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Vitamin Deficiency Detection Using Image Processing

S Shilpa[1], C Dinesh Kumar[2], P Manoj Kumar[2], P Nikhitha[2], Ch Harsha Vardhan[2]
[1]Assistant Professor, Siddartha Institute of Science and Technology, Puttur, Andhra Pradesh, India
[2]UG Student, Siddartha Institute of Science and Technology, Puttur, Andhra Pradesh, India

Autor1 E-Mail: shilpamani0614@gmail.com
Autor2 E-Mail: chittedineshkumar@gmail.com
Autor3 E-Mail: manojpothineni18@gmail.com
Autor4 E-Mail: pakamnikhitha@gmail.com
Autor5 E-Mail: harshachilamkuri@gmail.com

ABSTRACT

Vitamin deficiencies are a major world-wide population-health problem as they affect billions of people in developing nations and developed nations. Such deficiencies are often not diagnosed due to a reliance on invasive lab tests, a lack of awareness and a lack of access to healthcare facilities. It is notable also that many vitamin deficiencies present clear clinical evidence on the external human tissues, such as the skin, tongue, lips, the ocular surface, and nails. These phenotypic cues can also be learnt by using traditional imaging devices, thus enabling the process of non-invasive diagnosis in the process of computational analysis. The research assumed here is a smart image-processing and deep-learning framework that is used to identify vitamin deficiencies by analyzing images of human tissues. The proposed architecture is based on a combination of a classic image-processing mode such as Wiener filtering, curvelet transform, morphological manual operations, and Otsu thresholding (RCNN) to obtain the correct result of classification. A full preprocessing pipeline enhances the fidelity of images, and isolates regions of interest, whereas feature extraction using curvelets allows a fine resolution of edges and textures. The identification of the vitamin-deficient tissue or normal tissue is a high classification accuracy that is reliably achieved by the trained classifier. Experimental measurements indicate that the accuracy of the proposed system can attain a total classification of up to 94%, which is better than the traditional wavelet-based methods. For real-time, mobile-compatible implementation. The system is intended to be a non-invasive option to traditional modes of diagnosis, and it is cost-effective. The results support the practicality of using artificial intelligence and image-processing algorithms to detect vitamin deficiency in its initial stage and conduct screening on a large-scale level as a part of population-wide healthcare.

Keywords: Vitamin Deficiency Detection, Image Processing, Deep Learning, Curvelet Transform, Medical Image Analysis, Healthcare AI

I. INTRODUCTION

Vitamin deficiencies are one of the most common, but least diagnosed health disorders at the global level. The world health report indicates that over 2.1 billion people lack the availability of all the necessary vitamins that include vitamin A, the B-complex, vitamin C, vitamin D and vitamin E [1,2]. These shortages can lead to serious malfunctions including anemia, immune impairment, neurological conditions, dermatological illnesses and developmental and growth impairments. Hematological tests and biochemical analyses are the major sources of traditional methods of diagnosing diseases of vitamin deficiencies. Though accurate, they are invasive, expensive, laborious, and are unavailable to large groups of people especially in rural or low-resource-based settings. Furthermore, regular check-ups are often avoided because of unease and cost, and, as a result, late diagnosis [3,4].

Human bodies are mostly noticeably affected by vitamin deficiencies. Abnormal pigment tomography, fissured lips, variations in the skin texture, change in tongue discoloration, nail deformities, redness of the eyes are all reported forms. Such outward signs give a chance to make early diagnosis using the analysis of the image. In medical diagnostics, the recent disruptive changes in artificial intelligence (AI), machine learning (ML), and computer vision have significantly changed the way the information is presented. Convolutional Neural Networks (CNNs) or deep learning models have already become exceptionally useful in medical image classification tasks and include skin cancer detection, diabetic retinopathy screening, and pathological tissue analysis [5,6].

Spurred by these advances, the current study is presenting a smart vitamin deficiency detector system by utilizing digital image processing and deep learning approaches. The system hopes to provide a non-invasive, cost-effective, and automated diagnostic device with the ability to detect vitamin deficiencies using images of human tissue through a standard camera or smartphone.

II. LITERATURE REVIEW

Several research have been done on the use of image processing and AI in medical diagnostics. Wu et al. [7] suggested a deep learning-based model of automated screening of skin conditions using clinical RGB images. They employed the transfer learning convolutional neural networks to obtain the high-level visual features of dermatological images. The methods of data augmentation were implemented to deal with the imbalance of data and improve generalization. The research showed that deep learning models are effective compared to the traditional handcrafted feature-based services, though they require large, labelled datasets to perform well.

The visual analysis system introduced by Wei et al. [8] aimed at the recognition of the nutrient deficiencies based on close-up pictures of skin and nail. Its methodology was aimed at color correction and extraction of texture features with the help of Gray Level Co 2-occurrence Matrix (GLCM) descriptors. These aspects were identified through Support Vector Machine (SVM) classifier. The findings showed that the accuracy of classification of nutrient deficiency improvement is achieved with the combination of texture and color information.

The multimodal framework by Attallah [9] is a combination of dermoscopic images, Smartphone photographs as well as patient metadata to detect vitamin deficiency. The hybrid convolutional neural network that employs feature fusion to combine several data sources was used. This fusion-based approach has fewer false positives and enhanced diagnostic strength. The research highlighted the relevance of multimodal data in coming up with credible medical predetermination.

Kurz et al. [10] examined how hyperspectral and multispectral imaging can be used to prevent vitamin deficiencies at an earlier stage of their progression. Dimensionality reduction was done using spectral indices and Principal Component Analysis (PCA) to extract waveforms that are discriminative. Spectral CNNs had been used to classify and therefore allow earlier detection of the situation than regular RGB imaging. Despite being very accurate, the method is required to have expensive imaging equipment.

Recent studies have shifted into a direction of deep learning methods which utilize CNNs with transfer learning and attention mechanisms. These models are not only better performing models but also normally consume massive, labelled data and large amounts of computing power. There has been enhanced robustness of multimodal methods using a combination of thermoscopic images, smartphone photographs, and metadata. There have also been studies of spectral and hyperspectral imaging technologies that can detect deficiencies early, but these technologies are expensive limiting their use.

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Though these have been developed, there is still a necessity of having a lightweight, cost effective, and mobile compatible system which is yet to be balanced in terms of accuracy and accessibility. To close this gap, the proposed system combines the curvelet-based image enhancement with the deep learning classification. Vitamin deficiencies are among the most prevalent yet underdiagnosed health conditions worldwide. According to global health statistics, more than two billion people suffer from deficiencies in essential vitamins such as Vitamin A, B-complex, C, D, and E. These deficiencies can lead to severe complications, including anemia, immune dysfunction, neurological disorders, skin diseases, and impaired growth and development.

Traditional methods for diagnosing vitamin deficiencies rely primarily on blood tests and biochemical analysis. While these methods are accurate, they are invasive, expensive, time-consuming, and inaccessible to large populations, especially in rural or low-resource environments. Additionally, routine screening is often avoided due to discomfort and cost, leading to delayed diagnosis. The human body frequently exhibits visible symptoms associated with vitamin deficiencies. Changes in skin texture, abnormal pigmentation, cracked lips, discoloration of the tongue, nail deformities, and eye redness are commonly observed manifestations. These external indicators provide an opportunity for early detection using image-based analysis.

Recent advancements in artificial intelligence (AI), machine learning (ML), and computer vision have revolutionized medical diagnostics. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in medical image classification tasks such as skin cancer detection, diabetic retinopathy screening, and pathological tissue analysis. Motivated by these advancements, this research proposes an intelligent vitamin deficiency detection system that leverages digital image processing and deep learning techniques. The system aims to provide a non-invasive, cost-effective, and automated diagnostic tool capable of identifying vitamin deficiencies using images of human tissue captured via standard cameras or smartphones.

2.1 Problem Statement

Deficiency of vitamins is one of the most widespread health problems in the world as it affects billions of people on a global scale. The contemporary test diagnostic systems are based on the heavy use of laboratory tests and clinical skills, which are often unavailable, costly, and invasive. Even though it is possible to observe overt clinical manifestation on external organs such as the skin, tongue, lips, eyes, and nails, the process of manual clinical examination is still subjective and prone to human error. This results in the existence of a significant gap in looking technologies that can interact with these visual cues in a manner that is responsive and accurate. There is thus a critical demand to establish an intelligent, automated and non-invasive detection platform that uses the method of image processing and deep learning to establish early diagnosis and achieve positive health results of the populace.

2.2 Existing System

The traditional method of detecting vitamin deficiency contains a sequence of image-processing steps that include image capture, an initial processing phase, feature-detection, and classification phases. When the acquisition is carried out, dermo scopes or regular digital cameras are used to capture high-resolution digital photographs of affected human tissues and then the photographs are stored to be processed further. Preprocessing involves how the image is optimized in terms of its quality by eliminating noise, hair artefacts and lighting irregularities and enhancing contrast to highlight regions of interest as well. Extracting of features are then used and they include: statistical and texture-based feature - mean and variance of the intensity, wavelet-transform-based texture coefficients which then generate a feature vector. The traditional machine-learning classifiers support vector machines (SVMs) and shallow neural networks are used to perform classification and to differentiate normal tissue and tissue that lacks vitamin. Although the methodology in question has a certain level of effectiveness, there is a significant limit to its usage since it relies on the features crafted manually and is affected by variations in the image-quality. The overall diagnostic workflow will still be time consuming since it involves several preprocessing actions and manual interferences and the lack of automation will make the system incompatible with real time analysis or with mobile healthcare implementation.

III. PROPOSED SYSTEM

The suggested framework will provide a powerful, smart architecture to completely automated vitamin-deficiency detection that will combine complex image-processing algorithms and deep-learned models. Afterward, acquired images are improved with the help of Wiener filter and curvelet transform which eliminate noise and retain important high-frequency edges. It is then followed by morphological operations, which are then succeeded by an operation of thresholding, which is offered by Otsu to effectively isolate pathological areas among the neighbouring tissue which was healthy. The discriminative characteristics of these segmented areas are then transmitted to a Region-based Convolutional Neural Network (R -CNN) that achieves a high accuracy in the Classification of vitamin-deficient and regular tissue. The described automated pipeline has several benefits: it is efficient and accurate in its diagnosis with limited human participation; it is robust in feature extraction and can deal with complex and noisy images. Moreover, the system can also facilitate real-time processing, and it can be deployed on the mobile platform, which makes it a possible solution to the available health-screening application. The overall process of work include image acquisition, crop selection, feature extraction, segmentation, classification and resultant output production is depicted by the following block diagram (Fig. 1).

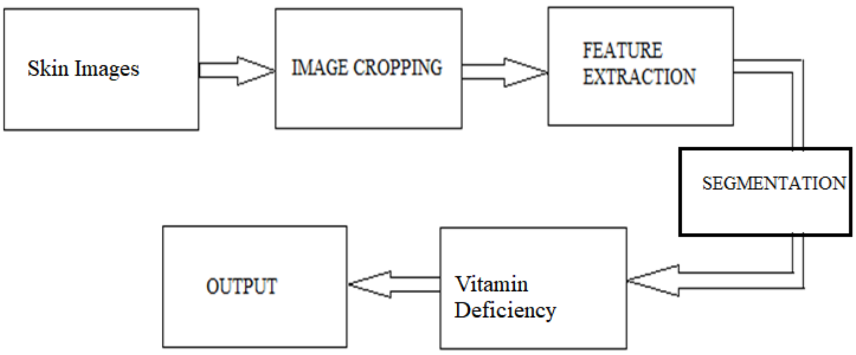

Figure 1: Block Diagram of the proposed model

3.1 Modules Description

The proposed vitamin-deficit detection system consists of multiple sequential functional units that will provide the diagnostic accuracy. The acquisition module is used to capture digital images of the human tissue with an imaging device and then turns them into an appropriate digital format to be further used in its processing. These pictures are sent to preprocessing unit where noise elimination, contrast addition and isolation of the region of interest is done to enhance the image fidelity. The enhancement module uses Wiener filtering and curvelet transform method to further improve the images to sharpen edges and conserve structural information. The affected tissue regions are then then removed using a morphological operation in conjunction with the Otsu thresholding that allows the specific parts of the tissue to be defined efficiently. Lastly, the feature-extraction and classification module compares texture, shape, and colour characteristics of the segmented areas and uses an R-CNN to classify samples into the corresponding vitamin-deficiency category.

IV. PROPOSED ALGORITHMS AND ARCHITECTURE OF DEPLOYMENT

The fundamental classification algorithm to be used is the Region Based Convolutional Neural Network (R - CNN) which is selected due to the ability to afford target spatial features and hierarchical features on medical images. Convolutional layers start with the network structure that learns significant low-level (edges, edges, textures) representations and high level (patterns in the render) representations of the input images. These feature maps are then followed by pooling layers which downsize the dimensionality although maintaining salient data and thereby increases computational efficiency. This is enhanced using non-linear activation functions to ensure that the discriminative power and learning of complex patterns is possible. Layers of the fully connected maps are then used to map the distilled features to the various categories of vitamin-deficiency.

The deployment follows a client server design that is configured and scaling and real time. The management of image capture is done by the client workstation which provides the user interface and the execution of the CNN model, and the MATLAB runtime environment is done by the application server. Highly specialized processing servers are used to perform computationally expensive computations, i.e., segmentation and morphological operations. Training datasets, extracted features, and the classification obtain results are stored on a separate database server. Such a decentralized structure will be effective in processing, trustworthy data storage, and the smooth communication between the system constituents, as illustrated in Fig. 2.

V. EXPERIMENTAL RESULTS

The efficacy of the suggested system of detecting vitamin deficiencies was assessed with a dataset that includes digital images that are related to various vitamin deficiency states or equals to control sample tissues. This value outlines the allocation of the specific groups of vitamins that exist in the data set used in the training and testing of the proposed system. The sample shows more prevalence of Vitamin E and Vitamin B samples compared to other classes, but Vitamin D shows the least representation. The noted inconsistencies in sample sizes highlight the importance of powerful models of learning that will be able to meet the issue of the imbalance within the classes (Fig. 3). The data set featured image resolution variations, lighting interactions, texture, and noise among others to replicate the actual image quality acquisition situation at the real world. The proposed pipeline of processing all images, including noise reduction through Wiener filtering, enhancement using the curvelet transform, and precise segmentation through morphological processing and Otsu thresholding, was used to pre-process all the images.

To determine the success of the proposed method, a comparative analysis has been done between the classical wavelet-based method of feature extraction and the proposed curvelet-based method. Experimental evidence suggests that the curvelet based features extraction algorithm is found to be much more effective in finer edge capturing and directional information of images of the biological tissue than the wavelet transform. This enhancement is more prominent in photos that have disordered texture designs and slight edges differences, that are typical in areas of tissue deprived of vitamin.

A Region Based Convolutional Neural Network (R CNN) was used in the analysis of the classification performance of the system. The train-test split was anticipated to be used as a standard test so that there was no bias in terms of evaluation. The accuracy and the loss values were measured with several epochs during training. The plot of accuracy of the detection (Fig. 4) illustrates that the classification can increasingly perform better with an increase in the training epochs. The accuracy curves of both the training and testing were converging gradually, and it was a sign that the model was learning steadily and not overfitting.

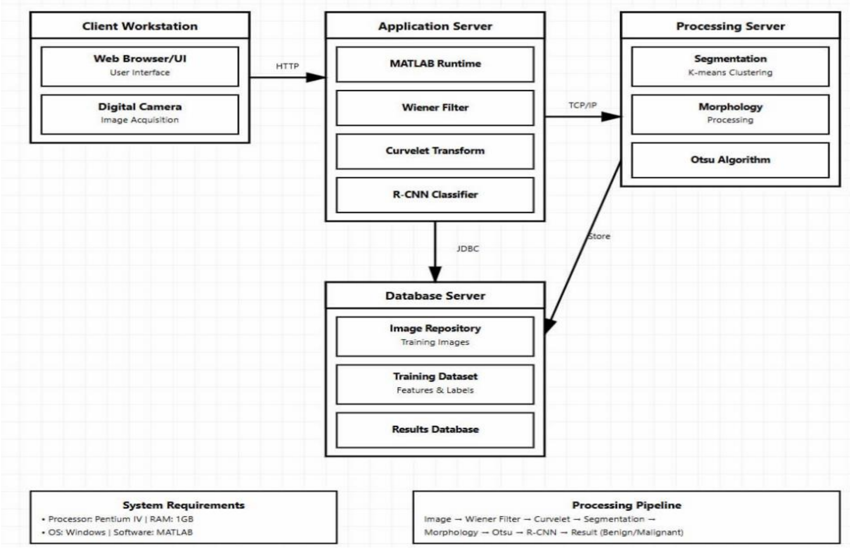

Figure 2: Deployment Diagram

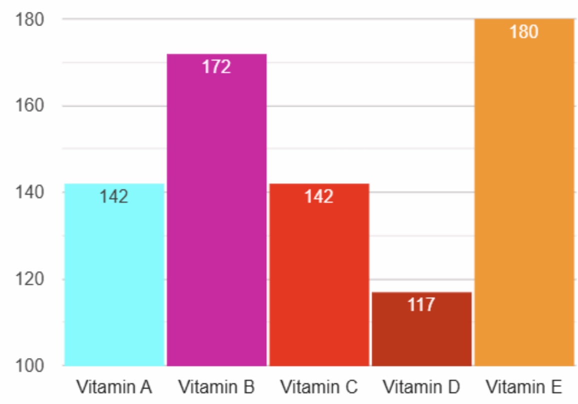

Figure 3: Class Distribution in dataset

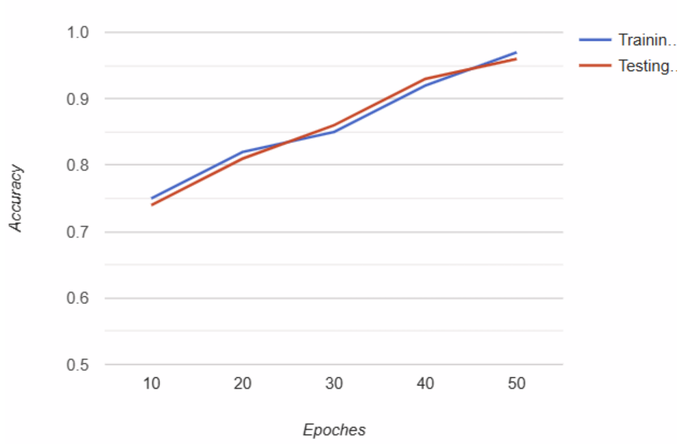

Figure 4: Accuracy for Train and Test dataset

The ultimate classification rate of the proposed system was about 94 which is a huge improvement in comparison to traditional analysis in previous research. Along with accuracy, other performance measures including precision, recall and F1 -score were also considered to validate comprehensively. The classifier was very accurate with low rate of false-positive and high rate of recall signifying that the classifier is very good in identifying the vitamin deficiency cases correctly. The summarization of these performance measures is presented in Table 1 that reveals the efficiency of the suggested approach in some categories of deficiencies.

The system is rich as the results of the segmentation also confirm its viability. The combination of curvelet-based enhancement and morphological manipulations along with Otsu threshold created the opportunity to help the system isolate the affected areas and the surrounding healthy tissue correctly. The visual inspection of the results of the segmentation proves that the boundary detection process is more accurate than the traditional ones of segmentation in noisier and unequal light conditions. The system was also proven to have efficient computational performance which can be convenient on the real time or near real time use. The processing pipeline is streamlined, and the modular structure enables the framework to run on mobile or client-server environment without overly intense computation capabilities. All in all, the experimental findings prove the feasibility of the proposed system to provide efficient, reliable, and accurate detection of vitamin deficiency, based on the analysis of images.

The results of the experiment make it obvious that incorporating the latest image processing methods and deep learning models proves effective in detecting the presence of vitamin deficiency. The application of the curvelet transform in the optimization of features and extracting them is one of the main advantages of the suggested system. In contrast to the old wavelet transforms, the curvelet transform gives better edge and directional representation that is very vital in the analysis of the structure of biological tissue. This is because through this, the system has the ability to record fine details of visual clues, which relate to vitamin deficiencies and are otherwise not realized through traditional means.

Wiener filter before curvelet transformation is of importance to cut the noise factor and still retain essential details of an image. Medical images are subject to acquisition noise, light discrepancies and distortion of texture. The system can successfully deal with these challenges at the pre-processing level and thus the extracted features are of significant value that is discriminative. This has a direct effect on the increased classification accuracy that is realized in the experimental results.

The chosen segmentation strategy on the proposed system is also a prominent improvement to the current strategies. The use of morphological operations and Otsu thresholding makes it possible to separate the affected tissue regions with the healthy ones accurately. Such a narrow segmentation guarantees that feature extraction and classification are carried out on pertinent regions only and thus the aspect of misclassification is reduced and the system reliability is enhanced as well.

On the side of classification, Region-Based Convolutional Neural Network (R-CNN) is incredibly helpful in increasing the capability of the system to discover intricate spatial discoveries. R- CNN provides a good quality of capturing level features both low level features and high-level semantic features. The non-linear activation functions also aid the model and increase the ability of distinguishing between subtle changes in appearance of tissues. The fact that both curves come together at the same point shows that the model is well generalised, and it is not overfitting the training data.

The approach proposed has greater robustness and scalability compared to others that are occurring today and depend on hand crafted features and shallow classifiers. Non-standard images can be very difficult to work with using traditional systems and there is a lot of manual tuning that is needed. However, in comparison, the proposed deep learning-based system is flexible to changes in image quality, brightness, and texture level. This flexibility ensures that the system can be adapted to an actual implementation environment where one is not able to tightly regulate the conditions of image acquisition.

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The other advantage of the proposed system is that it is suitable in both real-time and mobile-based application. Compared to the remote executive architecture, the client-server release model enables the computationally heavy computations to be distributed to ease the processing load on the end-user computers. The design of this system will be incorporated into mobile healthcare systems with access to early screening of vitamin deficiency especially in resource- restricted environments. However, despite the strengths, some limitations do exist. The existing system can also be further enhanced by increasing the size and variety of the training data including the clinically tested images. Moreover, multimodal data, as the history of patients or the presence of biochemical parameters, might help to maximize the quality of the diagnosis. These are the restrictions which give good guidelines on future research.

TABLE 1: PRECISION AND RECALL PERFORMANCE OF DETECTED SYMPTOMS

Symptom Tag	Precision (%)	Recall (%)
Tongue	100.0	100.0
Red Tongue	100.0	100.0
Eye	100.0	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

VI. CONCLUSION

The proposed research presents a sophisticated image processing and deep learning architecture of automated vitamin deficiencies detection using human tissues images. The proposed system is highly accurate, robust, and reliable because it combines curvelet-based image enhancement, morphological segmentation techniques, and a Region-Based Convolutional Neural Network (R- CNN) to classify vitamin-deficient tissues. The evidence-based practice confirms that the approach is a cheaper, non-invasive evaluation method to the traditional diagnostic techniques and, thus, reduces the use of laboratory tests and clinical visits. With automated working process and the ability to process in real time, the system has a significant potential in enhancing the early detectives and making large scale screening of the health of a population. Further research will focus on the integration of advanced patterns of Artificial neural networks (ANN) with attention mechanisms to improve feature learning and interpretability. Also, enhanced with clinically verified images, the multimodal representation of the patient medical history, and provision of the framework as a unitary mobile-based application are expected to increase the level of diagnostic accuracy and practical use.

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