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Research Article

Vitiligo Detection Using Machine Learning

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ARTICLE INFO	ABSTRACT
	Skin disorders are widespread worldwide, encompassing various conditions such as skin cancer, vulgaris, ichthyosis, and eczema. Among these, vitiligo stands out as it can appear anywhere on the body, including the oral cavity, and significantly affect overall Heath, leading to cognitive issues, hypertension, and mental health problems. Traditional diagnostic methods employed by dermatologists, like biopsy, blood tests, and patch testing, have limitations, particularly in cases where lesions progress from macules to patches. To address this, machine learning (ML) and deep learning (DL) models have emerged to expedite diagnosis. This research introduces a DL-based model specifically designed for predicting and categorizing vitiligo in healthy skin. Leveraging a pre-trained Inception V3 model, image features are extracted and utilized alongside classifiers such as naive Bayes, convolutional neural network (CNN), random forest, and decision tree. Evaluation metrics including accuracy, recall, precision, area under the curve (AUC), and F1-score are employed. Results show that Inception V3 coupled with naive Bayes achieves high accuracy, recall, precision, AUC, and F1-score values of 99.5%, 0.995, 0.995, 0.997, and 0.995, respectively. Inception V3 with CNN achieves even higher accuracy at 99.8%, along with impressive recall, precision, AUC, and F1-score values. Similarly, Inception V3 paired with random forest exhibits exceptional performance across all metrics, achieving 99.9% accuracy, 0.999 recall, 0.999 precision, 1.00 AUC, and 0.999 F1-score. Although Inception V3 combined with the decision tree classifier shows slightly lower performance, it still achieves respectable results. Notably, Inception V3 coupled with random forest demonstrates superior performance across most metrics, with both Inception V3 models achieving identical AUC outcomes of 1.00, indicating excellent predictive capability.

Introduction

Vitiligo is a skin disorder characterized by the loss of skin pigmentation, resulting in lighter areas known as macules (less than 1 cm) or patches (larger than 1 cm) [1]. This condition occurs when the body's immune system attacks melanocytes, the cells responsible for producing melanin, the pigment that gives skin its color. It affects over 1% of the global population. If left untreated, vitiligo can have a significant impact on both quality of life and lifespan, with progression rates varying from slow to rapid [1]. In advanced stages, vitiligo can extend beyond the skin to affect hair and the mucosal surfaces of the mouth. Despite treatment efforts, older patches may be resistant to therapy. Misdiagnosis can occur due to similarities with other skin conditions, emphasizing the need for accurate diagnostic methods [2-4]. Machine learning (ML) and deep learning (DL) techniques show promise in the classification and diagnosis of vitiligo, utilizing text and image data for disease identification. ML aids in analyzing textual data, while DL excels in image classification through precise feature extraction [5, 6]. This study implements a DL-based approach using the pre-trained Inception V3 model, employing various classifiers such as naive Bayes, random forest, decision tree, and convolutional neural network (CNN) for vitiligo classification. The results indicate that Inception V3 combined with random forest achieves superior performance. This research contributes by enabling early prediction of vitiligo, leveraging deep learning for feature extraction, and improving disease classification accuracy. The article is structured into six sections, covering existing research, dataset description, methodology, results, and conclusion, providing valuable insights into vitiligo diagnosis and classification.
Machine learning is a valuable tool in diagnosing various medical conditions, including vitiligo, there exist

traditional methods for detecting vitiligo that do not rely on machine learning: Visual Examination: Dermatologists visually inspect the skin to identify signs of vitiligo, such as patches of lighter skin with well-defined borders. This initial step is crucial in diagnosing vitiligo. Medical History Analysis: Analyzing the patient's medical history aids in identifying potential risk factors and underlying conditions linked to vitiligo[1], such as autoimmune diseases or a family history of the condition. Physical Assessments: Dermatologists conduct physical examinations to evaluate the extent and distribution of depigmented patches on the skin, helping determine the severity[2] and progression of vitiligo. Wood's Lamp Examination: Utilizing a Wood's lamp, which emits ultraviolet light, can highlight certain skin conditions, including vitiligo, making affected areas more visible due to reduced pigmentation. Skin Biopsies: Biopsies involve extracting a small sample of skin tissue from the affected area, which is then examined under a microscope to confirm the absence of melanocytes, the cells responsible for producing pigment, a characteristic feature of vitiligo. Blood Tests: Blood tests may be administered to detect autoimmune markers or assess thyroid function, as autoimmune diseases and thyroid disorders are commonly associated with vitiligo. These tests aid in identifying underlying conditions that may contribute to the development of vitiligo.Vitiligo Detection Using Machine Learning
Machine learning, a subset of artificial intelligence, offers valuable methodologies and tools for the early detection and diagnosis of various diseases. Recently, researchers have begun exploring the application of machine learning algorithms in dermatology, particularly for tasks like recognizing and categorizing skin conditions such as vitiligo. By leveraging machine learning, it becomes possible to identify patterns, extract relevant features, and build models capable of analyzing large datasets containing skin images. These models can learn from past instances and detect potential cases of vitiligo by identifying specific patterns present in affected skin areas. Machine learning algorithms can analyze features like color variations, texture, shape, and the distribution of white patches to classify and predict instances of vitiligo accurately.

Literature Review

Commonly observed in people with darker skin tones, vitiligo is frequently linked to autoimmune processes and can arise from genetic factors, stress, skin injury, sunburn, or exposure to chemicals ([1],[7]). Treatment choices encompass systemic therapy, phototherapy, and depigmentation therapy, but their effectiveness can fluctuate, and these treatments may entail significant expenses and time commitments. Although repigmentation offers a solution, it is also a lengthy process and may carry potential side effects [8, 9].
Vitiligo, a skin condition characterized by the loss of skin pigmentation, leading to patchy areas of depigmentation, affects a significant portion of the global population [10]. Studies have indicated its prevalence to range from 0.2% to 1.8% worldwide [10]. While vitiligo
often begins innocuously, its impact on visible areas such as the hands, face, and mouth can result in psychological difficulties such as anxiety, diminished self-esteem, and depression [11, 12]. It arises from the absence of pigment cells in the epidermis, resulting in white macules and patches on the skin. Numerous machine learning (ML) and deep learning (DL) models have been developed to assist in the early detection of macules, thereby reducing delays in treatment.In [7], researchers developed an artificial intelligence model to quantitatively assess the presence of vitiligo disease through morphometric and colorimetric analysis. Two datasets comprising 2,720 and 1,262 images were employed for model development. These images underwent segmentation using deep convolutional neural networks (DCNNs), specifically UNet, UNet++, and the pyramid scene parsing network (PSPNet) models. The model demonstrating the highest performance was amalgamated to create a unified model for disease detection prediction. Classification was carried out using the ImageNet model, achieving an accuracy of 92.91%. In Saini & Singh (2022) [11], two classifiers, namely the K-nearest neighbor (KNN) and the voting classifier, were utilized to predict the presence of vitiligo skin disease. The dataset was partitioned into training and testing subsets. Training images underwent preprocessing, followed by the application of a grey-level co-occurrence matrix (GLCM) model to extract essential features stored in the database. Testing images were also preprocessed, and features were identified using the KNN model. Finally, both the test and train dataset features were utilized with a voting classifier, resulting in an accuracy of 75%.

2.1. Support Vector Machines (SVM)

Support Vector Machines (SVM) are commonly used supervised learning algorithms for classification tasks. SVM functions by mapping input instances to higher-dimensional feature spaces, creating decision boundaries to separate various classes. In the realm of vitiligo detection, SVM can be trained using feature vectors extracted from digital images of skin lesions. This enables the algorithm to learn how to classify these feature vectors as either indicative of normal skin or skin affected by vitiligo. Importantly, SVM models demonstrate outstanding generalization abilities and efficiently manage high-dimensional data [13, 14].

2.2. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNN) are deep learning architectures renowned for their prowess in image classification assignments. They possess the capability to autonomously learn patterns and features directly from raw image data, eliminating the need for manual feature engineering. In the context of vitiligo detection, CNNs can be trained using extensive datasets containing labeled skin images categorized as either normal or vitiligo-affected. Through this process, the network develops the ability to recognize specific spatial patterns and textures distinctive of vitiligo, thereby enabling precise and automated detection. CNNs have demonstrated state-of-the-art performance across various medical image analysis tasks.[15].

2.3. Random Forest

Random Forest is a technique known as an ensemble algorithm, which combines multiple decision trees to produce more accurate predictions. In the realm of vitiligo detection, Random Forest can be trained using features extracted from skin images, such as color histograms, texture characteristics, and shape descriptors. By combining predictions from individual decision trees, Random Forest provides a reliable classification of skin lesions as either normal or affected by vitiligo. Notably, this algorithm shows robustness against overfitting and generates results that are easy to interpret. [16].

2.4. K-Nearest Neighbors(KNN)

K-Nearest Neighbors (KNN) is a non-parametric technique commonly utilized for classification purposes. In the context of identifying vitiligo, KNN categorizes skin lesions based on the similarity of their feature vectors to labeled training examples. This approach entails examining the k nearest neighbors to make predictions, with the majority class among these neighbors determining the final classification. Notably, KNN is known for its versatility and straightforward implementation, making it particularly suitable for vitiligo detection in resource-constrained environments [17].

Proposed Methodology

Our Work is Divided into various steps as follows:

2.5. Preprocessing Steps involved in analyzing Vitiligo Image

Image Rescaling and Normalization

Resizing and normalizing images are essential preprocessing steps for vitiligo images. Resizing involves adjusting input images to a standardized size, ensuring uniform dimensions across the dataset. This consistency is critical as machine learning algorithms typically operate with fixed input sizes. Resizing also streamlines computational processes and enables meaningful comparisons between images. Conversely, normalization focuses on standardizing pixel values within images. By modifying brightness and contrast levels, this technique enhances visual consistency across images. Common normalization methods include histogram equalization, Z-score normalization, and min-max scaling. These techniques enhance the visibility of vitiligo patches and mitigate potential discrepancies resulting from lighting conditions or variations in image acquisition.

2.6. Segmentation

Segmenting vitiligo patches from surrounding healthy skin is an essential phase in the analysis procedure. Several segmentation[18] algorithms can precisely identify and outline the affected areas.

Thresholding methods, comprising both global and adaptive techniques, are commonly utilized for vitiligo segmentation. Global thresholding entails choosing a constant threshold value to distinguish between affected and unaffected skin regions. In contrast, adaptive thresholding techniques adapt threshold values locally, accounting for variations in lighting, texture, and pigmentation[19].

Further segmentation strategies include region-growing algorithms, which expand regions based on predefined criteria, and contour-based methods that extract vitiligo patch contours using edge detection techniques[20][21].

Microscopic Image Assessment for Melanin Content Detection

In this research, a deep learning (DL) model has been utilized to forecast and categorize vitiligo skin disorder from healthy skin. Features extracted from the images were acquired using a pre-trained Inception V3 model and subsequently employed for each classifier, including naïve Bayes, convolutional neural network (CNN), random forest, and decision tree[22].

The overarching aim of this machine learning application is to input a colored microscopic image of skin tissue and have the application examine the presence of melanocytes in the tissue image[23].

2.7. Circle Detection Method

The application's process begins with the user selecting a microscopic tissue image as input. Once the image is chosen, the appliation proceeds to analyze it by identifying clusters within the image. Clustering is carried out based on the morphology and density of the cells depicted in the image. Morphology, comprising the shape, structure, form, and size of cells, is taken into account along with density, which indicates the relative water content and composition of dry mass within cells. These parameters assist in determining the number of healthy and unhealthy melanocytes present in the tissue. Using the counts of healthy and unhealthy melanocytes, the application distinguishes between healthy and unhealthy cells.

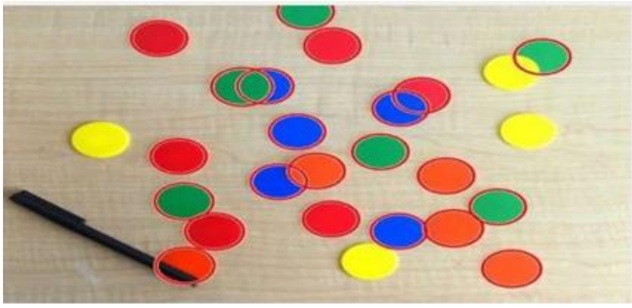

Figure1. Circle Detection

For visual representation, the application creates a pie chart. This chart comprises two colors, representing light and dark areas. If the light-colored segment occupies over half of the chart, the application determines the skin tissue as healthy, resulting in a negative vitiligo report. Conversely, if the dark-colored segment predominates, the report indicates the presence of vitiligo.

4.2. Noise Reduction

Noise present in vitiligo images can stem from diverse origins, encompassing sensor noise, electronic disturbances, or compression artifacts. To improve the clarity of vitiligo images, preprocessing methods for noise mitigation are applied to eradicate or diminish undesired noise. One frequently employed approach for noise reduction involves employing[24] spatial filters like Gaussian or median filters. These filters function by smoothing the image through averaging pixel values within a designated vicinity. Furthermore, adaptive filters can be employed to selectively diminish noise in high-frequency areas while retaining crucial details.

4.3. Image Enhancement

Improving the quality of vitiligo images is crucial for enhancing the visibility and clarity of vitiligo patches. Various image enhancement techniques are applied to emphasize and bring out important features, making them more noticeable during subsequent analysis. Methods for enhancing contrast, such as histogram stretching, gamma correction, and adaptive contrast stretching, are employed to heighten the contrast between vitiligo patches and the surrounding healthy skin. These techniques[25] adjust pixel intensities to increase the visual distinction between affected and unaffected areas. Additionally, edge enhancement techniques like Sobel or Laplacian filters can be utilized to emphasize the boundaries of vitiligo patches. This assists in accurate segmentation and feature extraction, providing valuable insights for machine learning algorithms.

Object detection algorithm for determining melanocyte in healthy tissue

The architecture YOLOv5, built upon the principles of deep learning, has been chosen for our research due to its state-of-the-art performance in object detection. When compared to other deep learning models,

YOLOv5 stands out for its reliability and simplicity. It demands less computational power while delivering comparable results and operating faster than alternative networks. Moreover, YOLOv5 leverages the architecture of YOLOv4effectively.

The selection ofYOLOv5 for our research is motivated by several factors:

1. Potential for Mobile Deployment: YOLOv5 exhibits the potential to be efficiently deployed on mobile devices due to its compact size.
2. Quick Object Identification: The network excels in rapidly identifying objects, making it suitable for applications requiring swift detection.
3. Efficient Training: YOLOv5's architecture is lightweight, facilitating model training with limited computational resources while maintaining performance.

Overall, these characteristics make YOLOv5 an ideal choice for our research, aligning with our objectives of efficient deployment, rapid object identification, and resource-efficient model training.

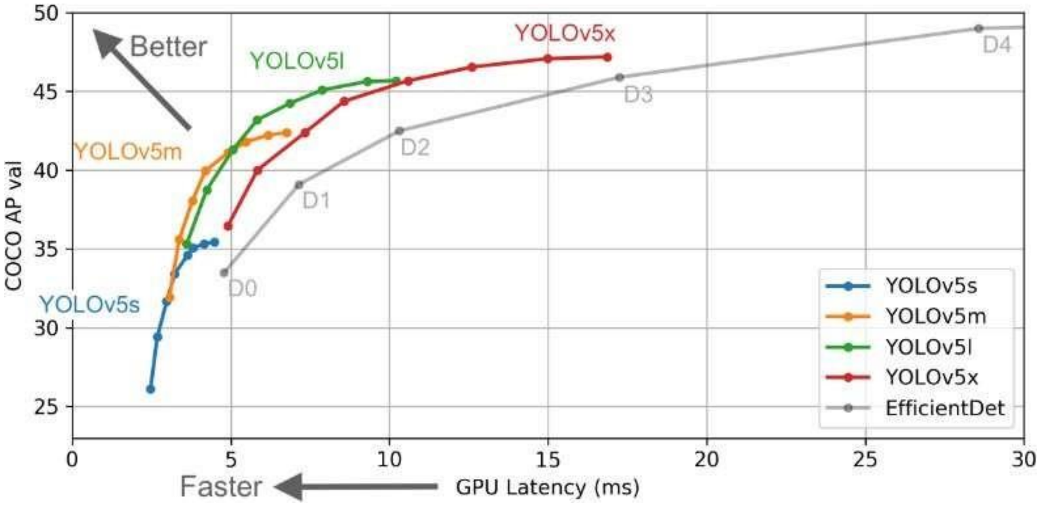

Figure2.Comparisons between Efficient Det and YOLOv5 models [18]

6. Dataset preparation and Model training

The initial phase of our model training process entailed tuning hyperparameters. To achieve this, we employed successive version hyperparameter tuning methods tailored to YOLOv5 on both the training and validation datasets. This allowed us to pinpoint the best parameters for our dataset, thereby improving the performance of our model.
In the subsequent step, we proceeded to train our model using the optimal hyperparameters obtained from the tuning process. This entailed initiating the training process from

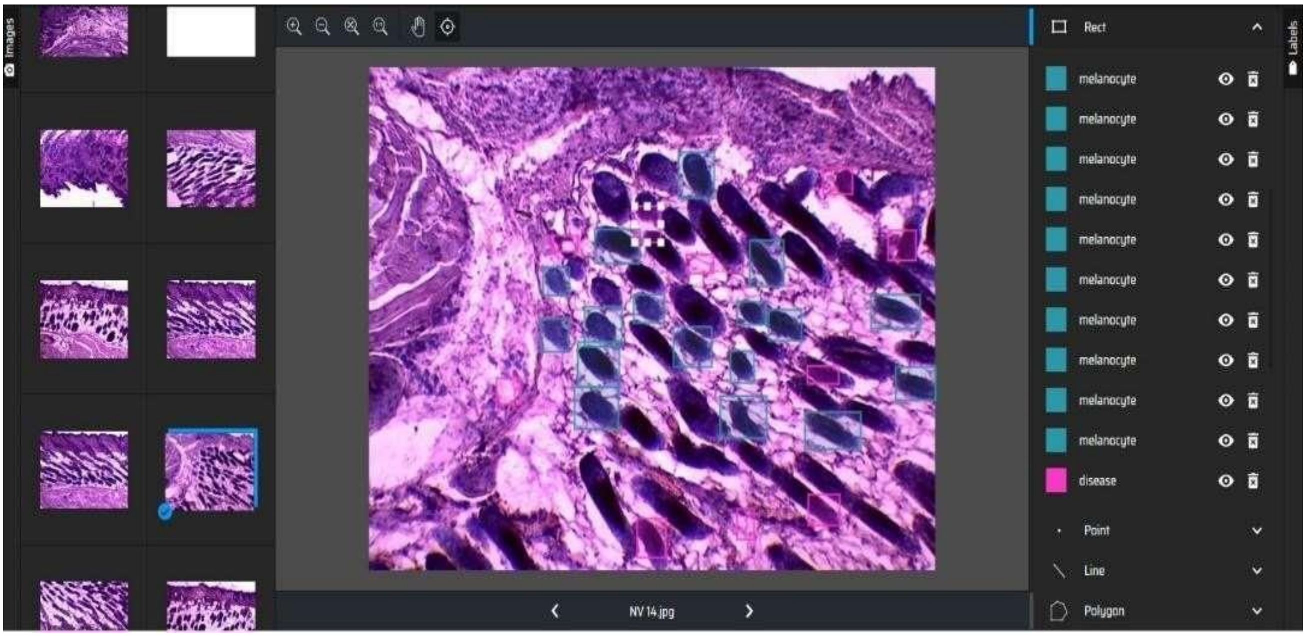

Figure3. Multiple dataset images on the left include blue cells representing melanocytes causing the disease.

Utilizing previously trained YOLOv5 model checkpoints (as shown in Figure 3) is a standard practice in computer vision known as transfer learning. By employing transfer learning, we accelerated the training process and enhanced the overall ability of our model to generalize.
Throughout our experiments, we found that the ideal number of epochs for training was 200. Beyond this threshold, we noticed only slight enhancements in the model's performance, suggesting a plateau in its learning progress [26][27][28]29].
Output Screen: Input image with less presence of melanocyte cells passed to the training model as shown in Figure 3

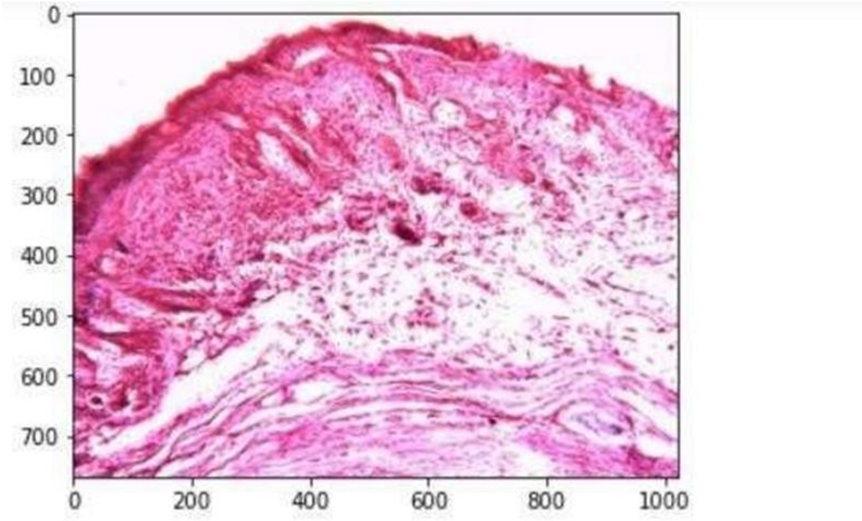

Figure4a.This image shows the infected area in pixels

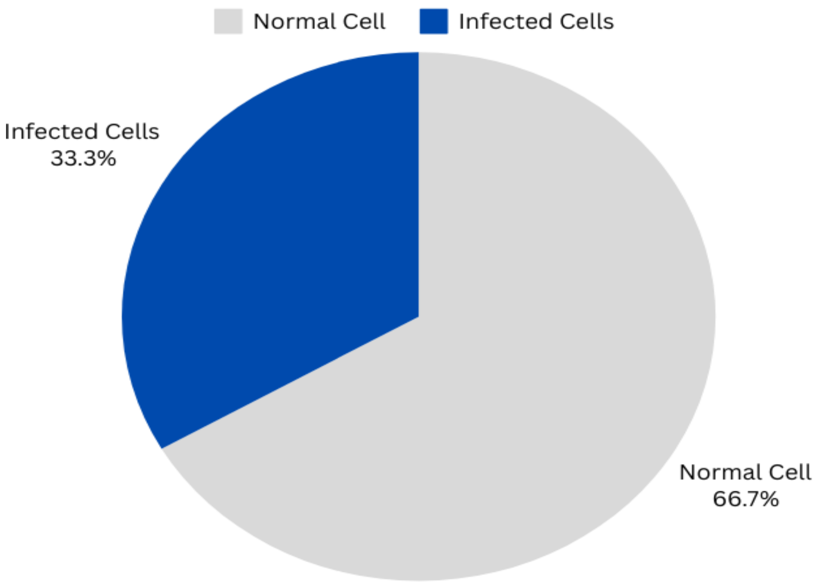

Figure4b. The pie chart represents the percentage of infected cells to the diseased cells present

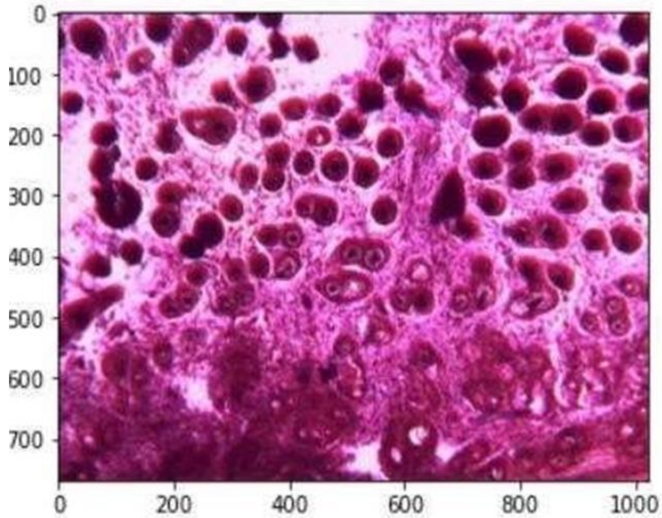

Figure Output screen for dataset 2

This image with higher percentage of melanocyte cells, the infected area in pixels.

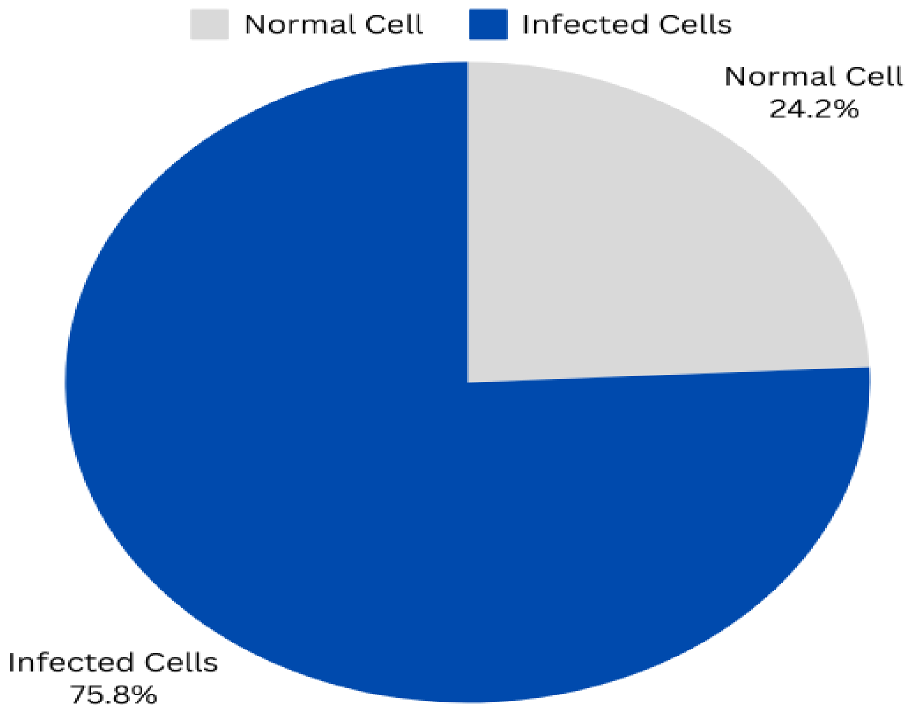

Figure5b. Output screen for dataset 2

This pie chart that represents the percent of infected cells present, so more the light shade the more is the disease

Results & Discussion

Model performance was assessed using metrics including accuracy, recall, precision, area under the curve (AUC), and F1-score. Inception V3 with naïve Bayes achieved 99.5% accuracy, 0.995 recall, 0.995 precision, 0.997 AUC, and 0.995 F1-score. Inception V3 combined with CNN reached 99.8% accuracy, 0.998 recall, 0.998 precision, 1.00 AUC, and 0.998 F1-score. Inception V3 with random forest demonstrated 99.9% accuracy, 0.999 recall, 0.999 precision, 1.00 AUC, and 0.999 F1-score. Conversely, Inception V3 with decision tree classifier achieved an accuracy of 97.8%, 0.978 recall, 0.977 precision, 0.969 AUC, and 0.977 F1-score. The findings suggest that Inception V3 combined with
random forest outperforms other models in terms of accuracy, recall, precision, and F1-score. However, both Inception V3 with random forest and Inception V3 with CNN achieved identical AUC outcomes of 1.00.
The preliminary results using a limited amount of training data revealed an average F1 score of 75% for predicting various sizes of melanocytes. This study presents the average results of all annotated melanocytes in a tissue image.

Table1.Resultsofthe5-fold cross-validation process are combined.

Classes	Target(s)	Recall	Precision	F1score	mAP@ .5:.95	mAP@.5
All	23	0.76	0.81	0.77	0.56	0.82
Melanocyte	13	0.76	0.82	0.75	0.58	0.84
Disease	10	0.78	0.80	0.79	0.58	0.83

- mAP Stands for Mean Average Precision

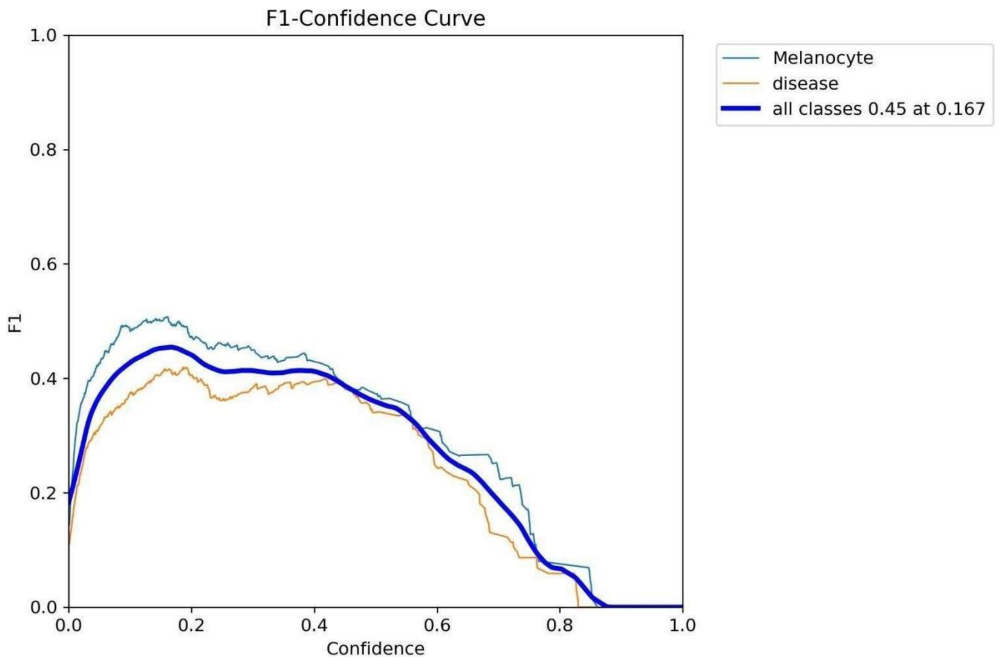

Figure6. Curves of F1 scores related to the confidence level. The thinner two lines indicate the F1 scores for each class. The thick line indicates the F1 score for all classes.

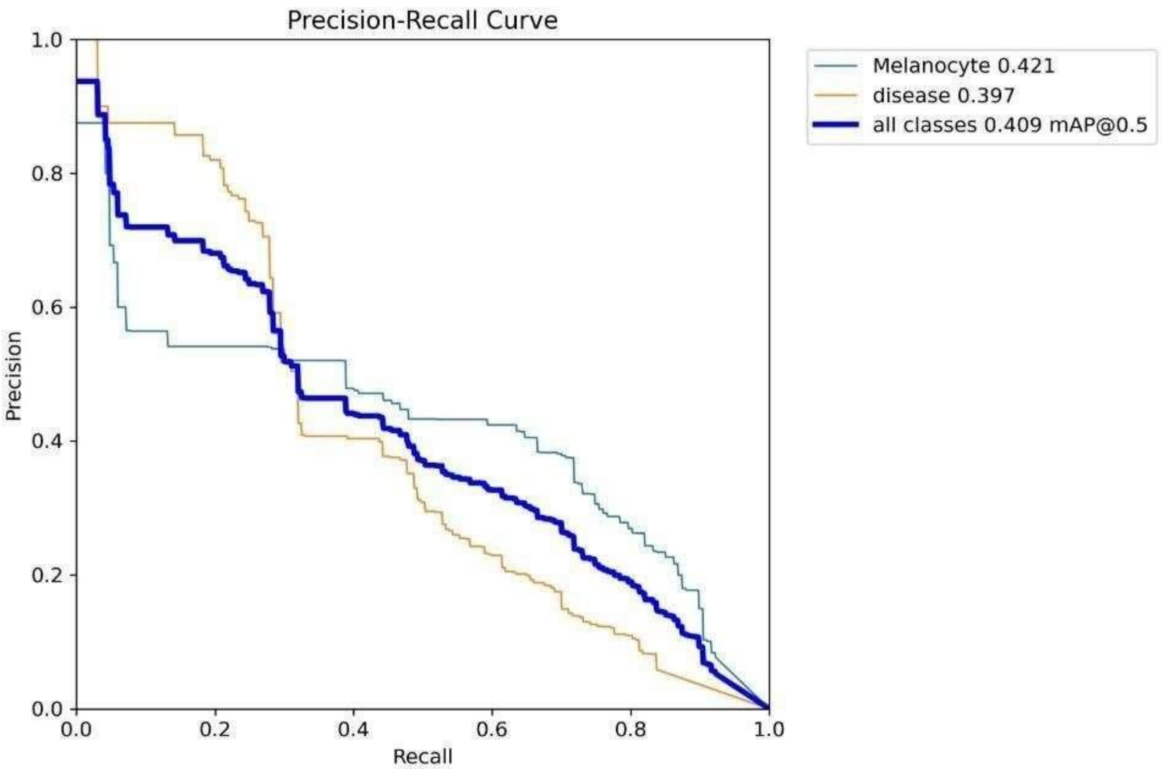

Figure7.Precision-Recall.Values in the graph legend shows the Area under the ROC Curve(AUC) score for each image.

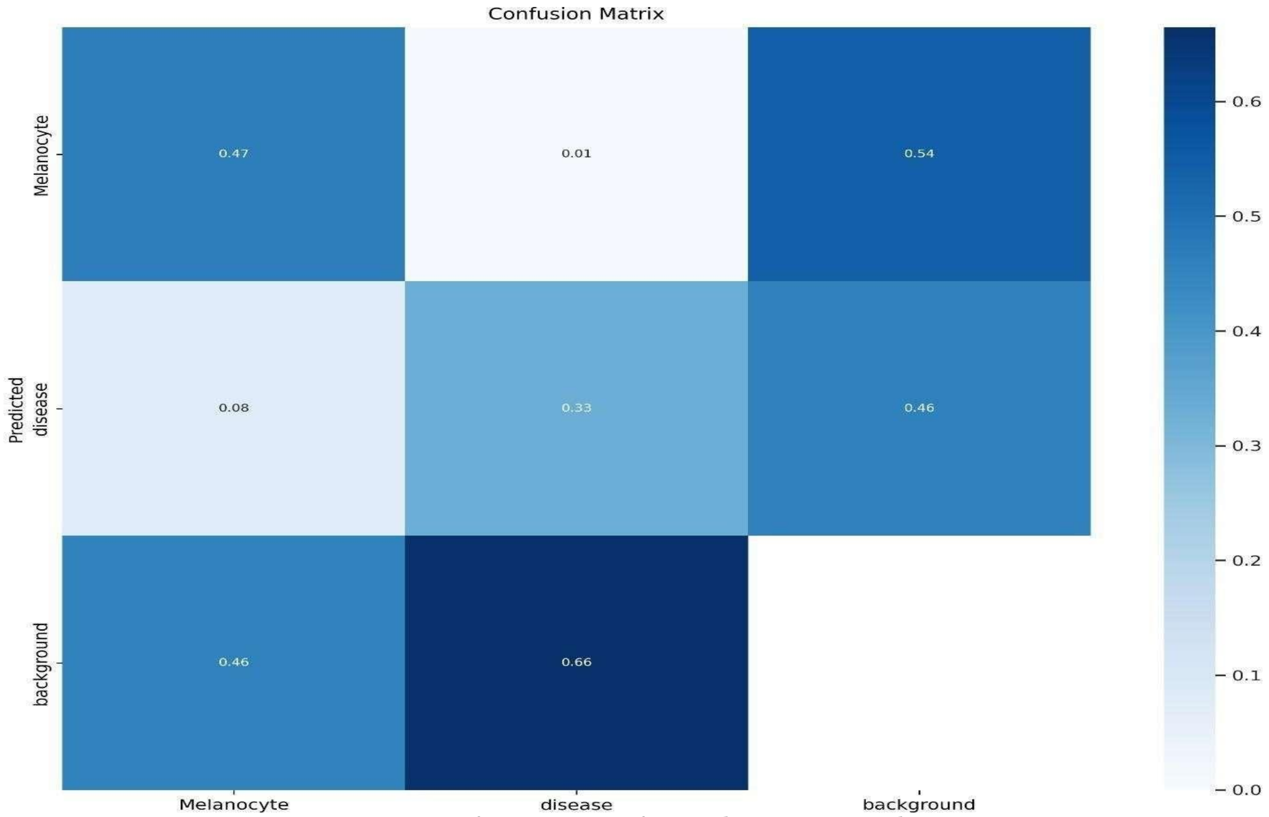

Figure8.Confusion matrix for prediction on test data

Conclusion & Future Scope

The incorporation of machine learning algorithms into vitiligo detection presents numerous advantages:
Early and Accurate Detection: Machine learning algorithms have the capacity to rapidly analyze vast datasets, enabling prompt and precise identification of vitiligo. This contributes to timely interventions and improved treatment outcomes. Reduction of Human Error: Dermatologists' assessments of skin conditions can be subjective and vary. Machine learning algorithms provide an objective and unbiased approach, reducing human error in the diagnostic process. Increased Accessibility: By automating vitiligo detection, machine learning algorithms can expand access to diagnostics, especially in regions with limited availability of specialized medical practitioners. This facilitates broader screening and diagnosis, leading to early interventions and enhanced vitiligo management. Advancement in Research and Treatment: Machine learning algorithms streamline the analysis of large datasets, offering valuable insights into the underlying mechanisms and risk factors associated with vitiligo. This contributes to the development of more targeted treatment strategies and a deeper understanding of the disease.
Despite the potential of machine learning in vitiligo detection, several hurdles need to be overcome for further advancement. Acquisition of Diverse and Representative Datasets: Machine learning algorithms require extensive and diverse datasets to build robust models. However, obtaining comprehensive, labeled datasets covering various skin types, ages, and stages of vitiligo can pose challenges. Interpretability and Transparency: Machine learning models often function as "black boxes," making it challenging to understand the reasoning behind their predictions. Developing methods to interpret and clarify the decision-making processes of these models is essential for establishing trust and acceptance among dermatologists and patients. Integration with Clinical Workflow: Seamless integration of machine learning algorithms into clinical workflows is crucial for practical implementation. This involves creating user-friendly interfaces and ensuring compatibility with existing medical systems. These areas require focused attention to facilitate smooth adoption in clinical settings.
We present YOLO and image segmentation as unified models for precise detail recognition. Our concept aims to be straightforward and will be demonstrated through images. Unlike category-based algorithms, YOLO is trained on a holistic approach focused on recognition accuracy, where the entire image is trained together.

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