Non-Tumorous Facial Pigmentation Disorder using Ensemble and Deep Learning - A Review

Arjun H*
Dept. of CSE, Bapuji Institute of Engineering and Technology,
Davanagere, Karnataka, India

ORCID ID: https://orcid.org/0009-0005-7672-0068
* Corresponding Author.

Gururaj T
Dept. of CSE, Bapuji Institute of Engineering and Technology,
Davanagere, Karnataka, India

ORCID ID: https://orcid.org/0000-0001-7850-6181

Abstract: Non-tumorous facial pigmentation, even though it's not lethal, has a negative impact on quality of life and could be a sign of systemic disorders. To overcome researcher developed an automatic diagnosis method such as voting-based probabilistic discriminant analysis has been explored but the accuracy of classification is not satisfactory due to the limited number of data for training and also another technique is data augmentation using synthetic minority over-sampling technique is applied to make full use of available training data but further improving the synthetic minority over-sampling technique to generate more diverse synthesized data and exploiting other advanced methods for data augmentation. In this review work, state-of-the-art research work related to non-tumorous facial pigmentation disorders analysis and classification have been systematically structured and presented. To be more specific, this literature study is centered on currently prevalent detection of non-tumorous facial pigmentation disorders based on Machine Learning and Deep Learning technologies like few shot algorithms and explainable AI. This literature assessment leads to conclude that five most common types of non-tumorous facial pigmentation disorders in Asia, namely freckles, lentigines, melasma, Hori's nevus, and nevus of Ota, is used for training and testing.

Keywords: Skin lesion, Facial-Pigmentation Disorders, Few-Shot Algorithm, Explainable AI(XAI).

1. Introduction

According to a study, an AI-based algorithm can correctly categorize facial features, such as pigmentation, among a heterogeneous group of humans but the study also discovered that, particularly for darker skin tones, the algorithm's accuracy was lower for skin pores and pigmentation indicators. According to the research, lighting circumstances may have an impact on the accuracy of assessments of skin uniformity and pigmentation, and demographic considerations may significantly alter the accuracy of AI algorithms, perhaps creating bias in particular groups. In a different study, the accuracy of classification of pigmented skin lesions by dermatologists was compared with the results of AI representations. The research discovered that there was significant variation in the reliability of AI models, with certain research reporting lower accuracy than dermatologists while other studies submitting higher AI or clinician reliability. The research found that the dearth of artificial intelligence (AI) models created for ethnicities with complexion of color was mostly due to two factors: a lack of openly accessible data from various groups and insufficient inclusion of patient-level metadata pertaining to skin color in the data used for training.

Biomedical image analysis plays a crucial role in various medical applications, including the detection and classification of facial pigmentation disorders. While there has been significant progress in automatically identifying and categorizing pigmented facial tumors like basal cell cancer, squamous cancer, and melanoma, it's noteworthy that limited attention has been given to the automatic classification of non tumorous facial pigmentation disorders.

Addressing this gap is important, considering that patients may underestimate the significance of non-tumorous facial pigmentation disorders[2]. The tendency to seek help from non-professional sources, such as beauty salons, can lead to incorrect diagnoses and inappropriate treatments. Although non-tumorous facial pigmentation disorders might not be as life-threatening as tumors, they still impact facial appearance and can serve as indicators of underlying health conditions. Further research and development in the field of biomedical image analysis could contribute to the automatic classification of non tumorous facial pigmentation disorders, improving early detection and accurate diagnosis. This could enhance patient awareness and facilitate timely professional intervention, minimizing the risk of wrong treatments and promoting overall skin health.

Non-tumorous facial pigmentation disorders refer to a group of skin conditions characterized by abnormal pigmentation on the face that are not related to cancerous growths. These conditions can vary in terms of their causes, appearances, and severity. Analyzing and classifying these pigmentation disorders is essential for proper diagnosis and treatment. And there are mainly 5 most common types of Non-Tumorous Facial Pigmentation Disorders: Melasma, Freackly, Lentigines, Hori's nevus and Nevus of ota[4].

2. Related works

Facial pigmentation disorders that are non-tumorous is a term that includes a wide variety of skin diseases that affect the face and are characterized by abnormal pigmentation but that are not directly related to benign or malignant proliferations. The causes, appearances, and severity of these rashes are extremely varied. Analyzing and classifying them due to the relevance of the state to the diagnosis and therapy. And there are 5 most common-types of Non-Tumorous Facial Pigmentation Disorders: Melasma, Freackly, Lentigines, Hori's nevus and Nevus of ota. However, the automatic identification of different skin lesion diseases from dermoscopy images is a significant challenge, since most lesion types have a high visual resemblance to one another, a vast intra-class variation of some lesion classes in terms of shape, size, color, and texture, these lesion types have low contrast, and dermoscopy images contain artifacts . These bottleneck issues introduce more hurdles and stress to traditional machine learning models to precisely differentiate melanomas with respect to non-melanoma skin lesions.

The application of a deep learning pre-segmentation method to auxiliary diagnostic procedures is also appreciated in many biomedical research studies. For example, such an automatic framework for skin lesion boundary segmentation is presented in [10], where features produced by Fully Convolutional Network were combined with a shallow network. The prior information of edge information channelized by the shallow network's specific filter domain and the features learned by FCN during the end-to-end training have demonstrated improved segmentation performance. Ali et al.[11] Border detection methodology in dermoscopy images of skin lesions to segment them has already developed . Two methods of contour/edge discovery were recommended, a prediction scoring strategy and a fuzzy edge filter in which the localization is normally maximum along the profile of some thresholded importance measure. Similarly, a deep learning residual network using feature pyramid attention for segmenting the transition zone and the peripheral in prostatic prostate zone in T2-weighted MRI images of the prostate was developed. More specifically, a supervised learning method was also developed on super-voxel texture features for brain tumor detection and segmentation[13,15] to differentiate between glioblastoma multiforme and solitary metastasis; from brain MR 3D images analysis[16,17].

In recent years, a lot of attention has been given to the use of deep learning convolutional neural networks to solve complex problems in medical image analysis [18-21] , especially dermoscopy image analysis[22,25] for melanoma detection and classification. Interestingly, there are already well-established deep learning CNN classifiers, including AlexNet[26] , VGGNet[27] , GoogLeNet[28] , ResNet[29], and DenseNet[30] which other convolutional networks have also deepened to improve their performance in various and challenging tasks[31,32] . Yu et al[24]. presented the two-cascade model, which uses deep residual networks to segment and classify skin lesions. They achieved state-of-the-art segmentation and classification accuracy of 94.9% and 85.5% on the ISIC 2016 challenge dataset.

Coupled with clinical criteria representation is the segmentation mask of skin lesions produced by UNet, and this was integrated and used in the diagnosis CNNs stage[33]. A two-stage model for skin lesion classification was proposed by Seeja and Suresh[34]. The first stage extracts color, texture, and shape features from segmented lesions using U-Net and the second stage inputs these extracted features into an SVM classifier that distinguishes benignant and malignancy of dermoscopy images.

A network for skin lesion recognition was proposed by Codella et al. . Their approach was based on a combination of convolutional neural network, SVM, and sparse coding[35]. In 2018, Yu et al. proposed a hybrid deep learning network that involved local descriptor encoding[25]. The experiment revealed that the combination of deep features extracted by ResNet with statistical fisher representations calculated at the patch-level could be used to distinguish different types of skin lesions. They used an SVM classifier with a Chi-squared kernel for classification. Our hybrid model's performance outperformed them all, with an overall diagnosis accuracy of 86.81% . Hagerty et al[23]. came up with a novel method earlierism that fuses hand-crafted features from traditional image processing with deep learning ResNet-50's learned features. This combined model allowed the creation of a reliable and powerful approach to raise the diagnostic accuracy of skin lesions while achieving an AUC of 89.0% with the ISIC 2018 dataset, where non-melanoma skin cancer cases were excluded.

3. Methodology

This paper covers the range of skin lesion detection through the review on classification and segmentation techniques. As it shows below, Fig1. briefly explores dermoscopy and the features, image segmentation and description of pre-processing techniques. This is followed by detailed examination of the two phases of skin lesion detection segmentation and classification through deep learning are also explained . Then the literature is reviewed and a comparison of the methods studied is included.

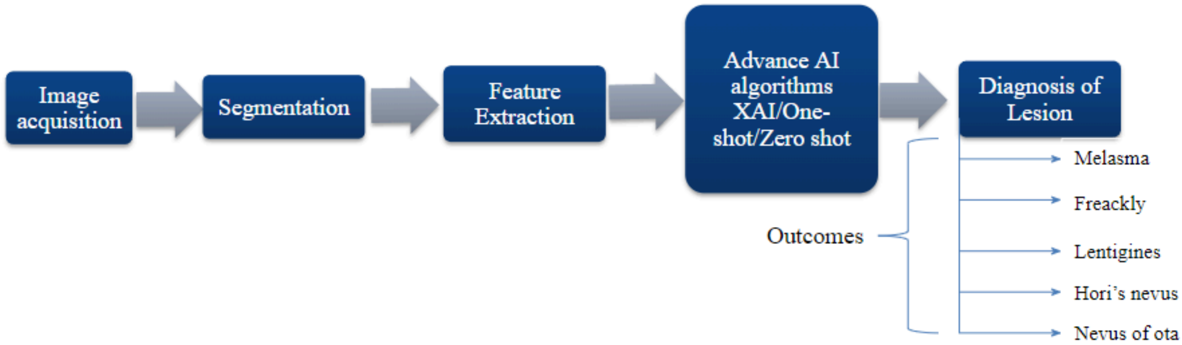

Fig1. Proposed Model for Non-Tumorous Facial Pigmentation Disorder using Ensemble and Deep Learning.

3.1 Image Acquisition:

The initial stage of image processing is image acquisition, also referred to as preprocessing. It encompasses retrieving the image from a source, typically a hardware-based one. This can be done via hardware systems such as cameras, encoders, sensors, etc. In the last several years, the use of deep learning has had a huge influence on a number of technological disciplines. In this field, machine vision, the capacity for systems to comprehend visuals on their own, is one of the most talked-about subjects. The act of converting a picture into a digital form and carrying out specific procedures in order to extract some useful data is known as image processing. When using specific preset digital signal processing techniques, the image processing system typically handles every image as 2D signals.

3.2 Segmentation Framework:

In order to reduce the level of detail of an electronic picture and enable additional processing or analysis of individual image segments, the technique known as image segmentation divides the image into subsets known as image segmentation. The process of assigning labels to individual pixels in an image to distinguish objects, persons, or other significant features is known as segmentation.

Object recognition is one common application of picture segmentation. Finding objects of interest in an image using an image division method is a typical approach before processing the complete image. Once the box's perimeter has been established by the method of segmentation, the object detector can begin to function. This increases reliability and decreases inference time by stopping a detector from scanning the full image.

Segmenting images is a fundamental component of machine learning techniques and systems. Numerous real-world uses for it exist, such as telescopic analysis of images, video surveillance, face identification and acknowledgment, self-driving cars imaging, and clinical picture research.

3.3 Feature Extraction:

Feature extraction refers to a fundamental process in machineFeature extraction that classifies images using an entity-based method. A substance, also known as a segment, is a collection of pixels with comparable spectral, geographical, and/or textural characteristics. learning and data analysis where relevant features are identified and extracted from raw data. These features are subsequently utilized to construct a more informative dataset.

When you're dealing with an extensive collection of data and need to reduce the number of resources without sacrificing any significant or pertinent information, the feature extraction technique comes in handy. Reducing the volume of unnecessary data in the information set is facilitated by feature extraction.

3.4 Explainable Artificial Intelligence (XAI):

It is defined by Gianfagna & Di Cecco[36], encompasses a range of techniques and methodologies aimed at elucidating the outcomes of machine learning (ML) model development in a manner comprehensible to humans. Two key terms associated with XAI are interpretability and explainability.

Interpretability (Thampi & Interpretable)[37], pertains to understanding cause and effect within an artificial intelligence (AI) system. It involves accurately predicting the model's outputs given an input, comprehending the model's decision-making process, observing how predictions change with alterations in inputs or algorithmic parameters, and detecting errors made by the model. Explainability (Thampi & Interpretable)[37] extends beyond interpretability by aiding in understanding how and why a model makes predictions in a human-understandable manner. It aims to elucidate the internal workings of the system using straightforward language, thereby reaching a broader audience. Explainability draws from various disciplines such as human-computer interaction (HCI), law, and ethics.

The necessity and significance of XAI lie in its ability to provide deeper insights than traditional evaluation metrics like classification accuracy. Relying solely on accuracy may overlook the complexities of the problem domain. Understanding the factors contributing to predictions is crucial for effective decision-making. XAI finds applications in model debugging, validation, and knowledge discovery.

XAI employs two main approaches: intrinsic and model-agnostic. In the intrinsic approach, interpretations are derived from the model's internal parameters, whereas the model-agnostic approach is used when the model operates as a black box, and its internal parameters are unknown. Explanations can take various forms, including intrinsic (post hoc) and model-agnostic (model-specific) explanations, as well as global or local explanations, each serving different purposes in enhancing the interpretability and explainability of ML models.

3.5 One shot algorithm:

The phrase One-Shot learning was initially used by [4, 5] and it refers to the ongoing difficulty in computer vision of extracting a large amount of knowledge on an object class from a single image.Though deep neural networks, great success in the large data domain, they generally perform poorly on few-shot learning tasks, where a classifier has to quickly generalize after seeing very few examples from each class. Most people think that for optimization using gradients in high capacity classifiers to work successfully, a lot of iterative steps across a large number of samples are needed. In the small data regime, where there aren't many marked samples to draw from, this kind of optimization fails.In this scenario, there are several samples with some marked instances per class instead of a single, sizable dataset.In addition to the reality that people even young children can typically make generalizations from a single example of a given object, this job is motivated by the fact that algorithms that perform well on it could have several practical uses. First of all, since numerous labeled instances are not needed to achieve respectable efficiency, they would ease the burden of data collection. Additionally, data in numerous fields has the trait of having a large number of classes but few samples in each class. This kind of data would be well captured by models with the capacity to generalize from a small number of samples. With just one instance of each additional class, one-shot learning seeks to classify the fresh categories that are not present in the training set.

While few-shot and zero-shot learning share similarities, they differ in the number of training instances that must be provided. Few-shot learning, also known as low-shot learning, is a type of education that is frequently classified as one-shot learning. It indicates that there are several images of novel groups of objects available, as opposed to just one.Identifying cases of objects that belong to new categories without the need for training examples is the goal of zero-shot learning techniques.

In the same way that an individual must explicitly alert the algorithm to samples holding fresh data if it misses them, the majority of one-shot learning systems still rely on oversight. Active learning is a type of semi-supervised training in which the model's algorithm chooses which data points need to be labeled automatically, reducing the quantity of oversight required to complete a job. The real names of these chosen examples would need to be requested from the human user, hence, the efficiency of data is essential to reducing this type of interaction between users.

3.5.1 Applications:

3.5.1.1 Face Recognition

Among the more relevant uses of computer vision is face recognition because it is a basic one-shot learning challenge and also of tremendous value for tasks like human re-identification in security applications and facial detection in smart gadgets. The aim of facial recognition technology is to identify a person's identity from a single photo that is fed into the algorithm. Furthermore, if the visual is not recognized, it indicates that the database within the system does not have the individual's photograph.It is not practical to utilize a convolutional neural network alone to address this issue for two distinct reasons:1) CNN cannot function with a restricted skill set. 2) Retraining the model each time an additional person's photo is added to the database is inconvenient.

CNNs' pattern training and translation capabilities have advanced the field of identification of face features of consistency. A characteristic harvester gathers information from an alignment face to provide a low-dimensional accountability, which is then used by a classifier to generate forecasts. In facial recognition algorithms that operated before CNNs, handmade attributes were extracted. In contemporary research, facial recognition is achieved using metrics training and feature acquisition by deep networks.

3.5.1.2 Meta-learning

Developing previous knowledge over earlier actions and encounters is known as the concept of meta- for few-shot learning. This allows new tasks to be acquired through little quantities of information. Any clearly identified class of machine learning problems, such as unsupervised learning and reinforcement education, can be used for the tasks. One important first step in developing adaptable agents who can continuously learn a wide range of activities during their entire lives is this method of being taught to learn, or meta-learning.

4. Types of Lesions

There are mainly 5 most common types of Non-Tumorous Facial Pigmentation Disorders: Melasma, Freackly, Lentigines, Hori's nevus and Nevus of ota.

4.1 Melasma: It presents as brown to gray-brown patches on the face, commonly appearing on the cheeks, chin, nose bridge, forehead, and above the upper lip. This condition is more prevalent in women, often triggered by hormonal fluctuations such as those experienced during pregnancy or through the use of oral contraceptives. Sun exposure and genetic factors also contribute to its development.

The factors lead to melasma:

Sun contact, hormonal fluctuations specific drugs (such as anti-seizure medications and those which boost the skin's reaction to ultraviolet rays), anxiety, thyroid conditions, and inheritance are just a few of the factors which can cause melasma. Sunlight promotes the body to generate more melanin, leading sun-exposed sections such as the arms, neck, and forehead to experience melasma. Hormones fluctuations, particularly during conception or when using contraceptive drugs, may result in melasma because they raise both estrogen and progesterone levels. Melasma can also result from drugs that increase skin sensitivity to sunlight. Melasma can also develop as a result of thyroid problems, stress, and genetics.

Variables put one at risk of having melasma:

A frequent pigmentation condition called melasma results in darker areas on the skin, primarily on the face. Though the precise etiology of melasma is unknown, it is thought to result from an excess of color produced in some areas of the skin by skin's own melanocytes which are the cells responsible for producing pigment. Melasma can be aggravated or brought on by sun exposure, skin tone, specific skin care products, and certain drugs. As much as fifty percent of melasma sufferers indicate that close relatives also have the ailment, suggesting that genetics may play a part. Hyperpigmentation or discolored patches of skin that are dark or grey in tone, is the main sign of melasma. Although there are no other medical symptoms associated with melasma, some people may find the sight of these patches annoying. In certain cases, treatment is not required because melasma can go away on its own, particularly after hormone medications are stopped.

4.2 Freackly: These small brownish spots on the skin arise from heightened melanin production and typically proliferate and darken when exposed to sunlight.

The factors lead to Freackly:

By taking precautions to shield the skin from the sun, freckles can be avoided. Melanin, the pigment that determines skin tone, builds up beneath the skin and causes freckles. Freckles occur on the outermost layer of skin when exposure to sunlight causes the skin cells to create more melanin as a defense against solar injury. Freckle formation is also largely influenced by inheritance, as some genes affect the type of melanin the body produces. A combination of their heightened susceptibility to ultraviolet radiation and biological tendency, those with pale complexion, red or blonde hair, and bright-coloured eyes are more likely to develop freckles.

Variables put one at risk of having Freackly:

Numerous sunburns, pale complexions, dark or brunette locks, translucent eyes, an inherited propensity to freckling, and ultraviolet (UV) absorption are some of the factors that increase the likelihood of developing freckles. Ultraviolet radiation and hereditary factors are the main causes of freckles. The freckles are more common in people with light complexions and in individuals who don't wear sunscreen on their exposed skin.

4.3 Lentigines: These harmless growths appear on parts of the body exposed to the sun, like the back of the hands and the face. They typically increase in number as people age, making them prevalent among middle-aged and older individuals.

The are the causes of Lentigines:

The cause of lentigines is pigment cells proliferation; they are larger, darker, and more numerous than freckles. Lentigo simplex is the most prevalent type of lentigo, yet its frequency is unknown. The typical circular or round lentigo simplex patches are dark brown or black in appearance. These lesions typically form between birth and early older age, while their exact etiology is unknown.

Variables put one at risk of having Lentigines:

A tendency to have vertigo is one of the risk variables for lentigo maligna melanoma (LMM), which is more likely to occur than superficial spreading melanoma (SSM).As opposed to LMM, increased nevus propensity is a better indicator of SSM. The greatest predictor for LMM is the quantity of solar lentigines, whereas the biggest factor for SSM is the amount of nevi.

4.4 Hori's nevus: These also known as acquired bilateral nevus of Ota-like macules (ABNOM), is a rare skin condition that presents as blue-gray patches on both sides of the face. It primarily affects women of Asian descent and typically emerges during the fourth or fifth decade of life.

The causes hori's nevus:

The primary causes of Hori's nevus, sometimes referred to as acquired bilateral nevus of Ota-like macules (ABNOM), are a mix of hormonal and genetic variables. Hori's nevus develops as a result of a combination of genetic and hormonal factors. In healthy skin, melanocytes pigment cells that produce melanin are mostly found in hair follicles and the epidermis, the top layer of the skin. Nevertheless, in the instance of Hori's nevus, these melanocytes are found in the dermis, the skin's lower layer, which results in a disorder called dermal melanocytosis. Hori's nevus is among the disorders that fall under the umbrella of dermal melanocytosis, which causes pigmentation to shift from black-brown to blue-gray. Hori's nevus can develop as a result of a number of factors, including UV radiation exposure, genetic predisposition, aging skin, epidermal inflammatory processes, and even use of specific cosmetics.

Variables put one at risk of having hori's nevus:

Hormonal effects and genetic background are risk factors for Hori's nevus. The likelihood of having Hori's nevus rises in families where the syndrome is present. Patients' age and the length of their illness are also related to the clinical characteristics of their Hori's nevus. And it can develop as a result of ultraviolet light exposure, genetic predisposition, aging skin, epidermal inflammatory processes, and use of specific cosmetics.

4.5 Nevus of ota: The Nevus of Ota manifests as heightened pigmentation surrounding the eye and its nearby structures, aligning with the distribution of the V1/V2 branches of the trigeminal nerve. This increased pigmentation results in a bluish or brownish hue observed in the eyes and/or the skin and eyelids on the face.

The causes Nevus of Ota:

A skin ailment called Nevus of Ota is typified by hyperpigmentation surrounding and occasionally inside the eye. It is a kind of dermal melanocytic hamartoma, also referred to as oculodermal melanocytosis. An excess of the melanocytes or cells that produce melanin, in the skin cells is what causes the illness.Nevus of Ota can manifest bilaterally, however it typically affects just one side of the face when it does. Usually appearing blue-gray or dark, the hyperpigmentation can be found on the cheekbones, forehead, and nostrils, the eyelids, and area surrounding the eyes. Of all occurrences of nevus of Ota, about half are present from birth, with the surviving cases often developing throughout puberty.Although the precise etiology of nevus of Ota is unknown, some medical professionals and researchers think that a mutation in the genome may be to blame, while others speculate that hormonal may be involved.

Variables put one at risk of having Nevus of Ota:

Genetic abnormalities, hormonal changes, radiation exposure, and other medical conditions are among the risk variables for Nevus of Ota. Abnormal pigmentation of the epidermis around the eyes, on the forehead, and occasionally inside the eyes is a characteristic of Nevus of Ota. Of all occurrences of nevus of Ota, about half are present from birth, with the other cases often developing throughout puberty. Although the illness is primarily diagnosed clinically, there is a higher risk of melanoma of the eyelids and glaucoma in these individuals (10% and 1 in 400, respectively). The Fig2 shows the trained images of the five types of non-tumorous skin pigmentation disorders in the classification problem.

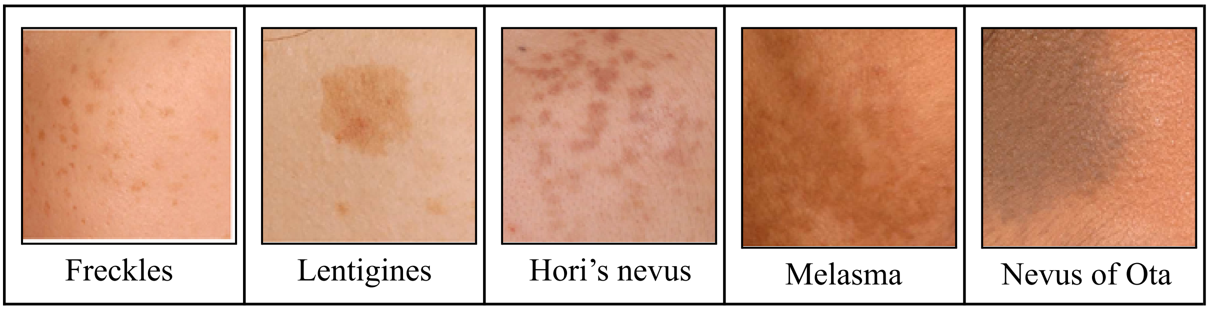

Fig2. shows trained images of the five types of non-tumorous skin pigmentation disorders in the classification problem.

5. Literature Review

This section will cover research conducted on related topics, with a primary focus on facial pigmentation data. The proposed studies suggest extracting features from these sample input waveforms. Furthermore, researchers advocate for using a diverse range of features to determine the most appropriate ones. Finally, several classification algorithms have been applied to the task of categorizing different types of Non-Tumorous Facial Pigmentation disorders.

Classification of non-tumorous skin pigmentation disorders using voting based probabilistic linear discriminant analysis[20],this paper describes a voting-based probabilistic linear discriminant analysis (V-PLDA) approach to categorizing non-tumorous skin pigmentation disorders. It focuses on five common types of disorders: freckles, lentigines, Hori's nevus, melasma, and nevus of Ota. In terms of categorizing these illnesses with a high within-class variation, the suggested V-PLDA method performs better than the original PLDA and other cutting-edge techniques. The work shows significant clinical possibilities for identifying pigmentation-related problems and attempts to establish a baseline for future studies in this field.

The research employed a number of methodologies, including the suggested V-PLDA model for the categorization of non-tumorous skin pigmentation disorders. In order to increase the precision of classification, the V-PLDA approach selects data that have an elevated likelihood of joining with the testing sample through a voting process. The table1 shows the accuracy of different methods used in the research and Fig3. shows the experimental results of the proposed VPLDA method and the methods compared are shown in the above bar graph. This approach performs better than its predecessor PLDA alongside other cutting-edge techniques for classifying images, especially when there is a significant within-class variance.

Table1. Classification Results with Different Methods.

Method	Accuracy (%)
SDA	67.63
LLC	71.47
IKSVM	73.30
V-PLDA	77.33

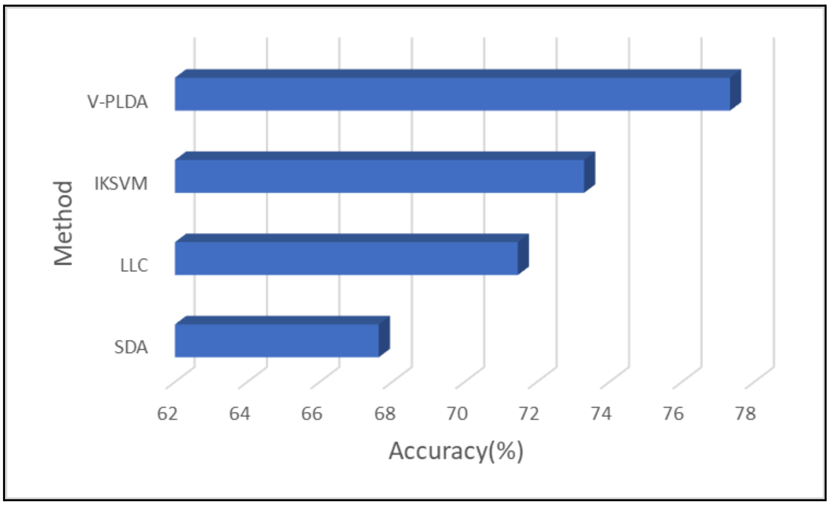

Fig3. The experimental results of the proposed VPLDA method and the methods compared are shown in the above bar graph.

This work proposes a voting based probabilistic linear discriminant analysis (V-PLDA) method to address the large within class variation issue in the classification of photographs with non-tumorous skin pigmentation.Utilizing just training instances with high likelihoods of collaborating with the evaluation examples of in the categorization manage, the recommended V-PLDA technique overcomes the huge within-class difference issue, as opposed to the unique statistical linear discrimination analysis method, which is better suited to low or mild within-class variation.The ultimate categorization decision is obtained using a vote method using the chosen samples for training. The V-PLDA approach doesn't call for any prior knowledge of the initial tests, in contrast to the tied-PLDA method.

Classification of Non-tumorous Facial Pigmentation Disorders Using Generative Adversarial Networks and Improved SMOTE[1][19], in this paper, we showcase the superior performance of our proposed method by comparing experimental results across three approaches: V-PLDA [2], Transfer Learning + Improved SMOTE [4], and Transfer Learning + PGAN with enhanced SMOTE. In this research they have been discussed to find ways to improve the picture collection for learning and the paper describes the categorization of non-tumorous face pigmentation diseases utilizing Generative Adversarial Networks (GAN) and Improved Synthetic Minority Oversampling Technique (SMOTE). More varied examples for training are produced by using GAN with Improved SMOTE, which results in a notable (>4%) improvement in classification precision over baseline techniques. The suggested technique efficiently augments data by combining GAN with Improved SMOTE, increasing the sorting model's precision as a whole.

Enhanced SMOTE and Progressives GAN (PGAN) are used in a two-step data enrichment strategy as part of the methodology to improve a relatively small training set for the classification of non-tumorous facial pigmented diseases. The identical standards listed in are used to assess the degree of similarity between the generated and original data in order to show how well PGAN with the enhanced SMOTE performs in comparison to the technique that uses the improved SMOTE alone. The analogy between each generated image and each original image is measured using the SSIM (Structural Similarity Index Measure) index [12]. After comparing each generated image to every original image, the highest SSIM index (HSI) is determined for each image.

Ruihan Gao[4] did the experiments on different lesions on limited images and they have found some different values for each category of lesion, the below table 2 tabulates the HSI range of the obtained pictures in every category. Five categories are denoted by capital letters: F stands for freckles; L for lentigines; M for melasma; H for Hori's Nevus; and O for Nevus of Ota. It is demonstrated that newer generated photographs are more distinguishable from the first images when the GAN model with the enhanced SMOTE is used. This demonstrates how GAN can increase the range of subjects found in every category and Fig4. shows an accuracy graph HSI range using different methods.

Table 2. HSI range using different methods

HSI	Improved SMOTE	PGAN with the improved SMOTE
F	0.878-0.998	0.774-0.957
L	0.877-0.997	0.727-0.976
M	0.882-0.997	0.691-0.954
H	0.908-0.998	0.662-0.965
O	0.882-0.999	0.684-0.949

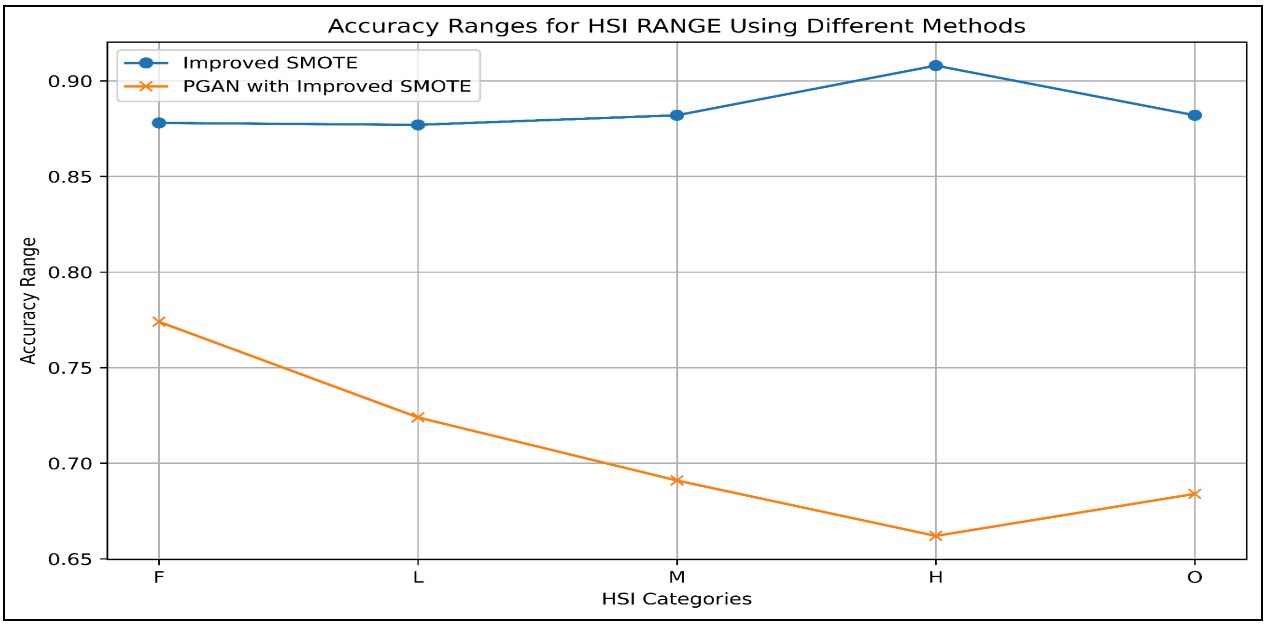

Fig4. Accuracy graph HSI range using different methods for Table 2.

A previously trained CNN model serves as the feature extractor and fully linked layers serve as the machine learning algorithm in the sorting model used in the present study. The feature extraction model selected is Inception-Resnet-v2 [14], which has been pre-trained on a broad dataset. This model is the same as the one used as a reference model in [3, 4].

This section includes table 3, which displays the overall accuracy and standard deviation achieved using the same classification model Inception-ResNet-v2 but with different data augmentation techniques and Fig5. shows an accuracy graph for Classification Results with Different Methods.

Table 3. Classification Results with Different Methods.

Method	**Accuracy (%)**
V-PLDA	77.33
Transfer Learning + Improved SMOTE (TS+IS)	87.33
Transfer Learning + PGAN with the Improved SMOTE (TL+ PGAN with SMOTE)	91.67

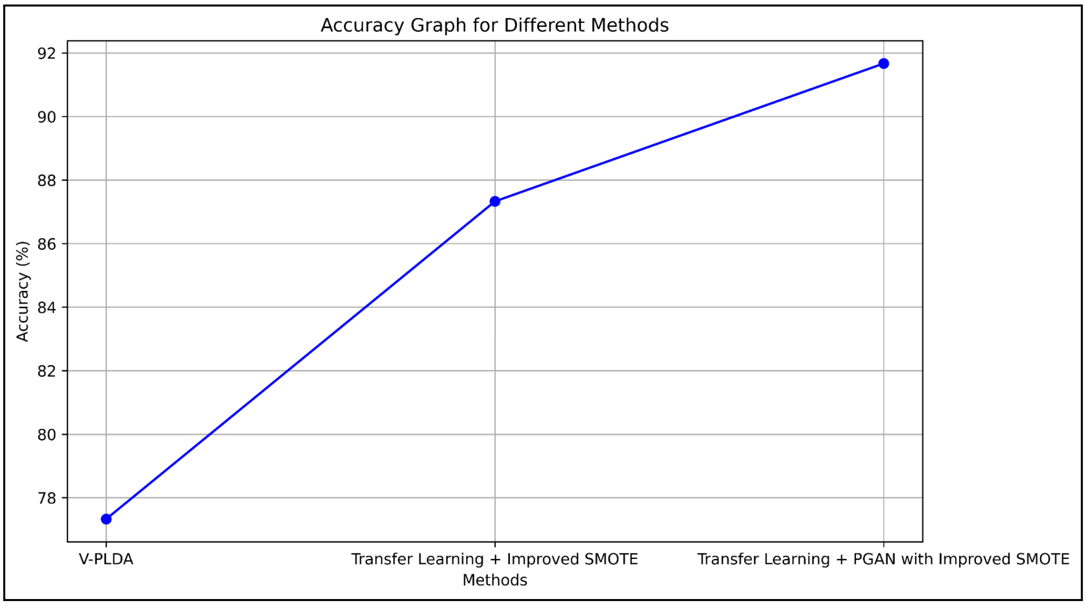

Fig5. Accuracy graph for Classification Results with Different Methods.

6. Conclusion

In this paper, we have conducted a survey encompassing over 100 papers, providing a comparative analysis of state-of-the-art techniques, models, and methodologies. Over the past few decades, researchers have devoted significant attention and effort to achieving accurate skin lesion diagnosis. Dermoscopic skin lesion images pose several challenges, including low contrast, multiple lesions, irregular and fuzzy borders, blood vessels, regression, hairs, bubbles, variegated coloring, and other distortions. The scarcity of large training datasets exacerbates these challenges. Given the recent strides in deep learning, particularly its exceptional performance in medical imaging, there is a growing need to assess the effectiveness of deep learning algorithms in skin lesion segmentation. This paper discusses the outcomes of various techniques, evaluating them based on parameters such as the Jaccard coefficient, sensitivity, specificity, and accuracy. The paper highlights major achievements in this domain, offering a detailed discussion of the employed techniques. Looking ahead, improvements in results are anticipated by leveraging the capabilities of deep learning frameworks along with additional pre and post-processing techniques, aiming to develop reliable and accurate diagnostic systems.

References

[1] Jiawei Peng, Ruihan Gao, Steven Thng, Weimin Huang, Zhiping Lin Classification of Non-tumorous Facial Pigmentation Disorders Using Generative Adversarial Networks and Improved SMOTE (2021) Nov:2021:3770-3773.

[2] Jose G. M. Esgarioa, Renato A. Krohlinga, Beyond Visual Image: Automated Diagnosis of Pigmented Skin Lesions Combining Clinical Image Features with Patient Data(2022).

[3] Mohammed A. Al-masni, Dong-Hyun Kima,Tae-Seong Kimb,Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification(2020) Jul:190:105351.

[4] Ruihan Gao, Jiawei Peng, Long Nguyen, Yunfeng Liang, Steven Thng, Zhiping Lin Classification of Non-tumorous Facial Pigmentation Disorders Using Deep Learning and SMOTE (2019) 2158-1525.

[5] L. Ballerini, R.B. Fisher, B. Aldridge, J. Rees, A color and texture based hierar- chical K-NN approach to the classification of non-melanoma skin lesions, Color Med. Image Anal. (2013) 63–86.

[6] N. K. Mishra, and M. E. Celebi., “An overview of melanoma detection in der- moscopy images using image processing and machine learning,” arXiv preprint arXiv:1601.07843, 2016.

[7] Y.I. Cheng, R. Swamisai, S.E. Umbaugh, R.H. Moss, W.V. Stoecker, S. Teegala, S.K. Srinivasan, Skin lesion classification using relative color features, Skin Res. Technol. 14 (Feb (1))(2008) 53–64.

[8] M.E. Celebi, H.A. Kingravi, B. Uddin, H. Lyatornid, Y.A. Aslandogan, W.V. Stoecker, R.H. Moss, A methodological approach to the classification of dermoscopy images, Comput. Med. Imaging Graphics 31 (Sep (6)) (2007), 362–373.

[9] H. Ganster, A. Pinz, R. Rohrer, E. Wildling, M. Binder, H. Kittler, Automated melanoma recognition, IEEE Trans. Med. Imaging 20 (Mar (3)) (2001) 233–239.

[10] L. Zhang, G. Yang, X.J. Ye, Automatic skin lesion segmentation by coupling deep fully convolutional networks and shallow network with textons, J. Med. Imaging 6 (Apr (2)) (2019).

[11] A.-R. Ali, J. Li, S.J. O’Shea, G. Yang, T. Trappenberg, X. Ye, A deep learning based approach to skin lesion border extraction with a novel edge detector in dermoscopy images, in: International Joint Conference on Neural Networks (IJCNN), Budapest, Hungary, 2019, pp. 1–7.

[12] Y. Liu, G. Yang, S.A. Mirak, M. Hosseiny, A. Azadikhah, X. Zhong, R.E. Reiter, Y. Lee, S.S. Raman, K. Sung, Automatic prostate zonal segmentation using a fully convolutional network with feature pyramid attention, IEEE Access 7 (2019) 163626–163632.

[13] M. Soltaninejad, G. Yang, T. Lambrou, N. Allinson, T.L. Jones, T.R. Barrick, F.A. Howe, X.J. Ye, Supervised learning based multimodal MRI brain tumour segmentation using texture features from supervoxels, Comput. Methods Progr. Biomed. 157 (Apr) (2018) 69–84.

[14] M. Soltaninejad, G. Yang, T. Lambrou, N. Allinson, T.L. Jones, T.R. Barrick, F.A. Howe, X.J. Ye, Automated brain tumour detection and segmentation using superpixel-based extremely randomized trees in FLAIR MRI, Int. J. Comput. Assisted Radiol. Surg. 12 (Feb (2)) (2017) 183–203.

[15] M. Soltaninejad, X. Ye, G. Yang, N. Allinson, T. Lambrou, Brain tumour grading in

different MRI protocols using SVM on statistical features, in: Medical Image Understanding and Analysis, London, UK, 2014, pp. 259–264.

[16] G. Yang, T.L. Jones, F.A. Howe, T.R. Barrick, Morphometric model for discrimination between glioblastoma multiforme and solitary metastasis using three-dimensional shape analysis, Magn. Reson. Med. 75 (Jun (6)) (2016) 2505–2516.

[17] G. Yang, T.L. Jones, T.R. Barrick, F.A. Howe, Discrimination between glioblastoma multiforme and solitary metastasis using morphological features derived from the p:q tensor decomposition of diffusion tensor imaging, NMR Biomed.27 (Sep (9)) (2014) 1103–1111.

[18] H. Chang, J. Han, C. Zhong, A.M. Snijders, J.H. Mao, Unsupervised transfer learning via multi-scale convolutional sparse coding for biomedical applications, IEEE Trans. Pattern Anal. Mach. Intell. 40 (May (5)) (2018) 1182–1194.

[19] Classification of Non-tumorous Facial Pigmentation Disorders Using Generative Adversarial Networks and Improved SMOTE, Jiawei Peng, Ruihan Gao, Steven Thng, Weimin Huang, Zhiping Lin (2021) Nov:2021:3770-3773.

[20] Classification of non-tumorous skin pigmentation disorders using voting based probabilistic linear discriminant analysis,Yunfeng Liang, Lei Sun, Wee Ser,, Feng Lin, , Steven Tien Guan Thng, , Qiping Chen,Zhiping Lin (2018) Aug 1:99:123-132.

[21] M.A. Al-antari, M.A. Al-masni, S.U. Park, J. Park, M.K. Metwally, Y.M. Kadah, S.M. Han, T.S. Kim, An automatic computer-aided diagnosis system for breast cancer in digital mammograms via deep belief network, J. Med. Biol. Eng. 38 (Jun (3)) (2018) 443–456.

[22] M.A. Al-masni, M.A. Al-antari, H.M. Park, N.H. Park, T.-S. Kim, A deep learning model integrating FrCN and residual convolutional networks for skin lesion segmentation and classification, in: 2019 IEEE Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (ECBIOS), Okinawa, Japan, 2019, pp. 95–98.

[23] J.R. Hagerty, R.J. Stanley, H.A. Almubarak, N. Lama, R. Kasmi, P. Guo, R.J. Drugge, H.S. Rabinovitz, M. Oliviero, W.V. Stoecker, Deep learning and handcrafted method fusion: higher diagnostic accuracy for melanoma dermoscopy images, IEEE J. Biomed. Health Inform. 23 (Jul (4)) (2019) 1385–1391.

[24] L.Q. Yu, H. Chen, Q. Dou, J. Qin, P.A. Heng, Automated melanoma recognition in dermoscopy images via very deep residual networks, IEEE Trans. Med. Imaging 36 (Apr (4)) (2017) 994–1004.

[25] Z. Yu, X. Jiang, F. Zhou, J. Qin, D. Ni, S. Chen, B. Lei, T. Wang, Melanoma recognition in dermoscopy images via aggregated deep convolutional features, IEEE Trans. Biomed. Eng. (2018, Aug).

[26] A. Krizhevsky, I. Sutskever, G.E. Hinton, Imagenet classification with deep convolutional neural networks, Adv. Neural Inf. Process. Syst. (2012) 1097–1105.

[27] K. Simonyan, and A. Zisserman, “Very deep convolutional networks for large scale image recognition,” arXiv preprint arXiv:1409.1556, 2014.

[28] C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Van-houcke, A. Rabinovich, Going deeper with convolutions, in: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2015, pp. 1–9.

[29] K. He, X. Zhang, S. Ren, J. Sun, Deep residual learning for image recognition, in:Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016.

[30] G. Huang, Z. Liu, L.V.D. Maaten, K.Q. Weinberger, Densely Connected Convolutional

Networks, in: Computer Vision and Pattern Recognition (CVPR), 2017, pp. 4700–4708.
[31] M. Lin, Q. Chen, and S. Yan, "Network In Network," in rXiv preprint arXiv:1312.4400, pp. 1-10, 2013.
[32] H. Chougrad, H. Zouaki, O. Alheyane, Deep Convolutional Neural Networks for breast cancer screening, Comp. Methods Progr. Biomed. 157 (Apr) (2018) 19–30.
[33] X. Li, J. Wu, H. Jiang, E. Z. Chen, X. Dong, and R. Rong, "Skin Lesion Classification Via Combining Deep Learning Features and Clinical Criteria Representations," bioRxiv preprint, pp. 1-7, 2018.
[34] R.D. S., A. S., Deep learning based skin lesion segmentation and classification of melanoma using support vector machine (SVM), Asian Pac. J. Cancer Preven.20 (2019) 1555–1561.
[35] N. Codella, J. Cai, M. Abedini, R. Garnavi, A. Halpern, J.R. Smith, Deep learning, sparse coding, and SVM for melanoma recognition in dermoscopy images, in: International Workshop on Machine Learning in Medical Imaging, 2015, pp. 118–126.
[36] L Gianfagna, A Di Cecco , Explainable AI with python, 2021, Pages 185-197.
[37] Ajay Thampi, Interpretable AI Building explainable machine learning systems, May 2022 ISBN 9781617297649, 328 pages.

Authors' Profiles

Arjun H is a part-time research scholar at VTU, Belgaum. He received his Master of Technology in Computer Science & Engineering from STJIT, Ranebennur, (VTU) and is currently working as an Assistant Professor in the Department of Computer Science and Engineering at BIET, Davangere and has more than 07 years of experience. His main area of interest includes studies related to Data Structure and DataBase Management systems. He has published a good number of research papers in reputed International Conferences and Journals.

Dr. Gururaj T is currently working as an Associate Professor in the Department of Computer Science and Engineering, Bapuji Institute of Engineering and Technology, Davangere affiliated to VTU. He received his Ph.D., in the Faculty of Computer and Information Sciences from MS Ramaiah Institute of Technology(MSRIT), Bangalore(VTU), and Master of Technology in Computer Science & Engineering from J. N. National College of Engineering, Shivamogga. (VTU). He has published a good number of research papers in reputed International Conferences and Journals. He is a member of ISTE and has more than 20 years of teaching experience. His main area of interest includes studies related to Big Data and its Applications, Data Science, Data Analytics and Bioinformatics.