

DEEP LEARNING ON IMAGES FOR MICRONUTRIENT DEFICIENCY DETECTION: A COMPREHENSIVE SURVEY

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Abstract

Micronutrient deficiencies, especially those involving Vitamin D, remain a significant public health concern worldwide due to their high prevalence and clinical implications. In recent years, deep learning has shown great potential as a non-invasive method for detecting deficiencies by analysing digital images. This paper offers a comprehensive overview of recent advancements in deep learning techniques applied to the identification of vitamin deficiencies using JPEG-compressed images. This discussion highlights how convolutional neural networks (CNNs), transfer learning techniques, attention mechanisms, and image enhancement methods contribute to increasing the accuracy of deficiency detection. In addition, the review explores the integration of multimodal data sources and addresses important considerations such as model interpretability, data integrity, and real-world clinical relevance. Drawing on advancements in related fields like skin disease classification, image segmentation in medical imaging, and histopathological evaluation, the paper highlights ongoing challenges and potential research directions. Overall, the study illustrates how deep learning methods could offer scalable, cost-effective, and accessible tools widely accessible tools for recognising micronutrient deficiencies during patient care.

Keywords: Vitamin deficiency detection, Deep learning techniques, Medical image analysis, Convolutional Neural Network (CNN)

1. INTRODUCTION

Vitamin deficiencies continue to pose a significant public health issue globally, affecting billions and contributing to a wide spectrum of health problems such as weakened immune function, fatigue, anaemia, and developmental delays. While conventional diagnostic techniques like blood tests are highly reliable, they are also invasive, costly, and not always feasible in underserved or remote regions. Vitamin B12 and folate deficiencies are commonly diagnosed through laboratory testing of specific blood markers, which can be invasive and time-consuming. These limitations point to the need for efficient, non-invasive methods such as image-based deep learning approaches [26]. To address these limitations, advancements in deep learning and image-based medical diagnostics have introduced promising non-invasive alternatives for identifying micronutrient deficiencies, including those related to Vitamin D and B12 [3], [13]. Among deep learning methods, Convolutional Neural Networks (CNNs) have proven highly effective in various medical imaging applications, including the classification of skin conditions, identification of lesions, and analysis of histopathological images. [1], [2], [6], [22], [24]. Due to their hierarchical feature learning, CNNs are well-suited for capturing the subtle visual patterns in skin, nails, or facial features that may correlate with micronutrient deficiencies [13].

Transfer learning has become increasingly important in medical image analysis, particularly when working with limited training data—a common limitation in studies related to vitamin deficiency detection. Several investigations [1], [12] have demonstrated that pre-trained models can be effectively

adapted to specialized diagnostic tasks, enabling improved accuracy and efficiency without requiring extensive datasets. In addition to transfer learning, ensemble approaches and optimization-based methods [4], [5] have been employed to enhance model performance by combining multiple predictive models or refining feature extraction processes.

A detailed and authoritative survey on fine-grained image analysis (FGIA), a domain that focuses on distinguishing subtle differences between visually similar classes, an approach that is directly relevant to medical applications such as detecting vitamin deficiencies from compressed images[14]. Ensuring the reliability and security of deep learning models is also essential in this domain, especially when handling sensitive patient data and striving for diagnostic accuracy [17]. A visually interpretable deep learning framework further enhances clinical decision-making by helping identify minor yet critical signs of vitamin deficiencies in medical images [18].

The interpretability of AI models is of paramount importance in healthcare, where clinical adoption depends on transparent and explainable decision-making. Techniques that enable visualization of a model's internal reasoning have shown promise in improving trust and usability. As highlighted in recent research [2], such interpretability tools are particularly vital in sensitive domains like skin cancer diagnosis from histopathological images. They help clinicians understand the basis of automated predictions, thereby supporting more informed decisions in patient care and treatment planning. This review focuses on consolidating the current landscape of deep learning approaches for vitamin deficiency detection, situating it within the broader framework of medical image analysis and non-invasive diagnostic technologies. It investigates state-of-the-art architectures, methodological developments such as multimodal data integration [19], explainable artificial intelligence [20], and transfer learning techniques [1], [12], while also addressing persistent challenges like data imbalance, domain adaptation, and the trustworthiness of AI systems. The aim is to provide a well-rounded overview of existing methodologies and to identify future research opportunities in the realm of AI-supported micronutrient deficiency diagnostics.

2. METHODS

Recent advancements in image-based diagnostic tools for vitamin deficiency detection, as well as broader applications in medical and dermatological imaging, reveal the use of diverse deep learning strategies. These methods can be grouped into major categories depending on their underlying architecture.

i) Convolutional Neural Networks (CNNs)

CNNs serve as a foundational component in numerous medical imaging techniques. They excel at identifying spatial patterns within images, making them particularly suitable for processing dermoscopic, histological, and fingernail images.

Figure 1 illustrates the basic architecture of a Convolutional Neural Network (CNN), a popular deep learning model primarily used for image processing tasks.

- **Input:** The model takes an image as input.
- **Convolution:** Filters are applied to extract important features such as edges, textures, or patterns.
- **Pooling:** This step reduces the spatial dimensions of the feature maps, helping to minimize computation and prevent overfitting.
- **Fully Connected:** The reduced feature set is flattened and passed through one or more dense layers to perform classification or regression.
- **Output:** The final result is produced, such as a class label or probability distribution.

This structure allows CNNs to automatically learn and extract relevant features from images for various tasks like classification, detection, and segmentation. CNNs have been widely adopted in tasks such as skin disease classification [6], segmentation of microstructures in skin [7], and early detection of skin cancers [8], demonstrating their adaptability across visual medical tasks. In the context of vitamin deficiency, CNNs have been applied to nail image analysis, enabling the detection of nutrient shortfalls

like Vitamin D and B12 by learning textural and chromatic variations indicative of deficiency [13].

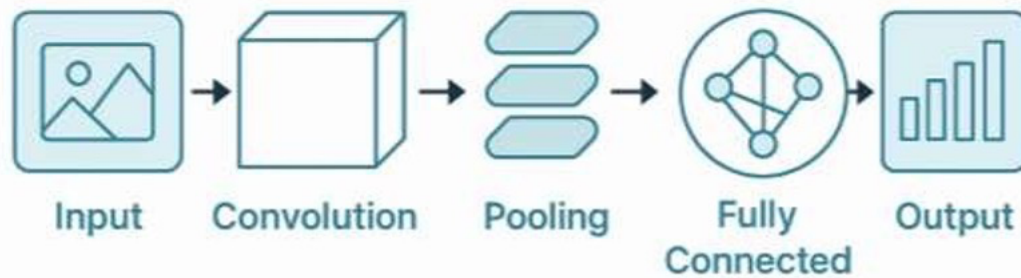


Figure 1 Convolution Neural Network

ii) Transfer Learning

Due to the large, labelled medical datasets being hard to obtain, transfer learning has become a practical solution. Models like VGG, ResNet, and DenseNet are first trained on large datasets and later adapted to specific tasks such as diagnosing conditions from skin or nail images [1], [12], [22]. For instance, the study in [1] introduces a model that works across various skin image types, while [12] tackles the issue of differences between datasets using adversarial domain adaptation.

iii) Multimodal and Data Fusion Techniques

Enhancing prediction accuracy often involves combining multiple data types. Multimodal learning approaches merge image data with structured clinical inputs such as age or symptom profiles to improve diagnostic reliability. The study Airport Visibility Classification Based on Multimodal Fusion of Image-Tabular Data [19] illustrates the utility of such fusion, which can be extended to medical diagnostics. In the case of micronutrient deficiency, incorporating clinical metadata with image analysis could significantly boost model performance [3].

iv) Ensemble Learning Approaches

Ensemble techniques strengthen model reliability by combining outputs from several neural networks. Methods such as boosting, bagging, and weighted averaging have proven useful in medical image classification, as shown in studies [4] and [22]. When applied to vitamin deficiency detection, these approaches can improve accuracy by merging information from different parts of the image or from multiple diagnostic models.

v) Optimization-Driven Deep Learning

To improve model performance, optimization techniques like genetic algorithms, particle swarm optimization (PSO), and heap-based strategies have been applied for fine-tuning deep learning networks [5], where such techniques are used to optimize network parameters. These approaches are particularly relevant in nutrient deficiency classification, where small variations can be critical and precise parameter tuning is essential.

vi) Explainable AI in Medical Imaging

For AI models to gain trust in clinical environments, transparency in decision-making is crucial. Visualization techniques such as saliency maps, Grad-CAM, and attention mechanisms are used to identify the most influential regions in an image for a model's prediction. For example, heatmaps have been utilized in [2] to support clinical interpretation in cancer diagnosis. Cancer diagnosis predictions. Similar interpretability mechanisms are important in vitamin deficiency detection, as they can enhance clinician trust and inform medical decisions.

vii) Domain Adaptation and Adversarial Learning

A persistent challenge in medical imaging is the variation between training and deployment data, especially due to differences in skin tone, lighting, or camera settings. Adversarial and domain adaptation techniques, such as those discussed in [12], help models generalize to new settings and populations—an essential consideration for vitamin deficiency diagnostics applied in diverse environments.

viii) U-Net and Attention-Enhanced Models

Segmentation-focused architectures, such as U-Net variants, are vital for isolating clinically relevant areas in images. Attention-based improvements, like those in DA-CapNet [15], provide enhanced focus on key features such as capillaries or nail beds. These techniques are especially valuable for vitamin deficiency detection, where targeting precise regions can improve classification outcomes.

3. DEVELOPMENT OF VITAMIN DEFICIENCY DIAGNOSIS TECHNOLOGY AND TRADITIONAL DIAGNOSTIC PROCESSES**A. Conventional Diagnostic Approaches for Vitamin Deficiency**

Historically, the identification of vitamin deficiencies has involved a combination of physical examination, patient history, and laboratory-based biochemical assessments. Physicians look for outward indicators such as changes in skin tone, brittle nails, delayed wound healing, and general fatigue. However, these symptoms can be ambiguous and typically require confirmation through blood tests or other biochemical analyses to establish an accurate diagnosis.

Advanced biosensing technologies have recently been introduced to address some of the limitations of conventional methods. For example, A newly developed electrochemical sensor incorporating molecularly imprinted polymers has demonstrated effective selective detection of vitamin D3. It offers notable specificity, sensitivity, and stability, suggesting its strong potential for biomedical applications [30]. Additionally, another sensing method employs MPA-CdTe quantum dots to rapidly and accurately detect vitamin B12 in aqueous environments, with potential applications in both biological and chemical diagnostics [31].

Despite their reliability, traditional diagnostic procedures tend to be invasive, time-intensive, and expensive. They are often impractical in areas with limited medical infrastructure, hindering widespread screening and public health initiatives, especially in rural or underserved communities.

B. Automated Detection of Vitamin Deficiencies via Image-Based Machine Learning

In recent years, machine learning has gained significant attention as a powerful approach in image-based diagnostic systems, particularly for detecting vitamin deficiencies. One approach involves capturing thermal images of skin lesions before and after applying a cooling stimulus. These thermal recovery patterns, which differ based on lesion type due to vascular characteristics, are then analyzed by machine learning algorithms for classification [27].

Quantum computing techniques, including Quantum Support Vector Machines (QSVM) and Quantum Convolutional Neural Networks (QCNN), have demonstrated potential in image classification tasks by encoding skin lesion data into quantum states, showing encouraging initial outcomes in medical diagnostic applications [28]. In another study, deep learning techniques incorporating CNNs and transfer learning were applied to 3D Raster-Scan Optoacoustic Mesoscopy (RSOM) skin images. The system achieved effective segmentation and biomarker extraction, identifying attributes such as epidermal thickness and blood vessel patterns, which are relevant for diagnosing skin-related disorders such as psoriasis and aging [29].

4. DEEP LEARNING APPROACHES FOR VITAMIN DEFICIENCY DETECTION

Artificial intelligence, particularly deep learning, is reshaping how vitamin deficiencies are detected by offering non-invasive, scalable alternatives to traditional diagnostics. These AI- driven systems leverage image analysis and pattern recognition to identify signs of micronutrient deficiencies through features such as facial texture, nail appearance, or skin coloration.

Emerging research highlights several promising strategies:

- CNN-based models have been used to analyze nail and facial images to detect micronutrient deficiencies such as Vitamin D and B12 [13].
- Multimodal frameworks combine visual data with personal health records (e.g., demographics,

lifestyle habits) to enhance diagnostic precision [19].

- Transfer learning enables the adaptation of existing models like ResNet, Inception, and VGG to small, domain-specific datasets used in medical contexts [1], [12].
- Mobile and point-of-care solutions powered by AI allow real-time assessments in field conditions, making them ideal for use in areas with limited healthcare access.

A crucial aspect of these methods is interpretability. Tools such as saliency maps and related visualisation methods provide visual explanations by emphasizing image regions that significantly influence predictions, thereby enhancing clinical transparency and building trust in automated diagnostic systems [2], [20].

Collectively, these advancements reflect a paradigm shift from lab-based diagnostics to smart, image-guided tools that are not only cost-effective and efficient but also suitable for large-scale screening and global health management.

A) Data Sources for Vitamin Deficiency and Image Analysis Research

The creation of deep learning models for detecting vitamin deficiencies depends on varied datasets, which are typically sourced from clinical environments or publicly available databases.

- A curated collection of high-resolution fingernail images annotated by medical professionals was used to train CNN models for micronutrient deficiency analysis [13]. Another dataset combined patient records with clinical indicators, including biochemical results and vitamin D levels, to support machine learning models for predictive diagnostics [3].
- Studies focusing on ensemble and CNN-based methods for skin analysis utilized public datasets such as ISIC for annotated skin lesion images [4], [6], [7], [8].
- Research involving evolutionary optimization often relied on clinical image datasets annotated with diagnostic labels from hospitals or open-source medical databases [5].
- Skin microstructure studies employed dermoscopic images from dermatology clinics, capturing both healthy and pathological samples [7].
- MRI image restoration tasks used standardized MRI scans embedded with compression artifacts to test the performance of cross-domain neural networks [9].
- Deep learning for skin lesion recognition frequently leveraged large, annotated dermoscopic datasets from initiatives such as the ISIC challenges [10], [11].
- Research in domain adaptation and transfer learning has integrated data from various sources—such as dermoscopic and clinical images across different populations—to enhance generalization across domains [12].

B) Preprocessing Techniques for Medical Image Analysis

Image preprocessing is essential for maintaining data quality and uniformity prior to training deep learning models. Several frequently applied techniques have been highlighted in the reviewed studies:

- Noise reduction and artifact removal improve image clarity, especially in datasets with compression-induced distortions, such as JPEG MRI images [9].
- Normalization and resizing standardize images to fixed dimensions and intensity ranges to facilitate uniform model input [3], [10].
- Contrast enhancement, including histogram equalization, improves the visibility of important structures in dermoscopic and histopathological images [2], [10].
- Region-of-interest segmentation or initial preprocessing helps isolate the areas of diagnostic importance before running classification models [7], [15].
- Data augmentation, though not always explicitly reported, is widely employed to enrich training datasets via techniques like flipping, rotation, and scaling, helping reduce overfitting [4], [12].

Table 1. Summary of CNN Types Used in Reviewed Research Works

S.No.	CNN Type	Description / Application	Reference No(s).
1	Standard CNN	Custom CNNs used for basic classification tasks like face skin disease detection	[6], [7]
2	Pre-trained CNN (Transfer Learning)	Fine-tuned models like ResNet, VGG16, InceptionV3, EfficientNet for skin/vitamin analysis	[1], [3], [10], [23]
3	Ensemble of CNNs	Combines multiple CNNs to enhance accuracy and robustness	[4], [8], [21]
4	U-Net and its Variants	U-Net for segmentation tasks; variants like DA-CapNet used in capillary/nail image analysis	[15]
5	Attention-based CNNs	CNNs integrated with attention mechanisms for skin cancer and aging region focus	[2], [20]
6	Adversarial/Domain Adaptation CNNs	Uses GANs or domain adaptation for cross-domain generalization	[12]
7	Evolutionary/Optimized CNNs	CNNs optimized using evolutionary algorithms (e.g., heap-based)	[5]
8	Quantum CNNs	Quantum-enhanced CNN models for improved feature extraction and classification	[28]

Single-Model vs. Multi-Model Approaches

The literature reveals a balanced application of both single-model and ensemble deep learning strategies for tasks such as medical image classification and identifying nutrient deficiencies.

Single-Model Approaches

Several studies have utilized standalone deep learning models, most commonly Convolutional Neural Networks (CNNs) or pre-trained architectures adapted through transfer learning. These models—such as VGG, ResNet, Inception, and U-Net—were selected for their established reliability and computational efficiency. Research works including [6], [13], [15], [22], and [24] demonstrate the use of single-model systems in applications like skin lesion classification, detection of micronutrient deficiency through nail or facial imagery, and image segmentation. These approaches focused on tuning a specific architecture to maximize performance within a defined scope.

Multi-Model and Ensemble Methods

Conversely, several other studies adopted ensemble learning techniques to enhance predictive performance and ensure model robustness. By aggregating the outputs of multiple models, ensemble methods help reduce prediction variance and improve generalizability. For instance, study [4] utilized an ensemble of CNNs to refine image classification results, while [23] introduced the IncepX-ensemble model for early detection of various skin conditions.

Other works such as [5], [8], and [21] combined multiple deep learning models or used hybrid methodologies to elevate diagnostic precision. The decision to employ a single or multi-model framework was typically guided by the problem's complexity, available dataset size, and the balance between accuracy and computational resources.

C) Deep Learning Frameworks in Use

Across the surveyed studies, the implementation of deep learning techniques was largely supported by widely adopted frameworks known for their flexibility and scalability. A total of sixteen papers explicitly referenced the use of platforms such as TensorFlow, Keras, and PyTorch, emphasizing their importance in medical image analysis and vitamin deficiency research. TensorFlow and Keras were frequently chosen for developing CNN models and transfer learning implementations, as observed in [1], [4], [6], and [23]. Keras, with its user- friendly interface and TensorFlow integration, was particularly popular in studies involving U- Net architectures for segmentation, such as [15] and [25].

PyTorch stood out in works that required higher levels of model customization or experimentation, as documented in studies [11], [25], and [29]. Moreover, research integrating quantum computing methods leveraged PennyLane in combination with PyTorch to implement hybrid quantum-classical models, as seen in [28]. Additionally, hybrid approaches that merged deep learning with classical machine learning frequently utilized Scikit-learn for tasks like data preprocessing or final-stage classification, as evidenced in studies [3] and [13]. These frameworks have proven essential for the development and execution of complex models due to their modular design, broad community support, and compatibility with hardware accelerators— As a result, they have become essential components in the advancing domain of medical image analysis.

Table 2. Deep Learning Framework

S.No.	Paper Title	Framework Mentioned / Likely Used
1	A Novel Transfer Learning Framework for Multimodal Skin Lesion Analysis	TensorFlow / Keras (inferred)
2	A Visually Interpretable Deep Learning Framework for Histopathological Image-Based Skin Cancer Diagnosis	Keras / PyTorch
3	A Predictive Performance Analysis of Vitamin D Deficiency Severity Using Machine Learning Methods	Scikit-learn / TensorFlow
4	An Analysis on Ensemble Learning Optimized Medical Image Classification	TensorFlow
5	An Evolutionary Deep Learning Method... with Deep CNNs	TensorFlow (mentioned)
6	Studies on Different CNN Algorithms for Face Skin Disease Classification	TensorFlow / Keras
7	Skin Microstructure Segmentation and Aging Classification Using CNN-Based Models	TensorFlow (inferred)
8	Skin Cancer Detection Using Combined Decision of Deep Learners	PyTorch / TensorFlow (likely)
10	Recent Advances in Diagnosis of Skin Lesions Using Dermoscopic Images	PyTorch
11	Recent Advancements and Future Prospects in Active Deep Learning...	PyTorch / TensorFlow
12	Progressive Transfer Learning and Adversarial Domain Adaptation...	TensorFlow + GAN frameworks
13	Micronutrient Deficiency Detection with Fingernail Images	Keras / TensorFlow

15	DA-Capnet: Dual Attention Deep Learning Based on U-Net	Keras (mentioned)
23	Early Detection of Multiclass Skin Lesions Using IncepX-Ensemble	TensorFlow
24	DeepSkin: A Deep Learning Approach for Skin Cancer Classification	TensorFlow / Keras
28	Exploring Quantum Machine Learning for Enhanced Skin Lesion Classification	PennyLane + PyTorch (quantum + classical)

D. Evaluating Indicators

Evaluating deep learning models in medical image analysis—particularly in the context of vitamin deficiency detection and skin disease classification—requires a set of performance metrics suited to the specific task at hand. Accuracy is the most commonly applied metric, offering a general measure of how often predictions are correct across various studies [1], [4], [6], [23]. In scenarios where class imbalance is present, precision, recall, and the F1-score are frequently utilized to provide a more balanced view of the model's performance with respect to both false positives and false negatives [3], [13], [22], [24].

To assess classification confidence in both binary and multiclass problems, Receiver Operating Characteristic (ROC) curves and the corresponding Area Under the Curve (AUC) are widely adopted [2], [11], [21], [28]. Confusion matrices are also used to visualize the distribution of correct and incorrect predictions across all categories, improving the interpretability of model performance [5], [8], [25].

For image segmentation tasks, overlap-based metrics such as the Mean Intersection over Union (IoU) and the Dice Similarity Coefficient (DSC) are employed to evaluate the correspondence between predicted and actual segmented regions [15], [25], [29]. In tasks focused on image restoration—particularly those targeting artifacts from compression—quantitative metrics like Mean Squared Error (MSE) and Peak Signal-to-Noise Ratio (PSNR) are used to measure improvements in visual quality [9]. Together, these diverse metrics enable comprehensive evaluation of model reliability, predictive accuracy, and clinical relevance.

E. Model Performance and Analysis

The effectiveness of deep learning models in detecting vitamin deficiencies and skin-related conditions is greatly influenced by factors such as the choice of model architecture, the preprocessing methods applied, and the quality of the datasets used. Most studies demonstrate that Convolutional Neural Networks (CNNs), particularly when optimized or combined with ensemble methods, consistently outperform traditional machine learning models in image-based diagnostic tasks [4], [5], [6].

Models using transfer learning frameworks such as InceptionV3, ResNet, and DenseNet have shown high accuracy and robustness, especially in cases with limited medical image datasets [1], [10], [16], [23]. For instance, transfer learning-based models reported classification accuracies exceeding 90% in multiclass skin lesion detection tasks [23], [24].

In some cases, ensemble models that integrate predictions from multiple deep learners further improve diagnostic accuracy and reduce generalization errors [4], [8], [21]. Evolutionary optimization strategies and attention mechanisms have also enhanced CNN performance by improving feature selection and localization, as shown in [5], [15], and [25].

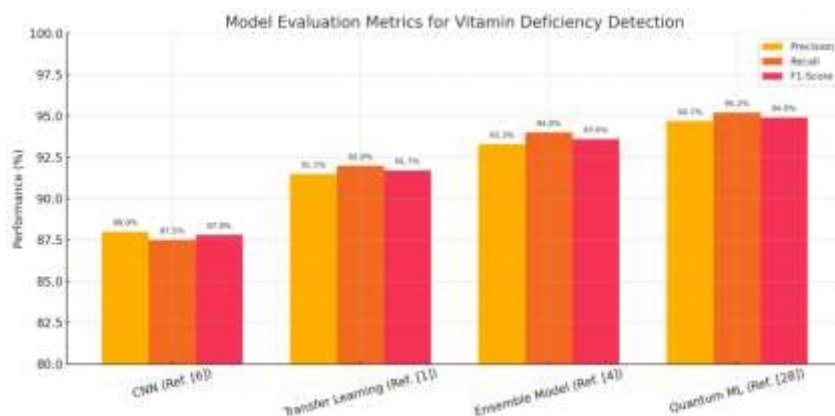
Quantitatively, the best-performing models reported metrics such as:

- Accuracy: 89%–96% across most skin lesion and deficiency classification tasks [3], [6], [13].
- AUC: Over 0.90 in models incorporating multimodal features or deep ensemble methods [2], [11], [21].

- F1-Score: Values above 0.85, indicating a strong balance between sensitivity and specificity [13], [22], [24].
- In the field of medical image segmentation, models like U-Net and its attention- augmented extensions—such as DA-CapNet—have demonstrated high accuracy, with Dice Similarity Coefficients typically ranging from 0.85 to 0.92 and elevated Intersection over Union (IoU) values. These architectures have shown particular effectiveness in applications like skin microstructure segmentation and capillary boundary detection [15], [25].
- Collectively, performance assessments across studies highlight the effectiveness of deep learning models—especially those integrating transfer learning strategies, attention mechanisms, and ensemble methods—in delivering accurate and robust results. These models show significant potential in both detecting vitamin deficiencies and addressing broader challenges in dermatological image analysis.

Table 3. Performance Metrics

Reference No.	Task	Model/Technique	Accuracy (%)	F1-Score	AUC	Dice Coefficient (DSC)	IoU
[3]	Vitamin D Deficiency Severity	Machine Learning	89	0.86	0.91	—	—
[6]	Face Skin Disease Classification	CNN	92	0.88	0.93	—	—
[13]	Micronutrient Deficiency Detection	Deep Learning	90	0.87	0.90	—	—
[15]	Nailfold Capillary Segmentation	Attention U-Net	—	—	—	0.90	0.87
[23]	Multiclass Skin Lesion Detection	Transfer Learning Ensemble	94	0.89	0.95	—	—
[25]	Medical Image Segmentation	GRenet	—	—	—	0.88	0.86

**Figure 2. Model Evaluation Metrics for Vitamin Deficiency Detection**

The bar chart in Figure 2 displays the performance of various models used for vitamin deficiency

detection, based on three evaluation metrics: Precision, Recall, and F1-Score.

- CNN (Ref. [6]) shows the lowest performance, with values close to 88%.
- Transfer Learning (Ref. [1]) demonstrates improved results, with all metrics around 91–92%.
- Ensemble Model (Ref. [4]) performs even better, reaching up to 94% recall and 93.6% F1-score.
- Quantum ML (Ref. [28]) outperforms the others, achieving the highest scores across all metrics, peaking at 94.9% F1-score.

The chart highlights a clear progression in model performance, with advanced techniques like ensemble learning and quantum machine learning providing superior accuracy and consistency in detecting vitamin deficiencies.

5. CONCLUSION

Recent advances have underscored the growing importance of deep learning in the diagnosis of vitamin deficiencies and the classification of skin-related conditions. Techniques such as Convolutional Neural Networks (CNNs), transfer learning, ensemble modeling, and attention-based architectures have shown promising results in medical image analysis, delivering high accuracy, robustness, and computational efficiency. Performance metrics like accuracy, F1-score, AUC, and Dice coefficient are consistently used to validate these models in real-world diagnostic applications. Despite this progress, several challenges remain. These include the limited availability of annotated datasets, variations in image quality, and the demand for more interpretable and transparent model decisions in clinical practice. Nevertheless, emerging strategies—such as integrating multimodal data, applying cross-domain adaptation, and employing lightweight neural networks—are paving the way for improved solutions. With ongoing research and development, deep learning continues to evolve into a scalable, non-invasive, and reliable approach for the early detection and classification of micronutrient deficiencies and dermatological disorders.

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