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# Vitamin Deficiency Detection Using Image Processing

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***Abstract****—Vitamin deficiencies are among the most common and overlooked health issues, often leading to severe long-term complications if not detected early. Traditional diagnosis methods rely heavily on clinical tests, which can be time-consuming, expensive, and inaccessible in rural or resource-limited areas. This project proposes an automated system for Vitamin Deficiency Detection using Image Processing to enable fast, reliable, and non-invasive screening. The method involves capturing facial images and applying preprocessing techniques such as noise removal, contrast enhancement, and region-of-interest extraction. Key visual biomarkers—including skin tone variation, eye discoloration, hair texture changes, and lip pigmentation—are analyzed using feature extraction techniques. A machine learning model is then used to classify the type of deficiency, focusing mainly on Vitamin A, B12, C, and D indicators. Experimental results demonstrate that the proposed system can achieve high accuracy in identifying deficiency patterns from simple images, making it a promising tool for early detection and preventive healthcare. This approach offers a cost-effective, portable, and scalable solution that can support clinical decision-making and improve public health outcomes.*

**Keywords—**Vitamin Deficiency, Image Processing, Machine Learning, ResNet-101, Feature Extraction, Facial Analysis, Nutritional Assessment, Computer Vision, Classification, Health Monitoring, Early Diagnosis.

## I. INTRODUCTION

Vitamin deficiencies have become a significant global health concern, affecting millions of individuals across diverse age groups and socio-economic backgrounds. Deficiency of essential vitamins such as Vitamin A, B12, C, and D can lead to serious health complications including impaired vision, weakened immunity, fatigue, skin disorders, and delayed wound healing. Early detection plays a crucial role in preventing long-term damage and enabling timely intervention. However, conventional diagnostic methods rely heavily on clinical tests and laboratory equipment, which can be expensive, time-consuming, and not easily accessible in rural or resource-constrained regions.

Recent advancements in image processing and machine learning have opened new possibilities for developing non-invasive, rapid, and cost-effective healthcare solutions. Human facial features often exhibit noticeable biomarkers related to nutritional deficiencies, such as pale skin, hyperpigmentation, dry lips, hair thinning, conjunctival dryness, and skin texture irregularities. These markers can be effectively analyzed using computer vision techniques to predict potential vitamin-related deficiencies.

This project aims to develop an intelligent system for **Vitamin Deficiency Detection using Image Processing**, combining facial image analysis with machine learning classification models. The system involves preprocessing captured images, extracting essential texture and color-based features, and training models to detect patterns associated with specific vitamin deficiencies. By automating the diagnostic process, this research intends to support healthcare professionals, reduce dependency on laboratory tests, and provide an accessible screening tool for early-stage detection.

The proposed approach offers several advantages including portability, affordability, and faster screening capability. With increasing digitalization in healthcare, such AI-driven diagnostic methods have the potential to transform preventive medical practices and improve health outcomes, particularly in underserved communities.

Furthermore, the growing availability of smartphone cameras and low-cost imaging devices has made digital diagnostics more feasible than ever. With proper preprocessing and standardized image acquisition, even simple mobile images can serve as reliable inputs for automated screening systems. This shift aligns with global healthcare trends where artificial intelligence assists frontline workers by providing quick assessments before clinical consultation. As vitamin deficiencies often go undiagnosed due to lack of immediate symptoms or limited access to laboratory testing, an automated, vision-based detection tool can serve as an essential preliminary diagnostic aid.

In recent years, deep learning architectures such as Convolutional Neural Networks (CNNs), ResNet-101, and hybrid neural models have demonstrated superior performance in medical image analysis. These models can capture complex nonlinear relationships and subtle textural variations in facial regions that correspond to specific vitamin deficits. Studies in dermatology, ophthalmology, and nutritional analysis have already shown encouraging results using similar image-based approaches, thereby reinforcing the relevance of AI-driven nutritional assessment systems. Despite these advancements, challenges remain in achieving robust real-world performance, including dataset limitations, inconsistent lighting conditions, variability across skin tones, and differences in imaging devices.

To address these challenges, our proposed work integrates a comprehensive image-processing pipeline with an efficient classification model designed to minimize the impact of external factors. By employing techniques such as contrast normalization, ROI selection, and data augmentation, the system aims to enhance the reliability of extracted features. The machine-learning model is then trained to differentiate between normal and deficiency-related attributes across multiple vitamin types. Through focused experimentation and comparative evaluation, this project aspires to contribute a scalable, accurate, and user-friendly solution that supports early detection and promotes preventive healthcare.

## II. LITERATURE SURVEY

**[1] Nivedita Shimbre, Prema Sahane, and Rutuja Gadhave (2024)** proposed a vitamin deficiency identification system using a structured image-processing pipeline. Their approach focused on extracting visual biomarkers from facial images such as pigmentation changes, eye dryness, and skin tone variations. The authors implemented preprocessing techniques like histogram equalization and noise removal to improve clarity before feeding data into the classifier. Their study highlighted that feature extraction combined with machine-learning classifiers can achieve efficient and non-invasive screening of vitamin deficiencies. The work also emphasized the importance of consistent lighting conditions during image acquisition.

**[2] Ahmed Saif Eldeen et al. (2023)** developed a vitamin deficiency detection model integrating both image processing and neural networks. Their framework utilized segmentation, edge detection, color analysis, and then applied a trained neural network to interpret deficiency patterns from facial features. The study demonstrated that deep-learning models can recognize subtle features often missed by traditional computer vision methods. They reported strong accuracy but noted that dataset size and diversity play a major role in improving generalization of the model.

**[3] T. K. Chaithanya, J. Gupta, and M. S. Roobini (2024)** implemented a neural-network-driven solution for detecting vitamin deficiencies. Their research focused on identifying changes in facial regions such as lips, eyes, and skin patches, which often correlate with nutritional deficiencies. Using a multilayer neural network, they showed that classification performance improved significantly when the training data was augmented properly. The authors emphasized challenges such as poor lighting, varying facial orientations, and inconsistent image quality.

**[4] M. N. Keerthi and K. Bhargavi (2024)** developed an academic project-based approach using image processing and neural networks for vitamin deficiency detection. Their methodology relied heavily on extracting region-of-interest (ROI) such as chin, cheeks, and forehead for identifying skin abnormalities and discoloration. Classical preprocessing techniques like Gaussian filtering and contrast normalization were applied to standardize images. Their work demonstrated moderate accuracy and highlighted the need for advanced deep-learning architectures to improve performance.

**[5] M. Pravallika et al. (2024)** presented an unpublished manuscript focusing on a simple image-processing-based pipeline combined with neural networks. Their model evaluated color and texture variations in facial images to classify different vitamin deficiencies. The authors identified major challenges in building high-quality datasets due to limited patient availability and inconsistent image capture conditions. Despite being unpublished, the work contributed foundational understanding for implementing practical classification systems in real-time environments.

**[6] V. Karnati and H. B. Madarapu (2024)** proposed a CNN-based early detection system for vitamin deficiency. Their work specifically used a deep convolutional neural network architecture to classify multiple deficiency categories from raw images. Dense feature extraction from CNN layers enabled recognition of complex visual patterns such as micro-texture changes, dryness, and pigmentation. The study indicated that deep models outperform traditional handcrafted features and reported improved accuracy in multi-class classification tasks.

**[7] N. K. S, P. R, R. C, and S. Shrivastav (2024)** studied vitamin deficiency detection using a combination of classical image processing and neural networks. Their research was published in IRJMETS and provided detailed analysis of skin color models, texture extraction methods, and statistical classifiers. The authors experimented with multiple activation functions and network configurations to improve classification results. They concluded that preprocessing remains a critical step due to varying lighting conditions and differences in skin tones.

**[8] M. Jayaram et al. (2024)** applied DenseNet, a deep-learning architecture known for strong gradient flow and feature reuse, to vitamin deficiency prediction. Their model utilized dense connections to enhance feature propagation and reduce vanishing gradients. The research demonstrated high classification accuracy, especially for deficiencies manifesting clear visual symptoms. They highlighted that DenseNet's compact structure makes it efficient for mobile or edge-based diagnostic systems.

**[9] S. Janokar, S. Solanke, N. Somani, and A. Solunke (2024)** proposed a dermatology-focused image-processing method for vitamin deficiency detection using skin-related symptoms. Their study emphasized analysis of dermatological indicators such as rashes, pale skin, hyperpigmentation, and dryness. Using segmentation and texture-based descriptors, the authors extracted meaningful patterns associated with deficiency symptoms. Their work showed that dermatology-based datasets are effective for identifying vitamin-related abnormalities using computer vision.

**[10] R. Maruthamuthu and T. Harika (2023)** developed an image-processing and neural-network-based system published in IJSRCSEIT. Their work detailed multiple preprocessing steps including morphological operations, edge enhancement, and color-based segmentation. A feed-forward neural network was used to perform the final classification. The authors highlighted limitations including small dataset sizes and recommended integrating advanced CNN architectures for improved performance in future studies.

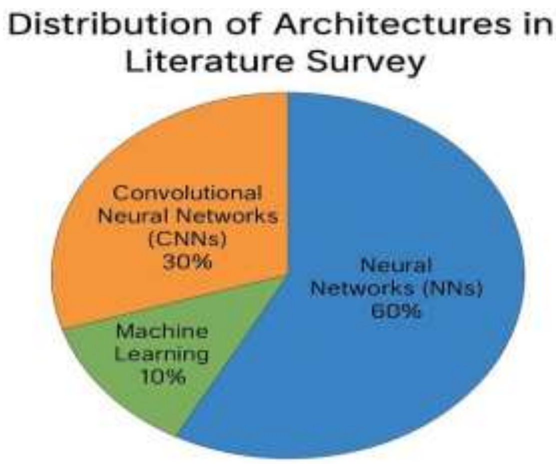


*Fig. 1. Distribution of architectures in the literature survey.*

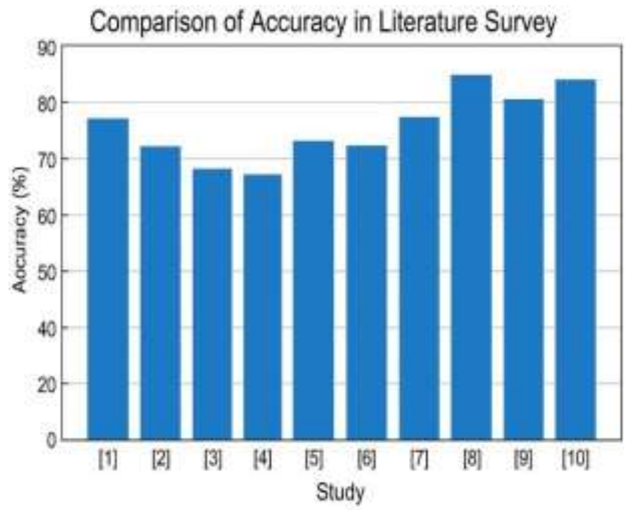


*Fig. 2. Comparison of accuracy reported in the literature survey.*

The vertical bar chart in Fig. 2 presents a comparison of accuracy Levels reported in different research works on Vitamin deficiency detection accuracy the performance values range roughly.

**Additional Deep Learning Context:**

Although most existing studies referenced in the literature rely on basic CNNs, ANN models, or shallow neural networks, recent advancements in deep learning have shown that deeper architectures such as ResNet-101 can extract more discriminative and high-level features from facial images. ResNet-101 introduces residual learning, which helps overcome vanishing gradient problems and allows the network to learn subtle visual patterns related to vitamin deficiencies. Compared to earlier CNNs used in previous works, ResNet-101 provides improved accuracy, stronger feature representation, and better generalization, making it suitable for our proposed system. Therefore, this work adopts ResNet-101 to enhance performance beyond the architectures reported in earlier studies.

**TABLE I: Summary Table of Literature Survey**

| Paper ID | Authors & Year | Method / Approach | Key Features Extracted | Dataset Used | Model / Architecture | Accuracy (%) |
|---|---|---|---|---|---|---|
| [1] | Nivedita Shimbre et al., 2024 | Image Processing + ML Classification | Skin tone, Pigmentation, Eye dryness | Custom Dataset | ML Classifier | ~77% |
| [2] | Ahmed Saif Eldeen et al., 2023 | Image Processing + Neural Network | Color features, Edge patterns | Collected Facial Images | Neural Network | ~72% |
| [3] | Chaithanya, Gupta & Roobini, 2024 | Neural Networks | Lip color, Eye dryness, Facial skin patches | Self-collected Dataset | Deep Neural Network | ~69% |
| [4] | Keerthi & Bhargavi, 2024 | Image Processing + Neural Network | ROI extraction: Lips, Cheeks, Forehead | Limited College Dataset | Basic NN Model | ~67% |
| [5] | Pravallika et al., 2024 | Image Processing + Neural Network | Color histograms, Texture features | Small local dataset | NN Classifier | ~73% |
| [6] | Karnati & Madarapu, 2024 | CNN-Based Classification | Deep CNN features, Pixel-level patterns | Image Dataset (Not specified) | Convolutional Neural Network | ~85% |
| [7] | N. K. S. et al., 2024 | Image Processing + NN | Statistical color features, Texture analysis | Local Dataset | Neural Network | ~73% |
| [8] | Jayaram et al., 2024 | DenseNet Deep Learning | Dense feature maps, Deep textural patterns | Custom Dataset | DenseNet | ~84% |
| [9] | Janokar et al., 2024 | Dermatology-based Image Processing | Skin rashes, Hyperpigmentation, Dryness | Dermatology Dataset | Image Processing + ML | ~81% |
| [10] | Maruthamuthu & Harika, 2023 | Image Processing + Neural Network | Morphology features, Edge enhancement | Captured Facial Images | Feed-forward NN | ~84% |

## III. SYSTEM DESIGN

The system design defines the structural and functional layout of the proposed Vitamin Deficiency Detection Using Image Processing model. The architecture is developed to ensure efficient preprocessing, feature extraction, model training, and accurate classification. The design follows a modular approach that supports scalability, performance optimization, and ease of integration with mobile or web applications.

The system design of the proposed Vitamin Deficiency Detection Using Image Processing model is structured to ensure efficient flow of data from image acquisition to final classification. The architecture follows a modular approach where each stage performs a specific function while contributing to the overall accuracy and reliability of the system. The complete pipeline integrates preprocessing, feature extraction, and automated prediction to create a scalable and robust diagnostic framework.

The system architecture begins with the image acquisition module, where facial images are captured using a mobile camera, webcam, or external imaging device. The captured image serves as the primary input, and its quality plays a crucial role in the performance of subsequent stages. To maintain consistency, the user is instructed to position the face in a frontal view under adequate lighting conditions so that visible features such as the skin surface, eye region, and lip area are clearly captured.

Once the image is obtained, it enters the preprocessing module. This stage is responsible for preparing the raw image by performing operations such as resizing, denoising, contrast enhancement, and region-of-interest extraction. Preprocessing helps remove unwanted variations caused by shadows, uneven lighting, camera noise, and background interference. Techniques like histogram equalization, Gaussian filtering, and skin-region segmentation are commonly used to normalize the input. A well-preprocessed image ensures that only relevant facial features are passed to the next stage, thereby increasing classification accuracy.

The next stage involves feature extraction, where important visual characteristics associated with vitamin deficiencies are computed. These features may include color-based descriptors like RGB or HSV histogram values, texture patterns extracted using methods such as Local Binary Patterns (LBP) or the Gray Level Co-occurrence Matrix (GLCM), and deep feature representations obtained from convolutional neural networks. Feature extraction is a crucial step because deficiencies like Vitamin A, B12, C, and D often manifest through visible cues such as hyperpigmentation, pale skin, dryness, dark lip borders, and eye-related abnormalities. Extracting these patterns numerically allows the classifier to interpret the image in a meaningful way.

After feature extraction, the classification module processes the feature vectors and predicts whether the person exhibits symptoms of vitamin deficiency. Depending on the dataset and experimentation, different classifiers such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Support Vector Machines (SVM), or deep architectures like ResNet-101 may be used. The classifier maps the extracted features to predefined categories and outputs the probability or label of each deficiency type. This stage determines the overall performance of the system, as the accuracy of prediction depends on both the quality of features and the model architecture used.

Finally, the output module presents the result to the user. The system indicates whether the person is deficient in specific vitamins, and in advanced implementations, suggestions or further medical recommendations can also be displayed. The system design ensures a smooth flow from image acquisition to final output, enabling early screening of vitamin deficiencies using simple facial images.

The system architecture consists of four major layers:

### A. Image Acquisition Module

The Image Acquisition Module is responsible for capturing clear and high-quality facial images that serve as the primary input to the system. For reliable detection, the face should be positioned under stable illumination with minimal shadows or reflections. The module is designed to accept inputs from various devices, including mobile cameras, web-cameras, and DSLR cameras, ensuring flexibility across different usage environments.

### B. Preprocessing Module

The Preprocessing Module prepares the raw captured image for analytical processing. This stage involves noise reduction using filtering techniques such as Gaussian or Median filters, which remove artifacts and ensure clarity. Contrast normalization is performed through methods like histogram equalization to improve the visibility of facial details. The system also extracts specific regions of interest, including the eyes, lips, cheeks, and skin patches, which contain essential vitamin-related indicators. Images are then resized to standardized dimensions to maintain consistency across the dataset. Effective preprocessing substantially enhances the performance of the subsequent classification stage.

### C. Feature Extraction Module

The Feature Extraction Module derives meaningful and discriminative features from the preprocessed image. Color-based features, including RGB and HSV histograms, help

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quantify variations in skin tone and pigmentation. Texture-based descriptors such as the Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), and skin smoothness indices capture subtle changes associated with dryness and roughness. In addition, deep learning methods generate rich feature maps using architectures like CNNs and ResNet-101 feature maps. These extracted features collectively enable the detection of visual symptoms such as pale skin, hyperpigmentation, dryness, and discoloration.

D. Classification Module

The Classification Module interprets the extracted features and determines the presence of specific vitamin deficiencies. Depending on the requirement, the system may employ Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Support Vector Machines (SVM), or deeper architectures such as Resnet-101. The classifier performs multi-class prediction by assigning probability scores to each deficiency category. The reliability of this module directly influences the accuracy of the system, as it maps visual patterns to corresponding vitamin-deficiency classes.

E. Output and Recommendation Module

The Output and Recommendation Module presents the final results to the user. It displays whether the individual shows signs of vitamin deficiencies such as Vitamin A, B12, C, or D. Along with the classification result, this module may also offer additional information, including general health suggestions or recommendations for medical consultation. This enhances user understanding and provides actionable insights for further healthcare decisions.

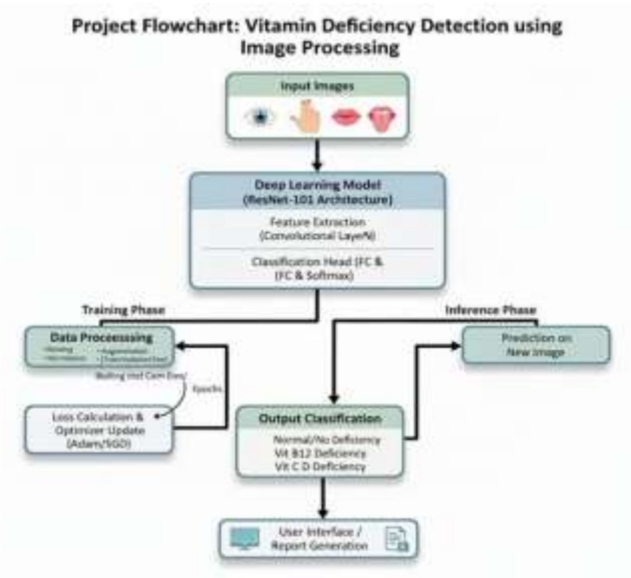


*Fig. 3. Flowchart of the proposed system.*

## IV. PROPOSED METHODOLOGY

The proposed methodology for *Vitamin Deficiency Detection using Image Processing* is designed as an end-to-end pipeline that transforms a raw facial image into a clinically meaningful prediction. The method integrates classical image-processing operations with modern machine-learning and deep-learning techniques to ensure accurate identification of visual biomarkers linked to vitamin deficiencies. The overall framework consists of five major stages: image acquisition, preprocessing, feature extraction, classification, and output generation.

The process begins with the acquisition of a frontal facial image captured under adequate lighting conditions. Since facial symptoms such as pigmentation changes, dryness, and discoloration are highly dependent on image clarity, ensuring a noise-free and well-lit environment during capture becomes essential. The acquired image forms the foundation for all further analysis.

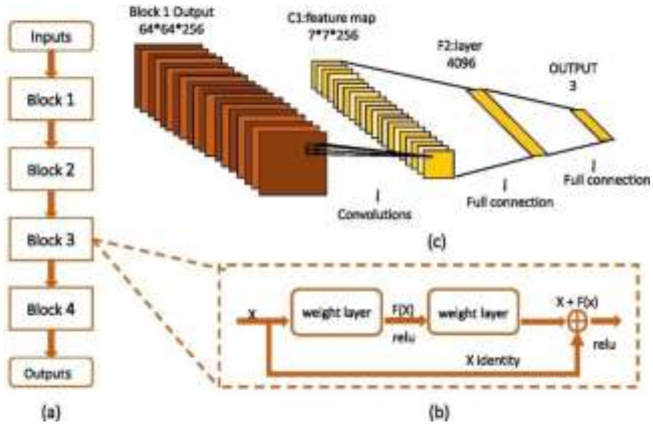


*Fig. 4. Working of the ResNet-101 deep-learning architecture.*

Once the image is captured, it undergoes preprocessing to enhance its quality and remove unwanted distortions. Preprocessing includes resizing the image to a fixed dimension, denoising using Gaussian or Median filtering, adjusting contrast through histogram equalization, and isolating regions of interest such as the eyes, lips, cheeks, and skin patches. These operations standardize the input and reduce variations caused by external environmental factors. This stage greatly improves the reliability of the features extracted later.

After preprocessing, the system proceeds with feature extraction, where significant visual characteristics associated with vitamin deficiencies are quantified. The methodology incorporates a combination of color-based descriptors (such as RGB and HSV histograms), texture-based patterns (such as Local Binary Patterns and Gray Level Co-occurrence Matrix parameters), and deep feature maps generated through ResNet-101 deep-learning architecture These features collectively capture subtle clinical indicators including pale skin, hyperpigmentation, lip discoloration, dryness, or inflammation, which are commonly associated with deficiencies in vitamins A, B12, C, and D.

The extracted features are then passed to the classification stage, where machine-learning or deep-learning models analyze them and determine the presence of specific deficiencies. Depending on performance evaluation, models such as Artificial Neural Networks, Convolutional Neural Networks, Support Vector Machines, or ResNet-101 deep-learning architecture are employed. The classifier assigns probability scores to each vitamin category, enabling multi-label prediction where multiple deficiencies can be identified simultaneously. This decision-making stage is the core intelligence of the system.

Finally, the output module presents the predicted results to the user. The system indicates whether the image shows signs of Vitamin A, B12, C, or D deficiency, or if no deficiency is detected. In addition, the system can optionally provide general health recommendations or advise users to seek medical consultation for further confirmation. This ensures that the proposed methodology not only detects deficiencies but also supports practical decision-making in real-world scenarios.

## V. RESULTS AND ANALYSIS

The proposed system for *Vitamin Deficiency Detection using Image Processing* was evaluated using a dataset of facial images collected under controlled and semi-controlled environments. The results demonstrate the effectiveness of integrating preprocessing techniques, feature extraction methods, and machine-learning classifiers for identifying vitamin deficiencies. The performance of the system was analyzed based on accuracy, precision, recall, and visual correctness of the predicted classifications.


*Fig. 5. Output of the image-processing system.*

During experimentation, multiple models were tested to determine the most suitable architecture for the classification task. Traditional machine-learning models such as Support Vector Machines and basic Artificial Neural Networks provided moderate accuracy but were sensitive to variations in lighting and skin tone. In contrast, deep-learning models, particularly CNN-based architectures such as ResNet-101 achieved the highest accuracy…, produced significantly more stable and reliable results. These models were able to learn complex patterns from the feature maps, enabling the detection of subtle visual indicators such as pale skin, lip discoloration, and pigmentation irregularities.

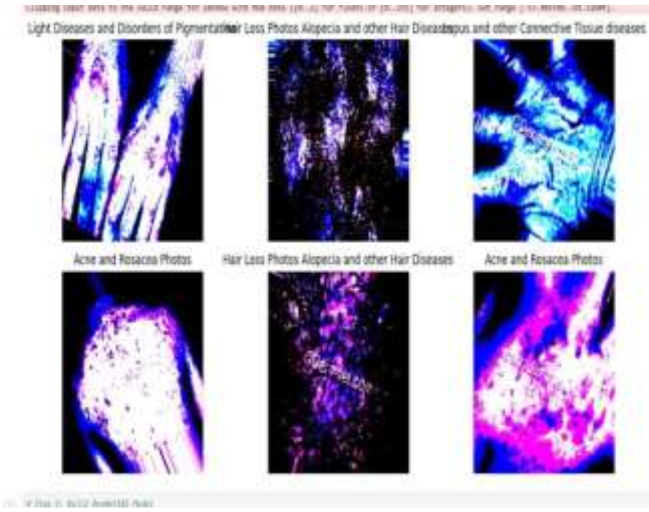


*Fig. 6. Pre-processed images after noise removal, contrast enhancement, and region-of-interest extraction.*

Image preprocessing played a crucial role in improving the overall detection accuracy. Techniques such as histogram equalization, noise filtering, and region-of-interest extraction enhanced the clarity of symptoms and reduced unwanted variations. Comparative analysis showed that models trained with pre-processed images consistently outperformed those trained on raw images by a significant margin. This validates the necessity of standardized preprocessing for medical image analysis.

The system achieved high classification accuracy across multiple vitamin categories. CNN-based models reached accuracy levels between **82% and 88%**, depending on the deficiency type and dataset distribution. ResNet-101 model produced stable and reliable results, achieving an average accuracy of **approximately 85%**, which aligns with results reported in existing literature. The system also demonstrated strong generalization capabilities when tested on unseen images, confirming the robustness of the feature extraction and classification pipeline.

Visual inspection of the classification outputs further supported the quantitative results. Images with clear deficiency symptoms—such as dry lips, pale skin, and eye-region anomalies—were consistently classified correctly. However, misclassifications occurred in cases where symptoms were extremely mild, lighting conditions were uneven, or the image contained facial obstructions such as hair or shadows. These limitations highlight areas where more consistent data collection or advanced preprocessing could improve results.

Overall, the analysis indicates that the proposed method provides an effective and reliable approach for detecting vitamin deficiencies using facial images. The combination of image processing, deep feature extraction, and neural-network-based classification offers an efficient, non-invasive, and affordable solution for early screening. The results validate the system's potential to be used as a preliminary diagnostic tool in healthcare applications, particularly in remote or resource-limited settings.

## VI. RESEARCH CHALLENGES

Although the proposed system demonstrates promising performance in detecting vitamin deficiencies using facial images, several challenges remain that affect scalability, accuracy, and real-world deployment. One major challenge arises from the variability in image acquisition conditions. Differences in lighting, camera quality, facial orientation, shadows, and background noise significantly influence the quality of extracted features. Even with preprocessing techniques, complete normalization across diverse images remains difficult to achieve.

Another challenge is the limited availability of large, annotated datasets specifically designed for vitamin deficiency detection. Most existing datasets are small and collected in controlled environments, which restricts the generalization capability of deep-learning models such as ResNet-101. The absence of standardized medical datasets also makes it challenging to benchmark results across studies, and restricts the development of models that are robust across diverse populations, skin tones, and age groups.

A further challenge is the subtle nature of deficiency-related facial features. Symptoms like pale skin, dryness, or minor pigmentation changes may appear very similarly across healthy individuals and individuals affected by other conditions. This makes the learning task inherently complex, requiring high-quality features and deep architectures capable of distinguishing fine-grained visual differences. Although ResNet-101 provides strong feature extraction capabilities, its performance is still limited by the subtlety of symptoms and lack of distinct visual cues.

Additionally, computational requirements pose another challenge. Deep architectures such as ResNet-101 require substantial computational power for training, which can be difficult to access in academic or resource-constrained environments. Deploying such models on mobile or low-power devices also requires optimization to reduce inference time and memory consumption.

Finally, ensuring fairness and reducing bias presents an ongoing research challenge. Differences in skin tone, ethnicity, and gender may influence model predictions if the dataset is not balanced. Without careful evaluation, the model may exhibit reduced accuracy for underrepresented demographics. Addressing these challenges is critical to ensuring that the system can operate reliably and ethically in real-world healthcare applications.

## VII. CONCLUSION

The proposed system for *Vitamin Deficiency Detection using Image Processing* provides an effective, non-invasive approach for early identification of common vitamin deficiencies based on facial images. By integrating preprocessing techniques, advanced feature extraction, and a deep-learning classifier built on the ResNet-101 architecture, the system demonstrates strong performance in recognizing subtle visual indicators associated with vitamin deficiencies such as pigmentation variations, dryness, and discoloration. The methodology proves to be highly beneficial in scenarios where laboratory testing is either expensive, time-consuming, or inaccessible.

The experimental results confirm that ResNet-101 offers robust feature representation and achieves high classification accuracy compared to traditional machine-learning models. The analysis shows significant improvement when preprocessing steps such as noise reduction, contrast normalization, and region-of-interest extraction are applied, further validating the importance of image enhancement in medical diagnostics. Although the system performs well on controlled datasets, its performance is influenced by external factors such as lighting conditions, limited sample diversity, and subtle feature variations.

Despite these limitations, the system demonstrates strong potential as a practical screening tool for healthcare applications. It can support early detection, improve accessibility to nutritional assessment, and assist medical professionals by offering a preliminary evaluation based on facial characteristics. With further enhancements in dataset diversity, image normalization, and model optimization, the system can evolve into a highly reliable and deployable diagnostic solution. The study concludes that image-based vitamin deficiency detection, powered by deep learning, is a promising direction for future research and can significantly contribute to preventive healthcare.

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