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A Review on Utilizing Machine Learning Classification Algorithms for Skin Cancer

Arshad A. Hussein[1, *], Adnan Mohsin Abdulazeez[2]

[1] Akre University for Applied Sciences, Technical College of Informatics -Akre, Department of Information Technology, Kurdistan Region, Iraq, email: Arshad.kurdy@auas.edu.krd
[2] Duhok Polytechnic University, Duhok, Kurdistan Region, Iraq, email: Adnan.mohsin@dpu.edu.krd
[*] Correspondence: Arshad.kurdy@auas.edu.krd

Abstract

Skin cancer is one of the most prevalent forms of cancer globally, with rising incidence rates posing significant challenges to healthcare systems. Early detection and accurate diagnosis are critical for effective treatment and patient outcomes. In recent years, machine learning (ML) algorithms have emerged as powerful tools for analyzing medical imaging data and assisting clinicians in diagnosing skin cancer. This review paper provides a comprehensive overview of the ML classification algorithms in the context of skin cancer detection and diagnosis. We discuss various types of skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma, along with their characteristics and diagnostic challenges. Furthermore, we review the current state-of-the-art ML techniques, such as support vector machines (SVM), K-Nearest Neighbor (KNN), and convolutional neural network (CNN), highlighting their strengths and limitations in skin cancer classification. A systematic search of academic databases, including Scopus, ResearchGate, Google Scholar, IEEE Xplore, Wiley Online Library, Elsevier, ScienceDirect, and Springer, was conducted. Continued evolution in skin cancer classification promises enhanced diagnostic accuracy and personalized treatment strategies.

Keywords: *Skin cancer, machine learning, melanoma, SVM, KNN, CNN.*

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I. INTRODUCTION

Skin cancer represents a significant public health concern worldwide, with its incidence continuing to rise. According to global statistics, skin cancer is among the most commonly diagnosed cancers, with melanoma being one of the most aggressive forms[1]. Early detection and accurate diagnosis are crucial for successful treatment outcomes and patient survival rates. However, the visual assessment of skin lesions by dermatologists can be subjective and prone to errors, leading to delayed diagnoses or unnecessary procedures[2][3]. In recent years, there has been growing interest in leveraging machine learning (ML) algorithms to assist in the detection and classification of skin cancer. ML techniques have shown promise in analyzing medical imaging data, such as dermoscopic images and histopathological slides, to aid clinicians in making more informed diagnostic decisions. [4][5]. These algorithms can learn complex patterns and relationships from large datasets, potentially enhancing the accuracy and efficiency of skin cancer diagnosis [6][7]. The aims to provide a comprehensive overview of the ML classification algorithms in the context of skin cancer detection and diagnosis. We will discuss the different types of skin cancer, including melanoma, basal cell carcinoma, and squamous cell carcinoma, highlighting their characteristics and diagnostic challenges. Furthermore, we will explore various ML algorithms, such as support vector machines (SVM), K-Nearest Neighbor (KNN),and convolutional neural network (CNN), assessing their strengths and limitations in skin cancer classification tasks, Additionally, we will examine publicly available datasets commonly used for training and evaluating ML models in this domain, discussing their characteristics and potential biases. This paper is organized as follows: Introduction is explained in section I. Type of skin cancer are presented in section II. Brief overview of machine learning is explained in section III. In section IV presented datasets for skin cancer classification. In section V limitations of machine learning for skin cancer diagnosis. In section VI challenges in translating research to clinical practice. In section VII ethical considerations in using machine learning for skin cancer diagnosis. In section VIII critical analysis of cited studies. In section Next, A Review and experimental Comparison are explained in section IX. Discussion and

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analyze are explained in section X. IN Section XI future directions for research. Describes. Conclusion in section XII.

II. TYPE OF SKIN CANCER

Skin cancer encompasses several types, each with distinct characteristics, risk factors, and diagnostic considerations. The three main types of skin cancer are melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). Understanding the differences between these types is essential for accurate diagnosis and appropriate management, as show in Fig 1, Melanoma: is the most aggressive form of skin cancer, originating from melanocytes, the pigment-producing cells in the skin. Risk factors for melanoma include excessive UV exposure, history of sunburns, fair skin, family history of melanoma, and presence of numerous moles. Melanoma often presents as an irregularly shaped, asymmetric lesion with variegated colors (e.g., brown, black, blue, red). Diagnostic challenges include differentiating melanoma from benign pigmented lesions and identifying early-stage melanomas that may lack typical features. Early detection and prompt treatment are critical for favorable outcomes, as melanoma can metastasize to other organs if left untreated[8]. Basal Cell Carcinoma (BCC): Basal cell carcinoma is the most common type of skin cancer, originating from basal cells in the epidermis. Risk factors for BCC include chronic sun exposure, older age, fair skin, history of sunburns, and genetic predisposition. BCC typically appears as a raised, pearly or translucent bump with rolled edges, often resembling a pinkish or flesh-colored nodule. While BCC rarely metastasizes, it can cause local tissue destruction if left untreated, leading to disfigurement and functional impairment. Diagnosis is usually straightforward based on clinical examination and may be confirmed by biopsy for suspicious lesions. Squamous Cell Carcinoma (SCC): Squamous cell carcinoma arises from squamous cells in the epidermis and is the second most common type of skin cancer. Risk factors for SCC include chronic sun exposure, immunosuppression, older age, fair skin, history of radiation therapy, and exposure to carcinogens (e.g., arsenic, coal tar). SCC often presents as a firm, red nodule or a flat, scaly lesion with a crusted surface, frequently occurring on sun-exposed areas like the face, ears, lips, and hands. While SCC has a higher metastatic potential than BCC, most cases are localized and can be cured with early detection and appropriate treatment. Diagnosis may involve biopsy for suspicious lesions and histopathological examination to confirm malignancy and assess tumor characteristics[9].

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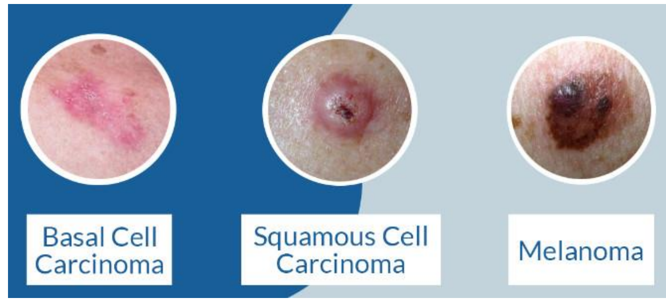

Fig. 1. The main types of skin cancer [8]

III. BRIEF OVERVIEW OF MACHINE LEARNING

Machine learning is driving massive improvement in the healthcare industry. It is expediting advancements in areas including, clinical operations, drug discovery, and surgery. Most importantly, machine learning in healthcare can detect early indicators of a disease more accurately such as in skin cancer, helping reduce the number of admissions and readmissions in hospitals and clinics[10]. the technology examines satellite data, social media reports, news, and even video sources to determine whether the ailment is controllable or will become lethal. Machine learning for healthcare opens a world of endless possibilities, freeing up medical professionals to find the best treatment plan and patient care rather than managing data. Machine learning (ML) is a field of computer science that allows computers to learn from data without explicit programming. In classification tasks, ML algorithms are trained on labeled data to predict the category (class) of new, unseen data points[11]. Fig. 2 shows a skin cancer diagnosis[12].

Common ML Classification Algorithms, Several algorithms excel at classification tasks, particularly when dealing with complex data like images. Here are the most important of these algorithms.

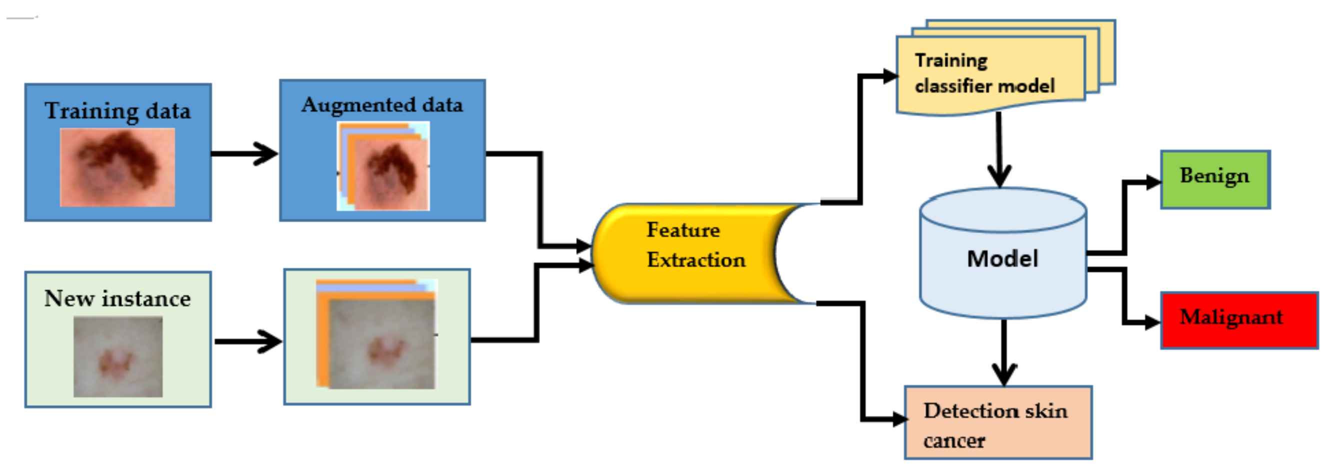

Fig. 2. Process skin cancer classification [12]

1. Support vector machine (SVM)

Support Vector Machines (SVMs) are now considered the most potent algorithms that have been devised so far. They are a subset of supervised machine learning methods that focus on categorizing datasets into meaningful clusters[13]. They are constructed based on the principles of decision planes and decision boundaries. Support Vector Machines (SVMs) strive to find the best hyperplane that optimizes the distance between the nearest points of different data groupings[14]. A group of examples that are located close to the ideal hyperplane is referred to as a 'Support Vector'. The Support Vector Machine (SVM) offers a comprehensive framework for classifying diverse data by selecting an appropriate kernel. This means that multiple machine learning structures may be constructed by using different kernels[15]. The most basic kind of Support Vector Machine (SVM) is referred to as 'linear', and it is used when the data can be separated by a straight line. SVMs with various kernel functions are used for non-linear data. Kernel functions transform data from a lower-dimensional space to a higher-dimensional one, enabling linear separation of the data[16]. SVMs have been used to provide access to bioinformatics. The SVM classifier is often used in medical image analysis, particularly in studies with a melanoma dataset, and has been shown to provide encouraging outcomes[17]. Protein function prediction, gene expression data categorization, and cancer detection are among the several uses of Support Vector Machines (SVMs).

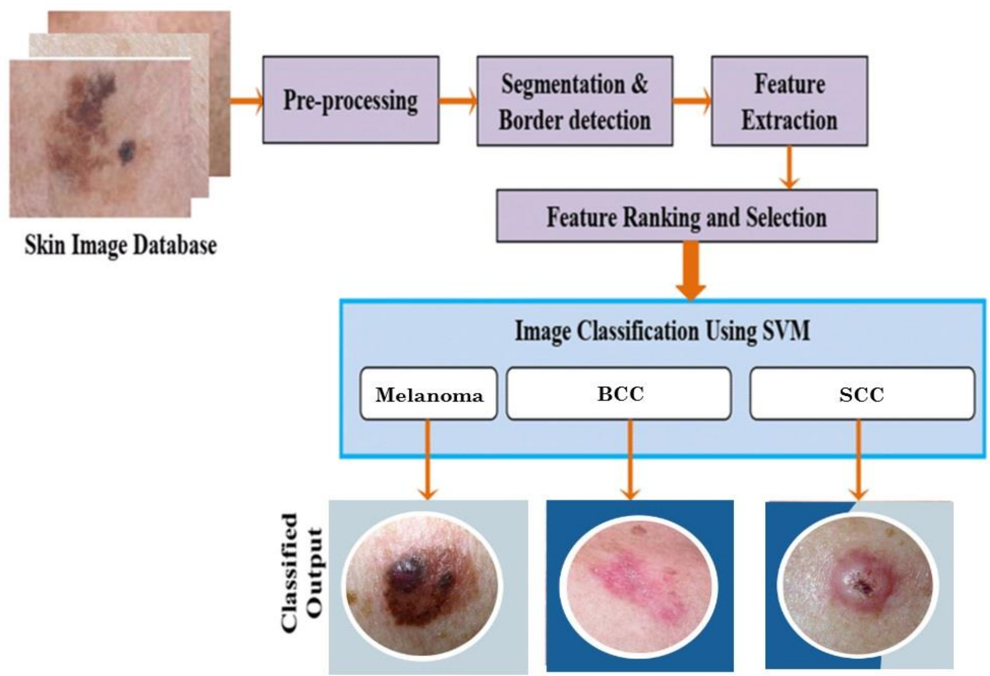

Fig. 3. Block diagram for skin cancer using SVM [17].

Fig. 3 represents a brief workflow to detect skin cancer with SVM[18]. To begin, one must get a substantial dataset consisting of photos and skin lesion information. The method involves multiple preprocessing processes, such as segmentation and border detection, feature extraction, feature ranking and selection ,then image classification using SVM for classify skin cancer[19][20].

2. K-Nearest neighbor

The K-nearest neighbor method is classified as a lazy learning algorithm. This method is considered to be one of the most fundamental and elementary machine learning algorithms that is currently accessible. It is applicable to both classification and regression tasks. It is very responsive to the data provided [21] [22]. This strategy has various benefits, and some have a high ac- curacy, being insensitive to outliers, and make no assumptions about the data. It has several uses and may be used for credit rating, loan management, and stock market predictions. This research focuses on the use of image classification to distinguish between benign and malignant lesion pictures[23].

Fig. 4 depicts a visual representation of the method used to detect and classify skin cancer using the K-Nearest Neighbors (KNN) algorithm[24].

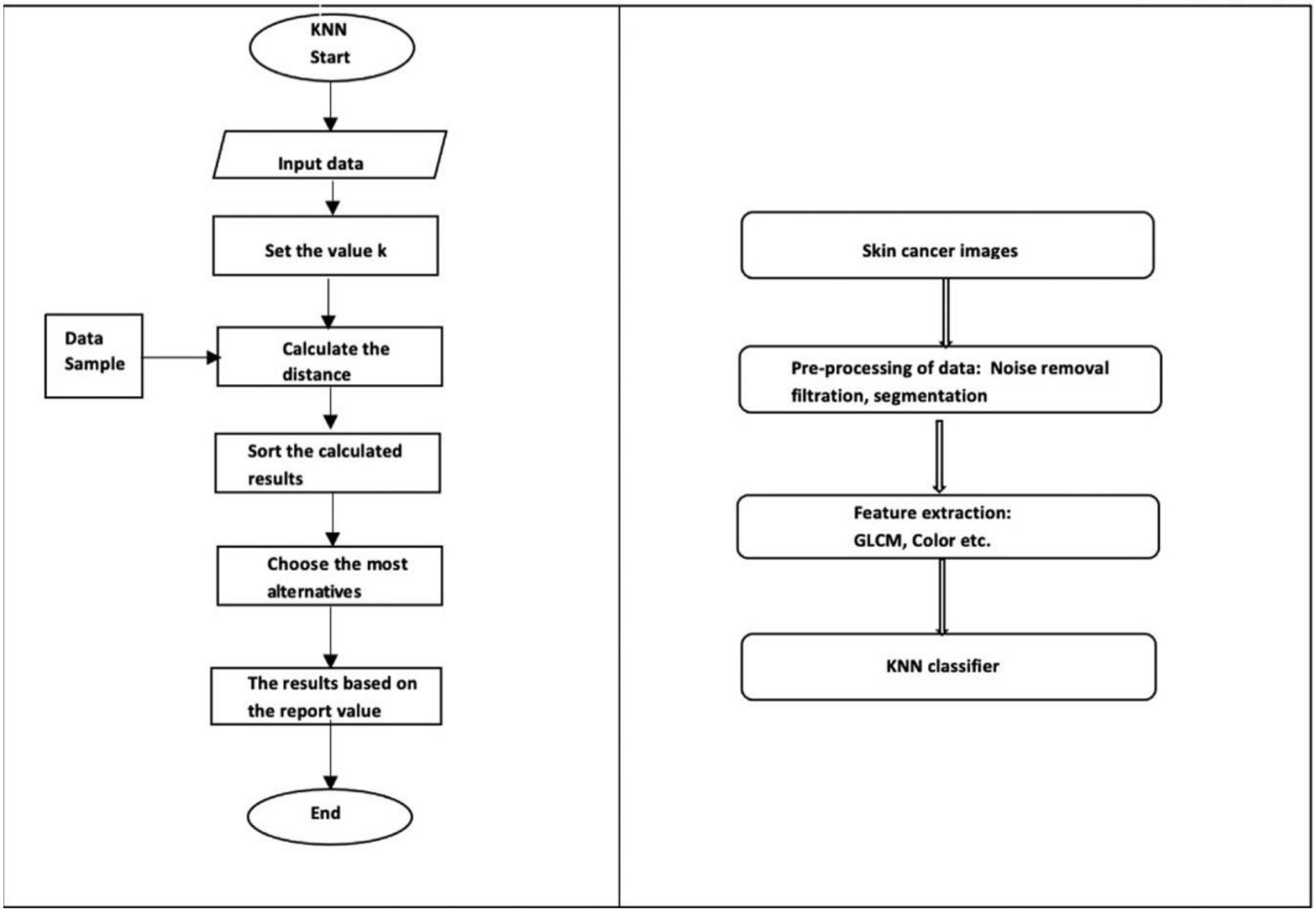

Fig. 4. Block diagram for skin cancer using KNN [25]

The algorithm is as follows: Step 1 Input the testing data, Step 2 Identify the parameter K, Step 3 Calculate the distance between the data that need to be eval- uated with the training set, Step 4 Arrange the distances in ascending order, Step 5 According to the value of 'K', pair it with the given data, Step 6 Assign the datapoint to closest class according to the Euclidean distance. The graphic on the right in Fig. 4 illustrates the whole procedure for detecting skin cancer[25]. The process may be divided into three distinct stages: preprocessing, feature extraction, and classification. The first step of the process is pre-processing, which is the use of an image filtering algorithm to eliminate any unwanted noise or artifacts. Next, we need to extract the features, namely the Gray-Level Co-occurrence Matrix (GLCM) and color features. During the last phase, a classifier is used to ascertain if the picture is benign or malignant. The classifier used in this portion of the study is the k-nearest neighbor algorithm[26]. The classifier is provided with skin cancer photos as input. This graphic depicts a broad sequence of events. Nevertheless, several investigations and experiments use distinct algorithms and approaches for pre-processing and feature extraction.

3. *Convolution neural network*

Convolutional Neural Network (CNN) is a kind of artificial neural network that use deep learning techniques to evaluate and process visual image-based data. CNNs, like artificial neural networks, acquire knowledge about the characteristics of the training set in order to distinguish between the various categories of the test set via the processes of feedforward and backpropagation[27],[28]. Convolutional Neural Networks (CNNs) exhibit higher performance in comparison to standard machine learning approaches, but they also need more processing resources. Convolutional Neural Networks (CNNs) typically have three kinds of layers: a convolutional layer, a pooling layer, and a fully connected layer. These layers are usually arranged in the order mentioned. As the number of layers increases, the network becomes more complicated and its ability to identify patterns also increases[29].

CNNs are mostly used in applications that rely on visual information. Disciplines that include the analysis of pictures, such as fingerprints, tumor cells, floral species, duplicate product identification, and facial recognition, use Convolutional Neural Networks (CNN) to analyze static images. CNNs are used in video processing to decompose the movie into frames, generating separate pictures. This utilization is mostly seen in real-time applications, particularly in the context of autonomous vehicles[30]. CNNs also make significant contributions to historical disciplines. If there is enough data, CNNs may be used to categorize historical writings, artifacts, and collections. CNNs are used for comprehending the environment and mitigating its profound fluctuations[31]. Convolutional neural networks (CNNs) are also used in applications related to voice processing.

Deep neural networks (DNN), convolutional neural networks (CNN), long- and short-term memory (LSTM), and recurrent neural networks (RNN) are the predominant deep learning architectures used in clinical medicine to identify cancer cells[32]. These models have also been used successfully in the classification of skin cancer, as show in Fig. 5.

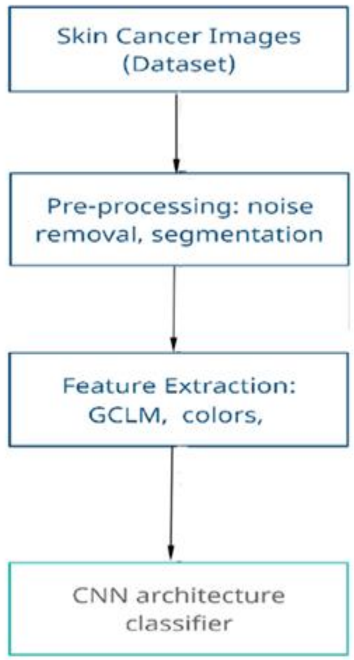

Fig. 5. Block diagram showing skin cancer classification using CNN [25]

Lesions may be classified via computer processing based on the properties of the picture. This approach use techniques like as morphological modifications and filtering to analyze the data obtained from different dermatoscopic pictures inputted into the application. Deep learning is used to detect unknown patterns within the training dataset. Machine learning has the potential to enhance dermatological treatment by increasing the probability of improving it, from the first diagnosis to tailoring therapy to individual patients [33]. The use of sentient intelligence machine learning algorithms in dermatology has been driven by recent advancements in accessing big datasets, such as electronic medical records and image databases, as well as quicker processing and more affordable data storage.

TABLE 1. SUMMARY OF MACHINE LEARNING ALGORITHMS

Algorithm	Accuracy	Strengths	Weaknesses
SVM	90-95%	Effective in high-dimensional spaces, robust to overfitting	Not suitable for large datasets, computationally intensive
KNN	85-90%	Easy to implement, no training phase	Sensitive to noise, high computational cost
CNN	95-98%	High accuracy, automatic feature extraction	Requires large datasets, computationally expensive

IV. DATASETS FOR SKIN CANCER CLASSIFICATION

Several publicly available datasets have been curated for training, validating, and benchmarking machine learning algorithms in the task of skin cancer classification. These datasets contain annotated images of skin lesions, along with corresponding clinical metadata and histopathological diagnoses[34]. Here are some commonly used datasets in the field of skin cancer classification .International Skin Imaging Collaboration (ISIC) Archive[35]. Is one of the largest repositories of dermatoscopic images, containing high-quality images of skin lesions captured using various imaging devices.

The dataset includes images of different types of skin lesions, such as melanoma, nevi, basal cell carcinoma, and squamous cell carcinoma. Annotations provided with the images include lesion type, patient demographics, and diagnostic labels from dermatologists. The ISIC Challenge datasets, released annually, provide standardized benchmarks for evaluating the performance of skin cancer classification algorithms. The HAM10000 (Human Against Machine with 10,000 training images) dataset consists of high-resolution images of skin lesions obtained from a dermatology clinic in Australia. The dataset contains images of melanocytic and non-melanocytic lesions, including melanoma, nevi, seborrheic keratosis, and basal cell carcinoma. Each image in the dataset is annotated with lesion type, histopathological diagnosis, and additional clinical metadata. HAM10000 is widely used for benchmarking machine learning algorithms in melanoma classification and lesion segmentation tasks [36]. The PH2 dataset comprises dermoscopic images of common pigmented skin lesions, including melanoma, nevi, and seborrheic keratosis. The dataset includes images acquired under standardized imaging conditions, along with manual annotations of lesion borders and histopathological diagnoses[37]. PH2 is frequently used for evaluating segmentation algorithms, as well as for training and testing machine learning classifiers for melanoma detection.

V. Limitations of Machine Learning for Skin Cancer Diagnosis

Despite their potential, machine learning algorithms face several limitations in the context of skin cancer diagnosis:

- **Class Imbalance:** Skin cancer datasets often have a higher number of benign samples compared to malignant ones, leading to class imbalance. This can result in biased models that perform well on the majority class but poorly on the minority class.
- **Interpretability:** Deep learning models, such as CNNs, are often considered "black boxes" because their decision-making processes are not easily interpretable. This lack of transparency can hinder their acceptance in clinical settings, where understanding the reasoning behind a diagnosis is crucial.
- **Regulatory Approval:** Before ML models can be implemented in clinical practice, they must undergo rigorous validation and obtain regulatory approval. This process ensures that the models meet the required standards for safety and efficacy but can be time-consuming and complex[38].

VI. Challenges in Translating Research to Clinical Practice

Implementing machine learning research findings into clinical practice presents several challenges:

- **Integration with Medical Workflows:** Incorporating ML tools into existing medical workflows can be complex, requiring adjustments to current practices and systems.
- **Data Privacy and Security:** Ensuring the privacy and security of patient data is paramount. ML models must comply with data protection regulations, which can complicate their deployment.
- **Regulatory Approvals:** Machine learning models must undergo extensive validation to comply with medical standards and regulations. This process can be lengthy and requires thorough documentation and testing.
- **Training Healthcare Professionals:** Clinicians need training to effectively use ML technologies. This involves not only understanding how to use the tools but also interpreting their outputs correctly[39].

VII. Ethical Considerations in Using Machine Learning for Skin Cancer Diagnosis

The use of ML in healthcare raises several ethical considerations that must be addressed to ensure patient safety and trust:

- **Patient Consent**
  Patients should be fully informed about how their data will be used and must provide consent. Transparent communication about the role of ML in their diagnosis is essential.
- **Data Privacy**
  Protecting patient data from unauthorized access and breaches is critical. Compliance with regulations such as GDPR and HIPAA is necessary to safeguard privacy.
- **Algorithmic Fairness**
  ML models must be designed and tested to avoid biases that could lead to unfair treatment of certain patient groups. Ensuring fairness and equity in ML algorithms is vital for ethical healthcare delivery[40].

VIII. Critical Analysis of Cited Studies

A critical analysis of the cited studies reveals the following:

- Study by V. Ma and M. V. Karki: This study reported high accuracy (97.8%) in melanoma detection. However, the dataset size and diversity may be limited, affecting the generalizability of the results. The use of specific feature extraction techniques, like the ABCD rule and GLCM, may not be robust across different imaging conditions.
- Study by T. F. Esener: While the study shows promising results, the methodology's reliance on certain pre-processing steps could introduce bias, limiting the model's applicability to different datasets.

IX. Leatriture review

A multitude of researchers have conducted studies in the domain of skin cancer. They used a diverse array of ML methods, such as SVM, KNN,CNN, and other. Below are few articles that have addressed this topic.

V. Ma and M. V. Karki [41] focused on the detection of skin cancer using machine learning techniques, specifically for the early detection of malignant melanoma, a dangerous type of skin cancer. The proposed algorithm applies feature extraction techniques such as the ABCD rule, GLCM, and HOG to improve accuracy and efficiency in detecting skin lesions. Pre-processing techniques are used to enhance the quality and clarity of skin lesion images, reducing artifacts, skin color, and hair. Segmentation is performed using the Geodesic Active Contour (GAC) method to separate the lesion part for further feature extraction. Features such as symmetry, border, color, and diameter are extracted using the ABCD scoring method, while HOG and GLCM are used for textural feature extraction. The extracted features are then passed to different machine learning classifiers, including SVM, KNN, and Naive Bayes, to classify skin lesions as benign or melanoma. The classification results obtained in this project show high accuracy (97.8%).

Gomathi, E. *et al.* [42] Presented a new dual optimization based deep-learning network (DODL net) for the purpose of detecting skin-cancer. The network was trained using dermoscopic pictures from the MNIST HAM10000 data-set. The DODL net employs a hybrid-approach, com-bining Bacterial Foraging Optimisation (BFO) and Particle Swarm Optimisation (PSO) algorithms, to extract features from the seg-mented pictures. The DODL net's performance is assessed by measuring particular metrics like precision, recall, F1 score, and accuracy. The proposed DODL net achieves an accuracy of 97.76% when applied to the MNIST HAM10000 dataset.

Hemalatha D. *et al.* [43] The symmetry, color, size, and form of a lesion are utilized to differentiate between benign and malignant skin cancer. Automated systems, particularly those based on deep learning techniques, are thought to help in early diagnosis, particularly when a batch of photographs has a wide range of diagnoses. comprises three stages: data collection and augmentation, model creation, and prediction. Image processing technologies are used in combination with the Inception V3 approach to enhance structure and accuracy to 84%.

Balaji Chaugule *et al.* [44] Machine learning and image processing methods were utilized to identify and classify several forms of skin cancer. The Dull razor technique and Gaussian filter are used to remove undesirable hair particles and smooth the dermoscopic pictures during the pre-processing step. The median filter is used to filter noise while still maintaining lesion edges. Color-based k-means clustering is used for segmentation since color is an essential factor in determining cancer kind. Asymmetry, Border, Color, Diameter (ABCD), and Grey Level Co-occurrence Matrix (GLCM) are used to extract statistical and textural features. On the ISIC 2019 Challenge dataset, the classification is performed using Multi-class Support Vector Machine (MSVM) with an accuracy of 96.25%.

Maad M. Mijwil [45] focused on the classification of skin cancer images using a deep learning network trained on over 24,000 skin cancer images. here architectures, namely InceptionV3, ResNet, and VGG19, were tested, and InceptionV3 was found to be the best architecture with a diagnostic accuracy of approximately 86.90%. The dataset used in the study consists of high-resolution images obtained from the ISIC archive between 2019 and 2020 .

Javaid A. *et al.* [46] Explored the use of image-processing and machine-learning techniques for the classification and segmentation of skin cancer. The proposed approach introduces an innovative-technique for enhancing the contrast of dermos-copic pictures. This technique is based on calculating the mean values and standard-deviation of pixels, and then using the OTSU thresholding-algorithm to segment the image. The seg-mented pictures are used to extract features such as Grey level Co-occurrence Matrix (GLCM) features for texture identification, histogram of oriented-gradients (HOG) object, and color identification features. PCA is used to reduce the dimensionality of HOG features. Synthetic minority oversampling method (SMOTE) is used to mitigate the issue of class imbalance via sampling. A standardized and scaled feature vector is used, and a wrapper-based technique for feature selection is suggested prior to classification. The classification task on the ISIC-ISBI 2016 dataset used classifiers such as Quadratic Discriminant, SVM (Medium Gaussian), and Random Forest. Among these classifiers, the Random Forest achieved the greatest accuracy of 93.89%.

R. Suchithra and K. Vanitha [47] Employed machine-learning and image processing-techniques to categorize skin-cancers. Prior to pre-processing, dermoscopy images are inputted. The picture is smoothed with a Gaussian-filter after removing undesired hair with a blunt razor. The median filter effectively removes noise while preserving the boundaries of lesions. During the seg-mentation process, color-based k-means clustering is used because of the significant role that color plays in predicting malignancy. The statistical and textural parameters are extracted using ABCD and Gray Level Cooccurrence Matrix. The features of interest include asymmetry, border color, and diameter, specifically measured using the GLCM method. The ISIC 2019 Challenge dataset comprises a collection of eight distinct categories of dermoscopic-images. A Multi class Support-Vector Machine (MSVM) was constructed for classification, with an accuracy of 96.25 percent.

Prakash A. J. *et al.* [48] Machine learning and image processing techniques are utilized for identifying and classifying different types of skin cancer using dermoscopy imaging. Pre-processing involves removing unwanted hairs, smoothing the image, reducing noise, and protecting lesion borders. Segmentation is done using color-based k-means clustering, as color is crucial in determining malignancy type. Feature extraction involves using Asymmetric, Boundary, Colour, Diameter (ABCD) and Gray Level Cooccurrence (GLC) matrix for statistical and textural analysis. used the ISIC 2019 dataset with 8 different types of dermoscopy images and achieved a classification accuracy of approximately 96.25% using Multi-class Support Vector Machine (SVM).

S. Likhitha and R. Baska [49] Applied CNN) method to achieve distinct categorization of skin-cancer and assessed the effectiveness of the Support Vector Machine (SVM) approach.

Algorithms such as CNN and SVM have been used to identify skin cancer, and the accuracy of these algorithms has been assessed. Two groups are subjected to statistical analysis, with a sample size of 20 for each group. The pretest g power is set at 80%. Upon evaluating the performance of the CNN algorithm, it is seen that the accuracy rate is 95.03%, but for the SVM method, it is 93.04%. The sample size will be calculated-based on the mean, standard-deviation, and standard-error, along with the indepen-dent samples test if the significance level is below one. Based on the statistical-data, the algorithm's accuracy is 0.490, specificity is 0.009, and the p-value is greater than 0.05, indicating that none of these results are statistically significant at the 0.05 level. The result indicates that the accuracy of the CNN algorithm surpassed that of the SVM algorithm in detecting skin cancer.

Saba T. *et al.* [50] Various computer-based solutions have been developed during the past two decades to solve melanoma segmentation and identification issues. suggested a novel automated technique for skin lesion identification and recognition using a deep convolutional neural network (DCNN) and finds that the proposed method surpasses numerous current approaches, achieving accuracy of 98.4% on the PH2 dataset, 95.1% on the ISBI dataset, and 94.8% on the ISBI 2017 dataset.

M. A. Ahmed Thaajwer and U. A. Piumi Ishanka [51] Image processing methods and Support Vector Machine (SVM) algorithms were used to develop a computer-aided detection system for early diagnosis of melanoma. Before applying morphological and thresholding approaches to segment the afflicted skin picture, multiple pre-processing procedures were used to improve and smooth it. The texture, color, and form properties of the skin photos are retrieved using the Grey Level Co-occurrence Matrix (GLCM) approach. The retrieved GLCM, color, and shape characteristics are then fed into the SVM classifier, which determines if the picture is malignant or benign melanoma. The classifier's accuracy is 83% when form, color, and GLCM characteristics are combined and applied.

Chendage, B. *et al.* [52] focused on the detection and classification of melanoma skin cancer using image processing techniques. involved four significant stages: pre-processing, segmentation, feature extraction, and classification. Pre-processing methods are used to enhance the images, followed by segmentation using thresholding to separate the cancer region. Statistical features are then extracted from the segmented region, and the K-Nearest Neighbor (KNN) classifier is used for classification. The accuracy of the KNN classifier in this research work is reported to be 93.4%.

P. Kavitha, V. Jayalakshmi, and S. Kamalakkannan [53] Proposed a sophisticated approach for identifying cancer and benign cells via the use of image processing methodologies. The Median Filter is first used to mitigate artifacts, skin color, hair, and other attributes of the generated pictures by eliminating noise from the skin lesion. The lesion portion is segmented separately using the Hybrid Partial Differential Equation with Fuzzy Clustering (HPDE-FC) approach, which is useful for feature extraction. The ABCD scoring technique is used to extract the features of asymmetry, border, color, and diameter. The obtained characteristics are promptly inputted into classifiers, such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), Random Forest (RF), and Nave Bayes (NB), to classify skin lesions as either cancerous (malignant) or non-cancerous (melanoma). Downloaded from the International Skin Imaging Collaboration (ISIC) are 325 photographs of normal skin lesions and 572 photos of malignant skin lesions. Achieving a classification accuracy of 97.7% is possible by using SVM classifiers.

A. Gautam and B. Raman [54] Visual techniques and biopsies are often employed to diagnose melanoma, however their accuracy varies. For melanoma classification, feature extraction approaches such as local binary pattern (LBP) and complete LBP (CLBP) have been used. For classification, many classifiers such as decision tree, random forest (RF), support vector machine (SVM), and k closest neighbor (kNN) have been employed. The accuracy of several feature descriptors and classifiers for recognizing and categorizing melanoma as benign or malignant was investigated. The study's dataset comprises of 947 dermoscopic pictures taken from the ISIC-Archive. The study's greatest accuracy was 80.3% while employing RF in CLBP.

K. Zaman and S. S. Maghdid [55] The researchers investigated the application of convolutional neural network (CNN) algorithms for categorizing skin cancer images based on kind, including Dermatofibromas (DF), Melanocytic Nevus (NV), Pigmented Benign Keratosis (BKL), and Vascular Lesion (VESC).The importance of using intelligent machines and deep learning algorithms in the field of cancer diseases for accurate identification and recognition of skin cancer images, leading to early detection and improved diagnosis outcomes, with CNN algorithms achieving 92.89 percent accuracy in classifying skin cancer images.

Karpagam, N. S. *et al.* [56] focused on differentiating and detecting nevus and melanoma skin diseases using image processing techniques. It employed a Gaussian filter to remove noise from skin images and utilizes SVM for classification, achieving a high accuracy of 97%, highlighted the challenges of diagnosing melanoma early due to its high mortality rate and the ease with which it spreads to healthy body parts. By evaluated the efficiency of the proposed technique and comparing results with other methods.

Mridha, K. *et al.* [57] The objective was to create accurate deep learning (DL) prediction models for classifying skin cancer. Two challenges were addressed: (i) handling a significant class imbalance problem, where the number of skin-affected patients is much smaller than the healthy class, and (ii) interpreting the model output to gain insights into the decision-making process. (iii) Suggest the development of a comprehensive healthcare system that encompasses all stages and aspects, using an android application. The usefulness of the proposed deep learning approach was investigated by comparing it with six well recognized classifiers. The evaluation focused on measures that measure both the capacity to generalize and the accuracy of classification. A research used the HAM10000 dataset and a fine-tuned Convolutional Neural Network (CNN) to accurately detect and classify the seven different types of skin cancer. The model underwent training utilizing two optimization algorithms (Adam and RMS-prop) and three activation-functions (Relu, Swish, and Tanh). In addition, a skin-lesion categorization-system was-created using XAI (Explainable Artificial Intelligence) techniques, specifically including Grad-CAM and Grad-CAM++ to provide explanations for the judgments made by the model. This technology aids clinicians in making accurate diagnosis of skin cancer in its early stages, achieving an 82% classification accuracy and a 0.47% loss accuracy.

R. Deva and G. Narsimha [58] The researchers conducted experiments using a diverse set of standard machine learning algorithms, which were combined through the stacking process. They collected data from web sources using various tools that could comprehend the logic of the pages and extract relevant information for the user. The researchers have reported using many classification algorithms on the acquired data. They have found that the stacked ensemble framework, consisting of a decision tree (DT) classifier and k-nearest neighbors (KNN), achieved a high performance of 95.8%. The proposed model is an automated system capable of actively retrieving data and executing different operations on it. Current methods include either researchers implementing single classification algorithms to analyze the data, or a few using ensemble processes without eliminating unnecessary data. The optimized stacking algorithm not only enhances performance but also facilitates informed decision-making during diagnosis due to its reliance on data-dependent methods.

Arora, G. *et al.* [59] The objective is to create computer-aided detection and diagnostic systems that can accurately categorize a lesion as either cancerous or non-cancerous by using a precise approach for extracting relevant features. Suggested combining the bag-of-feature approach with speeded up robust features for feature extraction, and use a quadratic support vector machine for classification. The suggested technique demonstrated an accuracy of 85.7%, a sensitivity of 100%, a specificity of 60%, and a training time of 0.8507 seconds in the classification of the lesion. The outcome and analysis of tests conducted using the PH2 dataset of skin cancer. Our technique achieved a higher performance accuracy, surpassing other state-of-the-art methods by an increase of 3%.

D. Keerthana, V. Venugopal [60] introduced two innovative hybrid CNN models that include an SVM classifier at the output-layer. These models are designed to accurately categorize dermoscopy pictures as either benign or malignant lesions. The collected characteristics from the first-second CNN models are combined and inputted into the SVM classifier for classification. The labels derived by a proficient-dermatologist are used as a benchmark to assess the effectiveness of the suggested model. The suggested models exhibited superior performance-compared to the state-of-the-art CNN models on the publicly accessible ISBI 2016 data-set. The suggested models attained an accuracy of 88.02% and 87.43%, surpassing the accuracy of typical CNN models.

TABLE 2. COMPARISON OF EXISTING TECHNIQUES/METHODS FOR THE SKIN CANCER USING MACHINE LEARNING ALGORITHM

Ref.	Year	Key Features/Focus	Methods/ Techniques	Dataset	Achieved Results
[42]	2023	Skin cancer detection using deep learning (DODL net) with dual optimization	(DODL net)	MNIST HAM10000	98.76%
[43]	2023	Investigation of DLT for skin cancer early detection	Inception V3	ISIC 2019 Challenge dataset	84%
[56]	2023	Image processing, Gaussian filter, SVM, Differentiating nevus and melanoma	SVM	ISIC	97%
[57]	2023	DL prediction models, CNN, XAI, Skin cancer classification	Deep Learning	HAM10000	82%
[60]	2023	Hybrid CNN-SVM models, Dermoscopy image classification	CNN, SVM	ISBI 2016	88.02%, 87.43%
[47]	2022	Skin Cancer prediction using Machine Learning	classification (MSVM)	ISIC 2019 Challenge	96.25%
[48]	2022	Early detection using ResNet-101 and Inception-v3	ResNet-101, Inception-v3	2437 Training, 660 Test, 200 Validation Images	84.09% (ResNet), 87.42% (Inception-v3)
[49]	2022	Melanoma diagnosis using segmentation and classifiers	SVM	ISIC, 1000 samples	89.43% (SVM)
[53]	2022	detecting malignant and non-cancerous cells	SVM, KNN, Random Forest, Naive Bayes	ISIC	97.7%
[59]	2022	Feature extraction (BoF, SURF), SVM classifier, Lesion classification	SVM	PH2 dataset	85.7%
[45]	2021	Classification of skin cancer images using deep learning networks	InceptionV3, ResNet, VGG19	ISIC archive (2019-2020)	~86.90%
[46]	2021	Skin cancer classification using image processing & ML	Quadratic Discriminant, SVM (Medium Gaussian), Random Forest	ISBI 2016 dataset	93.89%
[52]	2021	Melanoma detection using image processing	K-Nearest Neighbor (KNN)	ISIC,20,000 Samples	93.4%
[55]	2021	Skin cancer image classification using CNN algorithms	Convolutional Neural Network (CNN)	ISIC, 21,000 images	92.89%

[58]	2021	Stacked ensemble framework, Data gathering, DT classifier	KNN	ISIC	95.8%
[41]	2020	detection of skin cancer using machine learning techniques	SVM, KNN, and Naive Bayes	ISIC, 1000 samples	97.8%
[44]	2020	Detection and classification using ML & image processing tools	Multi-class Support Vector Machine (MSVM)	ISIC 2019 Challenge dataset	96.25%
[50]	2020	Skin lesion detection using DCNN	(DCNN)	PH2 dataset, ISBI dataset, ISBI 2017 dataset	98.4% (PH2), 95.1% (ISBI), 94.8% (ISBI 2017)
[51]	2020	Computer-aided detection system using image processing and SVM	Support Vector Machine (SVM)	ISIC,23,000 images	83%
[54]	2020	Melanoma classification using feature descriptors and classifiers	Random Forest (RF)	ISIC-Archive	80.3%

X. Discussion

The review of machine learning classification algorithms for skin cancer provides a comprehensive comprehension of the current condition of the field. Several studies have utilized algorithms such as Support Vector Machine (SVM), K-Nearest Neighbour (KNN), Naive Bayes, deep learning networks like Inception V3 and ResNet, CNN, and hybrid models that combine Convolutional Neural Networks (CNN) with SVM. These studies have shown high levels of accuracy, ranging from around 80% to almost 99%. The results emphasize the effectiveness of machine learning techniques in precisely recognizing and categorizing skin cancer lesions. A key finding is the efficiency of methods such as region extraction and classification utilizing deep CNN feature fusion. These techniques consistently obtained excellent accuracy rates on various datasets, demonstrating their strength and potential for use in clinical settings. Nevertheless, the presence of many methods and datasets presents certain difficulties, such as the need for larger and more diversified datasets to enhance the overall performance of models and mitigate inherent biases. Since these findings indicate potential for use in clinical settings, such as aiding in early identification and providing decision support for dermatologists, it is important to acknowledge the constraints and restrictions. The existing findings may not comprehensively encompass the intricacies of actual clinical situations; therefore, it is crucial to conduct further verification in genuine clinical environments. Furthermore, the evaluation of regulatory and ethical factors, together with the comprehensibility of deep learning models, continue to be of utmost importance. Future research should focus on the integration of domain knowledge, utilization of explainable AI approaches for model interpretability, and the creation of resilient ensemble or hybrid models to improve the accuracy and dependability of skin cancer diagnosis. Effective bridging of the gap between research findings and clinical applications will require collaborations among machine learning experts, dermatologists, and healthcare professionals.

XI. Future Directions for Research

Future research should focus on:

- **Developing Interpretable Models**: Creating models that clinicians can easily understand and trust.
- **Addressing Class Imbalance**: Using advanced data augmentation techniques to balance the datasets.
- **Improving Robustness**: Ensuring models perform well across different imaging modalities and patient demographics.
- **Integrating Genomic and Clinical Data**: Providing a more comprehensive approach to diagnosis and personalized treatment.
- **Collaboration**: Encouraging collaborative efforts between researchers, clinicians, and regulatory bodies to facilitate the translation of ML technologies into clinical practice.

XII. Conclusion

The machine learning algorithms in skin cancer classification holds great promise for improving diagnostic accuracy, facilitating early detection, and enhancing patient outcomes. Through the integration of clinical data and imaging modalities, machine learning models can leverage diverse sources of information to make more informed and reliable diagnostic decisions. However, several challenges, including data imbalance, interpretability, generalization, and clinical integration, must be addressed to ensure the clinical utility and adoption of these algorithms in real-world healthcare settings. Despite these challenges, there are numerous opportunities for future research and development in the field of skin cancer classification using machine learning. By leveraging multi-modal fusion, explainable AI, transfer learning, personalized medicine, and privacy-preserving techniques, researchers can overcome existing limitations and unlock new possibilities for personalized risk assessment, treatment planning, and patient care. Ultimately, the successful implementation of machine learning algorithms in skin cancer diagnosis requires interdisciplinary collaboration between computer scientists, clinicians, dermatologists, pathologists, and regulatory agencies. By working together, we can harness the power of artificial intelligence to revolutionize skin cancer diagnosis, improve healthcare delivery, and save lives.

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