Integration Model of Residual-Based Mixed CUSUM-EWMA Chart with Deep Learning-Based Automatic Optical Inspection

Luh Juni Asrini[1,2,*] and Kung-Jeng Wang[2]

[1]Department of Industrial Engineering, Widya Mandala Surabaya Catholic University, Surabaya, Indonesia
[2]Department of Industrial Management, Artificial Intelligence for Operations Management Research Center, National Taiwan University of Science and Technology, Taiwan
Email: juniasrini@ukwms.ac.id (L.J.A.); kjwang@mail.ntust.edu.tw (K.-J.W.)
*Corresponding author

Manuscript received October 16, 2023; revised January 5, 2024; accepted June 25, 2024; published November 17, 2024

***Abstract*—Challenges arise when it comes to identifying flaws in small-scale electronic components swiftly during quality inspections. While Convolutional Neural Networks (CNNs) are effective at detecting defects in Automatic Optical Inspection (AOI) systems, their primary focus is on individual samples and lacks the ability to provide real-time information about the production process for process control and monitoring. To address this, a combination of CNNs and statistical process control models can be employed to enable proactive quality inspection in high-speed production lines. By combining a control chart with CNNs, the system showcases outstanding detection performance for even slight variations in quality, as evidenced by the average run length falling within a specific range of shifts. This control chart has been effectively implemented in the manufacturing process of electronic conductors, allowing for systematic quality inspection of minute electronic components on a high-speed production line. The integration of the CNN-based AOI model and the residual mixed multivariate Cumulative Sum-Exponentially Weighted Moving Average (CUSUM-EWMA) model control chart enables simultaneous quality assessment at the individual product level and process monitoring at the system level, leading to efficient detection of defects. The novelty of this research lies in the innovative process control framework that merges the CNN-based AOI model with a residual-based mixed multivariate cumulative sum and exponentially weighted moving average control chart. This integration facilitates real-time monitoring of multivariate autocorrelated processes and enables effective identification of defects.**

***Keyword*—autocorrelated process, automatic optical inspection, deep learning, residual control chart**

I. Introduction

The complexity and interconnectedness of product qualities have increased over time, particularly in the case of electronic components produced through modern high-speed continuous automation. This complexity poses challenges for product quality inspection. Multivariate quality attributes and autocorrelated quality data further complicate the production process. Statistical Process Monitoring (SPM) is commonly used in manufacturing cycles to ensure quality control, particularly for independent serial samples. To effectively manage production and product qualities, it is crucial to have a reliable SPM model. However, conventional SPM encounters difficulties when dealing with autocorrelated and multivariate quality data.

Woodall and Montgomery [1] suggest that using a univariate mixed Cumulative Sum (CUSUM) and Exponentially Weighted Moving Average (EWMA) control chart, referred to as Motion Control Engineering (MCE), for independent measurement of various quality characteristics improves the false alert rate. According to research by Zaman *et al*. [2], multivariate MCE control charts such as Hotelling's T2, Multivariate Cumulative Sum (MCUSUM), multivariate Exponentially Weighted Moving Average (MEWMA), and their combinations outperform existing charts in detecting small mean variations. Despite the availability of multivariate control charts for simultaneous quality monitoring, SPM remains challenging when applied to multivariate variables with autocorrelation.

The concept of objective observation is challenged by accumulated knowledge over time, but this issue can be addressed by using residual-based control charts, as mentioned by Wang and Asrini [3]. Researchers have explored control charts for monitoring autocorrelated activities in response to this challenge. Thaga and Yadavalli [4] found that the residual Max-EWMA chart outperforms the residual Max-CUSUM chart when it comes to detecting moderate to significant shifts in the process mean. Khusna *et al*. [5] noted that the residual Max-MCUSUM control chart is more effective in detecting mean changes in autocorrelated multivariate processes rather than changes in covariance.

In recent times, identifying defects in tiny-scale components with high-speed throughputs, including electronic components, remains a challenge for quality inspection, as highlighted by Ojer *et al*. [6]. Automated Optical Inspection (AOI) is preferred over human inspection due to variations in assessment speed among human inspectors, as discussed by Huang and Pan [7], Hung *et al*. [8], and Prieto *et al*. [9]. However, Convolutional Neural Network (CNN)-based modern AOI technology, despite its application in object/defect detection, can generate excessive false alarms or miss early detections of quality decline, as it struggles to recognize signals from certain processes. Simultaneously, there is potential for applying statistical process monitoring to multivariate and autocorrelated process control in large-scale manufacturing lines. Although CNNs have renewed interest in AOI for defect detection, this renewed interest does not address the system's control state or the connection between various approaches and process control models, as pointed out by Lin *et al*. [10], Mai *et al*. [11], and Wang and Asrini [12].

The primary focus of this research is to combine image detection models with the AOI system in order to classify products into two categories: defect and non-defect. However, these integrated systems lack the capability to provide real-time information or monitoring of the production process. Apart from detecting faults, an effective AOI system for defect detection should also be able to estimate the likelihood of defects occurring during continuous production. On the other hand, a control chart system is necessary to proactively assess whether the production process is under control and establish a threshold for defect likelihood. In a continuous manufacturing process, particularly in a production line of significant scale, the integration of the CNN model into the AOI system holds great importance for the effectiveness of the control chart system. Hence, the combination of the CNN-based AOI model with a suitable process control chart is not only necessary but also holds promising potential. This study recognizes the need to monitor even subtle changes in the mean values of autocorrelated multivariate quality attributes within a production process. To address this, the proposed approach involves incorporating a residual-based multivariate MCE control chart alongside the deep learning model in the AOI system. By doing so, the aim is to enhance the overall monitoring capabilities and achieve more accurate and reliable quality control within the manufacturing process.

II. Literature Review

A. Statistical Process Control of Multivariate Auto-Correlated Processes

Continuous and batch operation processes often exhibit autocorrelation, which poses a challenge that researchers have been trying to address [13, 14]. One approach to tackle autocorrelation is to use residuals from a control chart and apply a time series model to filter out the autocorrelation. According to Psarakis and Papaleonida [15], if a change is detected in the mean or variance of the residuals, it implies that there has been a corresponding change in the mean or variance of the underlying process. Plotting the residuals on a control chart is a method used to detect such process changes. The underlying idea of using residual charts is that if the appropriate time series model is applied to the data, the residuals will follow independent and identically distributed random variables, aligning with traditional quality control theories. Building a Vector Autoregressive (VAR) model for multivariate autocorrelated data is crucial in this procedure.

Let $Y_{(i)} = \left[Y_{(1i)}, Y_{(2i)}, Y_{(3i)}, \cdots, Y_{(pi)}\right]$ represent the i-th sample of *p* quality attributes, where *i* ranges from 1 to *n*, and *n* is the total number of observations. The quality attributes correspond to a multivariate normal distribution with a given in-control mean vector μ_0 and variance-covariance matrix Σ, denoted as $Y_{(i)} \sim N(\mu_0, \Sigma)$. It is important to mention that the mixed multivariate CUSUM-EWMA control chart was developed by Zaman *et al.* [2, 16] for the purpose of monitoring process mean variation or shifts. This control chart incorporates the $S_{(i)}$ vector obtained from the MCUSUM chart as an input vector in the MEWMA control chart. MCUSUM, introduced by Crosier [17], can be represented as Eqs. (1) and (2).

$$\boldsymbol{C}_{(i)} = \sqrt{\left(\boldsymbol{S}_{(i-1)} + \boldsymbol{Y}_{(i)} - \boldsymbol{\mu_0}\right)^{\boldsymbol{T}} \boldsymbol{\Sigma}^{-1} \left(\boldsymbol{S}_{(i-1)} + \boldsymbol{Y}_{(i)} - \boldsymbol{\mu_0}\right)} \quad (1)$$

$$\boldsymbol{S}_{(i)} = \begin{cases} \boldsymbol{0}, & \text{if } \boldsymbol{C}_{(i)} \le \boldsymbol{k} \\ \left(\boldsymbol{S}_{(i-1)} + \boldsymbol{Y}_{(i)}\right)\left(\boldsymbol{1} - \frac{\boldsymbol{k}}{\boldsymbol{C}_{(i)}}\right), & \text{if } \boldsymbol{C}_{(i)} > \boldsymbol{k} \end{cases} \quad (2)$$

In the given context, where $S_{(0)}$ is a non-negative *p*-dimensional vector, Σ^{-1} represents the known inverse of the variance-covariance matrix of $Y_{(i)}$, and *k* is a positive constant reference value. The mixed multivariate CUSUM-EWMA control chart can be expressed by the following statistics.

$$Z_{(i)} = (1-\lambda)Z_{(i-1)} + \lambda S_{(i)} \quad (3)$$

$$\Sigma_Z = \frac{\lambda}{(2-\lambda)}\Sigma_S \quad (4)$$

$$MMCE_{(i)} = \sqrt{{Z_{(i)}}^T \Sigma_Z^{-1} Z_{(i)}} \quad (5)$$

In this scenario, where $Z_{(0)}$ is a non-negative *p*-dimensional vector, Σ_Z^{-1} represents the inverse of the variance-covariance matrix Σ_Z, and Σ_S denotes the variance-covariance matrix of the $S_{(i)}$ vector. If the value of $MMCE_{(i)}$ is greater than the Upper Control Limit (UCL) of the mixed multivariate CUSUM-EWMA control chart, then it indicates that the process is out of control. Conversely, if the value is below the UCL, it signifies that the process is in control. The UCL of the mixed multivariate CUSUM-EWMA control chart represents the upper boundary limit for control.

B. Convolutional Neural Network (CNN) for AOI System

Object recognition is a fundamental component in the realm of Automatic Optical Inspection (AOI) activities as it enables the detection and categorization of objects within an image [18, 19]). AOI techniques can be broadly classified into three subcategories: referential, non-referential, and hybrid approaches [20]. Referential techniques, including image subtraction [21], feature matching or template matching [22], and compression code comparison [23], are commonly utilized. However, these techniques often encounter limitations in performance due to challenges such as image misalignment and variations in ambient conditions during the image acquisition process. These factors can significantly impact the accuracy and reliability of the object recognition process.

The You Only Look Once (YOLO) model, proposed by Redmon *et al*. [24], has revolutionized object recognition by integrating multiple components into a single neural network. YOLO is a streamlined and efficient one-stage object detection Convolutional Neural Network (CNN) that divides the input image into a predetermined grid. Through regression techniques, YOLO accurately predicts the coordinates of bounding boxes and calculates class probabilities for a fixed number of anchor boxes within each grid cell. This innovative approach has showcased exceptional performance in terms of both average precision and real-time detection [24]. In an effort to overcome YOLO's limitations concerning localization accuracy and recall, Redmon and Farhadi [25] introduced Darknet-19, a custom network that serves as the underlying feature extractor. Additionally, they implemented various strategies to enhance YOLO's performance, resulting in an upgraded version referred to as YOLOv2.

A subsequent enhancement named YOLOv3 was introduced by incorporating Darknet-53, which includes additional convolutional layers and a residual network compared to Darknet-19 [26]. YOLOv3 offers improved detection precision while maintaining real-time performance. It can handle objects with various sizes and aspect ratios by estimating bounding boxes across multiple scales [26]. Consequently, YOLOv3 represents one of the most advanced object recognition techniques, providing a combination of high accuracy and speed, making it suitable for real-time monitoring system deployments.

III. Methodology

In the present study, a novel approach is proposed, combining a CNN-based AOI model with a residual-based mixed multivariate CUSUM-EWMA control chart. The utilization of YOLOv3, a CNN model, enhances the capabilities of the AOI system by enabling the detection of multiple defects on a single product while providing precise information about their locations. Each defect is represented as a likelihood value, ranging from 0 to 1, indicating the probability of the presence of an "object". The CNN model operates in real-time, enabling simultaneous identification of various classes or types of defects. To measure the multivariate auto-correlated data in this research, a Multi-output Least Squares Support Vector Regression (MLS-SVR) model developed by Xu *et al.* [27] is employed. This combination of advanced models and techniques offers an effective and comprehensive solution for defect detection and process control in the manufacturing industry.

Let $\mathbf{e}_i = \left(\mathrm{e_{i1}}, \mathrm{e_{i2}}, \dots, \mathrm{e_{ij}}, \dots, \mathrm{e_{im}}\right)$ represent the $m \times 1$ vector of residuals for the i-th observation. The residual vectors $\mathbf{e}_i$ are assumed to have two types of means. The good mean $\boldsymbol{\mu}_{e(in)}$ is derived from the in-control processes, while the bad means $\boldsymbol{\mu}_{e(out)}$ are obtained from the out-of-control processes. The residuals $\mathrm{e_{1j}}, \mathrm{e_{2j}}, \dots, \mathrm{e_{ij}}, \dots, \mathrm{e_{nj}}$ correspond to the j-th output of the MLS-SVR with n observations. Additionally, it is assumed that the vectors of residuals $\mathbf{e}_i$ have an identified in-control variance-covariance matrix $\boldsymbol{\Sigma}_{e(in)}$. The proposed control chart is developed based on the mixed multivariate CUSUM-EWMA statistics for independent processes [28] using the residuals from the MLS-SVR model.

The statistical values of residual mixed multivariate CUSUM-EWMA model control chart are derived by generating random variables according to Eq. (3). The vector $S_{(i)}$ in Eq. (3) is computed using Eqs. (1) and (2), replacing the vector $Y_{(i)}$ with the vector $\mathbf{e}_i$. Therefore, in this study, the composition of the vector $S_{(i)}$ is defined based on the residual vector, as shown in Eq. (6):

$$S_{e(i)} = \begin{cases} 0\,, & \text{if } C_{e(i)} \le k \\ \left(S_{e(i-1)} + \mathbf{e}_{(i)}\right)\left(1 - \frac{k}{C_{e(i)}}\right), & \text{if } C_{e(i)} > k \end{cases} \tag{6}$$

$$C_{e(i)} = \sqrt{\left(S_{e(i-1)} + \mathbf{e}_{(i)} - \boldsymbol{\mu}_{e(out)}\right)^T \boldsymbol{\Sigma}_{e(out)}^{-1} \left(S_{e(i-1)} + \mathbf{e}_{(i)} - \boldsymbol{\mu}_{e(out)}\right)}$$

Residual mixed multivariate CUSUM-EWMA chart can be exhibited as the following statistics.

$$Z_{e(i)} = (1-\lambda)Z_{e(i-1)} + \lambda S_{e(i)} \tag{7}$$

$$\Sigma_{Z_e} = \frac{\lambda}{(2-\lambda)}\Sigma_{S_e} \tag{8}$$

$$R\_MMCE_{r(i)} = \sqrt{{Z_{e(i)}}^T \Sigma_{Z_e}^{-1} Z_{e(i)}} \tag{9}$$

In the described framework, the p-dimensional vector $Z_{(0)}$ is constrained to be greater than or equal to zero. The matrix Σ_{S_e} represents the variance-covariance of the $S_{e(i)}$ vector, while $\Sigma_{Z_e}^{-1}$ is the inverse of the variance-covariance matrix Σ_{Z_e}. The parameter λ serves as a smoothing factor for the MEWMA component, taking on constant values between 0 and 1. Additionally, the reference value k for the MCUSUM component is a positive real number. When the value of $R\_MMCE_{r(i)}$ exceeds the upper control limit, it indicates that the process is out of control. Conversely, if $R\_MMCE_{r(i)}$ remains below the limit, the process is considered to be in control. The upper control limit, denoted as $UCL_{R\_MMCE_r}$, defines the threshold for the residual mixed multivariate CUSUM-EWMA model control chart. Moreover, the proposed process control framework, depicted in Fig. 1, illustrates the integration of the CNN-based AOI model with the residual mixed multivariate CUSUM-EWMA model control chart. This integration enables the monitoring of multivariate autocorrelated processes and efficient defect detection.

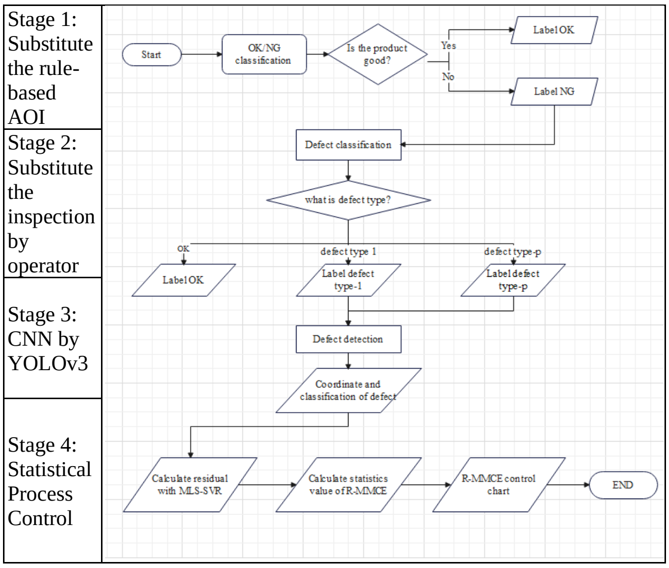


Fig. 1. Flowchart of proposed model.

IV. Result and Discussion

In order to showcase the extensive functionalities of the suggested model, a total of four simulated data sets are generated. These data sets are derived from the VAR (1) model using Eq. (10), allowing for a comprehensive evaluation of the proposed model's performance.

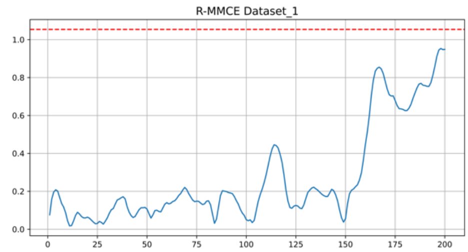
$$\begin{pmatrix} y_{1(i)} \\ y_{2(i)} \\ y_{3(i)} \\ y_{4(i)} \end{pmatrix} = \begin{pmatrix} 0.30 & 0.05 & 0.05 & 0.05 \\ 0.05 & 0.50 & 0.05 & 0.05 \\ 0.05 & 0.05 & 0.40 & 0.05 \\ 0.05 & 0.05 & 0.05 & 0.30 \end{pmatrix} \begin{pmatrix} y_{1(i-1)} \\ y_{2(i-1)} \\ y_{3(i-1)} \\ y_{4(i-1)} \end{pmatrix} + \begin{pmatrix} a_{1(i)} \\ a_{2(i)} \\ a_{3(i)} \\ a_{4(i)} \end{pmatrix} \tag{10}$$

where

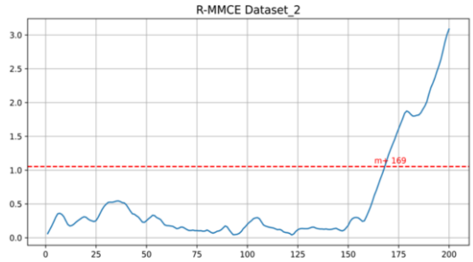
$$\begin{pmatrix} a_{1(i)} \\ a_{2(i)} \\ a_{3(i)} \\ a_{4(i)} \end{pmatrix} \sim N_4(\mathbf{0}, \mathrm{I}).$$

A total of 150 data samples are selected for the purpose of training the MLS-SVR model, enabling the determination of the optimal hyper-parameters. The remaining 50 samples are allocated for testing, where they are fitted with the aforementioned optimal hyper-parameters. Subsequently, residuals are computed based on the training and testing data sets, and control charts are constructed utilizing these residuals obtained from the MLS-SVR model.

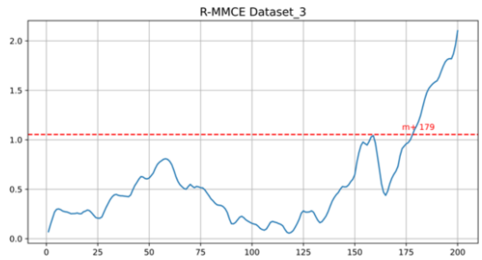
Fig. 2 illustrates the monitoring capability of proposed control chart for each dataset. Dataset 1, which does not exhibit any mean vector shift or covariance matrix shift, does not trigger any out-of-control signals according to residual mixed multivariate CUSUM-EWMA model control chart, indicating that it is within control. This demonstrates the effectiveness of residual mixed multivariate CUSUM-EWMA model control chart in detecting in-control processes. For datasets 2 and 3, the first out-of-control signals are detected by proposed control chart at the 169th and 179th data points, respectively. These out-of-control signals, indicated as "m^{+}", occur when the statistical value of residual mixed multivariate CUSUM-EWMA model control chart surpasses the Upper Control Limit (UCL). The reason for these out-of-control signals is the presence of a mean vector shift.



(a)



(b)



(c)

Fig. 2. Residual mixed multivariate CUSUM-EWMA model control chart for simulated datasets. (a) in-control; (b) mean shifting after sample 150th; (c) mean and covariance are shifting after sample 150th.

The proposed CNN-based AOI model is deployed for the purpose of monitoring the quality of real data within the manufacturing process of electronic connectors. This manufacturing process encompasses a series of stages, including stamping, electroplating, injection molding, assembling, and packaging, all of which occur on a high-speed continuous production line characterized by properties that are both multivariate and autocorrelated. These stages involve complex characteristics that are both multivariate (involving multiple quality attributes) and autocorrelated (with interdependencies between consecutive measurements). To ensure the quality of the products and monitor the manufacturing process effectively, an AOI system is installed at the final stage of assembly. The proposed CNN-based AOI model is specifically designed to analyze and detect defects in the electronic connectors using deep learning techniques. By integrating this AOI system with a control chart system tailored for multivariate and autocorrelated processes, the company can achieve simultaneous product checking and process monitoring. The integration of the deep learning-based AOI system with the control chart system brings numerous benefits. It reduces the reliance on manual inspection, as the AOI system can automatically analyze and classify the products based on their quality. Additionally, the control chart system can identify any deviations or abnormalities in the manufacturing process, allowing for timely corrective actions. By minimizing the need for manual inspection and reducing the number of products requiring rework, the company can improve efficiency, save costs, and enhance overall product quality.

The likelihood data generated by the YOLOv3 model serves as input for the residual mixed multivariate CUSUM-EWMA model control chart model. The data is divided into training and testing sets to evaluate the performance of the models. The MLS-SVR model, which is a multi-output least squares support vector regression model, requires input variables that are selected based on the partial autocorrelation function of the training data. In the case of electronic products, the appropriate time series model identified for the data is vector autoregressive, VAR (35), where lagged variables from the previous 35 time points are used as inputs. The training data is then used to train the MLS-SVR model, resulting in a mean squared error of 0.0012, indicating a good fit of the model to the training data. Fig. 3 visually represents the outcomes of monitoring the quality data of electronic components using the proposed CNN-based AOI model. Based on the residual mixed multivariate CUSUM-EWMA model control chart analysis, it is observed that an out-of-control signal emerges from sample 4-th, suggesting a change in the production process that requires attention. This finding provides engineers with sufficient time to implement corrective measures and maintain the quality of the electronic components.

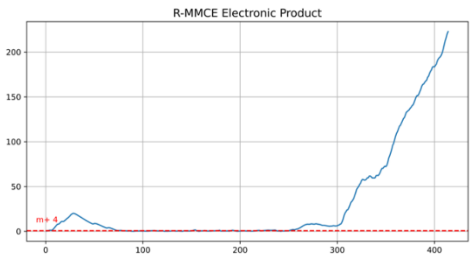


Fig. 3. Outcomes of monitoring the quality data of electronic components by the proposed model.

The residual mixed multivariate CUSUM-EWMA model control chart model proves to be effective in detecting these quality defects, making them easily identifiable for further analysis and improvement.

V. Conclusion

This research presents a new and innovative CNN-based AOI model that incorporates the residual mixed multivariate CUSUM-EWMA model control chart, utilizing MLS-SVR residuals for monitoring multivariate autocorrelated processes in a high-speed production line. The successful implementation of the proposed control chart in both simulated data and an actual electronic component manufacturing process has demonstrated its effectiveness in facilitating simultaneous product inspection and process monitoring. By integrating deep learning-based defect detection with the control chart system, this study has successfully bridged the gap between deep learning and process control models. The CNN-based AOI model allows for real-time quality inspection in the high-speed production line, utilizing online defect images, a capability that conventional AOI systems lack. This integration has proven to be a significant advancement in the field. The utilization of the residual mixed multivariate CUSUM-EWMA model control chart provides valuable insights into the quality of the production process. This empowers quality engineers to conduct detailed analysis and take proactive measures to address any detected deviations or defects. With the combination of the CNN-based AOI model and the control chart system, quality engineers now have the tools they need to ensure consistent and high-quality production in the fast-paced manufacturing environment.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Luh Juni Asrini: Methodology, writing-original draft preparation, programming, experiments, data analysis. Kung-Jeng Wang: Conceptualization, methodology, supervision. All authors had approved the final version.

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