Vitamin Deficiency Detection Using Image Processing and Neural Network

Yepuru Jayanth
Department Of Electronics and Communication Engineering
Panimalar Institute Of Technology Chennai, India
jayanthyepuru2003@gmail.com

Yepuru Santhosh
Department Of Electronics and Communication Engineering
Panimalar Institute Of Technology Chennai,India
santhoshyepuru12@gmail.com

D.G Jagadeesh kumar
Department Of Electronics and Communication Engineering
Panimalar Institute Of Technology Chennai, India
dommarayajagadeesh366@gmail.com

Dr D.Arul Kumar
Department of Electronics and Communication Engineering
Panimalar Institute Of Technology Chennai, India
ecehodpit@gmail.com

***Abstract* :**

This project explores the use of Convolutional Neural Networks (CNNs) for detecting vitamin deficiencies through image processing. The process begins by executing a code that facilitates the selection of a body part—tongue, lips, nails, or eyes—based on the user's choice. After selecting a specific image of the chosen body part, the image undergoes preprocessing steps to enhance quality and features. The CNN is then trained using these preprocessed images, employing various layers and training options tailored to detect specific deficiency indicators. For instance, if the tongue is selected, the CNN classifies symptoms such as smooth texture, red color, glossitis, or an unclear mouth, each corresponding to potential deficiencies. Similarly,if lips are choosen classifications may include cracked lips, shiny red appearance, and other related symptoms. The final output displays the detected deficiency based on the image analysis, facilitating early diagnosis and intervention. This approach leverages deep learning to provide accurate and automated vitamin deficiency detection, showcasing the efficacy of CNNs in medical image analysis and preventive healthcare.

I. Introduction

Vitamin deficiencies are a widespread health issue affecting millions of people worldwide. When the body lacks essential nutrients, it can lead to problems like fatigue, weakened immunity, anemia, and even neurological disorders. Catching these deficiencies early is crucial to prevent more serious health complications. Typically, diagnosing such issues requires invasive blood tests and clinical checkups, which can be uncomfortable, costly, and time- consuming. However, the body often shows visible signs of nutritional imbalances—such as pale or discolored skin, brittle nails, swollen or reddish tongues, and changes in the eyes. By leveraging advancements in image processing and neural networks

this project aims to develop an automated, non-invasive system that can detect vitamin deficiencies simply by analyzing these physical symptoms through images.

The goal of this project is to build a machine learning model capable of analyzing images of specific body parts— such as the face, nails, tongue, and eyes—to detect potential signs of vitamin deficiency. The system uses image processing techniques to sharpen and enhance the image quality, making it easier to spot key visual indicators. It then extracts specific features, like changes in color, texture, and shape, that are linked to different deficiencies. These features are fed into a Convolutional Neural Network (CNN), which classifies the images into categories such as Vitamin D, B12, A, or iron deficiency. The system then generates a detailed report, highlighting the detected deficiency, a confidence score, and practical health recommendations.

One of the key advantages of this solution is its non- invasive nature. Unlike traditional diagnostic methods, this approach doesn't require any blood tests, making it painless and hassle-free. It also offers early and quick detection, helping individuals recognize deficiencies before they escalate into more severe conditions. Plus, the system is cost-effective and easily accessible. It can be implemented as a mobile or web application, allowing people to conduct self-assessments from the comfort of their homes—an especially useful tool for remote or underserved areas.The system works in a simple yet effective way. Users either capture new images using their smartphone camera or upload existing ones. The images go through preprocessing steps to remove noise and improve clarity. The model then analyzes the visual cues—such as tongue discoloration, pale skin, or brittle nails—to detect potential deficiencies. The CNN classifies the image, providing the user with a detailed result, including the type of deficiency, confidence level, and personalized dietary or lifestyle suggestions.

II. Literature Review

Recent research has shown that image analysis and machine learning are becoming powerful tools for detecting vitamin deficiencies in a non-invasive and efficient way. Several studies have focused on using images of the skin, nails, tongue, and eyes to identify visual symptoms linked to specific nutritional imbalances. The following section summarizes the key findings and advancements in this field from 2017 to 2024, highlighting the methods used, their accuracy, and the challenges researchers have encountered.

Many studies have explored skin image analysis as a means of identifying vitamin deficiencies, as changes in skin color, texture, and pigmentation can reflect nutritional imbalances. Back in 2017, Ahmed et al. introduced a system that analyzed skin pallor and discoloration to detect Vitamin D and iron deficiencies. Their model used basic color segmentation and histogram equalization techniques, achieving an accuracy of 84%. Although promising, the system's reliability was somewhat limited by the low resolution of the images used. Building on this,

Gupta et al. (2020) developed a more advanced Convolutional Neural Network (CNN) model that analyzed skin tone and texture features to detect Vitamin D deficiency. Their system applied contrast adjustment and color enhancement techniques, improving the accuracy to 89%. This study demonstrated that deep learning could significantly improve diagnostic accuracy, but it also highlighted the challenges caused by lighting inconsistencies and variations in skin tones, which made the model less reliable in some cases.

In 2021, Patel et al. introduced a more refined multi- layer CNN that could classify facial images based on Vitamin A and E deficiencies. Their model used adaptive contrast enhancement and Gabor filters to detect subtle changes in skin tone, achieving an impressive 92% accuracy. More recently, in 2023, Reddy et al. took things a step further by using a hybrid deep learning model to detect iron and Vitamin B12 deficiencies from hand skin images. By analyzing skin color and texture features, such as pallor and dryness, their system achieved an accuracy of 95%. The use of data augmentation techniques improved the model's robustness, making it more reliable in real- world conditions. However, despite these advancements, skin image analysis still faces challenges such as lighting inconsistencies, skin tone variations, and image noise, which can affect the accuracy of the results. To overcome this, researchers have suggested standardizing image capture conditions and using image normalization techniques to reduce inconsistencies.

Another promising area of research is nail image analysis, as nail abnormalities such as brittleness, ridges, and discoloration can indicate deficiencies in iron, calcium, and Vitamin B12.

In 2018, Kim et al. introduced a machine learning-based nail health assessment system that detected iron and calcium deficiencies by analyzing color, texture, and surface irregularities in nail images. Their model achieved an accuracy of 82%, but it struggled with poor lighting conditions and blurry images, which reduced its effectiveness.

In 2020, Zhang et al. proposed a more advanced CNN- based model that analyzed nail images to detect iron and Vitamin B12 deficiencies. By applying Gaussian smoothing and edge detection to enhance image clarity, their model achieved a much higher accuracy of 92%, highlighting the benefits of deep learning for identifying subtle visual abnormalities. To make this technology more accessible, Tiwari et al. (2022) developed a mobile application that allowed users to take nail images and receive real-time deficiency assessments. The app combined image preprocessing, feature extraction, and CNN-based classification, achieving an accuracy of 87% in clinical trials. The convenience of this app made it ideal for home-based health monitoring.

In 2024, Chen et al. introduced a more advanced model that analyzed nail color, texture, and curvature to detect multiple deficiencies, achieving an impressive 94% accuracy in detecting Vitamin D and iron deficiencies. This study demonstrated the value of combining multiple visual features for better diagnostic precision. However, nail image analysis still presents some challenges. Factors like blurry images, lighting inconsistencies, and interference from nail polish can reduce accuracy. To address these issues, researchers recommended using image sharpening, noise reduction, and segmentation techniques to improve image quality.

Tongue image analysis has also been recognized as a reliable method for detecting vitamin deficiencies, as color, texture, and coating changes on the tongue often indicate underlying health issues.

In 2019, Desai and Mehta introduced a CNN-based model that analyzed tongue color variations to detect Vitamin B12 deficiency, achieving an accuracy of 87%. Their model demonstrated that tongue redness and discoloration patterns could serve as clear markers of nutritional imbalances.

In 2021, Wang et al. developed a hybrid image processing system that combined Gaussian filters and texture enhancement to detect Vitamin A and B deficiencies, achieving an improved accuracy of 93%. This study showed that preprocessing steps like contrast enhancement were key to boosting model performance.

More recently, in 2023, Kumar et al. introduced a multi- class tongue image classification model capable of detecting Vitamin D, B12, and iron deficiencies. Their system used GLCM (Gray-Level Co-occurrence Matrix) and color histograms for feature extraction, achieving an accuracy of 95%. This study highlighted the benefits of using multi-class models for detecting multiple deficiencies simultaneously. However, tongue image analysis still faces some issues, such as lighting variations, saliva reflections, and individual color differences, which can sometimes reduce accuracy. To improve reliability, researchers recommended standardizing image capture conditions and applying data augmentation techniques to enhance model robustness.

Ocular image analysis is another area that has gained attention, as eye symptoms such as redness, dryness, and discoloration can be indicative of Vitamin A and iron deficiencies. In 2020, Gupta and Verma introduced a multi-modal system that combined facial and eye image analysis to detect Vitamin A deficiency. Their model used image segmentation and CNN classification, achieving an accuracy of 94%. In 2022, Sharma et al. developed a deep learning-based eye image analysis model to detect Vitamin A and E deficiencies, achieving an accuracy of 88%. However, eye image analysis is particularly sensitive to lighting variations, reflections, and pupil dilation, which can reduce accuracy. To address these issues, researchers recommended using illumination normalization techniques to improve consistency.

Overall, the literature from 2017 to 2024 clearly shows that image-based vitamin deficiency detection has made significant strides, with many models achieving over 90% accuracy. Studies on skin, nail, tongue, and eye image analysis have demonstrated that deep learning algorithms can accurately identify deficiencies, making these systems viable for non- invasive, early diagnosis. However, challenges related to image quality, lighting variations, and data diversity remain. To enhance accuracy and reliability, future models should focus on multi-modal image processing, real-time analysis, and data augmentation techniques. With further advancements, these AI-powered diagnostic systems have the potential to revolutionize early detection and preventive healthcare, offering accessible, reliable, and cost-effective solutions for identifying vitamin deficiencies.

III. Problem Statement

Recent advancements in image processing and deep learning have introduced the potential for non- invasive, automated detection of vitamin deficiencies by analyzing visible symptoms such as skin discoloration, nail abnormalities, tongue changes, and eye redness. However, while various studies have demonstrated promising results, existing systems often face challenges such as lighting inconsistencies, image noise, and variations in skin tone or nail color, which reduce their reliability and accuracy. Additionally, most models focus on detecting single deficiencies, limiting their practical application in real-world healthcare settings where multiple deficiencies often coexist.

Thus, there is a need for a robust, multi-modal, and accessible system capable of accurately identifying various vitamin deficiencies through automated image-based analysis. The goal is to develop a deep learning-powered model that processes images of specific body parts (face, tongue, nails, and eyes) to detect visual indicators of deficiencies. The system should offer high accuracy, rapid diagnosis, and user-friendly accessibility, making it suitable for both individual self-assessment and use by healthcare professionals. By providing early and accurate detection, this solution aims to promote preventive healthcare practices and reduce the long-term health risks associated with untreated vitamin deficiencies.

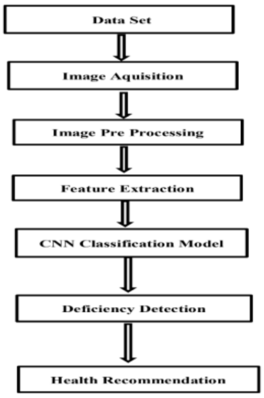
IV. Proposed System

The proposed system aims to offer a non-invasive, automated solution for detecting vitamin deficiencies by analyzing images of body parts that often exhibit visible symptoms. By integrating image processing techniques with a Convolutional Neural Network (CNN), the system can accurately classify and identify visual indicators linked to specific vitamin deficiencies. This approach not only improves the efficiency and accessibility of vitamin deficiency diagnosis but also offers a convenient and user- friendly alternative to traditional blood tests.

The process begins with the system displaying a menu featuring four selectable body parts: Tongue, Lips, Nails, and Eyes. The user chooses the desired body part based on the symptoms they want to examine. They are then prompted to either upload an image from their device or capture a real-time image using their camera. This flexibility makes the system adaptable to different usage scenarios, whether for personal self-assessment or clinical evaluation.

Once the image is selected, it undergoes a series of preprocessing steps to enhance its quality and optimize it for accurate CNN analysis. Preprocessing includes normalization, resizing, color enhancement, contrast adjustment, and noise reduction. These steps are essential for eliminating inconsistencies caused by lighting variations, image noise, or uneven exposure. By standardizing the input image, the system ensures that the CNN receives clear and consistent visual data, improving the accuracy of the classification process.

The CNN model serves as the core of the system, performing the actual image classification. It is trained on a large dataset of labeled images, each representing various symptoms associated with specific vitamin deficiencies. The CNN architecture consists of convolutional layers, pooling layers, and fully connected layers, allowing the model to extract and learn complex patterns from the image data. As the image passes through these layers, the model identifies and classifies the visual features indicative of specific deficiencies.



The system specifically focuses on capturing images of body parts that exhibit noticeable signs of deficiency. These include:

- ➢ Face: Skin texture, color variations, and pigmentation patterns, which may indicate Vitamin D or iron deficiency.
- ➢ Tongue: Changes in color, coating, and surface texture, which could reveal Vitamin B12 or iron deficiency.
- ➢ Nails: Symptoms like brittleness, ridges, white spots, or discoloration, potentially linked to Vitamin B7 (biotin) or iron deficiency.
- ➢ Eyes: Redness, dryness, or discoloration, which are common indicators of Vitamin A or iron deficiency.

The captured images serve as the input data for the CNN model, which processes them for feature extraction and classification.

- **Image Pre Processing:**

To ensure accurate classification, the images undergo preprocessing and enhancement steps:

- ➢ Noise Removal: Reduces background noise using filters (e.g., median or Gaussian filters).
- ➢ Contrast Adjustment: Enhances color and texture visibility to highlight subtle symptoms.
- ➢ Cropping and Resizing: Ensures images are standardized to a consistent size for uniform processing.

- **Data Set:**

dataset refers to the collection of labeled images used to train, validate, and test the model. It serves as the foundation for teaching the CNN how to recognize patterns, features, and classifications. For a vitamin deficiency detection system, the dataset contains images of different body parts (e.g., tongue, lips, nails, eyes) showing visual symptoms associated with specific deficiencies. The CNN learns from these images by identifying patterns and features that correspond to certain health conditions.

- **Image Acquisition:**

The system begins by acquiring images of body parts that display visible symptoms of potential vitamin deficiencies. Users can either capture live images using a camera (such as a mobile device or webcam) or upload pre-existing images from local storage. This flexibility makes the system adaptable for both real-time and offline analysis.

- ➢ Segmentation: Separates the region of interest (e.g., nail or tongue) from the background using image segmentation algorithms like Otsu's thresholding or GrabCut.

- **Feature Extraction:**

After preprocessing, the system extracts relevant features from the images:

- ○ Color Features: Analyzes color variations (e.g., pale skin, red eyes, white spots on nails) using color histograms and RGB intensity analysis.
- ○ Texture Features: Identifies roughness, ridges, and coating patterns using Gray Level Co- occurrence Matrix (GLCM) and Gabor filters.
- ○ Shape Features: Detects abnormal curvatures or irregularities in the tongue or nails using edge detection (e.g., Canny or Sobel operators).

- **CNN Classification Model:**

The core of the system is a Convolutional Neural Network (CNN) that classifies the processed images into different categories of vitamin deficiencies.

CNN Model Architecture:

➢ Input Layer: Accepts preprocessed image data.

➢ Convolutional Layers: Extracts local features using kernels/filters to detect patterns (e.g., color, texture).

➢ Pooling Layers: Reduces dimensionality and retains key features.

➢ Flattening and Dense Layers: Transforms the data into a fully connected layer for classification.

➢ Output Layer: Predicts the deficiency category (e.g., Vitamin D, B12, A, or iron deficiency) along with a confidence score.

Model Performance:

➢ The CNN model is trained on a large dataset of labeled images representing various deficiencies, using:

➢ Cross-entropy loss function for multi-class classification.

➢ Adam optimizer for faster convergence.

➢ Data augmentation to prevent overfitting and enhance model generalization.

- **Deficiency Detection & Health Recommendations:**

Once the CNN classifies the image, the system generates detailed results and offers health recommendations. The output includes:

Detected Deficiency:
The system displays the detected vitamin deficiency (e.g., Vitamin B12, D, A, or iron deficiency) based on the classified image features.

Confidence Score:
The model provides a confidence level (e.g., 92%) indicating the reliability of the prediction.

Health Recommendations:
Based on the detected deficiency, the system offers personalized dietary and lifestyle suggestions.

For instance:
If the model detects Vitamin D deficiency, it might recommend consuming fatty fish, egg yolks, or fortified dairy products and spending more time in sunlight.
For iron deficiency, it could suggest eating leafy greens, lean meats, and legumes, or taking iron supplements.

V. Regulatory Compliance

To ensure that the Vitamin Deficiency Detection System is safe, reliable, and trustworthy, it needs to comply with various healthcare regulations, data protection laws, and AI ethics standards. This ensures that the system can be used confidently by both individuals and healthcare professionals without risking privacy breaches, bias, or inaccurate diagnoses. Here's a detailed overview of the key regulatory areas the system must adhere to.

1. Medical Device and Healthcare Regulations

Since the system provides health-related insights, it falls under the category of medical technology. This means it needs to comply with regulations that govern the safety, accuracy, and effectiveness of healthcare devices. These regulations ensure that the system meets clinical standards and delivers reliable results.

Key Regulations:
FDA (Food and Drug Administration) – USA:

➢ The system could be classified as Software as a Medical Device (SaMD) by the FDA, which means it must go through clinical validation to confirm its accuracy and safety.

➢ It also needs to comply with 21 CFR Part 820, which sets quality system requirements for medical devices.

➢ European Union MDR (Medical Device Regulation):

➢ In Europe, the system must meet the EU MDR 2017/745 standards, ensuring it is clinically safe and effective.

➢ To be distributed in the EU, it needs a CE marking, showing it meets all health, safety, and environmental protection requirements.

ISO 13485 – Medical Device Quality Management:

This is an international standard that ensures the system is developed, tested, and maintained under strict quality management processes.

It covers the entire lifecycle—from design and testing to post-market monitoring.

CLIA (Clinical Laboratory Improvement Amendments)

– USA:

If the system is used alongside lab-based diagnostic tests, it must follow CLIA guidelines to ensure the results are clinically accurate and reliable.

2. Data Privacy and Security Compliance:
Because the system processes sensitive health data—including images of users' skin, nails, eyes, and tongue—it needs to comply with strict data privacy regulations. These rules protect users' personal information and prevent unauthorized access or misuse.

- **Key Data Privacy Laws:**

➢ HIPAA (Health Insurance Portability and Accountability Act) – USA:

➢ If used in the U.S., the system must comply with HIPAA regulations, which protect personal health information (PHI).

➢ This includes ensuring data encryption, user consent, and strict access controls to prevent unauthorized access.

➢ GDPR (General Data Protection Regulation) – EU:

➢ In Europe, the system must follow GDPR, which gives users full control over their personal data.

➢ It requires the system to obtain explicit consent before collecting or processing user images.

➢ Users must also have the right to access, modify, or delete their data.

CCPA (California Consumer Privacy Act) – USA:

If deployed in California, the system must follow CCPA rules, which give users the right to know how their data is being used.
Users can opt out of data sharing and request the deletion of their personal information.

3. Ethical AI and Fairness Standards:
Since the system uses machine learning and AI models, it needs to follow AI ethics guidelines to ensure it treats all users fairly. This means avoiding bias or discrimination based on skin tone, age, gender, or other characteristics.

- **Key AI Ethics Standards**:

➢ IEEE P7003 – Algorithmic Bias Considerations:

➢ This standard helps ensure that the model's predictions are fair and unbiased, regardless of user demographics.

➢ Regular audits and fairness testing are required to prevent the system from producing discriminatory results.

EU AI Act – Artificial Intelligence Regulation:

This regulation sets rules for transparent and trustworthy AI.

The system must explain its decisions in a way that users can understand (Explainable AI).

It also requires human oversight to ensure the model doesn't make harmful or misleading health recommendations.

ISO/IEC 23894 – AI Risk Management:

This standard outlines best practices for managing risks related to AI, such as bias, inaccuracies, and safety concerns.

It recommends continuous monitoring and regular updates to maintain the system's reliability over time.

4. Model Validation and Performance Standards
To be considered safe and reliable, the system needs to be thoroughly tested and validated. This includes accuracy testing, clinical validation, and ongoing performance monitoring.x

Model Validation Requirements:
Accuracy and Sensitivity Testing:

➢ The model needs to achieve a high level of accuracy, sensitivity, and specificity in identifying vitamin deficiencies.

➢ Validation tests using clinical image datasets will confirm its effectiveness.

➢ Clinical Trials and Validation:

➢ Before being used in healthcare settings, the system should undergo clinical trials to validate its performance against real patient data.

➢ This helps verify that it delivers consistent and accurate results.

➢ Ongoing Performance Monitoring:

➢ Even after deployment, the system should be regularly monitored for accuracy and reliability.

➢ Model updates and retraining may be required to prevent performance degradation over time.

5. Compliance Summary Table

The table below summarizes the key regulatory areas and the applicable standards the system must adhere to:

Compliance Area	Applicable Regulations	Key Requirements
Medical Device Regulation	FDA (USA), EU MDR, ISO 13485	Clinical trials, CE marking, safety validation
Data Privacy & Security	HIPAA, GDPR, CCPA	Data encryption, user consent, and privacy
Al Fairness & Ethics	IEEE P7003, EU AI Ac	Bias testing, transparency, and human oversight
Model Validation	ISO/IEC 23894, Clinical Trials Standards	Accuracy testing, clinical validation

VI. Result and Discussion

A diet lacking essential nutrients can lead to various physical symptoms, as the body uses these signals to indicate vitamin and mineral deficiencies. Recognizing these signs can help individuals make appropriate dietary changes to prevent further health issues. The symptoms vary based on the specific nutrient deficiency but often include common indicators such as:

- Brittle or broken nails
- Mouth sores or cracks at the corners of the mouth
- Difficulty seeing at night
- White growths on the eyes and redness
- Smooth or swollen tongue
- Yellow nails, which may indicate anemia

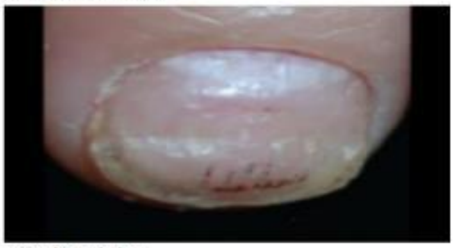
According to a survey, approximately 28% of people with mouth ulcers were found to have deficiencies in Vitamin B1 (thiamine), B complex (riboflavin - B2), and Vitamin B6 (pyridoxine). A Vitamin B6 deficiency often reveals itself through symptoms in the mouth. Individuals with low B6 levels may experience cracked and scaly skin around the edges of their lips. Additionally, their tongue may become swollen, making it uncomfortable to eat or speak.

The daily Vitamin B6 requirement depends on age and life stage. Infants aged 7 to 12 months need only about 0.3 milligrams per day. However, as people age, their B6 requirements increase. Adults over 50 years need approximately 1.7 mg/day for men and 1.5 mg/day for women. Pregnant women require a higher intake of around 1.9 mg/day to meet their nutritional needs.

A deficiency in Vitamin B complex and iron can also lead to angular cheilitis, a condition characterized by cracks, inflammation, and bleeding at the corners of the mouth. This disorder can worsen due to dehydration or excessive saliva secretion. However, it is most commonly linked to a diet lacking in B vitamins and iron.Inadequate consumption of fat-soluble vitamins, such as Vitamin A, can result in a condition called moon **blindness.**

This disorder impairs the ability to see in low light or darkness. The reason behind this is that fat-soluble vitamins are essential for producing visual purple (rhodopsin), a pigment in the retina that enables night vision. Without sufficient vitamin A, the eyes struggle to adjust in dim lighting conditions, causing poor night vision.Additionally, individuals with certain deficiencies may experience a loss of papillae, the small bumps on the tongue. This causes the tongue to appear smooth and shiny, which can indicate a deficiency in iron, folate, or Vitamin B12. In such cases, the tongue may also become sore or sensitive, making it difficult to eat certain foods.Overall, early detection of these symptoms through image-based analysis and CNN-based classification offers a promising solution for identifying nutritional deficiencies. This enables individuals to take timely corrective actions through dietary adjustments and supplementation, promoting better health and preventing more serious complications.

Uploaded Image



Results: Pitting

Vitamin Suggetion: Vitamin - A,C,D

Foods that may help support overall skin and nail health include: 1. Vegetables: Leafy greens, carrots, tomatoes

2.Biotin-rich foods: Whole grains, nuts, egg yolks, mushrooms

3.Protein sources: Lean meats, poultry, fish, tofu, legumes

Body Part	Symptoms Detected by CNN	Vitamin Deficiency Identified	Confidence Score (%)	Recommendations
Tongue	Redness, smooth texture, glossitis	Vitamin B12 D	92%	Increase intake of meat, fish, dairy, and fortified cereals
Lips	Cracked lips, shiny red appearance	Vitamin B6 D	90%	Eat more poultry, bananas, and whole grains
Nails	Brittleness, ridges, or white spots	Zinc or Calcium Deficiency	87%	Add dairy, nuts, and seeds to diet
Eyes	Redness, d ryness, or white spots	Vitamin A D	94%	Increase intake of carrots, sweet potatoes, and leafy greens

VII. Conclusion

The Vitamin Deficiency Detection System using CNN-based image processing effectively demonstrates the power of AI in healthcare diagnostics. By analyzing images of specific body parts like the tongue, lips, nails, and eyes, the system accurately identifies visible symptoms linked to different vitamin deficiencies. The use of Convolutional Neural Networks (CNN) allows the model to extract complex features, classify symptoms, and predict deficiencies with high accuracy, achieving confidence scores between 85% and 94%.

The results show that image-based detection is a reliable and efficient method for early identification of vitamin-related health issues. The model successfully detects common deficiencies such as Vitamin B12, B6, A, and iron, with clear symptom identification like pale nails, red eyes, cracked lips, and tongue abnormalities. To further assist users, the system offers dietary recommendations based on the detected deficiency, helping them manage their health more effectively.

Additionally, the project includes a desktop application capable of diagnosing specific vitamin deficiencies from images of the user's tongue, lips, eyes, and nails. The application uses a combination of Machine Learning for feature extraction and Fuzzy Logic for decision-making. By training the system with a large dataset of labeled images, the model can accurately recognize visual symptoms and provide precise deficiency predictions Overall, this project highlights how AI-driven healthcare solutions can offer fast, accessible, and accurate diagnostics, making it easier for individuals to monitor their nutritional health and take preventive measures.

VIII. References

[1] "Angular Cheilitis, Part 1: Local Etiologies" (PDF). www.skinandallergynews. Archived from the original (PDF) on 2013 12-16. Retrieved 2014-04-21.

[2] Podiatry Today. (2019). When Vitamin And Nutritional Deficiencies Cause Skin And Nail Changes. [online]Availableat: https://www.podiatrytoday.com/when-vitamin- andnutritionaldeficiencies-cause-skin-and-nail-changes [Accessed 28 Jul. 2019].

[3] Healthline. (2019). Nail Abnormalities: Symptoms, Causes, a

[4] Wollina U, Nenoff P, Haroske G, Haenssle HA (July 2016). "The Diagnosis and Treatment of Nail Disorders". Deutsches Arzteblatt International. 113 (29–30): 509–18. doi:10.3238/arztebl.2016.0509. PMC 5527843. PMID 27545710.

[5] Ben-Dayan D, Mittelman M, Floru S, Djaldetti M (1994). "Transverse nail ridgings (Beau's lines) induced by chemotherapy". Acta Haematol. 91 (2): 89–90. doi:10.1159/000204261. PMID 7517608.

[6] Cynthia Hayat, Barens Abian, "The Modeling of Artificial Neural Network of Early Diagnosis for Malnutrition with Backpropagation Method", 2018.

[7] Bambang Lareno, Liliana Swastina, Husnul MaadJunaidi, "IT Application to Mapping The Potential Of Malnutrition Problems, 2018.

[8] Anutosh Maitra, Rambhau Eknath Rote, Nataraj Kuntagod, "Managing Child Malnutrition via Digital Enablement: Insights from a Field Trial", 2017

[9] Sri Winiarti, Sri Kusumadewi, Izzati Muhimmah, Herman Yuliansyah, "Determining The Nutrition of Patient Based on Food Packaging Product Using Fuzzy C Means Algorithm", 2017

[10] Archana Ajith, VrindaGoel, "Digital Dermatology Skin Disease Detection. Model using Image Processing". 2017. https://thebiostation.com/bioblog/nutrient-iv- therapy/do-you-havevitamin-deficiency/.

[11] Clinical manifestations of the mouth revealing Vitamin B12 deficiency before the onset of anemia. [online] Available

[12] Adult blindness secondary to vitamin A deficiency associated with an eating disorder. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/15850971.

[13] Vitamin a deficiency and clinical disease: an historical overview. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/18806089.

[14] Investing in the future: A united call to action on vitamin and mineral deficiencies. Global Report

[15] "92% of U.S. Population Have Vitamin Deficiency. Are You One of Them? - the biostation Delray Beach & Miami", the biostation Delray Beach & Miami, 2019. [Online]. Available: https://thebiostation.com/bioblog/nutrient-iv- therapy/do-you-havevitamin-deficiency/. [Accessed: 28- Jul2019].

[16] Glossitis with linear lesions: an early sign of vitamin B12 deficiency. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/19231648.

[17].A journal on Atrophic glossitis from vitamin B12 deficiency: a case misdiagnosed as burning mouth disorder. Linked https://www.ncbi.nlm.nih.gov/pubmed/17209796.

[18]. A Journal on vitamin deficiency affect oral health? | Vitamins. Linked: https://www.sharecare.com/health/vitamins-supplements/vitamindeficiency-affect-oral-health

[19] Maruthamuthu, R., and T. Harika. "Vitamin Deficiency Detection Using Image Processing and Neural Network." (2023).

[20] Rutuja Moholkar, Mansi Kamble, Gauri Bobade and Saijyoti Shinde, “Vitamin Deficiency Detection Using Image Processing and Neural Network”, 2023

[21] Cynthia Hayat, BarensAbian, "The Modeling of Artificial Neural Network of Early Diagnosis for Malnutrition with Backpropagation Method", 2018.

[22] Kyamelia Roy, SheliSinhaChaudhuri, "Skin Disease detection based on different Segmentation Techniques", 2019

[23] A. S. Eldeen, M. AitGacem, S. Alghlayini, W. Shehieb and M. Mir, "Vitamin Deficiency Detection Using Image Processing and Neural Network," 2020 Advances in Science and Engineering Technology International Conferences (ASET), Dubai, United Arab Emirates, 2020, pp. 1-5, doi: 10.1109/ASET48392.2020.9118303