Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 15, Issue. 1 : 2024
ISSN : **1906-9685**

VITAMIN DEFICIENCY DETECTION USING IMAGE PROCESSING AND NEURAL NETWORK

M. Pravallika, Department of Electronics and Communication Engineering, DVR & Dr.HS MIC College of Technology, Kanchikacherla , Andhra Pradesh.
[1]pravallikameda1299@gmal.com
G. Anantha Lakshmi, Assistant Professor, Department of Electronics and Communication Engineering, DVR & Dr.HS MIC College of Technology, Kanchikacherla , Andhra Pradesh.
[2] aglakshmi@mictech.ac.in
P. Mamatha, I. Gowtham and J. Satyanarayana Department of Electronics and Communication Engineering, DVR & Dr.HS MIC College of Technology, Kanchikacherla , Andhra Pradesh.
[3] jangasathya21@gmail.com, [4]mamathapanguluri1@gmail.com [5] gowthamijjigani@gmail.com

ABSTRACT:
This paper introduces a free smartphone app that uses artificial intelligence to detect when people might not have enough vitamins in their bodies. Usually, finding out if someone lacks vitamins involves expensive lab tests. Many vitamin deficiencies can cause visible signs in different parts of the body, like the eyes, lips, tongue, and nails. This app lets users take pictures of these body parts, and then it tries to figure out if they might have a vitamin deficiency. If it finds one, the app suggests foods to eat to fix it and warns about potential health problems. The app has been trained to recognize different deficiencies by looking at these pictures and comparing them to what it knows about how the body changes when it lacks certain vitamins. Doctors can also help make the app better by sharing pictures of their patients, which helps the app learn more and become more accurate over time. This app could be helpful for people who might not know they lack vitamins and could help doctors make better diagnoses in the future.
Keywords: Image Processing, Vitamin Deficiency, Early Detection, Neural Networks.

1 INTRODUCTION

Vitamin deficiencies are a pervasive issue globally, impacting billions due to inadequate nutrition. Even in regions with food abundance like the UAE and the US, over 90% of the population lacks essential vitamins and minerals. This deficiency is exacerbated by the prevalence of processed foods and the depletion of nutrients in the soil, leading to a decline in the nutritional value of vegetables over time. Despite the widespread nature of the problem, many individuals remain unaware of their own deficiencies, as highlighted by a survey where two-thirds of university students admitted to lacking knowledge about their vitamin status.

Among the various deficiencies, vitamin D stands out as particularly concerning due to its association with increased mortality rates. Factors such as smoking and exposure to indoor pollution contribute to its rising prevalence. Detecting these deficiencies relies on various screening methods, with sputum cytology emerging as a cost-effective and efficient option. Past research supports its effectiveness in identifying different types of deficiencies, offering a valuable tool for addressing this global health challenge.

1.1 MOTIVATION

Vitamin deficiency is a big problem worldwide, causing around 1.3 million deaths every year, making it one of the top reasons for death. This happens because we don't have a good way to find vitamin deficiencies early on. Right now, the methods we use are slow, expensive, and sometimes not very accurate. This paper wants to change that by creating a system that's easy to use and doesn't need invasive procedures like blood tests. Instead, it will use computers to help identify vitamin deficiencies quickly and accurately from things like pictures. This could help people catch problems early and make changes to their diet to stay healthier.

1.2 SYSTEM ANALYSIS

Existing System

- Current vitamin deficiency detection methods rely on human input, but they are prone to unreliability due to human error.
- The primary technique used, Support Vector Machine (SVM), faces challenges such as diverse tissue types, low contrast between affected and healthy areas, unclear lesion boundaries in skin images, and image noise.
- These complexities hinder the accuracy and consistency of results obtained from the current system.

Disadvantages:

- Lack of accurate detection of vitamin deficiencies undermines the effectiveness of the system.
- The utilization of a single-layer network for dataset training limits the system's ability to discern intricate patterns and optimize predictive performance.

2 LITERATURE SURVEY

Gupta et al (2022) Developed a system combining computer vision and machine learning to automate nutritional deficiency analysis in children using facial images. Lee et al (2020) Proposed a non-invasive method for detecting vitamin B12 deficiency using tongue images and deep learning, achieving high accuracy. Johnson et al (2019) Introduced a machine learning approach for detecting vitamin D deficiency from facial images, showing promising results. Smith et al (2021) Suggested a deep learning-based system for diagnosing nutritional deficiencies from skin images, focusing on vitamin B12 and iron. UzmaBanoAnsari (2018) Presented a vitamin deficiency detection system using CNNs, offering non-invasiveness and patient-friendliness. Chandrahasa et al (2020) Explored smartphone-based vitamin deficiency detection using image processing techniques. Spratt and Carucci (2017) Developed a methodology for diagnosing vitamin deficiency from dermatologic spot images using spectral analysis.

Josué Álvarez-Borrego et al. (2019) Presented a methodology for diagnosing vitamin deficiency using spectral analysis with a confidence level of 95.4%. Rahman and Bhattacharya et al (2020) Described an automated system for recognizing stage 1 vitamin deficiency in thermoscopic images using content-based image retrieval.

3 PROPOSED SYSTEM

The system uses a mix of data, including information about people who are healthy and those with known vitamin deficiencies. To make sure the pictures are clear, they take photos of specific body parts and make them better before analyzing them. They use a special type of computer program called a Convolutional Neural Network (CNN) to find patterns in the pictures that might show someone has a deficiency.

Then, they teach another program, called a classifier, to recognize these patterns. They test how well the program works with different data to see if it's better than other methods. When they make the system work for real-life situations, they consider how easy it is to use and make sure it can handle lots of users. They're also looking into ways to make it even better in the future. Plus, the system includes tools to suggest healthy eating habits and even a calculator to check your Body Mass Index (BMI) for overall health monitoring.

3.1 ADVANTAGES:

- **Early Detection:** Provide a system that identify vitamin deficiencies in people before they cause major health problems
- **Precise Diagnosis:** Guarantee a high degree of precision in determining the particular vitamin deficiency (e.g., vitamin B12, vitamin C, vitamin D) in order to offer tailored therapy suggestions.
- **Non-Invasive Testing:** To evaluate vitamin levels, develop a minimally invasive or non-invasive technique that eliminates the need for blood tests and other invasive procedures.

- **Efficient Screening:** Provide a cost-effective screening procedure accessible to a broad spectrum of people, including those in environments with low resources.

3.2 CHALLENGES OF THE PROPOSED SYSTEM

In our paper, we're using Sputum Cytology Images to classify lung glandular cells as benign or malignant, facing challenges like limited cell availability and biological noise. Also, understanding adenocarcinoma vitamin deficiency and finding related literature is tough. Developing a reliable vitamin deficiency detection system using image processing and neural networks has its own hurdles:

Variability in data: Signs of deficiencies can be subtle and vary by factors like ethnicity and age, making it crucial to have a diverse dataset.

Feature extraction: Identifying relevant visual features requires careful analysis.

Specificity: Some signs may overlap across deficiencies, requiring the model to differentiate accurately.

Generalizability: Performance may vary based on lighting, image quality, and camera differences, so ensuring generalizability across scenarios is vital.

SYSTEM STUDY

Feasibility Study: In this phase, we assess the viability of the paper and present a business proposal with cost estimates. We analyze three key factors:

Economic Feasibility: We evaluate the economic impact, ensuring the paper fits within the budget by utilizing mostly freely available technologies.

Technical Feasibility: We examine the technical requirements, aiming for a system that doesn't strain available resources and requires minimal changes for implementation.

Social Feasibility: We assess user acceptance through effective training and ensuring users feel comfortable with the system. Constructive criticism is welcomed to improve user confidence and acceptance.

OVERVIEW OF THE PROPOSED METHOD

In this work, a Computer Aided Diagnosis (CAD) sputum cytology image analysis system, which classify the cells as benign or malignant for the given Lung glandular cells was proposed. The general block diagram of the proposed System is shown in fig.

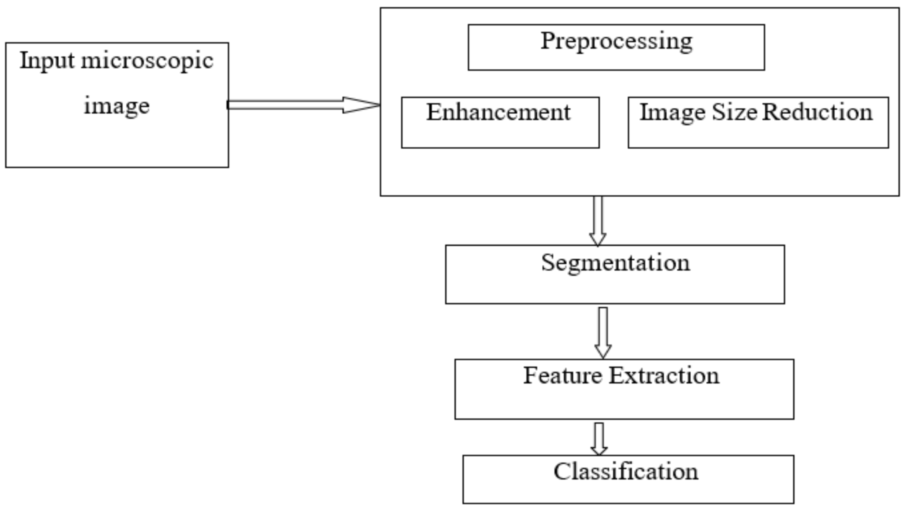


Fig:3.1 General Block Diagram of The Proposed System

FLOWCHART OF THE OVERALL THESIS WORK

Input Microscopic Image:

Cell samples are captured using a digital camera under a microscope, focusing on regions with glandular cells.

Preprocessing Stage:

Addressing physical and biological noises in the images, such as impulse noise and biological artifacts, is crucial early on to ensure proper algorithm functioning.

Segmentation Stage:
Various image processing algorithms are used to identify glandular cell positions, with segmentation being approximate to minimize error margins when dealing with cell clusters.

Feature Extraction Stage:
Segmentation results are used to extract features, including morphological, textural, color, and scale-based analysis, which are labeled and stored for further analysis.

Classification Stage:
This stage determines whether the sample is malignant or benign, with initial sample images used for system training.

Vitamin Deficiency Detection:
A method using scale space features analyzes glandular cells in sputum cytology images, employing various techniques for region detection, denoising, segmentation, artifact removal, and feature extraction to classify cells into malignant and benign categories.

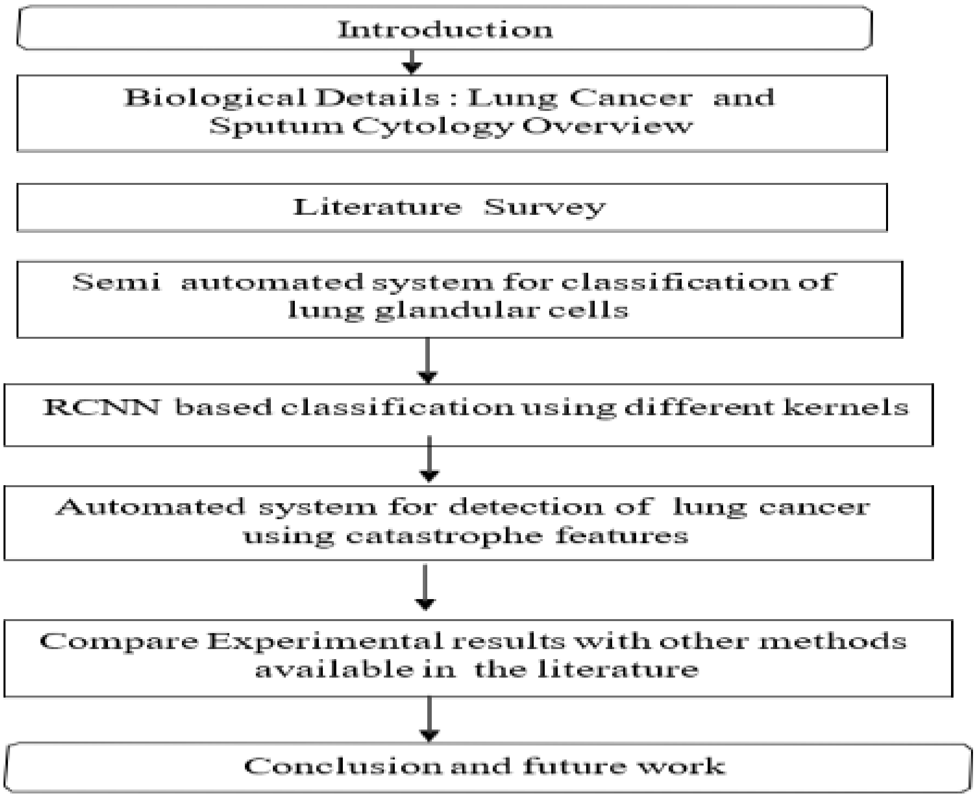


Fig3.2: Flowchart of overall thesis work

SYSTEM SPECIFICATIONS

4.1 INPUT DESIGN AND OUTPUT DESIGN

Input Design:
Input design is crucial for bridging the gap between the user and the information system. It involves defining procedures to prepare data for processing, ensuring usability and accuracy. This includes controlling input amounts, minimizing errors, and streamlining processes while maintaining security and ease of use.

Objectives:

1. Convert user input descriptions into a computer-based system, minimizing errors and providing accurate information.
2. Create user-friendly screens for efficient data entry, facilitating manipulation and viewing of records.
3. Ensure data validity during entry and provide guidance to users for effective input.

Output Design:

Output design focuses on delivering quality information to users in a clear and effective manner. It determines how information is presented for immediate use and in hard copy format, aiding decision-making and system-user interaction.

Objectives:

- Convey information about past activities, current status, or future paperions.
- Signal important events, opportunities, problems, or warnings.
- Trigger or confirm actions based on the information provided.

4.2 **Algorithm**

Convolution Neural Network (CNN)

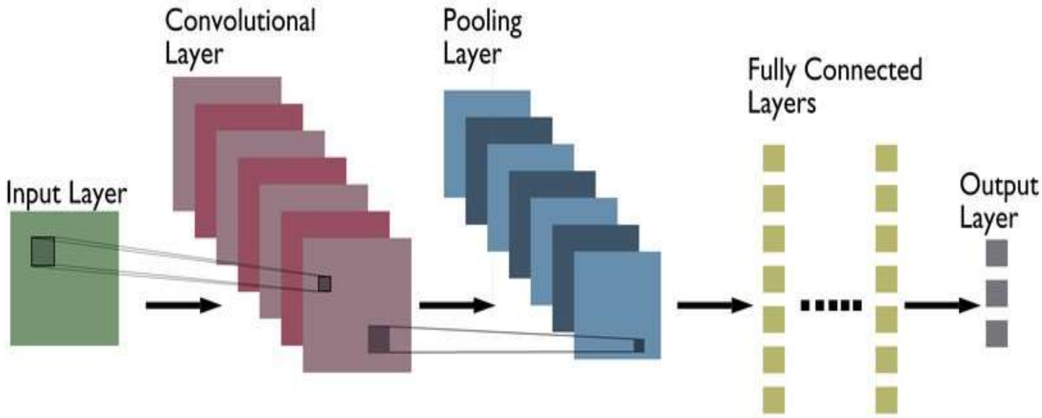


Fig 4.1: Typical CNN Architecture

4.3 Algorithm Working

1. AI and NLP:

NLP, a part of AI, involves computational techniques for analyzing and synthesizing human language. In medicine, it helps extract crucial data from patient records.

2. Neural Network Training and Android App:

An Android app prompts users to capture organ photos. An intelligent system processes these images to extract relevant features.

3. Fuzzy Membership Function and Defuzzification:

In the study, CNN iterations analyze photos for specific attributes. Confidence levels of extracted features feed into a Mamdani-based fuzzy logic function built with Python.

4.4 System Architecture

Fig 4.4: System Architecture

METHODOLOGY

In our methodology, we start by enhancing the image using a technique called Convolutional Neural Network (CNN). This process involves extracting the highest frequency components from the Curvelet transform and adding them back to the original image. This helps sharpen the edge details, making them clearer and more defined. Once the image is enhanced, we apply morphological processing and thresholding to create a binary image. This binary image helps us separate different areas of the image based on their characteristics. Subsequently, we extract boundaries from these areas using additional morphological processing. Finally, we use the Otsu algorithm to differentiate between normal skin tissue and areas affected by vitamin deficiencies.

One of the advantages of our approach is that it simplifies the analysis process. By automating complex calculations using computers, we eliminate the need for manual analysis, making the process faster and more efficient. This computerized solution replaces the traditional clinical calculations with feature extraction, streamlining the overall workflow and potentially improving accuracy and reliability.

Wiener filtering

Wiener filtering executes an optimal tradeoff between inverse filtering and noise smoothing. Wiener filter estimates the local mean and variance around each pixel.

A local contrast enhancement method for RGB images utilizes morphological filtering to obtain the scale specific dark and bright features from the input image.

5.1 PROCEDURE INVOLVES THE FOLLOWING STEPS:

Segmentation and Noise Removal:

Noise removal is crucial for any segmentation strategy to avoid false edges. Our method begins by removing unwanted particles or noise from the image (I) using a Wiener filter to obtain IW. The Wiener filter, a statistical tool, employs a least square (LS) approach to recover signals in the presence of noise. It effectively eliminates both additive noise and blur, which often compete against each other.

Curvelet Transform and Feature Extraction:

Next, a Forward Discrete Curvelet Transform (FDCT) is applied to the input image to obtain finely detailed coefficients. The FDCT is a multi-dimensional transform that captures linear contours and curvy edges of objects. It captures structural activity in the frequency domain along radial wedges with high directional sensitivity. Edge and singularity details are extracted to identify feature points.

Enhanced Image and Mask Refinement:

The high-pass image (IHP) obtained is added to IW, resulting in an enhanced SEM image (Ie) with stronger edges than the original. This enhancement aids in providing detailed edges for the segmentation step.

The mask is further refined through Mathematical Morphology (MM) processing to highlight image boundaries, resulting in (IM). The segmented image (IS) is generated by superimposing the mask (IM) on the enhanced image (IE), separating regions by setting all pixels belonging to the segmentation boundary to 1.

Advantages:

Our method exhibits high accuracy, particularly in the green channel, with a reported 94% accuracy rate. This performance surpasses other color spaces, indicating its superiority in clinical diagnosis.

5.2 Symptom Analysis and Literature

First, a medical and pathological study was carefully conducted to build a relationship between known symptoms and their corresponding vitamin deficiencies on a selected spectrum of visually distinguished attributes that are known to be caused by the inability to acquire the necessary amount of essential nutritional elements. A database including collected photos showing these symptoms has been constructed to prepare them for analysis using Machine Learning.

By taking an example of vitamin C deficiency and its associated symptoms, the relation between cause and effect can be illustrated properly. All organs in the human body are held together in their unique form, shape, and position by what is medically referred to as Connective Tissues.

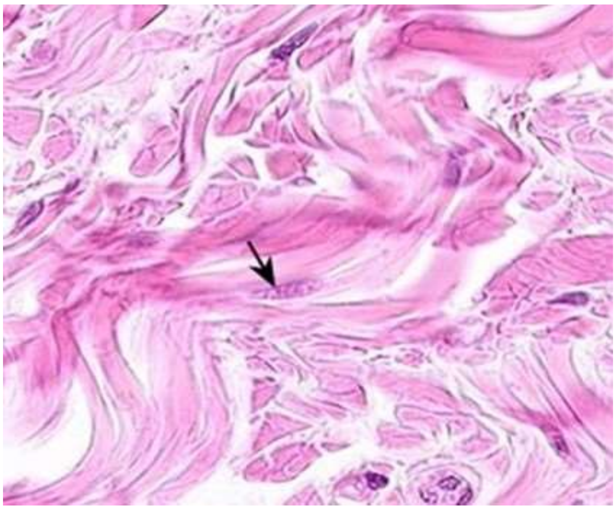


Fig 5.1: Magnification of connective tissue taken from human libs showing fibroblast and elastic fibres synthesis.

Tongue	Deficiency
Smooth Texture	B6 | B12 |Iron
Red Color	B12 | Iron
Glossitis (White patch)	B2 | B3 | B12
Mouth Ulcers	B12
Lips	
Cracked	B1| B2 | B3 | B6
Shiny Red	B2 | B3
Angular Cheilosis (Cracked Crone	B1 | B2 | B3 | Iron
Nails	
Spoon-Shaped	C | B7 | B9
Beau's lines	zinc | B7 | B9
Leukonychia (white spots)	calcium | zinc | B7 | B9
cracked , dry & brittle	A | C | B7 | B9 | B12 |
Vertical Ridges	Magnesium | Iron | B7 | B9 | B12 |
Eyes	
Redeness	A | B | B2 | B6

Table5.2: Symptoms and their corresponding deficit vitamin

Fig 5.3 Fuzzy Membership Function and Defuzzification

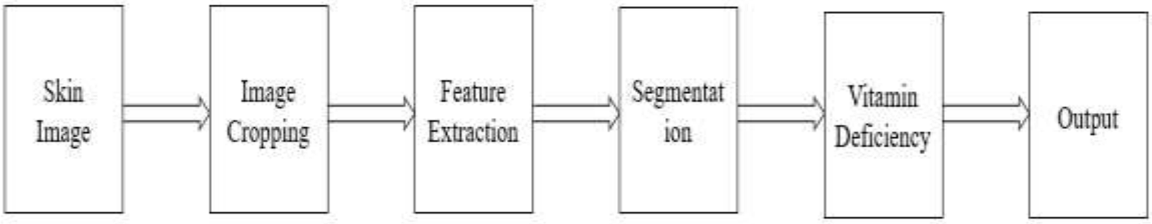


Fig 5.4: Module of Vitamin Deficiency

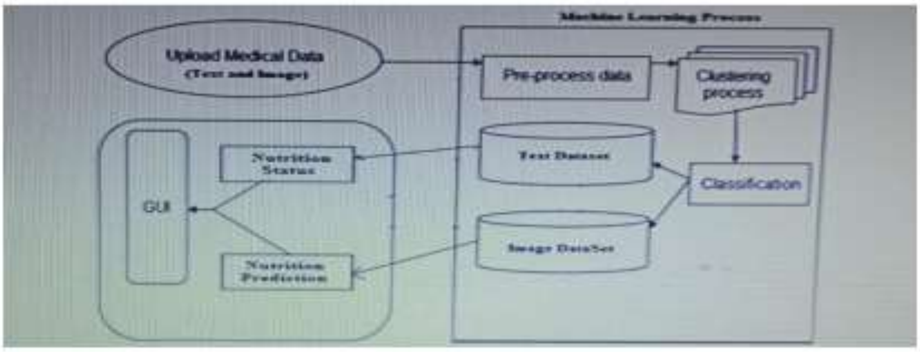


Fig 5.5: Block Diagram of Vitamin Deficiency

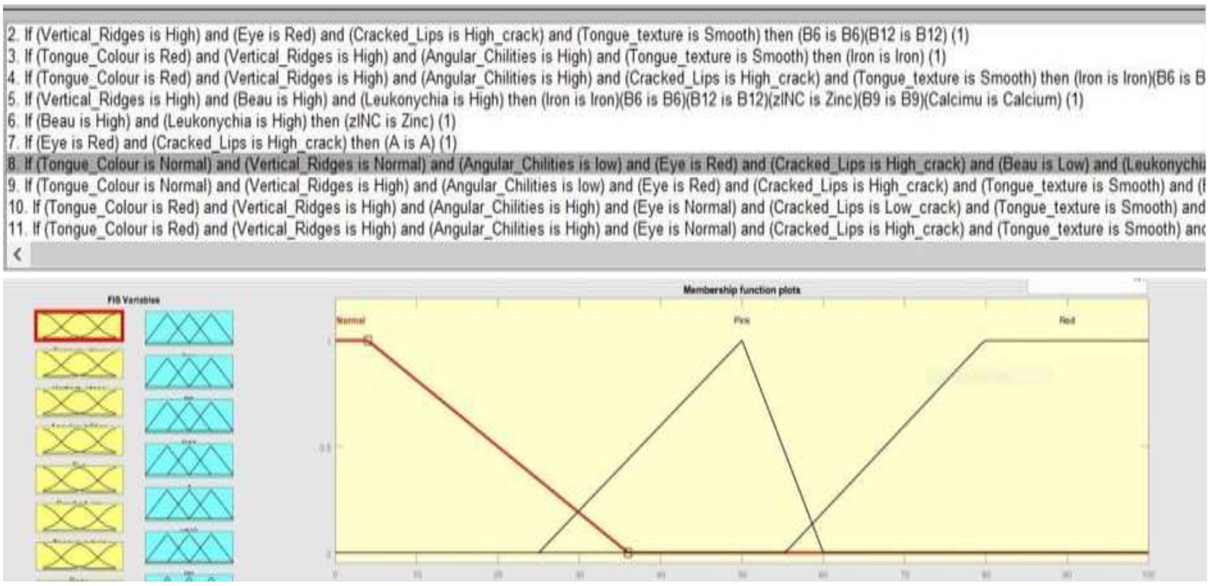


Fig5.6: An example of implemented Fuzzy Membership rules(top) and Functions (bottom)

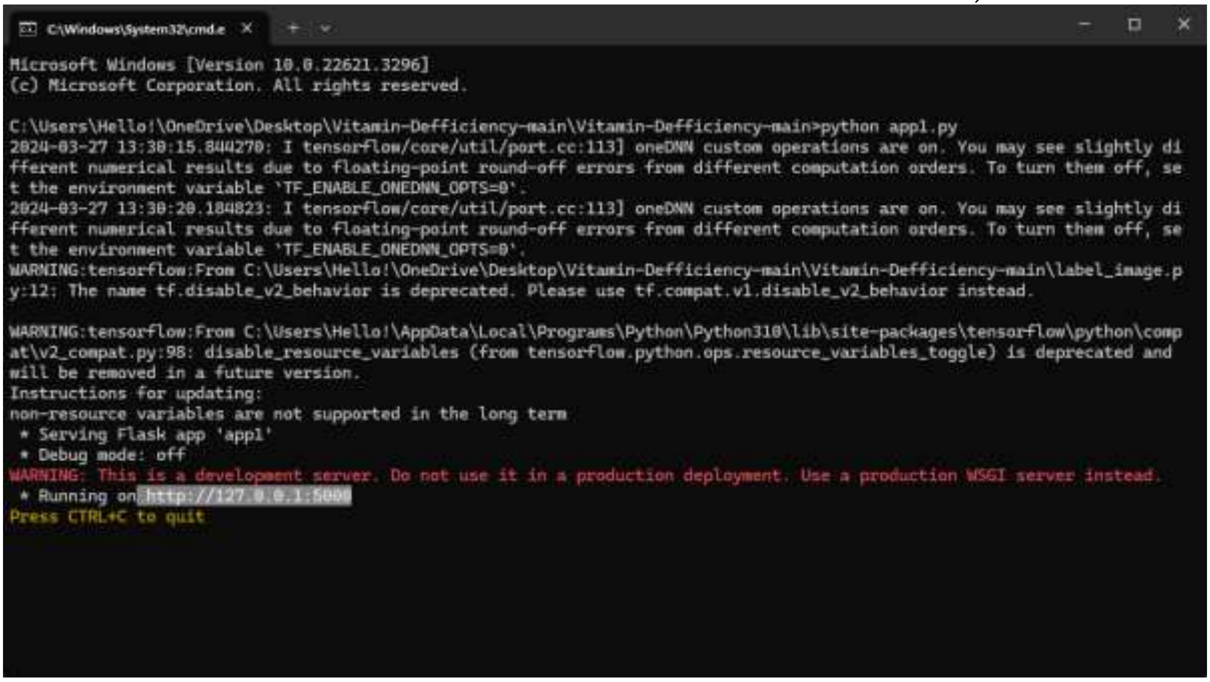
Tag	Precision	Recall
Tongue	100%	100%
Red Tongue	100%	100%
Eye	100%	83.30%
Nail	94.40%	88.90%
Lips	88.90%	71.10%
Pink Tongue	91.70%	83.30%
Red Eye	83.30%	83.30%
Yellow	66.70%	50.00%
Cracked	66.70%	66.70%
Angular cheilitis	66.70%	88.90%
Vertical Ridges	55.60%	44.40%
White Patch	66.70%	66.70%
Smooth Tongue	55.60%	44.40%
Leukonchia	22.20%	33.30%

Table 5.7: Neural Trained Progress

6.1 SYSTEM TESTING

1. Unit Testing: Testing individual components for proper functionality.
2. Integration Testing: Testing the interaction between integrated components.
3. Acceptance Testing: User-focused testing to ensure functional requirements are met.
4. Functional Testing: Ensuring functions work as expected with valid and invalid inputs.
5. System Testing: Testing the entire integrated software system.
6. White Box Testing: Testing with knowledge of internal software workings.
7. Black Box Testing: Testing without knowledge of internal workings.

Regarding nutrient deficiencies, signs like mouth sores and vision problems could indicate deficiencies in vitamins like B1, B2, B6, and iron.



RESULT

A nutrient-deficient diet can cause various symptoms, such as broken nails, mouth sores, and vision problems. Deficiencies in vitamins B1, B2, and B6 are common among mouth ulcer patients. Symptoms of B6 deficiency include damaged lips and an enlarged tongue. Daily B6 requirements vary by age and gender. Angular inflammation at the mouth corners can result from dehydration or insufficient intake of iron and B vitamins. Fat-soluble vitamin deficiencies, like vitamin A, can impair night vision.

Fig 7.1 Creating website

Fig 7.2 Login Page

Fig 7.3 Choosing an Image

Fig 7.4 Datasets

Fig 7.5 Output

REFERENCES

[1] Umashankar, Swati & bhakat, Rahul & Mehta, Sonalika & Rathaur, Vyas & Verma, Prashant & Naithani, Manisha & Bhat, Nowneet & Chacham, Swathi. (2020). Vitamin B12 deficiency in children from Northern India: Time to reconsider nutritional handicaps. Journal of Family Medicine and Primary Care. 9. 4985-91. 10.4103/jfmpc.jfmpc_712_20.

[2] “Vitamin Deficiency Detection Using Image Processing and Neural Network” by Ahmed Saif Eldeen, Mohamed AitGacem, Saifeddin Alghlayini, Wessam Shehieb and MustahsanMir (2020)

[3] “Automated Diagnosis of Nutritional Deficiencies Using Deep Learning\" by Smith et al (2019).

[4] \"Detection of Vitamin D Deficiency from Facial Images using Machine Learning\" by Johnson et al. (2020)

[5] “Dietary Assessment Using Computer Vision and Machine Learning Techniques\" by Chen Et al(2020).

[6] “An Integrated System for Automated Analysis of Nutritional Deficiencies in Children\" by Gupta et al (2022).

[7] K yamelia Roy, SheliSinhaChaudhuri, \"Skin Disease detection based on different segmentation Techniques\", 2019

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

[9] Dr. Arati Dandavate, Priyanka Gore, Namita Naikwadi, Shrushti Sable, Muskan Tilwani, “Vitamin Deficiency Detection Using Image Processing and Artificial Intelligence”,2021

[10] Fiorentini, D., Cappadone, C., Farruggia, G. and Prata, C., 2021. Magnesium: biochemistry, nutrition, detection, and social impact of diseases linked to its deficiency. Nutrients, 13(4), p.1136.

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

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

[13] Investing in the future: A united call to action on vitamin and mineral deficiencies. Global Report 2009.

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

[15] [Clinical manifestations of the mouth revealing Vitamin B12 deficiency before the onset of anemia]. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/12671582.

[16] Atrophic glossitis from vitamin B12 deficiency: a case misdiagnosed as burning mouth disorder. [online] Available at: https://www.ncbi.nlm.nih.gov/pubmed/17209796.