Anomaly Detection using XLSTM-VAE for Data Quality Monitoring in Liquid Argon Calorimeters

Proposal :

This project focuses on designing and testing a new approach to detect anomalies in time series data collected from the Liquid Argon Calorimeters used in the ATLAS experiment at CERN. Currently, LSTM-based Variational Autoencoders (LSTM-VAEs) are used for this task, but they struggle with a problem called catastrophic forgetting, which limits their ability to remember long-term patterns across multiple data blocks called LumiBlocks. To tackle this, I propose using XLSTM-VAEs, which improve on LSTMs by having extended memory and better architecture, enabling the model to process much longer sequences effectively. This project builds upon the existing ANNOTATOR framework and aims to deliver a reliable and scalable AI tool for monitoring data quality in high-energy physics experiments.

Expected Outcome :

- A fully documented XLSTM-VAE model integrated with the IRIS-HEP anomaly detection infrastructure.
- Complete source code for training, evaluation, and inference to ensure the work can be reproduced and built upon.
- A trained XLSTM-VAE model capable of capturing longer temporal dependencies, leading to better anomaly detection in the detector data.
- Performance comparisons showing how this model stands against traditional LSTM-VAE models, especially in handling data drift over time.
- A comprehensive technical report detailing the methods, implementation, experiments, and results, ready for publication on platforms like arXiv or Zenodo.

About Me :

I am currently in my third year pursuing a Computer Science degree at Vellore Institute of Technology. I am passionate about applying AI to solve practical problems, and I have gained valuable experience through internships, hackathons, and various projects. For example, I've worked on predicting ride-hailing times and developed an AI-powered grocery management system using deep learning tools like YOLOv5, EfficientNet, and OCR pipelines. I was also a semi-finalist in Flipkart

Grid 6.0. These experiences have helped me build a solid foundation in machine learning, model deployment, and full-stack integration. I am eager to contribute my skills and grow through this project.

Project Timeline (12 Weeks | 25 hrs/week|Start Date: Jun 1)

Week	Task
Week 1–2	Literature review on XLSTM-VAE and data quality monitoring methods
Week 3–4	Develop initial XLSTM-VAE model architecture
Week 5–6	Train and evaluate model on provided time series datasets
Week 7–8	Optimize model for anomaly detection and performance tuning
Week 9–10	Final testing, validation, and metrics evaluation
Week 11-12	Prepare project report and finalize deliverables

References :

- **Kingma & Welling (2013)** – *Auto-Encoding Variational Bayes* (arXiv:1312.6114): Foundational work establishing the Variational Autoencoder framework.
- **French (1999)** – *Catastrophic Forgetting in Connectionist Networks* (Trends Cogn Sci): Highlights challenges of forgetting in sequential learning tasks.
- **ATLAS Collaboration** – *ATLAS Public Data Quality (DQ) Monitoring Documentation*: Defines LumiBlocks and explains CERN's DQ monitoring framework.
  https://atlas.web.cern.ch/Atlas/GROUPS/DAQ/Doc/DQMonitoring/
- **Dai et al. (2019)** – *Transformer-XL: Attentive Language Models Beyond a Fixed-Length Context* (ACL): Discusses long-sequence modeling approaches relevant to XLSTM.
- **Kirkpatrick et al. (2017)** – *Overcoming Catastrophic Forgetting in Neural Networks* (PNAS): Presents continual learning techniques addressing model forgetting.