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Article

Deep Learning Model for Ayurveda Doshas Classification Using Nail Image

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Abstract: Analysis of nails is noteworthy from both biological as well as pathological point of view. Coming to Ayurveda, the nails act as an important indicator of impending bodily maladies. An exhaustive and conclusive evaluation leads to an effective course of action. Nail samples were gathered from individuals aged 17-30 from two local institutes in India. During the pre-processing stage, many techniques are employed to enhance image quality and reduce noise. These methods comprise rescaling, normalization, and segmentation techniques such as contrast-limited adaptive histogram equalization and histogram equalization followed by implementation of augmentation approaches. The advancements in deep learning have enhanced the convenience and precision of image processing. Classification strategy utilizing transfer learning has been suggested for detecting four groups of nail images based on ayurvedic principles. The approach incorporates a depth-wise separable convolutional neural network to classify the tri-dosha exhibits in human body. Furthermore, five state-of-the-art CNNs have been specifically designed for analyzing nail images, and their effectiveness has been assessed. The suggested model exhibits superior performance compared to the other high-end CNN architectures. Based on experimental research, the suggested model demonstrates a validation accuracy of 94.75% and a testing accuracy of 93.79% in the classification of nail images.
Keywords: Ayurveda, Deep Learning, Segmentation, Transfer Learning, Classification

1. INTRODUCTION

Ayurvedic medicine, a time-honored medical discipline, has a rich and extensive background in India. From a pragmatic standpoint, it might be defined as the "investigation of living organisms". Ayurveda promotes a healthy existence by attaining a condition of balance and unity between one's mental, physical and spiritual dimensions. It functions as a distinctive method for healing and treatment, as well as a particular discipline for improving one's future. The human body is governed by three fundamental energies: pitta, vata, and kapha. The overall understanding of an individual's dosha constitution is crucial for encourage optimal health and reducing the probability of illness in ayurvedic practices [21]. The amalgamation of advanced expertise and customary knowledge is likely to transform healthcare procedures. The field of deep learning has offered novel diagnoses for investigation and development. The utilization of deep learning approaches is utilized to classify various doshas by investigating nail images from the Ayurvedic viewpoint. A novel approach is utilized to detect the existence of digestive disorders in humans by analyzing the lunula areas of the nail samples. This study examines the correlation between lunula characteristics and tri-dosha derived on the principles of ancient Ayurveda theory. This research integrates the traditional Ayurveda theory with deep learning methods for the aim of classification. The nail images were obtained from individuals of various age groups in different institutes across India using a high-resolution smart camera. The collected photographs were annotated with the assistance of professional opinions from the field of Ayurveda. This article implemented pre-processing and segmentation techniques to increase the quality of images captured from the digital cameras with high resolution. It focused on tri-dosa classification by extracting relevant features from annotated image samples using the depth-wise separable convolutional neural network through the lens of Ayurveda.

This work assesses the comparative analysis of state-of-the-art CNN models to validate the results of the recommended model. This work discovers the assimilation of ayurvedic ideologies with contemporary expertise like deep learning, to improve healthcare solutions. The finding has important implications for adapting healthcare advancements with the assistance of dosha categorization based on the analysis of nail pictures through proposed deep learning model.

2. METHODOLOGY

This section of the study defines the systematic process of implemented approach to mix ancient ayurvedic knowledge with modern deep learning technology for nail image analysis and dosha classification. It outlines a comprehensive step-by-step strategy created to effectively and systematically accomplish the study's goals. Figure 1 represents the workflow of the process employed for nail analysis using ayurvedic aspects.

2.1 Dataset & Data Collection Process

Based on its color, texture and size, lunula, in Ayurveda, are considered as a symbol of an individual's Agni or the fire produced inside the body. According to the above Ayurvedic concept, the dataset of the present study can be classified into the following distinct groups of lunula: (1) Vata predominant (2) Pitta predominant (3) Kapha predominant (4) Equally composed Vata Pitta and Kapha, i.e. healthy condition.

1) Individuals with Vata constituents typically retain nails that are thin and prone to breakage. Additionally, they exhibit a tendency for biting their nails. This form of nails exhibits a slight or absent lunula, which recommends a weakened digestive system.

2) If the lunula surpasses the typical size, around 20% of the nail plate, it may point to an excessive presence of fire within the body. This can result in Pitta-related problems such as loose stools, hyperacidity, inflammation, and inadequate absorption of nutrients.

3) The absence of moons or very small moons suggests poor digestion or a lack of fire in the system caused by an imbalance of Kapha.

4) The nails of a healthy individual are uniformly colored and do not have any indentations or grooves.

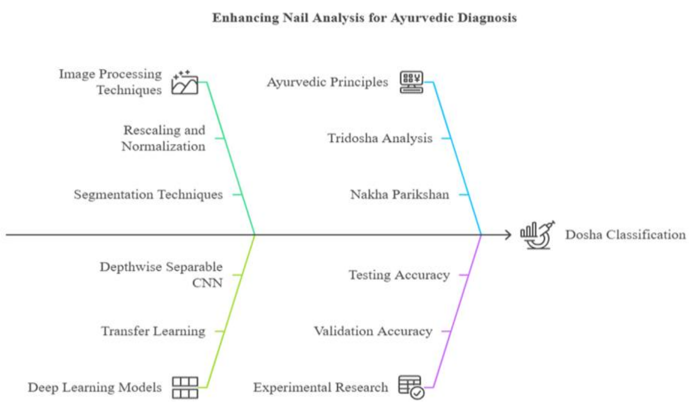

Figure 1. Workflow of the Proposed Work

Nail image samples were collected from individuals aged 17-30 years in two local institutes in India. Smartphones, compact cameras, and DSLR cameras with a resolution of 640 × 480 pixels were used for collection. The collected samples are then categorized into four groups based on the opinion of Ayurveda expert. A total of 1749 nail image samples were gathered, consisting of four classes: Vata dominant, Pitta dominant, Kapha dominant, and

Balanced Vata, Pitta, and Kapha (Healthy). Additional preprocessing procedures were implemented on the collected image samples. The collected samples of nail pictures are displayed in figure 2.

Figure 2. Collected Nail Image Sample

2.2 Pre-Processing

After collecting the nail sample images, preprocess techniques are applied before feeding them into the proposed model. Initially, some blurry and distorted images from gathered dataset are eliminated. Adjusting the nail image dataset for Nakha Parikshan through rescaling and normalization enhances model performance by standardizing pixel values and improving feature extraction. Normalizing CNN-based models ensures uniformity, while rescaling helps stabilize training by reducing fluctuations in lighting and contrast. These processes highlight subtle color and texture patterns that indicate dosha-specific variations in Ayurvedic nail diagnosis, while maintaining their biological relevance.

Then image augmentation function is applied on collected nail image samples in order to expand the size of dataset. Consequently, six conventional methods are incorporated to enhance training set and test set, including horizontal flip, vertical flip, shear, rotation, height, and breadth shift [7]. The initial number of nail image samples gathered was 1749, consisting of four classes. After applying the eight functions of data augmentation, the total number of samples increased to 10,494. Figure 3 represents augumented nail image samples after appling augmentaion functions.

Figure 3. Augumented Nail Image Samples

2.3 Segmentation

Applying the CLAHE (Contrast Limited Adaptive Histogram Equalization) segmentation technique to nail image samples can be a useful method for increasing image contrast and enhancing the visibility of features that are important for dosha categorization on nail image samples. Utilize the CLAHE method to improve the contrast of the nail image samples by selectively restricting the increase of local contrast. It supports in prominence restrained distinctions in the nail image samples, like lunula area and other features that are significant for dosha classification [7][10]. The histogram equalization applied after improving the images using CLAHE. The proposed framework provides the analysis of nail samples for identification and classification by using the ayurvedic aspects. The segmentation technique applied enable to improve the images by segmenting the region of interest for facilitating the feature extraction process for accurately categorizing the dosha. The outcomes of segmentation techniques applied on the images is shown in figure 4

Figure 4. Segmented Images

2.4 Proposed Model

A depthwise separable convolutional neural network is intended to diminution the computational intricacy of consistent convolutions though preserving or improving the final outcome. The procedure halts down the traditional convolution into two discrete operations: depthwise and pointwise convolution[1]. Succeeding the depthwise convolution, a 1x1 convolution is employed to amalgamate the produced feature vectors attained from the depthwise convolution. This phase enables the generation of new features by merging the channel-wise features produced by the depthwise convolution by means of linear functions. The reduction in parameters might consequence in quick training and interpretation, which is particularly beneficial for resource restricted environments such as mobile or edge devices. Figure 5 represents the successive process of the proposed work. The mathematical illustration of the depth-wise convolution work is denoted in equation (1) [17].

$$\text{DepthwiseConv2D}(I,K,S,P)_{i,j,k}=\sum_{di=0}^{K-1}\sum_{dj=0}^{K-1}\sum_{dc=0}^{Cin-1} I(i.S+di-P),(j.S+dj-P),dc \times Kdi,dj,dc,k \quad (1)$$

The spatial position in the output feature map is represented by (i, j), where i and j are coordinates. The index of the output channel is represented by k. The spatial position within the kernel is represented by (di, dj), where di and dj are coordinates. The dc denotes input channel index.

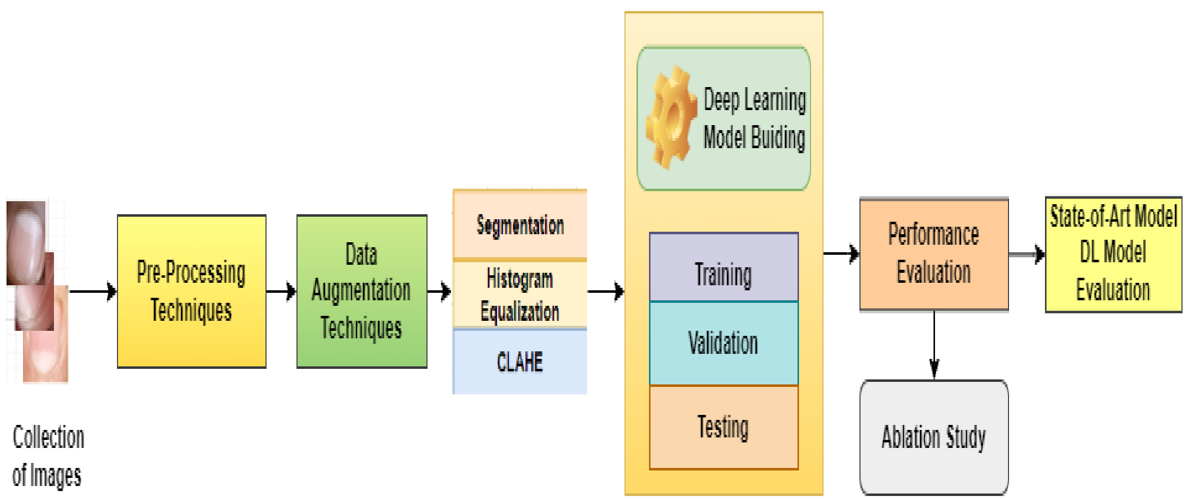

Figure 5. Workflow of the Proposed Model

The process of sliding a kernel across an input tensor is defined by the equation (1). It computes the element-wise product between the kernel and the equivalent input blotch, and then supplements up the outcomes to produce a single value in the output feature map. A proposed algorithm in more detail is explain below.

3. PROPOSED ALGORITHM

1. Obtain nail image samples from persons between the ages of 17 and 30 from local institutes in India.
2. Perform image pre-processing.
    2.1. Standardize the photos by rescaling and normalizing them to maintain consistency.
    2.2. CLAHE and histogram equalization to improve image quality and minimize noise is performed.
3. Apply the CNN to classify images.
    3.1. Create a depthwise separable CNN model to classify nail images into tri-dosha according to ayurvedic ideologies.
    3.2. Implement five distinct cutting-edge CNN architectures for accurately classifying dosha classes.
4. Proceed to train the proposed model as well as the fine-tuned CNN models using the pre-processed and enhanced dataset.
    4.1. Assess the efficiency of each model by utilizing validation and testing datasets.
    4.2. Evaluate the classification performance by measuring accuracy, precision, recall, and F1-score.
5. Evaluate the performance of the proposed model in comparison to five pre-tained CNN architectures.
6. Evaluate the experimental findings to determine the efficacy of the suggested technique in categorizing nail images through the lens of ayurveda.

The aforementioned algorithmic methods provide a systematic strategy to unify ayurvedic concepts with contemporary deep learning approaches for the analysis of nail images and the classification of doshas. The work intends to give strong evidence on the effectiveness of deep learning algorithms for dosha categorization in Ayurveda through a structured training and testing method. This will be further elaborated in the next part.

4. Training and Evaluation

Initially all nail image samples are scaled to 224×224 pixels before feeding them into proposed deep learning model. The first layer in CNN model takes an input of dimension 224, 224 and 3 and outputs a tensor with dimension 222, 222 and 32. After each convolution, batch normalization is performed followed by 2×2 maximum-pooling. Table I shows the kernel dimension for each layer and proposed depthwise CNN model. The generated feature maps using depthwise CNN technique is also shown in Figure 6.

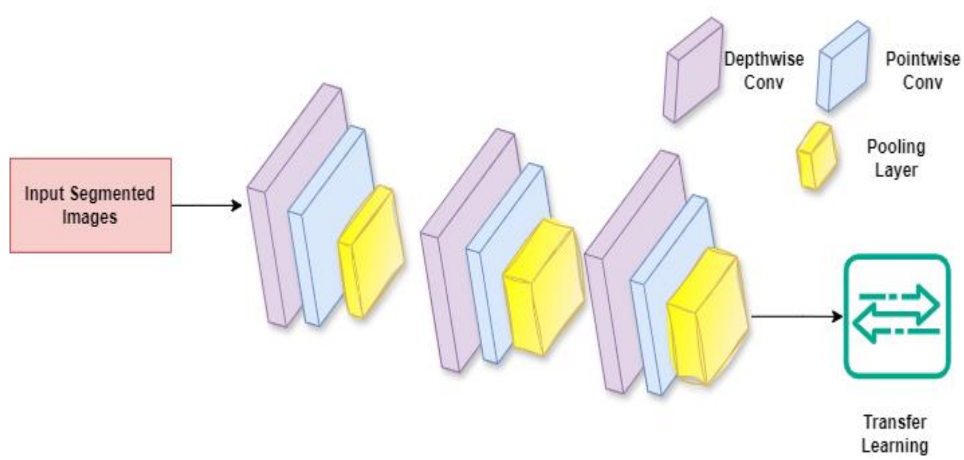

Figure 6. Proposed Depthwise CNN Architecture

SELU activation function is used in our proposed model to overcome issues such as vanishing or exploding gradients which are common challenges in deep neural network designs. As the network deepens, the activations approach a mean value of 0 and a variance value of 1 [27]. The proposed model starts with a standard 3×3 convolution, followed by 3 depthwise separable convolutions, and then concludes with two more standard 3×3 convolutions. During the training phase, using transfer learning and fine-tuning, as depicted in figure 7. In transfer learning approach model is equipped with pre-trained ImageNet weights. The randomly initialized weights are exclusively employed for training the ending dense layer. Next, the dense layers are trained using collected nail images dataset, and the nodes are initialized with various weights. The networks subsequently modified the weights using optimizers. The metric used to evaluate the performance of the model is the accuracy of the 10-fold cross-validation.

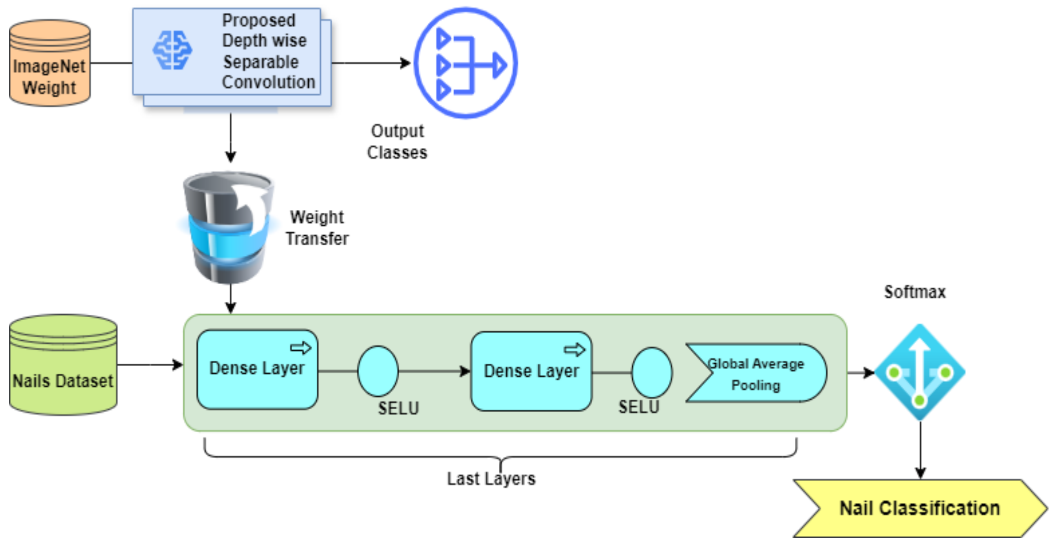

Figure 7. Transfer Learning with Proposed Model

Table 1 displays the parameters of the suggested model. Ultimately, two fully linked layers is deployed each consisting of 128 neurons. Additionally, a dropout layer with a rate of 0.3 between the dense levels is incorporated to mitigate overfitting. After each convolution, 2 × 2 max pooling and batch normalization were applied. The SELU activation function has been applied to all layers, except for the last dense layer, which utilizes the softmax activation function for the purpose of categorization of multi-classes of tri-doshas.

Table 1. Parameters of Proposed Model

Layer's	**Layer_Type**	**Kernel_Size**	**Strides**	**Neuron_Size**	**Mapping**	**ParamCount #**
Block(1)_conv_1	Convolutional	3 × 3	1	224 × 224	3	1792
Block(1)_mpool	Max Pool P1	2 × 2	2	224 × 224	64	0
Block(1)_dconv_1	Depth wise Conv	3 × 3	1	224 × 224	64	36928
Block(1)_mpool	Max Pool P1	2 × 2	2	112 × 112	64	0
Block(1)_dconv_2	Depth wise Conv	3 × 3	1	112 × 112	64	73856
Block(1)_dconv_3	Depth wise Conv	3 × 3	1	112 × 112	128	147584
Block(2)_mpool	Max Pool P2	2 × 2	2	56 × 56	128	0

Block(3)_conv_2	Convolutional	3 × 3	1	56 × 56	128	295168
Block(3)_mpool	Max Pool P3	2 × 2	2	28 × 28	256	0
Block(4)_conv_1	Convolutional	3 × 3	1	28 × 28	256	1180160
Block(4)_conv_2	Convolutional	3 × 3	1	28 × 28	512	23598038
Flatten	Flatten	---	---	---	25088	0
Fc1_Dense	--------	---	---	---	4096	102764544
Dense	DCNN	---	---	---	32	131104
Dense_1	DCNN	---	---	---	32	1056
Dense_2	DCNN	---	---	---	4	132
Output	Softmax	---	---	Classifier()	4	----

The weights were updated using various loss functions including Adam, RmsProp, Stochastic gradient descent, and Hinge loss. The performance of these loss functions was assessed. The hyper-parameters of the proposed deep learning model are provided in Table 2.

Table 2. Model's hyper-parameters

Validation	10-fold cross validation
Batch Size	128
Image Sample Input	10,494
Epochs	50
Training Data	8395
Angular Momentum	0.9
Drop out	0.2
Data Decomposition	8:2
Activation Function	SeLu
Input Image Size	224 × 224
Learning Rate	0.001

5. Results and Ablution Study

This section provides a comprehensive examination of the performance of different cutting-edge CNN models, as well as our own proposed model. Furthermore, the findings are thoroughly documented. The comprehensive outcome analysis has been thoroughly examined under suitable subheadings.

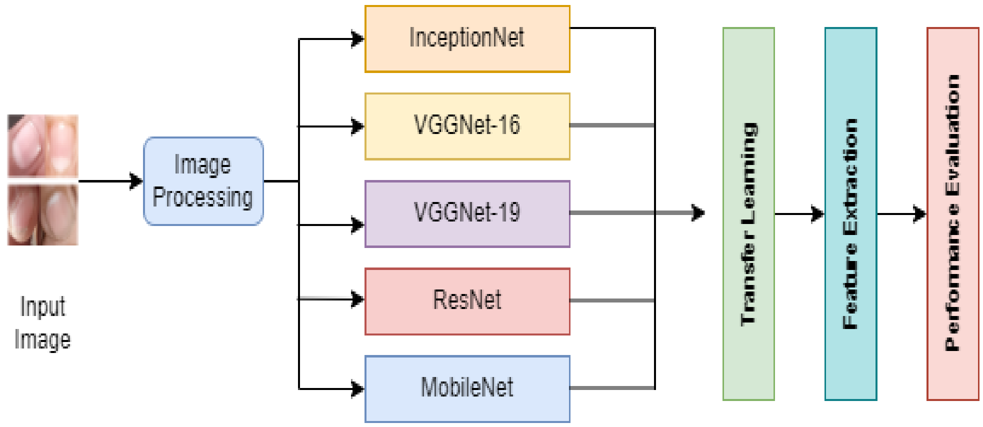

Figure 8: Implementing CNN Models for Nail Analysis

We employed distinct training, validation and testing sets for several occasions and documented the average outcomes. Fig. 8 depicts the utilization of cutting-edge Convolutional Neural Network (CNN) models for nail analysis and the subsequent evaluation process. Table 3 displays the average performance results of the nail dataset on various CNN architectures, including training, validation, and testing outcomes, after 50 iterations.

Table 3. Performance Analysis of Different CNN Architectures on Nail Dataset

Model	**Training Accuracy**	**Training Loss**	**Validation Accuracy**	**Validation Loss**	**Testing Accuracy**	**Testing Loss**
InceptionNet	82.4	2.73	80.48	2.38	78.52	3.6
VGGNet16	90.6	0.96	89.53	0.93	89.36	1.89
VGGNet-19	84.9	1.47	85.83	0.96	80.75	0.56
ResNet-50	79.3	2.43	76.35	1.94	75.28	2.84
MobileNet-V2	80.7	2.85	79.54	2.37	77.36	2.79
Proposed Model	94.75	0.13	93.79	0.128	93.64	0.26

Figure 9 displays the performance curve of five cutting-edge CNN architectures, utilizing transfer learning. Out of all the advanced CNN designs, the VGGNet-16 architecture achieved the highest level of accuracy.

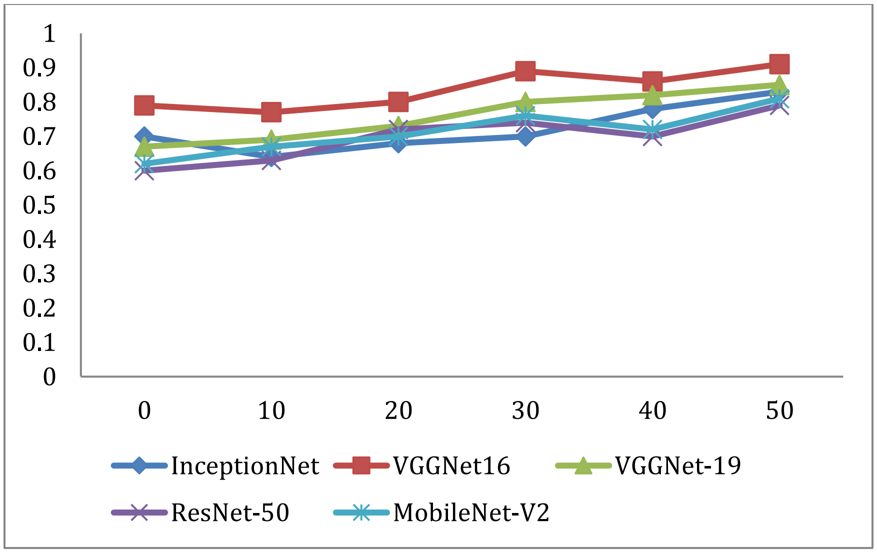

Figure 9. Performance Curve of five state of the art CNN Architectures

Confusion matrix for proposed model is shown in Table 4. Table 4 used to measure how good our classification model is performing. It compares the predictions made by the proposed model with the actual results.

Table 4. Confusion Matrix of Proposed Model

Class	Vata Dominant	Pitta Dominant	Kapha Dominant	Balanced
Vata dominant	232	5	17	12
Pitta dominant	6	203	5	8
Kapha dominant	11	14	157	15
Balanced	9	7	10	173

Table 5 shows that among the four classes, the Pitta dominating class has somewhat superior performance, with a precision of 91%, recall of 89%, accuracy of 94.91%, and F-measure of 90%. The Kapha dominating class had the lowest accuracy of 91.86% according to model outcomes. The primary cause of the low accuracy is the fact that symptoms generated by many classes might be quite similar and may coexist simultaneously. For instance, the symptoms of each dosha with a dominant Kapha or Pitta constitution may appear similar at certain points, leading to misdiagnosis. The positive and supportive results of the model in identifying dominant classes demonstrate the significant importance of deep learning in future identification and classification. Limitation of this research is that a more comprehensive analysis might be achieved if additional data were collected. The overall accuracy obtained by the proposed model with fine-tuned hyper-parameter is 94.75, recall 92.48, precision 92.29 and F1-score is 90.62.

Table 5. Performance Evaluation of Proposed Model

Class	TP	Accuracy	Precision	Recall	F1-Score
Vata dominant	258	93.21	87	90	89
Pitta dominant	229	94.91	91	89	90
Kapha dominant	189	91.86	80	83	81
Balanced	208	93.1	87	83	85

Based on the loss and accuracy curve, it is clear that the suggested model gradually reached convergence without exhibiting any signs of overfitting. We utilized multiple optimization algorithms, such as Adam, stochastic gradient descent (SGD), Rmsprop, Adagrad (Adaptive Gradient Descent), and AdaGrad, with varying learning rates on our model. Adam, an adaptive moment estimate optimizer, demonstrated superior accuracy compared to all other optimizers. Table 6 displays the results of employing various optimizers with adjustable learning rates on the nail dataset, showcasing their performance.

Table 6. Different Optimizers Performance with Variable Learning Rate on Nail Image Dataset

Optimizer	Learning Rate	Accuracy	Loss
Adagrad (Adaptive Gradient Descent)	.01	86.93	0.26
	.001	88.47	0.29
	.0001	88.35	0.31
RMSProp	.01	83.72	0.19
	.001	82.19	0.21
	.0001	83.86	0.27
Adam	.01	92.36	0.19
	.001	**94.74**	**0.13**
	.0001	93.81	0.14
SGD	.01	91.28	0.17
	.001	92.35	0.19
	.0001	92.83	0.17

Table 6 readily shows that the stochastic gradient descent (SGD), RMSProp, and Adagrad (Adaptive and Gradient Descent) optimizers had inferior performance compared to Adam. Adam and SGD exhibited comparable performance. Figure 8 depicts the accuracy and loss curve of the Adam optimizer with a learning rate of 0.001 on our dataset.

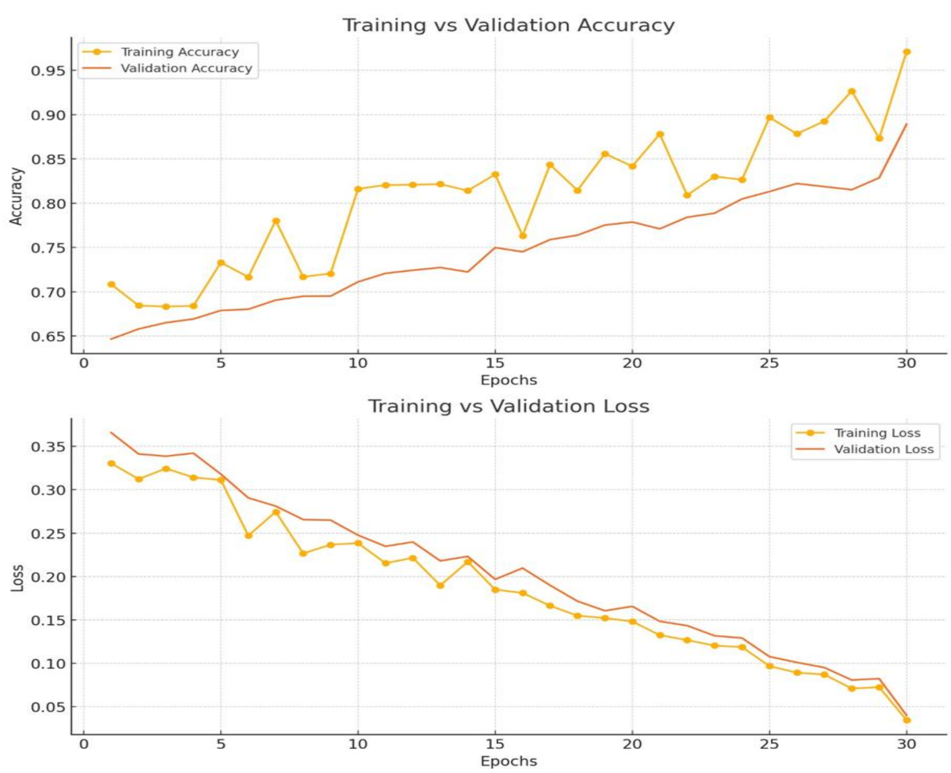

Figure 8. Accuracy and Loss Curve using Adam optimizer with 0.001 learning rate

6. COMPARATIVE ANALYSIS

Table 7 illustrates recent advancements in disease diagnostics utilizing machine learning techniques. By using KNN, SVM, LDA, QDA, and Decision Trees on a small dataset of 50 samples, Kumar. N et al. (2019) researchers achieved an accuracy of 96.29% in identifying conditions such as cold, fever, back pain, and pregnancy [24]. Lin et al. (2021) attained 89% accuracy (n=60) using Kernel SVM and Linear Classifiers to detect pancreatitis, appendicitis, and abnormalities in arterial blood flow [16]. Through statistical analysis, Dubey et al. (2022) predicted tri-dosha dominance in Ayurveda, reaching an accuracy of 91.6% (n=120) [8]. With an impressive accuracy rate of 99.7% (n=1025), Vayadande et al. (2024) developed a Decision Tree-based tool for heart disease and dietary recommendations [13]. Fatangare et al. (2025) employed Decision Trees and K-Nearest Neighbors for Nadi Pariksha (pulse examination), reaching an accuracy of 92% among 250 participants. In contrast, our proposed model for Nakha Parikshan (nail examination) achieved a 94.75% accuracy using 10,494 enhanced images, while Kamath et al. (2025) utilized XGBoost to identify dosha imbalances with a 96% accuracy rate [15]. The variation in accuracy is based on dataset size and complexity of methods. Comparative Analysis highlights the growing significance of machine learning tailored for various traditional treatments.

Table 7. Comparative Analysis with State-of-Art Techniques

Ref	Year	Disease	Technique	Dataset	Outcome
Kumar. N et al. [24]	2019	Cold, fever back pain pregnancy	KNN, SVM LDA, QDA, DT	50	96.29
Lin F. et al. [16]	2021	Changes in arterial blood flow normal, Pancreatitis, Appendicitis	Kernel SVM Linear classifiers	60	89
Dubey. S. et al. [8]	2022	Tri-dosha Dominance	Statistical Analysis	120	91.6
Vayadande. K. et al. [13]	2024	Heart Disease Diagnosis and Diet Recommendation System	Decision Tree	1025 data tables	99.70%
Fatangare et al. [9]	2025	Nadi Pariksha (Pulse Diagnosis)	DT and KNN classifiers	250 individuals, male and female, healthy and non-healthy subjects aged 18 to 75 including 140 healthy and 110 non-healthy subjects	92%.
Kamath. V. et al.[15]	2025	Dosha Imbalances	XGBoost classifier	--	96 %
Aggrwal. I. el al	2025	Nakha Parikshan	Proposed Model	10,494 Augmented Imges	

7. CONCLUSION

This work provides a framework for classifying tri-doshas relying on nail image samples through the lens of Ayurveda. This method unifies the traditional principles of Ayurveda with advance deep learning frameworks. The work primarily focused on collecting the image samples and exploring the standard ayurvedic concepts based on lunula size and its association with the different classes of dosha. Expert ayurvedic consultants pedantically annotated this data, ensuring the exactitude of dosha descriptions for each individual. During the pre-processing phase, a series of image improvement procedures were employed to increase clearness and minimalize blare, thereafter refining the feature of the collected dataset. Consequently, augmentation methods were used to develop the model's efficiency and capability to simplify identification process. The study offered a generalized design for dosha classification, employing a depthwise separable CNN model. The system was trained on annotated dataset by appropriate optimization procedures and loss functions for multi-class classification. The overall accuracy obtained by the proposed mode with fine-tuned hyper-parameter is 94.75, recall 92.48, precision 92.29 and F1-score is 90.62. Moreover, the recommended model's efficiency was estimated by relating it to five pre-trained CNN architectures: VGG19, VGG16, ResNet50, MobileNet-V2, and InceptionNet. This comparison discovered the dominance of the proposed method. This study not only supports to unification of the traditional ayurvedic aspects with advance technology, but also indicates how deep learning can contribute in classifying ayurvedic doshas. The approach has potential to enable future research in modified healthcare application that is based on ayurvedic ideologies.

FUNDING INFORMATION

No funding involved in the given research work.

INFORMED CONSENT

This study does not involve individual personal data or identifiable human subjects. Therefore, informed consent was not required.

ETHICAL APPROVAL

Permission to take nails images for the purposes of this research was obtained by all respondents, who were fully informed about the purposes of this research and how their nails images would be used and stored. All subjects have been anonymized.

CONFLICT OF INTEREST

On behalf of all authors, the corresponding author states that there is no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study were obtained from the first author. Data used with permission and are not publicly available due to licensing restrictions. Requests for access may be directed to the corresponding author, [IA]

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