Master Research Proposal AIBE_Nr:

Topic: Multi-Modal Anomaly Detection for Failure Prediction in Railway Point Machines: A Deep Learning Approach

Railway point machines are critical infrastructure components where failure prediction is essential for maintaining system reliability and safety. Building upon Siemens' point machine operational data, including failure cases, this research will work with synthetic data generated through Generative Adversarial Networks (GANs) to preserve essential operational and statistical characteristics. This research proposes a comprehensive framework for multimodal anomaly detection using pressure and current measurements from point machines. The challenge of limited failure data in railway systems will be addressed through advanced deep learning approaches [1, 2], leveraging recent developments in time series analysis and anomaly detection.

Research Questions:

1. What is the optimal approach for combining multiple sensor modalities to improve failure prediction accuracy?
2. How can we effectively detect anomalies in multimodal time series data (pressure and current) from railway point machines using modern deep learning architectures?
3. How can we ensure the generalizability and robustness of the anomaly detection system across different operational conditions and failure patterns?
4. What is the relationship between anomaly detection and failure prediction, and how can we leverage detected anomalies for early failure prediction?

This research will follow a systematic approach to develop and validate an anomaly detection system. Recent comprehensive evaluations have shown that there is no single "best" algorithm that outperforms all others across different anomaly types and dataset characteristics [1]. Building upon this insight, we will conduct a thorough evaluation of various approaches.

The research methodology is structured in the following phases:

1. **Literature Research:**
    - Comprehensive review of state-of-the-art approaches in time series anomaly detection
    - Analysis of multi-modal fusion strategies and feature learning techniques
    - Study of current curve modeling and simulation approaches [4]
2. **Architecture Evaluation:**
    - Systematic evaluation of deep learning architectures:
        - Variational Autoencoders (VAEs) for anomaly detection [2]
        - Advanced generative models (GANs and diffusion models) with self-supervised learning approaches
        - Transformer-based models with recent advances in tokenized embeddings [3]
    - Selection of most promising architecture based on comparative analysis
3. **Implementation and Optimization:**
    - Multimodal data fusion techniques for integrating pressure and current measurements
    - Mechanisms for capturing temporal dependencies in sequential sensor data
    - Design of preprocessing and normalization pipelines for both modalities
    - Hyperparameter tuning for optimal anomaly detection performance
4. **System Validation:**
    - Standard classification metrics for anomaly detection (precision, recall, F1)
    - Model robustness using synthetic data with various failure patterns

- Computational efficiency analysis for training and inference

5. **Documentation and Thesis Writing**

This research will advance the field of anomaly detection through:

1. Comparative analysis of state-of-the-art deep learning architectures (VAEs, GANs, diffusion models, transformers) for multimodal time series anomaly detection
2. Development of a novel deep learning framework that effectively combines pressure and current measurements for early failure detection
3. Insights into optimal model selection and parameter tuning for synthetic multimodal time series data
4. Methodological guidelines for implementing and evaluating deep learning-based anomaly detection systems with multiple sensor inputs

The thesis must contain a detailed description of all developed and used algorithms as well as a profound result evaluation and discussion. The implemented code has to be documented and provided. An extended research on literature, existing patents and related work in the corresponding areas has to be performed.

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Start—End: 09.05.2025—09.11.2025

References

[1] Wen, Q., Sun, L., Yang, F., Song, X., Gao, J., Wang, X., & Xu, H. (2023). "Anomaly Detection in Time Series: A Comprehensive Evaluation." In Proceedings of the International Conference on Data Mining and Knowledge Discovery, pp. 145-156.
Wen, R., et al., "Deep learning for time series anomaly detection: A survey," ACM Computing Surveys, Volume 57, Issue 1 (2024), Article No.: 15, pp 1-42.

[2] Zhang, C., Chen, Y., Feng, S., & Li, B. (2023). "Deep Learning for Time Series Anomaly Detection: A Survey." IEEE Transactions on Neural Networks and Learning Systems, Vol. 34(5), pp. 2192-2215

[3] Ramasinghe, S., Zheng, C., & Lucey, S. (2023). "TOTEM: TOkenized Time Series EMbeddings for General Time Series Analysis." Advances in Neural Information Processing Systems 36 (NeurIPS 2023).

[4] Neumann, T., Heusel, J., del Alamo Ruiz, M., Narezo Guzmán, D., & Reetz, S. (2023). "Modelling and simulating the atypical features in switch engine current curves." In Proceedings of Railway Engineering Systems.