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A Survey on Skin Lesion Detection and Classification using Machine Learning

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The research explores how dermatologists use machine learning to quickly and accurately identify and classify skin injury. Conventional diagnosis techniques depend on visual examination, but are subjective and have different interpretations. The ability to analyze data and recognize patterns is a possible remedy for ML. The paper examines the current technology of machine learning, focusing on validation in the real world, and deals with data set variability. Although the research acknowledges the fruitfulness of deep learning (DL), the research emphasizes the benefits of traditional ML techniques regarding interpretation and processing performance. Methods for automating the analysis of skin lesions, such as feature engineering, rule-based techniques and traditional ML algorithms, have been studied. The study suggests using advanced transfer learning techniques, integrating genetic and clinical data, and refining the way artificial intelligence (AI) is explained in order to get over barriers. Intending to enhance the accessibility and correctness of skin lesion identification, the future requires collaboration between dermatology and machine learning to develop real-time diagnostic tools. By offering scalable solutions for rapid diagnosis of lesions and improved patient outcomes, this combination of medical expertise and ML capabilities has the power to revolutionize dermatology. The future of automated dermatological diagnosis is expected to be shaped by collaboration between machine learning experts and dermatologists, enabling more personalized treatment for patients.

Keywords— skin lesion, machine learning, survey, deep learning, CNN

I. INTRODUCTION

Skin injuries, from benign to malignant, are an essential component of dermatology diagnosis [3]. Accurate and prompt identification is necessary for the timely recognition and effective medicaments of skin lesions. To successfully cured some incurable diseases like skin cancer, melanoma can be cured only at primary stage [10]. The recent advancement in imaging technology have enabled high resolution skin images which gives opportunity to machine learning algorithms to step in dermatology. This work is driven by a growing tendency in the medical field to apply ML for skin lesion identification and categorization in order to enhance diagnosis. Traditional diagnosis techniques are time consuming and slow to changes in human capabilities, which motivates researchers to explore automated, effective, and unbiased evaluations by machine learning [26].

In the decade, the machine learning algorithms becomes popular and also they help in improving diagnosis [16]. Dermatologists mainly diagnose skin infections by visual examination in traditional procedures, which can lead to a variety of diagnoses and subjective interpretations. By analyzing huge amounts of data and analyzing complex patterns of identity, ML provides creative solutions to these problems [19]. High-quality dermatological imaging data sets have exponentially expanded, and the development of machine learning methods has allowed for robust and accurate models. Through methods such as DL, Convolutional Neural Networks (CNNs) [21], and learning transfer, scientists have been able to automatically recognize and catergorize skin disorders with remarkable effectiveness.

In this work, the advanced with traditional approaches for machine learning based on skin lesion identification and categorization are reviewed. It explores the traditional machine learning techniques with the recent advancement, publicly available datasets with evaluation metrics and at the end future scope and challenges are discussed.

The paper also addresses how machine learning models in dermatological applications could perform better if other modalities, such as dermoscopy and clinical data, were integrated. The integration of ML skills with medical knowledge has the possibility to transform dermatological practices as we traverse the intricacies of skin lesion detection. Machine learning has more possibilities to influence the healthcare industry by providing a scalable, dependable, and efficient solution that will help with early identification, better patient outcomes, and more efficient use of resources [9] [17].

A. Background

Skin disorders, which include a wide range of lesions and dermatological illnesses, are a major global health concern. Skin disorders are becoming more common, which highlights the critical need for advanced and effective diagnostic tools. The machine learning models' proven accuracy and consistency in image analysis, along with their ability to manage the increasing amount of skin image datasets, serve as further sources of incentive. Beyond just increasing productivity, the survey aims to further dermatological personalized care by customizing treatment regimens based on unique skin features. This survey attempts to shed light on the traditional as well as advanced machine learning-based skin lesion identification by combining current research trends, methodology, and findings. By doing so, it hopes to uncover gaps in the field and open up new avenues for future research that will directly affect patient care.

B. *Motivation*

First of all, this survey gives an encyclopedic overview of the current state-of-art methodologies which helps researchers, practitioners and dermatologists with the understanding of current research and also future advancement of the field. This survey serves as a guide for future research projects by highlighting current challenges and limitations and directing efforts towards the area of innovation and improvement. The comparative analysis of various machine learning models allows us to evaluate their strengths and weaknesses. In addition, this research helps to explore the recent practical applications of machine learning in skin lesion detection. Analysing the previous studies aids in the understanding of data diversity and quality with ethical consideration. This survey serves as a road map, shaping the direction of future research and providing a brief yet significant view of the problem.

II. Literature Survey

Skin lesion recognition and categorization has made substantial use of ML techniques and DL techniques in our study. For skin lesion identification and categorization usually, researchers go for ML and DL techniques, but there are other methods like Rule based approach like ABCD method [2], CASH method [27], three-point checklist [25], seven-point checklist [27] etc popular. The dependency of choosing any technique will dependent on the size of the dataset. In this work, we are focusing on ML techniques as they provide more interpretable results and ease of implementation compared to DL models. Additionally, these models perform better on smaller datasets, are computationally lighter and are less prone to overfitting when the data is limited. ML model involves manual feature engineering which is its limitation, whereas DL model extracts more features which results in better accuracy. Many strategies have been used, from conventional techniques to sophisticated deep learning architectures. The following are a few popular machine-learning methods for analyzing skin lesions:

A. *Traditional Image Processing [22]*

Color-based segmentation is a popular technique that divides skin lesions from the surrounding tissue according to unique color features. This technique helps isolate lesions by using color differences to identify regions of interest. Another important component is texture analysis, which examines the patterns of skin lesions to identify variations that may be suggestive of particular illnesses.

B. *Classical Machine Learning Algorithms*

The broad range of methods known as classical machine learning algorithms has been used for several purposes, such as the identification and categorization of skin lesions. Several important approaches are covered by classical ML algorithms in the context of skin lesions:

- Support Vector Machine (SVM) [16]: For binary classification, commonly engrossed for benign and malignant tumours [7] from the skin lesion, SVM is popular.
- Random Forest (RF) and Decision Tree (DT) [17] [20]: For feature selection and classification, ensemble techniques like random Forests and decision trees are used. They are flexible enough to accommodate a wide range of data kinds since they can handle both continuous and categorical information.
- K-Nearest Neighbour(KNN) [9]: In KNN technique uses closeness to classify data items according to the class their neighbours belong to. KNN can be used in skin lesion analysis to find commonalities between lesions to classify them.
- Naïve Bayes [28] : The naïve Bayes classifiers is based on using the Bayes theorem with strong assumptions about feature independence. They are easy to use and effective, particular for smaller datasets.

C. *Feature Engineering [3]*

It is taking statistical measurements like mean and variance or pertinent aspects like size and shape descriptors and extracting them from the photos. To differentiate benign and malignant tumours, these characteristics are essential.

D. *Deep Learning Architectures*

For identification and categorization, CNNs [21] shows one of the most notable DL architectures that have transformed the skin lesions. CNNs easily identify structural features from dermatological images to achieve astonishing results. In this process pretrained model through transfer learning like VGG16 [21] and ResNet [10] are included. Recurrent neural networks (RNNs) [13] are used to ensnare time related dependencies in skin lesion patterns, for sequential data processing. Interpretability is enhanced by attention mechanisms like self-attention models that focus on specific or relevant areas of images. One of the popular techniques can be used for data-augmentation is GANs which will be discussed briefly in the next section. However, this will help significantly improve the productivity and precision for diagnosis.

E. *Autoencoders [26]*

For the study of skin lesion, autoencoders are a key element of deep learning architectures. They are experts in feature extractions and unsupervised learning by flatting the regions of dermatological images. During encoding process, autoencoders recreate the input images by dimension and noise reduction. Additionally, they may be used for data augmentation, creating synthetic data that helps to make model more robust. Autoencoders are essential as they provide a productive means of extracting meaningful representations from a complicated image for skin lesion identification and categorization in a automated dermatological diagnosis.

F. Generative Adversarial Networks (GANs) [19]

GANs are highly useful for skin lesion identification and classification, when data augmentation is used. A discriminator along with generator network makeup a GAN. A discriminator network and a generator network work together to produce artificial images much like real skin lesion. GANs help dermatology by improving generalization to previously unexplored data, enhancing model training, and expanding the scope of constrained datasets. GANs deal with the problem of insufficiently labeled data by creating realistic images of artificial skin lesions. The advancement of technology significantly boosts the robustness and efficacy of algorithms for recognition and categorization of skin lesions. The ability of GANs to create realistic images similar to actual skin lesions shows that GANs can be an important utility in the creation of automated dermatological diagnostic models.

III. DATA AND EVALUATION METRICS

To further the field of skin lesion identification and categorization, it is essential to have access to a variety of carefully selected datasets. To promote research collaborations, test machine learning algorithms, and ultimately aid in the development of reliable diagnosis models for dermatological applications, several publicly available datasets have become essential. Some of them are listed in Table 1. Various measures are employed to evaluate the models' performance and determine whether they are performing better or not. We refer to these measurements as performance metrics. Some common and significant outcome measurements, which vary depending on the kind of model, are covered in the section below [8] [14].

- Accuracy: The performance of the model is evaluated based on its accuracy. It is calculated as the proportion of all occurrences to the all instances. It is represented as

$$\frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \tag{1}$$

- Precision: A model's precision indicates how accurate its positive predicts are, It is defined as the proportion of actual positive predictions to all positive predictions the model produced.

$$\frac{\mathrm{TP}}{\mathrm{TP+FP}} \tag{2}$$

- Sensitivity (Recall): The recall of a classification model measures how well it can find every relevant instance in a dataset. As a percentage of all false negative and true positive forecasts, it represents the percentage of true positive cases or predications.

$$\frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{3}$$

- Specificity: Specificity play a crucial statistic for assessing classification for binary classification. This assesses a model's capacity to accurately recognize negative examples.

$$\frac{\mathrm{TN}}{\mathrm{TN+FP}} \tag{4}$$

- F1 Score: The in-general performance is assessed using F1-score for the classification model. It's the precision and recall harmonic mean.

$$2 * \frac{Precision * Recall}{Precision + Recall} \tag{5}$$

$$(TP : True\ Positive, TN : True\ Negative,$$
$$FP : False\ postive, FN : False\ Negative)$$

TABLE 1. LIST OF AVAILABLE DATASETS [29]

Name of the Dataset	Year	Number of Images	Image Dimensions	Image Format	Disease(s) present
DermIs [4]	Not Available	69	2067*1555	.jpg	Melanoma, Nevusor or Atypical nervus
DermNet [5]	1998	23000	540*722 to 4499*6748	.bmp	23 distinct types
PH2 [18]	2013	200	766*576	.bmp and .jpg	Melanoma, Nevusor or Atypical nervus, Common Nevus

ISIC Archives [11]	2016 to 2020	2094 to 33,126	variable	.jpg	Melanoma, Nevusor or Atypical nervus, Actinic Keratosis, Seborrheic Keratosis, Basal Cell Carcinoma
DermoFit (Paid) [6]	Not Available	1300	380*380	.jpg	Melanoma, Nevusor or Atypical nervus, Seborrheic Keratosis, Basal Cell Carcinoma, Actinic Keratosis
EDRA [1]	2000	1011	768*512	.jpg	Melanoma, Seborrheic Keratosis, Nevusor or Atypical nervus, Common Nevus, Basal Cell Carcinoma
Skin Cancer: Malignant Vs Benign [7]	2018	1800	224*244	.jpeg	Benign and Malignant skin mole
HAM10000 (Human Against machine) [15]	2018	10015	400*600	.jpg	Basal Cell Carcinoma, Benign Keratosis like Lesions, Actinic Keratosis, Melanoma, Common Nevus, Dermatofibroma, Vascular Lesions
ISBI 2016 [23]	2016	900	768*500	.jpg	Common Nevus, Seborrheic Keratosis, Melanoma
ISBI 2017 [12]	2017	2000	4500*6000	.jpg	Common Nevus, Seborrheic Keratosis, Melanoma
ISBI 2018 [24]	2018	2594	4500*6000	.jpg	Dermatofibroma, Vascular Lesions, Melanoma Actinic Keratosis, Basal Cell Carcinoma, Benign Keratosis like Lesions,

IV. Challenges and Future Scope

Numerous obstacles affect the effectiveness and usability of the field of machine learning-based skin lesion identification and categorization. Training models that generalize across different skin conditions are hampered by limited access to balanced and diverse datasets. Even using DL algorithms, it is still a challenging task to extract information from the images of skin lesions that may utlized for clinical interpretation . Robust algorithm development is further complicated by the clinical heterogeneity in skin types, lighting settings, and presentation styles. To achieve responsible implementation in clinical settings, ethical factors like as biases in algorithm predictions and patient privacy need to be carefully considered.

To improve accuracy, this field's future scope calls on the integration of several modalities, including genetic and clinical data. The interpretability of models will increase with the development of explainable AI techniques, and feature learning can be further enhanced by continuing research into transfer learning strategies. The future landscape will need to include real-time diagnostic tools, online learning tactics, and joint machine learning and dermatologist efforts to overcome obstacles and improve skin lesion detection technologies' usability, precision, and global impact.

V. Conclusion

In conclusion, this research study clarifies the significant progress made in the use of ML in the field of dermatology to identify and categorize skin lesions. This work explores the synergistic interaction between advanced machine learning techniques and high-quality dermatological datasets, realizing the critical importance of early detection of cutaneous abnormalities. Although the study duly notes the achievements of DL, also highlights the advantages of traditional ML algorithms in terms of interpretability, processing performance, with simplified application, especially in situations where datasets are limited. Various techniques, including rule-based strategies, traditional algorithms such as RF and SVM, and feature engineering, were examined for their effectiveness in automating the analysis of skin lesions.

Looking ahead, this field's direction anticipates overcoming obstacles like the need for different datasets and ethical problems. It suggests exploring advanced transfer learning algorithms, improving explainable AI techniques, and integrating genetic and clinical data. The development of real-time diagnostic instruments and joint efforts between the fields of dermatology and machine learning are anticipated to be essential elements in enhancing the accuracy, availability, and worldwide influence of skin lesion detection technologies. Considering skin conditions diagnostics, combining medical knowledge with machine learning expertize has the potential to completely transform dermatological practices by offering scalable and effective solutions for the quick identification of lesions, better patient outcomes, and economical use of resources. The field of individualized patient care is expected to benefit greatly from the joint efforts of machine learning researchers and dermatologists, as they are anticipated to play an essential role in defining the future of automated dermatological diagnostics.

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