



VitaML: Vitamin Deficiency Detection Using Machine Learning

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Abstract

Due to a lack of easily accessible and non-invasive diagnostic techniques, vitamin deficiencies are becoming a serious public health concern that frequently go undiagnosed. Conventional testing can be costly, time-consuming, and equipment-intensive. VitaML presents a machine learning-based framework that uses visible biomarkers, skin characteristics, and discoloration to detect vitamin deficiencies. VitaML seeks to develop a rapid, inexpensive, and user-friendly diagnostic tool by training classification models on a dataset of visual cues associated with particular deficiencies. This system can encourage preventive care, increase awareness of general nutritional health, and assist medical professionals in identifying problems early.

Keywords: Deficiencies, Equipment, Discoloration, Biomarkers.

1. Introduction

Due to a lack of simple, inexpensive, and non-invasive testing techniques, vitamin deficiencies are a prevalent health problem that frequently goes undiagnosed. Blood tests and other conventional techniques are effective but can be costly, slow, and require specialized lab equipment. A novel machine learning framework called VitaML was unveiled to close this gap. It uses visible indicators, skin texture, and discoloration to identify vitamin deficiencies. VitaML provides a rapid, simple, and inexpensive diagnostic tool by training classification models on datasets of visual signals. In the end, this system can improve health and reduce healthcare costs by assisting medical professionals in identifying problems early, promoting preventive care, and increasing public awareness of nutrition.

2. Methodology

So, the methodology used in the development of VitaML includes data collection, pre-processing, training the model, and system integration. First, facial images are collected from public medical datasets, in cooperation with clinics, and are augmented with a series of transformations aimed at increasing the dataset diversity. Pre-processing techniques, including noise reduction, histogram

equalization, and normalization, are thereby applied jointly with the region-of-interest extraction (eyes, lips, skin, and tongue) in order to highlight the visual biomarkers. Finally, to extract the features, a method of color histograms is used, along with a descriptor of texture and more deep learning methods such as Convolution Neural Networks (CNNs) that classify the deficiencies as such as Vitamin A, B12, C, D, Iron, or Protein. The classification results are displayed in a chatbot interface, which is accompanied by relevant information about the probable causes, advice on dietary measures, and preventive measures. Besides, the prototype system, which is built in Python with OpenCV and Tkinter for modules, is tested using the live webcam input and using the provided annotated datasets for testing accuracy, precision, recall, and the F1-score.

3. Design and Implementation

3.1. System Architecture

The proposed system is based on the client/server architecture. React.js is used in the frontend, which first collects the user's facial images and then transmits them to the backend using RESTful APIs. The backend side here is in Python (Flask). It is in charge of image preprocessing, model inference, and

response generation. Vitamin Deficiency is accomplished by classification by employing the training, deep learning model HDF5 (.h5) format. MongoDB database layer stores and prediction histories for further analysis.



Figure 1 Labelled Symptoms Dataset

Table 1 Facial Indicators and Related Vitamin Deficiencies

Tongues	Deficiency
Smooth Texture	B6 B12 Iron
Red Color	B12 Iron
Shiney Red	B12
Cracked, Dry, Brittle	B2 B3 B12
Vertical Ridges	B12 Iron
Redness	Vitamin A
Yellow eyes	Vitamin B12 Iron
Dry Skin	Vitamin A D

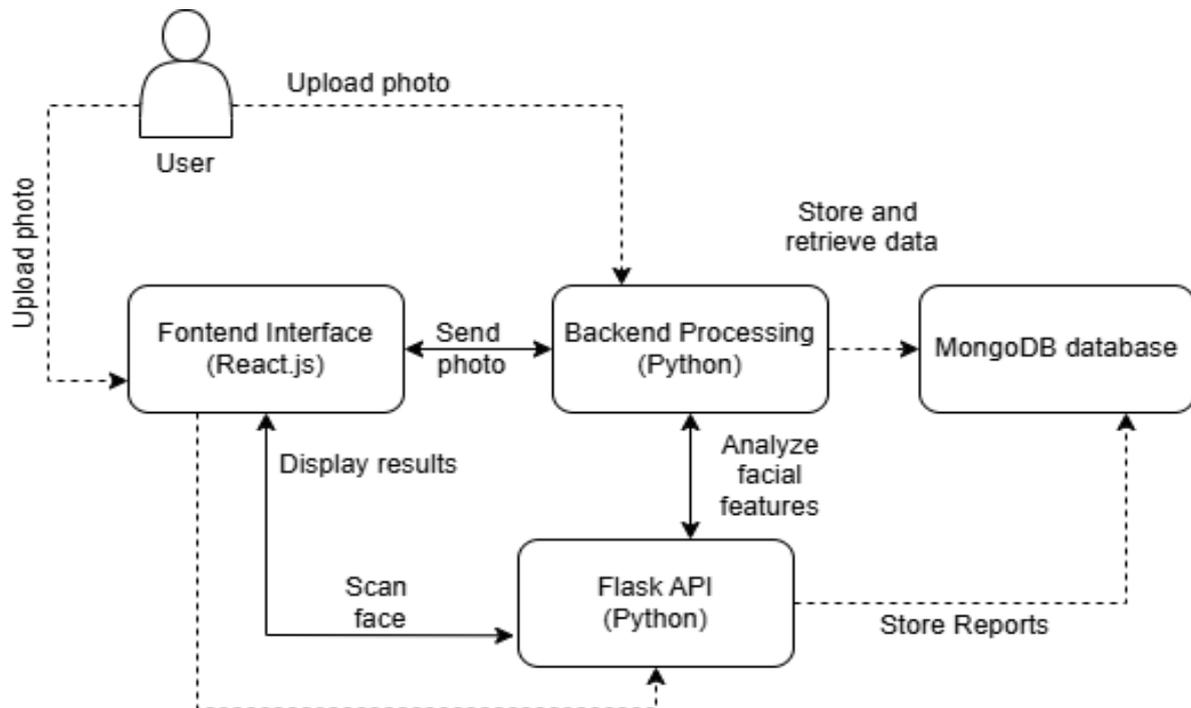


Figure 2 Overall system Architecture Diagram

3.2. Proposed System Implementation

The dataset is separated into different folders of vitamin deficiency symptoms. They are separated into Acne, bleeding gums, Cracked lips, Dark

Circles, Dry skin, Red eyes, and Yellowish eyes. Each folder contains a set of facial images corresponding to the title of the folders. The structure



follows Keras' `flow_from_directory`, where the labels of classes are chosen alphabetically by folders. Rotation, zooming, shifting, and horizontal flipping have been done to augment the training images, therefore, reducing over-fitting by increasing the robustness of the model. Then the image is normalized by scaling the pixel values to fit within the range [0,1]. Not only does this bring in a faster convergence for minima but also ensures that the features are learnt in a uniform manner. Finally, the training and inference operations use the same preprocessing procedure, avoiding prediction bias. TensorFlow and Keras are used in building a Convolutional Neural Network (CNN). Their architecture involves several convolutional and max-pooling layers for feature extraction, along with fully connected layers for classifications. The Softmax activation is used in the final layer to output probability values for the classes of the deficiencies. To tackle class imbalance, class weights are calculated and passed during training. Adam optimizer is adopted to optimize a model on categorical cross-entropy loss. Early stopping and learning rate reduction on plateau strategies are set to stabilize training and avoid overfitting. After training, the model is saved in a file named `vitamin_deficiency_model.h5` and deployed within a Flask-based backend. The final result is a probability vector obtained through inference using the trained convolution neural networks (CNN). The `argmax` function is used to declare the predicted class. For correct interpretation of predictions, the class labels are dynamically synchronized to the dataset directory structure during inference. Finally, class labels are inferred with dynamic synchronization of the dataset directory structure to ensure correct interpretations of the predictions. Once a deficiency is identified, vitamin-specific recommendations/instructions are output using a rule-based advisory module. The module is connected to a natural language AI model that offers diet suggestions, precautionary information, and general advice regarding the user's health. Finally, they are passed on to the user through a friendly frontend interface.

- Lips: The lips are a very good indicator of nutritional condition. A smooth texture and

red shine is an indicator of good hydration and nutrition. Nevertheless, the presence of dry, cracked, or split lips, as well as vertical lines/fissures, is typically an indicator of vitamin B-complex deficiency, in particular, Vitamin B2 (riboflavin) and Vitamin B12.

- Eyes: Visual clues of vitamin and mineral deficiency are provided in the eye region. Normal eyes are characterized by a clear sclera that is not extremely red. Constant redness or irritation may be a sign of Vitamin A deficiency which affects tear secretion and wellbeing of the ocular surface. A yellow sclera may be an indicator of Vitamin B12 or iron deficiency, a poor production of red blood cells or absorption of nutrients.
- Tongue: Tongue is a significant biomarker in the determination of nutritional deficiencies. A healthy tongue is moist and smooth in color and pinkish-red. Vitamin B12 or iron deficiency may be indicated by abnormal conditions which include a shiny red tongue, pale colored, or a smooth surface because of loss of papillae. Besides, the tongue may be dry, cracked, or inflamed, which also can be viewed as a pointer of current nutritional imbalance.
- Skin: The skin state is one of the most important external indicators of nutrition. When the skin is healthy, it is normally smooth, well-textured and well-hydrated with a natural shine. Such problems as dryness, flakiness, roughness, or lack of elasticity can indicate Vitamin A deficiency which is vital in regenerating skin cells and keeping the skin moist. Pale or dull skin color may also be associated with iron deficiency, as there are low hemoglobin levels. They are visible skin characteristics that have proven to be valuable as non-invasively detect vitamin deficiencies, and are successfully employed in machine learning models that are based on images.

4. Test results

4.1.Home Dashboard and System Entry Point

The interface displays the home page. This is where we get into after a successful login. The dashboard

shows VitaML, a personal health and wellness assistant based on AI. It assists in developing user trust and interaction.

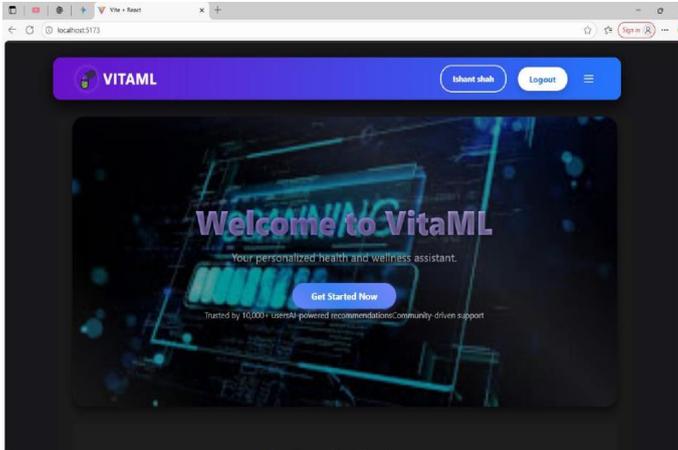


Figure 3 Landing Page

This interface makes access to system features such as scanning, analytics, and recommendations extremely easy. The dashboard is centered on the clarity and ability to react fast and thus allow the user to initiate health assessments with ease. This is a characteristic that plays a vital role in keeping users busy and having a smooth interaction which acts as the primary manoeuvre of all the analytical capabilities of the application.

4.2. User Authentication and Account Creation Interface

The interface provides the user authentication and account creation module of the VitaML system. This screen is developed in a way that allows onboarding to be secured and accessing the application to be personalized. The user should feed some basic details such as full name, email address and password. This assists the system to know the users and keep personal health information. The interface is designed in a simple and easily understandable format. This saves mental load besides making it easy to use. Additionally, there is a brief feature overview of what the system can offer, of which are nutrition tracking, personalized recommendations, and wellness monitoring. This module provides the security associated with the data storage, session management, and customized analytics, which are important in health-related applications.

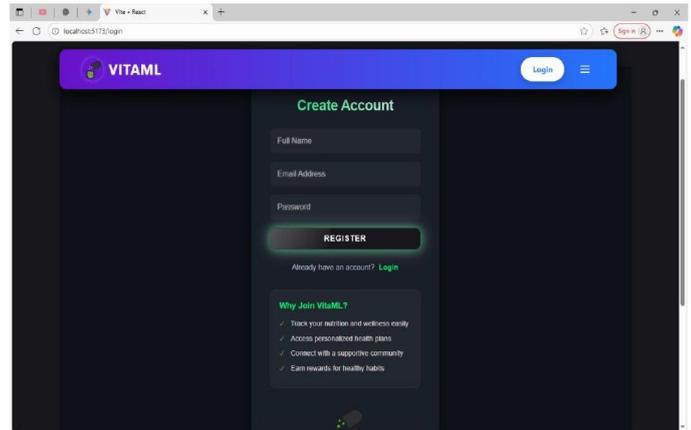


Figure 4 Registration Page

4.3. Image Capture and Analysis Module

Users take pictures and analyze them in the interface, which is a significant aspect of the VitaML system. This module enables the user to capture facial images using their device camera and then the image is analyzed in real-time to identify the visible health indicators that include the eyes, lips, tongue, and skin. The interface has straight forward controls such as Capture and Analyze and Back. These ensure that it is easy to navigate and prevent acting accidentally. This is the step, which bridges user interaction and machine learning models as the image taken serves as an input to diagnosing nutritional deficiency. The system is accessible, as it adds image capture in the app workflow and eliminates the use of external diagnostic tools.

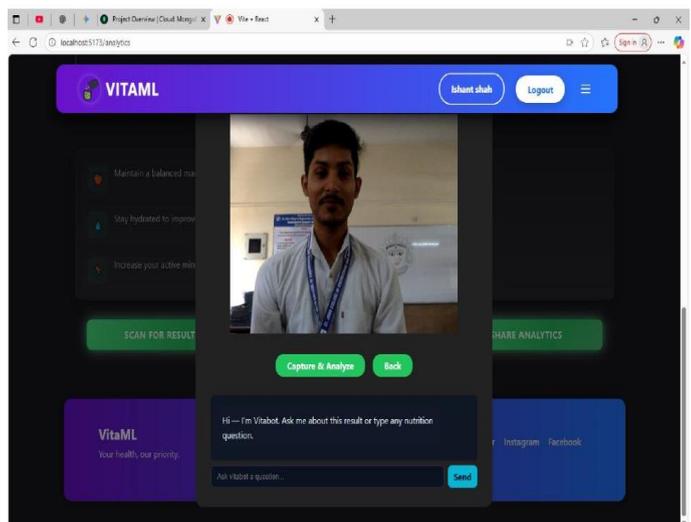


Figure 5 Interface

5. Discussion and Conclusion

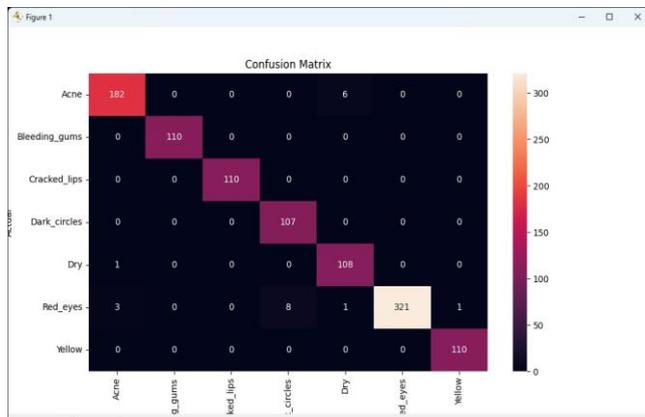


Figure 6 Confusion Matrix

The confusion report indicates the classification accuracy of seven different categories. The high values are observed in the diagonal parts, and it implies high predictive behavior. The Red_eyes category has the greatest true positive of 321 correct predictions in the model, and then Acnes with 182. The other categories such as Bleeding gums, Cracked lips and Yellow each have 110 correct classifications. Dry and Dark circles come almost second with 108 and 107 correct guesses respectively. Not many misclassifications are present, the Red eyes category being mixed with Dark circles (8 times) or Acnes (3 times).

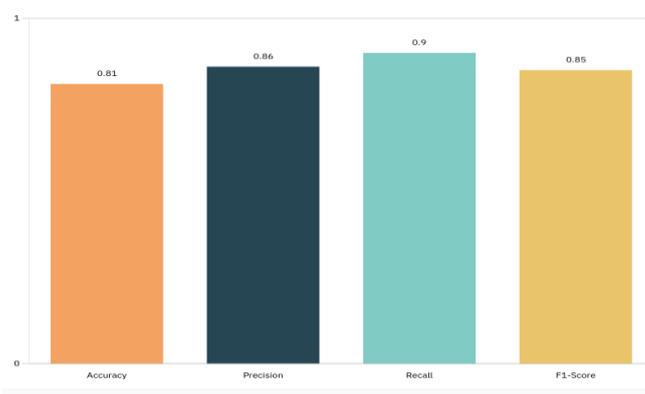


Figure 7 Performance Parameters

The performance of the model is measured with respect to four key metrics, as each of the main metrics have four vertical bars that are the measure on a scale of 0 to 1. The best performing metric is

recall at 0.9, which demonstrates a good capacity to determine the most situationally relevant ones. Then comes a Precision score of 0.86 followed by an F1-Score of 0.85 showing a good compromise between precision and recall. Finally, the general Accuracy is also registered at 0.81 which provides a clear picture of the model success to predict results within the dataset.

5.1.Backend Output and Structured Health Data Representation

The picture displays the organized JSON response of the system following analysis. This output contains the records, which are in the form of timestamps, the user IDs, the key performance indicators, the symptoms identified, the confidence rating, and the nutritional deficiencies. This data representation in the form of a structure guarantees scalability, traceability and interoperability. It enables the system to archive the past reports and can facilitate analysis or linking to other third-party systems in future. Confidence values enhance transparency by demonstrating the accuracy of the model predictions by the machine learning model.

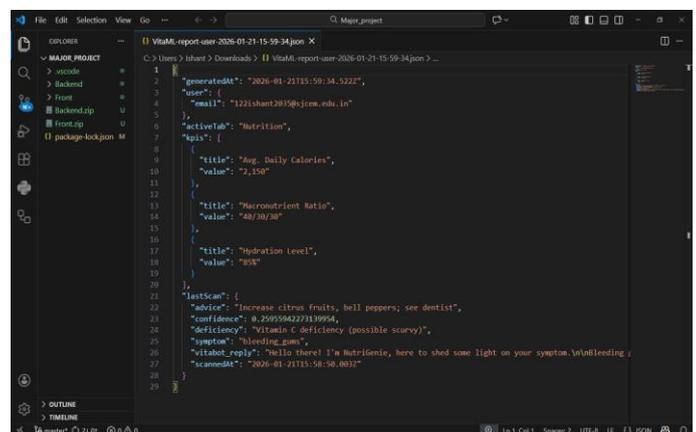


Figure 8 Report Sample

5.2.Analytical Results and AI-Driven Recommendations Interface

This interface will display the results of analytical VitaML generated and nutrition recommendations. It presents the observed symptoms, including bleeding gums, nutrition deficiencies, including Vitamin C deficiency, and the nutritional guidelines on practical diet. The chatbot is known as VitaBot and assists customers in learning the medical significance of

discoveries through understandable language. There are also precautionary warnings in the interface that point out that the system is not a replacement for professional medical diagnosis. This is a way of ensuring that ethical practices are upheld and that there is informed health awareness.

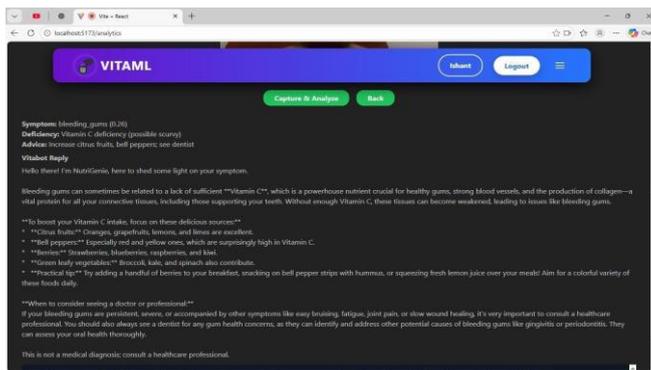


Figure 9 Output

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