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Fingernail Image-based Health Assessment Using a Hybrid VGG16 and Random Forest Model

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Abstract: Undetected changes in fingernails consisting of alterations in color, shape, size, or texture can be a reason for unfavorable results for the health of the human. It has been a challenge to detect diseases in the human body at an early stage through fingernail images. Various diseases including kidney disorders, melanoma, anaemia, liver disease, heart disease, and many other diseases, can be diagnosed through the images of fingernails. Early diagnosis of mild cases of a disease can help patients guide additional medical care to stop the progression of the disease. Recently, there has been a substantial amount of interest in applying deep learning to diagnose diseases through fingernail images. There are currently a few algorithms that include Densenet201, InceptionV3, Visual Transform, CNN, KNN, etc. that are used to diagnose diseases through human fingernail images. The limitations of these approaches were limited accuracy in diagnosing the disease through images of the fingernails. In this paper, a hybrid model is built using Random Forest classifier that uses the features extracted from VGG16. The dataset is built manually using 1343 images for the early diagnosis of diseases like kidney disorder, melanoma, and anemia. Moreover, the results obtained from this proposed methodology are compared with previous work done in disease detection through the images of the fingernails, which concluded that the proposed model has better performance than the previous works. The proposed method gives the results the following outcomes in the form of accuracy, precision, recall, and F1 score as 97.02%, 97.02%, 96.84%, and 97.01% respectively.

Keywords: VGG-16; Random Forest; Fingernail images; Hybrid Model; Health Assessment

1. Introduction

The main reason to visit dermatologists has been disorders in fingernails that form about 10% of the dermatological conditions[1]. The conditions of the fingernails may provide crucial information about the health of the particular human[3,35]. Many signs and symptoms are visible in the human body, especially the fingernails if an underlying disease or disorder exists. These crucial signs may signify a fatal disease at an early stage. This problem is essential from a technical point of view because of the capability for early disease detection by leveraging fingernail abnormalities. Fingernails often show signs of underlying diseases, but their importance is regularly overlooked. Early detection of those abnormalities via automatic image analysis can facilitate well-timed intervention and treatment, probably stopping the disease development. Therefore, developing a model that is able to correctly detect and classify fingernail abnormalities is vital for allowing proactive healthcare tracking and early diagnosis of diseases. It is necessary to solve this problem because detecting the disease at an early stage improves the results of the treatment significantly. Fingernail images offer an accessible method for disease detection. Early detection of the diseases enables proactive management of health. Fingernails tend to change in shape, size, texture, etc., in order to signify an underlying disease. Fingernails change color to signify fungal infection, respiratory conditions, or deprivation in oxygen level. Change in texture may be a sign of eczema[33], other changes include changes in shape which may depict hemochromatosis, lung disease, or cardiovascular disease. The proposed model is trained on three diseases namely kidney disorder, melanoma, and anemia. Kidney disorder has half the nail reddish or brown in color and the rest half the nail white in color as its symptom[28]. Fingernails get white spots which is a sign of anemia and dark stroke on the nail is a sign of melanoma[31]. The dataset is divided into four classes - Kidney Disorder, Anemia, Melanoma, and Healthy. Furthermore, Random

Forest (RF), K-Nearest Neighbour Algorithm (KNN), Support Vector Machine (SVM), Artificial Neural Network (ANN), and Convolutional Neural Network (CNN) were used individually and in combinations as an advancement to the diagnosis of the diseases through the fingernail images[1-8]. Initially, a number of different methods were used to detect the diseases through the human fingernails, techniques like image processing were used for the fingernail analysis[17], and RGB component analysis was used for the detection[11,18]. In advancement to that, fingernail segmentation was performed for the diagnosis. Later on, a hybrid deep learning approach introduced Vision Transform (also known as ViT) and other pre-trained CNN architecture which were utilized to classify nail images. The major drawbacks of the existing methods and the previous research done in this field include the low accuracy rate and a proper dataset of the images of the fingernails for the diagnosis of the diseases.

The purpose of this paper is to help diagnose any underlying fatal disease at an early stage, to help cure it in time. Sometimes, minor symptoms like the changes on the fingernails are ignored, which might be helpful for early diagnosis. This paper aims to contribute valuable insights into the application of this hybrid methodology for improved performance in tasks such as image classification. Hence, this contributes to advancing the integration of medical and artificial intelligence. The proposed model uses a hybrid approach where it takes VGG16 as the feature extractor and Random Forest as the classifier. VGG16 is a pre-defined and pre-trained architecture of the Convolutional Neural Network, it is a robust feature extractor due to its depth, simplicity, and effectiveness. Random Forest is a flexible and effective ensemble studying the set of rules used for classification. This classifier is used because it can deal with excessive dimensional characteristics and is scalable and interpretable.

The contribution made by this paper is as follows:

- A Deep Transfer Learning model is proposed particularly for disease diagnosis in the human body utilizing fingernail images.
- The VGG16 algorithm, which is a CNN-based pre-trained model, is utilized for the feature extraction from the images of the fingernails.
- The extracted features are further classified using the random forest classifier.
- Evaluation of the performance of the proposed model is conducted using a manually defined dataset.

Using a hybrid model that combines VGG16 for feature extraction and Random Forest for classification leverages the strengths of each method. VGG16[34], a deep convolutional neural network, excels at capturing tricky patterns and excessive-level capabilities from images, supplying sturdy and robust feature representations. Random Forest, an ensemble learning approach, gives outstanding classification performance with high robustness to overfitting and might take care of small to medium-sized datasets effectively. This combination permits for efficient feature extraction and powerful, interpretable classification, frequently leading to higher overall performance as compared to the use of both techniques separately, especially while dealing with complicated image data.

Further, this paper is divided into sections as follows: Section 2 provides an extensive overview and analysis the research done previously in this domain. The overall methodology used to build the model is described in Section 3. Section 4 discusses the evaluation of the model and its results. Ultimately, the paper is concluded in Section 5.

2. Literature Review

The section elaborates on the previous research conducted in the same domain. There have been several researches to find the best methodology to detect and diagnose diseases only by looking at the fingernails of a human. The research was initiated by using image processing techniques. Many used RGB variations in the fingernails to detect diseases. Machine Learning and Deep Learning Algorithms like Support Vector Machine (SVM), K-nearest neighbors Algorithm (KNN), Random Forest (RF), and Neural Networks have been used commonly for detection.

Alzahrani, Dalia A., et al.[1] have implemented deep learning for feature extraction and conventional machine learning for classification, a deep hybrid learning strategy is suggested for nail-based illness identification. The categorization of eczema, nails, melanoma, and healthy nails is the main topic of this investigation. DHL employed his SGD classifier for classification and DenseNet201 for feature extraction, outperforming transfer learning with an accuracy of 94%.

Mohammed, Aasim, et al.[2] have proposed a privacy-preserving machine learning and swarm learning network system for identifying illnesses with a particular focus on patient nail photos. Within the swarm learning framework, it uses transfer learning models to predict seven diseases with 80% accuracy. By detecting illnesses without exchanging personal data, this method ensures privacy while enabling edge devices to work together without the need for a central server.

Marulkar, Shweta, and Bhavana Narain.[3] have implemented a model using a deep learning framework, that diagnoses nine distinct kinds of nail disorders that use nail color to classify. Mainly focused disorders include those that cause beau's lines, hyperpigmentation, onychomycosis, and other particular conditions in addition to black, blue, grey, purple, red, white, and yellow nails. In this work, sophisticated feature extraction techniques are used such as RF, SVM, ANN, and KNN. The accuracy rate of the framework is 87.33%.

Ahmed, Mohammed Junaid, et al.[4] have implemented a hybrid model that combines a VGG16 CNN and a random forest classifier to classify EuroSAT Sentinel-2 images. Achieves 94.88% accuracy with training/testing acceleration. Take advantage of VGG16's spatial capabilities and data enhancements. Achieve efficiency and accuracy in satellite image processing and overcome the complexity of individual images.

Hemalatha, I., et al.[5] have used the traditional method to examine health by using nails. In this study, multiple image datasets have been used, consisting of changes in color, form, and texture of nails can be an indication of systemic and dermatological disease. The proposed model applies the SVM and KNN classification algorithms to detect disease after extracting features. The results have been shown in the form of accuracy, KNN is more accurate (96.81%) than SVM (83.82%).

Yamaç, Senar Ali, et al.[10] have proposed a work focused on predicting five nail disorders by using deep learning architecture. The research classifies five distinct nails: blue nail, clubbing, splinter haemorrhage, Muehrcke's lines, and onycholysis. The model implementing the RestNet101V2 architecture explores the validity of six current deep-learning models, it employs methods such as data augmentation, transfer learning, and convolutional neural networks (CNN); future work seeks to construct a mobile application for early disease detection and enhance classification performance. The model has achieved an accuracy of 89% using RestNet101V2.

Zuhal, C. A. N., and I. Ş. I. K. Şahin.[12] has explored the diagnosis of nail diseases using image processing and deep learning. Using his EfficientNet-B2 model with Noisy-Student weights, we achieve 72% accuracy and his AUC of 91% in disease detection from nail images. The proposed web application allows users to upload images for quick diagnosis. The purpose of this system is to use the appearance of nails to increase awareness of disease symptoms and potentially contribute to medical knowledge.

Wazarkar, Pranav S., et al.[15] have developed an Android application that uses TensorFlow and object identification to predict diseases from nail photos. To evaluate nail photos and predict diseases, the system uses CNN, a type of machine learning algorithm. Improving accessibility and facilitating early diagnosis of diseases are the main objectives of the application, especially in rural and remote areas. To demonstrate how successful deep learning is in predicting diseases based on nail image data, this study used CNN to achieve 75% testing accuracy and 98% training accuracy.

M. Togaçar, ˘ B. Ergen, Z. Comert,[16] have implemented a machine learning approach to identify Bangladeshi birds by species using VGG-16 and achieves 89% accuracy using SVM. This highlights the ecological importance of birds and addresses challenges in bird classification. This study describes dataset creation, feature extraction, and classification methods.

Yadav, Samir S., and Shivajirao M. Jadhav.[17] have examined a CNN-based method for classifying pneumonia on chest radiographs and compared SVM, transfer learning (VGG16, InceptionV3), and capsule networks. Data augmentation improves the performance of all methods. Transfer learning performs better than other learning methods on small datasets, especially for newly trained convolutional layers. Properly balancing network complexity is critical to accuracy.

Kurniastuti, Ima, and Ary Andini.[19] have used nail image analysis to identify diabetes mellitus early. Based on blood glucose levels, the research divides nail images into three categories: normal, prediabetes, and diabetes, using RGB histograms. A histogram analysis of 855 fingernail photos from the study showed that the red, green, and blue components in all categories had overlapping range numbers. The quality of fingernail color may be affected by lighting intensity during image acquisition, which could account for the overlap in RGB histograms. The work highlights the significance of taking lighting effects into account and makes recommendations for possible future research avenues, such as the extraction of textural information from nail photos to enhance analysis and diagnosis.

Malpe, Sachin.[21] have utilized pre-trained DL architectures and XGBoost to detect plant diseases, achieving a 96.16% f1 score with the VGG16+SVM model, notable for its computational efficiency. It addresses the need for efficient disease detection and treatment recommendations in agriculture. Hybrid transfer learning and XGBoost approach haven't been explored before, showing promise for future research in plant disease detection.

Indi, Trupti S., and Dipti D. Patil.[22] have used nail image analysis, which is a non-invasive technique for illness prediction. Early disease detection is critical in healthcare. Analyze characteristics such as color, shape, and texture of human nails. Systems for processing nail images to identify diseases use a variety of classification approaches, including SVM, KNN, ANN, Random Forest Classifier, and Decision Tree. A better way to diagnose diseases and monitor health is to combine nail image analysis with other body parameters.

Nijhawan, Rahul, et al.[25] have used convolutional neural networks (CNN) to propose a deep learning framework for identifying and classifying nail diseases. This addresses the difficulty of reliably diagnosing various nail diseases. By differentiating 11 different nail diseases, the proposed framework achieves an accuracy of 84.58%. Deep learning has been shown to outperform other state-of-the-art algorithms in feature extraction and disease classification when compared to other advanced algorithms such as SVM, ANN, KNN, and RF. The results show that deep learning approaches can also be used in the medical field to detect and classify diseases early.

The following table shows significant work done previously in this domain:

Table 1. Previous Work in disease detection through fingernails

Author	Methodology	Accuracy
Alzahrani, Dalia A., et al.[1]	Deep Learning (DenseNet201) for feature extraction and SGD Classifier for classification	94%
Mohammed, Aasim, et al.[2]	VGG-16 and InceptionV3 within Swarm Learning	80%
Marulkar, Shweta, and Bhavana Narain.[3]	CNN for feature extraction along with RF, SVM, ANN, and KNN for classification	87.33%
Hemalatha, I., et al.[5]	SVM and KNN	SVM- 83.82% KNN- 96.81%
sYamaç, Senar Ali, et al.[10]	ResNet101V2 model	89%
Wazarkar, Pranav S., et al.[15]	Comparative Study taking SVM, KNN, RF, and CNN	Testing – 75% and Training – 98%
Nijhawan, Rahul, et al.[25]	CNN for feature extraction along with RF, SVM, ANN, and KNN for classification	84.58%

3. Proposed Methodology and Materials

This section explains the entire procedure of the methodology. The crucial elements of the proposed model include dataset acquisition, data preprocessing, feature extraction, and result prediction through classification as shown in Fig. 1.

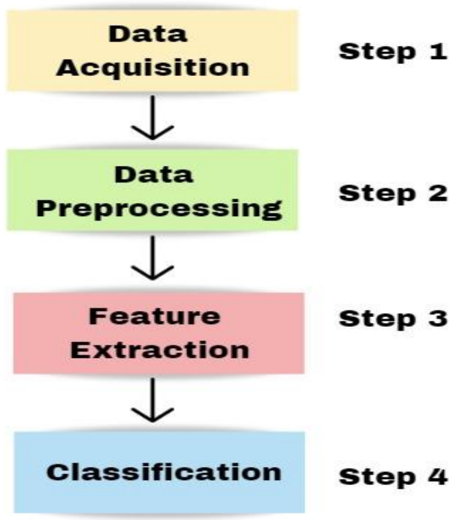

Fig. 1: Stages in the proposed model

3.1 Dataset Acquisition

This section explains the formulation of the dataset that has been utilized for this model for the diagnosis and identification of diseases in the human body through their fingernail images.

The images for the dataset for this model have been collected using datasets from Kaggle[27] and Roboflow[29]. The images collected in the form of data were annotated and trained using Roboflow into four classes: Healthy, Anemia, Kidney Disorder, and Melanoma. The images have been differentiated based on their discoloration or pigmentation.

Figure 2 represents the four classes taken into consideration. Table 2 illustrates the number of images that are taken for each class and the total number of images taken for the research.

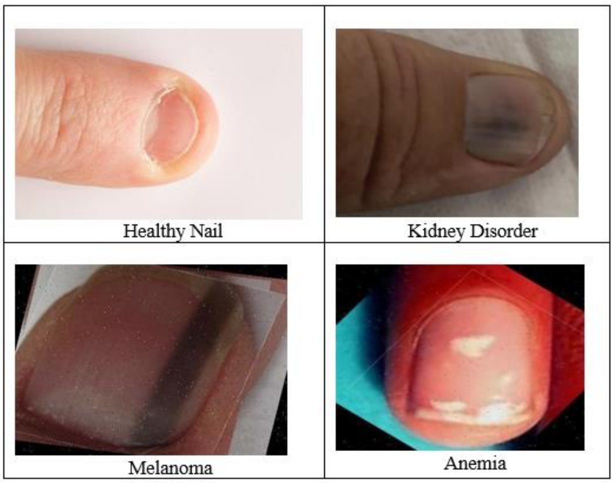

Fig. 2: Healthy and Unhealthy Fingernails

Table 2. Number of images in each class and total in the dataset

Category of Nails	Diseases	Train	Test	Total
Healthy Nails	-	550	150	**700**
Unhealthy Nails	**Anemia**	156	39	**195**
	Kidney Disease	108	48	**156**
	Melanoma	286	73	**359**
Total	-	**1100**	**310**	**1410**

3.2 Data Pre-processing

In this stage, the images of the dataset considered are resized, the pixels are normalized in the range of [0,1], and finally, the images are converted into a format that is fit to be taken as input by the model. The data pre-processing done for this model includes – resizing images into 224 x 224 pixels, these pixels are then normalized in the range of [0,1] and ultimately the images are taken in as input in the RGB format, hence converted to RGB format for this model.

3.3 Feature Extraction using VGG16

In this stage, the data is depicted in the numerical form. These numerical values prove to be helpful to identify the pattern and visualize the data[24]. This stage is crucial in order to identify better accuracy of the model[25].

To perform feature extraction VGG16 is employed. VGG16 architecture is well renowned for better accuracy in the feature extraction process. This feature extraction is done on the images of the dataset that are used as input. This (VGG16) is the most common feature extraction technique. Therefore, for this model, we have chosen VGG16 architecture in order to extract features from the images.

In this work, the VGG16, a convolutional neural network (CNN) architecture, is utilized to analyze the dataset that has been created using the four classes taken into consideration. To use the VGG16 according to the requirement for feature extraction, the topmost layer of the architecture is removed, which allows the use of the architecture to capture and represent the features that are meaningful and are in the image. Features that are utilized here mainly include color, texture, and shape. The images of the fingernail went under the data preprocessing stage where they were resized to 224 x 224 pixels, which is the requirement of the architecture. By feeding these resized images into the modified VGG16 network, we effectively utilized its deep convolutional layers to extract high-level features from the fingernail images. The extracted features were subsequently used as input for further analysis, i.e. classification.

3.4 Classification

In this study, we employed a Random Forest[32]. classifier to analyze extracted features from fingernail images for the purpose of classification. The classifier was trained to classify the input images into the health conditions taken into consideration for this proposed model which include kidney disorder, melanoma, anaemia and healthy nails. Feature extraction is performed on the images of the fingernails that capture the characteristics that may be an indication of some underlying disease. These extracted features are then taken as input for the random forest classifier, an ensemble of decision trees, in order to classify the images into predefined classes.

Here is the process that has been involved in the process of image classification:

1. The VGG16 architecture is utilized to extract features from the images that are given as input.
2. These extracted features from the VGG16 architecture are then taken in as input for the random forest classifier.
3. According to the features that are extracted, the classifier classifies the image into one of the four predefined classes – Kidney disorder, melanoma, anaemia or healthy.

3.5 Methodology

The model involves five main stages: data preprocessing to balance and format the dataset, feature extraction from fingernail images using the VGG16 model, training a random forest classifier with these features, and then testing and classifying the images. Finally, the random forest classifier categorizes the images into one of four predefined classes.: healthy, anaemia, kidney disorder, or melanoma.

The following is the pseudo-code for the proposed model:

```
BEGIN
Step 1: Load libraries and pre-trained model.
Import necessary libraries (NumPy, scikit-learn, TensorFlow/Keras, Matplotlib)
Load pre-trained VGG16 model without the top layer.

Step 2: Define Helper Functions.
function load_and_preprocess_image(file_path, target_size):
img = load image from filepath with target_size
img = convert image to array
img = expand dimensions to match VGG16 input shape
img = preprocess image using VGG16 preprocess_input
RETURN img

Step 3: Data Preparation
INITIALIZE image_paths and labels
INITIALIZE empty list to store features
FOR each image_path in image_paths:
    img = load_and_preprocess_image(image_path, target_size=(224, 224))
    feature = pass img through VGG16 model to extract features
    flatten feature
    append feature to features list
CONVERT features list to NumPy array
CONVERT labels list to NumPy array

Step 4:  Train-Test Split
SPLIT features and labels into training and testing sets (e.g., 80% train, 20% test)

Step 5:  Train Random Forest Classifier
INITIALIZE RandomForestClassifier
FIT RandomForestClassifier using training set features and labels

Step 6: Model Evaluation
PREDICT probabilities on the test set using trained RandomForestClassifier
```

END

The outcomes of this proposed model are calculated in terms of accuracy, precision, recall, and F1 score.

Figure 3 represents the methodology utilized for this proposed model.

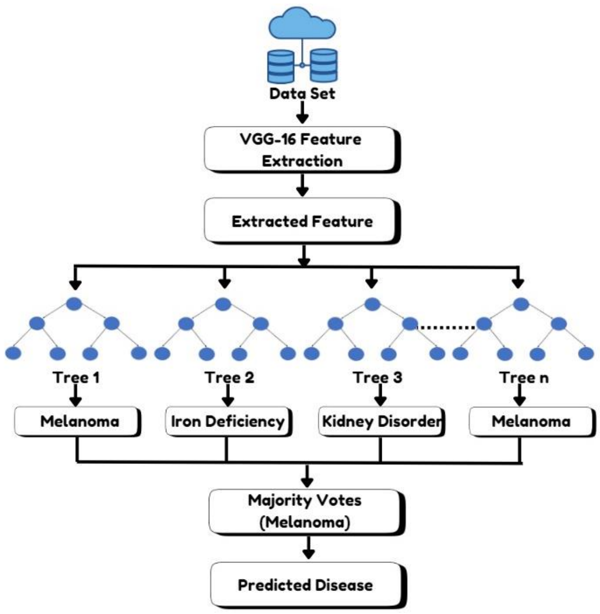

Fig. 3: Methodology

4. Result and Discussion

This section justifies the performance of the proposed model, showcasing its obtained results and comparing them with alternative methodologies.

4.1 Performance evaluation parameters:

The effectiveness of the proposed model is evaluated on the basis of key metrics: accuracy, precision, recall, and F1-score.

Accuracy: Accuracy serves as the most straightforward metric for evaluating the model's performance. It quantifies the proportion of correct classifications made by the model, indicating how closely the predicted values align with the actual labels. It can be mathematically calculated as the sum of total true positives (TP) and true negatives (TN) divided by the sum of total true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). This can be depicted as shown in Eq. 1:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

Precision: This is the measure of the performance of the model by identifying the positive predictions. This is mathematically calculated as total TPs divided by the sum of TPs and FPs. This can be shown as in Eq. 2:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

Recall: This is the parameter that refers to the ratio of relevant items that are correctly identified from the dataset defined. This is mathematically calculated as the ratio of the total TPs and the sum of TPs and FNs. This can be represented as in Eq. 3:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

F1-score: The F1-score provides a balanced measure of the model's precision and recall by calculating their harmonic mean. This metric ensures that both precision and recall are adequately considered, as shown in Eq. 4:

$$\text{F1\_Score} = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

Confusion matrix: The confusion matrix is utilized to evaluate the classification model's performance comprehensively. It summarizes the model's predictions by comparing them against the actual labels, providing a detailed breakdown of true positives, true negatives, false positives, and false negatives. Table 3 below illustrates the confusion matrix representation:

Table 3. Confusion Matrix representation

	Actual Positive	Actual Negative
Predicted Positive	True Positive	False Positive
Predicted Negative	False Negative	True Negative

4.2 Results based on the performance of the proposed model

This subsection describes the results obtained by the performance model proposed in this paper for the manually defined dataset. The effectiveness of the proposed model has been calculated using the following four parameters i.e., accuracy, precision, recall, and F1-score. The comparision with logistic Regression[1)] and SGD Classifier[1)] shows that the proposed model yielded the better results than other classifiers as shown in table 4.

Table 4. Comparative study of proposed with other classifiers

Feature Extractor	Classifier	Precision	Recall	F1-Score	Accuracy
VGG16	Random Forest	97.02 %	96.84%	97.01 %	97.02 %
VGG16	LogisticRegression	84%	83%	83%	82%
VGG16	SGDClassifier	74%	70%	68%	69%

The results obtained from the proposed model for the manually defined dataset have achieved an accuracy of 97.2% while the precision, recall, and the F1-score 97.02%, 96.84%, and 97.01%, respectively, as shown in the following Fig. 4

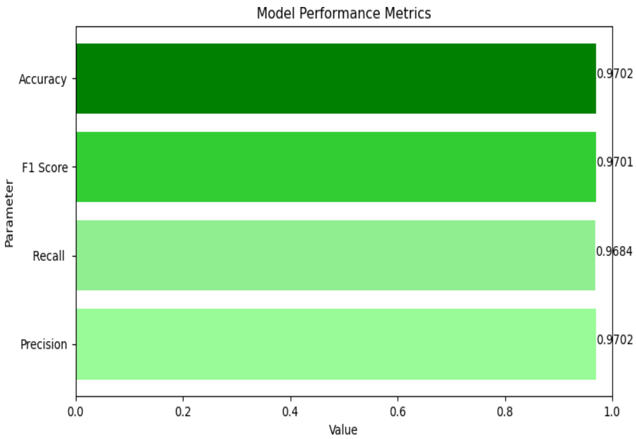

Fig. 4: Model Performance

Various different methods have been employed for classifying the symptoms on the fingernails into classes that are pre-defined. These classes are mainly healthy or unhealthy, and the unhealthy class may have subclasses of specific diseases according to their symptoms. Figure 5 shows a comparative graph of the previously employed methods for fingernail image classification based on the disease symptom it represents. The following Table 5 compares the proposed model with the previous models on the basis of accuracy.

Table 5. Comparative study of models and their accuracy

Author	Technology	Accuracy
Proposed Hybrid Model	VGG-16 + Random Forest	97.02%
Marulkar, Shweta, and Bhavana Narain.[3]	CNN	87.33%
	KNN	96.81%
	SVM	83.32%
Mohammed, Aasim, et al.[2]	VGG-16 + Inception	80%
Alzahrani, Dalia A., et al.[1]	DenseNet201 + SGD	94%

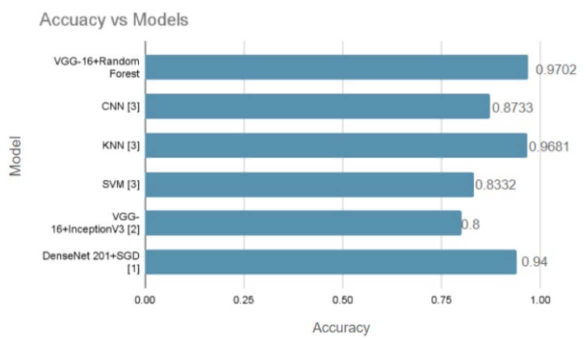

Fig. 5: Accuracy vs Model

5. Conclusion

The hybrid model combining VGG16 and Random Forest has proven to be highly effective in classifying fingernail images into specific disease categories. The model's performance, evaluated through metrics such as accuracy, precision, recall, and F1-score, exceeded those of alternative classifiers. With a 97.02% accuracy rate, the proposed model shows great promise for early diagnosis of diseases such as kidney disorder, melanoma, and anaemia through fingernail analysis.

The proposed hybrid model has several advantages, including high accuracy and effective feature extraction through VGG16, making it highly reliable for disease detection. It is scalable, non-invasive, and versatile for other image-based diagnostics. However, its disadvantages include a limited dataset, and narrow disease focus. Future work can be focused on expanding the dataset, including more diseases, integrating the model into mobile applications, exploring advanced architectures like ResNet, and improving robustness to handle variable image quality for broader applicability.

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