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Vitamin Deficiency Detection Using Image Processing and Neural Network

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Abstract

Vitamin deficiencies result in physical health problems which attack nails and tongues and skins of people globally. When medical practitioners identify vitamin deficiencies they should activate early diagnostic methods to enable adequate preventive actions and treatment approaches. A machine learning system uses pictures of nail and tongue and skin defects to forecast vitamin deficiency cases. This system evaluates anomalies through neural network analysis of Convolutional Neural Networks (CNN) along with MobileNet and Long Short-Term Memory (LSTM) networks that function across various deep learning depth levels at the top position where MobileNet serves as the hybrid model.The project consists mainly of an analysis component for nail and tongue pictures alongside a classification part for skin problems. The first part of the system applies SVM to work with CNN and MobileNet to spot Acral Lentiginous Melanoma Beaus Line and Koilonychia because these symptoms show different vitamin deficiencies. This module classifies skin images to identify health conditions which include Actinic Keratosis together with Basal Cell Carcinoma and Melanoma because these conditions present as vitamin deficiency symptoms.The essential part of this project involves creating a web- based application through Flask for users to submit images of their nails and skin and tongue for predictive analysis. The web application generates custom vitamin guidance which it defines through its detection of health concerns as well as dietary instructions to compensate for nutrient inadequacies. Performance evaluation of the system requires precision and recall measurement and confusion matrix analysis. The machine learning models acquire training from various datasets through evaluation procedures to develop accuracy in their prediction abilities. The development of an efficient health diagnostic tool for early vitamin deficiency recognition relies on modern machine learning techniques to fulfill healthcare prevention and management needs.

Keywords: Nutrient Deficiency, Deep Learning, Convolutional Neural Network , Vitamin Deficiencies, Machine Learning

I. INTRODUCTION

Deficiencies is crucial to stop health decline and apply suitable treatment plans. Clinical tests combined with blood sampling constitute standard vitamin deficiency diagnosis methods yet their procedures involve extended processing periods along with high costs which necessitate medical staff for interpretation.

The system created for this project focuses on building an automated identification mechanism for vitamin deficiencies through physical signs examination of nail, tongue and skin images. This system employs machine learning and deep learning approaches to analyze pictures of nail and tongue and skin manifestations in order to help users and healthcare staff detect vitamin deficiency without invasive testing requirements. Early detection of vitamin deficiencies requires a fast non-invasive cost- effective tool as the main objective of this project because it enables prompt intervention to prevent further health problems.

The system is designed in two main components: the first component focuses on the classification of nail and tongue images, while the healthcare professionals with an intuitive tool that uses picture analysis to enable efficient early diagnosis. The system performs identification of three nail disorders (Acral Lentiginous Melanoma and Beaus Line and Pitting) along with two tongue disorders (Actinic Keratosis and Melanoma) affecting the skin. A diagnostic tool operates as a smart device to forecast essential vitamin deficiencies including Vitamin B12 and Iron and Vitamin A and other vitamins through its patient-friendly system. Users can obtain custom vitamin recommendations and dietary recommendations through photo upload on this system. Users on this online platform receive early access to vitamin deficiency detection that enhances both public health prevention delivery and public health awareness.

B. *Objective*

The spread of vitamin deficiencies in the population leads to multiple health complications which express themselves via visible symptoms on the skin and nails as well as the tongue. Insufficient vitamin intake or absorption malfunctions lead to health conditions such as anemia along with bone disorders, immune system dysfunctions and multiple chronic diseases. Early diagnosis of healthcare professionals with an intuitive tool that uses picture analysis to enable efficient early diagnosis. The system performs identification of three nail disorders (Acral Lentiginous Melanoma and Beaus Line and Pitting) along with two tongue disorders (Actinic Keratosis and Melanoma) affecting the skin. A diagnostic tool operates as a smart device to forecast essential vitamin deficiencies including Vitamin B12 and Iron and Vitamin A and other vitamins through its patient-friendly system. Users can obtain custom vitamin recommendations and dietary recommendations through

Building a computer system to detect vitamin deficiency by observing visible symptoms in pictures of nails and tongue and skin represents the central purpose of this research. The system combines deep learning techniques together with machine learning procedures to provide affordable diagnosis of different vitamin deficiencies through visual assessment of physical pqualities. The designed platform provides photo upload on this system. Users on this online platform receive early access to vitamin deficiency detection that enhances both public health prevention delivery and public health awareness require specialized medical knowledge. Visual signs, like changes in nails, offer a non-invasive and affordable alternative for early detection. Research from organizations such as the World Health Organization highlights the importance of developing accessible diagnostic tools, especially for underserved communities.

- ML in Medical Diagnostics:

The processing of medical information through SVM and ANN shows efficient performance when dealing with image- based diagnostic assessments. ANN proves successful when used for medical imaging because it recognizes complex patterns to classify tumors and predict patient results.

- Role of DL in Image-Based Diagnostics:

CNN have revolutionized image processing, enabling automated feature extraction for disease detection. Studies demonstrate the effectiveness of CNNs in dermatological applications, such as identifying skin lesions and nail abnormalities. Pre-trained models like MobileNet and NASNetMobile have been widely used in medical imaging for their efficiency in resource-constrained environments. Researchers have applied transfer learning to fine-tune these models for tasks like X-ray analysis and pathological image classification.

- Application of Image Recognition:

Nail abnormalities, such as Koilonychia and Beau's lines, have been recognized as indicators of underlying nutritional deficiencies. Research in dermatology highlights that specific nail patterns correlate with particular deficiencies, making them suitable for image-based analysis. Recent advancements have seen the integration of AI models to identify nail conditions, reducing the dependency on expert dermatologists. Case studies demonstrate that DL models achieve high accuracy in classifying nail abnormalities, emphasizing their reliability compare traditional ML methods (e.g., SVM, Random Forest) with DL architectures like CNNs. Research indicates that while SVM performs well for small datasets, CNNs and pre-trained models outperform in scenarios with larger and more complex datasets. Lightweight models like MobileNet are favored for mobile and real-time applications due to their low computational overhead, while NASNetMobile achieves higher accuracy for detailed classification tasks. Studies advocate combining traditional techniques with DL for robust performance in healthcare applications healthcare professionals with an intuitive tool that uses picture analysis to enable efficient early diagnosis. The system performs identification of three nail disorders (Acral Lentiginous Melanoma and Beaus Line and Pitting) along with two tongue disorders (Actinic Keratosis and Melanoma) affecting the skin. A diagnostic tool operates as a smart device to forecast essential vitamin deficiencies including Vitamin B12 and Iron and Vitamin A and other vitamins through its patient-friendly system. Users can obtain custom vitamin recommendations and dietary recommendations through photo upload on this system. Users on this online platform receive early access to vitamin deficiency detection that enhances both public health prevention delivery and public health awareness.

The skin image classification component stands as the second main element. Analysis of nail and tongue structures enables recognition of three characteristic abnormalities such as clubbing and koilonychia and pitting which correlate with deficiencies in Vitamin B12, iron and Vitamin A. Visual signs on nails and tongue indicate possible health conditions connected to nutritional deficiencies. Actinic keratosis and basal cell carcinoma and squamous cell carcinoma together with different skin abnormalities display symptoms linked to deficiencies of Vitamin A and D and C.

Through image classification model analysis the system can perform precise diagnosis of these abnormalities.

Through machine learning and deep learning approaches the system operates as a picture sorter that divides images using various processing techniques. The system base classifier employs Support Vector Machine (SVM) as the core element that relies on traditional machine learning features in feature-based procedures. Through Convolutional Neural Networks (CNN) the system achieves performance improvement by obtaining hierarchical characteristics from unprocessed image information automatically. The proposed method links LSTM networks to MobileNet through two functions where MobileNet uses pre-trained weights for feature extraction and LSTM analyzes image data patterns.

A web application based on Flask gets implemented for system deployment. Users can submit nail pictures and tongue or skin images through the web application for analysis. The system accepts image transmission for model processing which leads to classification results that offer predictions about vitamin deficiencies to users. Users can receive bespoke vitamin recommendations and dietary plans from the system that may help treat and reduce established deficiencies. The application delivers a user-friendly platform to connect expert healthcare services with everyday users for self-check monitoring capabilities.

The database for this project is built using MySQL, storing information related to user inputs, image data, and predicted results. The application not only provides predictions but also tracks user history, making it a valuable tool for long-term health monitoring. The combination of machine learning, image processing, and web technologies enables the creation of a user-friendly and effective solution for early diagnosis.

This project contributes to the healthcare industry by offering a cost- effective, scalable, and non-invasive method to identify vitamin deficiencies based on visible signs. The system can assist both medical professionals and individuals in identifying potential health risks and taking preventive actions before deficiencies progress into more severe health issues. Furthermore, this project sets the foundation for expanding to other areas of health diagnostics using image analysis, highlighting the growing role of artificial intelligence in revolutionizing healthcare.

C. *Motivation*

Building a computer system to detect vitamin deficiency by observing visible symptoms in pictures of nails and tongue and skin represents the central purpose of this research. The system combines deep learning techniques together with machine learning procedures to provide affordable diagnosis of different vitamin deficiencies through visual assessment of physical pqualities. The designed platform provides compromised immune function. Conventional diagnostic methods, such as blood tests, can be invasive, time-consuming, and require specialized medical knowledge. Visual signs, like changes in nails, offer a non-invasive and affordable alternative for early detection. Research from organizations such as the World Health Organization highlights the importance of developing accessible diagnostic tools, especially for underserved communities.

D. *Scope*

Vitamin deficiencies are a widespread issue that can lead to serious health problems, yet they often go undiagnosed until more severe symptoms develop. Traditional diagnostic methods, including blood tests, can be costly, time-consuming, and require visits to healthcare professionals, making early detection a challenge for many individuals. The motivation behind this project stems from the need for a more accessible, non-invasive, and efficient way to identify vitamin deficiencies at an early stage. By leveraging machine learning and image processing techniques, this project aims to create a tool that can analyze common physical signs of vitamin deficiencies, such as abnormalities in nails, tongue, and skin. These signs often appear long before other symptoms manifest, providing an opportunity for early intervention. The goal is to bridge the gap between medical diagnostics and the general public, allowing individuals to monitor their health from the comfort of their homes. Furthermore, by integrating personalized recommendations for vitamin intake and dietary adjustments, the system not only diagnoses deficiencies but also empowers users to take preventive actions. This project seeks to enhance public health by providing a cost-effective and easily accessible solution to detect vitamin deficiencies early, thereby improving overall well-being and preventing long-term health complications.

This research establishes machine learning methods to inspect images of nails and tongue and skin structures for vitamin deficiency recognition purposes. The system aims to classify several vitamin deficiency-related medical conditions which affect nails (Acral Lentiginous Melanoma, Beaus Line) and tongue (Pernicious Anemia, Scurvy) and skin structures (Actinic Keratosis, Melanoma). Users gain benefits from a web-based system that uses deep learning models including CNN, MobileNet and LSTM to analyze images with high precision for uploaded pictures. The system produces customized predictions that users can access through it. Users receive dietary recommendations as primary prevention through the prediction system after obtaining diagnostic results from the system. Standard vitamin deficiencies are the specific focus of the system but future expansion plans involve adding detection capabilities for different health problems with observable symptoms. The system implements a modular structure to allow future content types and medical functions that promote self-directed health prevention among users through its design. Early detection capabilities accessible through the project work as both an improvement tool for public health and as a solution to reduce unidentified deficiency cases.

II. LITERATURE SURVEY

In the Early 20th century, laboratory animals experiments and clinical epidemiologic findings established the existence of the distinctive nutrients along with the signs and symptoms of its deficiency; subsequently, a blossoming of meticulously carried out clinical studies as well as field-based randomized trials that revealed the full scope and effects of deficiency between the poor of countries with low or middle- incomes, which in turn shifted the world's health policy. Numerous medical signs and symptoms of vitamin A absence are present from xerophthalmia (practically pathognomonic) to developmental problems and sensitivity to life-threatening infections (which are extremely complex). Many of the symptoms and signs of xerophthalmia, like other basic vitamin deficiency diseases (scurvy, rickets), have been around and known for a very long time. Reports on a lack of vitamin A and/or its signs can be conveniently categorized into "ancient" accounts, clinical descriptions from the eighteenth to nineteenth centuries (and their alleged etiologic associations), earlier twentieth- century laboratory

- **Role of DL in Image-Based Diagnostics:**

CNN have revolutionized image processing, enabling automated feature extraction for disease detection. Studies demonstrate the effectiveness of CNNs in dermatological applications, such as identifying skin lesions and nail abnormalities. Pre-trained models like MobileNet and NASNetMobile have been widely used in medical imaging for their efficiency in resource-constrained environments. Researchers have applied transfer learning to fine-tune these models for tasks like X-ray analysis and pathological image classification.

- **Application of Image Recognition:**

Nail abnormalities, such as Koilonychia and Beau's lines, have been recognized as indicators of underlying nutritional deficiencies. Research in dermatology highlights that specific nail patterns correlate with particular deficiencies, making them suitable for image-based analysis. Recent advancements have seen the integration of AI models to identify nail conditions, reducing the dependency on expert dermatologists. Case studies demonstrate that DL models achieve high accuracy in classifying nail abnormalities, emphasizing their reliability.

- **Comparative Studies on Algorithms:**

Multiple studies compare traditional ML methods (e.g., SVM, Random Forest) with DL architectures like CNNs. Research indicates that while SVM performs well for small datasets, CNNs and pre-trained models outperform in scenarios with larger and more complex datasets. Lightweight models like MobileNet are favored for mobile and real-time applications due to their low computational overhead, while NASNetMobile achieves higher accuracy for detailed classification tasks. Studies advocate combining traditional techniques with DL for robust performance in healthcare applications.

III. PROPOSED SYSTEM

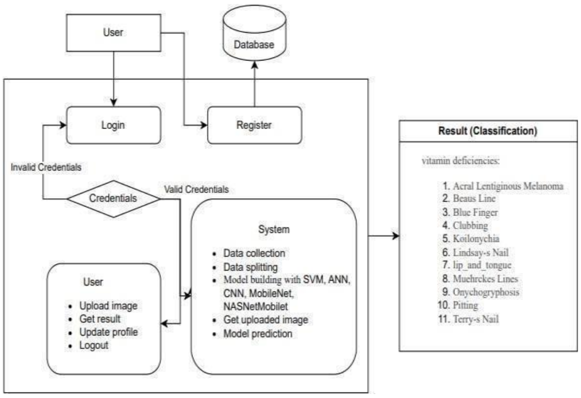


Fig. 1. Proposed system

The proposed system aims to provide an innovative, automated solution for detecting vitamin deficiencies based on visual signs observed in nail, tongue, and skin images. The system integrates advanced machine learning and deep learning models to classify abnormalities and predict deficiencies in essential vitamins, such as Vitamin B12, Vitamin A, Iron, and Vitamin C.

The system has two essential components which analyze nail and tongue images through the first module and perform skin image classification functions in the second module. The analysis of nail and tongue images depends on both traditional SVM and advanced deep learning CNN and MobileNet for extracting features and making classifications. The proposed skin image classification module utilizes CNN and MobileNet which performs feature extraction together with a hybrid method using Long Short-Term Memory (LSTM) networks for better detection of delicate image patterns.

A key feature of the proposed system is its user-friendly web application developed using Flask. Users can easily upload images of their nails, tongue, or skin for analysis. The system processes the images, classifies the abnormalities, and provides users with predicted vitamin deficiencies along with personalized dietary suggestions to address the deficiencies. This system is designed to be scalable, allowing for future updates and the inclusion of additional image types or health conditions. The system's ultimate goal is to offer an accessible, efficient, and non-invasive method for early detection and management of vitamin deficiencies.

IV.CLASSIFICATIONS

- Classifications, Vitamin Suggestions, and Dietary Recommendations

Model 1: Nail and Tongue Image Classification

The classification model for nail and tongue images identifies various vitamin deficiencies based on the abnormalities observed in the images. The model performs the following classifications:

1. Acral Lentiginous Melanoma (Nail Images)

a. Vitamin Suggestion: Vitamin A, C, E, D, B12
b. Dietary Recommendations: Foods such as berries, citrus fruits, leafy greens, carrots, fatty fish, and nuts are recommended to support overall health and skin health.

2. Blue Finger (Nail Images)

a. Vitamin Suggestion: Vitamin B12
b. Dietary Recommendations: To support cardiovascular and circulation health, foods like berries, oranges, leafy greens, fatty fish, and walnuts are recommended.

3. Clubbing (Nail Images)

a. Vitamin Suggestion: Vitamin B12
b. Dietary Recommendations: Heart-healthy fats such as avocados, olive oil, and nuts, along with fruits like berries and oranges, can help promote overall cardiovascular health.

4. Lindsay's Nail (Nail Images)

   a. Vitamin Suggestion: Vitamin Zinc
   b. Dietary Recommendations: Foods such as protein sources (meat, eggs, legumes), whole grains, nuts, and egg yolks can support nail and skin health.

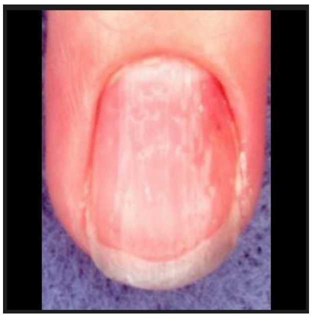
5. Muehrcke's Lines (Nail Images)

   a. Vitamin Suggestion: Vitamin A, C, E, D, and B Complex (B6, B9, B12)
   b. Dietary Recommendations: Consuming a variety of nutrient-rich foods like lean meats, poultry, legumes, biotin-rich foods (whole grains, nuts), and vegetables like carrots and spinach supports nail health.

6. Pernicious Anemia (Tongue Images)

   a. Vitamin Suggestion: Vitamin B12
   b. Dietary Recommendations: Include animal products like dairy, eggs, and fortified cereals, along with green leafy vegetables for a good B12 intake.

7. Pitting (Nail Images)



   a. Vitamin Suggestion: Vitamin A, C, D
   b. Dietary Recommendations: Foods such as leafy greens, carrots, tomatoes, and biotin-rich foods like whole grains and eggs are recommended to support skin and nail health.

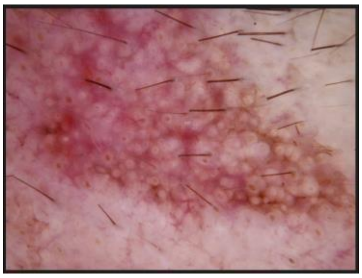
8. Terry's Nail (Nail Images)

   a. Vitamin Suggestion: Vitamin A, C, D, and B12
   b. For proper nail maintenance doctors prescribe patients to consume Vitamin A foods including carrots alongside sweet potatoes and dark leafy green vegetables. You should add citrus fruits, strawberries and bell peppers to your food schedule to obtain Vitamin C benefits. Salmon and mackerel among other fatty fishes together with fortified milk serve as Vitamin D sources which improve both skin and nail health. People should also consume eggs and dairy with fortified cereals for their Vitamin B12 content to enhance skin and nail health.

Model 2: Skin Image Classification

The skin image classification model detects various skin conditions that may be related to underlying vitamin deficiencies. These conditions include:

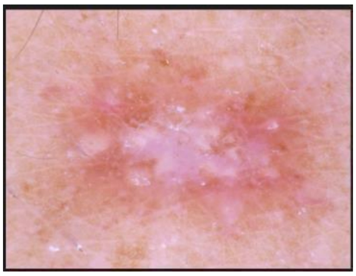
1. Actinic Keratosis



a. Vitamin Suggestion: Vitamin A, D

b. Dietary Recommendations: Foods rich in Vitamin A such as carrots, sweet potatoes, and leafy greens, along with Vitamin D-rich foods like fatty fish and fortified dairy products, help support skin health.

2. Dermatofibroma



a. Vitamin Suggestion: Vitamin C, E

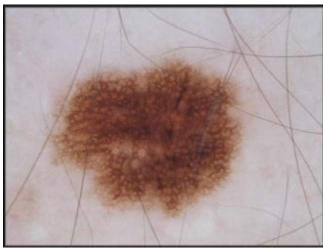
b. Dietary Recommendations: Antioxidant-rich foods such as citrus fruits, strawberries, and leafy greens, along with nuts and seeds, can support skin regeneration.

3. Melanoma

c. Vitamin Suggestion: Vitamin A, C, D, E

d. Dietary Recommendations: Foods like berries, citrus fruits, carrots, leafy greens, and healthy fats such as olive oil and avocado help in maintaining overall skin health.

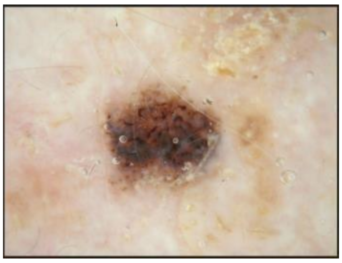
4. Nevus



a. Vitamin Suggestion: Vitamin A, D

b. Dietary Recommendations: Foods like oranges, sweet potatoes, leafy greens, and fatty fish such as salmon can help maintain skin health.

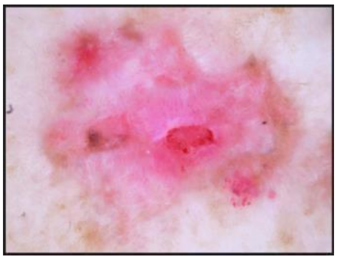
5. Seborrheic Keratosis



e. Vitamin Suggestion: Vitamin D, E

f. Dietary Recommendations: Foods rich in antioxidants, such as berries, tomatoes, and spinach, along with Omega-3 fatty acids from fish, can promote skin health.

6. Squamous Cell Carcinoma



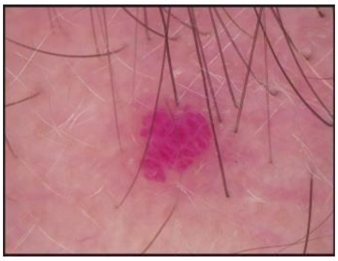
g. Vitamin Suggestion: Vitamin A, D

h. Dietary Recommendations: Include foods rich in Vitamin A like carrots and spinach, and Vitamin D-rich foods like fortified milk and fatty fish.

7. Vascular Lesion

i. Vitamin Suggestion: Vitamin C, K

j. Dietary Recommendations: Citrus fruits, bell peppers, and broccoli, along with leafy greens, can help improve vascular health and circulation.



By combining image classification with vitamin deficiency prediction, the system not only helps in identifying conditions but also suggests a dietary plan to improve the user's overall health based on the results of the classification.

METHODOLOGY

Image processing methods and machine learning techniques and deep learning methods collaborate through this project to detect vitamin deficiencies by analyzing visual signs in tongue, nail and skin photos. The system has three specific phases to execute:

1. The initial process begins with obtaining diverse datasets of images accompanied by labels for different vitamin deficiency cases in nails, tongues, and skin. Deep learning models require all images to be resized to a standard dimension of 224x224 pixels while pixel values also need normalization to achieve consistent data values. The model benefits from augmentation procedures through rotation and flipping and zooming actions to develop stronger model performance and reduce overfitting effects. The model demonstrates good performance on previously unknown images through this approach.

2. Feature Extraction and Model Development:

   - For Model 1 (Nail and Tongue Image Classification), traditional machine learning methods such as Support Vector Machines (SVM) are used in combination with deep learning models like Convolutional Neural Networks (CNN) and MobileNet. These models extract features from the raw image data, such as texture and shape abnormalities, to identify potential vitamin deficiencies like clubbing, koilonychia, and other related conditions.
   - The next model (Skin Image Classification) utilizes CNN and MobileNet to obtain spatial features from skin picture information. The model uses LSTM networking elements with hybrid learning capabilities to examine sequential data patterns in images which facilitates detecting intricate visualalerts for medical problems.

3. Model Training and Evaluation: The models are trained using labeled data, employing techniques like cross-validation to optimize hyperparameters and ensure the models' robustness. Evaluation metrics such as accuracy, precision, recall, and F1- score are used to assess the performance of the models on both the training and validation datasets. A confusion matrix is also generated to provide insights into the classification accuracy across different classes.

4. Deployment via Web Application: The trained models are deployed using a Flask-based web

application, enabling users to upload their images for real-time analysis. The application processes the uploaded images, feeds them through the trained models, and provides predictions on potential vitamin deficiencies. Additionally, the system suggests dietary adjustments and vitamin recommendations based on the classification results.

5. User Interface and Database Integration: The web application also includes a user registration and login system, where users' data and previous predictions are stored in a MySQL database for future reference. The system tracks the users' health conditions over time and offers them a way to monitor their vitamin intake.

V. IMPLEMENTATION

A. Support Vector Machine

To use a SVM for image classification, the first step is to prepare the data. This means converting the images into 1D arrays so the SVM can process them. For the SVM classifier, we use the RBF kernel, which works well for complex, non-linear classification problems. We use GridSearchCV to tune hyperparameters like the regularization parameter `C`, the kernel coefficient `gamma`, and the type of kernel (whether it's linear, RBF, or polynomial).

B. Convolutional Neural Network

- Mobilenet

The process of developing a CNN for image classification includes two important steps at the beginning. The dataset receives added diversity through ImageDataGenerator that performs resizing while

applying image flipping and zooming techniques. All pictures are

resized uniformly to grayscale dimensions between 150x150 or 224x224 pixels for consistent data input format.

The CNN model requires an entry layer to represent image status through 224x224x3 RGB display specification. The convolutional layers capture diverse picture features through their channels along with the ReLU activation function. Each sequential layer contains a following maximum pooled layer which accomplishes dimension reduction without sacrificing key features. The information completed the sequence of convolutional and pooling layers reaches fully connected layers which generate an output layer with 11 neurons corresponding to the 11 lack of nutrient classes. The system uses the Adam optimizer with unregulated cross entropy loss because multi- class classification demands such optimization methods. Model training occurs for 30 cycles by applying preparation data sets to approval on test data sets.

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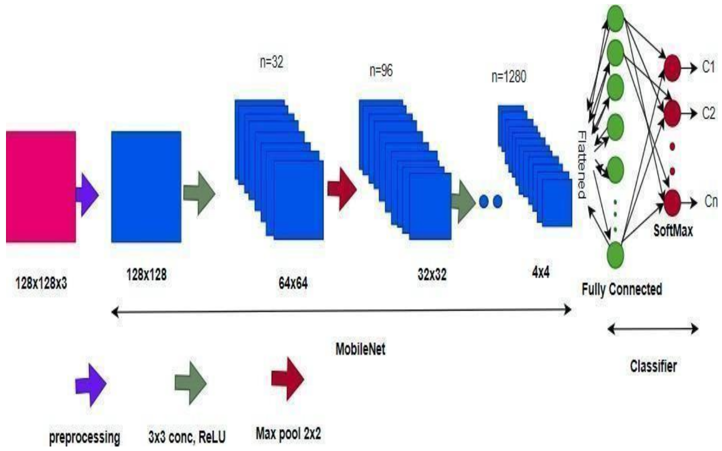

Fig 5.1 ***MobileNet***

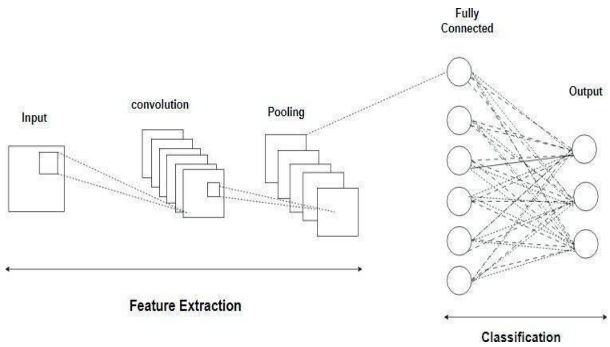

Fig: CNN Architecture

The process starts by preparing data needed to create a MobileNet model dedicated to image classification tasks. The use of ImageDataGenerator enables image augmentation using rescaling and flipping methods which enhance the dataset diversity. MobileNet requires images with dimensions of 224x224 or 299x299 pixels thus these images get resized to these prescribed input sizes. The base model employs MobileNetV2 available from TensorFlow when the flag `include_top=False` is enabled. The fully connected layers get removed to enable the utilization of pre-trained ImageNet weights through transfer learning. The model reduction was achieved by establishing an alpha parameter value of 0.35. Next, we add custom layers. The model incorporates a GlobalAveragePooling2D layer which shrinks the feature maps before connecting to a dense layer containing 1024 neurons activated by ReLU. This addition brings non- linear elements to the system. The model includes a dropout layer to stop overfitting from occurring. The last output layer has 11 neurons which are activated by softmax to help the model differentiate images into 11 vitamin deficiency categories. The model operates for 30-40 cycles during preparing before validation testing is conducted against the test data set. in spatial and sequential pattern detection. The model makes use of dropout layers together with batch normalization allowing stability in training while preventing overfitting from occurring. All layers in highlight mix implementation are fully connected until the model completes its classification process with softmax initiation. Optimized learning rates alongside early termination procedures yield effective results during the training of a half and half model with its cross-entropy misfortune capacity. The model is validated using metrics like accuracy, precision, recall, and F1-score, demonstrating its ability to leverage the complementary strengths of MobileNet and LSTM for accurate and efficient skin disease classification.

a) MobileNet

To implement MobileNet in this diagnostic system, we be- gin by selecting MobileNet lightweight architecture, which is ideal for mobile and embedded applications due to its efficient structure. MobileNet uses depth wise separable convolutionsto reduce the number of parameters, making it both fasterand less resource- intensive while still capturing critical image features. The skin image dataset is preprocessed, resized, and normalized to match MobileNet input shape (typically 224x224 pixels). During the initial layers, depth wise convo- lutions are applied, processing each color channel separately, followed by point wise convolutions to combine information across channels. This technique reduces computation without sacrificing accuracy. The model is then initialized with weightspre trained on Image Net, allowing it to leverage generalized image recognition capabilities. Fine-tuning is performed by training the model on the skin lesion dataset, adapting it specifically to dermatological images. Throughout training, MobileNet hyper parameters, such as width and resolutionmultipliers, are adjusted to find the optimal balance between speed and accuracy. Regularization techniques, like dropout, are applied to avoid over fitting. After training, the MobileNetmodel is validated on a test set, ensuring robust performance. Once tested, MobileNet is integrated into the system's ar-chitecture, enabling it to deliver quick, accurate skin lesion classifications, even on devices with limited computational power.

b) Hybrid Model (LSTM + MobileNet)

The hybrid method performs MobileNet-based lightweight feature extraction prior to employing LSTM for identifying temporal structures in the data. Approximately 224x224 pixel dimensions become necessary for skin lesion images before the normalization process begins in order to achieve stable model performance. The approach accepts supplemental information through augmentation to boost dataset randomness and protect the model from unstable conditions. MobileNet utilizes pretraining procedures before automatically readjusting itself for skin lesion input to create spatial features. MobileNet maintains its convolutional layers unchanged after stripping away the classification section to produce important image pattern feature maps. This operation converts the feature maps into sequence formats which make LSTM processes possible. Multiple layers of LSTM operate within MobileNet structure to discover sequential relations between features which result in spatial and sequential pattern detection. The model makes use of dropout layers together with batch normalization allowing stability in training while preventing overfitting from occurring. All layers in highlight mix implementation are fully connected until the model completes its classification process with softmax initiation. Optimized learning rates alongside early termination procedures yield effective results during the training of a half and half model with its cross-entropy misfortune capacity. The model is validated using metrics like accuracy, precision, recall, and F1- score, demonstrating its ability to leverage the complementary strengths of MobileNet and LSTM for accurate and efficient skin disease classification.

VI. RESULT & DISCUSSION

- Model 1 (Nail and Tongue images classification)

The results from both the MobileNet models show high accuracy, with MobileNet achieving an accuracy of 96.1% These results indicate that both models performed exceptionally well in classifying the nail images into the 11 categories of vitamin deficiencies.

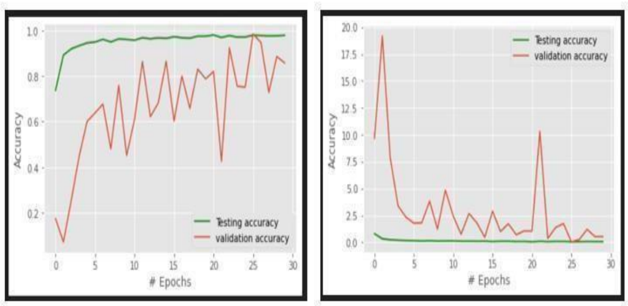

Fig: Accuracy plot for MobileNet

- Model 2 (Skin images classification)

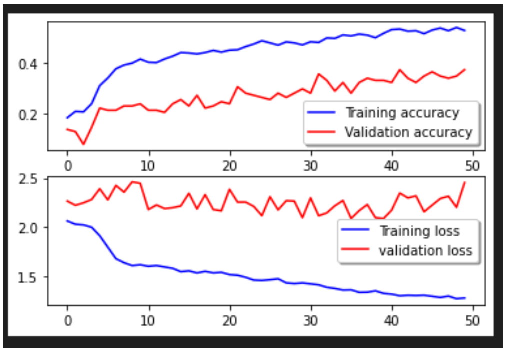

Fig: Accuracy plot

The Hybrid Model (LSTM + MobileNet) achieves a good balance of training and validation performance, with accuracy increasing steadily over epochs and no major overfitting observed. However, validation accuracy stabilizes at a lower level, which indicates room for improvement in model generalization. The confusion matrix highlights the model's strengths in correctly classifying certain classes while identifying potential challenges in distinguishing between similar lesion types. Future optimization, such as hyperparameter tuning or additional data augmentation, could further enhance the model's performance.

a) MobilNet

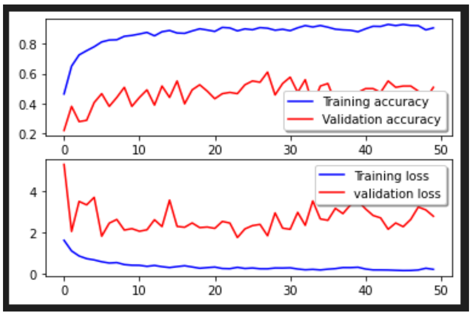

Fig: Accuracy plot

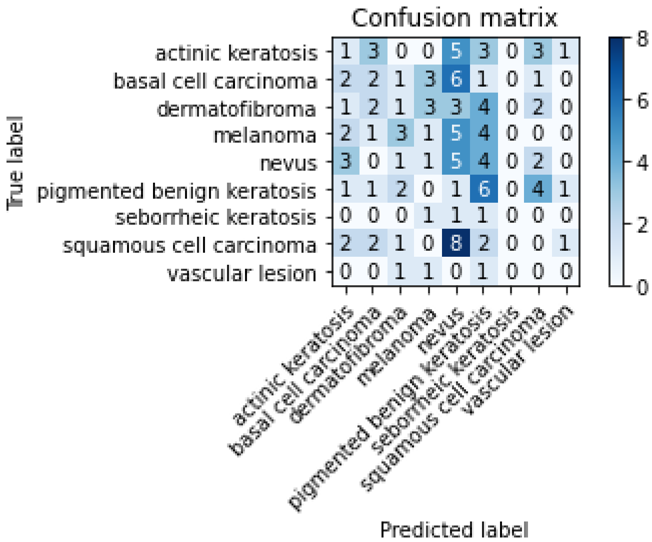

Fig: Confusion Matrix

The MobileNet model exhibits excellent training performance, characterized by high accuracy and minimal loss. However, fluctuations in validation accuracy and loss point to potential overfitting issues, emphasizing the need for strategies to enhance its generalization capabilities. The confusion matrix indicates that while the model excels in certain classes, there is misclassification in others, particularly among visually similar lesions. This performance reflects MobileNet's efficiency in feature extraction and its suitability for lightweight deployments, while further enhancements such as data augmentation or regularization techniques could improve its robustness and validation performance.

The model comparison for skin disease classification highlights that MobileNet outperformshers, achieving 90% training accuracy and 60% validation accuracy, demonstrating efficiency and generalization. In contrast, the CNN model overfits, with 90% training accuracy but only 20% validation accuracy, making it unsuitable without regularization. The Hybrid Model (LSTM + MobileNet) achieves moderate performance, with 50% training and 40% validation accuracy, requiring further optimization. Overall, MobileNet is the most effective, balancing computational efficiency and accuracy for this task

Algorithm	Accuracy
ANN	68.90%
SVM	45%
Mobilenet	90.50%

VII. CONCLUSION

The Vitamin Deficiency Detection project we chosen mobilenet to get model enhance with good performance and demonstrates the potential of ML and DL techniques in transforming healthcare diagnostics. By analyzing nail abnormalities through image recognition, this project provides a non-invasive, cost-effective, and accessible solution for detecting vitamin deficiencies.

The implementation of various algorithms, including traditional models like SVM and advanced DL models such as CNN, MobileNet, highlights the comparative strengths of different approaches. Lightweight models like MobileNet prove ideal for real-time and mobile applications, while achieves high accuracy for more detailed classifications.

The project's integration of a user-friendly interface enables individuals to upload nail images and receive accurate predictions along with actionable recommendations. This empowers users to take proactive steps toward managing their health, reducing the reliance on invasive procedures and specialized medical expertise. In conclusion, this system not only provides a reliable method for early detection of vitamin deficiencies but also contributes to preventive healthcare by enabling timely interventions. Future enhancements, such as incorporating additional biomarkers or extending the scope to other nutritional disorders, could further improve the system's utility and impact in addressing global health challenges.

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