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A Comprehensive Study on Skin Disease Detection using Deep Learning Approaches

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Abstract : Skin illnesses include a wide range of problems, from common dermatological issues to uncommon and complex disorders, and they collectively place a substantial strain on the world's healthcare systems. Immediate and accurate diagnosis is crucial for many disorders to be effectively controlled and treated, but it can be difficult because of the subjectivity of visual inspection and the variation in clinical presentations. The recent intersection of artificial intelligence and medicine has brought about innovative approaches to computer-aided diagnostics, resulting in changes in the field of dermatology. Because deep learning can analyze massive amounts of data and find complex patterns, it has become a powerful tool in the processing of identifying for more accurate and efficient diagnostic methods. The most recent advancements in deep learning techniques specifically created for the diagnosis of skin diseases are examined in this review paper. Examine the efficacy and performance of a number of algorithms, including the adaptable k-nearest neighbour, the robust support vector machine (SVM), and the complex convolutional neural networks (CNNs). Deep learning techniques for automated skin disease detection include generative adversarial networks (GANs) for creating synthetic data, recurrent neural networks (RNNs) for processing sequential data, and attention mechanisms for highlighting pertinent image regions. Every algorithm is carefully examined to determine its advantages and disadvantages, offering important information on how it might be used in dermatological practice. By shedding light on the field's emerging advancements in dermatology, this study aims to highlight a broader understanding of deep learning's potential to transform the diagnosis and treatment of skin disorders, ultimately improving patient outcomes and boosting the provision of healthcare services.

Keywords*:* Skin disease, early detection, deep learning, dermatology

Introduction

Skin disorders impact people of all ages and demographics and cover a broad range of ailments that present substantial management and healthcare delivery issues [1]. Accurate diagnosis and classification of dermatological issues has been made possible by deep learning algorithms in medical imaging, which has the potential to revolutionize clinical practice and improve patient outcomes [2]. The complexity of skin conditions highlights the need for accurate and efficient diagnostic tools. From common conditions such as acne and eczema to more serious conditions including cutaneous lymphoma and psoriasis [3]. However, there are still gaps in access to specialized dermatological care, especially in underserved populations, which causes treatment outcomes that fall short of ideal and delays in diagnosis.

In response to these challenges, there is an increasing need for automated systems that can accurately detect and classify skin illnesses. The research aims to address this need by creating a sophisticated multi-class deep learning model especially for dermatological diagnostics. In an effort to provide a trustworthy and understandable solution for patients and healthcare professionals alike, the model makes use of state-of-the-art picture recognition algorithms and a varied dataset that encompasses a wide spectrum of skin conditions. Although prior research has indicated the promise of deep learning for medical picture interpretation, the distinct features of skin diseases require a customized methodology [4]. Unlike internal diseases, dermatological conditions usually show up externally. As such, a detailed understanding of visual cues and subtle variations in skin texture, color, and pattern are necessary. The approach seeks to capture and evaluate these intricate visual cues to enable reliable and accurate classification of various skin disorders across different patient populations.

The objective is to advance the field of automated healthcare solutions by significantly adding to the growing body of information about deep learning in dermatology. Patients all around the world, especially those in underserved areas with little access to professional dermatological services, will have access to high-quality care thanks to the development of a reliable and user-friendly model that can accurately diagnose skin diseases. With the use of cutting-edge technology and interdisciplinary collaboration, the goal is to significantly enhance patient outcomes and the provision of dermatological healthcare on a global basis . By using cutting-edge research and technology, this project will help solve the unmet needs of those with skin illnesses and advance the discipline of dermatology. The use of deep learning techniques to dermatological practice has the potential to revolutionize the diagnosis and treatment of skin diseases and holds great promise for improving disease identification and management. Healthcare professionals may give patients with more precise and timely care by creating sophisticated diagnostic tools and utilizing artificial intelligence, which will ultimately improve patient outcomes and quality of life.

Figure 1: Types of Skin Diseases

Deep learning can be used to address the complex problems presented by skin diseases and open the door to a better future in dermatological healthcare through on-going research and innovation. Deep learning techniques have shown promise in recent times to revolutionize dermatological diagnosis. Scientists want to develop advanced diagnostic tools that accurately identify and classify a broad spectrum of skin disorders by utilizing deep learning algorithms and image recognition technologies. Better patient outcomes, more precise diagnoses, and more effective healthcare delivery could result from this innovative approach. Skin diseases are a broad category of ailments that can be identified in a number of ways. Melanoma lesions, non-melanoma cancers like squamous cell carcinoma and basal cell carcinoma, common problems like acne, and inherited illnesses like sickle cell anaemia are all included in this spectrum. Among the approaches used for diagnosis include computer-aided diagnostic (CAD), bio-impedance methods, and skin resistance evaluation over a wide frequency band [5]. Although CAD has not been utilized in dermatology traditionally, new developments indicate that it may improve the accuracy of diagnoses and provide individualized treatment recommendations based on predictions made by artificial intelligence. The potential for revolutionizing dermatological healthcare through the integration of artificial intelligence algorithms and enhanced diagnostic tools could lead to improved patient outcomes. Because of their variety and effects on the skin, the body's largest organ, skin disorders pose serious obstacles to healthcare and have an impact on the health of individuals.

Since skin is the body's most susceptible organ, skin disorders provide a substantial challenge to healthcare and have an influence on people's well-being due to their various nature. From acne to skin cancer, a number of disorders are influenced by variables like sunlight, infections, and pollution. To keep skin healthy, early diagnosis and appropriate treatment are essential. Accurate categorization is aided by feature selection approaches, which improve data mining processes. In order to improve dermatological care results (2024), this project seeks to construct an advanced skin disease picture classifier utilizing the Dragonfly Optimization

Algorithm (DFA) and integrate it into an easy-to-use platform. Skin disorders account for millions of dermatology visits annually in China, but they are a serious issue globally as well.

Taxonomy of CNN

Because skin disorders have a wide range of symptoms and affect public health, researchers are looking at cutting-edge technology for precise diagnosis and early detection. Skin disease detection has changed dramatically as a result of the emergence of Convolutional Neural Networks (CNNs) as essential instruments in medical imaging and diagnosis. This extensive study examines the many applications of CNNs in the detection of skin conditions, highlighting their elaborate architectural layouts, state-of-the-art techniques, and noteworthy medical advancements.

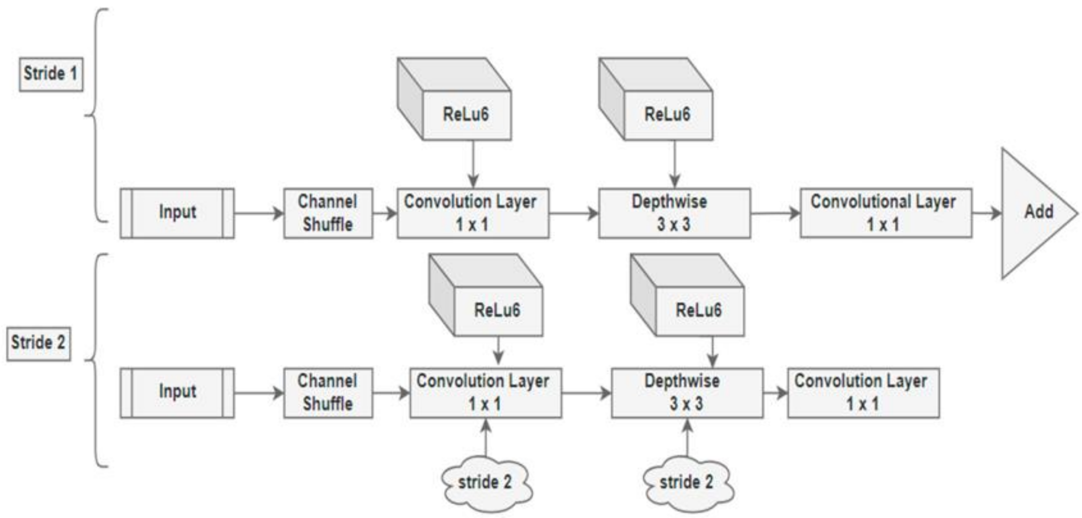

Figure 2: Classification of Skin Disease using CNN

Within the field of artificial neural networks, CNNs have demonstrated exceptional ability to interpret visual data, especially images. CNNs stand out in tasks requiring complex medical imaging pattern identification because they are skilled at extracting structured features from large datasets. Three essential layers can be found in the architecture of a standard CNN: the convolutional, pooling, and fully connected layers. The layer works together to examine pictures and identify complex patterns. The convolutional layer finds important features first, and then the pooling layer reduces the complexity of the input to make it easier to understand. The fully linked layer then enters the picture, deciphering these properties to allow for accurate classification [6]. The number of layers in a CNN determines its depth, which has a substantial impact on its ability to identify minute details and complex nuances in images. CNNs exhibit extraordinary versatility across a wide range of vision-centric domains, such as fingerprint analysis, tumour cell identification, floral species categorization, duplicate product detection, and even facial recognition. Their usefulness in a variety of uses is shown by their adaptability in managing image data. In the realm of skin disease diagnosis, CNNs are crucial for recognizing minute visual clues that point to malignant tumors. CNNs are also utilized in video processing, where they analyse individual video frames in real time. This characteristic highlights how CNNs are useful for more than just traditional medical imaging and is particularly relevant to driverless cars. One significant challenge is that models like multilayer perceptron’s rely on gradient descent to minimize discrepancies between the network's output and the desired outcome.

Research on Skin Identification using CNN

A large number of noteworthy CNN designs have been published, each contributing to the ever-growing body of knowledge on the diagnosis of skin illnesses. This study discusses the application of (CNNs) for deep learning-based skin disease identification. CNNs are highlighted as a crucial component of the system, responsible for recognizing and categorizing skin lesion images. The technique includes several important steps, including as

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feature extraction using the CNN model and pre-processing and enhancement of the picture to improve visibility and reduce noise. The generated features accurately represent a variety of skin disorders, enabling the classification of conditions like melanoma, psoriasis, eczema, squamous cell carcinoma, and basal cell carcinoma. The study highlights the value of CNNs in diagnosing problems automatically and highlights how well they perform challenging picture recognition tasks without the need for human assistance. The publication also provides instructions on how to forecast skin diseases. These instructions include importing libraries, loading and visualizing the dataset, dividing and pre-processing the data, creating and training the CNN model, assessing its efficacy, and storing the trained model for use in the future. Overall, the study emphasizes how CNNs significantly improve skin disease diagnosis by using deep learning methods. The researchers trained a CNN to classify skin illnesses and produced precise picture forecasts using deep learning techniques. In order to learn from and extract information from input datasets and ultimately provide predictions, CNNs employ layers of neurons. The design of it was inspired by the structure of the human brain. Convolutional, activation, max-pooling, and fully connected layers were among the hidden layers in the CNN model that was employed in this investigation. Together, these layers process the input photos, extract useful information, and forecast the output classes. Images were represented as arrays of matrices by the researchers using tensors, and these were subsequently split into RGB channels for processing. Using supervised learning, the CNN model was trained to identify features associated with particular kinds of skin malignancies by analysing labelled images. A number of methods, including accuracy, loss trend analysis, and batch size optimization, were used to improve the model's performance. The outcomes showed that sixty-four was the ideal batch size, with 86.34percent training accuracy and 64.22percent validation accuracy. The efficacy of the model was evaluated by picture prediction tests, which demonstrated high levels of accuracy in classifying skin cancer kinds, with confidence ranging from 70.1% to 99.22%. The researchers did, however, note possible problems including over-fitting, especially when dealing with illnesses that have comparable skin patterns. They proposed using data augmentation techniques and looking at more layers in later model iterations as a way to overcome this.

The groundbreaking work by LeCun, Bengio, and Hinton marked a significant turning point in the use of deep learning techniques in 2015 [6]. Their study highlighted the deep learning models' ability to recognize complex patterns, which has applications in the analysis of medical photos, such as the identification of skin conditions. The epidemiology of skin diseases in rural India was clarified by a population-based study carried out by Sinha et al. in 2014, underscoring the urgent need for easily accessible and precise diagnostic instruments [7]. This emphasizes how critical it is to use cutting-edge technologies, such as CNNs, to reduce healthcare inequities and enhance illness management in underserved areas.

Agarwal et al. (2011) addressed the obstacles to providing quality healthcare in rural India and emphasized the ongoing problems preventing rural residents from receiving appropriate medical treatment. To overcome these obstacles and provide fair access to healthcare, especially for dermatological disorders, creative solutions—especially those utilizing CNNs—are essential [8].

Deep residual learning research by He et al. (2016) opened the door to more efficient neural network architectures, which are now used in medical picture processing. This finding has implications for circumventing the constraints of traditional deep learning models, hence enhancing the accuracy and reliability of CNN-based skin disease detection systems [9]. In a novel application of deep convolutional neural networks (DCNNs) for picture categorization, Krizhevsky et al. [53] demonstrated how well CNNs could identify and classify complex visual input. The research findings have practical applications for dermatologists, particularly in the automated analysis of medical photos for skin condition detection [10]. The capabilities of deep learning models were proved by Esteva and colleagues (2017). The ability to automatically classify skin cancers highlights how technology is revolutionizing dermatological diagnoses. CNN-based methods provide increased efficacy and precision in the diagnosis of skin diseases, stimulating additional research and development in the area [11].

CNNs are used more widely in medical picture analysis, as highlighted by Rajpurkar et al. (2017)'s deeper learning-based pneumonia identification study [13]. The capacity of these models to identify related disorders is stimulating deep learning in dermatology by opening the door to accurate diagnosis and classification of a wide range of skin conditions. In 2020, Hamid et al. presented a hybrid method for classifying skin illnesses that makes use of deep convolutional error-correcting neural networks. This unique approach aims to improve the accuracy and reliability of illness categorization by continuously improving CNN-based techniques for better identification of skin diseases [14]. Parvatanini et al.'s 2021 study [15] examined the use of state-of-the-art deep learning architectures, such as LSTM and MobileNet V2 models, for automated skin disease classification. Their work advances the field of dermatological diagnostics by demonstrating the potential for precisely diagnosing and categorizing disorders through the integration of complicated neural network models. Li et al. (2022) [16] have demonstrated the importance of integrating self-attention processes into deep learning algorithms for the identification of skin disorders. This innovative approach provides valuable information on how to apply attention-based strategies to improve the precision and clarity of dermatological CNN diagnoses, which pave the way for further advancements in the field.

As technology advances, academics may look into hybrid systems in the future that combine CNN expertise with other cutting-edge technologies. Enhancements in preprocessing techniques and dataset augmentation, along with ongoing CNN designs improvements, offer prospects to greatly increase diagnostic accuracy. Additionally, the application of explainable AI techniques might improve the comprehensibility of CNN's diagnosis, fostering greater confidence among medical practitioners. The application of CNNs in medical research has great promise for raising diagnostic precision and bettering patient outcomes, particularly in the field of dermatology. One example of the collaborative relationship between medical research and technological innovation is the employment of CNNs in the diagnosis of skin diseases. Support Vector Machines (SVMs) are widely recognized for their ability to identify optimal decision boundaries in high-dimensional spaces, which enables them to effectively categorize non-linearly separable data. SVMs perform well in complicated classification tasks, but they are limited by large processing demands. This is especially true when handling large datasets, which causes extended training times and decreased performance in time-sensitive studies. Still, SVMs are known for their accuracy and adaptability when it comes to diagnosing skin conditions; they are particularly good at picking up on minute patterns in datasets with complex associations. [17] recognizes SVMs as potent supervised learning methods set apart by their margin-based classification strategy in their study on the combined use of (SVM) and (CNN) for skin disease classification. By developing a strong classification framework that can handle the variety of characteristics included in datasets linked to skin illnesses, their goal is to improve the accuracy of skin disease diagnosis.

Implementation of KNN for Skin Identification

The K-Nearest Neighbour (KNN) approach, a foundation of machine learning, shows its adaptability in both regression and classification tasks. KNN is well known for being straightforward and easy to understand, which makes it particularly suitable in circumstances when decision-making transparency is crucial. Its high accuracy, ability to withstand outliers, and lack of distributional assumptions are among its strong characteristics. KNN is used to categorize lesions based on their pathological characteristics in the field of skin disease detection. The optimal parameter K, or the number of closest neighbours to consider, is found by the algorithm by first using testing data as input. First, the distances between the training set and the evaluation data are computed using the approach. After matching the data according to the value of "K," it next sorts the distances and categorizes the data-points using the Euclidean distance. The algorithm is divided into three phases: feature extraction, classification, and pre-processing of the data. The diagnosis of skin diseases involves three basic steps: feature extraction, data processing, and classification. Pre-processing is the process of using picture filtering techniques to eliminate unwanted features or noise. In order to extract features, pertinent qualities like texture and chromatic information must be obtained. The final stage of the (KNN) algorithm uses a classifier to determine if a skin lesion is pathogenic. It's crucial to remember that different studies may employ distinct strategies and methods for feature extraction and data preparation.

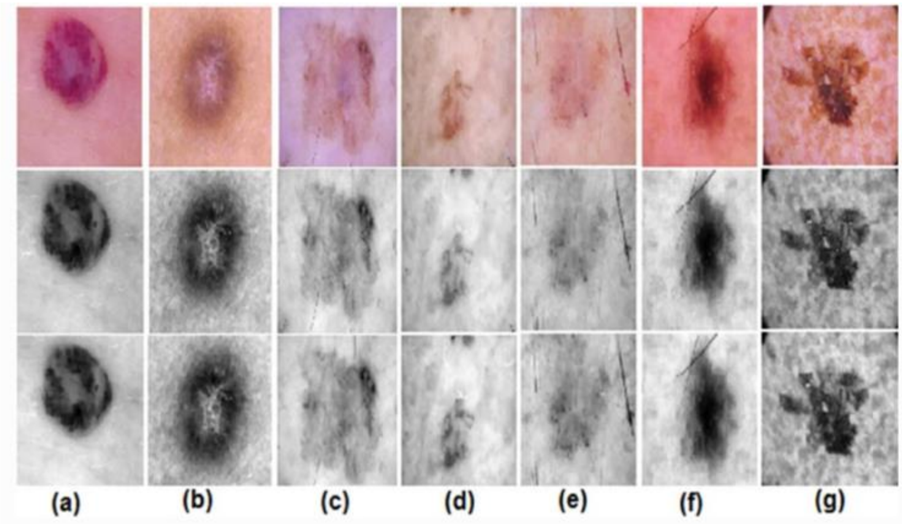

Figure 3: DWT feature extracted images of seven cancer types

The use of two classification algorithms—K-nearest neighbours (KNN) and Enhanced K Nearest Neighbour (EKNN)—for the aim of melanoma detection is covered in the research paper [18]. KNN is a non-linear classifier that is frequently applied to tasks involving regression and classification. KNN is used in the study [18] to categorize skin lesions according to characteristics taken from medical picture data. Based on the majority class among their closest neighbours in the feature space, the KNN algorithm assigns class labels to test examples. This method works well for finding patterns in data and doesn't require a training phase. According to the study, KNN can diagnose melanoma with an accuracy that is comparable to that of human professionals when it comes to skin cancer identification. However, as advancement over conventional KNN, EKNN, or Enhanced K Nearest neighbour, is presented. EKNN improves classification by giving features varying weights according to their correlation and significance. Predictions that are more accurate are produced by using this weight allocation approach to assist prioritize significant information throughout the classification process. In addition, EKNN uses the Euclidean distance metric to calculate the degree of similarity between instances, taking into account both the characteristics of the closest neighbors and their proximity. EKNN seeks to outperform classic KNN in skin cancer classification problems by integrating feature weighting and distance measurement. For better melanoma detection, the FSCC-MD-EKNN method combines EKNN-based feature set grouping and classification.

Even while KNN's interpretability and simplicity make it helpful in circumstances when transparency is crucial, there are still challenges. The accuracy of the algorithm can be impacted by noise, irrelevant attributes, and unbalanced feature sizes. Solving these problems is necessary to improve the results of categorization. KNN can be a helpful tool in the identification of skin diseases due to its simplicity and ease of interpretation. But one must be aware of its limitations, especially when dealing with noisy or unbalanced datasets [19]. The K-Nearest Neighbour (KNN) method is a well-known contender in current efforts to enhance the diagnosis of skin diseases. Its application has been the subject of numerous research studies, which have provided data on its effectiveness, relative performance, and potential downsides.

Dragonfly Optimization for Skin Identification

This paper describes the Dragonfly approach (DA), a metaheuristic optimization technique inspired by the feeding and migrating behaviors of swarming dragonflies. Each dragonfly's movement is controlled by five behaviors: separation, alignment, cohesiveness, attraction to a food source, and distraction from an adversary. In the DA, these behaviors represent potential solutions inside the search space (E). These movements are similar to how swarms of dragonflies navigate and interact as a group. There are two primary stages to the algorithm's operation: exploration and exploitation [20]. Local movement and flight path mutations happen during exploitation as dragonflies organize into subgroups to hunt for solutions in different parts of the search space. In the meantime, during exploration, dragonflies cooperate to fly over great distances in order to jointly survey the search region. To guarantee convergence to the global optima, the weights corresponding to the five behaviors are adaptively modified during the iterative optimization procedure. The dragonflies' movements are guided by equations that control their behaviors and the distance between nearby dragonflies. Levy Flight equation is also included to improve global search capabilities and unpredictability. The Dragonfly Algorithm shows promise for optimization and exploration problems by utilizing the collective behavior of dragonflies to efficiently optimize solutions in intricate search areas.

HOG Approach for Skin Identification

The study covered in this article uses the (HOG) technique to extract features from images of skin lesions. HOG is used to visualize the behaviour of skin lesions based on edge ordering in their distribution or force gradients, and to record local spatial changes. The HOG feature vector is produced by adding up the gradient computations for every pixel. This process includes block normalization and the creation of histograms for every block using gradient values. The objective of this technology is to accurately diagnose skin diseases through feature extraction and analysis. The research uses the (TGMM) algorithm for statistical modelling and disease diagnosis in addition to HOG. To model features and extract the type of disease present as well as affected skin patches, the Truncated Gaussian Mixture Model is utilized. This method makes it possible to comprehend pixel properties better and makes disease diagnostics more efficient. The Truncated Gaussian Mixture Model's Probability Density Function (PDF) is defined, and the pixel distributions within skin lesions are characterized by estimated parameters for mean, weight, and standard deviation. An all-encompassing method for identifying skin diseases is provided by the combination of the Truncated Gaussian Mixture Model for statistical modelling and HOG for feature extraction [21]. The goal of the study is to improve illness detection in dermatological applications by evaluating the collected features and applying statistical parameters.

Data Collection

Choosing the appropriate dataset is essential for directing research projects, especially when it comes to classification tasks, such as binary or multiclass classification. Their significance is clarified by a thorough analysis of the several standard datasets used in this research and other similar studies conducted in the same domain. Table 1 presents a comparative analysis of various datasets, encompassing significant variables such as the overall count of images, categories, and, on occasion, the allocation of training and testing sets.

Table 1: Models with similar methodologies

Ref	Model	Accuracy	F-Score	Precision	Recall	Images	Data
[22]	CNN	83.36%	1.32	1.36	12.96%	18524	Dermnet
[23]	GAN's	87.15%	2.53	2.68	26.87%	19635	Dermnet
[24]	Hybrid CNN	79.41%	7.89	8.96	39.48%	85475	Dermnet

This split helps researchers determine if the task includes binary or multiclass classification, which is in line with their study objectives in Table 2. It is particularly useful for datasets that have several categories.

Table 2: Benchmark Datasets

Data Collection	Training Set	Testing Set	Total	Class
DermAtlas	850	856	2000+	7
Skin Diseases Database	485	125	600+	10
Derm Detect	263	129	500+	5

Challenges in the Existing System

Skin diseases represent a large global burden on healthcare systems, encompassing a wide range of problems from mild irritations to serious infections and chronic illnesses. For management and treatment to be effective, diagnosis must be made accurately and promptly. However, there are a number of obstacles that healthcare workers must overcome in this respect, which calls for the investigation of novel strategies, such as machine learning algorithms like CNN, KNN, and SVM. Every algorithm has its own set of advantages and challenges when it comes to skin disease diagnosis. It is still important to achieve high levels of sensitivity, specificity, and accuracy, which calls for additional study and advancement. The availability of consistent and distinct datasets is a major obstacle that needs to be removed to guarantee accurate results comparisons. Researchers need to use larger datasets and carefully modify hyper-parameters to prevent over-fitting issues. The optimum performance of deep learning algorithms, such as CNNs, depends on training data from individuals with a range of skin tones. People with light skin make up the bulk of those with skin lesions in the datasets used today, which introduces biases and reduces accuracy. Incorporating diverse age groups, genders, and ethnicities into databases can help reduce biases and increase accuracy rates.

Interpreting the reasoning behind the decisions made by deep learning algorithms is another challenge. The decision-making process of algorithms is opaque, whereas dermatologists who are human provide detailed explanations for diagnosis. This opacity makes it challenging for dermatologists to evaluate data and render decisions. It is important to exercise caution when considering claims made by AI algorithms that they are superior to dermatologists, as these claims are often based on well controlled experiments that do not accurately reflect real-world diagnosing conditions. Furthermore, breakthroughs in deep learning may make it possible to detect skin disorders more accurately; nevertheless, problems with interpretability and dataset biases still need to be addressed. It is crucial to have balanced datasets that reflect a range of skin lesion features in order to maximize the performance of deep learning algorithms. Incorporating racial diversity can reduce biases, and dermatologists' participation in the dataset generation process can improve its quality. By creating synthetic images of uncommon lesion types, advanced learning frameworks such as Generative Adversarial Networks (GANs) help address the issue of dataset scarcity while also enhancing dataset comprehensiveness and algorithm performance. There is a noticeable shift away from relying just on the diagnosis of skin cancer and toward broadening the approach to include more than simply standalone artificial intelligence solutions. Integration of many deep learning models, each concentrating on analysing certain characteristics or features of skin lesions, is gaining increasing traction. This multi-model technique facilitates a comprehensive examination of multiple aspects, with each model offering predictions to provide a more precise diagnosis. A number of models designed to assist dermatologists in their diagnostic procedures may be hosted and synchronized globally as cloud computing and storage become more broadly accessible. Healthcare professionals and AI researchers alike underline how important it is to minimize technology misdiagnoses since they understand the profound impact errors have on following decisions.

As a result, the adoption of artificial intelligence (AI) solutions as supplemental tools to help contextualize and validate noisy data derived from real patients is increasing, hence increasing the predictive ability of this data. This trend is expected to persist until significant advancements in technical systems are achieved that provide meaningful information and understanding for the diagnosis of skin conditions in both local and remote healthcare settings. The use of AI in dermatology is always evolving, which highlights the necessity for on-going developments and collaboration to produce accurate and reliable diagnostic instruments.

Conclusions

Because of their numerous symptoms and detrimental consequences on quality of life, skin disorders represent a significant challenge to healthcare. A quick and accurate diagnosis is necessary for effective treatment and management. We hope to investigate state-of-the-art machine learning techniques used to differentiate between different kinds of skin diseases in this thorough review. Concentrate on evaluating the performance of three well-known algorithms: CNN, KNN, and LSVM, which have shown promise in the classification of a range of skin conditions. The paper thoroughly evaluates various approaches using a range of datasets from archives like

ISIC and ISBI, including PH2, MED-NODE, DermIS, DermQuest, and others. Consider the benefits and drawbacks of each algorithm in detail, with a focus on CNNs. Deep learning methods, like fully connected neural networks (CNNs) and feature extraction architectures, hold promise as alternatives to traditional machine learning techniques. Better overall diagnostic outcomes and reduced reliance on complex preprocessing techniques are two advantages of these strategies. Most importantly, it is stressed that meticulous adjustments must be made in order to guarantee the reliability of the test findings. Additionally, in order to facilitate result replication and render these results practically applicable and scalable in real-world scenarios, comprehensive descriptions of hardware specifications, model setups, and technological contexts are required.

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