Web Service Based Food Additive Inventory Management with Forecasting System

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Abstract—**Recently, food industries have been growing rapidly due to the development of novel technology. Numerous research has been conducted to improve products to satisfy the needs of customers. As a result, various food additives have been used to compose the product and which makes it difficult in recognizing and managing food additive stock. To be able to survive in a competitive world, the industry must find a practical stock management solution since under-stocking causes the industry to lose an opportunity to sell while over-stocking causes a deficit. This paper focuses on an inventory management and a stock forecasting system. Web service was implemented as a new approach for an inventory management system that helps to manage and to find the food additives that exist in the international food additive database authorized by Codex Alimentarius Commission. Using web services has many advantages than a traditional web base. The service provider does not have to reveal the database access method to the client, and the information or business model can be changed at any time, and no need to update the client side. The client can access the service via any platform. The web service has been developed through Hypertext Mark up Language 5 (HTML5), Node JavaScript (NodeJS), and My Structured Query Language (MySQL), Database Management System, Hypertext Preprocessor (PHP). The stock forecasting was done by Python with four machine learning models which are Naive Bayes, Decision Tree, Linear Regression and Support Vector Regression to predict stock of food additive. Accuracy is used to measure the performance of these techniques. The experimental result indicated that the most accurate model for stock forecasting is Linear regression.**

Keywords-machine learning; web service; food additives

I. INTRODUCTION

Nowadays, food-related technology has been rapidly developed to meet the demand of customers. Food industries owners have invested in unique food-related technology so that various new food additives can be discovered. These food additives are used by the food industries. The industries store many food additives in their stock, and it is hard to manage them since one additive can be called by many names depending which factory they are produced. Some additives are a restrict additive overabundantly use of it can be harmful to the consumer. Some additive returns the same effect, so the decision of which additive should be used is very difficult. For example, sweetener additives can be Sorbitols, Mannitol, Acesulfame, Aspartame, Cyclamates, Isomalt, Saccharins, Sucralose, Thaumatin, and so on. The key to success in today's global marketplace depends on the industries management of the supply chain. An effective inventory management system is one of the most important success keys. Under-stocking causes the industry to lose an opportunity to sell the product, while over-stocking may cause the expiration of the additive and leads to loss of investment fund.

Anigbogu et al. [1] proposed an intelligent model for sales and inventory management. Their work aimed to apply theory to the practical solution of inventory management. The system is intelligent because it can automatically provide demand and a time pattern for the inventory using fuzzy logic. However, the proposed approach still contains some restrictions since the system was run on a standalone system so the efficiency and optimization of the system cannot be measured.

Loizidies [2] proposed the development of a Software as a Service web application (SaaS) inventory management system. The system is a basic tool for tracking and monitoring sales and inventory for small business that cannot invest in their Inventory Management System. His work was implemented and test with Caterpro Ltd. The system was developed using HTML, CSS, PHP, MySQL, and Apache. However, this work did not include any intelligence model.

The Activity Based Costing analysis (ABC) is one of the most famous model and widely used for inventory management system [3, 4, 5, 6, 7]. It classifies products into three categories A, B, and C depends on the value of Stock Keeping Unit (SKU) and total inventory income. However, this model is not suitable for the changing circumstances or multi-criteria inventory classification (MCIC).

This paper focuses on food additive inventory management with web service. Moreover, machine learning techniques were implemented to overcome the MCIC challenge. The stock of food additives was predicted using four models of machine learning which are Naive Bayes, Decision Tree, Linear Regression, and Support Vector Regression. The rest of the paper is organized as follows. In Section 2, food chemistry, machine learning and web service background are reviewed. The system design and framework is presented in Section 3. The proposed algorithm and experiments are demonstrated in Section 4. Finally, the paper conclusion and discussion are shown in Section 5.

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II. PRELIMINARY

A. Food Chemistry

Food chemistry [8] is a scientific component of food, for example, Carbohydrate, Protein, and lipids including food processing with various additives. The Codex Alimentarius (CA) is the group of international standard food code that is maintained by Codex Alimentarius Commission (CAC). CA is grouped with the category of food, for example, a product from milk. It also can be categorized by the property of food additive, such as sweetener additive. Each additive has its own unique International Numbering System (INS). In 2017, the properties of food additives were divided into 303 food additives and 27 properties, for example, Anticaking agent, Bleaching agent, and Antifoaming agent.

B. Machine Learning

The Machine learning [9, 10, 11] is related to the algorithm that can automatically learn data and use that data to predict the trend of that dataset. Machine learning tasks are mainly classified into three categories which are supervised learning, unsupervised learning, and reinforcement learning. Machine learning was applied in this project to forecast additives selling volume in advance to avoid under-stocking and over-stocking situation.

C. Web service

In a traditional web-based system, the web application is developed from various programming languages such as PHP, ASP or JAVA. Web applications that develop with different languages are difficult to work together. Service-oriented architecture (SOA), acts as an autonomous interactive software [12]. Web services [13, 14, 15, 16] are developed according to SOA. It acts as a standardized and interoperable data sharing mechanism that helps web applications developed from different languages so that they can improve communication with each other correctly. Primarily, the web service framework is composed of three fundamental areas: communication, description, and discovery. For communication between software agents, the Simple Object Access Protocol (SOAP) is required. Universal Description, Discovery, and Integration (UDDI) is a directory that provides registry services for web service. A provider registers with UDDI to announce the service to clients. The clients use it to discover services over the network where Web Services Description Language (WSDL) is a language to help explain about the service, so the client learns variable and the Internet protocol that use to connect and the address of the service.

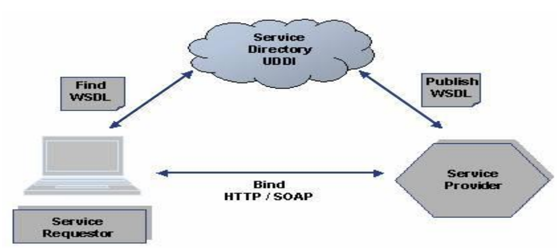

Figure 1. Web service Framework [1].

III. SYSTEM DESIGN AND FRAMEWORK

Figures 2 and 3 show the overall system framework and use case diagrams. Firstly, clients request services from a server via an API. Then the server connects to a database and response service to the client. There is two type of user which are member user and administrator.

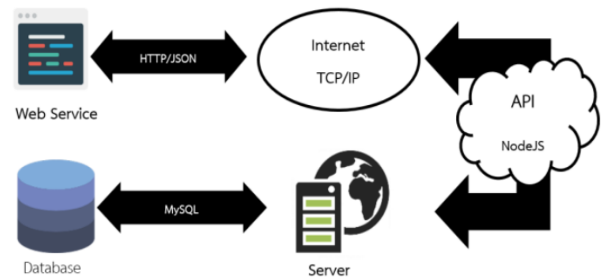

Figure 2. Overall System.

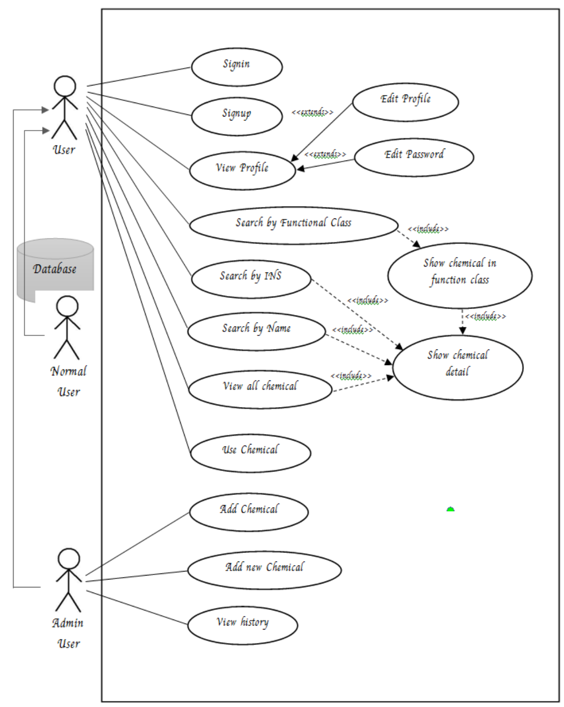

Figure 3. Use case Diagram.

IV. EXPERIMENT AND RESULT

Web service and machine learning were implemented at the faculty of engineering, King Mongkut's Institute of Technology Ladkrabang (KMITL), Thailand. The experiment was divided into two parts: Web service and Stock prediction with Machine Learning.

A. Web Service

Previously, web applications were used to serve students from each department separately; one server for each department, which causes many problems. For example, when the university changed policy, the new program had to be uploaded to every department server. Moreover, each department had to manage the additive stock separately, so the cut off rate was very high. The web service was implemented to provide services for students to buy the additive from a center inventory. When the university had new rules or new processes, the program was updated to just the web service server where the web applications from where each department could request the services. The web service provides various functions for member users and administrators. Firstly, a user must sign up to become a member. The member user can request a service such as searching for the INS of the additive, view the additive properties, and buy the additive. The administrator has more functions, such as management of the additive stock.

The service has been implemented on the Virtual Private Server (VPN), Digital Ocean. The server is called droplet, and the service charge depends on the size of the hard disk, CPU, Memory, and data transfer. In the experiment, web service is deployed with Ubantu operating system with 512 MB CPU, SSD 20 GB, and 1000GB data transfer. The web service is divided into two parts which are an administrator and a member section.

The server usage log is shown in Fig. 4. The peak time of service requests usually happens in the afternoon since mostly, the service was requested from the students of KMITL that had a class during that period. Also, ordinary users signed up to request services such as the search for information of the additive, but they did not buy any additive from the store. Overall, the web service's performance was better than previous web applications. When the policy of the university changed, the updated software was installed in the web service server only; then other applications could query a service from it.

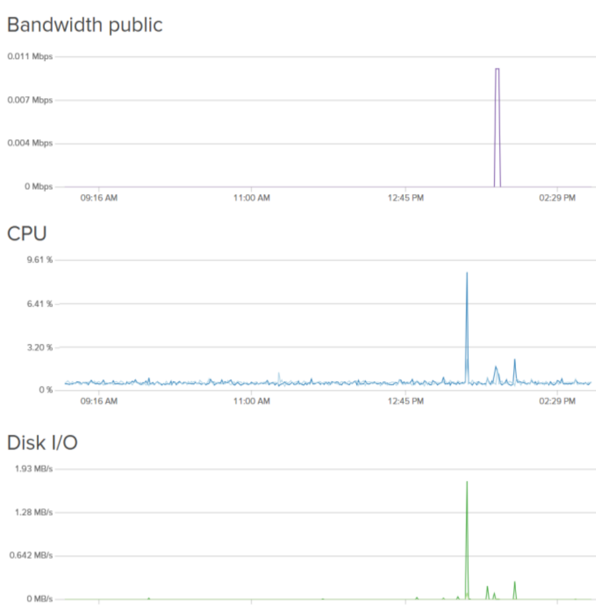

Figure 4. Server Usage log.

B. *Stock Prediction with Machine Learning*

The machine learning is applied to predict in which and when additives should be bought into the university inventory. The dataset used in this experiment was retrieved from the university inventory management database which contains all the selling transactions occurring for 100 days. There are 15,834 records with 6 attributes in this table consisted of UserID, INS_ID, INS_name, Quantity, BuyingDate, and UnitPrice. The four machine learning models were Naive Bayes, Decision Tree, Linear Regression and Support Vector Regression, and were applied in this work through Python with 60% learning data and 40% testing data to predict a stock of food additives. A forecasting system diagram is shown in Fig. 5. The dataset of food additive from the database were input to the four models to test for their accuracy. The examples of results that tested with INS no. 339 are shown in Fig. 6, 7, 8, and 9.

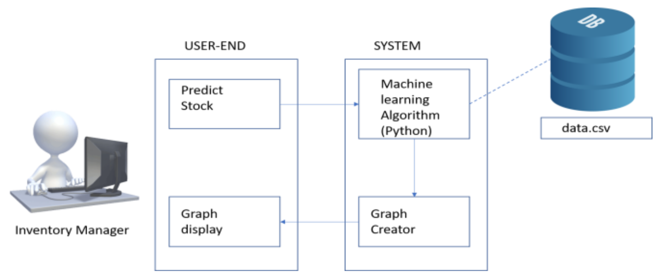

Figure 5. Forecasting System Diagram.

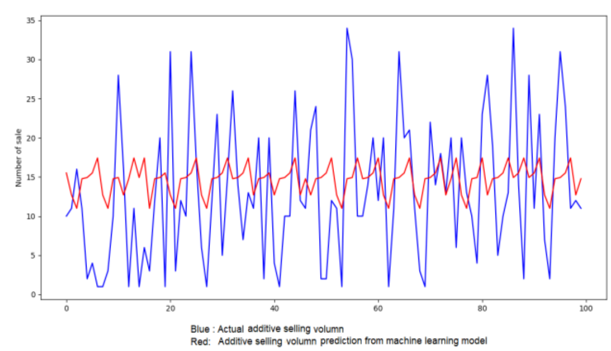

Figure 6. Decision Tree.

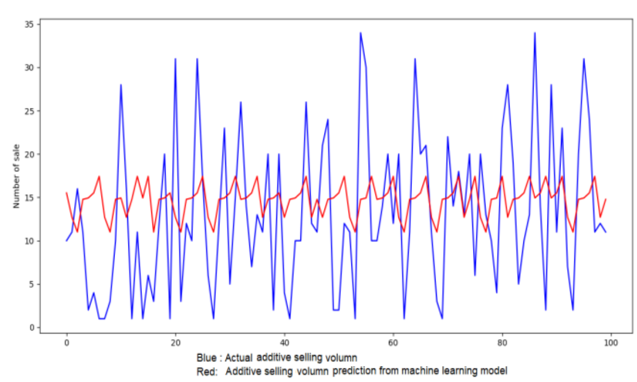

Figure 7. Linear Regression.

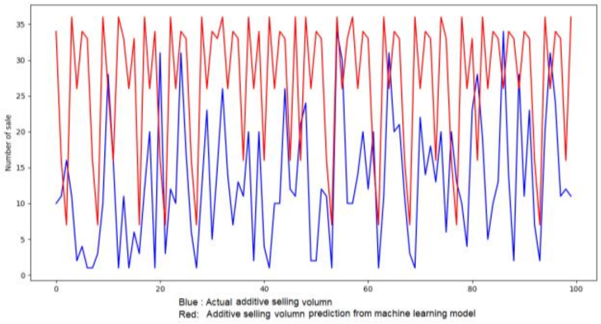

Figure 8. Naïve Bayes

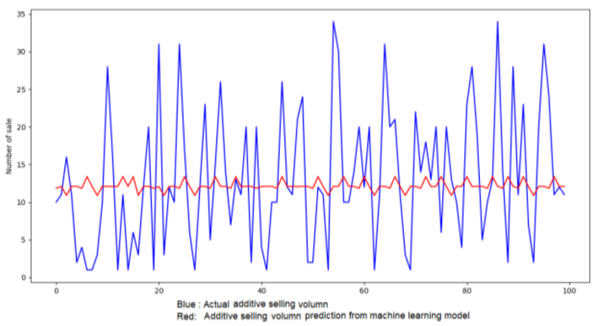

Figure 9. Support Vector Machine.

The figure shows a comparison between an actual additive selling volume and an additive selling volume predicted by machine learning where x-axis shows date and the y-axis show number of sales. The blue line is the actual additive selling volume, and the red line is the additive selling volume predicted by machine learning model. The accuracy of the model is measured by the Mean Sum of Square Error (MSE).

$$MSE = \sum_{i=1}^{n} \frac{(X_i - F_i)^2}{n}$$

Let X_i = Actual product selling
F_i = Prediction of product selling
n = number of food additive of transaction data

TABLE I. MSE FOR EACH MODEL IN AVERAGE

Model	MSE
Decision Tree	30.68
Linear regression	28.26
Naive Bayes	54.35
Support Vector Machine	82.84

The average efficiency of each model for all additive is shown in Table 1. The most accurate model is the Linear regression with 28.26% of MSE. This model fits the best for well-defined dataset such as predicting the additive that buyers buy the same amount of them every day. The accuracy of the decision tree model is almost same as the linear regression but it takes more training time than the linear regression model. Naïve Bayes, the shape of the red line and the blue line looks similar however, the MSE is large because of the class conditional independence. Support Vector Machine requires large feature sets while the university's dataset is too small so its MSE is highest among the four models.

V. CONCLUSION

In this work, web services are used to manage food additive inventory. The advantage over the traditional web-based platform is that the web service works with an interoperability concept. It can support a user that requests service from different platforms. The limitation of the specification of the server was tested with up to 300 users. The average of the server uptime reached 99.9%. Moreover, four machine learning models were applied to predict the selling unit of the additives, and it helped the inventory manager when making purchasing decisions from suppliers correctly. The most accurate model is Linear regression since mostly the additive was sold in a continuous response. Buying food additive according to the prediction, helping to reduce costs from over-stocking and under-stocking effectively.

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