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Food Quality Monitoring System Based on Smart Contracts and Evaluation Models

BIN YU[1], PING ZHAN[2], MING LEI[3], FANG ZHOU[4], AND PENG WANG[2]
[1]ICTT and ISN Laboratory, Xidian University, Xi'an 710071, China
[2]College of Food Engineering and Nutritional Science, Shaanxi Normal University, Xi'an 710062, China
[3]School of Computer Science, Shaanxi Normal University, Xi'an 710062, China
[4]Department of Anesthesiology, Xijing Hospital Fourth Military Medical University, Xi'an 710032, China

Corresponding authors: Fang Zhou (zhou_tools@126.com) and Peng Wang (wangpengdaxue@163.com)

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ABSTRACT Currently, food quality has become a major concern for the food industry. To efficiently detect food quality problems during the production process, food enterprises must build quality monitoring systems. However, in a traditional quality monitoring system, data tampering and centralized storage have become barriers to reliability. In addition, due to lack of sufficient automation, traditional quality monitoring approaches are usually inefficient. Fortunately, blockchain is a promising technology that is tamper-proof and decentralized. Moreover, smart contracts, which are executable codes on the blockchain platform, are able to conduct transactions between mutually untrusted parties and are self-executing and self-verifying. By combining smart contracts and quality evaluation models, this paper presents an intelligent quality monitoring system for fruit juice production. This system has the characteristics of high automation and high reliability. In this system, response surface models are established based on preproduction data, and the optimal production condition for each stage is identified. During the actual production process, smart contracts are executed to record production data on a blockchain. These data serve as the inputs for evaluation models. Based on the evaluation outcome, smart contracts will decide whether the production process can be resumed or not. To evaluate the feasibility of the presented system, a prototype version of the quality monitoring system for flat peach juice production is implemented based on the Ethereum platform and executed in the Remix IDE.

INDEX TERMS Quality monitoring, smart contracts, blockchain, evaluation models, ethereum.

I. INTRODUCTION

Due to the complexity of the relevant links involved in the food production process, pollution or deterioration in any link may directly influence the food quality. In recent years, food quality incidents have occurred frequently. These incidents not only endanger people's health and consumer confidence [1] but also have a strong adverse impact on food enterprises [2]. Many of these incidents, such as China's tainted milk scandal and clenbuterol event [3], [4], result from lack of effective monitoring during the production process. As a result, food quality concerns have renewed the focus on quality monitoring inside food enterprises.

Since monitoring can be regarded as a subsystem that is essential to food quality assurance, reliable and efficient food monitoring has become a prerequisite for food enterprise success [5]. To realize early food quality monitoring and evaluation, some statistical methods based on aroma or texture features [6]–[9], data mining [10]–[13] and machine learning [14]–[17] have been proposed. For each of these methods, aspects of the problem can be well solved. However, in a traditional food enterprise, the following two challenges remain: (1) data tampering for the benefit of a department or an individual [18]; and (2) centralized and opaque data storage for mass production data [19]. These challenges have become barriers to reliable and efficient quality monitoring throughout the production process.

As a permanent and immutable record, a blockchain is generated by superimposing encrypted data in chronological order [20]. With the characteristics of tamper-resistance, traceability, decentralization and cryptographic security, blockchain technology has become immensely

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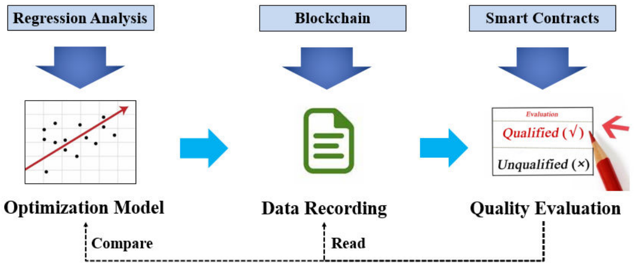

FIGURE 1. System overview.

popular in the latest research on food quality assurance [21]–[23]. Being an executable code on the blockchain platform, a smart contract acts as a digital agreement among participants. Because of the effective protection of rights and reduction of time and economic costs, smart contracts have also begun to be applied in food quality assurance over the past two years [24]–[26]. Regrettably, the blockchain and smart contract technologies discussed above mainly focus on traceability for effectiveness supervision and information retrieval, while quality evaluation and monitoring inside a food manufacturer have not yet been considered. Due to the tamper-resistance and decentralization of the blockchain and the self-execution of smart contracts, the challenges discussed above can be solved in a traditional food enterprise.

In this paper, we propose a monitoring framework that combines smart contracts and evaluation models for the automatic evaluation of the quality of fruit juice samples[1] generated in each production stage. The proposed framework consists of three sequential execution modules, namely, optimization production model establishment, production data recording and food quality evaluation, which are illustrated in Fig. 1. These three modules are respectively carried out prior to the production process and during and after each production stage. In the framework, production models are initially established based on pre-production data, and the optimal configurations are identified with the regression analysis method. These optimal production configurations serve as the standard in the production process. Then, after deployment, smart contracts record newly generated data at each production stage on the blockchain. Next, another smart contract evaluates these production data via partial least squares regression (PLSR) and principal component analysis (PCA) to measure the quality according to the data fitting degree. If the outcome value is below a given threshold, the production process is terminated in a timely manner by the smart contract. Based on the records on the blockchain, the production conditions at each production stage can be further optimized through comparison with the optimal configurations.

The primary contributions of this paper can be summarized as follows:

[1] In this paper, "samples" refers to the intermediates during a production process, while "products" represents the final goods after a production process.

(1) Based on the regression analysis method, the optimal production model is established for key production stages in fruit juice production. For the monitored data generated in each production stage, we develop evaluation models to check the sample quality with machine learning approaches.
(2) We propose a smart-contract-based monitoring system to evaluate the quality at each production stage. In this system, smart contracts are employed to record production data on a blockchain and invoke evaluation models.
(3) As a case study, a quality monitoring system for flat peach juice is exhibited to show the feasibility of the proposed system.

The remainder of this paper is organized as follows. Related work is reviewed in the next section. Section III introduces the preliminaries used in this paper. The framework architecture is presented in Section IV. Section V describes the implementation details in our framework and presents a case study. Finally, the conclusions of this study are presented, and future research directions are discussed.

II. RELATED WORK

Although research of blockchain and smart contract applications in quality assurance and traceability has been increasing steadily in recent years, there are almost no studies that have directly applied them to food quality monitoring. In this section, we will review the related works on traditional food monitoring and blockchain technology in food quality assurance.

A. FOOD QUALITY MONITORING METHODS

As an important feature, a flavour indicator, including aroma or texture, is usually employed to evaluate food quality in traditional monitoring approaches. The aroma quality is evaluated by using the PCA method, which is a critical method for reducing the dimensionality of high-dimensional data and widely used to evaluate the quality of juice products during thermal treatment [6] or non-thermal sterilization [7]. Additionally, the texture attribute is analysed by several statistical and bioinformatics methods. For example, the texture parameters of horse meat are determined for the analysis of quality changes during frozen storage [8], and the impact of pulsed electric fields (PEFs) on the flavour quality of turkey breast meat is determined based on the change in the texture attribute [9].

With the combination of new advanced intelligent technologies, such as data mining and machine learning, the efficiency and precision of food quality monitoring have been greatly improved. A food quality pre-warning system is proposed by Wang and Yue [10] with association rule mining and Internet of Things technologies for the timely monitoring of all the detection data of the whole supply chain. Wang *et al.* [12] analyse the application of three typical big data miming methods in food quality risk warning and select the most suitable method. Ma *et al.* [13] employ a parallel support vector machine (SVM) in a big data platform to realize dairy productions risk assessment. Bisgin *et al.* [16] demonstrate a new SVM-based technique and provide a good comparison of it with the artificial neural network (ANN) model in the detection of pantry beetles in food products. Based on an integration of the analytic hierarchy process and extreme learning machine (AHP-ELM), Geng *et al.* [17] establish a model to effectively deal with complex food inspection data.

B. FOOD QUALITY ASSURANCE WITH BLOCKCHAIN OR SMART CONTRACTS

Due to data transparency, blockchain enables companies to understand useful information quickly. In addition, the data immutability of blockchain ensures that the data are authentic and that data tampering is impossible. Based on these characteristics, blockchain technology has been widely used in many areas, including the Internet of Things (IoT) [27]–[31], finance [32]–[36], electronic medical records [37]–[39] and energy [40]. Acting as a digital agreement among participants, a smart contract is an executable code on the blockchain platform. With the ability of effectively protecting rights and reducing time and economic costs, smart contracts have been applied in various traditional and emerging fields [41]–[43].

The employment of blockchain and smart contracts in food quality assurance has begun to be studied in recent three years. Wu *et al.* [21] design a combined private-public ledger architecture that leverages distributed databases, blockchain technology and the hybrid peer-to-peer communication model to deliver independently validated product information to all stakeholders in pseudo-real time. Nakasumi [22] proposes a new blockchain scheme for information sharing by combining blockchain with a homomorphic encryption solution. In this scheme, users are able to own and control their production data without compromising security or limiting the ability of companies and authorities to provide encrypted transactions. Tian [23] establishes an agri-food supply chain system based on RFID and blockchain technology. This system realizes the traceability of trusted information throughout the agri-food supply chain to help agri-food markets enhance their food quality.

As a key feature of blockchain 2.0, smart contracts allow transactions to be safely conducted between mutually untrusted parties based on the blockchain network. Due to their self-execution and self-verification, smart contracts have begun to be applied in food quality assurance in the past two years. Mao *et al.* [24] provide a blockchain-based credit evaluation system to strengthen the effectiveness of supervision of food quality. The system gathers credit evaluation text from traders by smart contracts and analyses the gathered text with a deep learning network. Based on blockchain and EPC information services, a food quality traceability system is presented by Lin *et al.* [25]. This system makes use of on-chain and off-chain data to avoid data explosion and utilizes smart contracts to prevent data tampering and the exposure of sensitive information. Wang *et al.* [26] propose a product quality management system in which all product registration and transfer histories are perpetually recorded by using smart contracts.

Although the approaches and platforms discussed above can substantially promote food quality assurance, research on the application of blockchain and smart contracts to the quality monitoring field remains in the exploration stage, especially for the production process inside a food enterprise. In this paper, combining the advantages of blockchain, smart contracts and evaluation models, we propose an intelligent and reliable food quality monitoring system to automatically monitor and evaluate the quality of fruit juice samples generated in each production stage.

III. PRELIMINARIES

In this section, we will review the relevant background knowledge that will be used in this paper, including data analysis methods and blockchain and smart contract technologies.

A. QUALITY EVALUATION METHOD FOR FRUIT JUICE PROCESSES

In general, a fruit juice process consists of multiple steps, including raw material purchase, storage [44], crushing [45], pressing, ultrafiltration [46], pasteurization [47], enzymolysis [48], pouring and packaging. During the thermal and cold treatments, especially storage, pasteurization, enzymolysis and pouring, the quality of juice samples is highly likely to be decreased substantially. In particular, the changes in the characteristics of the flavour profile are often attributed to the appearance of an off-flavour or the loss of a key aroma [49].

To thoroughly investigate the volatile compounds in fruit juice, product samples are isolated and identified by using gas chromatography-mass spectrometry (GC-MS) combined with headspace solid-phase micro-extraction (HS-SPME) for the routine authentication of characteristic volatiles in peach, coconut, apricot, and other fruits [50]. In other studies, GC-MS with HS-SPME is widely used for the analysis of fruit volatile compounds in the monitoring of fruit quality [51].

Therefore, the investigation of changes in aroma compounds of juice samples plays an important role in the quality monitoring of fruit juice production [52]. Based on the large quantity of volatile chemical compound data that have been collected, several analytical methods have been developed for analysing and exploiting the information contained in these data.

To address high-dimensional and complex data, the PCA dimensionality reduction method is regarded as an effective technique for identifying correlations between characteristic volatiles of juices and for quantifying the level of flavour quality [53]. This method has been widely applied in the field of food quality evaluation based on similarity degree. Moreover, hierarchical cluster analysis (HCA) is a statistical method for identifying relatively homogeneous clusters of cases based on measured characteristics [54]. Starting with

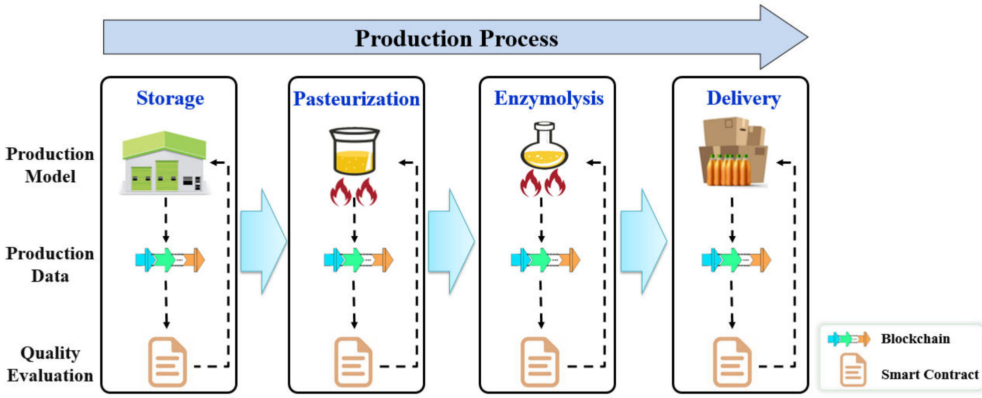

FIGURE 2. Four production stages in our system.

each case in a separate cluster, HCA combines the clusters sequentially and reduces the number of clusters at each step until only one suitable cluster remains. This approach has been widely used to establish the identification model of GC-MS for food quality [55]. Together with PCA, HCA can extract effective information from the original GC-MS data for the development of a PCA model, which has been adopted to increase the data handling efficiency and avoid the missed detection of characteristic volatiles [54]–[56].

As a technique for multivariate regression analysis, PLSR is used to investigate the relationship between two data sets by predicting one data set (Y) from the other set (X) [57]. The PLSR model can be used to study the correlations of individual compounds with sensory descriptors and their contributions to the characterization of samples [58]. For example, the GC-MS technique coupled with PLSR is an effective tool that is commonly used to identify key volatiles of fruit juice to quantify the level of flavour quality [59].

B. BLOCKCHAIN

As a decentralized, immutable and shared public ledger, a blockchain is composed of add-on blocks that include all transactions of the data and all execution outcomes [60]–[63]. Each of these blocks is hashed and linked to the next block; hence, these records constitute a secure, immutable and tamper-proof chain [64]. These transaction records are maintained by all network nodes. According to the transaction participants, a blockchain can be a public, consortium or private blockchain. As a completely decentralized structure, a public blockchain allows any node to read or write entries to it at any time. In contrast, in a consortium or private blockchain, only some trusted nodes are involved in the decision to create a new block. Due to this feature, consortium and private blockchains can be applied in identity authentication, copyright management and data storage services.

C. SMART CONTRACTS AND ETHEREUM

As codes that can execute automatically on a computer, smart contracts were proposed by cryptographer Nick Szabo in 1997 [65]. During their early period of development, smart contracts were regarded only as a design concept due to the lack of trusted execution environments and digital technologies. Fortunately, blockchain technology can overcome these disadvantages, which has enabled smart contracts to become a highly prominent application in the blockchain ecosystem [66]. According to predefined rules, a smart contract will be automatically executed once it is deployed on a blockchain.

Unlike Bitcoin, the Ethereum platform offers a Turing-complete script language and enables users to design any arbitrary smart contracts that can be precisely defined [67]. A smart contract in Ethereum can be written in a high-level language, such as Solidity [68]. Afterwards, a Solidity program is compiled into a low-level bytecode, which is called an Ethereum virtual machine (EVM) code. To facilitate the program development, developers can also create smart contracts based on available programming languages, such as Java and Python.

IV. SYSTEM MODEL

In this section, we will introduce a quality monitoring system that is realized by regression analysis and smart contract and evaluation technologies.

A. SYSTEM OVERVIEW

The monitoring system for fruit juice production proposed in this paper includes three main modules: optimization production model establishment, production data storage and sample quality evaluation. These three modules are utilized prior to the production process and during and after each production stage.

As illustrated in Fig. 2, four main stages of the production process are considered: raw material storage, pasteurization, enzymolysis and delivery. In the system, several experiments are conducted in the pre-production stage to determine the optimal production conditions for each production stage (Section IV-B). These conditions serve as the standard for the subsequent production process. During each production

TABLE 1. Example of raw material storage information stored by SC.

ID	Batch Number	Raw Material	Temperature	Duration	GC-MS Data	Storage Location	Timestamp	No.
1	2019100601	Flat Peach	0	40	...	No. 1 Warehouse	1567209601	1
2	2019100602	Apple	-1	30	...	No. 2 Warehouse	1567312732	1
3	2019100603	Grape	1	35	...	No. 3 Warehouse	1567484361	1
...	...	...	...	...	...	...	...	...

TABLE 2. Example of pasteurization information stored by PC.

ID	Batch Number	Temperature	Duration	GC-MS Data	Sterilizing Site	Timestamp	No.
1	2019100601	80	30	...	No. 1 Sterilization Machine	1567236428	2
2	2019100602	70	25	...	No. 2 Sterilization Machine	1567392371	2
3	2019100603	65	20	...	No. 3 Sterilization Machine	1567563215	2
...	...	...	...	...	...	...	...

stage, GC-MS data are the main elements preserved on the blockchain. On the blockchain, these preserved data cannot be altered and can be accessed by stakeholders in a decentralized and trusted manner with no intermediaries. The storage of data on the blockchain is realized by the first four smart contracts in Section IV-C. After each production stage, the obtained GC-MS data are evaluated by evaluation models. This process is automatically executed by the quality evaluation contract (QEC), which is the last smart contract introduced in Section IV-C. According to the necessity for unsupervised and supervised learning, PLSR or PCA is used to establish a suitable evaluation model (Section IV-D). Once the evaluation score is lower than the given threshold, the smart contract QEC will create a notification message and terminate the production process.

The remainder of this section will introduce the main modules in our system.

B. OPTIMIZATION PRODUCTION MODEL

In each stage of the pre-production phase, the volatiles of juice samples are monitored. Then, these volatiles are isolated and identified by HS-SPME combined with GC-MS. By taking the contents of volatile compounds and the sensory evaluation results as response values, an experimental Box-Behnken design is used to determine which experiments should be conducted in the experimental region being studied. The reaction function (y) and coded function (x) represent sensory evaluation scores and production conditions, respectively, for each stage. The variance for each assessed factor is partitioned into linear, quadratic and interactive components. Next, the optimal condition setting in each production stage is identified by the response surface methodology (RSM).

C. SMART CONTRACTS

Our system includes five smart contracts in total: a storage contract (SC), a pasteurization contract (PC), an enzymolysis contract (EC), a finished product contract (FPC) and a quality evaluation contract (QEC). The system manager deploys these contracts to the blockchain and publishes their contract addresses. The first four contracts are responsible for recording production data during the production process, while the last contract is responsible for evaluating the sample quality after each production stage. In the recorded production data, batch numbers are employed to precisely identify the different samples.

The function of each contract is described below:

(1) **Storage Contract (SC)**
In the early storage stage, even if the fruit appearance does not obviously change, changes in the levels of volatile components in the fruit can still be detected. Since these compounds affect the richness, fullness and sweet taste of the fruits to be processed, it is necessary to monitor and record the levels of volatile components during raw material storage. This process is automatically conducted by the storage contract (SC). This contract stores the information of a batch of raw materials by invoking function *storageData*. This function preserves the batch number, raw material name, storage temperature ($°C$), storage duration (day), GC-MS data, storage location and current time, which are listed in Table 1. In this table, the GC-MS data are stored in matrix form and are not presented due to space limitations. In the last column, "No. 1" indicates that this stage is the first stage in the production process.

(2) **Pasteurization Contract (PC)**
Pasteurization is used to kill bacteria and pathogens that can spoil food and make people sick. However, characteristic volatile components in fresh fruits are lost to a certain extent during this process. Hence, it is necessary to record the content of volatile components after the pasteurization process. The function *pasteurizationData* of the pasteurization contract (PC) is called to preserve the batch number, sterilizing temperature ($°C$), sterilizing duration (min), GC-MS data, sterilizing site and current time on the blockchain (see Table 2). In the last column, "No. 2" indicates that this stage is the second stage in the production process.

(3) **Enzymolysis Contract (EC)**
As a critical treatment in food processing, enzymolysis treatment aims to improve the flavour quality of food products by releasing the potential bound volatiles and reducing the contents of compounds with

TABLE 3. Example of enzymolysis information stored by EC.

ID	Batch Number	Temperature	Duration	Concentration	pH	GC-MS Data	Processing Site	Timestamp	No.
1	2019100601	30	40	0.5	4	...	No. 1 Production Line	1567210672	3
2	2019100602	20	30	0.8	6	...	No. 2 Production Line	1567328451	3
3	2019100603	30	50	0.6	7	...	No. 3 Production Line	1567536287	3
...	...	...	...	...	...	...	...	...	...

TABLE 4. Example of finished product information stored by FPC.

ID	Batch Number	GC-MS Data	Pouring Site	Packaging Site	Timestamp	No.
1	2019100601	...	No. 1 Pouring Machine	No. 1 Packaging Machine	1567262481	4
2	2019100602	...	No. 2 Pouring Machine	No. 2 Packaging Machine	1567426242	4
3	2019100603	...	No. 3 Pouring Machine	No. 3 Packaging Machine	1567593728	4
...	...	...	...	...	...	...

unnatural aromas. After this procedure, the GC-MS data will be automatically obtained. Then, the function *enzymolysisData* of the enzymolysis contract (EC) is invoked to store the batch number, enzymolysis temperature ($^\circ C$), enzymolysis duration (min), enzyme concentration ($g/100\ g$), pH value, GC-MS data, enzymolysis site and current time (see Table 3). In the last column, "No. 3" indicates that this stage is the third stage in the production process.

(4) **Finished Product Contract (FPC)**
After the above three key production stages, several steps remain in the production of the final product, such as pouring and packaging. These stages will also affect the final quality, which can be reflected in the levels of volatile components. To record the finished product information, the function *finishedData* in the finished product contract (FPC) is invoked to record the batch number, GC-MS data, pouring site, packaging site and current time (see Table 4). In the last column, "No. 4" indicates that this stage is the last stage in the production process.

(5) **Quality Evaluation Contract (QEC)**
The quality evaluation contract (QEC) is responsible for building a bridge between the production data on the blockchain and evaluation models off the blockchain. Given the batch number and the production stage, the function *evaluate* in QEC first obtains the GC-MS data from the blockchain. Then, it will invoke the PCA or PLSR method to evaluate the quality of the sample. If the evaluation outcome does not reach the threshold, a notification message will be created and the subsequent production process will be terminated to prevent further losses. Since production conditions are also recorded on the blockchain, they can be adjusted by comparison with the optimal conditions obtained in the pre-production phase (Section IV-B). Otherwise, the sample is regarded as qualified, and the production process will be continued.

D. QUALITY EVALUATION MODELS

For each production stage, taking the GC-MS data under the optimal conditions as the control group, evaluation models for the quality of samples are constructed based on the current GC-MS data. Since the quality levels in the first three production stages are unlimited, the potential correlation between them and the production conditions can be identified by an unsupervised method, namely, PCA. Prior to this analysis, the number of variables is reduced by using HCA dendrogram plots to identify the key compounds in the juice flavour. Meanwhile, to evaluate the quality of production steps with exact evaluation indicators, PLSR is employed to evaluate the finished product in the last production stage.

The above evaluation models are used to calculate the similarity between one batch of juice samples and the control group under the optimal production condition. If the similarity index is lower than a threshold, it is regarded as unqualified at this stage. In this case, the current production condition and the optimal production condition can be compared to identify the difference for further optimization.

The relationship among the optimization production model, smart contracts and evaluation models is illustrated in Fig. 3.

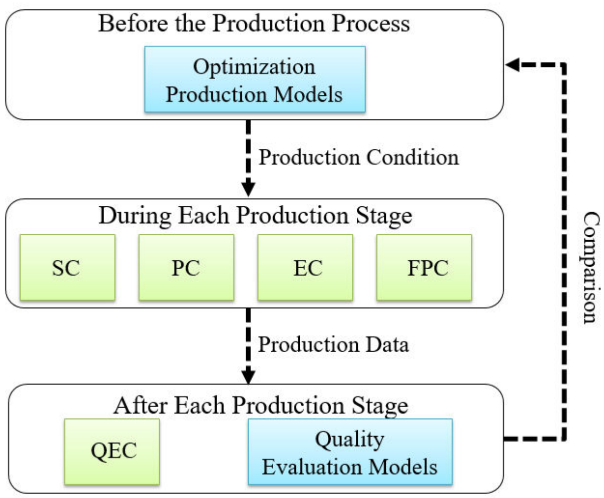

FIGURE 3. Relationship among the optimization production model, smart contracts and evaluation models.

V. SYSTEM IMPLEMENTATION

In this section, we will describe in detail the implementation of optimization production models, smart contracts and

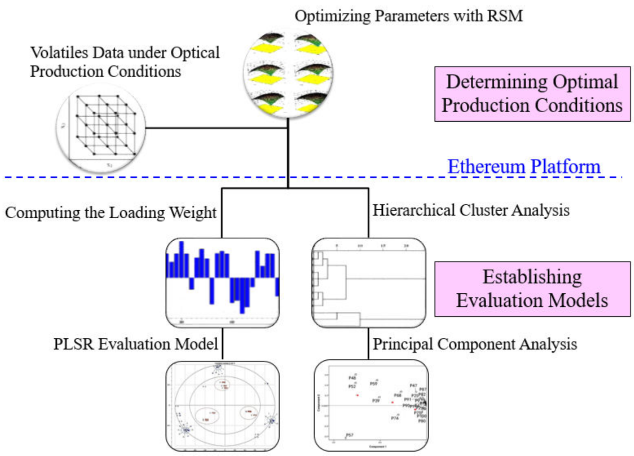

FIGURE 4. Implementation of our system.

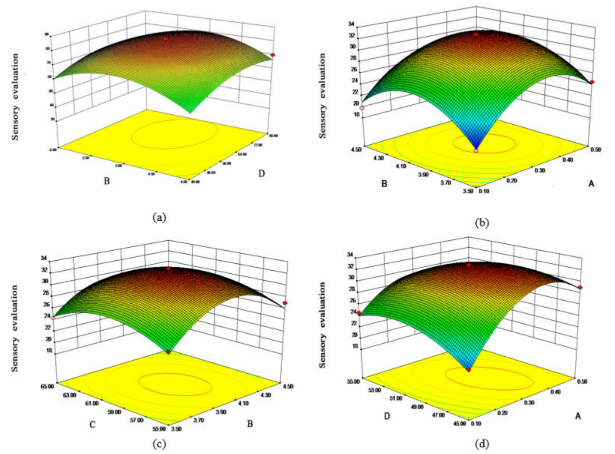

FIGURE 5. Response surface of enzymolysis treatment.

quality evaluation models. Fig. 4 presents these models and their relations intuitively.

A. OPTIMIZATION PRODUCTION MODEL IMPLEMENTATION

In the implementation of the optimization production model, RSM is employed to determine the optimal production condition setting.

The contents of volatile compounds in each juice production stage are measured by HS-SPME-GC-MS. A juice sample is subjected to several production conditions that are recorded by smart contracts as presented in Table 1 to Table 4. Meanwhile, the experiment region of treatment conditions is determined based on preliminary experiments. Box-Behnken central composite design is used to apply four variables (three levels of each variable) to practical production conditions. Reaction function (y) and coded function (x) represent sensory evaluation scores and production conditions, respectively. The variance for each assessed factor is partitioned into linear, quadratic and interactive components: $Y = b_0 + \sum_{i=1}^{j} b_i x_j + \sum_{i=1}^{j} b_{ij} x_i^2 + \sum \sum_{i \neq j=1}^{j} b_{ij} x_i x_j$. The RSM approach takes time complexity $O(t^2 s^2 + t^3)$ [69], where t is the number of production conditions for each sample and s is the number of samples in the pre-production stage.

As an example, Fig. 5 shows the established RSM model for the enzymolysis treatment of flat peach juice. The enzyme concentration (A), pH value (B), temperature (C) and duration (D) are regarded as the production conditions. Fig. 5 (a) shows that the sensory evaluation score depends on the duration of the enzymolysis treatment, as its linear effect is positive. The effect of the pH value on the evaluation is also significant, and its linear effect is negative. The sensory evaluation score varies with the enzyme concentration and the enzymolysis duration at constant temperature. Fig. 5 (b) and Fig. 5 (c) show that the sensory evaluation of the juice sample decreases almost linearly with duration at a constant temperature and enzyme concentration. Furthermore, Fig. 5 (d) shows that the enzyme concentration has a negative linear effect on the sensory evaluation at a fixed temperature and treatment duration. Then, after eliminating the non-significant term, the optimized equation is obtained as follows: $Y = 32.70 + 1.81A - 0.48C - 0.56D - 0.65AB - 2.28AD - 0.70BC - 5.77A^2 - 5.17B^2 - 2.92C^2 - 2.79D^2$. Finally, the optimal conditions for the enzymolysis treatment of a juice sample are identified by overlaying all the responses as follows: a pH of 4 with an enzyme concentration of $0.4\ g/100\ mL$ at $60°C$ for 50 minutes.

B. SMART CONTRACT IMPLEMENTATION

The smart contracts described in Section IV-C are implemented and tested using Remix IDE http://remix.ethereum.org/, which is a complete web-based development environment that offers rich features.

As this paper considers quality monitoring inside a fruit juice manufacturer, we suppose that the fruits are of the same maturity and satisfy the storage requirement. Therefore, data recording starts from the raw material storage stage. To achieve this, when a batch of raw materials is stored inside a warehouse, relevant data are automatically captured by devices and recorded on a blockchain by the *storageData* function in SC. A pseudo-code implementation of the *storageData* function is presented in Algorithm V.1. First, this function checks whether the current operating account is legal and whether this batch of raw materials is unregistered. If so, relevant data are recorded on the blockchain. Otherwise, the contract state reverts to the initial state and the transaction terminates. Since the functions *pasteurizationData*, *enzymolysisData* and *finishedData*, which are implemented in EC, PC and FPC, respectively, are similar to the function *storageData*, their implementation details are omitted.

After the data for one production stage have been recorded on the blockchain, the function *evaluate* in QEC is invoked to evaluate the quality of the sample. Algorithm V.2 presents a pseudo-code implementation of the *evaluate* function. With the batch number *batchNumber* and the sequence number of a production stage (*seqNumber*) as the search indices,

Algorithm V.1 *storageData*()

Input: Batch number (*batchNumber*), raw material name (*rawMaterial*), address of the message sender (*msg.sender*), storage temperature (*storageTemp*), storage duration (*storageDur*), GC-MS data ($GC - MSData$), storage location (*storageLoc*), authorization list (*AL*), current time (*now*)

if $msg.sender \in AL$ **then**
    if *batchNumber* does not exist **then**
        The variables *batchNumber*, *rawMaterial*, *storageTemp*, *storageDur*, $GC - MSData$, *storageLoc*, *now* are preserved on the blockchain;
    else
        Revert contract state and show an error;
    end
else
    Revert contract state and show an error;
end

Algorithm V.2 *evaluate*()

Input: Batch number (*batchNumber*), sequence number (*seqNumber*), authorization list (*AL*), threshold value (*thresholdValue*), address of the message sender (*msg.sender*)

if $msg.sender \in AL$ **then**
    Find the GC-MS data for the sample (as shown in Table 4);
    if $seqNumber == 4$ **then**
        Invoke the PLSR model to obtain the evaluation value *eValue*;
    else
        Invoke the PCA model to obtain the evaluation value *eValue*;
    end
    if $eValue < thresholdValue$ **then**
        Send a message to terminate the production process;
    else
        Create a notification message stating that this batch of samples meets the standard;
    end
else
    Revert the contract state and show an error;
end

the related transactions are selected from the blockchain. First, the GC-MS data for a sample are input into the quality evaluation model to determine the degree of data fitting. The PLSR model is used for the evaluation of a finished product ($seqNumber == 4$), while the PCA model is employed for other production stages. If the outcome value is lower than a specified threshold, this batch of samples is regarded as not satisfying the standard. In this case, the function will send a message to terminate the production process. Otherwise, a notification message stating that this batch of samples meets the standard is created and stored on the blockchain.

The time complexity for smart contract implementation is $O(mn)$, where m is the number of samples and n is the number of features for GC-MS data in each sample.

C. QUALITY EVALUATION MODEL IMPLEMENTATION

• Evaluation models with PCA

Samples at a production stage are first classified by HCA based on measured characteristics so that the invalid samples can be eliminated and the computational load can be reduced. Then, the quality of the samples is evaluated by PCA to obtain a standardized linear projection that maximizes the variance in the projected space. The principal axes b_m, where $m \in \{1, \ldots, M\}$, and the obtained multidimensional data vectors of volatiles $\{a_n\}$, where $n \in \{1, \ldots, N\}$, are the orthonormal axes onto which the retained variance under projection is maximal. The principal axes b_m are given by the largest associated eigenvalues λ_m of the sample covariance matrix $S = \sum_n (a_n - \bar{a})(a_n - \bar{a})^T / N$, where $\bar{a}$ is the mean value of the volatiles, such that $Sb_m = \lambda_m b_m$. The principal components of the observed vector a_n are given by the vector $x_n = B^T(a_n - \bar{a})$, where $B = (b_1, b_2, \ldots, b_M)$. Then, the variables x_m are uncorrelated such that the covariance matrix $\sum_n x_n x_n^T / N$ is diagonal with elements λ_m. The quality of the samples is evaluated by calculating the correlation of the principal axes and the data vectors of volatiles.

Considering the pasteurization stage in flat peach juice production as an example, the clustering analysis results are divided into six major types of volatile components. HCA is performed to discriminate among the volatiles quickly and efficiently. A larger Euclidean distance corresponds to a larger difference. The dendrogram reveals (Fig. 6) the relationship among the volatile components. The six volatile compounds are divided into two main clusters. The X-axis corresponds to the differences among the volatiles, and the Y-axis represents the Euclidean distance. When the Euclidean distance is smaller than 10, all the volatile compounds are divided into two categories: group 1 (ketones, others, alkanes, aldehydes, and alcohols) and group 2 (esters). The change in the ester content is found to be the main cause of the deterioration in the flavour of the pasteurized samples.

Furthermore, PCA analysis is performed to further identify the effects of thermal treatment on the characteristic volatile compounds in flat peach juice. As shown in Fig. 7, two flat peach juice samples are labelled as $S0$ and $S1$ ($S0$ is the control group, while $S1$ is a sample to be evaluated). The volatiles are labelled as $N1$-$N14$. Thus, the relationships between the 14 volatile compounds and the samples can be studied, and the interactions between the changes of conditions can be identified. The first two principal components ($PC1$ and $PC2$) are obtained from the PCA model, with a

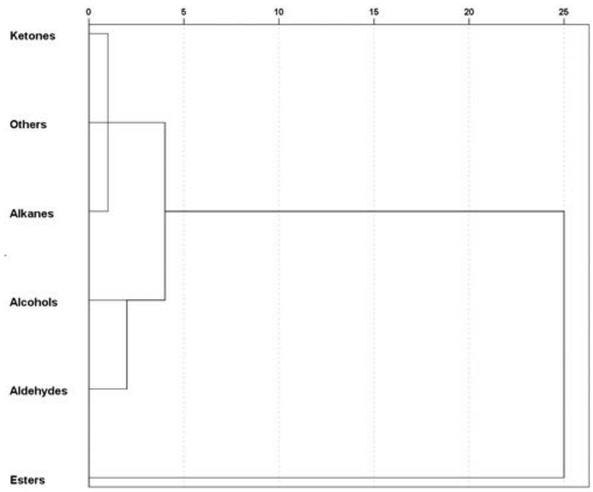

FIGURE 6. Dendrogram that was generated by HCA for the volatiles of flat peach juice samples.

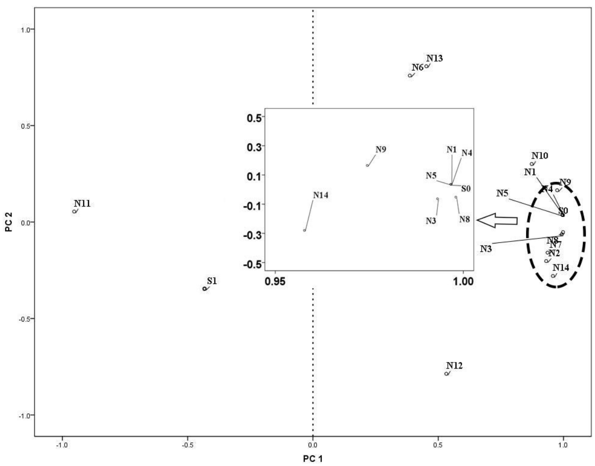

FIGURE 7. PCA model of a test sample and the control group.

cumulative variance of 87.052%. The X-matrix is composed of two kinds of samples, whereas the Y-matrix consists of the contents of volatiles. Moreover, sample $S1$ is located in the lower-left part of the figure, while $S0$ is in the rightmost part. Since the correlation between samples $S1$ and $S0$ is low, $S1$ is classified as unqualified. In addition, various compounds, such as $N1$, $N3$, $N4$, $N5$, $N8$, and $N9$ are situated around $S0$, which indicates that they have positive effects on $S0$. Hence, these compounds are regarded as the main reasons for the differences between two kinds of juice samples.

• Evaluation models with PLSR

As a technique of multivariate regression analysis, PLSR is employed in our system to understand the relationship between the production conditions and the changes of volatiles by predicting the set of conditions (Y) from the set of volatiles (X), where $X = (x_1, x_2, \ldots, x_p)$ and $Y = (y_1, y_2, \ldots, y_q)$. In the PLSR, orthogonal X scores are obtained by computing the loading weight of each volatile compound. The main steps can be summarized as follows: First, t_1 and u_1 are extracted as principal components, where t_1 and u_1 are linear combinations of X and Y, respectively. Then, the variables are centred on X_0 and Y_0, i.e., $t_1 = X_0W_1$ and $u_1 = Y_0C_1$, where W_1 is the loading weight of t_1 and C_1 is the loading weight of u_1. In this step, the covariance between t_1 and u_1 is maximized by solving $max\{Cov(t_1, u_1)\} = max\langle X_0W_1, Y_0C_1\rangle$ such that $||W_1|| = 1, ||C_1|| = 1$. Then, W_1 and C_1 are calculated by using the Lagrange equation, where $W_1 = X_0'Y_0Y_0'X_0$ and $C_1 = Y_0'X_0X_0'Y_0$. Therefore, the calculation of the first principal component is complete. Furthermore, the regression equations of t_1 and u_1 are built based on X_0 and Y_0, where $X_0 = t_1p_1' + X_1$, $Y_0 = u_1q_1' + Y_1^*$ and $Y_0 = t_1r_1' + Y_1$. Specifically, matrices $p_1 = X_0't_1/||t_1||^2$, $q_1 = Y_0'u_1/||u_1||^2$, $r_1 = Y_0't_1/||t_1||^2$ and X_1, Y_1^*, Y_1, respectively, are the residual matrices of the regression equations. The principal components will be calculated until the requirement is satisfied. Suppose the rank of X_0 is A. Then, $X_0 = t_1p_1' + \ldots + t_Ap_A'$ and $Y_0 = t_1r_1' + \ldots + t_Ar_A' + Y_A$. Based on these two equations, the regression equation can be easily obtained. With this approach, the changes in the aroma quality of samples that were treated by various production conditions are identified. In addition, the corresponding volatiles of the samples and the impact of the production conditions on their formation are investigated. Through these steps, the sample quality can be evaluated with various production conditions.

For example, in the last stage of flat peach juice production, a test sample FPS1 is evaluated with FPS0 as the control group. All variables are centred and scaled to 1/Sedv such that each variable has unit variance and zero mean prior to the PLSR analysis. The X-matrix is composed of 71 compounds, whereas the Y-matrix corresponds to sensory attributes and juice samples (Fig. 8). When the two PCs are considered, 79% of the volatile variables explain 73% of the variation among the sensory data and FPS samples. All variances are located between the inner ($r2 = 0.5$) and outer ellipses ($r2 = 1.0$). Fig. 8 shows that the FPS sample appears to be separated along PC1. The control group FPS0 is on the left side, while FPS1, which was treated by enzymatic hydrolysis, is on the right side of the plot. Sample FPS0, which is situated in the left-lower part, significantly correlates

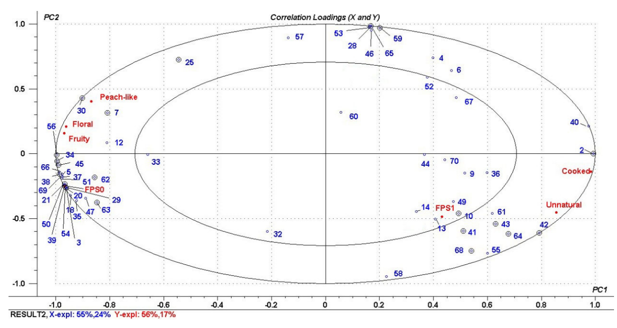

FIGURE 8. PLSR model of sensory attributes and volatiles for a test sample and the control group.

with the peach-like, floral and fruity attributes and strongly negatively correlates with all of the unpleasant sensory notes (cooked and unnatural). Finally, the potential relationships among the volatiles, samples, and sensory attributes are identified. Meanwhile, the correlation between the control group and test sample is low. According to this result, FPS1 is an unqualified flat peach juice product and should be forbidden to flow to the commodity market.

In the quality evaluation module implementation, three methods, including the PCA, HCA and PLSR, are utilized. The time complexities of these three methods are respectively $O(mn^2 + n^3)$ [70], $O(m^2)$ [71] and $O(n^3)$ [72], where m is the number of samples and n is the number of features for GC-MS data in each sample.

In this section, we give the implementation of the optimization production model establishment, production data recording and food quality evaluation. By utilizing the off-chain models with on-chain data in combination, our system makes use of the traceability of blockchain and auto-execution of smart contracts to achieve reliable and efficient quality monitoring inside a food manufacturer, which is greatly different from existing work applying blockchain or smart contracts on food quality assurance, including the product quality management system recording product registration and transfer histories in [26], the blockchain scheme for information sharing in [22], the agri-food supply chain system based on RFID and blockchain in [23], the blockchain-based credit evaluation system in [24], the food quality traceability system based on the blockchain and the EPC information services in [25].

VI. CONCLUSION

In this paper, we propose a reliable quality monitoring system within a fruit juice production enterprise. Combining smart contracts and machine learning technologies, our system consists of optimization production model establishment, production data recording and food quality evaluations, which are conducted throughout the production process. During production, if the sample quality at a production stage is designated as unqualified, then the subsequent stages are not carried out to prevent additional losses. By combining the off-chain models with on-chain data, our system can utilize the traceability of the blockchain and the auto-execution of smart contracts to achieve reliable and efficient quality monitoring. Although the production stages in our system are designed for fruit juice production, the proposed framework and approaches can be easily extended to general food production.

However, the search strategy in our system is still not efficient enough. Hence, in future work, we plan to optimize the storage structure of the data that are preserved on the blockchain to increase the search speed. Moreover, modern IoT devices, such as RFIDs and sensors [73], [74], can be added to our system for the realization of a fully automatic quality monitoring system.

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BIN YU received the Ph.D. degree in computer science from Xidian University, Xi'an, China, in 2019. He is currently a Lecturer with the School of Computer Science and Technology, Xidian University, Xi'an. His research interests include formal verification of software systems, blockchain, and smart contracts.

PING ZHAN received the Ph.D. degree from Jiangnan University, Wuxi, China, in 2013. She is currently an Associate Professor with the College of Food Engineering and Nutritional Science, Shaanxi Normal University, Xi'an, China. Her research interests include food flavor chemistry and food function.

MING LEI received Ph.D. degree in computer science and technology from Xi'an Jiaotong University, Xi'an, China, in 2019. He is currently a Lecturer with the School of Computer Science of Shaanxi Normal University. His research interests include wireless networks and intelligent optimization.

FANG ZHOU received the M.S. degree in neurobiology from Shanxi Medical University, Taiyuan, China, in 2019. She is currently pursuing the Ph.D. degree with the Department of Anesthesiology, Xijing Hospital Fourth Military Medical University, Xi'an, China. Her research interests include machine learning and neurosciences.

PENG WANG received the Ph.D. degree in agricultural engineering from Shihezi University, Shihezi, China, in 2019. He is currently a Lecturer with the College of Food Engineering and Nutritional Science, Shaanxi Normal University, Xi'an, China. His research interests include food flavor chemistry and food quality.