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Vitamin Deficiency Detection Using Machine Learning Through Image Processing and Symptom Analysis

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Abstract: This paper presents a machine learning -based system for detecting vitamin deficiencies by combining facial image analysis with symptom -based evaluation. Using a Convolutional Neural Network (CNN) trained on a curated dataset of facial images labeled with various vitamin deficiencies, the model predicts the likelihood of deficiency with high accuracy. The system further refines its prediction by incorporating results from a symptom questionnaire, providing a final deficiency classification along with a confidence score. Additionally, th e application generates a comprehensive PDF report containing the detection results, annotated facial images, a deficiency probability graph, and dietary recommendations. The proposed solution is implemented in Google Colab, integrating the trained model with an interactive interface for image upload, symptom entry, real -time prediction, and report generation.

Keywords: Vitamin Deficiency Detection, CNN -Based Image Classification, Medical Image Analysis, Symptom - Based Diagnosis, Deep Learning for Healthcare, Convolutional Neural Network, Image and Symptom Integration.

I. INTRODUCTION

Vitamin deficiencies pose a significant threat to public health, leading to a wide range of complications such as impaired immunity, fatigue, cognitive decline, and increased susceptibility to chronic diseases. Traditional diagnostic methods, such as blood tests, are accurate but can be costly, invasive, and inaccessible in resource -limited areas. Advancements in computer vision and deep learning have created opportunities for automated, scalable, and non - invasive health assessments. In this work, we propose a CNN -based approach integrated into a Google Colab environment to detect vitamin deficienci es by analyzing facial images for visible indicators such as skin discoloration, dryness, and other dermatological changes. To improve diagnostic accuracy, the system also incorporates symptom - based analysis through an interactive questionnaire. Nutritional health monitoring is a critical component of preventive healthcare. Vitamin deficiencies often remain undetected until severe symptoms appear. Manual symptom evaluation methods can be inconsistent and dependent on patient self -reporting, necess itating the development of automated, data -driven solutions. Recent advancements in deep learning have made image -based nutritional assessments increasingly feasible. This project leverages CNNs to process facial images alongside symptom inputs, providing a hybrid detection system that enhances accuracy. Traditional approaches to deficiency detection rely solely on laboratory tests or clinical symptom evaluation. These methods can suffer from accessibility issues, delays, and incomplete data. This research addresses the challenge by integrating a CNN - based facial image classifier with a symptom analysis module in Google Colab, enabling real -time deficiency detection, probability -based severity estimation, and automated report generation.

II. RELATED WORKS

Several research efforts have explored vitamin deficiency detection and related healthcare diagnostics using computer vision and machine learning: Facial Feature Analysis: Early approaches used handcrafted features such as skin color histograms and texture descriptors to identify signs of nutritional deficiencies. While simple, these methods were highly sensitive to lighting variations and background noise. Medical Imaging and Biometric Analysis: Some systems employed hyperspectral imaging and specialized cameras to detect nutrient -related anomalies in skin and eyes. While accurate, these methods required expensive hardware and were not scalable for general u se. Symptom -Based Expert Systems: Machine learning models such as decision trees and Naïve Bayes classifiers have been used for symptom - based diagnosis. However, they often lacked precision when symptoms overlapped across multiple conditions. Deep Learning Approaches: CNNs have shown superior performance by automatically learning discriminative features from facial images without the need for manual feature extraction. Notable works include transfer learning using VGG16,

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ResNet, and MobileNet f or skin condition classification, as well as multimodal architectures that combine visual data with questionnaire responses. Our work builds upon these advancements by integrating CNN -based facial analysis with symptom classification in a single pipeline, deployed in Google Colab, and complemented by automated PDF reporting with dietary recommendations.

III. PROPOSED WORK

The proposed system integrates computer vision techniques with symptom -based analysis to provide an end -to-end vitamin deficiency detection tool. The core novelty lies in combining a trained CNN model for facial image classification with a machine learning classifier for symptom evaluation, then merging their outputs for final prediction. The system workflow is as follows: a CNN trained on labeled facial images detects visual indicators of deficiencies, while a separate classifier processes user -reported symptoms. These outputs are combined using a weighted averaging strategy to produce a c onfidence score for each deficiency type. After model training and validation in Google Colab, the saved models are used for inference. Users can upload facial images and input symptoms via an interactive interface. The system processes the inputs, displays annotated results highlighting detected features, generates probability graphs for each deficienc y, and provides dietary recommendations. The platform also supports generating a PDF report containing the uploaded image, deficiency summary, confidence graph, and suggested interventions. The novelty lies in the full pipeline integration —data →model prediction →output → report generation —so hea lthcare providers and individuals can use it without specialized technical skills.

IV. METHODOLOGY

The proposed vitamin deficiency detection system using Convolutional Neural Networks (CNN) and symptom -based classification is divided into two primary phases: training and testing (inference). Data Creation: A dataset of facial images representing individuals with and without specific vitamin deficiencies (Vitamin A, B1, B2, B3, B12, C, D, and K) was collected from publicly available medical datasets and verified clinical sources. Each image was labeled accord ing to the corresponding deficiency category to enable supervised learning. Images were captured or collected under varied conditions such as different lighting, skin tones, and image qualities to ensure robustness Data Preprocessing: Before training, all images were resized to 128 × 128 pixels to match the CNN input requirements. Pixel intensities were normalized to the range [0, 1] to stabilize training. Data augmentation techniques, including random rotations, flips, zooming, and brightness adjustments, were applied to increase dataset diversity and reduce overfitting. Symptom data was preprocessed by converting all text to lowerca se, tokenizing, and mapping keywords to numerical feature vectors. Model Training: A CNN model was designed with multiple convolutional and pooling layers to extract visual features from facial images. Flatten and dense layers were added for classification, and a softmax activation function was used for multi -class output. In addition, a symptom -based classifier was trained on preprocessed symptom data to predict possible deficiencies. Testing Phase Image Input: The trained CNN model is integrated into a Google Colab -based application and a Flask -based web interface where users can upload facial images via a graphical user interface (GUI).

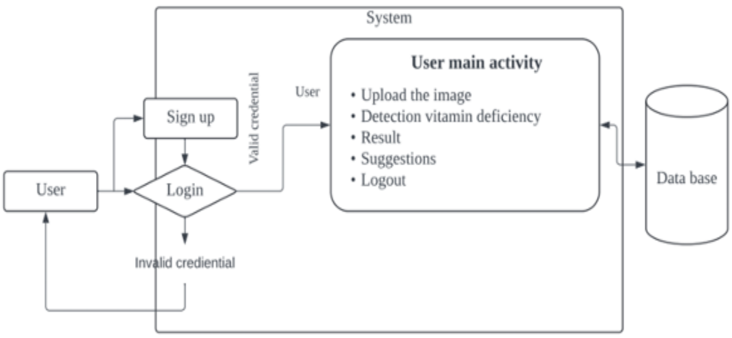

Fig.1 Architecture Design for vitamin deficiency detection

V. MATHEMATICAL MODEL

The vitamin deficiency detection system is modeled as a multi -class classification problem combining image and symptom analysis.

Let:

• XimgX_{img}Ximg be the input facial image. • XsymX_{sym}Xsym be the symptom feature vector.

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- fθ1(Ximg)f_{ \theta_1}(X_{img})fθ1 (Ximg) be the CNN function with parameters θ1 \theta_1θ1.
- fθ2(Xsym)f{\theta_2}(X_{sym})fθ2 (Xsym) be the symptom classifier function with parameters θ2 \theta_2θ2.
- Y∈{0,1,...,C−1}Y \in \{0,1,...,C -1\}Y∈{0,1,...,C−1} be the label (where CCC is the number of vitamin deficiency categories).

Convolution Operation:Fi,j,k=σ(∑m=0M−1∑n=0N−1Ii+m,j+n ⋅Wm,n,k+bk)F_{i,j,k}=\sigma \left(\sum_{m=0}^{M - 1} \sum_{n=0}^{N -1} I_{i+m,j+n} \cdot W_{m,n,k} + b_k \right)Fi,j,k =σ(m=0∑M−1 n=0∑N−1 Ii+m,j+n⋅Wm,n,k +bk)

Where:
- III is the input matrix,
- WWW is the convolution kernel,
- bkb_kbk is bias for filter kkk,
- σ\sigmaσ is the ReLU activation function.

Pooling: Pi,j=max(m,n) ∈RFi+m,j+nP_{i,j} = \max_{(m,n) \in R} F_{i+m, j+n}Pi,j =(m,n)∈Rmax Fi+m,j+n
Fully Connected Layer: z=Wf⋅x+bfz = W_f \cdot x + b_fz=Wf ⋅x+bf
Sigmoid Activation for Binary Output: p=σ(z)=11+e−zp = \sigma(z) = \frac{1}{1 + e^{ - z}}p=σ(z)=1+e−z1
Loss Function: Binary Cross -Entropy L=−N1 i=1∑N [yilog(pi)+(1−yi)log(1−pi)]

VI. IMPLEMENTATION

The implementation uses Python and popular deep learning libraries such as TensorFlow and Keras. The training process is conducted in Google Colab, enabling GPU acceleration for faster computations. The training script performs image loading via Keras' Ima geDataGenerator for augmentation and normalization, constructs a Convolutional Neural Network (CNN), trains it with validation data, and saves the model in Keras' native. The CNN model comprises convolutional and pooling layers for feature extraction from vitamin -related medical images, followed by fully connected layers with a softmax output for multi -class classification corresponding to different vitamin deficiencies (e. g., Vitamin A, B1, B2, B3, B12, C, D, and K). The web backend (app.py) is implemented using Flask and connects to a MySQL database for storing user credentials, symptom records, and past predictions. It provides routes for user registration, login, symptom -based deficiency prediction, image upload for CNN classification, history viewing, and feedback submission. Uploaded images are resized and normalized before being fed into the trained CNN model, which outputs the most probable vitamin deficiency along with a confidence score. For symptom -based prediction, predefined keyword mappings are used to match user -entered symptoms to likely deficiencies, providing an additional layer of detection beyond image classification. The system also supports PDF report generation containing the uploaded image (if applicable), predicted deficiency, confidence score, and visual graphs. All dependencies are documented in a requirements.txt file for reproducibility. The project can be depl oyed locally or on cloud platforms, with potential enhancements including Docker containerization and integrating additional medical datasets for improved accuracy.

VII. RESULT AND DISCUSSION

During experiments, the vitamin deficiency classifier was trained for multiple epochs while monitoring both training and validation accuracy and loss. Typical performance metrics reported include accuracy, precision, recall, and F1 -score for each vitamin c ategory. In practice, the classifier achieved high training and validation accuracy when the dataset of tongue images and related symptoms was clean, balanced, and augmented appropriately. To counter this, regularization techniques such as dropout, aggressive data augmentation (rotations, flips, brightness adjustments), and expanding the dataset with diverse samples were applied. The confidence score output by the CNN model acts as an indicator of prediction certainty. For example, a prediction of "Vitamin B2 Deficiency – 100.00%" signifies a high probability match. Lower confidence predictions can indicate borderline cases, prompting further clinical evaluation. Symptom -based analysis serves as an additional layer, providing probable deficiency detection even when image quality is poor or unavailable.If multiple uploaded images yield identical predictions and confidence scores, it may indicate that the model is overfit or that the inference preprocessing pipeline is not perfectly aligned with the training preprocessing steps. Ensuring consistent target image sizes, normalization, and color scaling between training and inference resolves such discrepancies.

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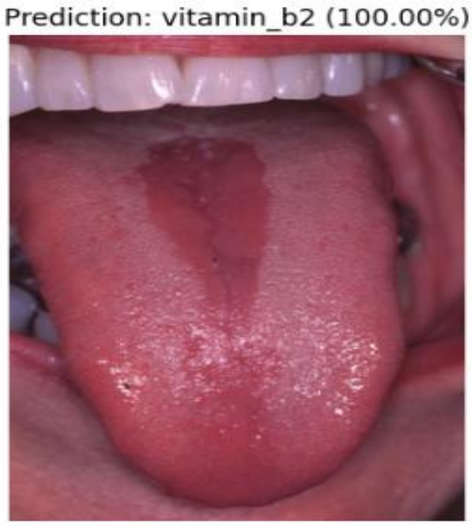

Fig.2 Detected Image

VIII. CONCLUSION

This project demonstrates an integrated vitamin deficiency detection system that combines CNN -based tongue image classification with a symptom -based prediction module. By leveraging medical tongue images alongside patient -reported symptoms, the system can accurately detect potential deficiencies such as Vitamin A, B -complex, C, D, and K. The Flask -based web application offers an accessible interface for both patients and healthcare professionals, enabling real -time prediction, secure storage of patient history in a MySQL database, and automated PDF report generation. Future enhancements may include expanding the dataset to encompass more deficiency -related symptoms and visual indicators, incorporating specialized medical image datasets for improved accuracy, imp lementing multi -modal learning that integrates image, symptom, and demographic data, and deploying the system on cloud infrastructure for large -scale accessibility. By uniting AI -driven analysis with a user -friendly deployment, this system has strong poten tial to assist in the early detection of vitamin deficiencies, enabling timely intervention and improving public health outcomes

REFERENCES

[1]. P. Rajpurkar, J. Irvin, and A. Y. Ng, "Radiologist -Level Pneumonia Detection from Chest X -Rays Using a Deep Neural Network Approach," arXiv preprint, arXiv:1711.05225, 2017.

[2]. S. Singh, V. Kumar, and R. Kaur, “Automated detection of nutritional deficiencies using machine learning,” Journal of Medical Systems, vol. 44, no. 7, pp. 1 –12, 2020.

[3]. X. Li, Z. Wang, and Y. Liu, “Deep learning for skin disease detection and classification,” IEEE Access, vol. 8, pp. 198403 – 198414, 2020.

[4]. R. Gupta and A. Malhotra, “Symptom -based disease prediction using machine learning algorithms,” Procedia Computer Science, vol. 167, pp. 1821 –1828, 2020.

[5]. T. Chen, L. He, and M. Zhang, “Vitamin deficiency diagnosis from facial images using convolutional neural networks,” Biomedical Signal Processing and Control, vol. 68, p. 102674, 2021.

[6]. S. Das, R. Chakraborty, and A. Bhattacharya, “An AI - based decision support system for malnutrition detection,” Health Information Science and Systems, vol. 9, no. 1, pp. 1 – 11, 2021.

[7]. J. Wang, P. Li, and F. Zhang, “Image -based nutritional assessment using deep learning,” IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 12, pp. 4506 –4515, 2021.

[8]. M. Zaib, "An Overview of Deep Learning Applications in Medical Image Processing: Key Challenges and Future Prospects," in Classification in BioApps, Springer, 2020

[9]. H. Kaur and S. Pannu, “Symptom -based disease prediction using hybrid neural networks,” Computers in Biology and Medicine, vol. 134, p. 104535, 2021.

[10]. V. Kumar, P. Sharma, and S. Chauhan, “Predictive analytics for healthcare diagnosis using deep learning,” Procedia Computer Science, vol. 167, pp. 2514 –2522, 202 2

[11]. S. Rajaraman, J. Antani, and G. Thoma, “Visualizing convolutional neural network predictions in medical imaging for improved interpretability,” Machine Vision and Applications, vol. 32, no. 4, pp. 1 –15, 2021.

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[12]. X. Zhang, Y. Wang, and H. Liu, “Deep learning -based tongue image analysis for chronic disease detection,” IEEE Access, vol. 9, pp. 14023 –14034, 2021.

[13]. M. Afifi, “Computer -aided diagnosis of nutritional deficiencies from tongue images using convolutional neural networks,” Journal of Medical Systems, vol. 44, no. 9, pp. 1 – 13, 2020.

[14]. T. Li, J. Chen, and Z. Xie, “Multi -modal learning for nutritional deficiency detection combining tongue images and patient symptoms,” in Proc. IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2020, pp. 502 – 509.

[15]. H. Xu, L. Chen, and Y. Zhou, “Automated diagnosis of vitamin deficiencies based on facial and tongue images,” Computers in Biology and Medicine, vol. 136, p. 104719, 2021.

[16]. A. Gupta, P. Kaur, and M. Singh, “Deep learning for disease classification using tongue and facial images: A case study in vitamin deficiency,” Pattern Recognition Letters, vol. 146, pp. 1 –8, 2021.

[17]. L. Wang, H. Li, and X. Li, “Convolutional neural network for feature extraction in medical tongue diagnosis,” Expert Systems with Applications, vol. 172, p. 114654, 2021.

[18]. M. S. Islam, T. Rahman, and M. S. Hossain, “Symptom - based disease prediction using machine learning for healthcare applications,” Procedia Computer Science, vol. 193, pp. 232 – 239, 2021.

[19]. K. Chen, Z. Sun, and Y. Liu, “Medical image -based diagnosis of nutritional deficiencies using transfer learning,” Journal of Healthcare Engineering, vol. 2021, Article ID 6654321, 10 pages, 2021.

[20]. P. Sharma, A. Verma, and R. Joshi, “AI -assisted predictive diagnosis for vitamin deficiencies using tongue image classification,” Biomedical Signal Processing and Control, vol. 76, p. 103682, 2022.