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A REVIEW OF AI-BASED FINGERNAIL IMAGE ANALYSIS FOR NON-INVASIVE DETECTION OF NUTRITIONAL DEFICIENCIES

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ABSTRACT

Nutritional deficiencies such as iron- deficiency anemia, vitamin B12 deficiency, calcium deficiency, and zinc insufficiency remains major public health burdens worldwide. Traditional diagnostic methods rely on laboratory testing, requiring infrastructure often inaccessible in low-resource settings. Fingernails serve as a non-invasive biomarker that reflects systemic nutritional and metabolic health. With recent advances in computer vision, deep learning, and mobile imaging, AI- driven analysis of fingernail photographs presents an emerging opportunity for scalable nutritional screening. This review provides a comprehensive survey of (1) clinical evidence linking nail biomarkers to nutrient status, (2) the state of AI and computer vision systems for nail and skin analysis, (3) illumination correction and color normalization for smartphone imaging, (4) multi-task learning for simultaneous medical condition prediction, and (5) explainable AI for clinical interpretability. Existing literature demonstrates strong clinical validity and technological feasibility, yet major gaps remain, particularly the absence of multi-deficiency diagnostic systems. This review outlines future research challenges and proposes directions for developing an integrated, explainable, smartphone-based nutritional screening framework.

KEYWORDS: Nutritional deficiencies; Smartphone-based diagnostics; Deep learning; Computer vision; Illumination correction; Multi-task learning; Explainable AI; Non-invasive screening Review.

I. INTRODUCTION

Nutritional deficiencies continue to be a major global health concern, affecting a large section of the population, especially in low-income regions
[1],[3]. Iron-deficiency anemia is the most prevalent, followed by vitamin B12 deficiency, calcium insufficiency, and zinc deficiency. These deficiencies contribute to impaired immunity, developmental delay, cognitive deficits, fatigue, and increased morbidity.
Traditional diagnostic approaches rely on blood- based tests such as hemoglobin (Hb), ferritin, serum B12, and calcium levels. Although accurate, these tests require:

- Clinical laboratory infrastructure
- Refrigeration and specialized equipment
- Trained phlebotomists and technicians
- Financial affordability
- Patient willingness for invasive procedures

Consequently, many individuals remain undiagnosed. Interestingly, fingernails reflect keratin structure, microcirculation, oxygenation, and long-term nutrient availability [1],[3]. Clinical studies show strong correlations between nail abnormalities and systemic deficiencies, making nails a promising, non-invasive biomarker.
Smartphones today include high-resolution cameras, powerful GPUs, and machine-learning capabilities. [2] Combined with advances in computer vision, these devices can perform medical screening tasks previously limited to specialized equipment.
In this context, the present review examines the potential of AI-driven fingernail image analysis as a scalable and cost-effective alternative to conventional diagnostic methods.

II. CLINICAL BASIS: FINGERNAIL BIOMARKERS OF NUTRITIONAL DEFICIENCY

Nails grow approximately 3 mm/month, providing a chronological record of systemic health. Dermato-clinical literature identifies specific nail features associated with nutritional deficiencies.

A. IRON-DEFICIENCY ANEMIA

Koilonychia, commonly referred to as spoon-shaped nails, is strongly associated with chronic iron deficiency and is considered a classic clinical indicator. It occurs due to keratin softening, altered nail matrix metabolism, and reduced structural integrity of the nail plate, which together lead to a concave deformation of the nail surface [3],[6]. In addition to structural changes, long-term anemia also affects the strength and composition of keratin, resulting in brittle and fragile nails. These changes reflect impaired oxygen delivery and reduced nutrient availability to the nail matrix, making nail morphology a useful non-invasive indicator of iron deficiency [1],[3],[5].

B. VITAMIN B12 AND PROTEIN DEFICIENCY

Vitamin B12 and protein deficiencies significantly impact nail morphology, particularly through changes in nail texture and pigmentation. Longitudinal ridges are commonly observed and are associated with reduced methylation processes, impaired keratin synthesis, and poor protein availability. These ridges serve as visible indicators of underlying nutritional imbalance and have been widely reported in dermatological literature [4]. Additionally, severe vitamin B12 deficiency can lead to hyperpigmented bands in the nails due to disruptions in melanin production pathways. Such pigmentation changes provide further visual cues for identifying systemic deficiencies through non-invasive observation [4],[5].

C. CALCIUM AND ZINC DEFICIENCY

Calcium and zinc play crucial roles in maintaining nail strength and structural integrity. Calcium contributes to keratinocyte adhesion, and its deficiency can result in nail fragility and distal splitting, clinically referred to as onychoschizia [3]. Similarly, zinc is essential for proper keratin formation, and its deficiency is often associated with the appearance of white spots, known as leukonychia, along with surface roughness. These manifestations highlight the importance of micronutrients in maintaining nail health and support the use of nail features as indicators of nutritional deficiencies [3],[6].

D. MULTIFACTORIAL NAIL CONDITIONS

Nail abnormalities are not exclusively linked to nutritional deficiencies but may also arise from a variety of systemic diseases. Baran et al. highlighted that conditions such as liver dysfunction, diabetes, renal disease, and thyroid disorders can produce nail changes that may visually overlap with deficiency-related patterns. This overlap increases the risk of misinterpretation when relying solely on visual indicators. Therefore, any AI-based diagnostic system must incorporate differential analysis to distinguish between nutritional and systemic causes, thereby reducing the likelihood of misclassification and improving diagnostic reliability [7].

III. AI AND COMPUTER VISION FOR NAIL IMAGE ANALYSIS

Computer vision techniques for nails have historically focused on infections, cosmetics, or dermatological lesions.

A. NAIL SEGMENTATION TECHNIQUES

In practice, accurate nail segmentation is a critical step in computer vision-based analysis, as it directly affects the reliability of downstream feature extraction and classification. This task is challenging due to background clutter, variations in skin tone, the presence of nail polish, and differences in hand positioning. Modern approaches primarily rely on deep learning architectures such as U-Net and SegNet for semantic segmentation, and Mask R-CNN for instance segmentation. These methods have demonstrated high accuracy in isolating nail regions from complex backgrounds. Additionally, traditional techniques such as thresholding and geometry-based fingertip localization are sometimes used in controlled environments. Kim et al. reported segmentation accuracies exceeding 95% using convolutional neural networks, validating the effectiveness of these approaches in real-world scenarios [9].

B. NAIL DISEASE CLASSIFICATION

Over the past few years, deep learning techniques have been increasingly applied to the classification of nail diseases, including conditions such as onychomycosis, psoriasis, onycholysis, and trachyonychia. These models, often based on architectures like ResNet, have achieved high accuracy levels ranging from 91% to 95%. Although these studies are not directly focused on nutritional deficiencies, they demonstrate the feasibility of using nail images for medical diagnosis and highlight the robustness of deep learning models in handling variations in nail shape, color, and texture [8].

C. SMARTPHONE-BASED ANEMIA DETECTION

A significant advancement in this domain is the work by Mannino et al., who developed a smartphone-based system for non-invasive anemia detection using nail-bed images. Their model estimated hemoglobin levels with an AUC of approximately 0.87, demonstrating the potential of optical biomarkers in clinical screening. However, the approach was limited to anemia detection and did not account for multiple nutritional deficiencies or variations in imaging conditions across different devices. These limitations highlight the need for more comprehensive and robust multi-condition diagnostic systems [2].

IV. Illumination Correction for Consumer- Device Imaging

Smartphone-based diagnostic systems face several challenges related to image acquisition, including unpredictable lighting conditions, glare and specular reflections, variations in camera sensor characteristics, and differences in skin tone. These factors can significantly affect the reliability of color- and texture-based feature extraction, which are critical for detecting nutritional deficiencies. Therefore, illumination correction plays a vital role in ensuring consistent and accurate analysis across diverse real-world conditions.

A. Deep Learning-Based Illumination Correction

Recent advancements in deep learning have enabled effective solutions for low-light and uneven illumination problems. Chen et al. (CVPR, "Learning to See in the Dark") demonstrated that deep neural networks can restore low-light images by learning illumination maps, reducing noise, and enhancing dynamic range. Such techniques are highly relevant for medical imaging applications where image quality directly impacts diagnostic accuracy. Further developments in structured illumination correction have improved the robustness of image preprocessing pipelines, making them suitable for smartphone-based health applications [10].

B. Specular Reflection Removal

Specular highlights and reflections introduce noise that can distort color-based biomarkers and obscure fine texture details such as ridges and surface irregularities. These reflections are particularly problematic in nail imaging due to the glossy surface of nails. Yin et al. proposed a reflection removal approach based on polarization-independent learning and light-field estimation, which helps in isolating true surface characteristics from lighting artifacts. Such methods are essential for improving the reliability of automated nail analysis systems [16].

C. Device-Independent Color Standardiztion

One more critical challenge, however, is the variation in color representation across different smartphone cameras. Differences in sensor properties and image processing pipelines can lead to inconsistent color measurements. Liu et al. demonstrated that device-independent color normalization can be achieved using learned color-transfer matrices and calibration-free approaches. This enables consistent analysis across devices and supports the development of a universal Auto-Illumination Corrector (AIC) for scalable deployment of diagnostic systems.

V. Multi-Task Learning for Medical Prediction

Nutritional deficiencies often occur simultaneously and share underlying biological mechanisms. For instance, both iron and vitamin B12 deficiencies affect erythropoiesis, while zinc and protein deficiencies influence keratin synthesis. Multi-task learning (MTL) leverages these relationships by enabling a single model to learn multiple related tasks simultaneously, thereby improving overall predictive performance and generalization [11].

In hard parameter sharing architectures, a shared encoder is used to extract common features such as nail texture, color variations, and ridge patterns, while separate task-specific layers are employed to predict different deficiencies, including iron-deficiency anemia, vitamin B12 deficiency, calcium deficiency, and zinc deficiency. This approach reduces model complexity and enhances learning efficiency by capturing shared representations [11],[12].

Soft parameter sharing techniques, particularly those based on attention mechanisms, further improve performance by dynamically weighting shared features across tasks. As a result, this approach helps improve both accuracy and overall robustness in practical scenarios. Additionally, multi-task learning frameworks commonly employ loss functions such as weighted cross-entropy and focal loss to address class imbalance, along with correlation-based penalties to capture inter-task dependencies. These strategies collectively contribute to improved multi-label clinical prediction accuracy [12].

VI. Explainable AI for Clinical Acceptance

Explainable Artificial Intelligence (XAI) is essential for building trust in medical diagnostic systems, particularly when used in clinical or semi-clinical settings. It enables clinicians and users to understand the reasoning behind model predictions, thereby improving transparency and acceptance.

Gradient-based visualization techniques such as Grad-CAM highlight the regions of an image that contribute most to a model's decision, allowing identification of relevant features such as discoloration or texture changes in nails [13]. Grad-CAM++ further enhances this capability by improving sensitivity to multiple small regions, making it particularly useful for detecting subtle patterns such as ridges, color variations, and brittle zones in nail images [14].

In dermatology, explainability has been shown to significantly improve clinician confidence in AI systems. Studies demonstrate that visual explanations help validate model predictions and support clinical decision-making. These principles can be effectively extended to fingernail analysis, where interpretability is crucial for distinguishing between different nutritional and systemic conditions [13],[14].

VII. Discussion

Despite significant advancements in both clinical understanding and AI-based analysis of nail features, several challenges remain. It is important to note that these challenges are interconnected. One major limitation is the absence of a comprehensive multi-deficiency diagnostic system. Most existing research focuses on either nail diseases such as fungal infections or single-condition detection, particularly anemia, leaving a gap in integrated nutritional assessment.

Another critical challenge is the lack of large-scale, publicly available datasets that link nail images with corresponding clinical and biochemical data. The development of such datasets would enable more robust model training and validation, significantly advancing research in this field.

Additionally, real-world variability introduces further complexity. Factors such as nail polish, mehendi (henna), and artificial nails can obscure natural nail features and introduce noise into the analysis. Cultural practices and cosmetic usage must therefore be considered when designing preprocessing and filtering techniques.

Finally, ensuring robustness under diverse environmental conditions remains essential. AI models must perform reliably across varying lighting conditions, including indoor and outdoor environments, as well as under different types of artificial lighting. Addressing these challenges is crucial for developing practical and scalable smartphone-based diagnostic systems.

VIII. Conclusion

AI-driven analysis of fingernail images represents a promising approach for non-invasive detection of nutritional deficiencies. Clinical evidence supports the diagnostic relevance of nail biomarkers, while advances in deep learning, illumination correction, multi-task learning, and explainable AI provide a strong technological foundation for such systems.

However, several challenges remain, including the lack of multi-deficiency diagnostic models, limited availability of large-scale annotated datasets, and variability introduced by real-world imaging conditions and cosmetic factors. Addressing these challenges is essential for improving model robustness and clinical applicability.

Future research should focus on developing integrated, explainable, and device-independent systems capable of accurately identifying multiple deficiencies simultaneously. Such solutions have the potential to significantly improve early detection and enable accessible, low-cost health screening, particularly in resource-limited settings.

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