Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 1 (2024)

Vitiligo Image Categorization Using Convolution Neural Network

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***Abstract*:** Vitiligo is a widespread skin condition characterized by the loss of melanocytes, resulting in chalky-white patches on the skin. The exact cause of vitiligo is not fully understood, but it is generally considered to be an autoimmune condition in which the body's immune system mistakenly attacks and destroys melanocytes. It affects a significant portion of the global population, with an estimated prevalence of 0.5-2%. This common pigment-related disorder is categorized into two main types: Segmental and Nonsegmental vitiligo. Categorizing vitiligo images using Convolutional Neural Networks (CNNs) involves developing a deep learning model that can automatically identify and classify images based on their features. Below is a high-level overview of the steps you can follow to implement vitiligo image categorization using CNN. The challenges posed by the subjectivity of dermatologist evaluations and the need for accurate diagnosis drive the demand for machine learning solutions. In response to this need, the research introduces an intelligent approach using Convolutional Neural Networks (CNNs) for Vitiligo classification. The proposed model, known as IVC, concentrates on classifying Nonsegmental vitiligo into its subtypes, such as Acrofacial, Focal, Generalized, and Mucosal vitiligo. To support this endeavour, a dataset of 368 vitiligo-infected photos has been thoroughly collected and categorised. The research aims to design a sophisticated framework for the precise detection and classification of Vitiligo. This innovative approach harnesses the power of AI and CNNs to enhance the accuracy of diagnosis, thereby addressing a critical need in the field.

Keywords: *Autoimmune disease, Vitiligo, Skin disorder, Hypopigmentation, Depigmentation, Melanin loss, Skin pigmentation.*

Introduction: Vitiligo, an autoimmune disorder affecting approximately 0.5-2% of the global population [1], leads to a reduction in melanin-producing cells, causing distinct white patches on the skin. While the exact causes remain unclear, factors like metabolic abnormalities, oxidative and inflammatory stress, autoimmune responses, neurological, and genetic influences are thought to contribute to its onset [2]. Despite being non-life-threatening, vitiligo substantially impacts patients' appearance and mental well-being. The disorder is broadly categorized into nonsegmental and segmental vitiligo, with various subtypes falling under the former [3]. Unfortunately, Misdiagnosis of illnesses such as Pityriasis alba and Nevus depigmentosus might make treatment more difficult.t. Early diagnosis and treatment are crucial to minimize the spread of white patches and aid fading of existing ones. Dermatologists' subjectivity in evaluating depigmented lesions underscores the need for standardized and objective diagnostic too. Deep learning (DL) techniques, particularly artificial intelligence (AI)-assisted approaches, have made notable progress in vitiligo detection. Recent publications, exemplified in Figure 1, depict advancements in AI-assisted vitiligo diagnosis, leveraging search data from Google Scholar to highlight the increasing role like "vitiligo" and "Deep learning" or "Machine learning" [4]. These developments underline the potential of AI-driven tools in enhancing accurate vitiligo classification and diagnosis. Vitiligo Image Categorization Using Convolutional Neural Networks (CNNs) represents a cutting-edge application of artificial intelligence in the field of dermatology. Vitiligo is a skin disorder characterized by the loss of pigmentation, leading to the development of white patches on the skin. Accurate and timely diagnosis of vitiligo is crucial for effective treatment and management. In this context, the integration of CNNs, a subset of deep learning algorithms [5] designed for image recognition tasks, has emerged as a promising solution. Convolutional Neural Networks excel in image categorization by mimicking the human visual system's hierarchical and interconnected processing of visual information. In the case of vitiligo, these networks can be trained on a vast dataset of skin images, enabling them to learn distinctive patterns and features associated with the condition[6][7]. The trained CNN can subsequently analyze and categorize new images, facilitating rapid and accurate identification of vitiligo-affected areas. The process begins with the collection of a diverse dataset encompassing various stages and manifestations of vitiligo. This dataset serves as the foundation for training the CNN, allowing it to recognize subtle nuances in pigmentation changes. The convolutional layers of the network apply filters to identify features like edges, textures, and colors relevant to vitiligo. As the information progresses through the network, pooling layers consolidate and prioritize the detected features, enabling the model to make comprehensive and informed predictions. The application of CNNs in vitiligo image categorization holds immense potential for enhancing diagnostic accuracy and efficiency in dermatological practice. By automating the analysis of skin images, healthcare professionals can expedite the identification of vitiligo, ensuring timely interventions and personalized treatment plans. Moreover, the utilization of AI in dermatology aligns with the broader trend of leveraging technology to augment medical diagnostics, ultimately contributing to improved patient outcomes and healthcare delivery. Convolutional Neural Networks (CNNs) play a crucial role in image categorization tasks, including the identification and classification of skin conditions such as Vitiligo. CNNs are adept at automatically learning hierarchical features from images. In the case of Vitiligo, these features may include patterns, textures, and shapes that are indicative of the skin condition. CNNs use convolutional layers to perform local feature extraction, capturing relevant information at different spatial scales. CNNs are designed to understand spatial hierarchies in images [8]. This is particularly beneficial for Vitiligo image categorization as the distribution and arrangement of depigmented patches can vary in size, shape, and location on the skin. CNNs can effectively capture these spatial relationships. Transfer learning is a common technique in which a pre-trained CNN model on a large dataset (like ImageNet) is fine-tuned on a specific task, such as Vitiligo image categorization. This leverages the knowledge gained from a diverse set of images and helps the model generalize better to the specific characteristics of Vitiligo images, even when the dataset for Vitiligo might be limited. CNNs benefit from data augmentation techniques to artificially increase the size of the training dataset. This is especially important when dealing with medical image datasets, which are often limited in size. Data augmentation involves applying transformations like rotations, flips, and scaling to generate additional training samples, helping the model generalize better. CNNs can be used for semantic segmentation, where the goal is not only to classify an image but also to identify the specific regions affected by Vitiligo. This can assist healthcare professionals in understanding the extent of the condition in a given image [9]. CNNs can be integrated with clinical data, such as patient history or genetic information, to improve the accuracy of Vitiligo diagnosis. This multi-modal approach allows the model to consider both visual features from images and relevant patient information. CNNs can be employed to automate the initial screening of images, allowing healthcare professionals to focus on more complex cases. This can lead to faster and more efficient diagnosis and treatment planning. It's important to note that the success of CNNs in Vitiligo image categorization relies on the availability of high-quality and diverse datasets, as well as collaboration between computer vision experts and dermatologists to ensure the accuracy and clinical relevance of the model's predictions [10]. Additionally, ethical considerations, patient privacy, and regulatory compliance should be taken into account when deploying such systems in a healthcare setting.

Related Work: The proposed work under consideration is an interdisciplinary field that involves aspects of computer vision, image processing, deep learning, and agriculture. A brief description of the existing literature is given as under: The authors in [11] introduced an innovative method in digital image processing aimed at accurately quantifying the extent of vitiligo lesions. Their approach involved employing Independent Component Analysis (ICA) to create images based on melanin content, which highlighted areas of the skin affected by melanin. Subsequently, they applied the Region Growing technique to differentiate vitiligo lesions from unaffected, healthy skin. This method's development and testing relied on a dataset comprising of 41 digital images of vitiligo lesions sourced from 18 patients. To classify vitiligo, the author in [12] proposed a learning vector quantization neural networkto categorize Vitiligo images into affected and non-affected regions. Matlab R2010 is used to develop the Learning vector quantization classification method. The accuracy of the LVQ neural network implementation is 92.22%. In [13] an effective strategy is introduced. Their approach involved utilizing the average probability values from three distinct convolutional neural network (CNN) models, all designed with similar architectures. These models were trained using three different color-space representations of the same vitiligo dataset, specifically YCrCb, RGB, and HSV. This strategy outperformed the individual networks, achieving an impressive classification accuracy rate of 87.8%. In [14] a novel system comprised of two distinct stages is devised. In the Front-End stage, they harnessed Mel Frequency Cepstral Coefficients and I-Vectors to extract specific features from the images. These features are then passed to the Back End stage, where classifiers like Support Vector Machines (SVM) and Artificial Neural Networks (ANNs) are employed to categorize these images. Remarkably, their approach yielded an impressive accuracy rate of 95.28%. The authors in [15] introduced an advanced artificial intelligence-based system for diagnosing vitiligo. This system comprises three distinct modules that excel at both generating and categorizing vitiligo images captured under Wood Lamp illumination, offering exceptional precision and image clarity. The initial module employs Cycle-Consistent Adversarial Networks (Cycle GAN) to transform input images into representations under Wood Lamp lighting. However, these initial Wood Lamp images tend to be of lower resolution. Consequently, the second module, known as Attention-Aware Dense Net with Residual Deconvolution (ADRD), is enlisted to enhance the resolution of the input images, ensuring better image quality. Finally, the system employs ResNet50, a deep convolutional neural network, for the crucial task of classifying these images. This comprehensive approach yields an outstanding performance, achieving an accuracy rate of 85.69%. The authors conducted a comprehensive investigation with the aim of eliminating the need for manual intervention in the segmentation of vitiligo images in [16]. They achieved this by leveraging Convolutional Neural Networks (CNNs), which are capable of autonomously performing the segmentation of vitiligo skin lesions. Khatibi and their team [17] introduced an innovative ensemble model, comprising both deep learning and traditional models, with the aim of attaining exceptional accuracy without the need for manual vitiligo lesion segmentation. The adoption of unsupervised segmentation techniques in their approach effectively eliminates the laborious and time-consuming nature of manual segmentation tasks. A MATLAB-based semi-automated graphical interface tool that employs image processing techniques to identify vitiligo patches specifically on the face is introduced in [18]. The tool's target audience is dermatologists who may not have expertise in image processing or software development. In [19] a convolutional neural network (CNN) is harnessed to address the task of classifying Vitiligo lesions through deep learning methodologies. To extract features from the images, they employed four pre-trained models: Inception-V3, VGG-16, VGG-19, and Squeeze Net. A Convolutional Neural Networks (CNNs) for the purpose of detecting vitiligo is utilized in [20]. They conducted a comparative analysis of the diagnostic accuracy of these CNNs with the evaluations of 14 human experts, each possessing varying levels of expertise in the field. A systematic approach aimed at identifying potential treatment targets for vitiligo is proposed in [21]. This method involved the fusion of network analysis and machine learning techniques. Additionally, this study delved into investigating the underlying mechanism of kaempferide in the context of vitiligo treatment. An Android application for the detection of skin conditions such as Vitiligo and Ringworm is mentioned in [22]. This application relies on information provided by patients regarding their symptoms and includes images of the affected area on the individual's body. Using this input, the system has the capability to identify patches indicative of Ringworm and Vitiligo. The system then generates a report that indicates whether the user's condition is positive or negative, based on the photographs and symptoms submitted. Additionally, the application offers brief home remedies for the detected condition and advises the user on whether it's advisable to consult with a dermatologist. A system utilizing transfer learning to differentiate among three types of dermatological skin conditions such as melanoma, vitiligo, and vascular tumor is introduced in [23]. They initiated the system by utilizing the Deep Learning model Inception V3. Following this, they fine-tuned the model to adapt it to the specific task of distinguishing between these skin diseases. The system achieved a test accuracy rate of 80.30%, demonstrating its effectiveness in classifying these conditions.

Model description and Methodology: Currently, the diagnosis of vitiligo is primarily determined based on the doctor's experience and subjective appraisal of the depigmented skin lesions. On the other side, routine clinical diagnosis may not be as accurate in recognizing early vitiligo, particularly for dermatologists with little clinical expertise. Therefore, a creative and efficient framework that delivers more comprehensive information and considerably lowers the rate of misdiagnosis by merging knowledge from many modalities must be developed in order to identify vitiligo at an early stage. goal achieve of this project is to establish a cost-effective and accurate intelligent system for identifying and categorizing Vitiligo. To effectively address any problem, it is crucial to adopt a structured approach that systematically leads to the desired solution. The research methodology for this study is outlined in Figure 1.

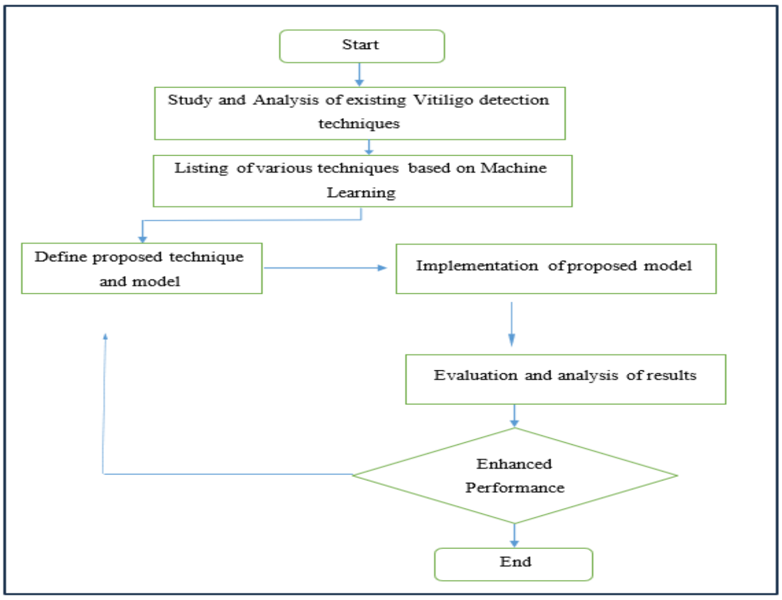

Figure 1: Proposed Methodology

Proposed intelligent Vitiligo Classifier

Suboptimal outcomes primarily stem from factors such as data bias, limited dataset size, and varying data collection methodologies. Convolutional Neural Networks (CNNs) have demonstrated their superiority over human experts in various image comprehension tasks [24]. Data collecting is the key step in the diagnostic process, and choosing the right dataset for machine learning studies is essential. An assortment of pictures showing lesions caused by vitiligo were gathered for this study from the Internet. This dataset includes people of various racial, ethnic, and skin tonal backgrounds. There are 43 pictures of mucosal vitiligo, 70 pictures of having acrofacial vitiligo, 78 pictures of focal vitiligo, and 90 pictures of generalized vitiligo. Putting raw data into a format that can be analyzed by computers and machine learning is known as data preparation. This preparation entails a number of activities, including data augmentation, noise reduction, labelling, and normalization. These steps are taken to make sure the data is presented for further processing in the best possible way.

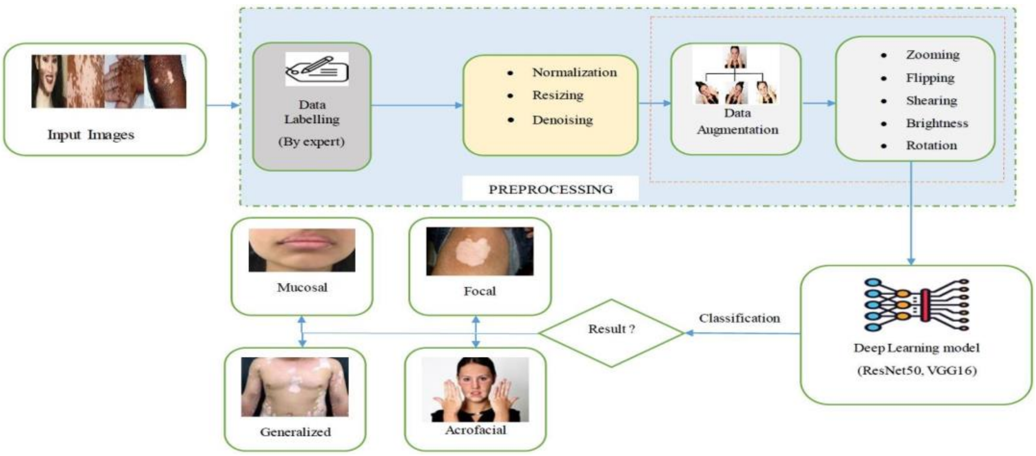

Figure 2. Intelligent Vitiligo Classifier

Data labeling refers to the act of attaching tags or labels to raw data. In the context of this study, suspected vitiligo images underwent meticulous examination by a dermatologist, who then manually assigned the images to their respective categories. The categorization encompassed four distinct types: There are four types of vitiligo: mucosal, focal, generalized, and acrofacial. Image normalization is a commonly utilized technique in image processing, aimed at adjusting the range of pixel intensities. This involves the application of a function that produces normalized versions of input images**.** Given the diverse sizes of input images, it is crucial to perform image resizing to ensure uniform dimensions. Deep learning models tend to train more efficiently on smaller, consistently-sized images, making it necessary to resize all images before feeding them into the deep learning model. Image denoising is the removal of unwanted noise or distortions from an image., Speckle noise, Poisson noise, Gaussian noise, and Salt & Pepper noise are all examples of noise in an image. A variety of picture denoising filters, including both conventional and fuzzy-based filters, can be used to accomplish successful denoising. By producing numerous copies of a real dataset, data augmentation techniques add more instances of it. To generate new data, this procedure requires making small adjustments to the existing dataset. The dataset size can be effectively enhanced by making various alterations such flips, translations, rotations, cropping, scaling, zooming, adding noise, and shearing. Convolutional Neural Networks (CNNs) represent a substantial leap in image recognition. CNNs are extremely effective at feature extraction and image categorization, making them extremely powerful tools. Deep convolutional neural network models are now routinely used for vitiligo categorization. To conduct classification tasks, this study will employ cutting-edge convolutional neural networks such as ResNet50 [25] and VGG16 [26]. A training subset will make up 70% of the dataset, while a testing subset will make up 30%. The proposed method splits the data into four categories: patients with acrofacial vitiligo, foci of vitiligo, generalized vitiligo, and mucosal vitiligo

Results: Deep learning models have been used to estimate the percentage of vitiligo from an input image as shown in figure 3, where each pixel in the density map represents the vitiligo pigment density at the corresponding location in the input image as shown in figure 4. Some models are designed to directly predict the count of individuals in a crowd from an input image. Besides detecting vitiligo, there is also emphasis on accurately localizing pigment pixels. Data labelling and prediction techniques within CNNs can be applied for this purpose. Robustness to changes in scale, viewpoint, and occlusion has been a focus, allowing models to perform well under different conditions. Techniques like data augmentation have been utilized to improve model generalization by creating variations in the training data. Pre-trained models on large datasets or related tasks have been used as a starting point, followed by fine-tuning on specific crowd estimation datasets.

We have also fine-tuned VGG16 and VGG19 CNN model and achieved training and validation accuracy of 99.4%, 99.3%, 95.8%, and 95.4% respectively as illustrated in table 2.

Table 1: Accuracy and Validation Comparison for VGG16 and VGG19 Training models.

Model	Size	Training- Accuracy	Validation - Accuracy	Parameters	Depth
VGG16	528 MB	99.4%	95.8%	138,357,544	23
VGG19	549 MB	99.3%	95.4%	143,667,240	26

Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 1 (2024)

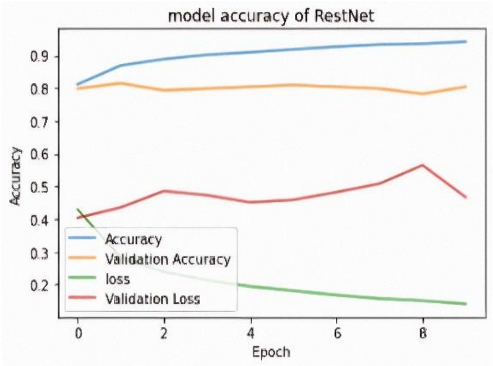

Figure 3: Training Accuracy, Validation Accuracy, Training Loss and Validation Loss.

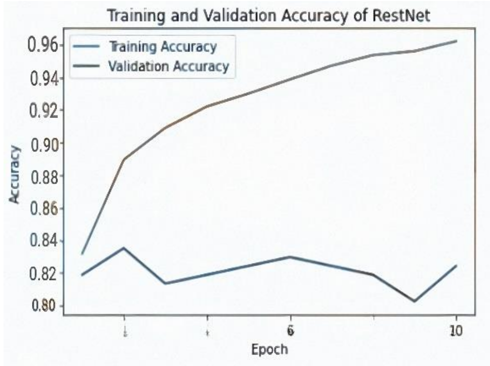

Figure 4: Training and Validation Accuracy at 30 Epochs

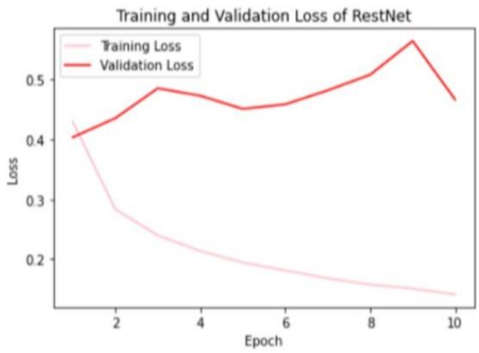

Figure 5: Training and Validation Losses at 30 Epochs

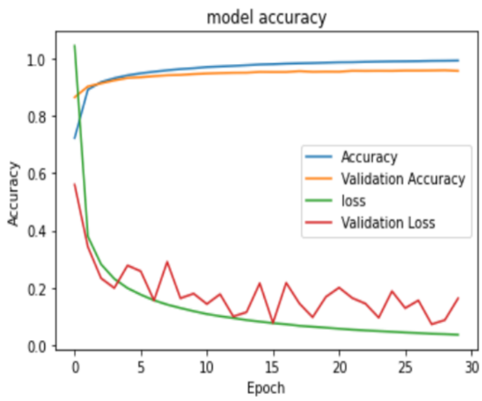

Figure 6: Model Accuracy of VGG16

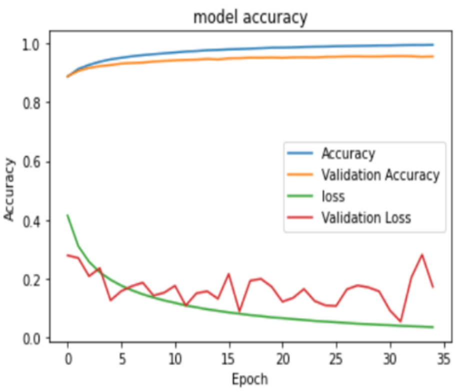

Figure 7: Model Accuracy of VGG19

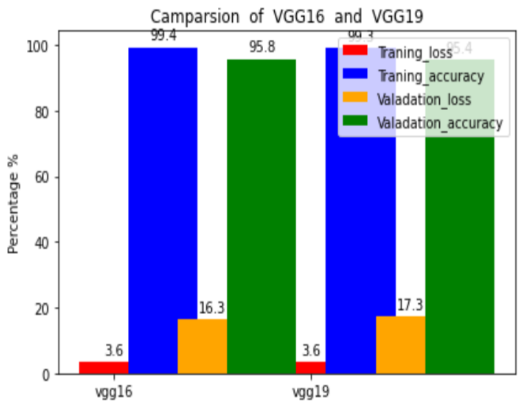

Figure 8: Comparison Between VGG16 and VGG19 Trainng Models.

Training Accuracy the percentage of correctly classified samples in the training dataset. It is calculated as the number of correct predictions divided by the total number of training samples as shown in figure 5. While high training accuracy indicates that the model is learning well on the training data, it doesn't necessarily guarantee good performance on new, unseen data. Validation Accuracy measures the percentage of correctly classified samples in a separate validation dataset. The validation dataset is not used during the training process and serves as an independent evaluation set. Training Loss is a measure of how well the model is performing on the training data. It represents a quantitative measure of the difference between the predicted values and the actual values for the training samples. validation loss measures the difference between predicted and actual values, but it is computed on the validation dataset. It provides an indication of how well the model generalizes to new, unseen data. An increase in validation loss may suggest overfitting, especially if training loss is decreasing. An analytical comparison was carried out between VGG16 and VGG19 model. VGG16 has 16 convolutional layers while VGG19 has 19 convolutional layers. Both models are available in keras API. Despite of the size, parameters and Depth of the VGG19 is larger than VGG16, VGG16 have shown slightly better training and validation.VGG-16 obtains 8.8% error rate which means the deep learning network is still improving by adding number of layers.VGG-19 obtains 9.0% error rate as shown in Figure 6 and Figure 7. Which means the deep learning network is not improving by adding number of layers. We try to increase the number of epochs, but after 30 epochs no improvement observed. When the epoch value is set to 30. The training and validation accuracy achieved for VGG16 and VGG19 are 99.4, 99.3, 95.8, and 95.4 respectively. The comparison between the accuracies of VGG16 and VGG19 are well demonstrated in figure 8.

Conclusion:

Various classification models are available, but ResNet50 demonstrates superior accuracy compared to other models. ResNet50 serves as a foundational architecture for numerous computer vision applications, including vitiligo classification. Following the successful implementation of classifiers, ResNet50 achieved an accuracy of 96.09% and a validation accuracy of 60.27%. As the dataset size grows, the model's accuracy is expected to further improve.

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