Vitamin Deficiency Detection Using Image Processing and Neural Network

Introduction

In the realm of healthcare, early detection of vitamin deficiencies plays a crucial role in preventing a wide range of health issues. Our project, **"Vitamin Deficiency Detection Using Image Processing and Neural Network,"** is designed to revolutionize the way we identify and address these deficiencies. This innovative project harnesses the power of artificial intelligence and image analysis to provide a cost-effective, accessible, and non-invasive method for diagnosing vitamin deficiencies.

Project Objective

The primary objective of our project is to develop a mobile application that empowers users to identify potential vitamin deficiencies by capturing images of specific body parts, namely the eyes, lips, tongue, and nails. The application will not only recognize deficiencies but also offer tailored recommendations for addressing these deficiencies, promoting better health and nutritional awareness.

Scope of Work

Our project involves various key components:

- **Symptom Analysis & Literature Review:** We have conducted extensive research to establish a connection between known symptoms and corresponding vitamin deficiencies, particularly in the tongue, lips, nails, and eyes.
- **Neural Network Training and GUI:** We've employed Convolutional Neural Networks (CNN) to recognize these symptoms and created an intuitive graphical user interface for image capture.
- **Fuzzy Membership Function and Defuzzification:** We've implemented a Mamdani-based Fuzzy Logic Membership Function to assess the confidence levels of extracted features and to suggest nutritional sources for deficiencies.

Methodology

To achieve our objectives, we have adopted a well-defined methodology:

1. **Data Collection:** We gathered a substantial database of images displaying symptoms and deficiencies for training our neural network.
2. **Mobile Application Development:** We've created an Android application with a user-friendly interface for image capture and analysis.
3. **Fuzzy Logic Implementation:** Using MATLAB, we developed a Fuzzy Inference System to interpret image analysis results and provide recommendations.

Expected Outcomes

Upon successful completion of the project, we anticipate the following outcomes:

- A user-friendly mobile application capable of detecting vitamin deficiencies based on captured images.
- Enhanced nutritional awareness among users.
- Provision of specific recommendations for addressing identified deficiencies.
- The potential for early detection and prevention of health issues related to vitamin deficiencies.

Significance and Innovation

Our project stands out due to its innovative approach to vitamin deficiency detection. By utilizing image analysis and AI, we aim to empower individuals to take charge of their health. The application's non-invasive nature and accessibility make it a unique and impactful solution in the field of healthcare.

Conclusion

"Vitamin Deficiency Detection Using Image Processing and Neural Network" is an exciting project that leverages cutting-edge technology to address a pervasive global health issue. We look forward to contributing to the advancement of healthcare by providing a practical and accessible tool for vitamin deficiency detection and nutritional awareness

Vitamin Deficiency Detection Using Image Processing and Neural Network

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***Abstract*— In this paper, a cost-free Artificial Intelligence-based application for smartphones built to detect vitamin deficiencies in humans using pictures of specific body organs is introduced. Recent vitamin deficiency detection methods require costly laboratory analysis. A wide spectrum of vitamin deficiencies can show one or more visually distinguishable symptoms and indications that appear in multiple locations in the human body. The application provides individuals with the capability to diagnose their possible vitamin deficiencies without the need to provide blood samples through the analysis of photos taken of their eyes, lips, tongue, and nails. The application then suggests a list of nutritional sources to fight the detected deficiency and the expected complications through nutritional micro-correction. The intelligent software was trained to distinguish and differentiate vitamin deficiencies with high confidence from imagery inputs of the selected body parts that are known to show different symptoms in terms of changes in the tissue's structure when the human body suffers a nutritional deficit. The platform also allows medical experts to assist in improving the range of detection and accuracy of the application through the contribution and verification of visual data of their patients allowing for more refined image analysis and feature extraction capabilities with the potential to surpass human's ability to diagnose medical conditions. This application is a useful tool for people to overcome a global problem that affects millions of people worldwide mainly as a result of inadequate nutritional awareness, and it will help healthcare workers in the long term in obtaining more accurate diagnoses.**

Keywords— Vitamins, AI, Deficiency, Smartphone, Diagnosis

I. INTRODUCTION

Vitamin deficiency underlines hundreds of health issues presented in our daily life, in which many health problems arise from the failure in acquiring the necessary spectrum of vital minerals and nutrition [1][2]. It is difficult to keep track of our nutritional needs accurately, especially if individuals are not aware of the type of deficiency they might be holding without medical consultation. Over 2 billion people worldwide suffer from vitamin deficiencies [3]. More than 1.2 billion individuals are Zinc deficient and half a million of them die each year. Similarly speaking, over 100,000 people die due to Anemia caused by iron deficiency. Locally, more than 90% of the UAE population suffers from deficiencies in a spectrum of vitamins. Statistics acquired on American soil show that more than 92% of the population is suffering from at least one mineral or vitamin deficiency, even though the entire country is not dealing with any sort of starvation crisis. With easily accessible cheap processed junk foods available everywhere, nutrient-rich foods are considered financially costly, and instead, they became more of a symbol of luxury rather than being the standard of daily food intake.

Researchers have found that the soil itself is deficient in micronutrients. In 2003, Canadian researchers compared the data of vegetable nutrient content to data from 50 years ago to find that the mineral content of cabbage, lettuce, spinach, and tomatoes had depleted from 400 milligrams to less than 50 milligrams which shows a regressive pattern of nutrient's natural availability. Even with the presence of a perfect diet for consumption, the odds are that something is missing. 50% of Americans are deficient in vitamin A, vitamin C, and magnesium, while 70% of elderly Americans and 90% of Americans of color are vitamin D deficient [4]. Earlier this year, a survey was conducted on a sample of 100 university students asking them if they were aware of having vitamin deficiency, 67% of them answered with a "no". while the sample size of this limited study is not sufficient to represent the population, but it may give an estimation of the actual status of social awareness.

II. METHODOLOGY

A. Symptom Analysis & Literature

First, a medical and pathological study was carefully conducted to build a relationship between known symptoms and their corresponding vitamin deficiencies on a selected spectrum of visually distinguished attributes that are known to be caused by the inability to acquire the necessary amount of essential nutritional elements. Specific body parts were chosen as they are known medically to show changes in texture, shape, color or appearance when an insufficiency in one or more of the essential vitamins is presented: the tongue[5][6][7], the lips [8][9], the nails [10][11][12][13][14] and the eye [15] as shown in Table. 1. A database including collected photos showing these symptoms has been constructed to prepare them for analysis using Machine Learning.

By taking an example of vitamin C deficiency and its associated symptoms, the relation between cause and effect can be illustrated properly. All organs in the human body are

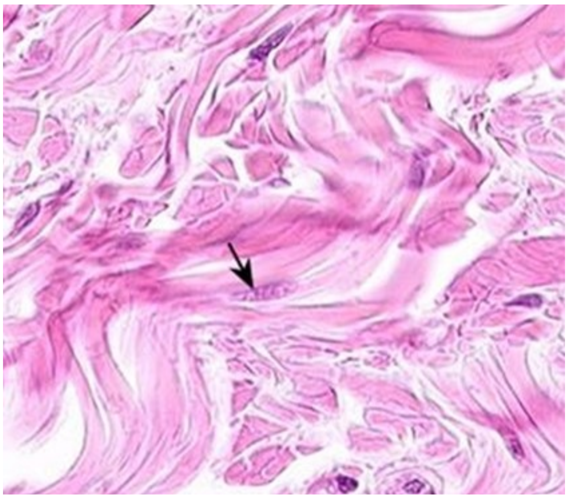

Fig 1. Magnification of Connective Tissue Taken from Human Lips Showing Fibroblast and Elastic Fibers Synthesis.

Table 1. Symptoms and Their Corresponding Deficit Vitamins.

Tongue	Deficiency
Smooth Texture	B6 | B12 |Iron
Red Color	B12 | Iron
Glossitis (White patch)	B2 | B3 | B12
Mouth Ulcers	B12
Lips	
Cracked	B1| B2 | B3 | B6
Shiny Red	B2 | B3
Angular Cheilosis (Cracked Crone	B1 | B2 | B3 | Iron
Nails	
Spoon-Shaped	C | B7 | B9
Beau's lines	zinc | B7 | B9
Leukonychia (white spots)	calcium | zinc | B7 | B9
cracked , dry & brittle	A | C | B7 | B9 | B12 |
Vertical Ridges	Magnesium | Iron | B7 | B9 | B12 |
Eyes	
Redeness	A | B | B2 | B6

held together in their unique form, shape, and position by what is medically referred to as Connective Tissues. Lips and nails are two of the sites to show the presence of this type of tissues as it is what gives them a firm and healthy texture and appearance. The elasticity of the firm texture of these organs is established by Elastic Fibers, in which they are produced by specialized cells called Fibroblasts (Fig. 1). For fibroblasts to synthesize and repair elastin, they require Ascorbic Acid; which is wildly known as vitamin C. The insufficient presence of vitamin C disrupts the process of elastin's production, resulting in dryness and weakness of the tissue's structure that emerges in the form of cracked lips, Angular Cheilitis (cracked sides of the mouth), and cracked nails.[16][17][18]

B. Neural Network Training and GUI

A simple graphical user interface (GUI) was designed to prompt the user to capture photos of the mentioned organs. An intelligent software was built to acquire, process, analyze and extract the features of interest from these photos. To create a platform capable of this task, Machine Learning algorithms were used to train a Neural Network for symptoms detection. Since Fully Connected Neural Network cannott be used to perform analysis on A x B x 3 colored images (in which A x B is pixel density and 3 is the number of color channels in matrix representation) due to the huge number of weights created in the first neural layer which will slow down the training process, Convolutional Neural Network (CNN) is used to train the neurons due to its effective efficiency [19]. Arrays with different pixel weights representing the color scale between -1.00 and 1.00 are used as filters by convolved multiplication across the target photo array. The summation then is divided by the total number of pixels in the filter to produce an output weight value for the next convolutional layer. Similarly speaking, the Sigmoid Squishification Weight Activation Function was replaced with Rectified Linear UNIT (ReLU) to asses with the speed and accuracy [20] of the propagation process by removing the negative values that represent dissimilarities between pixels. A bias can be added to elevate the activation range. The expression of the weighted sum is:

$$a^{(1)} = \sigma\left(W a^{(0)} + Bias\right) \quad .(1)$$

where $a^{(1)}$ is the target neuron of the second layer, $a^{(0)}$ is the source neuron of the input layer, W is the acquired weight of

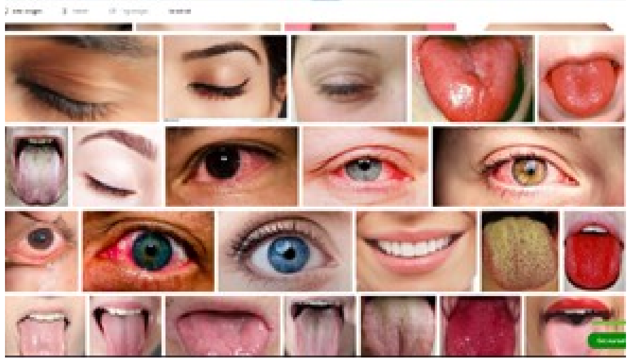

Fig 2. Labeled Symptoms' Database.

sensitivity and σ is the ReLU activation function represented as:

$$f(x) = \begin{cases} \varkappa & if\ \varkappa \geq 0 \\ 0 & otherwise \end{cases} \quad .(2)$$

$$ReLU\ (a) = \max(0, a) \quad .(3)$$

After repeated epochs of convolutional feedforward and backpropagation, filtering and pooling, the arrays shrink into a single list where maxima are calculated at the end of the last epoch of feedforward propagation. When another image is fed and analyzed in the same order, the maxima are then divided by the sum of the previous maximum of the trained iteration to calculate the confidence level out of 1. Because the database contains labeled (tagged) photos of each of the targeted visual attributes and features in the study to be extracted (Fig. 2). Cost Function and Gradient Descent are used at the output layer to provide an accurate and efficient update of weights in a supervised machine learning fashion as the latter directs the final layer toward the best local minima in the backpropagation update [21].

III. Fuzzy Membership Function and Defuzzification

As multiple iterations of the Convolutional Neural Network (CNN) are done using numerous photos containing the targeted attributes in the study mentioned earlier, the confidence level of each extracted feature is fetched and fed in a Mamdani – based Fuzzy Logic Membership Function built using MATLAB. The Fuzzy Logic rules are written in accordance with the strength and commonality of the analyzed visual attributes; in which the deficiency detected in one of the variables gains higher certainty the more it is detected in the other variables and vice versa (Fig. 3) Finally, a separate code will acquire the Defuzzification results to display a list of suggested and updatable nutritional sources of the detected deficient vitamins.

IV. Implementation

Since a large number of pictures containing symptoms is required to train a reliable image feature extraction classifier, and because access to up to date photos of real patients is not possible yet, Cloud Computing Service was used to achieve

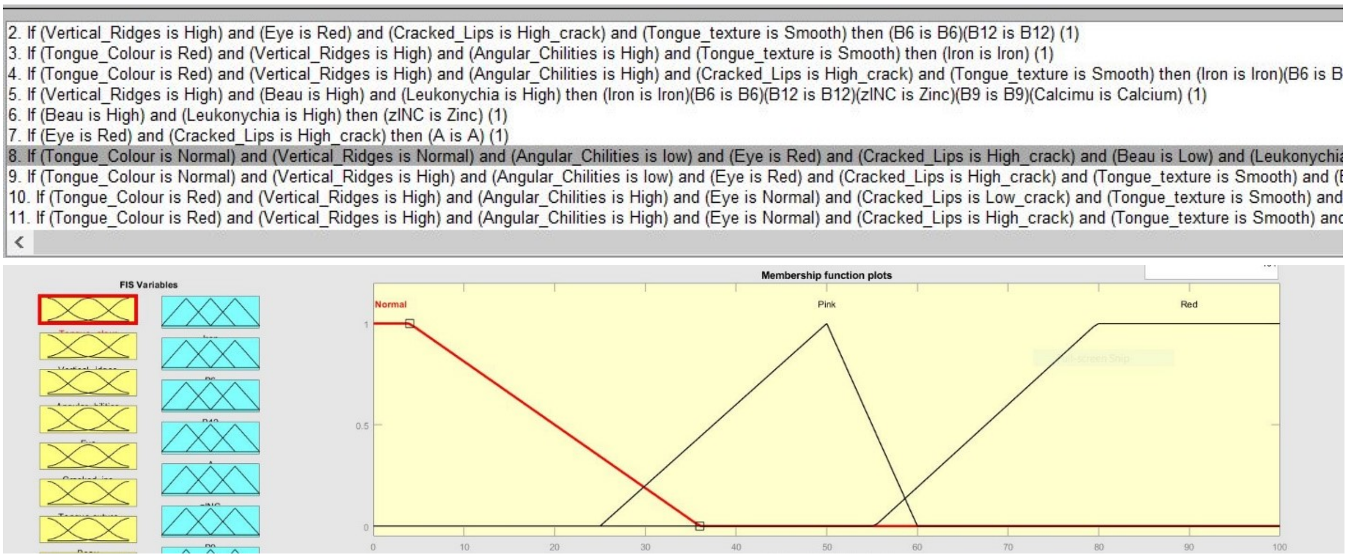

Fig 3. An Example of Implemented Fuzzy Membership Rules (top) and Functions (bottom).

accurate neural training iteration's results in a shorter time than what it would be required for such a big size of data using conventional methods. A TensorFlow format of the trained network was exported in a compact file [22]. A collection of photos of each symptom were carefully selected, tagged and fed to the platform as shown previously in Fig. 2. Table. 2 shows the precision (percentage of identified classifications that were correct) and recall (percentage of actual classifications that were correctly identified) of identification of organs and the symptoms involved. The trained TensorFlow classifier was imported and implemented in an android environment using Android Studio in the form of a mobile application. The greeting page displays Vita-Cam's logo then follows it with instructions on how to use the application with a list of recommendations that must be done before proceeding to take pictures - like removing eyeglasses or nail polish-. The application prompts the user to take four separate pictures of their tongue, lips, eyes, and nails in that sequence. When the user is ready to capture the required images, the software displays a camera interface with a guiding mask and automatically flips between front and back camera depending on the organ. Each picture is saved into a temporary directory for analysis then the results are saved into

Table 2. Neural Training Progress

Tag	Precision	Recall
Tongue	100%	100%
Red Tongue	100%	100%
Eye	100%	83.30%
Nail	94.40%	88.90%
Lips	88.90%	71.10%
Pink Tongue	91.70%	83.30%
Red Eye	83.30%	83.30%
Yellow	66.70%	50.00%
Cracked	66.70%	66.70%
Angular cheilitis	66.70%	88.90%
Vertical Ridges	55.60%	44.40%
White Patch	66.70%	66.70%
Smooth Tongue	55.60%	44.40%
Leukonchia	22.20%	33.30%

a text file to be fed into the fuzzy inference system. Using MATLAB, a Fuzzy Inference system was built to consider confidence rates higher than 75% as high influence weights on Mamdani's center of gravity. The Defuzzification result is processed to display details about the associated deficiencies to the user which is done by the integration of the Fuzzy Logic algorithm in a C++ format using MATLAB Coder, which allows the extraction of the Fuzzy Membership Functions and Inference to a compact C language library or Java. The user is required at the end to answer three questions to assist with the accuracy of the detection.

V. TEST RESULTS

Since the access to real medical data and profiles of patients was not obtained during this testing phase of this research project test photos with symptoms that indicate a selected spectrum of vitamin deficiency were picked from internet resources. The selected symptoms are known to be early indications of vitamin B6, B12, and Iron deficiencies, in which they have been used to verify feature extraction accuracy and precision of the diagnosis. Strawberry tongue (red color), Red eye, Angular Cheilitis (cracked lips) and Beau's lines (vertical ridges in nails) were the presented symptoms in this case. The classifier was able to successfully distinguish these attributes with a high confidence rate shown in Fig. 4. The Fuzzy Logic inference system interoperated the probabilities and concluded the correct diagnosis, then displayed the results as shown in Fig. 5.

The classifier identified the attributes of interest with good confidence. Using triangular and trapezoidal Fuzzy inference functions that are arranged according to medical observational estimations describing the intensity of the variable; the algorithm has successfully matched the expected results of a selected test case of Iron, B6 and B12 deficiencies with an average certainty of 81.7%. Screenshots of the application's interface in Fig. 6 show more tests that were conducted on a volunteer to verify the strength of the trained AI in extracting diverse symptoms. The symptoms obtained indicate non-severe deficiencies in vitamin B2, B3, and B12.

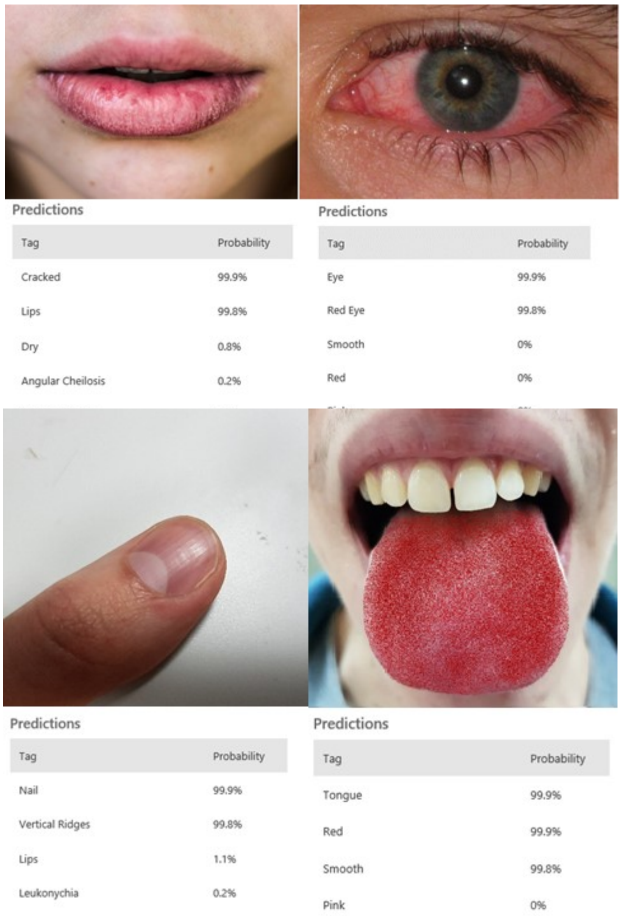

Fig 4. Feature Extraction for Each Parameter.

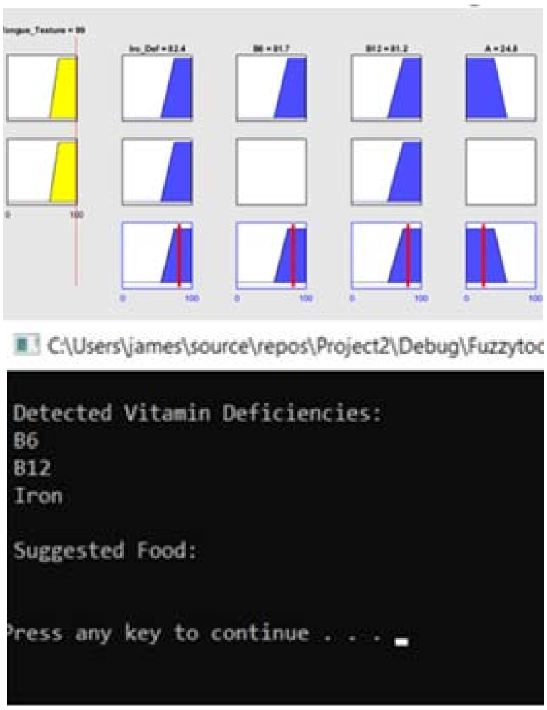

Fig 5. Defuzzification of Input Parameters (top), The Deficiencies Detected in Terms of Confidence Level are: 82.4% Iron, 81.7% B6, 81.2% B12. Final Output of the Detected Deficiencies (bottom).

VI. Discussion and Conclusion

An Android mobile application capable of providing a diagnosis of selected vitamin deficiency spectrum from photos of the user's tongue, lips, eyes, and nails using Artificial Intelligence has been implemented. The application used a combination of Machine Learning to achieve the extraction of certain features and attributes from the images and Fuzzy Logic decision-making algorithm to specify the type of deficiency. After specifying the visual symptoms associated with each deficiency through pathological research, a TensorFlow classifier was trained using a considerable number of labeled images of segmented symptoms for each organ individually with a minimum resolution of 439 x 335 pixels each. The classifier was installed into a simple GUI to provide offline functionality. the Defuzzification Rules of the Fuzzy Membership Functions have been adjusted in accordance with the commonality and the probability of the symptoms and can be updated by admins

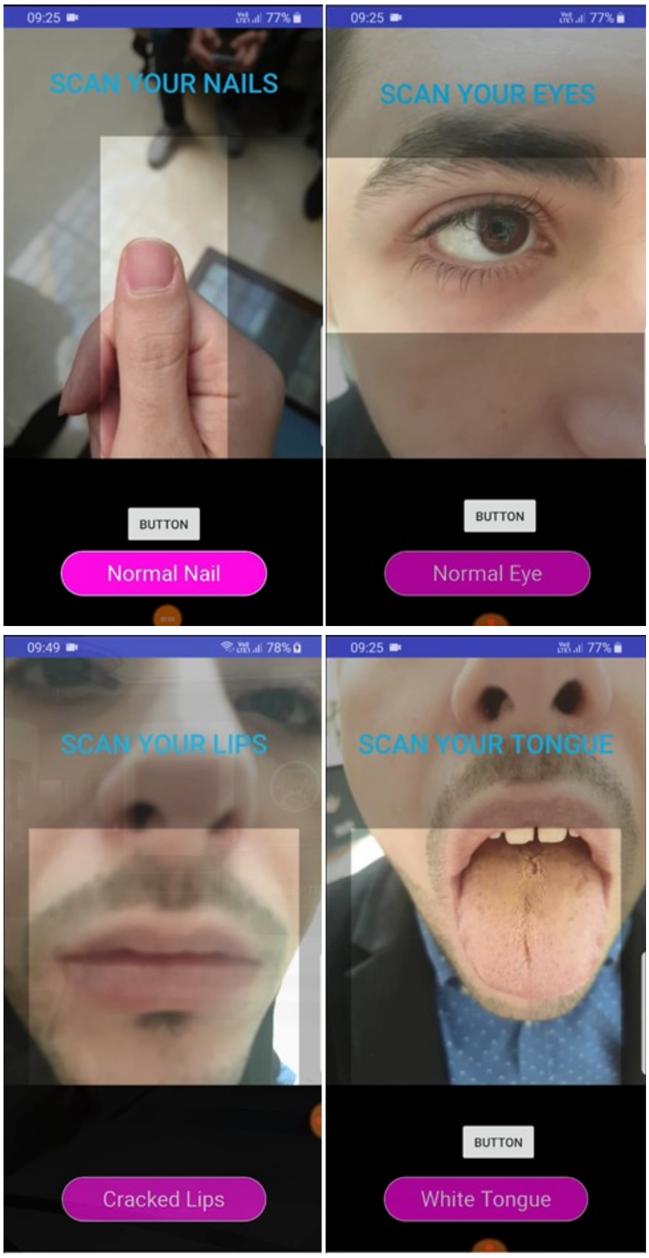

Fig 6. Feature Extraction Test (top) and User's Interface (bottom).

to improve the accuracy of the detection. Another layer of the decision-making algorithm displays a list of nutrients as well as compensational medications and supplementary products.

The approach was verified by associate professors in oral medicine, oral and maxillofacial surgery to be valid and acceptable. The test has shown the correct diagnosis corresponding to the symptoms. However, due to the limited access to images and profiles of cases with vitamin deficiencies, the application was not directly tested on patients.

The application is a new approach that allows self-diagnosis in a short time without the need for blood sample. The accuracy of the diagnosis can be exponentially improved by including more data with the direct contribution from medical practitioners, researchers, and experts through exclusive access to the database. The proposed solution's capabilities are not limited to vitamin deficiencies, but they can be extended to include early detection of other health problems using more resources besides the camera. The application - named Vita-Cam - is not a replacement for medical consultation, but it is a tool designed to boost the community's awareness of their missing nutritional needs and help them obtain a suitable diet, thus preventing further health complications caused by untreated vitamin deficiencies.

REFERENCES

[1] Adult blindness secondary to vitamin A deficiency associated with an eating disorder. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/15850971.

[2] Vitamin a deficiency and clinical disease: an historical overview. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/18806089.

[3] Investing in the future: A united call to action on vitamin and mineral deficiencies. Global Report 2009.

[4] "92% of U.S. Population Have Vitamin Deficiency. Are You One of Them? - the biostation Delray Beach & Miami", *the biostation Delray Beach & Miami*, 2019. [Online]. Available: https://thebiostation.com/bioblog/nutrient-iv-therapy/do-you-have-vitamin-deficiency/. [Accessed: 28- Jul- 2019].

[5] Glossitis with linear lesions: an early sign of vitamin B12 deficiency. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/19231648.

[6] [Clinical manifestations of the mouth revealing Vitamin B12 deficiency before the onset of anemia]. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/12671582.

[7] Atrophic glossitis from vitamin B12 deficiency: a case misdiagnosed as burning mouth disorder. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/17209796.

[8] Sharecare. (2019). How does vitamin deficiency affect oral health? | Vitamins. [online] Available at: https://www.sharecare.com/health/vitamins-supplements/vitamin-deficiency-affect-oral-health [Accessed 28 Jul. 2019].

[9] "Angular Cheilitis, Part 1: Local Etiologies" (PDF). www.skinandallergynews. Archived from the original (PDF) on 2013-12-16. Retrieved 2014-04-21.

[10] Podiatry Today. (2019). *When Vitamin And Nutritional Deficiencies Cause Skin And Nail Changes*. [online] Available at: https://www.podiatrytoday.com/when-vitamin-and-nutritional-deficiencies-cause-skin-and-nail-changes [Accessed 28 Jul. 2019].

[11] Healthline. (2019). *Nail Abnormalities: Symptoms, Causes, and Prevention*. [online] Available at: https://www.healthline.com/health/nail-abnormalities-2 [Accessed 28 Jul. 2019].

[12] Wollina U, Nenoff P, Haroske G, Haenssle HA (July 2016). "The Diagnosis and Treatment of Nail Disorders". Deutsches Arzteblatt International. 113 (29–30): 509–18. doi:10.3238/arztebl.2016.0509. PMC 5527843. PMID 27545710.

[13] Ben-Dayan D, Mittelman M, Floru S, Djaldetti M (1994). "Transverse nail ridgings (Beau's lines) induced by chemotherapy". Acta Haematol. 91 (2): 89–90. doi:10.1159/000204261. PMID 7517608.

[14] Park J; Li K (2010). "Multiple Beau's lines". New England Journal of Medicine. 362 (20): e63. doi:10.1056/NEJMicm0906698. PMID 20484394.

[15] Precision Nutrition. (2019). *All About Nutrient Deficiencies*. [online] Available at: https://www.precisionnutrition.com/aa-nutrient-deficiencies [Accessed 28 Jul. 2019].

[16] Nanci, Antonio. Ten Cate's Oral Histology: Development, Structure, and Function. Elsevier, 2018.

[17] Sodium L-ascorbate enhances elastic fibers deposition by fibroblasts from normal and pathologic human skin. [Online]. Available: https://www.ncbi.nlm.nih.gov/pubmed/25015208

[18] Junqueira, Luiz Carlos., and Anthony L. Mescher. *Basic Histology: Text and Atlas*. McGraw-Hill, 2010.

[19] CNN vs fully-connected network for image processing. [Online]. Available: https://towardsdatascience.com/cnn-vs-fully-connected-network-for-image-processing-8c5b95d4e42f.

[20] Carter, D. (2019). *Tensorflow — Neural Network Playground*. [online] Playground.tensorflow.org. Available at: https://playground.tensorflow.org [Accessed 28 Jul. 2019].

[21] Cs231n.github.io. (2019). *CS231n Convolutional Neural Networks for Visual Recognition*. [online] Available at: http://cs231n.github.io/neural-networks-1 [Accessed 28 Jul. 2019].

[22] TensorFlow. (2019). *TensorFlow | TensorFlow*. [online] Available at: https://www.tensorflow.org [Accessed 28 Jul. 2019].