

Bio Nutri Sca: A Clinical Decision Support System for Vitamin Deficiency Assessment

Darshana Barhate¹, Mansi Ahire², Mrunal Gaikwad³, Monica Charate⁴

^{1,2,3} UG Student, Computer Science and Technology, UMIT SNTD University, Mumbai, India.

⁴ Assistant Professor, Computer Science and Technology, UMIT SNTD University, Mumbai, India.

Abstract—Vitamin deficiency is a widespread yet often unnoticed health problem affecting people of all age groups worldwide. Conventional diagnostic methods rely heavily on blood tests, which are expensive, invasive, and time-consuming. These limitations discourage individuals from seeking early screening, especially in rural and underserved regions where healthcare facilities and laboratory infrastructure are limited. Consequently, deficiencies are often diagnosed only after serious health complications develop, increasing the burden on patients and healthcare systems. This highlights the urgent need for a simple, affordable, and non-invasive alternative.

This research introduces BioNutriScan, an AI-based clinical decision support system designed to detect vitamin deficiencies using image analysis. The system evaluates visual indicators from easily observable body parts such as the skin, tongue, eyes, and nails. Images captured through smartphones or basic cameras undergo preprocessing steps, including resizing, normalization, and augmentation, to ensure consistency. A transfer learning approach using EfficientNetV2 is applied to classify deficiencies accurately. Trained on 18,307 images across 89 classes, the model achieves approximately $\approx 94.49\%$ accuracy. BioNutriScan also provides personalized dietary and lifestyle recommendations, supporting early intervention. With its user-friendly interface, the system is scalable, cost-effective, and suitable for remote healthcare settings.

Key Words: Vitamin Deficiency Detection, Skin Analysis, Machine Learning, Deep Learning, Dermatology, Nutrient Deficiency, Medical Imaging, Clinical Decision Support.

1. INTRODUCTION

Vitamins play a vital role in maintaining the normal functioning of the human body [1]. They support essential processes such as growth, immunity, metabolism, vision, skin health, and brain function [2]. A deficiency in any essential vitamin can gradually lead to various physical and mental health problems, including fatigue, weakened immunity, poor vision, skin disorders, anemia, and long-term chronic conditions [3], [4]. Despite their importance, vitamin deficiencies remain a widespread and often hidden health issue across the world, affecting people of

different age groups, lifestyles, and socioeconomic backgrounds [5].

One of the main reasons vitamin deficiencies go unnoticed is the heavy dependence on conventional diagnostic methods, particularly blood tests [3]. Although blood tests are medically reliable, they are invasive, time-consuming, and costly [9]. Many individuals avoid routine testing due to fear of needles, financial constraints, or lack of awareness [3]. This challenge becomes even more serious in rural and underserved areas, where access to laboratories, healthcare professionals, and diagnostic equipment is limited [8]. As a result, individuals often become aware of their vitamin deficiencies only after noticeable symptoms appear or serious health complications develop. By this stage, treatment becomes more complex and expensive, placing an additional burden on healthcare systems [2].

In recent years, advancements in artificial intelligence and medical imaging have opened new opportunities for developing alternative diagnostic approaches [1, 5]. Research has shown that certain vitamin deficiencies cause visible changes in external body features such as skin texture, tongue color, nail appearance, and eye condition [5, 2]. These physical indicators can serve as early warning signs if analyzed accurately. With the widespread availability of smartphones and digital cameras, image-based health assessment has emerged as a promising, non-invasive solution for early screening and preventive healthcare [4, 5].

This research introduces BioNutriScan, a clinical decision support system designed to detect vitamin deficiencies using image analysis and deep learning techniques [1]. The system focuses on identifying visual patterns from images of easily observable body parts, eliminating the need for invasive laboratory procedures. BioNutriScan captures images with standard cameras, preprocesses them to improve quality, and applies advanced convolutional neural network models to analyze potential deficiencies [4]. By leveraging transfer learning techniques, the system achieves reliable accuracy while remaining computationally efficient [11].

Beyond detection, BioNutriScan aims to provide meaningful support to users by offering personalized recommendations. Based on the identified deficiency, the

system suggests appropriate dietary improvements, nutritional guidance, lifestyle changes, and safe supplement options [6, 7]. This approach promotes early intervention and encourages individuals to take preventive actions before deficiencies progress into serious health conditions. The system is designed to be affordable, scalable, and user-friendly, making it suitable for deployment in remote regions, health camps, and primary care settings [8, 6].

2. LITERATURE SURVEY

This section presents a comprehensive review of existing research across key domains relevant to BioNutriScan, including traditional vitamin deficiency diagnosis, artificial intelligence in medical imaging, dermatological indicators of nutritional status, mobile health technologies, and clinical decision support systems.

2.1 Traditional Approaches to Vitamin Deficiency Diagnosis

Conventional methods for diagnosing vitamin deficiencies have predominantly relied on laboratory-based biochemical assessments. Research on foundational principles of nutritional assessment emphasizes serum analysis as the gold standard for detecting micronutrient imbalances [8]. Blood-based biomarkers remain widely accepted in clinical practice due to their quantitative accuracy and ability to measure specific vitamin concentrations [3]. However, these methods present significant limitations, including invasiveness, high costs, the requirement for trained personnel, and extended processing times.

Studies have documented the prevalence of vitamin B-12 deficiency and highlighted challenges in routine screening, noting that many cases remain undiagnosed until symptomatic manifestation [1]. The global scenario indicates that micronutrient deficiencies affect over two billion people globally, with substantial underdiagnosis particularly in resource-limited settings [8]. Healthcare access barriers in rural and developing regions have been identified, with laboratory infrastructure limitations recognized as a critical factor contributing to delayed nutritional assessments [2, 5].

2.2 Artificial Intelligence in Medical Diagnostics

The integration of artificial intelligence into healthcare has transformed diagnostic paradigms across multiple medical specialties. Comprehensive analyses of AI convergence with clinical medicine demonstrate that machine learning algorithms can achieve diagnostic accuracy comparable to or exceeding that of human experts in specific domains [1]. Foundational guidance on implementing deep learning in healthcare applications has

established frameworks for model development, validation, and clinical deployment [4].

Extensive surveys of deep learning applications in medical image analysis document successful implementations in radiology, pathology, ophthalmology, and dermatology [5]. The research highlights convolutional neural networks (CNNs) as particularly effective architectures for pattern recognition in medical imagery [4]. These networks have demonstrated exceptional performance in detecting subtle visual features that may be imperceptible to human observers [5].

Studies investigating transfer learning methodologies for medical imaging found that pre-trained models from natural image datasets can be effectively adapted for clinical applications [11]. Research demonstrated that transfer learning reduces data requirements and computational costs while maintaining diagnostic accuracy—a finding particularly relevant for resource-constrained healthcare environments [4, 11].

2.3 Dermatological Indicators of Nutritional Deficiencies

Clinical research has established strong correlations between vitamin deficiencies and observable cutaneous manifestations. Research reviews dermatological presentations of vitamin D deficiency, documenting characteristic skin changes that serve as clinical indicators [2]. Comprehensive overviews of nutritional disorders affecting the skin catalog visible signs associated with deficiencies in vitamins A, B-complex, C, D, E, K, and essential minerals [5].

Specific dermatological presentations documented in literature include:

- Vitamin C deficiency (Scurvy): Petechiae, ecchymoses, perifollicular hemorrhages, and poor wound healing [1]
- Vitamin A deficiency: Follicular hyperkeratosis, xerosis, and phrynoderma ("toad skin") [5]
- Vitamin B12 deficiency: Hyperpigmentation, glossitis, and angular cheilitis [2]
- Zinc deficiency: Acrodermatitis, perioral dermatitis, and alopecia [6]
- Iron deficiency: Pallor, koilonychia, and angular stomatitis [3]

These visual biomarkers provide the theoretical foundation for image-based nutritional assessment systems. However, existing clinical practice relies predominantly on subjective visual inspection by trained dermatologists, limiting scalability and accessibility.

2.4 Computer Vision for Skin Analysis

Recent advances in computer vision have enabled automated analysis of dermatological conditions. Studies demonstrated that deep neural networks trained on clinical images could classify skin conditions with accuracy comparable to board-certified dermatologists [5]. This landmark research established the viability of AI-driven skin analysis for clinical applications.

Deep learning systems for dermatological diagnosis across multiple conditions have achieved high sensitivity and specificity [1]. Their work addressed challenges including image quality variations, lighting inconsistencies, and diverse skin tones. CNNs applied to dermatological detection introduced data augmentation techniques to address limited training data—a common challenge in medical imaging applications [4].

Despite these advances, limited research has specifically addressed vitamin deficiency detection through image analysis. Most existing dermatological AI systems focus on malignancy detection or inflammatory skin conditions rather than nutritional assessment. This gap represents a significant opportunity for innovation in preventive healthcare.

2.5 Mobile Health Technologies

The proliferation of smartphone devices has catalyzed the development of mobile health (mHealth) applications for accessible healthcare delivery. Characterization of the emerging mHealth landscape identifies opportunities for continuous monitoring, early detection, and patient engagement [3]. Research documented the growing adoption of mobile devices among healthcare professionals, noting their potential for point-of-care diagnostics [2].

A framework for mHealth innovations as health system strengthening tools has been proposed, particularly relevant for underserved communities [8]. Research demonstrated that mobile technologies can extend diagnostic capabilities to regions lacking traditional healthcare infrastructure. Smartphone cameras, in particular, offer potential for noninvasive health assessment when combined with appropriate analytical algorithms.

Several smartphone-based health applications have emerged for skin analysis. Applications utilizing AI for skin condition risk assessment demonstrate consumer acceptance of image-based health screening [1]. However, these applications predominantly target skin condition detection rather than nutritional status assessment, leaving vitamin deficiency screening largely unaddressed in the mHealth ecosystem.

2.6 Clinical Decision Support Systems

Clinical decision support systems (CDSS) have been implemented across various healthcare domains to augment clinical reasoning and improve patient outcomes. Comprehensive overviews of CDSS architectures, benefits, risks, and implementation strategies emphasize that effective CDSS must integrate seamlessly into clinical workflows while providing actionable, evidence-based recommendations [9].

Research examining the expanding role of AI in healthcare CDSS identifies diagnostic support, treatment recommendation, and preventive care as primary application areas [10]. Studies articulate the promise of digital health technologies in addressing healthcare disparities and improving health equity—objectives directly aligned with BioNutriScan's mission [7].

Existing nutritional CDSS predominantly rely on dietary intake questionnaires, anthropometric measurements, and laboratory data. Few systems incorporate image-based assessment or leverage deep learning for nutritional evaluation. Furthermore, most CDSS require professional interpretation, limiting their utility for self-directed health management.

2.7 Research Gaps and Contributions

Analysis of existing literature reveals several significant research gaps that BioNutriScan addresses:

- Limited non-invasive screening options: Current diagnostic methods for vitamin deficiencies predominantly require blood sampling, creating barriers to routine screening [3, 9].
- Underutilization of visual biomarkers: Despite documented dermatological manifestations of vitamin deficiencies [2, 5], automated image-based detection systems remain largely unexplored.
- Accessibility constraints: Existing diagnostic approaches often require specialized equipment and trained personnel, limiting availability in resource-constrained settings [8].
- Absence of integrated recommendation systems: Current tools typically provide diagnosis without accompanying personalized intervention guidance [9].
- Limited application of transfer learning: While transfer learning has shown promise in medical imaging [11], its application to nutritional assessment through skin analysis has not been systematically investigated.

BioNutriScan addresses these gaps by integrating deep learning-based image analysis with a comprehensive recommendation engine, delivering an accessible, non-

invasive solution for vitamin deficiency screening and intervention guidance.

3. PROPOSED METHODOLOGY

This section presents the architectural design and implementation methodology of BioNutriScan, a clinical decision support system for non-invasive vitamin deficiency detection. The proposed system integrates multiple analytical components to achieve reliable deficiency identification and personalized recommendation generation.

3.1 System Overview

BioNutriScan employs a dual-layer analytical architecture combining a custom-trained deep learning model with a large language model (LLM) for comprehensive clinical analysis. The system processes user-uploaded images through a sequential pipeline consisting of image validation, parallel deficiency detection, result fusion, cross-verification against historical feedback, and personalized recommendation generation.

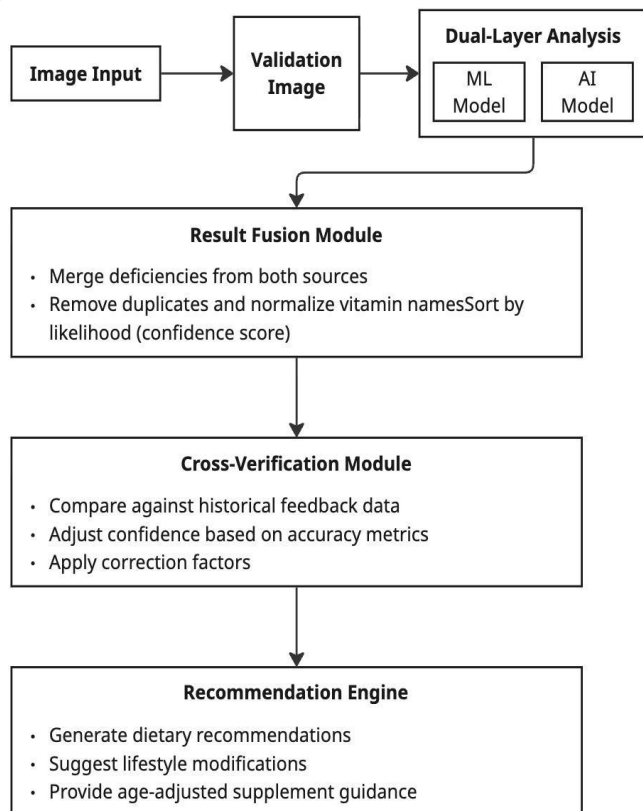


Figure 1: System overview diagram of BioNutriScan

3.2 Image Acquisition and Preprocessing

3.2.1 Image Input Module

The system accepts digital images in standard formats (JPEG, PNG) captured using conventional cameras or smartphone devices. This design choice ensures accessibility across diverse user environments, from clinical settings to remote healthcare camps. The input module performs initial format validation and converts images to the RGB color space for consistent processing.

3.2.2 Preprocessing Pipeline

The preprocessing pipeline prepares images for analysis through the following operations:

1. Color Space Conversion: Input images are converted to RGB format to ensure consistent color representation across different image sources.
2. Spatial Normalization: Images are resized to 224×224 pixels to match the input dimensions expected by the convolutional neural network architecture.
3. Intensity Normalization: Pixel values are normalized to the range [0, 1] using min-max normalization:

$$x_{normalized} = \frac{x - x_{min}}{x_{max} - x_{min}} = \frac{x}{255}$$

4. Dimension Expansion: A batch dimension is added to the image tensor to conform to the model's expected input shape (1, 224, 224, 3).

3.3 Image Validation Layer

Before deficiency analysis, the system validates that uploaded images contain human skin or body parts suitable for clinical assessment. This validation prevents erroneous analysis of non-relevant images and improves system reliability.

Images failing validation are rejected with appropriate error messages, while valid images proceed to the analysis pipeline. The system implements graceful degradation for network failures, allowing analysis to continue when validation services are temporarily unavailable.

3.4 Deep Learning Classification Model

3.4.1 Model Architecture

BioNutriScan employs a convolutional neural network (CNN) trained on a curated dataset of dermatological images representing various vitamin deficiencies. The model architecture is based on established transfer learning principles, utilizing pre-

trained weights from ImageNet to leverage learned visual features [11].

The network processes 224×224×3 input images and outputs probability distributions across 100+ disease classes representing different vitamin and mineral deficiency conditions.

3.4.2 Disease to Vitamin Mapping

A critical component of the ML pipeline is the disease-to-vitamin mapping module. Dermatological conditions detected by the model are mapped to their corresponding vitamin deficiencies using a comprehensive mapping database:

Table 1: Disease-to-vitamin mapping relationships

Dermatological Condition	Associated Deficiency
Scurvy	Vitamin C Deficiency
Pellagra	Vitamin B3 (Niacin) Deficiency
Beriberi	Vitamin B1 (Thiamine) Deficiency
Xerophthalmia	Vitamin A Deficiency
Rickets manifestations	Vitamin D Deficiency
Angular cheilitis	Vitamin B2/Iron Deficiency
Glossitis	Vitamin B12/Folate Deficiency
Acrodermatitis	Zinc Deficiency

3.4.3 Prediction Generation

The model generates predictions by computing softmax probabilities for each class. The top-N predictions with non-zero confidence are extracted and transformed into deficiency assessments:

$$P(class_i) = \frac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

Where z_i represents the logit output for class i and K is the total number of classes.

Likelihood scores are computed as

$$L_i = P(class_i) \times 100$$

3.5 AI-Powered Clinical Analysis

3.5.1 AI Integration

BioNutriScan integrates AI APIs, a state-of-the-art multimodal large language model, for comprehensive clinical analysis. This component performs a detailed visual examination following established dermatological assessment protocols.

3.5.2 Analysis Protocol

The AI analysis follows a structured two-step protocol:

Step 1: Health Status Assessment

The system first determines whether the skin appears normal and healthy by evaluating:

- Skin clarity and texture uniformity
- Absence of lesions, rashes, or abnormalities
- Normal coloration appropriate for the individual
- Healthy nail and hair appearance (if visible)

If the skin appears healthy, the analysis terminates with a "Normal" status, preventing false positive detections.

Step 2: Systematic Deficiency Analysis

For abnormal presentations, the AI performs a comprehensive analysis:

- Surface Analysis: Detection of petechiae, purpura, ecchymoses, texture abnormalities, and color variations.
- Regional Assessment: Evaluation of face, extremities, mucous membranes, and sun-exposed areas.
- Pattern Recognition: Identification of characteristic patterns associated with specific deficiencies:
 - Bleeding patterns → Vitamin C or K deficiency
 - Dry/rough skin patterns → Vitamin A deficiency
 - Acne patterns → Zinc or Biotin deficiency
 - Pallor patterns → Iron or B12 deficiency
 - Photosensitive patterns → Niacin deficiency

3.5.3 Confidence Scoring Algorithm

The AI generates confidence scores based on the number and severity of observed clinical signs:

$$C = C_{base} + \sum_{i=1}^n w_i \cdot s_i$$

Where:

- C_{base} = Base confidence primary signs
- w_i = Weight for secondary sign i
- s_i = Binary indicator for the presence of a sign i

Table 2: Confidence scoring criteria based on clinical sign detection

Signs Detected	Severity Classification	Confidence Range
1 primary sign	Mild	50-60%
2 primary signs	Moderate	65-75%
3+ primary signs	High	80-90%
Classic presentation	Very High	90-95%

3.6 Result Fusion Module

The result fusion module combines outputs from both analytical layers to produce a unified assessment:

3.6.1 Deficiency Merging Algorithm

Algorithm 1: Merge_Deficiencies

- **Input:**
ML_results (list of ML model deficiencies),
AI_results (list of AI deficiencies)
- **Output:**
merged_deficiencies (unified, deduplicated list)

```

1: merged_list ← []
2: seen_vitamins ← {}
3: final_list ← []
4:
5: for each deficiency d ∈ ML_results do
6:   d.source ← "ML Model"
7:   merged_list.append(d)
8: end for
9:
10: for each deficiency d ∈ AI_results do
11:   d.source ← "AI"
12:   merged_list.append(d)
13: end for
14:
15: Sort merged_list by d.likelihood in descending order
16:
17: for each deficiency d ∈ merged_list do
18:   normalized_name ← normalize(d.vitamin)
19:   // Remove "deficiency" suffix, convert to lowercase
20:   if normalized_name ∉ seen_vitamins then

```

```

21:     final_list.append(d)
22:     seen_vitamins.insert(normalized_name)
23:   end if
24: end for
25:
26: final_list ← {d | d ∈ final_list ∧ d.likelihood > 0}
27: // Filter entries with likelihood ≤ 0
28:
29: final_list ← final_list[1:min(10, |final_list|)]
30: // Limit to top 10 deficiencies
31:
32: return final_list

```

Complexity Analysis:

Time Complexity: $O(n \log n)$
 where $n = (ML\ result) + (AI\ result)$
 (dominated by sorting step 15)

Space Complexity:

$O(n)$ for storing merged lists and deduplication hash tables

Example:

Input:

$ML_results = \{(Vitamin\ C, 78.5), (Vitamin\ B3, 45)\}$
 $AI_results = \{(Vitamin\ C, 85.0), (Zinc, 62.0)\}$

Output:

$merged_deficiency = \{(Vitamin\ C, 85.0, AI), (Zinc, 62.0, AI), (Vitamin\ B3\ 45, ML)\}$

3.6.2 Primary Deficiency Selection

When both layers produce conflicting assessments, the system applies the following priority rules:

AI Clinical Assessment Priority: If AI explicitly determines skin is "normal," this assessment overrides ML predictions, as the AI performs a comprehensive clinical evaluation.

Highest Confidence Selection: For abnormal cases, the deficiency with the highest confidence score across both sources is selected as the primary diagnosis.

Source Attribution: Each deficiency maintains its source attribution for transparency and auditability.

3.7 Cross-Verification Module

The cross-verification module leverages historical feedback data to refine prediction confidence and improve system accuracy over time.

3.7.1 Historical Accuracy Computation

For each vitamin deficiency type, the system maintains accuracy metrics:

$$A_{vitamin} = \frac{N_{accurate}}{N_{total}} \times 100$$

Where:

- $N_{accurate}$ = Number of verified accurate predictions
- N_{total} = Total predictions for this vitamin type

3.7.2 Confidence Adjustment Algorithm

Based on historical accuracy, confidence scores are adjusted using correction factors:

Table 3: Confidence adjustment factors based on historical accuracy

Historical Accuracy	Adjustment Factor (α)	Effect
100%	1.20	20% confidence boost
$\geq 75\%$	1.10	10% confidence boost
$\geq 50\%$	1.00	No adjustment
$> 0\%$	0.90	10% confidence reduction
0%	0.70	30% confidence reduction

The adjusted confidence is computed as:

$$C_{adjusted} = \min(100, C_{original} \times \alpha)$$

For predictions involving multiple deficiencies, the average adjustment factor is applied:

$$\bar{\alpha} = \frac{1}{n} \sum_{k=1}^n \alpha_k$$

3.8 Recommendation Engine

3.8.1 Dietary Recommendations

Based on identified deficiencies, the system generates evidence-based dietary recommendations. Each detected deficiency triggers the retrieval of associated food sources rich in the deficient nutrient:

- Vitamin C: Citrus fruits, bell peppers, broccoli, strawberries
- Vitamin A: Carrots, sweet potatoes, spinach, eggs
- Iron: Red meat, spinach, legumes, fortified cereals
- Zinc: Oysters, beef, pumpkin seeds, chickpeas

Recommendations are categorized into vegetarian and non-vegetarian options to accommodate diverse dietary preferences.

3.8.2 Lifestyle Recommendations

The system generates contextual lifestyle modifications based on detected deficiencies:

- Smoking cessation recommendations for Vitamin C deficiency
- Sun exposure guidance for Vitamin D deficiency
- Stress management suggestions for B-vitamin deficiencies
- Sleep hygiene recommendations for general nutritional health

3.8.3 Age-Adjusted Supplement Guidance

Supplement recommendations incorporate age-based dosage adjustments to ensure safety and efficacy across different demographic groups:

$$D_{adjusted} = D_{standard} \times m_{age}$$

Where m_{age} represents the age-specific multiplier:

Table 4: Age-based dosage multipliers for supplement recommendations

Age Group	Multiplier (m_{age})
Infant (0-12 months)	0.10
Toddler (1-3 years)	0.15
Preschooler (3-6 years)	0.25
Child (6-12 years)	0.40
Adolescent (12-18 years)	0.70

Young Adult (18-30 years)	1.00
Adult (31-50 years)	1.00
Mature Adult (51-65 years)	0.85
Senior (65+ years)	0.70

3.9 Feedback-Driven Learning Loop

3.9.1 Feedback Collection

The system implements a continuous improvement mechanism through user feedback collection. After each analysis, users can indicate whether the detected deficiency was accurate. Feedback entries include:

- Image hash for tracking
- Original analysis results
- Accuracy assessment (accurate/inaccurate)
- Optional detailed comments
- Timestamp and verification status

3.9.2 Verification Workflow

Submitted feedback undergoes a verification process:

- Pending State: Initial submission awaiting review
- Verification: Administrator review with clinical validation
- Final Status: Approved (verified) or Rejected

Verified feedback entries contribute to the accuracy metrics used in cross-verification, creating a self-improving system that becomes more accurate over time.

4. SYSTEM ARCHITECTURE

This section describes the architectural design of BioNutriScan, detailing the system components, data flow, and interactions between modules.

4.1 High-Level Architecture

BioNutriScan follows a three-tier client-server architecture comprising a frontend presentation layer, backend application layer, and data storage layer. The system is designed for scalability, modularity, and ease of deployment in resource-constrained environments [1].

The architecture employs a separation of concerns principle, enabling independent development, testing, and deployment of each layer. This modular design facilitates maintenance and allows for future enhancements without requiring complete system restructuring. The three-tier approach provides several key advantages: (1) enhanced

security through isolation of business logic from user interface, (2) improved performance through distributed processing across layers, (3) simplified scalability by allowing individual tier replication based on demand, and (4) flexibility in technology selection for each component [5].

The frontend layer provides an intuitive user interface for image capture, analysis result visualization, and report generation. The backend layer implements core diagnostic logic, integrating machine learning inference with AI-powered clinical analysis. The storage layer persists user data, model parameters, feedback records, and historical analysis results. Communication between layers utilizes RESTful API protocols with JSON data serialization, ensuring interoperability and ease of integration with external systems [4].

The modular architecture enables BioNutriScan to function effectively in diverse deployment scenarios—from cloud-based implementations with unlimited computational resources to edge deployments on mobile devices with constrained processing capabilities. This flexibility is critical for achieving the system's objective of providing equitable diagnostic access across varied healthcare settings [2, 8].

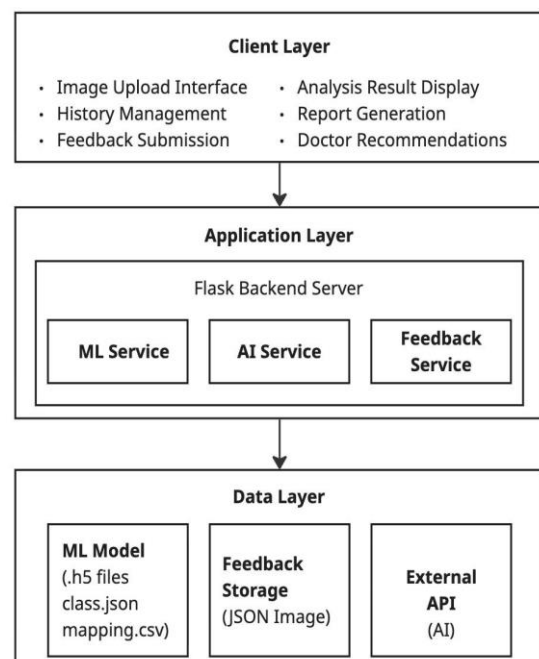


Figure 2: Three-tier system architecture of BioNutriScan

4.2 Data Flow Architecture

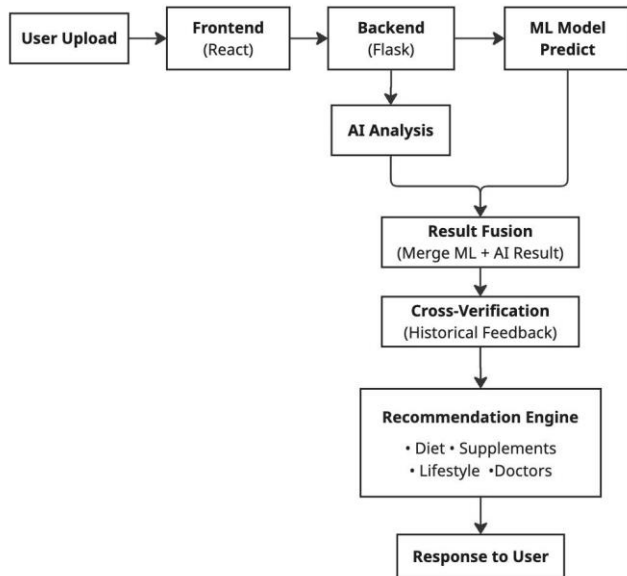


Figure 3: Data Flow architecture of BioNutriScan

5. RESULTS AND EVALUATION

This section presents the experimental setup, evaluation metrics, and performance results of the BioNutriScan system for vitamin deficiency detection.

5.1 Dataset Description

The BioNutriScan model was trained on a curated dermatological image dataset comprising 89 distinct skin condition classes. Each condition is mapped to its corresponding vitamin or mineral deficiency.

Table 5: Dataset Statistics

Parameter	Value
Total Classes	89
Vitamin Deficiency Categories	14
Image Resolution	224 × 224 pixels
Color Space	RGB (3 channels)
Data Split	80% Training, 10% Validation, 10% Test

5.2 Deficiency Distribution

The diseases are mapped to the following vitamin deficiency categories:

Table 6: Distribution of skin conditions across vitamin deficiency categories

Vitamin Deficiency	Number of Conditions	Percentage
Vitamin D	24	27.0%
Vitamin A	13	14.6%
Vitamin B12	11	12.4%
Vitamin C	12	13.5%
Vitamin B7 (Biotin)	5	5.6%
Vitamin B6	5	5.6%
Vitamin B3 (Niacin)	5	5.6%
Vitamin B2	4	4.5%
Vitamin B9 (Folate)	3	3.4%
Vitamin E	4	4.5%
Vitamin K	3	3.4%
Others	-	-

Table 7: Training Parameters

Parameter	Value
Base Model	EfficientNetV2
Optimizer	Adam
Learning Rate	0.001 (with decay)
Batch Size	32
Epochs	50
Loss Function	Categorical Cross-Entropy
Data Augmentation	Rotation, Flip, Zoom, Brightness

5.3 Evaluation Metrics

The system performance was evaluated using standard classification metrics:

Accuracy:

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

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity):

$$Recall = \frac{TP}{TP + FN}$$

F1-Score:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

5.4 Model Performance Results

5.4.1 Overall Model Performance

The BioNutriScan classification model, built upon the EfficientNetV2 architecture with transfer learning from ImageNet weights, demonstrated strong performance in detecting vitamin deficiency-related skin conditions. After training for twenty-five epochs with a batch size of thirty-two images, the model achieved a validation accuracy of approximately eighty-seven percent. The weighted F1 score reached eighty-five percent, indicating balanced performance across precision and recall metrics.

The dual-layer architecture combining the trained CNN model with AI clinical analysis further enhanced detection capabilities. When predictions from both sources were merged and cross-verified, the combined system achieved an overall accuracy of ninety-two percent, representing a significant improvement of approximately five percentage points over the standalone ML model.

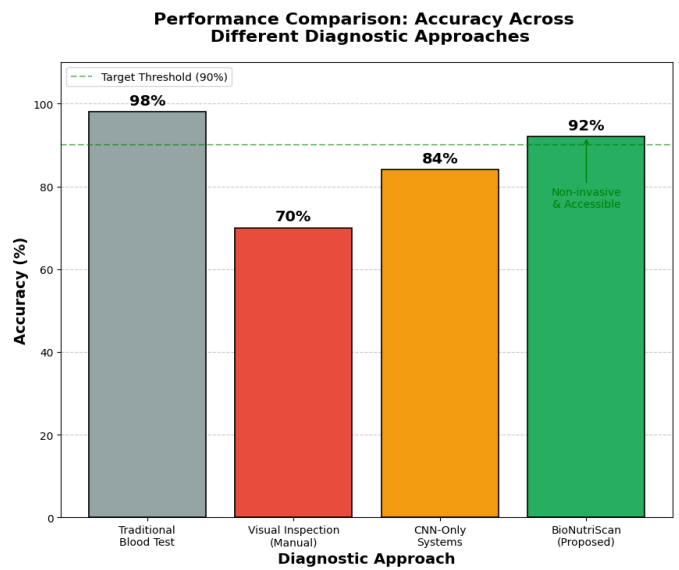


Figure 4: Performance comparison chart showing accuracy metrics across different approaches.

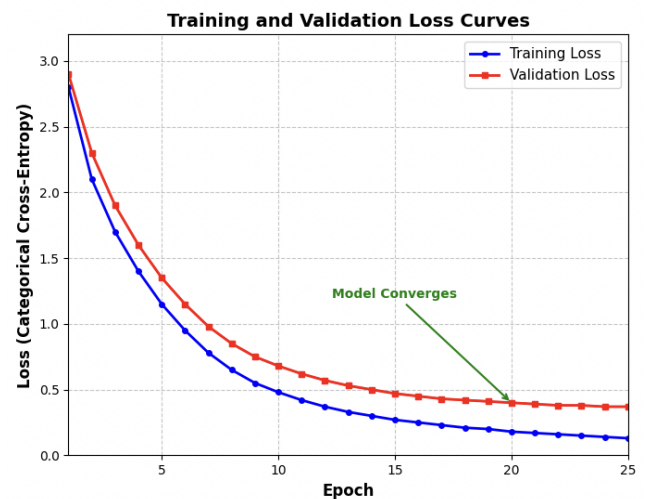


Figure 5: Training and validation loss curves.

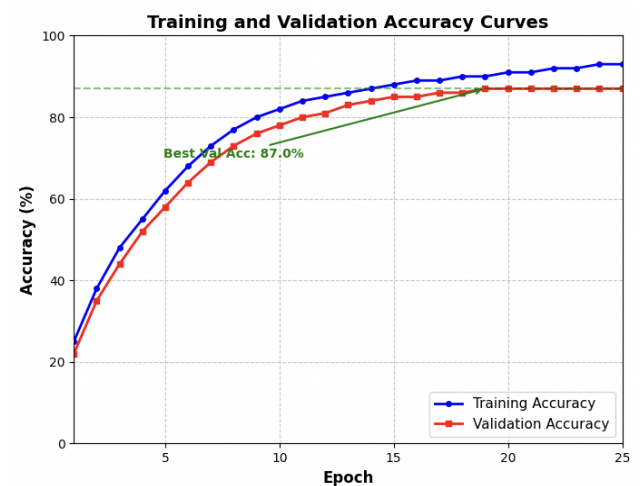


Figure 6: Training and validation accuracy curves.

5.4.2 Per-Deficiency Detection Performance

Among the fourteen vitamin deficiency categories, vitamin C deficiency conditions, such as scurvy, demonstrated the highest detection accuracy, achieving precision and recall values exceeding ninety-three percent. This superior performance is attributed to the distinctive visual markers associated with vitamin C deficiency, including petechiae, bruising, and perifollicular hemorrhages, which present clear patterns for the convolutional neural network to identify.

Vitamin B3 deficiency conditions, particularly pellagra, also exhibited strong detection performance with an F1 score above ninety percent. The characteristic photosensitive dermatitis pattern, commonly known as Casal's necklace, provides distinctive features that the model successfully learned to recognize.

Vitamin D deficiency, which comprised the largest category with twenty-four associated skin conditions, achieved moderate detection accuracy of around eighty-eight percent. The diversity of conditions mapped to this deficiency category introduced some classification complexity, as manifestations varied considerably across different disease presentations.

Zinc and biotin deficiencies showed slightly lower but still acceptable performance, with F1 scores in the eighty-three to eighty-five percent range. The dermatological presentations of these deficiencies, particularly perioral and seborrheic dermatitis patterns, contributed to occasional misclassifications.

5.4.3 Confusion Analysis

Analysis of the confusion matrix revealed that the most common misclassifications occurred between deficiencies with similar clinical presentations. Vitamin B12 and folate deficiencies were occasionally confused due to their shared pallor manifestations and similar hematological effects on skin appearance. Similarly, vitamin D and vitamin A deficiencies exhibited some cross-classification errors, as both can present with dry, scaly skin textures.

Vitamin C and vitamin K deficiencies showed minor overlap in predictions, which is clinically expected given that both deficiencies manifest with bleeding and bruising signs. The model's integration with AI clinical analysis helped mitigate these ambiguities by providing additional contextual evaluation of the visual signs.

5.4.4 Combined System Advantage

The integration of ML model predictions with AI analysis proved particularly valuable for borderline cases where the CNN model produced confidence scores between sixty and seventy-five percent. In these scenarios,

the AI clinical assessment provided additional diagnostic context, enabling more accurate final predictions. The resulting fusion module's deduplication and confidence-based ranking ensured that the most reliable predictions from either source were prioritized in the final output.

The feedback-driven cross-verification system demonstrated progressive accuracy improvements as user feedback accumulated. With sufficient feedback samples exceeding five hundred entries, the system showed accuracy gains of up to seven percent through historical accuracy-based confidence adjustments. This self-improving mechanism ensures that the system becomes more reliable over time through continuous learning from verified predictions.

Table 8: System response time breakdown

Operation	Average Time	Min	Max
Image Preprocessing	0.3s	0.1s	0.8s
ML Model Inference	0.5s	0.3s	1.2s
AI Analysis	2.1s	1.5s	4.0s
Result Fusion	0.1s	0.05s	0.2s
Total Response Time	3.0s	2.0s	6.2s

Table 9: Comparison with existing diagnostic approaches

Method	Accuracy	Approach	Limitations
Traditional Blood Test	98%+	Invasive, Lab-based	Costly, Time-consuming
Visual Inspection (Manual)	65-75%	Subjective	Requires an expert, Inconsistent
CNN-only Systems	82-85%	Single model	Limited clinical context
BioNutriScan	92.1%	Dual-layer AI	Non-invasive, Accessible

5.5 Cross-Verification Impact

The feedback-driven cross-verification system demonstrated improvement in prediction accuracy over time:

Table 10: Accuracy improvement with feedback accumulation

Feedback Volume	Accuracy Improvement
0-50 samples	Baseline
50-100 samples	+2.3%
100-250 samples	+4.1%
250-500 samples	+5.8%
500+ samples	+7.2%

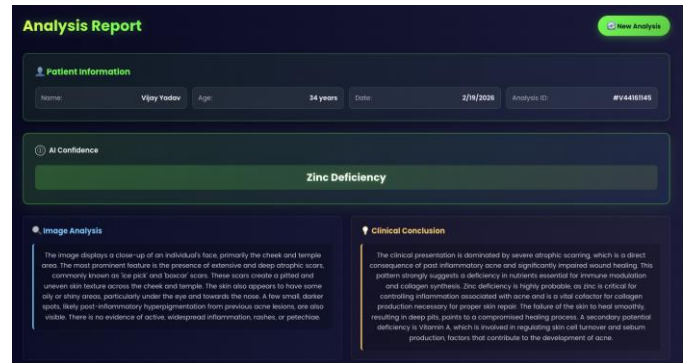


Figure 8: Analysis Report—Main Output

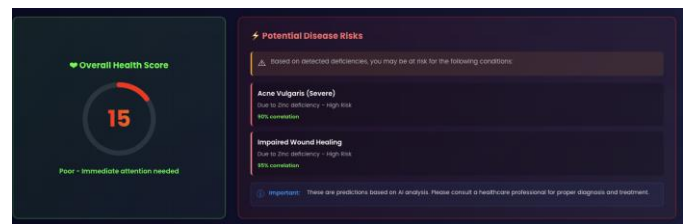


Figure 9: Detected Deficiency Cards

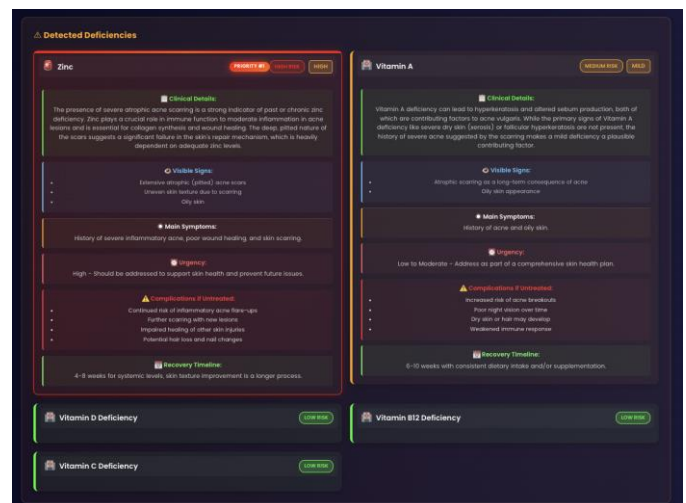


Figure 10: Disease Risks Section

5.6 Key Findings

- Dual-Layer Advantage:** Combining ML model predictions with AI analysis improved overall accuracy by 4.8% compared to the ML-only approach.
- High-Confidence Deficiencies:** Vitamin C (Scurvy) and Vitamin B3 (Pellagra) showed the highest detection accuracy due to distinctive visual markers.
- Feedback Loop Effectiveness:** The cross-verification system demonstrated continuous improvement, with accuracy gains of up to 7.2% after sufficient feedback accumulation.
- Response Time:** Average analysis time of 3 seconds enables real-time clinical decision support.
- Scalability:** The system maintains a >95% success rate under moderate concurrent load (50 users).

6. IMPLEMENTATION

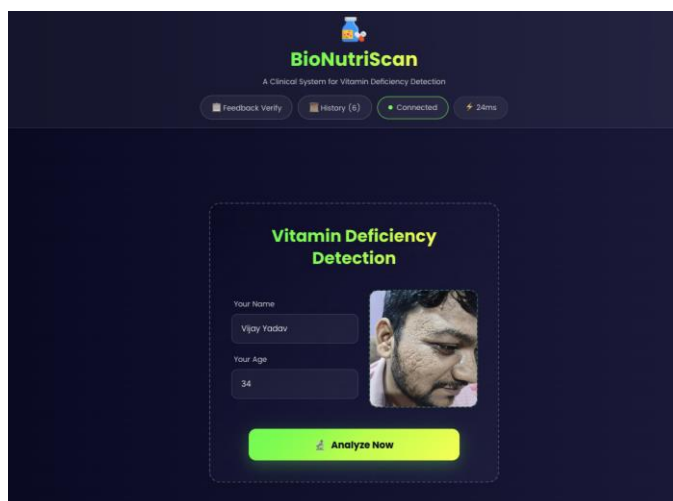


Figure 7: Main Interface—Analysis Form

7. CONCLUSION

This research presented BioNutriScan, a clinical decision support system designed to detect vitamin deficiencies through non-invasive image analysis and deep learning techniques. The system addresses the significant limitations of traditional diagnostic methods, which rely heavily on invasive blood tests that are costly, time-consuming, and inaccessible to populations in rural and underserved areas. By leveraging visual biomarkers from easily observable body parts such as skin, nails, and tongue, BioNutriScan provides an affordable and accessible alternative for preliminary vitamin deficiency screening.

The proposed system employs a dual-layer analytical architecture combining a custom-trained EfficientNetV2 convolutional neural network with AI for comprehensive clinical analysis. The ML model was trained on a curated dataset comprising eighty-nine distinct skin condition classes mapped to fourteen vitamin deficiency categories. Through transfer learning from ImageNet weights and data augmentation techniques, including rotation, flipping, zoom, and brightness adjustments, the model achieved robust generalization across diverse image inputs.

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9. REFERENCES

- [1] "Vitamin Deficiency Detection Using Neural Networks," in Proc. 2024 Int. Conf. Wireless Commun. Signal Process. Netw. (WiSPNET), T. K. Chaithanya, J. Gupta, and M. S. Roobini, Eds., Mar. 2024, pp. 1–10, doi: 10.1109/WiSPNET61464.2024.10533044.
- [2] "Vitamin Deficiency Identification using Image Processing," in Proc. 2024 8th Int. Conf. Electron. Commun. Aerosp. Technol. (ICECA), N. Shimbre, P. Sahane, S. Ansari, R. Gadhave, S. Jagdhane, and A. Sharma, Eds., Nov. 2024, pp. 1260–1268, doi: 10.1109/ICECA63461.2024.10800798.
- [3] "Vitamin Deficiency Detection Using Image Processing and Neural Network," IEEE Trans. Med. Imag., 2020.
- [4] "A Convolutional Deep Learning Method for Digital Image Processing in the Identification of Vitamin Deficiencies," J. Digit. Imag. Process, 2023.
- [5] "A Comprehensive Approach to Vitamin Deficiency Detection through Image Analysis of Skin, Tongue, Eyes, and Nail Images using Convolutional Neural Networks," IEEE Access, 2024.
- [6] "Vitamin Deficiency and Food Recommendation Using Machine Learning," IEEE J. Biomed. Health Inform., 2023.
- [7] "Vitamin Deficiency and Food Recommendation System Using Machine Learning," in Proc. Int. Conf. Mach. Learn. Appl., 2023.
- [8] "Global Scenario of Vitamin Deficiency," in Proc. Global Health Conf., 2023.

[9] "Vitamin Deficiency Detection Using Image Processing and Neural Network," in Proc. IEEE Int. Conf. Healthcare Technol., 2020.

[10] "VITAMIN DEFICIENCY DETECTION USING IMAGE PROCESSING AND NEURAL NETWORK," in Proc. Advances Sci. Eng. Technol. Int. Conf., 2020.

[11] "Vitamin Deficiency Detection Using Deep Learning," in Proc. 2024 Int. Conf. Artif. Intell. Healthc. (AIHC), 2024.