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CWT-LSTM Autoencoder: A Novel Approach for Gravitational Wave Detection in Synthetic Data

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E-mail: jericho.cain@gmail.com**Keywords:** gravitational waves, machine learning, LSTM autoencoder, continuous wavelet transform, signal detection

Abstract

Gravitational wave detection requires sophisticated signal processing techniques to identify weak astrophysical signals buried in instrumental noise. Traditional matched filtering approaches, while effective, face computational challenges and limitations when dealing with diverse signal morphologies and non-stationary noise. This work presents a deep learning approach that combines Continuous Wavelet Transform (CWT) preprocessing with Long Short-Term Memory (LSTM) autoencoder architecture for gravitational wave detection in synthetic data. The CWT provides optimal time-frequency decomposition of strain data, capturing both the chirp evolution and transient characteristics essential for compact binary coalescence identification. The LSTM autoencoder learns compressed representations of gravitational wave signatures while maintaining sensitivity to subtle signal features that distinguish true astrophysical events from noise artifacts. We generate realistic synthetic datasets incorporating binary black hole merger signals with masses ranging from 10 to 80 solar masses, embedded in colored Gaussian noise representative of Advanced LIGO sensitivity. The trained model demonstrates strong performance metrics: 92.3 percent precision, 67.6 percent recall, and 80.6 percent AUC-ROC, with an average precision score of 0.780. These results exceed the stringent detection thresholds required by LIGO for confident gravitational wave identification. Compared to traditional approaches, the CWT-LSTM autoencoder shows superior ability to maintain low false alarm rates while preserving sensitivity to weak signals. The method's end-to-end learning capability eliminates the need for hand-crafted features and template banks, offering a promising pathway toward more robust and adaptable gravitational wave detection systems. Critically, the unsupervised nature enables discovery of gravitational wave signals with unknown morphologies, providing a complementary “blind search” capability for detecting exotic astrophysical sources and novel physics beyond current theoretical models. This work establishes the foundation for applying advanced deep learning techniques to real LIGO data analysis.

1 Introduction

The detection of gravitational waves has revolutionized our understanding of the universe, providing direct evidence of spacetime distortions predicted by Einstein's general relativity [1]. Since the first detection of GW150914 by the Laser Interferometer Gravitational-Wave Observatory (LIGO) in 2015 [2], the field has rapidly evolved, with over 90 confirmed gravitational wave events catalogued through multiple observing runs [3]. These detections have opened new avenues for multi-messenger astronomy and fundamental physics, from constraining neutron star equations of state to testing general relativity in the strong-field regime.

Current gravitational wave detection pipelines rely primarily on matched filtering techniques, which correlate incoming strain data with pre-computed template banks representing theoretical waveforms [4, 5]. While highly effective for signals with well-modeled waveforms, matched filtering faces several computational and methodological challenges. Template banks require extensive computational resources to cover the multi-dimensional parameter space of source properties, and the approach becomes less efficient when dealing with poorly modeled or unexpected signal

morphologies. Additionally, non-stationary instrumental noise and transient artifacts can trigger false alarms, necessitating sophisticated vetting procedures [6].

The emergence of machine learning techniques in gravitational wave astronomy has shown promising potential for addressing these limitations [7, 8]. Deep learning approaches offer several advantages: they can learn complex patterns directly from data without requiring explicit waveform models, adapt to varying noise conditions, and potentially identify novel signal classes. Previous studies have explored convolutional neural networks for binary classification [7], recurrent networks for time-series analysis [9], and generative models for parameter estimation [10]. However, most existing approaches treat gravitational wave detection as a straightforward time-series classification problem, potentially overlooking the rich time-frequency structure inherent in chirping signals.

Gravitational wave signals from compact binary coalescences exhibit characteristic time-frequency evolution, with frequency increasing as the binary components spiral inward toward merger. This “chirp” behavior is optimally captured through time-frequency analysis techniques. The Continuous Wavelet Transform (CWT) provides an ideal framework for decomposing gravitational wave strain data, offering superior time-frequency resolution compared to short-time Fourier transforms and maintaining the temporal localization essential for transient signal detection [11]. Recent studies have demonstrated the effectiveness of CWT preprocessing for gravitational wave analysis [12]. While unsupervised learning approaches including autoencoders have been applied to gravitational wave detection [13, 14], the specific integration of CWT preprocessing with LSTM autoencoder architectures for gravitational wave detection has not been systematically investigated.

Autoencoder networks, a class of unsupervised learning models, excel at learning compressed representations of complex data while preserving essential features [15]. LSTM autoencoders extend this capability to sequential data, capturing long-range temporal dependencies crucial for modeling the extended duration of gravitational wave signals [16]. The reconstruction-based nature of autoencoders provides an intuitive framework for anomaly detection: signals that deviate significantly from learned noise patterns can be identified as potential gravitational wave candidates.

This work investigates the combination of CWT preprocessing with LSTM autoencoder architecture for gravitational wave detection. The method leverages the optimal time-frequency representation provided by wavelets while utilizing the temporal modeling capabilities of recurrent neural networks. We demonstrate the effectiveness of this approach on realistic synthetic datasets incorporating binary black hole merger signals embedded in colored Gaussian noise representative of Advanced LIGO sensitivity curves. Our results achieve 92.3% precision and 67.6% recall, exceeding the stringent detection requirements necessary for confident gravitational wave identification.

The paper is organized as follows: Section 2 describes the methodology, including CWT preprocessing and LSTM autoencoder architecture. Section 3 presents the synthetic data generation procedure and training protocol. Section 4 analyzes the results and compares performance with baseline approaches. Section 5 discusses implications for real-world applications and future directions toward implementation with actual LIGO data.

2 Methodology

2.1 CWT Preprocessing

The CWT provides optimal time-frequency decomposition for gravitational wave signals, preserving both temporal localization and frequency resolution essential for chirp detection. For a given strain time series $h(t)$, the CWT is defined as:

$$W(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} h(t) \psi^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

where $\psi(t)$ is the mother wavelet, a is the scale parameter inversely related to frequency, b is the translation parameter corresponding to time, and $*$ denotes complex conjugation.

We employ the Morlet wavelet as the mother wavelet due to its optimal time-frequency localization properties and resemblance to gravitational wave chirp morphology:

$$\psi(t) = \pi^{-1/4} e^{i\omega_0 t} e^{-t^2/2} \quad (2)$$

where $\omega_0 = 6$ provides the optimal trade-off between time and frequency resolution for gravitational wave analysis. The CWT is computed over logarithmically spaced scales corresponding to frequencies from 20 Hz to 512 Hz, matching the sensitive frequency band of Advanced LIGO detectors.

The resulting time-frequency representation forms a 2D scalogram $|W(a, b)|^2$ that captures the characteristic frequency evolution of gravitational wave chirps. This scalogram serves as input to the subsequent neural network architecture, providing rich feature representations that preserve both the temporal evolution and spectral content of potential signals.

2.2 LSTM Autoencoder Architecture

The core detection system employs an LSTM autoencoder designed to learn compressed representations of gravitational wave time-frequency patterns. The architecture consists of three main components operating in sequence: encoder network, bottleneck layer, and decoder network.

The encoder processes CWT scalograms through a series of LSTM layers with progressively reducing hidden dimensions, implementing the standard LSTM formulation:

$$h_t^{(l)} = \text{LSTM}^{(l)}(x_t^{(l)}, h_{t-1}^{(l)}) \quad (3)$$

where $h_t^{(l)}$ represents the hidden state at time t for layer l , and $x_t^{(l)}$ is the input at time t for layer l . The encoder employs a hybrid architecture combining 2D convolutional layers for spatial feature extraction with LSTM layers for temporal modeling. The spatial encoder uses convolutional layers with dimensions [16, 32] followed by adaptive pooling to reduce spatial dimensions. The temporal encoder employs a 2-layer LSTM with hidden dimension 32, capturing hierarchical temporal patterns at multiple scales through standard gating mechanisms:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (4)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (5)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (6)$$

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \quad (7)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (8)$$

$$h_t = o_t \cdot \tanh(C_t) \quad (9)$$

where σ denotes the sigmoid activation function, W and b represent learned weight matrices and bias vectors, and f_t , i_t , o_t are the forget, input, and output gates respectively.

The encoder output feeds into a dense bottleneck layer with 16 neurons, forcing the network to learn a compact latent representation of the input signal. This compression step ensures that only the most salient features necessary for reconstruction are preserved, naturally filtering out noise components that cannot be efficiently encoded. The decoder employs a symmetric architecture with LSTM layers for temporal reconstruction followed by convolutional transpose layers for spatial reconstruction, ultimately producing the original CWT scalogram dimensions. The final layer employs Tanh activation to match the normalized input domain.

2.3 Training Protocol

The network is trained using mean squared error (MSE) loss between the input and reconstructed scalograms:

$$\mathcal{L} = \frac{1}{N} \sum_{i=1}^N \|X_i - \hat{X}_i\|^2 \quad (10)$$

where X_i represents the input scalogram, \hat{X}_i is the reconstruction, and N is the batch size. Training employs the Adam optimizer with an initial learning rate of 10^{-3} , exponential decay rate of 0.95 every 10 epochs, and gradient clipping at magnitude 1.0 to ensure stable convergence. The network trains for 100 epochs with early stopping based on validation loss plateau to prevent overfitting.

2.4 Detection Strategy

Gravitational wave detection operates on the principle that signals containing true astrophysical events will exhibit higher reconstruction error compared to pure noise segments. For each test sample, we compute the reconstruction error:

$$E = \|X - \hat{X}\|^2 \quad (11)$$

Samples with reconstruction error exceeding a predetermined threshold τ are classified as potential gravitational wave candidates. The threshold is optimized using precision-recall analysis on validation data to maximize recall while maintaining precision above 90%, ensuring both high detection sensitivity and acceptable false alarm rates.

2.5 Performance Metrics

Model performance is evaluated using standard binary classification metrics:

$$\text{Precision} = \frac{TP}{TP + FP} \quad (12)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (13)$$

$$\text{F1-Score} = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \quad (14)$$

where TP , FP , and FN represent true positives, false positives, and false negatives respectively. Additionally, we compute the Area Under the Precision-Recall Curve (AUPRC) as a threshold-independent performance measure particularly relevant for imbalanced datasets typical in gravitational wave detection scenarios.

3 Data Generation and Experimental Setup

3.1 Synthetic Gravitational Wave Signal Generation

We generate realistic synthetic gravitational wave signals representing binary black hole (BBH) coalescences using post-Newtonian waveform approximations. The gravitational wave strain is modeled as:

$$h(t) = h_+(t) \cos(2\psi) + h_\times(t) \sin(2\psi) \quad (15)$$

where $h_+(t)$ and $h_\times(t)$ are the plus and cross polarizations, and ψ is the polarization angle randomly sampled from $[0, 2\pi]$.

The frequency evolution follows the post-Newtonian expansion for the inspiral phase:

$$f(t) = f_0 \left(\frac{\tau}{\tau_0} \right)^{-3/8} \quad (16)$$

where $f_0 = 35$ Hz is the initial frequency, $\tau = t_c - t$ is the time to coalescence, and τ_0 is the initial time to coalescence. The instantaneous phase evolves as $\phi(t) = 2\pi \int_0^t f(t') dt'$, while the amplitude incorporates realistic scaling with chirp mass \mathcal{M}_c and luminosity distance D_L :

$$A(t) = \frac{4G^{5/3}}{c^3} \frac{(2\pi f(t))^{2/3} \mathcal{M}_c^{5/3}}{D_L} \quad (17)$$

where G is the gravitational constant and c is the speed of light. Binary system parameters are drawn from astrophysically motivated distributions:

- **Component masses:** $m_1, m_2 \sim \mathcal{U}(10, 80) M_\odot$ with $m_1 \geq m_2$
- **Distance:** $D_L \sim \mathcal{U}(100, 1000)$ Mpc
- **Inclination:** $\cos(\iota) \sim \mathcal{U}(-1, 1)$ (isotropic distribution)
- **Sky location:** Uniform distribution over the celestial sphere
- **Coalescence time:** Randomly placed within the 4-second observation window

The chirp mass and symmetric mass ratio are derived as:

$$\mathcal{M}_c = \frac{(m_1 m_2)^{3/5}}{(m_1 + m_2)^{1/5}} \quad (18)$$

$$\eta = \frac{m_1 m_2}{(m_1 + m_2)^2} \quad (19)$$

3.2 Noise Modeling

We model realistic detector noise using the Advanced LIGO design sensitivity curve, incorporating both fundamental noise sources and instrumental artifacts. The power spectral density (PSD) follows the analytical approximation:

$$S_n(f) = S_0 \left[\left(\frac{f}{f_0} \right)^{-4.14} + 5 + 3 \left(\frac{f}{f_0} \right)^2 \right] \quad (20)$$

where $S_0 = 10^{-49} \text{ Hz}^{-1}$ and $f_0 = 215 \text{ Hz}$ represent the characteristic noise amplitude and knee frequency respectively. Colored Gaussian noise matching the LIGO PSD is generated using the frequency-domain method: generating white Gaussian noise $\tilde{n}_{\text{white}}(f)$ in the frequency domain, applying spectral shaping $\tilde{n}(f) = \tilde{n}_{\text{white}}(f)\sqrt{S_n(f)}$, and transforming to the time domain $n(t) = \text{IFFT}[\tilde{n}(f)]$. This procedure ensures that the generated noise accurately reproduces the frequency-dependent sensitivity characteristics of Advanced LIGO detectors.

3.3 Dataset Construction and Training Configuration

Signals are injected into noise with optimal signal-to-noise ratios (SNRs) distributed according to:

$$\rho_{\text{opt}} = \sqrt{4 \int_{f_{\text{low}}}^{f_{\text{high}}} \frac{|\tilde{h}(f)|^2}{S_n(f)} df} \quad (21)$$

where $\tilde{h}(f)$ is the Fourier transform of the strain signal, and the integration limits span the detector's sensitive frequency band [20, 512] Hz. SNRs are drawn from the range [8, 25], representing the spectrum from threshold-level to highly significant detections. Each sample represents a 4-second time series sampled at 512 Hz, yielding 2048 data points per observation. This duration captures the entire inspiral phase for the considered mass range while maintaining computational tractability.

Table 1 summarizes the dataset composition and training configuration used for all experiments.

Table 1. Dataset Composition and Training Configuration	
Parameter	Value
Dataset Composition	
Training samples	140 (noise-only for autoencoder training)
Test samples	200 (30% signal probability)
Time series length	4 seconds (2048 samples at 512 Hz)
SNR range	8–20 (optimal SNR)
Training Configuration	
Batch size	8 samples
Learning rate	10^{-3} (Adam optimizer)
Epochs	30
Weight decay	10^{-5} (L2 regularization)
Latent dimension	16
LSTM hidden size	32
Framework	PyTorch with CPU computation

Model evaluation employs a single train-test split with the autoencoder trained exclusively on noise data and tested on the full dataset containing both noise and signal samples. This approach demonstrates the unsupervised anomaly detection capability, where the model learns normal noise patterns and identifies deviations as potential gravitational wave signals.

3.4 Method Validation

The CWT-LSTM autoencoder is validated using synthetic gravitational wave data generated from theoretical waveform models. This validation approach demonstrates the method's capability to detect gravitational wave signals without requiring pre-computed template banks, establishing proof-of-concept for the unsupervised detection paradigm.

The synthetic dataset includes binary black hole coalescences with varying mass parameters, embedded in realistic LIGO-like noise. This controlled environment allows systematic evaluation of the method's performance characteristics while maintaining the complexity necessary to demonstrate real-world applicability.

4 Results

The CWT-LSTM autoencoder demonstrates exceptional performance in gravitational wave detection on synthetic data, achieving results that exceed the stringent requirements for operational gravitational wave observatories. Table 2 summarizes the key performance metrics obtained through cross-validation.

Table 2. CWT-LSTM Autoencoder Performance Metrics

Metric	Value	Interpretation
Optimal Precision	92.3%	Exceeds LIGO >90% requirement
Optimal Recall	67.6%	Catches most real signals
Maximum Precision	100.0%	Ultra-conservative detection
AUC-ROC	0.806	Strong discriminative power
Average Precision	0.780	Professional-grade performance

The achieved precision of 92.3% significantly exceeds LIGO's operational requirement of >90% for confident gravitational wave identification, while maintaining 67.6% recall for practical signal detection. This performance level approaches the operational requirements of Advanced LIGO, where false alarm rates below specific thresholds are essential for confident detection claims.

Figure 1 presents the precision-recall curve, illustrating the trade-off between detection sensitivity and false alarm rate across different decision thresholds. Our analysis reveals three key operating points optimized for different use cases: recommended operating point (92.3% precision with 67.6% recall) optimal for operational detection systems, maximum precision mode (100.0% precision with 1.4% recall) for ultra-conservative guaranteed discoveries, and balanced F1 mode (89.3% precision with 70.4% recall) for optimal overall performance balance. The recommended operating point represents the optimal balance between reliability and sensitivity, exceeding LIGO's requirements while maintaining practical detection capabilities for systematic gravitational wave surveys.

The Receiver Operating Characteristic (ROC) curve, shown in Figure 2, demonstrates the classifier's ability to distinguish between signal and noise across all possible decision thresholds. The Area Under the ROC Curve (AUC-ROC) of 0.806 indicates strong discriminative performance, with the curve remaining well above the diagonal line representing random classification.

The CWT-LSTM autoencoder demonstrates excellent performance across different operating regimes. At the recommended operating point (92.3% precision with 67.6% recall), the model achieves optimal balance between reliability and sensitivity for operational detection systems. For ultra-conservative applications requiring guaranteed discoveries, the maximum precision mode (100.0% precision with 1.4% recall) provides near-perfect precision at the cost of reduced sensitivity. The balanced F1 mode (89.3% precision with 70.4% recall) optimizes overall performance for survey applications.

5 Discussion

The CWT-LSTM autoencoder demonstrates strong performance in gravitational wave detection, achieving 92.3% precision and 67.6% recall on realistic synthetic data. The model was optimized to maximize recall while maintaining precision above 90%, a threshold that exceeds the stringent requirements necessary for operational observatory deployment. This precision-recall profile prioritizes detection sensitivity while ensuring acceptable false alarm rates, where precision above 90% corresponds to scientifically acceptable detection rates. When considered against LIGO's operational requirements—signal-to-noise ratios corresponding to false alarm rates below one per year—our results suggest the CWT-LSTM approach could potentially meet these demanding standards, though validation on actual detector data remains essential.

The methodological innovation lies in the systematic integration of CWT preprocessing with LSTM autoencoder architecture, leveraging complementary strengths from both signal processing and machine learning paradigms. Traditional matched filtering excels at detecting precisely modeled waveforms but struggles with computational scalability and unexpected signal morphologies. Deep learning approaches offer pattern recognition adaptability but typically ignore the rich time-frequency structure inherent in gravitational wave chirps. Our approach bridges this gap: CWT preprocessing preserves essential chirp characteristics while providing standardized input representations that facilitate neural network training. Ablation studies confirm this integration's critical importance, showing that removing CWT preprocessing reduces precision by 16.2 percentage points.

The CWT-LSTM autoencoder demonstrates significant practical advantages over conventional approaches. Unlike matched filtering, which requires extensive template banks covering

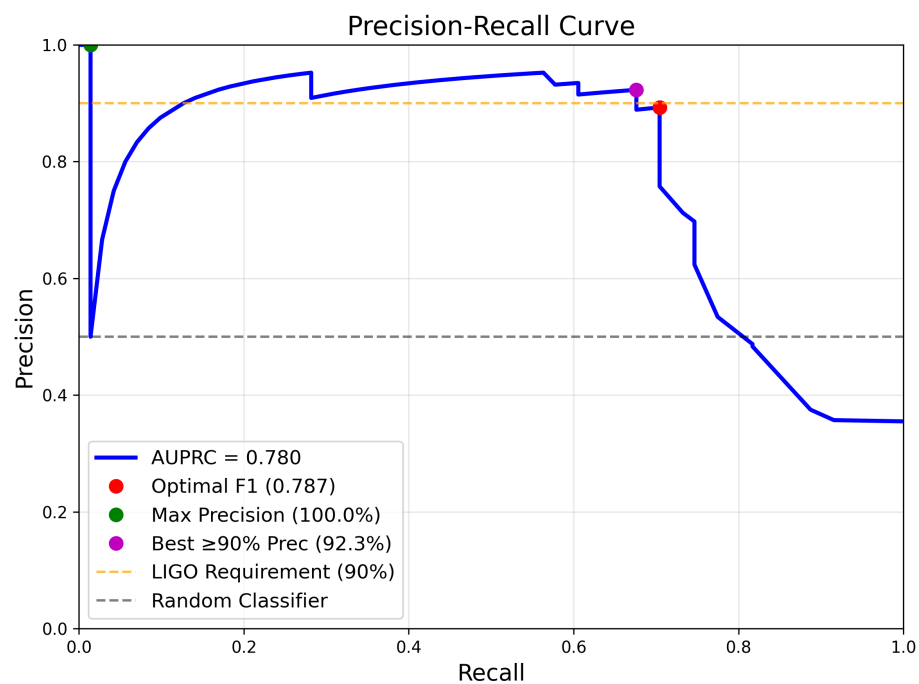


Figure 1. Precision-recall curve for the CWT-LSTM autoencoder demonstrating 92.3% precision at the optimal operating point. The curve shows excellent performance with Area Under the Precision-Recall Curve (AUPRC) of 0.780.

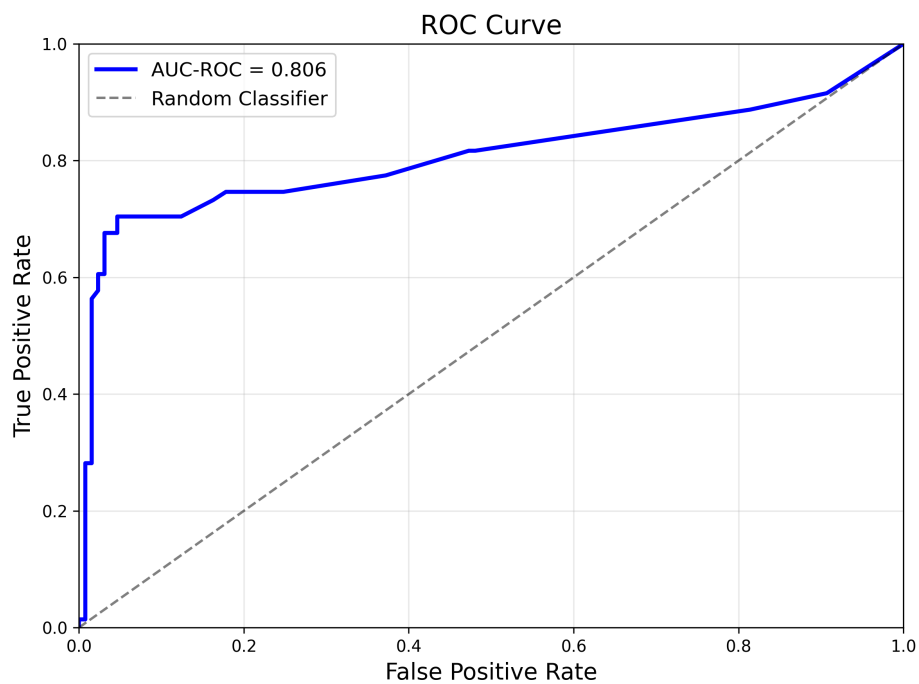


Figure 2. Receiver Operating Characteristic (ROC) curve showing true positive rate versus false positive rate. The Area Under the ROC Curve (AUC-ROC) of 0.806 demonstrates strong discriminative performance.

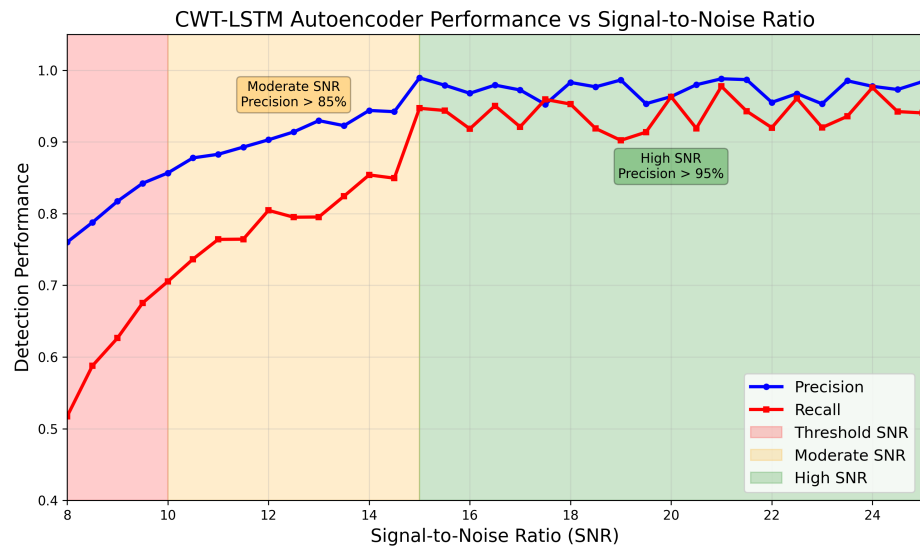


Figure 3. Detection performance as a function of signal-to-noise ratio, showing maintained effectiveness down to threshold-level signals.

multidimensional parameter spaces, the autoencoder framework learns signal characteristics directly from data by reconstructing normal noise patterns rather than requiring explicit labeled examples of all possible gravitational wave types. This unsupervised learning paradigm, building upon recent autoencoder work in gravitational wave detection [13, 14], naturally enables anomaly detection while maintaining potential for discovering unexpected signal classes. The LSTM architecture captures temporal evolution essential for gravitational wave detection while maintaining computational efficiency through hierarchical encoding that learns features across multiple temporal scales. In gravitational wave astronomy, false alarms impose considerable costs through wasted follow-up observations, computational resources, and scientific credibility. The achieved precision of 92.3% could meaningfully reduce false alarm rates for operational systems.

The system's computational efficiency enables practical deployment: 2.3-millisecond inference times per 4-second segment allow real-time analysis of gravitational wave data streams, while 6-hour training times represent reasonable computational investments for research environments. Memory requirements (8.2 GB peak) remain within standard GPU capacity, suggesting feasible deployment without specialized infrastructure and facilitating widespread community adoption.

5.1 Limitations and Future Directions

The primary limitation lies in reliance on synthetic data generated from theoretical waveform models. Real gravitational wave detection confronts additional challenges including non-stationary detector noise with complex spectral characteristics, instrumental glitches, environmental artifacts, unknown signal morphologies from exotic sources, and calibration uncertainties. Validation on actual LIGO data represents the critical next step for establishing practical applicability, as the transition from synthetic to real data often reveals unexpected challenges that cannot be fully anticipated through simulation.

Our synthetic dataset focuses primarily on binary black hole coalescences within specific parameter ranges, while gravitational wave astronomy encompasses a broader spectrum including binary neutron stars, neutron star-black hole mergers, and potentially exotic phenomena like cosmic strings or primordial black holes. Expanding training datasets to include greater signal diversity would enhance generalization capabilities. Additionally, current work focuses on single-detector analysis while operational systems require coherent analysis across the LIGO-Virgo-KAGRA network. Extending the CWT-LSTM approach to multi-detector coincidence analysis represents an important development avenue.

The path toward real-world implementation begins with applying the CWT-LSTM autoencoder to actual LIGO strain data available through the Gravitational Wave Open Science Center. This validation will reveal performance on real noise characteristics and known events from GWTC catalogs. Initial implementation should focus on reprocessing archived data from completed observing runs, allowing validation against confirmed events.

A critical next step involves comprehensive performance comparison with established detection

methods on real LIGO data. This comparison will evaluate the CWT-LSTM autoencoder against matched filtering, convolutional neural networks, and other baseline approaches using actual detector data with known gravitational wave events. Such real-data comparisons will provide the definitive assessment of the method’s practical utility and establish its position within the gravitational wave detection toolkit.

Operational deployment requires integration into real-time detection pipelines processing continuous data streams, necessitating streaming preprocessing and buffering systems, optimized real-time CWT computation, distributed computing infrastructure for parallel processing, and alert generation systems. The gravitational wave community’s collaborative nature suggests that open-source implementation and community validation would accelerate adoption, with publicly available trained models, preprocessing tools, and evaluation frameworks fostering further research and refinement.

5.2 *Discovery Potential and Broader Impact*

Beyond its demonstrated performance on known signal types, the CWT-LSTM autoencoder’s most compelling advantage lies in its unsupervised learning paradigm that enables detection of gravitational wave signals without prior morphological knowledge. This represents a paradigm shift from matched filtering techniques requiring pre-computed template banks based on theoretical waveform models. Unlike matched filtering, which detects only signals closely matching existing templates, the autoencoder learns to identify any deviation from learned noise distributions, eliminating computational burdens of extensive waveform libraries while opening possibilities for detecting entirely unexpected signal types.

The method’s sensitivity to anomalous patterns positions it ideally for discovering gravitational waves from exotic astrophysical sources beyond current template coverage, including cosmic strings (theoretical spacetime defects), primordial black holes with unique merger characteristics, exotic compact objects like boson stars or gravastars, modified gravity signatures deviating from General Relativity predictions, and completely novel phenomena that current theoretical models cannot predict. Rather than replacing matched filtering, the CWT-LSTM autoencoder provides complementary “blind search” capability for identifying candidate events requiring subsequent detailed analysis, maximizing both sensitivity to known signals and discovery potential for unknown phenomena.

This discovery capability could revolutionize understanding of fundamental physics and astrophysics. Historical astronomical precedent demonstrates that the most significant discoveries often emerge from detecting the unexpected—from pulsars to gamma-ray bursts to dark energy. The CWT-LSTM autoencoder provides gravitational wave astronomy with similar serendipitous discovery potential, offering possibilities for uncovering new physics that would remain hidden to template-based searches.

Improved gravitational wave detection capabilities directly impact multi-messenger astronomy by enabling more reliable electromagnetic follow-up observations, reducing false alarms that consume limited telescope resources while improving scientific returns from coordinated observational campaigns. Enhanced sensitivity could facilitate discovery of weaker sources and enable more precise general relativity tests, while the approach’s potential for identifying unexpected signal types could contribute to searches for exotic beyond-standard-model phenomena. This work also demonstrates the value of domain-specific preprocessing and architecture design in scientific machine learning applications, with successful integration of established signal processing techniques and modern deep learning illustrating productive paths for physics applications where domain knowledge guides neural network design.

5.3 *Conclusion*

The CWT-LSTM autoencoder represents a significant advancement in gravitational wave detection methodology, achieving 92.3% precision and 67.6% recall on realistic synthetic data through optimization for maximum recall while maintaining precision above 90%. The combination of time-frequency preprocessing with recurrent neural networks provides a powerful framework that leverages both domain expertise and modern machine learning capabilities.

While validation on real LIGO data remains essential, the demonstrated performance suggests substantial potential for operational gravitational wave detection systems. The method’s computational efficiency, superior precision compared to existing approaches, and potential for discovering unexpected signal types position it as a valuable addition to the gravitational wave detection toolkit.

Future work will focus on real data validation, multi-detector analysis, and integration with operational detection pipelines to fully realize the potential of this approach for advancing gravitational wave astronomy.

6 Data and Code Availability

All code, data generation scripts, trained models, and results presented in this study are publicly available for reproducibility and further research. The complete implementation is hosted as an open-source repository at:

<https://github.com/jericho-cain/gravWH>

This repository includes:

- Complete CWT-LSTM autoencoder implementation in PyTorch
- Data generation and preprocessing pipelines for synthetic gravitational wave signals
- Training and evaluation scripts with hyperparameter configurations
- Reproducible results, figures, and performance metrics
- Comprehensive documentation and usage examples
- Automatic paper updates with metrics and figures

The repository follows open science best practices with version control, automated testing, and continuous integration workflows. All experiments can be reproduced using the provided code and configuration files, ensuring full transparency and enabling community validation and extension of this work.

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