myCAST:
"A Personalized Stroke Identification and Prevention System"

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Overview

Strokes are a leading cause of death throughout the world, but little has been done to assess stroke susceptibility or provide retainable education for the subject matter. Various corrigible factors delay treatment, which reduces survival rates. If victims are hospitalized within three hours of their first symptoms, survival rates would dramatically increase. Hence, a mobile application for stroke self-examination and education was conceived. Self-examination was performed using a three-stage procedure. The first stage of the self-examination was a questionnaire that tested the user's perception of moderate stroke indicators. Detection of slurred speech followed. Users were prompted to repeat a predetermined phrase, which was converted to text using Google's Speech-to-Text API. This text was compared with the original prompt using a string distance metric. The final stage was a face paresis detector developed in MATLAB®. The detector captured a smiling self-portrait of the user. After identification, the user's mouth profile underwent a series of mathematical transformations, resulting in an asymmetry criterion which could be compared to archived data to yield another stroke identification metric. Finally, the proposed mobile application compiled the various stroke identification metrics and alerted the user to seek medical assistance if needed. An intelligent emergency contact button sent the user's GPS location and medical history to emergency services, fostering expedient communication and treatment. The application was validated on the authors.

Introduction

Strokes were the second leading cause of death worldwide in 2015, leading to 6.24 million fatalities; however, little has been done to assess stroke susceptibility or educate potential victims. Concern about the ever-increasing medical fees, limited health-care coverage, and the presumed unlikeliness of a stroke cause many at risk to disregard symptoms or avoid physician checkups – delaying treatment and reducing survival rates. Mobile devices have widespread usage globally; hence, they pose a promising solution to these problems while offering the user great convenience at virtually no operational cost. Understanding the two major categories of strokes is integral. Ischemic strokes are the most frequently occurring stroke type, comprising 87% of all cases, and result from obstructions in blood vessels supplying the brain. Some can be predicted from the occurrence of Transient Ischemic Attacks (TIAs), which are caused by temporary blood flow blockages and have alarmingly similar symptoms. The other major stroke type, hemorrhagic, are less common, occurring in only 15% of all stroke cases, but have a greater fatality rate. Hemorrhagic strokes are caused by leakage from a weakened blood vessel or the burst of an aneurysm. Alteplase IV r-tPA, the "gold standard" treatment for ischemic strokes, is only effective in an acute three-hour window after onset. Treatment for hemorrhagic strokes, requires prompt surgery. Hence, the need for fast identification is elucidated.

Methodology

Application Framework

The name of the proposed mobile application was Cerebrovascular Accident Self-Test (myCAST). When launched, the mobile application displayed a simplistic home screen with three buttons titled "Take Routine Self-Exam," "Stroke Education," and "Call 911 Now."

Education

This provision of the mobile application exhibits common stroke symptoms in an accessible format. Inclusion of symbols and acronyms was speculated improve associative memory in users and hence accelerate information retrieval.

Phase I: Questionnaire

The first component of myCAST's semi-automated self-examination was a questionnaire that surveyed the user's perception of moderate stroke indicators. The Android.RadioGroup package was utilized to create this questionnaire and results were stored in an SQLite database for future comparison, analysis, and transmission.

Phase II: Slurred Speech Detection

myCAST's slurred speech detector calculated the distinctiveness of the user's rendition of a predetermined phrase. Initially, the user was prompted to repeat a certain predetermined phrase. The received microphone feed was converted into text via Google's Speech-to-Text API (present in all devices with API level > 14). This text was compared with the prompt using the Levenshtein Distance string metric. The output from this algorithm characterized the dissimilarity between the two text strings and was stored in the SQLite database.

Methodology (Cont.)

Phase III: Facial Paresis Test

To detect facial paresis, myCAST prompted the user to capture a smiling self-portrait. Computationally-minimalistic, localized image processing followed. First, the Viola-Jones algorithm detected the user's face and their mouth. The resulting mouth region was binarized and the resulting profile was standardized using region properties. After that, the tilt of the mouth profile was corrected and the profile was cleaned using an iterative procedure. First, the median location of the activated pixels in each column of the mouth profile and their corresponding weightages were determined. After smoothing, a first order polynomial model was fit to the median data using weighted linear least-squares. This model is demonstrated and solved below.

$$y = \Psi H;\ \Psi = \begin{bmatrix} X_1 & 1 \\ \vdots & \vdots \\ X_n & 1 \end{bmatrix} \rightarrow \hat{\mathrm{H}} = (\Psi^T \mu \Psi)^{-1} \Psi^T \mu Y\ ;\ \mu = \begin{bmatrix} \varphi_1 & 0 & \cdots & 0 \\ 0 & \varphi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \varphi_n \end{bmatrix};\ \varphi_i = \begin{cases} \frac{1}{\sigma_i{}^2}, & \sigma_i \neq 0 \\ 1\ , & \sigma_i = 0 \end{cases}$$

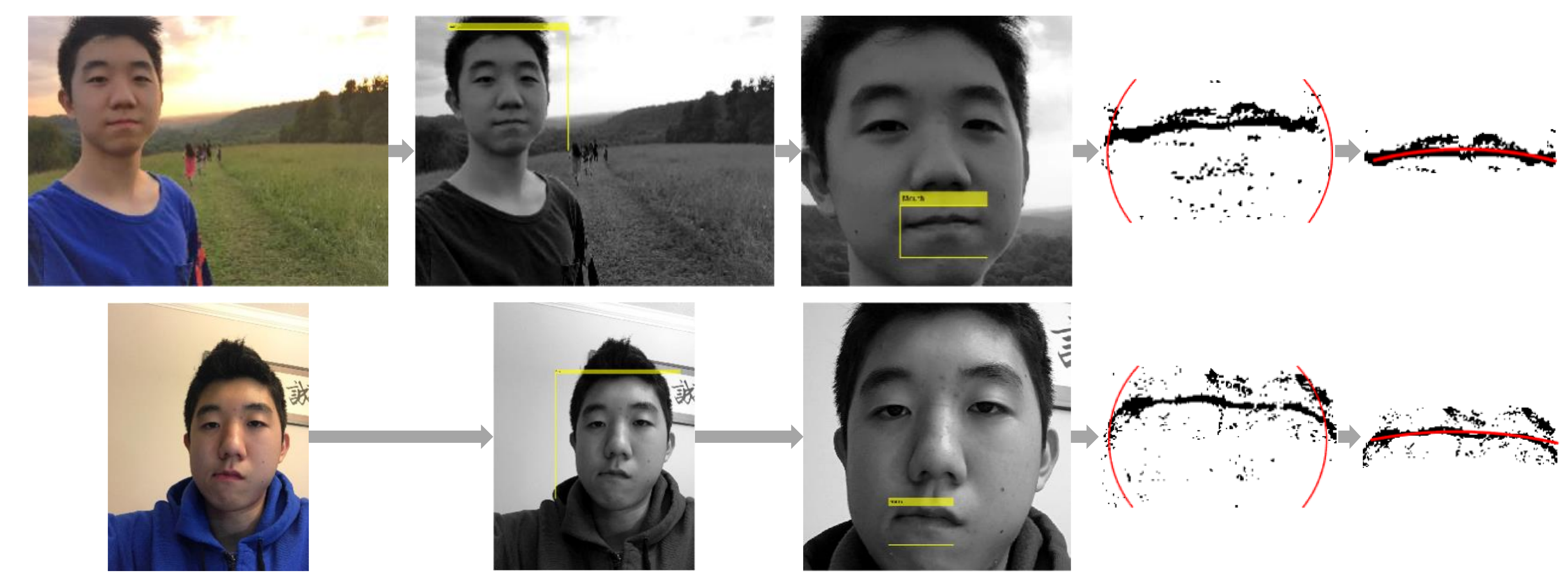
This was used to correct the tilt of the mouth profile, which is a rotation of a "straight" set of coordinates as shown below.

$$\begin{bmatrix} X_1 & \cdots & X_n \\ Y_1 & \cdots & Y_n \end{bmatrix} = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} X_1{}' & \cdots & X_n{}' \\ Y_1{}' & \cdots & Y_n{}' \end{bmatrix};\ \theta \approx \tan^{-1}\hat{\mathrm{H}}_1 \rightarrow \begin{bmatrix} X_1{}' & \cdots & X_n{}' \\ Y_1{}' & \cdots & Y_n{}' \end{bmatrix} = \frac{1}{1-2\sin^2\theta} \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} X_1 & \cdots & X_n \\ Y_1 & \cdots & Y_n \end{bmatrix}$$

A quadratic model of form $y = \hat{\mathrm{H}}_1 x^2 + \hat{\mathrm{H}}_2 x + \hat{\mathrm{H}}_3$ was fit to the rotated data using a similar method and the mouth profile was rotated by θ. Pixels in the rotated profile that deviate significantly from the quadratic were deleted to reduce its bias. Tilt correction and cleaning was repeated until θ fell below 0.1°. Then, the asymmetry was computed. The proposed asymmetry criterion has the form given by:

$$\left| \frac{1}{R} \sum_{i=1}^{R} (Y'_i - f(X'_i))^2 - \frac{1}{L-R+1} \sum_{j=R}^{L} (Y'_j - f(X'_j))^2 \right|;\ R = \left\lfloor \frac{-\hat{\mathrm{H}}_2}{2\hat{\mathrm{H}}_1} \right\rfloor$$

Outputs were stored in the database and compared to training values to detect facial abnormality with a high level of distinction.



Original Photo | Grayscale With Face | Mouth | Resized Profile | Best Profile With Model

Phase IV: Composite Susceptibility Metric

A linear-in-parameter (LIP) model was used to determine the final susceptibility. A "breadth-first" branch and bound approach was used to find the combination of variables leading to the most accurate LIP model. The underlying form of the aggregate model and the constrained, weighted linear least-squares solution is shown below.

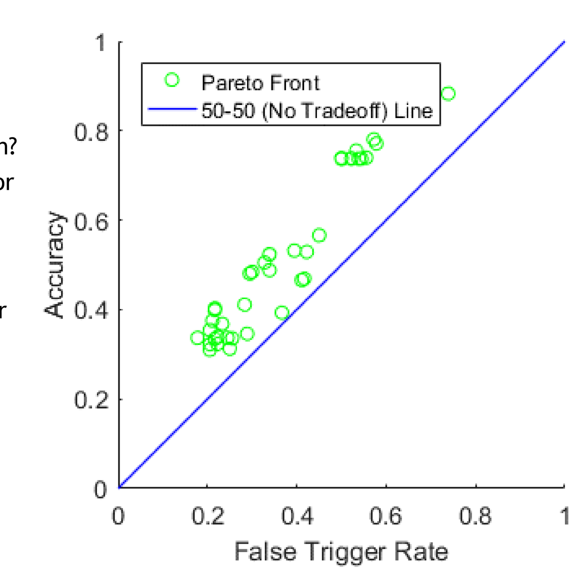
$$\beta_j = \begin{cases} 1, & \varsigma_j \geq K_1 \\ 0, & \varsigma_j < K_1 \end{cases};\ \varsigma_j = \sum_{i=1}^{6} \alpha_i Q_{i,j} \omega_i\ ;\ K_1 = 0.5, \alpha_i \in [0,1], Q_{i,j} \in [0,1] \rightarrow \min_{\omega} \frac{1}{2} \left\| W Q_{adj}{}^T \omega - W V^T \right\|^2 \text{ such that } \begin{cases} \sum_{i=1}^{6} \omega_i = 1 \\ 0 \leq \omega \leq 1 \end{cases};\ Q_{adj} = \begin{bmatrix} \alpha_1 & 0 & \cdots & 0 \\ 0 & \alpha_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \alpha_6 \end{bmatrix} * Q$$

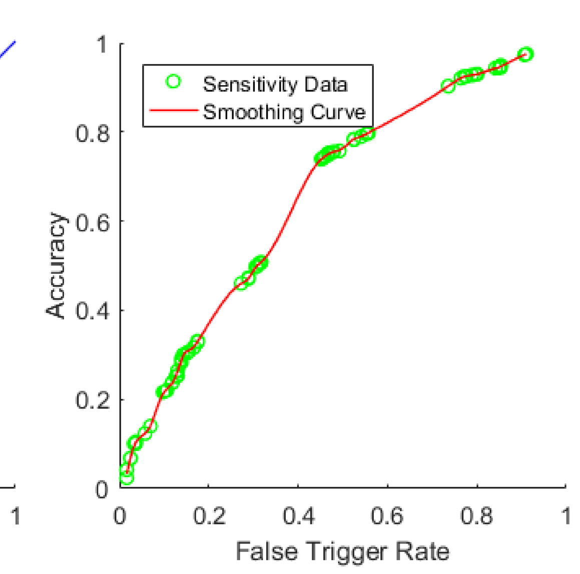
This model was fit to the data in the International Stroke Trial Database in a way such that the weights were normalized and the impact of those who did not have strokes (only 2.2% of the dataset) on the model fit was equalized. The final model was chosen from the resulting Pareto objective tradeoff front and assumed the following form:

$$\varsigma = 0.3493Q_1 + 0.305Q_3 + 0.0495Q_4 + 0.0876Q_5 + 0.2086Q_6$$

This was tested using 5.8 thousand data points and correctly identified strokes 74.11% of the time but false triggered 45.53% of the time.

Q_1: Have you recently experienced blurred or tunnel vision?
Q_2: Have you recently felt any numbness/tingling on one or both sides of your body?
Q_3: Have you recently felt any weakness on one side of your body or face?
Q_4: Have you recently felt SUDDEN confusion, dizziness, or nausea?
Q_5: Speech slur?
Q_6: Facial paresis?





Testing Frequency

The testing frequency was found by recursively solving a stroke probability model modified from a previous paper. The form of the modified model and the recursive, rearranged form used were given by:

$$\rho = 1 - (At^2 + Bt + 1)^{e^{(L_{com} - K_2)}} \rightarrow t_n = \frac{-B + \sqrt{B^2 - 4A\left(1 - e^{\left(\frac{\ln(1-(\rho(t_{n-1})+T))}{e^{(L_{com}-K_2)}}\right)}\right)}}{2A}$$

$$L_{com} = \begin{cases} 0.0505L_{AGE} + 0.0140L_{SBP} + 0.3263L_{\mathrm{HYPRX}} + 0.3384L_{\mathrm{DM}} + 0.5147L_{\mathrm{CIGS}} + 0.5195L_{\mathrm{CVD}} + 0.6061L_{\mathrm{AF}} + 0.8415L_{\mathrm{LVH}}\ , & male \\ 0.0657L_{AGE} + 0.0197L_{SBP} + 2.5432L_{\mathrm{HYPRX}} - 0.0134L_{SBP} * L_{\mathrm{HYPRX}} + 0.5442L_{\mathrm{DM}} + 0.5294L_{\mathrm{CIGS}} + 0.4326L_{\mathrm{CVD}} + 1.1497L_{\mathrm{AF}} + 0.8488L_{\mathrm{LVH}}, & female \end{cases}$$

Methodology (Cont.)

Testing Frequency (Cont.)

The following equation was used to convert t_n into standard military time while also taking into consideration user sleep patterns:

$$t_{c_n} = \begin{cases} t_b\ , & t_{u_n} \geq t_b \wedge t_s < t_b \\ t_w\ , & t_{u_n} < t_w \vee t_s > t_b \\ t_{u_n}, & else \end{cases};\ t_{u_n} = (8766t_n + t_i) \bmod 24, t_s = (t_{n-1} + t_i) \bmod 24$$

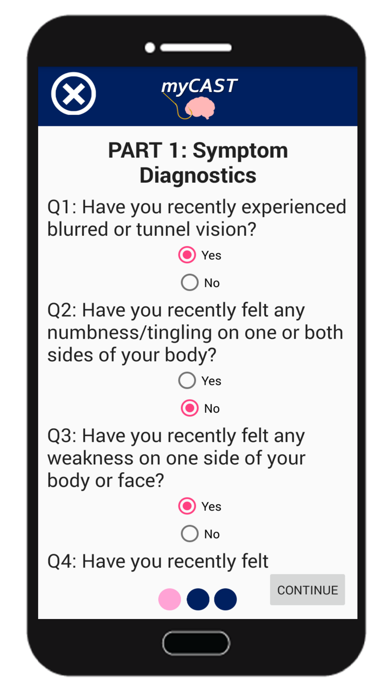
The models shown were able to apprise the probability of stroke based off medical history and previous self-test results. Hence, the proposed model was able to continuously adjust the interval between self-examinations for changing medical condition and aging.

Emergency Contact

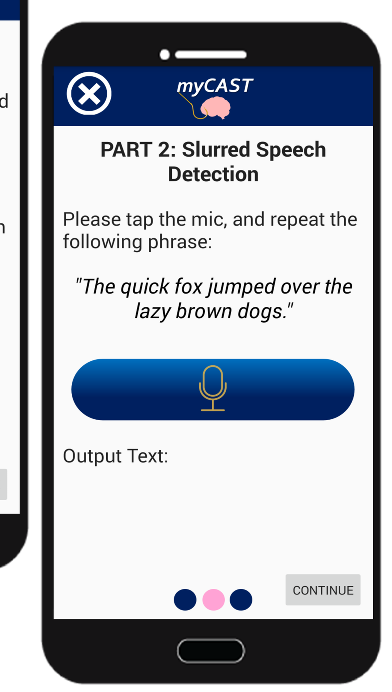
myCAST provided an expedient form of communication between potential stroke victims and emergency personnel. The innovative "Call 911 Now" button immediately dialed emergency services for the user and simultaneously sent the user's GPS coordinates and previously completed medical history (internally stored in the SQLite Database) to the dispatcher. This information could potentially expedite communication between the user and EMTs in the event of a real stroke emergency, reducing the delay between diagnosis and treatment.

Results

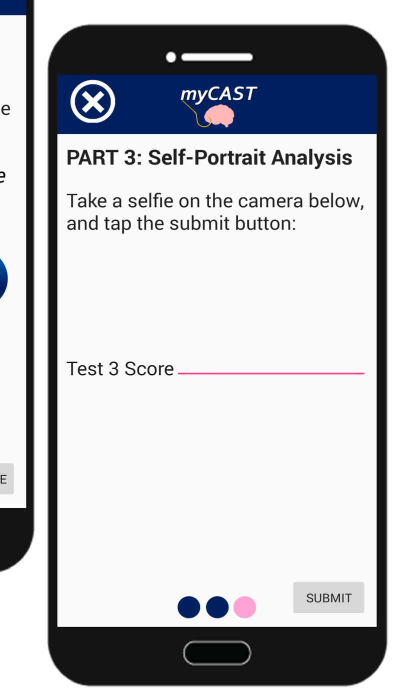
Procession of myCAST's Self-Examination



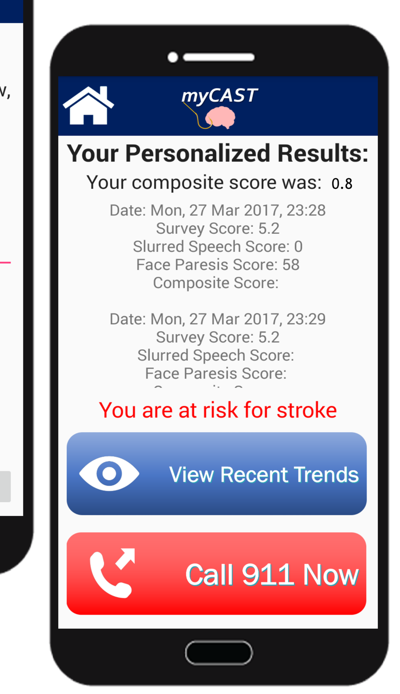
Mini-test 1: Questionnaire



Mini-test 2: Speech Slur



Mini-test 3: Self-portrait



Results Page

Conclusion & Future Work

In the short run, myCAST successfully appraised stroke susceptibility from archived self-tests.

- Calculated and stored data from each of the mini-tests in an SQLite database.
- Computed an overall composite susceptibility score in order to detect a stroke.
- Immediately contacted emergency services in the event of a stroke detection.
- Had low overall computational load, leading to optimal performance.

Future plans for myCAST include:

- Integration of heart rate abnormality and arm paresis detection using wearable devices.
- Implementation of the facial paresis test in the Android environment through the use of MATLAB® Coder (conversion to C++) and the *Android Native Development Kit.*
- Automatic dispatch of self-evaluation results to the user's primary care physician.
- Interactive education that is specifically targeted toward the user's risk factors.
- In-network adjustment for the composite metric and support for raw mini-test scores.

Thank You! Soon available on Android...