WEB SERVICE FOR LATEX TRADING DATA EXCHANGE AND LATEX VOLUME PREDICTION

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Thesis
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ABSTRACT

This research aimed to develop a web service system that helps latex traders develop their own latex trading programs easily. They can exchange latex trading data via the provided web services. This data exchange could be beneficial to their business plans.

Another aim of this research was to predict daily traded latex volume by using meteorological conditions and publish prediction results via a web service. Three classification methods were tested in order to select the most suitable one for building the prediction model, these were; decision tree, neural network, and support vector machine. The data used in this research was unbalanced. So the class distribution was adjusted by sampling with replacement and bias toward uniform distribution. Results from experiments showed that decision tree gave higher overall accuracy than the others. From class-by-class analysis, it was also robust to the overlearning of small classes. By increasing the volume of the smallest class, it improved the prediction of this class, yet kept the prediction of the others stably well.

KEYWORDS: WEB SERVICE / DECISION TREE / NEURAL NETWORK / SUPPORT VECTOR MACHINE / CLASS IMBALANCE

76 pages

เว็บเซอร์วิสสำหรับการแลกเปลี่ยนข้อมูลการซื้อขายน้ำยางและทำนายปริมาณน้ำยางพารา
WEB SERVICE FOR LATEX TRADING DATA EXCHANGE AND LATEX VOLUME PREDICTION

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บทคัดย่อ

งานวิจัยนี้มีวัตถุประสงค์เพื่อพัฒนาระบบเว็บเซอร์วิสที่ช่วยให้ผู้ประกอบการซื้อขายน้ำยางพาราสามารถพัฒนาระบบซื้อขายน้ำยางพาราของตนเองได้ง่ายขึ้น และสามารถแลกเปลี่ยนข้อมูลการซื้อขายระหว่างกันได้ผ่านการเรียกใช้เว็บเซอร์วิส การแลกเปลี่ยนข้อมูลนี้เป็นประโยชน์ต่อการวางแผนการดำเนินธุรกิจของตนเองได้

อีกวัตถุประสงค์หนึ่งของงานวิจัยคือการทำนายปริมาณน้ำยางพาราที่มีการซื้อขายในแต่ละวันโดยใช้ข้อมูลพยากรณ์อากาศและเผยแพร่ผลลัพธ์ผ่านเว็บเซอร์วิส งานวิจัยนี้ได้ทดสอบวิธีการจำแนก 3 วิธีคือ ต้นไม้ตัดสินใจ (decision tree), เครือข่ายประสาท (neural network), และซัพพอร์ตเวกเตอร์แมชชีน (support vector machine) เพื่อคัดเลือกวิธีที่เหมาะสมที่สุดในการสร้างโมเดลการทำนายปริมาณน้ำยาง ข้อมูลที่ใช้ในงานวิจัยมีความไม่สมดุล (unbalanced) จึงต้องปรับการแจกแจงคลาส (class distribution) ด้วยวิธีการสุ่มตัวอย่างแบบใส่กลับคืน (sampling with replacement) และปรับค่าความโน้มเอียง (Bias) เข้าสู่การแจกแจงแบบสม่ำเสมอ (uniform distribution) จากการทดลองพบว่าต้นไม้ตัดสินใจมีอัตราความถูกต้องโดยรวมสูงกว่าวิธีอื่น จากการวิเคราะห์รายคลาสพบว่าวิธีนี้มีความทนทานต่อการเรียนรู้คลาสเล็กมากเกินไป กล่าวคือเมื่อเพิ่มจำนวนข้อมูลในคลาสเล็ก ทำให้การทำนายคลาสนี้ปรับตัวดีขึ้น ในขณะที่การทำนายคลาสอื่นยังคงมีประสิทธิภาพดี

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CHAPTER I
INTRODUCTION

1.1 Background and Motivation

Rubber tree agriculture is one of the major economic sectors of Thailand, especially in Southern provinces. In Songkhla, the Southern economic hub, there were 815506.93 acres of rubber planting in 2013 which yielded 493,340 ton of rubber [1] worth approximately 249,288.97 million baht [2].

Latex is a product of rubber trees. Agriculturists tap the trees at night and collect latex in the morning. They sell the latex to latex traders who determine the price of latex from its concentration. The latex traders do the following tasks:

1. Weigh the latex.
2. Measure the percent of latex.
3. Calculate the concentration of latex by multiplying *weight* with *percent* to get the *dry rubber*.
4. Calculate total price by multiplying *dry rubber* with *daily price of latex*. The daily price of latex is determined by factories or middlemen.

The latex trading process is depicted by Figure 1.1

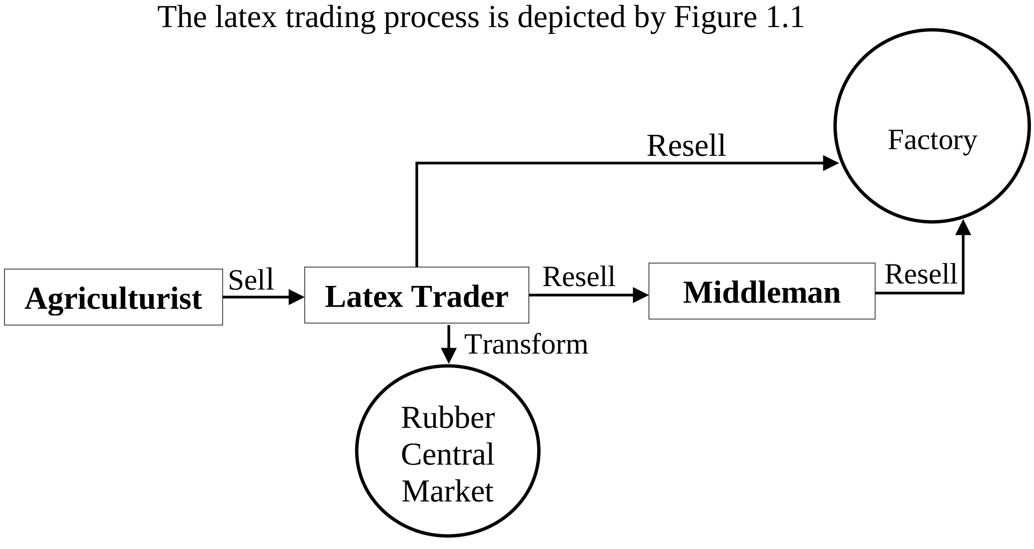


Figure 1.1 Latex Trading Process

Figure 1.1 shows latex trading process consisting of Agriculturist, Latex Traders, and Middleman. Once trading between agriculturists and latex traders is finished, the latex traders can possibly manage latex by: (1) reselling the latex to factory, (2) reselling the latex to middleman, (3) transforming the latex into product and selling it to rubber central market.

This research proposes a web service system for latex trading. It aims to help latex traders develop their own latex trading programs easier and exchange trading data with other latex traders. Also, latex traders can know daily latex volume and latex stock in local markets.

Web service enables web applications on different platforms to communicate with each other. Web service helps latex traders reduce the workload and cost of their system development.

In addition, the proposed system provides a latex volume prediction service that can help latex traders make production and trading plans as well as bargain with the middleman for higher price of latex.

The prediction is based on weather forecast data as weather condition is an important factor that affects daily latex volume. Techniques used for prediction are current state-of-the-art data mining techniques, namely decision tree, neural network, and support vector machine.

1.2 Research Objective

1.2.1 To develop a web service system that allows latex traders to development their latex trading program easier by calling the provided services.

1.2.2 To develop a web service system that exchanges trading data between latex traders and local markets.

1.2.3 To predict latex volume by using decision tree, neural network, and support vector machine.

1.3 Scope of Research

This research focuses on latex trading in Hatyai District, Songkhla Province.

1.4 Results

1.4.1 A web service system for exchanging latex trading data

1.4.2 Results of latex volume prediction from decision tree, neural network, and support vector machine.

1.5 Significance of the study

1.5.1 The proposed web service system can help latex traders save cost for developing individual latex trading programs because common services are provided by the system and their programs only need to call these services. In addition, the proposed system can help traders exchange trading data and visualize the movement of latex volume in the area.

1.5.2 Results of latex volume prediction can help production planning, trading plan and bargaining.

CHAPTER II
LITERATURE REVIEW

This chapter reviews literature about rubber trees and latex trading, weather conditions influencing latex collection, web service technology used for latex trading system, and data mining techniques used for latex volume prediction.

2.1 Rubber Trees and Latex Trading

The normal age of a rubber tree is up to 100 years and it can be as high as 100-130 feet. When the tree is about six years old, it can produce latex. The latex is white milky substance obtained by removing a sliver of its bark. This process is called latex tapping. Rubber trees bear fruits that spread seeds to reproduce.[3]

Rubber trees grow well in humid and tropical areas. Native rubber trees are found primarily in South America in such countries as Brazil, Bolivia, Peru, Colombia, and Venezuela. However, the trees can also be found outside their native lands primarily in tropical countries in Africa (such as Liberia, Ethiopia, and Uganda) and Asia (such as Brunei, Cambodia, China, India, Indonesia, Malaysia, Sri Lanka, the Philippines, Thailand, Singapore, Laos, Myanmar, and Vietnam).[4]

Rubber tree plantation in Thailand was initiated by Lord Ratsadanupradit Mahisornpakdee, the governor of Trang province, in 1899. Since then, it has become a major segment in Thailand's agriculture, especially in the Southern provinces.

2.1.1 Latex Collection and Latex Trading. Rubber trees are best tapped in cool weather. Agriculturists usually tap the trees between 1 AM - 4 AM. If the trees are tapped late, e.g. as late as 6 AM, the latex volume will decrease by 4-5%. The agriculturists can tap the rubber trees for 3-4 consecutive days and break for 1 day.

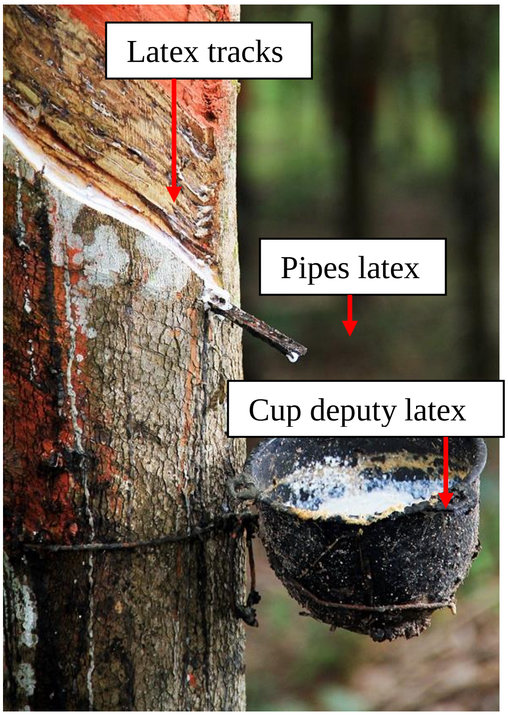


Figure 2.1 Latex flowing into cup [5]

Figure 2.1 shows an example of latex tapping. The latex will stop flowing after approximately 3 hours. After that, the agriculturists will collect the latex (Figure 2.2) and sell it to latex traders. [6]

Figure 2.2 Equipment for latex collection. [7]

The latex appearance is white, turbid, and thick liquid with slight aroma. Sometimes, the liquid is pale yellow. It is lighter than water (its density is 0.98 g/cm^3). It contains about 35% of dry rubber content (DRC) and 65% of water. This ratio may vary by the following factors: breed and age of rubber, season, tapping method, the frequency of tapping, and plantation method. [8]

Rubber Research Institute of Thailand has established Latex Central Market in Hatyai District, Songkhla Province, to help agriculturists with fair trading. Despite this attempt, there are still many highly competitive local markets. Most agriculturists sell their latex to various traders such as latex shops, latex cooperatives, and middlemen in such markets. Their decisions about where to sell the latex based on the cost of transportation and yield volume.

The average volume of latex trading in the Local Central Market is about 10-15 tons/day, depending on price and season. The trading volume is lowest, about 7-8 tons/day, during the wettest months (in the South), i.e. November and December. [9]

2.2 Weather Conditions

Weather conditions influence the amount of latex being collected. The amount of rainfall in planting area must be at least 1,350 mm, with at least 120-150 days of raining per year. The annual average relative humidity must be at least 65%. The annual wind speed must be at least 1 m/s. And the annual average temperature must be at least 25-28 ^{o}c. [10]

Therefore, given weather-related data, one can make a prediction about latex volume. There are three types of weather forecast: short range, medium range, and long range.

1. Short range forecast is to forecast the weather less than 72 hours ahead, using current weather monitoring data. The forecast period can be subdivided into

- Nowcast forecast period, which is less than 3 hours ahead.
- Very short range forecast period, which is less than 12 hours ahead.
- Short range forecast period, which is less than 72 hours ahead.

2. Medium range forecast is to forecast the weather more than 72 hours and up to 10 days ahead, using current meteorological data along with statistical data.

3. Long range forecast is to forecast the weather more than 10 days ahead, using statistical data.

Besides meteorological theories, weather observation is important and necessary for effective forecast. A meteorological station in Thailand observes weather conditions for both surface weather and upper weather. At the surface level, which is less than 10 meters above the ground, the observation is done every 3 hours [11]. At the upper level, which is about 30 km. above the ground, meteorological compounds such as atmospheric pressure, temperature, and wind are measured. [12] The meteorological station is also equipped with radars to observe the violence of rain in each area.[13]

There have been a few studies about the relationship between latex volume and weather conditions. For example, Rao et al. (1996) modeled the relationship between latex volume and climatic variables by using multiple regressions.[14]

Teerachai Lerkmongkolwit (2005) used climatic data to predict the amount of latex from rubber trees in Suratthani province by using nonlinear auto-regressive network with exogenous inputs (NARX) which is a complicated neural network. The prediction error was within ± 5% (confidence interval of 95%) compared to the actual amount of latex. [15]

2.3 Web Services

Web Service is a software system that enables the interaction between web applications written in different languages and running on different platforms. The interaction is generally based on standardized XML messaging [16]. Web service is a prominent technology in the third generation of the Web.

In the first generation of the Web, web contents were static. They were written only in Hypertext Markup Language (HTML) and information was transferred via Hypertext Transfer Protocol (HTTP). In the second generation of the Web, web contents were dynamic. They can be generated or changed upon user requests. And in the third generation of the Web, web service technology allows clients to request certain processing, i.e. services, from service providers. [17]

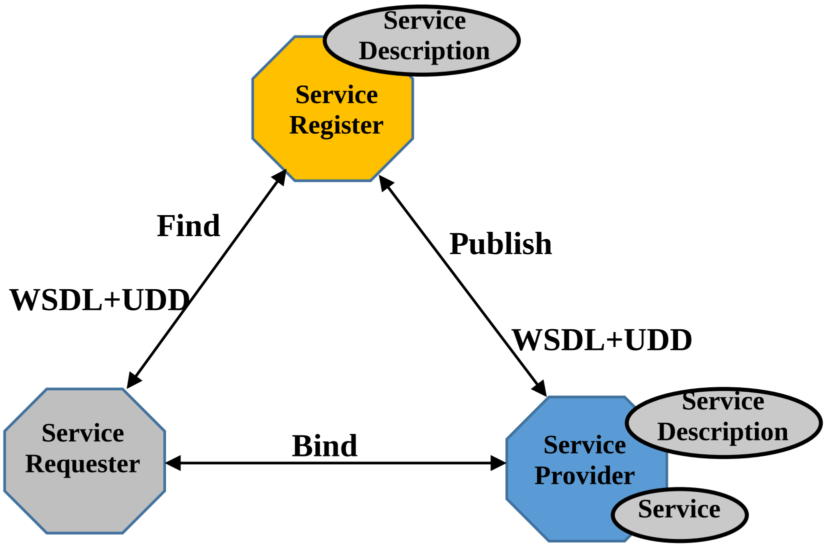


Figure 2.3 Architecture of web service [18]

Figure 2.3 shows the architecture of web service, consisting of three roles. They are service provider, service requester, and service registry. The service provider publishes its service, including service description written in Web Services Description Language (WSDL), to the service registry based on Universal Description, Discovery, and Integration (UDDI) specification. The service requester finds this service via UDDI interface. It can use the WSDL service description to directly bind to the service provider. [16]

2.3.1 SOAP (Simple Object Access Protocol) is a messaging protocol that allows programs running on different platforms to communicate with each other. This cross-platform interoperability is supported by Hypertext Transfer Protocol (HTTP), a web protocol installed by all major operating systems, and its Extensible Markup Language (XML).

A SOAP document itself is an XML document that specifies how one program can call another program in another computer and pass information to the callee. The callee sends back a response as specified by SOAP. SOAP also supports other transporting protocols besides HTTP.

SOAP calls are likely to pass firewalls because HTTP is typically port-80 compliant, whereas calls that use other protocols may be blocked for security reasons. Because of this, programs using SOAP can surely communicate with other programs anywhere [19]. In summary, SOAP enables programs to call functions from other programs, regardless of different hardware platforms, operating systems, or programming languages.

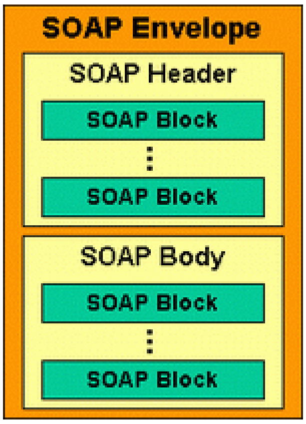


Figure 2.4 SOAP structure [19]

Figure 2.4 shows SOAP structure and Figure 2.5 shows SOAP document in XML format. It includes: SOAP envelop, which contains the whole document; SOAP header, which contains additional information about the service; and SOAP body, which is for calling service and showing result.

```
<soap:Envelope xmlns:soap="http://schemas.xmlsoap.org/soap/envelope/"
soap:encodingStyle="http://schemas.xmlsoap.org/soap/encoding/">
        <soap:Header>
              <!-- Header -->
              <i:local xmlns:i="http://www.i3t.or.th/ws/">
                    <i:currency>Bath</i:currency>
              </i:local>
        </soap:Header>
        <soap:body>
              <!-- Body -->
              <GetPrice>
                    <Item>Rose</Item>
                    <Quantity>100</Quantity>
              </GetPrice>
        </soap:Body>
        <soap:Fault>
              <!-- SOAP Node -->
        </soap:Fault>
</soap:Envelope
```

Figure 2.5 SOAP Documents [20]

2.3.2 WSDL (Web Services Description Language) is an XML-based format for describing a web service interface. It describes services and their binding to specific network addresses. WSDL has three parts: definitions, operations, and service binding. Figure 2.6 shows the relationship between these parts.

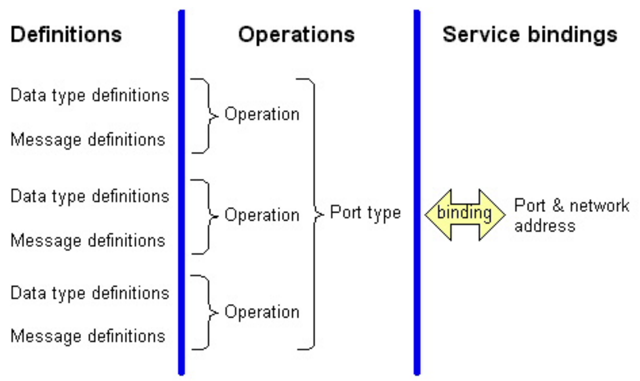


Figure 2.6 The relationship between basic parts of WSDL [21]

Definitions. Definitions are generally expressed in XML and include both data type definitions and message definitions. These definitions are usually based on some predefined XML vocabulary. The XML vocabulary may be either organization-specific or industry-wide. The former is designed and used within an organization. The latter is based on some agreements between organizations.

Operations. Operations describe actions for the messages supported by a web service. They are grouped into port types. There are four types of operations:

- One-way operations: The client sends a message to the endpoint (where the service is located) without expecting a response.
- Request/response operations: The client sends a message to the endpoint and the endpoint sends a response back.
- Solicit/response operations: The endpoint sends a request to the client and the client sends a response back.
- Notification operations: The endpoint sends a response to the client.

Service bindings. Service bindings connect port types to a port that is in turn mapped to a network address. This binding is commonly created by using SOAP. [21]

```
<?xml version="1.0"?>
<definitions name="HelloWorld" targetNamespace="urn:HelloWorld"
xmlns:tns="urn:HelloWorld"  xmlns:xsd="http://www.w3.org/2001/XMLSchema"
xmlns:soap="http://schemas.xmlsoap.org/wsdl/soap/"
xmlns:soapenc="http://schemas.xmlsoap.org/soap/encoding/"
xmlns:wsdl="http://schemas.xmlsoap.org/wsdl/"
xmlns="http://schemas.xmlsoap.org/wsdl/">
    <!--Type -->
    <types>
        <xsd:schema xmlns="http://www.w3.org/2001/XMLSchema"
targetNamespace="urn:Hello">
            <xsd:element name="getName" type="xsd:string" />
            <xsd:element name="HelloResponse" type="xsd:string" />
        </xsd:schema>
    </types>
    <!-- Message -->
    <message name="doHello">
        <part name="yourName" type="tns:getName" />
    </message>
    <message name="doHelloResponse">
        <part name="return" type="tns:HelloResponse" />
    </message>
    <!-- PortType-->
    <portType name="HelloPort">
        <operation name="doHello">
            <input message="tns:doHello" />
            <output message="tns:doHelloResponse" />
        </operation>
    </portType>
    <!-- Bingding -->
    <binding name="HelloBinding" type="tns:HelloPort">
        <soap:binding style="rpc" transport="http://schemas.xmlsoap.org/soap/http" />
        <operation name="doHello">
            <soap:operation soapAction="urn:HelloAction" />
            <input>
                <soap:body use="encoded" namespace="urn:Hello"
encodingStyle="http://schemas.xmlsoap.org/soap/encoding/" />
            </input>
            <output>
                <soap:body use="encoded" namespace="urn:Hello"
encodingStyle="http://schemas.xmlsoap.org/soap/encoding/" />
            </output>
        </operation>
    </binding>
    <!-- Service -->
    <service name="HelloService">
```

Figure 2.7 WSDL Document [22]

2.3.3 UDDI (Universal Description, Discovery, and Integration). UDDI is an integral part to the development of web services. It provides an open framework for registering and locating services offered by various providers.

As illustrated earlier in Figure 2.3, a web service requester needs to know the location of service it wants to bind to. There needs to be some kind of registry server that holds such information. The UDDI provides a standard mechanism, typically XML-based, for service providers to publish their web services, and for service requesters to locate them.[23]

Instead of traditionally searching services from UDDI server, a developer may search services directly from web service providers, for example Google (https://developers.google.com/maps/documentation/webservices), Amazon (https://aws.amazon.com), and etc.

2.3.4 XML (eXtensible Markup Language). Extensible Markup Language (XML) is used to describe data.

The XML standard provides flexibility to format information and share the structured data through networks.

According to formal recommendation by World Wide Web Consortium (W3C), XML code is quite similar to Hypertext Markup Language (HTML). The markup symbols in both HTML and XML describe the content of a file. The former carry web page content and describe how the content will be displayed. The latter carry data and describe how the data is structured. Thus, XML data is a self-defining. Upon receiving an XML file, the receiver can extract both data structure and data from that file. There is no need for the receiver to know or prepare the data structure in advance. [24]

Due to such advantages, XML is an integral part of web service that facilitates the interoperability. SOAP messages and WSDL documents are all XML-based. Their examples are shown in Figures 2.5 and 2.7 respectively.

Examples of works that employed web service technology are as follows. Kunathip Boonruangkhao (2008) developed Electronics Marketplace that collected details of products into the data center. Customers can pick products from the

Marketplace. And by using web service, vendors can transfer product information from their web systems to the Electronics Marketplace system. [25]

Settapong Tunyarittikorn (2008) developed E-Coupon Payment Model on web services business-to-customer (B2C) systems. This model covered information and prevented data tracking of buyers by using web services. It can run on different platforms without having to install additional programs.[26]

Pongsathorn Noimanee (2009) developed conference management system with web services technology. Various conference organizers can use this system without having to develop their own. [27]

2.4 Data Mining

The aim of data mining is to discover hidden knowledge in the data. This knowledge is usually represented as patterns or relationship between variables. Data mining cycle consists of four stages as follows:

1. Problem specification: To specify the scope of the analysis. In the context of this research, the goal is to predict latex volume, which can help latex traders plan for trading and bargaining the price of latex.

2. Data Mining: To use data mining techniques to extract patterns, such as prediction or classification models, from the data.

3. Application: To apply the results from data mining to new cases or in real business situations.

4. Performance measurement: To measure the results from data mining, for example, the accuracy of predicting latex volume.

There are many different tasks in data mining, including classification, estimation, and clustering. Choosing an appropriate task depends on application domain and the purpose of the analysis. This research focuses on classification task. Classification is the process of creating a model of independent variables (e.g. weather-related variables) that classifies the dependent one (e.g. latex volume), based on training data. Then, this model is used to predict the classes of unseen cases. Three well-known classification methods are chosen. They are decision tree, neural network, and support vector machine. [28]

2.4.1 Decision Tree. A decision tree (DT) is a classification model represented as a tree, as in Figure 2.8. It is like as organization structure, including root node, which is the top node in the tree; leaf node, which is a node with no children; internal node, which is a node with at least one child; and edge, which is a line connecting two nodes.[29] It is popular because the algorithm to construct a tree is not complex. The decision tree can be easily interpreted and understood.

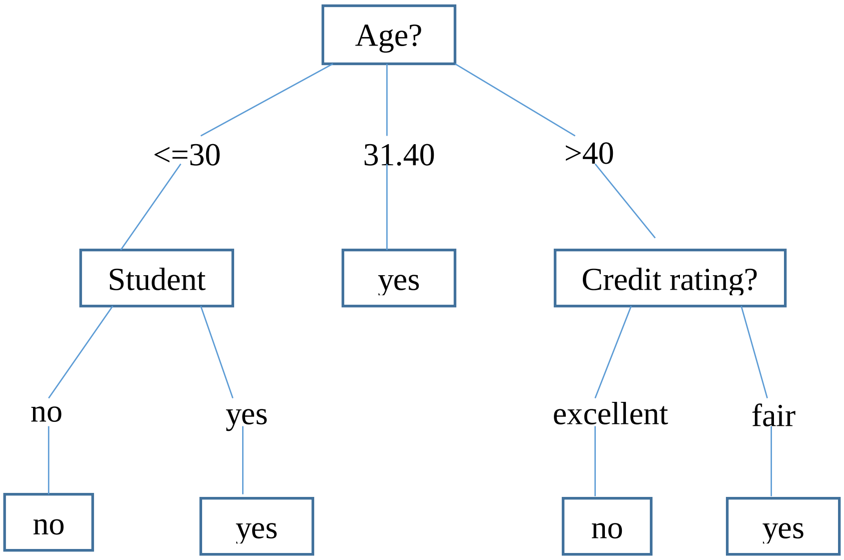


Figure 2.8 An example of decision tree.[28]

The idea of decision tree learner was originated by Hunt in the late 1950s and it has been followed by many others. The family of ID3, C4, C4.5, and C5.0 is one of them. ID3 was a simple system containing only 600 lines of Pascal, while C4.5 grew to about 9,000 lines of C. It is now available in many open source tools including Weka. Although C5.0 is a more recent and better algorithm, it is less popular than C4.5 because it is used mostly in commercial systems.[30]

C4.5 builds a decision tree from a set of training data, using the concept of information entropy. The training data is a set $S = s_1, s_2, \ldots$ of already classified samples or records. Each record S_i consists of vector of independent variables or attributes and the class in which S_i falls.

The algorithm runs in iterations. In each iteration, it chooses the attribute that best splits the samples belonging to different classes. The splitting criterion is normalized information gain. The attribute with the highest information gain or highest gain ratio is chosen as a new tree node. The C4.5 algorithm then recurs on the smaller subsets of samples. [31]

The information gain from splitting a sample ***S*** by attribute ***A*** is calculated from the following formula:

$$Gain(S,A) = E(S) - \sum_{v \in value(A)} \frac{|S_v|}{|S|} E(S_v)$$

S is a sample that includes vectors of attributes and class.

A is the attribute under consideration.

Value (A) is the set of possible values of ***A***, i.e. child nodes after splitting.

$\boldsymbol{S_v}$ is a sample at the child node where ***A*** = ***v***.

E(S) is the entropy of sample ***S***

$\boldsymbol{E(S_v)}$ is the entropy of sample $\boldsymbol{S_v}$

The gain ratio is calculated by normalizing the information gain as follows:

$$GainRatio(S,A) = \frac{Gain(S,A)}{SplitInfo(S,A)} = \frac{Gain(S,A)}{-\sum_{v \in value(A)} \frac{|S_v|}{|S|} \log \frac{|S_v|}{|S|}}$$

Once the decision tree is fully grown, it may consist of too many branches due to the presence of noises or outliers in the training data. Therefore, tree pruning is applied afterwards. The pruning also helps reduce the problem of over appropriateness (overfitting) with the training data. The pruning process removes branches that do not bring benefits to the classification, or whose absence increase the classification performance. [32]

2.4.2 Neural Network

Artificial neutral network or simply neural network (NN) [33] is a system that emulates biological neural network, such as the brain. The brain is considered a biological neural network since it possesses about 100 billion neurons that communicate by using electro-chemical signals. Synapses are junctions where those neurons are connected and there are thousands of connections between them. Each neuron gets incoming signals from other neurons. If the sum of the signals surpasses a threshold, a response will be sent through the axon. The attempt of NN is to create a computational model of biological neural network although it is impossible to capture the full complexity of the biological neurons.

Shown in Figure 2.9, an NN is composed of a network of artificial neurons (also known as "nodes"). These nodes are connected to each other, and each connection is assigned a value that indicates the strength (or weight) of connection. A connection can be inhibitory (negative weight, with the maximum being -1.0) or excitatory (positive weight, with the maximum being +1.0). There are three types of neurons in an NN: input nodes, hidden nodes, and output nodes. Each node, except input node, has summation function and transfer (or activation) function that processes incoming signals and pass the neuron's response to the others.

There are many types of NN but the one often used in data mining is feedforward multilayer perceptron, a non-recurrent network containing input, output, and hidden layers. This type of neural network allows signals to only travel in one direction.

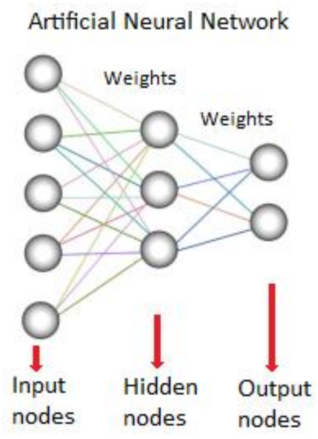


Figure 2.9 The architecture of neural network [33]

As illustrated in Figure 2.10, the input nodes read the values of independent variables of one record and pass them through the network. These values are also called activation values. The activation values reaching the next nodes (in the next layer) depend on the connection strengths. Each node in the next layer sums the activation values it receives and transforms the summed value by using its transfer function. The activation flows through the network, through hidden layers, until it reaches the output nodes. The output nodes then give output values that are combined to represent a predicted class. The difference between real class and predicted class, i.e. error, is propagated backward. After all connection strengths are adjusted with respect to the error, the NN begins processing the next record.

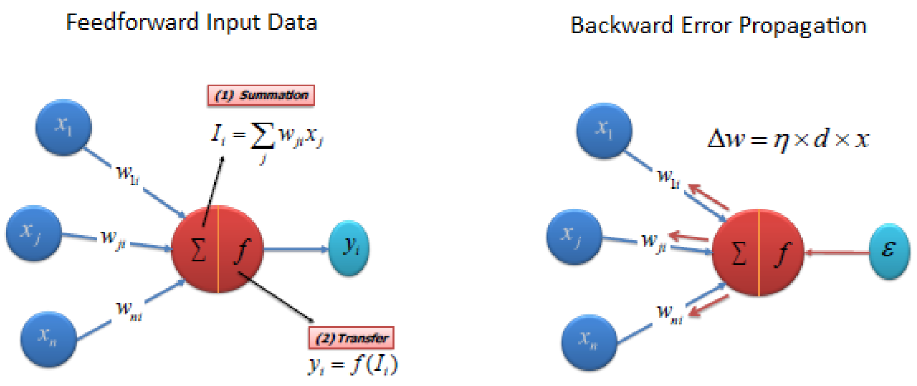


Figure 2.10 The forward and backward phases of neural network [33]

The transfer function transforms the total input signals (from the summation function) to an output signal. Four types of transfer functions are commonly used: unit step (threshold), sigmoid, piecewise linear, and Gaussian.

Unit step (threshold) function. The output is set at either of two levels, depending on whether the total input is greater than or less than a threshold value.

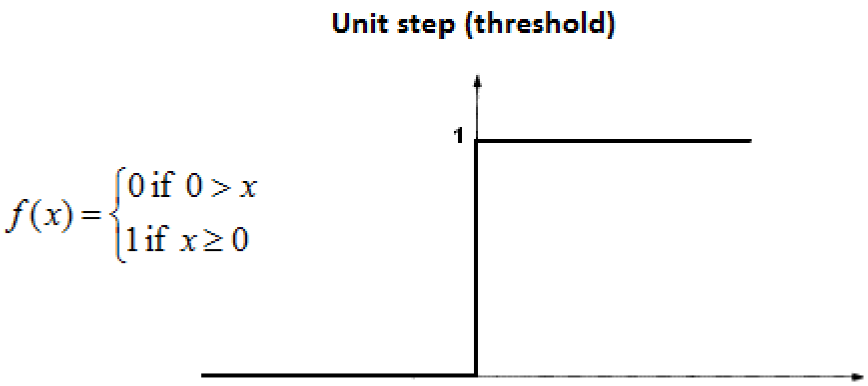


Figure 2.11 Unit step (threshold) function, where the threshold is 0 [33]

Sigmoid function. The sigmoid function is a function that gives sigmoid curve or "S" curve as shown in Figure 2.12 Popular sigmoid functions are logistic function whose values range from 0 to 1, and hyperbolic tangent (tanh) function whose values range from -1 to +1.

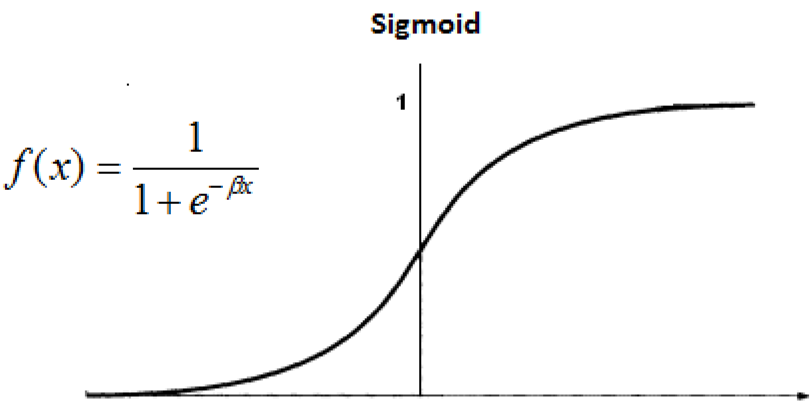


Figure 2.12 Sigmoid Function [33]

Piecewise linear function. The function is composed of multiple linear functions. The output is proportional to the total output.

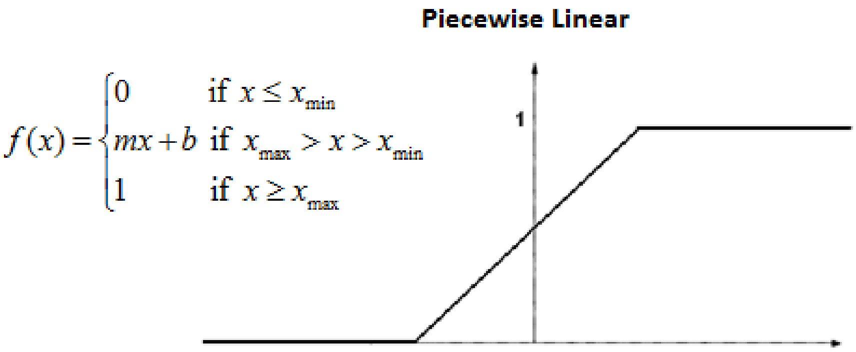


Figure 2.13 Piecewise linear function [33]

Gaussian function. The Gaussian function gives bell-shaped curves that are continuous as in Figure 2.14.

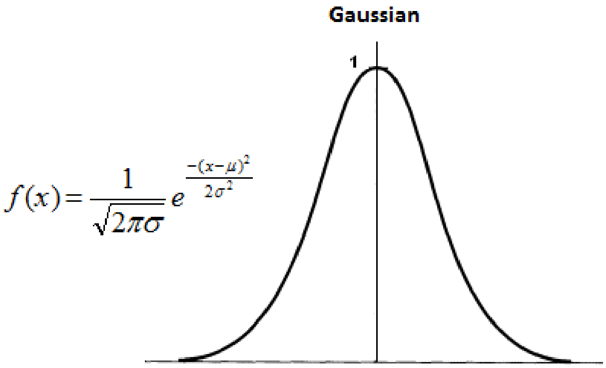


Figure 2.14 Gaussian function [33]

2.4.3 Support Vector Machine

Support Vector Machines (SVM) [34] distinguishes objects of different classes by using a decision plane. An example is shown in Figure 2.15. The objects are separated by a linear boundary such that all the RED objects are on the left side and all the GREEN objects are on the right side.

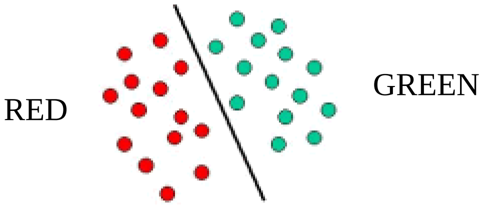


Figure 2.15 Linear separation in support vector machine [34]

The above linear separation is not always applicable in real practices. Most classification tasks are more complicated and thus require non-linear separation, as can be seen in Figure 2.16. SVM is very useful to handle these cases as follows.

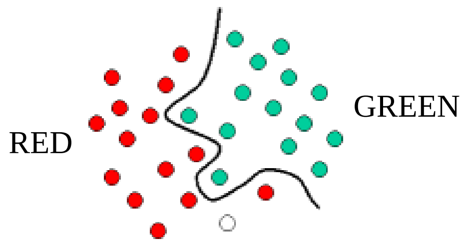


Figure 2.16 Non-linear separation in support vector machine [34]

Figure 2.17 shows how SVM simplifies the non-linear separation task. The original objects on the left side (input space) are rearranged to the ones on the right side (feature space) using a mathematical transformation function called kernel. The objects in the feature space are now linearly separable. Thus, instead of constructing a complex curve, the task is only to find an optimal line that can separate the GREEN and the RED objects. [23]

There are a number of kernels that can be used in SVM. These include linear, polynomial, radial basis function (RBF), and sigmoid.

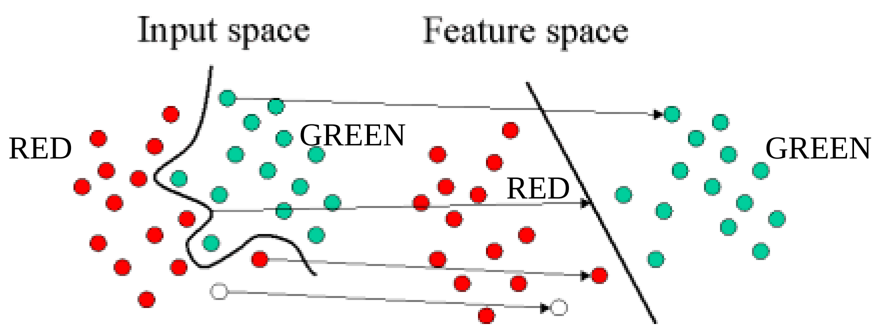


Figure 2.17 Kernel transformation from input space (non-linearly separable) to feature space (linearly separable) [34]

2.4.4 Comparison Between Decision Tree, Neural Network, and Support Vector Machine

Decision tree (DT), neural network (NN), and support vector machine (SVM) are chosen for the prediction of latex volume because they are well-known methods that differ in learning algorithms and resulting classification models. Other research that also compared between these methods are as follows.

Maria Seyagh (2011) [35] used support vector machines, neural networks, and decision trees to predict the anti-HIV activity in the organic compounds. In drug discovery research, it is difficult to predict biological activity of molecules from their chemical structures. Pattern classification has been recognized as a potential technique for this purpose. Three classification methods were applied in her study as mentioned above. From Table 1, all methods gave good results in learning (i.e. high accuracy on training set) and predicting unseen cases (i.e. high accuracy on test set). The latter results indicated that these methods were useful in the study of anti-HIV activity.

Table 2.1 The prediction accuracy of SVM, NN and DT, as reported by [47]

Methods	Training set (%)	Test set (%)
SVM	97.06	100
NN	97.06	92.90
DT	92.60	100

Comparing these methods in detail, SVM appeared to be slightly better than the other two methods. NN had worst performance on test set, implying possible overfitting. A major advantage of SVM is that it adopts the structure risk minimization principle, where the model is built by balancing between its complexity and data fitting. But NN uses traditional empirical risk minimization principle, where the model is built to only best fit the training data. Sometimes NN may suffer problems inherent to its architecture such as overtraining, overfitting, and network optimization. Another problem with NN is the reproducibility of results, due to the random initialization of NN parameteres and the variation of stopping criteria. DT avoids overfitting by tree pruning. Although its performance was slightly worse than the other two methods, its resulting tree model was more understandable to users.

Efstathios Kirkos (2008) [34] used classification methods to predict a firm's decision to choose an auditor based on its financial characteristics. The choosen methods were also DT, NN, and SVM. The evaluation was done by using 10-fold cross-validation.

In his study, he used the data of 338 UK and Irish firms. The input vector contained financial ratios and account values, as well as qualitative variables indicating the qualification cases and the auditor change. His results showed that DT outperformed the other methods, achieving an average accuracy rate of 83.73%. The average accuracy rates of quadratic polynomial SVM and NN were 79.29% and 75.44% respectively. With other kernels such as linear polynomial and RBF, SVM yielded even worse performance. The models from DT and SVM agreed that the level of debt had influence on the selection of an auditor. Companies with a high debt structure tended to choose a brand name auditor. Kirkos suggested additional research. For example, the auditors can be further categorized into international, national, and local ones. And as auditor choice may be influenced by managerial issues, additional variables related to managerial characteristics can help improve the prediction.

2.4.5 Class imbalance handling

When there is much difference between class sizes, a classifier may learn only big classes and ignore (or cannot learn the pattern of) small ones. As summarized by Jindaluang, Chouvatut, & Kantabutra (2014) [36], two strategies to handle this problem are undersampling and oversampling.

Undersampling strategy removes some records from the big class. This strategy has advantages when the class is big enough and the remaining records well represent that big class. Otherwise, records that represent certain features may be thrown away in the selection process, causing the classifier to suffer from underfitting. Works that employed this strategy are, for example, Tang & Zang (2006) [37].

On the other hand, oversampling strategy adds more records to the small class. The records being added may be the repeats of existing ones (such as Shatnawi

[38]), or newly synthesized ones. The latter technique is called SMOTE or synthetic minority oversampling (Blagus & Lusa [39]).

This oversampling strategy has advantages that important features in the big class are retained. However, its drawback is that it may take a long time to learn patterns from a large amount of data. And if the small class is oversampled too much, the classifier may suffer from overfitting.

CHAPTER III
RESEARCH METHODOLOGY

The purpose of this research is to develop a web service system for latex trading and latex volume prediction. The area in focus is Hatyai District, Songkhla Province. This chapter explains the following:

1. Data Collection
2. System Analysis and Design
3. Data Mining
4. Research Tools
5. System Evaluation

3.1 Data Collection

The data collection in this research consists of elements as follows:

3.1.1 Study latex trading process and collect daily volume of traded latex in Hatyai District of Songkhla, Thailand, in 2012-2013, from local traders.

3.1.2 Study weather forecasting and collect daily meteorological conditions in Hatyai District of Songkhla, Thailand, in 2012-2013, from the Thai Meteorological Department. After data consolidation, record matching, and cleansing, a data set of 653 records was derived. In this data set, each record corresponds to the data of each day. Nine independent variables are as follows:

- Daily average wind speed (knots)
- Daily average relative humidity (%)
- Daily average vapour presure (hPa)
- Daily average pressure (hPa)
- Daily average visibility (%)

- Daily average cloudiness (score 0-10)
- Daily average rainfall (millimetres)
- Daily average temperature (°C)
- Daily average dew point (°C)

3.2 System Analysis and Design

3.2.1 Target Users are divided into 2 groups as follows:

1.) Latex Traders are general system users. They (human users) can access the website of the proposed system, or let their client programs exchange data with the system via web services.

2.) System administrator.

3.2.2 Web Service. The proposed system offers 8 services as follows:

1.) Latex Price Service is for storing daily latex price data.

2.) Latex Buying and Reselling Service is for storing latex buying and reselling data.

3.) Latex Alert Service is for getting alerts about unusual trading.

4.) Latex Stock Service is for checking latex stocks of local traders.

5.) Latex Daily Price Service is for checking daily latex price in local trading.

6.) Latex Daily Alert Service is for showing alerts about unusual trading.

7.) Latex Volume Prediction Service is for predicting latex volume.

8.) Weather Service is for storing daily meteorological conditions.

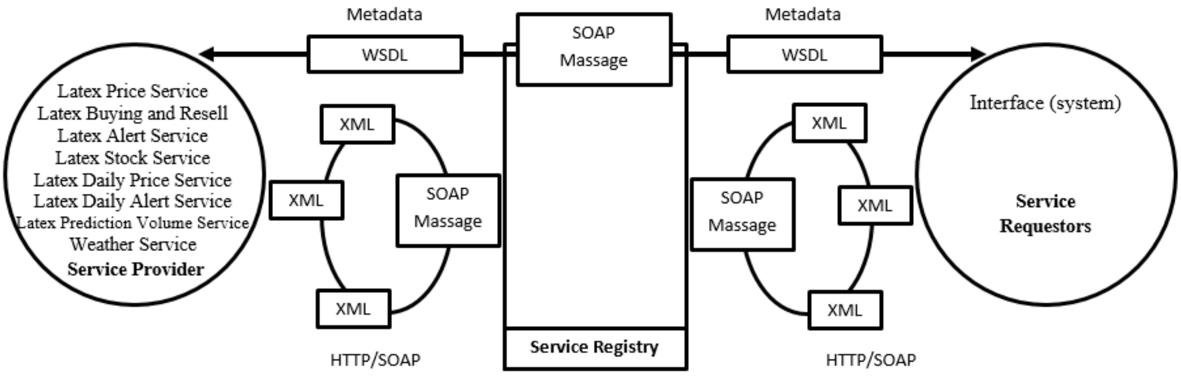


Figure 3.1 The design of web service

Figure 3.1 shows the design of web service which is divided into 3 parts as follows:

1. Service Provider stores services and their related HTML, database, text files, etc., and provides service descriptions (metadata).

2. Service Registry posts available services. In this research it is the same entity as Service Provider.

3. Service Requestor are client programs (of target users) that call the services.

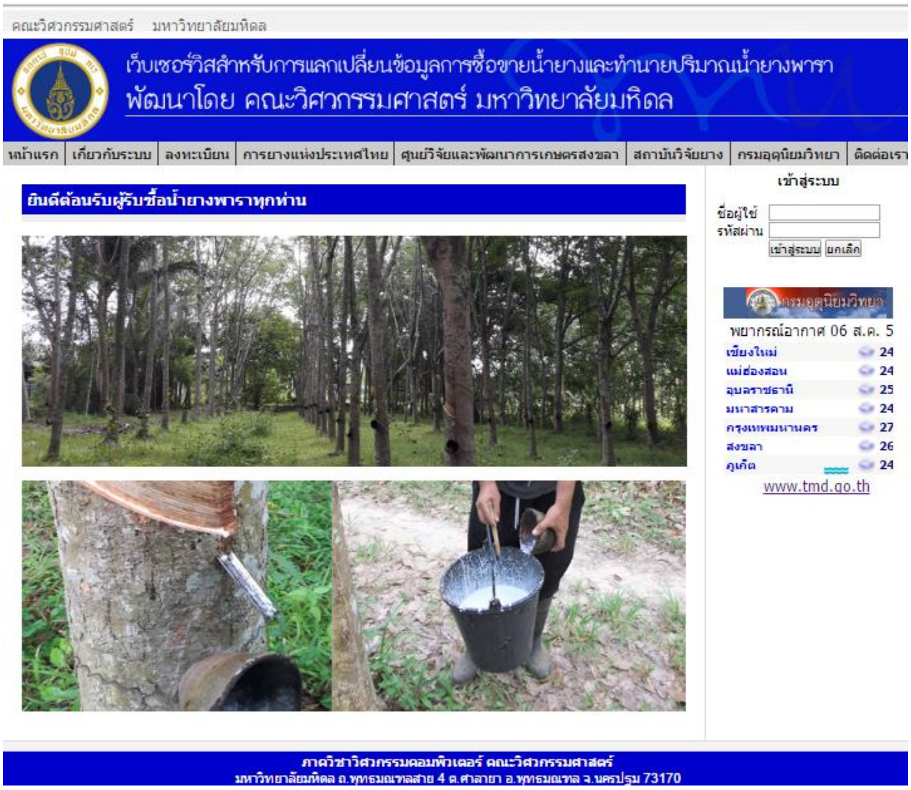


Figure 3.2 Website for providing web services

Figure 3.2 shows the website that provides the proposed web services, including terms of use and service descriptions.

3.2.3 Flow of Processing

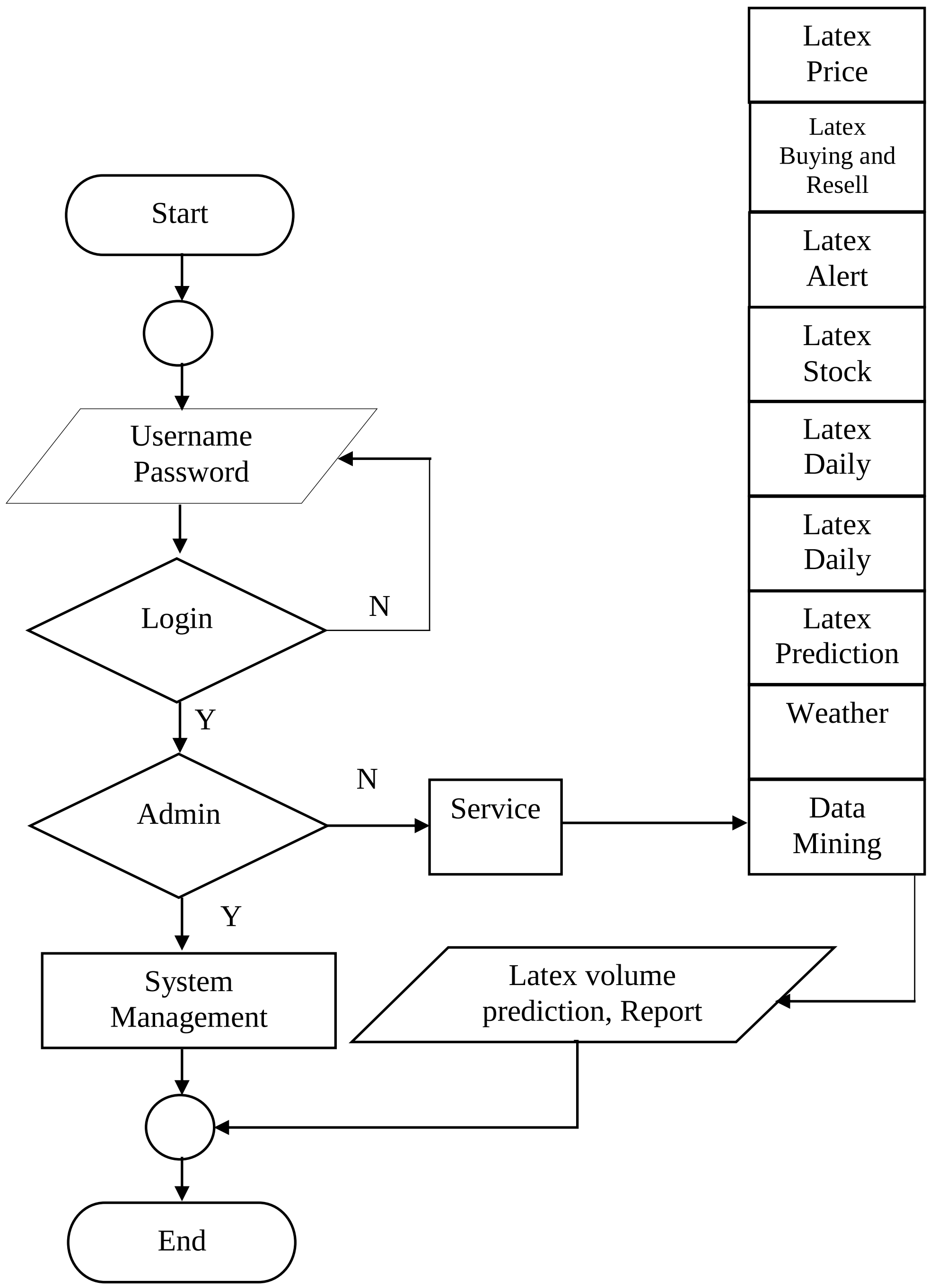


Figure 3.3 Flowchart of the proposed system

From Figure 3.3, Once a user accesses the system, he/she will be authenticated and checked for permission. The system divides users into 2 groups. The first group, system administrator, can manage the system. The second group, general user, can call services and transfer data to system.

3.2.4 Context Diagram is a component of functional modeling. It allows a team or an individual to produce a high-level model of existing or proposed systems. It defines the boundary of the system and its interactions with the critical elements. The diagram is shown in Figure 3.4.

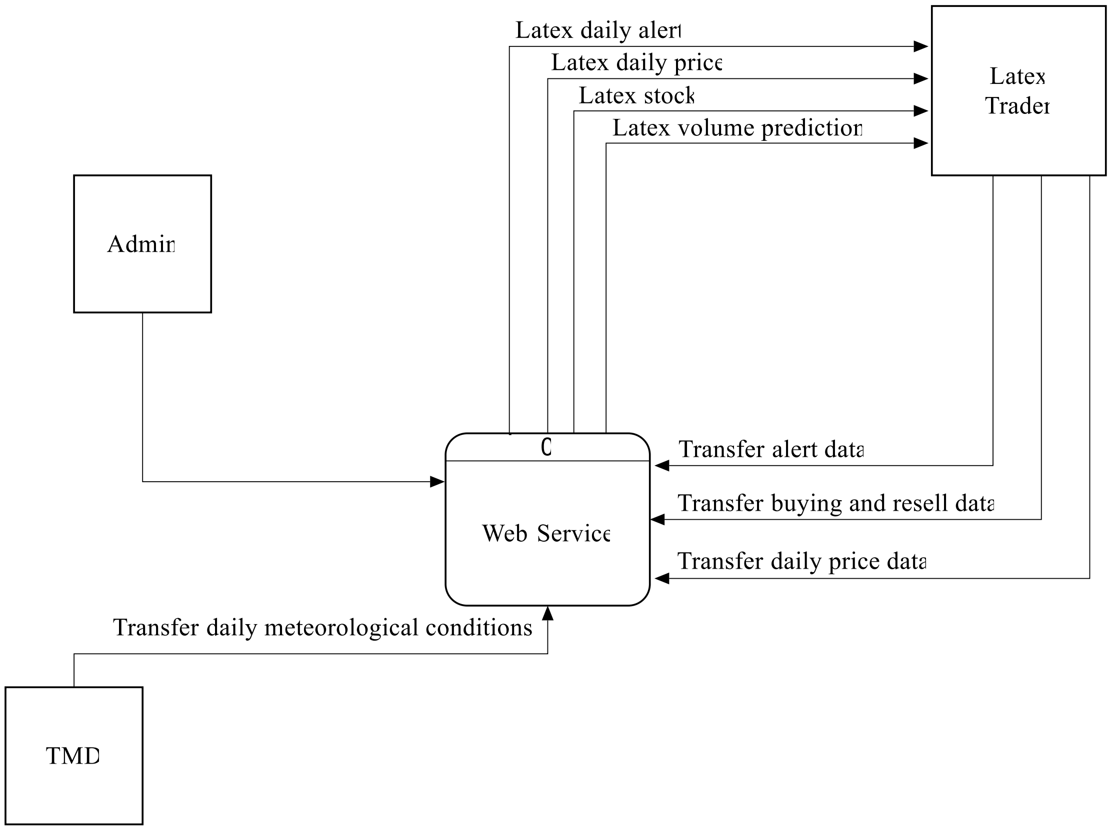


Figure 3.4 Context diagram of the proposed system

3.2.5 ER-**Diagram**. Figure 3.5 shows the relationship of elements of data in the system.

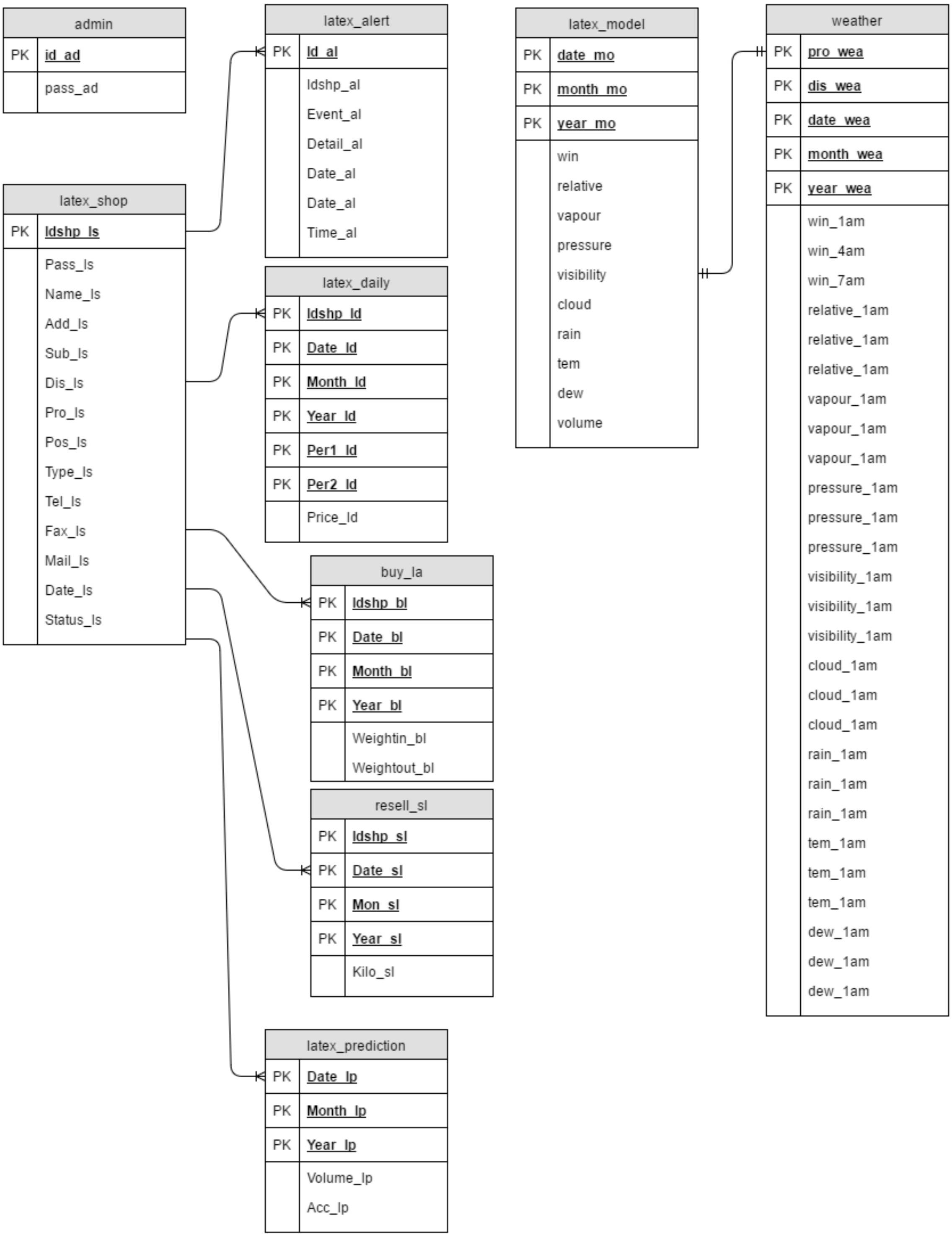


Figure 3.5 ER-diagram of the proposed system

3.2.6 Data Dictionary is the guideline that consists of table names, fields of data, types of data, and detail of data (descriptions) as shown in Tables 3.1 – 3.8.

Table 3.1 admin : storing information about user

TABLE NAME	admin	
Field	**Type**	**Detail**
id_ad	Varchar(10)	username
pass_ad	Varchar(10)	password (hashed)

Table 3.2 buy_la : storing information about latex buying

TABLE NAME	buy_la	
Field	**Type**	**Detail**
Idshp_bl	Varchar(10)	ID Shop
Date_bl	Int(2)	Date
Month_bl	Int(2)	Month
Year_bl	Int(4)	Year
Weightin_bl	Float	Weigh buy
Weightout_bl	Float	Weigh resell

Table 3.3 latex_alert : storing information about alerting events

TABLE NAME	latex_alert	
Field	**Type**	**Detail**
Id_al	int	Alert ID (auto run)
Idshp_al	Varchar(10)	ID Shop
Event_al	Varchar(100)	Event
Detail_al	Text	Detail
Date_al	Date	Date
Time_al	Time	Time

Table 3.4 latex_daily : storing information about daily latex price

TABLE NAME	latex_daily	
Field	**Type**	**Detail**
Idshp_ld	Varchar(10)	ID Shop
Date_ld	Int(2)	Date
Month_ld	Int(2)	Month
Year_ld	Int(2)	Year
Per1_ld	Float	Percent Start
Per2_ld	Float	Percent End
Price_ld	Float	Price

Table 3.5 latex_model : storing weather conditions for latex volume prediction

TABLE NAME	latex_model	
Field	**Type**	**Detail**
date_mo	Int(2)	Date
month_mo	Int(2)	Month
year_mo	Int(2)	Year
win	Float	Average Wind Speed
relative	Float	Average Relative Humidity
vapour	Float	Average Vapour Presure
pressure	Float	Average Pressure
visibility	Float	Average Visibility
cloud	Float	Average Cloudiness
rain	Float	Average Rainfall
tem	Float	Average Temperature
dew	Float	Average Dew Point
volume	Varchar(6)	Latex Volume

Table 3.6 latex_prediction : storing latex volume prediction

TABLE NAME	latex_prediction	
Field	**Type**	**Detail**
Date_lp	Int(2)	Date
Month_lp	Int(2)	Month
Year_lp	Int(2)	Year
Volume_lp	Varchar(6)	Latex Volume
Acc_lp	Float	Accuracy

Table 3.7 latex_shop : storing information about latex shop

TABLE NAME	latex_shop	
Field	**Type**	**Detail**
Idshp_ls	Varchar(10)	ID Shop (auto run)
Pass_ls	Varchar(7)	Password
Name_ls	Text	Name Shop
Add_ls	Varchar(50)	Address
Sub_ls	Varchar(20)	Sub district
Dis_ls	Varchar(20)	District
Pro_ls	Varchar(30)	Province
Pos_ls	Varchar(5)	Post Code
Type_ls	Varchar(30)	Trader type
Tel_ls	Varchar(10)	Telephone number
Fax_ls	Varchar(10)	Fax Number
Mail_ls	Varchar(50)	E-mail
Date_ls	datetime	Date registration
Status_ls	Varchar(1)	Status Shop

Table 3.8 weather : storing weather conditions at different times of the day

TABLE NAME	weather	
Field	**Type**	**Detail**
pro_wea	Varchar(15)	Province
dis_wea	Varchar(30)	District
date_wea	Int(2)	Date
month_wea	Int(2)	Month
year_wea	Int(4)	Year
win_1am	Float	wind speed at 1 AM
win_4am	Float	wind speed at 4 AM
win_7am	Float	wind speed at 7 AM
relative_1am	Float	relative humidity at 1 AM
relative_4am	Float	relative humidity at 4 AM
relative_7am	Float	relative humidity at 7 AM
vapour_1am	Float	vapour presure at 1 AM
vapour_4am	Float	vapour presure at 4 AM
vapour_7am	Float	vapour presure at 7 AM
pressure_1am	Float	pressure at 1 AM
pressure_4am	Float	pressure at 4 AM
pressure_7am	Float	pressure at 7 AM
visibility_1am	Float	visibility at 1 AM
visibility_4am	Float	visibility at 4 AM
visibility_7am	Float	visibility at 7 AM
cloud_1am	Float	cloudiness at 1 AM
cloud_4am	Float	cloudiness at 4 AM
cloud_7am	Float	cloudiness at 7 AM
rain_1am	Float	rainfall at 1 AM
rain_4am	Float	rainfall at 4 AM
rain_7am	Float	rainfall at 7 AM

Table 3.8 weather : storing weather conditions at different times of the day (Continue)

TABLE NAME	weather	
Field	**Type**	**Detail**
tem_1am	Float	temperature at 1 AM
tem_4am	Float	temperature at 4 AM
tem_7am	Float	temperature at 7 AM
dew_1am	Float	dew point at 1 AM
dew_4am	Float	dew point at 4 AM
dew_7am	Float	dew point at 7 AM

The purpose of this research is to develop a web service system for latex trading and latex volume prediction. The area in focus is Hatyai District, Songkhla Province. This chapter explains the following:

3.3 Data Mining

Latex Volume Prediction service uses meteorology parameters and latex trading data from the database for prediction. It gets prediction parameters from the users, generates command-line string, and sends this string to Weka. This research uses Decision Tree (DT), Neural Network (NN), and Support Vector Machine (SVM) for predicting latex volume. These three methods build prediction models from 9 independent variables (X1-X9) and a class variable (Y) as follows:

X_1 = Average wind speed (numeric)

X_2 = Average relative humidity (numeric)

X_3 = Average vapour presure (numeric)

X_4 = Average pressure (numeric)

X_5 = Average visibility (numeric)

X_6 = Average cloudiness (numeric)

X_7 = Average rainfall (numeric)

X_8 = Average temperature (numeric)

X_9 = Average dew point (numeric)

Y = Latex volume (nominal)

The class variable (Y) has 3 values: low, medium, and high.

Each variable's value is the average of measurements from midnight to 7 AM of that particular day. Class variable, i.e. traded latex volume, has three possible values: LOW (less than 500 kg. per trader), MEDIUM (less than 1500 kg. per trader), and HIGH (at least 1500 kg. per trader). The class distribution is shown in Figure 3.6.

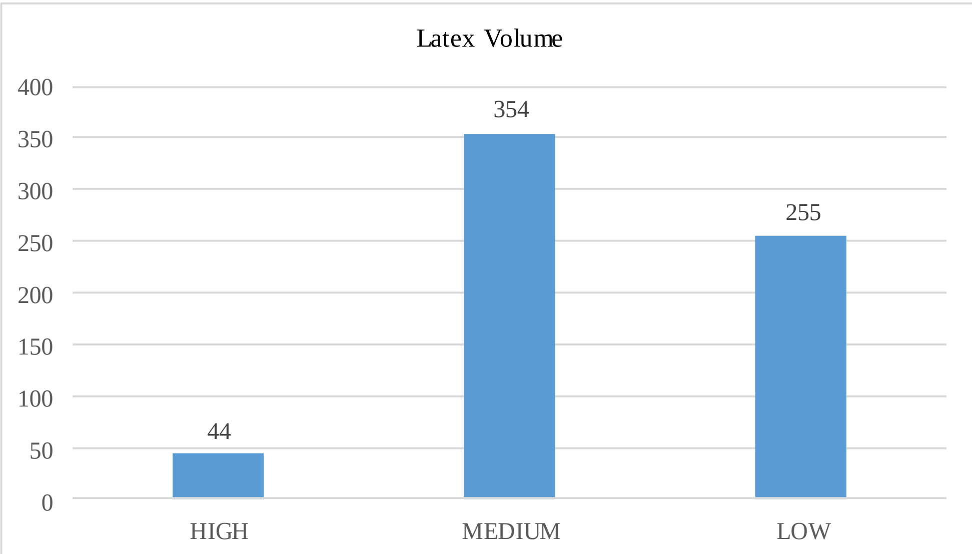


Figure 3.6 Distribution of class variable

Note that the trading data were collected from manual records of local traders, which were mostly incomplete. It was difficult to amass the total latex volume traded in the whole district. Thus, latex volume per trader was used instead. The categorization of latex volume into 3 classes was in agreement with the traders' opinions.

3.3.1 Experimental Setup

This research used decision tree (DT), neural network (NN), and support vector machine (SVM) for the latex volume prediction. These three methods built prediction models from 9 independent variables. Weka's classifiers were used with the following parameter setup:

• C4.5 decision tree (Weka's J48). All parameters were set as default.

• Neural network (Weka's MultiLayerPerceptron). All parameters were set as default.

• SVM (Weka's SMO). The kernel was polynomial. Other parameters were set as default.

As seen in Figure 3.6, the class distribution was unbalanced. The ratio of the biggest class (MEDIUM) to the smallest class (HIGH) was about 8:1. Resampling strategies were employed to adjust the class distribution, and their effects on the class prediction were examined. The experiments were divided into 3 sets as follows:

• Predict latex volume by using the original data.

• Predict latex volume by using resampled data (4 data sets). The new data sets were obtained from resampling (no bias) with replacement to increase the data sizes to 105%, 110%, 115%, and 120% of the original data size.

• Predict latex volume by using both resampled and balanced data (30 data sets). The new data sets were obtained from resampling with replacement (data sizes 100%, 110% and 120%) in conjunction with bias factor (ranging from 0.1 to 1.0). This method increased the volume of small classes or decreased the volume of big classes, depending on the bias factor. The factor close to 1.0 indicated the class distribution toward uniform.

Ten-fold cross validation was used when running each classifier on each data set. The evaluation of latex volume prediction was based on the overall accuracy and the F-measure of predicting each class. The F-measure of each class is the harmonic mean of its precision and recall. The precision of class C is the proportion of records predicted as C that actually belong to C. On the other hand, the recall of class C is the proportion of records in class C that are correctly retrieved (i.e. predicted).

3.4 Research Tools

3.4.1 Hardware

Note Book

- CPU AMD V120 2.2 GHz
- RAM 2GB
- Hard Disk 500 GB

3.4.2 Software

Windows 7

MySQL 5.0.51b

Abode Dreamweaver CS 3

PHP, XML

Appserv 2.5.10

Weka 3.7

3.5 Evaluation

3.5.1 The evaluation of web services is based on user satisfaction of using the website and connecting their client programs to the services.

3.5.2 The evaluation of latex volume prediction is based on the following metrics:

- The overall accuracy of volume prediction.
- The F-measure of predicting each individual class.

CHAPTER IV
METHODOLOGY

In this chapter, we show the results of latex volume prediction, web service system, and user satisfaction of using this system.

4.1 Result of Latex Volume Prediction

4.1.1 Predicting latex volume by using original data

The results are summarized in Figure 4.1 and Figure 4.2 The overall accuracy of DT, NN, and SVM were close. SVM performed better than the others by 1-2%, but this is only because it was slightly better at predicting MEDIUM and LOW. Due to the highly unbalanced data, all classifiers suffered when predicting HIGH. SVM suffered the most as the F-measure of this class is 0.0. These initial results exposed which classifier and which class were affected by the unbalanced data.

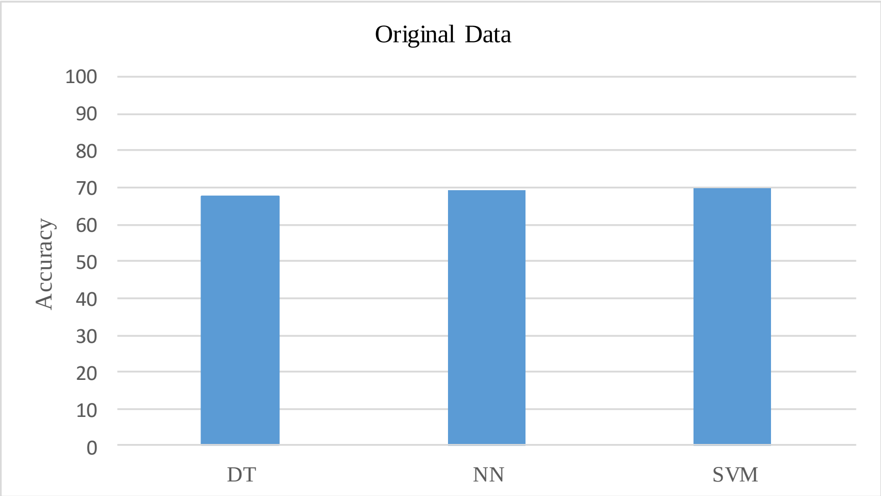


Figure 4.1 Overall accuracy (original data)

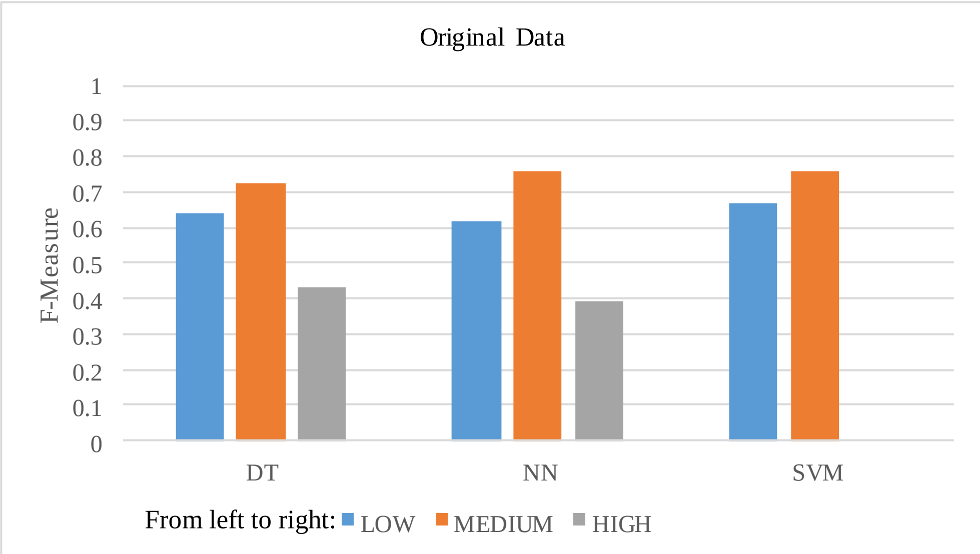


Figure 4.2 F-Measure of each class (original data)

4.1.2 Predicting latex volume by using resampled data

The results are summarized in Figure 4.3 and Figure 4.4 Given more but still unbalanced data, all classifiers had higher accuracy. In particular, DT improved the most because it could predict HIGH very well. However, SVM still could not learn this class as its F-measure was still 0.0.

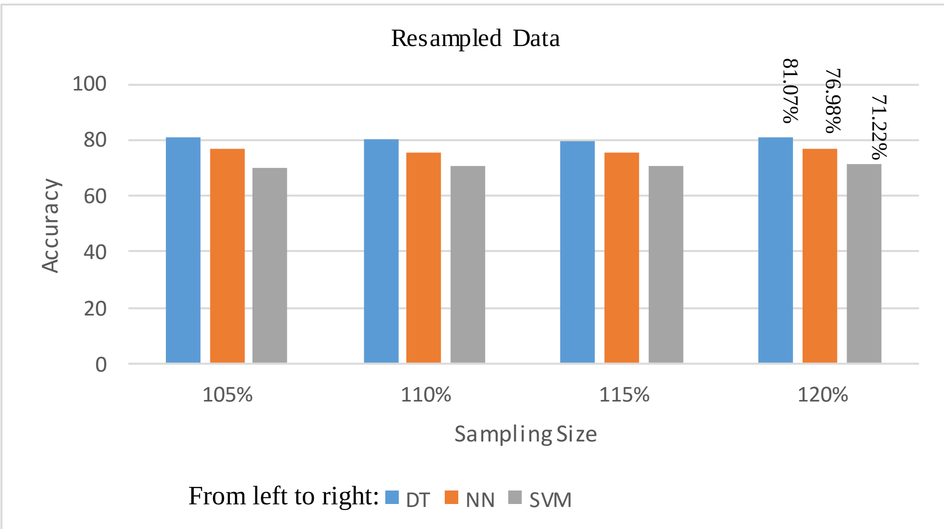


Figure 4.3 Overall accuracy (resampled data)

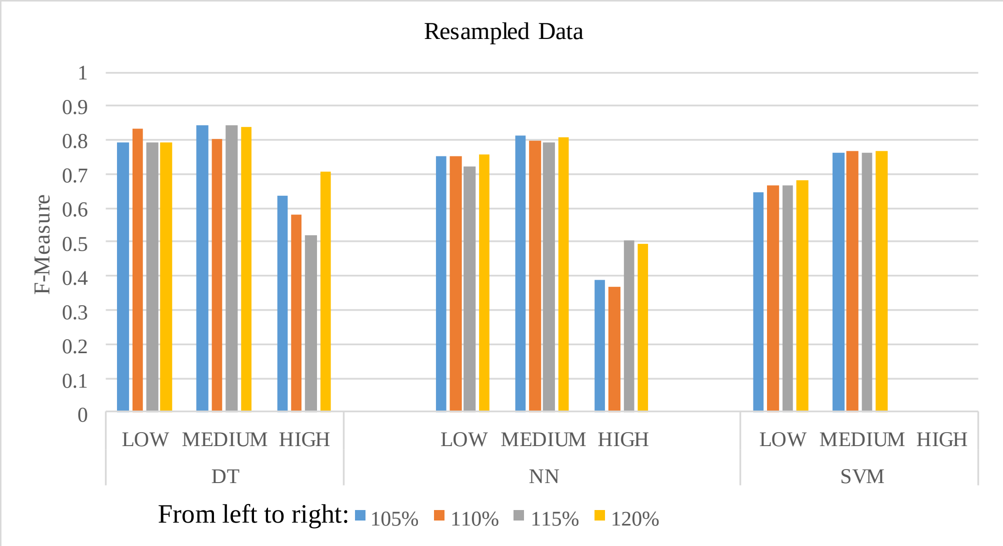


Figure 4.4 F-Measure of each class (resampled data)

4.1.3 Predicting latex volume by using both resampled and balanced data

Having adjusted the class distribution, all classifiers including SVM performed better. As observed in Figure 4.5, bigger data size yielded higher accuracy. But too big bias did not. This was more obvious in SVM. Its accuracy when the bias was 1.0 (uniform distribution) turned out to be lower than the accuracy when the bias was 0.1.

When the class distribution was closer to uniform, the volume of the biggest class (MEDIUM) may decrease too much and the volume of the smallest class (HIGH) may increase too much. As a result, the classifiers tended to focus on learning class HIGH at the expense of the other classes. As seen in Figure 4.6, in case of SVM, the F-measure of HIGH had a steep upward trend while the F-measure of MEDIUM had a steep downward trend. NN suffered a similar but not as severe problem because the F-measure of MEDIUM gradually trended downward. In case of DT, over learning HIGH did no harm to the prediction of the others. That is, although the F-measure of HIGH steeply trended upward, the F-measure of MEDIUM remained nearly stable.

Therefore, in the context of predicting latex volume by meteorological conditions and given unbalanced data, DT was the most appropriate method. This method was employed by the Latex Volume Prediction Service in the proposed web service system.

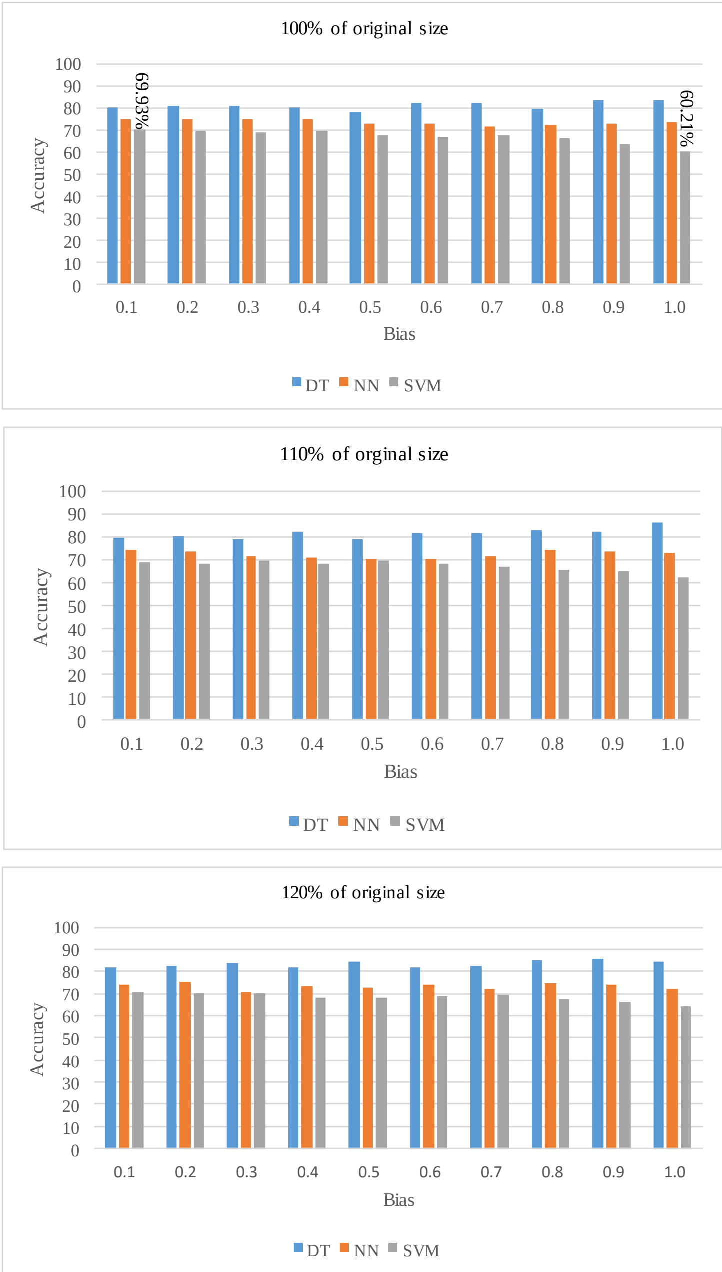
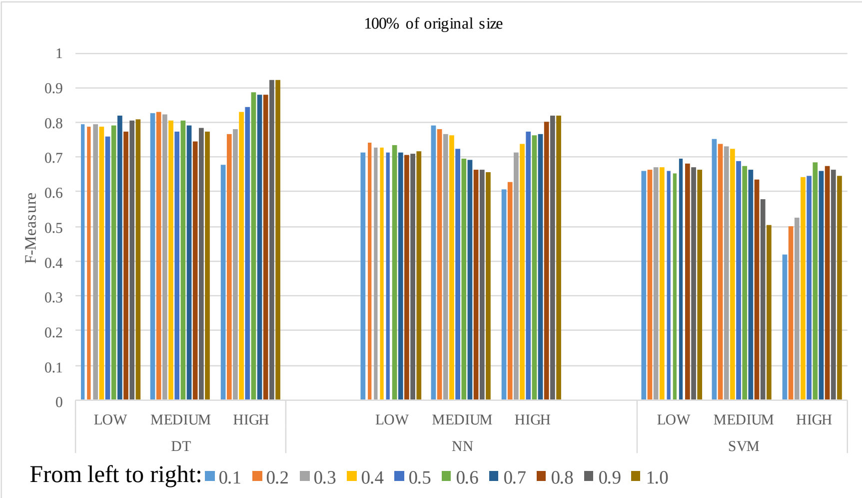
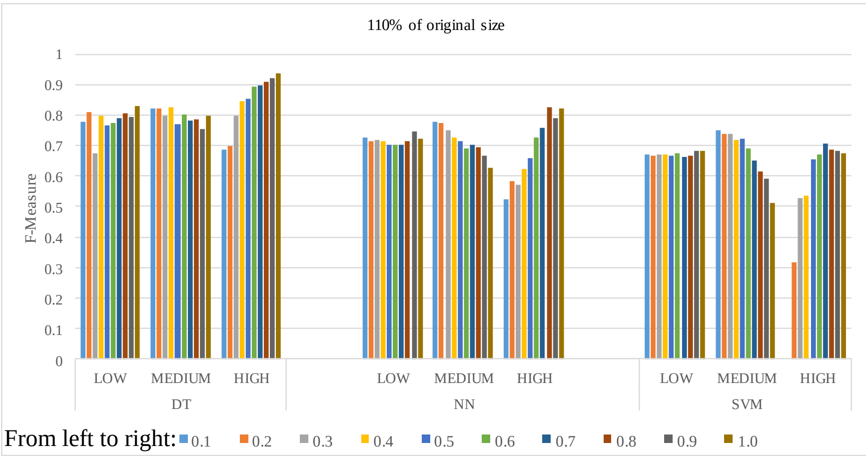


Figure 4.5 Overall accuracy (resampled and balanced data)





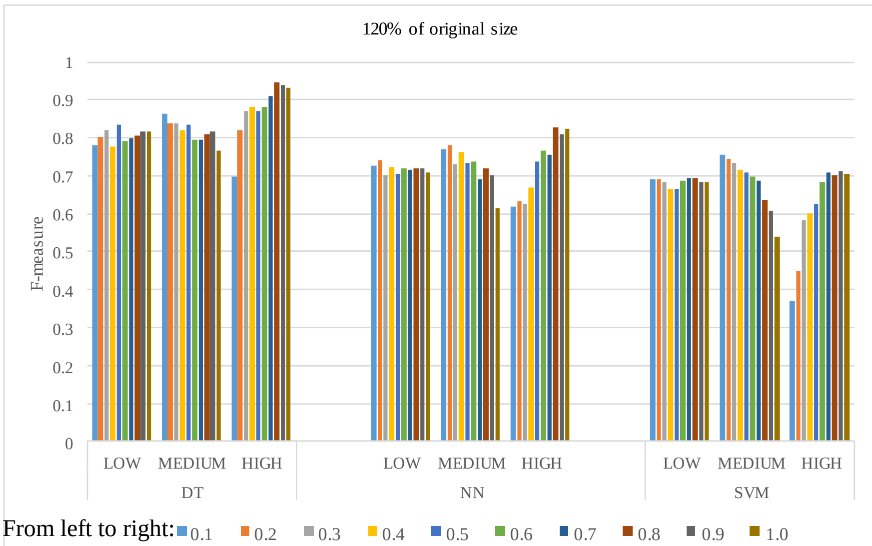


Figure 4.6 F-Measure of each class (resampled and balanced data)

4.2 Result of System Development

4.2.1 Provided Services

The web service system provides 8 services which can be connected and called by client web applications as follows:

1. Latex Price Service gets daily latex price from client applications.

2. Latex Buying and Reselling Service gets latex buying and reselling data from client applications.

3. Latex Alert Service gets alerts about unusual trading from client applications

4. Latex Stock Service calculates and sends latex stocks of local traders to client applications. Data used for the calculation is obtained from clients via Latex Buying and Reselling Service.

5. Latex Daily Price Service checks daily latex price in local trading. This service uses data from client applications via Latex Price Service.

6. Latex Daily Alert Service sends alerts about unusual trading to clients. These alerts are collected from client applications via Latex Alert Service.

7. Latex Volume Prediction Service predicts latex volume. This service uses daily meteorological conditions from the Thai Meteorological Department. The system receives daily meteorological parameters from Weather Service and predicts daily latex volume as follows:

(1) Export the latest meteorological parameters from the database into comma-separated values format (weathertoday.csv) and convert it to Weka’s attribute-relation file format (weathertoday.arff).

(2) Export meteorological parameters and known latex classes of previous days into latex.csv and convert it to latex.arff. The system checks class distribution. If one class is more than twice as big as another class, resampling with replacement (105% of original data size and 0.5 bias) will be applied. The new data set is saved to file latexmodel.model. But if no resampling is required, the original data is simply saved to latexmodel.model.

(3) Generate command-line string that calls Weka’s J48, using latexmodel.model as training data and weathertoday.arff as a new case to be predicted.

Weka then runs J48 classifier and returns a prediction. The result is saved to the database and can be sent to client applications.

8. Weather Service gets daily meteorological conditions from the client application of Thai Meteorological Department.

Note that the users must develop their own web applications (clients) that connect to the web service system and call each service.

4.2.2 Web service page for general system users

Figure 4.1 shows the first page of the web service system, including service usage and registration information and links to other external websites.

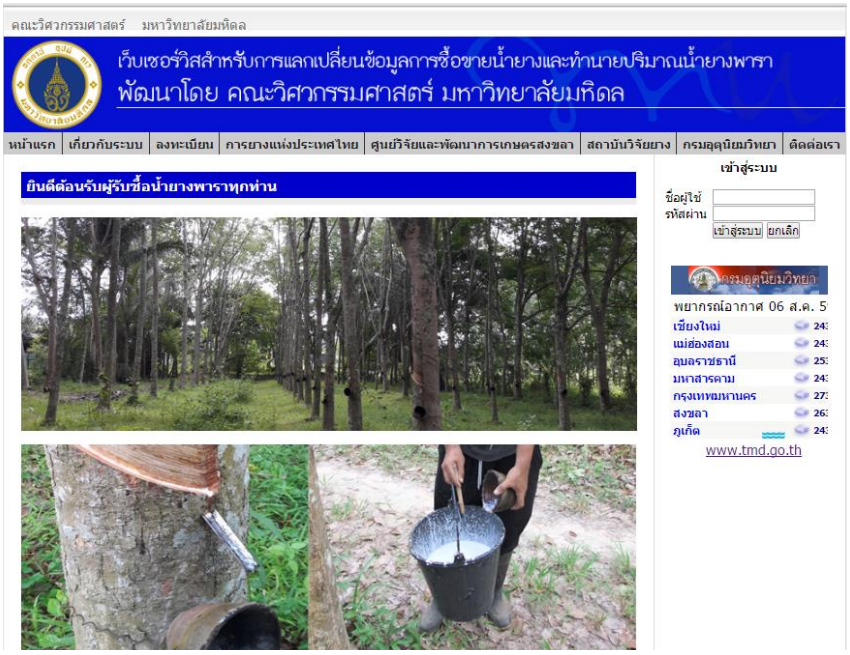


Figure 4.7 First page of web service system

4.2.2.1 About system menu “About system” menu provides the following information:

- “System Agreement” explains the agreement for calling services. In order to obtain the data from provided services (such as Latex Stock Service), the client applications must also send their data to the following services:

- Latex Price Service.

- Latex Buying and Reselling Service.
- Latex Alert Service.

- "Provided Services" lists services that send data to client applications:

- Latex Stock Service.
- Latex Daily Price Service.
- Latex Daily Alert Service.
- Latex Volume Prediction Service.

4.2.2.2 Registration menu Registration page allows the users to register, such that their applications can call the services. The system administrator will manually check the users' information and enable their accounts.

4.2.3 Web service page for administrators

Figure 4.2 shows administration page of the web site. The administrator can manage data in the system such as viewing, editing, and deleting the data.

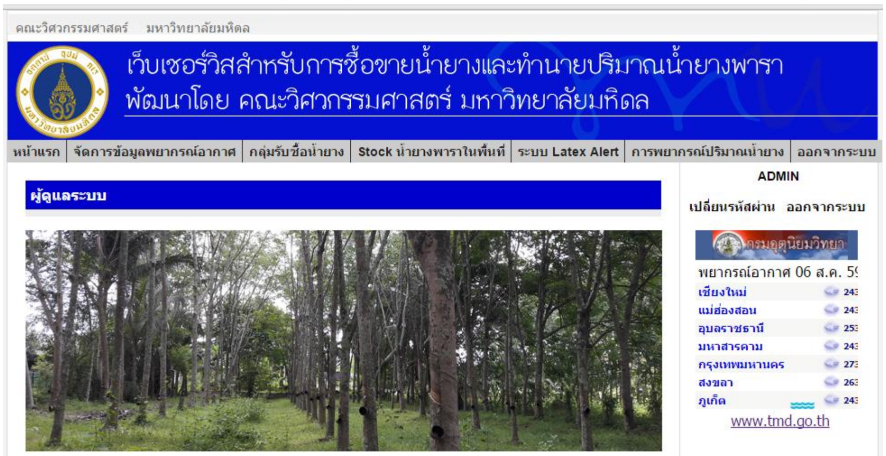


Figure 4.8 Administration page

4.3 Evaluation of Web Services

The web service system was evaluated by 5 system developers who had experience in web programming as summarized in Table 4.1.

Table 4.1 System Evaluators

Evaluator	Experience
1	Senior programmer in a private enterprise
2	Chief of Management Information System (MIS) in the computer center of a university
3	Instructor in web programing in a university
4	Engineer (Professional Level) in the computer center of a university
5	IT manager in a private enterprise

The evaluation was based on 2 main criteria. The first criterion addressed opinions about general appearance of the website and the provided information about web services. The second criterion addressed opinions about the functionality of the provided services. Five-scale rating system was used. Each sub-criterion was rated one of the following: (1) very poor, (2) poor, (3) neutral, (4) good, and (5) very good.

Table 4.2 Website Usability

Criterion	Number of Evaluators	Rating Result	
		$\bar{x}$	S.D.
1. The website is easy to access	5	4.20	1.095
2. Fonts are clear and easy to read	5	3.80	0.837
3. Color scheme on website is appropriate	5	4.00	0.707
4. Images on website are appropriate	5	3.80	0.447
5. The provided information is sufficient	5	3.80	0.837
Average	**5**	**3.92**	**0.573**

From Table 4.2, the average rating score was 3.92 and the standard deviation (S.D.) was 0.573, indicating that the website usability was quite good.

Table 4.3 Web Service Functionality

Criterion	Number of Evaluators	Rating Result	
		$\bar{x}$	S.D.
1. Terms and conditions of using web services is clear	5	3.60	1.140
2. Service descriptions are easy to understand	5	3.80	1.095
3. The provided services are sufficient	5	4.00	0.000
4. Service processing is fast	5	4.00	1.000
5. Results from web services are accurate	5	4.20	0.837
6. Results from web services are useful for business	5	4.60	0.548
Average	**5**	**4.03**	**0.691**

From Table 4.3, the average rating score was 4.03 and the standard deviation (S.D.) was 0.691, indicating that the web service functionality was quite good.

However, there were some feedbacks concerning the first 2 criteria. First, terms and conditions of using web services should be provided in the registration page and should be presented as a list. Second, service descriptions should be made clearer. Input and output variables should match the variables listed in WSDL. And the website should have a page for testing service calls. Another suggestion is to improve the authentication to ensure more security.

Following the evaluators' feedbacks, the website and service descriptions were updated accordingly. However, the security aspect requires major extension and therefore is left for future work.

CHAPTER V
CONCLUSIONS

5.1 Conclusions

This research aims to develop a web service system to exchange latex trading data between latex traders in local markets and publish daily latex volume prediction. The latex traders can develop their latex trading programs on any platform and let their programs call the services. There are 8 services available including: Latex Price Service, Latex Buying and Reselling Service, Latex Alert Service, Latex Stock Service, Latex Daily Price Service, Latex Daily Alert Service, Latex Volume Prediction Service, and Weather Service.

Another aim of this research is to predict the latex volume being traded in Hatyai District of Songkhla, Thailand, using 9 meteorological variables. Three classification methods: decision tree (DT), neural network (NN), and support vector machine (SVM) were used for the prediction. Sampling with replacement, in conjunction with bias factor, was used to handle class imbalance.

Based on experimental results, DT appeared to be the best choice. It is well aware that in other research, given different data, their choices of classifier may be different. Yet, this work contributes in presenting an empirical method to pick a proper one. First, classifiers and classes affected by class imbalance were identified from initial experiments. Then, class distribution was adjusted toward uniform. The trends of F-measures (of individual classes) over the class distribution indicated whether improving the prediction of the smallest class caused decline in the others. In this research, DT was chosen because of its robustness to this situation. The latex volume prediction was also incorporated into a web service.

The proposed web service system was evaluated by 5 experienced system developers. Overall, the usability of website and the functionality of services were satisfying.

5.2 Contributions

1.5.1 The proposed web service system can help latex traders save cost for developing individual latex trading program. If the latex traders develop full trading programs by themselves, the cost of development will be it high. And it will be difficult for them to aggregate and share the trading data.

The proposed system provides common services for their programs. Web service enables web applications on different platforms to communicate with each other by calling the provided services. In addition, the proposed system can help traders exchange trading data and visualize the movement of latex volume in the area.

1.5.2 Results of latex volume prediction, based on daily weather condition, can help latex traders estimate daily latex volume in the market. This can help them plan for trading and bargaining, and even further for rubber production.

5.3 Limitations

Latex trading data from local traders and daily meteorological conditions from Thai Meteorological Department were mostly incomplete, which could affect the accuracy of latex volume prediction.

5.4 Suggestions for Future Work

5.3.1 In this study, we focused only on latex trading in Hatyai District of Songkhla Province. Therefore, we would suggest the future study to gather trading data from all potential rubber areas in Thailand. Additional services may be added to support the requirements of other areas. It would benefit the traders to compare latex volume prediction across different areas.

5.3.2 According to the evaluators' feedbacks, the security of web service system should be improved, for example, regarding user authentication and secure data transfer between client programs and the web service system.

5.3.3 This study uses 3 classification methods: decision tree (DT), neural network (NN), and support vector machine (SVM) for latex volume prediction. Other methods such as multiple linear regression may also be tested. But for the prediction to be more reliable, the data should be complete.

REFERENCES

[1] *Area planting and yield of rubber tree in Songkhla Province* [Online]. Available: http://roc-thailand.org

[2] *Statistics of Rubber in Thailand* [Online]. Available: http://www.rubberthai.com/statistic/stat_index.htm

[3] *Rubber Tree (Hevea brasiliensis)* [Online]. Available: http://www.rainforestalliance.org/kids/species-profiles/rubber-tree

[4] C. Orwa, A. Mutua, R. Kindt, R. Jamnadass, and A. Simons, *Agroforestree database: a tree reference and selection guide version 4.0* [Online], 2008. Available: http://www.Worldagroforestry.org/af/treedb/

[5] *Sap slowly dripping from the tree to eventually process as rubber* [Online]. Available: https://www.plearnwan.com/trip/detail?id=19982

[6] *Latex Collection* [Online]. Available: http://www.coopthai.com/knikomry/parawater.html

[7] *Equipment for latex collection* [Online]. Available: http://www.bansuanporpeang.com/node/23227

[8] *The factors affecting of dry latex* [Online]. Available: http://live-rubber.com

[9] *A Study on the Operation of Field Latex Auction Market* [Online]. Available: http://www.rubberthai.com

[10] *Rubber Tree* [Online]. Available: http://www.baanjomyut.com/library_2/extension-3/rubber_tree/05.html

[11] *Knowledge of Meteorology*. Available: http://www.metsakon.tmd.go.th/bunyay.htm

[12] *Upper Weather* [Online]. Available: http://km.opsmoac.go.th/ewt_dl_link.php?nid=49

[13] *Meteorology Book* [Online]. Available: http://www.tmd.go.th/info/info.php?FileID=63

[14] P. S. Rao, C. K. Saraswathyamma, and M. R. Sethuraj, “Studies on the Relationship between Yield and Meteorological Parameters of Para Rubber Tree (Hevea Brasiliensis),” *Agricultural and Forest Meteorology*, vol. 90, pp. 235-45, 1998.

[15] T. Lerkmongkolwit, “Prediction of the Latex Volume by a Nonlinear Auto Regressive with Exogenous Input Model,” M.S. Thesis, Industrial Engineering, King Mongkut’s Institute of Technology North Bangkok, Bangkok, Thailand, 2005.

[16] *The World Wide Web Consortium Website. “Web Services Architecture.”* [Online]. Available: http://www.w3.org/TR/ws-arch

[17] L. Wall and A. Lader, *Building Web Services and .NET Applications*: McGraw-Hill/Osborne, 2002.

[18] *Architecture of web service* [Online]. Available: http://huihoo.org/openweb/ web_services_for_j2ee/index.shtml.htm

[19] *SOAP (Simple Object Access Protocol) definition* [Online]. Available: http://searchsoa.techtarget.com/definition/SOAP

[20] *SOAP* [Online]. Available: http://gear.kku.ac.th/ ~krunapon/courses/ 168493/ others/wsabc.html

[21] *Service Architecture* [Online]. Available: http://www.service architecture.com/ articles/webservices/web_services_description_language_wsdl.html

[22] *Web Services - WSDL: Sample WSDL Document* [Online]. Available: http://www.phpeveryday.com/articles/Web-Services-WSDL-Sample WSDLDocument-P478.html

[23] *UDDI* [Online]. Available: http://www94.homepage.villanova.edu/

[24] *XML (Extensible Markup Language) definition* [Online]. Available: http://searchsoa.techtarget.com/definition/XML

[25] K. Boonruangkhao, “Electronics Marketplace,” M.S. Thesis, Management of Information Technology, Walailak University, Nakon Si Thammarat, Thailand, 2008.

[26] S. Tunyarittikorn, “E-Coupon Payment Model on Web Services,” M.S. Thesis, Computer Science, King Mongkut’s Institute of Technology North Bangkok, Bangkok, Thailand, 2009.

[27] P. Noimanee, “Development of a conference management system with web services technology,” M.S. Thesis, Computer Science, Uhulalongkorn University, Bangkok, Thailand, 2009.

[28] S. Auwatanamongkol, *Data mining*. Bangkok: Bangkon Block Part., Ltd.,2014.

[29] *Decision Tree* [Online]. Available: http://theory.cpe.ku.ac.th

[30] *Decision Tree Discovery* [Online]. Available: http://ai.stanford.edu/

[31] W. Xindong, K. Vipin, Q. J. Ross, and et al., “Top 10 algorithms in data mining,” *Knowledge and Information Systems,* vol. 14, pp. 1-37, 2008.

[32] R. Piriyakul, *Dara Warehouse*. Bangkok: Ramkhamhaeng University Press, 2013.

[33] *Artificial Neural Network* [Online]. Available: http://www.saedsayad.com/ artificial_neural_network.htm

[34] E. Kirkos, “Support vector machines, Decision Trees and Neural Networks for auditor selection,” *Journal of Computational Methods in Science and Engineering,* vol. 8, pp. 213-24, 2008.

[35] M. Seyagh, “Pattern recognition: Application of Support Vector Machines, Artificial Neural Networks and Decision Trees for anti-HIV activity prediction of organic compounds,” *Proceedings of the International Conference on Multimedia Computing and Systems (ICMCS),* Ouarzazate, Morocco, 2011, pp. 1-6.

[36] W. Jindaluang, V. Chouvatut, and S. Kantabutra, “Under-sampling by algorithm with performance guaranteed for class-imbalance problem,” *Proceedings of the International Computer Science and Engineering Conference (ICSEC),* Khon Kaen, Thailand, 2014, pp. 215-221.

[37] W. Tang and Y. Zang, “Granular SVM with repetitive undersampling for highly imbalanced protein homology prediction,” *Proceedings of the IEEE International Conference on Granular Computing*, Georgia, USA, 2006, pp. 457-460.

[38] R. Shatnawi, “Improving software fault-prediction for imbalanced data,” *Proceedings of the International Conference on Innovations in Information Technology (IIT),* Abu Dhabi, United Arab Emirates, 2012, pp. 54-59.

[39] R. Blagus and L. Lusa, “SMOTE for high-dimensional class-imbalanced data,” *BMC Bioinformatics*, vol. 14, p. 106, 2013.

APPENDICES

APPENDIX A
CLASSIFICATION RESULTS

Table A.1 Number of records of each class (original data)

Class		
HIGH	**MEDIUM**	**LOW**
44	354	255

Table A.2 Overall accuracy (original data)

DT	NN	SVM
67.68%	69.21 %	69.98%

Table A.3 Precision, Recall, and F-Measure of each class (original data)

Decision Tree (C4.5)			Neural Network			Support Vector Machine			Class
Precision	Recall	F-Measure	Precision	Recall	F-Measure	Precision	Recall	F-Measure	
0.668	0.616	0.641	0.716	0.545	0.619	0.719	0.624	0.668	LOW
0.700	0.757	0.727	0.686	0.847	0.759	0.690	0.842	0.758	MEDIUM
0.486	0.386	0.430	0.591	0.295	0.394	0.000	0.000	0.000	HIGH

Table A.4 Number of records of each class (resampled data)

Sample Size (%)	Class		
	HIGH	MEDIUM	LOW
105	46	371	267
110	48	389	280
115	50	407	293
120	52	424	306

Table A.5 Overall accuracy (resampled data)

Sample Size (%)	DT	NN	SVM
105	80.99	76.75	69.73
110	80.05	75.59	70.71
115	79.33	75.2	70.53
120	81.07	76.98	71.22

Table A.6 Precision, Recall, and F-Measure each class (resampled data)

	Decision Tree			**Neural Network**			**Support Vector Machine**			
Sample	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Class
105	0.823	0.768	0.795	0.767	0.738	0.752	0.739	0.573	0.646	LOW
	0.824	0.860	0.842	0.783	0.846	0.813	0.679	0.873	0.764	MEDIUM
	0.625	0.652	0.638	0.538	0.304	0.389	0.000	0.000	0.000	HIGH
110	0.831	0.754	0.790	0.766	0.736	0.750	0.770	0.586	0.665	LOW
	0.802	0.877	0.838	0.767	0.828	0.796	0.681	0.882	0.768	MEDIUM
	0.579	0.458	0.512	0.500	0.292	0.368	0.000	0.000	0.000	HIGH
115	0.786	0.802	0.794	0.757	0.693	0.724	0.772	0.590	0.669	LOW
	0.822	0.826	0.842	0.753	0.838	0.793	0.769	0.875	0.765	MEDIUM
	0.571	0.480	0.522	0.690	0.400	0.506	0.000	0.000	0.000	HIGH
120	0.802	0.781	0.791	0.795	0.727	0.757	0.773	0.611	0.682	LOW
	0.820	0.851	0.836	0.769	0.847	0.806	0.686	0.873	0.768	MEDIUM
	0.733	0.654	0.708	0.595	0.423	0.494	0.000	0.000	0.000	HIGH

Table A.7 Number of records of each class (resampled and balanced data)

Sample Size	Bias	Class		
		HIGH	**MEDIUM**	**LOW**
110	0.1	67	374	276
	0.2	86	359	272
	0.3	105	344	268
	0.4	124	329	264
	0.5	143	314	259
	0.6	263	299	255
	0.7	182	284	251
	0.8	201	269	247
	0.9	220	254	243
	1.0	239	239	239
120	0.1	73	408	301
	0.2	94	329	297
	0.3	115	375	292
	0.4	136	359	288
	0.5	156	342	283
	0.6	177	326	279
	0.7	198	310	274
	0.8	219	293	270
	0.9	240	277	265
	1.0	261	261	261

Table A.8 Overall accuracy (resampled and balanced data)

Sample Size	Bias	DT	NN	SVM
110	0.1	79.49	73.77	68.75
	0.2	80.19	73.22	68.06
	0.3	78.66	71.54	69.31
	0.4	81.86	70.71	67.92
	0.5	78.49	69.97	69.27
	0.6	81.17	70.15	68.20
	0.7	81.45	71.54	66.66
	0.8	82.84	73.91	65.13
	0.9	82.00	73.36	64.85
	1.0	85.77	72.66	62.34
120	0.1	81.71	74.04	70.97
	0.2	82.24	74.96	70.24
	0.3	83.63	70.58	69.94
	0.4	81.60	73.30	68.19
	0.5	84.12	72.47	68.11
	0.6	81.45	73.65	69.05
	0.7	82.73	71.73	69.43
	0.8	84.78	74.93	67.26
	0.9	85.54	74.16	66.36
	1.0	84.16	72.03	64.24

Table A.9 Precision, Recall, and F-Measure each class (resampled 110% and balanced data)

		Decision Tree			**Neural Network**			**Support Vector Machine**			
Sample Size	**Bias**	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Class
110	0.1	0.820	0.743	0.779	0.733	0.717	0.725	0.758	0.601	0.671	LOW
		0.787	0.861	0.822	0.749	0.807	0.777	0.657	0.874	0.750	MEDIUM
		0.741	0.642	0.688	0.659	0.433	0.523	0.000	0.000	0.000	HIGH
	0.2	0.811	0.805	0.808	0.760	0.676	0.716	0.740	0.607	0.667	LOW
		0.812	0.830	0.821	0.732	0.822	0.774	0.647	0.852	0.736	MEDIUM
		0.725	0.674	0.699	0.639	0.535	0.582	0.810	0.198	0.318	HIGH
	0.3	0.793	0.743	0.676	0.781	0.664	0.718	0.754	0.612	0.672	LOW
		0.791	0.805	0.798	0.684	0.826	0.748	0.653	0.849	0.738	MEDIUM
		0.759	0.838	0.796	0.689	0.786	0.570	0.820	0.390	0.529	HIGH
	0.4	0.826	0.773	0.798	0.718	0.712	0.715	0.726	0.621	0.669	LOW
		0.815	0.833	0.824	0.695	0.763	0.728	0.634	0.833	0.720	MEDIUM
		0.813	0.879	0.845	0.723	0.548	0.624	0.831	0.395	0.536	HIGH
	0.5	0.779	0.749	0.764	0.721	0.687	0.704	0.729	0.614	0.667	LOW
		0.776	0.761	0.768	0.713	0.720	0.716	0.634	0.838	0.722	MEDIUM
		0.811	0.902	0.854	0.638	0.678	0.658	0.892	0.517	0.655	HIGH
	0.6	0.773	0.773	0.773	0.717	0.686	0.701	0.705	0.647	0.675	LOW
		0.818	0.783	0.800	0.656	0.726	0.689	0.615	0.789	0.691	MEDIUM
		0.858	0.926	0.891	0.782	0.681	0.728	0.889	0.540	0.672	HIGH
	0.7	0.798	0.785	0.791	0.722	0.681	0.701	0.678	0.645	0.661	LOW
		0.800	0.761	0.780	0.671	0.739	0.704	0.592	0.722	0.651	MEDIUM
		0.855	0.940	0.895	0.790	0.725	0.756	0.841	0.610	0.707	HIGH

Table A.10 Precision, Recall, and F-Measure each class (resampled 110% and balanced data) (Continue)

		Decision Tree			Neural Network			Support Vector Machine			
Sample Size	**Bias**	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Class
	0.8	0.841	0.773	0.806	0.725	0.704	0.715	0.668	0.668	0.668	LOW
		0.797	0.773	0.785	0.698	0.695	0.696	0.574	0.665	0.616	MEDIUM
		0.852	0.970	0.907	0.809	0.841	0.824	0.778	0.612	0.685	HIGH
	0.9	0.823	0.765	0.793	0.734	0.761	0.747	0.676	0.687	0.682	LOW
		0.762	0.744	0.753	0.697	0.642	0.668	0.564	0.622	0.592	MEDIUM
		0.877	0.968	0.920	0.771	0.809	0.789	0.737	0.636	0.683	HIGH
	1.0	0.857	0.803	0.829	0.707	0.736	0.721	0.678	0.686	0.682	LOW
		0.817	0.782	0.799	0.675	0.582	0.625	0.515	0.506	0.511	MEDIUM
		0.894	0.987	0.938	0.786	0.862	0.822	0.675	0.678	0.676	HIGH

Table A.11 Precision, Recall, and F-Measure each class (resampled 120% and balanced data)

		Decision Tree			**Neural Network**			**Support Vector Machine**			
Sample Size	**Bias**	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Class
120	0.1	0.116	0.808	0.781	0.736	0.721	0.728	0.778	0.618	0.689	LOW
		0.209	0.819	0.865	0.755	0.784	0.769	0.676	0.860	0.757	MEDIUM
		0.013	0.850	0.699	0.667	0.575	0.618	0.750	0.247	0.371	HIGH
	0.2	0.828	0.778	0.802	0.743	0.741	0.742	0.777	0.623	0.692	LOW
		0.826	0.849	0.838	0.755	0.804	0.779	0.662	0.855	0.746	MEDIUM
		0.792	0.851	0.821	0.743	0.553	0.634	0.769	0.319	0.451	HIGH
	0.3	0.833	0.805	0.819	0.724	0.682	0.702	0.753	0.627	0.684	LOW
		0.832	0.845	0.839	0.690	0.773	0.730	0.657	0.832	0.734	MEDIUM
		0.857	0.887	0.872	0.724	0.548	0.624	0.813	0.452	0.581	HIGH
	0.4	0.817	0.743	0.778	0.785	0.670	0.723	0.733	0.611	0.667	LOW
		0.799	0.841	0.820	0.709	0.822	0.761	0.636	0.813	0.714	MEDIUM
		0.860	0.904	0.882	0.711	0.632	0.669	0.786	0.485	0.600	HIGH
	0.5	0.858	0.813	0.835	0.737	0.675	0.705	0.735	0.608	0.665	LOW
		0.829	0.836	0.833	0.707	0.763	0.734	0.625	0.819	0.709	MEDIUM
		0.839	0.904	0.870	0.745	0.731	0.738	0.808	0.513	0.627	HIGH
	0.6	0.796	0.785	0.791	0.734	0.703	0.718	0.740	0.642	0.687	LOW
		0.810	0.782	0.796	0.719	0.755	0.737	0.626	0.785	0.697	MEDIUM
		0.849	0.921	0.883	0.775	0.757	0.766	0.802	0.593	0.682	HIGH
	0.7	0.807	0.792	0.799	0.735	0.697	0.715	0.745	0.650	0.694	LOW
		0.816	0.774	0.795	0.707	0.677	0.692	0.619	0.774	0.688	MEDIUM
		0.868	0.960	0.911	0.711	0.808	0.757	0.806	0.631	0.708	HIGH

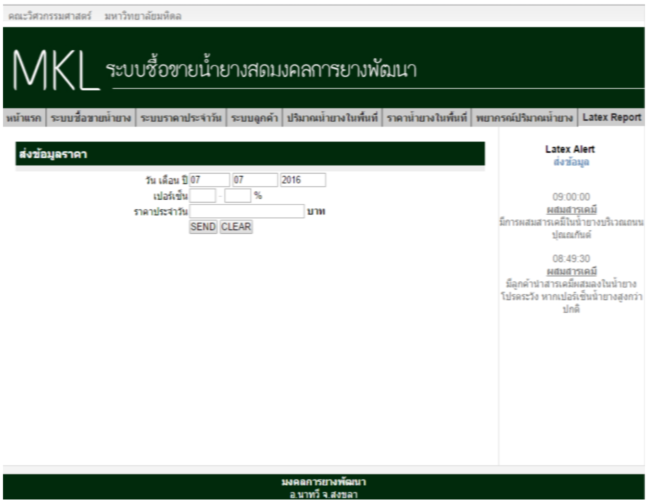
Table A.12 Precision, Recall, and F-Measure each class (resampled 120% and balanced data) (Continue)

Sample Size	Bias	Decision Tree			Neural Network			Support Vector Machine			
		Precision	Recall	F-Measure	Precision	Recall	F-Measure	Precision	Recall	F-Measure	Class
120	0.8	0.839	0.774	0.805	0.735	0.707	0.721	0.714	0.674	0.693	LOW
		0.807	0.812	0.810	0.700	0.741	0.720	0.597	0.683	0.637	MEDIUM
		0.908	0.986	0.945	0.840	0.813	0.826	0.750	0.658	0.701	HIGH
	0.9	0.852	0.785	0.817	0.724	0.713	0.719	0.701	0.664	0.682	LOW
		0.821	0.809	0.815	0.714	0.693	0.703	0.583	0.632	0.607	MEDIUM
		0.894	0.988	0.939	0.790	0.829	0.809	0.727	0.700	0.713	HIGH
	1.0	0.817	0.820	0.818	0.690	0.732	0.710	0.681	0.686	0.683	LOW
		0.809	0.728	0.766	0.659	0.579	0.616	0.541	0.536	0.538	MEDIUM
		0.892	0.977	0.932	0.801	0.851	0.825	0.705	0.705	0.705	HIGH

APPENDIX B

PROVIDED SERVICES

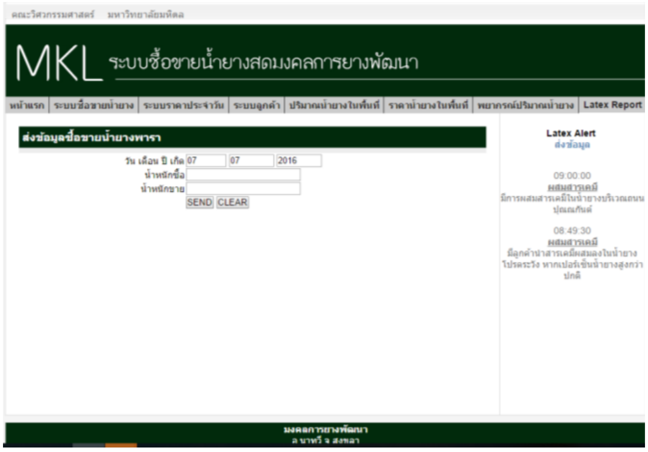
Service Description



Client Program (Latex Trader’s)

Figure B.1 Latex Price Service

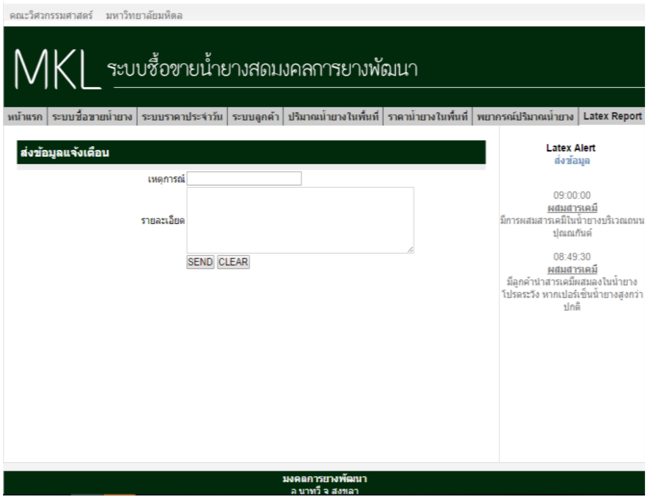
Service Description



Client Program (Latex Trader’s)

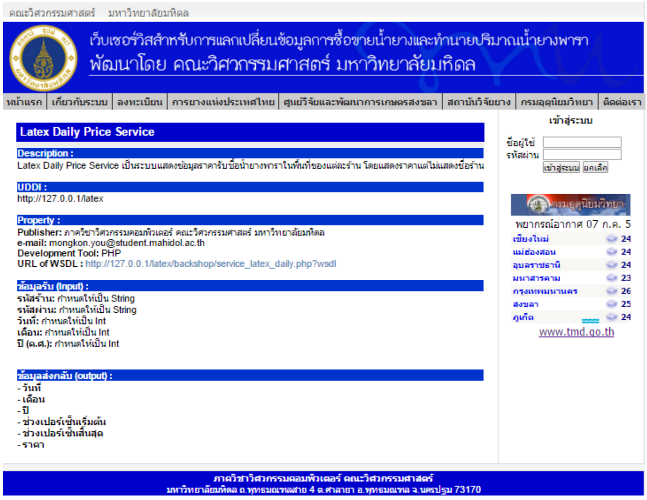
Figure B.2 Latex Buying and Resell Service

Service Description

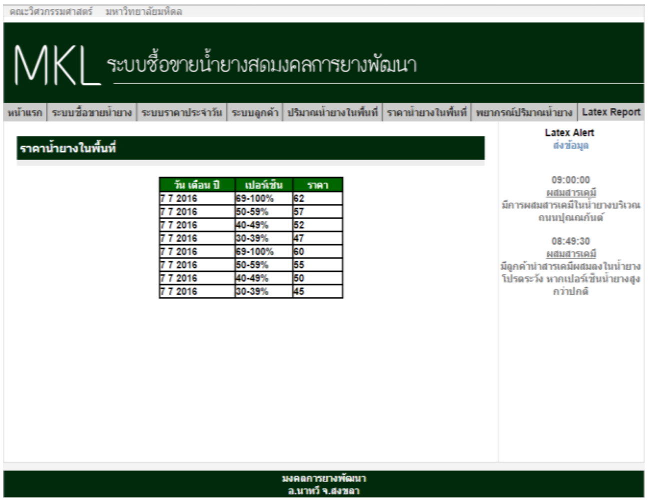


Client Program (Latex Trader's)

Figure B.3 Latex Alert Service



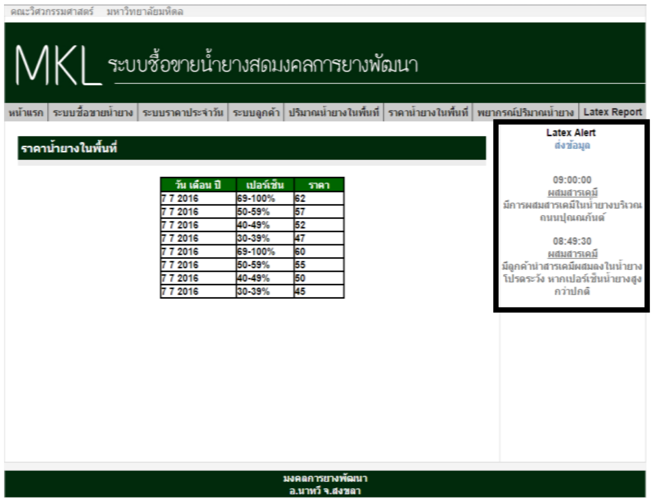
Service Description



Client Program (Latex Trader’s)

Figure B.4 Latex Daily Price Service

Service Description



Client Program (Latex Trader's)

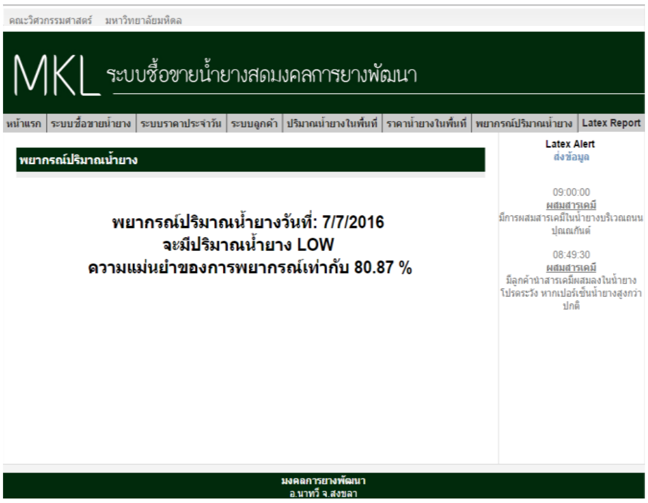
Figure B.5 Latex Daily Alert Service

Service Description

Client Program (Latex Trader's)

Figure B.6 Latex Stock Service

Service Description



Client Program (Latex Trader’s)

Figure B.7 Latex Volume Prediction Service

APPENDIX C
QUESTIONNAIRE

แบบประเมินผลความพึงพอใจ
เว็บเซอร์วิสสำหรับการแลกเปลี่ยนข้อมูลการซื้อขายน้ำยาง
และทำนายปริมาณน้ำยางพารา
(สำหรับผู้เชี่ยวชาญ)

คำชี้แจง

1. แบบประเมินชุดนี้ สำหรับเชี่ยวชาญ เป็นแบบประเมินความพึงพอใจเกี่ยวกับการใช้ เว็บเซอร์วิสสำหรับการแลกเปลี่ยนข้อมูลการซื้อขายน้ำยางและทำนายปริมาณน้ำยางพารา ที่พัฒนาขึ้นมา เพื่อบริการข้อมูลการทำนายปริมาณน้ำยางพารารายวันในพื้นที่ให้กับผู้ค้าน้ำยาง

2. การแสดงความคิดเห็นของผู้ประเมินเกี่ยวกับความพึงพอใจที่มีต่อระบบที่ได้ พัฒนาขึ้นมาตราส่วนประมาณค่าที่อยู่ ด้านขวามือจำนวน 5 ช่อง โปรดกาเครื่องหมาย ✓ ลงในช่องทางด้านขวามือที่ตรงกับความ คิดเห็นของท่าน โดยกำหนดค่าความหมาย ดังนี้

5 หมายถึง มีความพึงพอใจต่อการใช้งานระบบในระดับดีมาก

4 หมายถึง มีความพึงพอใจต่อการใช้งานระบบในระดับดี

3 หมายถึง มีความพึงพอใจต่อการใช้งานระบบในระดับปานกลาง

2 หมายถึง มีความพึงพอใจต่อการใช้งานระบบในระดับน้อย

1 หมายถึง มีความพึงพอใจต่อการใช้งานระบบในระดับน้อยมาก

3. แบบประเมินนี้มีจำนวน 2 หน้า ซึ่งแบ่งเป็น 2 ด้าน ดังนี้

3.1. ด้านการใช้งานเว็บไซต์

3.2. ด้านการเรียกใช้เซอร์วิส

ด้านการใช้งานเว็บไซต์

รายการประเมิน	ระดับความพึงพอใจ				
	5	**4**	**3**	**2**	**1**
1. ความสะดวกในการเข้าใช้งาน					
2. ความชัดเจนของข้อความ					
3. ความเหมาะสมของการใช้สีบนเว็บไซต์					
4. ความเหมาะของรูปภาพที่ใช้ตกแต่งบนเว็บไซต์					
5. ความเหมาะสมของการนำเสนอข้อมูล					

ด้านการเรียกใช้เซอร์วิส

รายการประเมิน	ระดับความพึงพอใจ				
	5	**4**	**3**	**2**	**1**
1. ความเหมาะสมของการอธิบายข้อตกลงการใช้งานเซอร์วิส					
2. ความเหมาะสมของการอธิบายวิธีการเรียกใช้งานเซอร์วิส					
3. ความเหมาะสมของจำนวนเซอร์วิส					
4. เรียกใช้เซอร์วิสได้อย่างรวดเร็ว					
5. ข้อมูลที่ได้จากการเรียกใช้เซอร์วิสมีความถูกต้อง					
6. ข้อมูลที่ได้จากเซอร์วิสมีประโยชน์ต่อธุรกิจ					

ข้อเสนอแนะ

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BIOGRAPHY

NAME	Mr. Mongkon Youngtanurat
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