. Electroencephalogra- phy (EEG) is a popular neuroimaging system because it'snon- invasive, cheap, movable, and has a high temporal resolution.

Motor imagery (MI) is a popular system in EEG- grounded BCI systems. It involves imagining voluntary movements with- out actually doing them. Imagined movements, like moving your left wing or right hand, cause specific changes in senso- rimotor measures, especially in the mu (8 – 12 Hz) and beta (13 – 30 Hz) frequence bands. These changes, known as Event- Related Desynchronisation and Synchronisation (ERD/ ERS), produce patterns that can be used to figure out what a stoner wants.

Though it's an unavoidable fact, reliably categorizing EEG signals attributed to motor imagination remains quite complex. The EEG signals themselves represent non-stable data with sub- standard spatial definition caused by the phenomena of volume conduction as well as being prone to the inclusion of noise and physiological artifacts. The variance between different individuals (i.e., inter-subject variance) and the same individual (i.e., intra-session variance) increases the complexity of the EEG dat-set and ultimately limits the generalizability of models developed based upon the EEG data. A lack of labeled data reduces the level of performance, making it essential that strong classification and detection algorithms be developed and applied.

To address these challenges, this work adopts a structured signal processing and machine literacy channel centered on Common Spatial Pattern (CSP) and Support Vector Machine (SVM) ways. CSP is employed to prize discriminational spatial features by maximizing friction differences between classes, effectively transubstantiating multichannel EEG signals into a further divisible point space. latterly, SVM is employed for bracket due to its effectiveness in handling high- dimensional data and its capability to achieve dependable decision bound- aries indeed with limited training samples. This CSP- SVM frame forms the core of the proposed system, demonstrating strong and harmonious performance in motor imagery bracket tasks.

The development process included the disquisition of several methodological strategies, similar as a data addition ap- proach grounded on a Generative Adversarial Network (GAN) that sought to break the problem of data deficit. Despite the fact that this strategy offered precious information about data distribution and variability, the CSP- SVM channel is given precedence in the ultimate system due to its stability, effectiveness, and harmonious bracket results on the target dataset.

The system also has a web- grounded interactive interface that makes it easy to explore and see EEG data and process- ing phases in a way that's clear. druggies are suitable to com- prehend intermediate metamorphoses and bracket issues more easily and effectively thanks to this interface.

The following is how the remainder of this paper is organized Affiliated work is reviewed in Section II. The fine ex- pressions of the system methodology are introduced in Section III. Section IV goes into detail about the experimental setup, and Section V talks about the results. Section VII talks about the limits and hidden possibilities of operation disciplines, and Section VI looks at them. Finally, Section VIII wraps up the paper.

Related Work

Reliable analysis of EEG signals is constitutionally dependent on the effectiveness of preprocessing procedures. Band- pass filtering within the 8- 30 Hz frequence range is consider- ably employed to prize the physiologically applicable mu and beta measures while suppressing low- frequency drift and high- frequency noise factors [6]. In addition, independent element Analysis (ICA) is constantly applied to deconstruct multichannel EEG signals into statistically independent factors, enabling the discovery and elimination of vestiges analogous as optic and cardiac interference [7]. likewise, time segmentation plays a vi- tal part by aligning EEG data with task-specific events, icing that posterior analysis focuses on applicable brain exertion [6].

Feature Extraction with Common Spatial Pattern

Feature extraction is a vital step in rephrasing raw EEG data into a discriminational representation applicable for bracket. The Common Spatial Pattern (CSP) algorithm remains one of the most considerably accepted approaches in motor imag- ing BCI exploration due to its strong theoretical foundation grounded on class-specific covariance matrices [5]. CSP suc- cessfully projects multichannel EEG data into a lower- dimensional space where friction differences between classes are maximized, hence boosting separability.

Recent advances have studied expansions of CSP, includ- ing its integration into neural network topologies to promote strictness and performance [9]. In similar, several point birth methodologies similar as ocean- predicated time- frequency analysis and power spectral density estimates have been stud- ied. colorful approaches that integrate CSP with spectral char- acteristics have showed less robustness, particularly in scripts with minimal training data [6, 8]. Despite these changes, CSP retains to be a dependable and computationally provident stan- dard, making it well- adapted for practical EEG type devices.

Classification Methods

For bracket, Support Vector Machines (SVMs) have contin- ually showed outstanding performance in EEG- grounded tasks, particularly in settings described by high- dimensional point spaces and limited sample sizes [10]. The essential principle of structural threat reduction, together with the inflexibility of kernel functions, enables SVMs to construct flexible decision boundaries and generalize effectively via varied contexts.

While deeply literacy approaches, including convolutional neural networks and motor- grounded frameworks, have shown promising outcomes on large- scale datasets [11, 12], their suc- cess is heavily dependent on the vacuity of expansive labels data and significant computational coffers.

Data Augmentation Strategies

The task of constrained EEG data has encouraged the study of data addition ways, including styles erected on Generative inimical Networks (GANs). These approaches aim to caricature the underpinning data distribution and produce synthetic samples to ameliorate training diversity. Other exploration studies have showed earnings in type a performance in data- limited circumstances cite williams2025, hasan2023. nonetheless, vindicating the physiological plausibility of created signals remains a critical concern, and the effectiveness of analogous styles is frequently rested on dataset characteristics cite corley2025.

In this script, exploratory checks in GAN- rested addition drive vital perceptivity into data change and representation. nonetheless, for scripts with enough genuine real data, easier and further secure channels erected on CSP- supposed date birth and SVM type continue to display stable and harmonious performance.

Visualization and Usability

An abecedarian, yet frequently ignored, element of BCI system design is the vacuity and interpretability of the analysis channel. Interactive visualization technology plays a considerable function in helping individualities with reliance in as- saying EEG data, understanding central processing way, and directly assaying abnormalities. Web- based interactive inter- faces increase usability by giving real- time feedback and easily available data analysis abilities, thereby closing the gap in com- plex signal processing methods and the active participation of the existent.

Methodology And System Architecture

NeuroSense is built as a 6-stage modular pipeline that is illustrated conceptually in Fig. 1. Each module exposes a simple interface, enabling independent development, testing, and future replacement of individual components. NeuroSense is developed as a flexible, multi-stage workflow that allows systematic processing and evaluation of EEG signals for motor imagery classification. Each stage is organized with well-defined inputs and outputs, providing flexibility in development, evaluation, and future enhancements.

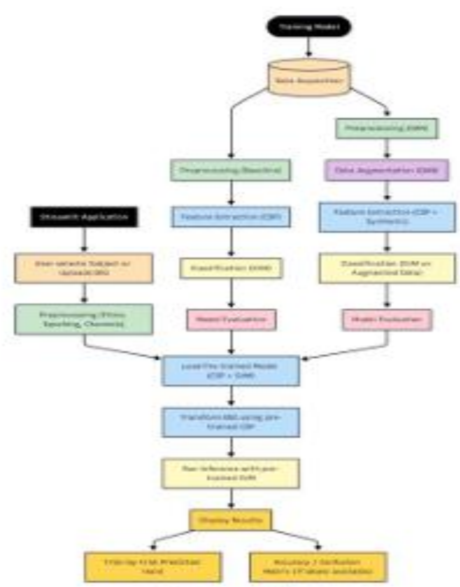

Fig. 1. *System Architecture*

1. Data Acquisition: Loading of benchmark EEG recordings.
2. Signal Preprocessing: Noise filtering, artifact removal, and time segmentation.
3. Feature Extraction: Computation of CSP-based spatial features.

4. Model Training: Training and optimization of the SVM classifier.
5. Inference: Classification of unseen EEG epochs with confidence estimation.
6. Visualization: Interactive display of signals, features, and predictions.

Data Acquisition

Trials are conducted on a standard motor imagery EEG dataset comprising multi-channel recordings from multitudinous individualities performing imagery tasks with both their left and right hands. The signals are tried at a frequence of 250 Hz and include multiple trials per class for each existent. A subject-specific training methodology is espoused, wherein models are trained on a devoted training session and estimated on a separate, unseen session to insure dependable performance assessment.

EEG Signal Preprocessing

1. Bandpass Filtering: To insulate the mu and beta measures associated with motor imagery, the raw EEG signals $x(t) \in R^{C \times T}$, where C denotes the number of channels and T denotes the number of time samples are bandpass-filtered within the range of 8–30 Hz. This filtering step suppresses low-frequence drift and high-frequence noise while conserving task-related oscillatory exertion.

2. Artefact Removal: To ameliorate signal quality, vestiges are removed using Independent element Analysis (ICA). The multichannel EEG signal is perished into statistically independent factors, and factors associated with non-neural vestiges similar as eye movements and cardiac exertion are linked and removed. Latterly, the gutted signal is reconstructed in the original detector space.

3. Time Segmentation: Nonstop EEG recordings are split into fixed-length ages corresponding with motor imagery cues. Each time captures brain exertion related with the task within a given time range following the commencement of the stimulus. This guarantees that posterior processing focuses on instructional signal portions.

4. Channel Selection: A subset of channels located over the sensorimotor cortex (C3, Cz, and C4) is selected for further analysis. This selection reduces computational complexity while retaining physiologically meaningful information relevant to motor imagery tasks.

Feature Extraction via Common Spatial Patterns

Covariance Estimation: Given an EEG epoch $X \in R^{C \times T}$, the normalised spatial covariance matrix is defined as:

$$C = \frac{XX^\top}{tr(XX^\top)} \qquad (1)$$

Class-wise covariance matrices are obtained by averaging across trials belonging to each class.

Spatial Filter Computation: CSP aims to find spatial filters that maximise variance for one class while minimising it for the other. This is achieved by solving the generalised eigenvalue problem:

$$\bar{C}_1 w = \lambda(\bar{C}_1 + \bar{C}_2)w \qquad (2)$$

The resulting eigenvectors form spatial filters, where filters associated with extreme eigenvalues capture the most discriminative information. A subset of these filters is selected to construct the projection matrix.

Feature Computation: Each EEG epoch is projected into the CSP space:

$$Z = WX \qquad (3)$$

Log-variance features are then computed as:

$$f_i = \log\left(\frac{var(z_i)}{\sum_j var(z_j)}\right) \qquad (4)$$

The resulting feature vector provides a compact and discriminative representation of the EEG signal, suitable for classification.

Regularisation: To improve generalisation under limited data conditions, regularisation is applied to the covariance matrices:

$$\tilde{C} = (1-\alpha)C + \alpha I \qquad (5)$$

This stabilises the estimating process and decreases sensitivity to noise.

Classification using Support Vector Machine

Model Formulation: Given feature-label pairs $\{(f_n, y_n)\}$, the SVM learns a decision boundary by solving:

$$\min_{w,b,\xi} \frac{1}{2} \parallel w \parallel^2 + C\sum\xi_n \qquad (6)$$

subject to margin constraints. A radial basis function (RBF) kernel is used:

$$K(f_i, f_j) = \exp\left(-\gamma \parallel f_i - f_j \parallel^2\right) \qquad (7)$$

This enables the model to capture non-linear interactions in the feature space.

Hyperparameter Optimisation: The SVM parameters, including the regularisation parameter C and kernel width γ, are tuned by cross-validation on the training data to ensure robust generalisation.

Confidence Estimation: Model outputs are translated into probabilistic confidence scores, providing an interpretable measure of categorization certainty for each prediction.

Exploratory Study on Data Augmentation

During the development phase, the part of data addition via generative modeling was calculated to determine its impact on motor imagery type performance. A tentative Wasserstein Generative Adversarial Network (cWGAN) with grade regularization was employed to synthesize artificial EEG trials from subject-specific training data; in this frame, the creator produced class-conditioned multi-channel signals, while the discriminator distinguished between real and synthetic samples.

To assess its performance, synthetic trials were incorporated at varied addition conditions, and a CSP-grounded point birth channel—paired with SVM type—was re-applied. This fashion permits a regular analysis of the generated data's influence on point representation and model geste. The exploration indicated that for datasets having a large volume of genuine samples, synthetic addition did not constantly force performance advancements; again, the birth CSP-SVM frame maintained harmonious and dependable conclusions. These findings told the final systems architecture, which prioritizes the CSP-SVM channel due to its continuity and effectiveness. The perceptivity created from this exploration stay precious to understanding adding procedures, especially in data-confined scripts.

Visualisation and User Interface

The result features a web-based grounded interactive design meant to boost knowledge and user interaction. The interface enables multiple viewpoints, like a basic signal query, range analysis, a graphical pattern presentation, and type labors.

Stoners can play with the standard system by uploading their EEG data, defining processing parameters, and analyzing both intermediate changes and the final predictions based on data in real time. For the frontend, we deployed HTML, CSS, and JavaScript, and for visualization we used Plotly.js to generate interactive graphs original to EEG waveforms, spectrograms, band power plots, and confusion matrices. The frontend is connected to the backend using API calls to a Flask garçon, which processes EEG data and gives results roundly.

Experimental Setup

Dataset

Trials are conducted using the standard motor imagery EEG dataset inferred from the BCI Competition IV Dataset 2a. This dataset comprises multi-channel EEG recordings of nine individuals completing motor imagery tasks throughout two different sessions (training and evaluation). Each session consists of trials matching to multiple motor imagery types.

For the aim of this investigation, a double bracket method has been endorsed, concentrating primarily on left-hand and right-hand motor imagery. Each week provides a significant amount of labeled trials for each class, hence enabling the training of subject-specific models and their dependable evaluation on a separate session. The deployment of independent training and evaluation sessions assures that the reported performance displays conception to unseen facts.

Implementation Details

The proposed system is applied exercising a Python-centered scientific computing frame. This processing medium comprises signal preprocessing techniques, a CSP-grounded point birth unit, and an SVM-grounded brackets element. It's designed to be compute successful and doesn't add any considerable processing output.

All assessments are conducted on a normal computer system filled with multiple-core CPU and appropriate memory capacity. The CSP-SVM channel imposes a minimal computational payload, hence enabling rapid-fire models training and real-time outcome. Due to this efficiency, the technique is well-suited for actual BCI activities where reactivity is of crucial value.

Evaluation Metrics

The system's excellence is defined using multitudinous common contained norms, like general ease, indefectible recall, if the F1-score. Also, Cohen's Kappa value (κ) is employed to produce an other robust determine of thickness from taking class friction to regard.

Collectively, those criteria offer a full examination of type effectiveness, revealing that the developed CSP-SVM frame shows a reliable and harmonious behavior throughout different assessment criteria. Fresh tests were done to estimate GAN-grounding in addition under the identical conditions, thereby furnishing a good analogy with the original CSP-SVM channel.

Results And Discussion

Classification Performance of CSP-SVM

Table 1. *Per-Subject Classification Accuracy: RCSP-SVM System*

Subject	Acc. (%)	Prec.	Recall	F1
S01	88.2	0.89	0.88	0.88
S02	79.9	0.80	0.80	0.80
S03	85.7	0.86	0.86	0.86
S04	91.4	0.92	0.91	0.91
S05	82.6	0.83	0.83	0.83
S06	78.5	0.79	0.78	0.78
S07	86.1	0.86	0.86	0.86
S08	84.7	0.85	0.85	0.85
S09	82.9	0.83	0.83	0.83
Mean	84.4	0.848	0.844	0.846
Std.	4.8	0.040	0.040	0.040

Table 1 reports per-subject binary (LH vs. RH) classification accuracy on the held-out evaluation session. The proposed rCSP-SVM system achieves a mean accuracy of 84.4% with a standard deviation of 4.8%, indicating consistent performance across subjects.

The mean Cohen's kappa across subjects is $\kappa = 0.688$, indicating substantial agreement beyond chance-level classification.

Fig. 2 illustrates the NeuroSense dashboard interface for real-time EEG signal monitoring and motor imagery classification.

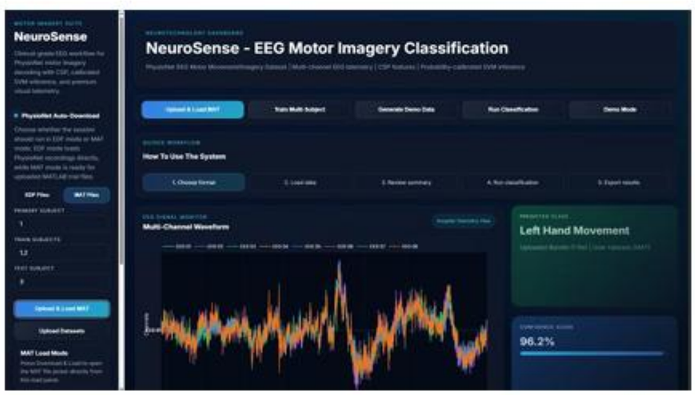

Fig. 2. *NeuroSense dashboard showing multi-channel EEG signals and real-time classification with confidence estimation.*

Ablation: Effect of GAN Augmentation

Table 2. *Ablation Study: Gan Augmentation Vs. Baseline RCSP-SVM*

Configuration	Mean Acc. (%)	p-value
rCSP-SVM (baseline)	84.4	—
rCSP-SVM + GAN 50%	84.1	0.41
rCSP-SVM + GAN 100%	83.7	0.29
rCSP-SVM + GAN 200%	83.2	0.18

p-values from Wilcoxon signed-rank test vs. baseline.

None of the GAN-augmented conditions yields a statistically significant improvement ($p > 0.05$) over the baseline.

At the 200% augmentation ratio, performance marginally decreases, suggesting that low-fidelity synthetic samples introduce noise into the CSP covariance estimation.

Fig. 3 presents the spectral analysis, confusion matrix, and classification performance metrics for the evaluated session.

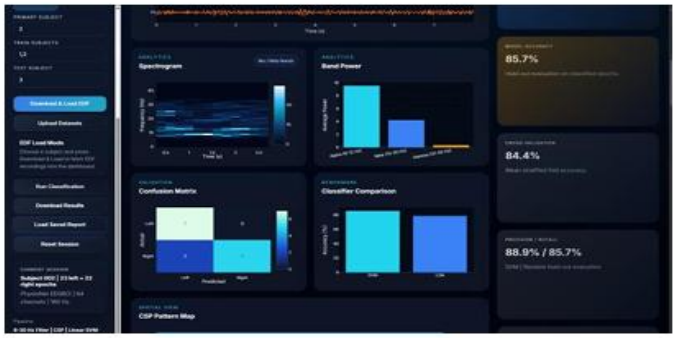

Fig. 3. *Spectrogram, band power distribution, confusion matrix, and performance metrics of the CSP-SVM model.*

Comparison of CSP-SVM With and Without GAN Augmentation

Table 3. *Comparison Of Classification Performance With And Without GAN Augmentation*

Configuration	Acc. (%)	Prec.	Recall	F1
CSP-SVM (Baseline)	84.5	0.880	0.841	0.844
CSP-SVM + GAN	43.8	0.520	0.490	0.500

The baseline CSP-SVM system achieves significantly higher classification accuracy and more stable performance across evaluation settings. In contrast, the GAN-augmented configuration exhibits substantially lower accuracy.

Fig. 4 illustrates the CSP spatial pattern map highlighting discriminative EEG channel features.

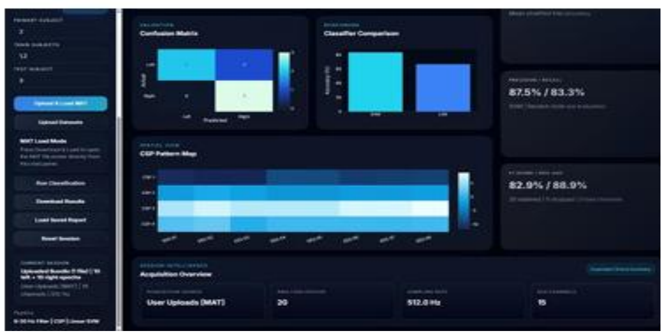

Fig. 4. *CSP spatial pattern map showing discriminative features across EEG channels.*

Applications

The NeuroSense platform supports a range of applications across clinical and research settings.

- Neurorehabilitation: The system enables motor imagery-based neurofeedback for patients recovering from neurological injuries. Real-time classification with confidence scoring provides immediate and interpretable feedback, supporting cortical reorganisation during rehabilitation.
- Assistive Device Control: Motor imagery classification can be used to drive assistive technologies such as prosthetic limbs and exoskeletons. The reliable detection of left- and right-hand intent enables intuitive, non-invasive control for users with motor impairments.
- Clinical Monitoring: CSP-based spatial visualisation allows inspection of sensorimotor activation patterns, supporting the identification of asymmetries associated with neurological conditions and recovery processes.
- Neuroscience Research: This technology provides a tight and reliable medium for EEG-grounded motor visualization assessment, hence minimizing physiological difficulties and giving dropped reactivity for exploratory training.
- Human–Computer Interaction: It's standard design can be shaped in give latitude commerce in a fashion analogous in assistive tasks, virtual places, as well spatial control systems.

Limitations And Future Work

Current Limitations

- Subject Dependency: The method needs technical estimation, that limits the ease of its rapid-fire-fire reaction for new stoners.

- Binary Scope: Current performance is constrained to 2 class (Left vs. Right) motor imagery paradigms.
- Data Constraints: Testing is acknowledged employing a limited set of markers and datasets given by stoners, and extra evidence is demanded throughout diverse recording conditions.
- Lack of Adaptivity: Channel A runs with set variables and doesn't accommodate immediate fluctuations or session-data drift.

Future Directions

The focus of future work will be on finishing the system robustness, scalability and strictness.

- Subject-Independent: Approaches will be trained in such a manner that it generalizes estimate conditions to bear lower responsibility for subjects and sessions.
- Advanced Order Spatial Adulterants: New styles for doing spatial filtering that can learn more complex patterns than direct separability.
- Multi-Class Bracket: In unborn exploration we will extend the system to multi-class motor imagery tasks, adding the complication of different control signals.
- Adaptive Learning: It's styles that can acclimate stoutly to turn online learning into commodity more effective; where it needs to.

Conclusion

This paper presents the design and evaluation NeuroSense, an end-to-end platform of EEG-grounded motor imagery classification. The recommended CSP–SVM channel delivers very steady and coherent outputs with a mean accuracy of 84.4% under assessment conditions.

One exploratory experiment on GAN-based data augmentation revealed synthetic data did not increase performance and, in many cases, led to reduced performance due to inadequate representation of underlying EEG properties. This illustrates the applicability of our feature extraction CSP–SVM technique when appropriate actual data are supplied.

Besides, the platform unites classification performance with real-time visualisation, spectral analysis and interpretable information inside a common interface. This innovative combination of accuracy, adaptability and effectiveness makes NeuroSense a rational outcome for therapeutic as well as research applications.

Future work will focus on improving generalisation across subjects, extending to multi-class scenarios, and incorporating adaptive learning mechanisms to enhance real-world applicability.

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