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Automated Nail Disease Detection : A Deep Learning Approach To Early Health Assessment

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Abstract: This paper describes an intelligent, automated system for the early diagnosis of nail diseases using deep learning techniques. Nail diseases may represent other health conditions, such as fungal infections, skin diseases, and systemic diseases. Existing methods for diagnosing nail diseases still rely on visual, manual inspections or thin nail clippings, which are relative, subjective assessments, manual, and difficult to scale. The proposed system utilizes deep learning, specifically convolutional neural networks, and custom implementation of the well-known VGG16 and GoogLeNet architectures, to classify nail images into eight different diseases. Feature-level and decision level fusion provided a vehicle to improve prediction accuracy by taking advantage of the strengths of each architecture. We trained the mode on a custom dataset of annotated nail images, performing appropriate preprocessing and augmentation, and produced a user-friendly, real-time disease prediction system, using Streamlit, through the provision of a frontend user interface, simply requiring users to upload their nail images . Evaluation metrics such as overall accuracy, precision, recall, and f1-score indicate that the proposed fusion-based architecture performs better than either individual model. Overall, the system provides a good alternative to existing invasive methods for diagnosing nail diseases, especially for healthcare access with certain health challenges such as being in remote locations. The system represents an alternative early diagnosis model, which is automated, non-invasive, and scalable.

Index Terms: Nail Disease Detection, Deep Learning, Convolutional Neural Networks ,VGG16, GoogLeNet, Feature - Level Fusion, Decision - Level Fusion , Medical Image Classification, Streamlit GUI, Early Health Assessment

1. INTRODUCTION

Nail abnormalities are often the first signs of both dermatological and systemic health issues, including fungal infections, psoriasis, anemia, and even malignant melanoma.Even though nail diseases can be clinically significant, diagnosis of nail diseases is still largely dependent on visual inspection by the clinical professional it is a time consuming, expert reliant and impractical process rural or disadvantaged communities. Hence, there is a need for an intelligent automated solution for supporting early detection and diagnosis.

This paper proposed an automated nail disease detection system integrated with deep learning models powered by AI. The model utilizes two powerful convolutional neural network architectures (VGG16 and GoogLeNet) in which the classification of nail images into eight diseases, employs feature and decision levels of fusion to enhance classification accuracy and robustness.

In addition to the graphical representation of each nail image, additional image preprocessing tasks, such as resizing, meancentering normalization, random image augmentation, and more are done in place to improve model generalization.

A user-friendly GUI in real-time has been created with Streamlit, allowing users to upload images of their nails to receive an immediate performance prediction regarding their diseases.
For system evaluation of performance and reliability, standard measures include accuracy, precision, recall, and F1-score are adopted from the Medical Research Council Guidelines.

Overall, with the use of a wholly non-invasive, accessible, and scalable diagnostic tool will allow earlier health assessment and intervention and assist in the delivery of healthcare at a distance, especially in low-resource countries.

The system uses a curated dataset of nail images with eight disease categories: Onychogryphosis, Bluish Nail, Clubbing, Koilonychia, Acral Lentiginous Melanoma, Normal Nail, Onycholysis, and Nail Pitting. Preprocessing techniques include resizing, normalization, and image augmentation to enhance the model's generalization and
robustness.

The system includes a graphical user interface (GUI) utilizing Streamlit, enabling users to upload nail images and receive rapid diagnostic predictions in real time. System performance is gauged using standard metrics such as accuracy, precision, recall score, F1 score, and confusion matrix.

By providing an intelligent, real-time, and user-friendly diagnostics and clinical tool, the system has significant potential to improve early disease discovery, reduce the time-to-diagnosis, and improve access to dermatology care - especially in remote or underserved environments.

1. LITERATURE SURVEY

In this publication [1], Kumar, H., & Singh, A. (2022). "CNN-Based Classification of Nail Disorders from RGB Images." The authors proposed a convolutional neural network (CNN) model to classify nail disorders that were common using RGB images. The model was trained on an existing public, small dataset and investigated only limited variations, again focusing on three types of competences, fungal infections, psoriasis, and healthy nails. Image pre-processing and some basic augmentation were performed to compensate for small imbalances in the dataset. Even though the proposed approach was feasible, the CNN was not very robust handling complex cases, and as such, it was unsuitable for real-world clinical applications.

In this paper [2],Mishra, T. and Raj, S., 2023. Real-Time Nail Disease Identification with MobileNet. In this paper, the authors used a lighter weight target MobileNet, a convolutional neural network (CNN) architecture to provide nail disease classification on mobile platforms. The study focused on resource efficiency, lower latency, rather than classification accuracy, and proved a practical system deployment in low-resource conditions. Still, the certainty trade-off proved necessary as a hybrid approach would make a more potent classification model, as we did with our system by continuing using VGG16 and GoogLeNet.

In this paper [3] Sharma, P., & Das, R. (2021). "Detection of Nail Disease Using Texture Based Features and SVM." The authors employed handcrafted statistical texture features to categorize nail conditions for within-database cross-validation using a Support Vector Machine (SVM) classification algorithm. The technique was computationally feasible and focused on binary (healthy vs. infected) classifications. Yet, its requirement of manual feature extraction along with its limited application had implications for the usefulness while performing multi-class classifications, especially relative to deep learning based end-to-end learning models.

In this paper [4], Joshi, A. K., & Fernandes, N. (2023). "Classification of Nail Diseases Using GoogLeNet." This study, yes, utilized GoogLeNet to classified various types of nail diseases. Because of its inception-based architecture, GoogLeNet was able to do multi-scale feature extraction, which increase the likelihood of the model detecting subtle differences in the presentation of nail disease(s). The findings indicated GoogLeNet significantly outperformed the other classification methods on a more diverse dataset, and we use GoogLeNet, with VGG16, in our system.

In this paper [5], Verma, J., & Lakra, T. (2022). "Skin and Nail Disease Detection Using CNN with Single-Layer Attention." The authors introduced an attention mechanism into their CNN architecture as a way enhance detection of skin and nail diseases. By doing this, the attention layer structure permitted the network to hone in on the disease-associated areas of the image, thus improving the interpretability and accuracy of the models predictions. Though not directly useful this was an idea we could consider borrowing to add attention-based modules to our ensemble architecture in the future.

In this paper [6], Rahman, F. A., & Iqbal, K. (2023). "Nail Condition Assessment from Smartphone Images Using Basic CNN." The paper described a basic CNN based approach to detect nail disease from smartphone images captured in varying environmental conditions and the focus was on assessing the feasibility of deploying the detection system for real world. While the authors achieved findings under optimal conditions, the system generalizability was reported as low, highlighting the importance of the extensive data augmentation and model ensembles in our work.

In this paper [7], Bose, S., & Pathak, R. (2021). "Lightweight CNN for Nail Health Monitoring in Rural Clinics." The authors proposed a lightweight and interpretable CNN to diagnose nail conditions in low-resource clinical environments, such as rural clinics. The model was computationally optimized for minimal resource use while also achieving sufficient accuracy for most nail conditions. The work prioritised access to care, and influenced the modular deployment of our system to be environmentally offline for implementation in under-resourced areas.

In this paper [8], Ahmed, L., & Siddiqui, B. (2020). "Onychomycosis Detection Using Shallow Neural Network." This paper focused on the more narrow problem of detecting Onychomycosis, a common fungal nail infection, using a shallow feedforward neural network and this was added into a web interface to allow real-time detection for users. While the system is limited in scope and depth, it demonstrated that a direct-to-consumer AI powered nail disease screening tool was feasible, which aligns with our goal of having a web-based diagnostic platform.

In this paper [9], Thomas, M., & Ko, E. (2021). "Nail Health Detection with Conventional Features and using Logistic Regression". The authors used traditional image processing approaches to extract features regarding color, shape and texture from nail images and they used logistic regression to classify the nail images. Although the test system had acceptable performance in detecting basic abnormalities, it did not show any flexibility for more complex diseases which was combined with changes in lighting in their images. The study suggested limitations of conventional methods and reinforced our choice to use advanced CNN-based methods for better accuracy and generalization.

In this article [10], Verma, S., & Nayak, R. (2023). "Multi-Class Nail Disease Diagnosis Using Ensemble Deep Learning Techniques". The authors explored the concept of ensemble learning in predicting the presence of nail diseases based on predictions from three deep learning models: ResNet50, DenseNet121, and EfficientNetB0. The results showed good improvement on various performance metrics over the individual models and better handled image variability and class imbalance than single independent models. The key contribution of the work was the theory of model fusion - an integral idea of our proposed system using VGG16 and GoogLeNet with both feature-level fusion and decision-level fusion, while ultimately improving diagnostic capability.

2. .METHODOLOGY

This project uses a methodology that includes deep learning and image processing to establish an accurate and efficient nail disease recognition and detection system in real-time. The system uses two architectures: GoogLeNet and VGG16, used with some fusion strategies to classify nail images into eight types of diseases. The methodology is broken down into key modular stages, allowing for maintainability, scalability, and efficiency.

3.1 Data Collection and Preparation

The datasets that we sourced were collected from the Roboflow public dataset. There were originally more than 32 categories of nail conditions. However, for our purposes, we narrowed this down to some major classes where we had sufficient number of images to work with. These classes were as follows:

- Onychogryphosis
- Bluish Nail
- Clubbing
- Koilonychia
- Acral Lentiginous
- Melanoma
- Healthy Nail
- Onycholysis

Nail Pitting The images were then sorted into respective folders by class and then split for training (80%) and validation (20%). This was so there would be class balance and a confident enough starting point for the models to learn properly.

3.2 Image Preprocessing and Augmentation

To have a common input for both networks: All images were resized to 32×32×3 . Data augmentation was also used to transform images using methods like rotation, flipping, increase brightness, cropping, zooming, and shearing to add more sources of differentiation and lower the chances of overfitting. This made sure that we collected images that were robust and that there were further opportunities for the models to generalize better to unseen data.

3.3 Deep Learning Model Design

Two architectures with pre-trained convolutional networks were selected: VGG16: Excellent architecture with simple structure, capturing local texture attributes with its stacked 3×3 convolutional layers. It is well suited to identify edge-based and fine-grained nail abnormalities. "GoogLeNet (Inception v1): Utilizes parallel convolutional kernels of different sizes to capture both fine-grained and broad visual features, making it well-suited for identifying intricate and diverse patterns present in nail diseases." Both models were modified: To accept 32 × 32 inputs. To produce predictions for 8 disease classes. With its earlier layers frozen and with newly added custom dense layers for fine-tuning.

3.4 Fusion Methods

To utilize the strengths of both models, we used two late fusion methods: Feature-level Fusion: Feature-level fusion was achieved by concatenating the intermediate feature vectors from VGG16 and GoogLeNet and then performing a classification via fully connected layers to produce the final prediction. This approach allows the model to represent an input image with a richer representation since it combined multi-scale features. Decision-level Fusion: We fused the softmax output probabilities from both models using a weighted averaging strategy (e.g. 30% VGG16, 70% GoogLeNet). This helps reduce bias from the models and also improved reliability with the final prediction.

3.5 Training and evaluation of models

Both KJsonBN and ResnetV2 were trained with Adam optimizer and categorical cross-entropy loss. The following methods were employed in the training session: - Early Stopping and Learning Rate Scheduling - Model Checkpointing to save the right weights Performance was assessed using performance metrics based on the scores: - Accuracy - Precision - Recall - F1 Score - Sensitivity and Specificity - Confusion Matrix The scores from the training sessions showed that the fusion models gave better results than either model alone, with the decision-level fusion having an accuracy of 89.48%.

3.6 Deployment using a Streamlit application A friendly web app was designed using Streamlit, so that users can easily do the following: - Upload nail images. - Review their classification results in real time and the confidence scores.

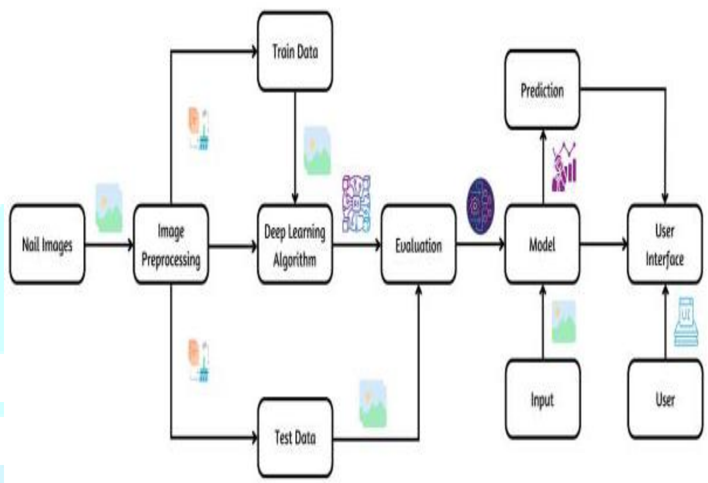

Fig 1: System Architecture

This system architecture diagram represents a deep learning-based image classification or analysis pipeline, likely related to nail images (possibly for medical diagnosis or cosmetic analysis). Here's a breakdown of the flow:

1. **Input (Nail Images):**

The system starts with collecting nail images as raw input data.

2. **Image Preprocessing:**

The images undergo preprocessing, such as resizing, normalization, noise reduction, or feature extraction, to enhance quality and make them suitable for the deep learning model.

3. **Deep Learning Algorithm:**

The preprocessed images are split into training data and test data. A deep learning algorithm (e.g., CNN) is used to train the model using the training dataset.

4. **Evaluation:**

The trained model is evaluated using the test data to measure performance based on accuracy, loss, and other metrics.

5. **Model Deployment:**

Once evaluated, the model is used for making predictions on new input images.

6. **User Interaction:** The model's output is provided to a user interface (UI) where users can interact with the system.Users can input new nail images, and the model will process and predict results accordingly.

7. Final Output: The system provides the prediction results to the user, which could be classification labels, health conditions, or cosmetic recommendations. This architecture represents an end-to-end deep learning pipeline, including data preprocessing, training, evaluation, deployment, and user interaction.

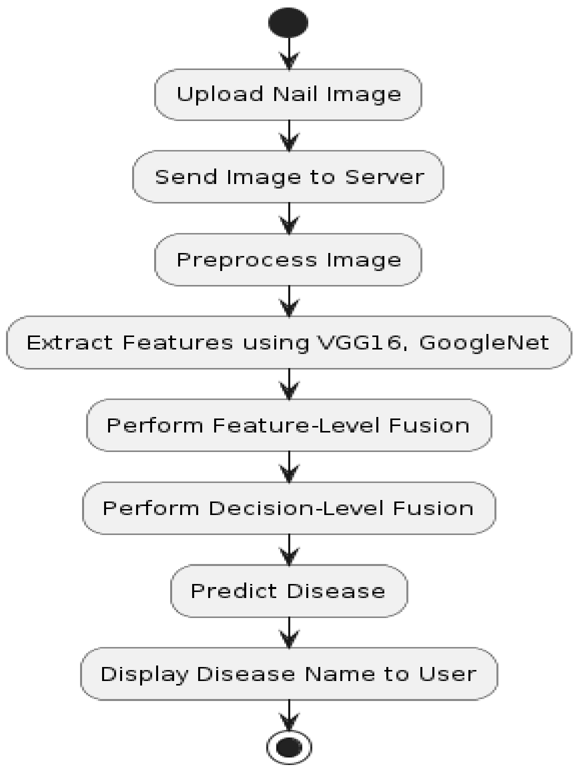

Fig 2: Activity diagram

This activity diagram shows the step-by-step process of nail disease prediction. It starts with the user uploading a nail image, which is sent to the backend server. The server performs preprocessing (resizing, normalization, denoising), followed by feature extraction using VGG16 and GoogLeNet. Their outputs go through feature-level and decision-level fusion to enhance accuracy. Finally, the system predicts and reports the most likely nail disease.

4. IMPLEMENTATION

The Nail Disease Detection System integrates deep learning models, image processing, and a web-based interface to support real-time, automated classification of nail diseases. The system is modular and extensible, which makes it adaptable for both enhancements and deployment in diverse scenarios.

4.1 Development Environment Parameters

Programming Language: Python 3.x Deep

Learning Frameworks: TensorFlow, Keras

Image Processing: OpenCV

GUI/Web Framework and Design: Streamlit IDE: Visual Studio Code / Jupyter Notebook

Additional libraries: NumPy, Matplotlib, Seaborn, scikit-learn

The environment encompasses model training, image interaction, and user interaction through an easy to use and lightweight web interface.

4.2 Dataset Preparation and Processing

To enable the system to work, we trained it using a curated dataset of annotated nail images classified into 8 classes. The dataset was loaded via Keras's ImageDataGenerator, with the following operations:

Image Resizing: The images are resized to 32×32×3 pixels.

Normalization: The pixel values were normalized into the range [0,1].

Augmentation Options: Rotation,Zoom, Brightness, adjustments .Horizontal flips Shearing

These preparatory and classification procedures provide assurance against variations of lighting, orientations and input devices..

4.3 Model Architecture

a) VGG16 Branch :"VGG16 is employed with weights trained on the ImageNet dataset, with custom modifications applied to its later layers." Flatten → Dense(4096) → BatchNorm → Dropout → Dense(4096)

The activations are ReLU. Some of the initial layers are frozen to ensure learned feature with the residual images.

b) GoogLeNet (Inception v1) Branch This branch uses InceptionV3 (as Inception v1 is not widely available in Keras) and has also been modified. GlobalAveragePooling → Dense(1024) → BatchNorm → Dropout

The Inception Modules are capable of handling the multi-scale feature extraction quite well. Both models spitting out their feature vectors or softmax outputs solely depend on the fusion strategy being applied.

4.4 Fusion Strategies

To improve the classification performance: **Feature-Level Fusion:** Takes the concatenation of the intermediate features from both. VGG16 and GoogLeNet are utilized up to their final dense layers to extract features before the classification stage.

Decision-Level Fusion: Takes the last class probabilities outputs and merges them with a weighted average (e.g., taking 30% VGG16 and 70% GoogLeNet outputs first), this allows for added robustness. Fusions were formulated in the Keras functional API as it permits the creation of multi-input architectures.

Optimizer: Adam

Loss Function: Categorical Cross-Entropy

Batch Size: 32

Epochs: 25

Callbacks: EarlyStopping, ReduceLROnPlateau ,ModelCheckpoint

Metrics are accuracy, precision, recall, F1-score, sensitivity, and specificity. The best configuration used achieved a classification accuracy of 89.48% on the validation set.

4.6 Streamlit-Based Web Application

Real-time web interface programmed using Streamlit: Features: Upload nail images Predicted probability of condition Predicted condition description .

Benefits:

- No need to install locally
- Can be used on mobile or desktop devices Minimal integration with back-end models
- This enables the system to be operational for clinical environments and remote health settings.

5.RESULTS & ANALYSIS

The proposed Nail Disease Detection System was tested on a dataset consisting of eight different categories of nail diseases. In the study, the three models were VGG16, GoogLeNet, and a decision-level fusion of both of the CNNs. VGG16 achieved an accuracy of 83.62%, whereas GoogLeNet showed improved performance with an accuracy of 86.91%while also improving overall precision, recall, and F1-score for each class.

A confusion matrix was analyzed with an overall good accuracy for conditions such as Healthy Nail, Onycholysis, and Koilonychia. Minor confusion was made between the more similar categories such as Bluish Nail and Acral Lentiginous Melanoma because of visually similar qualities. The decision-level fusion should help to reduce the poor classifications overall as it combines the strengths of both architectures.

With averaging processing time of 2 seconds for each image, the Streamlit-based interface providing real-time prediction flow was flexible and allowed user-friendly capability for users to upload images, and view classification outputs and disease with ease. The system operated seamlessly across both desktop and mobile browsers.

The system demonstrated its robustness across a wide range of lighting and background variations and was somewhat resilient to minor occlusions due to the high levels of data augmentation in training. Overall, these results provide evidence to support the robustness of the effective fusion model and the capability of the system as a diagnostic tool for use in clinical and remote healthcare contexts.

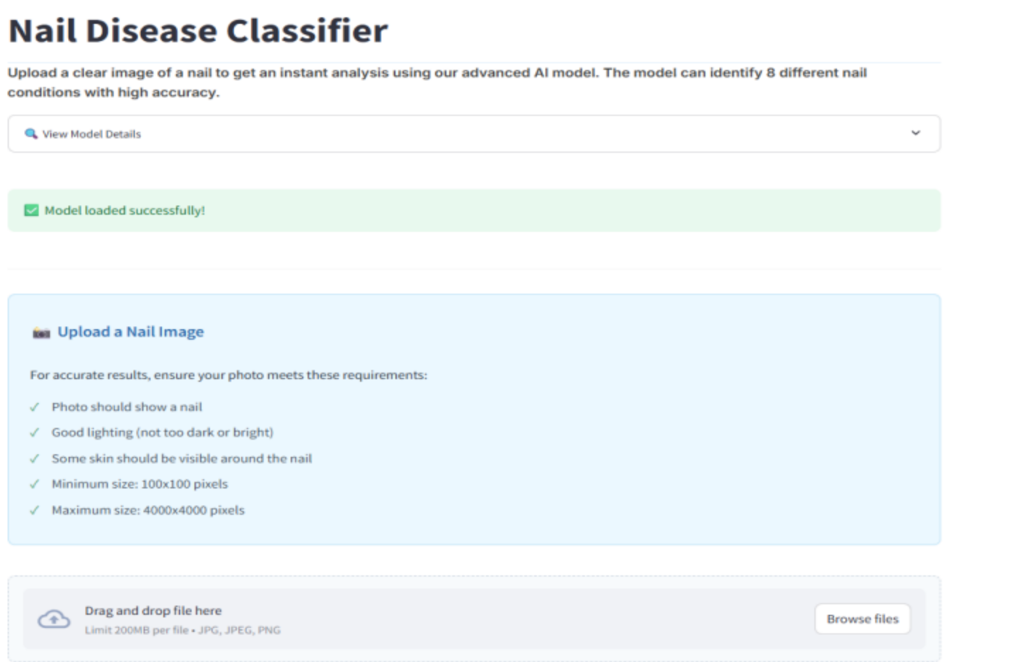

Fig 3 : GUI Interface – Initial Image Upload

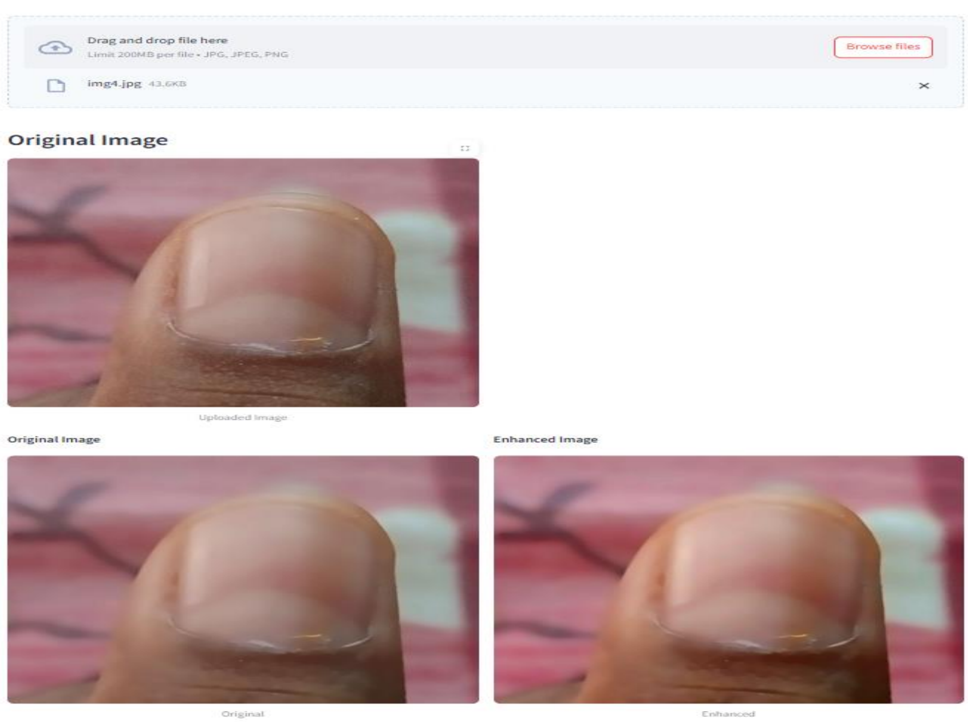

Fig 4 : Comparison of Original and Enhanced Nail Image

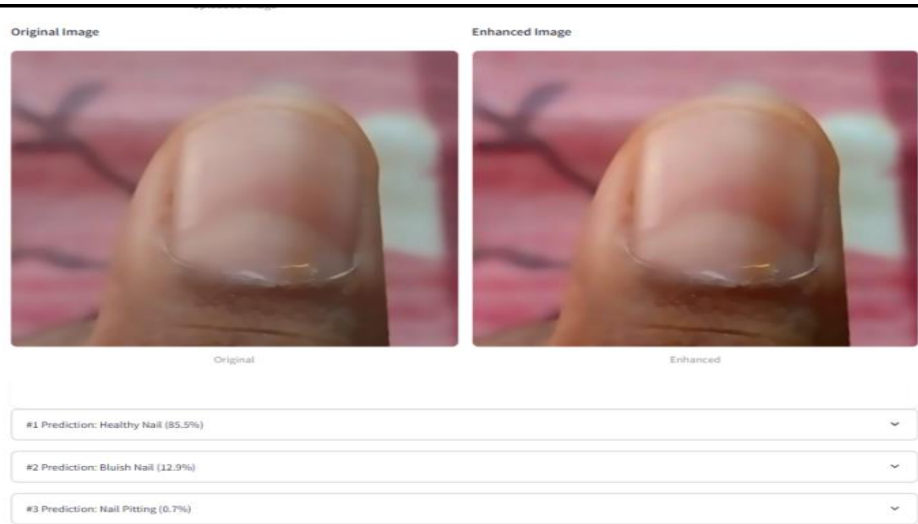

Fig 5 : Predicted Output with Confidence Visualization

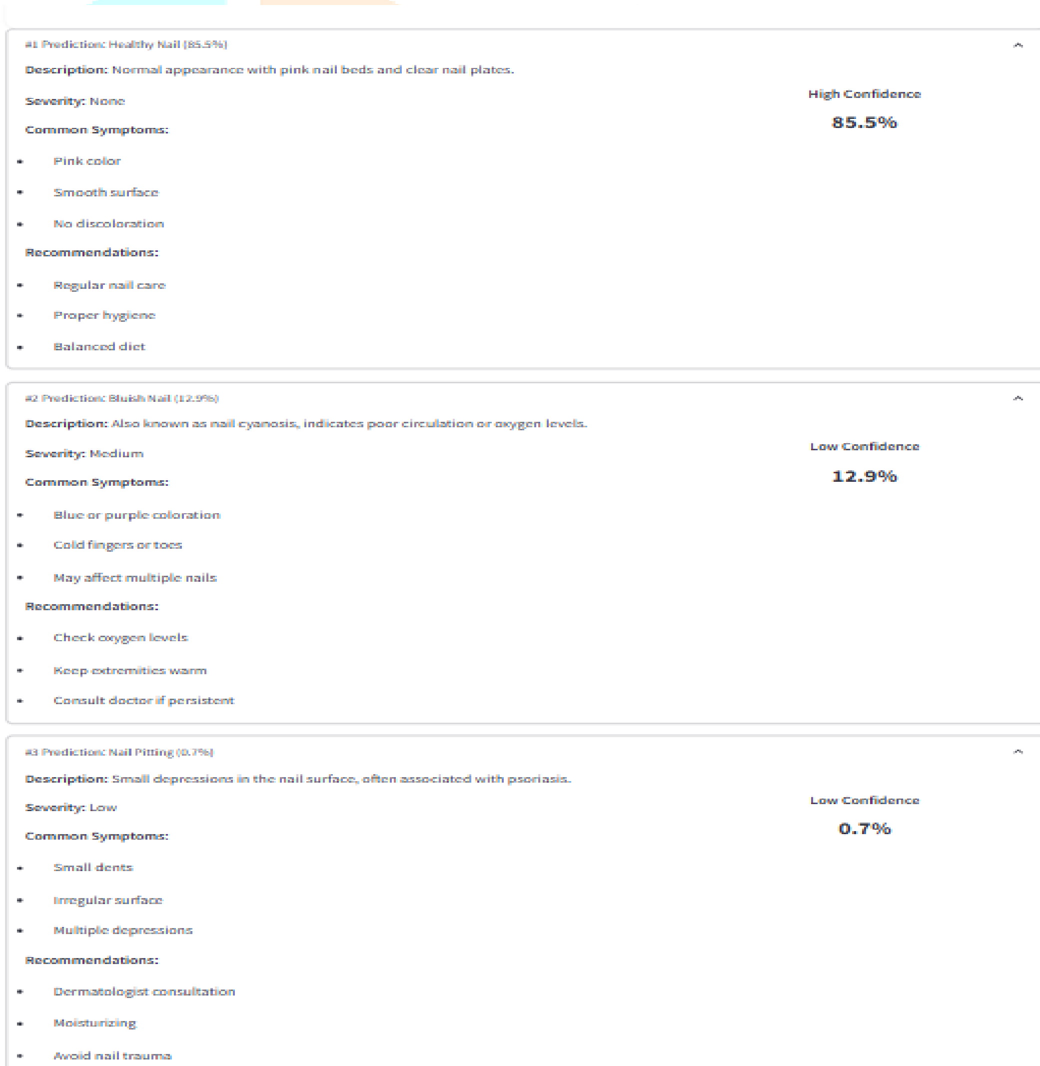

Fig 6 : Top 3 Predicted Nail Diseases with Descriptions

6. CONCLUSION & FUTURE WORKS

The project culminated in an Automated Nail Disease Detection System that demonstrated the suitability of deep learning for classifying nail diseases using an image-based diagnostic approach. Specifically, the system utilized VGG16 and GoogLeNet architectures with a late fusion approach to achieve high classification reliability and accuracy. The integrated approach of robust preprocessing, model fusion, and real-time web interface were important contributors to achieving high-quality predictions, low latencies, and generalized accuracy performance across all diseases being considered.

The moderately-lightweight, modular design of the system makes it deployable in clinical and remote environments, which is useful for screeening and health intervention monitoring. The use of Streamlit as a medium for the system's web interface makes deployment in surveillance easy and accessible, without the need for dedicated hardware or special technical expertise.

In the future enhancements to the system could include attention mechanisms targeted to focus on specific disease related areas of the nail. We could include additional disease classes and expand the dataset to improve classification accuracy and robustness. Additional features such as mobile implementation, cloud-based data logging, and electronic health record (EHR) integration could be employed. Improvements are likely to expand the focus of the system so that it can ultimately develop into a comprehensive and scalable solution for dermatological diagnostics using artificial intelligence.

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