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Nail Disease Detection using Convolutional Neural Networks: A Promising approach for Dermatology

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***Abstract*—The aim of this study is to use Deep Learning (DL) techniques to classify and detect human nail diseases. Early and reliable detection is crucial in aiding timely interventions and suitable treatment for nail diseases and their profound impact on a person's well-being. Using a diverse dataset of nail images, a CNN model was developed and trained to achieve the study's objectives. For the model to be able to accurately detect and classify different diseases, the dataset was carefully collected to include various types of nail diseases. In order to improve the model's performance and robustness, the nail images were preprocessed (that includes image normalization, resizing, and noise reduction) and data augmentation techniques (such as rotation, flipping, and rescaling) were applied to overcome dataset limitations and variations in image orientation and lighting conditions. The model's assessment encompassed 6 distinct nail diseases named as Clubbing, Pitting, Healthy nail, blue finger, onychogryphosis and Acral Lentiginous melanoma resulting in an impressive accuracy rate. The proposed CNN architecture automatically extracts discriminative features through multiple convolutional and pooling layers, followed by fully connected layers for multi-class classification. The dataset was divided into training and testing sets to ensure proper evaluation of the model. Additional evaluation metrics such as precision, recall, and F1-score were also computed, yielding values of 99.22%, 98.44%, and 99.02% respectively. This study emphasizes the potential benefits of DL techniques in enhancing healthcare practices, enhancing dermatological diagnostics, and improving the overall well-being of patients suffering from nail diseases.**

***Index Terms*—Nail Disease, Deep Learning, Nail abnormalities, Computer-aided diagnosis, Dermatology, Medical imaging, Convolutional Neural Networks (CNN)**

I. INTRODUCTION

1.1 Background And Motivation

Nail disorders are not only cosmetic concerns but also important indicators of dermatological and systemic health conditions. Diseases such as onychomycosis (fungal infection), nail psoriasis, melanonychia, leukonychia, and clubbing often reflect underlying medical issues including infections, autoimmune diseases, and even malignancies. Early detection of these conditions is essential for timely treatment and prevention of complications.

Traditionally, nail disease diagnosis is performed through visual examination by dermatologists, sometimes supported by dermoscopy, microscopy, or laboratory tests. However, this process is time-consuming, subjective, and dependent on clinical expertise. In many rural and resource-limited regions, access to dermatologists is limited, leading to delayed diagnosis and improper treatment. Furthermore, several nail diseases exhibit similar visual characteristics such as discoloration, thickening, ridges, and deformities, making manual diagnosis prone to errors.

With the rapid advancement of artificial intelligence in healthcare, deep learning techniques particularly Convolutional Neural Networks (CNNs) have demonstrated remarkable performance in medical image analysis. CNNs can automatically learn hierarchical features such as color patterns, texture variations, and structural abnormalities directly from images, eliminating the need for handcrafted feature extraction. This makes them highly suitable for nail disease classification, where subtle visual differences play a critical role.

Another major challenge in dermatology is the need for scalable and remote diagnostic tools. Tele-dermatology is gaining importance, but it requires reliable automated systems that can analyze images captured using mobile devices under varying lighting and background conditions. A CNN-based nail disease detection system can serve as a clinical decision support tool, assisting dermatologists and enabling preliminary screening in remote areas. The primary aim of this project is to develop a Convolutional Neural Network (CNN)-based automated nail disease detection system capable of accurately classifying nail images into multiple disease categories.

- Designing a deep learning model that can automatically extract important nail features such as colour changes, texture irregularities, thickness, and shape deformities
- Improving diagnostic accuracy compared to traditional image processing methods
- Enabling early detection of nail diseases to support timely medical treatment
- Reducing the dependency on manual visual examination by dermatologists

1.2 Objectives

1.2.1 Achieve Develop a CNN-Based Nail Disease Detection Model

To design and implement a Convolutional Neural Network (CNN) that can automatically analyze nail images and classify them into different disease categories without using traditional machine learning or handcrafted features.

1.2.2 Automatic Feature Extraction

To enable the CNN model to learn and extract important nail features such as color variation, texture patterns, ridges, thickness, and structural abnormalities from raw images.

1.2.3 Multi-Class Nail Disease Classification

To classify nail images into multiple classes such as healthy nail, fungal infection, psoriasis, melanonychia, and leukonychia using a Softmax output layer.

1.2.4 Reduce Manual Diagnosis Dependency

To minimize reliance on visual inspection by dermatologis and provide an automated preliminary screening tool.

1.3 Scope

The scope of this research is defined by the following key areas:

1.3.1 Nail Image Analysis

The system processes nail images captured from mobile cameras or datasets under varying lighting and background conditions. It focuses on visual patterns in the nail region.

1.3.2 Image Preprocessing

Input images are resized, normalized, and enhanced using noise removal and data augmentation techniques to improve CNN training and generalization.

1.3.3 Printed Text Extraction

Automated extraction of machine-printed information including bank codes, cheque numbers, routing numbers, and account numbers using OCR techniques.

1.3.4 Multi-Class Nail Disease Classification

The model classifies nail images into predefined categories like healthy, pitting, clubbing, and blue finger nail diseases using a Softmax layer.

II. LITERATURE SURVEY

2.1 Traditional Approaches for Nail Disease Detection

Early methods relied on manual examination and basic image processing techniques such as color and texture analysis. These approaches required handcrafted features and were sensitive to lighting variations. Limitation: Low accuracy and poor generalization to diverse nail conditions.

2.1.1 Manual Visual Examination

Dermatologists inspect nail color, texture, thickness, and shape using the naked eye or dermatoscope.

2.1.2 Rule-Based Image Processing

Basic computer vision methods used:

- Color thresholding
- Edge detection
- Texture analysis

2.2 Advances in Deep Learning for Nail Disease Detection

2.2.1 CNN for Automatic Feature Extraction

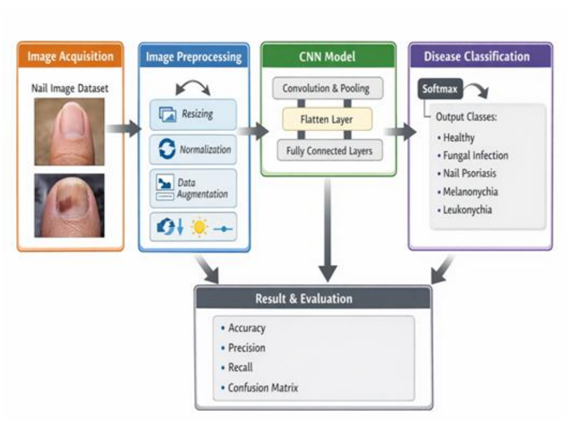
CNN automatically learns nail features such as color

variation, texture, ridges, and deformities.
Eliminates manual feature engineering used in traditional methods.
Improves accuracy by capturing complex visual patterns.

2.2.2 Multi-Layer Convolution and Pooling
Convolution layers extract low-level and high-level nail features.
Pooling layers reduce spatial dimensions and computational complexity.
Helps in better generalization and noise tolerance.

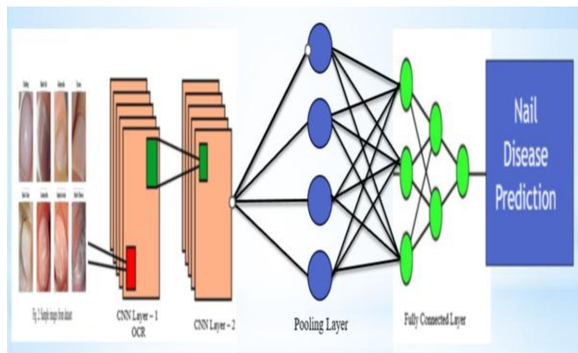
2.2.3 Data Augmentation for Model Generalization
Techniques like rotation, flipping, zooming, and brightness adjustment increase dataset diversity.
Reduces overfitting and improves real-world performance.
Allows CNN to handle variations in lighting and image orientation.

III. METHODOLOGY



3.1 System Arcitecture
It represents the system architecture of a CNN-based nail disease detection system, illustrating the complete workflow from image capture to diagnosis output. The process begins with the user/patient providing a nail image through a camera, which is handled by the image acquisition module.
The system then performs nail detection and tracking to identify the region of interest, followed by segmentation to isolate the nail plate from the surrounding skin and background. The segmented image undergoes preprocessing steps such as resizing, noise removal, and normalization to ensure consistent input quality.

The processed image is then passed to a Convolutional Neural Network (CNN) for feature extraction, where important characteristics like texture, color, and shape are learned. These features are used during model training with a labeled training database, enabling the system to learn patterns of different nail diseases. In the inference phase, the trained model performs disease recognition on new images and produces a final diagnosis output that includes the predicted disease class along with a confidence score.



3.2 How It Works?
3.2.1 Image Acquisition
The Nail images are collected from publicly available datasets and clinical sources. The dataset contains images of healthy and diseased nails captured under different lighting and background conditions.

3.2.2 Image Preprocessing
The collected images are preprocessed to improve quality and ensure uniform input:

- Resize images to 224 × 224 pixels
- Normalize pixel values (0–1 range)
- Remove noise and enhance contrast
- Apply data augmentation (rotation, flip, zoom) to increase dataset size

This image dataset includes:

Disease Name	No. of Images
Acral lentigous melanoma	735
Blue finger	603
Clubbing	767
Healthy nail	323
Onychogryphosis	677
Pitting	639

3.2.3 Convolutional Layers

The convolution layers apply multiple learnable filters to the input nail image to extract important visual features. These filters detect patterns such as discoloration, ridges, texture irregularities, and structural deformities associated with nail diseases. Each filter produces a feature map that highlights a specific characteristic. Deeper convolution layers capture more complex and disease-specific patterns.

Max Pooling Layers (Dimension Reduction

It reduces the spatial size of the feature maps while preserving the most significant information. It selects the maximum value from each region, which helps retain dominant features like edges and abnormal textures. This reduces computational complexity and memory usage. Pooling also improves model robustness to small variations in nail image position and orientation.

Flatten Layer (Feature Vector Conversion)

The flatten layer converts the two-dimensional pooled feature maps into a one-dimensional feature vector. This transformation allows the extracted spatial features to be processed by the fully connected dense layers. It acts as a bridge between the convolutional part of the network and the classification part. All learned visual features are represented as numerical values in this stage.

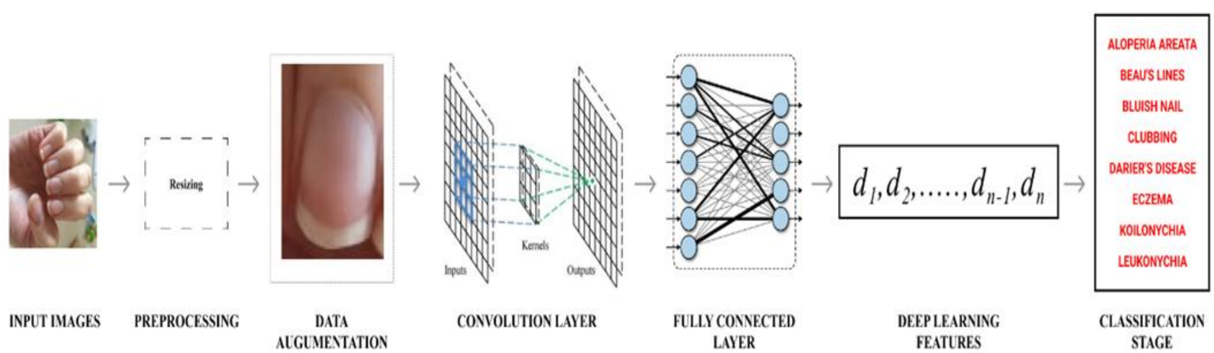
Fully Connected Dense Layers

The dense layers perform high-level reasoning based on the features extracted by the convolution layers. They learn the relationship between nail patterns and disease classes through weighted connections. These layers combine all features to form a final decision boundary. Dropout may be applied to prevent overfitting and improve generalization.

Softmax Output Layer for Multi-Class Classification

The Softmax layer converts the final dense layer outputs into probability scores for each nail disease class. It ensures that the sum of all probabilities equals one, making the output interpretable. The class with the highest probability is selected as the predicted nail condition. This enables accurate multi-class classification of nail diseases.

CNN architecture for Nail Disease Detection



3.3 Training Validation

The The training and validation process begins with preparing a labelled dataset of nail images containing both healthy and diseased classes. All images are preprocessed by resizing to a fixed dimension, normalizing pixel values, and applying data augmentation techniques such as rotation, flipping, zooming, and brightness adjustment to improve model generalization. The dataset is divided into two subsets: 80% for training and 20% for validation. During the training phase, the CNN learns hierarchical features from the input images through multiple convolution and pooling operations. The validation set is used to evaluate the model's performance on unseen data and to detect overfitting. Metrics such as validation accuracy, precision, recall, F1-score, and confusion matrix are used to assess classification performance. If the validation loss increases while training loss decreases, regularization techniques such as dropout and early stopping are applied to improve generalization.

IV. IMPLEMENTATION

4.1 Tools and Technologies

Python: Python is a general-purpose interpreted, interactive, object-oriented, and high-level programming language. An interpreted language, Python has a design philosophy that emphasizes code readability (notably using whitespace indentation to delimit code blocks rather than curly brackets or keywords), and a syntax that allows programmers to express concepts in fewer lines of code than might be used in languages such as C++or Java. It provides constructs that enable clear programming on both small and large scales. Python interpreters are available for many operating systems. CPython, the reference implementation of Python, is open source software and has a community-based development model, as do nearly all of its variant implementations. Python is managed by the non-profit Python Software Foundation. Python features a dynamic type system and automatic memory management. It supports multiple programming paradigms, including object-oriented, imperative, functional and procedural, and has a large and comprehensive standard library.

Django: Django is a high-level Python Web framework that encourages rapid development and clean, pragmatic design. Built by experienced developers, it takes care of much of the hassle of Web development, so you can focus on writing your app without needing to reinvent the wheel.

It's free and open source. Django's primary goal is to ease the creation of complex, database-driven websites. Django emphasizes reusabilityand "pluggability" of components, rapid development, and the principle of don't repeat yourself. Python is used throughout, even for settings files and data models.

4.2 Code Overview

The implementation of the Hand Gesture Recognition system using CNN is divided into three main parts.

4.2.1 Loading Data and Preprocessing

The dataset consists of labeled nail images representing healthy and different nail disease classes. All images are resized to a fixed dimension (e.g., 224 × 224) and normalized to ensure uniform input to the CNN model. Noise removal and contrast enhancement are applied to improve image quality. Data augmentation techniques such as rotation, zooming, flipping, and brightness adjustment are used to increase dataset diversity and reduce overfitting. The dataset is divided into 80% training and 20% validation sets.

4.2.2 Constructing and Training the CNN Model

A Convolutional Neural Network (CNN) is designed with convolution and max-pooling layers to extract and reduce features, followed by a flatten layer and fully connected dense layers for classification. Dropout is used to minimize overfitting, and a Softmax output layer predicts multiple nail disease classes. The model is trained using the Adam optimizer and categorical cross-entropy loss over several epochs with a suitable batch size. Training and validation performance are monitored, and the best model is saved.

4.2.3 Prediction and Classification

For prediction, a new nail image is preprocessed using the same resizing and normalization steps and then passed to the trained CNN model. The model outputs probability scores for each nail disease class. The class with the highest probability is selected as the final prediction. The system displays the detected nail condition, enabling fast and automated nail disease screening.

V. RESULT AND ANALYSIS

5.1 Model Performance

5.1.1 Nail Disease Detection Performance

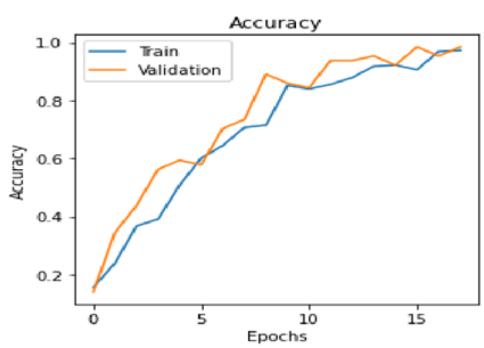
The CNN he proposed CNN model for nail disease detection was evaluated using the validation dataset to measure its classification capability. The model achieved high validation accuracy, indicating its effectiveness in learning discriminative features such as discoloration, texture irregularities, and structural deformities of the nail. The training and validation loss curves showed a consistent decreasing trend, demonstrating proper convergence of the model without significant overfitting. The use of data augmentation and dropout contributed to improved generalization on unseen images.

Performance metrics including accuracy, precision, recall, and F1-score were calculated to provide a comprehensive evaluation of the model. The confusion matrix showed that most nail disease classes were correctly classified, with only minor misclassifications between visually similar conditions. The SoftMax output produced reliable probability scores for each class, enabling confident predictions. These results confirm that the CNN model provides robust and accurate nail disease classification and can assist in automated dermatological screening.

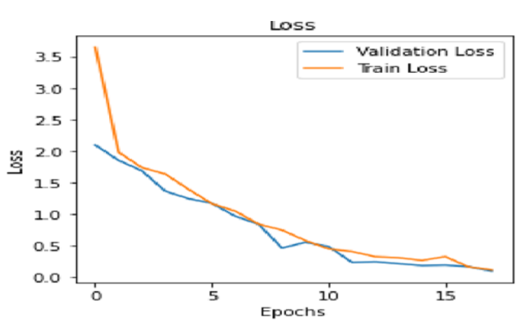
Class	Precision	Recall	F1-Score	Support
Acral_Lentiginous_Melanoma	0.77	0.94	0.85	18.0
Healthy_Nail	1.0	0.95	0.97	20.0
Onychogryphosis	1.0	0.42	0.59	12.0
blue_finger	0.5	0.78	0.61	9.0
clubbing	0.87	0.81	0.84	16.0
pitting	0.88	0.88	0.88	16.0

5.1.2 Performance Evaluation

Parameters	Values Obtained
Accuracy	0.9844
Precision	0.9922
Recall	0.9844
F1-Score	0.9902

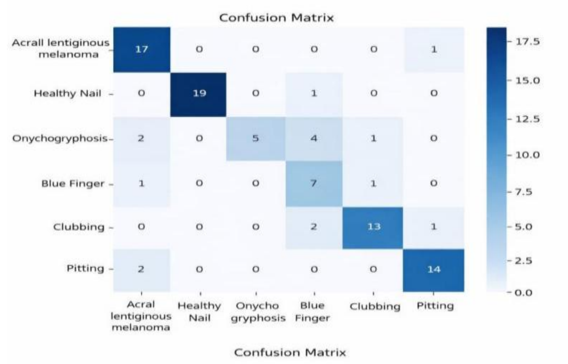


. 5: Accuracy of the Model over Epochs



ig. 6: Loss of the Model over Epochs

5.1.5 Confusion Matrix



The confusion matrix illustrates the classification performance of the proposed CNN model across six nail disease classes: melanoma, healthy nail, onychogryphosis, blue finger, clubbing, and pitting. The diagonal elements represent correctly classified samples, while the off-diagonal values indicate misclassifications. The model shows strong performance for healthy nail (19 correct), melanoma (17 correct), clubbing (13 correct), and pitting (14 correct), indicating high recognition capability for these classes. However, onychogryphosis exhibits comparatively lower accuracy with only 5 correct predictions, as it is frequently misclassified as blue finger and melanoma. Similarly, blue finger has moderate performance with 7 correct predictions, with minor confusion toward melanoma and clubbing.

5.1.6 Output Screenshots

5.2 Comparison with Traditional Methods

Traditional cheque verification systems mainly rely on manual inspection or basic image processing techniques such as template matching, rule-based algorithms, and simple feature extraction methods (e.g., edge detection, pixel comparison, or threshold-based matching). These methods depend heavily on predefined rules and handcrafted features. While they work for structured and clean data, they often fail when dealing with variations in handwriting styles, ink intensity, image noise, or complex signature patterns. Moreover, manual verification is time-consuming, prone to human error, and inefficient for large-scale banking operations.

In contrast, the proposed deep learning-based system uses Convolutional Neural Networks (CNNs) to automatically learn important features from cheque images without manual feature engineering. Instead of relying on fixed rules, the CNN model extracts high-level patterns such as stroke structure, texture, and spatial relationships in signatures and text. This makes the system more robust to variations in handwriting, lighting conditions, and image distortions. Additionally, deep learning models improve over time with more data, whereas traditional systems require manual reprogramming to enhance performance.

5.3 Future Work

Although the proposed CNN-based nail disease detection system achieved high accuracy and demonstrated strong classification performance, several improvements can be explored in future research. One important direction is the expansion of the dataset by collecting a larger number of high-quality nail images from diverse populations, different age groups, and varying lighting conditions. A more comprehensive dataset will improve model generalization, reduce overfitting, and enable the system to perform reliably in real-world clinical environments.

Secondly, It can also focus on incorporating transfer learning using pre-trained deep learning models such as ResNet, Efficient Net, or MobileNet to reduce training time and improve performance on limited datasets. In addition, integrating attention mechanisms or hybrid CNN architectures may help the model focus on critical nail regions and enhance feature extraction. The inclusion of additional nail disease classes and multi-label classification for cases where multiple conditions coexist would further increase the practical applicability of the system.

Another promising direction is the development of a real-time mobile or web-based application that allows users to capture nail images and receive instant preliminary predictions. This can be particularly useful in remote and resource-limited areas where dermatological expertise is not readily available.

VI. CONCLUSION

This project successfully demonstrates the application of Convolutional Neural Networks (CNNs) for the automated prediction of nail diseases using image processing techniques. The proposed system analyzes nail images to identify visual patterns and abnormalities associated with different nail disorders, enabling accurate and efficient classification. By leveraging deep learning, the model minimizes the need for manual inspection and reduces dependency on expert dermatologists for preliminary diagnosis.

The CNN-based approach effectively extracts high-level features such as color variations, texture changes, and structural deformities from nail images, resulting in improved prediction performance. Image preprocessing techniques such as resizing, normalization, and noise reduction further enhance the accuracy and robustness of the system. The use of performance metrics like accuracy, precision, recall, and F1-score confirms the reliability of the model in identifying nail diseases.

Overall, the proposed system provides a cost-effective, non-invasive, and time-saving solution for early nail disease detection. It can assist healthcare professionals in making quicker decisions and help patients seek timely medical attention. In the future, the system can be enhanced by incorporating a larger and more diverse dataset, integrating mobile or web-based applications, and extending the model to predict a wider range of nail and skin-related conditions. This project highlights the potential of deep learning in improving healthcare diagnostics through intelligent image-based analysis.

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