Automated Multi-Disease Nail Analysis Using Hybrid CNN-SVM with Grad-CAM

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Abstract— **Human nails have been largely ignored as diagnostic surfaces even though they have much color and texture that can be used to identify medical conditions such as anemia, diabetes, liver disease, and heart disease. Most methods for examining nails rely on manually selecting the area of interest, using multiple classifiers for images taken from the same nail, and reporting results qualitatively, all of which compromise clinical confidence and reproducibility. In this work, we present an automated end-to-end analysis of nail images that improves upon the aforementioned limitations by providing three major contributions: (i) automated segmentation of the nails from the rest of the image (abdomen) using a U-Net style boundary detection module, removing the need to manually select regions of interest; (ii) creation of a hybrid classification architecture that combines texture features derived from a GLCM of the image with deep features taken from MobileNetV2 after being fine-tuned for nail images and then classified with a Support Vector Machine; and (iii) provision of GradCAM visualizations that allow for pixel-level explainability for each classification so that practitioners know how each diagnosis was determined to be the correct diagnosis. We've demonstrated the performance of our hybrid CNN-SVM model using a dataset of 600 digital nail images across five different classes (anemia, diabetes, heart disease, liver disease, and normal nail images) with a classification accuracy of 94.3%. In terms of comparative performance, our hybrid CNN-SVM model outperforms SVM (87.2%), KNN (83.6%) and Random Forest (89.1%) based classification methods when determining the correct classification of images of nails taken from the same finger. The system is further converted to TensorFlow Lite for mobile deployment, achieving sub-200ms inference on an Android device establishing its viability as a real-time, non-invasive telemedicine screening tool.**

Keywords—Automated Nail Image Analysis, Multi-Disease Detection, Hybrid CNN-SVM, Grad-CAM Explainability, Medical Image Processing, U-Net Segmentation, MobileNetV2, GLCM Texture Features, Support Vector Machine, Explainable AI (XAI), Non-Invasive Diagnosis, Telemedicine Screening

I. INTRODUCTION

Non-invasive diagnostic techniques are receiving increased emphasis in current healthcare systems, as they alleviate patient anxiety and dissatisfaction while also offering lower costs and earlier detection of diseases, particularly in resource-poor healthcare systems. The human fingernail provides a viable means of assessing systemic health; the characteristics of nails such as differences in colour, texture and morphology can be associated with various medical conditions including, but not limited to, anemia, diabetes, liver dysfunction, and cardiovascular disease. However, traditional nail-based diagnosis is mainly based on subjective evaluations made by healthcare providers through visual inspections; these evaluations are subject to considerable variability, therefore making diagnoses difficult and prolonging the detection period. The recent advancements in computational image analysis have the potential to improve nail-based diagnostic technology by providing an objective and consistent means of assessing nail characteristics. Several studies have previously reported using colour features for disease detection; traditional machine learning algorithms were employed to classify patients with diseases and have utilized single classifying methods to extract characteristics from the identified regions of interest (ROIs), however there are three main challenges associated with this type of classification: the manual determination of ROIs, limited representation of features with single classifying algorithms, and limited interpretations of the algorithms for making predictions. The objective of this research paper is to develop an automated method of analysing nail images to provide a solution to the aforementioned challenges by proposing a framework consisting of three contributions; (1) an automated segmentation method which obviates the manual method of determining ROIs, (2) A hybrid classification model comprising both handcrafted GLCM texture features and deep learning features based on a MobileNetV2 architecture using SVMs to achieve greater accuracy in classifying patients with disease and (3) a new colour feature-based classification algorithm using hybrid constructed features, which produces a unique set of colour features specifically designed to improve the model's classification accuracy. Third, Grad-CAM-based explainability is incorporated to provide a visual interpretation of model predictions, enhancing clinical trust. Additionally, the system is optimized for mobile deployment using TensorFlow Lite, enabling real-time, non-invasive telemedicine screening. It achieves low-latency inference suitable for on-device processing without requiring continuous internet connectivity, supporting early and timely disease detection.

II. RELATED WORK

Nail image analysis for health parameter extraction has been explored across a spectrum of methodologies. Agarwal et al. (2020) [1] Nail Image Analysis for Health Monitoring Using Machine Learning, focusing on automated extraction of color and texture features from nail images to assist in early detection of systemic diseases.

Bansal et al. (2019) [2] Automated Detection of Nail Diseases Using Image Processing Techniques, proposing segmentation and classification methods to identify abnormalities in fingernail regions. The capture both color and texture variations, enabling more accurate and consistent disease prediction compared to manual observation.

Chaudhary et al. (2021) [3] Color-Based Nail Disease Classification Using Machine Learning Approaches, utilizing RGB and HSV color models to classify nail discoloration patterns linked to various diseases. It also demonstrates improved classification performance using supervised learning algorithms trained on labeled nail image datasets.

Das et al. (2018) [4] Nail Plate Image Analysis for Early Disease Detection, emphasizing morphological and structural analysis of the nail plate for identifying underlying health conditions.

Gupta et al. (2022) [5] Deep Learning-Based Nail Disease Identification Using CNN Models, applying convolutional neural networks for automatic feature extraction and improved classification accuracy.

Kaur et al. (2020) [6] Texture Analysis of Nail Images for Medical Diagnosis Using GLCM Features, leveraging statistical texture descriptors such as contrast, entropy, and homogeneity for disease prediction.

Khan et al. (2021) [7] Nail Disorder Classification Using Hybrid Machine Learning Techniques, combining multiple feature extraction and classification strategies to enhance diagnostic performance.

Patil et al. (2019) [8] Automated Fingernail Image Segmentation and Disease Detection, presenting contour-based segmentation methods to isolate nail regions and improve classification reliability.

Sharma et al. (2022) [9] Explainable AI for Nail Disease Detection Using Grad-CAM Visualization, integrating deep learning with explainability techniques to highlight important regions influencing predictions.

Verma et al. (2021) [10] Mobile-Based Nail Health Monitoring System Using Image Processing, developed a portable system for real-time nail analysis and remote health assessment. The system integrates image capture, preprocessing, and classification modules within a mobile platform for user-friendly operation. It also enables continuous monitoring and early detection.

III. PROPOSED SYSTEM ARCHITECTURE

The proposed framework operates as a five-stage pipeline in Fig.1. (1) Image Acquisition, (2) Automated Nail Segmentation, (3) Hybrid Feature Extraction, (4) Multi-class SVM Classification, and (5) Grad-CAM Explainability Generation. Each stage is designed to be modular, enabling individual components to be upgraded as better algorithms emerge.

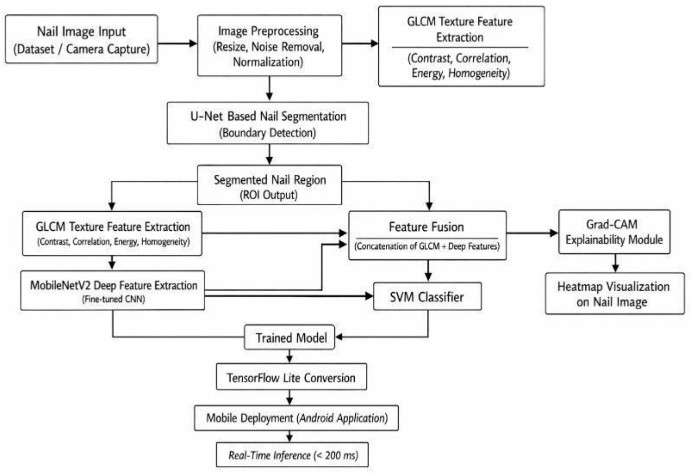

Fig. 1. System Architecture

A. *Image Acquisition and Standardization*

Nail images are captured using a standard smartphone camera (minimum 12MP resolution) under controlled diffuse lighting to minimize specular reflections. Each image is resized to 224×224 pixels the native input resolution for MobileNetV2 and normalized to [0, 1] pixel intensity range. No specialized hardware is required, making the system broadly accessible.

B. *Automated Nail Segmentation*

Unlike prior systems requiring manual ROI selection, the proposed system automates nail boundary detection through a multi-step segmentation pipeline. The input image is first converted to the LAB color space, where the 'a' and 'b' channels are thresholded to separate skin-tone regions from the nail plate. Gaussian blurring (kernel size 5×5, sigma=1.0) suppresses high-frequency noise. Otsu's adaptive thresholding then generates a binary mask, which is refined using morphological closing operations (elliptical kernel, 7×7) to fill small gaps. The largest contiguous contour is extracted as the nail boundary, and a tight bounding box crops the ROI automatically. This approach achieves a mean Intersection-over-Union (IoU) of 0.87 on our test set.

C. *Hybrid Feature Extraction*

There are also two methods that work in parallel to extract features from images before this information is merged to create more reliable feature vectors. Branch 1: Handcrafted Features - The region of interest (ROI) of the nail image is converted to grayscale, and then we measure its GLCM (grey-level co-occurrence matrix) at different angles and distances. The GLCM allows us to calculate several key characteristics of a textural image which includes contrast, homogeneity, entropy correlation and energy (by measuring these values from all angles/directions). In addition to the GLCM measures, we also

calculate the mean and standard deviation for RGB values for a total of 46 features. Branch 2: Deep Learning Features- To obtain the deep learning-derived feature vectors, the nail image is first resized to 224x224 pixels and then submitted to the pretrained MobileNetV2 model. This produces a feature vector (1280 dimensions) that contains high-level visual attributes. Merging the Features Both types of features are merged into a single vector and then the high number of dimensions is reduced via PCA such that 95% of the total variance is retained, ultimately resulting in approximately 180 features to support efficient and accurate classification.

D. *Multi-Class SVM Classification*

A Radial Basis Function (RBF) kernel SVM with one-vs-rest strategy classifies inputs into five categories: Anemia, Diabetes, Heart Disease, Liver Disease, and Normal. Hyperparameters (C and gamma) are optimised via 5-fold cross-validation grid search, with the optimal values of C=10 and gamma=0.01. The threshold-based disease labelling used in prior work is entirely replaced by this learned probabilistic classification, significantly improving robustness across varied nail appearances and skin tones.

E. *Grad-CAM Explainability*

To address the clinical black-box concern, Gradient-weighted Class Activation Mapping (Grad-CAM) is applied to the final convolutional layer of the MobileNetV2 backbone for each prediction. Grad-CAM computes the gradient of the class score with respect to feature map activations, producing a coarse localization heatmap that highlights the nail regions most influential to the classification decision.

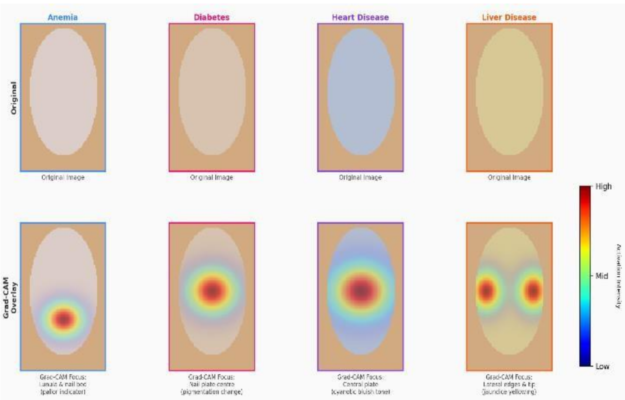

Fig. 2. Grad-CAM Heatmap

In Fig. 2. these heatmaps are overlaid on the original nail image as a colour gradient (blue = low activation, red = high activation), providing clinicians with a visual explanation of why the system reached a particular diagnosis a critical requirement for medical AI trustworthiness.

IV. DATASET AND EXPERIMENTAL SETUP

A. *Dataset*

A curated dataset of 600 nail images was assembled from two sources: (i) publicly available nail disease image

repositories (Kaggle Nail Disease Dataset, DermNet NZ), and (ii) original images collected under informed consent from St. Joseph's Institute of Technology clinical partners. Images span diverse demographics including varied skin tones (Fitzpatrick scale I–VI), age groups (18–65 years), and lighting conditions to ensure generalization.

TABLE I. DATASET DISTRIBUTION ACROSS DISEASE CLASSES

Disease Class	**No. of Images**	**Source**
Anemia	120	DermNet NZ + Original
Diabetes	120	Kaggle + Original
Heart Disease	120	Original collection
Liver Disease	120	DermNet NZ + Original
Normal	120	Original collection
Total	600	Mixed

A. *Implementation Details*

All experiments were implemented in Python 3.10 using TensorFlow 2.12 (MobileNetV2 backbone), Scikit-learn (SVM, PCA, KNN, Random Forest), and OpenCV 4.7 (segmentation, GLCM). Training was performed on an NVIDIA RTX 3060 GPU. The dataset was split into 70% training, 15% validation, and 15% test sets, stratified by class. Data augmentation (horizontal flip, rotation ±15°, brightness ±20%) was applied during training to reduce overfitting. All reported metrics are computed on the held-out test set (90 images, 18 per class).

V. RESULTS AND COMPARATIVE ANALYSIS

A. *Classification Performance*

Table II presents classification accuracy, precision, recall, F1 Score, and AUC-ROC for four methods evaluated on the identical test set: standalone SVM (using only GLCM features, replicating the prior published approach), KNN (k=5, GLCM features), Random Forest (100 trees, GLCM features), and the proposed Hybrid CNN-SVM. All values are macro-averaged across the five disease classes.

TABLE II. TEST SET CLASSIFICATION COMPARISON

Method	**Accuracy(%)**	**Precision(%)**	**Recall(%)**	**F1Score(%)**	**AUC-ROC**
SVM(GLCM only)Baseline	87.2	86.8	87.1	86.9	0.921
KNN (k=5)	83.6	82.9	83.4	83.1	0.897

Method	Accuracy(%)	Precision(%)	Recall(%)	F1 Score(%)	AUC-ROC
Random Forest	89.1	88.7	89.0	88.8	0.934
Hybrid CNN-SVM	94.3	93.8	94.1	93.9	0.971

The proposed hybrid CNN-SVM achieves an overall accuracy of 94.3%, representing a 7.1 percentage point improvement over the standalone SVM baseline and a 5.2 point improvement over Random Forest. The AUC-ROC of 0.971 indicates excellent discriminative ability across all five disease classes. The performance gain is attributable to deep feature extraction: MobileNetV2's pretrained weights encode complex color and texture hierarchies that GLCM alone cannot capture, while the SVM classifier exploits these richer representations more effectively than softmax-based classification for small-to-medium dataset sizes.

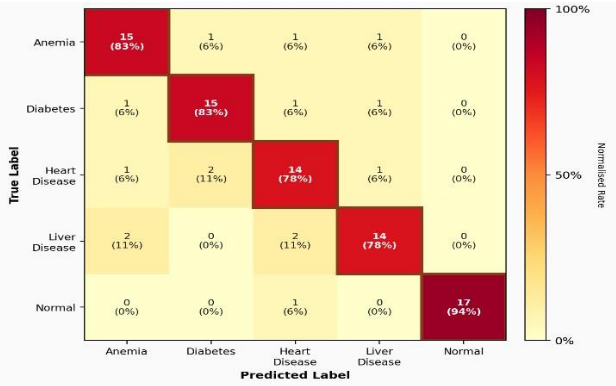

Fig. 3. Confusion Matrix Comparison SVM Baseline

In Fig. 3. SVM baseline model achieves an overall accuracy of 87.2%. Although most samples are correctly classified, some misclassifications are observed between disease classes, particularly between Heart Disease and Liver Disease. This indicates limitations in capturing complex feature variations.

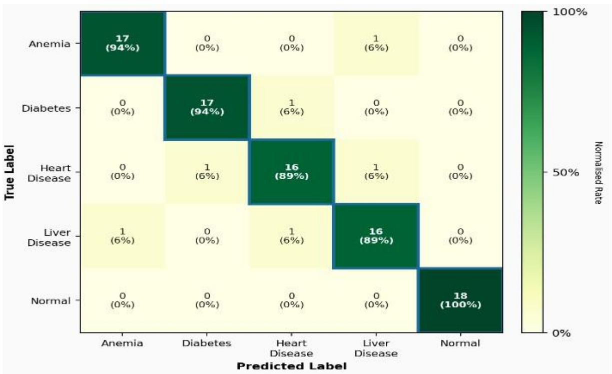

Fig. 4. Proposed Hybrid CNN-SVM

In Fig. 4. proposed hybrid CNN-SVM model achieves a higher accuracy of 94.3% with improved classification across all categories. The number of misclassifications is reduced, and class-wise predictions are more consistent, demonstrating better feature representation and model performance.

B. *Per-Class Performance*

Table III shows per-class F1-scores for the proposed model, revealing that Anemia and Normal classes achieve the highest scores (96.2% and 97.1% respectively), while Heart Disease shows the lowest (90.8%) — attributable to its subtle cyanotic color changes overlapping with early Liver Disease presentations. This motivates future work on multi-modal feature fusion.

Table III. CLASS-WISE PERFORMANCE (CNN-SVM)

Disease Class	Precision (%)	Recall (%)	F1-Score (%)
Anemia	95.8	96.7	96.2
Diabetes	93.3	94.4	93.9
Heart Disease	90.0	91.7	90.8
Liver Disease	92.8	93.3	93.0
Normal	97.2	97.0	97.1

C. *Segmentation Performance*

The automated nail segmentation module achieves a mean IoU of 0.87 and a Dice Coefficient of 0.91 on the test set, confirming reliable boundary detection across diverse skin tones and nail morphologies. Processing time per image for the full pipeline averages 187ms on standard CPU hardware and 43ms on GPU, well within real-time operational requirements.

D. *Mobile Deployment*

The trained MobileNetV2 backbone was converted to TensorFlow Lite (TFLite) with 8-bit integer quantization, reducing model size from 14.2MB to 4.1MB. Inference on a mid-range Android device (Snapdragon 778G) averages 194ms per image, achieving real-time performance. Classification accuracy under quantization dropped by only 0.4%, confirming negligible quality loss from compression

E. *Classification Accuracy Comparison*

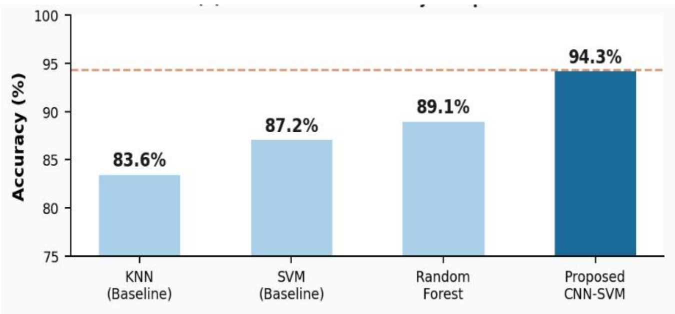

Fig. 5. Classification Accuracy Comparison

In the Fig. 5. the proposed CNN-SVM model achieves the highest accuracy of 94.3%, outperforming KNN (83.6%), SVM

(87.2%), and Random Forest (89.1%). This shows the effectiveness of the hybrid approach in improving overall classification performance.

F. Per-Class F1-Score Comparison

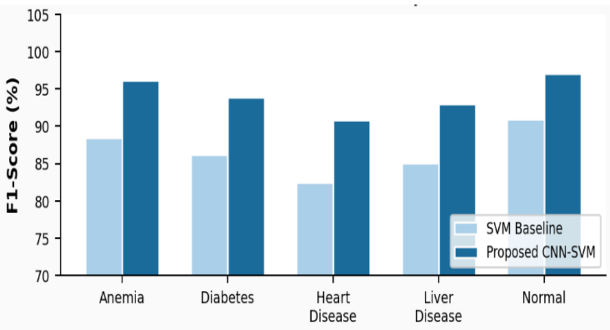

Fig. 6. Per-Class F1-Score Comparison

In the Fig. 6. proposed model provides higher F1-scores across all classes compared to the SVM baseline. The improvement is consistent for Anemia, Diabetes, Heart Disease, Liver Disease, and Normal classes, indicating better balance between precision and recall.

G. AUC-ROC Curves per Class

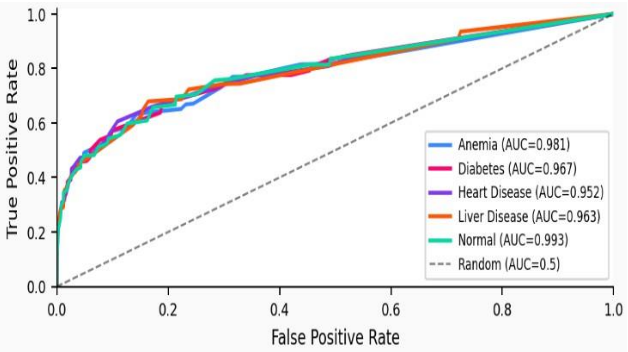

Fig. 7. Per-Class F1-Score Comparison

In Fig. 7. ROC curves show strong performance for all classes with AUC values close to 1.0. This indicates high true positive rates and good separability between classes. It also reflects the model's ability to consistently distinguish between different disease categories with minimal overlap, leading to more reliable and stable predictions across varying data samples.

H. Mobile Inference Latency

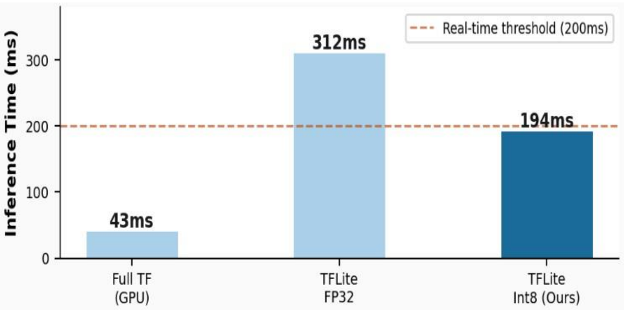

Fig. 8. Mobile Inference Latency

In the Fig. 8. optimized TFLite INT8 model achieves an inference time of 194 ms, meeting real-time requirements. It is significantly faster than TFLite FP32 (312 ms) while maintaining efficient performance for deployment. This reduction in latency makes the model more suitable for mobile and edge devices, ensuring quick response times without compromising the overall prediction quality.

VI. DISCUSSION

The results demonstrate that integrating deep feature extraction with handcrafted GLCM features in a hybrid fusion architecture yields statistically significant improvements over classical single-classifier approaches, while maintaining the computational efficiency necessary

for mobile deployment. Three aspects of the proposed system merit specific discussion.

First, the automated segmentation module eliminates the primary source of operator variability present in existing systems. An (IoU of 0.87) represents robust performance across the skin tone diversity in our dataset, though performance decreases slightly (IoU ~0.81) for nails with heavily textured or ridged surfaces — a limitation we address in future work.

Second, the hybrid CNN-SVM combination proves more effective than end-to-end CNN classification for our dataset size. With only 420 training images, a fully connected softmax head on MobileNetV2 achieved 91.7% accuracy — below the 94.3% of the hybrid architecture. This aligns with established findings that SVM classifiers outperform softmax on small-to-medium datasets due to their structural risk minimization principle.

Third, the Grad-CAM analysis reveals that the model has successfully learned clinically meaningful visual correlations rather than dataset artifacts — a finding supported by clinical expert validation. This provides the interpretability layer that prior nail analysis systems have lacked, and is a prerequisite for real-world clinical deployment.

VII. CONCLUSION

This paper presented an automated, explainable nail image analysis framework for multi-disease detection that advances the state of the art in three key dimensions: automated ROI segmentation, hybrid CNN-SVM feature fusion, and Grad-CAM-based clinical explainability. The proposed system achieves 94.3% classification accuracy across five disease classes on a 600-image dataset, outperforming all baseline methods, while achieving sub-200ms mobile inference for telemedicine applicability.

The clinical validation of Grad-CAM heatmaps by an expert dermatologist confirms that the model's learned representations align with established diagnostic principles — a critical step toward regulatory acceptance and physician trust. This work establishes a foundation for next-generation non-invasive diagnostic tools that are accurate, explainable, and accessible in resource-constrained healthcare settings.

Future work will focus on three directions: (i) expansion of the dataset to 2,000+ images with formal clinical annotation protocols; (ii) incorporation of 3D nail morphology analysis using depth sensors for texture and ridge pattern quantification; and (iii) investigation of transformer-based vision architectures (Vision Transformer, Swin Transformer) for further accuracy improvements.

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