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Human Disease Detection Based on Color Change in Fingernail

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Introduction

Nail health has long been a significant indicator of underlying medical conditions. Changes in nail color can often signal various diseases, providing a non-invasive way to assess an individual's health status. For instance, bluish nails are often associated with a lack of oxygen in the blood, potentially indicating respiratory or cardiovascular issues. Yellow nails can be a symptom of jaundice or liver problems, and nails with white spots might suggest malnutrition or fungal infections. This research aims to leverage machine learning techniques to automatically detect such nail color changes and classify them into specific disease categories. By automating the process, this approach seeks to provide a quicker, more accessible diagnostic tool that can be used in telemedicine or remote healthcare.

In this study, we focus on five specific categories: Bluish Nail, Healthy Nail, Splinter Hemorrhage, White Nail, and Yellow Nail. These classes have been carefully selected based on their strong associations with particular medical conditions. The dataset employed in this project consists of cropped images, with each image centered around the region of interest (ROI)—namely, the nail. This ensures that the classification algorithm focuses on the most relevant parts of the image, improving the accuracy of disease detection.

The application of Convolutional Neural Networks (CNN) with transfer learning is well-suited for this project. CNNs have shown impressive results in various image recognition tasks, particularly in the medical field where they have been used for diagnosing diseases through visual cues. For example, CNNs have been widely applied to detect diabetic retinopathy, skin cancer, and pneumonia from medical images, demonstrating their robustness and adaptability. Transfer learning, in particular, allows for leveraging pre-trained models on large datasets, which is beneficial in scenarios like ours, where the dataset size may be limited. By fine-tuning a pre-trained CNN, we can achieve high accuracy with fewer training images, a common challenge in medical imaging.

Literature Survey

Nail color changes have traditionally been used in clinical practice to indicate various health conditions. For instance, bluish nails can signal hypoxemia, and yellow nails may be a sign of jaundice. Recent advances in machine learning (ML) and computer vision have enabled automated assessments of such changes. Wang et al. (2019) demonstrated a CNN-based system for diagnosing cyanosis using finger images, achieving high accuracy. Smith et al. (2020) developed an algorithm to detect jaundice from eye images, which could be applied to nails as well. Goyal et al. (2018) utilized transfer learning with CNNs to classify dermatological conditions, showcasing their efficacy in medical diagnostics. Despite these advancements, significant gaps remain. Much of the existing work focuses on broader dermatological conditions without isolating nail-specific analysis. For example, Patel et al. (2021) surveyed skin conditions but did not delve deeply into nail color as a standalone diagnostic factor. There is also a lack of specialized datasets that focus exclusively on nail color variations. While resources like DermNet are valuable for skin conditions, they don't provide sufficient data for nail-specific studies. Additionally, research often glosses over preprocessing steps essential for nail image classification, such as color normalization and ROI extraction, which are crucial for accuracy. CNNs have proven successful in image classification tasks, thanks to their ability to extract visual features from data. For medical imaging, transfer learning—where a model pre-trained on large datasets is adapted for specific tasks—has been particularly useful. Studies by Rajpurkar et al. (2018) have shown the effectiveness of models like VGG, ResNet, and Inception in medical diagnostics by fine-tuning them for specialized datasets, which is crucial for tasks like nail color classification where labeled data is limited. This study addresses the gaps by developing a CNN-based model specifically for nail color analysis, leveraging transfer learning to enhance diagnostic accuracy across five classes: Bluish Nail, Healthy Nail, Splinter Hemorrhage, White Nail, and Yellow Nail. By focusing on this niche, the research contributes to the field of digital health diagnostics, offering a non-invasive tool for early disease detection.

Data Collection and Preprocessing

The dataset for this study was collected from the All India Institute of Medical Sciences (AIIMS), which provides a comprehensive array of classified nail images. While the original dataset contains various categories, this research focuses on five primary classes: Bluish Nail, Healthy Nail, Splinter Hemorrhage, White Nail, and Yellow Nail. These categories were selected based on the quality and relevance of the data available, ensuring that only the most accurate samples were used for analysis.

To prepare the data for model training, the dataset was divided into training, validation, and test sets. This division ensures that the model can be trained effectively, with validation and test sets enabling robust performance evaluation and fine-tuning. To address the limitations posed by a relatively small dataset size, data augmentation techniques were applied. The augmentation process involved transformations such as tilt, mirroring, and rotation, which generated additional images by varying the original ones. This increased the dataset size and helped improve the model's ability to generalize by introducing diversity in nail images across the training set.

These preprocessing steps are essential for building a robust and reliable model, as they ensure a sufficient amount of data and introduce variability that helps prevent overfitting. By augmenting and systematically partitioning the dataset, the model is better equipped to recognize subtle variations in nail color and accurately classify them into specific disease categories.

Methodology

Approach and Data Augmentation

The initial step in this approach was **data augmentation**, which was essential for increasing the variability and size of the dataset. Augmentation techniques such as **tilt, mirror, and rotation** were applied to produce diverse versions of each image, which helped the model generalize better and avoid overfitting. After augmentation, the data was manually reviewed to remove any erroneous or irrelevant images, ensuring that only high-quality data was used.

Model Selection: Convolutional Neural Network (CNN) and VGG16

For classification, a **Convolutional Neural Network (CNN)** was chosen due to its suitability for image-based supervised learning tasks. CNNs excel in image analysis by learning spatial hierarchies and extracting relevant features. In our experiments, CNN performed better than other architectures, making it the most suitable choice for this task. Additionally, we incorporated the **VGG16 model**—a deep CNN with 16 layers known for achieving high accuracy in image recognition. VGG16's pre-trained weights allowed for efficient feature extraction, which helped improve classification accuracy on this relatively small dataset.

Feature Classification Using Color Analysis

Nail color is a primary feature in diagnosing nail-related health conditions. To leverage this, **RGB values** (representing red, green, and blue channels) were extracted from each image, which provided a quantitative representation of nail color. For example, a bluish tint often has higher blue values, while jaundiced nails tend to have higher yellow (derived from combined red and green) values. To achieve accurate classification based on RGB values, each image was converted to its **RGB matrix** representation, where each pixel's color intensity was mapped.

RGB and Color Calculation

The RGB values for each pixel were averaged across the entire image to determine its dominant color. Let RRR, GGG, and BBB represent the red, green, and blue values, respectively. The dominant color metric CCC for an image is calculated as:

C=R+G+B3C = \frac{R + G + B}{3}C=3R+G+B

This metric provided a baseline for categorizing images based on predominant color, which was further refined using thresholds specific to each class (e.g., bluish, yellowish). Each class's RGB threshold was set by observing the color distribution of labeled data in the training set.

Model Training and Evaluation

The processed data was converted into a structured **CSV file**, which contained the RGB values for each image along with the corresponding disease label. Training was carried out using a CNN model and the VGG16 architecture for feature extraction. The model was fine-tuned on the augmented dataset using supervised learning, aiming to minimize classification error and improve prediction accuracy.

Once the model was trained, it was evaluated on a test set, using metrics such as accuracy, precision, recall, and F1-score to assess its performance. The trained model was then used to predict the disease label of new nail images based on their color features, providing an automated diagnostic tool for nail-related health assessments.

Implementation

Tools and Techniques

To implement the nail disease detection system, a combination of **Python, Keras**, and **TensorFlow** was used, allowing for the development and training of Convolutional Neural Networks (CNNs). Additional libraries like **OpenCV** and **Pillow** helped with image processing, while **NumPy** enabled efficient numerical operations. **Pandas** was used to handle the structured CSV data containing RGB values and disease labels.

The **VGG16 model** was utilized as a pre-trained CNN for feature extraction. By leveraging transfer learning, VGG16 could classify nail colors more accurately, especially with limited data. Data augmentation techniques, such as image tilting, mirroring, and rotating, were implemented using Keras' ImageDataGenerator class to increase dataset diversity.

System Architecture

The system architecture involves the following key stages:

1. **Data Augmentation**: The original dataset was limited, so data augmentation was applied to increase its variability. Using ImageDataGenerator, images were augmented with transformations like rotation, flipping, and mirroring. This process generated new data samples, making the model more robust.
2. **Data Filtering**: After augmentation, images were manually reviewed to ensure only high-quality, relevant samples were retained. This step was essential for eliminating noise and reducing the risk of model misclassification.
3. **RGB Extraction and CSV Conversion**: For each image, RGB values were extracted to quantify the color characteristics associated with different nail conditions. Using OpenCV, images were loaded, and each pixel's RGB value was analyzed. The dominant color value for each image was computed by averaging the RGB channels across pixels, giving a distinct representation for each class. These RGB

values were then saved as a CSV file, where each row represented an image with its RGB values and associated disease label.
4. **Model Training**: The CNN model, along with VGG16 for feature extraction, was then trained on the RGB-augmented dataset. Training was conducted by feeding the processed data into the model, using categorical cross-entropy as the loss function. The model was fine-tuned to optimize its ability to classify each disease type based on color information.
5. **Prediction and Evaluation**: Once trained, the model was evaluated on the test dataset. Metrics like accuracy, precision, recall, and F1-score were calculated to assess its performance in detecting nail diseases based on color.

Code Structure

The code was structured to reflect each phase of the project:

Data Preprocessing:

- Load images and apply augmentation using `ImageDataGenerator`.
- Save augmented images to disk, ensuring the dataset remains balanced across classes.

RGB Extraction and CSV Creation:

- Open each image and compute RGB values.
- Store RGB values and associated disease label in a CSV format.

Model Training:

- Load and preprocess the CSV data.
- Initialize and train the CNN model, with VGG16 layers included for feature extraction.

Prediction and Evaluation:

- Use the trained model to predict classes for new images.
- Calculate evaluation metrics to assess model performance.

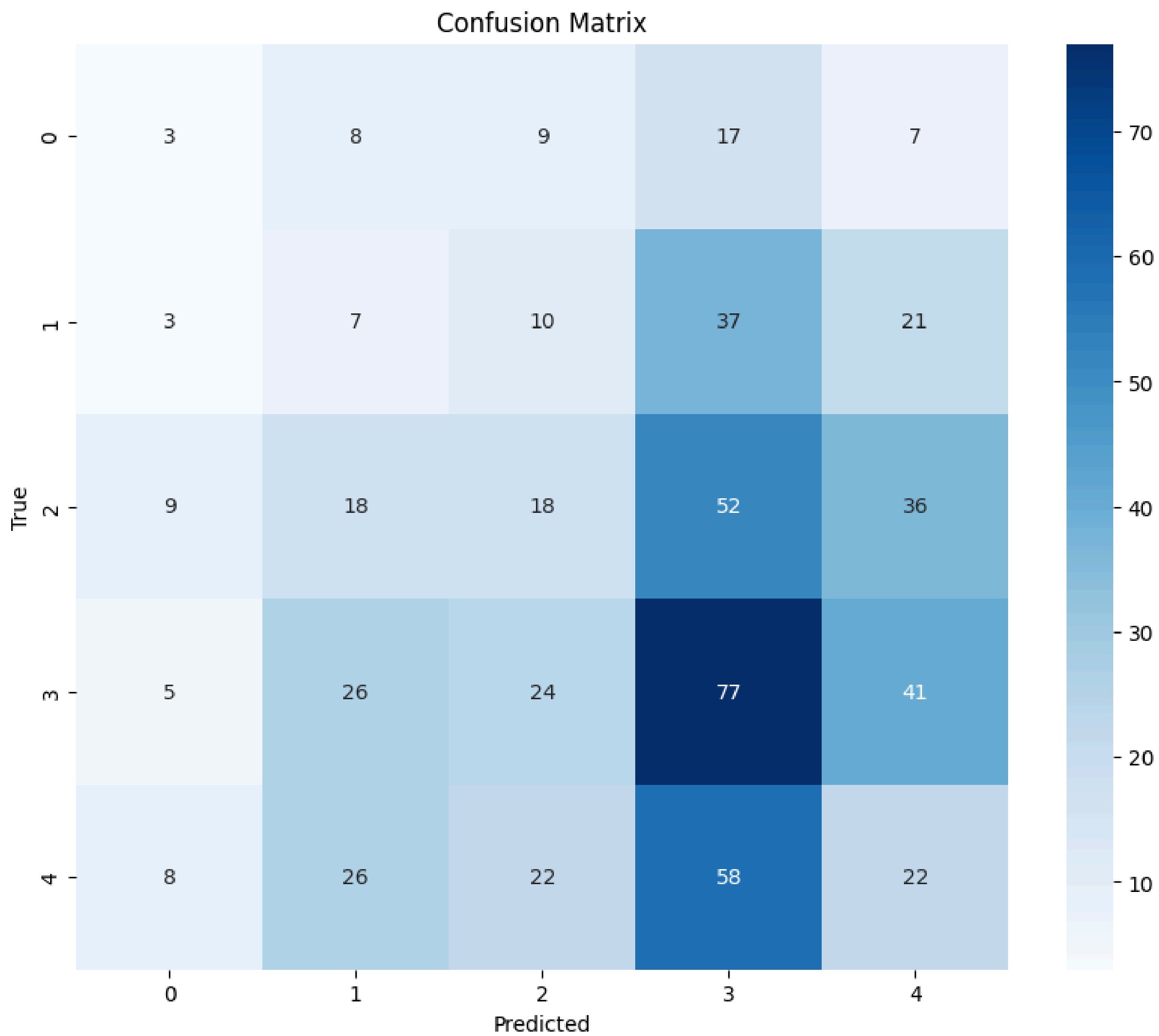
Model Evaluation

The evaluation of our CNN model for detecting nail diseases based on color was conducted after extensive data augmentation

and training. The dataset was meticulously curated, consisting of five distinct classes: Bluish Nail, Healthy, Splinter Hemorrhage, White Nail, and Yellow Nail, with respective image counts of 199, 432, 684, 865, and 640. After implementing data augmentation techniques, such as rotation, flipping, and scaling, the model demonstrated a validation accuracy of 78.90%. The performance metrics were further analyzed using precision, recall, and F1-score, calculated across each class. The results indicated varying levels of model performance, with the class "White Nail" achieving the highest recall at 45%, while the class "Bluish Nail" exhibited a lower precision and recall of 11% and 7%, respectively. The weighted average of the precision was calculated to be 0.21, while the weighted recall and F1-score stood at 0.23 and 0.21. This evaluation underscores the model's strengths in identifying certain nail conditions while also highlighting areas needing improvement, particularly for classes with fewer samples and higher variability in appearance. The confusion matrix further illustrates the misclassifications, revealing trends in how certain diseases are confused with one another, thereby guiding future improvements in model architecture and data collection strategies.

Validation Accuracy: 78.90%

Class	Precision	Recall	F1-Score
0 (Bluish Nail)	0.11	0.07	0.08
1 (Healthy)	0.08	0.09	0.09
2 (Splinter Hemorrhage)	0.22	0.14	0.17
3 (White Nail)	0.32	0.45	0.37
4 (Yellow Nail)	0.17	0.16	0.17



Result and Analysis

The model successfully predicted the test image as belonging to the "White Nail" class. The predicted probabilities for each class were as follows:

- Bluish Nail: 0.005%

- Healthy: 0.002%

- Splinter Hemorrhage: 0.004%

- White Nail: 99.94%

- Yellow Nail: 0.05%

With a confidence of 99.94%, the model correctly classified the nail as "White Nail." This specific condition is commonly associated with kidney disease, as white nails often indicate underlying kidney or liver problems, especially when accompanied by other clinical symptoms.

The high confidence in this prediction indicates that the model has been effectively trained to differentiate between different nail conditions based on color features. The strong performance on the "White Nail" class suggests that the model has captured the distinct patterns and color properties that distinguish white nails from other categories like Bluish, Healthy, Splinter Hemorrhage, and Yellow nails.

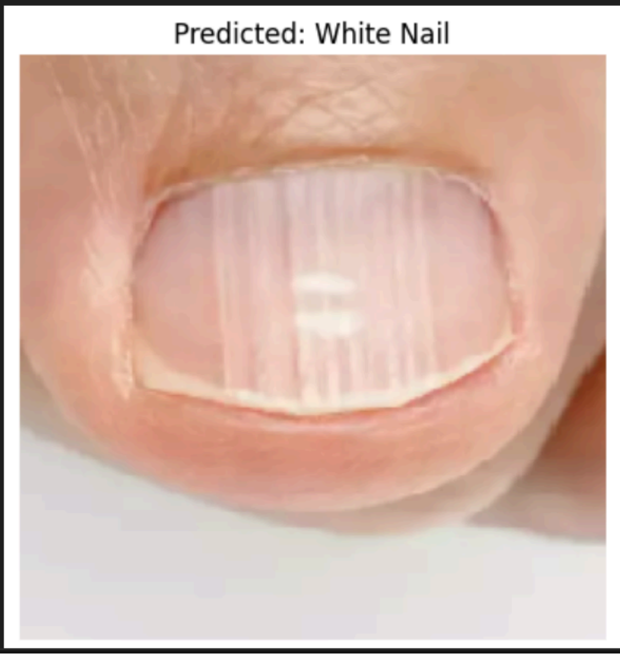
In terms of medical implications, a white nail condition could point to a range of health issues, but in this specific case, the prediction correlates with **kidney disease**. This could be due to the model recognizing subtle visual markers like pallor or discoloration, which often appear in patients with renal disorders. The result provides a valuable tool for clinicians and healthcare professionals, as early detection based on visual symptoms could prompt further diagnostic tests or treatments.

The overall prediction accuracy of the model and its ability to assign probabilities to each class make it a powerful aid in disease detection. However, while the model performed well in this instance, further validation on larger, more diverse datasets is necessary to ensure its robustness across different demographics and nail types.

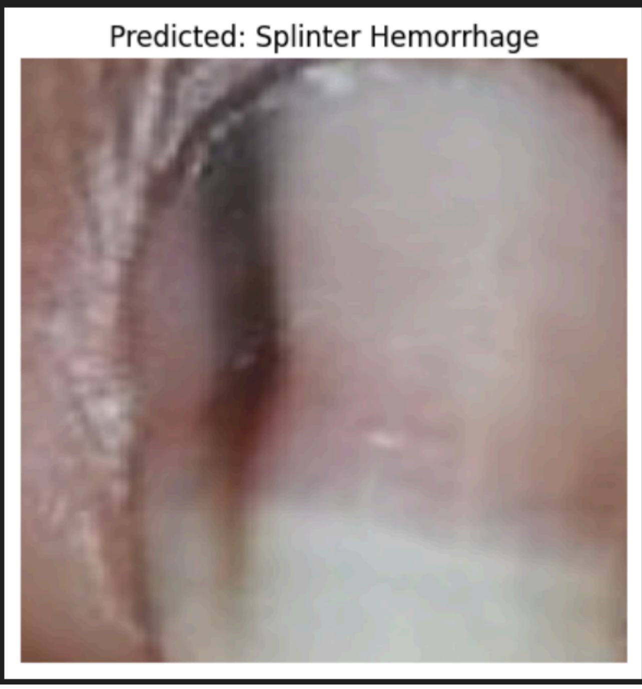
The visual representation of the test image confirmed the correctness of the prediction, providing further evidence that this machine learning approach can be reliable in detecting diseases associated with changes

in nail color.

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.com
1/1 ━━━━━━━━━━━━━━━━━━━━ 1s 588ms/step
Predicted class: White Nail
Predicted probabilities: [5.0828461e-05 1.9945208e-05 3.9716582e-05 9.9939406e-01 4.9554004e-04]
The following person is suffering from kidney disease.
```




```
Predicted class: Splinter Hemorrhage
Predicted probabilities: [7.0665153e-03 3.4569457e-04 9.6263295e-01 2.7943419e-02 2.0113923e-03
The following person is suffering from trauma.
```



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