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Smart Detection of Vitamin Deficiencies: Leveraging CNN and Image Processing for Precise Diagnosis

Anantha Murthy[1], Meghana K[2], Mangala P Shetty[3] and Melisha Shalini Pinto[4]
[1-4]Department of MCA, NMAM Institute of Technology, NITTE (Deemed to be University), Nitte, Karnataka, India
Email: anantham2004@gmail.com, meghanamgnak@gmail.com

***Abstract*— Vitamin deficiency has become a prevalent global public health concern, especially in medical centers. Moreover, the growing prevalence has major implications for disease severity, mortality, and morbidity. Because of certain drawbacks that exist concerning cost and time in conventional diagnostic techniques, interest has shifted towards automated processes for correct prediction and cost-effectiveness in diagnosing Vitamin deficiency. The revised abstract succinctly summarizes the objectives, innovative methodology, and key findings of this research effort and holds great potential to revolutionize the diagnostic aspects of medicine in terms of efficiency as well as accuracy.**

This program addresses a major worldwide health issue that affects millions owing to a lack of dietary understanding. In the long run, it will allow healthcare staff to make more accurate diagnoses. The suggested method combines image-processing techniques with convolutional neural networks to provide early, non-invasive screening, individualized recommendations, and healthcare decision assistance. Future enhancements will involve dataset extension and more study into CNN architectures for improved accuracy and implementation.

***Index Terms*— Vitamins, Diagnosis, Deficiency, Convolutional-Neural-Networks. AI, Image Processing.**

I. Introduction

Vitamin deficiency is one of the major global health disorders and has resulted in a variety of diseases as well as disabilities. Traditional diagnostic methods are invasive, expensive, and inaccessibly performed, especially in countries of distant or resource-poor situations. Early detection of the cases resulting from deficiency is needed for proper intervention. Conventional diagnostic methods like blood tests are problematic because of their invasiveness in nature, along with time consumption and cost, which limit their accessibility to underserved regions. In recent years, deep learning has had great promise for applications in health for non-invasive detection and monitoring. However, most such studies have drawbacks related to lacking scalability and accessibility, mainly driven by high technical or financial requirements. The research aims to work through these drawbacks by developing an accessible yet reliable diagnostic tool using deep learning. Our method applies image processing and CNNs to detect the presence of visual signs in organ images of deficiencies for vitamins A, B, C, D, and E. This original idea will apply computer vision to assess images of specific parts of the body, thereby providing an effective alternative for diagnosis that could be highly useful in several environments. The prevalence statistics highlight the relevance of this work. More than 2 billion people globally suffer from different vitamin deficiencies.

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This condition has serious implications for public health[3]. For example, zinc deficiency has infected more than 1.2 billion, and annually it causes half a million deaths, while iron deficiency contributes to anemia and over 100,000 deaths every year[14]. In the UAE, more than 90% of the population suffers from a deficiency in a required nutrient, and the same figures apply in the United States, where over 92% of people lack at least one essential vitamin or mineral.
This paper contributes to the emergence of a novel, non-invasive method for detecting vitamin deficiencies using image processing and the aid of CNNs, to ensure an accurate and user-friendly tool in early detection and prevention of vitamin deficiencies.

II. LITERATURE SURVEY

A paper regarding "Deep Learning technique dense-net application to predict vitamin deficiency"[15]. Would summarize recent research conducted on vitamin deficiency detection, deep learning applications in health sciences, and exploitation of convolutional neural networks for image processing to diagnose health disorders. This review is based on a synthesis of the data obtained from several studies, focuses on methodologies and results, and assesses the potential of advanced neural network architectures for the non-invasive diagnosis of vitamin deficiencies.
T. Kalavathi Devi, K.N. Baluprithviraj, M. Madhan Mohan, S. Uma Devi, P. Sak. Vinodha in 2023 Non-invasive prediction of micronutrient deficit by applying sequential learning techniques[9] is useful for giving personalized diet regimens according to individual needs. The interactions of various vitamins and their deficiencies are examined. A suitable diet for specific vitamin deficiencies is identified. Early diagnosis of vitamin deficits is made possible through machine learning. Vast amounts of data are efficiently analyzed to reveal patterns and relationships. The people are educated to eat well. More data will improve the accuracy. There could be some limitations in little awareness of context and ethical issues. The approach towards finding the deficiencies of the vitamin includes image capture, preprocessing of the image, and feature extraction using pre-trained convolutional neural networks followed by classification. In-vitro experiments in multiple datasets have allowed for more accurate results to support non-invasive early screening as well as personalized recommendations and decision support in health care[9].
Researchers recently identified certain features and characteristics in images and applied machine learning for the identification of vitamin deficiency along with the application of fuzzy logic in the paper [6]. This research work introduces an AI system where the presented program determines vitamin deficiency based on particular physical characteristics.
Researchers created an AI-powered mobile application that can detect several vitamin deficiencies by identifying the fingernails, lips, tongue, and eyes of a patient uploaded from the mobile app. Researchers worked on the possibility of applying Machine Learning together with the Explainable Artificial Intelligence techniques to develop a more accessible system that could be used for the identification of Vitamin A deficiency through analysis of Electronic Health Records of symptoms. They applied several machine learning approaches on a relatively small dataset comprised of ocular signs and diagnoses to test the possibility of using these methods for early diagnosis of Vitamin A deficiency[6].
In the research paper "A Predictive Performance Analysis of Vitamin D Deficiency Severity using Machine Learning Methods" the author tried to predict the level of VDD among 18-21 years old college students through non-invasive methods. In this research paper, the researchers obtained information related to age, gender, weight, and physical activity and tested the performance of different classifiers based on machine learning techniques. Among them, the Random Forest Classifier elicited 96% accuracy and proved to be an efficient one[5].

III. METHODOLOGY

A. Dataset

The system included a very diverse dataset, with 2,000 training images and 400 test images. These represented a wide range of features, from bluish nails to possible glaucoma symptoms in the eyes[11]. Such diversity in the dataset would expose a variety of human vitamin deficiencies. This will further improve the model's capability to identify and classify symptoms, according to a wide range of visual features related to different kinds of vitamin deficiencies. All the images in this dataset were carefully collected from open-source repositories, relying mostly on Google Photos. This provides a wide representation of real-life cases, useful diversity, and authenticity in the dataset. It focuses on the development of robust classification models that can recognize the various presentations of vitamin deficiencies within diverse populations and make the necessary adjustments.

B. Data Pre-Processing

To prepare it for training, oversampling was done to remove imbalances in classes for the removal of the risks of classification bias due to the majority class. It was then SMOTE (Synthetic Minority Oversampling Technique) sampled with the help of this technique that increased the minority samples to enhance the robustness of the model. Finally, the dataset was split 80/20 as a training and test set, respectively. This split is stratified, therefore, the ratio of target labels in both data sets is preserved, hence it is a balanced representation.

After splitting MinMax Normalization scaling has been applied. So the features get transformed into a uniform range [0, 1]. This will ensure that all features are equally contributed during training and aids the convergence rate of the neural network as well. Scaling was done by using the formula:

$$X_{\text{scaled}} = \frac{X - \min(X)}{\max(X) - \min(X)} \quad - \qquad (1)$$

C. Symptom Analysis

To identify symptoms of vitamin deficiencies, we conducted a medical and pathological analysis to identify visual indicators that mark the deficiency of specific vitamins. We recorded these indicators in terms of changes in texture, color, and shape of body parts, such as skin, eyes, and nails[1]. This information forms the basis of our feature extraction.

Example Vitamin C Deficiency[10]; Vitamin C is necessary for the synthesis of collagen, which acts to keep connective tissues intact. Areas of the body containing abundant connective tissue include the skin, lips, and nails. A deficiency prevents normal synthesis of collagen, creating the symptomatology of cracked lips, dry skin, or brittle and cracked nails. These signs were photographed and placed in a photo archive for later reference.

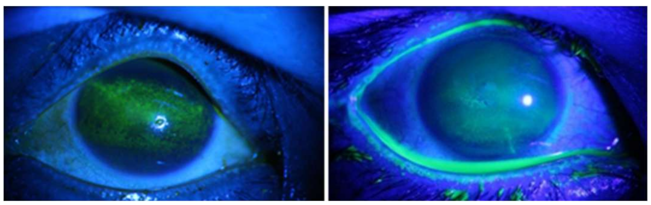

Fig 1. The pictures of eyes

Fig 2. The collected data Set

D. Feature Extraction

We did feature extraction using a pre-trained architecture, CNN that is able to identify and learn complex image patterns. Its architecture, with residual blocks, was able to draw deeper representations without facing the vanishing gradient problem that suited our task of distinguishing slight changes related to vitamin deficiencies.

The pre-trained model was further fine-tuned for our collected photo library to define characteristic attributes of each type of deficiency. In order to do that, we reused transfer learning by moving learned parameters from the original model and adding custom layers that were more appropriate for our specific classification needs. A process like this does indeed improve training efficiency, especially with far fewer data requirements needed in terms of achieving high accuracy.

E. Proposed System

This system is going to be able to predict vitamin deficiencies by indicative analysis of symptoms from images, using various CNN architectures. The design of this proposed system needs to be highly accessible and requires only a digital image for analysis. Moreover, a variety of CNN architectures is to be proposed for use in the working of this proposed system to increase the accuracy and reliability of the recognition for a wide range of symptoms and types of deficiencies[12]. Since it automatically learns features from images end-to-end, the design of features by hand becomes unnecessary. The system will also be engineered for speed and non-invasiveness, suitable for implementation in various settings, including rural areas with very minimal health facilities. The idea is to apply recent advances in computer vision to extract visual features that are strongly predictive of vitamin deficiencies. The model with the highest accuracy on the validation dataset will be selected as the main deficiency prediction model. The core architecture of the system consists of a succession of convolutional layers that aid in the hierarchical representation of the visual patterns in the organ images. In so doing, it can detect the complex features of color variations, texture differences, and structural abnormalities so vital in the decision about several vitamin deficiencies.

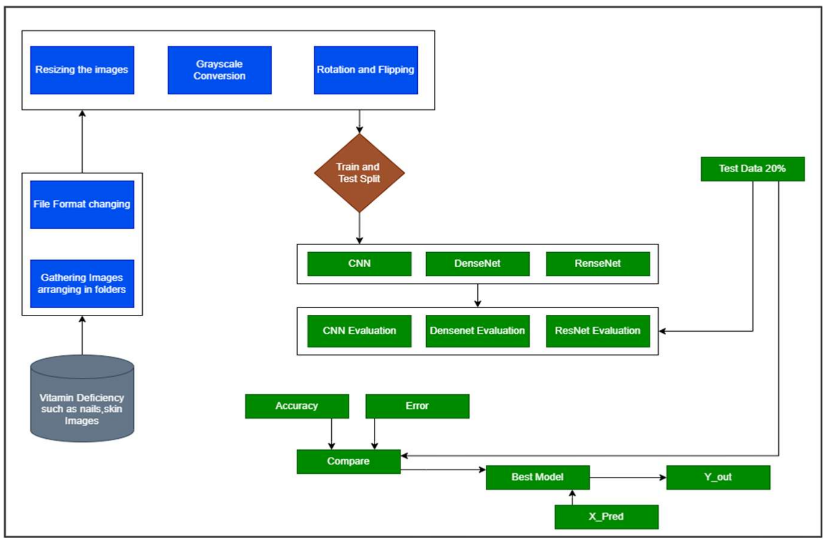

Fig 3. Block Diagram of the system

F. Fuzzy Membership Function and Defuzzification

The CNN goes through numerous iterations on extensive collections of photos containing specific features. Each run extracts features and generates confidence levels, which are inputted into a Mamdani-based Fuzzy Logic Membership Function developed in MATLAB[6]. The rules in Fuzzy Logic are based on the strength and commonality of the analyzed visual attributes. They indicate that if a deficiency is identified in one variable, the more deficiencies are found in the other variables, the higher the certainty. Conversely, if a deficiency is detected in one variable, the lower the deficiencies in the other variables, the lower the certainty. Lastly, a different code utilizes the Defuzzification results to provide recommendations for nutritional sources that can be adjusted to address the identified vitamin deficiencies.

IV. Implementation

In fact, it needed many pictures with symptoms in order for the training of an image feature extraction classifier to go through well[2]. Because current images of real patients were not accessible. The following table 1 shows the symptoms according to nutritional deficits. Big datasets benefit from neural training rounds in terms of churning out more trustworthy findings much faster compared to prior methods. The trained network was saved as a compressed file in TensorFlow format.

For this purpose, a set of photos of each symptom was selected, with due care, categorized, and fed into the platform. Each image evaluation result will be stored in a temporary directory and as text sent into the fuzzy inference system. In that respect, a Fuzzy Inference system has been developed with the use of MATLAB. By looking at below table implementation would be held.

In this system, the frontend was powered by HTML, CSS, and JavaScript; everything was powered by Python. The working architecture provides options for choosing one among five different models, namely CNN ResNet, and DenseNet to enable multiple predictive analytics. The images are standardized to dimensions of 224x224 after the model selection process and before the use of model.predict(). The output would not only identify symptoms such as blue nails, skin abnormalities, or glaucoma eyes but also provide relevant precautions and identify the type of deficiency associated with each symptom observed.

V. RESULT AND DISCUSSION

Based on the proposed strategy in this proposal, a comparison was done, and it is confirmed that CNN, DenseNet, and ResNet models demonstrate excellent outcomes while trying to classify data into five categories: Normal, Vitamin A, Vitamin B, Vitamin C, and Vitamin D. It performed well compared to others mainly because of more accurate predictions along with fewer misclassifications.

TABLE I. CLASSIFICATION REPORT FOR CNN.

Class	Precision	Recall	F1-Score	Support
Normal	0.90	1.00	0.95	9
Vitamin A	0.60	0.60	0.60	5
Vitamin B	0.80	0.80	0.80	10
Vitamin C	1.00	1.00	1.00	12
Vitamin D	0.86	0.75	0.80	8
Accuracy			0.86	44
Macro Avg	0.83	0.83	0.83	44
Weigthed Avg	0.86	0.86	0.86	44

TABLE II. CLASSIFICATION REPORT FOR DENSENET.

Class	Precision	Recall	F1-Score	Support
Normal	1.00	1.00	1.00	9
Vitamin A	1.00	0.80	0.89	5
Vitamin B	0.91	1.00	0.95	10
Vitamin C	1.00	1.00	1.00	12
Vitamin D	1.00	1.00	1.00	8
Accuracy			0.98	44
Macro Avg	0.98	0.96	0.97	44
Weigthed Avg	0.98	0.98	0.98	44

TABLE III. CLASSIFICATION REPORT FOR RESNET.

Class	Precision	Recall	F1-Score	Support
Normal	0.81	0.44	0.55	9
Vitamin A	0.47	0.82	0.57	5
Vitamin B	1.00	0.19	0.35	10
Vitamin C	0.52	0.52	0.51	12
Vitamin D	0.34	0.74	0.49	8
Accuracy			0.50	44
Macro Avg	0.63	0.54	0.50	44
Weigthed Avg	0.65	0.50	0.49	44

Fig 4. Home page

VII. CONCLUSION

Artificial intelligence is used by a web application to identify particular vitamin deficits using pictures of the skin, eyes, and nails[18]. The database includes pre-processed photos of glaucoma eyes as well as skin and nail abnormalities brought on by specific vitamin shortages. Real-time recognition of fresh data is facilitated by the high precision with which these neural network models identify such anomalies[16]. This does not take the place of medical advice, nor do any of these methods. This could be a novel way to stop chronic diseases linked to untreated vitamin deficiencies from developing. Unfortunately, because there weren't enough images of patients with vitamin deficiencies, the model could not be validated on the patients. This predictive tool can be enhanced many times over for improved diagnosis by adding more data and including specialists, researchers, and doctors into the database. The test resulted in an accurate diagnosis based on the symptoms. However, due to restricted access to photographs and profiles of vitamin deficiency cases, the program was not tested directly on patients. Combining additional data and input by health care workers, scientists, and experts with direct access to the databases will increase the reliability of the diagnosis. The scope of what the envisioned solution can do surpasses just the determination of vitamin deficiency; with more assets beyond the cameras, it can be used for the early detection of various health problems. As this application is not designed to act as medical advice but to raise awareness regarding nutritional needs and how to help others maintain a suitable diet that will prevent further health complications from untreated vitamin deficiencies[17], then it would be impossible to have such an application in use without its recommendations toward curing.

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