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**Research Article**

# Human Prakriti classification based on skin color using machine learning algorithms and image processing techniques

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**ABSTRACT**

In the field of Ayurveda, the term Prakriti represents an individual's intrinsic physiological and psychological constitution, which is traditionally categorized into three types: Vata, Pitta, and Kapha. Prakriti's precise identification is essential for providing personalized healthcare interventions. Nevertheless, conventional methods for assessing Prakriti are predominantly subjective and susceptible to variability. This study introduces an objective and automated methodology for classifying human Prakriti through the analysis of skin colour, utilizing image processing and machine learning techniques. High-resolution images of skin are subjected to pre-processing and feature extraction to generate colour histograms, texture metrics, and statistical colour parameters. A variety of machine learning classifiers, including K-Nearest Neighbours (KNN), Support Vector Machines (SVM) with Sigmoid, Linear, and Gaussian kernels, as well as Random Forest, are utilized for the classification task. Comparative evaluations indicate that the Random Forest and SVM with Gaussian kernel classifiers achieve superior accuracy, underscoring the efficacy of integrating image processing methodologies with advanced machine learning algorithms. The proposed system provides a standardized, efficient, and reliable approach to Prakriti classification, effectively merging traditional Ayurvedic concepts with contemporary technological innovations.

**Keywords:** Machine learning, Image processing, Human Prakriti(Tridosha), Segmentation, Precision, Recall, F1-Score

## INTRODUCTION

Ayurveda, the traditional Indian system of medicine, emphasizes the unique constitution (Prakriti) of each individual, which governs their physical, physiological, and psychological characteristics. Prakriti is broadly classified into three types—Vata, Pitta, and Kapha—each associated with distinct attributes, including skin texture, tone, and colour. Ancient Ayurvedic literature highlights that the appearance of one's skin is vital in determining one's Prakriti. For instance, individuals with a Vata constitution often have dry and rough skin with a darker tone. At the same time, Pitta types are characterized by sensitive skin with a reddish or fair complexion. In contrast, Kapha types typically exhibit smooth, oily skin with a lighter, whitish tone. Facial skin is considered a significant aspect, as it prominently reflects the body's internal balance and constitution. Therefore, objectively analyzing facial skin features can provide valuable insights into an individual's Prakriti, serving as a non-invasive diagnostic approach.

This research investigates the correlation between Ayurvedic constitutional types (*Prakriti*) and observable dermatological features, aiming to establish a quantifiable link for personalized skin health assessments. Leveraging established image analysis and pattern recognition methodologies, we examine the efficacy of computational techniques in identifying and characterizing skin lesions. A critical review of the current literature indicates a notable research gap: the absence of a standardized, integrated framework for analysing *Prakriti*-related skin variations in conjunction with quantitative lesion detection. To address this, we propose a novel analytical model that combines Ayurvedic principles with advanced image feature extraction, culminating in a detailed evaluation of its diagnostic potential and clinical implications.

The structure of this research paper is outlined with an objective and a review of related work in machine learning and image processing. Moreover, the details of the proposed model, elaborating on its methodology and implementation, are then framed in the methods section. Finally, the concluding section summarizes the findings and highlights potential directions for future research in the results and discussion sections, respectively.

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## OBJECTIVES

A machine learning methodology for the classification of Prakriti utilizes computational analysis of physiological data to discern patterns that are indicative of individual constitutions. By training algorithms on datasets that link specific features to established Ayurvedic principles, this model aspires to automate and standardize the assessment process.

This approach presents the potential for enhanced efficiency and objectivity in comparison to traditional evaluation methods, which frequently depend on subjective interpretation.

The incorporation of machine learning aims to reconcile ancient wisdom with modern technology, thereby offering a tool for personalized health insights. Through comprehensive training and validation, the objective is to develop a dependable system that enables individuals to gain a deeper understanding of their unique Prakriti.

## RELATED WORK

Machine learning algorithms provide a robust method for identifying patterns and making accurate predictions from complex datasets. [1] [2] [3]

In the context of Prakriti classification, essential skin features—such as color and texture—are extracted using image processing techniques. These features can then serve as input for various machine-learning models. Algorithms such as K-Nearest Neighbours (KNN) [4], Support Vector Machines (SVM) with linear, sigmoid, and Gaussian kernels, and Random Forest classifiers have proven particularly effective in this domain [5]. These models are applied on the collection of images, where each instance of an image corresponds to a specific Prakriti type: Vata, Pitta, or Kapha. By learning from these datasets, the algorithms can generalize and predict the Prakriti of new, unseen individuals based on their skin attributes. This method for Prakriti identification provides a scientific approach to complement and modernize traditional Ayurvedic practices [6] [2]. Furthermore, integrating assessments like Nadi Tarangini, which records pulse variations, adds an objective measure to traditional pulse-based diagnostics. This combined approach enhances the accuracy of the Prakriti classification and supports Ayurvedic practices with measurable parameters. This study focuses on the role of image processing and statistical classification techniques in Prakriti identification, particularly through skin color analysis. By integrating these methodologies with Ayurvedic knowledge, this research aims to establish a structured and reproducible approach to Prakriti assessment, reducing subjective variations and supporting personalized healthcare applications. Image processing plays a crucial role in the accurate extraction of skin features from facial images, which is essential for Prakriti classification. The process begins with image acquisition, followed by pre-processing techniques such as noise removal, contrast enhancement, and skin segmentation to isolate the skin region from the background and non-skin elements, such as hair and eyes. Colour space transformations (e.g., RGB to HSV or YCbCr) are commonly applied to emphasize variations in skin colour [7] [8] [9] [5]. Subsequently, statistical and textural features—such as colour histograms, mean intensity, standard deviation, and texture patterns—are extracted to quantify the unique characteristics of the skin. These features capture subtle differences in skin tone, smoothness, and pigmentation, which correlate with different Prakriti types. By automating this extraction process, image processing ensures consistency, objectivity, and scalability, providing reliable input data for machine learning models to classify Prakriti based on skin attributes. In year of 2003, a face detection technique that combines skin color modelling, segmenation and template matching was introduced and presented in which the approach was to achieve robust face detection across varied backgrounds and lighting conditions with high accuracy and speed though the work related to reduce false detection rates in complex scenarios needs to be get focused. In recent times, by reviewing more than one hundred key publications, this study investigates how datasets, features, and classification techniques are employed [10] [11]. Furthermore, it explores the prominent obstacles within this dynamic domain, such as ensuring dataset diversity, model generalizability, and real-world application. In the year 2016, the work explores various applications of image processing in fields such as video sequences and traffic signal recognition, where machine learning frameworks have been effectively utilized. The study found that machine learning introduced a novel model that significantly improved image processing capabilities, addressing many challenges encountered in earlier methods. Its implementation in image processing has provided a viable approach for developing robust frameworks. While content recognition in images was not as successful in diagnostic applications, the results were promising enough to justify further research and advancements in this domain. In 2018, presents a comprehensive study on various image processing strategies. It provides an overview of key techniques, including grayscale conversion, segmentation, feature extraction, and classification methods [12] [13]. Image segmentation using Otsu's method and thresholding proves to be a well-referenced approach, even in noisy images [14] [15]. These segmented regions can enhance contrast in shadows within paintings or reveal underlying conceptual patterns. For feature extraction, datasets containing leaves, fruits, and objects achieve optimal data extraction using the Scale-Invariant Feature Transform (SIFT) method, while image sets such as flowers and plants yield the best results using HSV color-based and shape extraction techniques. [16]

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Morphological operators play a crucial role in enhancing image clarity and reducing noise for improved processing. Image classification, a key aspect of image processing, is explored using Artificial Neural Networks (ANN) and Support Vector Machines (SVM) as classifiers. Additionally, the paper examines edge detection techniques, highlighting the Canny edge detector as the most effective due to its adaptability, lower sensitivity to noise, and ability to detect sharper edges compared to other methods. Overall, this study provides insights into the most effective image processing techniques and their applications, offering valuable guidance for future research in this domain [17] [18] [19].

## METHODS

The study utilized a dataset consisting of 350 images for training, allowing the system to learn patterns in skin color variations associated with different Prakriti types. To evaluate its effectiveness, the trained model was tested on a separate set of 150 images. During testing, the predicted classifications were compared with the actual Prakriti labels to measure accuracy and reliability. This approach helps in assessing how well the system distinguishes between Vata, Pitta, and Kapha skin types based on the extracted features. Classifications were compared with the actual Prakriti identification with the Nadi taragnini device to measure accuracy and reliability. This approach helps in assessing how well the system distinguishes between Vata, Pitta, and Kapha skin types based on the extracted features.

### 1. Input: Human Face Image

The process begins by capturing or uploading a human face image. The input image should be taken under controlled lighting conditions to minimize variations caused by external factors. The image should primarily focus on the facial region to ensure accurate skin analysis.

### 2. Apply Green Masking

Green masking is applied to isolate the skin region from the rest of the image. This technique enhances the detection of skin pixels by filtering out non-skin regions such as hair, background, and clothing. The process involves applying a predefined threshold in the HSV or YCbCr color space, which helps in extracting the skin pixels more accurately. [10] [5]

### 3. Extract Skin Color Histogram

Once the skin region is extracted, the next step is to analyse its colour distribution. A skin color histogram is generated to capture the frequency of different skin tone values. This histogram provides crucial statistical information about skin texture and pigmentation, which serves as a key feature for classification [20] [21] [22].

### 4. Feature Selection

From the skin color histogram, relevant features such as mean, standard deviation, and skewness of color components (RGB, HSV, or YCbCr) are extracted. Feature selection helps in reducing dimensionality and selecting only the most significant attributes that contribute to the classification process [23] [24].

### 5. Apply Machine Learning for prakriti classification

Various machine learning algorithms are applied to classify human Prakriti based on the extracted skin color features. K-Nearest Neighbors (KNN) helps in finding the closest matching patterns, Support Vector Machine (SVM) efficiently separates different classes, and Naïve Bayes is used for probabilistic classification.
Table 1 provides an insight to various machine learning algorithms used in classifying human prakriti based on skin color detection.

**Table 1. Glimpses of Machine learning algorithms**

| Machine learning Algorithms used | Equation | Explanation |
|---|---|---|
| [25]K-Nearest Neighbourhood | $d(x, x\,i) = \sqrt{\sum_{k=0}^{n} (xj - xij)^2}$ ............(1) | The KNN algorithm classifies a data point based on how its neighbours are classified. The mathematical formulation involves calculating distances, usually Euclidean, between points:<br>Where:<br>- x is the novel data point of an image.<br>- x_i is a neighbouring data point. |

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| | | - $x_j$ is the jth feature of the data point that is the adjacent colour shade value for Prakriti from human skin color pixel.<br>The algorithm finds the k nearest facts and allows the common label among those neighbours. [11] |
| Random Forest | **Gini Impurity:**<br>$Gini(p) = 1 - \sum(p_i^2)$ .............(2)<br>**Entropy:**<br>$Entropy(p) = -\sum(p_i \log_2(p_i))$ ...(3)<br><br>The final prediction for classification is:<br>$\hat{y} = mode(y_1, y_2, ..., y_T)$ ........(4) | Random Forest is a collaborative learning method that operates by building manifold decision trees. The productivity is the mode of the lessons (classification) or the mean prophecy (regression).<br>For each tree, the model studies using a subset of the data (bagging).<br>The decision rule at each node of a tree is based on some criterion (e.g., Gini impurity or entropy). [24] |
| [26]SVM Linear | $f(x) = sign(w^T x + b)$ ...................(5) | In linear SVM, the algorithm tries to find a hyperplane that best separates the data into classes.<br>Where:<br>- w is the weight vector.<br>- x is the input feature vector.<br>- b is the bias term. |
| SVM Gaussian | $f(x) = sign(\sum(\alpha_i y_i K(x_i, x) + b))$ ...................(6) | For SVM with a Gaussian kernel (Radial Basis Function or RBF kernel), the kernel function is:<br>$K(x_i, x_j) = \exp(-\|\|x_i - x_j\|\|^2 / 2\sigma^2)$<br>Where:<br>- $x_i$ and $x_j$ are input vectors.<br>- $\sigma$ is a parameter that controls the width of the Gaussian kernel. |
| SVM Sigmoid | $K(x_i, x_j) = \tanh(\alpha x_i^T x_j + r)$ ...................(7) | In SVM with a sigmoid kernel, the kernel function is used to map data into a higher-dimensional space.<br>Where:<br>- $\alpha$ is a scaling factor.<br>- r is a constant. - tanh is the hyperbolic tangent function. |

Based on the patterns learned from machine learning models, the system classifies an individual into one of the prarkriti types(tridosha) such as Vata, Pita, Kapha or combination of these tridosha.

**6. Output: Prakriti Type**

Finally, the classified Prakriti type is displayed as the output. The results can be used for Ayurvedic consultations, personalized skincare, and health recommendations. The system ensures a reliable and efficient classification of Prakriti based on scientifically extracted skin color features and machine learning techniques.

## RESULTS

In proposed model, the traditional Darshana method is used to determine someone's Ayurvedic constitution, or Prakriti. This involves carefully observing their physiological and psychological characteristics to categorize them into Vata, Pitta, or Kapha. Getting this classification right can be tricky and needs a very thorough process. As an input model had a clear photo of the person with a smartphone, making sure to use natural light and a 3:4 aspect ratio. This helped to see their facial features properly and ensured nothing artificial was interfering with observations. The aim of doing this is to have an accurate data is key for Prakriti analysis. Before we could look at specific facial traits and figure out their dominant Prakriti, we first had to identify their face in the picture. The process is depicted in Figure 1.

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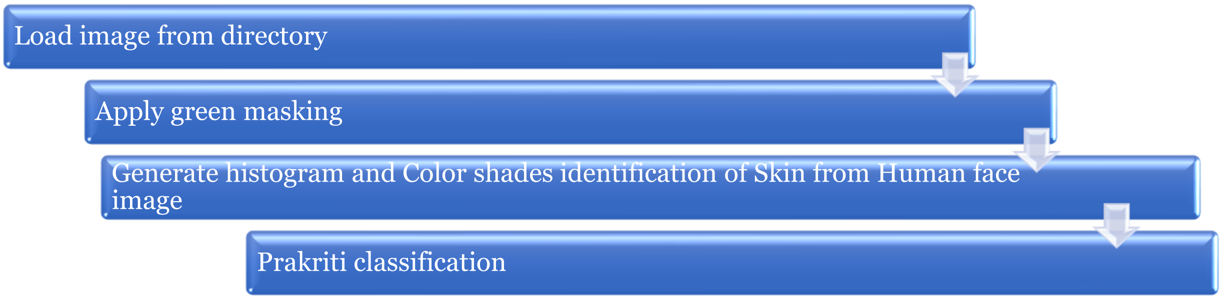


**Figure 1. Process of proposed model for Prakriti classification**

Finding a face in a picture involves a few steps. First, we need to separate the face from everything else in the background. To do this, model uses a technique that focuses on color, specifically a green mask, to tell the difference between skin and non-skin. This color trick helps us isolate the face, removing any distractions from the background, and lets us focus on the overall features and skin color pixels. The classification of extracted facial skin segments for dominant prakriti determination was conducted utilizing a suite of machine learning algorithms. The methodological parameters, including algorithm configurations, training protocols, and performance evaluation metrics, are comprehensively documented herein. Figure 2 illustrates a histogram depicting the distribution of identical color shades extracted from a human face image. The histogram represents the frequency of pixel intensities across different shades, highlighting the dominant color variations present in the image [27] [28] [29] [8]. Peaks in the histogram indicate prevalent shades, while lower frequencies correspond to less common tones. This analysis helps in understanding the skin tone distribution, which is crucial for applications such as image classification, facial recognition [9] [21] [24], and Prakriti-based skin color assessment.

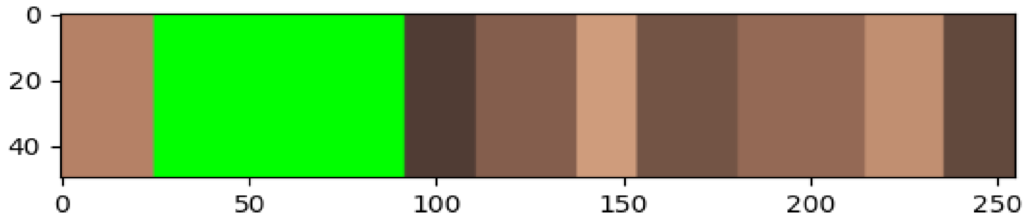


**Figure 2. Histogram of indentical Color shades after green masking on Human Face Image**

Figure 3 shows a line plot representing the distribution of RGB (Red, Green, and Blue) values based on color intensity and the number of pixels. The plot helps visualize how different color components vary across the image. Peaks in the plot indicate dominant colors, while lower points represent less prominent shades. This analysis is useful for understanding color variations in an image and can assist in processes like color-based segmentation and classification.

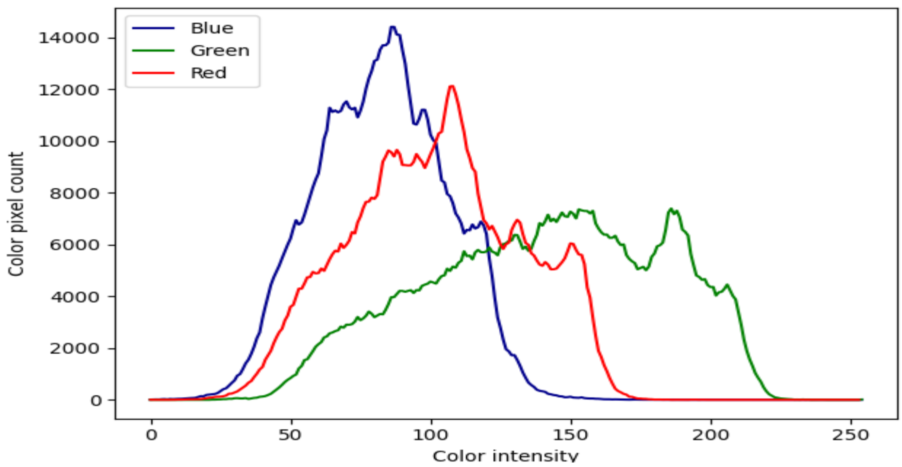

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**Figure 3. Line plot of RGB values with color intensity and pixel counts.**

Figure 4 illustrates a three-dimensional plot that represents the distribution of color values associated with the dominant dosha. The plot visualizes the relationship between three primary color components—Red (R), Green (G), and Blue (B)—which collectively define the skin tone variations observed in different dosha types. Each point in the 3D space corresponds to a specific color shade derived from facial skin images, allowing for a detailed analysis of color distribution. The plot helps in identifying clusters of similar color values, which can be associated with specific dosha types (Vata, Pitta, or Kapha). The positioning and density of these clusters provide insights into how different skin tones are linked to the three dosha categories. A higher concentration of points in a specific region suggests a dominant color range for a particular dosha, while scattered points indicate greater variability in skin tone. This representation is useful for visualizing patterns in skin color and understanding how different doshas exhibit distinct color characteristics. It also aids in feature extraction and classification, making it an essential tool in analyzing skin tone variations for Prakriti assessment using image processing techniques.

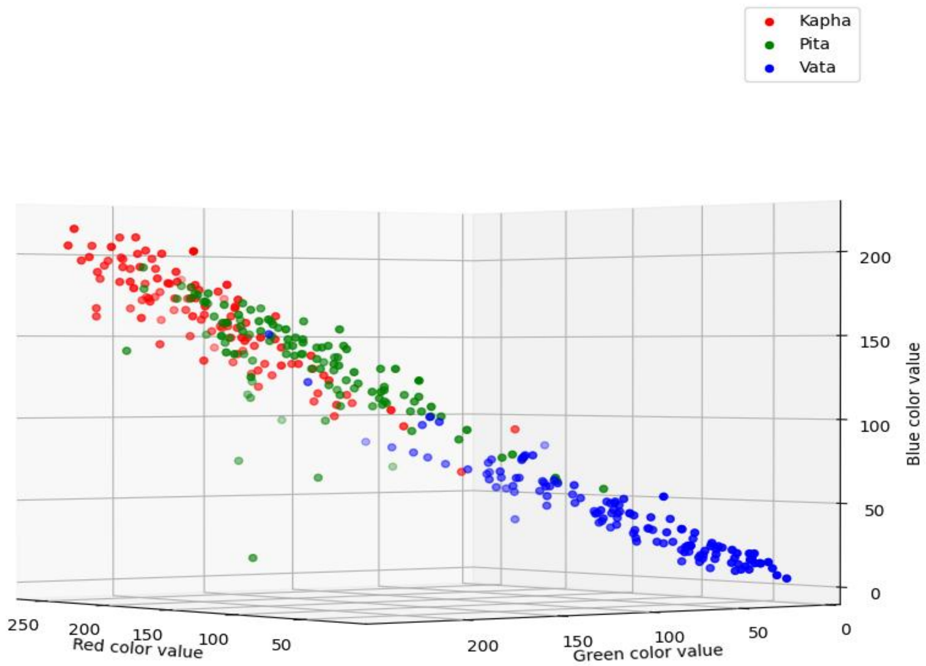


**Figure 4. 3D color values of dominant dosha**

Figure 5 shows a confusion matrix representing the classification results obtained using a Support Vector Machine (SVM) with a linear kernel. The matrix compares the predicted class labels with the actual class labels to evaluate the performance of the classification model. In the confusion matrix, the rows represent the actual categories, while the columns indicate the predicted categories. The values along the diagonal represent correctly classified instances, whereas the off-diagonal values show misclassified cases. A higher number of correct classifications along the diagonal suggests better model accuracy. This confusion matrix helps in understanding how well the model distinguishes between different categories and highlights areas where misclassifications occur. By analyzing these results, improvements can be made to enhance the accuracy and reliability of the classification process.

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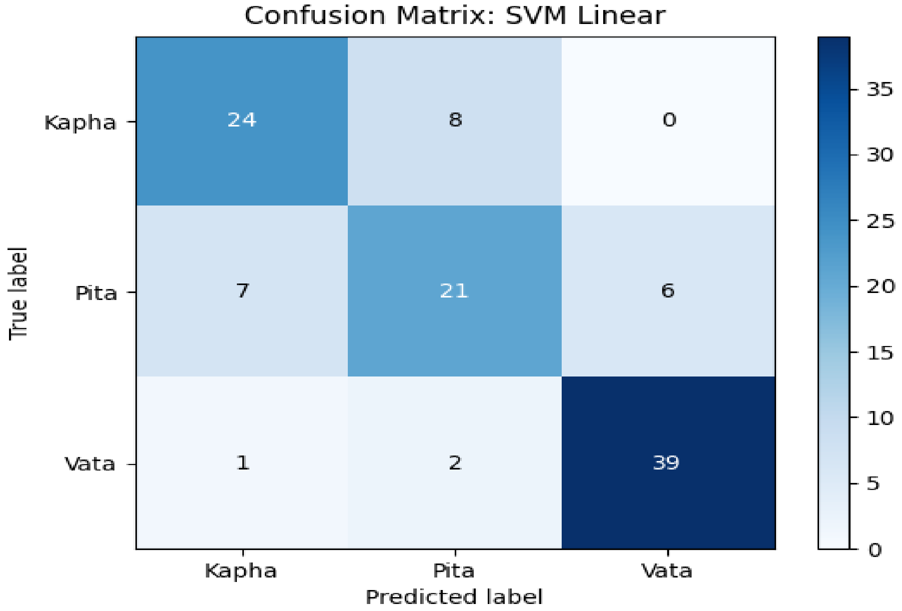


**Figure 5.** **Confusion matrix using SVM Linear**

Figure 6 shows a confusion matrix that represents the classification results of a Support Vector Machine (SVM) model using a Gaussian (Radial Basis Function) kernel. The matrix compares the predicted class labels with the actual class labels to evaluate the model's performance. In the confusion matrix, the rows indicate the actual categories, while the columns represent the predicted categories. The diagonal values show the number of correctly classified instances, whereas the off-diagonal values indicate misclassified cases. A higher number of correct classifications along the diagonal suggests better accuracy.

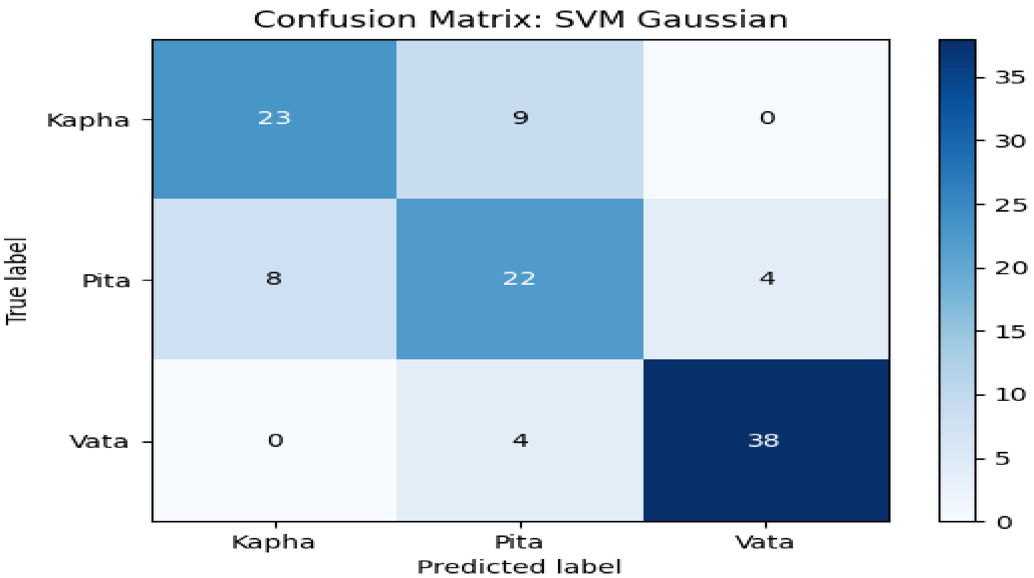


**Figure 6.** **Confusion matrix using SVM Gaussian**

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Figure 7 displays a confusion matrix that evaluates the classification performance of the Random Forest classifier. The matrix compares the predicted class labels with the actual class labels to measure the accuracy of the model. In this confusion matrix, the rows represent the actual class labels, while the columns indicate the predicted class labels. The diagonal values show the number of correctly classified instances, while the off-diagonal values represent misclassified cases. A higher number of correctly classified instances along the diagonal suggests better model accuracy. The Random Forest classifier, which is based on multiple decision trees, improves classification by averaging the predictions from different trees. This method helps reduce errors and enhances reliability. The confusion matrix provides a clear assessment of how well the classifier distinguishes between different categories and identifies areas where misclassification occurs.

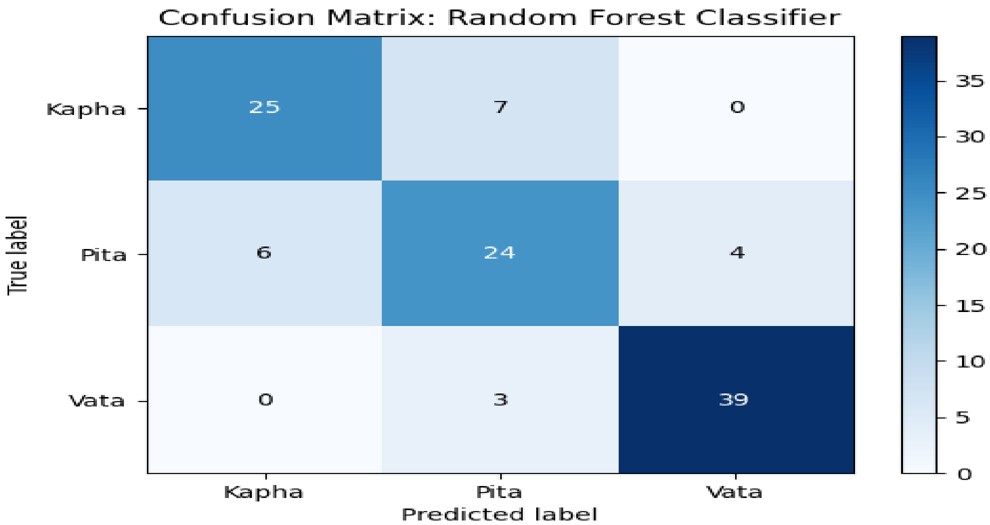


**Figure 7.** **Confusion matrix using Random Forest**

Figure 8 illustrates the confusion matrix for the K-Nearest Neighbors (KNN) classifier, providing a detailed evaluation of its classification performance. The matrix presents a comparison between actual and predicted class labels, offering insights into the model's accuracy and reliability. In this matrix, the rows correspond to the actual class labels, while the columns represent the predicted labels. The diagonal elements indicate correctly classified instances, whereas the off-diagonal elements highlight misclassifications. A higher concentration of values along the diagonal suggests better classification accuracy. The performance of the KNN classifier is influenced by factors such as the choice of the parameter KKK (number of neighbors) and the distance metric applied for classification. The confusion matrix serves as a crucial tool in assessing the effectiveness of KNN in pattern recognition and classification tasks. It also helps in identifying areas where parameter optimization or feature selection may be required for improved classification outcomes

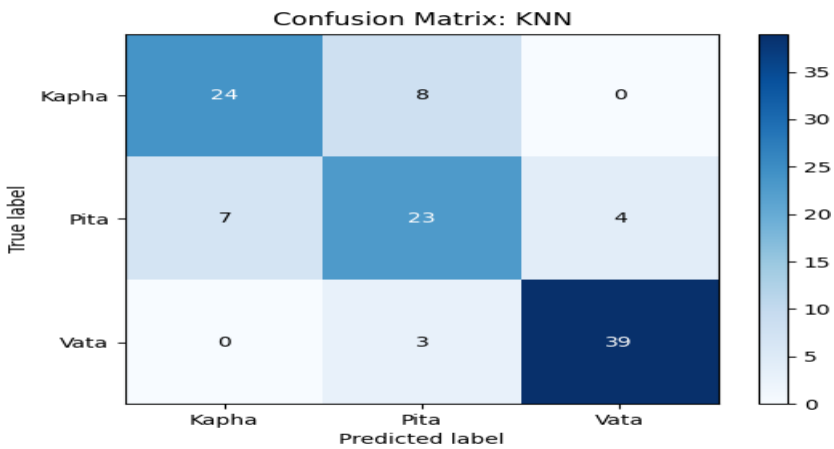


**Figure 8.** **Confusion matrix using KNN**

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Figure 9 illustrates the confusion matrix for the Support Vector Machine (SVM) classifier utilizing the Sigmoid kernel, providing a detailed evaluation of its classification performance. The confusion matrix systematically compares the actual class labels with the predicted labels, allowing for an assessment of the model's reliability in differentiating between categories. In this matrix, the rows denote the actual class labels, while the columns indicate the predicted labels. The diagonal elements correspond to correctly classified instances, whereas the off-diagonal elements represent misclassified cases. A higher concentration of values along the diagonal suggests improved classification accuracy, signifying that the model effectively captures patterns within the iamge pixels. The Sigmoid kernel in SVM applies a transformation that aids in handling non-linear relationships within the data. The analysis of this confusion matrix helps in identifying classification trends, potential model limitations, and areas requiring further parameter optimization. This assessment contributes to the refinement of classification methodologies, ensuring more precise predictions in future studies.

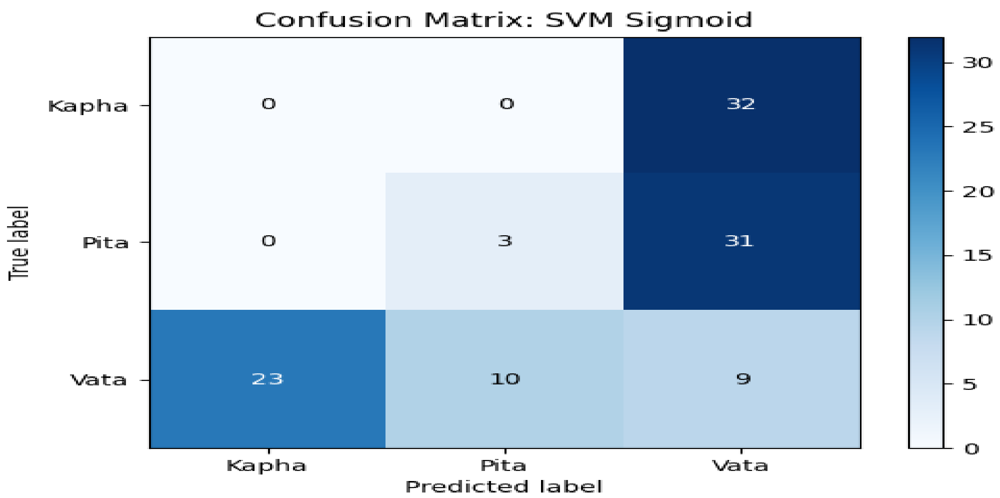


**Figure 9. Confusion matrix using SVM Sigmoid**

## DISCUSSION

The results of the Prakriti classification, derived from the aforementioned procedural steps, are tabulated in Table.2, providing a comparative analysis of the precision, recall, and accuracy performance of each utilized algorithm [30] [31].

**Table 2. Result summary using various machine learning algorithms**

| Machine learning algorithm | Precision | Recall | Accuracy | Dominant Prakriti Class |
|---|---|---|---|---|
| KNN | 91 | 93 | 92 | Vata |
| Random Forest | 91 | 93 | 92 | Vata |
| SVM linear | 87 | 93 | 90 | Vata |
| SVM Gaussian | 90 | 90 | 90 | Vata-Pita |
| SVM Sigmoid | 12 | 21 | 16 | Vata |

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Table 2 presents a comparative evaluation of various machine learning algorithms based on precision, recall, and accuracy in classifying dominant Prakriti types. The results indicate that K-Nearest Neighbors (KNN) and Random Forest performed the best, both achieving 92% accuracy, effectively classifying Vata Prakriti with minimal misclassification. SVM with a Linear Kernel also showed strong classification ability with 90% accuracy, though its slightly lower precision suggests a higher tendency for false positives. SVM with a Gaussian Kernel achieved 90% accuracy as well, successfully identifying both Vata and Pitta Prakriti, indicating its capability in handling complex patterns. However, SVM with a Sigmoid Kernel performed poorly, with significantly lower accuracy (16%), suggesting it is not suitable for this classification task. These findings emphasize the importance of selecting appropriate models and kernel functions for accurate classification. The ability of the Gaussian SVM to classify multiple Prakriti types highlights potential overlaps in skin color features, requiring further refinement in feature extraction techniques. Overall, the results suggest that KNN and Random Forest are the most reliable models for Prakriti classification, while improvements in feature selection and hybrid modeling could further enhance classification performance.

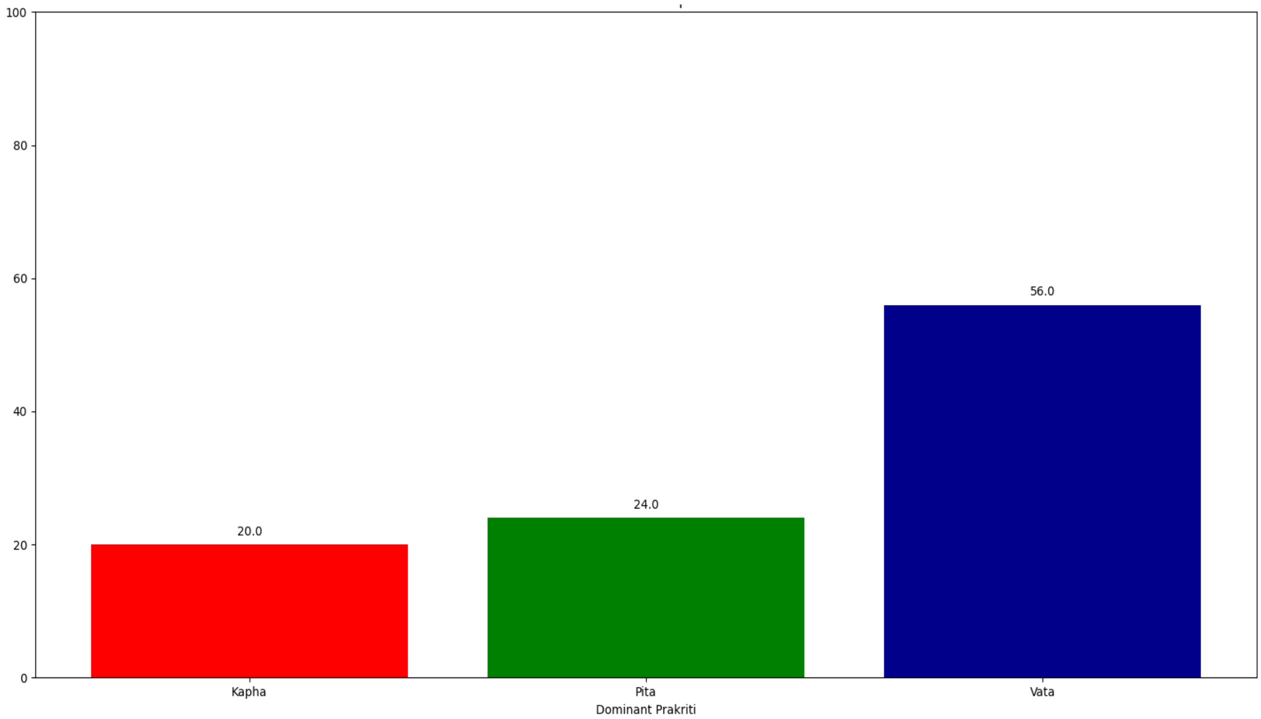


**Figure 10. Classified Prakriti Graph based on color pixel values**

The KPV Bar Graph in Figure 10. illustrates the distribution of dominant Prakriti types based on image pixel values, with the x-axis representing the three Prakriti categories (Kapha, Pitta, and Vata) and the y-axis depicting their respective percentage values. The analysis reveals that Vata Prakriti has the highest representation, accounting for 56% of the image pixel values, followed by Pitta Prakriti at 24%, while Kapha Prakriti holds the lowest proportion at 20%. These variations suggest that Vata Prakriti is more prevalent in the analyzed images, potentially influenced by specific skin color features, tonal variations, and textural attributes. The observed differences in percentage values may be attributed to factors such as color intensity, brightness, and contrast levels within the images, highlighting the need for precise image processing techniques to enhance classification accuracy. This study underscores the significance of refining feature extraction methods and classification models to ensure a balanced and reliable classification of Prakriti types based on image-based analysis. The findings contribute to the broader understanding of skin color-based Prakriti classification, providing a foundation for further advancements in image processing and machine learning-based frameworks.

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