Pattern Analysis & Machine Intelligence Praktikum: PAMI-SS/25

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Anomaly detection in radar data using VAE

Project report

Older adults often live alone and are at risk of falling and remaining on the floor due to physical frailty. Many have no close person who regularly checks on them. For this reason, we are developing a software solution that enables remote monitoring and can promptly alert physicians or emergency services in case of an emergency.

Objective

The system is designed to detect accidents and critical conditions without unnecessarily compromising residents privacy. Detection is contactless and discreet so daily life is not disturbed.

Technical concept

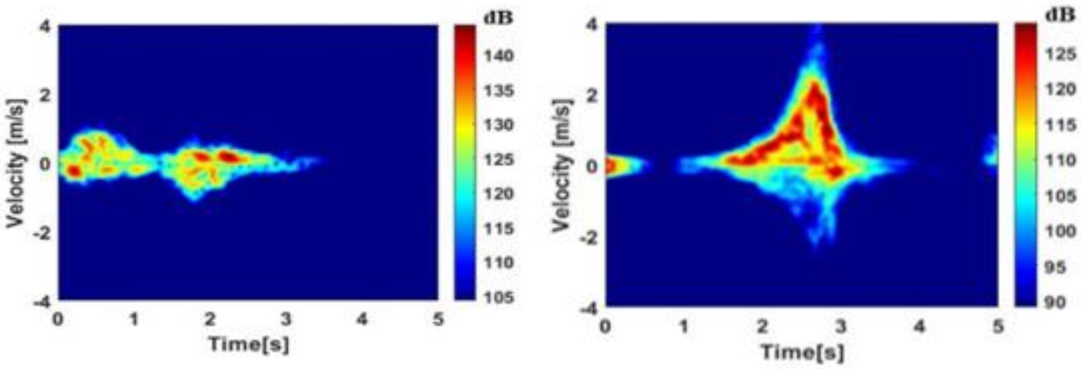
For sensing we plan to install two radar sensors per room: one at eye level and one near the floor. The sensors capture motion states such as falling, sitting, or bending. These signals are converted into an image-like format suitable for machine learning.

Machine Learning Approach

The core of the project is an anomaly detection model based on a Variational Autoencoder (VAE). As a reference we use the paper "Variational Autoencoder based Anomaly Detection using Reconstruction Probability" by Jinwon An and Sungzoon Cho (2015). Existing implementations by Michele De Vita (https://github.com/Michedev/VAE_anomaly_detection) were designed for tabular data and rely on outdated libraries, so adaptations were necessary. I refactored the source code and made it compatible for training on our radar-derived image-like data.

Training und Testing

The radar images are named according to the pattern "<ExpID>P<SubjectID>A<ActivityID>R<RunID><SegmentIndex><Mode>.png". Activities A01–A05 correspond to normal actions, while A06 denotes a fall and is treated as an anomaly. In the recordings, sitting is shown on the left side and falling on the right side.



Figur 1: Radar Image of the signal when setting and falling

Dataset and Training Configuration

A total of 5,844 images were used for training; the test set comprises 1,125 images. Due to limited computational resources, the model was initially trained for 15 epochs. Despite the shortened training, the model already shows promising results. The thresholds (alpha/threshold) must be recalibrated and cannot be adopted unchanged from the referenced paper.

Test Results and Metrics

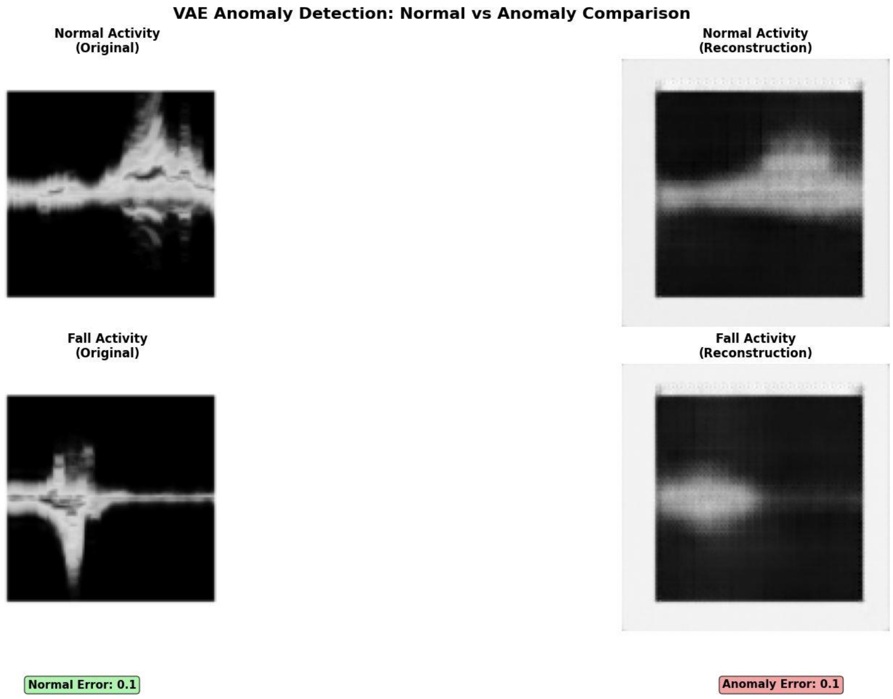
The performance of the trained Variational Autoencoder (VAE) for anomaly detection in the Micro-Doppler signatures was evaluated using various metrics and visualizations. The test dataset consisted of 1116 normal and 9 anomalous samples.

Quantitative Evaluation

The chosen model configuration (based on the Alpha Threshold, 9) yielded the following classification results:

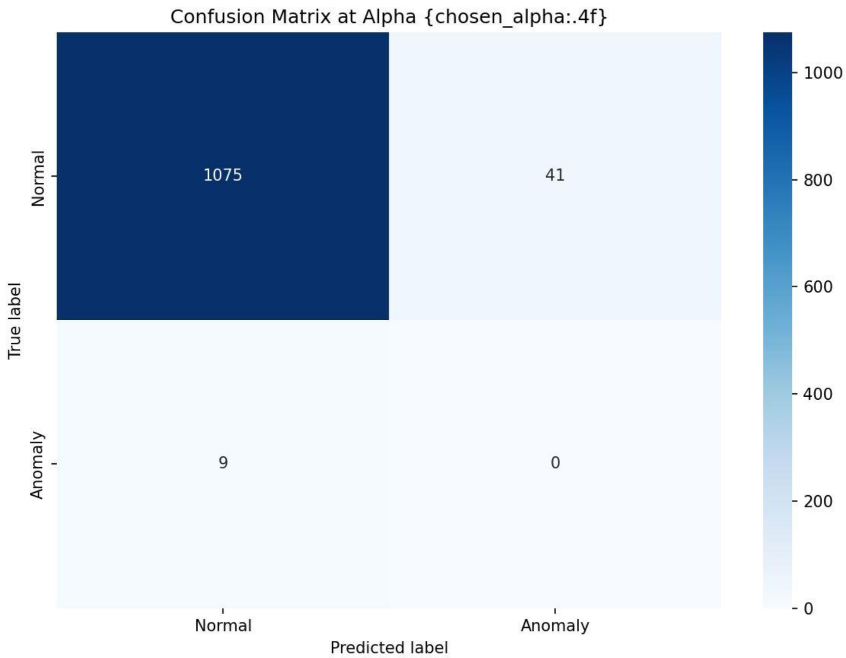
```
Classification Report:
              precision    recall  f1-score   support

      Normal       0.99      0.96      0.98      1116
     Anomaly       0.00      0.00      0.00         9

    accuracy                           0.96      1125
   macro avg       0.50      0.48      0.49      1125
weighted avg       0.98      0.96      0.97      1125
```

Figur 2: Classification Report



Figur 3: Origina vs. Reconstruction Images

Reconstruction Error: The visual comparison shows that the reconstruction error for the Normal Activity 0.1 and the Fall Activity Anomaly 0.1 is identical. This clearly demonstrates that the VAE reconstructs the anomalous activity just as well as the normal activity, rendering the reconstruction error ineffective as an anomaly score in this configuration.



Figur 4: Confusion Matrix

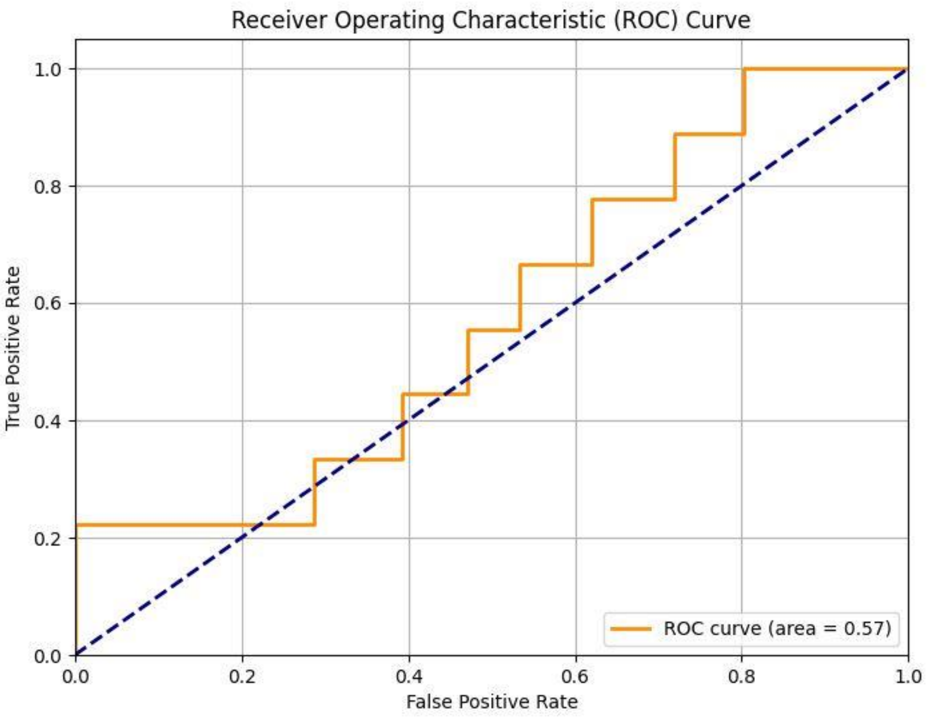
The Confusion Matrix confirms these scores:

- True Negatives (TN): 1075
- False Positives (FP): 41 (Normal samples incorrectly classified as Anomaly)
- False Negatives (FN): 9 (Anomalies incorrectly classified as Normal)
- True Positives (TP): 0

The model exhibits excellent classification of normal activities (Precision/Recall of 0.99/0.96). However, the Precision and Recall for the Anomaly class are 0.00, indicating that the model failed to correctly identify any of the nine true anomalies (TP=0). The model prioritizes avoiding False Negatives for normal data, at the expense of anomaly detection.

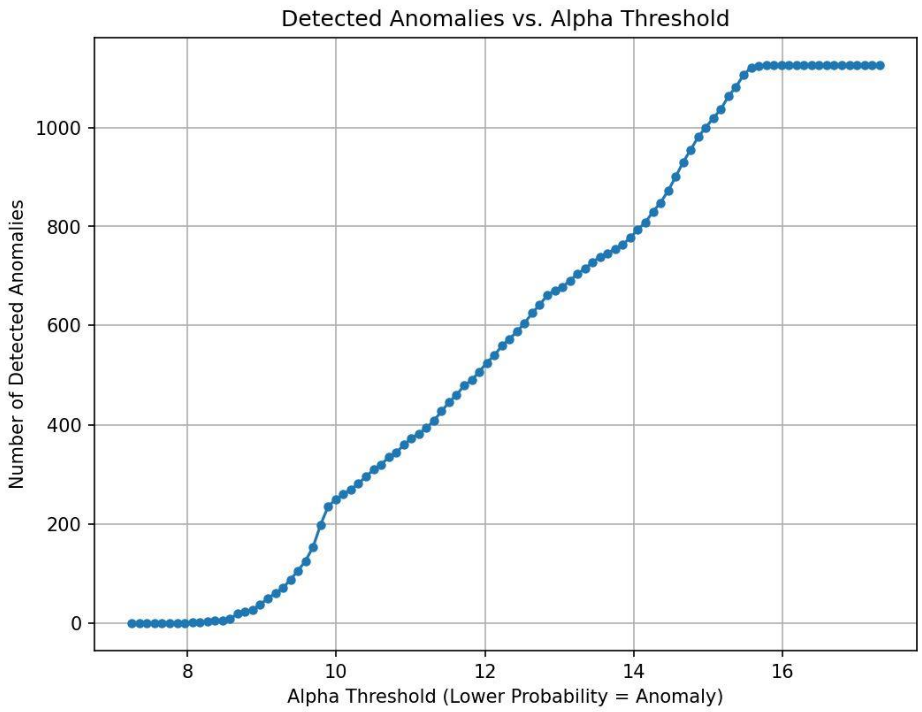
Model Performance Analysis

1. ROC Curve: The Receiver Operating Characteristic (ROC) curve analysis shows an Area Under the Curve (AUC) of 0.57. This value lies on the diagonal line, suggesting that the model's classification ability is no better than random guessing.



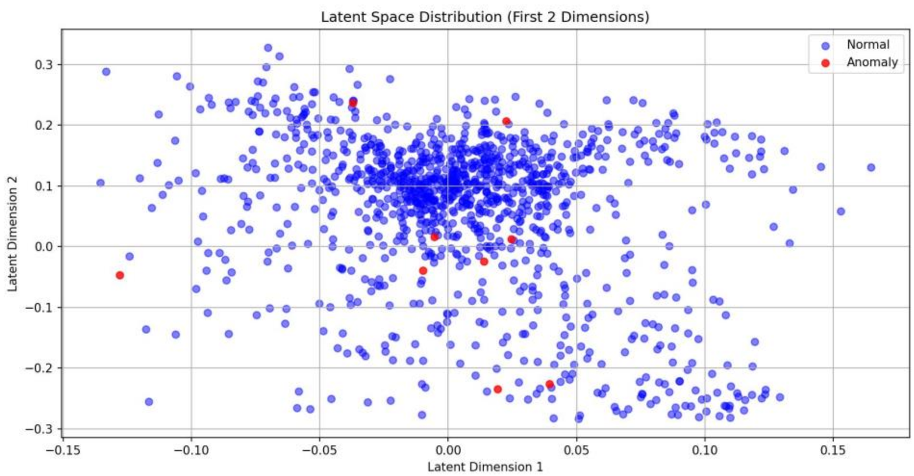
Figur 5: ROC

2. **Threshold Analysis:** The *"Detected Anomalies vs. Alpha Threshold"* plot confirms that while a stricter threshold detects fewer total events, the currently selected threshold results in TP=0 while still generating FP=41.



Figur 4: Alpha Threshold

3. **Latent Space Distribution:** The visualization of the first two latent dimensions shows a high degree of overlap between normal (blue) and anomalous (red) samples. This poor separability directly supports the low AUC value and indicates the encoder has not successfully learned distinct representations for the two classes.



Figur 5: Latenen space Distribution

Conclusion

Despite a high overall accuracy (96%), which is primarily due to the severe class imbalance, the critical metrics for anomaly detection (Recall and F1-Score for the "Anomaly" class, and the AUC) decisively show that the current VAE model setup or the chosen alpha-threshold does not achieve effective anomaly detection. Model optimization or a targeted threshold adjustment is essential to improve the identification of true anomalies.