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VitaDetect: Deep Learning Based Vitamin Deficiency Detection System

Anchith Shanthivana C[1], Anjali V[2], Lakshmi Arpan[3], Pratham B G Rai[4]

Department of Computer Science & Engineering, Vivekananda College of Engineering & Technology, Puttur, Karnataka, India[1-4]

Abstract: VitaDetect is a preliminary, non-invasive vitamin-deficiency screening prototype combining EfficientNetV2S image classification with a Multi-Layer Perceptron (MLP) trained on questionnaire data. It predicts Normal, Vitamin A, Vitamin B-12, Vitamin C, and Vitamin D classes. The image dataset was audited for duplicates, conflicting labels, and corrupted images; the symptom branch uses Scikit-Learn preprocessing and SMOTE. Since the modalities have no shared patient identifiers, recall-weighted decision-level fusion with disagreement arbitration is used. On independent test sets, image and symptom models achieved 75.61% accuracy on 783 photographs and 78.00% on 600 records. A React/Vite frontend and Flask backend support up to four photos per assessment.

Keywords: vitamin deficiency detection, deep learning, EfficientNetV2, symptom classification, multimodal learning, late fusion, uncertainty handling, data quality auditing

I. INTRODUCTION

Vitamin deficiencies may be associated with visible changes in the skin, eyes, tongue, or nails, as well as systemic symptoms. VitaDetect supports preliminary screening only and does not replace laboratory testing or clinical assessment. It predicts five classes: Normal and deficiencies of Vitamins A, B-12, C, and D.

The system extracts visual evidence from up to four photographs, processes questionnaire data, and combines both probability outputs at decision level. Disagreement or low confidence triggers an uncertainty warning rather than an overconfident result.

An audit of the initial approximately 20,000-image collection removed cross-split duplicates, conflicting labels, and corrupted or low-resolution files, leaving 5,697 images. The symptom branch uses approximately 4,000 records. Because the datasets lack shared patient identifiers, feature-level joining is not reliable; the application uses recall-calibrated late fusion and CPU inference through Flask, with React/Vite and Tailwind CSS on the client.

II. RELATED WORK

Prior studies explored deficiency screening from nail, tongue, facial, and skin images, web-based guidance, CNNs, ResNet, transformers, and conventional machine learning [1]–[26]. These approaches suggest that visual patterns and structured health indicators can both support preliminary screening.

Challenges include visual similarity between classes, image-quality variation, limited clinical variables, and single-deficiency scope. VitaDetect addresses these issues with two branches, class-imbalance handling, recall-weighted fusion, and uncertainty reporting.

III. METHODOLOGY

A. System Architecture

VitaDetect accepts up to four photographs and a symptom questionnaire. Images are resized to 256 × 256 pixels for EfficientNetV2S; a Scikit-Learn ColumnTransformer encodes categorical inputs and scales continuous features for the MLP. The resulting probability distributions enter the late-fusion module.

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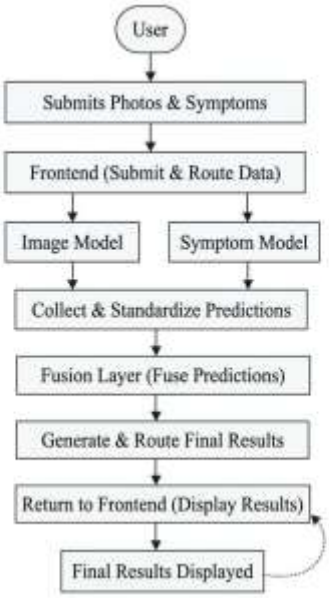


Fig. 1. System architecture of VitaDetect.

B. Image Model

The image branch uses ImageNet-1k-pretrained EfficientNetV2S with a five-class head comprising global average pooling, batch normalization, dense ReLU layers, dropout, and softmax.

EfficientNetV2S (approximately 21 million parameters) was selected over ConvNeXtSmall (approximately 50 million). The latter exceeded 86% training accuracy but plateaued at 72–73% validation accuracy; EfficientNetV2S reduced the train–validation gap to about 7–8 percentage points.

Training first froze the backbone and optimized the new head, then unfroze the top 15% of layers at a lower learning rate while keeping Batch Normalization frozen. Mixup, RandomOverSampler, flips, rotation, and zoom supported training.

C. Symptom Model

The symptom MLP uses 4,000 records mapped as Healthy/Normal, Night Blindness/Vitamin A, Anemia/Vitamin B-12 (engineering proxy), Scurvy/Vitamin C, and Rickets/Osteomalacia/Vitamin D. SMOTE oversampled minority classes. Anemia is not clinically equivalent to B-12 deficiency; this mapping is a project-level proxy.

D. Late Fusion and Uncertainty

Let $P_I(c)$ and $P_S(c)$ denote the visual and symptom probabilities for class c. Class-specific weights are derived from standalone recall values:

$$w_I(c) = \frac{R_I(c)}{R_I(c) + R_S(c)}, \quad w_S(c) = \frac{R_S(c)}{R_I(c) + R_S(c)}.$$

For agreement, weighted probability vectors are combined and renormalized. For disagreement, each branch's confidence is multiplied by its class weight; the higher-authority branch supplies the prediction. Disagreement or maximum fused confidence below 0.45 raises the uncertainty flag.

E. Implementation

The React/Vite client handles image previews, questionnaire input, and results. Flask validates requests, runs both models, applies fusion and uncertainty rules, and returns predictions and guidance as JSON. Models load once at startup.

TABLE I CORE SOFTWARE COMPONENTS

Component	**Technology / Detail**
Image model	EfficientNetV2S, ImageNet pretrained, 256 × 256
Symptom model	MLP with Scikit-Learn preprocessing and SMOTE

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Component	Technology / Detail
Training	TensorFlow/Keras; Google Colab GPU
Backend	Python 3.10+, Flask, Flask-CORS
Frontend	React 18+, Vite, JavaScript
UI	Tailwind CSS
Deployment	Local Windows CPU inference

TABLE II CLASS-SPECIFIC LATE-FUSION WEIGHTS

Class	Image Model Weight	Symptom Model Weight
Normal	0.523	0.477
Vitamin A	0.549	0.451
Vitamin B-12	0.473	0.527
Vitamin C	0.663	0.337
Vitamin D	0.446	0.554

IV. RESULTS AND DISCUSSION

A. Image Model Performance

On 783 independent photographs, the image model achieved 75.61% accuracy and 0.7604 macro F1. Normal and Vitamin C performed best (F1 0.9971 and 0.9562); Vitamin A and B-12 had the weakest recall, while Vitamin D recall was 60.00%.

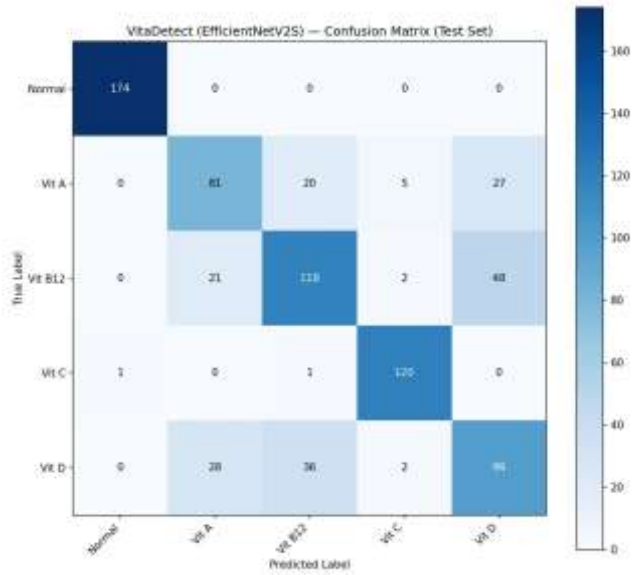


Fig. 2. Image model (EfficientNetV2S) confusion matrix on the independent, leakage-free test set.

B. Symptom Model Performance

The symptom MLP achieved 78.00% accuracy on 600 records. Normal, B-12, and D were more stable; Vitamin A and C had only 18 and 14 test samples, so their class metrics are less certain.

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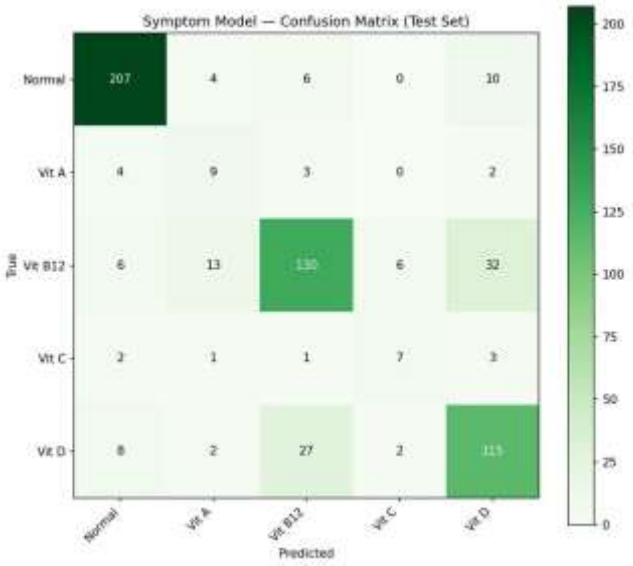


Fig. 3. Symptom model confusion matrix on the independent test set.

Errors mainly occur between visually similar classes: Vitamin D and B-12 are confused in both directions, with smaller A/B-12 confusion. Test-time augmentation averages original and horizontally flipped predictions; prior measurements estimated a 1–3% accuracy gain.

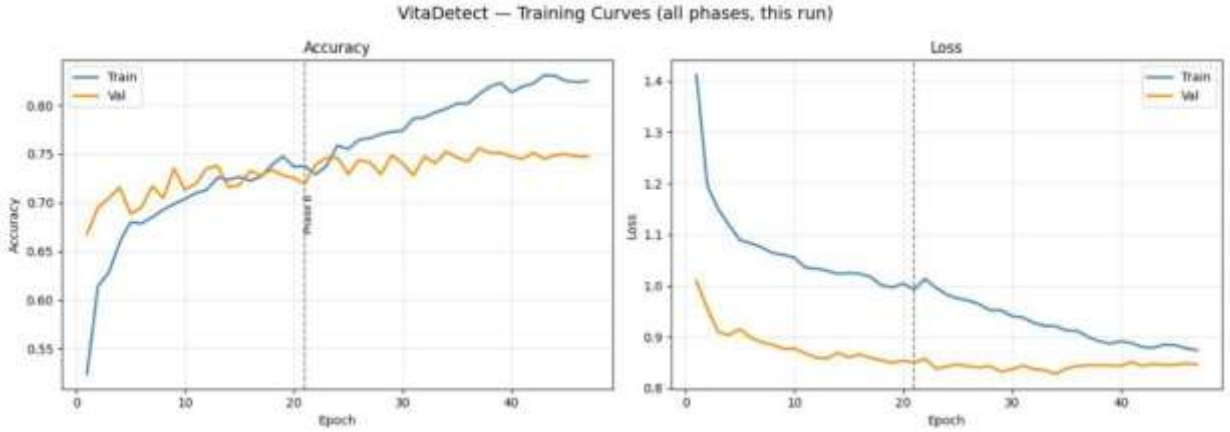


Fig. 4. Training and validation accuracy and loss across the two-stage EfficientNetV2S training run.

Training accuracy rose to about 0.82–0.83 while validation accuracy settled near 0.75. The narrower gap than in the ConvNeXtSmall trial supports better generalization by the smaller backbone.

C. Fusion and Functional Validation

Because the test sets are independent and lack patient-level pairing, end-to-end multimodal accuracy cannot be calculated. Validation therefore focused on fusion behavior: consensus combines modalities, class-specific weights favor the stronger branch, and disagreements use authority scores rather than averaging alone.

TABLE III FUNCTIONAL TESTING RESULTS

Test	**Expected result**	**Outcome**
Valid photo upload	Photo accepted and passed to image branch	Verified
Multiple photos	Up to four processed with confidence weighting	Verified
Symptom checklist	Structured inputs validated	Verified
Generate prediction	Both branches inferred and fused	Verified



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Test	Expected result	Outcome
Fusion normalization	Fused probabilities sum to 1	Verified
Low-confidence disagreement	Uncertainty flag and warning shown	Verified
Guidance rendering	Guidance and clinical disclaimer shown	Verified

End-to-end CPU inference took approximately 680 ms. Fused probabilities summed to one, and a simulated disagreement with maximum confidence 0.39 correctly triggered the uncertainty warning. This is decision-level validation, not clinical multimodal accuracy.

V. LIMITATIONS AND FUTURE SCOPE

Limitations include weaker visual performance for Vitamins A and B-12, persistent B-12/D visual overlap, unpaired modality datasets, the proxy Anemia-to-B-12 label mapping, and small A/C symptom test samples. Dietary and lifestyle guidance is educational and requires clinical review.
Future work should collect larger Vitamin A/ophthalmology datasets and paired, clinically verified photographs and questionnaires, followed by external validation across image quality and populations. This would enable reliable measurement of multimodal performance.

VI. CONCLUSION

VitaDetect combines visual and symptom models for preliminary screening, achieving 75.61% and 78.00% independent test accuracy. Data cleaning and comparison favored EfficientNetV2S for generalization. Recall-weighted fusion and agreement-aware arbitration account for class-level strengths, while uncertainty warnings reduce overconfident reporting. The React/Vite and Flask prototype still requires paired clinical data, external validation, and clinical review before broader use.

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