Using Neuro-evolution for Time Series Anomaly Detection - Thesis Proposal

Aryan Jha*, Travis Desell†, and Alexander Ororbia‡
Rochester Institute of Technology
Rochester, NY, USA
axj2613@rit.edu*, tjdvse@rit.edu†, ago@cs.rit.edu‡

***Index Terms*—Anomaly Detection, Recurrent Neural Network, Neuro-evolution, Auto-encoder, Forecasting, Multivariate Time Series**

I. Summary

This research aims to employ neuro-evolutionary methods, particularly the Evolutionary eXploration of Augmenting Memory Models (EXAMM) algorithm as described by Orobia, ElSaid and Desell [1], to automate the design and optimization of recurrent neural network architectures for effective multivariate time series anomaly detection. The study aims to expand the current implementation of the EXAMM algorithm to allow for time series anomaly detection. The algorithm would be used to jointly optimize a forecasting-based model and a encoder-decoder reconstruction-based model as shown by Hang Zhao et al. [2] to compare against real data over calculated thresholds. Real data falling outside the threshold confidence intervals would be classified as anomalous and their effectiveness would be evaluated on benchmark multivariate time series datasets across diverse domains and against state-of-the-art anomaly detection methods currently used.

II. Overview

Time series anomaly detection refers to the data analysis methodologies used to identify significant deviations from the normal behavior of temporally dependent attributes [3]. In its most basic usage, detected anomalies could be omitted from the dataset to mitigate the impact of noise or atypical events on any statistical analysis or inference made from the data. However, more recently anomalies themselves have become points of interest; the detection of these outliers are useful to identify underlying issues within the observed processes. For example, the timely recognition of abnormalities in user behavior could be crucial in fraud and intrusion detection. The amount of sensors used in modern applications and the size of time-series data collected through them makes manual detection of anomalies virtually impossible, necessitating the need to automate this process.

Recurrent Neural Networks (RNNs) have shown promise in encapsulating the complex and dynamic nature of multivariate time series data [4], and could be a useful tool to capture the temporal patterns that indicate anomalies. Training optimal RNN architectures, however, is a challenging endeavor and depends heavily on refining hyper-parameters such as the number, size and weight distributions for hidden layers of the network. Taking inspiration from biological evolutionary processes such as reproduction, mutation, recombination, and selection, neuro-evolutionary algorithms could be used to address this very problem and generate optimal RNNs and their hyper-parameters.

III. Hypothesis

The application of neuro-evolutionary methods using memory structures to capture temporal patterns will facilitate the creation of optimized RNN architectures that significantly improve the precision and recall of multivariate time series anomaly detection compared to existing methods.

IV. Evaluation

The performance and effectiveness of the anomaly detections made using our evolved RNNs would be scored using the composite F-score (Fc1), defined by Garg et al. [5] as the harmonic mean of the time-wise precision and event-wise recall. Anomaly threshold can be set automatically using the principle of Extreme Value Theory, which was shown to be successful for thresholding anomaly scores by Ya Su et al. [6]. The benchmark multivariate time series datasets used would be varied and preprocessed to introduce synthetic anomalies spread out stochastically, for detection. Based on the above mentioned criteria, our model would be rigorously evaluated and compared against state-of-the-art anomaly detection methods currently employed and other similar solutions proposed in academia.

V. Architectural Overview

This project will integrate the implementation of the EXAMM algorithm with time series forecasting mechanisms and autoencoders. The RNN architectures will be designed and optimized to capture temporal patterns indicative of anomalies. The forecasting-based model would be focused on generating single-timestamp prediction, while the reconstruction-based model would be used to learn a latent representation of the entire time-series.

VI. List of Principal Deliverables

1) Technical paper detailing the research methodology, findings, and contributions.

2) Complete code-base of the developed system, data preprocessor and evaluator, made available open-source on GitHub, and archived into a single file.
3) Input/Output examples and demonstration showcasing the system's functionality and performance.
4) User manual providing guidance on system deployment and usage.
5) Design documentation outlining the system architecture, algorithms, and components.
6) A dedicated web page for the project tracking biweekly progress and updates.

VII. Schedule

This project would span a period of 15 weeks between Jan 16, 2024 and Apr 30, 2024, spread across 6 phases based on the following schedule:

1) Jan 16, 2024 to Feb 8, 2024 (weeks 1 - 3): Literature survey and preliminary research.
2) Feb 9, 2024 to Mar 2, 2024 (weeks 4 - 6): System design and architecture planning and development.
3) Mar 3, 2024 to Apr 9, 2024 (weeks 7 - 12): Code Implementation of planned architecture.
4) Apr 10, 2024 to May 1, 2024 (weeks 13 - 15): Evaluation against benchmark datasets and performance analysis.
5) May 2, 2024 to June 25, 2024 (weeks 16 - 22): Documentation and preparation of the technical paper.
6) June 26, 2024 to July 15, 2024 (weeks 23 - 25): Final revisions, testing, and defense preparation.
7) July 16, 2024: Target defense date.

VIII. Current Status

The most frequently employed techniques for identifying abnormal time points and intervals are long short-term memory networks and autoencoders [3]. Consequently, an LSTM-based encoder-decoder anomaly detection model has been implemented over the EXAMM algorithm codebase, showing promising results on EXAMM sample data from a coal-fired power plant, with artificially introduced Gaussian anomalies on random data instances. Currently, I am experimenting with different parameter combinations to possibly further refine the networks in the training and evolution.

I am in the process of comparing accuracy and recall results with other LSTM-based encoder-decoder anomaly detection models that do not employ neuroevolution to check for evidence of improvements using our model.

Additionally, I have started drafting the thesis document based on the following rough template:

1) Introduction
2) Neural Networks
    a) Recurrent Neural Networks
3) Memory cells
    a) LSTM
4) Neuroevolution
    a) EXAMM
5) Anomaly Detection
    a) Methods
6) My Methodology
7) Results
8) Conclusions
    a) Future Work

References

[1] A. Ororbia, A. ElSaid, and T. Desell, "Investigating recurrent neural network memory structures using neuro-evolution," in *Proceedings of the Genetic and Evolutionary Computation Conference*, ser. GECCO '19. New York, NY, USA: Association for Computing Machinery, 2019, p. 446–455. [Online]. Available: https://doi.org/10.1145/3321707.3321795

[2] H. Zhao, Y. Wang, J. Duan, C. Huang, D. Cao, Y. Tong, B. Xu, J. Bai, J. Tong, and Q. Zhang, "Multivariate time-series anomaly detection via graph attention network," in *2020 IEEE International Conference on Data Mining (ICDM)*, 2020, pp. 841–850.

[3] G. Li and J. J. Jung, "Deep learning for anomaly detection in multivariate time series: Approaches, applications, and challenges," *Information Fusion*, vol. 91, pp. 93–102, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1566253522001774

[4] H. Hewamalage, C. Bergmeir, and K. Bandara, "Recurrent neural networks for time series forecasting: Current status and future directions," *International Journal of Forecasting*, vol. 37, no. 1, pp. 388–427, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0169207020300996

[5] A. Garg, W. Zhang, J. Samaran, R. Savitha, and C.-S. Foo, "An evaluation of anomaly detection and diagnosis in multivariate time series," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 33, no. 6, pp. 2508–2517, 2022.

[6] Y. Su, Y. Zhao, C. Niu, R. Liu, W. Sun, and D. Pei, "Robust anomaly detection for multivariate time series through stochastic recurrent neural network," in *Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*, ser. KDD '19. New York, NY, USA: Association for Computing Machinery, 2019, p. 2828–2837. [Online]. Available: https://doi-org.ezproxy.rit.edu/10.1145/3292500.3330672