### **Department of Computer Science and Engineering**

**North South University**  
 **Semester Name: Fall 2025**  
 **Course Code:** CSE499A

Project Title: "Context-Aware Few-Shot Anomaly Detection in Time-Series Data"

### Submitted By (Group 1):

|  |  |
| --- | --- |
| **Name** | **Student ID** |
| **A. Alim** | 2212073642 |
| **Farea Mahdea** | 2132730642 |
| **Anik Barua** | 2211155642 |

**Supervisor:**

Dr. Mohammad Shifat-E-Rabbi [MSRb]  
 Lecturer, Department of CSE  
North South University

📅 **Submission Date:22/10/2025**

## **Proposed Project: "Context-Aware Few-Shot Anomaly Detection in Time-Series Data"**

### **Project Overview:**

* **Problem Statement**: Detecting rare or anomalous events in machine or sensor data is a challenge, especially when labeled data is limited. The difficulty is further compounded in time-series data where past states or context are crucial for accurate anomaly detection.
* **Objective**: To accurately identify anomalies using a minimal amount of labeled data by leveraging past information (e.g., previous timestamps or machine states) as context. The project will explore the use of multiple models in a hybrid, ensemble, or multi-task framework to enhance detection accuracy.
* **Technologies**: Python, scikit-learn, TensorFlow/Keras, PyTorch, LSTM Autoencoder, One-Class SVM, Siamese Network, Transfer Learning, Ensemble Learning, Meta-Learning.

### **Recent Research Summary:**

1. **HVAC System-based Few-Shot Anomaly Detection**:
   1. **Research**: A domain adaptation method using LSTM Autoencoder for detecting anomalies with few-shot data in HVAC systems.
   2. **Reference**: [ScienceDirect](https://www.sciencedirect.com/science/article/pii/S2405896324003392)
2. **FADScr: Reinforced Data Selection**:
   1. **Research**: FADScr model improves anomaly detection and classification with few-labeled data using reinforced data selection.
   2. **Reference**: [SpringerLink](https://link.springer.com/article/10.1007/s10115-025-02572-6)
3. **FS-ADAPT: Unsupervised Domain Adaptation**:
   1. **Research**: FS-ADAPT framework enhances anomaly detection and classification with minimal labeled data.
   2. **Reference**: [ScienceDirect](https://www.sciencedirect.com/science/article/abs/pii/S0020025523011957)
4. **FastRecon: Few-Shot Industrial Anomaly Detection**:
   1. **Research**: FastRecon model detects industrial anomalies using minimal data.
   2. **Reference**: [CVF Open Access](https://openaccess.thecvf.com/content/ICCV2023/papers/Fang_FastRecon_Few-shot_Industrial_Anomaly_Detection_via_Fast_Feature_Reconstruction_ICCV_2023_paper.pdf)
5. **FewSOME: One-Class Few-Shot Anomaly Detection**:
   1. **Research**: FewSOME model uses Siamese networks for one-class anomaly detection.
   2. **Reference**: [CVF Open Access](https://openaccess.thecvf.com/content/CVPR2023W/VAND/papers/Belton_FewSOME_One-Class_Few_Shot_Anomaly_Detection_With_Siamese_Networks_CVPRW_2023_paper.pdf)

### **Proposed Methodology:**

This project will employ a multi-model approach using the following techniques:

#### **1. Ensemble Learning:**

* Combine the predictions from multiple models (e.g., LSTM Autoencoder, One-Class SVM) using techniques such as **bagging**, **boosting**, and **stacking**. This will improve anomaly detection performance by considering the strengths of different models and reducing bias.

#### **2. Transfer Learning:**

* Use pre-trained models from related domains and fine-tune them on our dataset. This will enable the use of **few-shot learning** while benefiting from the knowledge learned from larger datasets, making it an effective method for anomaly detection in scenarios with limited labeled data.

#### **3. Feature Engineering with Multiple Models:**

* Extract features from time-series data using **LSTM Autoencoder** and use those features as inputs for other models like **One-Class SVM** or **Random Forest** to improve anomaly detection accuracy by integrating insights from multiple models.

#### **4. Anomaly Scoring Combination:**

* Generate separate anomaly scores from each model (e.g., LSTM Autoencoder, One-Class SVM, Siamese Network) and combine them using techniques like **weighted averaging** or **max-voting** to make the final decision more robust and reliable.

#### **5. Active Learning:**

* Implement **active learning** where the model selects uncertain or ambiguous data points and requests labeling, helping improve performance with fewer labeled samples. This will be especially useful in training multiple models efficiently.

#### **6. Meta-Learning (Learning to Learn):**

* Use **meta-learning** to help the model adapt quickly to new data by learning optimal learning strategies. This will allow the model to effectively generalize across different anomaly detection tasks with minimal labeled data.

#### **7. Multi-Task Learning:**

* Train the model on multiple related tasks simultaneously. For example, alongside anomaly detection, the model can also perform **predictive maintenance** or **fault detection**, which can help improve the overall anomaly detection performance by providing additional context.

### **Proposed Technologies & Framework:**

* **Programming Language**: Python
* **Libraries**: scikit-learn, TensorFlow/Keras, PyTorch
* **Models**: LSTM Autoencoder, One-Class SVM, Siamese Network
* **Additional Techniques**: Transfer Learning, Ensemble Learning, Meta-Learning, Active Learning
* **Dataset**: Time-series data from HVAC systems or other small-scale datasets

### **7-Month Work Plan:**

**Month 1: Data Collection & Preprocessing**

* **Objective:** Collect and preprocess time-series data.
* **Tasks:**
  + Collect time-series data from HVAC systems or related small-scale datasets.
  + Label the data and scale it appropriately.
  + Create contextual information (e.g., timestamps, machine states) to assist in anomaly detection.
  + Perform initial data exploration and visualization.

**Month 2: Feature Extraction & Initial Model Setup**

* **Objective:** Implement feature extraction techniques and set up initial models.
* **Tasks:**
  + Use LSTM Autoencoder for feature extraction from time-series data.
  + Set up initial models (LSTM Autoencoder, One-Class SVM).
  + Train the LSTM Autoencoder model and fine-tune its hyperparameters.
  + Perform an initial analysis of feature relevance.

**Month 3: Model Development & Initial Training**

* **Objective:** Develop models and start the training process.
* **Tasks:**
  + Train the One-Class SVM and Siamese Network for anomaly detection.
  + Integrate LSTM Autoencoder with One-Class SVM.
  + Implement initial anomaly detection and assess the performance.
  + Start implementing transfer learning techniques for fine-tuning pre-trained models.

**Month 4: Integration of Advanced Techniques**

* **Objective:** Combine and enhance models using advanced techniques.
* **Tasks:**
  + Implement ensemble learning techniques like bagging, boosting, and stacking.
  + Fine-tune models using transfer learning and meta-learning.
  + Integrate multiple models for a hybrid approach (e.g., LSTM Autoencoder, One-Class SVM, Siamese Network).
  + Start implementing active learning to label uncertain data points.

**Month 5: Multi-Task Learning & Model Evaluation**

* **Objective:** Implement multi-task learning and refine models.
* **Tasks:**
  + Implement multi-task learning to enhance anomaly detection by integrating predictive maintenance or fault detection tasks.
  + Continue fine-tuning models using active learning.
  + Evaluate individual models and the ensemble model using evaluation metrics such as Precision, Recall, F1-Score, and ROC-AUC.

**Month 6: Model Fine-Tuning & Hyperparameter Optimization**

* **Objective:** Refine the models for improved accuracy.
* **Tasks:**
  + Fine-tune the models and perform hyperparameter optimization.
  + Further improve the ensemble model by adjusting the anomaly scoring combination technique.
  + Experiment with different active learning strategies to improve model efficiency.
  + Perform cross-validation to ensure generalizability.

**Month 7: Final Evaluation, Report Preparation & Publication**

* **Objective:** Finalize the models and prepare for publication.
* **Tasks:**
  + Perform a final evaluation of the models using the chosen metrics.
  + Combine anomaly scores from multiple models and finalize the decision-making process.
  + Prepare the research paper, documenting the methodologies, results, and conclusions.
  + Prepare the paper for submission to a reputable journal.

### **Conclusion:**

This project offers:

* **Innovation**: Using past context to detect anomalies, along with multiple models to enhance detection accuracy.
* **Feasibility**: Simple yet effective models like LSTM Autoencoder and One-Class SVM can be integrated with advanced techniques like ensemble learning and transfer learning.
* **Publishability**: The hybrid approach and multi-model framework are highly suitable for publication in reputed journals.

This project is designed to be completed within 7 months, with potential for publishing the findings in an established journal. Would you like to proceed with this approach? If so, I can provide detailed guidelines on data collection, model development, and evaluation.