Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 5, May : 2025
https://doi.org/10.36893/iej.2025.v54i05.04

Nutrient Scope: A Vision-Based Approach to Vitamin Deficiency Analysis

1. Mr. K. Amrutasagar, 2. K. Shanmukha Kiran, 3. G. Subhash, 4. G. Srikanth, 5. B. Swapna

1 Assistant Professor, Department of CSE(AI&ML), SR Gudlavalleru Engineering College, Krishna, Andhra Pradesh, India

2, 3, 4, 5 Student, Department of CSE(AI&ML), SR Gudlavalleru Engineering College, Krishna, Andhra Pradesh, India

Abstract: Vitamin deficiency is a terrible disease that kills people all over the world because it causes aberrant cells to develop and spread out of control. An essential organ that creates a barrier of defence against the environment is the skin tissue. However, the skin tissue is vulnerable to illness since it is found on the exterior. The most deadly type of vitamin deficiency in people is vitamin deficiency. If caught early, stage 1 vitamin deficiency can be totally treated. Which one is cancerous can only be determined by a skilled dermatologist. Additionally, which one is not cancerous? The development of new moles or modifications to preexisting moles are typical signs of Stage 1 vitamin deficiency. Performing a physical examination with dermoscopy is one of the initial procedures in diagnosing Stage 1 Vitamin Deficiency. Without a dermatoscope, it is exceedingly difficult to visually identify these Stage 1 vitamin deficiencies since their boundaries are frequently blurry. A variety of pre-processing and image filtering techniques are used to the dermoscopy picture of vitamin deficiency. Segmentation is used to distinguish the area impacted by the vitamin deficiency from the healthy skin tissue. When it comes to helping medical professionals diagnose and treat patients, medical photographs are essential. Techniques for digital image processing can more precisely detect the characteristics and offer the relevant illness status.

Index Terms *-Vitamin Deficiency Detection, Skin Tissue Segmentation, , Wiener Filtering, Curvelet Transform, Morphological Processing, Otsu Algorithm, Automated Pre-Screening System, Adenocarcinoma Detection, Sputum Cytology Images.*

1. INTRODUCTION

Vitamin D Deficiency is one of the most prevalent forms of vitamin-related health issues worldwide, posing a significant threat to public health despite advancements in medical science and technology. It is associated with a high mortality rate and continues to affect populations globally [2]. Among the various types of vitamin deficiency, adenocarcinoma has emerged as one of the most alarming conditions, primarily due to the rising prevalence of smoking. In addition to smoking, other contributing factors include exposure to harmful fumes from indoor pollution, genetic predispositions, and environmental influences [4]. As reported by several studies, these factors have significantly increased the risk of Vitamin D Deficiency in high-risk populations [2] [5].

Detecting Vitamin D Deficiency at an early stage can drastically improve survival rates. Various imaging modalities such as X-rays, CT scans, and MRIs are used in the diagnostic process. However, these methods have their limitations, including cost, invasiveness, and the need for highly skilled personnel [3]. Sputum cytology, a non-invasive and cost-effective technique, has proven to be a valuable pre-screening tool for identifying vitamin deficiencies. Studies indicate that pre-screening with sputum cytology can significantly enhance survival rates in patients [4]. Despite its advantages, manual screening is often hampered by the scarcity of expert cytopathologists and the sheer volume of patients requiring diagnosis [1].

To address these challenges, an automated system for Vitamin D Deficiency detection using digital image processing techniques has become a necessity. Automated systems have the potential to analyze sputum cytology images effectively, reducing the burden on healthcare professionals while ensuring accuracy and efficiency. This research focuses on developing a pre-screening system capable of identifying adenocarcinoma through advanced image processing methods, thereby offering a reliable, low-cost, and scalable solution for early diagnosis [1][5].

2. LITERATURE REVIEW

Vitamin deficiency detection through image processing and neural networks is a breakthrough approach to addressing the high costs and accessibility issues associated with traditional diagnostic methods. This innovative research introduces a free artificial intelligence-based smartphone application capable of analyzing images of bodily parts, such as the eyes, lips, tongue, and nails to detect vitamin deficiencies. Many vitamin-related conditions manifest visibly in these regions, allowing the software to identify signs of deficiency without invasive procedures like blood tests. After detection, the application provides dietary suggestions to correct the deficiency through nutritional micro-correction. The model is trained to recognize and classify vitamin deficiencies with high accuracy and is continually improved through contributions from healthcare professionals, thereby enhancing its reliability and expanding its diagnostic capabilities [5].

Although vitamin deficiencies are relatively rare in industrialized nations, they persist among individuals with unbalanced diets, alcoholism, or those who have undergone gastrointestinal surgery. Imaging technologies serve a crucial role in confirming the clinical diagnosis of vitamin deficiency by revealing classical pathological patterns. These imaging findings are particularly useful in monitoring the effectiveness of treatment and in cases where a diagnosis might not be immediately apparent. Familiarity with radiological indicators of deficiencies in vitamins such as B1, B12, C, D, and K can help radiologists detect and diagnose cases early, enabling prompt treatment. Early diagnosis is vital, as

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 5, May : 2025
https://doi.org/10.36893/iej.2025.v54i05.04

many symptoms can be rapidly alleviated with proper vitamin supplementation [6].

The use of CNN (Convolutional Neural Networks) in image processing for vitamin deficiency detection represents a paradigm shift in preventive healthcare. A novel desktop application has been developed that bypasses the need for traditional blood tests by analyzing skin images uploaded by users. The algorithm identifies visual patterns and anomalies associated with vitamin shortages and generates detailed reports outlining any deficiencies. Moreover, it offers tailored dietary advice to enhance the user's vitamin intake and mitigate health risks. This approach supports early detection and timely intervention, which is crucial in preventing conditions such as anemia, infections, maternal and infant mortality, and cognitive and physical developmental delays [7].

Research into basal cell carcinoma (BCC) and squamous cell carcinoma (SCC) has highlighted the importance of early detection to avoid severe treatment outcomes. A study conducted in Australia assessed the correlation between carcinoma growth rates and various factors including patient demographics, tumor characteristics, and medical check-up frequency. Results revealed that BCCs tend to increase in size the longer they are left untreated, whereas SCCs showed less consistent growth patterns. Larger tumor sizes in SCCs were associated with variables such as older age, male sex, and lack of frequent medical skin checks. These findings emphasize the importance of timely medical evaluations and underscore the role of regular dermatological screenings in managing skin cancer risks [8].

The British Association of Dermatologists has periodically updated its guidelines for managing basal cell carcinoma to reflect the latest clinical evidence and therapeutic strategies. These recommendations offer a comprehensive overview of BCC diagnosis, epidemiology, investigation, and management, with clear grading of evidence quality. By following these updated guidelines, healthcare providers can ensure the most effective and evidence-based care for patients with BCC. Continuous guideline revisions are crucial for addressing emerging challenges in skin cancer management and for incorporating advancements in treatment modalities and diagnostic techniques [9] [10].

3. METHODOLOGY

3.1 Proposed Work

The proposed system utilizes advanced image processing techniques to enhance and analyze skin tissue images for the detection of Vitamin Deficiency. Initially, the images undergo Wiener filtering to remove noise while preserving important edge details. A Forward Discrete Curvelet Transform (FDCT) is then applied to extract high-frequency components, capturing structural details such as edges and singularities. These high-pass features are added to the original image to produce an enhanced image with sharper edges, which aids in accurate segmentation. Morphological processing and thresholding are subsequently performed to refine the image and extract the boundaries of the affected regions. Finally, the Otsu algorithm is used to segment and distinguish healthy skin tissue from

Vitamin Deficiency-affected regions, providing a reliable basis for further diagnosis.

This system aims to replace manual calculations with an automated, computerized solution capable of early-stage detection of Vitamin Deficiency. By integrating methods like Wiener filtering, Curvelet Transform, and morphological processing, the proposed approach ensures high accuracy in detecting abnormal tissues. The solution is both cost-effective and scalable, making it suitable for wide-scale deployment, especially in regions with limited access to expert dermatologists or cytopathologists. The proposed methodology not only improves diagnostic accuracy but also enhances survival rates by enabling timely detection and treatment of Vitamin Deficiency.

3.2 System Architecture

The architecture of the proposed Vitamin Deficiency detection system is designed to efficiently process and analyze medical images for accurate diagnosis. It begins with the Image Acquisition phase, where digital images of skin tissue are captured using a digital camera or other imaging modalities. These images, primarily in RGB format, are collected from diverse sources and serve as the input to the system. The next phase is Image Preprocessing, where Wiener filtering is applied to eliminate noise and enhance the image quality while retaining critical edge details. The preprocessed image is then subjected to a Forward Discrete Curvelet Transform (FDCT), which extracts high-frequency components to capture detailed structural features such as edges and singularities.

Following preprocessing, the enhanced image undergoes Morphological Processing to refine the boundaries and highlight the affected regions. The system then applies Thresholding to generate a binary image, segmenting the Vitamin Deficiency-affected regions from healthy skin tissue. The final segmentation is achieved using the Otsu Algorithm, which ensures clear distinction between normal and abnormal regions. This modular architecture allows for seamless integration of various image processing techniques, providing a scalable and cost-effective solution for Vitamin Deficiency detection. By automating the detection process, the system reduces the reliance on manual screening, offering improved diagnostic accuracy and timely detection.

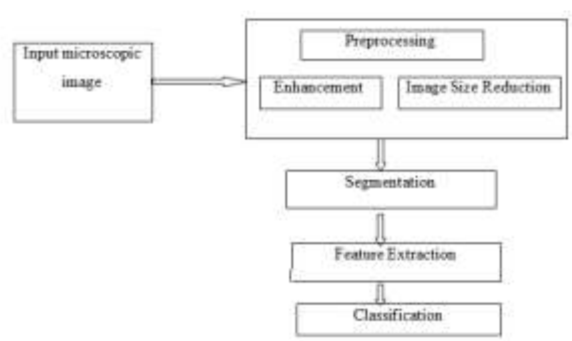


Fig 1: Proposed System Architecture

3.3 Modules

3.3.1 Image Acquisition

- Collect digital images of skin tissue using cameras or imaging modalities like dermoscopy.
- Ensure input images are in RGB format for processing.

3.3.2 Image Preprocessing

- Apply Wiener filtering to remove noise and preserve edge details.
- Enhance image quality for better segmentation and feature extraction.

3.3.3 Feature Extraction

- Use Forward Discrete Curvelet Transform (FDCT) to extract high-frequency details like edges and singularities.
- Add high-pass features to the original image to enhance structural details.

3.3.4 Morphological Processing and Thresholding

- Perform morphological operations to refine image boundaries.
- Apply thresholding to create a binary image for clear segmentation.

3.3.5 Segmentation and Classification

- Use the Otsu algorithm to separate Vitamin Deficiency-affected regions from healthy tissue.
- Classify the segmented regions into normal or abnormal using RCNN.

3.3.6 Result Analysis and Diagnosis

- Generate diagnostic results based on segmented images and classification.
- Provide insights for early detection and treatment of Vitamin Deficiency.

3.3.7 Automated Pre-Screening System

- Implement the automated system for large-scale deployment.
- Reduce reliance on manual screening by cytopathologists.

3.4 Algorithms used

The following algorithms are applied for detection of Vitamin Deficiency.

3.4.1 RCNN

The RCNN algorithm for Vitamin Deficiency detection begins with Input Image Acquisition, where skin tissue images are captured in RGB format using devices like digital cameras or dermoscopes. These images undergo Image Preprocessing using Wiener filtering to remove noise while preserving edge details, followed by enhancement using high-frequency details extracted via Curvelet Transform. In the Feature Extraction phase, convolutional layers identify significant features such as edges, patterns, and textures, while pooling layers reduce spatial resolution to retain dominant features. Non-linear activation functions, like ReLU, are then applied to enable the model to learn complex patterns.

Next, Region Proposal Generation identifies areas of interest potentially affected by Vitamin Deficiency. Segmentation is performed using the Otsu algorithm to distinguish between affected and healthy regions, and these segmented regions are passed through fully connected layers for final classification. The algorithm outputs diagnostic results, highlighting affected areas and classifying the Vitamin Deficiency stage to assist in early detection and medical decision-making. This process ensures accurate and automated detection while minimizing reliance on manual screening.

3.4.2 AlexNet

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 5, May : 2025
https://doi.org/10.36893/iej.2025.v54i05.04

A deep convolutional neural network (CNN) called AlexNet was created specifically for image categorization consists of three fully linked layers and five convolutional layers. For quicker training, ReLU (Rectified Linear Unit) activation is used, extensively employed in AI research, object identification, and picture recognition.

3.4.3 EM Algorithm

An iterative technique for estimating parameters in probabilistic models is the Expectation-Maximization (EM) Algorithm. Two steps are alternated until convergence is reached: Expectation (E-step): Makes an estimate of the concealed or missing data using the parameters as of right now. In order to maximize the likelihood function, the model parameters are updated via maximization (M-step), often utilized in image processing, natural language processing, and clustering.

4. EXPERIMENTAL RESULTS

The Performance of our proposed system is going to measure using the following measures.

Accuracy: How well a test can differentiate between healthy and sick individuals is a good indicator of its reliability. Compare the number of true positives and negatives to get the reliability of the test. Following vales specifies Training and Testing Accuracy of proposed system.

Training Accuracy: **0.98,** Testing Accuracy: **0.97**

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Precision value of proposed system as follows.

Precision: **0.97**

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class. Recall value of proposed system as follows.

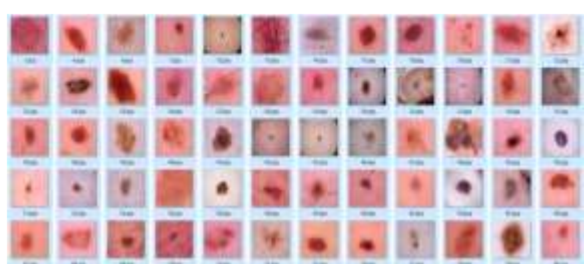
Recall: **0.96**

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

mAP: **0.96**

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic.

F1 Score: **0.96**



Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 5, May : 2025
https://doi.org/10.36893/iej.2025.v54i05.04

Fig 2: Dataset for Proposed system

Fig 3: Login page

Fig 4: Uploading of images

Fig 5: Predicted results and suggestions

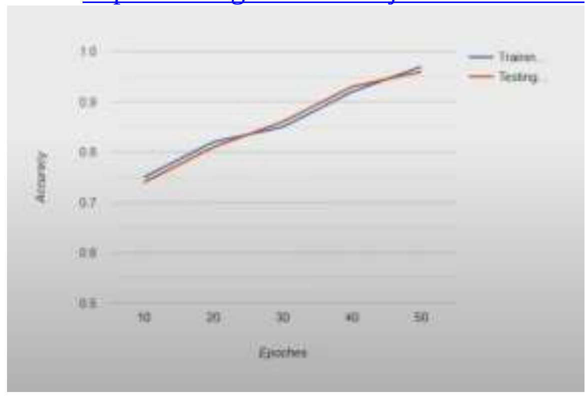


Fig 6: Accuracy plot

5. CONCLUSION

The implementation of the vitamin deficiency detection system has proven to be an effective tool for preliminary health assessments, offering users a quick and accessible way to analyze their nutritional status. The system leverages a structured approach, combining user-reported symptoms, dietary habits, and an AI-based recommendation engine to generate personalized results. By designing a multi-page web application, the project ensures an intuitive user experience, guiding individuals through data input, analysis, and personalized recommendations. The use of automated deficiency detection and customized dietary suggestions has made the system a valuable resource for individuals seeking to improve their nutritional health.

This system successfully addresses the growing need for accessible and data-driven health assessment tools. While it does not replace laboratory tests, it serves as an essential first step in detecting possible deficiencies and encouraging individuals to seek medical advice when necessary. With continuous enhancements in AI, real-time data integration, and medical validation, the system has the potential to become an invaluable tool in preventive healthcare and nutrition management

In this research, the scratch image is segmented for form analysis using a traditional image processing approach. Following a demonstration of the dataset and methodology employed in this research, performance analysis reveals that the algorithm can extract forms even more effectively than the labels. Lastly, several enhancement recommendations are made in order to better optimize the algorithm.

6. FUTURE SCOPE

The vitamin deficiency detection system has demonstrated its effectiveness as a preliminary health assessment tool, but there are several areas where it can be expanded and improved. With advancements in artificial intelligence, wearable health devices, and medical data integration, the system can evolve into a more comprehensive preventive healthcare solution. Future enhancements can focus on increasing accuracy, improving user engagement, and expanding accessibility through multiple platforms

REFERENCES

[1] M. J. Eide, M. M. Asgari, S. W. Fletcher, A. C. Geller, A. C. Halpern, W. R. Shaikh, L. Li, G. L. Alexander, A. Altschuler, S. W. Dusza, A. A. Marghoob, E. A. Quigley, and M. A. Weinstock;, “Effects on skills and practice from a web-based Vitamin Deficiency course for primary care providers,” J. Am. Board Fam. Med. 26(6), 648–657 (2013).

[2] American Vitamin Deficiency Society. Vitamin Deficiency Facts and Figs. (2014).

[3] N. R. Telfer, G. B. Colver, and C. A. Morton; British Association of Dermatologists, “Guidelines for the management of basal cell carcinoma,” Br. J. Dermatol.159(1), 35–48 (2008).

[4] A. Kricker, B. Armstrong, V. Hansen, A. Watson, G. Singh-Khaira, C. Lecathelinais, C. Goumas, and A. Girgis, “Basal cell carcinoma and squamous cell carcinoma growth rates and determinants of size in community patients,” J. Am. Acad. Dermatol. 70(3), 456–464 (2014).

[5] E. A. Gordon Spratt and J. A. Carucci, “Vitamin Deficiency in immune suppressed patients,” Facial Plast.Surg. 29(5), 402–410 (2013).

[6] S. Ogden and N. R. Telfer, “Vitamin Deficiency,” Medicine (Baltimore) 37(6), 305– 308 (2009).

[7] K. Korotkov and R. Garcia, “Computerized analysis of pigmented Skin Tissue lesions: a review,” Artif. Intell.Med. 56(2), 69–90 (2012).

[8] A. O. Berg, D. Best; US Preventive Services Task Force, “Screening for Skin Tissue Vitamin Deficiency: recommendations and rationale,” Am. J. Prev. Med. 20(3 Suppl), 44–46 (2001).

[9] M. M. Rahman and P. Bhattacharya, “An integrated and interactive decision support system for automated Stage 1 Vitamin Deficiency recognition of dermoscopic images,” Comput.Med. Imaging Graph.34(6), 479–486 (2010).

[10] A. G. Isasi, B. G. Zapirain, and A. M. Zorrilla, “Stage 1 Vitamin Deficiency non-invasive diagnosis application based on the ABCD rule and pattern recognition image processing algorithms,” Comput. Biol. Med. 41(9), 742–755 (2011).