# DESIGN OF A MULTI-SCALE FLIGHT PARAMETER DATA ANOMALY DETECTION ALGORITHM


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## ABSTRACT


Anomaly detection in flight parameter time-series data is crucial for aircraft operation. While the DCdetector model excels at detecting long-duration anomalies with its dual-attention contrastive structure, it underperforms for short-duration anomalies. This paper proposes two multi-scale optimized models based on DCdetector: a multi-scale segmentation model and a multi-scale concatenation model. The segmentation model divides input data into multiple scales using pooling layers for separate feature extraction, while the concatenation model merges multi-scale features before processing. Experiments on flight datasets show both models improve short-duration anomaly detection without compromising long-duration anomaly performance.


## METHODOLOGY

Fig 1 presents the architecture of our multi-scale segmentation model based on DCdetector. The key innovation is a multi-scale feature extraction mechanism where input time-series data undergoes multi-scale downsampling through varying pooling windows, generating subsequences at different temporal resolutions, enabling simultaneous capture of macro trends and micro anomalies.

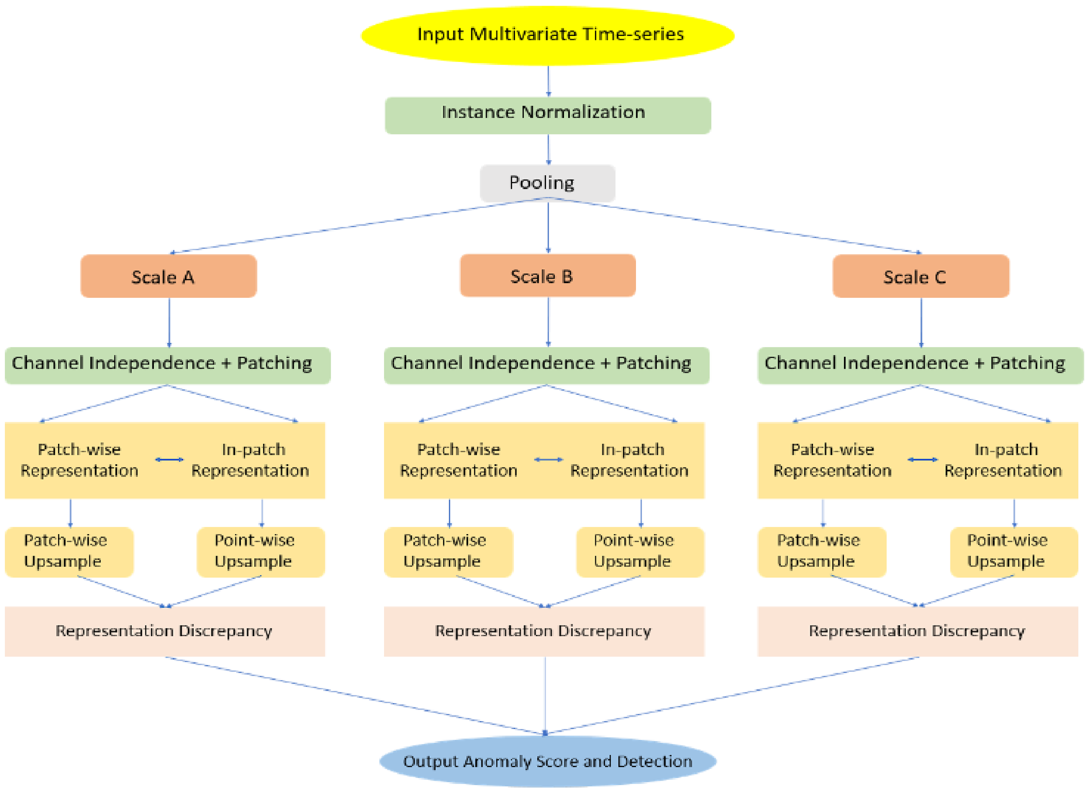


Fig. 1. Multi-scale segmentation model.

The enhanced multi-scale concatenation model (Fig. 2) extends the segmentation model by introducing cross-scale feature fusion. After multi-scale decomposition and dual-branch feature extraction, it concatenates all scale features with original representations for joint processing through dual-attention and difference representation modules.

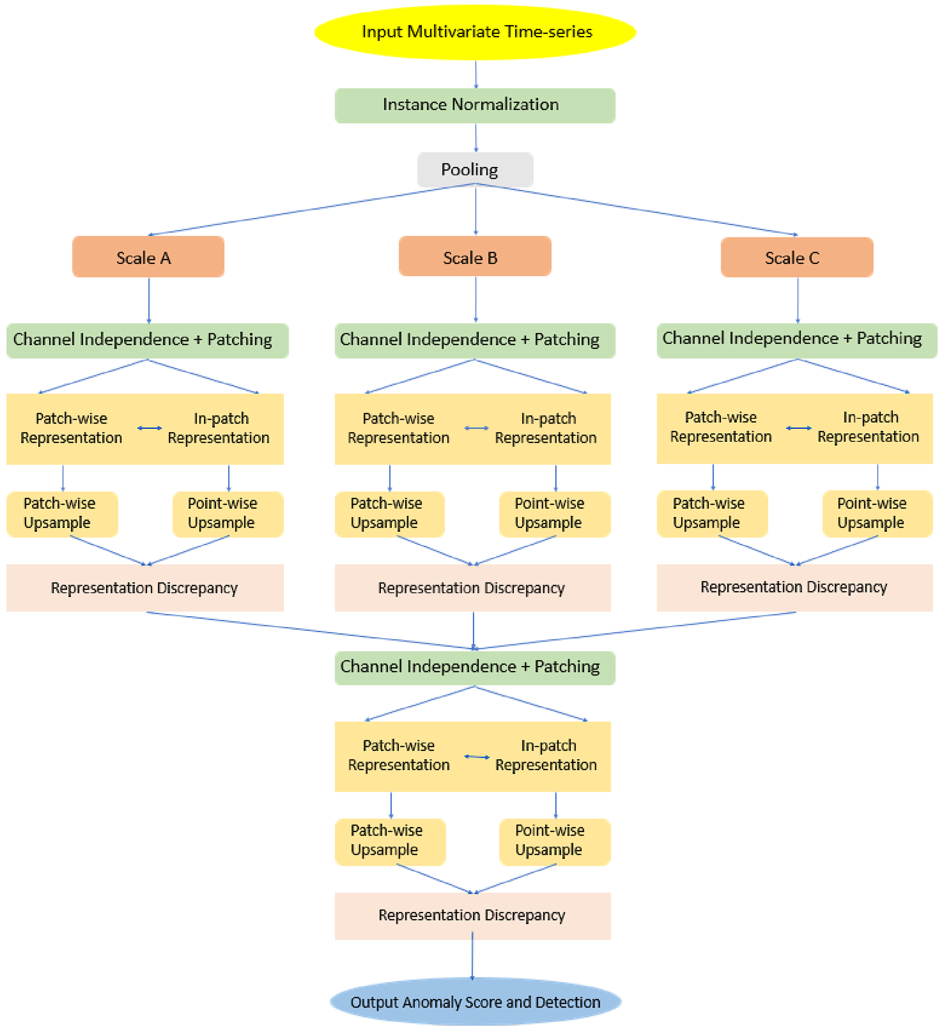


Fig. 2. Multi-scale concatenation model.

## EXPERIMENTS

The DCdetector model demonstrates strong performance in detecting long-duration anomalies in flight data but fails to identify short-duration anomalies, as shown across multiple datasets. Table I presents the model's detection performance on unmodified UCR, UCR_AUG and MSL datasets, where average precision and recall rates represent means across all test sequences.

Table. I. Anomaly Detection Performance Across Original Datasets

| Dataset | Average Anomaly Length | Average Prediction Count | Average Precision | Average Recall Rate |
|---|---|---|---|---|
| UCR | 460 | 697 | 64.13% | 100% |
| UCR | 10 | 212.66 | 0.56% | 14.0% |
| UCR_AUG | 2434.4 | 2407.73 | 91.22% | 84.53% |
| UCR_AUG | 10 | 207.26 | 2.13% | 13.3% |
| MSL | 7716 | 8285 | 92.17% | 98.33% |
| MSL | 10 | 665 | 0% | 0% |

The multi-scale partitioning model greatly improves short anomaly detection. Fig. 3 compares results between the original DCdetector (without multi-scale pooling) and the multi-scale partitioning model on the UCR_1 dataset, and Fig. 4 illustrates the detection results under varying pooling scale combinations.

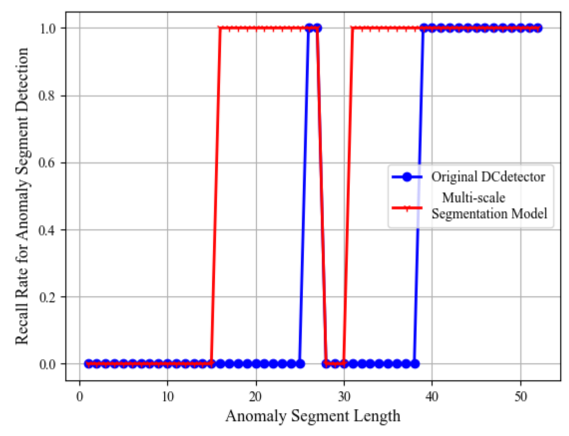


Fig. 3. Comparison With/Without Multi-scale Pooling Module

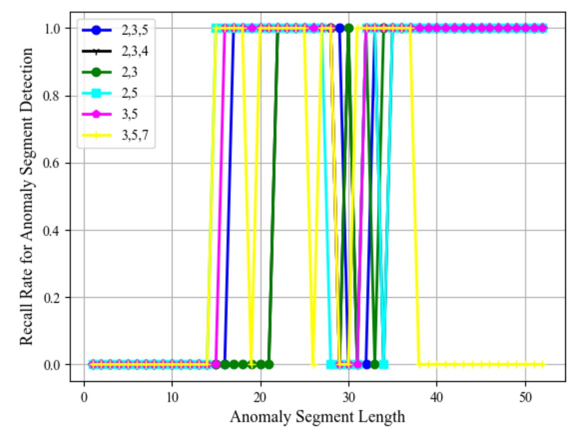


Fig. 4. Comparative Performance of Multi-scale Segmentation Model at Different Scales

Comparative experiments (Fig. 5) evaluate the multi-scale concatenation model against the partitioning model and original DCdetector on UCR_1 across varying anomaly lengths. Fig. 6 shows performance varying scale combinations.

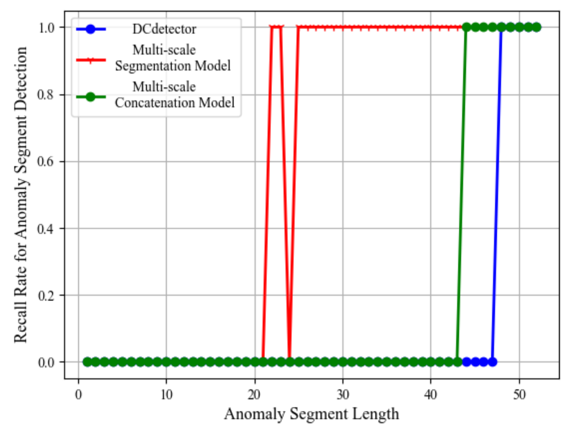


Fig. 5. Comparative Performance of Different Anomaly Detection Models

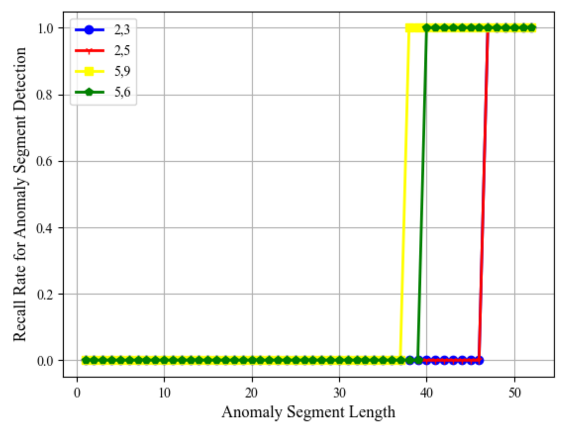


Fig. 6. Comparative Performance of Multi-scale Concatenation Model at Different Scales

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