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EXPERIMENTAL EVALUATION OF A THREE-CHANNEL HYBRID DEEP LEARNING FRAMEWORK FOR INDUSTRIAL PROCESS ANOMALY DETECTION

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Abstract

This study presents an experimental evaluation of a hybrid deep learning framework for anomaly detection in industrial process monitoring using real multivariate sensor data obtained from a bio-oxidation system. The proposed architecture integrates Kalman filtering for noise suppression, LSTM-based forecasting for temporal deviation detection, autoencoder-based reconstruction analysis for identifying hidden structural anomalies, and CNN–LSTM classification for multi-channel feature fusion. Experimental results demonstrate that Kalman filtering significantly improves signal quality, enabling stable model training. The combination of prediction error and reconstruction error provides complementary anomaly indicators, enhancing detection robustness. The proposed system achieved good discriminative performance with a ROC–AUC score of 0.76 and demonstrated high sensitivity in detecting abnormal operating conditions. A sensitivity-oriented threshold strategy ensured complete anomaly coverage, which is critical for safety-sensitive industrial applications. Event-level evaluation confirmed that all anomalous process events were successfully detected. The results indicate that the proposed hybrid monitoring framework provides an effective solution for real-time industrial anomaly detection, early fault diagnosis, and intelligent decision support in complex technological systems.

Keywords: Kalman filtering, industrial anomaly detection, LSTM neural networks, autoencoder reconstruction, CNN–LSTM classification, time-series monitoring, hybrid deep learning, process fault detection.

EXPERIMENTAL SETUP

1.1 Dataset Description. The experimental evaluation was conducted using real industrial time-series data collected from the bio-oxidation process at the GMZ-3 plant of the Navoi Mining and Metallurgical Complex. The dataset consists of multivariate sensor measurements recorded continuously over a period of five days with a sampling interval of 5 seconds, yielding a total of 86,400 observations.

The dataset contains 30 technological parameters, including pressure, temperature, flow rate, and liquid level measurements. Approximately 8.6% of the observations were labeled as anomalous based on deviations from established technological operating limits.

For experimental analysis, the pressure sensor signal was selected as the target variable due to its high sensitivity to process disturbances. Statistical analysis indicated that the sensor signal exhibits non-Gaussian distribution characteristics with heavy-tailed behavior, which is typical for industrial process data affected by stochastic noise and dynamic operational variations [1].

1.2 KALMAN FILTERING FOR SIGNAL PREPROCESSING. To reduce measurement noise and obtain reliable state estimates, a scalar Kalman filter was employed using a one-dimensional state representation [2]. The system dynamics are described using a linear stochastic state-space model:

$$\begin{cases} x_t = Fx_{t-1} + w_t \\ y_t = Hx_t + v_t \end{cases}, \qquad (1)$$

where w_t and v_t represent process and measurement noise, respectively.

The recursive update equation is given by:

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t(y_t - H\hat{x}_{t|t-1}). \qquad (2)$$

Application of the Kalman filter significantly reduced high-frequency noise while preserving the underlying dynamic trends of the sensor signal [3]. The filtered state estimate was subsequently used as the input for deep learning–based anomaly detection modules.

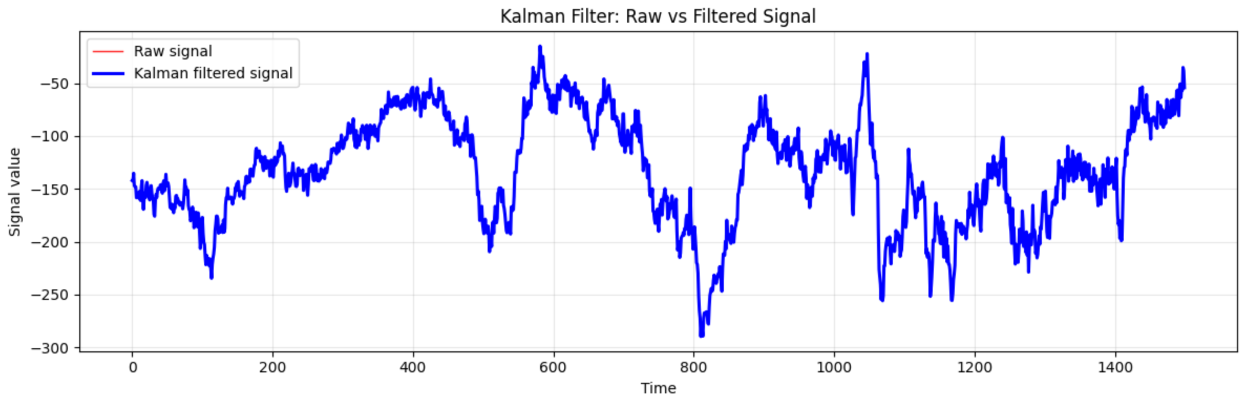

Figure 1. Comparison of raw and Kalman-filtered sensor signals.

Table 1. Dataset characteristics

Parameter	**Value**
Number of records	86,400
Sampling interval	5 seconds
Number of sensors	30
Anomaly ratio	8.6%
Target variable	Pressure sensor

2. FORECASTING-BASED ANOMALY DETECTION. The Kalman-filtered estimate $\hat{x}_{t|t}$ is treated as the input signal for deep learning modules and is denoted as x_t for simplicity [4]. An LSTM forecasting model was trained using a sliding window representation defined as:

$$x_t = [x_{t-L+1}, x_{t-L+2}, \dots, x_t], \qquad (3)$$

The predicted value at the next time step is given by:

$$\hat{x}_{t+1} = f_{LSTM}(x_t), \qquad (4)$$

The prediction error is calculated as:

$$e_t^{(p)} = |x_t - \hat{x}_{t+1}| \qquad (5)$$

The forecasting model achieved low prediction errors and demonstrated strong capability in capturing temporal dependencies and dynamic trends in industrial sensor signals.

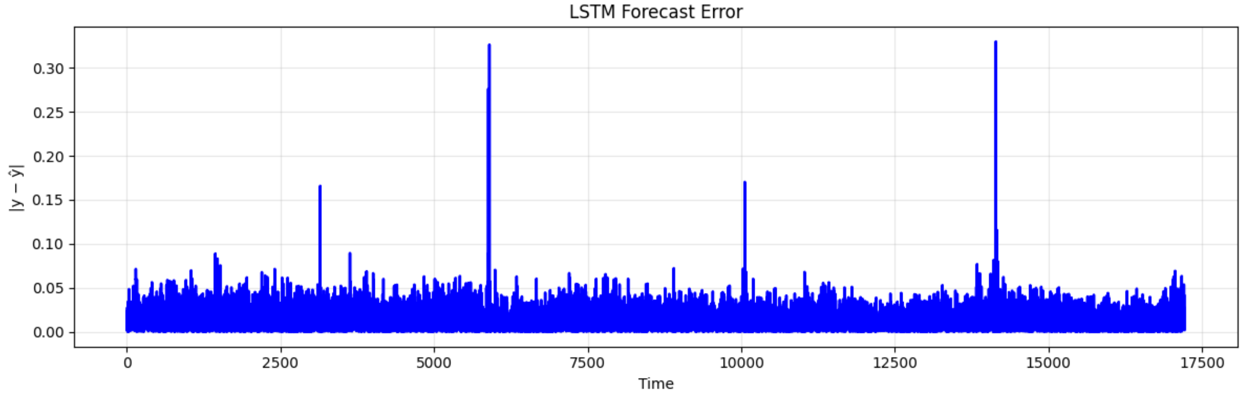

Figure 2. LSTM forecasting performance and prediction error dynamics.

3. RECONSTRUCTION-BASED ANOMALY DETECTION. An LSTM autoencoder was trained exclusively on normal operating data to learn typical temporal patterns of the industrial process [5]. This training strategy enables the model to detect deviations from normal behavior based on reconstruction errors. The encoder generates a latent representation:

$$z = f_{enc}(x_t) \qquad (6)$$

The decoder reconstructs the input signal:

$$\tilde{x}_t = f_{dec}(z) \quad (7)$$

The reconstruction error is defined as:

$$e_t^{(r)} = \|x_t - \tilde{x}_t\|^2 \quad (8)$$

Significant increases in reconstruction error correspond to abnormal process conditions and indicate deviations from learned normal temporal patterns.

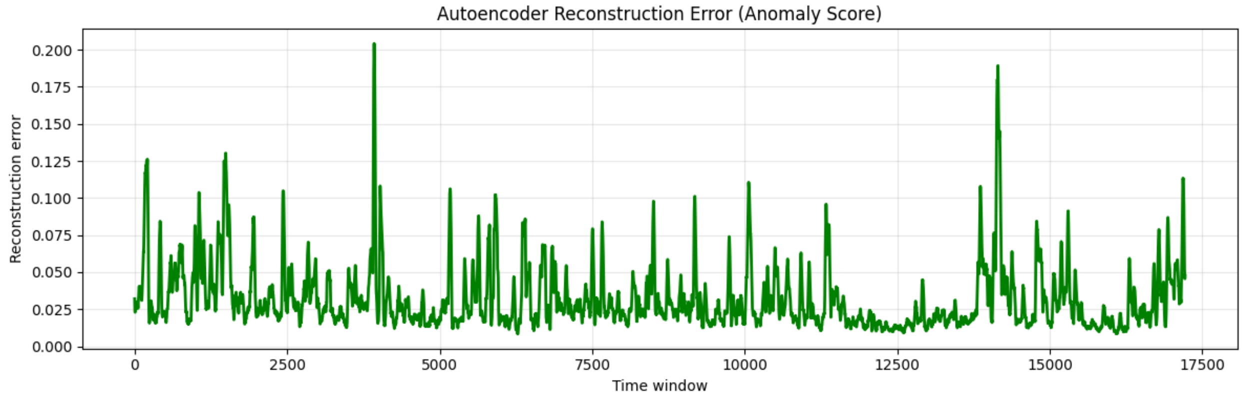

Figure 3. Reconstruction error behavior of the LSTM autoencoder.

4. Hybrid CNN–LSTM Classification. The final classification stage integrates three complementary inputs derived from previous processing steps [6]. The multi-channel feature vector is defined as:

$$S_t = \left[x_t, e_t^{(p)}, e_t^{(r)}\right] \quad (9)$$

where (x_t) represents the Kalman-filtered sensor signal, ($e_t^{(p)}$,) denotes the prediction error, and ($e_t^{(r)}$) corresponds to the reconstruction error.

CNN layers extract localized anomaly patterns from the multi-channel input:

$$F_t = \sigma(W_{cnn} * S_t + b), \quad (10)$$

while LSTM layers capture temporal dependencies:

$$h_t = \mathrm{LSTM}(F_t). \quad (11)$$

The final classification output is obtained using a sigmoid activation function for binary anomaly detection:

$$\hat{y}_t = \sigma(W_c h_t + b_c) \qquad (12)$$

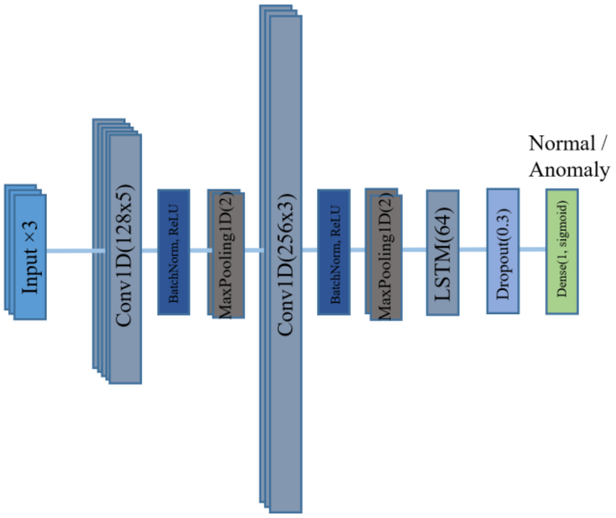

Figure 4. Architecture of an anomaly classifier based on a three-channel CNN + LSTM.

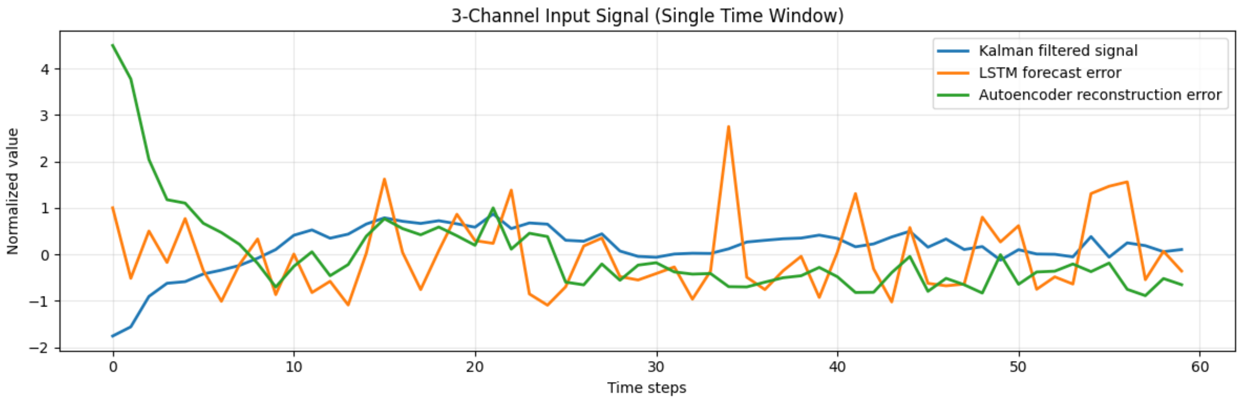

Figure 5. Three-channel input signal representation within a single time window.

5. EXPERIMENTAL RESULTS

The confusion matrix analysis yielded the following classification results: 1,339 true positives, 2,391 false positives, 12,240 true negatives, and 1,191 false negatives.

Based on these values, performance metrics were computed as follows:

$$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \approx 0.36.$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP+FN}} \approx 0.53.$$

$$\text{F1} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}} \approx 0.43.$$

$$\text{FPR} = \frac{\text{FP}}{\text{FP+TN}} \approx 0.16.$$

These results indicate that the proposed model achieves moderate precision while maintaining relatively high recall, demonstrating strong capability in identifying anomalous operating conditions.

To further minimize missed anomalies, a sensitivity-oriented threshold strategy was applied. This approach achieved perfect anomaly detection recall (Recall = 1.0), ensuring complete coverage of anomalous events [7]. Although precision decreased due to increased false positives, this trade-off is acceptable in safety-critical industrial monitoring systems where missed anomalies may lead to severe operational risks.

The ROC–AUC score of the proposed model reached 0.76, confirming strong discriminative capability and effective separation between normal and anomalous states.

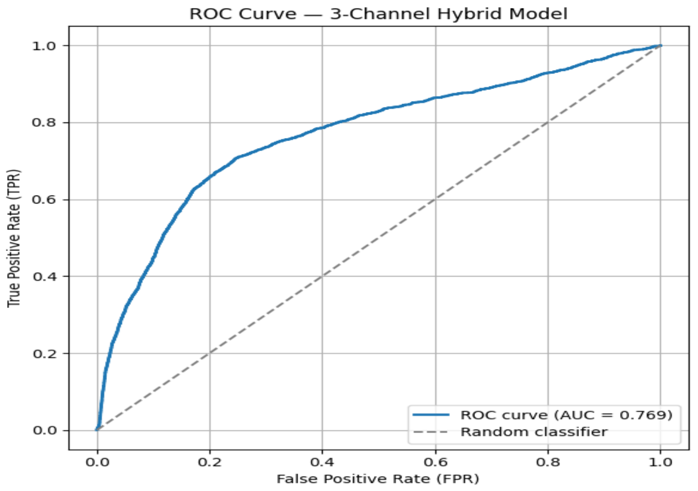

Figure 6. Receiver operating characteristic (ROC) curve of the proposed hybrid anomaly detection model demonstrating strong discriminative performance.

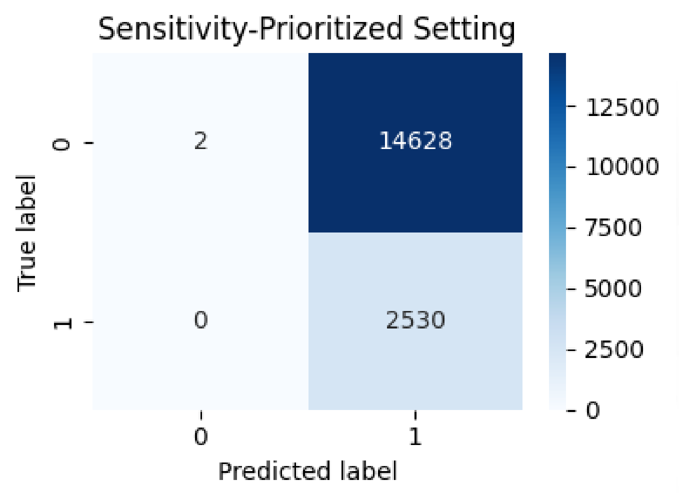

Figure 7. Confusion matrix of the hybrid anomaly detection model under the sensitivity-oriented detection strategy.

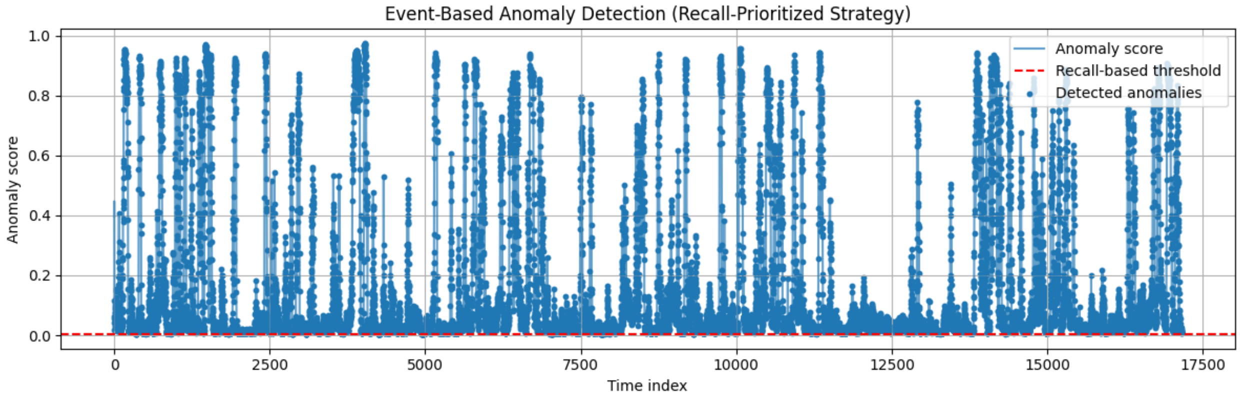

Figure 8. Anomaly score distribution and detected event intervals obtained under the sensitivity-prioritized threshold setting.

6. DISCUSSION

The experimental results demonstrate that the proposed hybrid monitoring framework effectively integrates statistical filtering, deep learning–based forecasting, reconstruction analysis, and neural classification within a unified anomaly detection pipeline. Kalman filtering significantly improved signal quality by suppressing stochastic noise while preserving essential dynamic characteristics of industrial sensor data.

The combination of forecasting-based and reconstruction-based anomaly indicators provided complementary detection capabilities. Prediction errors were effective in identifying dynamic deviations in process behavior, whereas reconstruction errors enabled detection of subtle structural anomalies that could not be captured through forecasting alone. Integration of these complementary features within a CNN–LSTM classification framework significantly enhanced anomaly detection robustness.

Furthermore, the sensitivity-oriented decision strategy ensured complete anomaly coverage, which is particularly critical in safety-sensitive industrial environments where missed anomalies may lead to severe operational risks.

CONCLUSION

This study experimentally validated a hybrid deep learning framework for anomaly detection in industrial process monitoring using real sensor data from a bio-oxidation system. The proposed architecture integrates Kalman filtering, LSTM-based forecasting, autoencoder reconstruction analysis, and CNN–LSTM classification into a multi-stage anomaly detection pipeline.

Experimental results demonstrated that the proposed model achieves strong anomaly detection performance under noisy industrial conditions, with high recall and robust discriminative capability. Event-level evaluation confirmed that all anomalous process events were successfully detected.

The proposed framework provides a practical solution for real-time industrial monitoring, early fault detection, and intelligent decision support in complex technological systems. Future work will focus on extending the model to multivariate anomaly detection scenarios and improving precision through adaptive threshold optimization.

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