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A Comprehensive Study on Machine Learning and Deep Learning Models for Skin Cancer Detection

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Abstract
Lesions, which can be benign or malignant, are abnormal tissue areas that occur on the skin or within internal organs. Malignant lesions, including types of skin cancer like Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), and Melanoma (MM), pose significant health risks and necessitate early detection and treatment. Machine learning (ML) and deep learning (DL) algorithms have become crucial tools for identifying and diagnosing skin cancer. This paper discusses the various forms of skin cancer, the application of ML algorithms such as LSTM, ARIMA, SVM, KNN, and Decision Trees in skin cancer detection, and the role of DL methods like CNN, transfer learning, and reinforcement learning in improving diagnostic accuracy. Through a literature survey, we explore recent advancements in skin cancer detection using ML and DL technologies, this research highlights the potential of integrating ML and DL into routine dermatological practice, offering a powerful tool for enhancing diagnostic accuracy, reducing the rate of unnecessary biopsies, and ultimately improving patient outcomes. Future work will aim to address the challenges, refine model performance, and enhance practical applicability in clinical environments.

Keywords: *Lesion, skin cancer, detection, early, ML, DL, dermoscopic images*

1. Introduction

Lesion is an abnormal area of tissue or skin which has undergone some form of damage or disease. Lesions can be in various ways, including spots, bumps, sores, or other irregularities. These abnormalities can occur on the skin or within other organs, like brain, lungs, liver. The appearance and characteristics of lesions can vary widely depending on their type, location, and underlying cause.

Lesions can be categorized as either malignant or benign. Benign lesions are often not a major health risk as they are not malignant. They may require treatment if they cause discomfort or aesthetic concerns, but they won't spread to other body parts. Examples of benign lesions include moles, warts, and benign tumors like lipomas.

Malignant lesions, on the other hand, are cancerous and can be life-threatening. There is a chance that these lesions will infiltrate surrounding tissues and spread to other areas of the body. Early detection and diagnosis were crucial for malignant lesions to prevent the spread of cancer and improve the prognosis. Common examples of malignant lesions include SCC, BCC and MM.

The diagnosis and treatment of lesions often involves a combination of clinical examination, imaging studies, and sometimes biopsy or other laboratory tests. Depending on the kind, location, and severity of the lesion, there are a variety of treatment options available, like radiation therapy, chemotherapy, topical medicines, and surgical removal.

1.1 Skin cancer

Skin Cancer is indeed a serious and common type of skin lesion. Detailed information about the different forms of skin cancer and related diagnostic advancements are as follows:

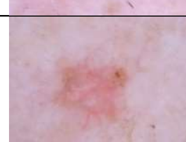
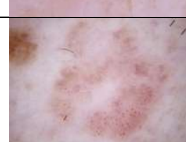
1.1.1 Forms of Skin Cancer

Skin cancer can manifest in several forms, each with distinct characteristics and treatment approaches. The three most common types (Table1) are:

1.1.1.1 Basal Cell Carcinoma (BCC)

- *Development:* BCC develops from the basal cells at the bottom of the epidermis, often in areas exposed to sunlight for prolonged periods. The cumulative effects of UV exposure damage the DNA in these cells, leading to cancerous growths.
- *Appearance:* It typically appears as a small, shiny, smooth, waxy, or pale lump. It may also present as red patches with rough, dry, or scaly regions. Sometimes, BCC can ulcerate or bleed.
- *Growth Rate:* BCC has a moderate growth rate, making it relatively easier to diagnose and treat if caught early. However, if left untreated, it can cause significant local damage, eroding skin, tissue, and bone.

Table 1. summarizing the initial, mid, and late stages of MM, SCC and BCC:

Type of Skin Cancer	Stage	Sample Image	Description
BCC	Initial		Small, shiny bump or nodule, often pearly or translucent.
	Mid		The lesion grows larger, may develop a central depression or ulceration.
	Late		Pronounced lesion with visible ulceration and potential local tissue destruction.
SCC	Initial		Small, firm red nodule or a flat sore with a scaly crust.
	Mid		Lesion enlarges, surface becomes more irregular and crusted.
	Late		Significant growth with potential ulceration and invasion into deeper skin layers.
MM	Initial		Mole that changes in color, size, or feel; irregular edges and varying colors.

	Mid		Lesion becomes larger, more irregular in shape and color; increased risk of spreading to lymph nodes.
	Late		Advanced melanoma with significant changes in size, color, and shape; potential metastasis to other parts of the body.

1.1.1.2 Squamous Cell Carcinoma (SCC)

- *Development:* SCC begins in squamous cells in the top layer of the skin. These cells are flat and scale-like, and SCC occurs due to cumulative UV exposure and damage, which causes DNA mutations.
- *Spread:* Unlike BCC, SCC can spread to other parts of the skin and metastasize to other organs at an early stage. This ability to spread makes SCC more dangerous if not treated promptly.
- *Appearance:* SCC manifests as small, smooth lumps that may be red, scaly, and crusted. They can also present as sores that do not heal or as thickened, rough patches.

1.1.1.3 Melanoma (MM)

- *Development:* The most deadly type of skin cancer, known as MM, begins in the melanocytes, which are the cells that produce pigment (melanin). UV radiation causes DNA damage in these cells, leading to uncontrolled growth and cancer.
- *Appearance:* It is characterized by asymmetrical shape, uneven borders, and various colors (brown, black, red, blue, or white). MM can develop in or next to an old mole or show up as a fresh dark patch on the skin [1-3].

2. Machine Learning Algorithms in Detection of skin cancer

Machine Learning algorithms like LSTM, ARIMA, Linear Regression, Decision trees, SVM, KNN are used for skin cancer detection, more detailed information is shown below and overview in Table2.

2.1 Long Short-Term Memory (LSTM)

Recurrent neural networks (RNNs) of a particular kind called LSTM networks were created in response to the limitations of conventional RNN in terms of long-term dependency. LSTMs achieve this through a sophisticated architecture comprising memory cells and gates. An LSTM cell has 3 distinct gates: input, forget and output gates. Forget gate discards irrelevant information from cell state, input gate update, cell state with new information, and output gate retrieves useful data from cell state for the current output. Because of its structure, long-term relationships may be captured by LSTMs, which makes them useful for applications like speech recognition, natural language processing, and time series prediction [4].

2.2 Autoregressive Integrated Moving Average (ARIMA)

ARIMA are extensively utilized in time series analysis and forecasting across various industries. ARIMA(p, d, q) is the notation for the ARIMA model, in which 'q' number of moving average sections. 'd' number of differences required to render time series stationary, 'p' number of autoregressive term's, and ARIMA models are powerful tools to capture temporal dependencies in data, makes them ideal for demand forecasting, financial market analysis, and other applications involving time series data [5].

2.3 Linear Regression

A basic statistical technique for simulating and examining the connection between one/more independent and dependent variable is called linear regression (LR). In data analysis and predictive modeling, it is frequently used to ascertain the linear connection between variables. There are two forms of LR: multiple linear regression (MLR) and simple linear regression (SLR). Whereas MLR uses several independent variables, SLR just uses one. Through the process of adapting linear equation to observed data, both types seek to forecast the value of a numerical dependent variable [7].

2.4 Decision Trees

Decision Tree (DT) algorithms are prevalent in various fields, like pattern recognition, machine learning, image processing. DT is the hierarchical model comprising leaf, branch and root nodes. A feature test is represented by each internal node, in which a numerical characteristic is contrasted with a threshold value. The results of these tests are represented by branches, and the ultimate categorization is shown by leaf nodes. DT aims to partition data recursively according to the most significant features, leading to a clear and interpretable structure that facilitates decision-making [6,7].

2.5 K-Nearest Neighbors (KNN)

KNN is a popular machine learning technique that is very successful for classification jobs. Unlabeled observations are categorized by KNN by placing them in same class as the most comparable labeled ones. KNN works by identifying 'K' closest labelled data point (neighbors) to the given unlabelled point and determining its class based according to majority class among these neighbors. The value of 'K', chosen by the user, significantly influences the algorithm's performance. It is crucial to select an appropriate 'K' to balance the bias-variance trade-off and ensure accurate classification [8,9,10].

2.6 Support Vector Machine (SVM)

SVM have garnered significant attention within the machine learning community for their robust classification capabilities. SVMs are non-parametric classifiers that excel in identifying the optimal hyperplane to segregate different class's. Distance between hyperplane and closest data points from any class is called margin, and it is this distance that determines ideal hyperplane. Critical data points were referred to as support vectors. By maximizing margin, SVMs enhance accuracy of classification. SVMs are versatile and useful for classification and regression tasks [10].

Table2. overview of the machine learning algorithms' for the identification of skin cancer:

Algorithm	Key Features	Strengths	Weaknesses
SVM	Non-parametric; finds optimal hyperplane; uses support vectors; handles high-dimensional data	Effective for high-dimensional data; good for binary classification; versatile with kernel functions	Can be computationally intensive; Performance may vary depending on parameter and kernel choices.
KNN	Classifies based on 'K' nearest neighbors; non-parametric; lazy learning	Simple and intuitive; no training phase needed	Computationally expensive for large datasets; sensitive to choice of 'K' value
Decision Trees	Hierarchical model; uses feature tests; consists of root, branches, and leaf nodes	It manages both category and numeric data and is simple to visualize and understand.	overfitting; can become complex and unwieldy
Linear Regression	models the basic and numerous versions of a linear connection between independent and dependent variables.	Simple to implement and interpret; good for understanding relationships	Assumes linearity; sensitive to outliers; limited to linear relationships
ARIMA	Time series forecasting;	Effective for short-term	Requires stationary data;

	uses autoregressive, integrated, and moving average components	forecasting; captures temporal dependencies	can be complex to configure parameters
LSTM	Type of RNN; uses memory cells and gates (forget, input, output); retains long-term dependencies	Captures long-term dependencies; effective for sequential data	Computationally intensive; complex architecture

3. Deep Learning (DL) Methods for Skin Cancer Detection

DL techniques have significantly improved skin cancer detection by leveraging advanced algorithms to analyze and classify medical images. These methods include supervised learning, semi-supervised and self-supervised, reinforcement, and ensemble learning, and overview of this models are specified in Table3.

3.1. Supervised Learning

In the supervised learning paradigm of machine learning, models are trained using data that has been labeled. Each data point consists of features and the corresponding label. Algorithms learn the function from input-output pairs, inferring from the labeled training data to predict class labels for new, unseen examples.

- **CNN**: CNN is frequently used to classify images; it automatically extracts relevant details from unprocessed image data to find patterns in skin lesions.
- **Transfer Learning**: This technique involves fine-tuning pre-train models (like ResNet, VGG) on specific skin cancer datasets, leveraging general knowledge for improved performance with less data.
- **Augmentation and Feature Extraction**: Enhancements like data augmentation and feature extraction improve model performance by increasing the diversity of training data and refining feature analysis.

Supervised learning requires extensive computation resources and large labeled datasets for training, with training times ranging from hours-weeks based on dataset size and model complexity. On the other hand, their quick inference times make them appropriate for real-time applications. Training can be resource-intensive, especially on GPUs or TPUs, but inference is much less demanding [11].

3.2. Semi-Supervised Learning

Semi-supervised Learning makes use of significant amounts of unlabeled data in addition to a limited amount of labeled data. This approach helps in scenarios with limited annotated samples by improving model accuracy through both types of data.

3.3. Self-Supervised Learning

Self-supervised Learning involves in generating auxiliary tasks from the data itself to pre-train models. These models are then fine-tuned for specific tasks like skin cancer detection, which enhances performance with minimal labeled data.

By utilizing both unlabeled and labeled data, semi-supervised models have the potential to decrease the requirement for extensive labeled datasets and training time. Mean teacher and Virtual Adversarial Training (VAT) are two techniques that efficiently use unlabeled data to reduce total training time and retain inference efficiency [12,13].

3.4 Reinforcement Learning (RL)

RL trains an agent to maximize rewards according to interactions with an environment. Deep Q-Learning Networks (DQN) are popular models in this area.

- **Deep Q-Learning Networks (DQN)**: These models can be adapted for skin cancer classification, where an agent is trained to classify images and receive rewards based on classification accuracy. For imbalanced data, rewards are designed to be higher for correctly classified minority class samples, guiding the agent to find optimal classification strategies.

Reinforcement learning models are resource-intensive which may require significant time for training. Whereas, once trained, they will make real-time decisions, which is important for game playing and robotics applications [14].

3.5 Ensemble Learning (EL)

EL combines outputs of multiple DL models to improve overall effectiveness. This method is used across various tasks, including skin cancer detection.

- **Bagging**: Trains multiple models concurrently, combining the results by voting or averaging. This technique helps in reducing variance and improving model accuracy.
- **Boosting**: Sequentially trains models where each model corrects errors from the previous ones, focusing on challenging cases.
- **Stacking**: Involves training the meta model on output's of individual models to achieve better predictions.

Ensemble methods include:

- **Negative Correlation-Based Ensembles**: Promote diversity within various networks.
- **Implicit/Explicit Ensembles**: Lessen the amount of training required by simulating ensemble behavior with a single model.
- **Homogeneous and Heterogeneous Ensembles**: Utilize various algorithms, not limited to DL-based models.

'Unweighted model averaging, majority voting, Bayes optimum classifier, layered generalization, super learner, consensus, and query by committee' are some of the fusion rules used to combine model outputs. Unweighted model averaging and majority voting are commonly used, with other rules like average output probability and cubic precision-based weighting also applied.

Ensemble learning improves predictive performance but increases computational load during both training and inference. Despite the higher resource demands, the accuracy and robustness achieved often justify additional computation cost [15].

Table3. summarizes the main DL methods used for skin cancer detection.

Method	Description	Key Techniques	Resource Requirements	Strengths	Examples
Supervised Learning	Models are trained on labeled data	Convolutional Neural Networks	High during training; lower during inference	Accurate prediction, fast	CNNs, VGG, ResNet

	to predict class labels for new examples.	(CNNs), Transfer Learning, Augmentation, Feature Extraction		inference for real-time applications	
Semi-Supervised Learning	Combines a small amount of labeled data with large amount of unlabeled data.	Virtual Adversarial Training (VAT), Mean Teacher	Varies; reduces labeled data requirements and training time	Improves accuracy with limited label data; efficient with unlabeled data	Skin cancer classification with limited annotations
Self-Supervised Learning	Generates auxiliary tasks from data to pre-train models, which are then fine-tuned.	Self-supervised pre-training tasks	Reduces labeled data need, enhances performance with minimal annotations	Enhances model performance with minimal labeled data	Pre-training with auxiliary tasks
Reinforcement Learning	Trains an agent to maximize rewards through interactions with an environment.	Deep Q-Learning Networks (DQN)	Resource-intensive; significant time for training	Effective for optimizing strategies for imbalanced data; real-time decision-making	Classification with reward-based learning
Ensemble Learning	Combines predictions from multiple models to improve overall performance	Bagging, Boosting, Stacking, Negative Correlation-Based Ensembles, Homogeneous and Heterogeneous Ensembles	High during training; efficient during inference	Improves accuracy and robustness; handles diverse model outputs	Majority voting, stacking, boosting

4. Literature survey

In this section, various related works for skin cancer detection using Image processing, machine learning, and deep learning by other researchers are specified below, and overview is specified in Table4 and Table5.

4.1 Deep Learning

[16] used ISIC dataset to study how data augmentation affected InceptionV3 training for binary skin cancer categorization. They used 3 different augmentation strategies: hybrid, online, and offline. Through their studies, they assessed how well InceptionV3 performed using each technique. Offline augmentation achieved an accuracy of 67.42%, while online augmentation reached 90%, highlighting its effectiveness. The combined offline and online approach yielded an accuracy of 88.76%.

[17] proposed an innovative skin cancer binary classification method that leverages ensemble model based on pre-trained convolutional neural networks (CNNs). They combined InceptionV3, VGG16, and EfficientNetB0 models, using the dataset of 2,637 dermoscopy images from ISIC. To mitigate overfitting and enhance generalization, they applied data augmentation techniques. Ensemble method, which used EfficientNetB0, VGG16, InceptionV3, obtained 91.19% accuracy in identifying instances malignant and benign. In contrast, individual models reached accuracy 89.85% (InceptionV3), 89.55% (VGG16), and 90.87% (EfficientNetB0), demonstrating the ensemble's superior performance, particularly the combination of EfficientNetB0, VGG16, InceptionV3, for accurate diagnosis of skin cancer.

[18] created a brand-new adversarial technique which produces fresh adversarial instances by using loss gradients in regard to input images. Classification algorithms are then trained and assessed using these artificial images. Using pre-trained models such as ResNet101, DenseNet121, VGG19, VGG16, their study examined the efficacy of training with/without this adversarial method. The outcomes showed that ResNet101 attained an 84.77% accuracy for MM classification when trained using the adversarial strategy.

[19] used deep learning to create an automated system for MM identification. Standard databases for skin lesion including ISIC-2020, Med-Node, PH2 were used by their system, which also included significant pre-processing to enhance the visual quality. For binary classification, the approach employed an ensemble of Inception-V3 and ResNet50 models together with semantic segmentation using FCN-8. On enhanced dermoscopy images, the findings showed remarkable efficiency, with 93.4% segmentation accuracy and 94% classification accuracy.

[20] investigated the efficacy of deep characteristics taken from 8 modern CNN models for the identification of MM. Their research also investigated normalization and boundary localization. Evaluating their methods on several datasets, like HAM10000, ISIC 2017, ISIC 2016, PH2, they found that combining DenseNet-121 and Multi-Layer Perceptron (MLP) achieved exceptional accuracy 81%, 81.16%, 80.47%, 98.33%, respectively. This combination surpassed the performance of various CNNs and exceeded some traditional techniques.

In [21] developed a new system to classify MM images as malignant/benign using transfer learning and deep learning. They utilized MobileNetV2 as foundational model for their approach, which achieved a high accuracy of up to 85%, outperforming other models.

[22] used deep-CNN for classifying seven different skin lesion types using HAM10000, ISIC 2017 dataset. Their approach involved refining existing networks such as DenseNet201, ResNet50, InceptionV3 by removing output layers, incorporating fully connected and pooling layers, and integrating few existing layers. The upgraded ResNet50 obtained 86.69% accuracy when these updated models were fine-tuned, which was 3% higher than that of other comparable approaches.

[23] presented a deep learning method for dermoscopic image-based automatic 'MM region segmentation'. Their technique merged fuzzy C-mean clustering with RCNN to achieve accurate localization. Their method produced excellent MM segmentation results with 94.8% accuracy, 97.81% sensitivity, 94.17% specificity on ISIC-2016 dataset.

Using transfer learning, a highly developed ROI based MM classification system was developed in [24]. They focused on important discriminative features when extracting ROIs from images using an improved k-means algorithm. Their method achieved remarkable accuracy rates of 97.4% and 97.9% on DermQuest and DermIS datasets, after training the model just on photos of MM cells.

Researchers [25] developed CNN to detect MM at early stage. They trained and validated the model using 514 dermoscopy images from ISIC dataset. CNN achieved 74.76% accuracy and 57.56% validation loss, despite certain issues with image quality.

In [26], model developed for classifying skin lesion as either malignant or benign. Their model achieved 97.49% accuracy, surpassing various leading methods. Their model, evaluated using CNN, showed strong AUC scores for various lesion comparisons: 86% for distinguishing solar lentigo from MM, 85% for separating seborrheic keratosis from MM, 93% for differentiating seborrheic keratosis from BCC, and 77% for distinguishing nevus from melanoma.

Another study [27] introduced the two-stage framework for automatic melanoma diagnosis using Fully Convolutional Networks (FCNs). This approach, based on GoogLeNet, VGG16, enhances accuracy of lesion segmentation. The results of these networks are combined with characteristics that are hand-crafted and derived from segmentation lesions using deep residual networks in a hybrid framework. SVM is used for classification. Impressive rate of accuracy of 85.3% and 88.92% were obtained by this technique on ISIC 2017 and ISBI 2016 dataset, respectively.

In [28], an Internet of Things (IoT) system was developed which integrates Deep Learning and transfer learning techniques to aid medical professionals in skin lesions diagnosis. This system utilized the range of CNNs like NASNet, DenseNet, MobileNet, Xception, Inception-ResNet, ResNet, VGG for feature extraction. Various classifiers, such as KNN, MLP, RF, SVM, Bayes, were employed for lesion classification. Using PH2 and ISBI-ISIC datasets, the system achieved notable accuracies of 96.805% and 93.167%, respectively.

In [29], researchers created an automated system for classifying skin lesions by leveraging pre-trained deep-NN and transfer learning. They fine-tuned the weights of deep-CNNs and employed various strategies, such as modifying the classification layer and augmenting the dataset. Their approach yielded impressive accuracy rates: 96.86% for the MED-NODE dataset, and 95.91% for ISIC dataset, 97.70% for Derm (Quest & IS) dataset.

In [30], a real-time object detection system was developed using YOLOv2 to identify MM from dermoscopic images automatically. This method achieved 86% accuracy for mole diagnosis, with a 85.90% specificity and 86.35% sensitivity.

[31] employed deep learning techniques to automatically identify MM in dermoscopy images. The initial step included preprocessing images to eliminate undesired aberrations, such hair, and then segmenting skin lesions automatically. Next, CNN was used to categorize the images. PH2 dataset's, preprocessed and raw image information were used to assess classifier performance. Results showed excellent sensitivity, specificity, and accuracy, with an impressive 93% accuracy in detecting melanoma and specificity, sensitivity ranging from 86% to 94%.

In [32], researchers developed a Computer-Aided Diagnosis (CAD) system using deep learning with CNN. They applied feature extraction and transfer learning with pre-trained models (VGG16, AlexNet). Results showed that using transfer learning with VGG16 achieved higher accuracy 97.5%, along with 96.87% specificity, and 100% sensitivity.

Table4. Overview of related works using deep learning for skin cancer detection

Reference	Technique	Dataset	Results
[16]	Data augmentation for InceptionV3	ISIC archive	Offline: 67.42%, Online: 90%, Hybrid: 88.76%
[17]	Ensemble models (InceptionV3, VGG16, EfficientNetB0)	ISIC archive (2,637 images)	91.19% accuracy for ensemble, individual models: InceptionV3: 89.85%, VGG16: 89.55%, EfficientNetB0: 90.87%
[18]	Adversarial training using loss gradients	N/A	ResNet101: 84.77% accuracy for melanoma classification
[19]	Automated detection with ensemble (Inception-V3, ResNet50), FCN-8	PH2, Med-Node, ISIC-2020	Segmentation: 94%, Classification: 93.4%
[20]	Deep features from CNNs and boundary localization techniques	PH2, ISIC 2016, ISIC 2017, HAM10000	DenseNet-121 with MLP: 98.33%, 80.47%, 81.16%, 81% respectively
[21]	Transfer learning with MobileNetV2	N/A	Up to 85% accuracy
[22]	Enhanced CNNs for multiple skin lesions	ISIC 2017 HAM10000	Enhanced ResNet50: 86.69% accuracy
[23]	MM region segmentation using deep learning	ISIC-2016	94.17% specificity, 97.81% sensitivity, 94.8% accuracy
[24]	ROI-based classification with transfer learning	DermIS, DermQuest	97.9% and 97.4% accuracy
[25]	CNN	ISIC archive	Accuracy: 74.76%, Validation loss: 57.56%
[26]	Binary classification with CNNs	N/A	Average accuracy: 97.49%
[27]	FCNs for segmentation and SVM for classification	ISIC 2017, ISBI 2016	85.3% (ISIC 2017), 88.92% (ISBI 2016)
[28]	IoT system with CNN	ISBI-ISIC, PH2	96.805%, 93.167% accuracy
[29]	Automated system with transfer learning and pre-trained DCNNs	MED-NODE, Derm (IS & Quest), ISIC	96.86%, 97.70%, 95.91% accuracy
[30]	YOLOv2	N/A	85.90% specificity, 86.35% sensitivity, 86.00% accuracy
[31]	MM detection using deep learning	PH2	Accuracy: 93%, Sensitivity and Specificity: 86%–94%
[32]	CAD system using CNNs with transfer learning	N/A	96.87% specificity, 100% sensitivity, 97.5% accuracy

4.2 Machine Learning

[33] studied the classification of malignant and benign lesions using geometric features with KNN. Their methodology yielded a precision rate of 89% when applied to DermIS dataset.

[34] proposed, highly efficient model for skin lesion classification, focusing on hyperparameter optimization with a political optimizer. Evaluated on the ISIC-17 dataset, their method achieved the 98.78% specificity, 97.36% sensitivity, 97.86% average accuracy, outperforming SVM and BPN models.

[35] investigated image processing techniques for skin cancer detection using dermoscopy images. They compared three classifiers (Naive Bayes, ANN and SVM) on segmented images. SVM achieved specificity 72%, sensitivity 70%, accuracy 71%. Naïve Bayes had specificity 56%, sensitivity 90%, accuracy 71%.

[36] focused on developing algorithms for automatic MM diagnosis, including lesion segmentation and disease classification. The Linear SVM model achieved superior performance with 90.1% specificity, 71.8% sensitivity, and accuracy 89.2%. In comparison, the Non-linear SVM model had a lower sensitivity 67.5%,and 85.3% accuracy, but a slightly higher specificity at 90.9%. ISIC2017 dataset was used for training and evaluation.

[37] introduced the "Automated Skin-Melanoma Detection (ASMD)" system, which uses the Melanoma-Index (MI) and incorporates texture enhancement, "Bi-dimensional Empirical Mode Decomposition (BEMD)", and image processing. The system achieved an impressive classification accuracy of over 97.50% with Radial Basis Function (RBF) and SVM algorithms.

[38] developed the binary classification approach for seborrheic keratosis, nervus and MM using hand-crafted features and KNN on ISIC 2017 dataset, achieved an accuracy 68%, with sensitivity and specificity both at 80%.

[39] presented a robust method for skin disease identification through image analysis, which involved image segmentation, gray scale conversion and noise reduction. SVM achieved 89% accuracy in detecting conditions like acne, psoriasis, MM, rosacea.

[40] introduced the advanced method for digital hair removal and image enhancement using Gaussian filtering, Black-Hat transformation, morphological filtering. The method included automatic Grabcut segmentation to outline lesions, with feature extraction done via 'Gray Level Co-occurrence Matrix (GLCM)'. Classification models (SVM, Decision Tree (DT)) and KNN showed exceptional accuracy, with SVM outperforming the others, achieving scores of and 97% on HAM10000, 95% on ISIC-2019 dataset.

[41] developed an effective strategy for skin lesion segmentation and disease classification. They employed the unique dynamic graph-cut algorithm for accurate segmentation of lesion and the Naïve Bayes to classify disease, using ISIC 2017 dataset. Their method achieved accuracies of 92.9% for keratosis, 91.2% for MM, 93% benign, highlighting its effectiveness in skin disease diagnosis.

[42], the machine learning approach using SVM is utilized for melanoma skin cancer detection. The method demonstrated strong performance with 96.9% accuracy, 90.2% specificity, 95.7% sensitivity. The dataset comprised over 5,341 images of both MM and non-MM skin lesions, sourced from ISIC (International Skin Imaging Collaboration).

Table4. Overview of related works using machine learning for skin cancer detection

Reference	**Technique**	**Dataset**	**Results**
[33]	Geometric features with KNN	DermIS dataset	Precision: 89%
[34]	Hyperparameter optimization with Political Optimizer	ISIC-17 dataset	Specificity: 98.78%, Sensitivity: 97.36%, Accuracy: 97.86%
[35]	Image processing, Naive Bayes, ANN, SVM	Dermoscopy images	SVM: Specificity: 72%, Sensitivity: 70%, Accuracy: 71%;

			Naive Bayes: Specificity: 56%, Sensitivity: 90%, Accuracy: 71%
[36]	Linear and Non-linear SVM	ISIC2017 dataset	Linear SVM: Specificity: 90.1%, Sensitivity: 71.8%, Accuracy: 89.2%; Non-linear SVM: Specificity: 90.9%, Sensitivity: 67.5%, Accuracy: 85.3%
[37]	Melanoma-Index (MI), Texture enhancement, BEMD, RBF and SVM	Not specified	Accuracy: 97.50%
[38]	Hand-crafted features with KNN	ISIC 2017 dataset	Accuracy: 68%, Sensitivity: 80%, Specificity: 80%
[39]	Image segmentation, gray scale conversion, noise reduction with SVM	Not specified	Accuracy: 89%
[40]	Digital hair removal, image enhancement with Gaussian filtering, Black-Hat transformation, GLCM, SVM, DT, KNN	HAM10000, ISIC-2019 datasets	SVM Accuracy: 97% (HAM10000), 95% (ISIC-2019)
[41]	Dynamic graph-cut algorithm for segmentation, Naive Bayes for classification	ISIC 2017 dataset	Accuracy: 92.9% (keratosis), 91.2% (MM), 93% (benign)
[42]	SVM for melanoma detection	ISIC dataset (5,341 images)	Accuracy: 96.9%, Specificity: 90.2%, Sensitivity: 95.7%

5. Challenges in skin cancer detection

Various challenges identified for skin cancer detection is specified below.

- *Data Quality and Diversity:* Ensuring the dataset encompasses a broad spectrum of skin cancer types, lesion appearances, and ethnic backgrounds to prevent bias and improve generalizability.
- *Model Interpretability:* Enhancing the transparency of machine learning models to allow dermatologists to understand and trust the predictions.
- *Overfitting and Model Robustness:* Addressing issues related to overfitting on training data and ensuring model performance remains consistent across diverse clinical settings.
- *Integration into Clinical Workflow:* Developing user-friendly interfaces and seamless integration strategies for incorporating these models into existing dermatological practice.
- *Regulatory and Ethical Considerations:* Navigating regulatory approvals and addressing ethical concerns related to patient data privacy and the role of AI in medical decision-making.

6. Research Objectives

The overall aim of this research is to study the effectiveness of combination the digital image processing techniques and deep learning techniques in analyzing dermoscopic images, detection of skin lesions, and identify their category. The following are the objectives of the proposed research;

- To identify suitable pre-processing techniques for enhancing the quality of dermoscopic images used in automated detection of skin lesions.
- To develop efficient semantic segmentation algorithm for separating the lesion from the skin region in the dermatoscopy image.
- To study the accuracy of vision transformer (ViT), a deep learning technique in classifying the skin lesions and compare their performance with the existing techniques.

7. Conclusion

The detection and classification of skin lesions, particularly malignant ones like BCC, SCC, and MM, are critical for improving patient outcomes. Machine learning and deep learning have significantly advanced this field by providing powerful tools for analyzing medical images. Techniques like LSTM, SVM, CNN, and ensemble learning have shown promise in accurately detecting skin cancers, especially when combined with strategies like data augmentation and transfer learning. The literature review highlights the rapid progress in this area, with several studies demonstrating high accuracy rates in skin cancer classification. However, challenges remain, particularly in the areas of model interpretability, computational efficiency, and the need for large labeled datasets. Future research should focus on overcoming the challenges, potentially by integrating advanced DL models with innovative ML techniques, to further enhance the early detection and treatment of skin cancer.

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