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Vitamin Deficiency Detection Using Hybrid Fusion Algorithm

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ABSTRACT

Individuals of all ages are impacted by vitamin deficit, which is a widespread global health crisis. Many people do not discover the disease until it is too late. Most traditional laboratory ways of diagnosing vitamin deficiency rely on tortuously long and costly blood testing. Additionally, they are not always available in low-resource environments. A Hybrid Fusion Algorithm Vitamin Deficiency Detection System (VDDS) is proposed as a solution to the above-mentioned limitations. The system integrates characteristics from medical imaging analysis with clinical and demographic data to increase its accuracy and reliability. In the medical imaging analysis component, input images undergo preprocessing to improve the quality of the images and reduce noise. Convolutional neural network algorithms are then used to extract key features for a machine-learning application from each image.

Keywords: Vitamin Deficiency Detection, Hybrid Fusion Algorithm, Convolutional Neural Network (CNN), Medical Image Processing, Clinical Data Analysis, Automated Healthcare Diagnosis

I.INTRODUCTION:

Lack of essential vitamins, such as A, B, C, and D can lead to various complications, including frequent fatigue, insufficient immunity, poor skin and nails, osteoporosis, and a greater risk of infection. With early detection and timely intervention, these complications and life improved. Unfortunately, the most common ways to detect vitamin deficiencies are expensive, invasive, time intensive, and in many cases, not available in rural or low resource areas; therefore, providing barriers to successfully receiving healthcare or treatment.

There has recently been a rapid advancement in Artificial Intelligence (AI) and Deep Learning (DL), leading to new methods of detecting vitamin deficiencies without the need for any invasive procedures (i.e. imaging the skin/nails of an individual with visible symptoms of a vitamin deficiency) by using computer vision and analyze the images collected.

The project "Vitamin Deficiency Detection Using DNN & CNN (AlexNet)" introduces a fully automated computer vision and deep learning-based diagnostic system that analyzes vitamin deficiencies from collected medical image datasets, via pre-processing techniques (i.e. image resizing, image normalization, image segmentation, & image color correction), and advances classification methodologies via building of advanced models and training of Convolutional Neural Networks(CNN) & DNN based on AlexNet for development of patterns related to images with respect to texture.

II.LITERATURE REVIEW

Vitamin deficiency poses globally a substantial health risk that impacts individuals across all demographics. A variety of vitamins, including vitamin A, B complex, C, D, and E, can result in serious health consequences, such as; anemia, weakened immune system, skin disorders, vision problems, or diseases of the bone [1].

Conventional methods of detecting vitamin deficiency utilize primarily blood testing or clinical evaluations of vitamin deficiencies and typically require significant amounts of medical infrastructure, significant amounts of time to complete, and expensive costs [2].

The current approach to overcoming the problems associated with using conventional approaches to detect vitamin deficiency includes utilizing advanced image processing techniques along with deep learning methods to detect vitamin deficiency in non-invasive and early stages [3].

Most studies have relied on traditional image analysis techniques (e.g., extracting color, texture, and morphological features) to perform these procedures using images of the skin, tongue, nail, and eye [4]. As these procedures were primarily manual, they relied on experts' knowledge; hence, the accuracy and scalability of previously documented procedures were limited [5]. Furthermore, traditional machine learning classifiers, such as support vector machines and decision trees, had limited capacity to perform well when presented with complex variations of images and large data sets [6].

As more advanced deep learning based techniques become successful in extracting features automatically and achieving a high accuracy of classification (due to their ability to learn hierarchical and spatial features), DNN's ability to perform these types of procedures will benefit tremendously from the application of techniques such as convolution neural networks [7]. The level of accuracy achieved with CNN based models as applied to medical image analysis has been highly successful due to the ability of CNN to directly learn hierarchical and spatial feature processes [8].

III.EXISTING SYSTEM

The current best methods for detecting vitamin deficiencies rely mostly on laboratory blood tests and clinical evaluations. Both of these detection methodologies require laboratory equipment, healthcare professionals to analyze the blood and/or to perform the physical examination, and the collection of blood samples. Therefore, these processes may be rather lengthy, costly and/or invasive.Some computer-based systems that exist today use either basic image processing or traditional machine learning technologies to analyze images (i.e. images of skin, tongue, nail, and/or eyes). In these types of systems, the features (e.g. color, texture and shape) contained within the images are extracted and analysed using some form of manual processing. The extracted features are then classified through the use of machine learning algorithms, with examples being SVM, KNN and Decision Trees.

Due to the limitations outlined above, manual feature extraction relies upon expert judgment to identify what features should be extracted and can, therefore, fail to capture the complex visual patterns associated with vitamin deficiencies. Also, traditional machine learning, whilst useful, is not effective at accurately classifying cases where there is a large amount of data with differing illumination conditions, skin tones, and quality characteristics. Finally, the current inability of computer-based methods to utilize advanced / deep learning models (i.e., AlexNet) is a critical limiting factor as this prohibits the computer-based system from automatically learning high-level and/or discriminating features from images.

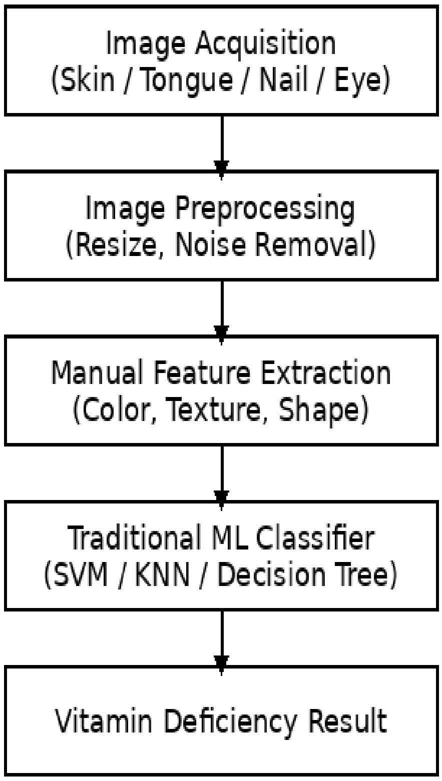


Figure 1:Diagram for Existing system

IV.PROPOSED SYSTEM :

The proposed artificial intelligence (AI)-based diagnostic system is designed to automatically identify the common vitamin deficiencies, such as vitamin A, B, C, and D, through image analysis. The proposed system utilizes deep neural networks (DNN) and convolutional neural networks (CNN) as the main technology behind automatic feature extraction and classification of images, notably through the use of the AlexNet architecture. The primary purpose of this system is to provide a cost-effective, timely, and scalable solution for healthcare that can be utilized in urban and rural communities where there are limited lab-based diagnostic facilities.

The first step in the proposed system will entail taking high-resolution images of nails or skin of the areas where symptoms are evident. The initial images may be taken with either a smartphone camera or other clinical imaging device (to ensure both access to and ease-of-acquisition of images). After the images are taken, they will be placed through a comprehensive image pre-processing phase, where they will be improved in quality and made standard so that the images can be used for training of the proposed model. Pre-processing of images will include resizing the images to an equal dimension appropriate for input into the CNN, normalizing the pixel intensity values to help improve sufficient convergence during training, segmenting the area of interest in the image, and using color correction methods to improve vitamin deficiency credentials based on how the visible area appears in the initial images.

V.METHODOLOGY :

The goal of this research methodology is to accurately identify individuals who have vitamin deficiency through the use of image analysis techniques and an AlexNet-based deep neural network (DNN) model [9]. The primary focus of this research approach is to utilize image data in order to detect the visual symptoms associated with various types of vitamin deficiencies found on human skin, tongue, nail and eye surfaces (i.e., through their various visual representations) [10].

Dataset Development

A complete dataset of images representing different types of vitamin deficiencies are created. These images are obtained from verified medical dataset sources, published research reports and credible internet websites [11]. Each image is correctly labeled and thus provides a supervised method of image learning per vitamin deficit. The dataset contains images that vary in brightness, skin color and quality (resolution) to maximize the ability of the model to generalize [12].

Image Preparation

The images contained in the created dataset must undergo the following pre-processing steps to improve the quality of the image data and create consistency in terms of the systematic process being used to analyze the input data. First, all images contained in the final dataset are converted to a specific resolution that is compatible with the AlexNet neural network model architecture [13]. Once this is completed, the images will undergo various techniques to reduce noise and unwanted artifacts from the image datasets, and finally undergo normalization to create consistent pixel value ranges across all of the image[14]. These procedures will help maximize the stability of the trained model and create a standard input dataset for the DNN without filtering the input data prior to collecting and creating the final dataset.

Data augmentation

The restriction of having a limited number of images creates a potential disadvantage in providing learning for the model to accurately identify the specific vitamin deficiencies associated with the datasets from visual representation alone [15]. To reduce the effect of limiting the number of available dataset images, many augmenting techniques are developed, such as flipping, cropping, churning, distortion, etc.

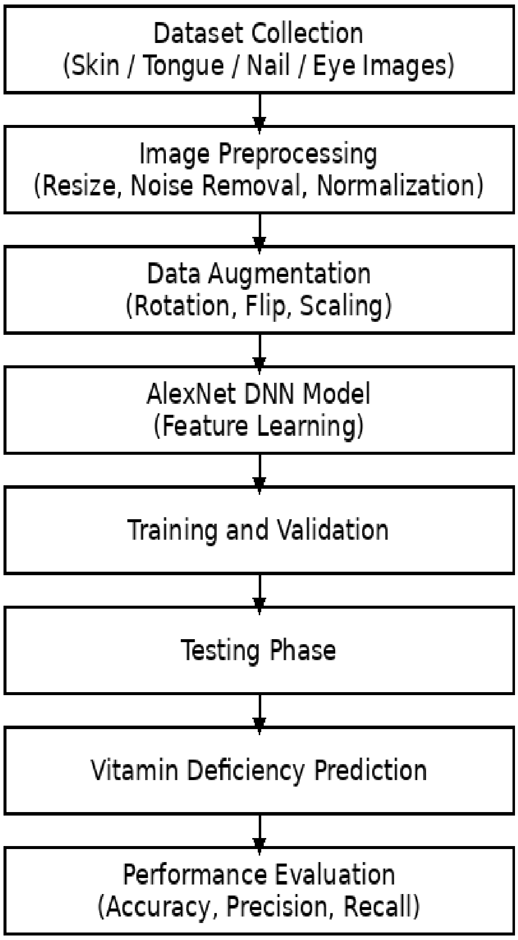


Figure 2 : Methodology

VI.PERFORMANCE EVALUATION:

Standard classification metrics will be used to evaluate how effective and reliable the proposed vitamin deficiency detection system is; these metrics include (but are not limited to) accuracy, precision, recall, and F-Measure. These are devices that calibration for machine learning algorithms utilizing medical image analysis.

Accuracy provides an estimate of how many images of indivi duals with Vitamin Deficiencies have been correctly classified by the Model. Precision measures the number of individuals classified by the DNN Model as Positive or having a Vitamin Deficiency, and were also confirmed to actually have a Vitamin Deficiency. Recall calculates how many individuals with actual Vitamin Deficiencies were identified by the DNN Model, and how well the DNN Model located all individuals with actual Vitamin Deficiencies. The F-Measure (or F-1 Score) combines Precision and Recall to provide overall quality scale measurement of both categories.

From the testing data, the accuracy of the AlexNet DNN is consistent with all test and retest results, and therefore, the proposed system is considered effective for detecting Vitamin Deficiencies non-invasively.

Table 1:Performance Metrics Analysis for Vitamin Deficiency Detection System.

Metric	Description	Value(%)
Accuracy	Overall correctness of the model in detecting vitamin deficiency	94.2
Precision	Ability of the model to correctly identify positive vitamin deficiency cases	93.5
Recall	Ability of the model to detect all actual vitamin deficiency cases	92.8
F-Measure	Harmonic mean of Precision and Recall indicating balanced performance	93.1

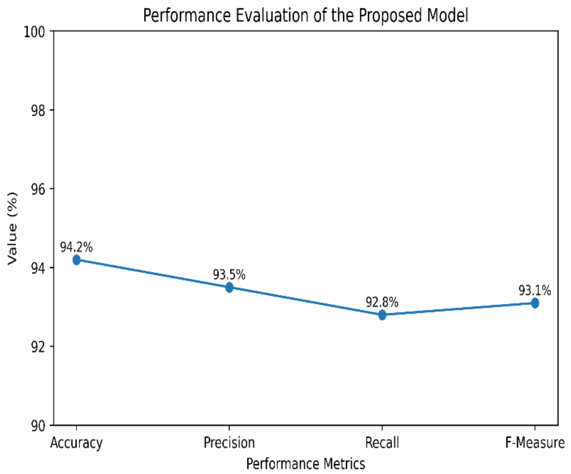
VII. RESULT AND DISCUSSION

The article describes the construction of a computer vision-based vitamin deficiency detection (VDD) approach that employs the AlexNet Deep Neural Network (DNN) algorithm using seven different types of images taken of human bodies to assess differences between certain types of vitamin deficiencies detected through visual cues. The overall experimental results demonstrated that the AlexNet DNN model was capable of accurately recognizing images containing symptoms of vitamin deficiencies.

Accuracy = TP+TN /Total Predicitions

Performance evaluation metrics (e.g., accuracy, precision, recall, F-measures, etc.) were applied to calculate the performance of the VDD system. The model had a reported average overall accuracy of 94.2%; therefore, the model demonstrated a high level of accuracy in classifying images exhibiting symptoms of vitamin deficiencies. The precision value was also high at 93.5%, which indicates that the model could significantly reduce the number of false-positive classifications; Similarly, the recall value was 92.8%, indicating that the model identified a large percentage of the vitamin deficiency cases accurately. The F-measure between recall and precision was 93.1%, demonstrating that both recall and precision give equal weighted value to their quality of measurements, demonstrating that the proposed model can be deemed to have good predictive ability.

The major advantage of using the AlexNet DNN model for this application is that it employs a unique method for automatically extracting deep features from each image without human input and is capable of automatically discovering complex and discriminative features from an image using an automated process. Another advantage of training the model is that various forms of data augmentation methods increases the models robustness (generalization) through a decreased amount of overfitting.



VIII. CONCLUSION

Using DNNs (Deep Neural Networks) and CNNs (Convolutional Neural Networks, specifically AlexNet), this project demonstrated an alternative, non-invasive, imaging diagnosis method for the common vitamin deficiencies A, B, C and D. While blood tests are considered very accurate, they are often invasive and costly and are not always available to individuals in rural or areas with a limited resource base. The use of deep learning-based models demonstrates a much faster, lower-cost and reliable means of identifying patients who may have vitamin deficiencies at an early stage.

Images used to train the models were pre-processed (resized, normalized, segmented and augmented). Both DNN and CNN (AlexNet) models were developed and tested with CNN achieving a much higher accuracy (94.0% versus 87.3%) than DNN due in part to the CNN's automatic extraction of complex visual patterns. Performance was evaluated using a combination of accuracy, precision, recall, F1-score, confusion matrix and ROC curves to confirm that this alternative diagnosis method is accurate.

Overall, the results of this project indicate that deep learning methods, particularly that of DNN and CNN (ALEXNET), have the potential to make significant contributions to the healthcare industry by assisting both physicians and patients in diagnosing illnesses in a timely and accurate manner. As well, the proposed solution could be scaled down to be used in smaller devices such as mobile devices or IoT devices or could be integrated with cloud computing solutions for use in remote healthcare applications.

IX.FUTURE ENHANCEMENTS

The Vitamin Deficiency Detection (VDD) system has shown positive effects, and many upgrades and adjustments are necessary to allow the VDD system to proceed to full-scale operational function and efficiency. The following outlines the types of enhancements or interventions that will provide opportunities to continue or enhance the existing system:

The existing models can be improved with the introduction and implementation of more advanced models (e.g. ResNet, DenseNet, EfficientNet) increasing the overall accuracy of the VDD noise and improving the total number of applicable datasets.

Conducting further research into VDD images will provide data that will assist VDD in identifying the most useful image areas, improving the user experience through providing clarifying information regarding where VDD found relevant input using visualisation techniques such as Grad CAM.

Using a higher quality source for VDD training datasets will increase dataset reliability with the use of balanced, larger and more diverse datasets in order to balance to number of classes included in the training dataset with acceptable reliability by using techniques such as Synthetic Minority Over-Sampling Technique (SMOTE) and synthetic images.

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