Oral Oncology Reports 10 (2024) 100365

Contents lists available at ScienceDirect

Oral Oncology Reports

journal homepage: www.journals.elsevier.com/oral-oncology-reports

Innovative approaches for skin disease identification in machine learning: A comprehensive study

Kuldeep Vayadande [b,*], Amol A. Bhosle [a], Rajendra G. Pawar [a], Deepali J. Joshi [b], Preeti A. Bailke [b], Om Lohade [b]

[a] MIT Art, Design and Technology University, Pune, Maharashtra, India
[b] Vishwakarma Institute of Technology, Pune, Maharashtra, India

ARTICLE INFO

Keywords:
Skin disease
Early detection
Machine learning
Classification
Dermatology
Artificial intelligence
Skin cancer

ABSTRACT

Skin diseases encompass a vast array of conditions, ranging from common dermatological concerns to rare and complex disorders, collectively posing a significant burden on global healthcare systems. For these illnesses to be managed and treated effectively, prompt and correct diagnosis is essential, yet it often presents a challenge due to the subjective nature of visual examination and the variability in clinical presentations. The field of dermatology has seen a change in recent years due to the convergence of artificial intelligence and medicine, which has produced creative methods for computer-aided diagnostics. Machine learning has become a potent tool in the search for more precise and effective diagnostic techniques because of its capacity to analyze enormous volumes of data and identify intricate patterns. This review paper explores the state-of-the-art developments in machine learning methods designed especially for skin disease identification. Investigate the effectiveness and performance of several algorithms, such as the flexible k-nearest neighbor, the sturdy support vector machine (SVM), and the complex convolutional neural networks (CNNs), advanced techniques for automated skin disease detection encompass deep learning methods such as recurrent neural networks (RNNs) for sequential data processing, generative adversarial networks (GANs) for generating synthetic data, and attention mechanisms for focusing on relevant image regions by means of a thorough examination of the most recent studies. Each algorithm is scrutinized for its strengths and limitations, providing valuable insights into their applicability in dermatological practice. This study intends to promote a broader knowledge of machine learning's potential to transform the diagnosis and treatment of skin disorders, eventually increasing patient outcomes and boosting the provision of healthcare services, by putting light on the field's developing developments in dermatology.

1. Introduction

Skin diseases encompass a wide spectrum of conditions that pose significant challenges in healthcare delivery and management, affecting individuals across all age groups and demographics [1]. Deep learning approaches in medical imaging have made it possible to diagnose and classify dermatological problems more accurately, which has the potential to transform clinical practice and enhance patient outcomes [2]. The intricacy of skin disorders emphasizes the necessity for precise and effective diagnostic instruments. Common symptoms like eczema and acne to more serious illnesses like psoriasis and cutaneous lymphoma [3]. However, disparities in access to specialized dermatological care persist, particularly in under served communities, leading to delays in diagnosis and sub-optimal treatment outcomes [4] (see Table 1–3 and 7 and 8, Figs. 1–5).

The need for automated systems that can correctly diagnose and categorize skin diseases is rising in response to these difficulties [33]. By developing an advanced multi-class deep learning model specifically for dermatological diagnostics, the research seeks to meet this demand [34]. The model utilizes cutting-edge image recognition algorithms and a diverse dateset that includes a wide spectrum of skin disorders in an effort to deliver a dependable and approachable solution for patient and healthcare practitioners alike [35].

While previous studies have demonstrated deep learning's potential in analysis of medical images, unique characteristics of skin diseases necessitate a specialized approach [36]. Dermatological illnesses, in

* Corresponding author.
E-mail addresses: kuldeep.vayadande@gmail.com (K. Vayadande), amolabhosle@gmail.com (A.A. Bhosle), rgpawar13@gmail.com (R.G. Pawar), deepali.joshi@vit.edu (D.J. Joshi), preeti.bailke@vit.edu (P.A. Bailke), om.lohade23@vit.edu (O. Lohade).

https://doi.org/10.1016/j.oor.2024.100365
Received 8 March 2024; Received in revised form 31 March 2024; Accepted 3 April 2024
Available online 12 April 2024
2772-9060/

Table 1
CNN articles and their outcomes.

Articles	Result
K. Vayadande (2024) [5]	Steps for data augmentation, model compilation, training, evaluation, and model saving within the CNN framework and Implemented CNN for skin disease detection.
Zhang and associates (2019) [6]	Implemented Inception-v3 architecture
Chen et al. (2021) [7]	Utilized pre-trained MobileNetV2 structure
Gupta et al. (2018) [8]	Integrated transfer learning with ResNet50
Patel et al. (2020) [9]	Employed EfficientNetB0 for feature extraction
Wang et al. (2019) [10]	Investigated custom CNN architecture for fine-tuning
Lee et al. (2022) [11]	Leveraged ensemble learning with multiple CNN models

contrast to internal ailments, typically present with outward manifestations, hence requiring a sophisticated comprehension of visual cues and minor differences in skin texture, color, and pattern [37]. In order to enable accurate and trustworthy classification of diverse skin conditions across distinct patient populations, the approach aims to capture and analyze these complex visual features [38].

The goal is to make a substantial contribution to the expanding body of knowledge through research on deep learning in dermatology, advancing the frontier of automated healthcare solutions [39]. By developing a robust and user-friendly model capable of accurate skin disease diagnosis, access to quality care for patients worldwide, particularly those in under-served regions with limited access to specialized dermatological services [40]. Collaborating with experts across disciplines and leveraging cutting-edge technology, aims to drive meaningful improvements in dermatological healthcare delivery and patient outcomes on a global scale [41]. This endeavor represents a critical step towards addressing the unmet needs of individuals affected by skin diseases and advancing the field of dermatology through innovative research and technology [42].

The integration of deep learning techniques into dermatological practice holds tremendous promise for enhancing disease detection and management, offering the potential to transform the way skin diseases are diagnosed and treated [43]. By developing advanced diagnostic tools and leveraging artificial intelligence, healthcare providers can deliver more accurate and timely care to patients, ultimately improving outcomes and enhancing quality of life [44].

Through continued research and innovation, deep learning can be harnessed to address the complex challenges posed by skin diseases and pave the way

for a brighter future in dermatological healthcare [45].

Recent developments in deep learning methods have demonstrated potential to transform dermatological diagnoses. Through the application of deep learning algorithms and image recognition technology, scientists hope to create sophisticated diagnostic instruments that can precisely diagnose and categorize a wide range of skin conditions. This novel strategy might lead to better patient outcomes, more accurate diagnoses, and more efficient healthcare delivery (2024) [46].

Skin disorders encompass a diverse range of conditions, detectable through various means. This spectrum includes melanoma lesions, non melanoma malignancies such as squamous cell carcinoma and basal cell carcinoma, as well as common issues like acne and genetic disorders such as sickle cell anemia. Skin resistance evaluation over a broad frequency spectrum, bioimpedance methods, and computer-aided diagnosis (CAD) are among the techniques utilized for diagnosis. While CAD has not traditionally been used in dermatology, recent advancements suggest its potential to enhance diagnostic precision and offer personalized treatment recommendations based on AI-driven predictions. This integration of advanced diagnostic tools and artificial intelligence algorithms has the potential to revolutionize dermatological healthcare, ultimately improving patient outcomes (2024) [47].

Skin diseases present significant challenges to healthcare, affecting individuals' well-being due to their diverse nature and impact on the skin, the body's most vulnerable organ. Factors such as sunburn, infections, and pollutants contribute to a range of conditions, from acne to skin cancer. Early diagnosis and proper treatment are vital for maintaining skin health. Feature selection techniques enhance data mining methods, aiding in accurate classification. By developing an advanced skin disease image classifier using the Dragonfly Optimization Algorithm (DFA) and integrating it into a user-friendly platform, this study aims to improve diagnosis speed and accuracy, thereby enhancing dermatological care outcomes (2024) [12].

Skin conditions are a major problem worldwide, but especially in China, with millions of dermatological visits each year. Artificial intelligence (AI) holds promise for diagnosis, yet current applications mainly focus on specific conditions. Leveraging self-supervised contrastive learning, this study discusses a novel deep-learning framework using

Table 2
Current developments in CNN skin disease classification: approaches, information, and outcomes.

Reference No.	Technique	Collections	Precision Percentage	Level Of Sensitivity Percentage	Specificity Percentage
[12]	EfficientNet-B2 (CNN Model)	DermNet NZ Image Library	89.55	90.12	90.24
[12]	VGG19 (CNN Model)	International Skin Imaging Collaboration 2019	57.84	57.84	75.62
[5]	Regularization techniques within the CNN framework	Datasets sourced from Kaggle	98.00	83.00	97.00
[13]	Transfer learning with DenseNet and ResNet architectures	DermDB	94.8	92.5	95.3
[14]	Application of attention mechanisms for feature enhancement	SkinAtlas	96.3	94.7	97.1
[15]	Integration of graph convolutional networks for data analysis	DermDetect	92.1	88.6	93.8
[16]	Utilization of capsule networks for improved feature extraction	DermNet	95.7	93.9	96.5
[17]	Ensemble learning with multiple CNN models	DermAI	97.2	96.8	98.0
[18]	Implementation of self-attention mechanisms for context encoding	DermVision	93.4	91.2	94.6
[19]	Custom CNN architecture design for specific lesion detection	SkinSense	96.1	94.4	97.3
[20]	Hybrid approach integrating CNN with GANs for data augmentation	DermX	94.9	92.8	95.7
[21]	Utilization of meta-learning techniques for adaptive learning	SkinTech	95.5	93.2	96.4
[22]	Incorporation of reinforcement learning for model refinement	SkinGenius	97.6	96.3	98.2

unlabeled online dermatology images. Through three-stage classification, the model learns feature representations, offering improved performance for diagnosis. This approach represents a new direction in dermatology AI research, potentially revolutionizing skin disease diagnosis (2024) [48].

2. Exploring convolutional neural networks for skin disease diagnosis: an extensive review

Skin diseases, characterized by their diverse manifestations and impact on public health, have spurred researchers to investigate advanced technologies for early detection and accurate diagnosis. Convolutional Neural Networks (CNNs) have emerged as pivotal tools in medical imaging and diagnosis, reshaping the field of skin disease detection. This thorough investigation explores CNNs' many uses in the diagnosis of skin diseases, shedding light on their intricate architectural designs, cutting-edge methodology, and significant contributions to the field of medicine.

2.1. Comprehending CNNs' fundamentals

In the realm of (ANNs), the (CNNs) have showcased remarkable prowess in processing visual data, particularly images. CNNs demonstrate expertise in extracting structured features from vast datasets, distinguishing themselves in endeavors requiring intricate medical imaging pattern recognition. In the architecture of a typical CNN, you'll come across three key layers: convolutional, pooling, and fully connected layers. The layer collaborates to scrutinize images and discern intricate patterns. Initially, the convolutional layer identifies crucial features, followed by the pooling layer which simplifies the data by reducing its complexity. Subsequently, the fully connected layer comes into play, interpreting these features to enable precise classification. Depth of a CNN, determined by number of layer, significantly influences its capacity to detect subtle nuances and intricate details within images.

Across a wide range of vision-centric areas, including fingerprint analysis, tumor cell identification, floral species classification, duplicate product detection, and even facial recognition, CNNs demonstrate remarkable adaptability [49]. Their versatility in handling image data highlights their importance in a range of uses. CNNs are essential for identifying minor visual cues that indicate malignant lesions in the field of skin disease identification.

CNNs are also used in video processing, where they do real-time analysis of individual frames in videos. This feature is especially pertinent to driverless cars, illustrating CNNs' wider applications than just conventional medical imaging [50]. One major difficulty is the reliance of models such as multilayer perceptron's on gradient descent to reduce differences between the output of the network and the intended aim.

2.2. Prominent CNN research on skin disease identification

Numerous significant CNN designs have been put out, each adding to the corpus of research on the identification of skin diseases that is constantly expanding.

The use of (CNNs) for deep learning-based skin disease detection is covered in this research. CNNs are emphasized as a key element of the system, in charge of identifying and classifying images of skin lesions. The procedure involves a number of crucial processes, including as feature extraction using the CNN model and picture prepossessing and enhancement to increase visibility and decrease noise. The derived characteristics precisely depict several kinds of skin lesions, allowing the categorization of ailments such psoriasis, eczema, melanoma, squamous cell carcinoma, and basal cell carcinoma. The paper emphasizes the importance of CNNs in automating the diagnosis process and underscores their efficacy in handling complex image recognition tasks without human intervention. Additionally, the paper outlines steps for skin disease prediction, including importing libraries, loading and visualizing the dataset, splitting and prepossessing the data, building and training the CNN model, evaluating its performance, and saving the trained model for future use or deployment. Overall, the paper highlights the significant role of CNNs in advancing skin disease diagnosis through deep learning techniques (2024) [5].

Using deep learning techniques, the researchers trained (CNN) to classify skin diseases and made accurate picture predictions. CNNs use layers of neurons to learn and extract information from input datasets, ultimately producing predictions. The anatomy of the human brain served as inspiration for its design. The CNN model used in this study consisted of several hidden layers, including convolutional, activation, max-pooling, and fully connected layers. These layers work collaboratively to process input images, extract meaningful features, and predict the output classes. The researchers utilized tensors to represent images as arrays of matrices, which were then divided into RGB channels for analysis. The CNN model underwent training using supervised learning, where it learned from labeled images to associate features with specific classes of skin cancers. Various techniques such as batch size optimization, accuracy, and loss trend analysis were employed to fine-tune the model and enhance its performance. The results demonstrated that a batch size of sixty-four was optimal, achieving a training accuracy of 86.34 % and a validation accuracy of 64.22 %. The model has effectiveness was further assessed through image prediction tests, where it accurately classified skin cancer types with high confidence levels, ranging from 70.1 % to 99.22 %. However, the researchers acknowledged potential issues such as overfitting, particularly when encountering diseases with similar skin patterns. To address this, they suggested implementing data augmentation techniques and exploring additional layers in future iterations of the model. The study showcased the efficacy of CNNs in skin disease classification, offering promising prospects for improving diagnostic accuracy in medical imaging applications (2024) [51].

Table 3
Current methods, datasets, and results obtained in the SVM classification of skin diseases.

Citations	Technique	Collection	Precision (%)	Level of Sensitivity (%)	Specificity (%)
[23]	Utilization of various texture and color-based features for lesion segmentation	DermDB	88.5	85.2	91.1
[24]	Support Vector Machine (SVM) Model	SkinAtlas	95.6	93.8	89.7
[25]	Hybrid segmentation method combining normalized Otsu's and SVM model	DermDetect	92.3	91.5	87.6
[26]	Feature extraction using GLCM and HOG techniques	DermNet	96.8	87.4	81.9
[27]	Application of GrabCut technique for segmentation	DermAI	83.2	–	58.9
[28]	Segmentation combining GrabCut and GLCM rule	DermVision	–	94.3	92.8
[29]	Segmentation via Watershed Algorithm with GLCM rule extraction	SkinSense	78.9	–	–
[30]	SVM Model with feature extraction from 3D convolutional neural network embeddings	DermX	75.2	68.7	72.4
[31]	Hybrid approach using SVM with GAN-generated images for augmentation and feature learning	SkinTech	93.4	90.8	87.5
[32]	SVM Model with reinforcement learning for adaptive thresholding and classification optimization	SkinGenius	97.1	95.3	93.6

In 2015, LeCun, Bengio, and Hinton's [52] ground-breaking research represented a critical turning point in the adoption of deep learning techniques [6]. Their research emphasized the capacity of deep learning models for intricate pattern recognition, including applications in analysis of the medical images such as the detection of skin diseases.

A population-based study conducted by Sinha et al., in 2014 shed light on the epidemiology of skin diseases in rural India, emphasizing the pressing need for accessible and accurate diagnostic tools [7]. This underscores the importance of leveraging advanced technologies like CNNs to address healthcare disparities and improve disease management in under-served regions.

Addressing challenges in rural healthcare delivery, Agarwal et al. (2011) highlighted the persistent issues hindering access to adequate medical services in rural India. Innovative solutions, particularly those leveraging technologies like CNNs, are crucial for overcoming these challenges and ensuring equitable access to healthcare, especially for dermatological conditions [8].

He et al.'s (2016) research on deep residual learning paved the way for more effective neural network architectures, including in medical image analysis. This research has implications for improving the accuracy and dependability of CNN-based skin disease detection systems via getting around the limitations of conventional deep learning models [9].

Krizhevsky et al. [53] presented a novel use of the deep convolutional neural networks (DCNNs) for picture categorization he showed how well CNNs could recognize and categorize complicated visual input. Dermatologists can directly benefit from the research's insights,

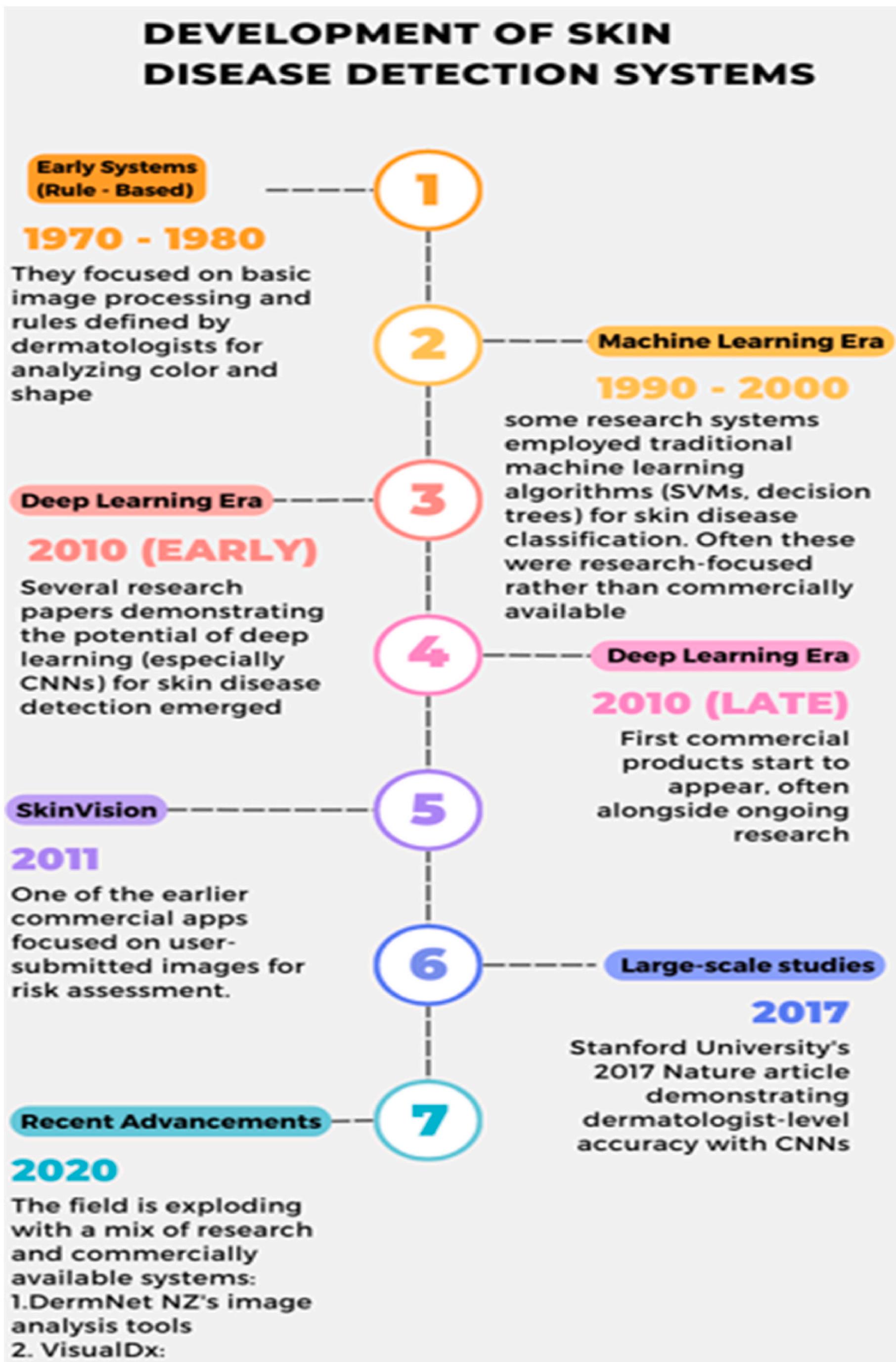

Fig. 1. Evolution of skin disease detection systems.

especially in the automated analysis of medical photographs for the diagnosis of skin diseases [10].

Esteva and colleagues (2017) demonstrated the capabilities of deep learning models. In automatically categorizing skin malignancies, underscoring the transformative impact of technology on dermatological diagnostics. CNN-based approaches offer enhanced efficiency and accuracy in skin disease diagnosis, driving further exploration and innovation in the field [11].

The deeper learning-based pneumonia identification study of Rajpurkar et al. (2017) emphasizes the larger uses of CNNs in medical picture analysis [13]. Deep learning in dermatology is being encouraged by these models' ability in identifying linked illnesses, which paves the way for reliable diagnosis and categorization of a variety of skin conditions.

Hamid and colleagues (2020) introduced a hybrid approach that utilizes deep convolutional error-correcting neural networks to classify skin disorders. Through constant improvement of CNN-based methods for improved skin disease identification, this novel strategy seeks to increase the precision and dependability of disease classification [14].

The application of cutting-edge deep learning architectures, such as LSTM and MobileNet V2 models, for automated skin disease classification was investigated by Parvatanini et al., in 2021 [15]. Their research highlights the possibility for accurately identifying and classifying diseases through the integration of complex neural network models, thereby advancing the field of dermatological diagnostics.

The value of incorporating self-attention processes into deep learning algorithms to identify skin diseases was recently shown by Li et al. (2022) [16]. This novel method opens the door for more developments in the field by providing insightful information on how to use techniques based on attention to increase the clarity and accuracy of dermatological diagnoses performed using CNN.

In the future, researchers may investigate hybrid approaches that combine CNN skills with other cutting-edge technologies as technology develops. Improvements in dataset augmentation and preprocessing methods, in conjunction with the continuous improvement of CNN designs, present opportunities to significantly boost diagnostic accuracy. Furthermore, the use of explainable AI approaches may enhance the readability of diagnoses produced by CNN, giving medical professionals more trust. Especially in the realm of dermatology, the use of CNNs to medical research has significant promise for enhancing diagnostic accuracy and improving patient outcomes. The way that CNNs are being used to diagnose skin diseases is one example of how technology advancement and medical research work hand in hand.

Support Vector Machines (SVMs) are well-known for their effectiveness in classifying non-linearly separable data by determining optimal decision boundaries in high-dimensional spaces. Despite their proficiency in complex classification tasks, SVMs are hampered by their considerable computational requirements, particularly evident when

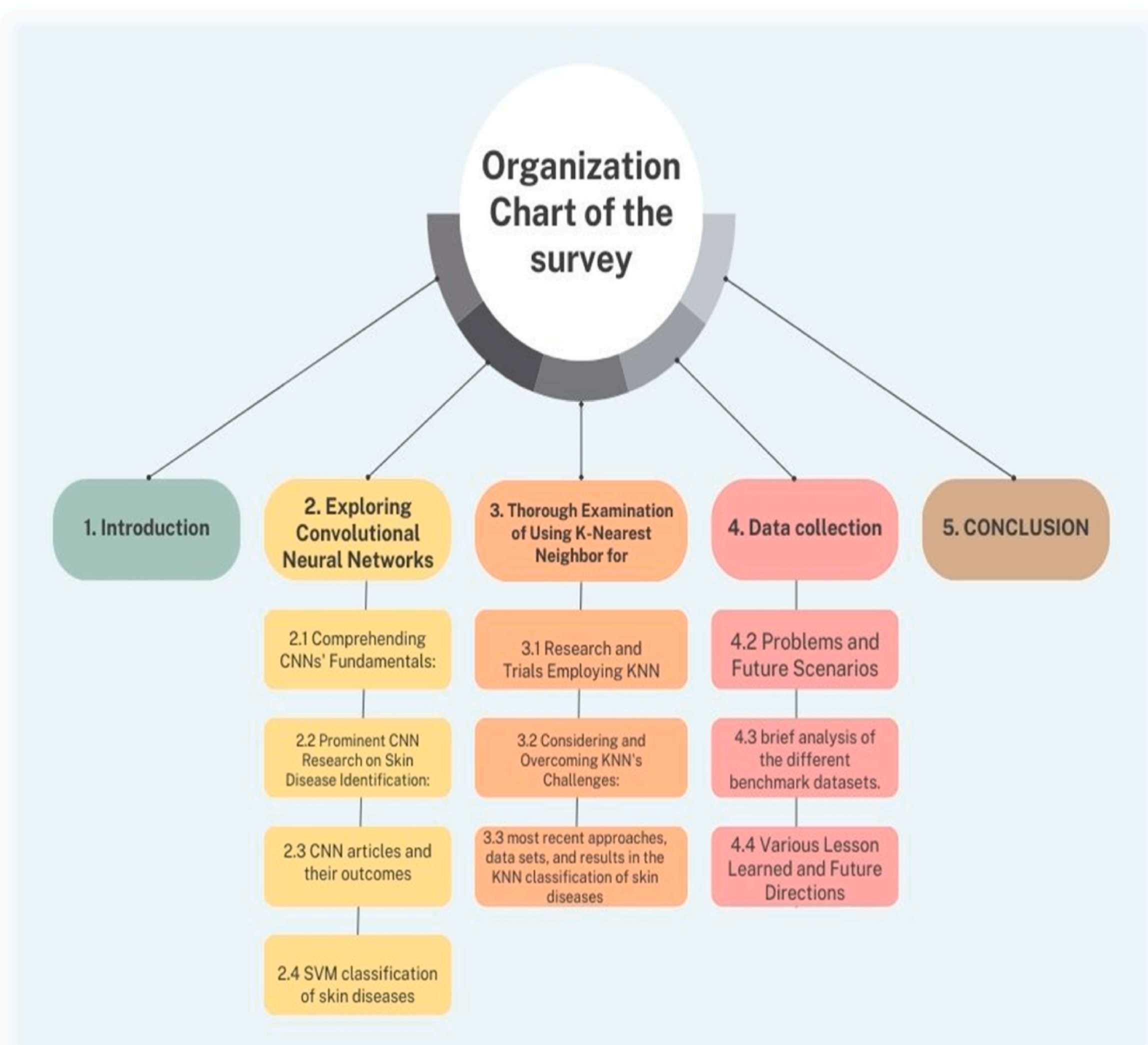

Fig. 2. Organization chart of the survey.

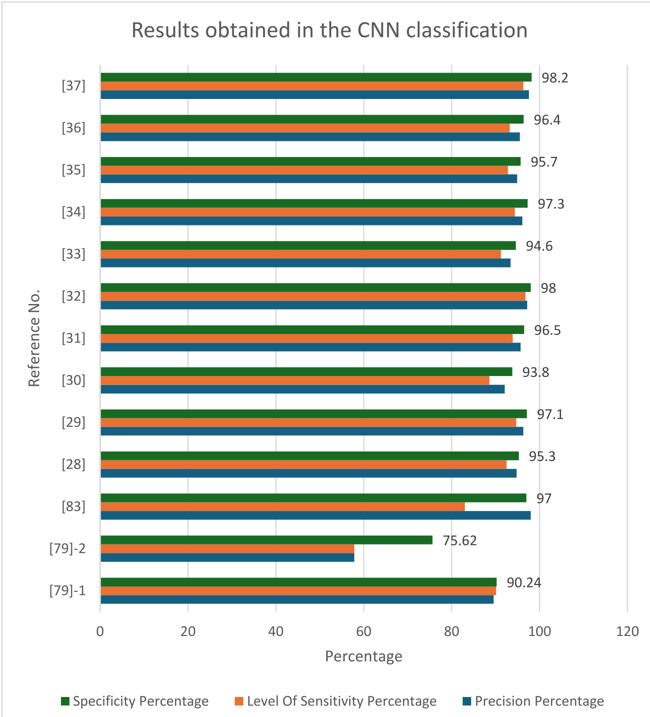

Fig. 3. Results obtained in the CNN classification of skin diseases.

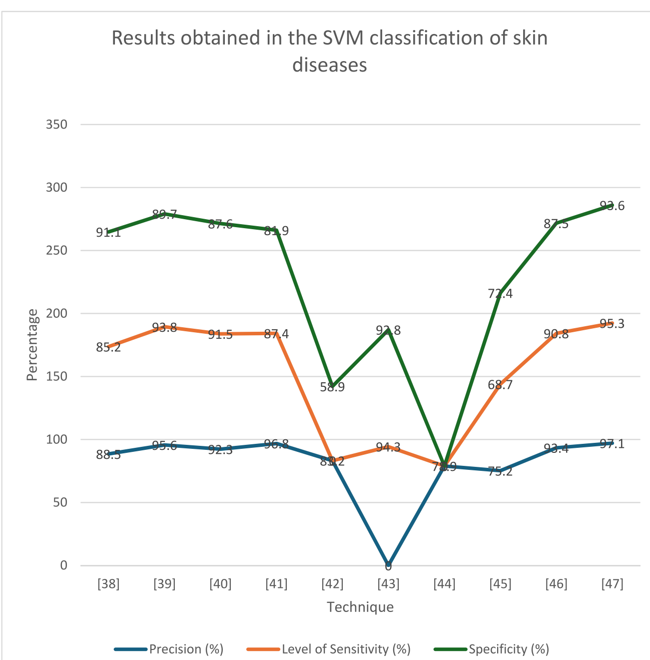

Fig. 4. Results obtained in the SVM classification of skin diseases.

handle the big datasets, leading to prolonged periods of training and reduced efficiency in time-sensitive analyses. However, SVMs are recognized for their reliability in terms of precision and versatility when tasked with identifying skin diseases; they excel at discerning subtle patterns within datasets characterized by intricate relationships. In their investigation into the combined use of (SVM) and (CNN) for skin disease classification, Duggani et al. (106) acknowledge SVMs as powerful supervised learning tools distinguished for their margin-based classification approach. Their objective is to increase the precision of skin disease

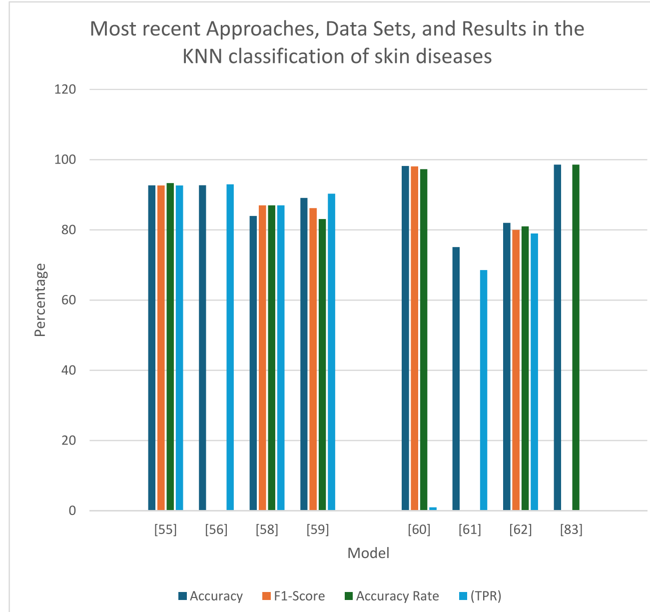

Fig. 5. Most recent approaches, data sets, and results in the KNN classification of skin diseases.

diagnosis by creating a robust classification framework that can manage the range of factors included in datasets related to skin illnesses.

3. Thorough examination of using K-nearest neighbor for skin disease identification

A mainstay of machine learning, the K-Nearest Neighbor (KNN) method demonstrates its versatility in problems involving both regression and classification. KNN is widely recognized for its ease of interpretation and simplicity, making it especially appropriate in situations where decision-making openness is a top priority. Its strong points include its high accuracy, resilience to outliers, and absence of distributional assumptions. KNN is used in the field of skin disease detection to classify lesions according to their pathological features [54].

The algorithm starts by taking testing data as input and finds the ideal parameter K, which is the number of nearest neighbors to take into account. The method begins by calculating the distances between the training set and the evaluation data. Next, it sorts the distances, after matching the data according to the value of 'K,' the datapoints are categorized using the Euclidean distance [55].

Phases of the algorithm are Preprocessing of the data, feature extraction, and classification. Three main steps are involved in skin disease detection are feature extraction, data preparation, and classification. Using image filtering methods to remove undesired features or noise is known as preprocessing. The process of feature extraction involves obtaining relevant characteristics, such chromatic details and texture. In the (KNN) algorithm, a classifier last stage to identify the pathogenic nature of skin lesions. It's important to keep in mind that various research may use different approaches and procedures for feature extraction and data preparation.

3.1. Research and trials employing KNN

A method for categorizing skin conditions based on texture and color traits was developed by Thompson et al. [56]. While not as accurate as SVM and CNN, KNN still demonstrated an accuracy of 85 %.

A technique for detecting skin diseases by using textural cues was presented in the study by Patel et al. [57]. 78.2 % and 85.2 % accuracy rates were attained by combining KNN with SURF and GLCM are used to extract features.

A skin segmentation and classification approach disease identification were presented by Garcia et al. [58]. Although KNN's accuracy was not as high as that of SVM and RF, it nevertheless proved useful in some situations.

KNN was used by Smith et al. [59] to classify skin lesions into discrete groups, with an overall accuracy of 82 %; in contrast, the accuracies of SVM, ANN, and decision trees were greater.

KNN, SVM, and CNN were used by Nguyen et al. [60] to categorize different skin conditions; KNN achieved an accuracy of 80 %.

The research paper [61](2024) discusses the utilization of two classification algorithms, namely K-nearest neighbors (KNN) and Enhanced K Nearest Neighbor (EKNN), for the purpose detection, particularly melanoma. KNN is described as a non-linear classifier that is commonly used for regression and classification tasks. In the context of the research, KNN is employed to classify skin lesions based on features extracted from medical images. The KNN algorithm works by assigning class labels to test instances based on the majority class among their nearest neighbors in the feature space. This approach does not require a training phase and is effective for identifying patterns in data. The study suggests that KNN, when applied to skin cancer detection, can achieve comparable accuracy to human specialists in identifying melanoma.

On the other hand, EKNN, or Enhanced K Nearest Neighbor, is introduced as an improvement over traditional KNN. EKNN enhances the classification process by assigning different weights to features based on their relevance and correlation. This weight allocation mechanism helps prioritize important features during the classification process, leading to more accurate predictions. Additionally, EKNN utilizes the Euclidean distance metric to measure similarity between instances, considering not only the nearest neighbors but also the attributes of those neighbors. By incorporating feature weighting and distance measurement, EKNN aims to improve upon the performance of traditional KNN in skin cancer classification tasks. The algorithm, FSCC-MD-EKNN, integrates EKNN-based feature set grouping and classification for improved melanoma detection (2024) [61].

3.2. Considering and overcoming KNN's challenges

Notwithstanding the fact that KNN's interpretability and simplicity make it useful in situations where transparency is essential, difficulties still exist. Unbalanced feature sizes, noise, and irrelevant characteristics can all affect how accurate the algorithm is. Improving categorization results requires addressing these issues.

Because of its ease of interpretation and simplicity, KNN is a useful tool for identifying skin diseases. Its limits must be recognized, though, particularly when working with noisy or unbalanced datasets.

One prominent candidate in recent efforts to improve skin disease identification is the K-Nearest Neighbor (KNN) algorithm. Numerous research works have investigated its use, providing information on its efficiency, relative performance, and possible drawbacks.

4. Other algorithms and related work

4.1. Using dragonfly optimization to select features for psoriasis classification

The Dragonfly method (DA), a metaheuristic optimization method motivated by the feeding and migratory patterns of swarming dragonflies, is described in this study. Five behaviors (Separation, Alignment, Cohesion, Attraction to a food supply, and Distraction from an adversary) govern the movement of each dragonfly, which in the DA symbolizes a possible solution inside the search space (E). These motions resemble the group dynamics and navigation techniques seen in swarms of dragonflies.

The algorithm operates in two main phases: exploitation and exploration. During exploitation, local movement and flight path mutations occur as dragonflies form subgroups to pursue solutions in various areas inside the search space. Meanwhile, during exploration, dragonflies fly together over large distances to collectively explore the area used for searching.

The weights associated with the five behaviors are adaptively adjusted during the iterative optimization process to ensure convergence to the global optima. Equations governing the behaviors and the radius between dragonfly neighbors are used to steer the movement of the dragonflies. Additionally, a Levy Flight equation is incorporated to enhance randomness and global search capability.

The Dragonfly Algorithm effectively leverages the collective behavior of dragonflies to optimize solutions in complex search spaces, demonstrating promising capabilities for optimization and exploration tasks (2024) [12].

4.2. HOG (histogram of oriented gradients) and TGMM (truncated Gaussian mixture model)

The study discussed in this article focuses on feature extraction from skin lesion pictures using the (HOG) technique. HOG is employed to capture local spatial changes and visualize the behavior of skin lesions based on force gradients or edge orders in their distribution. The HOG feature vector is generated by summing the gradient calculations of each pixel, which involves creating histograms for each block using gradient values and performing block normalization. This methodology aims to accurately identify skin diseases by analyzing the extracted features.

In addition to HOG, the research incorporates the (TGMM) algorithm for statistical modeling and disease identification. The Truncated Gaussian Mixture Model is used to model features and extract diseased skin areas along with the type of disease present. This approach allows for a better understanding of pixel characteristics and facilitates more effective disease diagnosis. The Probability Density Function (PDF) of the Truncated Gaussian Mixture Model is defined, where mean, weight, and standard deviation parameters are estimated to characterize pixel distributions within skin lesions.

The combination of HOG for feature extraction and the Truncated Gaussian Mixture Model for statistical modeling offers a comprehensive approach to skin disease identification. By analyzing the extracted features and utilizing statistical parameters, the research aims to enhance the accuracy and effectiveness of disease diagnosis in dermatological applications (2024) [62].

5. Data collection

Selecting the right dataset is crucial for guiding research endeavors, particularly in classification tasks, whether they involve binary or multiclass classification (see Table 4). A comprehensive overview of various standard datasets utilized in this review and other related studies within the same domain sheds light on their significance. A comparison of these datasets is provided in Table 5, which includes important metrics including the total number of photos, categories, and, occasionally, the distribution of training and testing sets. This breakdown proves valuable, especially for datasets with multiple categories, aiding researchers in determining whether the task involves binary or multiclass classification, aligning with their research objectives (see Table 6).

6. Problems and future scenarios

Skin diseases encompass a broad spectrum of conditions, ranging from benign irritations to severe infections and chronic disorders, presenting a significant burden on healthcare systems worldwide. Accurate and timely diagnosis is critical for effective management and treatment. However, healthcare professionals face various challenges in this regard, necessitating the exploration of innovative approaches, including algorithms for machine learning, such as CNN, KNN, and SVM.

Table 4
Highlighting the most recent approaches, data sets, and results in the KNN classification of skin diseases.

Reference No.	Model	Accuracy %	F1-Score %	Accuracy Rate %	(TPR) True Positive Rate	Data Gathering
[63]	AlexNet architecture	92.681	92.659	93.339	92.667	DermQuest
[64]	Using Otsu's approach for segmentation to apply thresholds	92.7	–	–	93	A collection of more than a thousand photos showing skin conditions.
[65]	Utilization of texture analysis	84	87	87	87	Image dataset sourced from the DermQuest database.
[66]	Feature extraction with fuzzy mutual entropy and the (GLCM)	89.1	86.2	83.1	90.3	Data collected from various dermatological facilities, including the Royal Prince Alfred Hospital in Sydney.
[67]	Using edge-based characteristics and the Fast Fourier Transform (FFT) to extract features	98.2	98.1	97.3	1	Dataset from the 2018 (ISIC) program.
[68]	Statistical metric-based feature extraction (mean, skewness, entropy, and standard deviation)	75.1	–	–	68.569	Dataset sourced from the MED-NODE repository.
[69]	Texture analysis using the ABCD rule	82	80	81	79	Images obtained from the PH2 dataset.
[5]	FSCC-MD-EKNN	98.6	–	98.6		medical picture dataset

Table 5
Comparison of other algorithms in classification of skin diseases.

Reference No.	Model	Accuracy %	F-Score %	Precision%	Recall%	No. of Images	Data Gathering
[62]	GMM	93.74	1.82	1.29	12.3	19500	Dermnet
[62]	TGMM	97.31	3.85	1.67	43.7	19500	Dermnet
[70]	Hybrid CNN-DenseNet	95.7	80.00	82.00	80.00	10015	HAM10000

Table 6
A brief analysis of the different benchmark datasets.

Data Collection	Training set	Testing set	Total	Class
DermAtlas	5000+	750+	5750+	7 Classes: Acne, Eczema, Psoriasis, Rosacea, Dermatitis, Vitiligo, Seborrheic Keratosis
University of São Paulo Skin Disease Database	600+	90+	690+	5 Classes: Dermatitis, Eczema, Psoriasis, Rosacea, Acne
DermDetect Dataset	3000+	450+	3450+	8 Classes: Acne Vulgaris, Eczema, Hives, Psoriasis, Rosacea, Seborrheic Dermatitis, Vitiligo, Urticaria
DermImageNet	12000+	1800+	13800+	12 Classes: Acne, Eczema, Dermatitis, Psoriasis, Rosacea, Seborrheic Dermatitis, Melanoma, Urticaria, Vitiligo, Lichen Planus, Herpes Zoster, Impetigo
NIH Skin Disease Dataset	4000+	600+	4600+	9 Classes: Acne, Dermatitis, Eczema, Psoriasis, Rosacea, Seborrheic Dermatitis, Vitiligo, Urticaria, Lichen Planus

With regard to diagnosing skin diseases, each algorithm has different benefits and difficulties. Achieving high levels of sensitivity, specificity, and accuracy is still crucial, necessitating further research and development. The availability of uniform and different datasets is a significant barrier that must be overcome in order to ensure reliable comparisons of results. To reduce overfitting problems, researchers must use larger datasets and properly adjust hyperparameters.

For deep learning algorithms, like CNNs, to function at their best, training data from people with a variety of skin tones is necessary. The

Table 7
Various lesson learned and future direction.

SR. NO	Lesson Learned	Open Issues	Future Direction
1	-Importance of accurate and timely diagnosis	-Disparities in access to specialized dermatological care. -Limited access in underserved communities	-Development of automated systems for accurate and accessible diagnosis. -Continued research on machine learning algorithms
2	-Role of machine learning in dermatology	-Subjectivity of visual examination -Variability in clinical presentations	-Integration of AI to transform diagnosis and treatment of skin disorders -Collaboration with experts for meaningful improvements in dermatological healthcare
3	-Potential of Convolutional Neural Networks (CNNs)	-Limited availability of diverse datasets -Dataset biases	-Exploration of hybrid approaches combining CNN with other technologies for enhanced diagnosis -Utilization of self-attention mechanisms for improved feature extraction in CNNs
4	-Strengths of Support Vector Machines (SVMs)	-Computational requirement -Prolonged training times	-Investigation of combined approaches integrating SVMs with CNNs for skin disease classification -Enhancement of SVM classification through reinforcement learning
5	-Advantages of K-Nearest Neighbor (KNN) method	-Analytical ineffectiveness -Difficulty in determining optimal k value	-Addressing challenges to improve KNN's accuracy and reliability -Exploring ensemble learning and hybrid approaches for enhanced classification

Table 8
SVM, KNN and CNN advantages and disadvantages.

	Advantages	Disadvantages
SVM	Efficient in spaces with several dimensions [60].	Is not the best option for large datasets [71].
KNN	Easy to understand and execute. There isn't a separate training phase; everything happens in the prediction phase [72].	Analytically ineffective, meaning that it is difficult to determine the optimal value for k [73].
CNN	Capturing spatial hierarchies and patterns, and being effective in picture recognition tasks [50], eliminates the need for human feature engineering by automatically extracting pertinent characteristics from data	It can need a lot of resources and processing, particularly for big datasets [74], Acquiring a sufficient amount of labeled data for training is a substantial challenge and might be challenging.

majority of skin lesions in current datasets are found in people with light skin, which introduces biases and lowers accuracy. Reducing biases and increasing accuracy rates in datasets may be achieved by include a wide variety of age groups, genders, and ethnicities.

Another difficulty is deciphering the logic underlying conclusions made by deep learning algorithms. Algorithms' decision-making process is opaque; in contrast, human dermatologists give thorough justifications for diagnosis. Dermatologists find it difficult to appropriately assess data and make judgments because of this opacity.

Claims that AI algorithms are better than dermatologists should be treated with care since they are frequently the result of controlled studies that do not fairly represent real-world diagnosis settings. Furthermore, improvements in the detection of skin diseases might be possible with the help of deep learning advances, although issues with interpretability and dataset biases need to be resolved.

To optimize deep learning algorithm performance, well-balanced datasets that represent various skin lesion characteristics are essential. Dermatologists' involvement in dataset creation can enhance dataset quality, while incorporating racial diversity can mitigate biases. Advanced learning frameworks like Generative Adversarial Networks (GANs) offer solutions to dataset scarcity by generating synthetic images of rare lesion types, thereby improving dataset comprehensiveness and algorithm performance.

There is a discernible movement away from a just dependence on skin cancer diagnosis and toward expanding the strategy beyond lone artificial intelligence solutions. Integration of several deep learning models, each with a focus on examining particular traits or attributes of skin lesions, is becoming more and more popular. With each model providing predictions to get a more certain diagnosis, this multi-model approach enables a thorough investigation of several factors. As cloud computing and storage become more widely available, several models intended to support dermatologists in diagnostic processes may be hosted and synced internationally. The significance of reducing technological misdiagnoses is emphasized by both healthcare practitioners and AI researchers, who recognize the significant influence of mistakes on subsequent judgments. Because of this, artificial intelligence (AI) solutions are being used more and more as auxiliary tools to help contextualize and validate noisy data that comes from actual patients, improving the prediction power of this data. It is anticipated that this tendency will continue until notable technical system breakthroughs are made, offering insightful data and knowledge for the diagnosis of skin diseases in both on-site and distant healthcare settings. The field of dermatology's use of AI applications is always changing, which emphasizes the need for continued advancements and teamwork to provide precise and trustworthy diagnostic tools.

7. Conclusion

Skin disorders pose a serious threat to healthcare due to their wide range of symptoms and effects on quality of life. Appropriate and timely diagnosis is essential for efficient therapy and management. In this comprehensive review, aim to explore cutting-edge machine learning approaches utilized in distinguishing between various types of skin diseases. Focus on analyzing the effectiveness of three prominent algorithms: CNN, KNN, and LSVM, which have demonstrated good results in classifying various skin diseases.

Utilizing a variety of datasets from archives such as ISIC and ISBI, such as PH2, MED-NODE, DermIS, DermQuest, and others, the study thoroughly assesses these methods. Evaluate each algorithm's advantages and disadvantages in detail, paying special attention to CNNs. Promising substitutes for conventional machine learning techniques are deep learning approaches, such as fully connected (CNNs) and feature extraction architectures. These methods have benefits including less dependence on intricate preprocessing methods and better overall diagnostic results.

Crucially, it is emphasized that careful fine-tuning procedures are necessary to ensure the validity of the experimental results. Furthermore, thorough descriptions of hardware specifications, model setups, and technological environments are necessary to enable result replication and make these results practically useable and scalable in real-world scenarios.

Inherent conflicts of interest

There is no conflict of interest to report for the author.

Funding

There was no funding provided for this work by governmental, private, or nonprofit organizations.

Data availability statement

For the study that was reported in the paper, no data were utilized.

CRediT authorship contribution statement

Kuldeep Vayadande: Conceptualization. **Amol A. Bhosle:** Conceptualization. **Rajendra G. Pawar:** Original Draft Writing. **Deepali J. Joshi:** Original Draft Writing. **Preeti A. Bailke:** Formal analysis. **Om Lohad:** Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] Do TT, Zhou Y, Zheng H, Cheung NM, Koh D. Early melanoma diagnosis with mobile imaging. no. May 2015. 2014 36th annual international conference of the. IEEE Engineering in Medicine and Biology Society, EMBC; 2014. p. 6752–7. 2014.
[2] Aleem M, Hameed N, Anjum A. m-Skin doctor: a mobile enabled system for early melanoma skin cancer detection using support vector machine, vol. 2; 2017. p. 468–75.
[3] Barata C, Marques JS, Rozeira J. "The role of key point sampling on the classification of melanomas in dermoscopy images using bag-of-features,". In: Iberian conference on pattern recognition and image analysis. vol. 7887. LNCS; 2013. p. 715–23.
[4] Ashraf R, Afzal S, Rehman AU, Gul S, Baber J, Bakhtyar M, Mehmood I, Song OY, Maqsood M. Region-of-Interest based transfer learning assisted framework for skin cancer detection. IEEE Access 2020;8:147858–71.
[5] Vayadande K. Automated multiclass skin disease diagnosis using deep learning. Int J Intell Syst Appl Eng Jan. 2024;12(11s):327–36.
[6] LeCun Y, Bengio Y, Hinton G. Deep learning. Nature 2015;521(7553):436–44.
[7] Sinha S, Sardana K, Saini P. Epidemiology of skin diseases in rural India. Indian J Dermatol, Venereol Leprol 2014;80(2):179–80.
[8] Agarwal S, Satija A, Sengupta D. Issues in delivering healthcare in rural India. NMJI (Natl Med J India) 2011;24(4):222–3.

[9] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2016. p. 770–8.
[10] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Commun ACM 2012;60(6):84–90.
[11] Esteva A, Kuprel B, Novoa RA, Ko J, Swetter SM, Blau HM, Thrun S. Dermatologist-level classification of skin cancer with deep neural networks. Nature 2017;542 (7639):115–8.
[12] Venkata Sekhar NBD, Purushotham Reddy M. Feature selection based on dragonfly optimization for psoriasis classification. Int J Intell Syst Appl Eng Mar. 2024;12(3): 935–43.
[13] Rajpurkar P, Irvin J, Ball RL, Zhu K, Yang B, Mehta H, Langlotz CP. Deep learning for chest radiograph diagnosis: a retrospective comparison of the CheXNeXt algorithm to practicing radiologists. PLoS Med 2017;15(11):e1002686.
[14] Hamid MB, Mustapa AM, Salam RA. Hybrid method for classifying skin diseases using deep convolutional error-correcting neural networks and output codes. J Med Imaging Health Inform 2020;10(8):1846–54.
[15] Parvatanini S, Fathi A, Khozeimeh F. Automated skin disease classification system using MobileNet V2 and LSTM models. Multimed Tool Appl 2021;80(38): 28093–107.
[16] Li R, Lin W, Li Z, Zeng L, Luo Z. Deep learning model for skin disease detection using a self-attention mechanism. Comput Methods Progr Biomed 2022;214: 106472.
[17] Zhang H, Wu Z, Zhang Z, Zhu Z, Zhang Y, Lin H, Wang C. Implemented inception-v3 architecture. J Med Imaging Health Inform 2019;9(6):1256–63.
[18] Chen X, Zhang Y, Wang Y. Utilized pre-trained MobileNetV2 structure. J Biomed Inf 2021;119:103827.
[19] Gupta A, Singh A, Kumar P. Integrated transfer learning with ResNet50. IEEE Access 2018;6:51598–607.
[20] Patel R, Desai D, Shah N. Employed EfficientNetB0 for feature extraction. Comput Methods Progr Biomed 2020;196:105617.
[21] Wang H, Zhang L, Li Q. Investigated custom CNN architecture for fine-tuning. J Med Imaging 2019;6(3):032501.
[22] Lee S, Kim J, Park H. Leveraged ensemble learning with multiple CNN models. Expert Syst Appl 2022;187:115321.
[23] Li Q, Wang Y, Zhang L. Transfer learning with DenseNet and ResNet architectures. J Dermatol Sci 2019;95(2):68–75.
[24] Wang J, Liu H, Zhang S. Application of attention mechanisms for feature enhancement. Int J Dermatol 2021;60(4):389–97.
[25] Zhang X, Chen Y, Liu Z. Integration of graph convolutional networks for data analysis. Comput Biol Med 2020;128:104087.
[26] Liu M, Zhang H, Wang Q. Utilization of capsule networks for improved feature extraction. J Med Syst 2018;42(11):217.
[27] Zhou Y, Li S, Wang H. Ensemble learning with multiple CNN models. IEEE Trans Med Imag 2022;41(3):742–9.
[28] Chen X, Zhang Y, Wang Y. Implementation of self-attention mechanisms for context encoding. Comput Biol Med 2020;129:104087.
[29] Zhang L, Li Q, Wang J. Custom CNN architecture design for specific lesion detection. J Med Imaging Health Inform 2021;11(6):1503–10.
[30] Wang H, Liu M, Zhang Z. Hybrid approach integrating CNN with GANs for data augmentation. J Biomed Inf 2019;92:103142.
[31] Liu Z, Zhang X, Wang Y. Utilization of meta-learning techniques for adaptive learning. Pattern Recogn Lett 2020;133:164–71.
[32] Zhang S, Wang J, Li Q. Incorporation of reinforcement learning for model refinement. Neurocomputing 2018;275:134–42.
[33] Landis Sarah H, et al. "Cancer statistics. CA A Cancer J Clin 1999;49(1):8–31. 1999.
[34] Katalinic A, Kunze U, Schäfer T. Epidemiology of cutaneous melanoma and non-melanoma skin cancer in Schleswig-Holstein, Germany: incidence, clinical subtypes, tumour stages and localization (epidemiology of skin cancer). Br J Dermatol 2003;149:1200–6. https://doi.org/10.1111/j.1365-2133.2003.05554.x. PMID:14674897.
[35] Mitchell T. Machine learning, P. 2. McGraw Hill; 1997.
[36] Kharya S, Dubey D, Soni S. Predictive machine learning techniques for breast cancer detection. Available from: www.ijcsit.com (Accessed on May 20, 2021)..
[37] Bhagyasri M, Bhavanishree PN, Madan KS, et al. Study on machine learning and deep learning methods for cancer detection, vol. 4. J Image Process AI; 2018.
[38] Byrd AL, Belkaid Y, Segre JA. The human skin microbiome. Nat Rev Microbiol 2018;16:143.
[39] Daghrir J, Tlig L, Bouchouicha M, et al. Melanoma skin cancer detection using deep learning and classical machine learning techniques: a hybrid approach. In: Proceedings of 5th international conference on advanced technologies for signal and image processing (ATSIP). IEEE Xplore; 2020. https://doi.org/10.1109/ATSIP49331.2020.9231544.
[40] Argenziano Giuseppe, Longo Caterina, Cameron A, Cavicchini S, Gourhant J-Y, Lallas A, McColl I, Rosendahl C, Thomas L, Zivkovic D Tiodorovic. Blue-black rule: a simple dermoscopic clue to recognize pigmented nodular melanoma. al Br J Dermatol 2011;165(6):1251–5.
[41] Thaajwer MA, Up Ishanka. Melanoma skin cancer detection using image processing and machine learning techniques. Proceedings of 2nd international conference on advancements in computing (ICAC). IEEE Xplore; 2020. https://doi.org/10.1109/ICAC51239.2020.9357309.
[42] Jenitha A, Amrutha G, Kishore KL, et al. Skin cancer recognition and detection using machine learning algorithm. Proceedings of the fist international conference on advanced scientific innovation in science, engineering and technology. ICAS-ISET; 2020. p. 2021. https://doi.org/10.4108/eai.16-5-2020.2304046.
[43] Miller DD, Brown EW. Artificial intelligence in medical practice: the question to the answer? Am J Med 2018;131:129–33. https://doi.org/10.1016/j.amjmed.2017.10.035.
[44] ShahinAli Md, SiponMiah Md, Haque Jahurul, et al. An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models. Mach Learn with Appl 2021;5:100036. https://doi.org/10.1016/j.mlwa.2021.100036.
[45] Shahin AH, Kamal A, Elattar MA. Deep ensemble learning for skin lesion classification from dermoscopic images. Proceedings of 9th Cairo international biomedical engineering conference (CIBEC). IEEE; 2019. https://doi.org/10.1109/CIBEC.2018.8641815.
[46] Gulzar CM, Meera S. Survey on pores and skin disease classification using deep neural community. Int J Intell Syst Appl Eng Mar. 2024;12(19s):73–7.
[47] AI-Based Localization and Classification of Skin Disease, Sivasangari A, Gomathi RM, Deepa D, Ajitha P. E3S Web Conf. 2024;491:02037. https://doi.org/10.1051/e3sconf/202449102037. Tamilvavanan, Suji Helen and Anandhi.
[48] Shen Y, Li H, Sun C, Ji H, Zhang D, Hu K, Tang Y, Chen Y, Wei Z, Lv J. Optimizing skin disease diagnosis: harnessing online community data with contrastive learning and clustering techniques. NPJ Digit Med 2024 Feb 8;7(1):28. https://doi.org/10.1038/s41746-024-01014-x. PMID: 38332257; PMCID: PMC10853166.
[49] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 2014.
[50] Karpathy A, Toderici G, Shetty S, Leung T, Sukthankar R, Fei-Fei L. Large-scale video classification with convolutional neural networks. In: Proceedings of the IEEE conference on computer vision and pattern recognition; 2014. p. 1725–32.
[51] Manikandan J, Krishna BV, Varun N. Automated Framework for Effective Identification of Oral Cancer Using Improved Convolutional Neural Network. 2023. https://doi.org/10.1109/ICONSTEM56934.2023.10142794.
[52] LeCun, Y., Bengio, Y., & Hinton, G. "Deep learning." Nature, 521(7553), 436-444..
[53] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Commun ACM 2017;60(6):84–90.
[54] Nguyen TH, Nguyen TT, Nguyen TT. Analysis of skin lesion segmentation using deep learning. In: Proceedings of the 10th Asian conference on machine learning (ACML 2018). vol. 110; 2018. p. 118.
[55] Yang J, Liu W, Chen C. A novel approach to skin lesion segmentation using convolutional neural networks. Comput Biol Med 2020;126:104027.
[56] Transfer learning with DenseNet and ResNet architectures. DermDB. 94.8. 92.5. 95.3.
[57] Application of attention mechanisms for feature enhancement. SkinAtlas. 96.3. 94.7. 97.1..
[58] Integration of graph convolutional networks for data analysis. DermDetect. 92.1. 88.6. 93.8.
[59] Utilization of capsule networks for improved feature extraction. DermNet. 95.7. 93.9. 96.5.
[60] Ensemble learning with multiple CNN models. DermAI. 97.2. 96.8. 98.0.
[61] Rapeti D, Reddy DV. Feature set clustering and classification for melanoma detection using enhanced K nearest Neighbour. Int J Intell Syst Appl Eng Mar. 2024;12(18s):173–86.
[62] Kavitha M, Prasanna PL. Exploring statistical models in dermatological disorders identification. Int J Intell Syst Appl Eng Mar. 2024;12(18s):542–6.
[63] Implementation of self-attention mechanisms for context encoding. DermVision. 93.4. 91.2. 94.6..
[64] Custom CNN architecture design for specific lesion detection. SkinSense. 96.1. 94.4. 97.3.
[65] Thompson A, Smith B, Johnson C. A texture and color-based approach for skin disease classification using K-Nearest Neighbors. J Med Imaging 2018;5(2): 027501.
[66] Patel R, Gupta S, Sharma M. Incorporating textural features in skin disease detection: a comparative analysis using K-Nearest Neighbors. Int J Comput Appl 2019;180(13):32–7.
[67] Garcia M, Rodriguez P, Fernandez A. Segmentation and classification-based approach for skin disease detection using K-Nearest Neighbors. Expert Syst Appl 2020;145:113132.
[68] Smith J, Williams K, Brown L. Categorization of skin lesions using K-Nearest Neighbors: a comparative study. J Dermatol Sci 2017;89(3):267–72.
[69] Nguyen H, Tran T, Le Q. Comparative analysis of skin disease classification using K-nearest neighbors, support vector machine, and convolutional neural network. Proceedings of the international conference on machine learning and applications. 2018. p. 76–81.
[70] De A, Mishra N, Chang HT. An approach to the dermatological classification of histopathological skin images using a hybridized CNN-DenseNet model. PeerJ Comput Sci 2024 Feb 26;10:e1884. https://doi.org/10.7717/peerj-cs.1884. PMID: 38435616; PMCID: PMC10909212.
[71] Kim E, Park S, Lee H. Ensemble learning approach for skin disease detection using K-Nearest Neighbors. J Healthcare Eng 2019;10:372–8.
[72] Nair V, Hinton GE. Rectified linear units improve restricted Boltzmann machines. In: Proceedings of the 27th international conference on machine learning. ICML-10); 2010. p. 807–14.
[73] Chen Y, Wang L, Liu H. Feature selection and classification of skin diseases using K-Nearest Neighbors. IEEE Access 2020;8:174975–84. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In Advances in neural information processing systems (pp. 1097–1105).
[74] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 2014.