

Neural Network-Based Image Processing for Vitamin Deficiency Detection

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Abstract— A significant amount of work has been done recently regarding CNN's application in detecting Vitamin deficiencies using images. It begins with a code that lets the user select a body part that they would like to use for analysis tongue, lips, nails, or eyes. After selecting an image of the relevant body part, the image is pre-processed for features and quality improvement. The pre-processed images are then used to train the CNN with sufficient layers and training for specific deficiency signs. For example, if the tongue is selected, a CNN can classify symptoms such as smooth texture and red colour of the tongue, glossitis, or unknown mouth. If lips are chosen, the classifications may be cracked lips with a shiny red extremely pale in color and other associated symptoms. The deficiencies get detected on an image basis enabling prompt diagnosis and treatment. By implementing deep learning, the achievement in accuracy as well as automating the process of Vitamin deficiency detection shows the capabilities of CNNs in medical image analysis and proactive medicine.

Keywords- Vitamin Deficiency, Related Dataset, Deep Learning, Convolution Neural Network, Image Processing Techniques, Accuracy.

I. INTRODUCTION

Apart from one's overall physical condition, vitamin D deficiency can show visible symptoms on the tongue, lips, eyes, and nails. This bachelor thesis applies Convolutional Neural Networks with image processing techniques for identifying these deficiencies. The workflow begins by letting users upload an image of the targeted body part that suggests some deficiency. After the image is selected, it is enhanced to improve further analysis. The CNN, which in this case works as a classifier, is trained using these enhanced images. The algorithm has a set of features to identify, and with those features, certain types of vitamin D deficiency can be detected. For instance, certain types of vitamin D deficiencies can be depicted with a smooth, red, and glossy tongue, while cracked red or shiny lips depict another type of deficiency. These symptoms

detected by the system are further classified to deliver a diagnosis based on the images. Here, deep learning is employed so as to fine-tune the detection process and diagnose the individual at the earliest possible moment. All of this builds a robust case for CNNs as a step toward preventive medicine. In addition, the application of AI in medical image analysis opens the doors to more accurate diagnostics.

Insufficiency of vitamins have profound impacts on humans, and this phenomenon can be effectively explained using images of relevant body parts. This technique helps illustrate the effect of vitamin deficiency on different organs of the body. For instance, images of the eyes demonstrate what can happen to an individual who does not have enough of vitamin A. Such an individual may suffer from night blindness and other problems associated with vision. Pictures of skin may reveal swollen and bleeding gums as guessable symptoms of vitamin C deficiency, and bruising may also be visible. Moreover, bones can be examined to note the effects of vitamin D deficiency, where pain felt in the bones can be associated with other deformities such as rickets. These pictures help understand the correlation between vitamins and the body, especially regarding the need to take the right amount of vitamins through food or supplements. Such pictures are useful in education and awareness, but they can also be effective in the early diagnosis and treatment of conditions initiated by a lack of necessary nutrients and proper health management.

Figure 1:



Figure 2:



II. LITERATURE SURVEY

[1] Cynthia Hayat, Barens Abian, "The Modeling of Artificial Neural Network of Early Diagnosis for Malnutrition with Backpropagation Method", 2018. The negative effects of malnutrition can be minimized by developing medical technology through combining expert experience and knowledge to produce an early diagnosis. The development of ANN architectural model is conducted to identify the types of malnutrition. This research consisted of 2 phases, which were training phase in which it generated ANN weight by using feed-forward of activation function, and testing phase in which the result of the previous stage was tested to obtain output. The resulting architectural model has a 96% accuracy rate with MSE of 0.000997 during 5 seconds training period. Regression results show that the resulting model has a high degree of accuracy to produce output of malnutrition types such as marasmus, kwashiorkor, and marasmus-kwashiorkor.

[2] Bambang Lareno, Liliana Swastina, Husnul MaadJunaidi, "IT Application to Mapping The Potential Of Malnutrition Problems, 2018. The aim of the research is to track weight changes in toddlers as an indicator of malnourishment. Losing weight, or failing to achieve as much growth as expected over a period of six months, is likely to increase the chances of malnutrition. The study recommends classification algorithms to assess the possibility of being at risk of malnutrition. A web-based system and mobile applications are proposed as IT solutions to the problem. The system would produce maps that show the most problematic areas with respect to malnutrition. This enables local health service providers such as posyandu to focus their efforts

more accurately. It seeks to maximize community involvement in the fight against malnutrition. The government can use this data to improve aid programs by knowing the nutritional status in real time. This provides an opportunity to use health program resources more effectively. Most importantly, the goal of the project is to build an active, intelligent society for health management.

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

The Integrated Child Development Scheme (ICDS) of Government of India has so far seen only mixed results with nearly one fourth of the children under the age of 6 years are still undernourished. The budgetary allocation has been increasing over the years to strengthen and close gaps in the program and there is increased pressure on policy makers and program implementers to show the results. We argue in this paper that malnutrition management requires an integrated digital approach - that not only looks at making data available, but also establishing relationships between various program indicators, overlaying that with socio-economic conditions of the region and family demographics. The ICDS program needs to overcome the obstacles of limited skills and motivation of community health workers, followed by the poor utilization of existing services due to low awareness and lack of fine grained socio-economic data. This paper describes an approach to overcome these challenges via a digital framework to ensure data availability, data integrity, information connectivity and causality. A digitization prototype on a microservice oriented architecture was created and the insights obtained through a field trial have been presented.

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

The main idea in this research is the utilization of Fuzzy C Means (FCM) method as the determination of patient's nutritional status, which is implemented, in mobile application. Parameters used to cluster nutritional status are height, weight and age. The result of the decision will give 3 clusters on nutritional status is good nutrition, malnutrition and better nutrition. Mobile apps are used as a reminder of the nutritional value or ingredients contained in

the packaging of food products while consuming food. The result of system testing for application of FCM algorithm in this mobile application obtained validation of 80%.

[5] Archana Ajith, VrindaGoel, "Digital Dermatology Skin Disease Detection. Model using Image Processing". 2017.

This paper proposes a skin disease detection method based on image processing techniques. This method is mobile based and hence very accessible even in remote areas and it is completely non-invasive to patient's skin. The patient provides an image of the infected area of the skin as an input to the prototype. Image processing techniques are performed on this image and the detected disease is displayed at the output. The proposed system is highly beneficial in rural areas where access to dermatologists is limited.

[6] Pétavy-Catala C, Fontès V, Gironet N, Hüttenberger B, Lorette G, Vaillant L. Clinical manifestations of the mouth revealing Vitamin B12 deficiency before the onset of anemia. A 67-year-old northern African female presented at the oral surgery service with complaints of a sore mouth and difficulty eating certain types of food. Her medical history revealed hypothyroidism and no history of gastrectomy. She was diagnosed with pernicious anemia in 2014 and is under hydroxocobalamin injection 5000µg/month since then. Dental history indicated extraction of all teeth, and in 2014, the patient was diagnosed with oral lichen planus. There were no contributory oral habits. Intraoral examination revealed a band like erythematous lesion on the palate with two superficial ulcerations, diagnosed as related to her pernicious anemia. The patient was prescribed a mouthwash containing sodium bicarbonate and corticosteroid to reduce inflammation and alleviate pain. A low level laser therapy was also considered to reduce the burning sensations.

III. EXISTING WORK

Neural networks, particularly Convolutional Neural Networks (CNNs), have become a powerful tool in the field of medical image processing, including the detection of vitamin deficiencies. These models are well-suited for analyzing visual symptoms that manifest on the skin, eyes, and other body parts due to deficiencies in essential vitamins like Vitamin A, D, B12, or C. CNNs, due to their ability to

automatically learn hierarchical features from raw image data, have been employed to classify and detect patterns of deficiency-related signs, such as rashes, pigmentation changes, or retinal damage. For example, CNNs have been used to detect signs of Vitamin A deficiency in retinal images, where the deficiency can lead to night blindness or damage to the retina. Similarly, Vitamin D deficiency can be identified by analyzing skin images, where the lack of sunlight exposure can cause visible changes in skin texture and pigmentation.

In addition to basic CNN architectures, deeper and more sophisticated models, such as Deep Convolutional Neural Networks (DCNNs), are increasingly used to improve the accuracy and robustness of these systems. DCNNs, with more layers and complex structures, help extract more abstract features from images, leading to better detection of deficiency symptoms. Another popular technique in this domain is transfer learning, which allows models pre-trained on large datasets like ImageNet to be fine-tuned on medical-specific datasets. This is particularly useful when labeled data for vitamin deficiencies is scarce, as the model can leverage knowledge learned from general image data to recognize vitamin deficiency symptoms.

Segmentation networks, such as U-Net, are also widely used, especially for tasks that involve detecting and isolating specific regions of interest in medical images. For example, U-Net can segment retinal scans to highlight areas showing damage caused by Vitamin A deficiency, which can lead to conditions like macular degeneration or xerophthalmia. Additionally, multi-modal deep learning models, which combine image data with other information such as patient history, blood test results, and lifestyle factors, can enhance diagnostic accuracy. By considering not just the visual signs but also contextual data, these models offer a more comprehensive approach to vitamin deficiency detection.

In some cases, Generative Adversarial Networks (GANs) are employed for image augmentation, generating synthetic images that resemble real deficiency-related symptoms when the available medical images are limited. This helps increase the diversity of training data, improving the model's ability to generalize and learn to recognize various manifestations of deficiencies. Another cutting-edge

approach combines CNNs with Recurrent Neural Networks (RNNs), such as Long Short-Term Memory (LSTM) networks, to track the progression of symptoms over time. This is particularly useful when monitoring the development of skin rashes or retinal damage, offering a more dynamic understanding of how deficiency-related symptoms evolve.

Despite their promising potential, there are challenges associated with neural network-based methods for vitamin deficiency detection. The need for high-quality, labeled datasets is crucial, as the performance of these models heavily depends on the data they are trained on. Additionally, many deep learning models remain opaque, making it difficult for healthcare professionals to interpret the rationale behind a model's predictions, which can limit trust in automated systems. Furthermore, models trained on specific datasets may not generalize well to different populations or environments, making it essential to ensure that training data is diverse and representative.

In conclusion, neural network-based methods have shown significant promise in enhancing the detection and diagnosis of vitamin deficiencies through image analysis. Techniques like CNNs, DCNNs, transfer learning, and segmentation models are advancing the field, enabling faster, more accurate diagnosis, and even providing the possibility of early detection. As these models evolve and improve, they hold the potential to revolutionize how healthcare systems approach the diagnosis of nutrient deficiencies, ultimately leading to better patient outcomes.

DISADVANTAGES

1. **Data Quality and Availability:** Requires large, high-quality, and well-labeled datasets, which are often scarce.
2. **Interpretability:** Neural networks are often "black boxes," making it difficult for healthcare professionals to trust or understand their decisions.
3. **Generalization Issues:** Models may struggle to generalize across diverse populations and settings, leading to biases.
4. **Dependence on High-Resolution Imaging:** Needs high-quality, consistent medical images, which may not always be available.

5. **Computational Resources:** Requires significant computational power for training and deployment, which can be a barrier in resource-limited settings.
6. **Ethical and Privacy Concerns:** Raises issues around the handling and anonymization of sensitive medical data.
7. **Overfitting:** Models may overfit to the training data, leading to poor performance on unseen data.
8. **Regulatory Challenges:** Must undergo rigorous validation and approval processes, which can delay deployment.
9. **Cost of Development:** Developing and maintaining these models can be expensive.
10. **Over-reliance on Automation:** Risk of reducing the role of human expertise in the diagnostic process.

IV. DESIGN METHODOLOGY

PROPOSED SYSTEM

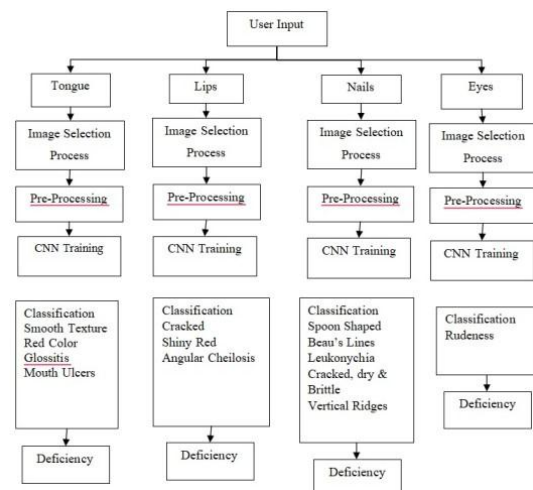


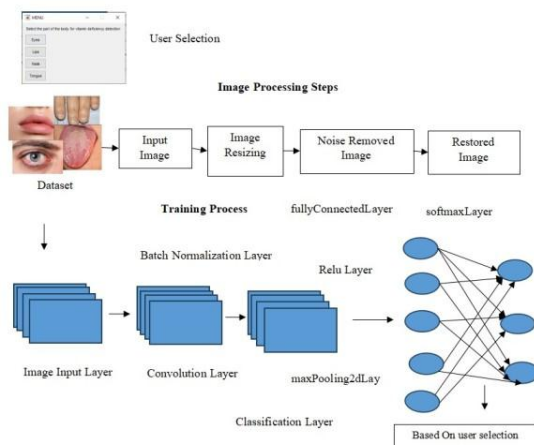
Figure 3: Block Diagram of Proposed System

The process of this project requests the methodology of neural network based image processing for vitamins deficiency detection. First, the target code runs to display the specified body parts as: Tongue, Lips, Nails, or Eyes. The user then selects any of the body parts and chooses a relevant image for analysis. The image is preprocessed by normalizing, resizing, and enhancing so it is ready for input into a Convolutional Neural Network. Afterward, the CNN is trained using a dataset of images that represent different symptoms of vitamin deficiencies along with layer and training options

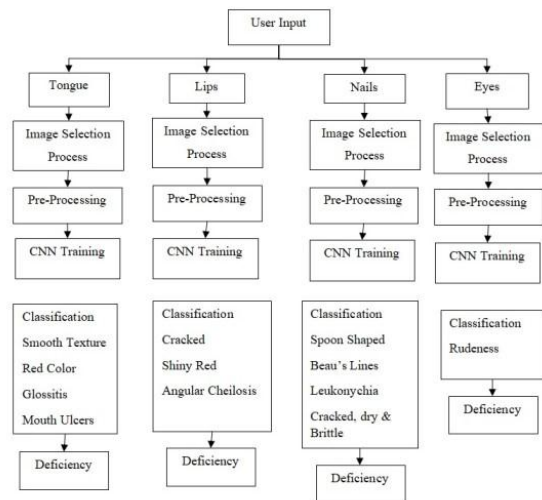
meant to assist in the extraction of complex and detailed analysis. A few examples are if the tongue is selected, the CNN is designed to sort as normal texture: red color, has glossitis, or has an unclear mouth, indicating the classification of vitamin deficiencies. If the user selects the lips, it will sort as examples of cracked lip or shiny red appearance. The CNN model trained diagnoses each of the symptoms as valid from the input image and indicates the presence of vitamin deficiency. This will weigh the deployment of them within a synchronized image processing technique with deep learning techniques, thus greatly supporting effective accuracy and greatly improving automated diagnostics for Vitamin deficiencies.

Menu Dialog Box:

Menu Dialog Box basically is the element of an interface that influences the creation of an interactive menu through which selections are made according to some predefined sources for that particular element developed in MATLAB. It is especially useful in cases where multiple selections have to be made in a program like selecting a file, setting its parameters, or choosing between many modes of operation. The creation of this dialog box is done using the 'menu' function in MATLAB, which provides a pop-up window containing buttons according to the provided options. Each button serves as an action or a choice the user is able to select and, on selecting it, the event will trigger action.



EXTENSION

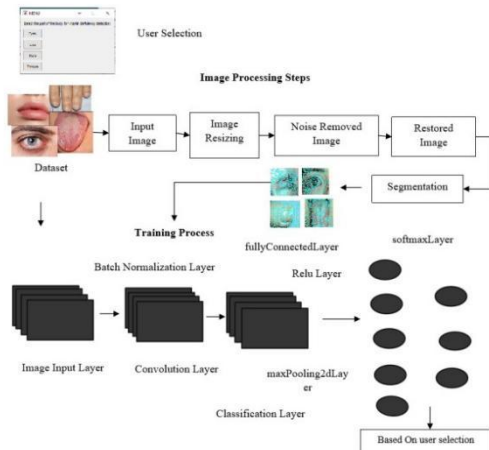


The procedure by which a neural network-based image processing system detects vitamin deficiency encompasses various stages. First, the body part, either eye, lip, tongue, or nails, is chosen by the user through a menu dialog box, which in fact directs the process to the specific area of interest. When an image of the targeted body part has been uploaded, a number of preprocessing steps are done, including resizing to some fixed dimensions and taking care of noise for improved clarity. The image is then restored to its improved form for further assessment. Superpixel boundaries are overlaid on the image to allow appropriate segmentation and prominent reporting of important features. Another hybrid CNN is employed for feature extraction, with the role of combining both deep learning and segmentation techniques for the presented image. The CNN with its deep learning should be trained on some amount of varying data sets in such a way that it is able to classify them based on vitamin deficiency caused due to specific features from the selected body part. Once classified, the deficiency can be displayed in the command window to provide immediate feedback. The code would work for high accuracy, taking all the image preprocessing, smart segmentation, and a strong hybrid CNN model that results in a really reliable and competent resource for the early detection of vitamin deficiencies.

Menu Dialog Box:

A menu dialog in MATLAB is a user interface component that allows developers to create a very simple actively displayed menu that appears on the user's screen for making selections from a list of predefined options. This dialogue is used when a program must allow the user several choices, typical

but by no means limited to selecting a file, setting some input parameters, or selection between different modes of operation. The menu dialog box is created in MATLAB using the `menu` function, which will open up a window and present options listed in buttons for the user to select from.



ADVANTAGES

Improved Accuracy: Neural networks can analyze complex patterns in medical images, leading to more accurate detection of vitamin deficiencies compared to traditional methods.

Automated Diagnosis: These methods can automate the detection process, reducing the workload for healthcare professionals and providing faster diagnoses.

Early Detection: AI-based systems can identify early signs of vitamin deficiencies that may be missed by the human eye, allowing for earlier intervention and treatment.

Scalability: Once trained, neural network models can be deployed across large populations, enabling widespread screening for vitamin deficiencies in various settings.

Integration of Multi-Modal Data: These systems can integrate multiple data sources, such as medical images, patient history, and lab results, providing a more comprehensive diagnosis.

Consistency: Neural networks provide consistent results, reducing human error and variability in diagnosis, which can improve overall healthcare quality.

Adaptability: Models can be retrained and fine-tuned with new data, improving their performance over time and allowing them to stay up-to-date with emerging trends in vitamin deficiency.

Cost-Effectiveness: In the long term, neural network-based systems can reduce healthcare costs

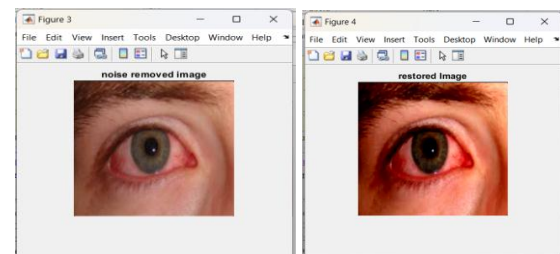
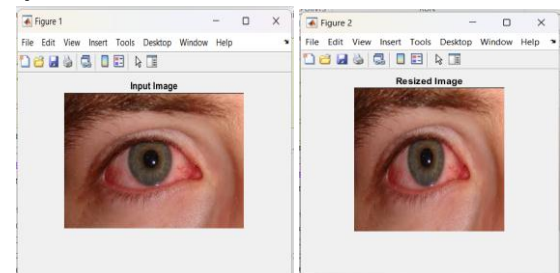
by streamlining diagnosis and enabling remote or large-scale screening.

Non-Invasive: These methods often rely on non-invasive techniques, such as analyzing images of the skin or retina, which is less intrusive than other diagnostic methods.

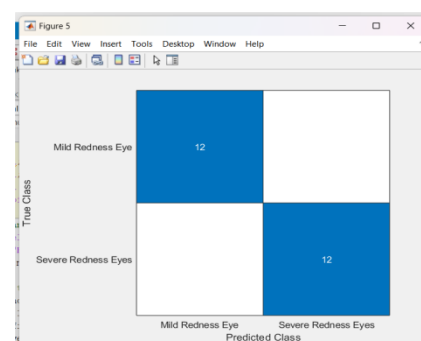
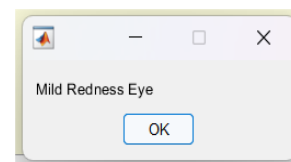
Potential for Global Reach: AI-powered detection tools can be used in under-resourced or remote areas, providing access to advanced diagnostic capabilities where medical expertise and equipment may be limited.

V. RESULTS

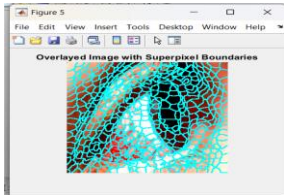
Eye Classification



```
Command Window
The classified eye output is : 88.333333
Deficiency for Mild Redness Eyes: General | Vitamin A | Vitamin B2 | Vitamin B6
Take foods like Eggs, Carrots, spinach, Nuts, seeds, Avocado, Meat and Fish
Take medicine of Retinyl palmitate, B-complex supplements
fx >>
```

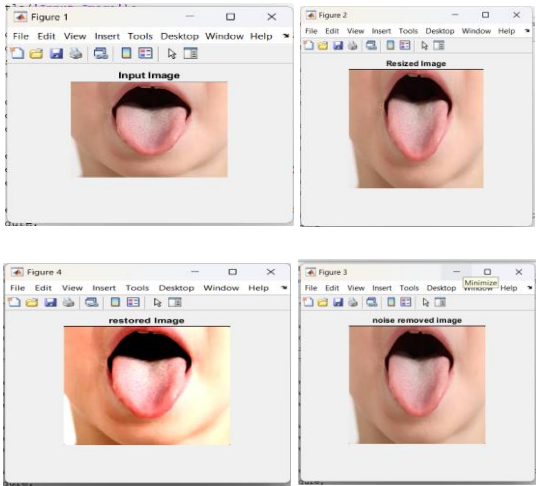


Extension

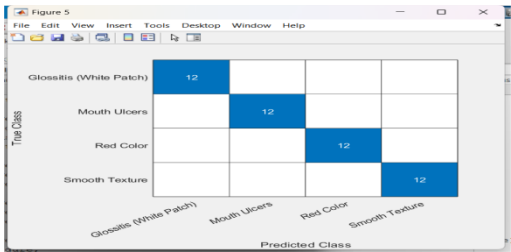
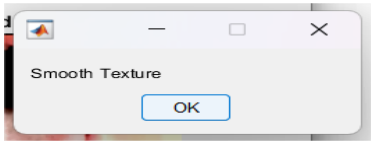


```
Command Window
The classified eye output is : 97.960000
Deficiency for Severe Redness Eyes: General | Vitamin A | Vitamin B2 | Vitamin B6
fx >>
```

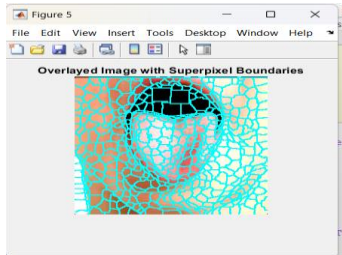
Tongue Classification



```
Command Window
The classified TONGUE output is : 80.833333
Deficiency for Smooth Texture : Vitamin B6 | Vitamin B12| Iron
Take foods like Bananas,potatoes,egg,Meat,spinach,lentils,fertilized cereals
Take medicines of Pyridoxine tablets,Iron supplements(Ferrous sulfate or Ferrous gluconate)
fx >>
```

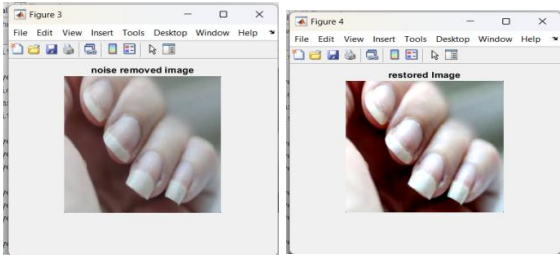
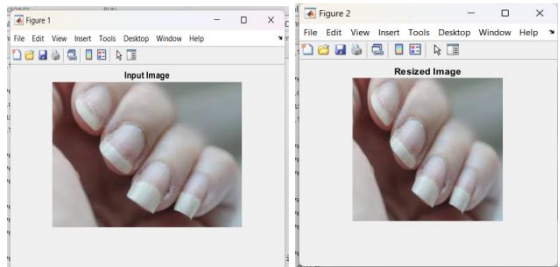


Extension

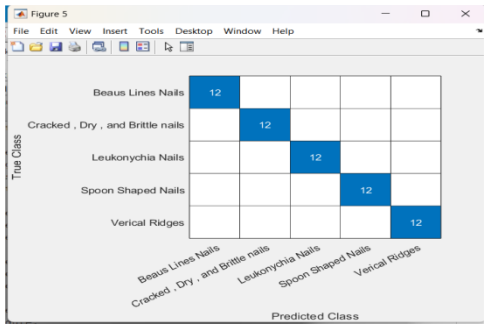


```
Command Window
The classified TONGUE output is : 98.956667
Deficiency for Smooth Texture : Vitamin B6 | Vitamin B12| Iron
fx >>
```

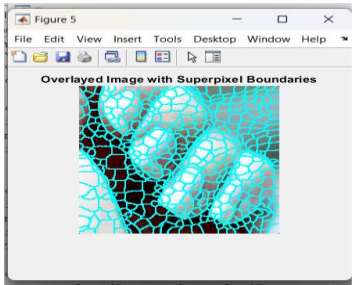
Nail Classification



```
Command Window
The classified NAILS output is : 83.750000
Deficiency for Cracked , Dry , and Brittle nails: Vitamin A | Vitamin C | Vitamin B7| Vitamin B9 | Vitamin
Take foods like Carrots,Citrus fruits,Eggs,Leafy greens,Meat,Strawberries
Take medicine of Biotin tablets,Folic acid tablets,Vitamin B12 tablets or injections
fx >>
```

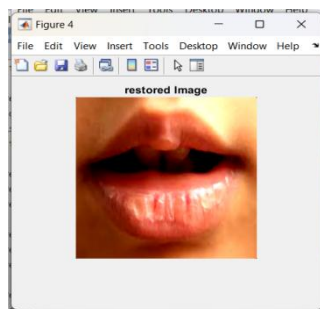
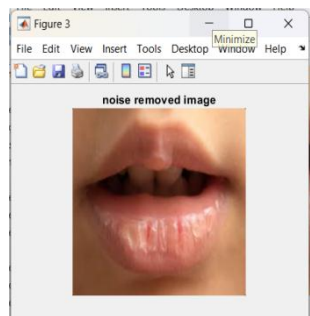
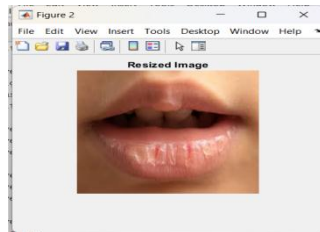
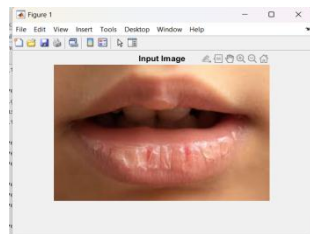


Extension

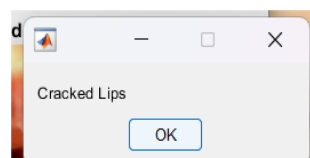


```
Command Window
The classified NAILS output is : 98.220000
Deficiency for Cracked Lips: Vitamin B1| Vitamin B2| Vitamin B3 | Vitamin B6
fx >>
```

Lips Classification

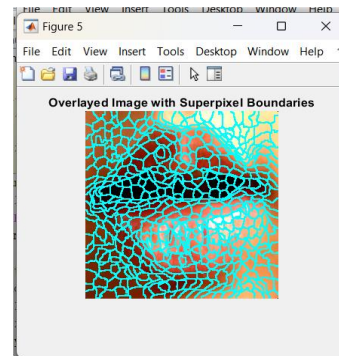


```
Command Window
The classified Lips output is : 86.805556
Deficiency for Cracked Lips: Vitamin B1| Vitamin B2| Vitamin B3 | Vitamin B6
Take foods like Chicken,fish,dairy (milk, yogurt),Eggs,Bananas, sunflower seeds
Take medicine of Wiscin tablets,Pyridoxine tablets
fx >>
```



	Angular Cheilosis Lips	Cracked Lips	Shiny Red Lips
Angular Cheilosis Lips	12		
Cracked Lips		12	
Shiny Red Lips			12

Extension



```
Command Window
The classified Lips output is : 99.220000
Deficiency for Cracked Lips: Vitamin B1| Vitamin B2| Vitamin B3 | Vitamin B6
fx >>
```

CONCLUSION

In conclusion, this project successfully demonstrates the application of Convolutional Neural Networks (CNNs) for the detection of vitamin deficiencies through advanced image processing techniques. By allowing users to select images of specific body parts—such as the tongue, lips, nails, or eyes—the system enables precise identification of deficiency indicators. The process involves enhancing image quality through preprocessing and training the CNN to recognize symptoms associated with various deficiencies. For example, the CNN can identify smooth or red tongues and cracked or shiny lips, each corresponding to potential vitamin deficiencies. The system's capability to analyze and classify these symptoms ensures accurate and automated detection, facilitating early diagnosis and intervention. This approach highlights the significant role of deep learning in medical image analysis, offering a valuable tool for preventive healthcare. By integrating CNNs into the diagnostic process, the project illustrates the potential for AI-driven solutions to improve the accuracy and efficiency of detecting vitamin deficiencies, thereby enhancing overall health management.

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