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Assessing General Well-Being using De-identified Features

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***Abstract*—The UN has predicted that cell-phone ownership will reach 5 billion in 2010. This proliferation of cell phones and connectivity offers an unprecedented opportunity to access vast populations, including previously hard-to-reach populations in rural areas and mountainous zones and underserved populations. Cell phones now can provide capabilities for the developing world that includes text, image processing and image displays. The available standardized interfaces can be leveraged to create powerful systems. In particular, digital cameras of cell phones provide easy to use interfaces for capturing useful information on the general well-being and emotive features of individuals. However, photographic images contain private and sensitive personal information in its raw form and thus considered unsuitable for online services. Therefore, there is a need for a computational algorithm for extracting anonymous digital features (for example, Hamming distance) from captured facial expression images for estimating different states of well-being. We have developed computer algorithms predicting well-being states from anonymous facial expression features. The research outcome can be used in a variety of online services including suggesting useful health information to improve general well-being.**

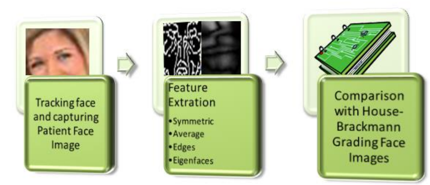
Keywords-component; Facial, palsy, Anonymous feature, SVM, face, SOM, Health Informatics, eHealth, Medical Data Analysis

I. INTRODUCTION

At end 2009, it is estimated that 2.75 billion people, or 56% of global population, do not have access to basic financial services for saving, borrowing or transacting, let alone health services. Cell phone-based low-cost medical diagnosis technologies have great potential to provide health services efficiently, timely, conveniently, and reliably.

Whereas in developed countries, machine learning techniques, such as support vector machines (SVMs), have shown significant potential as aids to medical and health practice [1]. Conventionally, specialist doctors, such as psychiatrists, consciously and unconsciously analyze observable symptoms, such as the language of their patients for assessment purposes using diagnostic classification systems, such as DSM IV [2]. To provide a more objective clinical diagnosis, SVMs have been applied to conversations of patients and clinicians [3].

Cell phones can now provide previously unavailable capabilities in both developing and developed world,



(a) Real-time House-Backmann Grading Process

(b) Real-time facial nerve assessment

Figure 1 The overall process of automated House-Brackmann Grading of face images.

including text, imaging and displays. The available standardized interfaces can be leveraged to create powerful systems. In particular, digital cameras of cell phones provide easy to use interfaces for capturing useful information about the general well-being of individuals. Therefore, in the past years, many non-invasive infection detection systems have been developed, such as non-contact thermal imaging, breath detector, and skin and urine analyser.

We propose low-cost cell phone-based application for detecting infectious diseases from facial-visual cues. However, photographic images contain private and sensitive personal information in its raw form and thus not suitable for online services. Therefore, we have developed a computational algorithm for extracting anonymous feature data (for example, Hamming distance and Principal Components) from captured facial expression image data; and a computational algorithm (e.g., Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs)) that can predict different well-being states from anonymous feature data.

In particular, we investigate how SVM is applied to automate the diagnosis of Bell's palsy from the de-identified anonymous feature data. Figure 1 illustrates an automated diagnosis of Bell's palsy using smart phones, such as Android mobile devices. The proliferation of mobile phones now enables us to collect high quality image data conveniently at home, even by parents of children. In particular, digital cameras of cell phones provide easy to use interfaces for capturing useful information about general well-being of individuals. Mobile devices have been used in rapid diagnosis of health conditions [4], health social networks [3], and improving livelihood of rural areas of developing countries [5]. The rapid penetration of mobile devices worldwide now opens up new opportunities to provide more convenient and cost effective means of diagnosing various health conditions associated with Bell's palsy, such as cold and flu.

II. BACKGROUND

This section provides an overview of the core techniques focusing on telemedicine, automated health assessment technology, support vector machines (SVMs), and Emergent and Self-Organizing Map (ESOM). In particular, the significance of generating human-comprehensible explanations from classifiers, and the meanings to explain the decision-making process of a machine learning system to a human user who may not be a domain expert, or having familiarity with information technology.

A. Telemedicine

Telemedicine is the use of communication technologies, such as telephone, video conferencing, or the Internet, to provide and support health care to remote regions. Telemedicine was initially developed to provide health care to rural and underserved populations [6], but distance is no longer a major factor to define its name. In fact, its applications have been extended to all types of health care including psychiatry consultations in inner cities [7-9]. While the greatest benefits come from its use in rural and underserved populations, as it makes otherwise unavailable health care available to many patients, its driving force is now more on making health care more cost-effective, affordable, accessible, efficient, and convenient for both health care providers and consumers. For instance, [10] teleconferences of doctors on improving communication between primary and secondary health care, [9] reported case studies of telepsychiatry via videoconferencing and their potential to improve patient care and satisfaction, and reduce emergency department overcrowding. Frantzidis, et al. [11] developed a remote monitoring system for the elderly and chronically ill. Tang, et al. [12] used a multimedia system to improve medication adherence in elderly care. The growing number of aged population indicates that this form of telemedicine will become an important research area for many developed countries.

Almost all technologies reviewed herein could be used in conjunction with tele-mental health technology. For instance, it is possible to use automated speech analysis methods (e.g., [3, 13-15] while the patients are being interviewed by psychiatrists to provide objective analysis of speech and language disorder or to monitor improvements in mental health conditions.

Much needed research is now being devoted to the development of more sophisticated Telemedicine technologies that integrate various technologies, such as mobile breathing sound analyser [16] and recommender system [3]. The papers reviews some of these technologies, with the aid of quantitative evaluation, rather than anecdotal qualitative evaluations [9]. It also examined the use of modern communication technologies for tele-health and contemporary issues in health, such as impact of technology on health services delivery, and its impact on relationship between patients and health care providers.

B. Automated Health Assessment Systems

Many health assessment methods are time consuming and highly subjective. To improve efficiency as well as to provide more objective assessments, various automated health assessment methods have been developed. The methods can be broadly classified based on the type of data collected and analysed. We shall now review the image analysis-based methods.

Cowie, et al. [17] reviewed the use of image analysis techniques in detecting emotional cues from facial expressions (that is, still face images) and gestures (that is, movements of facial features). According to [17], there are two emotion detection paradigms. The first paradigm detects the (seven) archetypal expressions. The second paradigm detects the non-archetypal expressions (for example, modulated, falsified, or mixed expressions). The majority of existing literature and available data clearly focus on the method of detecting archetypal expressions (e.g., [18-20]. Much research needs to be done for the detection of richer non-archetypal emotional expressions and gestures. These approaches now focus on the detection of action units (AU) defined by [21]. For instance, Valstar and Pantic [22] has used a facial point detector based on Gabor-feature-based boosted classifiers, achieving AU recognition rate of 95.3%. On the application of facial expression detection method on the diagnosis of mental health problems, Stone and Wei [23] used a facial expression detector to measure cognitive load, which is conventionally assessed using EEG or EMG measurements. However, there is little research on the use of facial emotional detection methods for clinical diagnosis of mental health problems. This may be due to the fact that image processing techniques are more difficult than other techniques, such as sound processing, and large variations on emotional expressions make it difficult to develop reliable measurements that are correlated with underlying psychological problems.

Instead of relying on face detection methods, Nambu, et al. [24] developed a simple image processing technique for monitoring behaviours and diagnosing poor health in the elderly. The researchers developed an automatic diagnosis system that can assess physical conditions as well as mental conditions from behaviours of elderly watching TV. They used the recordings of the starting time of watching TV, obtained from a running monitor of the television. Initially, they tried to utilize various other sensors, such as a running monitor of electric appliances or door switches, but found the resulting data difficult for objective analysis. The data appears to be uncorrelated. The start times of watching TV are recorded by dividing each day into 15min intervals. An interval is given a certain value, say 1, when an elderly participant starts the TV in the interval and another value, say 0, otherwise. This way, a 30×96 pixel image could be constructed for visualizing behaviours of the elderly watching TV. Their hypothesis was that the subjects watched the television at roughly fixed times if they were healthy. To measure productiveness of their TV watching behaviour, the researchers measured non-randomness of the patterns on the visualized behaviour using the maximum entropy method (MEM). The image compression rate was measured as an indication of the health condition. The lower compression rate (that is, the larger size of compressed image) was used as an indication of unhealthy condition.

C. *Support Vector Machine*

Cortes & Vapnik [25] introduced support vector machines which is a novel approach to machine learning. SVMs are based on the structural risk minimization principle in order to overcome the over-fitting problems. Support vector machines find the hypotheses from the hypothesis space H of a learning system which approximately minimizes the bound on the actual error by controlling the empirical error using training samples and the complexity of the model using the VC-dimension of H. SVMs are universal learning systems [26]. In their basic form, SVMs learn maximal margin hyperplanes (linear threshold functions). A hyperplane can be defined by a weight vector $\boldsymbol{w}$ and a bias b:

$$\mathbf{w} \cdot \mathbf{x} + b = 0$$

The corresponding threshold function for an input vector $\boldsymbol{x}$ is then given by:

$$f(\mathbf{x}) = sign(\mathbf{w} \cdot \mathbf{x} + b)$$

However, it is possible study polynomial classifiers, radial basis function (RBF) networks and three or more layered neural networks by mapping input data $\mathbf{x}$ to some other (possibly infinite dimensional) feature space $\phi(\mathbf{x})$ and using kernel functions $K(\mathbf{x}_i,\mathbf{x}_j)$ to obtain dot products, $\phi(\mathbf{x}_i)\bullet\phi(\mathbf{x}_j)$, of feature data.

D. *Emergent Self-Organizing Map*

Emergent Self-Organizing Map (ESOM) [27], also known as a Kohonen map having a large number of map neurons, is a technique using nonlinear projection neurons arranged in a map M, usually in 2D (i.e., $M \subset \Re^2$), for visualization of high dimensional data. Two types of ESOM grid structures have been commonly in use: Hexgrid (honeycomb like) and Quadgrid (as a lattice) maps.

ESOM usually forms a (2D) grid of prototype neurons, which are represented using high-dimensional vectors with a similar number of features of input data. The density of data in the vicinity of the neurons, and the distances between the neurons, are taken into account for better visualization. For example, an ESOM map can be visualized using

1. Distance-based Visualization called U-Map (from U-Matrix) [28];
2. Density-based Visualization called P-Map (from P-Matrix) [29]; or
3. Distance- and Density-based Visualization called U*-Map (which combines the U and P map) [29].

The different types of maps visualized the high dimensional data space on a floor space layout using a landscape like visualization for distance and/or density structure of the high dimensional data space. Structures emerge to the top of map by clustering of many neurons during the learning phase. The emerging structures are the main concept of ESOM. It can be used to achieve visualization, clustering, and classification. The clustering of ESOM is based on the U*C clustering algorithm described by [30].

III. METHODOLOGY

The project aims to develop computer algorithms predicting well-being states from facial expressions:

1. Computational algorithm of extracting anonymous feature data (e.g., Hamming distance and Principal Components) from captured facial expression image data; and
2. Prediction algorithm (e.g., Artificial Neural Networks and Support Vector Machines) that learns a function y=Model(x) of predicting different well-being states y from the anonymous feature data x. Here, Model is usually a black box.

Our main hypothesis is that an automated machine learning algorithms (e.g., ANNs) can learn a prediction function y=Model(x) from a set of training sample data (X,Y), where Y = well-being states (i.e., an answer to a question in the questionnaire) and X = anonymous feature data of the corresponding facial expression image data, such as Hamming distance between left and right halves of the facial images. This can be tested by measuring accuracy, specificity, sensitivity of predicting well-being states from the anonymous features. Earlier studies [1, 31] in computational methods for the detection of facial palsy from single facial images had an accuracy of more than 70%, suggesting that the method may be suitable for real world applications.

In order to prove the main hypothesis, we collected a total of 46 facial palsy images and 21 normal face images in our earlier studies. We included the details in this paper for reference in the later sections. We then further collected 61 face images from JCU Singapore students. The students filled in a questionnaire to describe their general well-being states, such as energetic, happy, feeling chill, feeling having a cold or flu. The questionnaire lasted about 10mins.

Table 1. House-Brackmann Grading System for Bell's Palsy. Source [1].

Face	Grade	Characteristics
Forehead	I. Normal	Normal function
	II Mild Dysfunction	Slight weakness to good function
	III. Moderate Dysfunction	Noticeable slight to moderate movement
	IV. Moderately Severe Dysfunction	Obvious weakness or disfiguring asymmetry
	V. Severe Dysfunction	Barely perceptible motion
	VI. Total Paralysis	No movement
Eye	I. Normal	Normal function
	II Mild Dysfunction	Complete closure with minimal effort
	III. Moderate Dysfunction	Obvious weakness, eye closure with effort
	IV. Moderately Severe Dysfunction	Incomplete eye closure
	V. Severe Dysfunction	Barely perceptible eyelid movement
	VI. Total Paralysis	No movement
Mouth	I. Normal	Normal function
	II Mild Dysfunction	Slight asymmetry or weakness of mouth movement
	III. Moderate Dysfunction	Obvious but no disfiguring weakness
	IV. Moderately Severe Dysfunction	Asymmetry at rest
	V. Severe Dysfunction	Barely perceptible mouth movement
	VI. Total Paralysis	No movement

Each question in the questionnaire indicates a well-being state Y (e.g., Runny nose?). The facial expression images are processed to extract anonymous feature data X, such as Hamming distance. The questions in the questionnaire and features of facial expression image data form a training data set for a computational machine learning algorithm. The aim of this data set is further to test whether a computational learning algorithm (e.g., Artificial Neural Networks) can automatically generate a high-performance prediction function y=Model(x).

The overall process of developing the Model function is as follows. The face images of the questionnaire are processed to generate a non-identifiable feature data set. This feature data set is then used to train machine learning algorithms (e.g., Artificial Neural Networks (ANNs), Naive Bayesian Classifier, Decision Tree, and Support Vector Machines). We then use the models to predict answers to the questions in the questionnaire (e.g., "Do you have runny Nose = Yes/No?").

We train various machine learning algorithms (Naive Bayesian Classifier, ANNs,, SVM, and Decision Tree) and test their performances using the questionnaire data. Our aim is to test the computational machine learning algorithms in predicting the answers to the questions in the questionnaire from features of facial expression images.

Examples of non-identifiable features are the Hamming distances (i.e., differences) between the left and right halves of face images, edge detection and segmentation of the face images and other measures of symmetry, such as geometrical measurements of symmetry. These features cannot be used to identify individuals. We identify such features at the above second step in order to find non-identifiable features that maximize the prediction function. We can then be able to

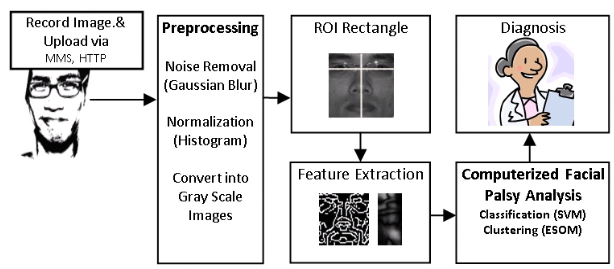


Figure 2 Process of automated House-Brackmann Grading of face images. Source [1].

collect such non-identifiable data through various online survey methods to test further how effective the features are in predicting well-being states as patients will be more conformable to share non-identifiable data.

A. Extracting De-identified Features

Figure 2 illustrates the process of extracting de-identified features from facial expressions and predicting well-being states of the users as House-Brackmann Grading (see Table 1 for the descriptions of the grading scale) or questionnaire answers. To remove noises, a 2D Gaussian blur filter is applied on the sample face images. The images are then converted into grey scale images and normalized using a Histogram equalization process. An automated face-area detector is developed using the Haar Cascade classifier [32] implemented on OpenCV (Open Source Computer Vision: http://opencv.org) API. Haar Cascade classifier combines Adaboost algorithm for feature selection and a cascade of classifiers for rapid scanning of face images. The face-area

Figure 3 Intermediate images of face images: significant face edges; difference between left and right face. Source [1].

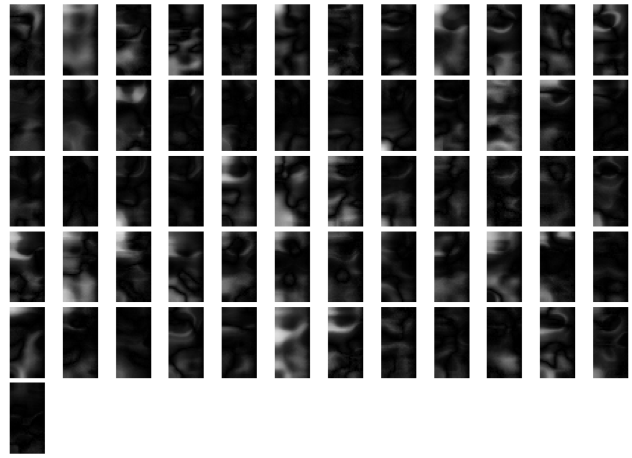
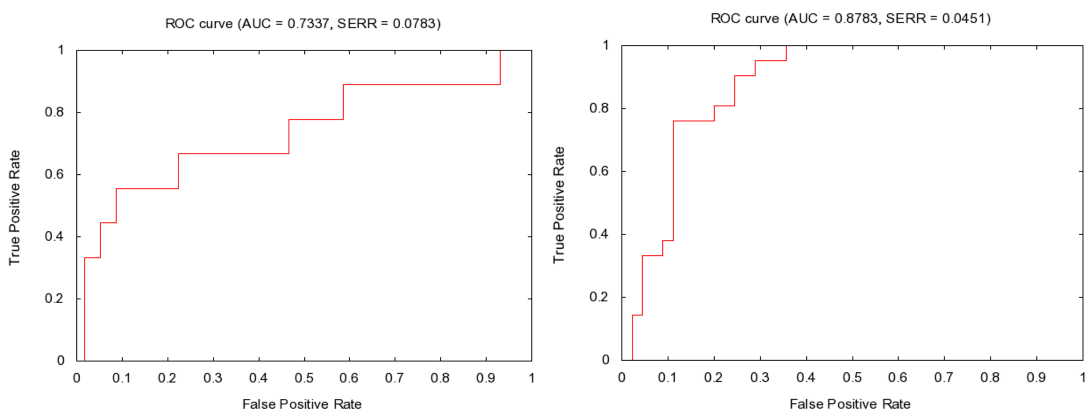


Figure 4 Intermediate images of 61 smiling face images.



(a) (b)

Figure 5 ROC using (a) Ten principal components (b) Hamming Distances of left face and right face. Source [1].

detector automatically locates a face in a sample image and places a region of interest (ROI) rectangle. The detector is calibrated such that it detects an ROI rectangle area that encloses the far edges of the eyes, the top of the eye brows, and the bottom of the lower lip. The face edges are extracted using a Sobel edge detector. The differences between left and right half images of faces are measured using Hamming Distance [33], i.e., the number of positions at which the corresponding pixels are different. Therefore, each image is represented by 100 Hamming distance values. Principal component analysis (PCA) is then performed on the Hamming distance features and the top-ten principal components are selected as the set of features of sample data sets. To compute the principal components, the Hamming distance features of face images are represented on a 100x67 matrix (100 rows and 67 columns), where each column is the Hamming distance features of a face image. Eigenvectors are computed using OpenCV API. The top ten eigenvectors are selected by sorting them in descending order of their eigenvalues. The images are then classified using 5-ary classifiers (a multi-class classifier).

For the training data sets, the rectangle is manually rotated and/or moved to centre the faces inside the rectangle such that the centre line of the rectangle passes through the centre of the face, that is, between the eyes and the centre of nose. The rectangle regions of the face images are then extracted, rescaled, and down sampled to 100×100 pixel square grey-scale images.

IV. Evaluation of the De-Identified Features

In our previous study [1, 31], we have collected 46 facial palsy images from hospitals and 21 normal face images from a public database. The resolutions of the facial palsy images and normal face images were about 691×1024 and 150×180, respectively. The facial palsy images were obtained from Mater Misericordiae Health Services in Brisbane. These images show facial weaknesses, such as not being able to close both eyes, twitching of the corner of mouth when smiling, and asymmetry cheeks. The normal images were

Table 2. Performance Metrics Using Emergent Self-Organizing Map. Source [1].

Grade	Generalization	Recall	F-Measure	GMts	GMtr
I.	59.38%	91.43%	72.00%	59.54%	93.54%
II	93.75%	97.14%	95.42%	80.23%	98.37%
III.	87.5%	100.00%	93.33%	62.06%	100.00%
IV.	90.63%	100.00%	95.08%	56.73%	100.00%
V.	68.75%	97.14%	80.52%	69.63%	95.74%

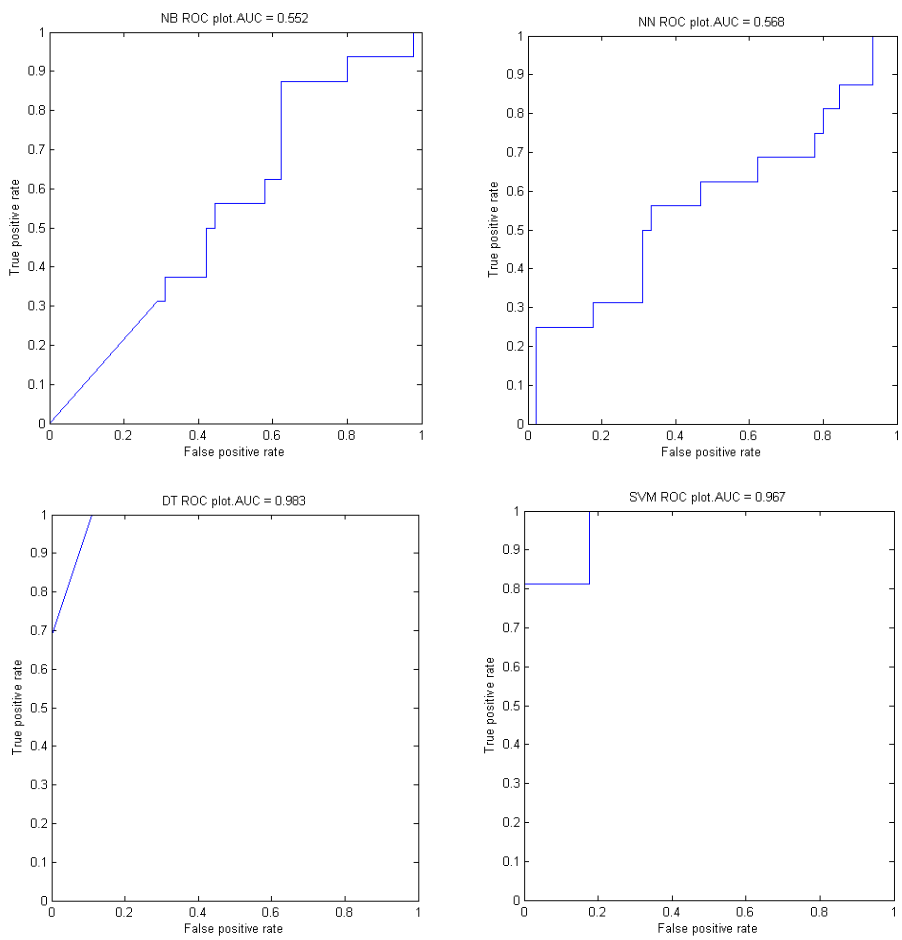


Figure 6 ROC curves for predicting feel-fit general well-being state.

obtained from Asian Emotion Database [34]. The data were then arranged into train and test data sets separately. We first graded the images manually into five scales using the House-Brackmann grades. Due to the insufficient number of images, we were not able to obtain grade VI images. We then further collected 61 smiling face images from students at the JCU Singapore campus.

Figure 3 shows the intermediate images of normal face and palsy images with asymmetry mouth. The second column of figure 3 shows the differences between left and right faces when we fold the face images symmetrically. The differences are measured using Hamming Distance [33], that is, the number of positions at which the corresponding pixels are different. Therefore, each image is represented by 100 Hamming distance values. Figure 4 shows all of the Hamming Distance features of the 61 students.

For our initial experiment, principal component analysis (PCA) is performed on the Hamming distance features of the 46 facial palsy images and 21 normal face images, and the top-ten principal components are selected as another set of features of the sample data sets. To compute the principal components, the Hamming distance features of face images are represented in a 100x67 matrix (100 rows and 67 columns), where each column is the Hamming distance

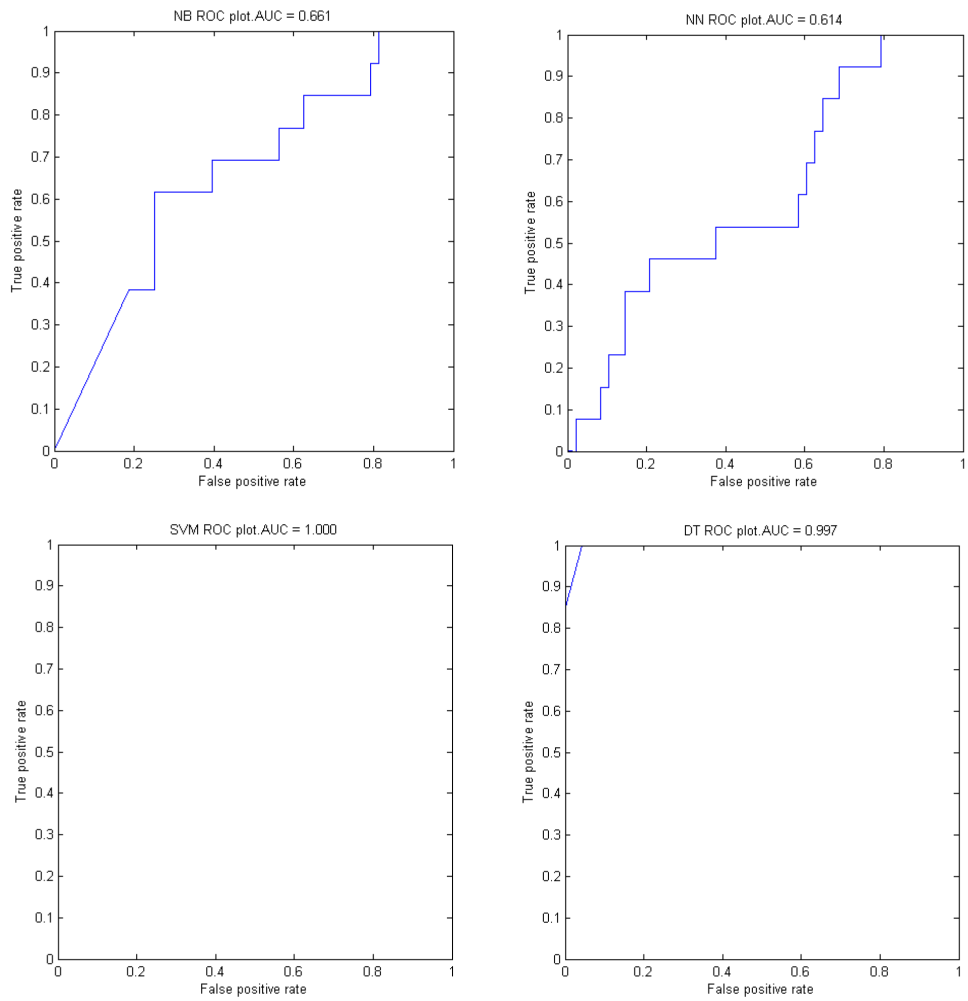


Figure 7 ROC curves for predicting feel-pleased general well-being state.

features of a face image. The 5 groups of images are then classified using 5-ary classifiers.

Figure 5(a) shows the ROC (Receiver Operating Curve) curve of SVM with ten principal components, the area under the curve is 0.73. Figure 5(b) shows the ROC curve of Hamming distance with SVM which gives better results of about 0.87. It provides good curves for palsy data as shown. Table 2 shows the results of using ESOM classifier on the principal component features. The results are encouraging; the F-measure is above 72%. Especially in the case of Grade II, III, and IV, the results are above 90%.

In our second experiment, we directly use the Hamming distance features after normalizing down sampled smiling face images (50x50 pixels), which is much smaller than our earlier samples. The purpose of using such smaller image size to test whether images transferred over Multimedia Messaging Service (MMS) could be used for diagnosis. This is often desirable in many areas where mobile broadband services, such as 3G, are not available. The features are then used to evaluate their diagnostic power. Four classifier are evaluate using leave-one-out cross validation. Figure 6 shows the ROC curves of four classifiers (SVM, Naive Bayesian, Decision Tree, ANN) for predicting 'feel-fit' general well-being state. The classification performances of the classifiers for predicting 'feel-fit' are 0.54, 0.72, 0.74, and 0.74, respectively. Figure 7 shows the ROC curves for predicting 'feel-pleased' general well-being state. The classification performances of the classifiers are 0.67, 0.75, 0.79, and 0.79, respectively. Except for Naive Bayesian, most of the classifiers performed well in predicting general well-being states. In particular, SVM and Decision tree classifiers showed good performance.

V. Conclusion

The results indicate that the automated machine learning algorithms can learn to predict various well-being states including House-Brackmann score of Bell's Palsy from anonymous features of the facial expression image data.

Traditional diagnosis involves a medical doctor taking a thorough history of patient and determines the onset of paralysis, the rate of progression and so on. The use of automated grading system greatly reduces the duration of diagnosis while increasing consistency, because references of all palsy images are stored to provide comparisons. The results are very encouraging. We showed that by using face symmetry Hamming distance combined with Emergent Self-Organizing Map, we are able to achieve classification rate of up to 95%.

House-Brackmann score provides the general state of well-being of subjects without stating any specific disease or well-being states. The second experiment shows that specific diagnosis of well-being states can also be done using very small image samples (50x50 pixels), which can be easily transferred using readily available Multimedia Messaging Service (MMS). The coverage of MMS is equivalent to 2G cell phone networks, and therefore it is ideal for serving those who need medical diagnosis most.

Our further research will now migrate the current diagnosis methodology to using a cell-phone as a mobile facial palsy assessment tool. This can provide timely diagnosis to patients situated in not easily accessible areas, emergency situations and areas with high medical cost, and lastly for the underserved populations. Unlike existing medical diagnostics, such as contact thermal imaging, our method can utilize existing cell phones and infrastructure to provide a robust, non-invasive, and rapid assessment method based on the simple analysis of images. The developed system can be rapidly deployed to many needed communities over the Internet. In the next five years, most residents in African continent will have cell phones. Our low-cost cell phone-based data collection and diagnostics systems can be used to construct a world-wide database of diagnostic images and cases to discover the causes and spread of diseases and global patterns of disease development.

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