Study on Desktop Smart Production Line and Diagnosis Technology

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Abstract: Smart manufacturing is a development tendency in the manufacturing industry. Thus, this study aimed to construct a desktop smart production line using a virtual and a real system. The data measured by various sensors were collected and combined with an intelligent predictive diagnosis system to achieve online diagnosis, analysis, and prediction of the health status of the machine. We designed an interactive information collection service for the convenience of users. We allowed users to obtain specific information easily and quickly, improve the convenience of controllers and devices, and meet the need for long-term monitoring. Moreover, we focused on reducing production scenarios from cell manufacturing to factory product inspection using robotic arms, three-dimensional printers, and small and complex processing machines with intelligent predictive diagnostic systems. In this regard, the visual recognition function of the robotic arm can perform a product appearance inspection. Finally, in the machine network platform integrating all the controllers, when the machine fails, the information is sent to the user in real time through the communication service software, and the operator can take corresponding measures depending on the warning actions received, such as remote control of the machine, to ensure production efficiency and quality.

Keywords: Machine networking platform, Visual recognition, Predictive diagnostic performance system, Principal component analysis.

1. INTRODUCTION

The Internet of Things (IoT) can be applied to the manufacturing industry to connect machines, sensors, and personnel information in the factory, save and analyze data through big data and cloud platforms, improve the base station configuration and optimization of small factories, and improve service reliability, as discussed by Liu *et al*. [1]. Tao *et al*. [2] indicated that the development of the industry will be deeply affected by artificial intelligence when transforming from traditional to intelligent manufacturing, thus seeking to make future manufacturing systems more resilient. Considering machine vision, Xiang [3] used automatic assembly to discuss positioning accuracy, and observed that a large offset and low positioning accuracy affected the smoothness of the assembly, which indicates the importance of positioning accuracy. Gongal *et al*. [4] developed a mechanical vision system composed of a three-dimensional (3D) camera and applied it to the screening of orchard apples. Through this system, the size of apples in the canopy can be estimated, effectively helping producers manage their farms, improving the performance of agricultural machinery, and reducing labor dependence. Lee *et al*. [5] proposed an advanced information analysis combined with the IoT to effectively increase machine efficiency, and transformed their big data system into a tool for predictive analysis and deliberation. LaCasse *et al*. [6] conducted feature screening for data and identified the features of large and complex data through feature quantification to produce simple and meaningful results. Fujishima *et al*. [7] offered a detailed introduction to innovative methods of sensing technology. To improve cutting efficiency, using the new coolant sensor as an example, a large amount of data was collected, the improvement of the cutting efficiency by the new sensor was enabled, and a large amount of cutting data was obtained. Farid *et al*. [8] proposed a measurement method for an axiomatic design knowledge base and structure matrix for use in an automated manufacturing system, and employed a large-scale flexible system to solve the configuration problem, which explains how to reconstruct the measurement requirements in an automated intelligent manufacturing system. Qureshi *et al*. [9] indicated that the combination of cognitive radio and IoT technology reduces the time required for data calculation, and can increase the level of data transmission and transmission speed, such that the IoT can be used by many users and thus solve the problem of big data management. Kumar *et al*. [10] studied the effect of the color of the light source on the surface roughness.

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Moreover, they used a self-developed machine vision system to capture light sources of different colors and apply them on a 3D printed workpiece, determined the difference in the surface texture characteristics of the workpiece, and compared the results. Wang *et al*. [11] proposed a machine vision method for product quality detection, which removed content irrelevant to the image background through Gaussian filtering, and introduced reverse residual blocks as the basic construct of neural networks, effectively reducing model size and offloading calculations, and improving detection accuracy and overall calculation efficiency. Fantoni *et al*. [12] discussed the importance of gripping equipment in the automated production process, categorizing gripping equipment for different industries, and monitoring the effects of different sensors on the gripping jaws; finally, they summarized and explained the new tendency of gripping equipment, alluding to the future use of robotic arms in the automated production process. Zhang *et al*. [13] indicated that the complexity of the environment and the diversity of objects hinders the accurate determination of the appearance of objects by robots. Therefore, they used auxiliary markers to perform rough positioning and deep learning for the sake of multi-target detection and to plan motion trajectories to enable the robot to effectively grasp an object. Min *et al*. [14] studied the rail surface profile and rail position using LabView, developed a program and a defect detection system, and obtained defect characteristics by tracking the direction chain code; moreover, they detected the position of the target area, such that the best value could be obtained. Dong *et al*. [15] developed a dynamic principal component analysis method to model dynamic data through the covariance of components and predicted values. To achieve real-time monitoring, dynamic changes were separated from static changes to improve the reliability of fault detection. In intelligent manufacturing, parts are worn during the operation of the mechanism, which indirectly affects their fatigue life. To predict the fatigue life of the mechanism, Bi *et al*. [16] modeled and measured the wear and fatigue life of a screw actuator via the Adhesive Wear Archhard's law. Based on the amount of wear, they found that the sliding speed, external lubrication, interface temperature, material properties, and loading cycle affected the fatigue life. Chan *et al*. [17] developed a process for instant monitoring of the mean time prior to degradation. The principal component analysis (PCA) method can determine the main basis vector of the data features. We developed a miniature machine tool health monitoring application to monitor the machine health online in the context of an actual application. Tripathi *et al*. [18] proposed an innovative agile model using the lean, smart, and green approach to improve operational performance within the limited constraints of Industry 4.0. Azizi [19] proposed two artificial intelligence optimization paradigms that can optimize a series network. Zhang *et al*. [20] proposed a new behavioral property of the manufacturing system, resilience, which is discussed. 21. García *et al*. [21] proposed a systematic review of the literature, to determine the trends in emergent control in the context of industry 4.0, and the challenges and future directions.

This study focuses on intelligent networking and health diagnostics. Smart prediction is based on measuring the machine vibration and the vibration generated by an external force during on-site processing using an accelerometer and feeding back the measured vibration signal to the intelligent pre-diagnosis system of the computer, all in real time. The line graph allows managers to monitor the health of the machine at any time. A detection technology that determines the surface or contour of a product via non-contact optical equipment and then uses computer image processing to check the product's surface defects or determine the contouring is often used in automated factories to improve the traditional measuring approach based on human eye, brain, and hand movements. Visual sensing equipment is used to detect product defects, identify product types, and classify products. When the machine is abnormal in processing, abnormal alarm information can be sent to the manager in real time such that the manager can obtain first-line information and control the status of the production line at any time. A remote monitoring system to achieve intelligent production lines was developed in this study. The developed smart networking platform and a small analog production line remotely monitored the working conditions of the production line through mobile communication applications, allowing managers to receive station information at any time, control the production efficiency of machines, and monitor their health status.

2. METHODS

Previously, when smart diagnosis and networking were not yet introduced, engineers could not immediately grasp the latest developments of the production line, often resulting in errors that could not be eliminated immediately and affected the production capacity. To overcome these problems, this study first established a simulated production line and added intelligent pre-diagnosis and Line Bot networking technology to establish the connection between the machine and the engineer for crisis management.

Smart pre-diagnosis involves performing spectrum analysis and time-domain analysis on the vibration signal generated by the operation of the robotic arm in a predetermined time interval by a sensor to obtain multiple time-domain feature values. PCA was performed on domain feature values, and multiple analysis data were obtained. For each analysis data, a Gaussian model was developed and a Gaussian mixture was applied to obtain a Gaussian mixture model. It is used to obtain the difference between both the models, the Gaussian mixture model and the preset model. Finally, the diagnostic result of the tool was verified according to the difference value and the preset threshold value [17].

Principal component analysis (PCA) is a technique that reduces the dimensionality of a data set and increases interpretability while minimizing information loss, maximizing the variance of variables by creating new uncorrelated variables. Finding such variable variance is the principal component.

Principal component analysis is the basis for multivariate data analysis based on projection methods. The most important use of PCA is to represent multivariate data tables into smaller sets of variables (summary indices) in order to observe trends, jumps, clusters, and outliers. This overview can reveal the relationship between observations and variables and between variables. The goal is to extract important information from the data, taking a visual model as an example, as shown in Figure **1**, to find lines, planes and hyperplanes in k-dimensional space to approximate the data as much as possible in the least squares sense. A line or plane is a least-squares approximation of a set of data points such that the variance of the coordinates on the line or plane is as large as possible.

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Principal component analysis mainly performs dimensionality reduction through the following four steps.

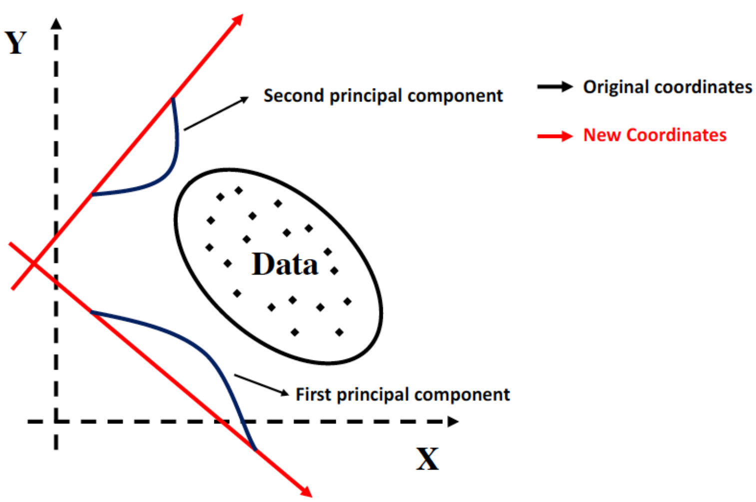

Figure 1: Schematic of the PCA [17].

2.1. Normalized Data

The variables that make up a dataset often have different units and different methods. This can lead to confusion in the system, such as generating very large numbers during calculations. To make the process more efficient, it is a good practice to center the data at mean zero and make it unit-free. This can be done by subtracting the current mean from the data and dividing by the standard deviation. This maintains the correlation and ensures that the total variance is equal to 1.

2.2. Covariance Matrix

Principal component analysis attempts to collect most of the information in a data set by identifying the principal components that increase the variance of observations as much as possible. A covariance matrix is a symmetric matrix with rows and columns equal to the number of dimensions in the data. By calculating the mean between the two data, the offset of the eigenvalue or variable is known.

2.3. Calculate Eigenvectors and Eigenvalues

Eigenvectors are linearly independent vectors that do not change direction when a matrix transformation is applied. Eigenvalues are scalars that represent the size of the eigenvectors. The eigenvectors of the covariance matrix point in the direction of maximum variance. Larger eigenvalues account for more variance. In other words, the eigenvector with the largest eigenvalue corresponds to the first principal component.

2.4. Perform Dimensionality Reduction

Eliminating information helps in dimensionality reduction. But with each additional principal component, the percentage of total variance drops, and the dimensionality can be further reduced by eliminating the least significant principal components. At this stage, it must be decided how many principal components are sufficient and how much information loss we can tolerate. Finally, the data is projected from the original feature space into a reduced space composed of principal components.

Among matrix decompositions, singular value decomposition is a fairly well-known method. It has the same characteristics as Eigenvalue and Eigenvector. The matrix product of the decomposed vectors can be restored to the original matrix, and it can decompose the singular matrix and the non-singular matrix. The solution steps are as follows.

First, define the matrix as A. A is an m×n matrix. After the conversion of singular values, a set of singular values and two sets of singular vectors are obtained to obtain a diagonal matrix, which can also be used as an image. A characteristic value of data.

$$\mathrm{A} = [u_1 \dots\ u_n]\begin{bmatrix}\sigma_1 & & \\ & \ddots & \\ & & \sigma_n\end{bmatrix}\begin{bmatrix}v_1^T \\ \vdots \\ v_n^T\end{bmatrix} \tag{1}$$

After finishing formula (1), we can get:

$$\mathrm{A} = \sigma_1 u_1 v_1^T + \cdots + \sigma_n u_n v_n^T \tag{2}$$

where $u_1 \dots u_n$ are the orthonormal vectors of the A matrix, but not all matrices are square, so we rewrite the equation as

$$\mathrm{A}_{m\times n} = \mathrm{U}_{m\times n}\Sigma_{m\times n} v_{n\times n}^T \tag{3}$$

Expand the A matrix to get

$$\mathrm{A} = \mathrm{U}\Sigma V^T = [u_1 \dots\ u_n]\begin{bmatrix}\sigma_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_n\end{bmatrix}\begin{bmatrix}v_1^T \\ \vdots \\ v_n^T\end{bmatrix} = [u_1 \dots\ u_n]\begin{bmatrix}\sigma_1 v_1^T \\ \vdots \\ \sigma_1 v_n^T\end{bmatrix} =$$

$$\sigma_1 u_1 v_1^T + \cdots + \sigma_n u_n v_n^T = \sigma_1 u_1 v_1^T + \cdots + \sigma_r u_r v_r^T \tag{4}$$

and $\sigma_{r+1} = \sigma_{r+2} = \cdots = \sigma_n$, is $u_r v_r^T$ the projection matrix of u_r.

3. PRODUCTION LINE PLANNING AND DESIGN

The objective of this study was the development of a small-scale simulation production line. The main equipment included a 3D printer (A), a robotic arm (B), a compound processing machine (C), a single-axis moving platform (D), and a pneumatic cylinder (D), as shown in Figures **2** and **3**. First, the model is processed using a 3D printer. After the processing, the workbench of the 3D printer sends the model forward. Currently, the workbench presses the light shield sensor, which starts controlling the machine. The arm is used for Automated Optical Inspection image recognition, distinguishing between good and defective products. If secondary processing is required, the robotic arm clamps the model to the next workstation, the compound processing machine; otherwise, it is sent directly to the mobile device. The finished products are separated on the platform, and the pneumatic cylinder is used to push the products off the platform and place them in the product storage area (F).

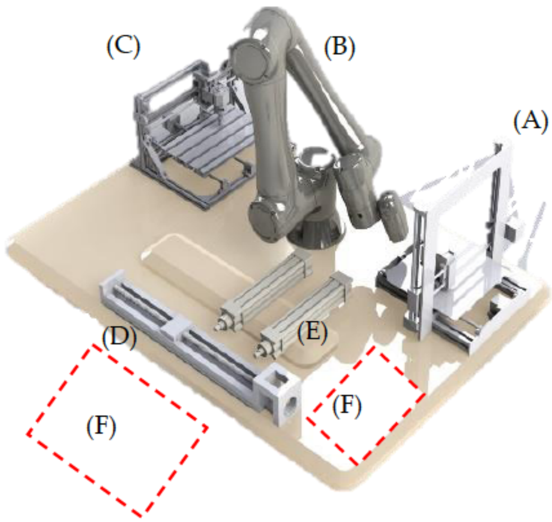

Figure 2: Virtual desktop smart production line.

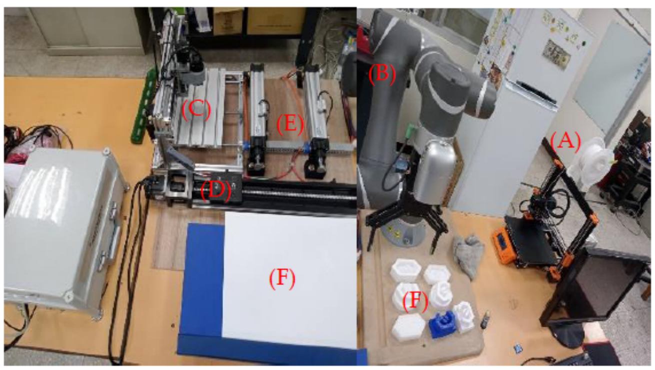

Figure 3: Desktop smart production line.

4. MACHINE NETWORKING SYSTEM ARCHITECTURE DIAGRAM OF THE PRODUCTION LINE

The networking system, shown in Figure **4**, is intended to reduce the production line of unit manufacturing to enable the inspection of the factory, using 3D printers and composite processing machines to simulate on-site processing machines. The visual identification function of the robotic arm can be used for product appearance inspection to integrate all controllers on the machine networking platform and cooperate with the intelligent predictive diagnosis system. When the machine fails, the information can be sent to the user side through the communication service software in real time, and the user can also take corresponding actions and measures in response to the machine's warning, such as remotely controlling the machine to stop its running.

5. IMAGE VISUAL RECOGNITION

The robotic arm used in this study was the TM5-900 from the TM robot series. This robotic arm has two main functions: TM-flow software compilation and a TM-vision vision system.

5.1. TMflow Software Compilation

This software can simplify the compilation time of the program; moreover, it has intuitive editing software

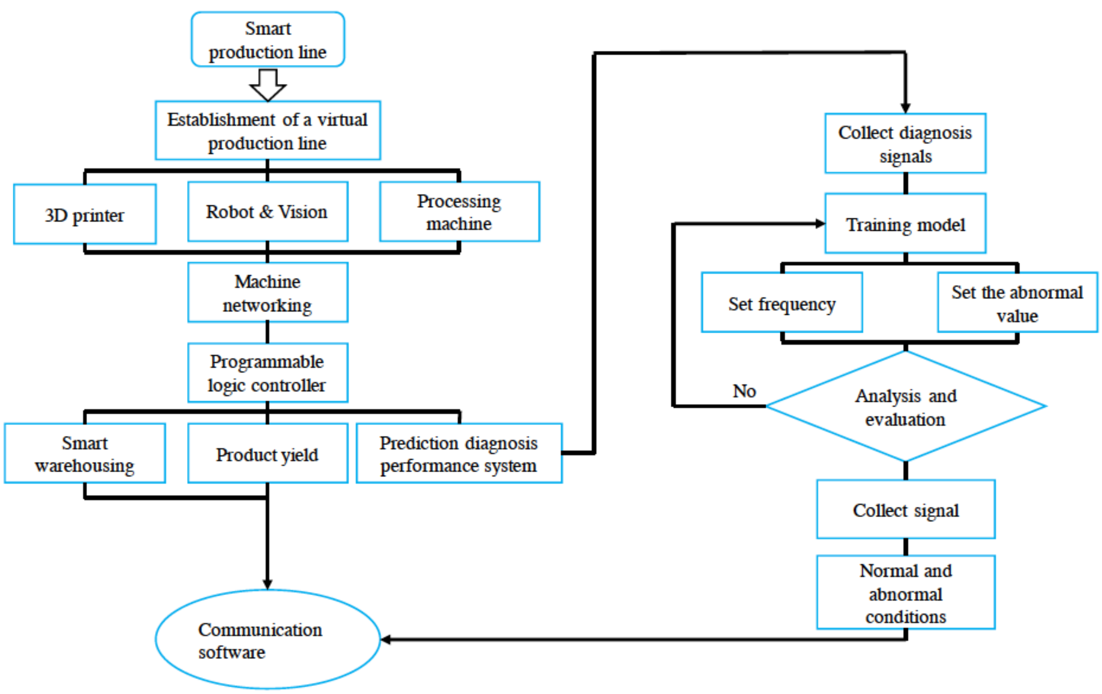

Figure 4: Flow chart of the study.

and a full graphical flow chart, and can be used during operation. The products in this study are mainly divided into round, squared, and hexagonal. Because there is a certain angle of deviation when the product is artificially placed, we used the machine vision system to increase the discrimination angle range of the squared and hexagonal products, such that the production line staff can place them in the discrimination range at any angle. This process can also be used for arm gripping.

5.2. TM-Vision Visual System

Figure 5: TM-vision visual system.

The second aspect of the TM5-900 robotic arm is the vision system, as shown in Figure **5**. No additional hardware or software is required. This function can be applied directly through the vision node of the TM-flow, which can detect the outlines and features of the object and preview execution results.

6. INTELLIGENT PREDICTIVE DIAGNOSIS SYSTEM

This system can monitor the health of a machine in real time using a vibration sensor. If the vibration signal exceeds expectations, a warning is issued on the computer.

6.1. Sensor Installation

The mechanical vibration signal can quickly reflect the health status of the robotic arm. This pre-diagnosis system consists of an accelerometer installed on the robotic arm, as shown in Figure **6**. The system collects the vibration signal of the arm during movement through the accelerometer and sends the vibration signal back to the pre-diagnosis system to determine the damage done to the arm. The sensitivity of the accelerometer used in this study is 50 mV/g.

6.2. Establishment of a Smart Diagnosis Model

The analysis and diagnosis software was developed on the Visual Studio platform, and *PCA* was used for modeling and analysis. Smart manufacturing can be performed by instant monitoring of the mean time before degradation. The robotic arm can enable pre-diagnosis, robotic intelligent predictive maintenance, and equipment failure analysis of machineries.

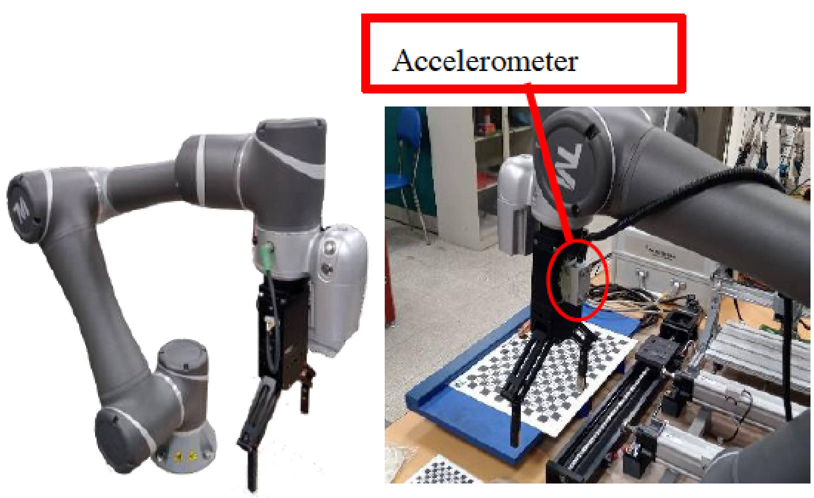

Figure 6: Installation of the accelerometer on the robot arm.

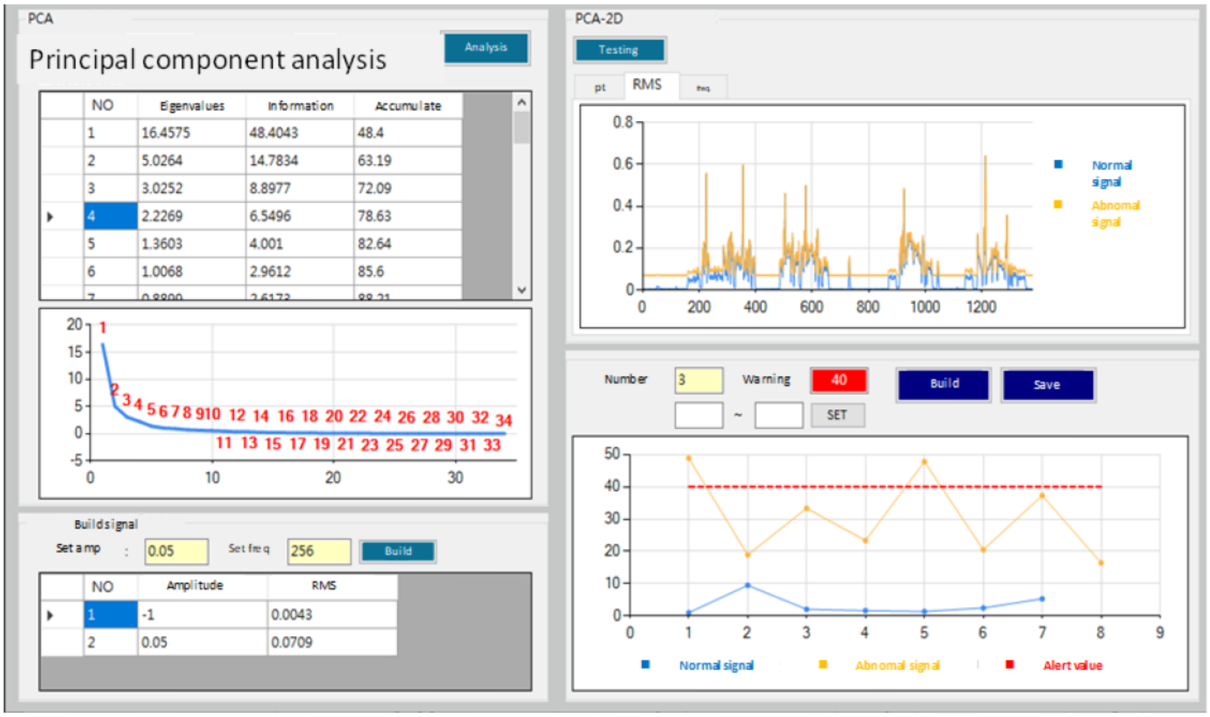

Figure 7: Building of a diagnostic model.

An accelerometer was used to capture the feature data to compare the healthy and abnormal feature maps, and to cooperate with the Gaussian Mixture Model Module to predict the abnormal frequency, set the warning line, and establish a diagnostic model, as shown in Figure **7**.

6.3. Smart Diagnosis Results

The diagnosis performed through the model and the diagnosis result of the arm are shown in Figure **8**. The green line represents the diagnostic result. The blue line (area 1) shows the state of the arm operating normally, and the diagnosis results are all below the

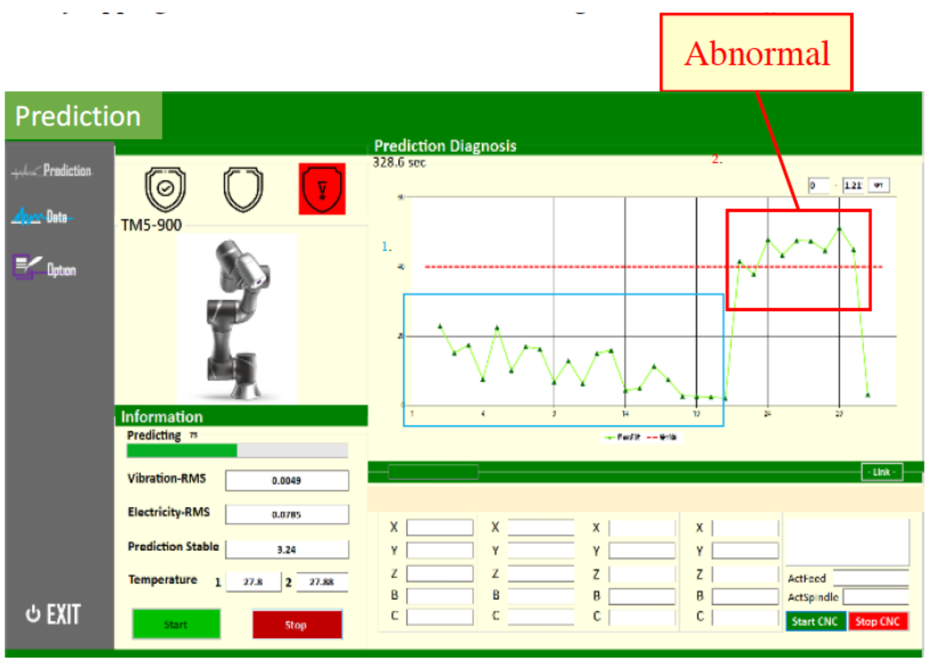

Figure 8: Diagnosis result.

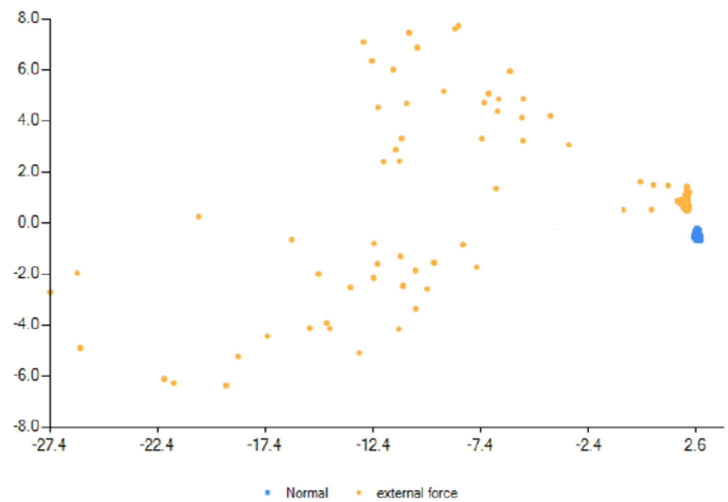

Figure 9: Principal component analysis.

warning line; the red line (area 2) shows the state of the arm when it is abnormally actuated, artificially tapping the arm to simulate collision. The diagnosis result is higher than the warning line.

6.4. Principal Component Analysis

In response to the diagnosis results, we used PCA to evaluate the health of the robotic arm. From the analysis results, as shown in Figure **9**, it *could* be observed that when the arm was moving normally, the feature point distribution was convergent. In contrast, when the arm *wa*s subjected to an external force, the feature points *were* scattered owing to the external force. Therefore, from the figure, it is possible to clearly distinguish between a healthy and an abnormal condition, which has a very significant impact on the characteristics.

7. NETWORK PLATFORM

The networking platform was designed using Microsoft Visual Studio, as shown in Figure **10**. In addition to integrating controller information into the system, the platform can facilitate arm internal information, program setting and modification, and the remote monitoring of processing screens, as shown in Figure **11**. To enable users to conveniently grasp the status of the production line in real time, we employed the Line Bot program in the Line communication software. When a problem occurs in the arm, an alarm message is instantly sent back to the line message of the manager, as shown in Figure **12**. This function allows managers to obtain first-line information without continuously monitoring the processing panel, providing greater flexibility and convenience for users.

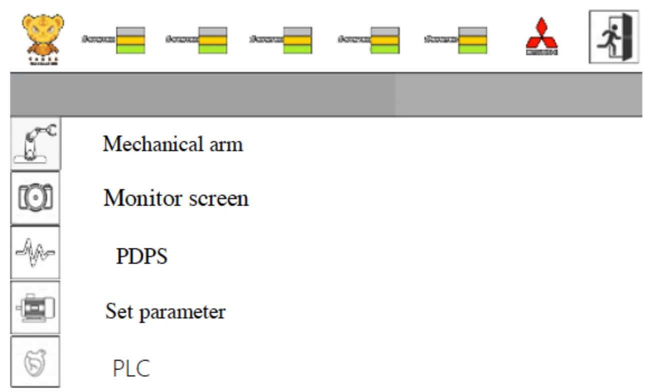

Figure 10: Networking platform.

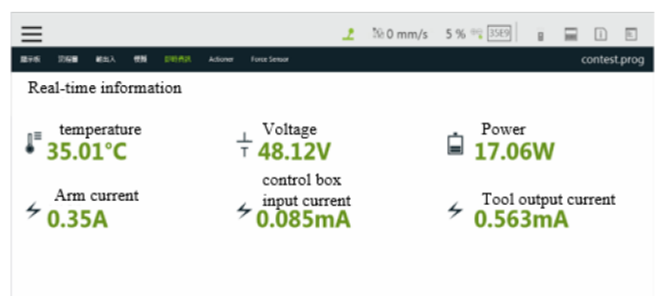

Figure 11: Arm's internal information.

8. RESULTS AND DISCUSSION

Because large-scale testing will lead to indefinite results and financial risks, a small simulated production line processing machine that resembles the actual production line was built. In this study, the health status monitoring method and communication networking software were applied to the simulated production line, a diagnostic module was established for health monitoring, and the PCA method was used to verify it.

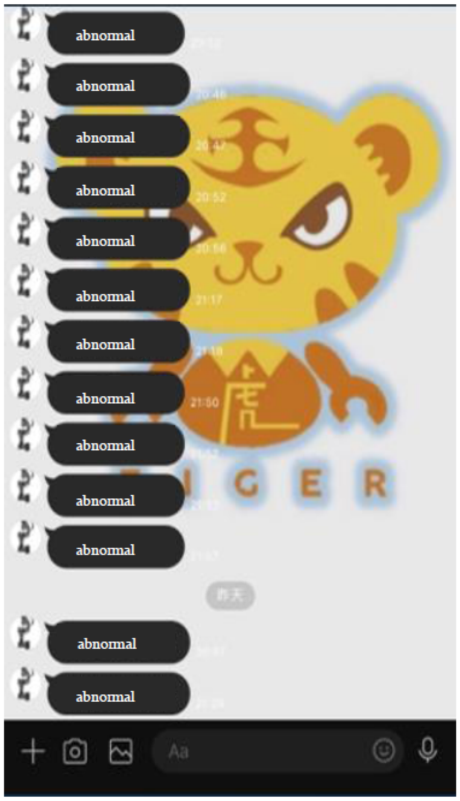

Figure 12: Machine abnormal message.

Finally, the abnormalities in the process were conveyed to the user by the communication software. The results are as follows:

(1) Collect vibration signals and build training models

The robot arm was selected as the vehicle, and the vibration signal of the arm during normal movement was captured through the accelerometer sensor. A training model was developed based on the normal signal that was in turn used to develop a diagnosis model along with a Gaussian mixture module and set up a warning line, and then, this module was applied to the intelligent diagnosis software for its health.

(2) Diagnosis and verification using PCA

The health status of the arm was monitored using diagnostic software. As an event of an abnormality, we provided the arm with an external force to simulate the state of failure when the arm collides with the machine. According to the monitoring results, the monitoring value of the arm was lower than the warning line, when the arm was in normal action. Once the arm was affected by an external force, the monitoring value exceeded the warning line. Then, PCA was performed for both conditions, and the characteristics were compared. From the distribution, the arm was in a state of convergence in the normal action; in contrast, when the arm was abnormal, it was characterized by a state of dispersion, which can be obtained by borrowing. The health status of the arm was distinguished by feature distribution.

(3) Communication software networking

The network platform monitored the internal information of the arm and transmitted the error information to the user through the Line communication software such that the user could act immediately on the problem. This greatly reduced the downtime of the machine and effectively improved the production efficiency.

9. CONCLUSIONS

With advancements in technology, the digitization of industry has become an inevitability. In this study, intelligent pre-diagnosis technology was employed by installing accelerometers on a robot arm, analyzing the vibration signals collected, and monitoring the machine status. A simulated production line was established and combined with a networking platform to integrate different machine functions, allowing the machine to actively report the production status. If there is an abnormal alarm on the machine, the user can be alerted in real time. Thus, the user can quickly address the problem, which reduces the uncertainty that arises during processing and the risk of product failure; moreover, the user can grasp the processing time and predict the failure of the machine, such that the machine downtime can be considerably reduced, which reduces the processing costs and improves productivity. Therefore, enterprises can operate more comprehensively, continuously improving the quality of products and services, and reducing production costs. Reductions in costs and manufacturing time, as well as the availability of high-quality, flexible, and efficient products and services can also be achieved. In the future, the application of 5G communication will become increasingly convenient. In the 5G era, communication is fast and accurate. Industrial networking must keep pace with the development of science and technology and make good use of the convenience offered to transform production and business models.

AUTHOR CONTRIBUTIONS

Formal analysis, writing, and funding acquisition: Tzu-Chi Chan; data curation: Jyun-De Li, Yi-Fan Su;

software: Yi-Hao Chen; Zhong-Rui Chang; Teng-Chieh Chang; Chen-Yang Hung; Chui-Chan Chiu; writing-review and editing, Arindam Dutta; Sabbella Veera Venkata Satyanarayana Reddy. All authors have read and agreed to the published version of the manuscript.

FUNDING

The authors are greatly indebted to the National Science and Technology Council for supporting this research through contracts (grant numbers: 111-2221-E-150 -024 -MY2 and 111-2622-E-150 -009).

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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Received on 17-10-2022 Accepted on 05-12-2022 Published on 08-12-2022

DOI: https://doi.org/10.31875/2409-9694.2022.09.11