Noise Reduction in Communication Signals Using Deep Neural Networks

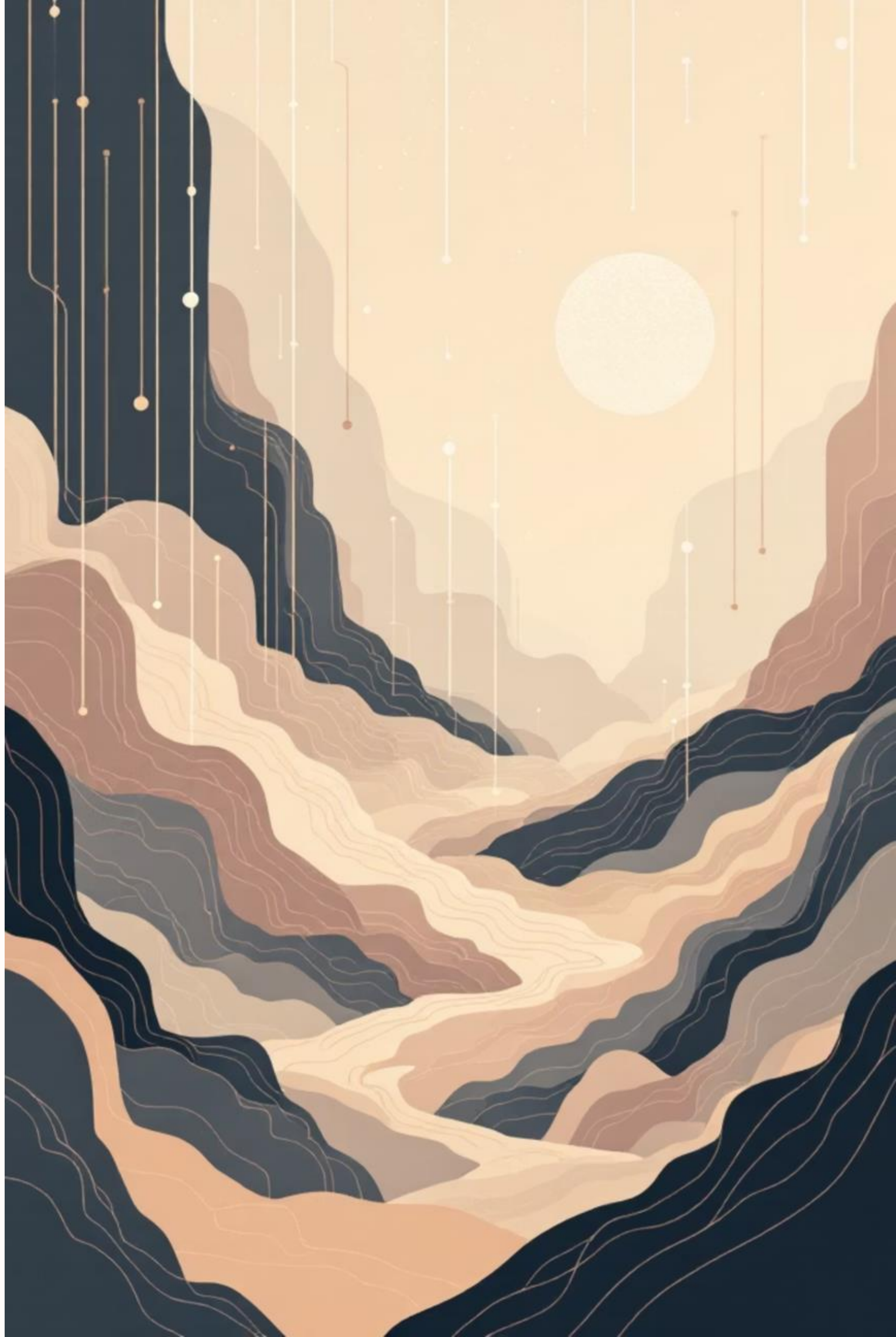
DIGITAL SIGNAL PROCESSING

MACHINE LEARNING

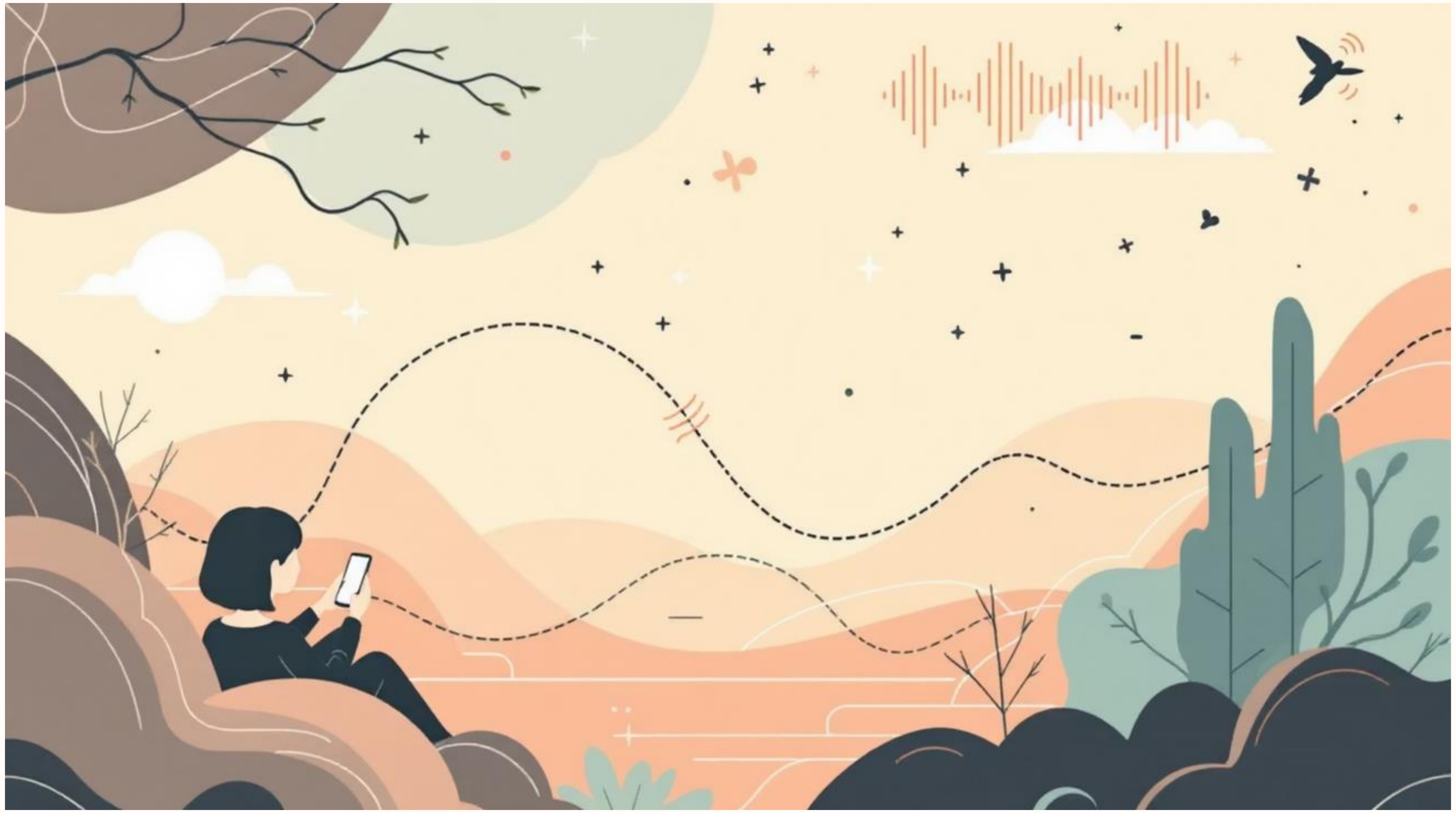
Exploring Deep Learning techniques to enhance signal quality by removing Gaussian noise from composite sinusoidal signals.

AAKASH GANGOTRI 1032240115

ABEER CHOUDAHA 1032233636



The Challenge



Real-World Signal Corruption

Transmitted signals face inevitable corruption from thermal sources, interference, and channel degradation. Recovering the original clean signal is critical for data integrity.

Traditional filters are computationally cheap but struggle to preserve high-frequency details or adapt to complex noise patterns.

Project Objectives

01

Generate Synthetic Signal

Create composite signal representing communication waveform

02

Simulate Noisy Channel

Introduce Gaussian White Noise to test conditions

03

Implement DNN

Train sequential Deep Neural Network for noise suppression

04

Benchmark Performance

Compare DNN results with Moving Average filter

Signal Generation & Noise Addition

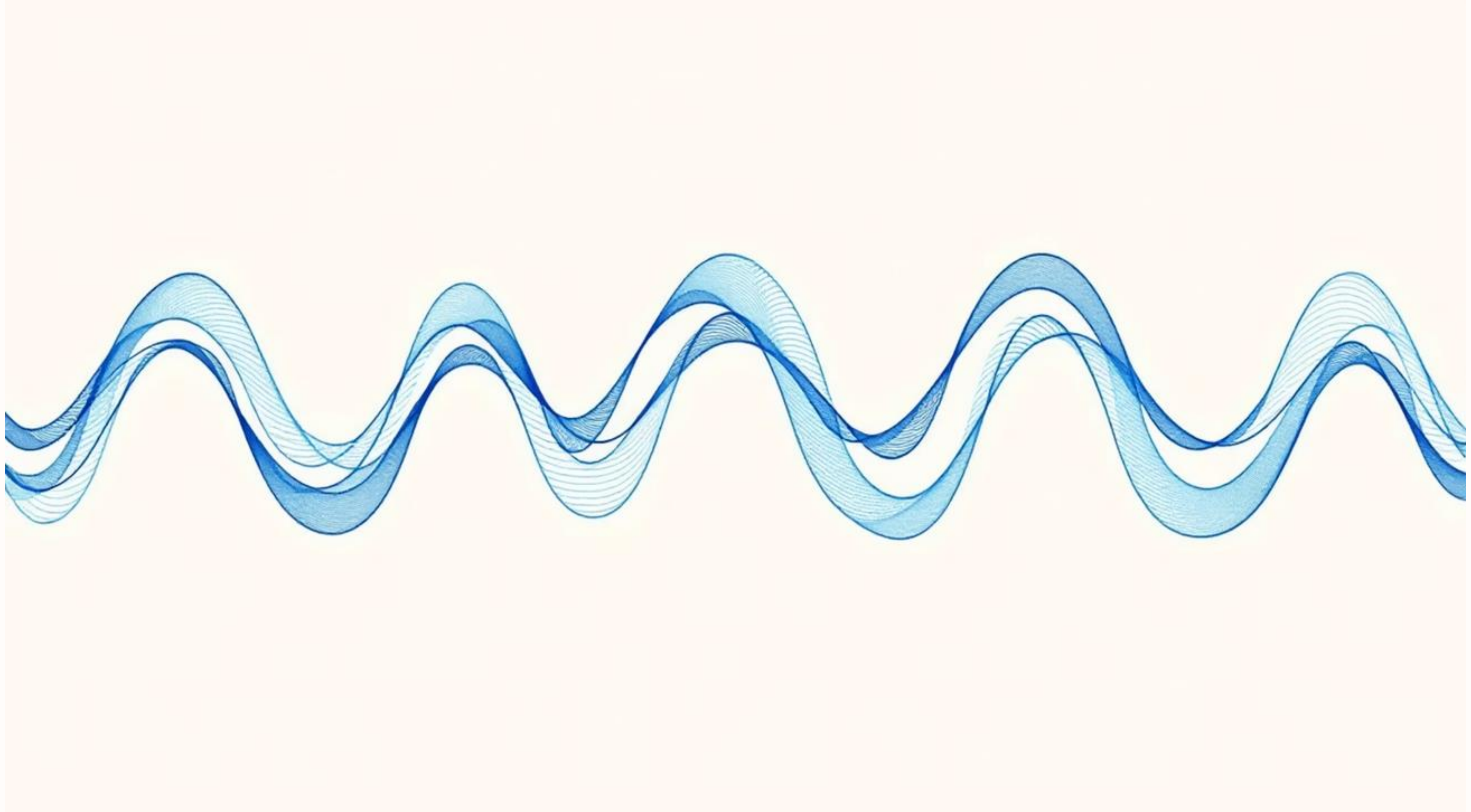
Clean Signal Composition

Synthetic signal composed of two distinct frequencies (5 Hz and 12 Hz) simulating complex waveform:

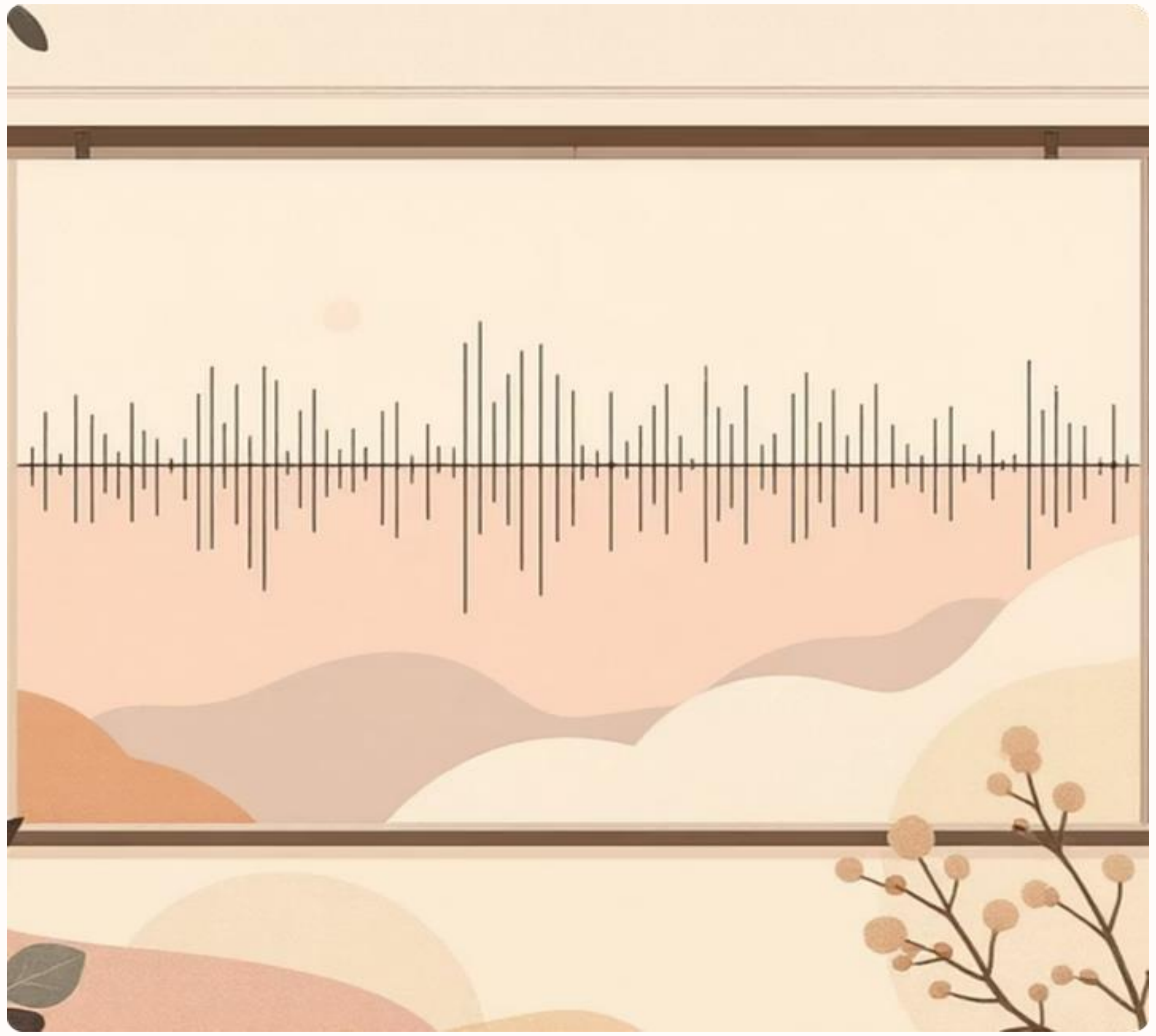
$$y(t) = \sin(2\pi \;\, 5t) + \sin(2\pi \;\, 12t)$$

Gaussian noise added with standard deviation σ:

$$y_{noisy}(t) = y(t) + N(0, \sigma^2)$$



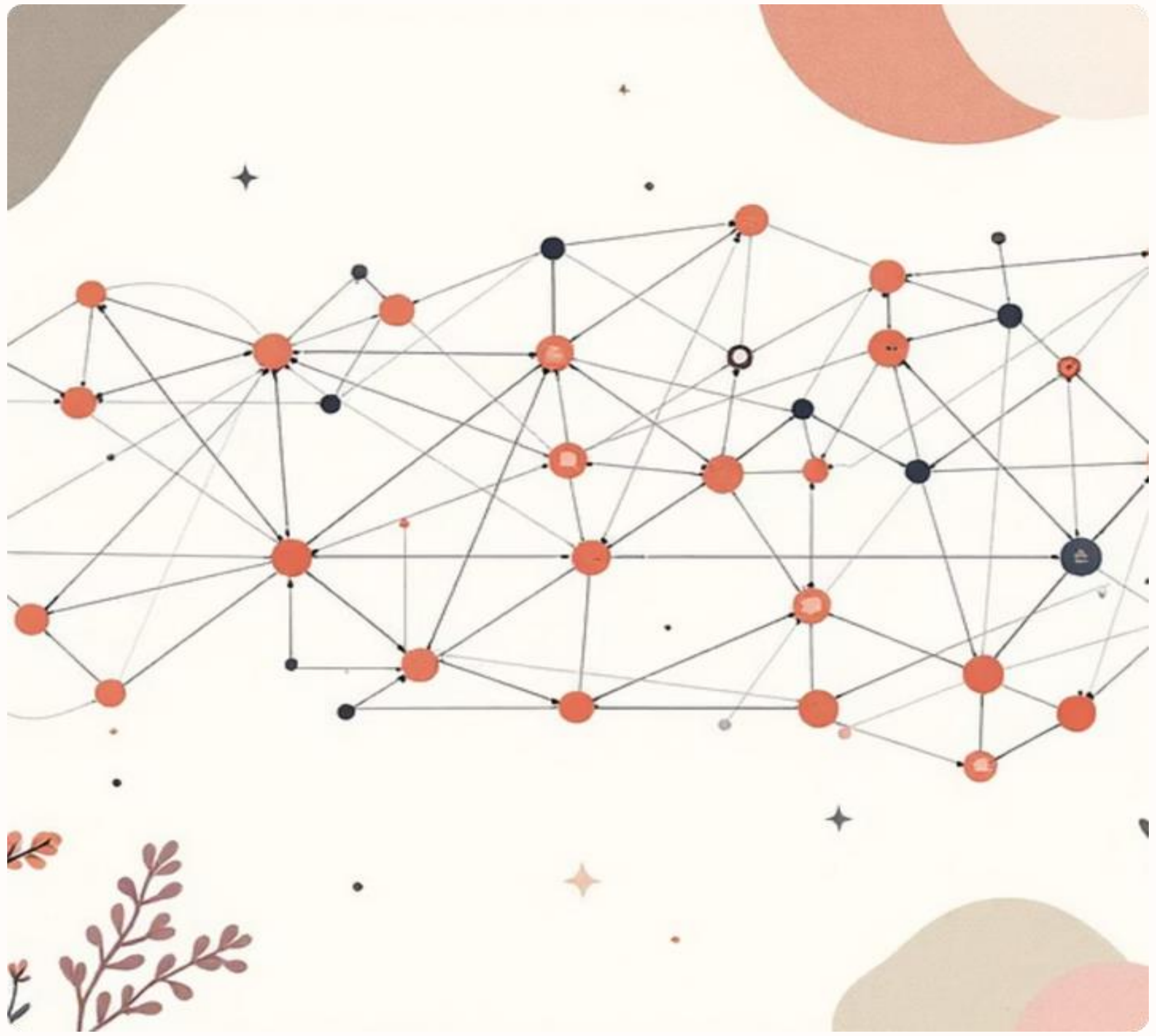
Two Approaches Compared



Moving Average Filter

Traditional Method

Window size: 5. Averages signal points within sliding window to smooth fluctuations. Fast and simple but degrades high-frequency components.



Deep Neural Network

Proposed Method

Feed-forward DNN learns regression map predicting clean amplitude from noisy input. Leverages non-linear ReLU activation for complex pattern recognition.

DNN Model Architecture

Input Layer

Receives noisy signal amplitude

Hidden Layer 1

64 neurons, ReLU activation

Hidden Layer 2

64 neurons, ReLU activation

Output Layer

1 neuron, linear activation

Training Configuration: Adam optimizer, MSE loss function, 100 epochs

Performance Metrics

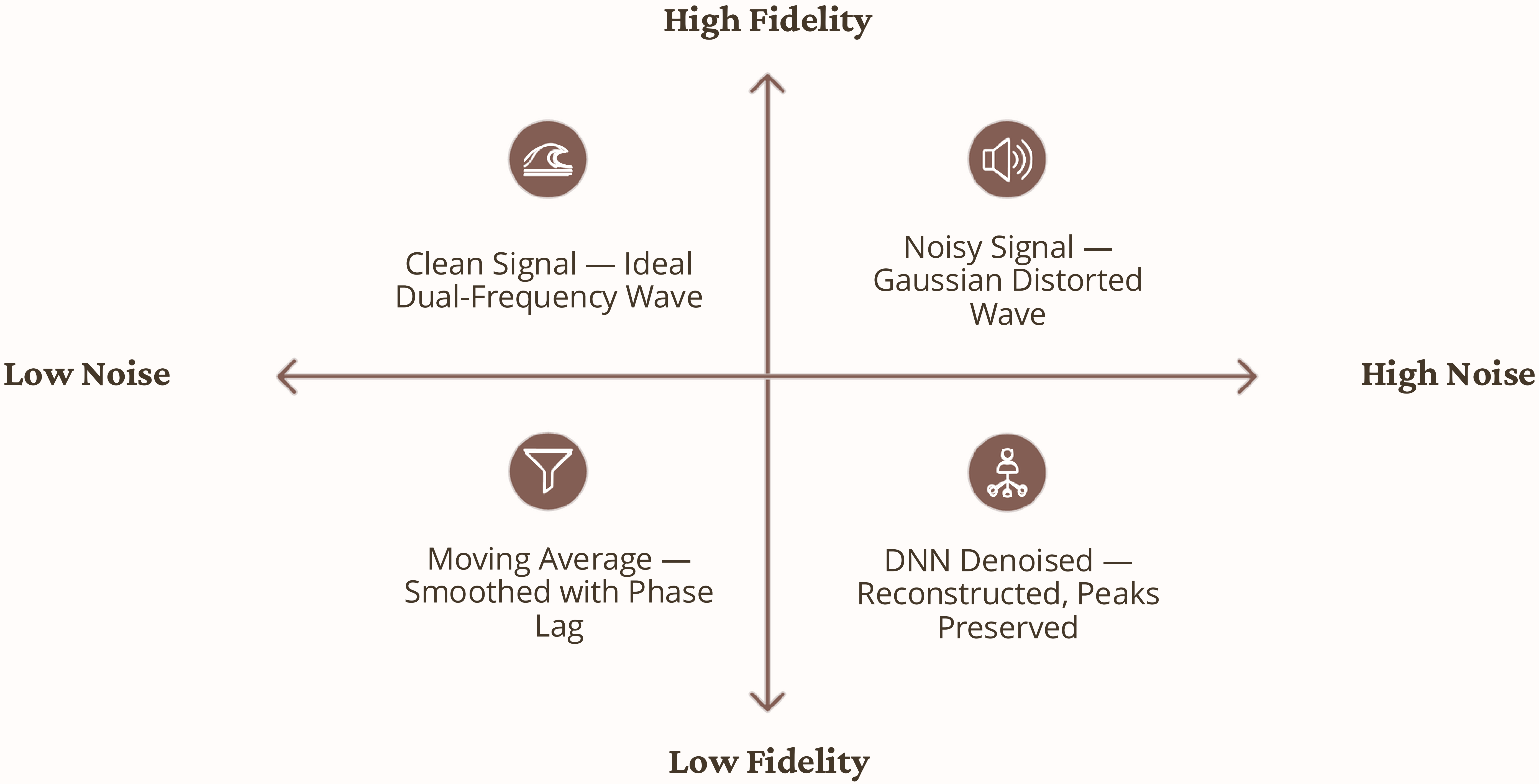
Mean Squared Error (MSE)

Measures average squared difference between estimated and actual values. Lower is better.

Signal-to-Noise Ratio (SNR)

Ratio of signal power to noise power, expressed in decibels (dB). Higher is better.

Experimental Results



The DNN successfully reconstructed the wave shape, preserving peaks better than the moving average while the MA filter exhibited phase lag and attenuation of high-frequency components.

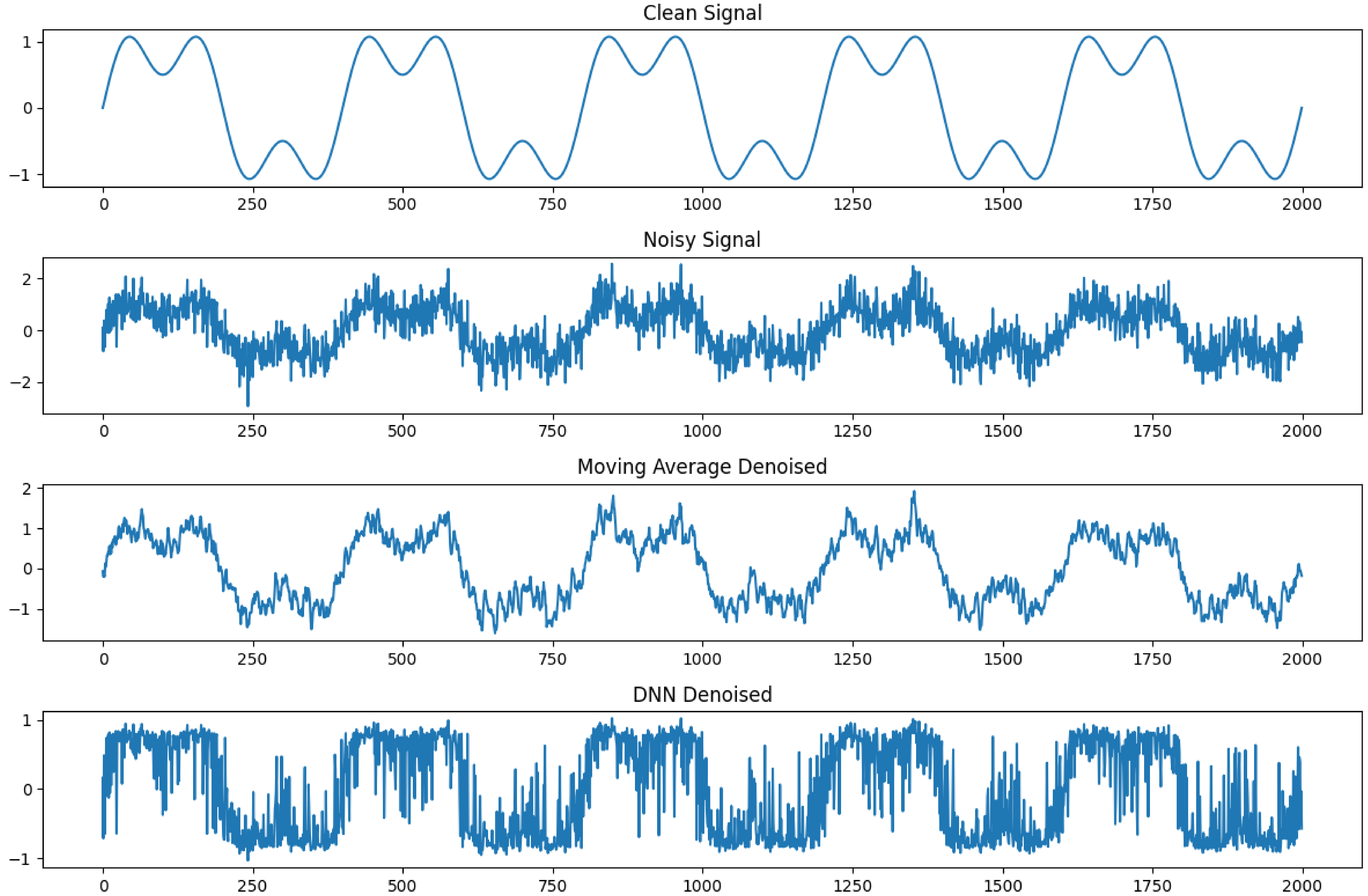
Quantitative Performance Comparison

Metric	Input (Noisy)	Moving Average	DNN
SNR (dB)	Low	Moderate	**High**
MSE	N/A	Moderate	**Low**

The DNN approach showed higher output SNR and lower MSE, indicating successful learning to distinguish signal patterns from stochastic noise.

Key Finding

Training loss curve demonstrated effective MSE minimization over 100 epochs, indicating successful convergence without significant overfitting.


Clean Signal
Noisy Signal
Moving Average Denoised
DNN Denoised
0
250
500
750
1000
1250
1500
1750
2000

Conclusion & Future Scope

Project Success

Deep Neural Networks successfully demonstrated superior signal denoising compared to traditional Moving Average filters. The DNN learned to distinguish underlying signal patterns from noise, providing robust reconstruction.

Future Directions

- Implement RNN/LSTM for time-series advantages
- Optimize for real-time embedded device deployment
- Extend to audio and voice signal denoising