



Stroke Risk Assessment and Emergency Mobile Application in a Hospital in Thailand

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Abstract

Background: Cerebrovascular diseases or stroke tend to cause high mortality in Thailand. An essential responsibility of a hospital is the development of medical care to support the safety of patients. For this purpose, a smartphone application was developed for the risk assessment and emergency system for stroke treatment in a hospital in Thailand.

Methods: The proposed application involved the risk assessment related to the occurrence of stroke evaluated by the health status and face image using analytical geometry and face detection technology. The social network Application Programming Interface (API), LINE Notify API, and Global Positioning System (GPS) were used to inform the Stroke team in the Suratthani hospital about emergency cases, followed their requirement in 2020.

Results: From the testing, the facial angulation classification, calculated using a support vector machine (SVM), had 92.38% accuracy. The system also provided an emergency call and text messaging that includes patient's current location and personal information to the stroke team directly, which gave an opportunity for the patient to receive treatment quickly.

Conclusion: The emergency system can help quickly perform the risk assessment of stroke. Our proposed system provides automated management.

Keywords: Stroke; Support vector machine; Face detection; Application; Screening

Introduction

World Health Organization (1) has reported that the cerebrovascular diseases had the second rank in the list of diseases with the highest death rate, in 2019. Among the about 80 million patients, approximately 5.5 million deaths result from the cerebrovascular diseases. According to the report of public health statistics in Thailand, 304,807 people had a stroke in 2017, and the annual numbers tend to increase in Thailand (1-2).

Stroke is the leading cause of disability in the elderly and will cause death, although the death rate from stroke is also associated with obesity and diabetes as comorbidities. Still, rapid identification of the symptoms could reduce the mortality rate. The risk factors for stroke are complex. There are many variants of stroke, with the basic levels divided into hemorrhagic and ischemic strokes. Assessing the symptoms with a set of



short questions regarding age of the patient, recent known times of physical weakness, and eye deviations (3).

The Stroke FAST Track approach uses the following observation methods: i) observe the facial muscles from a smile; ii) observe the weakness of the arms; iii) observe the speech; and iv) duration of the symptoms. In an emergency, this approach can help identify and diagnose preliminary symptoms well (4-5).

Observing the patient's face is the most obvious way to observe the symptoms. Due to the expression of weakness in the face such as the mouth being crooked, inability to speak clearly, unable to close the eyes completely, while the symptoms of amblyopia of 1 or 2 eyes may not be immediately visible. The facial expressions during a stroke are similar to facial paralysis showing numbness on one side of the face, only one side of the face, inability to close the eyes completely, distorted mouth, unclear speech, or whistling sound, and often sudden symptoms (6 - 7). The difference in these two diseases is that the stroke of the limbs affects one side of the body, while facial paralysis affects only the face.

Smartphone applications for cerebrovascular patients named CU Fast Track and App Stroke KKU have been developed by Chulalongkorn Stroke Center and Khon Kaen University, respectively (8-9). They were implemented by using questionnaires for stroke risk factor checklist and by linking to the hospitals. There is increasing evidence of application in hospitals (4, 10 - 11). To assist in the early detection of stroke symptoms, face detection will be used in this study. The smile and mouth detections were important for assessing symptoms associated with stroke (12, 13).

The purposes of this study were to develop a smartphone application for facial stroke assessment and to report the individual risk evaluation based on cardiovascular (CV) risk factors and face detection. In addition, for an emergency stroke case, call the national emergency medical center for getting him/her to the hospital immediately and to contact the stroke team by sending

personal information via social network. The knowledge of stroke and the connection with the administration of Stroke Team in a Surat Thani hospital were proposed as a case study. The advantages of the application include preliminary self-check assessment at home and early detection of stroke risks for smart healthcare.

Materials and Methods

Normally the disease screening uses a questionnaire (3-4,6,8-9) provided by medical research center or organization. In this research, the questionnaire was based on the Thai CV Risk score, suitable for Thai people who were 30-70 years old without heart or blood circulation problems. This questionnaire was made from 32 patient's data files of government hospital data in Thailand (14-15). Calculation formula of Thai cardiovascular was provided by the Faculty of Medicine, Ramathibodi Hospital, Mahidol University, Bangkok, Thailand. Cardiovascular and Metabolism Center was used it to assess the risk of developing cardiovascular disease. Thai CV Risk score required for risk prediction data on age, gender, smoking, diabetes (DM), systolic blood pressure (SBS), waist and height. The results range from low risk (<10%), to moderate risk (10%-20%) and high risk (>20%) (16). The stroke screening tool was adopted from the Thai CV Risk.

Face detection and facial angulation calculation

Commonly, for a normal person's face, the facial central axis is drawn through the nose (L2) and perpendicular to the line which is drawn through both eyes (L1) as shown in Fig. 1. In addition, it is also perpendicular to the line between two endpoints of lips (L3). On the other hand, the stroke patient cannot lift both corners of the mouth to the same level while smiling. Therefore, the stroke patient's lips are pulled to one side, and the center of lower lip (x_4, y_4) is shifted away from the center of the face.

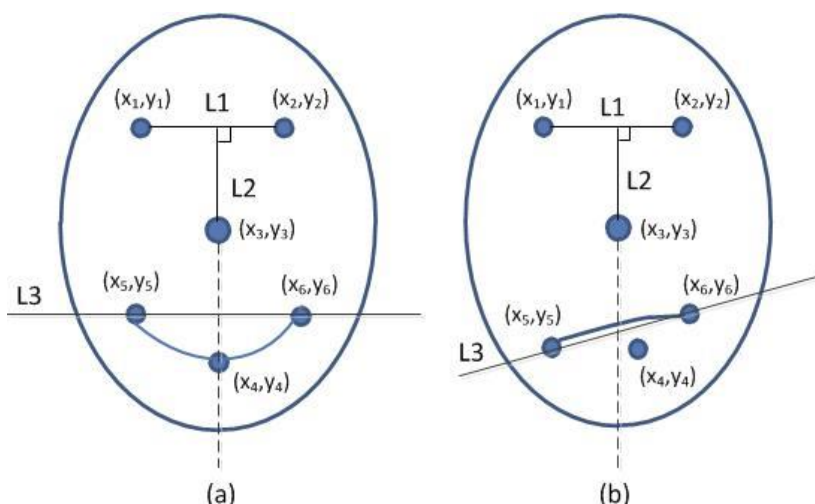


Fig. 1: Essential Points and Lines: (a) Normal face (b) Stroke patient's face

With Face Detection API of Google Firebase Machine Learning Kit, the essential points of smiling face image can be detected. There are 4 important points, two points for the eyes and two endpoints of the lips, which were used to gener-

ate two straight lines (L1, L3) and calculate the angle (θ) between the straight lines. Most stroke patient's faces have this sort of angulation between L1 and L3, shown in Fig. 2. A large angle θ serves to indicate high degree of stroke severity.

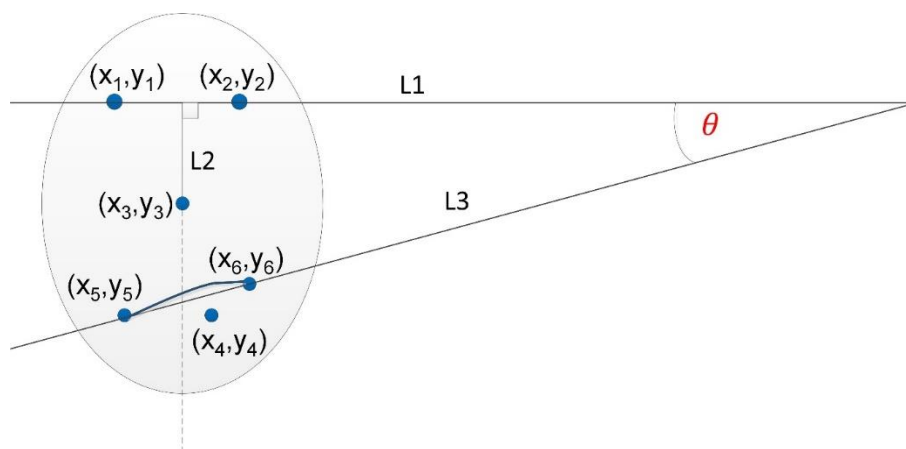


Fig. 2: The facial angle θ between 2 straight lines

The steps for calculating the distortion of the mouth (degree of the angle θ) from a smiling face image were as follows:

1. Get 4 coordinates on smiling face image by face detection API: 2 eyes and 2 endpoints of lips.
2. Generate 2 straight line equations (L1, L3):

- a. For each line, find the slope between 2 coordinates is

$$slope = \frac{(y_j - y_i)}{(x_j - x_i)}$$

while (x_i, y_i) and (x_j, y_j) are the coordinates on that line

b. Instead one coordinate of each straight line into the following equation

$$y - y_i = m(x - x_i)$$

as m is the slope of the straight line

(x_i, y_i) is a coordinate of the straight line

3. Calculate the angle θ between 2 lines, the formula was derived from the angle between two-line equation with geometry theory:

$$\theta = \arccos \frac{1 + mn}{\sqrt{1 + m^2} + \sqrt{1 + n^2}}$$

where m is the

slope of L1 and n is the slope of L3

All the above steps are automated in the mobile application. After delivering the angle in degrees, the value will be used to assess the stroke risk by a classification model.

The facial angulation Classification

The facial images of stroke and paralysis patients are very similar, so this project used such images from the facial paralysis institute website. The training dataset consisted of 36 paralysis facial images and 27 normal person facial images and. The delivered distortion angle of every image was recorded along with personal facial ratio, a ratio between the length of lips to the distance of the eyes, and the true class, before training the classifier algorithms.

Classification algorithms

This project aimed to classify the facial images into two groups (stroke/normal). All distortion angles were used to train two algorithms. The Decision Tree classification algorithm gave a binary tree, while the Support Vector Machine (SVM) searched for a separating plane with a gap between the groups. Training used 10-fold cross validation for both models.

Decision Tree

The common classification algorithm is decision tree. This article used C4.5 algorithm (17-18). The algorithm began with attribute selection to be a node and divide instances into the subsets based on their attribute values then each branch extending from the node and the criteria were generated, repeated steps until all instances have the same class.

SVM

The SVM aims to find the decision line with maximum margin between two classes. The decision line was linear equation which generated from m attributes, a weight of each attribute (w) and the bias value (b) as follows (19):

$$f(x) = \sum_{j=1}^m w_j x_j + b$$

The risk assessment calculation for the application

The assessment of the stroke risk consisted of 3 main parts, the computation of Thai CV risk score, facial angulation classification, and individual risk assessment as shown in Fig. 3.

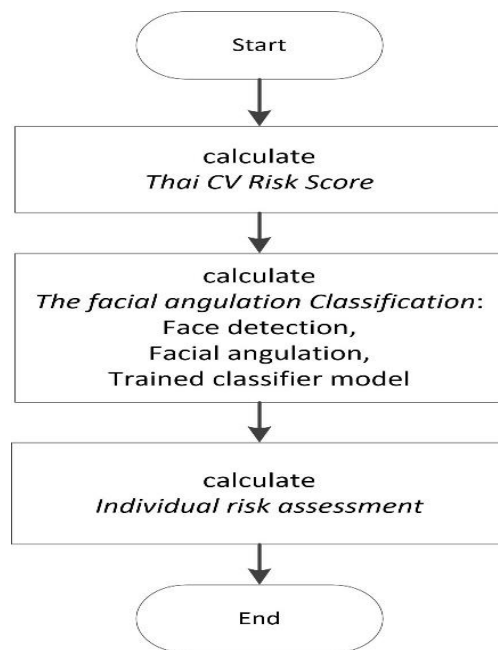


Fig. 3: The core computation sequence in the application

Thai CV risk score calculation

The risk score of cardiovascular disease for Thai people, to forecast the risk categories of cardiovascular disease which will be happening in 10 years further. The equation for Full Score calculation for 10 years predicted event model (14, 16) is:

$$\begin{aligned}
 FullScore = & (0.079442 \times Age) \\
 & + (0.127658 \times Gender) \\
 & + (0.019350987 \times SBP) \\
 & + (0.5845435 \times Diabetes) \\
 & + (0.4593124 \times Smoking) \\
 & + (0.03512566 \\
 & \times (Waist / Height) \times 100)
 \end{aligned}$$

The variable value definition is as follow:

Gender = 1, only if a person is male, else be zero

SBP is a value of systolic blood pressure (SBP).

Diabetes = 1, only if a person has diabetes, else be zero

Smoking = 1, only if a person is a current smoker, else be zero

Waist and Height are in the centimeter unit.

The transformation of the Full Score to the percentage is as follows:

$$P_{FullScore}(\%) = (1 - (0.964588)^{\exp(FullScore - 7.720484)}) \times 100$$

The result $P_{fullscore}$ value was interpreted into 5 categories and applied to suggest the self-care in-

struction. In the application, the percentage which equal or higher than 20 were implied to a high-risk level, as shown in Table 1, and used the extremely high self-care instruction suggested to the user.

The facial angulation classification calculation

The input of classification was user's facial image. Therefore, after the user picked one on his/her image, the application called the face detection API to detect the important points and compute the facial ratio and angulation afterwards the trained classifier model was used to predict the stroke class label. The label was an input data of individual risk assessment step then it interpreted into risk score as follows: class "Y" (stroke), risk score = 3; class "N" (normal), risk score = 0 (zero).

Individual risk assessment

The assessment of face was done to calculate the patient's score result. The interpretation of stroke risk assessment level in this study was based on the risk scores from stroke screening and classification of face detection, with three levels defined as follows: low risk group: ≤ 2 ; moderate risk group: 3-4; high risk group: ≥ 5 as shown in Table 1. When the patient had undergone both processes, a risk result would be displayed to the patient. A higher score indicates higher risk of having a stroke.

Table 1: The interpretation and decision table of individual risk assessment

1.1 $P_{fullscore}$	1.2 Risk score	1.4 The stroke class label*	1.5 Risk score	1.7 Total risk score	1.9 Risk assessment level
	1.3 (rs_1)		1.6 (rs_2)	1.8 (rs_1+rs_2)	1.10
1.11 < 10%	1.121	1.13N	1.140	1.151	1.16Low
		1.17Y	1.183	1.194	1.20Moderate
1.21 => 10 and < 20%	1.222	1.23N	1.240	1.252	1.26Low
		1.27Y	1.283	1.295	1.30High
1.31 >= 20	1.323	1.33N	1.340	1.353	1.36Moderate
		1.37Y	1.383	1.396	1.40High

* N = Normal class, Y = Stroke class

Results

Comparison of algorithms

The accuracy of stroke detection from face recognition by the 2 techniques is shown in Fig. 4(a). The assessment revealed that both were in line with visual inspection. The more accurate technique was SVM (92.38%), while Decision Tree scored 90.48% correct calls. An error assessment by using Mean Absolute Percent Error (MAPE) was also done. The results are shown in Fig. 4(b). The technique with the least error was

SVM (9.52%), while Decision Tree had 13.52%. When analyzing errors from each technique based on the standard interpretation criteria, MAPE below 10 indicates highly accurate detection. The range 10 – 20 is for good detection, 20-50 for reasonable detection, and over 50 for inaccurate detection (20). Therefore, when considering the results of stroke detection from face recognition in this research, the most accurate technique was SVM that showed highly accurate detection or very low errors. Decision Tree showed good detection.

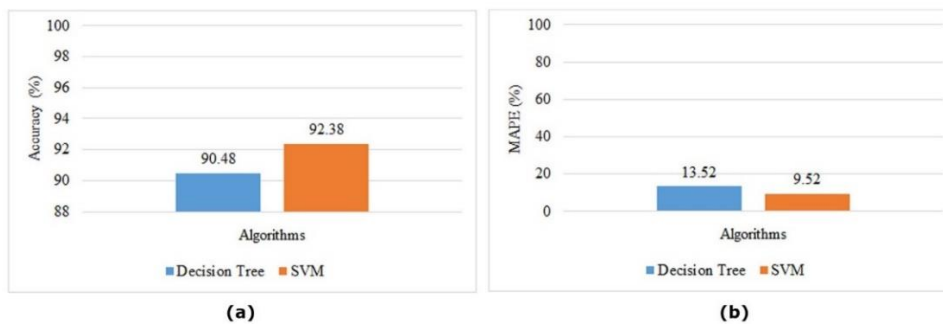


Fig. 4: (a) Accuracy of stroke detection, and (b) MAPE of Stroke detection

SVM Model

After training the SVM algorithm, the distorted angle weight, facial ratio weight and the bias value were -1.589, -1.665 and -0.910 respectively.

These data were used to establish the decision line or trained SVM model to produce function value.

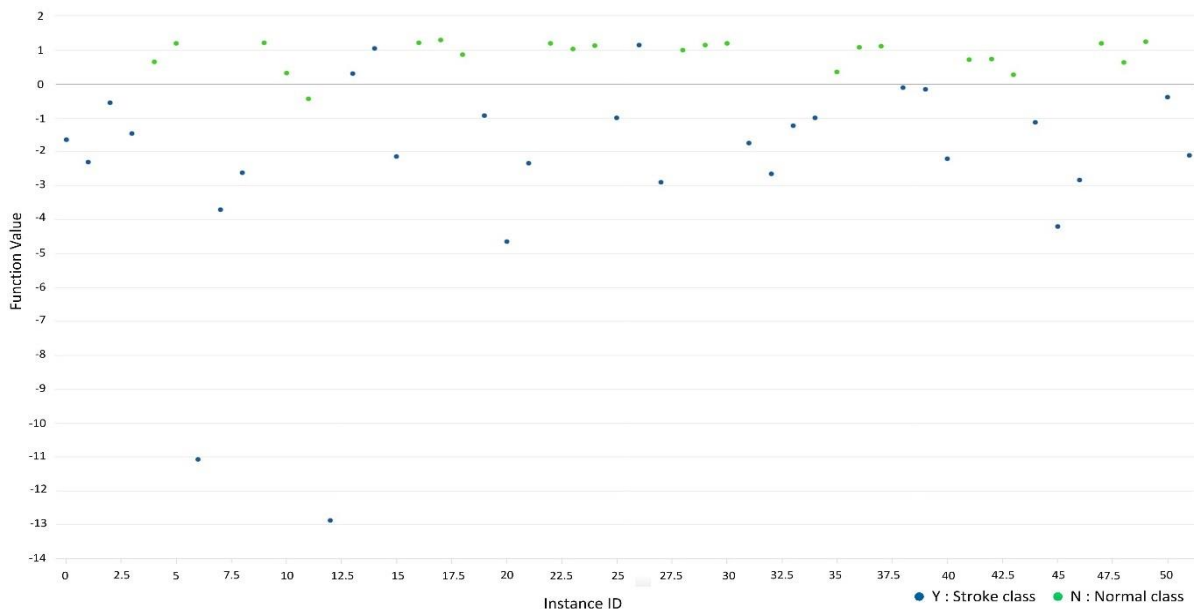


Fig. 5: the SVM predicted function value of each instance in dataset

The new instances will be predicted based on the function value ($f(x)$). If function value is less than zero ($f(x) < 0$), the instance will belong to stroke class (Y) and if it is greater than zero ($f(x) > 0$), the instance will belong to the normal class (N) as shown in Fig. 5.

Implementation

The usage of mobile phones is increasing and widely used. Therefore, we implemented the system as a mobile phone application. This system was designed into 2 core parts, which are stroke risk assessment and emergency system. The

stroke risk assessment is calculated from health information analysis and mouth distortion from face detection API analysis. Moreover, this part also includes the user interface to get data and show the assessment result, as in Fig. 6. Another part is the emergency system, it consists of a medical emergency call and emergency notification to the stroke team as in Fig. 5. In the context of the system there are two user groups; people with symptoms and the stroke team; and two external systems are Firebase Face Detection and social network application LINE API.

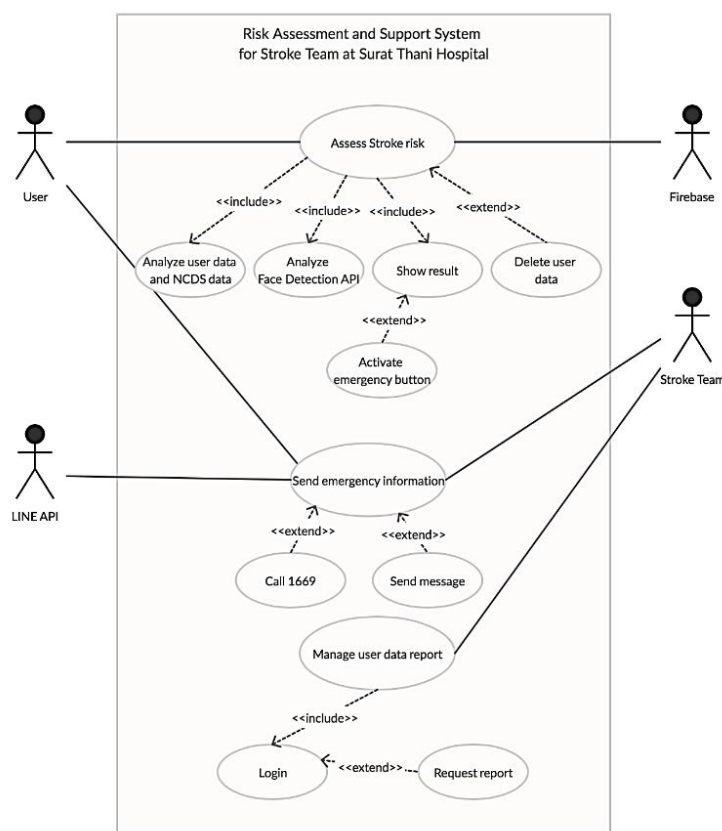


Fig. 6: Use Case diagram

The main menu of the application contains stroke risk assessment, and medical emergency call, as shown in Fig. 7. This system consisted of

three processes: stroke screening, face detection, and emergency module.

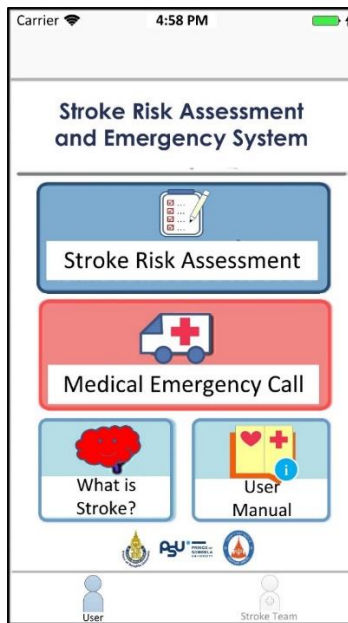


Fig. 7: Interface of the main menu

Stroke screening

The users were required to first register to create the user profile including ID card number, name, gender, age, address, and emergency contact person and phone number as primary information. After finishing the registration, the user's information will be recorded in the database. The user was also required to provide health information, such as blood pressure, height, and NCDs (Non-

Communicable Diseases) data. Health-related questions on risk behaviors were further asked, including exercise habits, alcohol consumption level, and smoking status. The information given by the user will also be stored in the database and the risk score was calculated using CV Risk. The interface of the registration system is shown in Fig. 8.

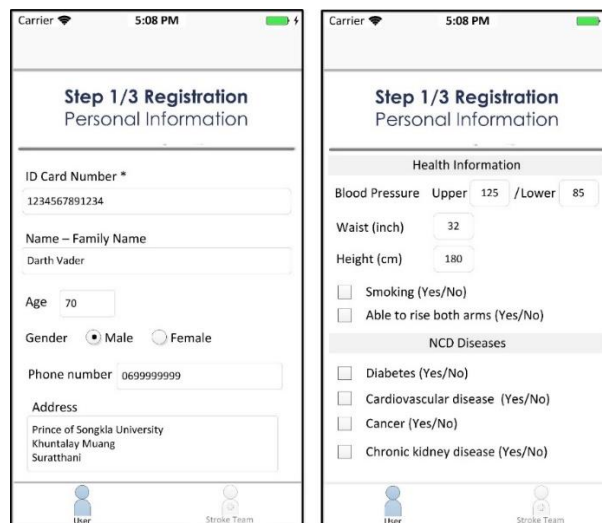


Fig. 8: User Interface for stroke screening

Face Detection

The proposed face detection user interface is illustrated in Fig. 9. The menu of the application provided an option to take a photo of the face. The image will be used to identify facial landmarks. In the face image evaluation process, the Firebase Face Detect API will be used to calculate key points on the face, including the left eye, right eye, tip of the nose, left lip, right lip, and lip

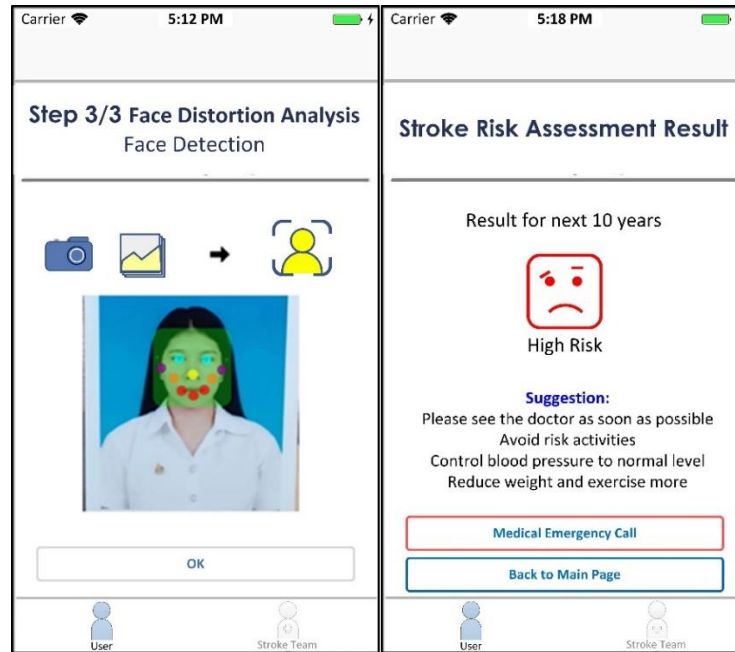


Fig. 9: User Interface for face detection

base. When the important points had been obtained, the calculation with analytic geometry was used to extract distortion angle for the face. The results from face detection were used by the SVM classifier to call normal or abnormal symptoms. After that, the input given by Thai CV and face detection will be analyzed to assess the stroke risk group (Fig. 10). High-risk cases will be passed to the Stroke Team.

Fig. 10: User Interface for results

Emergency module

The application automatically passed the emergency cases to the Stroke Team. For emergency notification, the user can choose to call 1669 or send a message to the Stroke Team at Surat Thani Hospital via LINE. A service application was developed to be able to send messages to the Stroke Team at Surat Thani Hospital via LINE using the information that was already entered. The Stroke Team will receive information including current user's location using a Global Positioning System (Fig. 11).

Usability Test result

The application was tested by 12 expertise in software developers. There were five topics and five score levels; 1 (very poor) to 5 (very good). The results were as follows: ease of use (4.58); data security (4.33); flexibility of use (4.25); response time (4.17); navigability (4.00). The overall usability was good, the application was highly easy to use with good flexibility and navigability. The processing was fast, caused by response time was good. Moreover, the private information stored on mobile phone that referred to the good data security for user.

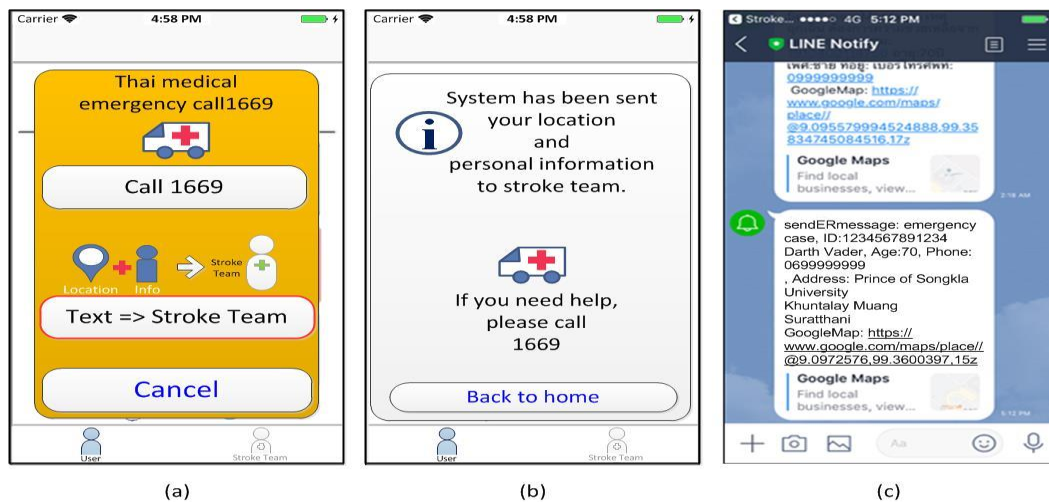


Fig. 11: User Interface for emergency module

Discussion

Mobile health is widely used in public health services. Especially stroke applications, most of their services followed FAST approach; dropped face, weak arms, speech difficulties and less time to hospital (4,5,6,10). Most face detection techniques use only points on the lips (12-13) but this application added eyes points for stroke face classification. The top accuracy classifier was SVM model (13) which was used also. Moreover, rapid emergency call and stroke patient's location can reduce time to hospital (10) and communication between stroke team and follow teams via text message can collaborate each other (11) therefore this application provided emergency call and sent user's GPS location and emergency notification via social network to the hospital's stroke team. In addition, prehospital stroke screening was used in many applications but the application introduced Thai CV risk score (14-15). In Thailand, there are stroke electronic health records (8) and emergency call application (10) therefore this application can fill up the personal stroke screening that suitable for Thai people and communication with hospital stroke team.

Conclusion

This study attempted to support the medical treatment of stroke in Thailand after preliminary

symptoms, followed by Stroke FAST tracking. The system includes screening, face detection, health care information for stroke patients, and emergency contacts. Emergency Call 1669 or location and personal information will be passed on to hospital when the case appears severe. The application makes it easy for the users, and helps the patient detect stroke in an automatic way. The hospital may be able to provide acute stroke care for the high-risk stroke group. The hospital provided the knowledge and awareness of stroke and NCDs, as well as ways to prevent risks. Future studies should improve the evaluation of risk of stroke to update health status records automatically. This will be beneficial for nurses and doctors in the future.

Journalism Ethics considerations

Ethical issues (Including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

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Conflicts of interest

The authors declare that there are no conflicts of interest.

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