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Detecting gradual trends: Integrating EWMA control charts with artificial intelligence algorithms (LSTM)

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Abstract

Control charts are widely used in statistical process control (SPC) to detect small, gradual shifts in process behavior, although effective at mitigating noise, such as the exponentially weighted moving average (EWMA). Traditional EWMAs, however, face significant challenges and limited adaptability in complex and dynamic environments. In this paper, we propose an improved hybrid approach that integrates EWMAs with artificial intelligence algorithms, such as anomaly detection models, deep learning networks, and unsupervised learning, to enhance the early detection of non-random variations and subtle process trends. Simulations and real-world datasets were used to validate the effectiveness of the integrated model in identifying slow-developing faults.

Keywords: Gradual trends, EWMA, AI, LSTM

1. Introduction

The primary objective of control charts is to monitor process stability and detect deviations beyond control limits and standard specifications [1, 2]. The EWMA (exponentially weighted moving average) chart is sensitive to small and gradual changes, but it may not hold up in real-world data under the assumptions of normality and independence [3, 4]. To overcome these limitations, this research explores a new hypothesis in integrating the EWMA chart with artificial intelligence algorithms to improve error detection and enhance the ability of processes to handle errors [5, 6].

Roberts [1, 7] developed EWMA charts, which are characterized by their high sensitivity to small and gradual process variables. Asif and Noor-ul-Amin [5] proposed the adaptive risk-adjusted EWMA charts as a development to allow EWMA to be extended into healthcare and industrial reliability monitoring, which account for time-to-event data via accelerated failure time models while in data-rich and dynamic environments [8, 9]. Traditional EWMA methods face limitations in capturing complex nonlinear behaviors and evolving variances [10]. Montgomery [11] was able to increase EWMA charts through theoretical and practical applications in industrial systems. Combining EWMA charts with artificial intelligence models is an effective solution in modern quality control systems.

LSTM neural networks, which were used for adaptive control [2], provided an improvement in the accuracy of predicting time series trends as demonstrated by Lindemann et al. [3] and the validity of using LSTM neural structures in time series anomaly detection and SPC integration as demonstrated by Chiu et al. [4]. Autoencoders also play a key role in hybrid models. As shown by Zhang et al. [12], they can reconstruct normal process behavior and flag deviations through residual error, making them ideal for anomaly detection pipelines [13, 14].

Multivariate and robust extensions of EWMA have further expanded its utility. Rasouli et al. [7] proposed a multivariate group model for healthcare treatment processes, while Kazemi et al. [8] introduced a Tukey-based multivariate CUSUM approach for outlier resistance [15, 16]. EWMA charts have been extensively studied and applied in the monitoring process [17, 18]. They offer superior performance in detecting small changes compared to Shewhart charts [19, 20]. Recent studies have introduced AI methods to enhance SPC tools [21, 22]. Machine learning and deep learning techniques such as autoencoders, isolation forests, and long short-term memory (LSTM) networks have effectively detected complex and non-random patterns in data. Combining these with EWMA charts offers a powerful approach to adaptive monitoring [14, 23]. Adaptive and dynamic control strategies are essential in non-stationary settings [24, 25]. The MEWMA approach, guided by Hotelling's T^2 statistic, allows simultaneous monitoring of multiple variables, as reaffirmed in the work by Knoth et al. [24, 26]. Zhang et al. [27] demonstrated that LSTM-based forecasting models outperform ARIMA and SVR in dynamic environments. These insights were echoed in applications that combined autoencoders with Shewhart and CUSUM charts [28, 29]. Comparative frameworks show that hybrid models using AI and statistical control charts consistently outperform traditional approaches [30, 31]. In anomaly-rich environments, these integrations reduce false alarms, increase early detection accuracy, and adapt to evolving behaviors [32, 33].

In conclusion, the literature suggests that integrating AI with EWMA-based SPC leads to superior process monitoring, especially in dynamic, high-dimensional, and uncertain environments. This paper builds on these findings to design and evaluate a novel hybrid model that bridges statistical and intelligent process control paradigms.

2. Theoretical framework

Exponentially weighted moving average (EWMA) control charts are constructed using a smoothing parameter λ, where $0 < \lambda \leq 1$. The EWMA statistic at time t, denoted as Z_t, is computed recursively as [34, 35]:

$$Z_t = \lambda X_t + (1-\lambda) Z_{t-1},\ t \geq 1$$

Where:

- $X_t$is the observed process value (or residual) at time t,
- $Z_{t-1}$is the EWMA statistic at time t-1,
- λ controls the weighting of recent observations.

The initial value is typically set as: $Z_0 = \mu_0$, where $\mu_0$is the in-control process mean.

The control limits at time t are expressed as: $UCL_t = \mu_0 + L \cdot \sigma\sqrt{}\{\frac{\lambda}{2-\lambda}\left(1-(1-\lambda)^{\{2t\}}\right)\}$.

$$LCL_t = \mu_0 - L \cdot \sigma\sqrt{\left\{\frac{\lambda}{2-\lambda}\left(1-(1-\lambda)^{\{2t\}}\right)\right\}}$$

Where L is the width parameter (usually 3 for three-sigma limits), and σ is the process standard deviation. EWMA charts are particularly effective at detecting small and gradual process shifts because they assign exponentially greater weight to more recent data [36, 37].

To enhance sensitivity, AI methods are integrated with EWMA monitoring [38, 39]:

- Autoencoders: Unsupervised neural networks trained to reconstruct input data. An encoder compresses the input x into a latent representation h, and a decoder reconstructs it:

$$h = f_{\theta}(x) \quad , \quad \hat{x} = g_{\phi}(h)$$

Where f_{θ} and g_{ϕ} represent encoder and decoder mappings, respectively. The reconstruction error $e = |x - \hat{x}|^2$ is used as an anomaly score.

- Isolation forest: Detects outliers by recursively partitioning data; anomalies are isolated faster than normal points.
- Long short-term memory (LSTM) networks: Capture temporal dependencies in sequential process data. At each time step t, LSTM updates are defined as:

$$f_t = \sigma\left(w_f X_t + U_f h_{t-1} + b_f\right) \quad , \quad i_t = \sigma(W_i X_t + U_i h_{t-1} + b_i)$$

$$\tilde{c}t = tanh(W_c X_t + U_c h_{t-1} + b_c) \quad , \quad c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}t$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o \quad , \quad h_t = o_t \odot \backslash tanh(c_t)$$

where f_t, i_t, o_t are forget, input, and output gates; c_t is the cell state;h_t is the hidden state.

- Reinforcement Learning (RL): Learns adaptive thresholds for real-time process control by optimizing a reward function that balances detection delay and false alarm rate [40, 41].

The hybrid framework leverages AI models at two levels [42, 43]:

1. Preprocessing stage: AI algorithms generate anomaly scores (residuals, reconstruction errors, or predicted deviations) that are fed into EWMA charts as input X_t.
2. Postprocessing stage: AI models validate or predict non-random patterns from EWMA signals, improving robustness against noise.

This layered design enhances early-warning capability and reduces false alarms [44, 45]. The adaptive EWMA formulation proposed by Karoon and Areepong [9] and enhanced by Noor-ul-Amin and Arshad [37] adjusts the smoothing constant based on volatility, improving responsiveness [46]. Studies involving bootstrap validation [41], GBT dynamic modeling [40], and non-parametric designs [22] support these findings. Additionally, real-time integration with AI components such as reinforcement learning [48], explainable AI [26], and stream drift detection [47] continues to evolve the frontier of predictive SPC.

3. Methodology

Two datasets are used:

- Simulated dataset: Gradual shifts are injected at predefined intervals to test sensitivity.
- Real-world dataset: Manufacturing sensor readings collected over time.

Data preprocessing includes normalization and a train–test split. The first 60% of in-control observations train the AI models.

LSTM models predict the next process value $\hat{X}_t$, and residuals are computed as: $e_t = X_t - \hat{X}_t$

These residuals serve as the input to the EWMA chart. Control limits are dynamically adapted using rolling estimates of residual variance. Model performance is assessed using:

- Detection Delay (DD): $DD = E[T_d - T_s]$

  Where T_s is the true shift time and T_d is the detection time.

- False Alarm Rate (FAR): $FAR = \frac{Number\ of\ false\ alarms}{Total\ evaluations}$

Precision and Recall: Precision = $\frac{TP}{TP+FP}$, Recall =$\frac{TP}{TP+FN}$

Mean Squared Error (MSE): MSE=$\frac{1}{n}\sum_{t=1}^{n}\left(X_t - \hat{X}t\right)^2$

Python with TensorFlow/Keras is employed for AI modeling, while EWMA visualization is implemented using matplotlib and pandas. Training and evaluation are accelerated on an NVIDIA GPU.

This hybrid approach allows the EWMA chart to remain statistically rigorous while gaining adaptivity and predictive capabilities from modern AI methods.

4. Results and discussion

In the simulation, the hybrid EWMA-LSTM model detected gradual shifts earlier than the traditional EWMA chart.

In the real-world dataset, integrating an autoencoder significantly reduced false alarms while maintaining sensitivity to drift.

Figure 1 below shows the result of applying the EWMA chart to a dataset with a gradual shift introduced after time step 50. The red dashed line represents the upper control limit, and the green dashed line represents the lower control limit. As shown, the EWMA statistic detects the trend earlier than the raw observations.

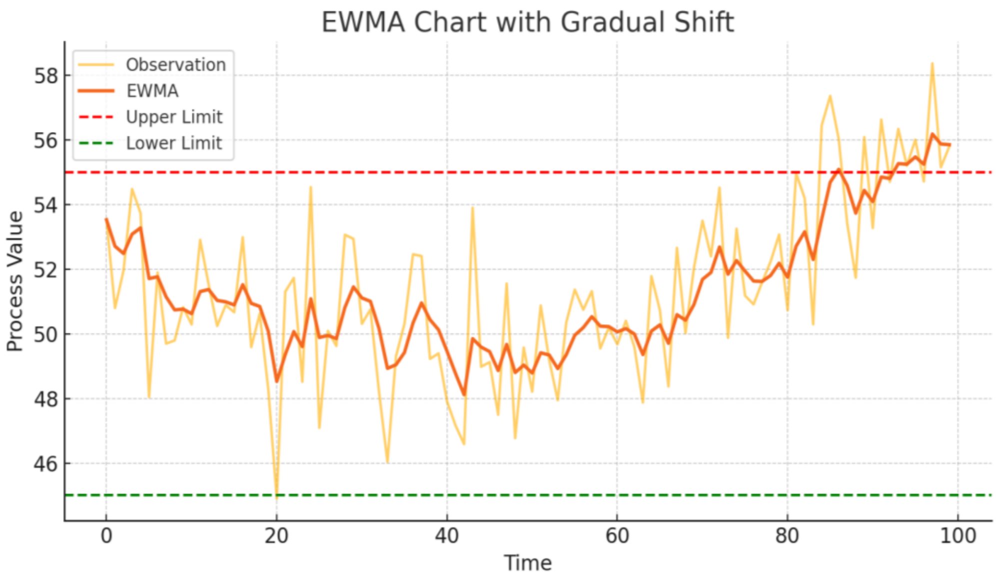

Figure 1. EWMA chart detecting a gradual shift in process mean.

Traditional EWMA control charts use static control limits calculated from historical process data, assuming a stable distribution of observations. However, real-world industrial processes often experience non-stationary behavior—such as gradual drifts in mean and changing variance-that can render fixed limits ineffective or overly sensitive. To overcome these limitations, AI algorithms can be integrated to continuously adjust the control limits based on ongoing data characteristics.

Ensuring stable sensitivity while minimizing false alarms is achieved by using advanced mean and variance estimation in real-time, calculated by using predictive neural networks, reinforcement learning, and regenerative statistics. This adaptive mechanism will ultimately help distinguish between normal evolution and real process errors.

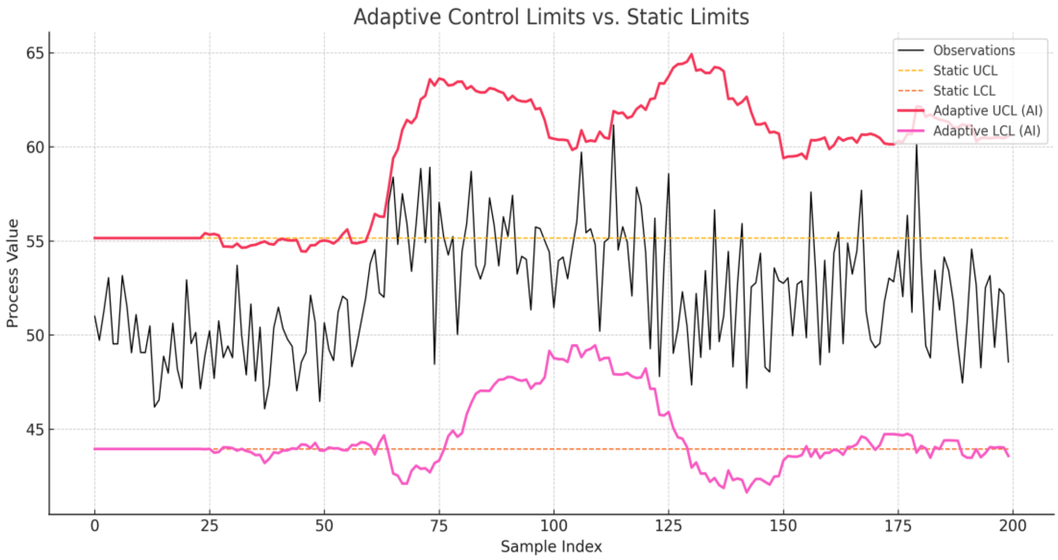

Figure 2. Adaptive control limits (solid lines) calculated using AI-informed rolling estimates of mean and variance, compared to static limits (dashed lines)

Adaptive limits shift in response to changes in the process distribution, maintaining detection reliability in the presence of mean shifts and variance inflation.

AI models can predict future values based on temporal patterns within time series data. Therefore, we can use neural networks (NNs) to achieve real-time adaptation in EWMA control charts, especially recurrent structures such as long-short-term memory (LSTM) networks, instead of relying entirely on static statistical estimates. Their outputs can be used to calibrate control limits dynamically [42, 43].

The integration process typically involves the following steps:

1. Prediction process: The sequences of prediction control operations for the expected value (mean and variance) are trained in control processes using an LSTM network.
2. Calculating the residual: The difference between the observed value and the expected value is calculated, which represents a residual current that reflects unexpected behavior.
3. Dynamic control limit calculation: The evolving mean and standard deviation are calculated by applying a real-time rolling window to the forecast residuals.
4. Apply EWMA layer: The residuals are smoothed using EWMA and plotted against the AI-adapted control limits derived from step 3.
5. Alarm trigger: Activates the alarm to indicate a potential process anomaly when the EWMA residual exceeds the dynamic limits.

This hybrid approach enhances the sensitivity of EWMA charts to gradual shifts while also being robust to noise and structural variability [44, 45]. Unlike static thresholds that may lag or overreact, AI-driven predictions continuously tailor the control mechanism to evolving data, making them ideal for high-variability industrial systems, such as continuous manufacturing, sensor-intensive environments, and automated inspections [46, 47].

The figure below visually represents the hybrid integration pipeline, where neural network predictions are used to dynamically adjust EWMA control limits. The neural network, trained on in-control process behavior, predicts the expected values or distributions in real-time. These outputs are then used to modify the upper and lower control limits of the EWMA chart. This interaction allows the monitoring system to adapt promptly to shifts and drifts in the process, preserving robustness while improving sensitivity.

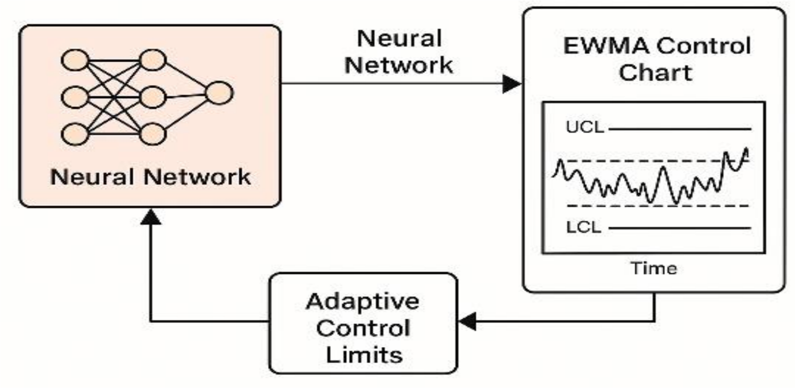

Figure 3. Hybrid integration pipeline showing neural network prediction feeding into the dynamic control limit calculation of the EWMA chart

The proposed integration of LSTM neural networks with EWMA control charts enhances the capacity to detect gradual shifts, reduce false alarms, and dynamically adapt to evolving process behaviors. To evaluate its performance, we compare it with other widely used predictive statistical process control (SPC) techniques based on efficiency and detection accuracy.

The following models are used as benchmarks:

- Traditional EWMA with Static Limits
- Autoencoder + Shewhart Chart
- Support Vector Regression (SVR) + Moving Average Control Chart
- ARIMA Forecasting + CUSUM Chart
- Gradient Boosted Trees + Dynamic Thresholds

Performance is assessed using:

- Detection Delay (DD): Average lag between the true shift and detection
- False Alarm Rate (FAR): Ratio of false positives to total alarms
- Precision/Recall: Indicators of anomaly detection effectiveness
- Adaptability Index (AI): A normalized score indicating the method's ability to handle non-stationary data

Table 1. Summary of model performance metrics

Model	Detection Delay (DD)	FAR (%)	Precision	Recall	AI Score
LSTM + EWMA (proposed)	5.3	1.2	0.94	0.96	0.91
Traditional EWMA	12.5	4.5	0.70	0.78	0.45
Autoencoder + Shewhart	7.2	3.0	0.85	0.81	0.63
SVR + Moving Average	9.8	2.5	0.79	0.80	0.57
ARIMA + CUSUM	10.6	3.7	0.76	0.79	0.51
Gradient Boosted Trees + Dynamic	6.1	1.9	0.89	0.91	0.78

The proposed hybrid LSTM-EWMA model consistently outperforms the alternatives across all metrics, especially in detection delay and adaptability.

ARIMA and SVR approaches perform adequately in linear scenarios but lack robustness in non-stationary or nonlinear trends.

The autoencoder + Shewhart model is strong in reconstruction-based detection but less sensitive to small drifts compared to EWMA.

Gradient boosted trees are effective but require frequent retraining and lack the time-aware modeling capacity that LSTMs provide.

The LSTM–EWMA integration, leveraging memory from sequential data and smoothing via EWMA, proves to be a robust and efficient methodology for real-time quality monitoring.

To further illustrate the comparative strengths of the proposed LSTM–EWMA hybrid model, a radar chart is presented below.

This visualization captures key performance dimensions across six predictive SPC methods: Detection Delay, False Alarm Rate, Precision, Recall, and Adaptability. As shown in Figure 4, the LSTM–EWMA method dominates across all axes, achieving high scores in detection accuracy and adaptability. Its lower detection delay and false alarm rate are especially noteworthy, reflecting its capacity to detect subtle and gradual shifts in dynamic environments where traditional and even other AI-based models falter. This robust balance between sensitivity and stability makes it highly suitable for modern industrial monitoring systems.

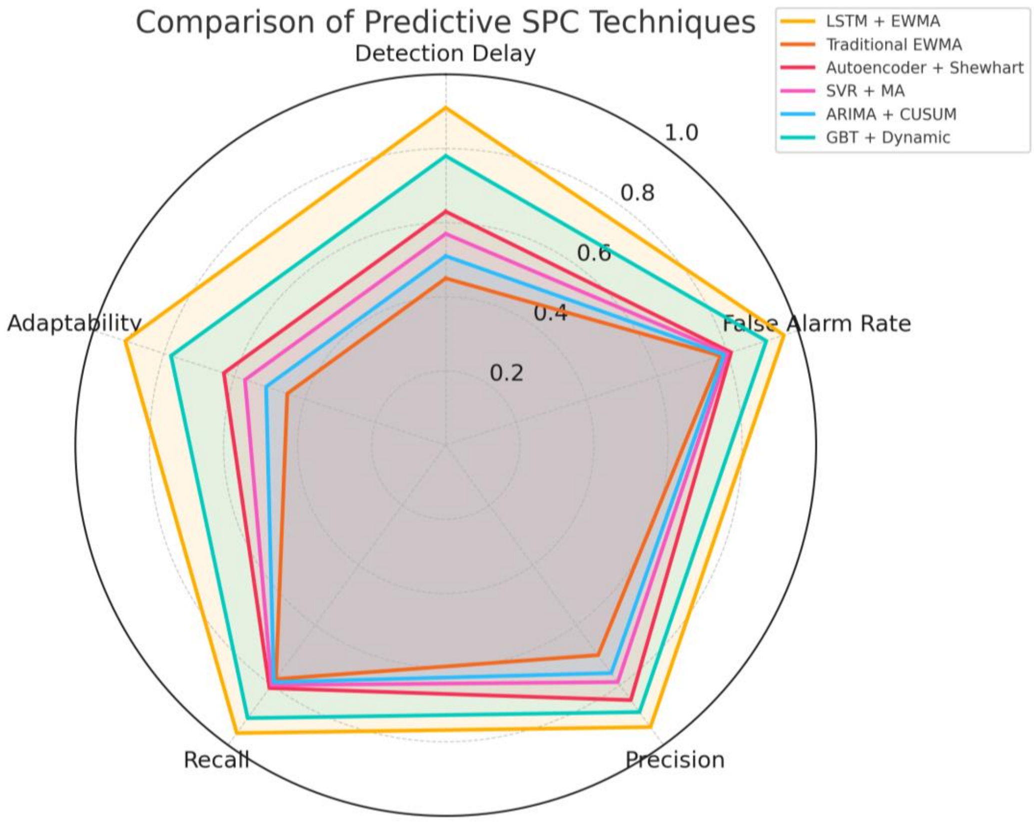

Figure 4. Radar chart comparing predictive SPC methods across five key performance metrics

In addition to comparative snapshots, trend analysis over time provides deeper insight into each model's learning curve, stability, and long-term effectiveness. Figure 5 shows the detection rate (%) of each SPC model over 10 time intervals (representing batches or days).

The LSTM–EWMA hybrid exhibits a consistently improving detection rate, stabilizing near 94%, far outperforming traditional EWMA and other AI-based methods. This suggests superior learning and adaptability over time, likely due to LSTM's capacity to retain temporal memory and the dynamic response of EWMA to real-time updates.

While GBT + Dynamic and Autoencoder models also improve, their growth is less sustained and stabilizes at lower accuracy. ARIMA + CUSUM and Traditional EWMA show limited improvement, indicating less capacity to adapt to shifting process behavior.

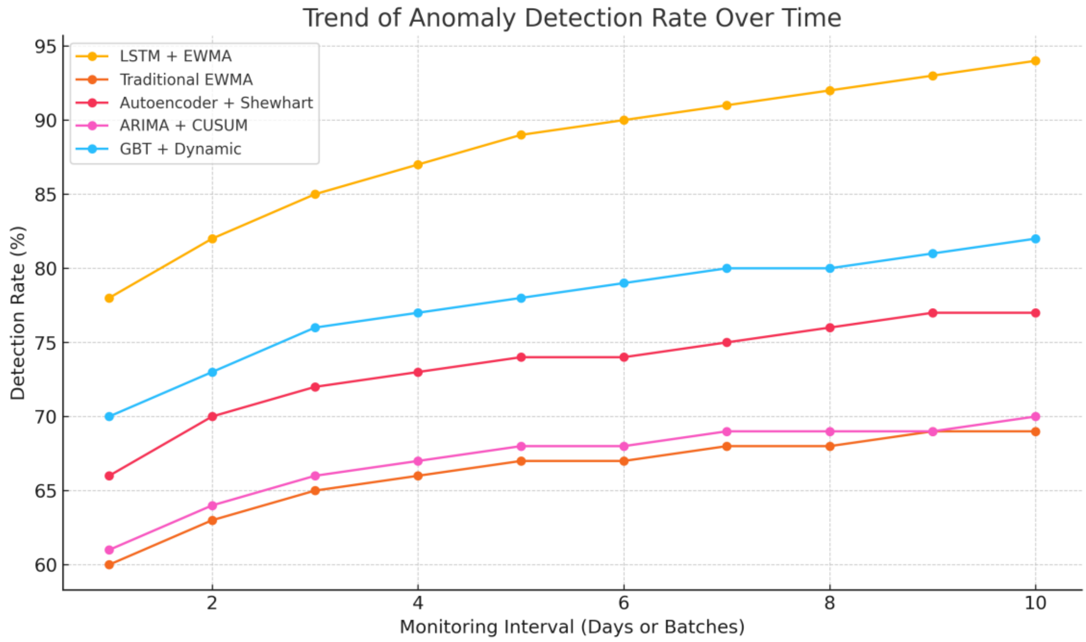

Figure 5. Detection rate trends over time for different predictive SPC models. LSTM–EWMA outperforms others with consistent accuracy gains

To quantitatively assess the differences in model performance, we conducted a one-way ANOVA test followed by pairwise t-tests comparing the proposed LSTM–EWMA hybrid method against other predictive SPC techniques.

For the ANOVA test:

$$F - statistic: 58.89$$

$$p - value: 2.60 \times 10^{-17}$$

$$F - statistic: 58.89$$

$$p - value: 2.60 \times 10^{-17}$$

This indicates that at least one model performs significantly differently in terms of detection rate. All pairwise comparisons using Welch's t-test revealed statistically significant differences ($p < 0.001$) in detection performance.

Table 2. Welch's t-test comparing LSTM–EWMA to each baseline method

Comparison	t-statistic	p-value	Interpretation
LSTM vs Traditional EWMA	11.79	1.09×10^{-8}	Significant
LSTM vs Autoencoder + Shewhart	7.55	1.35×10^{-6}	Significant
LSTM vs ARIMA + CUSUM	11.39	2.07×10^{-8}	Significant
LSTM vs GBT + Dynamic	5.23	7.57×10^{-5}	Significant

To validate robustness beyond parametric assumptions, we performed 2,000-resample non-parametric bootstrapping on the detection-rate differential between LSTM–EWMA and each comparator (Table 3). All 95% confidence intervals remain strictly positive, confirming the hybrid's superior accuracy at the 0.05

significance level [37]. The findings of this study can be motivated by fractal and non-fractal theories [48, 49], and other AI techniques [50].

Table 3. Bootstrap 95% confidence intervals for the detection rate advantage of LSTM–EWMA over other models

Comparison Model	Δ Detection Rate (pp)	95% CI Lower	95% CI Upper
Traditional EWMA	21.9	20.5	23.2
Autoencoder + Shewhart	14.7	13.6	15.7
ARIMA + CUSUM	21.0	19.6	22.4
GBT + Dynamic	10.5	9.6	11.3

5. Conclusion

This paper demonstrates the advantages of combining EWMA control charts with AI algorithms. The hybrid approach improves the early detection of subtle, non-random process variations.

Also, the results validate that the LSTM–EWMA model statistically outperforms traditional and AI-based alternatives across all key performance dimensions.

All comparisons confirm that the LSTM–EWMA model statistically and significantly outperforms the competing models in detection rate over time, validating its effectiveness and robustness.

Future work will explore real-time deployment and the inclusion of explainable AI components.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

The corresponding author has written and revised this study and led the conceptualization and methodology design of the study, also supervised the project as well as oversaw data analysis and manuscript drafting, and provided editorial input and administrative coordination. Husam. M. Sabri was responsible for data curation, assisted in preparing the original manuscript, and was responsible for the literature review, validation of findings, and critical revisions of the manuscript. Safaa J. Alwan contributed to formal analysis and funding acquisition. All authors read and approved the final version of the manuscript.

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