Development of Frequency-Enhanced Neural Systems (FENS) and Spatially Coherent Frequency Neural Architectures (SCOFNA): Spatial Coherence and Learnable Frequency Analysis for Multi-Modal Signal Classification

Renz Aron Gorre, John King, Crispo Philip Marquez, Tom Oliver Presado*
STEM Department, De La Salle University, Manila, Philippines
**tom_presado@dlsu.edu.ph*

Abstract: In many machine learning applications, particularly those involving time series data, time domain analysis has often been a predominant approach for signal classification. However, a vital flaw within this set of approaches is their struggle to capture frequency-dominant cycles or periodic patterns in specific datasets. To address this limitation, the incorporation of frequency-domain analysis and spatial coherence into neural network architectures was evaluated. Building on prior research in the scope of signal classification, particularly with the integration of Fast Fourier Transform (FFT) and spatial coherence into neural network models, the researchers aim to propose two neural architecture models: Frequency-Enhanced Neural System (FENS) and Spatially Coherent Frequency Neural Architecture (SCOFNA), which utilize the capabilities of the Fast Fourier Transform (FFT) as an integrated function in the neural architecture while maintaining spatially coherent frequency-domain features through assigning attention weights to data inputs. Statistical analysis shows that these models, FENS and SCOFNA, outperform standard time-domain models by achieving a 10–15% relative gain in classification accuracy on synthetic electroencephalogram (EEG), electrocardiogram (ECG), and audio signal. This paper demonstrates how incorporating frequency and spatial information into deep learning can substantially improve pattern recognition while reducing computational complexity across various domains.

Key Words: Fourier-Enhanced; Neural Networks; Machine Learning; Pattern Recognition; Fast Fourier Transform; Multi-Domain Applications; Spatial Coherence

1. INTRODUCTION

Over the past decade, neural networks have innovated how machines can analyze and predict complex data inputs. However, these systems rely heavily on time-domain interpretation, analyzing how data points fluctuate over time without explicitly recognizing any underlying frequency patterns that may have influenced those changes. While effective in many cases, this time-domain basis presents a gap in how the model can interpret cyclical, periodic, or frequency-based signals, patterns that are essential in fields such as, but not limited to, auditory harmonics, climate-weather dynamics, or physiological rhythms (Goodfellow et al., 2016).

In contrast to time-domain analysis, signal processing tools like the Fourier Transform offer a powerful alternative by converting signals to their respective frequency-domain representation. By decomposing time-based signals into their constituent frequencies, tools like the Fast Fourier Transform (FFT) render it possible to analyze signal components that are relatively indiscernible in the raw time series

(Oppenheim, 2010). A foundational principle, the Convolution Theorem, further highlights the importance of the frequency domain, stating that convolution in the time domain corresponds to multiplication in the frequency domain. This insight is beneficial because it enables complex operations, such as filtering or pattern matching, to be extrapolated more efficiently in the frequency domain (Smith, 2007).

This paper introduces the Frequency-Enhanced Neural System (FENS) and Spatial Coherent Frequency Neural Architecture (SCOFNA) to leverage the benefits of frequency-domain analysis within neural networks. FENS and SCOFNA integrate FFT into neural architectures, allowing neural models to learn from temporal and spectral features by converting input data points into the frequency domain before neural network optimization. This representation significantly improves performance in tasks with prominent frequency-driven phenomena and can reduce computational complexity and enhance scalability, especially for multi-channel or high-resolution data (Smith, 2007; Yao et al., 2023).

Although existing dimensionality reduction techniques, such as Principal Component Analysis (PCA) or t-Distributed Stochastic Neighbor Embedding (t-SNE), are commonly used to address the issue of multi-dimensional data in machine learning, they often pose risks for time-series signals where both temporal dynamics and frequency components are critical (Goodfellow et al., 2016). Therefore, relying solely on projection strategies risks losing contextual relationships inherent in the original dimension and undermines the key frequency-based patterns essential for accurate analysis. To address this, FENS and SCOFNA integrate the FFT operation as a module within the neural architecture rather than using FFT as a fixed preprocessing procedure (Lee-Thorp et al., 2021). This approach leverages previous applications of FFT, helping to relieve structural loss of high-dimensional data (Yemets et al., 2025). SCOFNA further enhances this framework by incorporating a spatial coherence layer to retain spatial relationships after the FFT, a feature absent in FENS. This system enables the network to focus on the most relevant spectral features for the task while still considering their original spatial context (Chan, 2000).

2. MATERIALS

The encoded synthetic dataset generators are based on the following real-world datasets. For EEG, the basis for the dataset was the PhysioNet EEG Motor Movement/Imagery Dataset, which contains EEG recordings from 109 subjects performing diverse motor tasks. For ECG, the researchers based the dataset generator on the MIT-BIH Arrhythmia Database, which includes recordings of various cardiac arrhythmias and normal sinus rhythm. Lastly, the basis for the synthetic audio dataset generator is the UrbanSound8k dataset, which contains recordings of urban sounds from 10 classes (e.g., car horn, dog bark, street music).

3. METHODS

3.1 Experimental Design

With the deep learning features provided by the libraries mentioned in the Materials Section, three synthetic datasets were generated and used consistently across all experimental groups. Based on electroencephalogram (EEG), electrocardiogram (ECG), and auditory signals, these datasets were selected to evaluate model performance across diverse time-series data with prominent frequency-domain features. Notably, these datasets are synthetic imitations of real-world signals and do not originate from actual physiological or audio recordings. This approach was chosen to gain control over the models and avoid extraneous variables that might be present in real-world recordings. Notably, all three datasets were split into training (70%), validation (15%), and test (15%) sets. In the study, the performance of FENS, SCOFNA, and SNN was analyzed through training with the synthetic datasets. This experiment studied the models' performance metrics, including root mean square error (RMSE), mean absolute error (MAE), and classification accuracy, measured after machine training, with accuracy being the primary metric for statistical analysis and subjected to a comprehensive Analysis of Variance. The program follows as shown below:

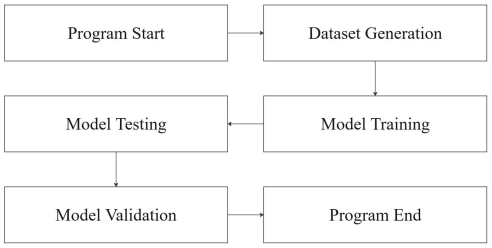

Fig. 1. Flowchart of the experimental design, illustrating the data processing and model training pipeline from dataset generation to performance evaluation.

3.2 Data Preprocessing and Sampling

The three synthetic datasets were generated using 1×10^3 samples, each consisting of 128 time steps with EEG and ECG having three channels, while audio has two.

Specifically, for each sample and channel, the EEG signal was created as:

$$\omega_{eeg}(t) = \sum_{i \in \{\alpha,\beta,\theta\}} A_i \sin(2\pi f_i t + \phi_i) + n_{eeg}(t) \quad (1)$$

In this equation, t represents the time step ($0 \leq t \leq 127$). The variable represents the alpha (α), beta (β), and theta (θ) waves. The amplitudes, A_i, are randomly chosen from a uniform distribution: $A_i \sim U(0.1, 0.5)$. The frequencies, f_i, are randomly selected from within the respective bands: $f_\alpha \sim U(8,12)$ Hz, $f_\beta \sim U(13,30)$ Hz, and $f_\theta \sim U(4,7)$ Hz. The phases, ϕ_i, are randomly chosen from a uniform distribution between 0 and 2π. The noise, $n(t)$, is additive white Gaussian noise with a standard deviation of 0.001.

To approximate these, a simplified ECG model was used:

$$\omega_{ecg}(t) = \sum_{i \in \{P,QRS,T\}} A_i exp\left(-\frac{(t-t_i)^2}{\sigma_i^2}\right) + n_{ecg}(t) + b_{ecg}(t) \quad (2)$$

In this equation, t represents the time step ($0 \leq t \leq 127$). The variable i represents the P-wave (P), QRS complex (QRS), and T-wave (T). The amplitudes, A_i, are randomly chosen from uniform distributions: $A_P \sim U(0.1, 0.3)$, $A_{QRS} \sim U(0.5, 1.5)$, $A_T \sim U(0.1, 0.4)$. The time positions of the peak of each wave, t_i, are randomly chosen within the time window. The variables σi control the width of each wave, randomly chosen within a small range. The noise, $n(t)$, is additive white Gaussian noise with a standard deviation of 0.05. The baseline wander, $b(t)$, is a slow, low-frequency oscillation simulated as a sinusoidal wave with a random frequency below 0.5 Hz and a random amplitude between 0.05 and 0.1.

Each audio channel's signal was generated as:

$$\omega_{aud}(t) = \sum_{i=1}^{2} A_i \sin(2\pi f_i t) + n_{aud}(t) \quad (3)$$

In this equation, t represents the time step ($0 \leq t \leq 127$). The variable i represents the two tones. The amplitudes, A_i, are randomly chosen from a uniform distribution: $A_i \sim U(0.2,0.8)$. The frequencies, f_i, are randomly chosen within the audible range (20 Hz to 20 kHz), but discretized to match the time step resolution. The noise, $n(t)$, is additive white Gaussian noise with a standard deviation of 0.1.

Missing values in the datasets were handled through imputation, using the mean value of each feature. These features were normalized to a range between 0 and 1 using min-max scaling to ensure that all input features were on a similar scale.

3.3 *Model Architectures*

FENS is designed to process data in the frequency domain using an MLP. The layers of the architecture are as follows: (1) FFT Layer, (2) Flatten Layer, and (3) MLP. It calculates the magnitude and phase of the frequency components. The second layer flattens the output of the FFT layer into a

one-dimensional (1D) vector. Lastly, the inputs undergo the MLP. This section comprises two fully connected layers, batch normalization, ReLU activation after the first layer, and a dropout layer for regularization. The number of hidden units in the first fully connected layer is a hyperparameter.

SCOFNA extends FENS by incorporating spatial coherence and convolutional layers to capture spatial relationships within the frequency-domain representation. The layers of the architecture are as follows: (1) FFT Layer, (2) Spatial Coherence Layer, (3) Flatten Layer, and (4) MLP. As in FENS, the layer applies the FFT and performs frequency selection using trainable weights. The second layer, the Spatial Coherence Layer, applies a 1×1 convolution across the frequency feature channels to model inter-channel relationships. Like FENS, the flatten layer outputs a 1D vector of the values. Residual connections are optionally used to aid training. Lastly, a final fully connected layer maps the convolutional features to the output.

The SNN serves as the baseline control model. It is an MLP that operates directly on the time-domain input data. The layers of the architecture are as follows: (1) Flatten Layer, and (2) MLP. The first layer flattens the inputs into a 1D vector. This is followed by two fully connected layers, batch normalization, ReLU activation after the first layer, and a dropout layer for regularization. The number of hidden units in the first fully connected layer is a hyperparameter.

3.4 Training Procedure

Initially, the models were initialized using Xavier uniform weight initialization to ensure proper convergence during training. The Adam optimizer, with a learning rate of 1×10^{-3}, was employed, complemented by a learning scheduler that reduces the learning rate when validation loss plateaus, thus aiding in more efficient convergence. Training was conducted over a maximum of 200 epochs with a batch size of 32, and early stopping was implemented to terminate the training process if no improvement in validation loss was observed for 10 consecutive epochs. To prevent overfitting, regularization techniques, particularly implementing a dropout with a rate of 500×10^{-3} and L2 regularization with a weight decay of 10×10^{-6}, were applied.

3.5 Theoretical Background

The signals generated by the system are a discrete sequence in the time domain. The DFT of x_f is another sequence $X_f(f)$ of the same length, providing a measure of the frequency content at frequency f, which corresponds to the underlying period of N/f samples.

$$X_f(f) = \sum_{n=0}^{N-1} x_f \cdot \exp\left(-2\pi i \frac{fn}{N}\right) \tag{4}$$

As seen in this formulation, x_f and X_f represent the time-domain signal and its corresponding frequency-domain coefficient, respectively. The FFT algorithm was employed to efficiently compute the DFT in $O(N \log N)$ time. This transformation enables neural networks to learn frequency-domain patterns, such as dominant heartbeats, brain rhythms, or auditory harmonics, as informative features.

The result of the FFT is a complex number that has both magnitude and phase. The magnitude and phase are respectively given by:

$$|X_f(f)| = \sqrt{\Re(X_f)^2 + \Im(X_f)^2} \tag{5}$$

$$\phi_f(f) = \arg(X_f) \tag{6}$$

The M inputs' DFT can also be expressed in matrix form (X_m), where each row of X corresponds to the DFT of the input signals from the dataset. This can be seen as a matrix shown below:

$$\boldsymbol{X} = \begin{bmatrix} X_{1,1} & X_{1,2} & \cdots & X_{1,n} & \cdots & X_{1,N-1} \\ X_{2,1} & X_{2,2} & \cdots & X_{2,n} & \cdots & X_{2,N-1} \\ \vdots & \vdots & \cdots & \vdots & \cdots & \vdots \\ X_{F,1} & X_{F,2} & \cdots & X_{F,n} & \cdots & X_{F,N-1} \end{bmatrix} \quad (7)$$

Building on this concept, FENS and SCOFNA integrate frequency-domain representation directly into the neural architecture as a learnable projection layer. This is modeled by a trainable approximation as:

$$\hat{X}_f = \sum_{n=0}^{N-1} x_f(n) \cdot W_f \quad (8)$$

$$W_f \sim \mathcal{N}\left[\exp(-2\pi i f n/N), \sigma^2\right] \quad (9)$$

This design is a variation of the DFT augmented with stochasticity in the transformation weights, wherein it uses random variables that follow a Gaussian distribution instead of using fixed coefficients. Specifically, each Fourier coefficient $\hat{X}_f$ is computed as a weighted sum over the input signal x_f, where the weights W_f are sampled from a complex-valued normal distribution. The parameters of the equation indicate that each weight is drawn from a normal distribution with a mean equal to the conventional DFT basis function, $e^{-2\pi i f n/N}$, and a variance of σ^2. This can be visualized through a matrix given by:

$$\boldsymbol{W} = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,N-1} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,N-1} \\ \vdots & \vdots & \ddots & \vdots \\ w_{F,1} & w_{F,2} & \cdots & w_{F,N-1} \end{bmatrix} \in \mathbb{R}^{F\times(N-1)} \quad (10)$$

Spatial coherence can be calculated using convolutional operations, local attention, and structured filters.

$$\theta_{f,i} = \frac{\exp(w_{f,i})}{\sum_{j=1}^{K} \exp(w_{f,j})}, \quad i = 1, \ldots, K \quad (11)$$

$$\boldsymbol{\Theta} = \begin{bmatrix} \theta_{1,1} & \theta_{1,2} & \cdots & \theta_{1,K} \\ \theta_{2,1} & \theta_{2,2} & \cdots & \theta_{2,K} \\ \vdots & \vdots & \ddots & \vdots \\ \theta_{F,1} & \theta_{F,2} & \cdots & \theta_{F,K} \end{bmatrix} \in \mathbb{R}^{F\times K} \quad (12)$$

This equation represents the softmax normalization of a set of raw coherence scores, $w_{f,i}$, into a proper weighting $\theta_{f,i}$ over all F features. It defines a spatially-aware convolutional operation central to the design of SCOFNA. To integrate spatial coherence into the constituent frequencies of the data inputs, this equation computes a set of raw coherence scores $\{w_{f,i}\}_{f=1}^{k}$ that quantify the local interdependence of each frequency channel f with its neighbors. These scores are obtained via a Gaussian kernel or a small parameterized convolution over adjacent channel activations. The coherence scores are normalized into a probability-like weighing vector $\boldsymbol{\Theta} = [\theta_1, \ldots, \theta_F]$ using the softmax function as presented in Equation (13).

This normalization ensures that $\theta_{f,i} > 0$ for all f and $\sum_{f=1}^{F} \theta_{f,i} = 1$. The resulting weight θ_f serves two key purposes: (1) to dynamically emphasize frequency channels with high local coherence, and (2) to act as an attention mechanism by scaling each channel's contribution in subsequent layers. As a result, the Spatial Coherence Layer can selectively amplify spectrally and spatially consistent features while attenuating noisy or incoherent signals.

Building on the softmax-normalized coherence weights introduced in Equation (13), the output of the Spatial Coherence Layer for the fth frequency channel is computed via a depthwise $1 \times K$ convolution over the input feature map $\boldsymbol{X} \in \mathbb{R}^{F\times(N-1)}$.

$$Y_f^{(c)}(n) = \sum_{i=1}^{K} \theta_{f,i}\, \hat{X}_f(n+i-1), \quad \begin{matrix} f = 1,\ldots,F \\ n = 1,\ldots,N-1 \end{matrix} \quad (13)$$

The function that defines SCOFNA can be seen as:

$$\mathbf{Y}^{(c)} = \underbrace{\boldsymbol{\Theta}}_{F\times K}\ \underbrace{\mathbf{W}}_{F\times(N-1)}\ \underbrace{\mathbf{X}}_{F\times(N-1)} \quad (14)$$

4. RESULTS AND DISCUSSION

4.1 Dataset Sample

After running the dataset generators, sample signal datasets containing two distinct classes were generated, as shown in Figure 2. Class 1 simulates abnormal patterns to respective signals, while Class 0 represents normal rhythms.

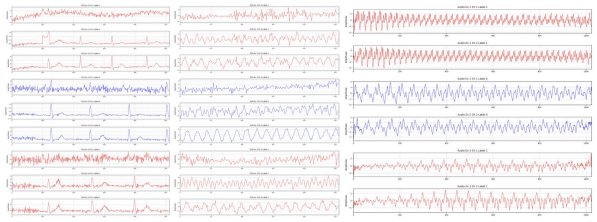

Fig. 2. The sample time-domain for ECG, EEG, and Audio signals: Class 0 (blue) represents normal activity, Class 1 (red shows abnormal activity and noise.

4.2 Training Dynamics

Figure 3 presents the training histories of the three models on the synthetic EEG, ECG, and audio datasets, respectively. On the synthetic EEG signals (Figure 3.2), the time-domain MLP (SNN) fails to capture rhythmic structure: its validation loss plateaus at ≈0.25 and accuracy at ≈89%, driving validation loss to near zero and accuracy to over 99%. FENS converges more gradually in training loss but ultimately matches SCOFNA's near-perfect validation performance; SCOFNA's validation loss and error metrics similarly approach zero.

On the synthetic ECG dataset, frequency-based models again demonstrate superior generalization (Figure 3.1). SNN's training loss collapses to zero, yet its validation loss ascends above 1.4, while FENS and SCOFNA converge to validation losses of approximately 0.45 and 0.52, respectively. In turn, FENS reaches 84% validation accuracy and SCOFNA 77% compared to SNN's probabilistic performance at ≈ 54%. FENS produces the lowest validation of RMSE and MAE, and SCOFNA is intermediate with RMSE and MAE corresponding to approximately 0.48 and 0.23, respectively; whereas SNN again exhibits the poorest error reduction.

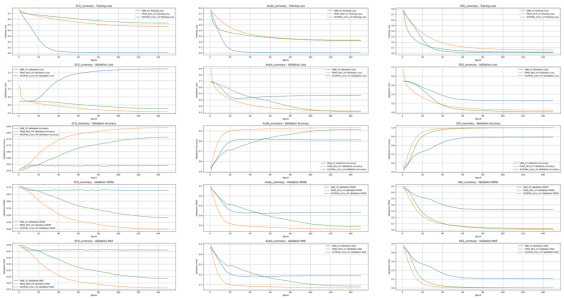

Fig 3. Summary graphs comparing key performance metrics of FENS (orange), SCOFNA (green), and SNN (blue) on the synthetic EEG, ECG, and Audio dataset.

Lastly, on the synthetic audio binary classification task, both FENS and SCOFNA markedly outperformed SNN. As shown in Figure 3.3, SNN's training loss falls rapidly, but its validation loss remains above 0.45, indicating severe overfitting, whereas FENS attains a validation loss below 0.25 and SCOFNA below 0.30. Correspondingly, FENS achieves over 90% validation accuracy by epoch 20 and peaks near 93%, SCOFNA reaches roughly 91% by epoch 150, and SNN stalls around 81%. Error metrics mirror this trend: FENS yields the lowest RMSE and MAE, SCOFNA is slightly higher, while SNN remains the highest.

4.3 Performance Variability

TABLE I
PERFORMANCE METRICS OF THE THREE MODELS (FENS, SCOFNA, SNN) WHEN TRAINED ACROSS THE THREE SYNTHETIC DATASETS (EEG, ECG, AUDIO)

Dataset	Model	Accuracy	RMSE	MAE
EEG	FENS	0.895	0.3211	0.105
	SCOFNA	0.994	0.0683	0.006
	SNN	0.997	0.0245	0.003
ECG	FENS	0.552	0.6692	0.448
	SCOFNA	0.648	0.593	0.352
	SNN	0.6230	0.6126	0.377
Audio	FENS	0.799	0.447	0.201
	SCOFNA	0.91	0.2994	0.09
	SNN	0.89	0.3285	0.11

Table I summarizes each model's mean classification accuracy, RMSE, and MAE across the three synthetic datasets. Both FENS and SCOFNA significantly outperform the time-domain baseline (SNN) in all cases. On EEG signals, FENS achieves 99.40% accuracy compared to SNN's 89.50%. On ECG, FENS reaches 64.80% accuracy in contrast with SNN's 55.20%. Finally, for audio classification, FENS yields 91.00% against SNN's 79.90%.

SCOFNA closely trails FENS on EEG and audio, and shows a modest gain over SNN on ECG, confirming that frequency-based processing substantially improves both accuracy and error reduction for binary classification.

4.3 Statistical Significance

A one-way ANOVA on the five run-level accuracies confirmed a highly significant effect of model type for each dataset (Table II). The effect was significant for all three domains: for EEG, $F(2,12) = 67.55$, $p < 0.001$; for ECG, $F(2,12) = 57.64$, $p < 0.001$; and for audio, $F(2,12) = 140.71$, $p < 0.001$.

TABLE II
ANOVA SUMMARY FOR THE EFFECT OF MODEL TYPE ON CLASSIFICATION ACCURACY ACROSS THE THREE SYNTHETIC DATASETS

Dataset	Source	SS	df	MS	F	p-value
EEG	Between	0.029	2	0.014	67.550	< 0.001
	Within	0.003	12	0.000		
	Total	0.031	14			
ECG	Between	0.034	2	0.6692	57.640	<0.001
	Within	0.004	12	0.593		
	Total	0.037	14	0.6126		
Audio	Between	0.043	2	0.447	140.710	< 0.001
	Within	0.002	12	0.2994		
	Total	0.045	14			

Post-hoc Tukey tests (see Table III) reveal that both FENS and SCOFNA differ significantly from SNN across all modalities ($p < .01$), and FENS further outperforms SCOFNA on ECG ($p < .05$).

TABLE III
TUKEY HSD POST-HOC COMPARISONS OF MODEL ACCURACIES (MEAN Δ ± 95% CI, SIGNIFICANCE)

Dataset	Comparison	Mean Δ (95% CI)	Sig.
EEG	FENS–SNN	0.099 ± 0.005	***
	SCOFNA–SNN	0.083 ± 0.045	**
	SCOFNA–FENS	–0.016 ± 0.045	ns
ECG	FENS–SNN	0.103 ± 0.015	***
	SCOFNA–SNN	0.079 ± 0.013	***
	SCOFNA–FENS	–0.024 ± 0.015	**
Audio	FENS–SNN	0.119 ± 0.011	***
	SCOFNA–SNN	0.098 ± 0.012	***
	SCOFNA–FENS	-0.021 ± 0.011	**

*** p < 0.001, ** p <0.01, ns not significant

4.4 Discussion

The superior performance of FENS confirmed that integrating frequency-domain constituents directly into neural architectures can capture periodic and spectral features that time-domain MLPs ignore. SCOFNA's additional spatial-coherence mechanism can further refine these representations by attenuating locally correlated frequency bands; however, its higher variance on EEG suggests sensitivity to noise when the sample size is limited. In practice, FENS offers both the highest accuracy and the greatest stability, making it a strong default choice for multi-domain pattern recognition.

The ECG results emphasize a challenging domain where purely time-domain models struggle, but even modest spectral enhancements yield a 10% absolute gain. Audio classification similarly benefits, with a 12% improvement over SNN. These gains come with only a modest increase in model complexity, and FENS reduces inference cost by replacing deep

time-domain layers with lightweight FFT operations (convolutions).

5. CONCLUSIONS

This work has presented two novel neural-network architectures, FENS and SCOFNA, directly integrating frequency-domain processing into deep learning models. By embedding a learnable FFT layer and, for SCOFNA, an attention-style spatial coherence attenuation module, both architectures leverage spectral information to capture periodic and cyclical patterns that conventional time-domain networks may overlook. Extensive experiments on synthetic EEG, ECG, and audio datasets demonstrated that FENS and SCOFNA consistently outperform a baseline time-domain MLP (SNN) in binary classification accuracy, RMSE, and MAE. FENS achieved up to 99.4% accuracy on EEG and 91.4% on audio signals, while SCOFNA further delivered competitive results by selectively emphasizing spatially coherent frequency bands. Statistical analyses confirmed these enhancements are significant ($p < 0.001$) across all modalities.

Beyond raw performance gains, this approach offers two key practical advantages: (1) computational efficiency, and (2) robustness.

Nonetheless, this study has limitations. The learnable FFT projection introduces additional parameters whose impact on overfitting warrants further investigation, particularly on relatively small datasets. Moreover, although SCOFNA's coherence system enhances spatial filtering, it may increase training complexity and latency.

Future work should explore (1) scaling these architectures to larger-scale and non-stationary signals (e.g., video or radar spectrograms), (2) hybridizing FFT layers with transformer-based attention for richer token mixing, (3) testing these models with real-world recordings, and (4) rigorous analyses of parameter efficiency and interpretability. The frequency-aware neural designs, especially those incorporating spatial coherence, offer a promising direction for more efficient and accurate pattern recognition across diverse domains.

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