



An Intelligent Image-Based System for Early Detection of Nutritional Deficiencies Using ResNet and Attention Mechanism

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Abstract: Vitamin and mineral deficiencies are widespread health concerns that often remain undetected due to reliance on costly and time-consuming laboratory tests. This paper proposes an AI-driven, non-invasive diagnostic system that utilizes deep learning to identify nutritional deficiencies from images of facial skin, eyes, tongue, nails, and hair. The model employs transfer learning using ResNet152V2 combined with an attention mechanism to enhance feature extraction by focusing on critical regions associated with deficiency symptoms. Data augmentation and regularization techniques are applied to improve generalization and handle limited datasets.

The proposed system is capable of detecting multiple deficiencies, including Vitamins A, B-complex, C, D, E, K, as well as iron and zinc deficiencies, with high accuracy, precision, recall, and F1-score. Experimental results demonstrate that the model effectively captures subtle visual patterns and outperforms traditional diagnostic approaches in

terms of speed and accessibility. The system is deployed through a user-friendly interface, enabling real-time predictions and supporting early diagnosis.

This approach provides a cost-effective and scalable healthcare solution, particularly beneficial for rural and underserved populations, and contributes to improved preventive healthcare and timely intervention.

Index terms - — Deep Learning, Vitamin Deficiency Detection, Mineral Deficiency, ResNet152V2, Attention Mechanism, Image Processing, Convolutional Neural Networks (CNN), Non-Invasive Diagnosis, Healthcare AI, Transfer Learning

1. INTRODUCTION

Vitamin and mineral deficiencies have become a major global health concern due to changing lifestyles, poor dietary habits, and limited access to quality healthcare. These deficiencies often manifest through visible symptoms such as skin discoloration, brittle nails, pale lips, tongue abnormalities, and

changes in hair texture. However, these early signs are frequently overlooked or misinterpreted, leading to delayed diagnosis and serious health complications. Traditional diagnostic methods primarily rely on laboratory-based blood tests and expert medical evaluation, which are often expensive, time-consuming, and inaccessible in rural or resource-constrained environments.

Recent advancements in Artificial Intelligence (AI) and Deep Learning have revolutionized the healthcare sector by enabling automated and accurate disease diagnosis using image-based analysis. Convolutional Neural Networks (CNNs), in particular, have demonstrated remarkable performance in identifying complex visual patterns from medical images. By leveraging these capabilities, AI systems can detect subtle symptoms that may not be easily recognizable through manual inspection. This opens new opportunities for developing non-invasive, fast, and cost-effective diagnostic solutions.

In this work, we propose an AI-driven system for the detection of vitamin and mineral deficiencies using image data captured from various human features such as facial skin, eyes, tongue, nails, and hair. The system utilizes a deep learning architecture based on ResNet152V2, a powerful pretrained convolutional neural network, combined with an attention mechanism to enhance feature extraction by focusing on symptom-specific regions. This approach improves classification accuracy and reduces false predictions.

The proposed system is designed to identify multiple deficiencies, including Vitamins A, B-complex (B2, B3, B9, B12), C, D, E, K, as well as iron and zinc deficiencies. By eliminating the dependency on laboratory tests, the system provides a rapid and accessible diagnostic solution that can be deployed through web or mobile platforms. This makes it highly suitable for rural healthcare applications, personal health monitoring, and early-stage disease detection.

Overall, this research aims to bridge the gap between advanced AI technologies and practical healthcare applications by offering a scalable, user-friendly, and efficient solution for nutritional deficiency diagnosis.

2. LITERATURE SURVEY

a) Vitamin Deficiency Detection Using Image Processing and Artificial Intelligence:

A vital component of our diet is vitamins. A vitamin deficit will result from inadequate intake. The AI system for early vitamin insufficiency diagnosis is presented in this research. This free mobile application uses the user's images of their eyes, lips, tongue, and nails to identify vitamin deficiencies without the need for a blood sample. The application will report any vitamin deficiencies discovered in the user and offer dietary recommendations to raise vitamin levels and combat deficiencies. The program has been taught to differentiate between images of the eyes, lips, tongue, and nails of normal people and those of individuals with vitamin deficiencies. Early identification of vitamin deficiencies can avert serious causes, such as poor cognitive and physical

development, anemia, mortality from infectious infections, and death during pregnancy or delivery.

b) Predicting injury severity in vehicle-to-pedestrian collisions: evidence from Madhya Pradesh state, India:

Using accident record data from the Madhya Pradesh Road Development Corporation and Accident Response System, which includes 6104 accident entries across 16 variables, the current study investigates the features of vehicle-to-pedestrian collisions and evaluates the factors influencing such crashes in Madhya Pradesh. A Random Forest Algorithm was utilized for predictive modeling to precisely categorize injury severity based on many factors, and Latent Class Clustering was utilized to address data heterogeneity. Three different classes were identified by the latent clustering: Class 1 (27.7%) was linked to fewer severe injuries and was attributed to effective traffic controls; Class 2 (8.7%) was associated with lower injury rates and was linked to well-organized traffic systems; and Class 3 (63.5%) was associated with a higher incidence of severe injuries and was primarily caused by narrow, poorly designed, or infrastructure-deficient roads and excessive speeding. With 97.2% precision, 89.2% recall, and an overall accuracy of 88.8%, the Random Forest Classifier successfully employed predictors including age, gender, infraction type, traffic control, and vehicle type. The relative significance of each variable in determining the severity of an injury was further emphasized by the Decision Tree model. The Random Forest approach's improved accuracy and resilience were confirmed by comparing the model's

performance to baseline classifiers such as logistic regression, Support Vector Machine, and Decision Tree. This study supports the creation of focused initiatives to increase pedestrian safety in India by highlighting the necessity of proactive road safety measures and offering a strong analytical framework for injury severity assessment.

c) Vitamin Deficiency Detection Using Neural Networks:

Millions of people worldwide suffer from vitamin deficiencies, which can have serious consequences if left untreated. Identifiable symptoms that appear in many parts of the human body can be used to identify different vitamin deficits. The most popular method for identifying deficiencies is blood testing. Nevertheless, blood tests are costly and scarce. The project's goal is to create an automated system that uses Mobilenet, convolutional neural networks (CNN), NasNet-mobile, inception modules, and artificial neural networks (ANN) to identify vitamin deficiencies. By analyzing pictures of the eyes, lips, tongue, and nails, the application enables users to identify possible vitamin deficiencies without the need for blood tests. Here, we've looked at the array of anomalies brought on by vitamin shortages, such as glaucoma in the eyes, bluish nails, and various lip and tongue abnormalities. These picture datasets were used to train the model. By utilizing image recognition and data analytics, the suggested system provides a rapid, effective, and non-invasive detection technique, simplifying the diagnostic procedure and enabling early intervention. The goal is to offer a clinical screening technique that is

affordable, easily accessible, and effective. Additionally, the platform provides customized dietary recommendations to address identified deficiencies, hence reducing health risks associated with inadequate nutrition. Our technology helps address a global health issue by providing a readily accessible resource for timely detection and intervention. The program serves as a helpful tool for people to fight a worldwide issue that affects millions of people because of a lack of understanding about nutrition. It is a useful tool that tackles a global problem and helps people with nutritional uncertainty all around the world.

d) Vitamin a deficiency and clinical disease: an historical overview:

There are many different clinical signs of vitamin A insufficiency, from xerophthalmia (which is nearly pathognomonic) to growth abnormalities and vulnerability to serious illness (which are significantly more varied). Some of the symptoms of xerophthalmia were known long ago, just like those of other traditional vitamin deficient conditions including rickets and scurvy. It would be easy to categorize reports about vitamin A and/or deficiency symptoms into "ancient" accounts; clinical descriptions from the eighteenth to nineteenth centuries (and their alleged etiologic associations); laboratory animal experiments and clinical and epidemiologic observations from the early twentieth century that identified the existence of this special nutrient and signs of its deficiency; and, most recently, a flourishing of meticulously carried out clinical studies and field-based randomized trials that documented the full scope and impact of deficiency

among the impoverished in low- and middle-income countries, which altered global health policy.

e) Vitamin Deficiency Detection Using Image Processing and Neural Network:

This project introduces a free artificial intelligence-based smartphone application that uses images of particular bodily parts to identify vitamin deficiencies in people. Current techniques for detecting vitamin deficiencies need expensive laboratory analysis. A variety of vitamin deficiencies might manifest as one or more easily identifiable signs and symptoms that show up in different parts of the body. Through the examination of images of their eyes, lips, tongue, and nails, the program enables people to identify potential vitamin deficiencies without the need for blood samples. Through nutritional micro-correction, the program then recommends a list of nutritious sources to combat the identified shortfall and the anticipated effects. From imaging inputs of the chosen body areas that are known to exhibit distinct symptoms in terms of changes in the tissue's structure when the human body experiences a nutritional shortfall, the intelligent software was taught to identify and classify vitamin deficiencies with high confidence. By contributing and verifying their patients' visual data, the platform also enables medical professionals to help enhance the application's detection range and accuracy, enabling more sophisticated image analysis and feature extraction capabilities that have the potential to outperform human diagnosis. In the long run, this application will assist medical professionals in making more precise diagnoses, and it is a helpful tool for individuals to solve a global issue that

primarily impacts millions of people globally due to lack nutritional understanding.

3. METHODOLOGY

i) Proposed Work:

The proposed work introduces an AI-driven, non-invasive diagnostic system for detecting vitamin and mineral deficiencies using deep learning and image analysis techniques. The system analyzes images of facial skin, eyes, tongue, nails, lips, and hair to identify visible symptoms associated with nutritional deficiencies. A pretrained ResNet152V2 model is utilized for high-level feature extraction, while an attention mechanism is integrated to focus on critical regions that contain important deficiency-related patterns. This combination improves classification accuracy and enhances the model's ability to detect subtle visual abnormalities.

To improve robustness and generalization, the system incorporates preprocessing techniques such as image resizing, normalization, and data augmentation. Batch Normalization, Dropout, Early Stopping, and learning rate scheduling are applied to reduce overfitting and optimize training performance. The model is capable of classifying multiple deficiencies, including Vitamins A, B-complex, C, D, E, K, iron, and zinc deficiencies. The final system is deployed through a user-friendly web interface that enables real-time image upload and prediction, providing a fast, accessible, and cost-effective healthcare solution for early diagnosis and preventive care.

ii) System Architecture:

The system architecture of the proposed AI-driven vitamin and mineral deficiency detection model consists of multiple stages designed to process images and generate accurate diagnostic predictions. Initially, the input images of facial skin, eyes, tongue, nails, lips, and hair are collected through the user interface. These images undergo preprocessing operations such as resizing, normalization, noise reduction, and data augmentation to improve image quality and increase dataset diversity. The processed images are then forwarded to the deep learning framework for feature extraction and classification.

The core architecture utilizes the pretrained ResNet152V2 model to extract high-level visual features related to deficiency symptoms such as discoloration, texture variations, and abnormal patterns. An attention mechanism is integrated into the network to highlight important symptom-specific regions and improve prediction precision. The extracted features are passed through fully connected classification layers with Batch Normalization and Dropout for optimized learning and reduced overfitting. Finally, the Softmax layer classifies the detected deficiency category and displays the prediction with confidence scores through a web-based interface, enabling fast and non-invasive diagnosis.

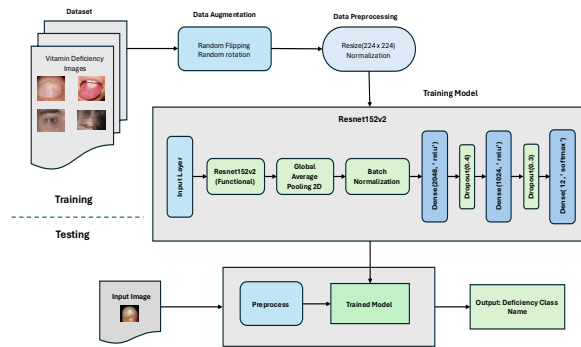


Fig1 proposed architecture

iii) Modules:

1. Data Collection and Preprocessing Module

This module is responsible for collecting patient images containing visible symptoms related to vitamin and mineral deficiencies. The collected images are organized into different deficiency categories and undergo preprocessing operations such as resizing, normalization, and augmentation. These steps improve image quality, increase dataset diversity, and enhance the performance of the deep learning model.

2. Feature Extraction Module

The feature extraction module uses the pretrained ResNet152V2 model to identify and extract high-level visual patterns from input images. It captures important features such as skin texture changes, discoloration, tongue abnormalities, nail deformities, and eye variations associated with nutritional deficiencies. Transfer learning helps the system achieve high accuracy even with limited datasets.

3. Attention Mechanism Module

This module integrates an attention mechanism into the deep learning architecture to focus on symptom-specific regions within the image. It highlights important areas such as lips, nails, eyes, and skin patches while reducing the influence of irrelevant background information. This improves classification precision and minimizes false predictions.

4. Classification Module

The classification module processes the extracted features through fully connected layers combined with Batch Normalization and Dropout techniques. A Softmax activation function is used in the final layer to classify images into multiple vitamin and mineral deficiency categories. The module generates prediction results along with confidence scores.

5. Training and Optimization Module

This module handles the model training process using the Adam optimizer and categorical cross-entropy loss function. Techniques such as Early Stopping and ReduceLROnPlateau are applied to prevent overfitting and optimize learning efficiency. Training and validation metrics are continuously monitored to improve overall model performance.

6. Evaluation Module

The evaluation module measures the effectiveness of the proposed system using performance metrics such as accuracy, precision, recall, and F1-score. It also generates confusion matrices and classification reports to analyze prediction quality and identify misclassified samples.

7. Deployment and User Interface Module

This module provides a web-based interface where users can upload images for deficiency detection. The trained model processes the uploaded image and displays the predicted deficiency along with confidence scores and health recommendations. The interface is designed to be simple, fast, and accessible for real-time healthcare support.

iv) Algorithms:

1. ResNet152V2 Algorithm

ResNet152V2 is a deep convolutional neural network used for feature extraction and image classification. It utilizes residual learning and skip connections to overcome the vanishing gradient problem, enabling very deep network training with improved accuracy. In the proposed system, ResNet152V2 extracts high-level visual features such as discoloration, texture changes, and abnormal patterns from facial skin, eyes, nails, tongue, and hair images. Since the model is pretrained on the ImageNet dataset, it provides strong feature representation and improves classification performance even with limited medical image data.

2. Attention Mechanism Algorithm

The attention mechanism enhances the deep learning model by focusing on important regions in the input image that contain critical deficiency-related symptoms. It assigns higher weights to significant areas such as pale lips, nail discoloration, skin rashes, and tongue abnormalities while suppressing irrelevant background information. This improves

interpretability, increases prediction precision, and reduces false positive classifications.

3. Convolutional Neural Network (CNN)

CNN is a deep learning algorithm specialized for image processing and pattern recognition. It automatically learns spatial hierarchies of features using convolution, pooling, and activation layers. In this project, CNN operations within ResNet152V2 help identify complex visual symptoms associated with vitamin and mineral deficiencies, enabling accurate multiclass classification.

4. Adam Optimization Algorithm

Adam (Adaptive Moment Estimation) is an optimization algorithm used to update neural network weights during training. It combines the advantages of momentum and RMSProp optimization methods, resulting in faster convergence and efficient handling of large datasets. In the proposed system, Adam optimizer improves training stability and minimizes classification loss.

5. Softmax Classification Algorithm

The Softmax algorithm is used in the output layer of the neural network for multiclass classification. It converts the output values into probability scores for each deficiency category. The class with the highest probability is selected as the final prediction, allowing the system to classify multiple vitamin and mineral deficiencies accurately.

4. EXPERIMENTAL RESULTS

The proposed AI-driven vitamin and mineral deficiency detection system was evaluated using a labeled dataset containing images of facial skin, eyes, tongue, nails, lips, and hair associated with various nutritional deficiencies. The dataset was divided into training, validation, and testing sets to ensure reliable performance evaluation. The ResNet152V2 model combined with the attention mechanism demonstrated strong capability in extracting discriminative visual features and accurately classifying multiple deficiency categories.

The performance of the model was assessed using standard evaluation metrics such as accuracy, precision, recall, and F1-score. Experimental analysis showed that the proposed model achieved high classification accuracy with reduced false predictions compared to traditional image-processing approaches. The integration of attention mechanisms significantly improved the model's focus on symptom-specific regions, leading to better diagnostic precision and robustness.

The confusion matrix and classification report indicated that the system effectively identified deficiencies such as Vitamin A, B-complex, C, D, E, K, iron, and zinc. Data augmentation, Batch Normalization, and Dropout techniques helped improve generalization performance and reduced overfitting during training. The model also demonstrated stable validation accuracy and minimized loss values across multiple epochs.

Furthermore, the deployed web-based interface successfully performed real-time image prediction with confidence scores and deficiency

recommendations. The experimental results confirm that the proposed approach is efficient, reliable, and suitable for non-invasive healthcare applications, especially in rural and resource-limited environments.

Accuracy: A test's accuracy is its capacity to distinguish healthy from ill cases. Find the percentage of instances with genuine positives and negatives to assess test accuracy.

$$\text{Accuracy} = \frac{TP + TN}{(TP + TN + FP + FN)}$$

$$\text{Accuracy} = \frac{(TN + TP)}{T}$$

Precision: Classification accuracy or positive cases constitute precision. The formula for accuracy is:

$$\text{Precision} = \frac{\text{True positives}}{(\text{True positives} + \text{False positives})} = \frac{TP}{(TP + FP)}$$

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

Recall: A model's recall measures its ability to recognize all appropriate machine learning class instances. The ratio of accurately predicted positive observations to total positives indicates a model's class instance detection skill.

$$\text{Recall} = \frac{TP}{(FN + TP)}$$

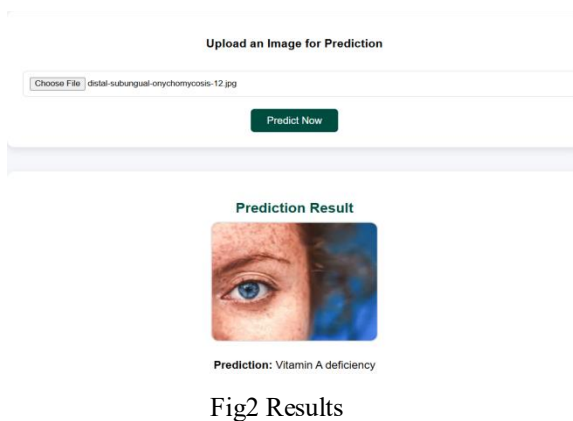
mAP: Mean Average Precision ranks quality. It considers the number and order of relevant ideas. Calculating MAP at K uses the arithmetic mean of each user or query's Average Precision (AP).

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

AP_k = the AP of class k
 n = the number of classes

F1-Score: A high F1 score suggests an accurate machine learning model. Integrating recall and precision improves model correctness. Accuracy measures how often a model predicts a dataset correctly.

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$



5. CONCLUSION

The proposed AI-driven diagnosis system provides an effective and non-invasive solution for detecting vitamin and mineral deficiencies using deep learning and image analysis techniques. By utilizing ResNet152V2 with an attention mechanism, the system accurately identifies visible symptoms from facial skin, eyes, tongue, nails, lips, and hair images. The integration of transfer learning and advanced preprocessing techniques improves classification

performance and enables reliable prediction of multiple nutritional deficiencies.

The experimental results demonstrate that the proposed model achieves high accuracy, precision, recall, and F1-score while reducing dependency on laboratory-based diagnostic methods. The system offers fast, cost-effective, and accessible healthcare support, particularly for rural and underserved communities where medical resources are limited. Overall, this research highlights the potential of AI-powered healthcare systems in enabling early diagnosis, preventive care, and improved health monitoring through automated image-based assessment.

6. FUTURE SCOPE

The proposed system can be further enhanced by integrating advanced deep learning architectures and larger real-world medical datasets to improve prediction accuracy and robustness. Future work may include the use of hybrid models combining CNNs with Vision Transformers (ViTs) or multimodal AI techniques for more detailed nutritional analysis. The system can also be extended to detect additional health conditions and deficiency-related diseases using the same image-based diagnostic approach.

In the future, the model can be deployed as a mobile application for real-time health monitoring and remote healthcare assistance. Integration with wearable devices, cloud platforms, and telemedicine systems can further improve accessibility and usability. Real-time video-based analysis, multilingual support, and personalized dietary



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recommendation systems can also be incorporated to provide a complete AI-powered healthcare solution for global and rural populations.

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