MULTI-MODAL INTEGRATION OF EEG- FNIRS USING DATA AUGMENTATION CGAN

GUIDED BY
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OBJECTIVE :-

- We propose a novel approach to augment multi-modal EEG-fNIRS data using Conditional Generative Adversarial Networks (CGAN). By leveraging the complementary information from EEG and fNIRS signals, our CGAN- based framework generates synthetic data that preserves the underlying brain activity patterns.

- Experimental results demonstrate the effectiveness of our approach in enhancing data diversity, improving model generalization, and reducing overfitting. This work has significant implications for brain-computer interface (BCI) research, enabling more accurate and robust analysis of brain activity.

INTRODUCTION :-

- The integration of multiple neuroimaging modalities, such as electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS), has shown great promise in enhancing our understanding of brain function and behavior.

- By combining the strengths of EEG's high temporal resolution and fNIRS's ability to measure hemodynamic responses, multi-modal integration can provide a more comprehensive understanding of cognitive processes.

INTRODUCTION :-

- Data augmentation techniques offer a potential solution to the challenge of limited data availability. By generating synthetic data that mimics the characteristics of real data, data augmentation can increase the size and diversity of the training dataset, improving the performance and generalizability of machine learning models.

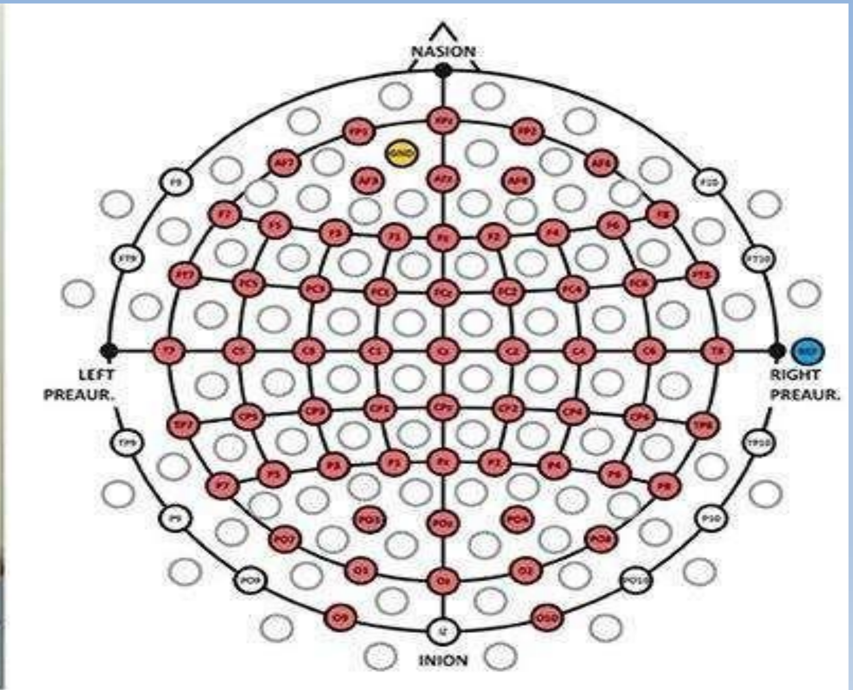
- This research explores the integration of EEG and fNIRS data using data augmentation techniques to enhance the accuracy and robustness of cognitive state assessment and brain-computer interface (BCI) systems.

- By leveraging the complementary information provided by EEG and fNIRS, and augmenting the dataset with synthetic samples, this research aims to develop more accurate, robust, and generalizable models for a wide range of cognitive research and technology applications.

EXPLANATION OF IMPORTANT TERMS :-

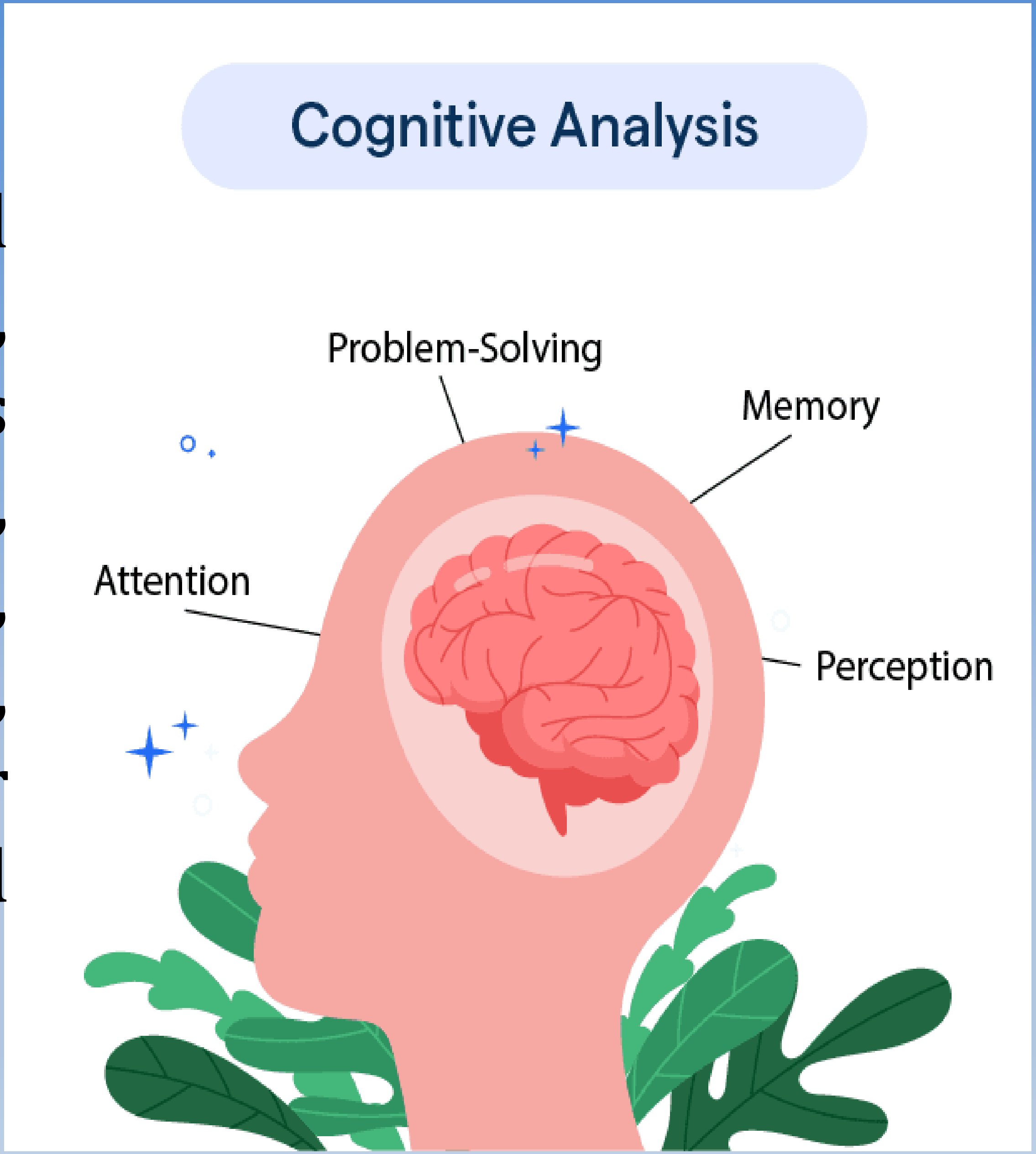
MOTOR IMAGERY :-

- Motor Imagery (MI) is the mental process of imagining a specific movement of a part of the body without actually performing the movement. During MI, the brain activates motor-related regions in a way similar to actual physical movement, even though no real muscle activity occurs.



COGNITIVE TASKS :-

Cognitive" refers to mental processes like thinking, learning, and understanding. It encompasses various abilities and functions, including perception, memory, judgment, and reasoning. In essence, cognitive refers to the way our minds work to acquire, process, and use information.



Cognitive Task :-

1. Think
2. Learn
3. Remember
4. Problem-solve
5. Perceive
6. Understand Cognition

involves various brain functions, including:

1. Attention
2. Memory
3. Language
4. Reasoning
5. Decision-making Cognitive abilities are essential for daily life, enabling us to process information, adapt to situations, and interact with the world around us.

EEG (Electroencephalogram) :-

EEG stands for Electroencephalography. It's a neurophysiological measurement technique that records electrical activity in the brain through electrodes placed on the scalp.

EEG is used to:

1. Diagnose and monitor neurological disorders (e.g., epilepsy, seizures)
2. Study brain function and activity
3. Investigate sleep patterns and disorders
4. Develop brain-computer interfaces (BCIs)EEG measures electrical signals produced by brain activity, providing insights into brain function and behavior.

FNIRS :-

Functional Near-Infrared Spectroscopy (fNIRS) is a non-invasive brain imaging technique that measures changes in blood oxygenation levels in the brain.

It uses near-infrared light to detect:

1. Oxygenated hemoglobin (HbO)
2. Deoxygenated hemoglobin (HbR)

fNIRS is used to:

1. Study brain activity and function
2. Monitor cognitive processes (e.g., attention, memory)
3. Investigate neurological disorders (e.g., stroke, Alzheimer's)
4. Develop brain-computer interfaces (BCIs)fNIRS offers advantages like portability, low cost, and minimal setup compared to other neuroimaging methods.

Multimodal fusion:

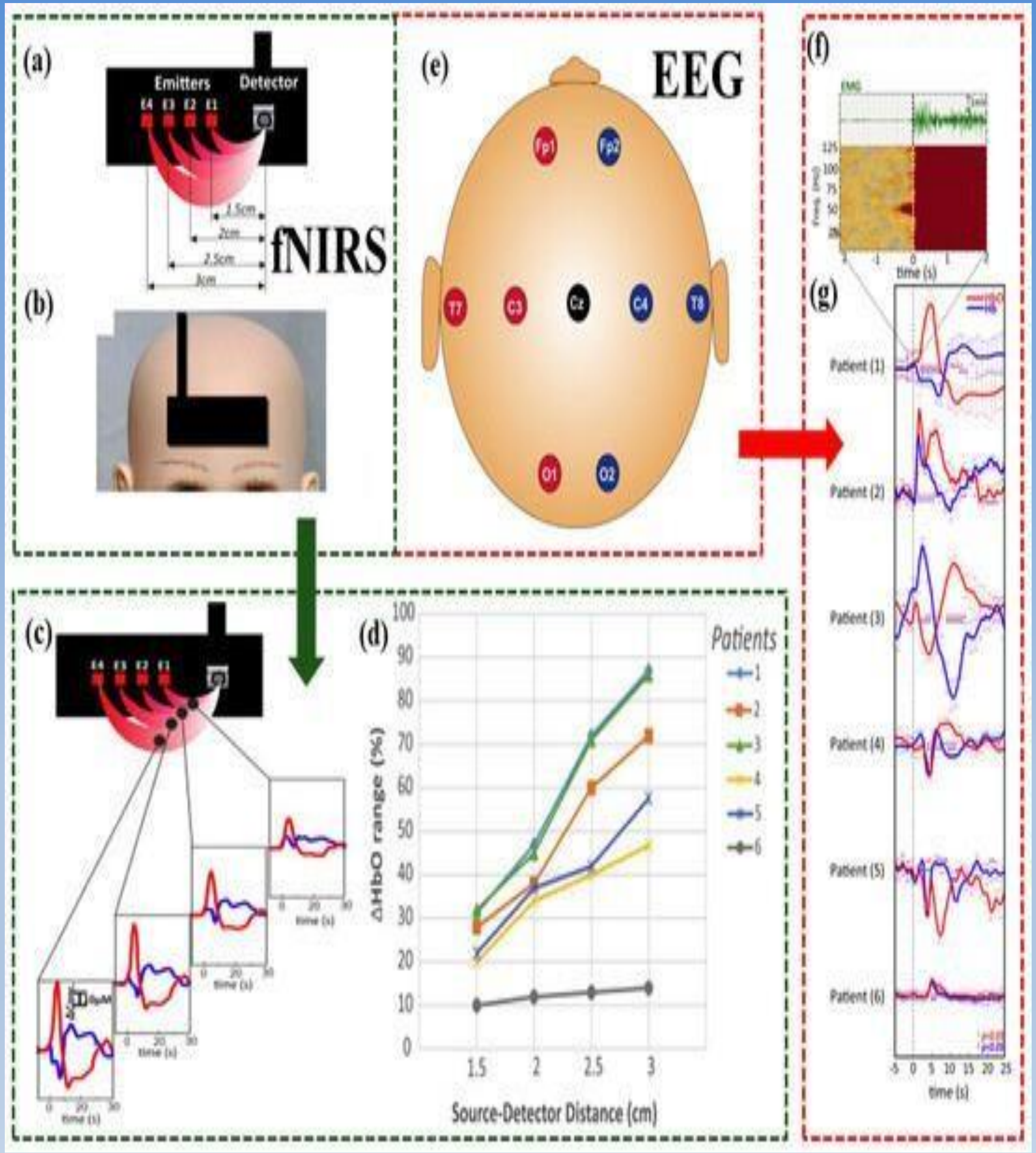
Combining data from multiple sources or modalities to improve accuracy, robustness, or user experience.

Examples of multimodal systems include:

1. Voice assistants with visual feedback
2. Gesture-based interfaces with audio feedback
3. BCIs that use EEG and eye-trackingMultimodal systems can enhance user experience, improve accessibility, and increase interaction flexibility.

MULTI MODAL INTEGRATION :-

Multimodal refers to the use of multiple modes or channels of communication, interaction, or data representation. In the context of brain-computer interfaces (BCIs) or human-computer interaction.



LITERATURE SURVEY:

S.N0	AUTHORS AND YEAR OF PUBLICATION	Title	Methodology used	Merits and Demerits
1.	Buccino, A. P., Keles, H. O., Omurtag, A., Bleichner, M., Benedictus, M., and Orellana, C. (2016).	Hybrid EEG-fNIRS asynchronous brain- computer interface for multiple motor tasks	Unlike synchronous BCIs that require predefined triggers, this system **operates continuously** without external cues.	**Merits:** Allows continuous monitoring, making it more **natural and user- friendly** for real-world applications. **Demerits:** Delayed response due to **slow hemodynamic changes** compared to EEG signals.
2.	Khan, M. J., Hong, M. J., and Hong, K.-S. (2014)	Decoding of four movement directions using hybrid NIRS-EEG brain-computer interface	EEG detects electrical brain activity. NIRS measures **hemodynami c responses** (blood flow changes).	**Merits:**Useful for **motor rehabilitation** and **prosthetic control.** **Demerits:**Requires **complex signal processing** and **data synchronization** between EEG & NIRS.

LITERATURE SURVEY:

S.NO	AUTHORS AND YEAR OF PUBLICATION	TITLE	Methodology Used	Merits and Demerits
3.	Ahn, M., and Jun, S. C. (2015).	Performance variation in motor imagery brain computer interface	This review synthesizes findings from various studies to identify factors contributing to performance variability in MI-BCIs.	**Merits:** The review consolidates diverse factors affecting MI-BCI performance, offering a holistic understanding of performance variability. **Demerits:** the review does not extensively evaluate the effectiveness of interventions aimed at reducing performance variability.
4.	Buxton, R. B., Uludaˇg, K., Dubowitz, D. J., and Liu, T. T. (2004).	Modeling the hemodynamic response to brain activation	➢ BOLD Signal Modeling ➢ Neurovascular Coupling ➢ Neural Response Nonlinearity	**Merits:** The study successfully combined various modeling approaches to provide a unified framework for understanding the hemodynamic response to neural activation. **Demerits:** certain aspects of the proposed models were speculative experiment.

TYPES OF MULTI MODEL INTEGRATION :-

- MI+MI:

  - **Imagining multiple motor tasks**
  - It can involve **multiple different imagined movements** either **at the same time** or **one after another** for complex control in Brain-Computer Interface (BCI) systems.

- MOTOR IMAGINARY+COGNITIVE:

  - **Motor Imagery (MI):** Imagining a movement (like moving the right hand, left hand, feet, etc.).
  - **Cognitive Task:** Thinking-related activities (like solving math problems, imagining music, counting, focusing on a word).

TYPES OF MULTI MODEL INTEGRATION :-

COGNITIVE+COGNITIVE :

Cognitive + Cognitive means that in a Brain-Computer Interface (BCI) system, **two or more different cognitive tasks** are used — **without any motor imagery** involved.

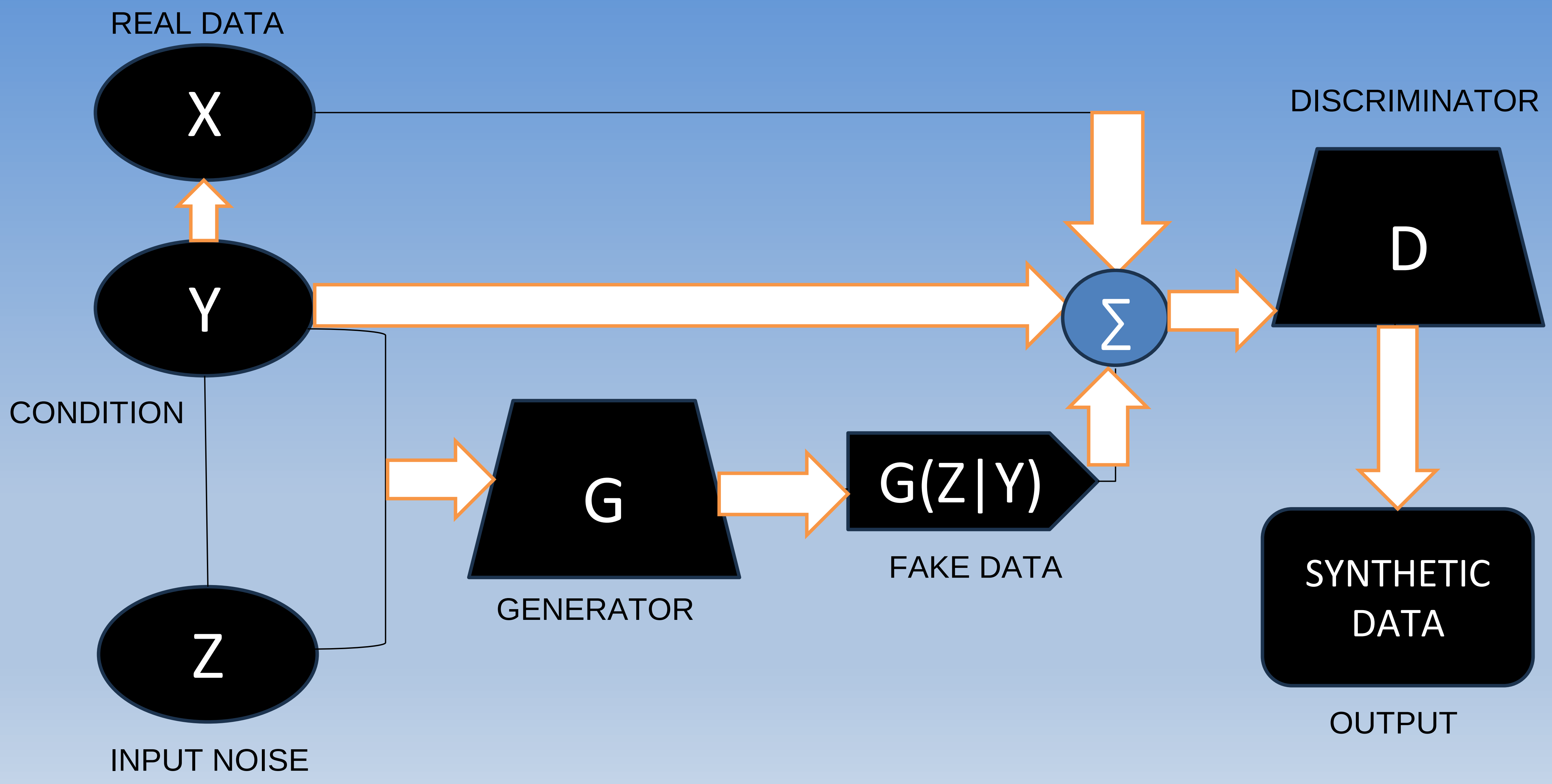
Here, the user **only uses mental activities related to thinking, memory, calculation, visualization, attention**, etc.

Different cognitive tasks produce **different patterns** of brain activity, which can be recognized by AI models.

DATA AUGMENTATION USING CGAN :-

A Conditional Generative Adversarial Network (cGAN) is an extension of the traditional GAN (Generative Adversarial Network), where both the generator and discriminator receive additional information (a condition), such as class labels or data attributes, to generate more controlled and realistic data.

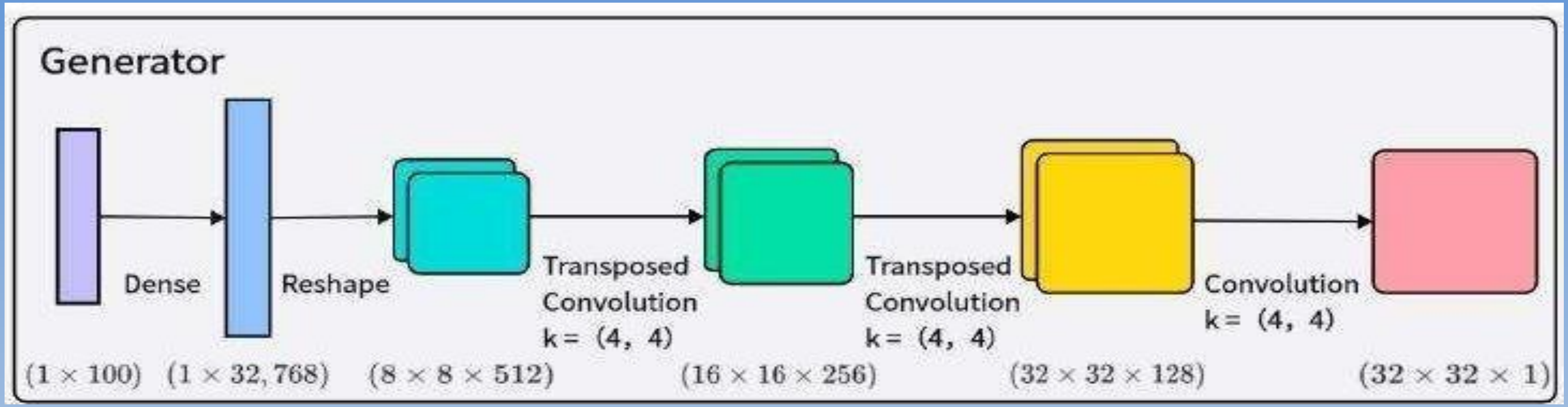
ARCHITECTURE OF CGAN :-

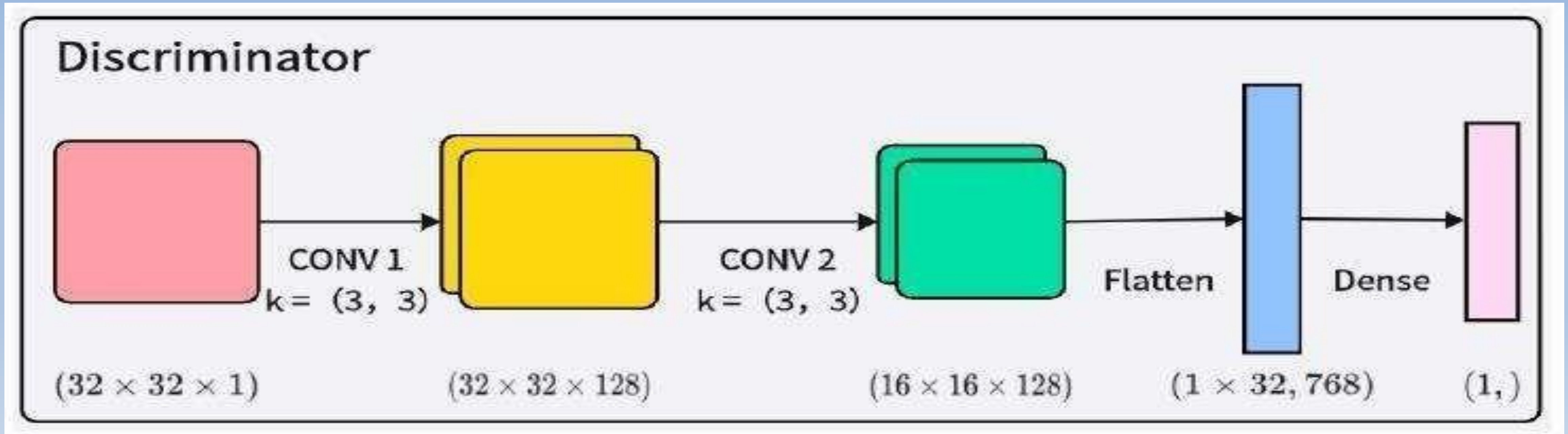


CGAN PROCESS:-

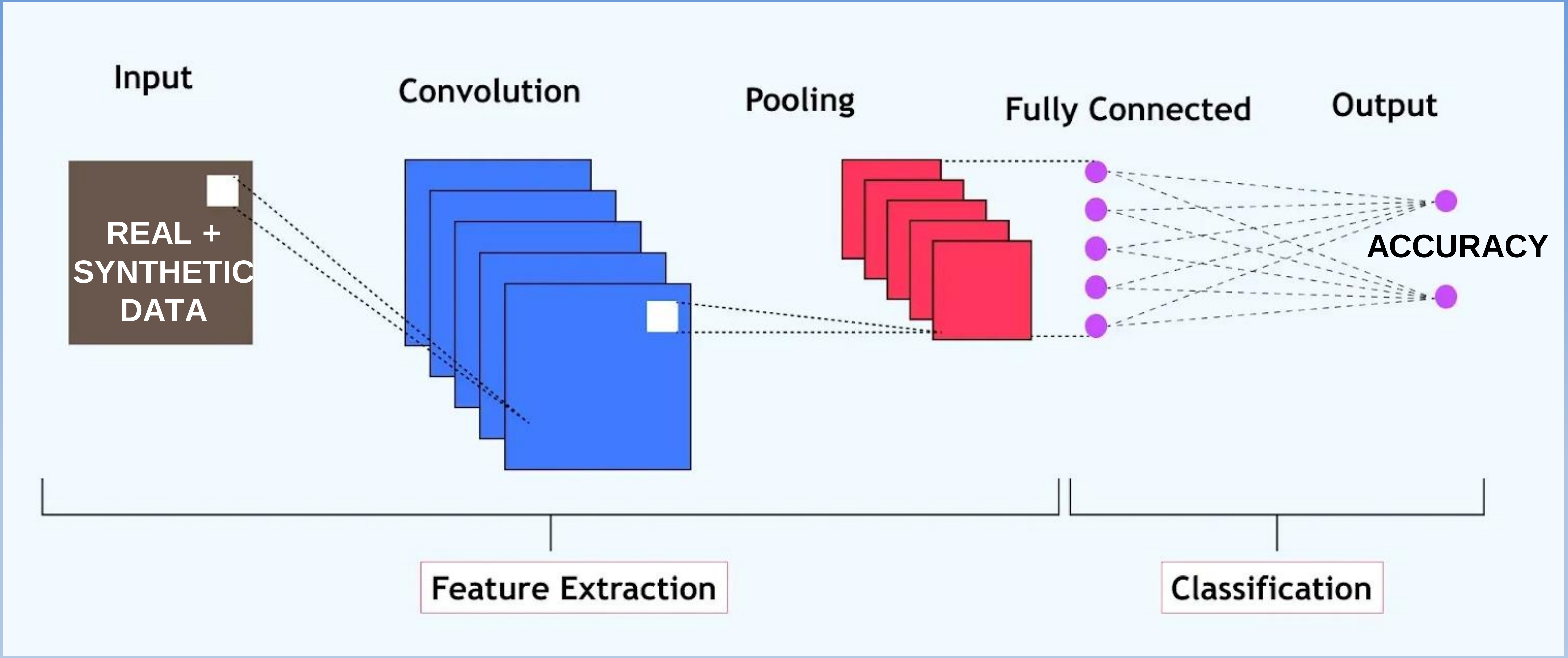
- **Real Data (x)**: This is actual data sampled from the true dataset.
- **Conditioning Information (y)**: This is extra data e.g., labels or additional context that controls what the generator creates.ex: left hand,right hand.
- **Conditioning Information (y) for discriminator**: The same extra information (**y**) that was given to the generator.
- **Random Noise (z)**: This is a vector of random values that provides variety to the generated data.

DATA AUGMENTATION USING CGAN :-

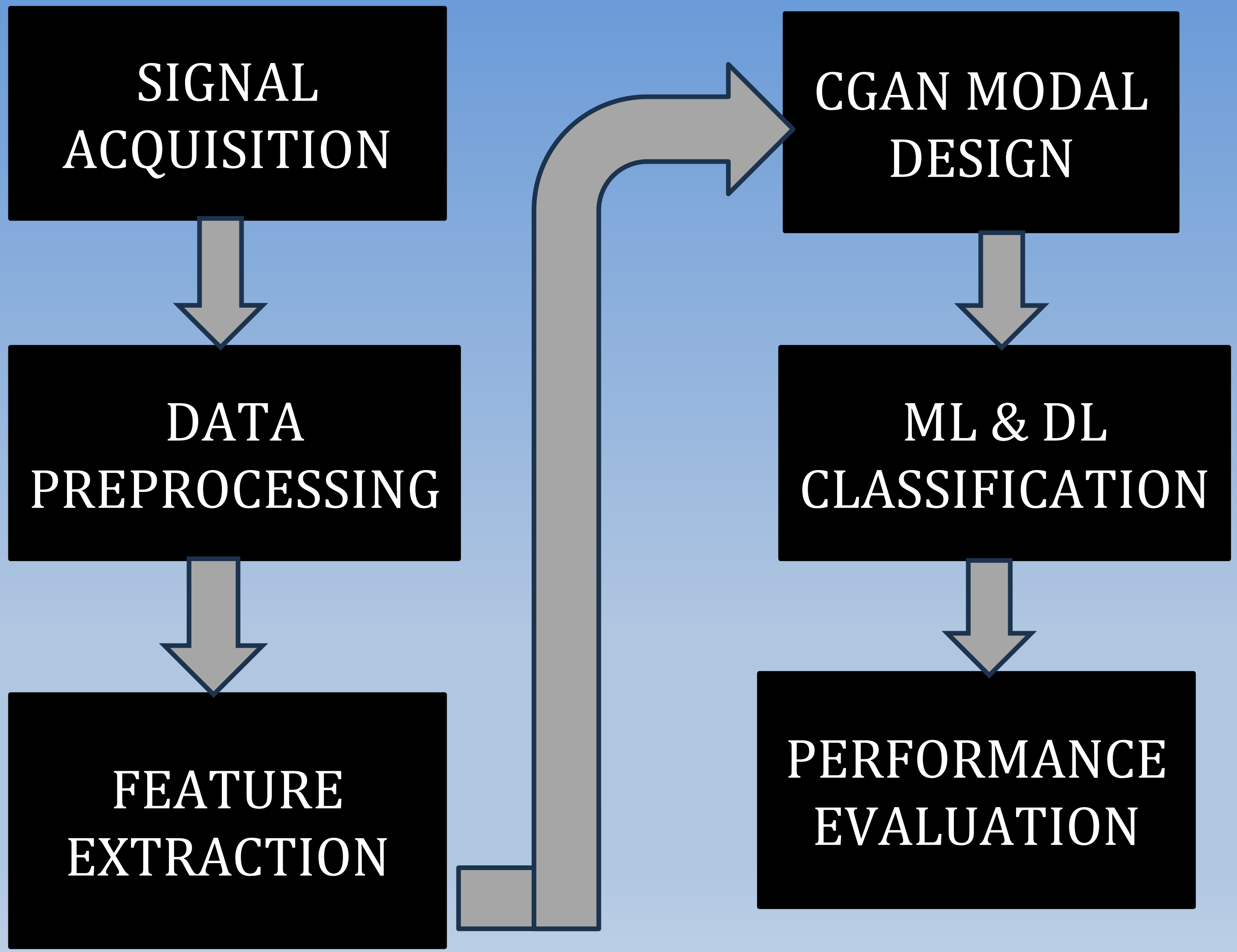




ARCHITECTURE OF CNN :-



BLOCK DIAGRAM OF THE PROCESS :-



DATASET :-

MI – EEG & MI – FNIRS

https://www.sicotj.org/articles/sicotj/full_html/2021/01/sicotj210087/sicotj210087.html

MI – EEG & COGNITIVE – FNIRS

https://www.kaggle.com/datasets/thngdngvn/bci-competition-iv-data-sets-2a

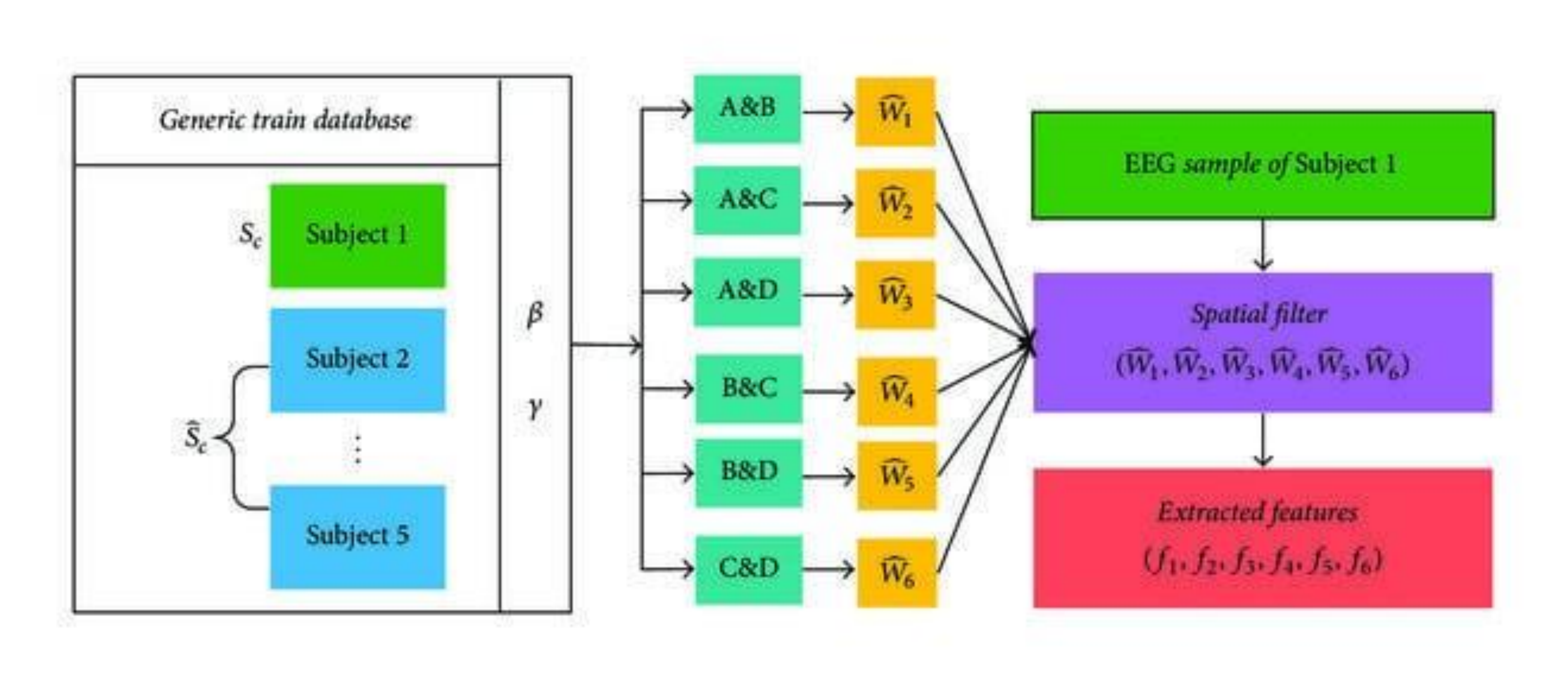
COGNITIVE – EEG & COGNITIVE – FNIRS

https://pubmed.ncbi.nlm.nih.gov/38533112/

Data Preprocessing :-

- EEG Processing :-
  - Bandpass Filtering :
    - Removes unwanted noise (e.g., muscle artifacts, power-line interference).
- fNIRS Processing :
  - Baseline Normalization:
    - Ensures consistency in hemoglobin signals.

Feature Extraction :-



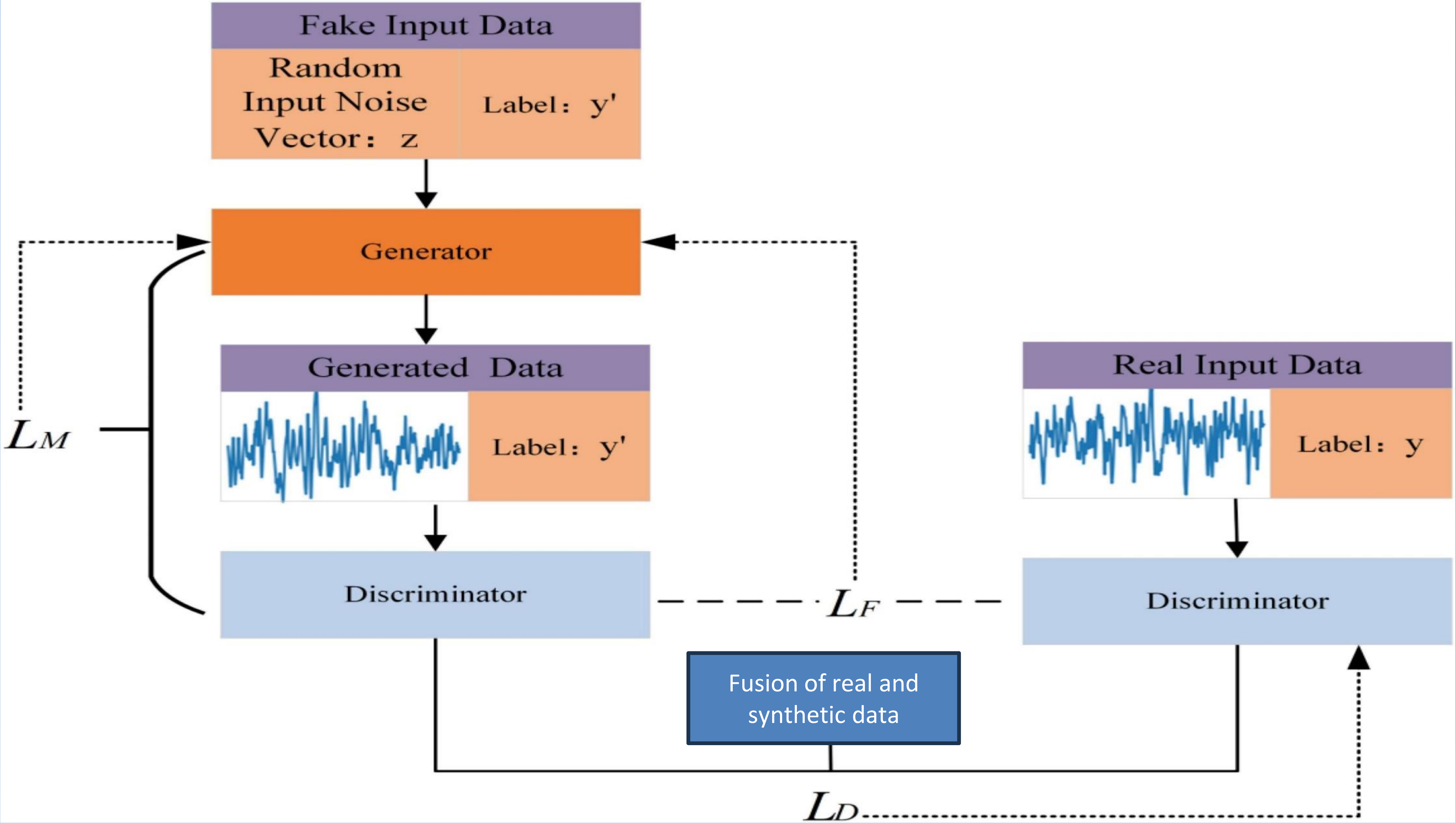
Feature Extraction :-

- EEG :
  - Common Spatial Patterns (CSP):
    - Improves discrimination of motor imagery classes.
  - Wavelet Transform:
    - Captures both time and frequency domain features.
- fNIRS:
  - Hemodynamic Response Features:
    - Extracts oxygenated (HbO) and deoxygenated hemoglobin (HbR) variations.

cGAN Model Design :-

- Traditional data augmentation (e.g., noise addition) is limited.
- cGAN generates realistic synthetic EEG-fNIRS data conditioned on class labels.
- Model Components :
  - Generator (G):
    - ✓ Takes a random noise vector + class label and outputs synthetic EEG-fNIRS signals.
  - Discriminator (D):
    - ✓ Differentiates between real and synthetic signals.

CGAN PROCESS :-



Model Training :-

- Training the cGan :
  - Optimize Generator so that it can fool the Discriminator .
  - Optimize Discriminator (D) to improve classification of real vs. fake data.
  - Loss Functions ensure both networks improve iteratively.

Synthetic Data Generation :-

- Generating EEG-fNIRS Data :
  - Use trained cGAN to generate new brain signals.
  - Conditioned on class labels (e.g., left-hand, right-hand movement).

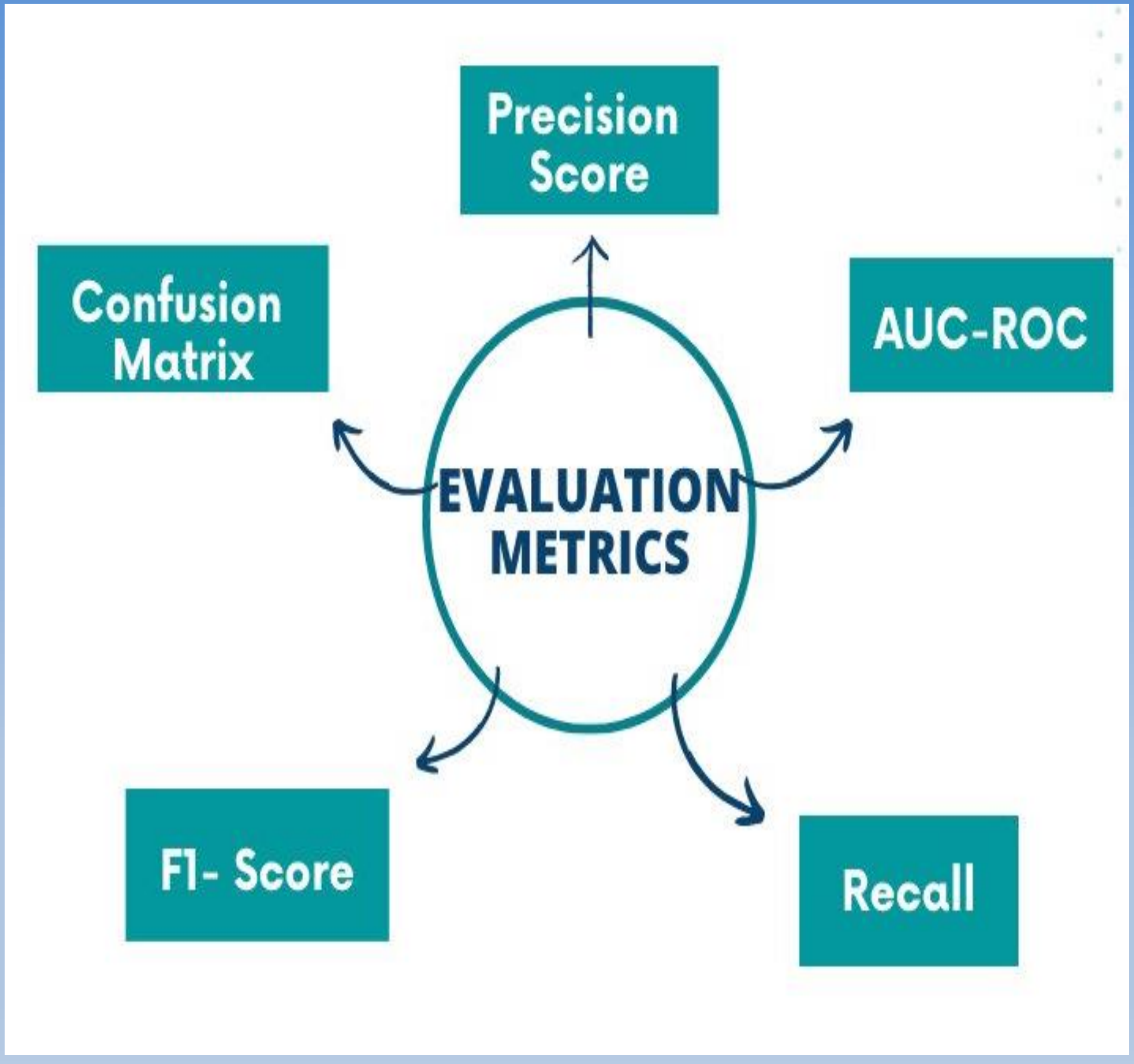
Deep Learning Classification :-

- Train deep learning models on real + synthetic data :
  - CNN (for spatial features).
- Compare performance :
  - Without synthetic data(baseline).
  - With cGAN-augmented data* (improved accuracy).

Performance Evaluation :-

- Accuracy Improvement :
  Synthetic data helps improve BCI classification by 5-10%.

- Statistical Similarity :
  t-SNE visualization shows real & synthetic data cluster together, confirming realism.



Classification Metrics:

1. Accuracy: Accuracy = (TP + TN) / (TP + TN + FP + FN)

2. Precision: Precision = TP / (TP + FP)

3. Recall: Recall = TP / (TP + FN)

4. F1-Score: F1-Score = 2 * (Precision * Recall) / (Precision + Recall)

Multi-Class Classification Metrics:

1. Confusion Matrix: A table used to evaluate the performance of a classification model.

2. Classification Accuracy: Accuracy = (∑ diagonal elements of confusion matrix) / (∑ all elements of confusion matrix)

Conclusion :-

- Findings :

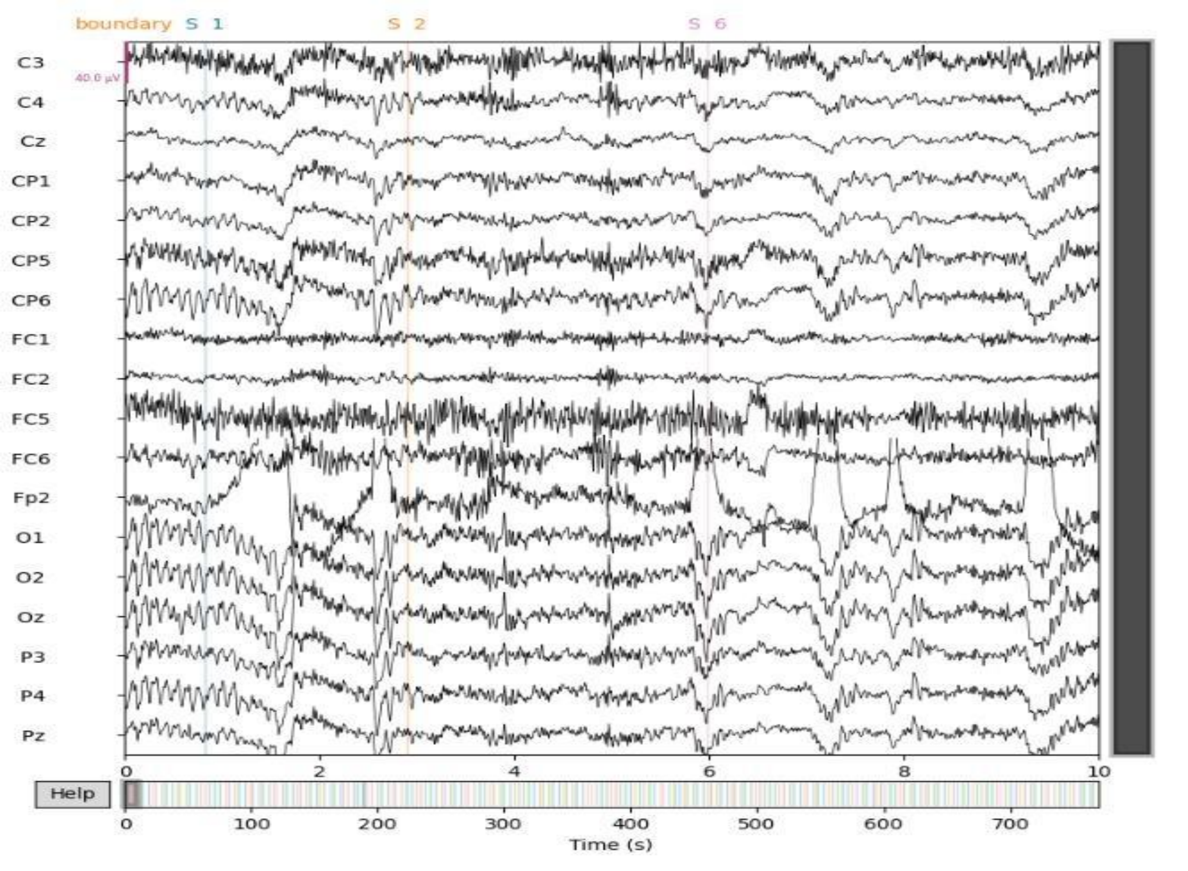
Deep learning models (CNN) trained with synthetic data showed higher accuracy than models trained only on real data.Accuracy gain: 5-10% improvement after augmenting using CGAN training data with synthetic EEG-fNIRS signals.Hybrid EEG-fNIRS models outperformed EEG-only models, proving the advantage of using multi-modal data.Model Without Augmentation with cGAN AugmentationCNN (EEG-only)75%

MI – EEG & MI – FNIRS :-

```
ch_names: C3 , C4 , Cz , CP1 , CP2 , CP5 , CP6 , FC1 , FC2 , FC5 , FC6 , ...
chs: 18 EEG
custom_ref_applied: False
dig: 18 items (18 EEG)
highpass: 0.0 Hz
lowpass: 250.0 Hz
meas_date: unspecified
nchan: 18
projs: []
sfreq: 500.0 Hz
>
Filtering raw data in 1 contiguous segment
Setting up band-pass filter from 1 - 40 Hz

FIR filter parameters
---------------------
Designing a one-pass, zero-phase, non-causal bandpass filter:
- Windowed time-domain design (firwin) method
- Hamming window with 0.0194 passband ripple and 53 dB stopband attenuation
- Lower passband edge: 1.00
- Lower transition bandwidth: 1.00 Hz (-6 dB cutoff frequency: 0.50 Hz)
- Upper passband edge: 40.00 Hz
- Upper transition bandwidth: 10.00 Hz (-6 dB cutoff frequency: 45.00 Hz)
- Filter length: 1651 samples (3.302 s)

Using matplotlib as 2D backend.
[Parallel(n_jobs=1)]: Done  17 tasks      | elapsed:    1.0s
```




```
eeg_features shape: (160, 18, 1001)
eeg_Labels shape: (160,)
```

OUTPUT :-

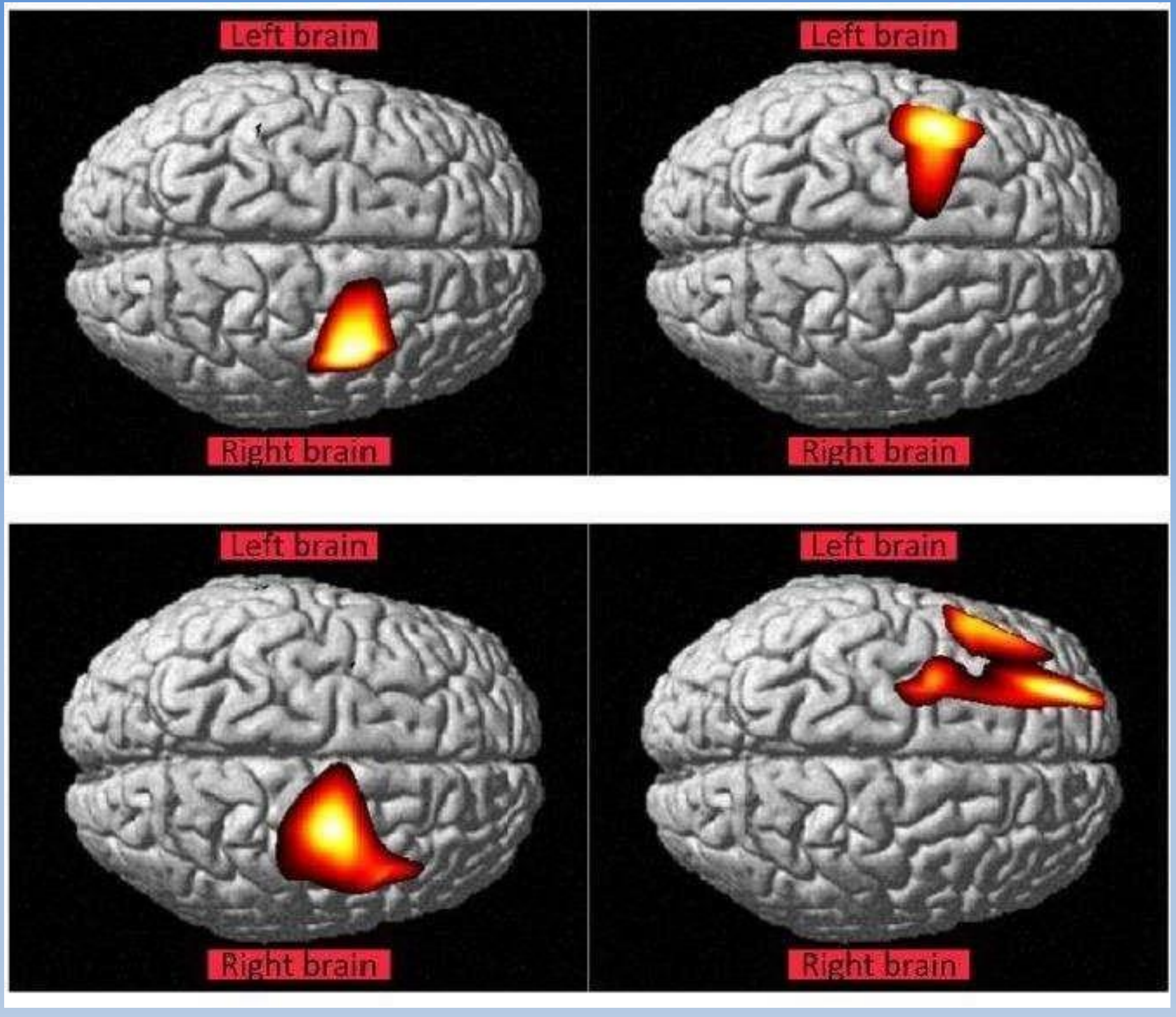
	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
rf	Random Forest Classifier	0.8026	0.9094	0.8026	0.8285	0.7979	0.7368	0.7470	2.5280
ridge	Ridge Classifier	0.6838	0.0000	0.6838	0.6831	0.6673	0.5782	0.5859	1.7900
lr	Logistic Regression	0.6776	0.0000	0.6776	0.6831	0.6635	0.5699	0.5784	2.9850
svm	SVM - Linear Kernel	0.6088	0.0000	0.6088	0.6080	0.5971	0.4787	0.4846	2.0640
nb	Naive Bayes	0.4919	0.7384	0.4919	0.4939	0.4679	0.3235	0.3361	1.8080
dt	Decision Tree Classifier	0.4724	0.6487	0.4724	0.4873	0.4571	0.2967	0.3060	2.5960
knn	K Neighbors Classifier	0.4173	0.6764	0.4173	0.4271	0.3831	0.2232	0.2391	1.9750

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 87ms/step - accuracy: 0.8239 - loss: 1.1418
20/20 ━━━━━━━━━━━━━━━━━━━━ 2s 90ms/step - accuracy: 1.0000 - loss: 0.0029
```

- CNN Test Accuracy using the raw data: 0.8342
- CNN Train Accuracy using the raw data: 1.0000

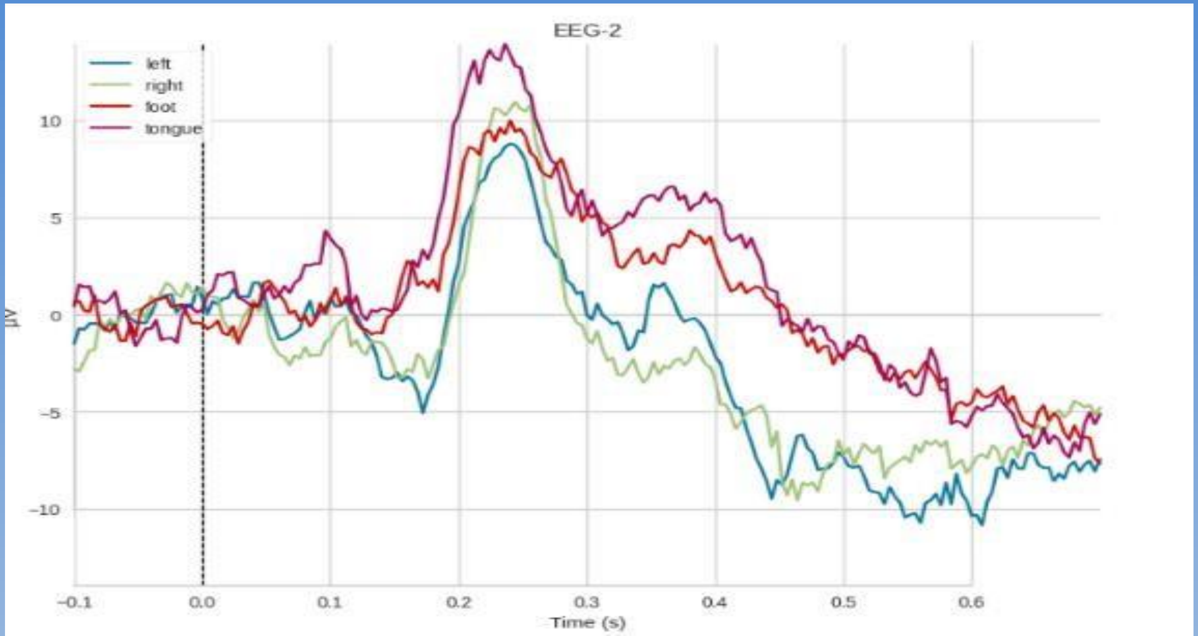
MI – EEG & COGNITIVE– FNIRS :-

	Description	Value
0	Session id	5311
1	Target	target
2	Target type	Multiclass
3	Target mapping	7: 0, 8: 1, 9: 2, 10: 3
4	Original data shape	(230, 12530)
5	Transformed data shape	(230, 12530)
6	Transformed train set shape	(161, 12530)
7	Transformed test set shape	(69, 12530)
8	Numeric features	12529
9	Preprocess	True
10	Imputation type	simple
11	Numeric imputation	mean
12	Categorical imputation	mode
13	Fold Generator	StratifiedKFold
14	Fold Number	10
15	CPU Jobs	-1
16	Use GPU	False
17	Log Experiment	False
18	Experiment Name	clf-default-name
19	USI	4e34



MI – EEG & COGNITIVE– FNIRS :-

```
fNIRS signals shape: (2726, 156)
Labels shape: (12,)
```

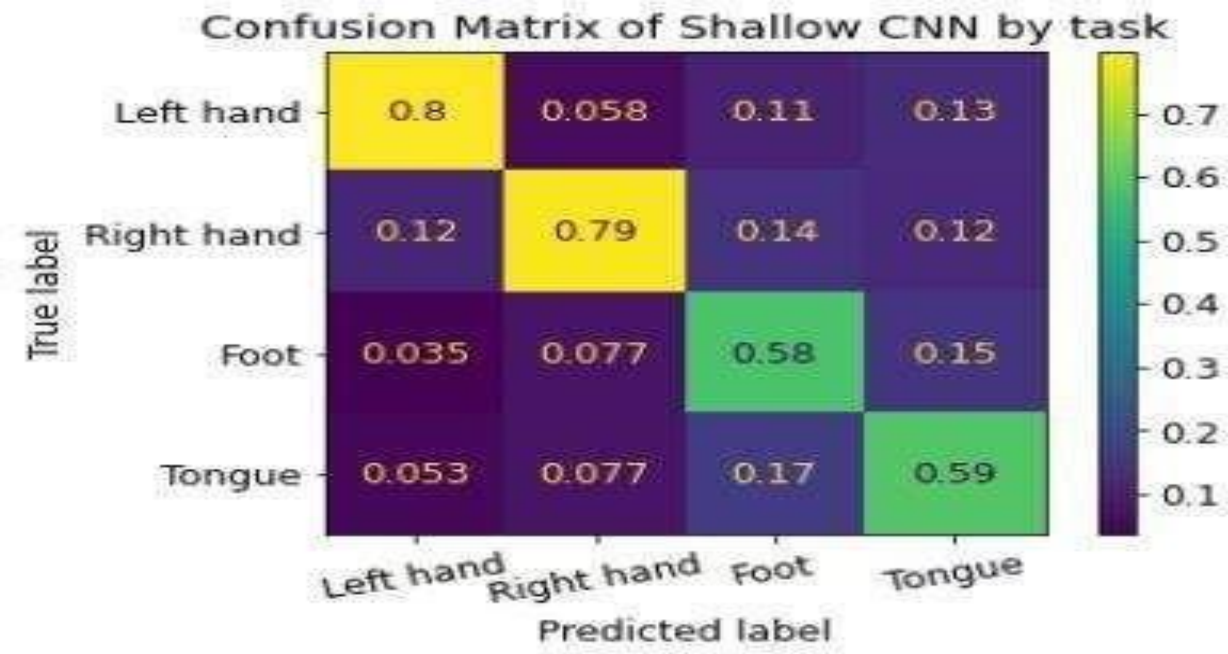



```
Extracting EDF parameters from /content/data/A05T.gdf...
GDF file detected
Setting channel info structure...
Could not determine channel type of the following channels, they will be set as EEG:
EEG-Fz, EEG, EEG, EEG, EEG, EEG, EEG, EEG-C3, EEG, EEG-Cz, EEG, EEG-C4, EEG, EEG, EEG, EEG, EEG, EEG, EEG, EEG-Pz, EEG, EEG, EOG-left, EOG-central, EOG-right
Creating raw.info structure...
Reading 0 ... 686119  =      0.000 ...  2744.476 secs...
Used Annotations descriptions: ['1023', '1072', '276', '277', '32766', '768', '769', '770', '771', '772']
Not setting metadata
288 matching events found
No baseline correction applied
0 projection items activated
Using data from preloaded Raw for 288 events and 501 original time points ...
0 bad epochs dropped
 eeg_features shape: (288, 25, 501)
eeg_Labels shape: (288,)
```

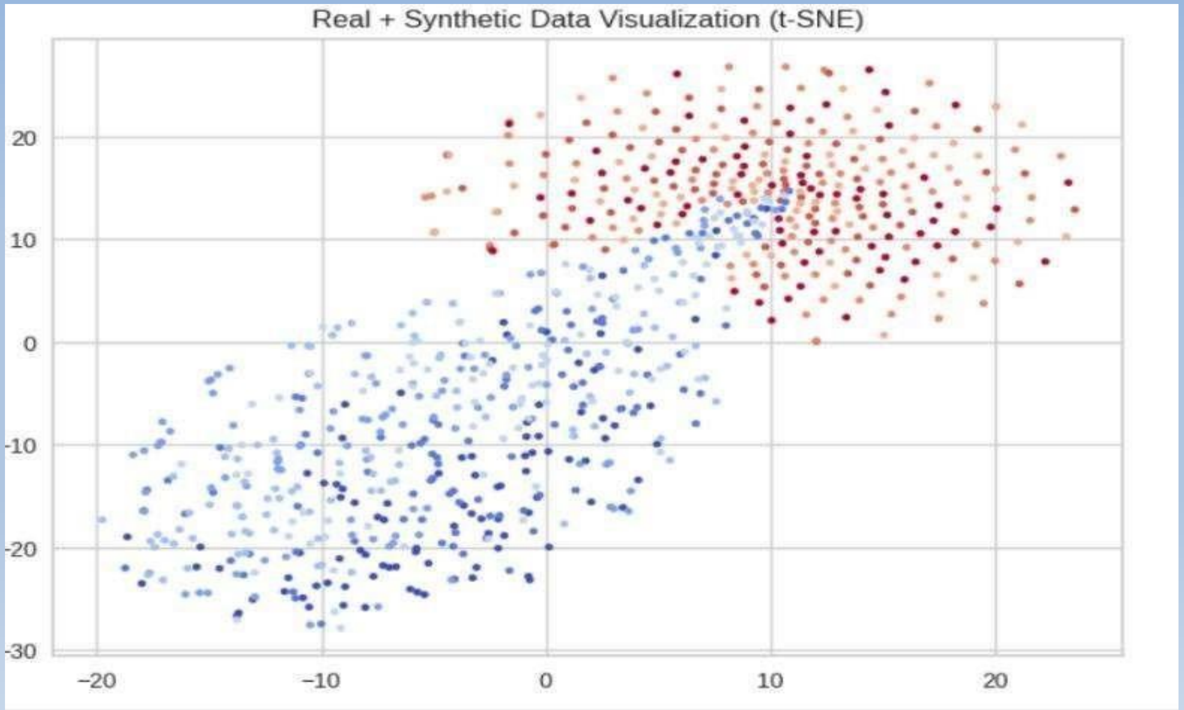
OUTPUT :-

```
5/5 ━━━━━━━━━━━━━━━━━━━━ 0s 87ms/step - accuracy: 0.7239 - loss: 1.1418
20/20 ━━━━━━━━━━━━━━━━━━━━ 2s 90ms/step - accuracy: 1.0000 - loss: 0.0029
```

- CNN Test Accuracy using the raw data: 0.7342
- CNN Train Accuracy using the raw data: 1.0000

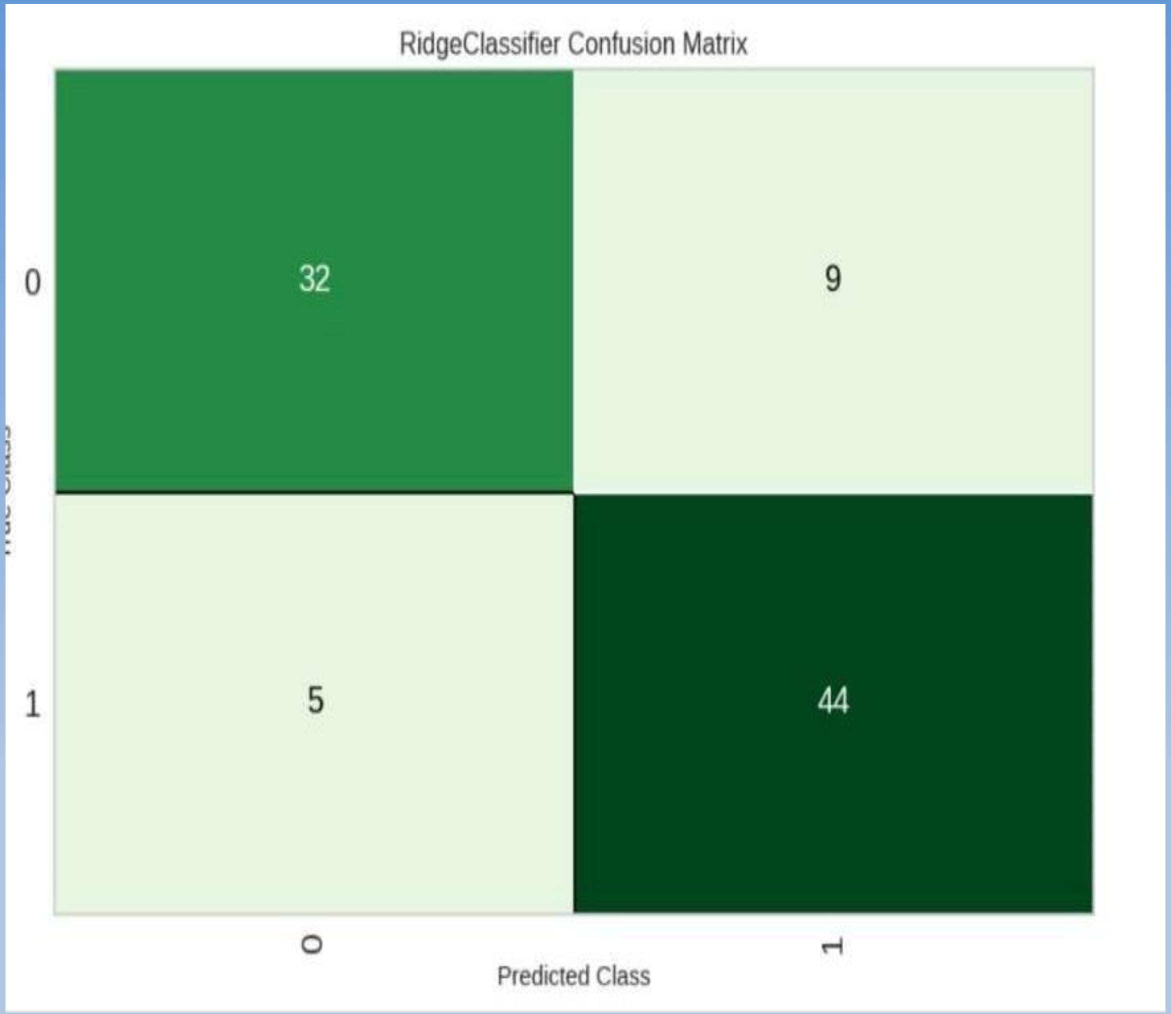


	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
rf	Random Forest Classifier	0.7460	0.9224	0.7460	0.7709	0.7353	0.6613	0.6740	2.5250
ridge	Ridge Classifier	0.6474	0.0000	0.6474	0.6769	0.6364	0.5285	0.5423	2.8140
lr	Logistic Regression	0.6404	0.0000	0.6404	0.6650	0.6312	0.5195	0.5300	5.2390
svm	SVM - Linear Kernel	0.6279	0.0000	0.6279	0.6722	0.6163	0.5031	0.5154	3.5420
dt	Decision Tree Classifier	0.5287	0.6849	0.5287	0.5158	0.5061	0.3702	0.3802	4.8410
knn	K Neighbors Classifier	0.4857	0.7076	0.4857	0.5276	0.4760	0.3130	0.3243	2.8870
nb	Naive Bayes	0.4732	0.6965	0.4732	0.4896	0.4320	0.2985	0.3236	1.8970



COGNITIVE – EEG & COGNITIVE – FNIRS :-

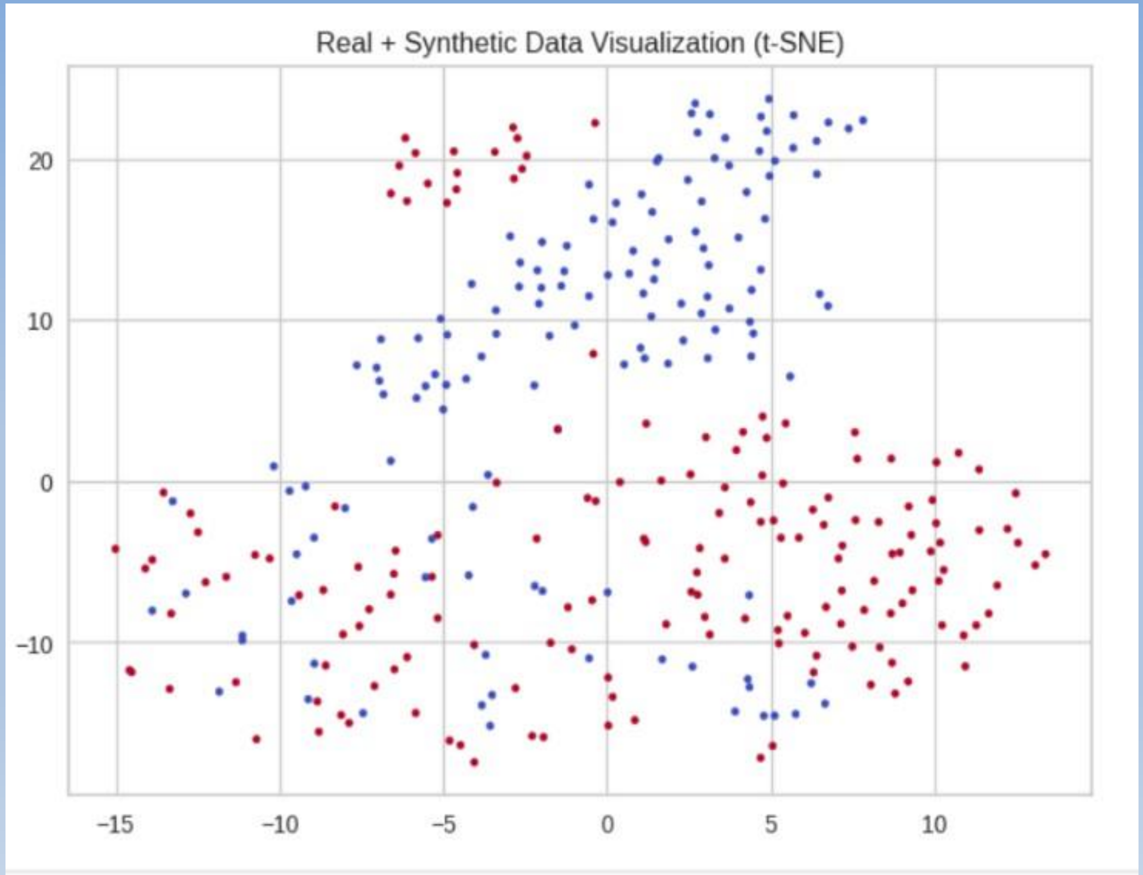
	Description	Value
0	Session id	5967
1	Target	target
2	Target type	Binary
3	Original data shape	(100, 16)
4	Transformed data shape	(100, 16)
5	Transformed train set shape	(70, 16)
6	Transformed test set shape	(30, 16)
7	Numeric features	15
8	Preprocess	True
9	Imputation type	simple
10	Numeric imputation	mean
11	Categorical imputation	mode
12	Fold Generator	StratifiedKFold
13	Fold Number	10
14	CPU Jobs	-1
15	Use GPU	False
16	Log Experiment	False
17	Experiment Name	clf-default-name
18	USI	3ead



OUTPUT :-

```
2/2 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step - accuracy: 0.8569 - loss: 0.5201
8/8 ━━━━━━━━━━━━━━━━━━━━ 0s 5ms/step - accuracy: 1.0000 - loss: 0.0136
🔹 CNN Test Accuracy using the raw data: 0.8167
🔹 CNN Train Accuracy using the raw data: 1.0000
```

	Model	Accuracy	AUC	Recall	Prec.	F1	Kappa	MCC	TT (Sec)
ridge	Ridge Classifier	0.8952	0.8783	0.9030	0.9117	0.9026	0.7879	0.7963	0.0820
lda	Linear Discriminant Analysis	0.8952	0.8783	0.9030	0.9117	0.9026	0.7879	0.7963	0.0260
lr	Logistic Regression	0.8810	0.8783	0.8939	0.8986	0.8892	0.7591	0.7719	0.6240
rf	Random Forest Classifier	0.8762	0.9459	0.9136	0.8708	0.8885	0.7495	0.7582	0.1860
knn	K Neighbors Classifier	0.8714	0.9433	0.9045	0.8687	0.8839	0.7402	0.7462	0.0400
et	Extra Trees Classifier	0.8619	0.9528	0.9212	0.8457	0.8785	0.7190	0.7314	0.1460
lightgbm	Light Gradient Boosting Machine	0.8333	0.9222	0.8523	0.8441	0.8424	0.6661	0.6755	0.2520
svm	SVM - Linear Kernel	0.8238	0.8592	0.8227	0.8530	0.8276	0.6457	0.6609	0.0780
xgboost	Extreme Gradient Boosting	0.8190	0.9093	0.8417	0.8293	0.8322	0.6347	0.6401	0.1050
ada	Ada Boost Classifier	0.8143	0.8298	0.8242	0.8406	0.8281	0.6247	0.6316	0.1100
gbc	Gradient Boosting Classifier	0.8095	0.9094	0.8083	0.8370	0.8194	0.6187	0.6240	0.1710
qda	Quadratic Discriminant Analysis	0.8000	0.8592	0.7977	0.8274	0.8077	0.5986	0.6077	0.0250
nb	Naive Bayes	0.7952	0.8179	0.8326	0.8032	0.8146	0.5854	0.5927	0.1070
dt	Decision Tree Classifier	0.7905	0.7893	0.7909	0.8285	0.8031	0.5778	0.5891	0.0840
dummy	Dummy Classifier	0.5429	0.5000	1.0000	0.5429	0.7034	0.0000	0.0000	0.0230



RESULT:-

Robustness Against Data Limitations :-

- GAN-augmented training sets mitigated the problem of limited BCI training data.Reduced overfitting in deep learning models due to increased data diversity.Models generalized better across subjects, handling inter-subject variability more effectively.

Potential for Real-Time BCI Systems :-

- The project demonstrated that cGAN-generated data can be used in real-time BCI applications.Future scope includes:
- Subject-specific cGANs → Personalizing augmentation for individual users.
- Adaptive BCI training → Continuous learning to adapt to user-specific brain activity changes.

RESULT :-

TYPES OF INTEGRATION	CNN ACCRURACY WITHOUT AUGMENTATION	CNN ACCRURACY WITH AUGMENTATION (CGAN MODAL)
MI-EEG & MI-fNIRS	60%	84%
MI-EEG & COGNITIVE-fNIRS	56%	73%
COGNITIVE-EEG & COGNITIVE-fNIRS	50%	81%

RESULT :-

TYPES OF INTEGRATION	BEST CLASSIFIERS (ML CLASSIFIERS)	ACCRURACY WITHOUT AUGMENTATION	ACCRURACY WITH AUGMENTATION (CGAN MODAL)
MI-EEG & MI-fNIRS	Random forest classifier	63%	80%
MI-EEG & COGNITIVE-fNIRS	KNN & Random forest classifier	50%	73%
COGNITIVE-EEG & COGNITIVE-fNIRS	Ridge classifier	72%	90%

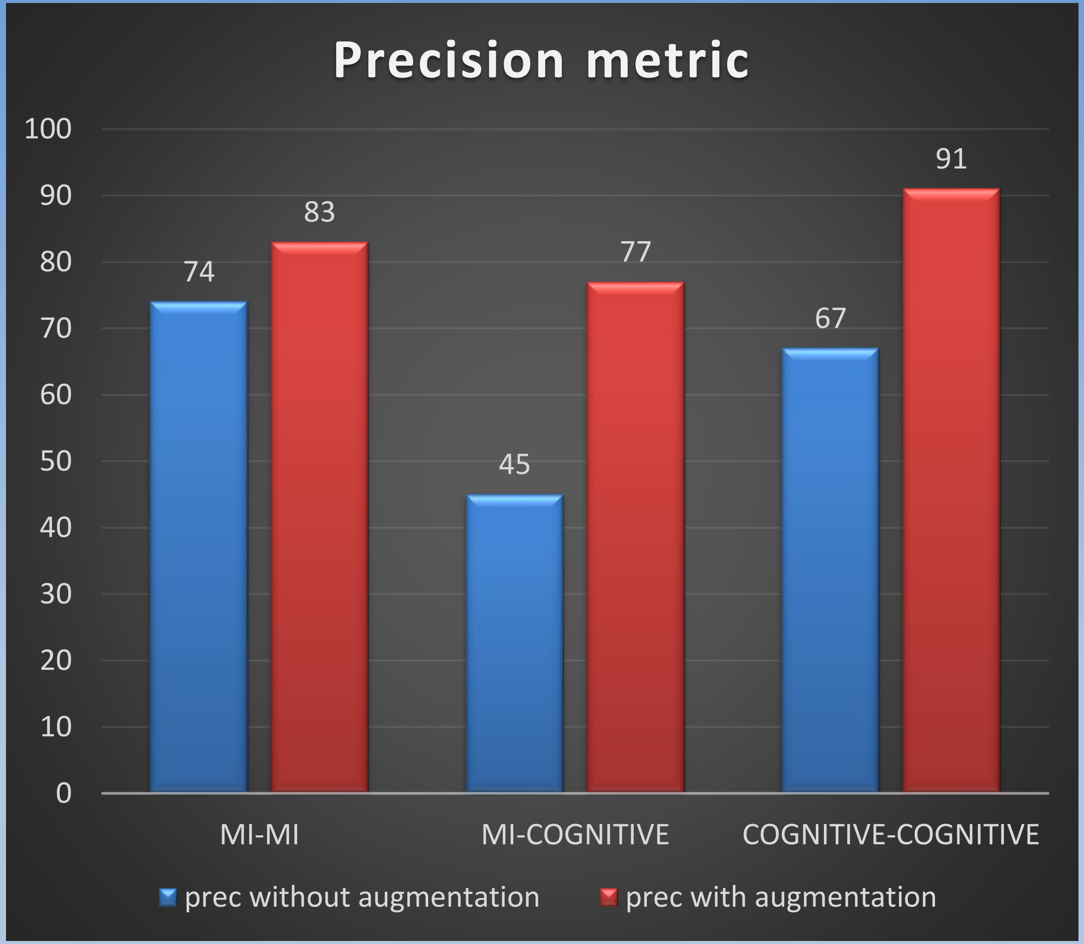
RESULT :-

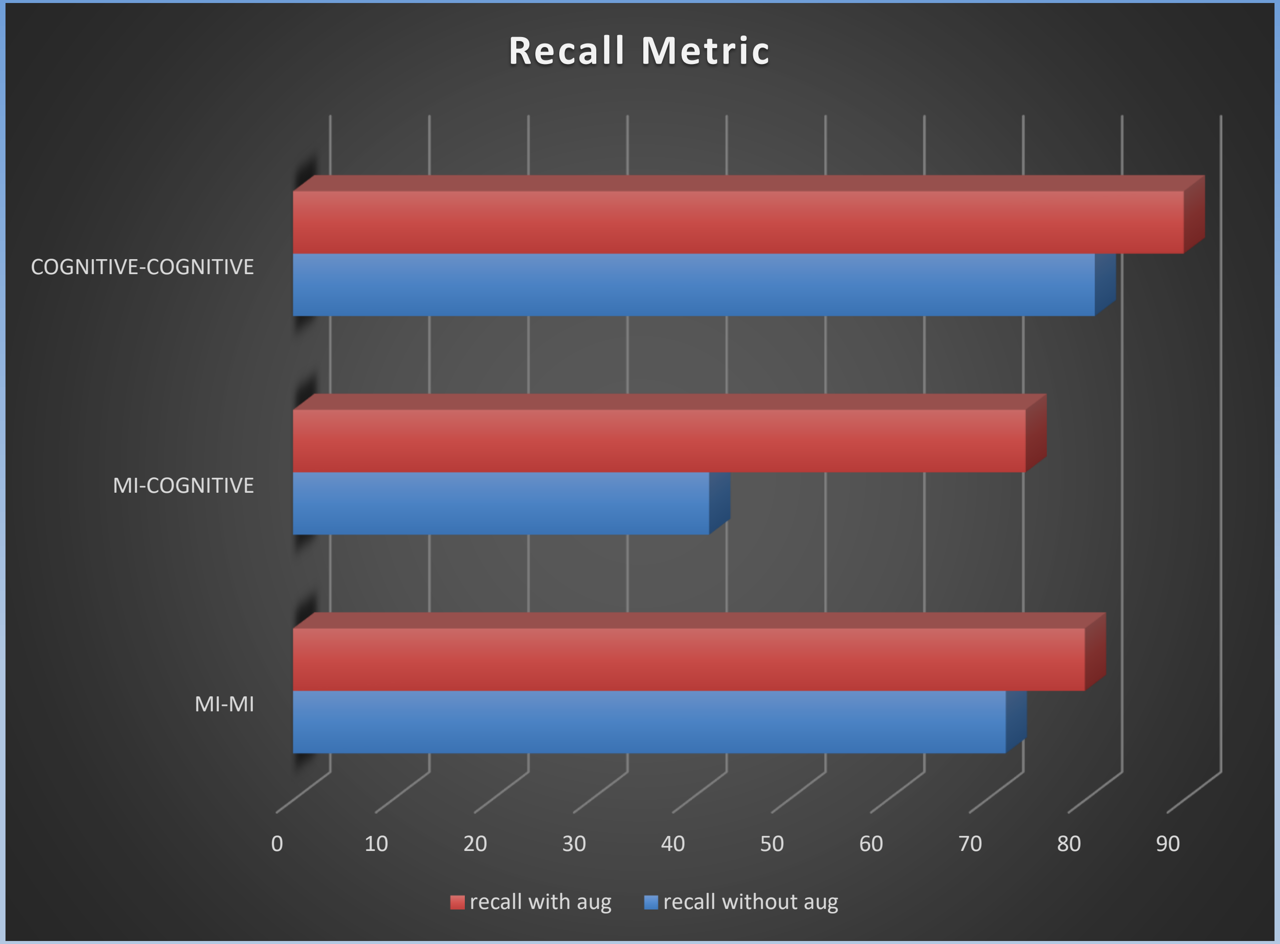
TYPES OF INTEGRATION	BEST CLASSIFIERS (ML CLASSIFIERS)	AUC WITHOUT AUGMENTATION	AUC WITH AUGMENTATION (CGAN MODAL)
MI-EEG & MI-fNIRS	Random forest classifier	80%	94%
MI-EEG & COGNITIVE-fNIRS	Random forest classifier	64%	92%
COGNITIVE-EEG & COGNITIVE-fNIRS	Random forest classifier & Extra tree classifier	65%	95%

RESULT:-

TYPES OF INTEGRATION	BEST CLASSIFIERS (ML CLASSIFIERS)	F1 SCORE WITHOUT AUGMENTATION	F1 SCORE WITH AUGMENTATION (CGAN MODAL)
MI-EEG & MI-fNIRS	Logistic regression & Random forest classifier	72%	79%
MI-EEG & COGNITIVE-fNIRS	KNN & Random forest classifier	41%	73%
COGNITIVE-EEG & COGNITIVE-fNIRS	Dummy classifier & Ridge classifier	76%	95%

OUTPUT :-


Precision metric
100
90
80
70
60
50
40
30
20
10
0
74
83
45
77
67
91
MI-MI
MI-COGNITIVE
COGNITIVE-COGNITIVE
prec without augmentation
prec with augmentation


Recall Metric
COGNITIVE-COGNITIVE
MI-COGNITIVE
MI-MI
0
10
20
30
40
50
60
70
80
90
recall with aug
recall without aug

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THANK YOU