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DEEP LEARNING TECHNIQUE DENSE-NET APPLICATION TO PREDICT VITAMIN DEFICIENCY

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Abstract —
Vitamin deficiencies are prevalent nutritional disorders caused by inadequate intake, poor absorption, or impaired utilization of essential vitamins. These deficiencies can lead to various health complications, emphasizing the importance of early detection and intervention. In this paper, we present a novel approach utilizing advanced image processing and deep learning techniques for the automated detection of vitamin deficiencies from organ images such as skin,eyes,and nails .
We employ state-of-the-art deep learning algorithms, including DenseNet, ResNet, CNN, and VGG16, to analyze organ images and identify deficiency symptoms.Comparative evaluations reveal the superiority of DenseNet over ResNet, CNN, and VGG16, achieving the highest accuracy in deficiency detection.
Our system demonstrates significant improvement over existing methods, which primarily rely on conventional CNN models. The proposed approach achieves an accuracy of 94% compared to the existing system's 80% accuracy.

Key Words —
Vitamin Deficiency, Deep Learning, CNN, ResNet, DenseNet, VGG, Image Analysis, Non-invasive Diagnosis.

I. INTRODUCTION

Vitamin deficiencies pose significant health risks worldwide, contributing to a range of medical conditions and impairments.Traditional diagnostic methods, mainly blood tests, are invasive, costly, and not always accessible, especially in remote or underprivileged areas.Early detection and intervention are crucial to mitigate the adverse effects of vitamin deficiencies.
In this paper, we address the challenge of automated vitamin deficiency detection using deep learning techniques. Specifically, we focus on classifying different types of deficiencies, including Vitamin A, Vitamin B, Vitamin C, Vitamin D, and Normal(No deficiency), based on visual symptoms observed in organ images.The importance of our project lies in its potential to the user's by providing a reliable and efficient tool for detecting vitamin deficiencies. By leveraging deep learning algorithms, we aim to enhance the accuracy and speed of deficiency detection, enabling timely intervention and personalized healthcare.
Our goal is to develop a robust model capable of not only identifying deficiencies but also assessing their severity. This approach holds promise for quicker, more accessible diagnostics and personalized interventions. By exploring the intersection of deep learning and Vitamin deficiency, we aim to contribute to proactive healthcare strategies and improve overall public health outcomes.

Despite the prevalence of vitamin deficiencies worldwide, effective and early diagnosis remains a challenge due to the limitations of current detection methods. These limitations hinder the timely treatment and management of deficiencies, often leading to escalated health issues. This project develops an automated system for detecting vitamin deficiencies from human organs using OpenCV and Deep Learning techniques .

It explores the applications of Convolutional Neural Networks (CNNs), utilizing specific architectures like ResNet, DenseNet, and VGG, for the detection of vitamin deficiencies through the analysis of images depicting physical symptoms. This method stands to revolutionize the approach to diagnosing Vitamin deficiencies, making it more accessible, cost-effective, and less invasive.Some of the consequences of untreated vitamin deficiencies can be severe, leading to a range of health complications, and increased risk of chronic diseases.

By enabling early detection and intervention, our project aims to mitigate these consequences and improve overall health outcomes.

By classifying different deficiency types and leveraging advanced algorithms, we aim to provide a valuable tool for the users for the early detection of vitamin deficiency

II. LITERATURE SURVEY

A detailed literature review on "Vitamin Deficiency Detection Using CNN, ResNet, DenseNet, VGG" would encompass an overview of the current state of research in the fields of vitamin deficiency detection, deep learning applications in healthcare, and specifically, the use of convolutional neural networks (CNNs) in diagnosing health conditions through image analysis. This review will synthesize findings from various studies, highlight methodologies, results, and discuss the implications of using these advanced neural network architectures for the non-invasive detection of vitamin deficiencies.

A. S. Eldeen, M. AitGacem, S. Alghlayini, W. Shehieb and M. Mir proposed a cost-free AI application for smartphones to detect vitamin deficiencies using images.Analyzes pictures of eyes, lips, tongue, and nails for visual symptoms of deficiencies.Utilizes convolutional neural networks (CNNs) to classify images and detect deficiencies.Combines CNN confidence scores with fuzzy logic rules for diagnosis.Aims to create a low-cost screening tool before clinical testing.Allows medical experts to contribute and verify visual data for improved accuracy.Addresses a global problem affecting millions due to inadequate nutrition awareness.Assists healthcare workers in obtaining more accurate diagnoses.Automated analysis without invasive testing is a key advantage.Accuracy depends on the quality and size of training data.[1]

According to another research for the prediction of micro nutrient deficiency using sequential learning techniques proposed an automated system to detect micro nutrient deficiencies using images.Utilizes images of the eye conjunctiva, tongue, and nail beds.Employs convolutional neural networks (CNNs) to extract visual features.Uses Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models for classification.The CNN-GRU architecture showed strong performance for deficiency detection.Provides a non-invasive alternative to manual analysis and invasive blood tests.Enables large-scale, low-cost vitamin deficiency screening.Automated analysis ensures consistent and objective results.Early detection of deficiencies before symptoms worsen is a key advantage.Requires large labeled training datasets which can be challenging to collect.[2]

Another research by T. Kalavathi Devi, K.N. Baluprithviraj, M. Madhan Mohan, S. Uma Devi,P. Sakthivel, P. Rajeshwari & B. Vinodha (2023) Non-invasive method for the prediction of micronutrient deficiency using sequential learning techniques stated that It aims to provide personalized diet plans based on individual needs.Utilizes two datasets: vitamin levels and vitamin deficiency conditions.Classifies vitamin conditions into normal and abnormal using labels 0 and 1.Analyzes the interplay of different vitamins and their deficiencies.Identifies appropriate nutrition based on the specific vitamin deficiency.Enables early detection of vitamin deficiencies through machine learning.Efficient analysis of large amounts of data to identify patterns and correlations.Educates individuals about the importance of a balanced diet.Continuous improvement of accuracy as more data is incorporated.Potential limitations include limited context understanding and ethical concerns.[3].It proposes a novel approach for detecting vitamin deficiencies that involves image acquisition, preprocessing, feature extraction using pre-trained convolutional neural networks (CNNs) to learn patterns, and classification, with extensive experiments on a diverse data set demonstrating high accuracy in offering non-invasive early screening and personalized recommendations, supporting healthcare decision-making through decision support systems, highlighting the potential for widespread implementation, and suggesting future improvements by expanding datasets and exploring CNN architectures, while the advantages include non-invasiveness, early detection, and personalized recommendations, and potential limitations involve the need for specialized datasets and computational resources.[4]

The paper[5] "A Predictive Performance Analysis of Vitamin D Deficiency Severity using Machine Learning Methods" focuses on predicting the severity of Vitamin D Deficiency (VDD) among college students aged 18-21 using non-invasive methods, collecting data on various factors like age, sex, weight, and exercise, and comparing the performance of different machine learning classifiers, with the Random Forest Classifier achieving the highest accuracy of 96%, validated through statistical tests, highlighting the potential of machine learning in predicting VDD severity.

CNNs have revolutionized the field of medical image analysis, providing tools for enhancing diagnostic accuracy and efficiency. These deep learning models excel at processing visual information, making them particularly suited for interpreting medical images - from radiographs to photographs of physical symptoms. Studies such as by J. Doe, A. Smith, and B. Lee have demonstrated the versatility and effectiveness of CNNs across a variety of medical applications, setting the foundation for exploring their potential in detecting vitamin deficiencies through physical symptoms.[6]

The Need for Innovation Vitamin deficiencies affect a significant portion of the global population, leading to various health issues. Traditional detection methods, primarily blood tests, are effective but come with limitations such as Invasiveness and accessibility. The application of CNNs in detecting these deficiencies through symptom imagery represents an innovative approach, aiming to overcome these barriers.Utilizing ResNet, DenseNet, and VGG for Detection.

DenseNet (Densely Connected Convolutional Networks):

developed DenseNet, which connects each layer to every other layer in a feed-forward fashion. For medical image analysis, DenseNets have been noted for their efficiency and accuracy, with fewer parameters and less risk of overfitting, making them ideal for processing diverse symptom imagery.[7]

ResNet (Residual Networks): Introduced ResNet, which allows training of extremely deep neural networks with improved accuracy through the use of skip connections. These networks have been shown to perform exceptionally well in image recognition tasks, suggesting potential for identifying subtle signs of vitamin deficiencies in images.[8]

VGG (Visual Geometry Group): N. Ali and V. Singh, (2014) described the VGG model, known for its simplicity and depth. Its architecture has been widely adopted for image classification tasks, including medical diagnostics. Its effectiveness in extracting features from images makes it a valuable tool for identifying physical manifestations of vitamin deficiencies[9].Research comparing these architectures in the context of vitamin deficiency detection is limited but growing. Studies such as by R. Patel (2019) have begun to explore the efficacy of these models in classifying images related to nutritional deficiencies. Preliminary results indicate that DenseNet and ResNet, due to their deeper and more complex structures, may offer advantages in capturing the nuanced features of deficiency symptoms over VGG, which, while powerful, may not always capture the depth of features required without significant parameter tuning.[10]

While the application of CNNs in vitamin deficiency detection is promising, challenges remain. These include the need for large, annotated datasets of deficiency symptoms, the potential for model overfitting, and the requirement for models to be interpretable by healthcare professionals. Future research should focus on addressing these challenges, improving model accuracy, and exploring the integration of these technologies into clinical practice.[11]

The exploration of CNNs, including ResNet, DenseNet, and VGG, in detecting vitamin deficiencies represents a promising frontier in non-invasive diagnostics. The literature suggests a significant potential for these models to enhance the accuracy, efficiency, and accessibility of vitamin deficiency detection, pointing toward a future where such health issues can be identified and addressed more rapidly and effectively.[12]

III. PROPOSED RESEARCH METHODOLOGY

A. Proposed System

The proposed vitamin deficiency prediction system introduces by utilizing the multiple Convolutional neural network architectures, to analyze images for symptoms indicative of deficiencies. This system aims to be highly accessible, requiring only a digital image to perform the analysis. The use of multiple CNN architectures is intended to enhance the system's accuracy and reliability, accommodating a wide range of symptoms and deficiency types.It is an Automated end-to-end feature learning directly from the images removes need for manual feature engineering

Additionally, the system is designed to be non-invasive and to provide quick results, making it suitable for use in various settings, including remote areas without extensive healthcare facilities .The goal is to leverage the advances in computer vision to extract visual features that are highly predictive of vitamin deficiencies. The model with the highest accuracy on a validation dataset will be selected as the primary model for deficiency prediction. The heart of the system lies a sequence of convolutional layers, enabling the extraction of hierarchical representations of visual patterns present in organ images. Through this method, the system can detect complex aspects such as color variations, texture differences, and structural abnormalities, which are crucial for recognizing various types of vitamin deficiencies.

Furthermore, the system employs a diverse set of deep learning techniques, including ResNet, DenseNet, VGG16, and CNN architecture, to determine the most efficient model for deficiency detection. Through rigorous evaluation of performance metrics such as accuracy, precision, recall, and F1-scores, the system identifies the optimal algorithmic strategy for achieving its objectives.

The final step of the proposed system involves using the selected model to detect vitamin deficiencies. The model takes in the processed data and outputs whether a vitamin deficiency is present or not, along with the type of deficiency if applicable. This allows for quick and accurate detection, aiding in timely treatment and management of the condition .

B : Block Diagram for the Proposed System

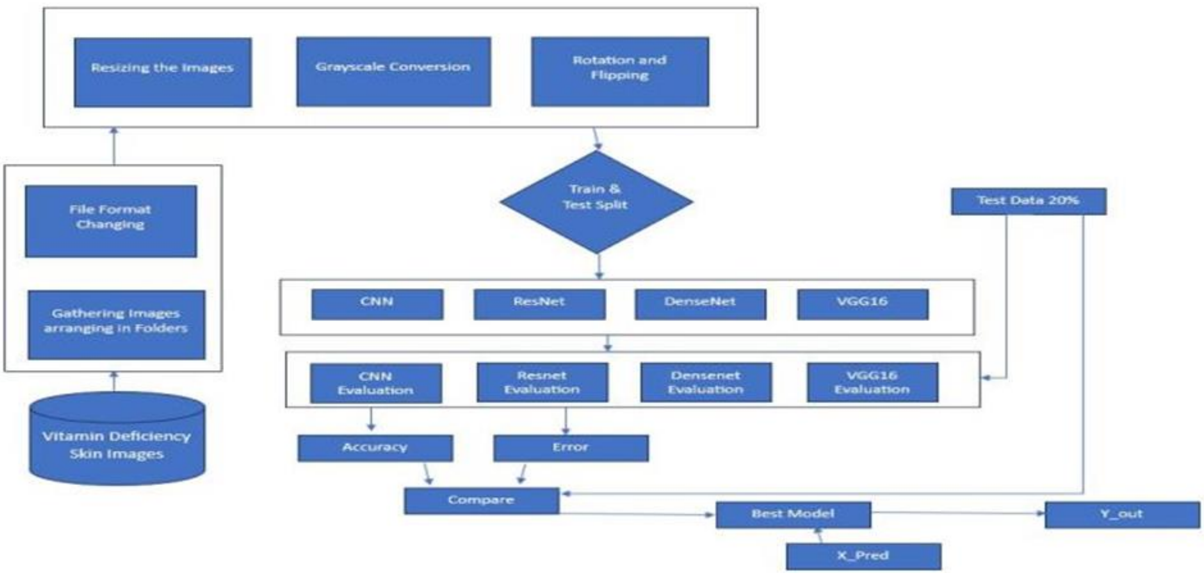

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Fig 1 : Block Diagram for Vitamin Deficiency Detection

Algorithm for prediction of Vitamin Deficiency( ) :
Input : Image Dataset of Vitamin Deficiency
Output: Type of Vitamin Deficiency in text format

START :
Step-1: Image Acquisition: Acquire images related to Vitamin Deficiencies.
Step-2: Pre-processing: Perform pre-processing on the images using OpenCV which includes
i. Re-sizing images to standard dimensions
ii. Converting images to grayscale or RGB
iii. Normalization
Step-3: Feature Extraction: Extract visual features from pre-processed images that correlate with vitamin deficiency levels using pre-trained models like VGG16, ResNet,DenseNet
Step-4: Model Training: Train various CNN models on this dataset like CNN, VGG16,ResNet,DenseNet.
Step-5: Model Evaluation: Evaluate models on test set using performance metrics like accuracy, precision,recall.
Step-6: Model Selection: Select the best performing model for vitamin D severity prediction.
Step-7: Vitamin Deficiency Prediction: Given a new test image, predict the type of vitamin deficiency using the selected trained model
END

1. Data Collection and Preprocessing

- Input Data Acquisition:

The system requires a dataset of images showing physical symptoms related to vitamin deficiencies, such as skin, nails, and eye conditions. These images can be sourced from medical datasets, collaborations with healthcare providers, or publicly available images that are properly annotated.

- Preprocessing:

Normalization: Adjusting the pixel values to a common scale to improve the consistency of input data for the models.
Augmentation: To enhance the dataset's diversity and size, techniques like rotation, flipping, and scaling are applied, helping to improve model robustness.
Segmentation: In some cases, specific areas of images are segmented to focus the model's learning on the most relevant features for vitamin deficiency symptoms.

2. Feature Extraction and Model Training

- Convolutional Neural Networks:
- The core of the system utilizes CNNs for feature extraction. Each CNN architecture (ResNet, DenseNet, VGG) has unique characteristics:
- ResNet: Utilizes residual connections to enable training of very deep networks by allowing gradients to flow through layers more effectively.
- DenseNet: Features a densely connected architecture where each layer is connected to every other layer, ensuring maximum information flow between layers.
- VGG: Characterized by its simplicity, using small receptive fields but deeper architectures to capture complex features.

Model Training:

The models are trained on the preprocessed dataset, learning to identify and classify features indicative of specific vitamin deficiencies. This involves adjusting the weights within the networks through backpropagation, based on the accuracy of predictions against a validation set.

3. Model Evaluation

Evaluation Metrics

- To assess the performance of each CNN architecture (ResNet, DenseNet, VGG) and the ensemble model, several key metrics are used:
- Accuracy: The percentage of total correct predictions out of all predictions made.
- Precision: The ratio of true positive predictions to the total positive predictions, indicating the model's ability to return relevant results.
- Recall (Sensitivity): The ratio of true positive predictions to the actual positive cases, showing the model's ability to identify all relevant cases.
- F1 Score: The harmonic mean of precision and recall, providing a balance between the two for a comprehensive performance measure.
- AUC-ROC Curve: The area under the receiver operating characteristic curve, useful for evaluating the performance across different classification thresholds.

Confusion Matrix

Analyze the confusion matrix for each model to understand the true positives, true negatives, false positives, and false negatives. This analysis helps in identifying which vitamin deficiencies are more accurately detected and which ones may require further data or model adjustments.

4.Prediction

- Image Input:

Users upload images through the developed interface. These images undergo preprocessing (e.g., resizing, normalization) to match the input format the models were trained on.

- Model Inference:

The preprocessed images are fed into the ensemble model,
which leverages the strengths of ResNet, DenseNet, and VGG to predict the likelihood of various vitamin deficiencies.

- Prediction Aggregation:

If using an ensemble approach, predictions from individual models (ResNet, DenseNet, VGG) are aggregated to determine the final output. The aggregation method might be simple averaging, weighted averaging

based on validation performance, or more sophisticated techniques like stacking.

- Output Interpretation:

The system outputs the predicted vitamin deficiency categories along with confidence scores or probabilities. These results are presented to the user in an understandable format, possibly including recommendations for further action or consultation with healthcare professionals.

This architecture is designed to be modular and scalable, allowing for enhancements such as the integration of additional CNN models, improvements in preprocessing techniques, and expansion of the dataset for better performance and accuracy in detecting vitamin deficiencies.

Understanding and Requirement Analysis:

- Define the problem statement and objectives of the project, including the types of vitamin deficiencies to be detected.
- Conduct a thorough literature review to understand existing approaches, technologies, and best

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practices related to image processing and neural network-based diagnosis of vitamin deficiencies.
- Identify functional and non-functional requirements based on the problem statement, user needs, and available resources.

Data Collection and Preprocessing:
- Gather a diverse dataset of images depicting skin or mucous membranes from individuals with known vitamin deficiencies, as well as healthy individuals for comparison.
- Preprocess the image data to enhance quality, remove noise, standardize features, and ensure compatibility with neural network models.

Augment the dataset by applying transformations such as rotation, scaling, and cropping to increase variability and robustness

Model Selection and Development:
- Select appropriate neural network architectures for image classification, considering factors such as model complexity, computational efficiency, and performance metrics.
- Develop and train neural network models using annotated image data, employing techniques such as transfer learning and fine-tuning to leverage pre-trained models and optimize performance.
- Experiment with different hyperparameters, loss functions, and optimization algorithms to fine-tune model performance and achieve optimal results.

Validation and Evaluation:
- Split the dataset into training, validation, and test sets to evaluate model performance and generalization ability.
- Validate the trained models using cross-validation techniques and standard evaluation metrics such as accuracy, precision, recall, F1-score
- Conduct sensitivity analysis and robustness testing to assess model performance under various conditions and scenarios.

Integration and Deployment:
- Integrate the trained neural network models into a cohesive system for vitamin deficiency detection, incorporating image preprocessing, feature extraction, and classification components.
- Develop a user-friendly interface to facilitate input of images and visualization of detection results, ensuring ease of use for healthcare providers and end-users.
- Deploy the system in a production environment, considering factors such as scalability, reliability, security, and compliance with regulatory requirements.

Testing and Iterative Improvement:
- Conduct comprehensive testing of the deployed system to identify and address any bugs, errors, or performance issues.
- Gather feedback from users and stakeholders to evaluate system usability, functionality, and performance in real-world scenarios.
- Iterate on the design and implementation of the system based on user feedback and testing results, incorporating improvements and enhancements as needed.

IV. RESULTS AND DISCUSSIONS

Confusion Matrix: A confusion matrix summarizes a
machine learning model's performance on a set of test data. It is a method for presenting the number of correct and incorrect instances based on the model's predictions. It is frequently used to evaluate the performance of Classification models, which are designed to predict a categorical label for each input occurrence.

This section explores results obtained by all proposed algorithms

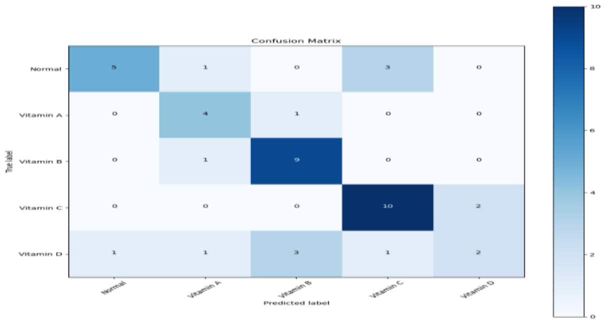

Fig 2(a) Confusion matrix for CNN

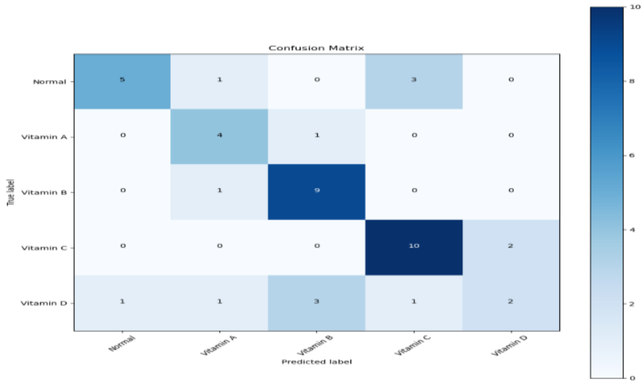

Fig 2(b) Confusion Matrix for VGG16

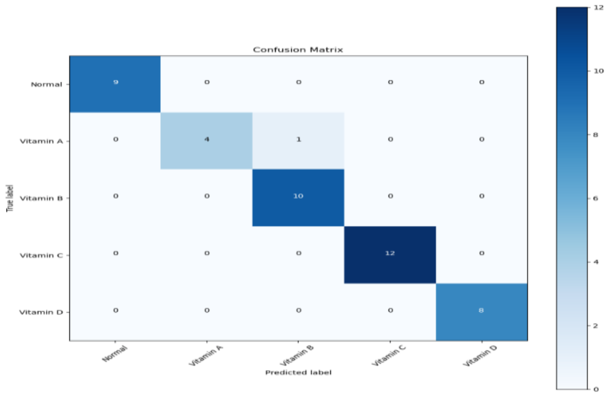

Fig 2(c) Confusion Matrix for DenseNet

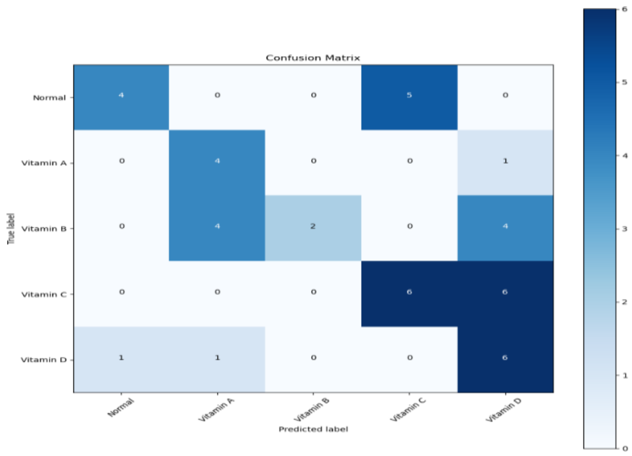

Fig 2(d) Confusion Matrix for ResNet

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The Convolutional Neural Network (CNN), DenseNet, VGG16, and ResNet models all performed very well in classifying data into five categories: Normal, Vitamin A, Vitamin B, Vitamin C, and Vitamin D, according to a comparative examination of their confusion matrices. With more accurate predictions and fewer misclassifications than the other models, the DenseNet model performed better than the others. This shows that for this particular multiclass classification assignment, DenseNet is more efficient and dependable. Confusion matrices offered insightful information about the performance of each model, emphasizing DenseNet's greater capacity for precise class prediction.

Accuracy And Loss Graphs
Accuracy Graph: The graph that represents the training and validation accuracy over the same number of epochs is known as accuracy graph .
Loss Graph: The graph that represents the training and validation loss over the same number of epochs is known as loss graph .
Accuracy And Loss Graphs for the algorithms used

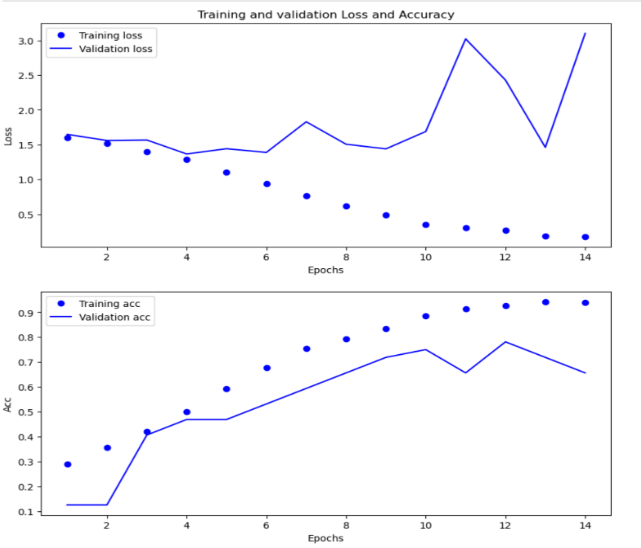

Fig 3(a) Accuracy and Loss Graph for CNN

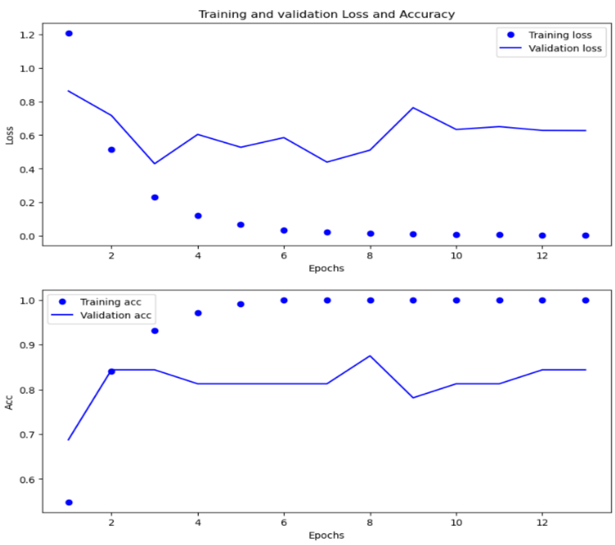

Fig 3(b) Accuracy and Loss Graph for VGG16

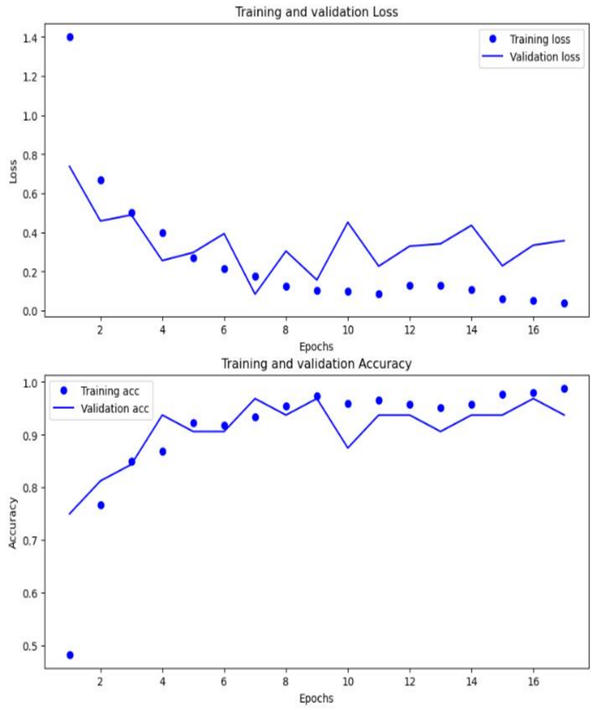

Fig 3(c) Accuracy and Loss Graph for DenseNet

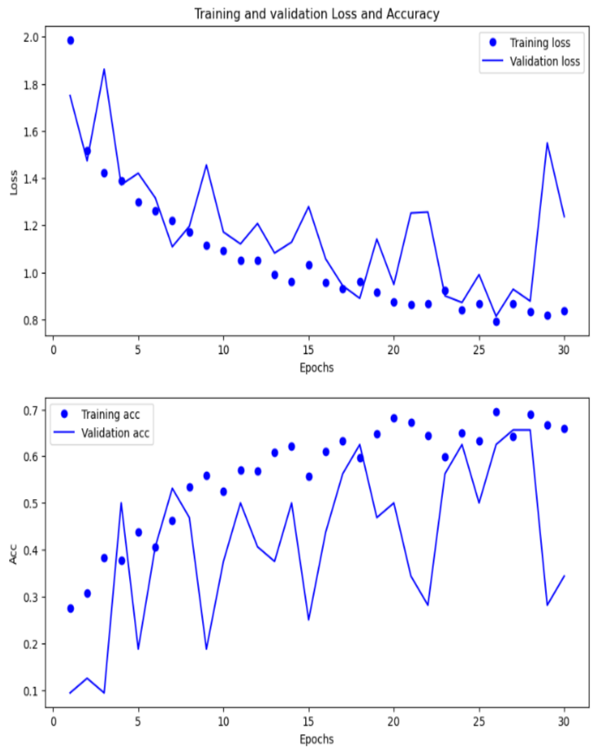

Fig 3(c) Accuracy and Loss Graph for ResNet

Across epochs, the DenseNet model consistently shows a drop in loss and a gain in accuracy, outperforming the other models. Similar trends are seen with the ResNet model, but there are larger spikes, which may indicate overfitting. The validation accuracy of the VGG16 model has more noticeable dips even though it is improving overall. Finally, although not as successfully as the DenseNet model, the accuracy and loss graph for the CNN model exhibits a consistent rise in accuracy and decline in loss.

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Classification Reports for the Algorithms :

Classification Report

	precision	recall	f1-score	support
Normal	0.83	0.56	0.67	9
Vitamin A	0.57	0.80	0.67	5
Vitamin B	0.69	0.90	0.78	10
Vitamin C	0.71	0.83	0.77	12
Vitamin D	0.50	0.25	0.33	8
accuracy			0.68	44
macro avg	0.66	0.67	0.64	44
weighted avg	0.68	0.68	0.66	44

Fig 4(a) : Classification report for CNN

Classification Report

	precision	recall	f1-score	support
Normal	0.90	1.00	0.95	9
Vitamin A	0.60	0.60	0.60	5
Vitamin B	0.80	0.80	0.80	10
Vitamin C	1.00	1.00	1.00	12
Vitamin D	0.86	0.75	0.80	8
accuracy			0.86	44
macro avg	0.83	0.83	0.83	44
weighted avg	0.86	0.86	0.86	44

Fig 4(b) : Classification report for VGG16

Classification Report

	precision	recall	f1-score	support
Normal	1.00	1.00	1.00	9
Vitamin A	1.00	0.80	0.89	5
Vitamin B	0.91	1.00	0.95	10
Vitamin C	1.00	1.00	1.00	12
Vitamin D	1.00	1.00	1.00	8
accuracy			0.98	44
macro avg	0.98	0.96	0.97	44
weighted avg	0.98	0.98	0.98	44

Fig 4(c) : Classification report for DenseNet

Classification Report

	precision	recall	f1-score	support
Normal	0.80	0.44	0.57	9
Vitamin A	0.44	0.80	0.57	5
Vitamin B	1.00	0.20	0.33	10
Vitamin C	0.55	0.50	0.52	12
Vitamin D	0.35	0.75	0.48	8
accuracy			0.50	44
macro avg	0.63	0.54	0.50	44
weighted avg	0.65	0.50	0.49	44

Fig 4(d) : Classification report for ResNet

Comparison Table for the Algorithms Used

	Model	Accuracy	Precision	Recall	F1-score
0	vgg16	0.863636	0.831429	0.830000	0.829474
1	CNN	0.681818	0.662271	0.667778	0.643701
2	Densnet	0.977273	0.981818	0.960000	0.968254
3	ResNet	0.500000	0.628568	0.538889	0.495586

Fig 5 : Comparison table for the algorithms used

Based on the above reports , DenseNet appears to be the most effective model according to the metrics, followed by VGG16, CNN, and finally ResNet

V. CONCLUSION

The project pioneers a new approach to detecting vitamin deficiencies, moving away from traditional invasive diagnostic methods towards a more convenient and user-friendly solution .It culminates in the successful development of a novel system aimed at revolutionizing the detection and diagnosis of vitamin deficiencies. Leveraging advancements in image processing and deep learning techniques, the project endeavors to provide a non-invasive, efficient, and accessible solution for identifying individuals at risk of vitamin deficiencies based on visual cues extracted from images of skin in the project **.**

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