Development of an Intelligent Vitiligo Detection Classifier

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Vitiligo, a widespread depigmenting skin condition is characterized by loss of melanocytes in a selective manner, resulting in nonscaly, chalky-white macules. Vitiligo is a common pigment-degrading skin disease, apparently marked by white patches on the skin and broadly classified into two categories: Segmental vitiligo and Nonsegmental vitiligo. An extensive survey of AI-based diagnostic systems for segmental and nonsegmental vitiligo has also been presented. The dermatologist's experience and subjectivity in visual perception of depigmented skin lesions play a big role in Vitiligo diagnosis and its classification. So, there is a dearth need to implement machine learning approaches to improve diagnosis accuracy. Motivated by the fact, the intelligent convolutional neural networks (CNNs) based Vitiligo classification model IVC has been proposed in the research work to classify the Nonsegmental vitiligo into its subtypes like Acrofacial, Focal, Generalized and Mucosal vitiligo. The dataset consisting of 507 vitiligo infected images has been collected and manually labeled to accomplish the whole research work.

Keywords: IVC, ResNet50, Vgg16, Melanocytes, CNNs.

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1 Introduction

Vitiligo is an autoimmune disease believed to affect 0.5-2% of the world's population [1]. Vitiligo is a condition in which the cells that produce melanin, the major skin pigment, are dramatically reduced. Although the pathogenesis of vitiligo is unknown, many factors, including metabolic imbalances, oxidative stress, inflammatory stress, autoimmune, neurological, or genetic disorders, may all play a role in its development [2]. Although it does not affect human health, it alters the appearance of patients and causes mental instability. Nonsegmental vitiligo and segmental vitiligo were the two primary kinds of vitiligo recognized by an international consensus in 2011. Acrofacial, mucosal, generalized, focal, mixed, and rare variants are all classified as nonsegmetal vitiligo [3]. Since vitiligo is often mistaken with other skin conditions like Pityriasis alba and Nevus depigmentosus, it can lead to misdiagnosis, making treatment more difficult. The spread of white spots on the skin will be minimized, and existing white spots will gradually fade if patients can be diagnosed and appropriately treated in the early stage. The dermatologist's experience and subjectivity in visual perception of depigmented skin lesions play a significant role in this type of diagnosis. For the categorization of this condition, standardized and objective deep learning (DL) tools are viewed as a viable support system capable of providing a trustworthy diagnosis of skin lesions. The publications on this topic published in the last six years reveal that AI-assisted vitiligo detection has advanced significantly. Figure 1 depicts the publications that are relevant to this topic. The statistics from Google Scholar were used to create this graph. A combination of keywords like "vitiligo" and ("Deep learning" OR "Machine learning") was used to generate the search results.

The organization of the paper is as follows: Vitiligo disease is briefly discussed in the introduction part of section I. Section II discusses numerous techniques being explored by various researchers for vitiligo diagnosis. Comparative analysis of methodologies is elucidated in section III. Various open gaps and challenges are illustrated in section IV. A new intelligent framework for the classification of vitiligo disease is proposed in section V. Finally, section VI concludes the study by addressing some key points.

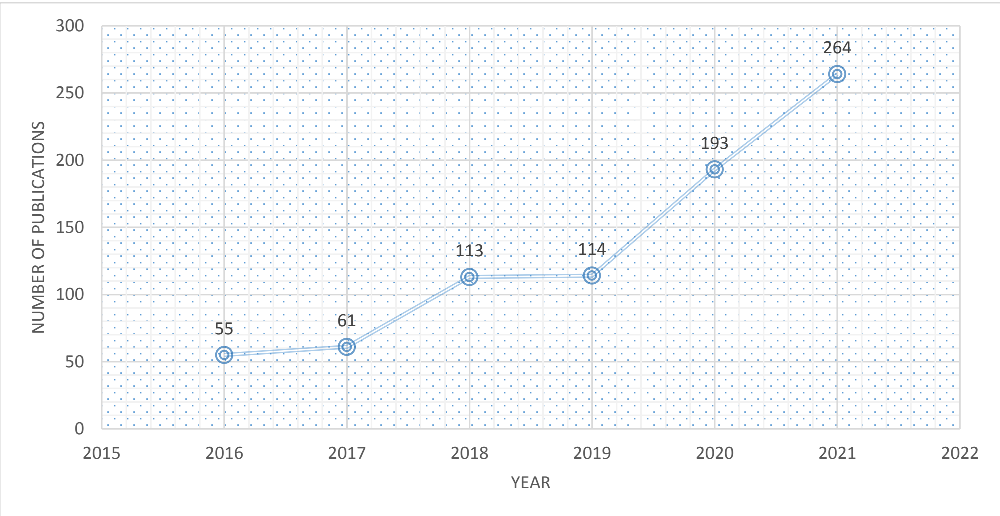

Figure 1: A plot of the number of publications as a function of year. This figure was created using Google Scholar results.

2 Literature Survey

This section gives a quick insight into the current Vitiligo detection techniques.

- Hermawan et al. [4] proposed a novel digital image processing approach for objectively determining vitiligo lesion area. Independent Component Analysis (ICA) was used to generate melanin based images that reflect skin areas affected by melanin, followed by the Region Growing procedure to separate vitiligo lesions from healthy skin. The proposed approach was developed using 41 digital pictures of vitiligo lesions taken from 18 patients.
- To classify vitiligo Jyotsna et al. [5] used a learning vector quantization neural network to 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%.
- J. Liu et al. [6] presented a strategy in 2019 based on the probability average value of three convolutional neural network (CNN) models with similar architectures that were trained using three different color-space pictures (YCrCb, RGB, and HSV) for the same vitiligo dataset. The strategy used excels individual networks with a classification accuracy of 87.8%.
- C. Salamea et al. [7] developed a new system that consists of two stages. In the Front End, Mel Frequency Cepstral Coefficients and i-Vectors are used to extract the image's specific features. In the Back End, attributes extracted in the front end are received, and classifiers like Support Vector Machines (SVMs) and Artificial Neural Networks (ANNs) are used to classify these images. The accuracy rate of 95.28% was achieved.
- Wei Luo et al. [8] proposed an intelligent system in 2020 based on artificial intelligence for the diagnosis of vitiligo. This system consists of three modules that can generate and classify vitiligo images in Wood Lamp with high precision and high resolution. The first module used in the system is Cycle-Consistent Adversarial Networks (Cycle GAN) which converts the input images into Wood Lamp images. The wood images generated by Cycle GAN are low in resolution. Hence the second module, namely Attention-Aware DenseNet with Residual Deconvolution (ADRD), is used to improve the resolution of the input images. Finally, ResNet50, which is based on deep convolutional neural networks, is used to classify the images, and a performance of 85.69% was achieved.
- Makena et al. [9] provided a systematic study in 2020 to remove manual intervention in vitiligo image segmentation and used CNNs which automatically perform vitiligo skin Lesion segmentation. Convolutional Neural Networks based on U-Net and watershed post-processing were employed for vitiligo segmentation. This strategy removes both human variability and manual segmentation time, resulting in forecasts that require little adjustment.
- To segment images and localize vitiligo lesions Khatibi et al. [10] proposed a novel unsupervised stack ensemble model of deep and conventional models to achieve high accuracy. Unsupervised segmentation approaches eliminate the need for manual vitiligo lesion segmentation, which is a difficult and time-consuming job. This paper proposes a novel consensus function that, when compared to the majority voting consensus function, can increase the performance of the suggested stacked ensemble model.
- Based on image processing Paolo et al. [11] proposed a semi-automatic graphical interface tool programmed in MATLAB to detect vitiligo patches on the face. This tool is designed for dermatologists who aren't professionals in image processing or software development. This tool works only on face images. Further, a user needs to select a face contour, and then this tool displays whether vitiligo is present in this area or not. For huge picture databases, this strategy is impractical.
- Varinder et al. [2] used convolutional neural networks (CNNs) to solve the challenge of classifying Vitiligo lesions using deep learning-based techniques. For feature extraction, four pre-trained

models were employed: Inception-V3, VGG-16, VGG-19, and SqueezeNet. Then four classification models using these pre-trained models were used: kNN (k-nearest neighbors), SVM (Support Vector Machine), Convolutional Neural Network, and Logistic Regression. By using Inception-V3, the highest level of accuracy was achieved.

- Zhang et al. [12] in 2021 Employed CNNs for vitiligo detection and compared the diagnostic accuracy of the CNNs with 14 human experts having different levels of experience. Two datasets, primary (Chinese in-house) as well as secondary (Open Source), were used in this study. VGG, ResNet, and DenseNet models were used for the classification of vitiligo images. By using transfer learning, classification results were improved. In general, CNN's achieved more accuracy in detecting vitiligo than human experts
- Wang et al. [13] proposed a systematic methodology for discovering possible treatment targets for vitiligo by integrating network analysis and machine learning, and further, the underlying mechanism of kaempferide was investigated in this study. A random forest model was created using gene expression profiles from normal and vitiligo skin samples to discover the discriminating and select significant transcriptomic characteristics for vitiligo. Then, using a network-based analytic approach, the vitiligo protein-protein interaction subnetwork (VitNet) was built, and possible treatment targets in the VitNet were predicted.
- Dipali D. Awasekar [14] developed an Android application for detecting skin illnesses such as Vitiligo and Ringworm. With the use of symptoms reported by patients and pictures of the affected area on the victim’s body, the system will be able to detect Ringworm and Vitiligo patches. The system will generate a report indicating if the condition is positive or negative based on the photograph and symptoms provided by the user and will provide short home cures as well as advice the user to visit a dermatologist.
- A system based on transfer learning was proposed by Neha et al. [15] to distinguish between three forms of dermatological skin diseases: melanoma, vitiligo, and vascular tumor. As a starting point, the Deep learning model Inception V3 was employed. After fine-tuning the model, test accuracy was 80.30 %.

3 Comparative Analysis

Table 1.1 summarizes the research on several vitiligo detection strategies based on numerous deep learning and machine learning methodologies proposed by several researchers.

Table 1.1: Analysis of Vitiligo detection techniques

Author	**Objectives**	**Method**	**Dataset**	**Dataset size(No of images used)**	**Result (Accuracy)**
Hermawan et al. [4] (2011)	Developing a novel digital image processing approach for objectively determining vitiligo lesion area.	Independent Component Analysis (ICA)	Private (Hospital Kuala Lumpur, Malaysia)	41	99%
Jyotsna et al. [5] (2017)	Detecting Vitiligo skin disease using LVQ neural network	LVQ neural network	Open Source	NA	92.22%

J. Liu et al. [6] (2019)	Classifying Vitiligo images based on the probability average of three convolutional neural networks.	Xception Iceptionv3 Vgg16 Resnet50	Private	38677	87.8%
C. Salamea et al. [7] (2020)	Detecting Vitiligo using Cepstral Coefficients	ANN SVM	Private	800	95.28%
Wei Luo et al. 8] (2020)	Developing a vitiligo diagnosis system to help doctors in vitiligo diagnosis	ResNet50	Private (Air Force General Hospital)	80,000	85.69%
Makena et al. [9] (2020)	Introduced a CNN that quickly and robustly performs automatic vitiligo segmentation without manual intervention.	U-Net	Private (UC Davis Medical Center)	308	73.6%
Khatibi et al. [10] (2020)	Localizing vitiligo lesions in skin images using an Unsupervised stack ensemble of deep and convolutional image segmentation.	Unsupervised stack ensemble method	Private (Royan Institute for Stem Cell & Technology)	877	97%
Paolo et al. [11] (2020)	Developing a semi-automatic tool based on image processing to detect facial vitiligo patches	NA	Private	NA	NA
Varinder et al. [2] (2020)	solving the problem of classifying Vitiligo lesions using convolutional neural networks based on the deep learning-based approach	Four different classifiers are used	Open-source	696	98.0%

Zhang et al. [12] (2021)	Aimed to assess the performance of deep learning methods for diagnosing vitiligo by deploying Convolutional Neural Networks (CNNs) and comparing their diagnosis accuracy with that of human raters with different levels of experience	VGG ResNet DenseNet	Chinese in-house dataset and Open-source	2876 and 1341	96.84%
Wang et al. [13] (2021)	Development of a Multi-Target Strategy using Machine learning and Network Analysis methods for the treatment of vitiligo	Random Forest	Open-source	NA	92.6
Dipali D. Awasekar [14] (2021)	Developed an Android application using image analysis for the detection of Vitiligo and Ringworm disease.	NA	Open Source	142	NA
Neha et al. [15] (2021)	Classifying three diseases: Vitiligo, melanoma, and vascular tumor used Transfer Learning	Inception V3	Open Source	240	97.63 %

4 Open Gaps and Challenges

Various challenges involved in the present vitiligo detection approaches are:

- **Early detection not possible:** Early detection of vitiligo is not possible by using conventional clinical practices. These procedures used dermatologists' experience and subjectivity in visual perception of depigmented skin lesions for vitiligo diagnosis.
- **Lack of good studies and accuracy**: There is a lack of good studies on early vitiligo diagnosis. Also, the existing systems for detecting vitiligo are not much efficient as these systems lack accuracy.
- **Overfitting problem:** Although substantial accuracy may be obtained with a small sample size, but the model loses generalizability when applied to huge data due to the overfitting problem.

5 Proposed Intelligent Vitiligo Classifier

It is obvious from sections 2 and 3 that there is a significant disparity in the effectiveness and accuracy of various vitiligo detection strategies. The poor results are mostly because of data bias, small dataset size, and a variety of data gathering techniques and procedures. CNN's outperformed human experts in numerous image understanding tasks [16]. Multiple types of research have been carried out to diagnose vitiligo by using CNNs, but no study has been attempted to categorize vitiligo into subtypes. This research proposes an intelligent vitiligo classifier as shown in Figure 2 to address these limitations and subdivide vitiligo into subgroups.

5.1 Dataset Description

The most substantial part of the diagnosis system is data acquisition, and choosing a suitable sample for machine learning trials is imperative. The dataset of Vitiligo infected lesions was gathered from the Internet for this study. Patients of various races, ethnicities, and skin colors are included in this dataset. The dataset contains 230 images of Generalized vitiligo, 138 images of Acrofacial vitiligo, 78 images of focal vitiligo, and 61 images of Mucosal vitiligo.

5.2 Data preprocessing

Data preprocessing converts raw data into a format that computers and machine learning can understand and evaluate. Data preprocessing includes operations such as normalization, resizing, noise removal, data labeling, and data augmentation. These operations can be done to get the data in an efficient format.

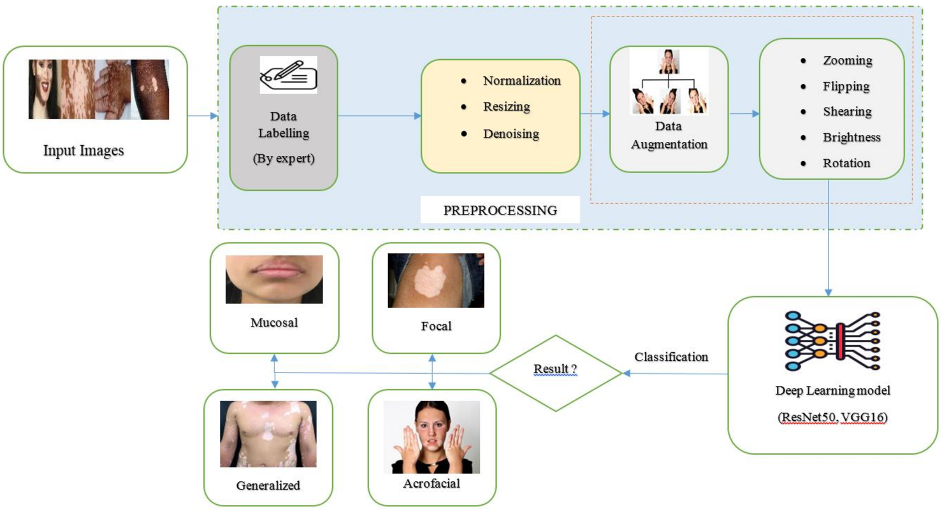

Figure 2: Intelligent vitiligo classifier

5.2.1 Data Labelling

The process of adding tags or labels to raw data is known as data labeling. Every image suspected of having vitiligo was thoroughly analyzed by the dermatologist from the Department of Dermatology, Shri Maharaja Gulab Singh Hospital Jammu, Jammu & Kashmir India, and the image was then labeled manually into the appropriate category. The dermatologist categorized the images into four categories: Mucosal vitiligo, Focal vitiligo, Generalized vitiligo, and Acrofacial vitiligo.

5.2.2 Normalization

Image normalization is a common image processing technique for adjusting the intensity range of pixels. A function could be used that generates a normalization of input images.

5.2.3 Resizing

Since the input images are of varying sizes, image resizing is critical to ensure that all of the images are

of the same size. Deep learning models mostly train quickly on smaller images and accept inputs of the same size, all images must be scaled to the same size before being fed into the deep learning model.

5.2.4 Denoising

The process of eliminating noise or distortions from an image is known as image denoising. Diverse kinds of noises such as Poisson noise, Speckle noise, Gaussian noise, and Salt and Pepper noise may be present in an image. To accomplish the goal of denoising many image denoising filters such as fuzzy-based filters and traditional filters might be utilized.

5.2.5 Data Augmentation

To artificially enhance the size of an actual dataset, data augmentation techniques produce numerous replicas of it. So, all we have to do to collect new data is to make a few tiny changes to our existing dataset. To enhance the amount of the dataset, minor adjustments such as flips or translations, rotations, cropping, scaling, zooming, adding noise, and shearing can be done.

5.3 Deep Learning model

Image recognition gets breakthrough advancement when Convolution Neural Network (CNN) emerges. CNN is very powerful at extracting features and classifying images. Deep convolutional neural network models are currently commonly employed for vitiligo classification. Therefore, classification will be done by using state-of-the-art convolutional neural networks such as ResNet50 [17] and VGG16 [18]. Here 70% of the images will be used for training and 30% of the images will be used for testing. The proposed methodology will divide the data into four categories: class 1 will represent patients with Acrofacial vitiligo, class 2 will represent patients with Focal vitiligo, class 3 will represent patients with Generalized vitiligo and class 4 will represent patients with Mucosal vitiligo.

6 Conclusion

This study primarily focuses on presenting an elevated review of current vitiligo detection algorithms that employ machine learning and deep learning. Although several studies were conducted for diagnosing vitiligo by using different types of machine learning as well as deep learning approaches. These approaches lack accuracy and performance because of data bias, minimal dataset size, and a range of data collection approaches and procedures. There has been a lot of research into diagnosing vitiligo, however, no study has attempted to categorize vitiligo into subtypes. The proposed model would categorize vitiligo into subtypes like Acrofacial, Mucosal, Focal, and Generalized vitiligo. Therefore, the current study needs to be implemented in the near future for the efficient classification of vitiligo disease which will be of great use to the medical community and researchers in planning for improved medication.

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