Efficient Production Management System with a Packaging Quality Control Module

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Abstract: The paper presents a comprehensive study aimed at improving the efficiency of the mayonnaise manufacturing and packaging process by analyzing the key performance indicators of the mayonnaise making machine, developing the structure of a packaging quality recognition system, and modeling a convolutional neural network to identify packaging defects. The article analyzes key performance indicators for productivity, energy efficiency, product quality and equipment downtime. A system has been developed for recognizing the quality of packaging, which is part of the indicator of the level of product defects, based on the use of modern machine vision algorithms. The final part of the study presents the results of modeling and training a convolutional neural network for automatic detection of packaging defects. Experimental results demonstrate a high level of accuracy and reliability of the proposed system, which makes it possible not only to timely identify defective products, but also problems in the operation of the machine in the early stages of its operation. This in turn helps reduce waste, improve production process efficiency and reduce maintenance costs.

1 INTRODUCTION

Improving the efficiency and quality of production processes is a key challenge for the modern food industry. The production of mayonnaise as one of the popular food products requires special attention to quality control at all stages of the production cycle. One of the most important components of this process is the analysis of key performance indicators (KPIs) [1], [2] of production equipment, which allows timely identification of problems and optimization of machine operation.

In addition to control over the production process, the quality of the final product, in particular its packaging, is also important. Packaging defects can lead to significant losses for both the manufacturer and the consumer. Incorrect or damaged packaging not only detracts from the appearance of the product, but can cause mayonnaise to spoil due to the penetration of air or bacteria. This leads to a reduction in expiration date, possible complaints from consumers and additional costs for processing or disposal of defective products [3]. Therefore, the development of an effective system for recognizing packaging defects is a necessary condition for ensuring high quality standards [4]-[6].

In this context, machine learning and modern image processing techniques play an important role in automating quality control processes. Convolutional neural networks (CNNs) have proven to be a powerful tool for pattern recognition and can be effectively used to identify defects in product packaging [7], [8]. However, confidence is required regarding the capture of individual defects characteristic of the process being studied. Such defects, in addition to the typical obvious tears, damage and missing parts of the packaging, also include the absence of a manufacturing date and a significant printing defect. Using CNN in combination with KPI analysis opens up new opportunities for automating quality control and increasing production efficiency.

The goal of this research is to create an integrated system that combines analysis of mayonnaise machine KPIs, system structure for packaging quality recognition, and CNN modeling for defect detection. The combination of these aspects will not only improve the quality of the final product, but also ensure timely identification and elimination of problems in the operation of production equipment.

2 LITERATURE REVIEW

Performance measurement and management methodology (PMM) provides management with many critical, useful and necessary functions and consists of three stages: performance planning, performance improvement and performance analysis [9]. Equipment KPIs are typically used to identify problems related to equipment performance. These include: low productivity, frequent breakdowns, high maintenance costs. Careful analysis and monitoring of key performance characteristics allows tracking changes in equipment performance and reliability [10], [11]; make informed, timely decisions to relevant specialists regarding drawing up plans for various types of repair work, modernization or replacement of equipment; optimize costs for equipment maintenance and repair, improve product quality[12]. KPIs must be measurable, achievable, relevant and timely.

KPIs are also tools for management, decision support and forecasting [13]. Accurate performance forecasting allows you to refocus decisions to optimize performance while reducing cost and effort. For this purpose, various methods of artificial intelligence [14], machine learning [15]-[17], etc. have been actively used recently.

In the production of mayonnaise, packaging defects can affect the quality of the product, its shelf life and demand. The main types of packaging defects include deformation, problems with the lid, printing defects on the packaging, and mismatched labels.

The article uses two main methods to achieve the research goal: analysis of key performance indicators (KPIs) of production equipment, development of a system for recognizing packaging quality, and CNN modeling for identifying packaging defects.

3 METHODS

Considering [1], [2], it can be argued that KPIs of equipment for the production of mayonnaise are a set of indicators used to quantify the performance and reliability of the equipment. For sauce production equipment, the following KPIs can be distinguished (Fig. 1): productivity (the amount of sauce that can be produced by the equipment per hour, day or week), downtime (the time during which the equipment does not work due to breakdown or maintenance), maintenance costs (the total cost of all types of expenses associated with equipment maintenance), uptime (operation time (may be an average indicator) of equipment without breakdowns), product quality (sauce quality), energy efficiency (the amount of energy resources used by the equipment during mayonnaise production), resource efficiency (amount of resources (except energy) used by the equipment in the production of sauce), defect rate (proportion of products that do not meet standards from the total production volume), packaging deficiency (percentage of sauce packs that do not meet quality standards and must be removed from the line.

Cloud platforms provide centralized data storage, processing and visualization, which helps identify trends, predict failures and optimize production processes. Visualization of key performance indicators is carried out using dashboards that provide clear graphs, charts and other visual elements for monitoring that meet quality standards), uptime (measured as total uptime without failures), resource efficiency (use of ingredients and energy), failure and downtime rates, and identification of packaging shortages.

To effectively use KPIs, it is necessary to improve the data collection and analysis system, which is integrated into the production process and includes industrial Internet of Things (IoT) architecture. Integration of other KPIs into the cloud is carried out through field buses of the machine control system and IoT gateway (for example, Raspberry Pi). The IoT gateway acts as a central node that collects data from various sensors and devices (Fig. 2 also shows exchange protocols), including cameras that monitor the quality of packaging. The IoT gateway processes data on site and transfers it to the cloud for further analysis and storage of production processes in real time. As a dataflow development platform, Node-RED is the ideal tool for creating such dashboards.

Dashboards created in Node-RED can be accessed through web interfaces or specialized applications on phones and tablets, allowing you to quickly respond to changes and make informed decisions. This makes production management more flexible and efficient, helping to improve overall productivity, reduce costs and ensure high product quality.

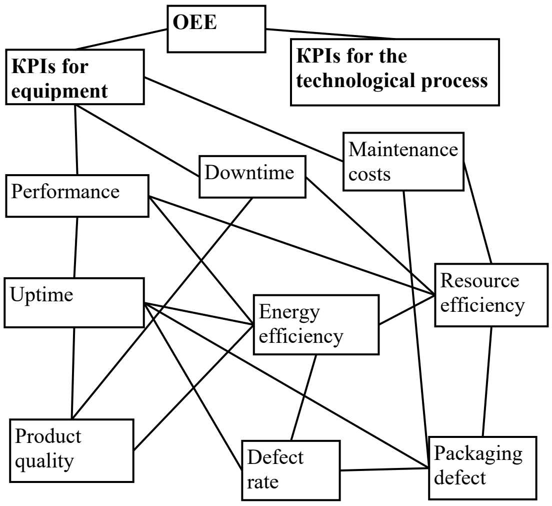

Figure 1: KPIs connection diagram for mayonnaise production.

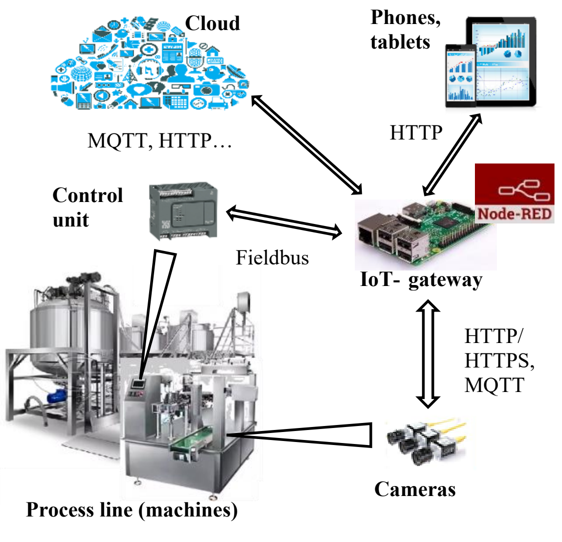

Figure 2: Automated control system with integration.

CNN modeling for mayonnaise packaging defect detection involves data collection and annotation, image pre-processing, model building and training, and model performance evaluation. The images are captured using high quality cameras installed on the production line. To ensure data diversity, images are collected from different angles, under different lighting conditions and with different types of defects implemented (simulated) by the developer. To quickly implement the system, several training samples were collected and a decision was made to use pre-trained models. The images are manually annotated to label defects (Fig. 3).

Transfer learning [18] is a popular deep learning method that uses already trained models for new tasks. This approach offers significant benefits, making training faster, more accurate and cost-effective. Pre-trained models have knowledge of basic features and patterns, saving time and resources that would otherwise be spent on training from scratch. This leads to better results, especially when the data set for a new problem is small or limited. Transfer learning helps avoid overfitting and saves computing resources. However, transfer learning also has disadvantages. Models may not be flexible for specific tasks, and retraining may require significant resources. There are also architectural limitations, risk of overfitting, licensing restrictions, influence of biases and knowledge limitations. Therefore, it is recommended to use transfer learning as a quick start, and then, after collecting a representative sample of typical defects, retrain the model from scratch for better adaptation to the task.

Figure 3: Examples of a dataset for recognizing packaging defects.

Before using the image to train the model, pre-processing is carried out, including: normalization, reducing pixel resolution to reduce computational complexity to 620x288, data augmentation (rotation, horizontal and vertical display, changing brightness and contrast) to increase data diversity.

The model architecture includes the following layers:

- base model without an upper classification layer, which allows you to save all pre-trained features.
- Global Average Pooling 2D to reduce spatial dimensions and obtain one value for each channel.
- Dense layer – a fully connected layer with 1024 or 512 neurons for additional training on a new data set.
- Dropout layer to reduce overtraining by randomly disconnecting neurons during training, values of 0.05 and 0.2 were used.
- the original layer with the softmax function for classifying the presence of defects.

To train the model, we used the binary cross-entropy loss function and the Adam optimizer. The batch size is the entire set, the number of epochs is 20. To evaluate the performance of the model – the proportion of correctly classified images, taking into account that the number of defective and normal samples is the same, the Accuracy metric was used.

4 SIMULATION RESULTS

Python and R programming languages were used to develop the CNN model for rapid implementation. Python was used to develop and train the CNN model using libraries such as TensorFlow or PyTorch. R, known for its statistical and visualization capabilities, is used for data preprocessing and analysis of results.

Table 1 shows the results of training the specified network with different hyperparameters. Apparently, the accuracy on the test set for the last two architectures is 1.00, that is, the model achieved an ideal result, classifying all images without errors. This indicates the model's strong ability to recognize packaging defects, although further testing on more diverse data sets may be required to confirm the generalization ability of the model.

Table 1: Training results.

Architecture for CNN	Loss		Accuracy	
	Training set	Test set	Training set	Test set
1. n_dense=1024, dropautrate=0.05	0.31	0.93	0.65	0.50
2. n_dense=1024, dropautrate=0.2	0.34	0.91	0.32	1.00
3. n_dense=512, dropautrate=0.2	0.37	0.89	0.34	1.00

For test samples p_i, (where i=1,2,3 is the network architecture), a detailed determination of the probability of the presence of non-defective packages is presented. Figure 4 shows four samples from the test set.

The probability for the first architecture on all samples is less than the threshold (threshold =0.5), that is, even good samples are classified as bad – here the model is clearly overtrained. The second and third architectures have different p_i values. Considering that when the model is functioning, it is unacceptable for defective products to reach the manufacturer, the second architecture was finally chosen. This choice was also confirmed by considering Learning curves (Fig. 5).

The implementation of the developed CNN model in Node-RED can be done through special nodes that allow to run Python code. In addition, there are nodes that allow to run R scripts, which integrates statistical analysis directly into the data stream. This combination of Python and R provides a flexible and powerful system for automatically detecting packaging defects, which improves the efficiency of the developed model.

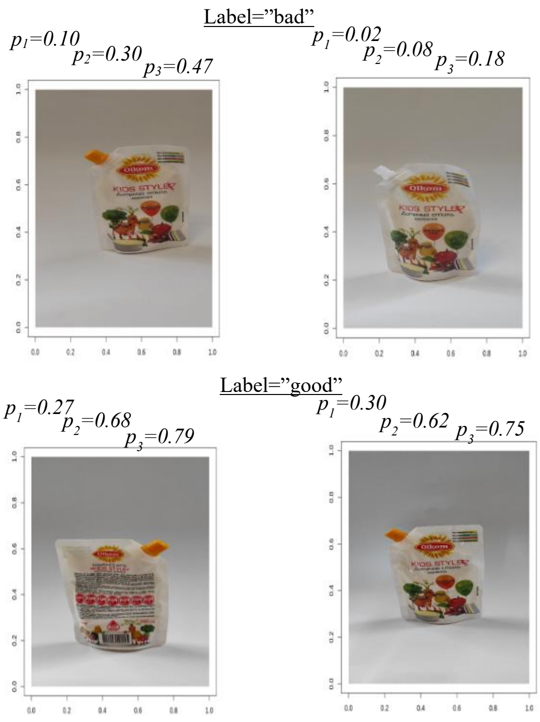

Figure 4: Test results.

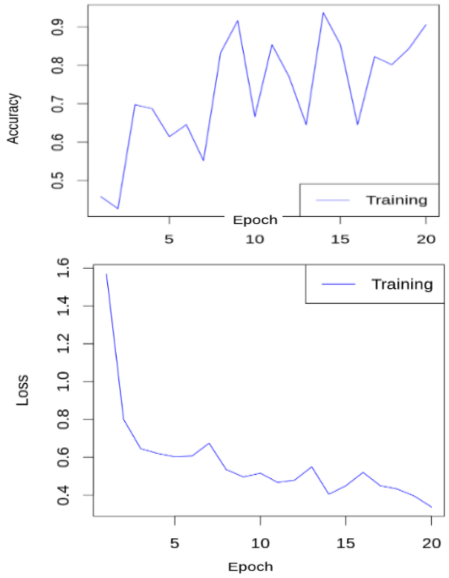

Figure 5: Learning curves on the training sample.

5 CONCLUSIONS

An integrated system for efficient mayonnaise production management, including a packaging quality control module, was successfully developed.

1) The IoT-based KPI monitoring system provides automated real-time data collection and visualization, enabling the timely tracking of productivity, downtime, and defect rates to optimize equipment operation.
2) The packaging defect recognition subsystem was implemented using a CNN model with the Transfer Learning approach.Experimental results demonstrate high accuracy: two CNN architectures achieved an accuracy of 1.00 on the test set. Based on learning curve analysis and reliability requirements, an architecture was selected to minimize the passing of defective products.
3) The proposed integrated system significantly reduces the number of defective products, improves the overall efficiency of the production process (OEE), and lowers the costs associated with error correction and maintenance.

Future work will focus on gathering a more representative defect sample to retrain the model from scratch, thereby improving its generalization ability.

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