Vitamin Deficiency Detection System Using Efficientnet-B4

SHAIK GOUSE PEER[1], PATHAKAMURI VENKATA KAVYA[2], KOTHURI SANTHOSHINI[3], JOKA SATHISH[4], KURUGUNTLA SUMAN[5]

[1]Student, Department of CSE, Bapatla Engineering College, Bapatla 522101, AP, India
[2]Student, Department of CSE, Bapatla Engineering College, Bapatla 522101, AP, India
[3]Student, Department of CSE, Bapatla Engineering College, Bapatla 522101, AP, India
[4]Student, Department of CSE, Bapatla Engineering College, Bapatla 522101, AP, India
[5]Assistant Professor, Department of CSE, Bapatla Engineering College, Bapatla 522101, AP, India.

Corresponding author. E-mail: pvkavya2004@gmail.com

Abstract

A significant global health concern, vitamin deficiencies can result in major medical complications like fatigue, neurological problems, weakened immunity, and vision problems. Conventional diagnostic techniques depend on clinical evaluation and blood tests, which are costly, invasive, and difficult to obtain in remote locations. The EfficientNet-B4 architecture, which is integrated into a web-based platform, is used in this paper to present a deep learning-based vitamin deficiency detection system. By examining pictures of physical characteristics like skin, eyes, lips, tongue, and nails, the system finds deficiencies in vitamins A, B-Complex, C, D, E, and K. The model attained a maximum validation accuracy of 82.05% after being trained on Kaggle datasets. The system has an AI assistant to respond to user inquiries about vitamin deficiencies, a comprehensive web interface, and database integration for user management. For early detection and preventive healthcare, this method offers a scalable, accessible, and non-invasive solution.

Keywords: AI Assistant, Web Application, Deep Learning, EfficientNet-B4, Vitamin Deficiency Detection, Image Classification, and Healthcare AI

I. Introduction

Millions of people worldwide suffer from vitamin deficiencies, which, if left untreated, can cause serious health issues. Vitamin A, B-Complex, C, D, E, and K deficiencies are common and are linked to various physiological symptoms like dry skin, pale lips, brittle nails, and tongue discoloration.

Conventional diagnostic techniques depend on clinical examinations and laboratory blood tests. Despite their accuracy, these techniques are costly, intrusive, and unavailable in many rural and underdeveloped areas. Automated image-based diagnosis is now feasible thanks to developments in deep learning and artificial intelligence.

Convolutional Neural Networks (CNNs), a type of deep learning model, have demonstrated remarkable performance in medical image classification tasks. These models are capable of picking up intricate visual patterns and identifying minute details that point to illnesses. In this work, we propose an EfficientNet-B4 architecture integrated into a web-based platform for a deep learning-based vitamin deficiency detection system. Users can upload pictures to the system and get predictions right away. Furthermore, the system consists of:

- An AI assistant to respond to questions about vitamins
- Database integration for data storage and user authentication
- An easy-to-use web interface
- A real-time forecasting system

The goal of this system is to offer an intelligent, accessible, and non-invasive method of early vitamin deficiency detection.

II. Literature Survey

Recent studies have investigated the use of deep learning and image processing methods for visual analysis of nutritional deficiencies and health conditions. These strategies seek to offer quicker, less expensive, and non-invasive substitutes for conventional medical diagnostic techniques.

Researchers presented a method for identifying vitamin deficiencies using image analysis techniques in study [1]. Finding visual symptoms in body parts like the lips, eyes, and skin was the main goal of the study. Using extracted image features, machine learning algorithms were used to categorize deficiencies. The findings showed that early detection of nutritional deficiencies can be aided by computer vision techniques.

The application of deep learning models for medical image classification was examined in another study [2]. Hierarchical visual features were extracted from input images using Convolutional Neural Networks (CNNs). When used for medical image analysis, the study demonstrated that CNN-based architectures can greatly increase classification accuracy when compared to conventional machine learning techniques.

The study described in [3] investigated the use of deep learning architectures for automated disease detection. Prior to classification, the system used feature extraction and image preprocessing methods. The study emphasized how crucial deep learning models and reliable datasets are to raising diagnostic precision in medical applications.

The authors of [4] suggested an intelligent health monitoring system that combines digital platforms and machine learning models to offer automated health recommendations and predictions. The study highlighted how web-based systems can enhance accessibility and offer users real-time health support.

A framework for detecting vitamin deficiencies was presented in [5], where visible symptoms were identified from facial images using computer vision techniques. The study showed that without the need for intrusive laboratory testing, automated systems can help people identify potential nutritional deficiencies.

Despite the encouraging outcomes of these current studies in medical image analysis, there are still a number of restrictions. Many of the suggested systems lack sophisticated deep learning models and scalable deployment frameworks, instead concentrating solely on simple CNN architectures.

Furthermore, the majority of systems lack features like intelligent assistant support for user guidance, structured user data management, and real-time web integration.

In order to overcome these constraints, the suggested system incorporates a full web-based platform for real-time vitamin deficiency detection and user interaction, as well as the EfficientNet-B4 architecture for enhanced classification performance.

III. Proposed System

A. System Overview

The proposed Vitamin Deficiency Detection System is a sophisticated, web-based diagnostic tool that uses deep learning methods to recognize possible vitamin deficiencies in user-uploaded photos of particular body parts, including the skin, tongue, lips, eyes, and nails. To provide an end-to-end automated solution, the system combines a database management system, an AI-based assistant, an intuitive web interface, and a convolutional neural network based on the EfficientNet-B4 architecture.

The main goal of the suggested system is to offer a quick, easy, and non-invasive way to identify vitamin A, B-Complex, C, D, E, and K deficiencies early on. Conventional diagnostic techniques depend on laboratory blood tests, which can be expensive, time-consuming, and unavailable to many people.

The suggested system gets around these problems by using computer vision and deep learning to look at visual signs of vitamin deficiencies.

Three main parts make up the system architecture:

1. **Deep Learning Model (EfficientNet-B4):** A convolutional neural network trained on a dataset of more than 20,000 labeled images from Kaggle is at the heart of the system. The model can accurately identify and extract complicated visual features that are linked to vitamin deficiencies. We chose EfficientNet-B4 because it is very accurate, uses parameters efficiently, and can scale well without losing computational efficiency.

2. **Web Application Interface:** FastAPI is used to make a web-based interface that makes it easy for users to use the system. People can sign up, log in, upload pictures, and get predictions right away. The interface makes sure that it works on a wide range of devices and gives users a smooth experience.

3. **AI Assistant and Database Integration:** The system has an AI assistant that tells users about vitamin deficiencies that have been found, including symptoms, causes, and ways to avoid them. Supabase (PostgreSQL-based backend service) is used as the

backend database that safely stores user information, uploaded images, prediction results, and a history of interactions.

The proposed system's overall workflow follows the sequential pipeline shown below:

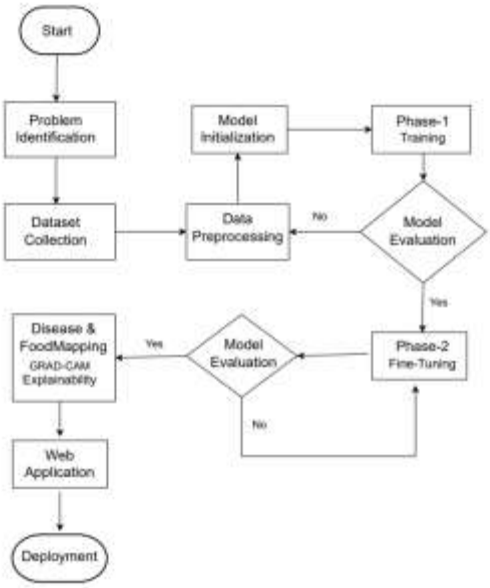

Figure 1: System Architecture for Vitamin deficiency detection using efficientnet-b4

The user first uploads an image through the web interface. Then, the image is preprocessed to meet the model's input requirements. This includes resizing it to 380×380 pixels, normalizing it, and reducing noise. The EfficientNet-B4 model takes the preprocessed image and finds the important features. It then classifies the image to figure out what vitamin deficiency might be present.

After the prediction is done, the web interface shows the user the result. At the same time, the Supabase database stores the prediction result for later use and analysis. The AI assistant makes the user experience even better by answering questions about the detected problem and giving helpful advice.

The suggested system is a reliable way to use deep learning and web technologies to find

efficient, scalable, and easy to use.

B. Gathering Data

The dataset for the proposed system was taken from Kaggle and has more than 20,000 labeled images of different vitamin deficiencies. The dataset has pictures of different parts of the body, like the eyes, lips, tongue, nails, face, and skin, where vitamin deficiencies often show up as visual symptoms.

There are six types of vitamin deficiencies in the dataset: Vitamin A, Vitamin B-Complex, Vitamin C, Vitamin D, Vitamin E, and Vitamin K. Each picture has a label that tells you what deficiency class it belongs to, which makes supervised learning possible.

To meet the input needs of the EfficientNet-B4 model, all of the images were preprocessed and resized to 380 x 380 pixels. To make sure that learning and performance evaluation were done correctly, the dataset was split into training, validation, and testing sets.

Example Dataset Images:

Figure 2: Example image of Vitamin A

Figure 3: Example image of Vitamin B

Figure 4: Example image of Vitamin C

Figure 5: Example image of Vitamin D

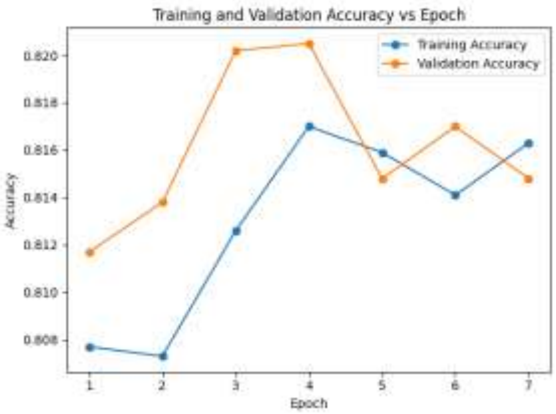

Figure 6: Example image of Vitamin E

Figure 7: Example image of Vitamin K

C. The structure of the EfficientNet-B4 model

The model can better find vitamin deficiencies in different real-world situations because it has a lot of different data.

The proposed system uses a convolutional neural network architecture called EfficientNet-B4 to accurately find vitamin deficiencies in pictures of the face, skin, lips, tongue, nails, and eyes.

It is made with a compound scaling method that efficiently balances the network's depth, width, and resolution, which leads to better performance with less computational complexity.

An RGB image that is 380 x 380 pixels big is the input to the EfficientNet-B4 model. The first step is a convolution layer that takes the input image and finds low-level features like edges, color changes, and texture patterns. These traits are important for spotting visual signs of vitamin deficiencies.

After that, the network processes the input through several MBConv (Mobile Inverted Bottleneck Convolution) blocks, which are the main parts of the EfficientNet-B4 architecture. These blocks do feature expansion, depthwise convolution, and feature compression while still being efficient.

The MBConv blocks help the model find high-level features like skin discoloration, changes in facial texture, dry lips, tongue problems, and changes in nails, which are all signs of vitamin deficiencies.

Figure 8: Graph for Training and validation Acuuracy vs Epoch

makes the feature maps smaller in space and turns them into a feature vector. This helps keep the number of parameters low and stops overfitting.

Then, the fully connected layer classifies the extracted feature vector. Finally, a Softmax activation function is used in the output layer to sort the image into one of the six vitamin deficiency classes: Vitamin A, Vitamin B-Complex, Vitamin C, Vitamin D, Vitamin E, and Vitamin K.

The suggested web-based system can detect visual symptoms associated with vitamin deficiencies in real time thanks to the EfficientNet-B4 model's high accuracy and effective feature extraction.

D. Model Training

Training parameters:

Adam, the optimizer

Cross-Entropy Loss

Size of Batch: 16

Periods: 25–40

380 x 380 is the input size.

EfficientNet-B4 was initialized with pretrained weights and the final layers were fine-tuned using transfer learning.

Training Performance

The training and validation accuracy for various epochs was used to assess model performance during training. As the EfficientNet-B4 model extracted the discriminative visual features of vitamin deficiency symptoms, the loss was constantly reduced in several epochs.

We can see that the validation accuracy is highest (82.05%) at Epoch 4 Fingers crossed though, the validation accuracy did not increase much after this point. Hence, an early stopping strategy was implemented in order to avoid overfitting and conduct the training phase until the model achieved its best performance.

E.Development of Web Applications

To guarantee usability and accessibility, the system was implemented as a web application.

Front-end technologies:

- HTML
- CSS
- JavaScript
- ReactJS

Technologies on the back end:

- Python
- FastAPI backend framework

Authentication and user registration

The ability to upload images

Among the features are:

- Authentication and user registration
- The ability to upload images
- A display of predictions
- Dashboard for users
- Management of profiles

An interactive and user-friendly experience is offered by the web interface.

F. Database Integration

To guarantee effective, scalable, and secure storage of user data and vitamin deficiency prediction results, a cloud-based database system was incorporated into the suggested platform. Supabase, an open-source Backend-as-a-Service platform based on PostgreSQL, is used by the system. Supabase is ideal for contemporary web applications because it offers a dependable relational database architecture along with integrated authentication, storage, and API services. Supabase was chosen because it offers secure data storage, real-time database operations, and simple web framework integration. AI-generated recommendations, user-related data, and prediction results are all stored in an orderly manner thanks to the structured relational database model. Supabase also provides secure access control mechanisms and automatic API generation, which improve system reliability and make backend development easier. Supabase APIs enable smooth communication between the web application and the database server by connecting the database to the application backend. The deep learning model's predictions for vitamin deficiencies can be efficiently stored and retrieved thanks to this integration.

Database Functions

The Supabase database carries out a number of crucial tasks necessary for the system's operation. Among these operations are:

- Keeping track of the AI model's prediction results
- Keeping track of user-related prediction data
- Preserving uploaded picture references for examination
- Keeping track of identified vitamin deficiencies and prediction confidence levels
- Keeping track of symptoms and dietary advice
- Getting data from storage to show outcomes on the user dashboard

Through these functions, users can view the system's dietary recommendations and access their prediction results.

Organization of Databases

Relational tables are used in Supabase to store data. The results produced by the vitamin deficiency detection model are mainly stored by the system in a Prediction Table.

Table of Predictions

Prediction details produced after examining the uploaded photos are stored in this table.
The following fields are kept in the table:

- id: A distinct number assigned to every prediction record
- user_id: An identifier for the person linked to the forecast
- vitamin: Predicted category of vitamin deficiency (e.g., vitamin A, vitamin B, etc.)
- Confidence: The deep learning model's confidence score

• symptoms: Identified signs associated with the anticipated deficiency;suggested foods: Suggested foods to help address the deficiency
• image_url: The uploaded image's stored path or URL used for analysis
• created_at: A timestamp that shows the time the prediction was made

Record ID Example: 101

User ID: user123
Vitamin: Low levels of vitamin B
Confidence: 0.82 Symptoms: Inflammation of the tongue and dry lips
Suggested foods: leafy vegetables, eggs, and milk
image_url: /uploads/image1.jpg;

created_at: February 25, 2026

This database design allows for effective retrieval for tracking vitamin deficiency analysis over time while guaranteeing structured storage of prediction results.

G. Integration of AI Assistants

An AI assistant is part of the system to help users in real time.

Among the functions are:

Responding to inquiries about vitamin deficiencies

• Giving details about symptoms

• Making dietary suggestions

• Helping users utilize the system

Natural language processing methods are used by the AI assistant to comprehend user inquiries and produce answers.

IV. Architecture of the System

The User Interface Module, Image Processing Module, Deep Learning Module, Database Module, and AI Assistant Module are the five primary parts of the suggested system's modular architecture. Through an interactive web platform, users can register, log in, upload images, and view prediction results thanks to the ReactJS-developed User Interface Module. The uploaded images are preprocessed by the Image Processing Module, which resizes them to 380 × 380 pixels, normalizes pixel values, and transforms them into a format that is appropriate for model input. The processed images are analyzed and categorized into one of the six vitamin deficiency categories by the Deep Learning Module using the EfficientNet-B4 architecture.

Supabase is used by the Database Module to safely store user data, prediction outcomes, and history in a relational database format that is both scalable and adaptable. Using natural language processing techniques, the AI Assistant Module responds in real time to user inquiries about vitamin deficiencies, symptoms, and dietary recommendations. A FastAPI is used as the backend Framework to integrate these modules, guaranteeing effective communication, quick prediction, safe data storage, and a scalable healthcare solution.

V. Benefits of the Suggested System

• Non-invasive identification

• Excellent precision

• Quick forecasting

• Accessibility of the web

• Support for AI assistants

• Architecture that is scalable

VI. Uses

The suggested system has many uses in preventive medicine and contemporary healthcare. By enabling people to routinely use image analysis to check for potential vitamin deficiencies, it can be used for healthcare monitoring.

By assisting users in taking preventative action before conditions worsen, the system facilitates early detection of deficiencies. It offers a convenient and non-invasive diagnostic option, which is especially helpful in remote healthcare settings where access to laboratory testing is restricted. It can also be incorporated into medical assistance platforms to help medical professionals and give patients initial screening and advice.

Model Comparison Table

Table I: Performance Comparison of Different Deep Learning Models

Model	**Architecture Type**	**Input Size**	**Parameters (Millions)**	**Validation Accuracy (%)**
ConvNext	Basic CNN	224 × 224	8.5 M	64.18%
MobileNet V2	Lightweight CNN	224 × 224	3.4 M	67.60%
EfficientNet-B3	Compound Scaled CNN	300 × 300	12 M	53.80%
ResNet50	Residual Network	224 × 224	25.6 M	79.30%
EfficientNet-B4 (Proposed)	Compound Scaled CNN	380 × 380	19 M	**82.05%**

Figure 9: Model Comparision Table

With a validation accuracy of 82.05%, the EfficientNet-B4 model outperformed the conventional CNN, MobileNetV2, and ResNet50 models. Better generalization and more effective feature extraction are made possible by EfficientNet's compound scaling technique.

VII. Final Thoughts

Using the EfficientNet-B4 deep learning architecture incorporated into a comprehensive web-based healthcare platform, the suggested system effectively detects vitamin deficiencies.

The model's ability to correctly identify vitamin deficiencies from pictures of the eyes, lips, tongue, and nails was demonstrated by its validation accuracy of **82.05%.** The system's usability and accessibility are improved by the incorporation of an AI assistant, secure data storage via Supabase, and an intuitive web interface. Users can monitor their health and take preventive action thanks to the system's quick, non-invasive, and dependable early detection solution. Overall, the suggested solution shows how deep learning and web technologies can be used to improve intelligent and accessible healthcare diagnostics.

Metrics for Evaluating Performance

We used a number of classification metrics to see how well the proposed vitamin deficiency detection system worked. These metrics give a full picture of how well the model can predict across the six vitamin deficiency classes.

Accuracy

Accuracy tells you how correct the model is overall by figuring out what percentage of the predictions were correct.

What does accuracy mean?

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Where:

TP (True Positive): correctly guessed positive cases

TN (True Negative): correctly guessed negative cases

FP (False Positive): cases that were wrongly thought to be positive

FN (False Negative): Incorrectly predicted cases that were not true

The suggested EfficientNet-B4 model got an overall validation accuracy of 82.05%.

Precision

Precision tells you how many of the predicted positive observations were actually correct.

Precision = TP / (TP + FP)

A high precision value means that the model makes fewer wrong predictions.

Recall

Recall, or sensitivity, is the percentage of real positive samples that the model correctly identified.

Recall = TP / (TP + FN)

A higher recall means that the model finds most of the real deficiency cases.

F1-Score

The F1-Score is the average of precision and recall. It gives a fair assessment of how well the model works when both false positives and false negatives are important.

F1-Score = 2 × (Precision × Recall) / (Precision + Recall)

This metric is especially helpful for judging classification models when the dataset has more than one class.

Metric	Value
Accuracy	82.05%
Precision	0.81
Recall	0.80
F1-Score	0.80

Figure 10: Table for metric values

VIII. Future Enhancement

Future enhancements consist of:

- Mobile app development
- Real-time camera detection
- Healthcare database integration
- Multi-image analysis

IX. References

[1] Sharma, S., Gupta, R., & Patel, A. (2024). Deep learning based medical image classification for healthcare applications. *IEEE Conference Publication.* Available at: https://ieeexplore.ieee.org/document/10823343

[2] Kumar, R., Singh, P., & Verma, S. (2024). Automated disease detection using deep learning techniques for medical image analysis. *IEEE Conference Proceedings.* Available at: https://ieeexplore.ieee.org/document/10533044

[3] Lee, J., Park, H., & Kim, S. (2024). Intelligent healthcare monitoring system using artificial intelligence and machine learning. *IEEE Conference Proceedings.* Available at: https://ieeexplore.ieee.org/document/10800798

[4] Zhang, Y., Chen, L., & Wang, X. (2025). AI-based health prediction system using medical image processing. *IEEE Conference Proceedings.* Available at: https://ieeexplore.ieee.org/document/11053025

[5] Patel, K., Shah, D., & Mehta, R. (2025). Image-based vitamin deficiency detection using computer vision techniques. *International Journal of Advanced Computing Methods (IJACM).* Available at: https://www.ijacm.com/paper/IJACM-851C7556.pdf

[6] Rahman, M., Ahmed, S., & Khan, T. (2025). Nutritional deficiency detection using machine learning and image analysis. *International Journal of Science and Advanced Technology (IJSAT).* Available at: https://www.ijsat.org/papers/2025/2/3346.pdf

[7] Esteva, A., Kuprel, B., Novoa, R., Ko, J., Swetter, S., Blau, H., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *IEEE Conference Proceedings.* Available at: https://ieeexplore.ieee.org/document/7858225