UNIVERSITY of WASHINGTON

Accelerated AI Algorithms for Data-Driven Discovery

UNRAVELING GRAVITATIONAL RIPPLES: NEURAL NETWORK CLASSIFICATION

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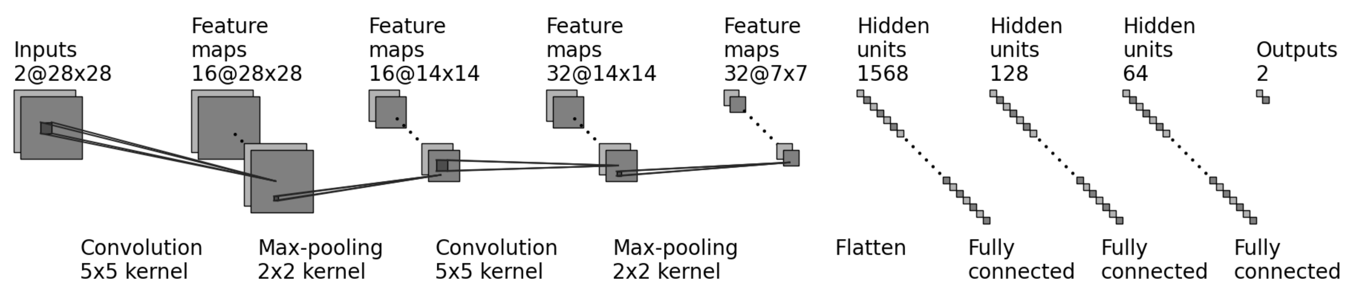
INTRODUCTION

- **Dataset source:** Glitch dataset originates from the Laser Interferometer Gravitational-Wave Observatory (LIGO) in Hanford, WA, and Livingston, LA.
- **LIGO observatory:** Designed to identify and understand the sources of gravitational waves using light and space characteristics.
- **Dataset categories:** Consists of four distinct data categories - Glitch, Background, Sine-Gaussian (SG), and Binary Black Hole (BBH).
- **Objective:** Develop a binary classifier to identify signals as either Glitch/Background or Sine-Gaussian/Binary Black Hole using GASF vs Spectrogram.

METHODOLOGY

- **Image Conversion:** Convert time series data to 2D images using Gramian Angular Summation Fields (GASFs) with the pyts library.
- **Image size:** GASF images are 28x28 pixels for a balance between performance and accuracy.
- **Data splitting:** Split data into training (70%, 102227 images), testing (15%, 21910 images), and validation (15%, 21908 images) sets.
- **CNN architecture:**
  - Two *convolution layers* with *batch normalization* and *max pooling layers* applied after each convolution layer three subsequent *fully connected layers* with dimensions 1568x128, 128x64, and 64x2, respectively.
- **Training:** Trained for 16 epochs, learning rate of 5e-6, batch size of 677, L2 regularization with coefficient 0.001.
- **Loss function and optimizer:** Cross-entropy loss function and Adam optimizer.



Basic structure of our convolutional neural network (CNN).

DATA ANALYSIS

- **Scaling:** Utilized the StandardScaler function to ensure data was normalized before conversion to GASF images.
- **Model output:** Probability predictions of images for background or signal compared to ground truth targets with Softmax function.
- **Testing and accuracy:** Tested trained model against a separate testing dataset, achieved an overall accuracy of 97%.
- **Misclassification patterns:** Model tends to misclassify when detectors have conflicting data.
- **Possible flaws:** Confusion may arise from contradictory signals between detectors or flaws in observatory data capture.

Gramian Angular Summation Fields (GASF)

- **Definition:** Method for visualizing time series data in a two-dimensional image format.
- **Conversion:** Converts time series into a symmetric matrix which represents the pairwise angles between points in the time series.
- **Application:** Provides visual representation of complex temporal patterns which is useful for tasks like classification of time series data.

QUICK FACTS ABOUT OUR CNN

> ~ **97%** testing accuracy

> Data split of **70%** training, **15%** validation, and **15%** testing

> Dataset contains a total of **146045** gravitational wave time series data points

> Applied **Gramian Angular Summation Field** (GASF) algorithms to encode gravitational wave data as 2D images for classification

> Neural network contains **2** convolutional / max-pooling layers followed by **3** fully connected layers and an output

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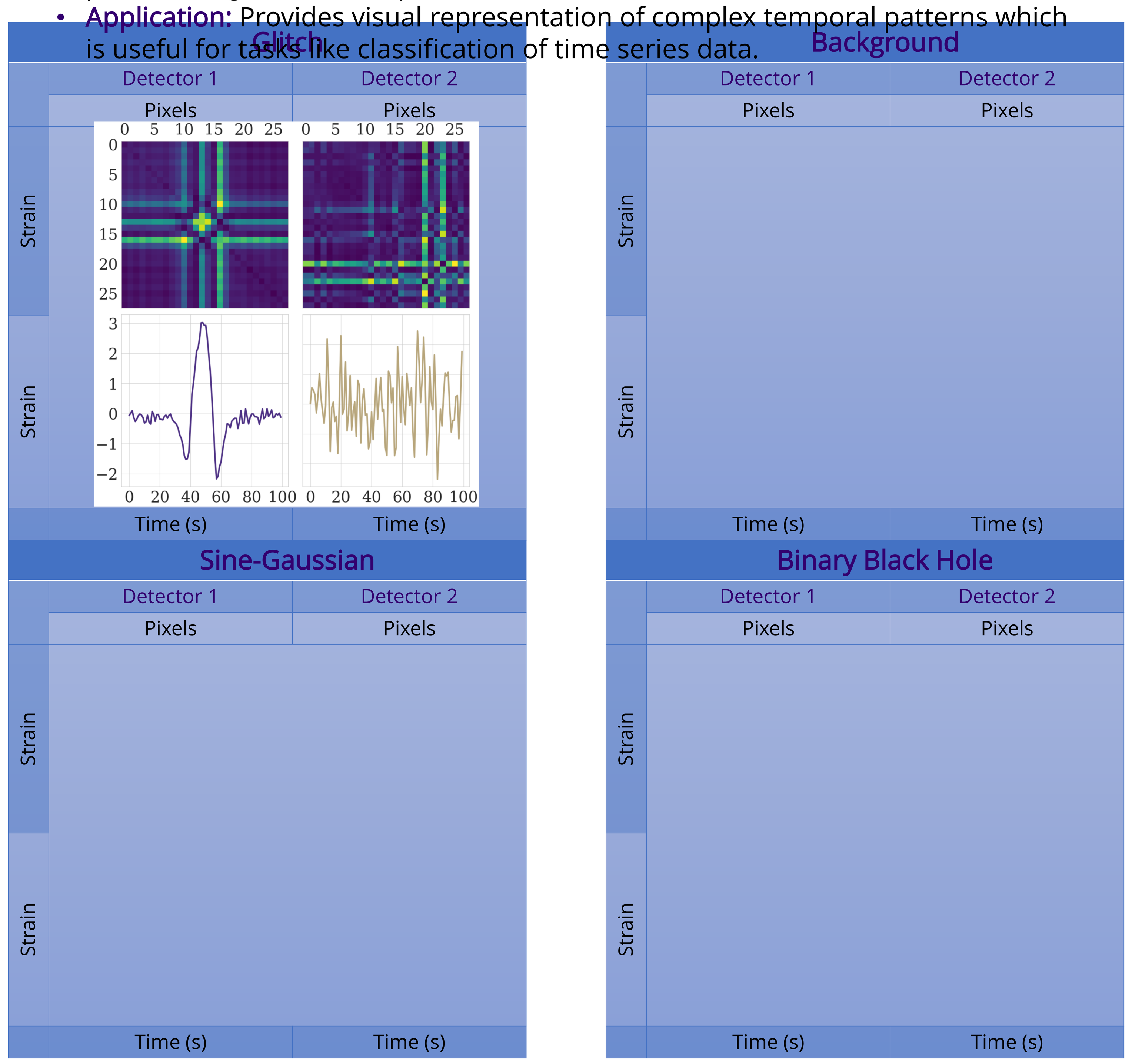


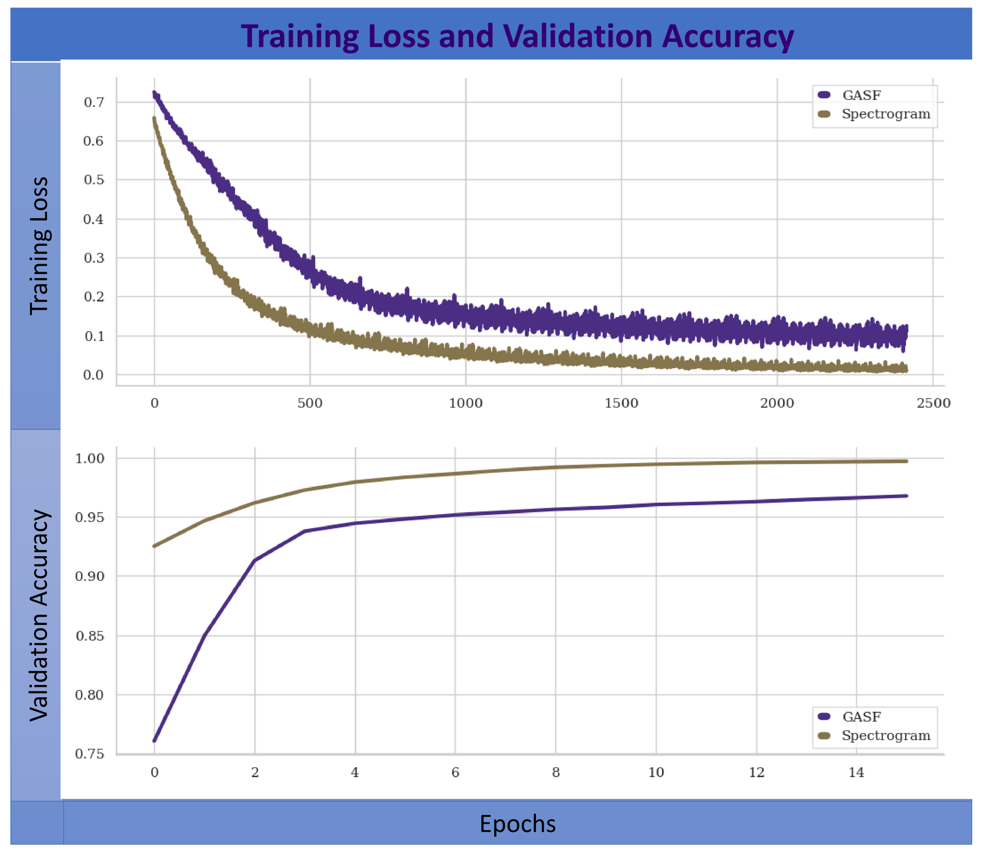
An example of the four signal categories derived from the time series data, along with their corresponding GASF images captured by both Detector 1 and Detector 2.

RESULTS

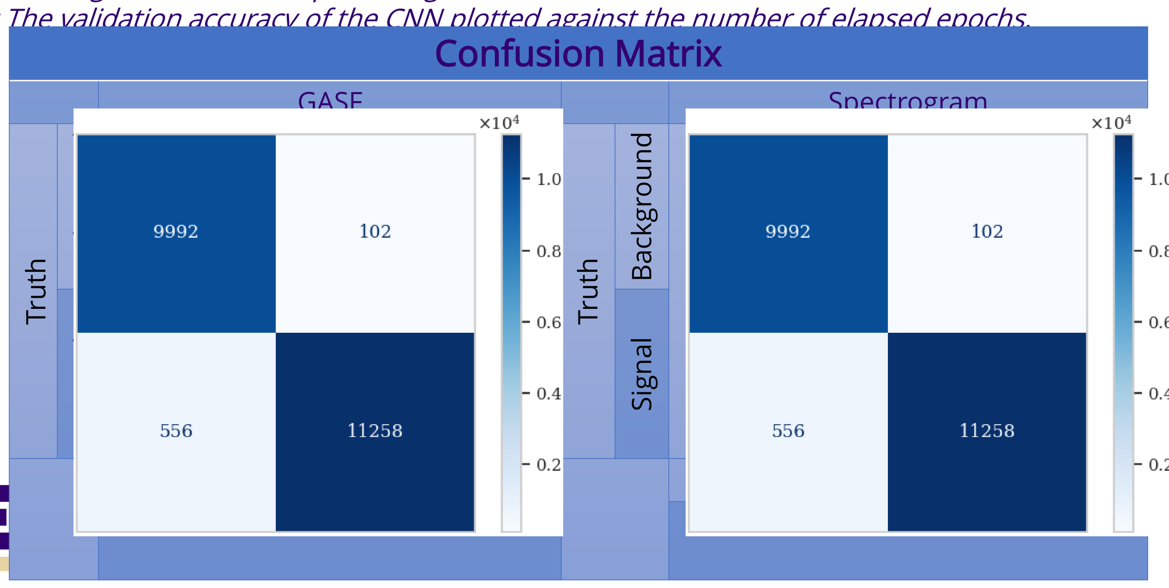
- **Model performance:** After 16 epochs and over 2400 iterations, training loss reached 0.1, while the validation accuracy approached 96%.
- **Testing accuracy:** CNN model demonstrated an exceptional accuracy of 97% when evaluated on the testing dataset.
- **Comparison with literature:** Similar CNN architectures in the literature achieved higher accuracies, such as 99% (Fernandes et al., 2018) and 98.8% (George D. et al., 2023).
- **Dataset differences:** Our dataset consisted of separate time series for gravitational wave signal data and noise data, while other works had to apply more complex noise filtering methods.
- **Image conversion:** Gramian Angular Summation Fields were effective for image conversion in our case, while others found Fourier transforms more suitable for handling complex noise and background through frequency domain filtering.

CONCLUSION

- **Objective:** Analyzing the potential of CNNs for classifying gravitational waves strain data as background noise/glitches or transient sine-gaussian/binary black hole merger signals.
- **Approach:** Utilized a streamlined variation of a CNN based upon versions existing in literature.
- **Performance:** Exceeded the anticipated 85% accuracy by attaining an impressive testing accuracy of 97%.
- **Comparison:** Achieved accuracy slightly below more complex CNNs documented in literature and slightly lower than the spectrogram method.
- **Further exploration:** Examining the efficacy of the GASF technique in transforming time series data into images and feeding them through a basic CNN, by using a dataset of more contaminated gravitational waves for analysis.



Top: The training loss of the CNN plotted against the number of iterations.
Bottom: The validation accuracy of the CNN plotted against the number of elapsed epochs.



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[1] Z. Wang and T. Oates. Encoding Time Series as Images for Visual Inspection and Classification Using Tiled Convolutional Neural Networks. In *The Twenty-Ninth AAAI Conference on Artificial Intelligence.* (AAAI), January 2015.

[2] T. S. Fernandes, et al. Convolutional Neural Networks for the classification of glitches in gravitational-wave data streams, arXiv:2303.13917v1 [gr-qc], March 2023.

[3] D. George, H. Shen, and E. A. Heurta. Glitch Classification and Clustering for LIGO with Deep Transfer Learning. *Phys Rev. D*, 97:101501, May 2018.

ACKNOWLEDGEMENTS

[1] Z. Wang and T. Oates. Encoding Time Series as Images for Visual Inspection and Classification Using Tiled Convolutional Neural Networks. In *The Twenty-Ninth AAAI Conference on Artificial Intelligence.* (AAAI), January 2015.

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