

A Survey and Analysis of Intelligent Detection for Nail Disease Diagnosis Using Artificial Intelligence

V J Rajakumar¹, A Somasundaram²

¹Research Scholar, Department of Computer Science, Sri Krishna Arts and Science College, Coimbatore, Tamil Nadu, India
Email: [vjraja270683phd\[at\]gmail.com](mailto:vjraja270683phd[at]gmail.com)

²Assistant Professor, Department of Computer Science & Application, Sri Krishna Arts and Science College, Coimbatore Tamil Nadu, India

Abstract: *Nail diseases present common dermatological pathologies that include both nail plate and the tissues around them, and they often represent clues of fungal infections and inflammatory diseases or underlying systemic pathologies. The incidence of nail disorders in the world has increased significantly, which explains the high significance of early and precise diagnosis of these complications and securing of proper treatment measures. Some diagnostic methods that are regularly used include dermoscopy, laboratory analysis and clinical examination. To make the process of automatic detection and categorization of nail diseases out of medical imagery possible, Machine Learning (ML) methods have been included to permit feature extraction, selection and classification. However, traditional ML algorithms rely heavily on hand-designed features, require a lot of preprocessing, and they are often prone to failure when faced with a complex and high-dimensional image dataset. To overcome these constraints, a more effective and advanced method has occurred, and this is known as Deep Learning (DL). Unlike the classical methodologies and classical ML algorithms, DL models automatically train hierarchical and discriminative feature directly on raw nail images hence providing better accuracy, strength, and scalability. The current research provides a systematic review and a survey of currently existing methods of detecting nail diseases based on the idea of DL, analyzing their structure, strengths, weaknesses and comparing their performances.*

Keywords: Nail disease detection, Medical image classification, Machine Learning, Deep Learning

1. Introduction

Nails are essential protective mechanisms in the human body; they reverse the mechanic forces when the fingertips are subjected to force and protect the tissues of the body. Nail color, texture, thickness, and growth pattern deviations could be used as clinical measures to suggest a range of pathological problems, such as fungal infections, psoriasis, and melanoma. Over the last few years, the prevalence of the nail disorders has increased, which can be explained by the lifestyle changes, environmental factors, and decreased immune effectiveness [1]. Although many nail diseases have insignificant early stages of disease, some infections could enter the surrounding tissues or infect the circulatory system, leading to serious morbidity. Therefore, it is necessary to effectively and timely diagnose nail disease to stop disease progression and achieve the best results.

Nail diseases present as conspicuous abnormalities of the nail plate or neighbouring tissues and they are often reported in the larger community. Even though the majority of those conditions are mild and harmless, specific manifestations can be associated with severe dermatological or systemic pathologies, which highlights the clinical value of correct diagnosis [2]. Finding changes in nails early on is important to avoid complications, cut down on wasted medical time, and help doctors better manage their patients' health.

Nail disorders have been classified based on clinical presentation which includes discoloration, thickening, deformity, surface irregularities or locations of nail plate separation. Certain conditions, including fungi, are principally associated with nail texture and thickness, and others, e.g. melanoma, are manifested by non-typical pigmentation. Certain abnormalities are local to the nail unit, and others can indicate having some systemic or dermatological disease.

Despite the fact that most of the nail changes are non-life threatening and mild, there are some conditions that may be life threatening when ignored. A majority of the nail diseases do not show any symptoms or cause pain at the beginning and they are often difficult to diagnose [3]. Proper hygiene, prolonged exposure to moisture, trauma, invasion by microbes, nutritional deficiency, immunosuppression, chronic disease, and age are some of the determinants of the epidemiology of nail disorders.

Early detection and accurate diagnosis of nail complications from a central plan in alleviating the complications and preventing morbidity, particularly in the infectious etiology or malignancies. Nail diseases occur throughout the lifespan and are infectious, inflammatory, metabolic, or neoplastic in term of their causes with the most common being fungus. The traditional clinical examination usually includes visual examination, dermoscopy, microbiological screening and, as required, histopathology inspection [4]. However, the problem of differential diagnosis is still tedious, as there are similar phenotypic manifestations and the ethereality of manifestations in the very early stages. Delayed diagnosis particularly of malignant entities such as subungual melanoma is linked to a significant reduction in survival outcomes. Consequently, early diagnosis of nail changes and careful evaluation of these changes are important for the management and prognosis of this disease.

Traditional method of prompt identification of nail disorders mostly relies on clinical examination and conventional diagnostic modalities. Visual inspection is typically performed by dermatologists to evaluate nail colour change, nail thickness, nail texture, and nail morphology; this method is, however, subjective in nature, and it depends on the experience of the examiners. Dermoscopy (onychoscopy) provides enhanced views of the structure of the nail, and it is

more likely to show the patterns of pigmentation, colonisation by fungi and vascular defects, though it also requires professional interpretation. The laboratory tests that are typically used to provide confirmation of pathogenic infection are mycological tests, including potassium hydroxide (KOH) test and fungal culture [5]. Biopsy which is coupled with histopathological examination is done in suspected malignant situations in order to get a definite diagnosis despite its invasive nature. Electronic recording of photographs is regularly being used to track the progress of the disease. However, the use of these standard imaging and diagnostic modalities are limited to inter-observer, delayed, turnaround times and sensitivity of the modalities is limited in the case of early detection of cancers. Artificial Intelligence (AI) is changing dermatology by letting computers do things that used to need clinical knowledge and visual inspection. In the realm of detecting nail diseases, AI combines various sub-disciplines, such as ML and DL for image analysis, and therefore, to some extent, improves the level of diagnosis and efficiency of the nail disease detection. Convolutional Neural Networks (CNN) have shown high accuracy and specificity in the diagnosis and classification of nail pathology including normal nails, fungal infections, inflammatory diseases and malignant lesions [6]. AI algorithms can also be used with a process of differential diagnosis, to reduce false classification in the case of conditions that are visually similar. Moreover, AI can be used to provide automated severity scoring in diseases, such as nail psoriasis, of subungual melanoma, and nail fold capillaroscopy analysis to identify connective tissue diseases. In addition to diagnostic functions, AI helps in personalised treatment schedule, long distance tracking, disease activity, and patient education. AI is very crucial in promoting early detection and full management of nail diseases by improving accuracy, consistency, and efficiency.

Figure 1 below illustrates the general workflow of a nail disease detection system. The process starts with data acquisition whereby the nail images would be procured in repositories like the Kaggle or other clinical databases. The tasks of data preprocessing include image size reduction, image normalisation, image noise removal, image augmentation to improve the quality of images and enhance the model performance. The DL structures in the feature extraction stage extracts salient features (texture, colour patterns, share of structural variation) of the nail image representations.

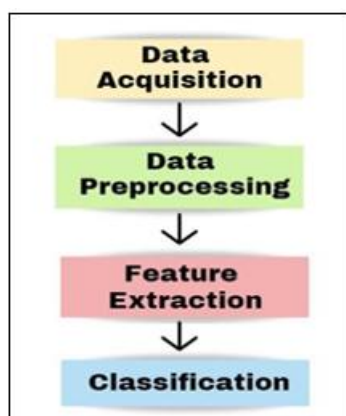


Figure 1: Process of Nail Disease Detection

The DL structures in the feature extraction stage extract salient features. Lastly the classification phase uses a model that takes advantage of these derived features that will be used to classify images and adopt categorical labels such as Healthy, Anemia, Kidney Disorder, and Melanoma, and will guarantee correct and independent disease prediction.

The rest of the paper is set up like this: Section II provides a complete overview of the current DL methods for finding nail diseases. Section III compares these methods and points out important trends in nail image analysis, such as the types of architectures, datasets, and methods used. Section IV talks about how to use quantitative metrics to evaluate the performance of certain DL models to find the best ways to accurately diagnose nail disorders. In conclusion, the main findings are presented in Section V, limitations in the current scope are outlined, and possibilities for future research in the area of AI assisted detection of nail diseases are proposed.

2. Survey on Nail Disease Detection using ML and DL models

Pinoliad et al. (2020) [7] presented OnyxRay, a mobile version that helps identify nail abnormalities and propose potential systemic illness. The system enables the user to take images of the fingernails with the help of a smart phone camera, which is an easy and convenient tool of diagnostic support. The images taken are processed through a Custom Vision machine learning model which identifies the visible nail abnormalities which are associated with underlying health conditions. According to the identified patterns, the application provided potential systemic disease recommendations to help users to be early warned and screened. The possibility of combining mobile technology with machine learning to form user-friendly healthcare systems to measure non-invasive nail-based diseases.

Abdulhadi et al. (2021) [8] suggested a classification framework of human nail disease identification where transfer learning is employed. The pre-trained CNNs, which are trained on the big datasets like ImageNet to classify nail pathologies given small medical images. Comparative research studies were undertaken between AlexNet, VGG16, GoogleNet, ResNet50, and DenseNet201 with a view to determining the optimal architecture to use in ensuring nail disease classification. However, the limitation of the system is that it is only applicable within a narrow range of disease categories and that it uses a limited amount of data, possibly creating a barrier to generalisation to a wide variety of clinical situations at the real-world level.

Jia et al. (2022) [9] presented an automatic detection and evaluation of nail psoriasis based on DL technique. The system consists of separate modules for nail detection, nail lesion detection and quadrant classification, which are subsequently integrated with a scoring algorithm to automatically calculate the Nail Psoriasis Severity Index (NAPSI). The automated-assessment of nail psoriasis severity, which reduces the dependency on manual visual inspection. However, from a lesion detection perspective, the relatively poor lesion detection performance and multi-branch architecture may negatively impact the robustness and also amplify computational complexity in the clinical deployment.

Dhanashree et al. (2022) [10] developed a ML based system of early disease detection by analyzing fingernail images. The collected nail microscopic images were preprocessed using microscopic nail processing techniques to obtain the necessary segments of the nail image like the lunula and nail plate. The extraction of the features was done using the Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) to extract significant texture and structure of the nail surface. To classify them, several ML models were used, such as the Support Vector Machine (SVM), Multiclass SVM and CNN to detect possible disease conditions. Ant Colony Optimization (ACO) was also incorporated to the classification method to maximize the performance of the system as an additional optimization strategy.

Regin et al. (2022) [11] suggested a DL based framework for automated nail disease detection and classification using image analysis. The system analyzes nail images to identify disease-specific characteristics, particularly focusing on color variations and structural deformities associated with different nail disorders. The relevant features were extracted from the images of the nails of the patients during the pre-processing, the dataset was then set up for training and testing of the model. CNN was used for feature extraction and classification, due to their ability to learn complex patterns in the visual images. Nevertheless, the quality of the images and the homogeneity of the datasets may be critical for the effectiveness of the system, which may limit its practical use in real-world clinical scenarios.

Düzayak et al. (2023) [12] developed a diagnostic algorithm based on ML algorithm for the detection of onychomycosis from the image of nail appearance. The AI-led decision support systems aims to reduce the clinician and laboratory induced errors involved in conventional diagnostic techniques, native examination, PAS staining, nail culture, etc. Feature-selection algorithms were used to select the most discriminative features and then multiple ML models were used to classify them. The handcrafted feature extraction and may need additional validation on larger and more diverse datasets to guarantee generalisability within real - world clinical settings. Prajeeth et al. (2023) [13] implemented a smart system for nail diseases diagnosis and associated systemic problems using DL and object detection techniques. The system considers the color, shape, and area of spread of the nails, and it helps to evaluate the severity of the disease and correlate the findings with the possible internal disorders. It also helps in integration with the electronic medical records for improved clinical workflow. However, the use of various modules for detection and analysis adds to the system complexity and may require significant computational resources to implement for real time deployment.

Yamaç et al. (2023) [14] suggested an ensemble-based DL framework for automated nail disease detection using a majority voting strategy. The predictions of seven different dL architectures to improve classification performance and make the models more stable than when they are used alone. An ensemble approach was used to aggregate the output of variants CNN models like MobileNet, VGG16 and DenseNets. The ensemble model helps to reduce the bias and increase the reliability of the result in the detection of nail disorders. This is a very supportive framework that helps non-invasive,

remote screening and as a result, assist telemedicine applications and clinicians to make more informed judgements. However, the combination of multiple DL architectures adds to computational complexity, which can possibly make the deployment difficult in resource-constrained environments.

Soğukkuyu et al. (2023) [15] proposed transferring learning-based methodology for melanonychia, Beau's lines, and nail clubbing using nail image. The framework is based on the pretrained architectures of VGGNet - including VGG16 and VGG19 - to automatically extract deep visual features to infer the disease. Transfer learning makes it easy to perform models efficiently by taking advantage of prior learned image representations to improve the accuracy of models even if the domain specific data are limited. The main objective of the system is to distinguish nail abnormalities that are visually similar but cause problems in the diagnosis of the patient if they are to be evaluated with the naked eye. However, the proposed method is restricted for three types of diseases and may require more data and extensive validation to make it widely useful in clinical settings.

Wang et al. [16] presented MSG-YOLO, a lightweight deep learning architecture for the automatic detection of clubbing fingers. The network takes advantage of a multi-scale dilated residual module to extract features to expand the receptive field as well as retain fine details of the local area important for detecting small changes in shape. The architecture then further adds a Selective Feature Fusion Pyramid Network (SFFPN), which dynamically refines and merges the multi-scale feature maps to eliminate redundancy and achieve the information flow fidelity. Group normalization and parameter shared convolutions are used for detection's head which simplifies the model and improve the computational efficiency. Nonetheless, overall performance is also dependent on the heterogeneity of the training datasets and to what extent the system has been clinically validated on diverse populations to be used in the real world.

Nguyen et al. (2024) [17] has proposed a DL-based approach for automatic detection and morphological classification of nail fold capillaries to facilitate early detection of vasculature related pathologies. The method includes an extended YOLOv8 detection head which is able to process the objects at different scales. To strengthen the representational power of the network, Efficient Channel Attention (ECA) is used, which is accompanied by data augmentation and hyper parameter optimisation. Additionally, the SAHI pipeline is integrated to enhance localisation of small and variably sized capillaries in high-resolution imagery, and hence increase the performance of real-time inference. The addition of these modules of augmentation adds more complexity to the architecture; however, it allows more accurate and robust detection.

Sharma et al. (2024) [18] proposed a hybrid fingerprinting scheme for health evaluation using fingernail images. The proposed method combines deep feature extraction by modifying the VGG16 network with the Random Forest classifier. The collection of data included a wide variety of fingernail images to reflect the presence of different health conditions to ensure that the representations learned were as

comprehensive and meaningful as possible. Pre-processing steps standardised image quality and removed noise in order to ensure consistent input conditions. During feature extraction, the augmented VGG16 learned autonomously high-level representations of visual data, in particular subtle object patterns associated to colour, textures features and object structural changes. The Random Forest then analysed these representations to go on to assign the correct category of health to each image.

Pellegrino et al. (2024) [19] used Roboflow and YOLOv8 for identifying nail abnormalities by combining. To begin, Roboflow was used for instance segmentation annotations on a Nail Abnormality Dataset. For three different dataset versions, Roboflow was applied on images that was augmented by different data augmentation approaches, which increased the dataset's diversity and made the model more generalizable. Utilizing the pre-processed and enhanced dataset, the custom YOLOv8n model was subsequently trained. Several measures were then used to assess the model's performance. Nevertheless, system accuracy is subject to conditions of imaging and specific hardware capabilities, which may have implications for system reliability in different clinical settings.

Shandilya et al. (2024) [20] showed an independent framework for finding nail disorders based on a hybrid capsule CNN architecture for early diagnosis. By first setting up a baseline CNN and then adding capsule networks and dynamic routing to better capture spatial hierarchies, were able to identify six nail conditions: Blue Finger, Clubbing, Pitting, Onychogryphosis, Acral Lentiginous Melanoma, and healthy nails. Techniques for adding data were used to make the model more general. However, the addition of capsule layers and dynamic routing makes the architecture more complicated and requires more computing power, which may make it harder to use in real-time clinical settings where resources are limited.

Shandilya et al., 2024 [20] presented an autonomous model for nail disorders detection using a hybrid capsule – CNN architecture that is well optimized for early diagnosis. The next step in the design involved building a baseline CNN and then adding capsule networks and dynamic routing layers to ensure that spatial hierarchical information is better captured. This set-up allowed to identify 6 different conditions from the nail, namely Blue Finger, Clubbing, Pitting, Onychogryphosis, Acral Lentiginous Melanoma, and healthy nails, and was assisted by data augmentation techniques to improve the generalisation. However, the addition of capsule layers and dynamic routing add to the complexity of the architecture and computation requirements, which may pose a limitation when the model is to be deployed in a real-time clinical setting with limited resources.

Tuncer et al. (2024) [21] developed an automated nail capillary detection system utilizing YOLOv8. The YOLOv8 architecture was utilized to ascertain the capillary count, thickness, and density of images acquired from a microscope of the nail bed. Dataset acquisition entailed collection and recording of capillaroscopic images which was processed and stored in an integrated database system. During the preprocessing, images were standardized to have consistent

input quality for the model training and inference. In the detection stage, the YOLOv8s model automatically detected the capillary structures and extracted the morphological features such as the diameter and distribution. The entire system was installed on a single board computer allowing for portable and real time analysis.

Indriani (2025) [22] introduced a DL based graph attention network for classification of nail diseases. ResNet is used to obtain deep features from the nail image then it represents the relations between samples by modeling the inter-sample relations with a Graph Attention Network (GAT). To improve relational learning, graph edges are made with cosine similarity. This makes sure that nail disease patterns that are numerically similar are strongly connected in the graph structure. There are several types of nail diseases, such as Acral Lentiginous Melanoma, Onychogryphosis, Clubbing, Pitting, Blue Finger, and Healthy Nails. However, building graphs and using attention mechanisms make the approach more complicated, which could make it harder to scale.

Panchbhai et al. (2025) [23] made some changes to DenseNet169 to create a DL network that could find nail diseases. They did this by using Leaky ReLU for activation and long Short-Term Memory layers to extract features from nail images. To make the model stronger, data balancing techniques like SMOTE were used to fix the problem of class imbalance. The framework showed strong performance, achieving high accuracy for nail disease detection. Nevertheless, the used architecture is a sophisticated model requiring a lot of computational resources, which could prevent the use case in resource-constrained clinical environments. Pakpahan et al. (2025) [24] introduced an automated system for nail diseases diagnosis using deep learning based on YOLOv8 and FastAPI. The model was trained using PyTorch on Google Colab, which provides accelerated processing by using GPU. The YOLOv8 model was used for the object detection in real time, which allows simultaneous detection of nail conditions, localizing and classifying them. The implementation of a real-time and accessible diagnostic support tool, as well as the focus on increasing the size of the datasets and robustness under different environmental conditions, make continued development relevant. However, the narrow size of the dataset limits the generalization of the model to different real-world scenarios and may cause the data to be biased.

Hossain et al. (2026) [25] suggested a DL based framework for automatic nail diseases identification using adversarial learning and visualization features. Adversarial training has been added for increased robustness with noisy or adversarial inputs and so as to improve stability and reliability of the model. SHAP-based visualization was used to identify important image regions in classification decisions. However, the approach is still limited to 2D image-based classification and does not incorporate the clinical metadata.

3. Comparative Analysis

This section compares the above-mentioned models, highlighting its advantages, disadvantages, datasets employed and performance measures, as in Table 1.

Table 1: Summary of Recent ML and DL Models for Nail Disease Detection

Author & Year	Techniques Used	Merits	Demerits	Dataset Used	Performance Metrics
Pinoliad et al. (2020) [7]	Custom Vision API	Accessible mobile-based screening tool, non-invasive detection, user-friendly interface.	May depend on image quality and lighting conditions	Dataset such as Muehrcke's Lines and Terry's Nail are used.	For Muehrcke's Lines Accuracy = 99%
Abdulhadi et al. (2021) [8]	AlexNet, DenseNet201	Utilizes CNNs on ImageNet to address limited medical data.	Limited to a small number of disease categories which may reduce generalization to diverse clinical scenarios.	ImageNet dataset	Accuracy = 96.39%, Recall = 90.44%, Specificity = 97.47%, Precision = 91.12%, F-Score = 90.60%
Jia et al. (2022) [9]	Faster R-CNN, ResNet-50	Structured multi-stage pipeline improves clinical interpretability.	multi-stage architecture increases computational complexity	The nail psoriasis image dataset West China Hospital, China	Accuracy = 0.765%
Dhanashree et al. (2022) [10]	SVM, BCT	Hybrid ML approach improves classification performance.	Performance may depend on image quality and dataset size.	Datasets from Kaggle and Messidor.	Accuracy = 94.67%
Regin et al. (2022) [11]	CNN, Neural Network, AlexNet	Automatically learns complex visual pattern.	The task became considerably more complicated due to the lack of a pre-existing database.	Dataset is extracted from an image of a patient's nail and processed with the Weka tool.	Accuracy = 95%, Precision = 90%
Düzayak et al. (2023) [12]	CNet, EDT, SVM	Uses nail appearance images for non-invasive diagnosis.	May require larger and more diverse datasets for generalizability.	Sakarya Karasu Public Hospital, Turkey.	Accuracy: 97.25%, Sensitivity: 0.96%, Specificity: 0.97%
Prajeeth et al., 2023 [13]	YOLOv5, Mask R-CNN	Automated diagnosis of nail diseases, evaluates nail color, shape.	High system complexity, requires substantial computational resources.	Custom SLIIT Nail Disease Dataset	Accuracy = 95.6%
Yamaç et al. (2023) [14]	Ensemble DL	Improved robustness and reliability, reduced model bias.	High computational complexity due to multiple models.	17 nail disease classes with 655 images	Accuracy = 75%
Soğukkuyu et al. (2023) [15]	VGG16 and VGG19	Automatically extracts deep visual features without manual feature engineering.	Transfer learning models can still require considerable computational resources.	Kaggle Dataset	For VGG16: Accuracy = 94%, For VGG19: Accuracy = 93%
Wang et al. (2024) [16]	MSG-YOLO	Efficient feature extraction for subtle morphological changes, lightweight model, reduces redundancy.	Performance may depend on dataset diversity	Highland Medical Research Center of Qinghai University, China	Accuracy = 93.64%
Nguyen et al. (2024) [17]	YOLOv8	Handles multi-scale and small capillaries, supports real-time inference	Increased architectural complexity due to multiple enhancement components	Dataset collected from Osaka University Hospital and Chonnam National University.	Precision = 0.745%, Recall = 0.739%, mAP@50 = 0.799%, mAP@50-95 = 0.463%
Sharma et al. (2024) [18]	VGG16	Captures high-level visual features, effective for subtle color, texture, and structural changes	Depends on quality and diversity of dataset, added complexity from hybrid model	Kaggle dataset and Roboflow29 dataset	Accuracy = 97.02%, precision = 97.02%, recall = 96.84%, F1 score = 97.01%
Pellegrino et al. (2024) [19]	Roboflow, Yolov8	Supports precise Warfarin dosing, reduces reliance on manual observation.	Hardware limitations, may vary in different clinical environments.	Dataset are Splinter Haemorrhage, Terry's Nail, Spoon Nail, Healthy Nail	For Terry's Nail: Accuracy = 89.55%, Precision = 0.84%, Recall = 0.71%
Shandilya et al. (2024) [20]	CNN-CapsNet	Captures spatial hierarchies, effective for multiple nail conditions	Increased architectural complexity and computational demand.	The Nail Disease Detection dataset taken from Kaggle platform.	Accuracy = 99.25%, Precision = 97.35%, Recall = 96.79%, F1-Score = 97.07%
Tuncer et al. (2024) [21]	Yolov8	Automated capillary detection, extracts quantitative morphological features.	Performance may depend on image quality and hardware constraints of SBC.	The images were collected at the Elazığ Firat University, Turkey	mAP50: 0.882%, F1-score: 0.83%
Indriani (2025) [22]	GAT and ResNet	Improves classification of visually similar nail diseases.	Increased computational complexity due to graph construction.	Gather nail disease images from Kaggle.	Accuracy = 88%, F1-Score = 0.8602%, Precision = 0.8801%, Recall = 88.73%

Panchbhai et al. (2025) [23]	DenseNet169, Leaky ReLU, LSTM, SMOTE	Strong feature extraction, handles class imbalance effectively.	Computational demand, may limit deployment in resource-constrained environments	Kaggle Dataset	F1 score = 89.9%, AUC = 98.2%
Pakpahan et al. (2025) [24]	YOLOv8 and FastAPI	Accessible diagnostic support tool, efficient training using GPU.	Limited dataset size, restricted generalization to diverse real-world conditions	The dataset from the Kaggle	Accuracy = 97%, Precision = 93%, Recall = 88%, mAP0.5 = 89%
Hossain et al. (2026) [25]	InceptionV3, DenseNet, EfficientNetV2, ResNet50	Enhanced model stability, interpretable predictions through visualization of critical regions.	Relies only on 2D image-based classification, does not incorporate clinical metadata	Kaggle Dataset	Accuracy = 95.57%

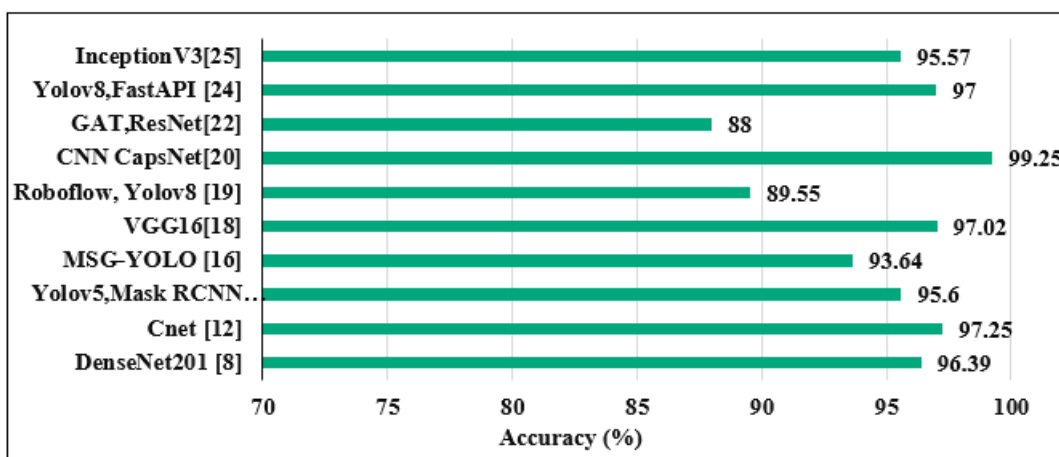


Figure 2: Graphical analysis of various ML and DL based nail disease prediction Models

4. Performance Analysis

This part checks how well the ML and DL-based nail disease detection and classification models work by looking at their accuracy. Figure 2 shows how well the proposed models work for automatically predicting nail diseases by analysing nail images. This includes classifying diseases, figuring out how bad they are, and finding morphological features. This evaluation shows that the models can find different nail disorders and help with early diagnosis by analysing images.

5. Conclusion

Early and accurate identification of diseases of the nails is important to prevent complications and enable early treatment and to identify underlying systemic disease. Conventional diagnostic modalities based mainly on visual examination and manual extraction of features often exhibit variation and lack of reproducibility. A DL based models have been proposed for autonomous detection, classification and severity evaluation. This survey presents a comprehensive analysis of the DL methods used for nail image analysis including the type of method used, pros and cons of the methods, the data set used and performance evaluation metrics. The review found that CNN based architectures with attention mechanisms and capsule networks significantly enhance the diagnostic accuracy, robustness and real time applicability compared to other diagnostic steps. The inclusion of heterogeneous data modalities (i.e. clinical metadata, patient history, high-resolution imaging) has the potential to make automated nail disease identification systems more reliable and enable more informed clinical decision-making.

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