Non-invasive Diabetes Detection using Facial Texture Features Captured in a Less Restrictive Environment

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Abstract— The prevalence of Diabetes Mellitus (DM) worldwide has risen dramatically with 1 of 3 deaths happening in Western Pacific region according to the 2017 report of International Diabetes Federation. The Philippines ranks 5th in WP with the most cases of diabetes. Local experts and IDF estimate that half of the people with diabetes are unaware they have it and will likely remain undiagnosed. Conventional ways to detect if a person has diabetes are often invasive and painful such as puncturing fingers for blood sample. Though non-invasive DM detection techniques have gained consideration in more analysts, presently they have restrictive set-up for image capture. This paper explores the performance of using mobile device as a convenient tool for image capture of DM and healthy dataset for non-invasive detection using facial block texture features and Gabor filter. Filipino participants that undergo regular check-ups for diabetes monitoring were chosen within the age inclusion criteria of 20 to 79 years old in which surveys for Philippines assessed the occurrence of diabetes to be most prevalent according to IDF and World Health reports. For each subject, a mobile device 12mp and 7mp cameras were used to take the photo placed 30 cm in front of the face under normal lighting condition to ensure full coverage and avoid unnecessary background. A ratio of 70:30 training to testing set was maintained and extracted facial blocks were classified using SVM and KNN. A total of 100 images from each camera were captured, preprocessed, filtered and iterated to compare performance of data. 90% accuracy, 93% sensitivity and 93% specificity were achieved for 12mp with SVM. For the 7mp camera, an accuracy of 80% using SVM and 93% sensitivity using KNN were achieved after increasing the predictors obtained for classification.

Index Terms— Diabetes Mellitus, Gabor Filter, Texture Features.

I. INTRODUCTION

The major cause of fatality and disability worldwide are chronic diseases. Considered among the most common chronic disease is diabetes. According to the WHO report in 2016, about 1.6 million deaths are directly attributed to diabetes each year. The IDF Diabetes Atlas 8th Edition 2017 estimated 158.8 million adults living with diabetes in Western Pacific aged 20-79 have about 54% cases undiagnosed.

Diabetes Mellitus is a chronic, metabolic disease characterized by elevated levels of blood glucose. Insulin is the hormone that regulates glucose to get into the cells for energy. The body does not make insulin with type 1 diabetes. With type 2 diabetes most common in adults, the body has insulin deficiency or insulin resistance. Too much glucose in the blood consequently affects and damages the heart, eyes, kidneys, or nerves.

In the Philippines, diabetes is among the ten fatal diseases as of 2017 survey. The country ranks 5th in Western Pacific based on the IDF Atlas 2017 with 3.9 million diabetic Filipinos out of 65 million. The total people worldwide with diabetes as predicted by health professionals for 2025 has already been reached as early as 2016.

Access to affordable treatment including insulin, is critical to the survival of people with diabetes. The current treatments available to diabetics are usually inconvenient and costly. Blood tests can show if a person has diabetes. Traditional DM diagnostic methods draw blood from the patient such as A1C test, FPG test, OGTT test and 2-hPG test. All four techniques are invasive and cause pain as well as discomfort [4]. The common method to detect diabetes is Fasting Plasma Glucose test that usually takes up to 12 hours and requires blood sample to be analyzed taken from a fingertip [2][5].

Currently, with the staggering increase of diabetic patients, a significant need for affordable and stress-free detection method for important markers of diabetes rises. Painless and non-invasive way to detect DM is a promising technology reducing the lengthy and expensive cycles of visiting hospitals. Disease intervention for pre-diabetes is another solution. Researchers have found out that DM can be classified through the analysis of facial blocks [1]. However, with the restrictive set-up for image capture, processing facial blocks takes time. With fewer literatures available, DM detection using facial texture features has not been much explored [4].

This study aims to build a non-invasive diabetes detection and explore the performance of using mobile device as convenient tool for image capture.

1) To build a dataset of captured facial images from a less restricted environment using mobile phone.
2) To implement facial texture extraction using Gabor filter and classify using Support Vector Machine and K-Nearest Neighbors.
3) To measure and compare the performance of the non-invasive system with existing methods in terms of Accuracy, Sensitivity and Specificity.

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II. RELATED WORKS

A. Image Acquisition and Dataset

Fig. 1. Designed device for facial image capture [17]

For image acquisition, the set-up for a particular image capture device detailed by B. Zhang, B.V. K. Vijaya Kumar, and D. Zhang [17] has been adopted by majority of the researches on DM detection based on facial features. Their dataset of 426 images with 142 Healthy samples and 284 DM samples has been used in other studies.

The researchers [4], [17] used a black box shown in Fig. 1 as image capture device with a centered 3-CCD camera and lamp on each side. Each subject was noted to individually place their head on the chin rest facing the camera. 45◦ angle between the incident and emergent light was followed from the Commission Internationale de l'Eclairage [7].

Similar set-up was implemented in the studies of B. Zhang and P. Zhang [2], S. Ting and B. Zhang [12], B. Zhang, T. Shu, and Y.Y. Tang [13]. In the study of Pavana S., and Dr. Shailaja K. [6], the facial image dataset was comprised of 40 images with 20 DM and 20 healthy. 70:30 ratio for training and testing was observed.

B. Facial Blocks and Image Pre-processing

As for the facial blocks, researchers B. Zhang and P. Zhang [2] extracted four blocks from the captured facial image after pre-processing. Block F on the forehead, Block N on the bridge of the nose, and Blocks R and L below the right and left eyes respectively were analyzed for DM detection.

This study used the specific facial regions mentioned by T. Shu, B. Zhang, and Y. Y. Tang [4] as reference on deciding which facial blocks to focus. Four facial blocks were extracted from each facial image representing the main regions from TCM. Based on the different regions of the face, the status of the internal organs can be determined according to Traditional Chinese Medicine (TCM) [7][8][9].

Pre-processing of the facial images is important according to A. Sajjanhar, and A.A. Mohammed [11] in order to better discriminate the features to be obtained. Raw captured images may include non-facial regions so image cropping is performed. Cropping often results images with varying sizes so image resizing is also applied.

C. Facial Texture Feature Extraction

S. Ting and B. Zhang [12] extracted texture features from facial blocks using Gabor filter to represent the samples. Each block was described by texture value. First, they generated a custom-sized 2-D Gabor filter bank comprised of 40 filters. Using the filter bank of five scales and eight orientation combination, the texture features of a facial image were calculated resulting to a column vector with one texture value for each filter. The computed mean vector was assigned the texture value of the facial block. Each filter was convolved with a facial block to produce a response which is the texture value or the mean of all its pixels. By taking the mean of all forty texture values, the final texture value of a facial block was calculated.

B. Zhang, T. Shu, and Y.Y. Tang [13] proposed Improved Patch Ordering (IPR) and Simplified Patch Ordering (SPR) to detect 100 DM vs. 100 Healthy samples using Gabor filter to extract texture features from four facial blocks.

Pavana S., and Dr. Shailaja K. [6] extensively studied the effects of texture features extracted using Gray Level Co-occurrence Matrix (GLCM) on detecting DM. Contrast, correlation, energy, Haralick's features and homogeneity were extracted. 20 DM facial images and 20 Healthy facial images comprised the dataset.

T. Shu, B. Zhang, and Y. Y. Tang [4] covered four texture feature families in comparing the effects of different texture feature extractors in detecting DM. The four texture feature families were model-based, signal processing-based, statistical, and structural texture feature [10]. According to their experiments, statistical and signal processing base texture feature families gave better outcomes in detecting DM than structural and model based. The researchers iterated that statistical feature includes Gray-level Co-occurrence Matrix, Image Gray-Scale Histogram, and Local Binary Pattern. On the other hand, signal based includes Gaussian, Gabor Filters, and Steerable.

D. Classification and Performance Parameters

Shown in the Table 1 is a summary of recent studies using facial texture features for non-invasive detection of DM. Various algorithms and techniques to detect DM were also extensively reviewed by M. A. Kadam, K. S. Kadge, S.S. Mane, S. P. Naikwadi, and V. C. Kulloli [3], [12], [13], [17].

Table 1. Performance of previous DM Detection Methods

Study	Year	Features	Techniques		Accuracy	Sensitivity	Specificity
[6]	2017	Texture	GLCM	SVM	91.67	100	83.33
[4]	2017	Texture	IGH	k-NN	93.62	99.64	86.18
				SVM	99.02	99.64	98.26
			Gabor Filter	k-NN	96.18	98.66	93.12
				SVM	83.72	87.90	78.44
[1]	2016	Color, Texture	RGB to Lab, Gabor Filter	k-NN	94.28	90.32	92.50
				SVM	97.14	93.75	95
[2]	2016	Color	SRA - OMP		99.06	99.65	97.93
[14]	2016	Color	Non-base	SVM	82.77	86.44	79.10
[13]	2015	Texture	Gabor Filter	IPR	99.38	100	98.75
[12]	2014	Texture	Gabor Filter	k-NN	99.82	99.64	100
				SVM	99.82	99.64	100
[17]	2014	Color	SRC		97.54	95.77	100

III. METHODOLOGY

Diabetes Mellitus was detected through the analysis of texture features of three facial blocks from each of the images of 50 DM and 50 healthy participants. Image pre-processing was done prior to facial blocks feature extraction. Shown in Fig. 2 is the framework of the implemented method. Training and testing set of the database undergo the same stages for classification.

A. Conceptual Framework

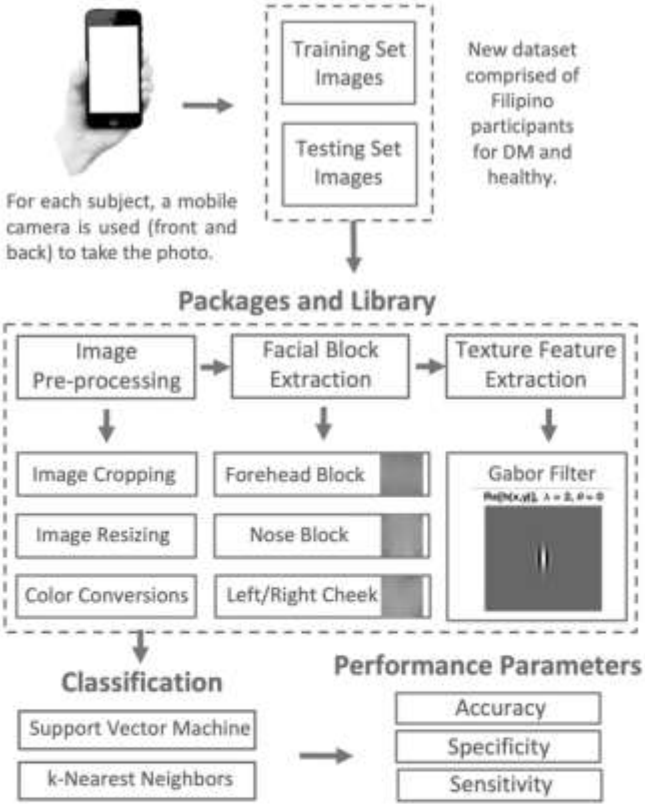

Fig. 2. Non-invasive DM Detection System

B. Image Acquisition and Dataset

The dataset comprising of Filipino diabetic and healthy participants were obtained from Butuan City, Cagayan de Oro, Cebu, Iligan City and Quezon City with respective contacts that were photographed in a less restrictive environment. Participants were chosen as individuals that undergo regular check-up and regular hospital visit for health status and diabetes monitoring. Cross-validation was done with their records of maintenance and diabetes diagnosis. The ratio of 70:30 for training and testing implemented in the previous studies was maintained.

For each subject, the 12mp front camera and 7mp back camera of a mobile device were used to take the photo for comparison. The device was placed 12 inches in front of the face under normal lighting condition as detailed in Fig. 3, to ensure full coverage and avoid unnecessary background. Image capture was done during daytime either outdoors or indoors with considerable amount of outside light from open spaces. Lighting condition maximized was from natural sunlight considering far flung areas which do not have electricity and where majority of undiagnosed cases due to lack of access to proper DM detection is widespread.

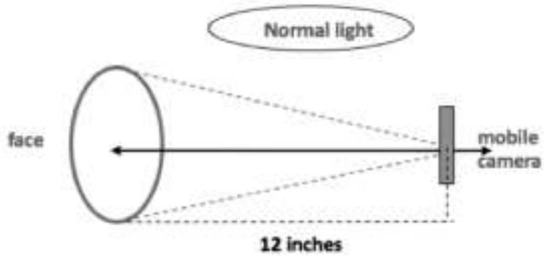

Fig. 3. Less restrictive image capture set-up

The camera used for capturing the facial images was an Iphone 7 model featuring wide color display (P3) and 12-megapixel back camera that has optical image stabilization reducing handshake and motion. The 7-megapixel front camera has an auto image stabilization.

C. Facial Regions and Image Pre-processing

All four regions mentioned in TCM were extracted with 3 facial blocks specifically F, N, R or L included in the analysis per image. Blocks detailed in Fig.4 were obtained from each of the dataset. The chin region under the lips was not considered in this study. Also, subjects of the database have no facial hairs for males and no make-up for female participants. Each image captured in truecolor was converted into grayscale for the Gabor filter. Forehead, nose, left cheek and right cheek blocks were all resized to 64 x 64. Before feature extraction stage, all facial block images were made uniform in size. Listed below are image pre-processing techniques performed to better discriminate the texture features obtained.

- Image cropping – to avoid non-facial regions and to keep the desired facial area.
- Image resizing – for uniformity of the facial image size which may have been varied due to image cropping.
- Color conversion – converts original RGB (truecolor) image into grayscale for Gabor filter processing.

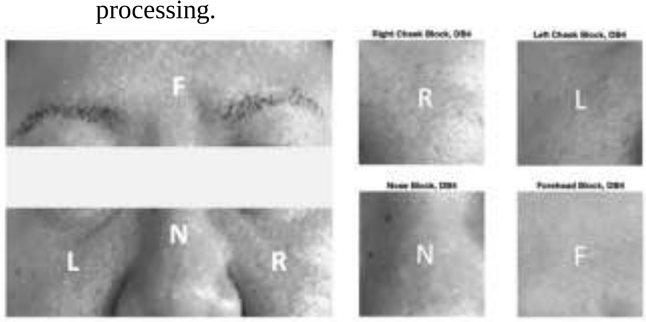

Fig. 4. Extracted facial blocks

D. Texture Feature Extraction

For facial texture feature, a method from signal processing base texture family was incorporated in the analysis specifically Gabor filter, an algorithm for edge detection. Gabor filter was characterized with varying lambda λ (wavelength) and theta values θ (orientation) at different degrees of interval to find the best parameters for texture extraction of the Filipino dataset with images taken in a less restrictive environment using a mobile device. The final Gabor implemented has a total of 40 GFs in the filter bank with combination of 5 wavelengths, minimum value at 2.828 incremented in 0.5 multiples and eight orientations, starting from 0 to 360 degrees in intervals of 45 degrees.

Gabor filter frequency and orientation representations are likable to the human visual system [5]. Generally, 2-D Gabor filter is a Gaussian kernel multiplied by a sinusoid and has parameters namely wavelength, orientation, aspect ratio and bandwidth. Wavelength controls the width of the strips of the function. Orientation governs the Gabor envelope orientation. The height of the function depends on the aspect ratio while the overall size of the Gabor envelope varies with the bandwidth.

As mentioned in the study of S. N. Padawale, and B. D. Jadhav [1] equation 1 gives the mathematical equivalent of the filter where $x' = x.\cos\theta + y.\sin\theta$, $y' = -x.\sin\theta + y.\cos\theta$, λ is the wavelength, σ is the variance, θ is the orientation, and γ is the aspect ratio of the sinusoidal function. Multiplication of variances and orientation gives the total of 2-D GFs in GF bank.

$$G((x,y)) = \mathrm{Exp}\left(\frac{x'^2 + \gamma^2 . y'^2}{-2\sigma^2}\right)\cos\left(2\pi\frac{x'}{\lambda}\right) \quad (1)$$

$$R_k(x,y) = G_k(x,y) * im(x,y) \quad (2)$$

In the equation 2 above, im (x, y) is a block of facial image, * is 2-D convolution. The texture value of each response is the mean of all of its pixels. The final texture value of a facial block can be calculated by taking the mean of all texture values. For this study, two different sets of texture features were extracted from each facial block as predictors for classification. For Method 1, the mean texture value was calculated similar to previous studies. For Method 2, a total of 6 texture features were obtained from each block namely mean, variance, kurtosis, std, entropy, and skewness. Every facial sample was represented by the combination of texture features from each of the three facial blocks.

E. Classification and Performance Parameters

DM and Healthy images were classified with k-Nearest Neighbors and Support Vector Machine using the texture features extracted from the facial blocks. 70% of the dataset was used for training classification and the remaining 30% was utilized for testing. All three measure of performance listed below were computed in this study.

Accuracy- given by the formula in Eq. 3 is the measure of correctly classified samples in its respective class to the total dataset samples.

$$Accuracy = \frac{T.P. + T.N.}{T.P. + F.P. + T.N. + F.N.} \quad (3)$$

where: T. P. - True Positive   T. N. - True Negative
F. P. - False Positive   F. N. - False Negative

Sensitivity - also known as recall or the true positive rate is given by formula in Eq. 4.

$$Sensitivity = \frac{T.P.}{T.P. + F.P.} \quad (4)$$

Specificity – also known as the true negative rate is defined by the formula in Eq. 5.

$$Specificity = \frac{T.N.}{T.N. + F.N.} \quad (5)$$

IV. RESULTS

A. Filipino Dataset

Listed in Tables 2 and 3 below are the demographic details of the diabetic and healthy dataset from the different provinces in the Philippines.

Table 2. New diabetic dataset with Filipino participants

Place of Residency	Gender		Age	Yrs. since Diagnosed	Type of Diabetes	Maintenance
	F	M				
Butuan City	11	12	22-70	1-20 yrs	Type 2, A	Glucovance, Galvus Met, Glimepiride, Globitur, Insulin, Metformin,
Cagayan de Oro City	3	6	30-59	1-10 yrs	Type 2	Galvus Met, Insulin, Metformin,
Cebu City	3	2	30-70	8-40 yrs	Type 2	Diamicron, Genovia, Metformin, Zyrova
Iligan City	7	5	52-87	2-34 yrs	Type 1-2	Diamicron, Galvus Met, Globitur, Insulin, Metformin, Minidiab, Tradjenta
Quezon City	1		40-49	5 yrs	Type 2	Metformin

Table 3. Non-diabetic dataset with Filipino participants

Place of Residency	Gender		Age Range					
	F	M	20-29	30-39	40-49	50-59	60-69	70-79
Butuan City	4	1	4	1				
Cagayan de Oro City	4	2	5	1				
Cebu City	21	7	7	9	4	6	2	
Iligan City	1	4	5					
Quezon City	3	3	5	1				

B. Performance Parameters

The highest value for AUC recorded is displayed in Fig. 5 with the respective ROC curve. This was obtained from the 12mp back camera using Method 1-SVM. Method 2 for this resulted to a near AUC=0.90.

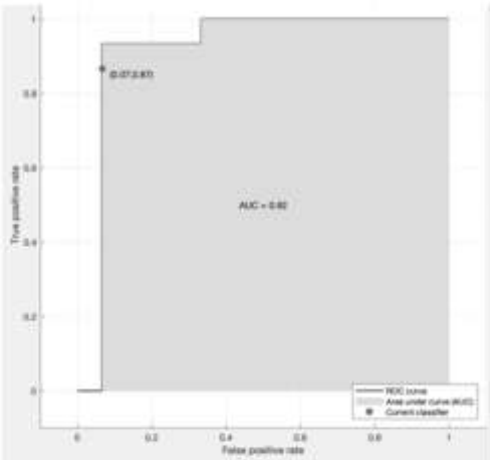

Fig. 5. AUC for Back Camera using Method1, SVM

Performance of the back and front cameras in terms of Accuracy, Sensitivity and Specificity are shown in Fig. 6 to Fig. 8 respectively. For the front camera, Method 2 increased overall performance of SVM while increased in Accuracy and Sensitivity for KNN was noted. Extracting more predictors increased the SVM sensitivity for the 12mp.

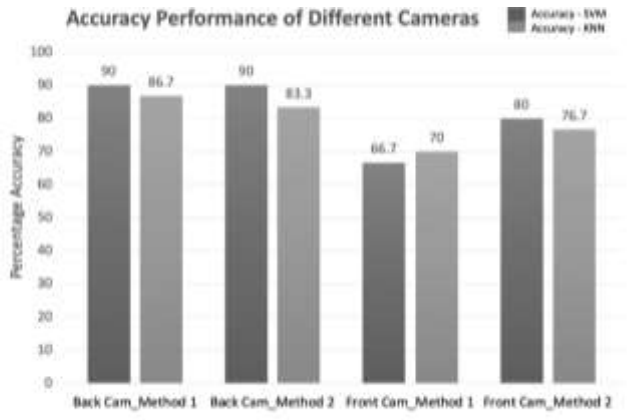

Fig. 6. Accuracy Performance of 12mp and 7mp

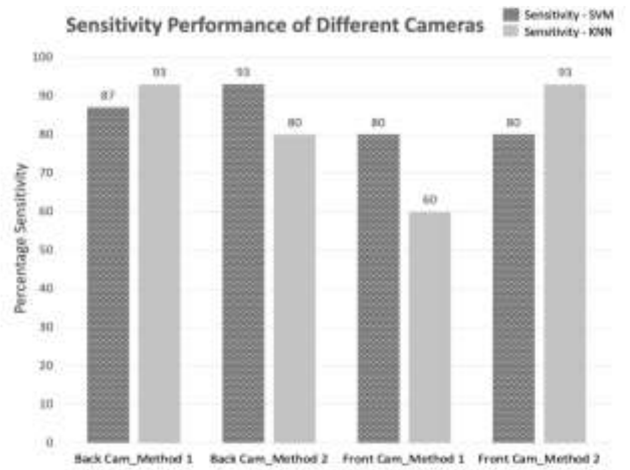

Fig. 7. Sensitivity Performance of 12mp and 7mp

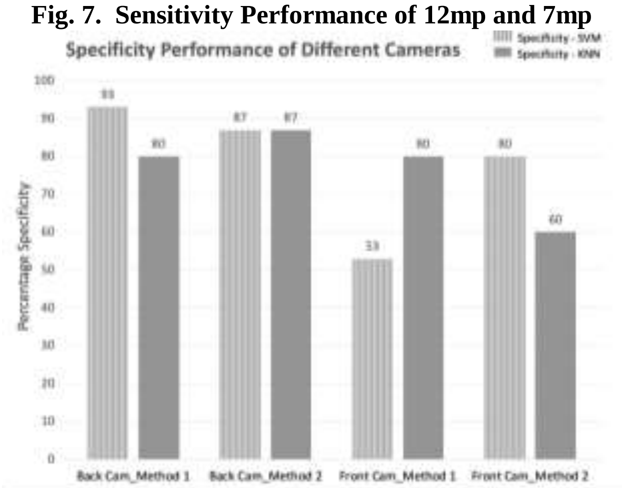

Fig. 8. Specificity Performance of 12mp and 7mp

Table 4. Performance Summary of Two Cameras

		Accuracy		Sensitivity		Specificity	
Camera	Method	SVM	KNN	SVM	KNN	SVM	KNN
Back Cam	Method 1	90%	86.70%	87%	93%	93%	80%
	Method 2	90%	83.30%	93%	80%	87%	87%
Front Cam	Method 1	66.7%	70%	80%	60%	53%	80%
	Method 2	80%	76.7%	80%	93%	80%	60%

It can be observed from the summary in Table 4 that obtaining more predictors potentially increases performance with minimal trade-off. May this serve as basis for improving the system to make use of mobile device as convenient tool for DM detection. Improving pre-processing is also suggested.

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