EMGNEU: MOBILE HEALTH APPLICATION FOR NEUROMUSCULAR DISORDERS DIAGNOSIS

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***Abstract**: Neuromuscular disorders term refers to all diseases that affect nerves and muscles. Amyotrophic Lateral Sclerosis (ALS, also called Lou Gehrig's disease) is one of the most common neuromuscular diseases worldwide. Individuals with ALS may suffer from voluntary muscles (legs and arms muscles) weakness and difficulty in swallowing or breathing. Recently, mobile technology is used in the health sector to improve the quality of and access to health care. Mobile health applications help patients to monitor their treatments when it becomes difficult to obtain attention from health workers regularly.*

EMGNeu is a mobile health application that aims to help ALS patients to discover their disease once it occurs based on EMG signal. That is by focusing on new trends of integrating artificial intelligence methodologies as support vector machines into mobile telemedicine solutions. EMGNeu doesn't only help patients to track their neuromuscular conditions but it also helps their physician as well. Physicians are able to track their patients by receiving alerts when the disease is discovered and sending recommendations to the patients to help them monitoring their emergency case until they could obtain medical help.

***Keywords**: mHealth, Neuromuscular disorders, EMG signal, SVM Classifier, Bioinformatics*

***ACM Classification Keywords**: I.2 Artificial Intelligence; I.2.1 Applications and Expert Systems - Medicine and science*

Introduction

E-Health can be defined as the use of information and communication technologies in health sector [World Health Organization, 2015]. M-Health is one of the most important technologies among information and communication technologies which are widely used recently. It conducts both patients and physicians to track and monitor diseases and public health which are known as e-Health. It improves quality and capacity of health care systems as it deals with mobiles utilities including Bluetooth, GPS (Global Positioning System), messaging service and many other applications. In addition to patient safety, m-Health saves time and expense to patient and physician as well as managing the deadly diseases.

There are two types of muscle diseases namely: (a) Neuromuscular disorders, and (b) Myopathy (MYO). Neuromuscular disorders include diseases that affect nerves and muscles and causes muscle numbness, weakness and twitching. Amyotrophic lateral sclerosis (ALS) is a motor neuron disease that affects nerve cells in the brain and the spinal cord. Myopathy (MYO) includes diseases of skeletal or voluntary muscles and causes theses muscles to become weak but they don't affect the nerve system. Electromyography (EMG) signal shows the electrical activity of a muscle which represents the muscle response during different actions and it provides significant information for identification of various diseases like neuromuscular diseases, muscle degeneration and nerve injury. In order to use EMG signal as a diagnosis signal, significant features must be extracted from the raw signal as using the raw signal itself in the classification process results in poor classification system with very low accuracy. So that the feature extraction process is considered the most important phase in building a successful diagnostic system. In the last decade, wavelet transform (WT) approved its efficiency in analyzing non stationary biomedical signals such as EMG signals. It transforms the signal into both time and frequency domains.

This work presents the initial results for a simple Mobile Health (mHealth) application for Neuromuscular Disorders diagnosis. The application is based on the wavelet transform approach for features extraction process and SVM model for classification process. This paper is organized as follows: Section 2 includes the related work, Section 3 discusses the support vector machine classification model for Electromyography Signal, Section 4 presents the modules of EMGNeu mobile health application and the role of each module and finally, Section 5 concludes the paper.

Related Work

Many of recent researches used support vector machine (SVM) in EMG signal classification either for actions and movements identification or for neuromuscular disorders classification. More recent, Gurmanik et al. [Kaur, 2009] proposed a technique for diagnosis of neuromuscular disorders based on multi-class SVM and autoregressive (AR) features. Bassam et al. [Moslem, 2011] proposed the use of a committee machines with a Support Vector Machines as the component classifier in order to boost the classification accuracy of multichannel uterine (EMG) signals. Kouta et al. [Kashiwagi, 2011] also proposed a classification system for four waist motions by constructing a strong multi-classifier using a combination of four SVMs. SVM was also hybridized with particle swarm optimization (PSO) by Abdulhamit [Subasi, 2013] to improve the EMG signal classification accuracy.

There are other classification algorithms have been employed to classify EMG signal such as k-nearest neighbor [Fattah, 2012], extreme learning machine (ELM) [Sezgin, 2012], radial basis function neural networks [Diab, 2012], fuzzy logic and probabilistic neural network [George, 2012]. Support vector machines are also widely used in researches of mobile health applications based on artificial intelligent techniques. Alan [Michael, 2012] used SVM in developing a Smartphone based mobile medical application to discriminate between Parkinson's postural tremor and essential postural tremor based on the internal built-in accelerometer sensor of a Smartphone. Patrick et al [Kugler, 2013] proposed two applications they performed on their developed framework. The first application was a real-time classification of fatigue during running and the second is using EMG for the detection of Parkinson's disease during walking. In both applications they used SVM as the classifier. Edmond et al [Mitchell, 2013] presented a framework that allows for the automatic identification of sporting activities using commonly available Smartphone's based on their internal accelerometers sensors. They used DWT to extract features from sensor data and then those features have used as input to a SVM-based classifier.

The Support Vector Machine Classification Model for Electromyography Signal

Database Description

The proposed method in this study was tested on a dataset includes real single - channel EMG signals detected from normal, myopathic and neuropathic muscles using a standard concentric needle electrode during low and constant level of contractions [Nikolic, 2001]. The dataset consists of a normal control group, a group of patients with MYO and a group of patients with ALS. The control group consisted of 5 normal subjects aged 21 - 37 years, 2 females and 3 males. All of them were in general good shape. None in the control group had signs or history of neuromuscular disorders. The group with MYO consisted of 5 patients; 3 males and 2 females aged 26 - 63 years. All 5 had clinical and electrophysiological signs of myopathy15. The ALS group consisted of 5 patients, 3 males and 2 females, aged 35 - 67 years. Besides clinical and electrophysiological signs compatible with ALS, 3 of them died within a few years after onset of the disorder, supporting the diagnosis of ALS. Signals recorded from brachial biceps were selected to test our system as they were the most frequently investigated in the three groups. 15 datasets are utilized from the whole datasets. Each dataset contains a total of 262,134 samples of SEMG signal with a sampling rate of 23,438 samples per second. Thus, the time duration of each of these datasets is 11.184 sec. Each dataset was subdivided into 64 distinct frames, each consisting of 4096 samples.

Features extraction approach

Wavelet transform is one of the more efficient techniques for processing non stationary signals such as biomedical signals (e.g. EMG). Wavelet transforms the signal into its time-frequency domains. There are two types of wavelet analysis, discrete wavelet transform (DWT) and continuous wavelet transform (CWT). Both of them consume low time for signal processing. CWT is more consistent, but DWT approved its efficiency in analyzing non stationary signals although it yields a high-dimensional feature vector. In our research, discrete wavelet transform (DWT) is used for analyzing EMG signal and extracting significant features which are very useful in identification of healthy, myopathic and neuropathic subjects.

Five features of EMG signal are taken into consideration in this research. Root Mean Square (RMS), Mean Absolute Value (MAV), Zero Crossing (ZC), Slope Sign Change (SSC) and Standard Deviation (SD). Each one of these features is used as input to the classification process which is the next phase after feature extraction process. CWT can be expressed by the following equation:

$$\psi(a,b) = \frac{1}{\sqrt{|a|}}\,\psi\left(\frac{t-b}{a}\right) \tag{1}$$

Where parameter a is the scale, b is the time location and $\psi(t)$ is the ‘mother wavelet’ which can be taken as a band - pass function. The factor $\sqrt{(|a|)}$ is ensures energy preservation, which is the same for all values of a and b. The equation of DWT can be given by:

$$x(t) = \sum_{k=-\infty}^{\infty}\sum_{l=-\infty}^{\infty} d(k,l)\,2^{\frac{k}{2}}\,\psi(2^{-k}t-1) \tag{2}$$

where $a = 2k$, and $b = 2kl$, and $d(k,l)$ is a sampling of $W\ (a,b)$ at discrete points k and l.

In this work Daubechies wavelet function of degree four (db4) was applied on each frame of the healthy, MYO and ALS subjects in training and testing data so that the next step is to extract time and time-frequency features from the resulted processed signal.

Successful classification system is mainly dependant on the efficiency of feature extraction stage. There are two approaches for extracting significant information from EMG signal. Those approaches are spectral and temporal approaches. This section presents the various set of time and time-frequency features we employed in our research.

(a) Mean Absolute Value (MAV)

Mean Absolute Value (MAV) is the average of the absolute value of all time samples. It can be represented by the following function:

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|x_i|, \quad for\ i = 1, \dots, I-1 \tag{3}$$

The parameter N is the number of samples and I is the number of channels.

(b) Standard Deviation (SD)

Standard Deviation (SD) represents the deviation of the mean value around the origin axis of a given segment of signal. SD can be defined as

$$\sigma = \sqrt{\frac{1}{N-1}\sum_{i=0}^{N-1}(x_i - \mu)^2} \tag{4}$$

where x_i is the signal, μ is the mean, N is the number of samples and σ is the standard deviation.

(c) Root Mean Square (RMS)

Root Mean Square is related to standard deviation and is used to calculate constant force and non - fatiguing contraction [Phinyomark, 2009]. It can be defined by:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}x_i^2} \tag{5}$$

(d) Zero Crossing (ZC)

Zero Crossing (ZC) counts the number of times that the EMG signal changed from positive to negative. A threshold condition should be considered to extract this feature from noisy SEMG signal. This feature provides an approximate estimation of frequency domain properties [Phinyomark, 2009]. It can be expressed by the following function:

$$ZC = \sum_{n=1}^{N-1} [sgn(x_n \times x_{n+1}) \cap |x_n - x_{n+1}| \geq t], \qquad sgn(x) \begin{cases} 1, & if\ x \geq t \\ 0, & otherwise \end{cases} \tag{6}$$

t represents the threshold parameter.

(e) Slope Sign Changes (SSC)

Slope Sign Changes (SSC) is similar to ZC. It represents the number of slope changes between positive and negative among three consecutive segments of the signal [Phinyomark, 2009]. It also requires a threshold condition to avoid the interference in SEMG signal. SSC can be defined by

$$SSC = \sum_{n=2}^{N-1} \left[f[(x_n - x_{n-1}) \times (x_n - x_{n+1})] \right], \qquad f(x) \begin{cases} 1, & if\ x \geq t \\ 0, & otherwise \end{cases} \tag{7}$$

where t is the threshold parameter.

Signal Classification

Various classification techniques have been proposed by many researchers. SVM is a powerful learning method which aims to find the best the best hyper plane that can separate data perfectly into its two classes. Multi-classification was recently achieved by combining multiple SVMs. There are two schemes of SVM multi-classifier: (a) One Against All which classify each class against remaining classes and (b) One Against One which classify between each two classes. In our research, One Against All SVM classifier with Gaussian radial basis kernel function (RBF) and sigma equal 1 was used in identification of ALS subjects against myopathy and healthy subjects. RBF used in selected SVM can be represented as

$$K(x_a, x_b) = \exp\left(-\frac{\left\|x_a - x_b\right\|^2}{2\sigma^2}\right) \tag{8}$$

The results shown in Table 1 indicate the performance of applying SVM for each group and with different set of features.

Table 1. SVM Classification Table

Disorder/Feature	MAV	RMS	SSC	SD	ZC	MAV,RMS,SSC,SD,ZC
ALS	94.9%	98%	67.6%	97.8%	77%	92.7%

As shown in Table 1, the higher accuracy for ALS classifiers was obtained by using RMS feature as input to the SVM with accuracy 98%.

EMGNeu: Mobile-Health application

EMGNeu application includes an intelligent remote diagnosis technique for m-Health Application in neuromuscular disorders. This will focus on new trends of integrating artificial intelligence methodologies as SVM into mobile telemedicine solutions. This application will display EMG signal through the mobile device which will process this signal, alerts patient and sends urgent events to the responsible physician as shown in Figure 1.

Signal Processing and Classification Implementation

All signal processing phases such as signal analysis, feature extraction and signal classification were at first implemented on MatLab 2013a using wavelet toolbox, statistics toolbox and SVM and then the MatLab code was translated into C# to be implemented on windows phone OS 7.1 and the application was tested on windows phone emulator. For signal classification phase, RMS feature was extracted and used as input feature to SVM classifier with RBF kernel function. As shown in Table 1, this classifier approved its efficiency in classifying EMG signal with an accuracy of 98%.

Figure 1. Proposed application architecture for patient emergency

Application Modules

(a) Profile and Settings Module

This module will be for both patient and physician. The module will be responsible for the application user profile and settings. The user selects whether he is patient or physician. If the user is the patient then he is enabled to select his application settings such as displaying an alert directly after ALS disorder diagnosis, sending messages and emails automatically after the disease is diagnosed. Figure 2 shows a screenshot of profile and settings module.

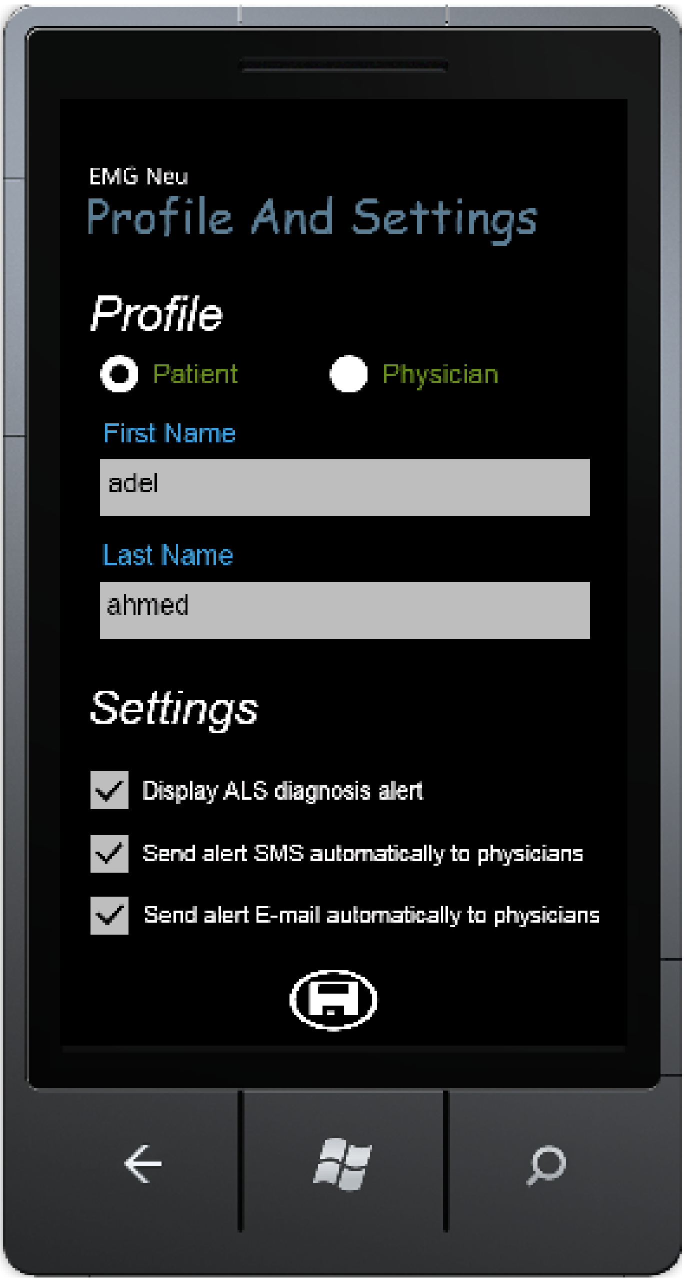

Figure 2. Profile and Settings Module Screenshot

(b) Physician and Patient data module

This module is for both the patient and the physician. Though this module, the patient can save his physician communication data in the application so that the application can send alert to the physician according to his data. Also the physician can save his patient communication data in the application so that the physician can send recommendations to the patient through the application according to this data. As a feature, the patient can call his physician and the physician can call his patient through this module. Figure 3 shows screenshots of physician and patient data module.

Figure 3. Physician and Patient data module Screenshots

(c) Signal Displaying and Alert Module

This module is for the patient and it is the main module in the application. It will be responsible for displaying real-time EMG signal of the patient so that the patient will be able to track his own neuromuscular condition based on EMG signal. This module is also responsible for EMG signal analysis, features extraction and signal classification phases. As a result from the classification phase, if ALS disorder has been detected from the displayed signal the patient will be informed with an alert, and a message and an email will be sent to his physician according to the physician data saved in physician data module. The alert will be displayed and message and email will be sent to the physician according to the patient settings. Screenshots of this module are shown in Figure 4.

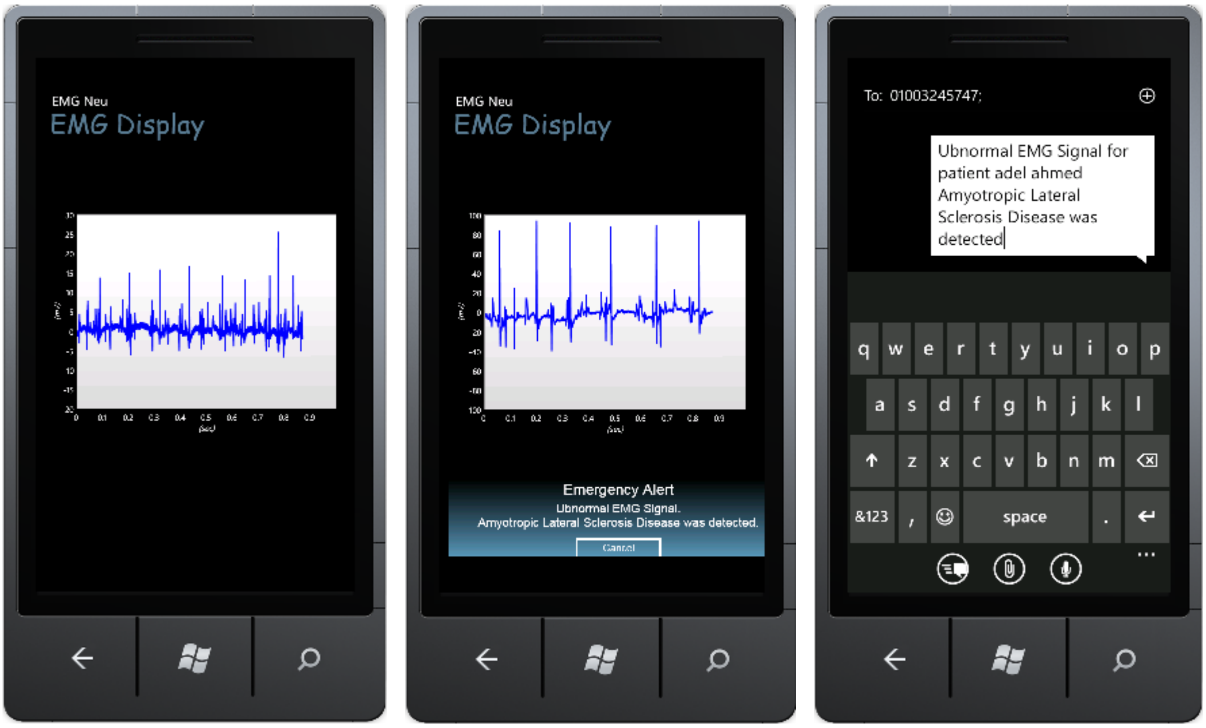

Figure 4. Signal Display and Alert Module Screenshots

(d) Sending Recommendations Module

This module is for the physician. After the physician receives the alert message or email that tells him that the application has detected ALS disorder from the EMG signal of his patient, he may certainly need to send recommendations to the patient to help him monitoring his disease until he could visit and check him. This module enables the physician to send recommendations through a message or an email to his patient according to patient communication data saved in the application. Figure 5 shows screenshots of this module.

Conclusion

Amyotrophic lateral sclerosis is one of the most common neuromuscular disorders worldwide. It is a progressive motor neuron disease which in a later stage its patients may become totally paralyzed. As a result, the patients always need to track their health conditions and response to any emergency events as soon as possible. EMGNeu mobile health application developed in this research will enable patients to track and monitor their neuromuscular conditions based on EMG signal. The application is consisted of four modules: profile and settings module, patient and physician data module, signal displaying and alert module and sending recommendations module. The main and the most important module in the application is signal displaying and alert module. In this module patient EMG signal is displayed and ALS disorder is detected from the signal. ALS detection system was developed through three phases. At first the signal is analyzed using discrete wavelet transform. Then, RMS feature is extracted from the analyzed signal and used as input feature to the classifier. Finally, SVM classifier with RBF kernel function is used in classifying the signal and detecting ALS disease. If ALS was detected from the signal, this module displays an alert to patient and sends another to the responsible physician. The used SVM classifier approved its efficiency in ALS diagnosis with a high accuracy of 98%.

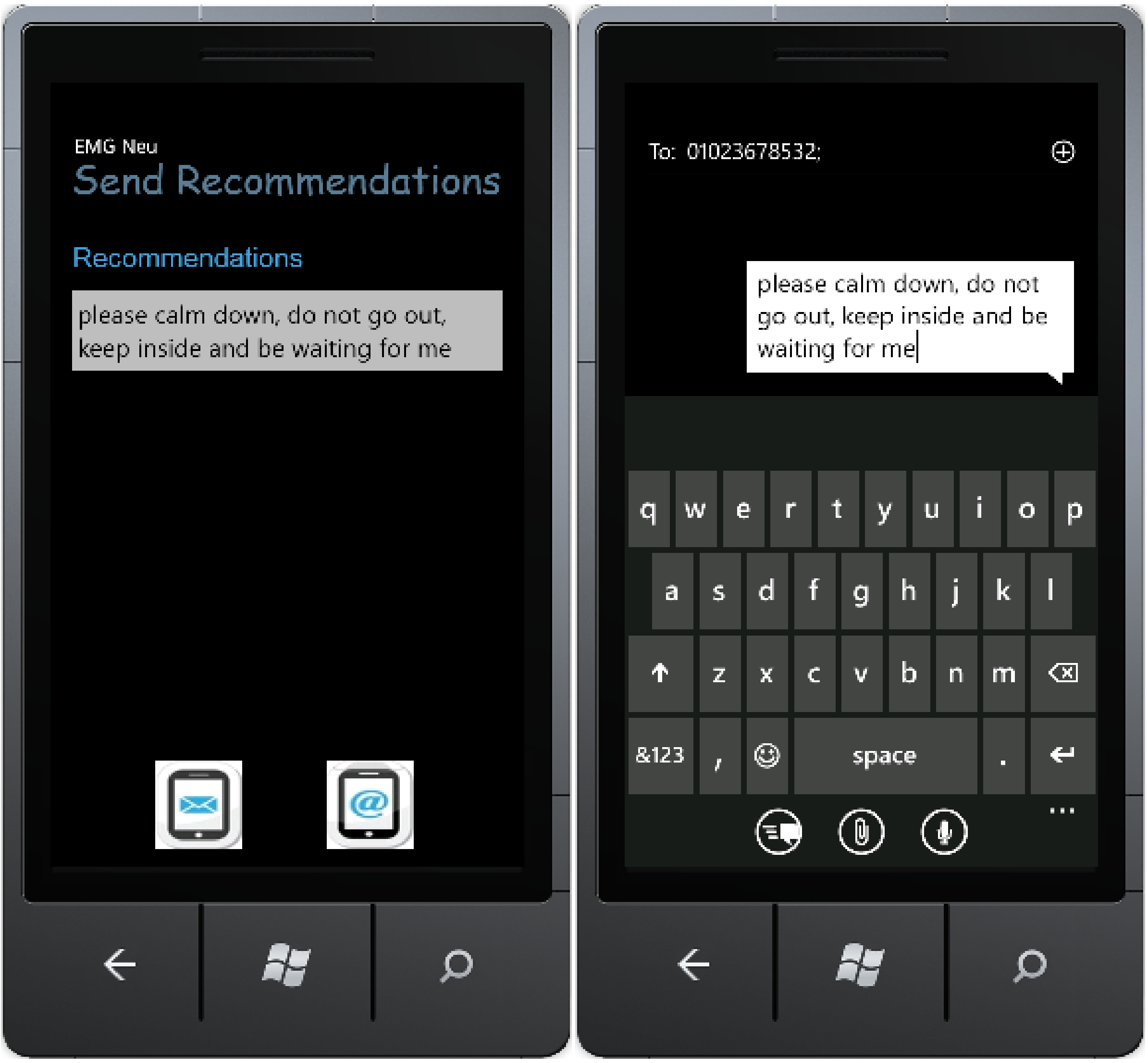

Figure 5. Send Recommendations Module Screenshots

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