Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 3, Issue 6 (2025)

Classification and Detection of Skin Lesions Through Machine Learning Methods

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Article Details

Keywords: Skin Cancer, Machine Learning, Convolutional Neural Network

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ABSTRACT

Early detection of skin problems aids in the detection and treatment of disease conditions at an early stage before the disease progresses. Due to recent advances in computer vision and machine learning, researchers are developing tools that can learn from image-based data and detect these lesions autonomously. We present the top studies that are related to the automation of skin lesion detection, segmentation, and classification in this report. We begin with identifying the drawbacks of visual inspections performed by humans and the reasons why health systems must adopt automatic and reliable analysis. Then we review the most recent methods of classifying skin lesions, and how to differentiate between a type of lesion on dermoscope images, ordinary photographs, and other images. We compare both advantages and disadvantages of both pathways, classic machine-learning rules and modern deep networks. Next, the issues of noticing and describing lesions appear, with an emphasis on methods that create definite boundaries to measure their size and shape. Some main approaches to segmentation are outlined together with the challenges they encounter in the world, the common data repositories relied upon by testers, and the grading metrics. These techniques range from deep-learning models, graph tricks, and region-growing schemes. We also stroll through the large databases, benchmark activities, and evaluation criteria that all people use within the sphere. The HAM10000 dataset that was publicly announced is utilized to analyze the skin lesions in this paper, and it provides an accuracy of 97.86% on a proposed Convolutional Neural Network (CNN) model. To spur skin-lesion work in dermatology, we conclude by describing current trends, persistent obstacles, and potentially fruitful research directions.

INTRODUCTION

Skin cancer is becoming an increasingly common disease across the globe due to changes in lifestyle, ultraviolet (UV) radiation exposure, as well as environmental changes [1]. Skin cancer is a key and prevalent public health problem globally, affecting millions of people yearly. Broadly, skin cancers can be classified into two categories: melanoma and non-melanoma skin cancer (NMSC), as shown in Figures 1 and 2.

FIGURE 1. MELANOMA SKIN CANCER [2]

FIGURE 2. NON-MELANOMA SKIN CANCER [3]

Although non-melanoma malignancies like squamous cell carcinoma (SCC) or basal cell carcinoma (BCC) tend to be more common, almost the majority of deaths due to skin cancer are caused by melanoma, hence its designation as the most lethal form of skin cancer. Outdoor activities and tanning bed misuse have proportionately affected the steadily rising incidence of skin cancer. Global warming and the thinning of the ozone layer serve this increase the amount of UV light reaching the Earth's surface [4]. The World Health Organization estimates that annual global new cases of skin cancer number between 2 to 3 million for NMSC and 132,000 for melanomas, with skin cancer accounting for almost half of all cancer cases. Skin types are predisposed to developing skin cancers, with the fair-skinned and light-haired being more vulnerable since they produce less melanin, which acts as a natural sunscreen against UV light [5]. Skin cancer patients' survival rates increase with early diagnosis. Early detection of skin cancer, especially melanomas, allows for very minimal treatment. Delays in detection and treatment lead to metastases, thereby greatly reducing chances of survival and making the cancer more challenging to cure. This shows the need for accurate, reliable, and easily accessible methods for diagnosing skin lesions at an early stage. In the past, skin cancer was diagnosed through eye examination and dermoscopic analysis [6]. Dermoscopy is the examination of a lesion by a trained dermatologist, who uses a dermatoscope as a portable instrument with which to magnify and illuminate the skin's surface. However, its high subjectivity interpretation is due to its reliance on human skill and visual cues, and therefore, even highly qualified professionals are not immune to subjective judgments [7]. The training and experience of dermatologists must be mobilized to cover the more complex patterns, whether or not they have a definitive biopsy or pathologic testing. It may take longer and be highly costly, thus making it rather impractical in resource-challenged or remote regions where specialists may not be immediately available. For a conclusive diagnosis, biopsy is still the gold standard in addition to dermoscopy, wherein a very small sample of tissue is extracted from the lesion for pathological examination [8]. Biopsy usually provides a very high degree of diagnostic certainty, but it is an invasive procedure that warrants time for processing and may cause complications or discomfort to the patient.

Therefore, the quest for non-invasive methods as automated diagnostic tools that could give fast and accurate answers has gained more traction lately. Here, we have machine learning and artificial intelligence stepping in to fill that void, providing adjuncts for the early recognition of skin cancer as well as redistributing some of the workload from dermatologists can radically change the diagnosis of skin lesions in dermatology. Computational systems can assess dermoscopic images and identify skin lesions with astonishing accuracy through machine learning and deep learning [9]. This accuracy is often equal to or superior to that of an experienced dermatologist. These techniques can uncover nuanced patterns in images that indicate early-stage melanoma or other cutaneous malignancies. Machine learning algorithms apply trends that have been identified using labeled training data, where each image is associated with an appropriate diagnosis [10]. After being trained on a large dataset, the model can generalize its learning to classify new, unseen images. When examining skin lesions, we consider several factors such as asymmetry, irregular borders, color change, and diameter, which are all useful for early diagnosis of melanoma. Deep learning, a subfield of machine learning, has been a valuable asset to dermatology because it uncovers complex hierarchical features in raw data, rather than it being up to the observer to extract features by hand. Image-based applications find convolutional neural networks (CNNs) especially useful [11]. CNNs provide an invaluable contribution to the awareness of skin cancer with the high accuracy of tasks related to categorizing skin lesions, segmenting lesions' features, and potentially even detecting melanoma. Proper classification of various categories of skin lesions is an important step towards the diagnosis of skin cancer and effective decision towards treatment. General categories of skin lesions include benign, premalignant, and malignant. Non-cancerous, etiologically benign lesions are the moles (nevi), seborrheic keratoses, dermatofibromas, and angiomas. They may, however, appear identical at times to a malignant lesion; thus, it is significant that non-specialist healthcare providers diagnose them accurately, hence preventing possible unneeded biopsies and surgeries [12]. Premalignant lesions, such as actinic keratosis and Bowen disease, are not yet cancerous but have a risk of turning into malignant disease when not treated. Such lesions tend to show abnormal cell growth that is not invasive to close tissues and which may need monitoring or treatment despite having few symptoms.

Malignant lesions are however malignant and can transfer to other bodily organs in case they are not identified and treated early enough. There are three main categories of cancerous skin lesions, namely melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) [13]. The most aggressive melt A is known as melanoma, and it is the one produced by the melanocyte, which are melanin-producing cells, and it is characterized by the fast spreading of cancerous cells known as metastasis. The most frequently occurring skin cancer is BCC, which usually develops with a slow growth rate, spreads not as frequently, but which still may lead to extreme local damage in case of negligence [14]. The SCC is more aggressive and deadly as compared to BCC and is more likely to metastasize, posing serious health hazards unless acted upon in time, because they are develops in the skin's squamous cells. Knowledge of these categories is a key to developing effective diagnostic algorithms powered by AI and making patients healthier. Clinical diagnosis of skin lesions is commonly performed with the use of defined diagnostic guidelines, one of which is the ABCDE rule, or Asymmetry, Border irregularity, Color variation, Diameter greater than 6 mm, and Evolution over time

[15]. These standards assist clinicians in deciding whether a lesion is likely to be benign or malignant. Nonetheless, visual inspection may sometimes not give a concrete diagnosis, particularly to practitioners who are not specialized [16]. This is one of the limitations that showcase the increased need for AI-based diagnostic systems, which are to assist dermatologists and provide better and more consistent judgments. The availability of quality annotated datasets is essential in the development of such tools. The datasets form the baseline to train and test machine learning algorithms that would be able to categorize skin lesions in the clinical context. The International Skin Imaging Collaboration (ISIC) Archive is one of the most abundantly and diversely populated collections of dermoscopic imaging labeled with their types of skin lesions, including basal cell carcinoma, nevi, melanoma, etc. Challenges to benchmark algorithm performance are also hosted at the ISIC Archive on an annual basis. The PH2 dataset is another important dataset consisting of 200 dermoscopic photos devoted to nevi, atypical nevi, and melanoma. [17] Though effective to be use in segmentation and classification tasks, the PH2 dataset is also limited due to its small size and lack of patient metadata details. Although useful, these datasets tend to be imbalanced, such that the malignant lesions, such a melanoma, are underrepresented in such datasets as compared to the benign lesions.

This imbalance may bias a model in predicting benign diagnoses, even at the cost of missing extremely important malignant cases. To eliminate this problem, researchers apply various methods, e.g., data augmentation, oversampling of underrepresented classes, and data synthesis, to improve the performance of the model and guarantee a higher level of generalizability in different clinical conditions [18]. The development of models to classify and detect skin lesions has undergone several machine learning and deep learning included in the spectrum of traditional algorithms to more progressive neural networks. Conventional machine learning methods, e.g., Support Vector Machines (SVM), Random Forest (RF), and K-Nearest Neighbors (k-NN), have proved to be relatively effective in previous research work. SVM especially works effectively with high-dimensional data, and it achieves this by finding the most optimal hyperplane that divides the various classes in the feature space [19]. It has also been extensively applicable in the classification of skin lesions, notably in situations where the concept of manual feature extraction is feasible. One of the most popular ensemble methods used in dermatology, Random Forest, is robust and interpretable since it is based on the results of several decision trees. In the meantime, k-NN performs classification depending on the distances to labeled data, and, although being rather easy, it can also be effective provided that it is accompanied by suitable feature extraction methodologies [20]. By contrast, the past years have seen skin lesion classification being shaken up by deep learning methods, particularly Convolutional Neural Networks (CNNs). CNNs are also targeted at automatically discovering hierarchical features within raw pixel data and thereby detecting complex patterns and subtle abnormalities that might otherwise be missed by a human clinician. Their capability to generalise to unknown data and perform at high classification rates has made them the benchmark in image-based diagnosis, such as classification of skin lesions, as either benign or malignant. Proper classification of various categories of skin lesions is an important step towards the diagnosis of skin cancer and effective decision towards treatment. General categories of skin lesions include benign, pre-malignant, and malignant [21]. Non-cancerous, etiologically benign lesions are the moles (nevi), seborrheic keratoses, dermatofibromas, and angiomas. They may, however, appear identical at times to a malignant lesion; thus, it is significant that non-specialist healthcare providers diagnose them accurately, hence preventing possible unneeded biopsies and surgeries. Premalignant lesions, such as actinic keratosis and Bowen disease, are not yet cancerous but have a risk of turning into malignant disease when not treated. Such lesions tend to show abnormal cell growth that is not invasive to close tissues and which may need monitoring or treatment despite having few symptoms [22]. Malignant lesions are however malignant and can transfer to other bodily organs in case they are not identified and treated early enough. There are three main categories of cancerous skin lesions, namely melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). The most aggressive melt A is known as melanoma, and it is the one produced by the melanocyte, which are melanin-producing cells, and it is characterized by the fast spreading of cancerous cells known as metastasis. The most frequently occurring skin cancer is BCC, which usually develops with a slow growth rate, spreads not as frequently, but which still may lead to extreme local damage in case of negligence [23]. The SCC is more aggressive and deadly as compared to BCC and is more likely to metastasize, posing serious health hazards unless acted upon in time, because they are developing in the skin's squamous cells. Knowledge of these categories is a key to developing effective diagnostic algorithms powered by AI and making patients healthier. Proper classification of various categories of skin lesions is an important step towards the diagnosis of skin cancer and effective decision towards treatment. General categories of skin lesions include benign, pre-malignant, and malignant [24].

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Knowledge of these categories is a key to developing effective diagnostic algorithms powered by AI and making patients healthier. Proper classification of various categories of skin lesions is an important step towards the diagnosis of skin cancer and effective decision towards treatment. General categories of skin lesions include benign, premalignant, and malignant. Non-cancerous, etiologically benign lesions are the moles (nevi), seborrheic keratoses, dermatofibromas, and angiomas. They may, however, appear identical at times to a malignant lesion; thus, it is significant that non-specialist healthcare providers diagnose them accurately, hence preventing possible unneeded biopsies and surgeries. Premalignant lesions, such as actinic keratosis and Bowen disease, are not yet cancerous but have a risk of turning into malignant disease when not treated. Such lesions tend to show abnormal cell growth that is not invasive to close tissues and which may need monitoring or treatment despite having few symptoms. Malignant lesions are however malignant and can transfer to other bodily organs in case they are not identified and treated early enough. There are three main categories of cancerous skin lesions, namely melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC). The most aggressive melt A is known as melanoma, and it is the one produced by the melanocyte, which are melanin-producing cells, and it is characterized by the fast spreading of cancerous cells known as metastasis [27]. The most frequently occurring skin cancer is BCC, which usually develops with slow growth size spread not as frequently, but which still may lead to extreme local damage in case of negligence. The SCC is more aggressive and deadly as compared to BCC and is more likely to metastasize, posing serious health hazards unless acted upon in time, because they are developing in the skin's squamous cells. Knowledge of these categories is a key to developing effective diagnostic algorithms powered by AI and making patients healthier. Transfer learning allows researchers to leverage pre-trained CNN models, such as VGG16, ResNet50, and InceptionV3, which have been trained on large image datasets like ImageNet [28]. These models can then be fine-tuned for skin lesion classification, significantly reducing the amount of data and computational resources required for training. Ensemble learning methods, such as bagging and boosting, combine the predictions of multiple models to improve accuracy. These methods have been shown to work well in skin lesion classification tasks, as they combine the strengths of various algorithms.

LITERATURE REVIEW

With the development of machine learning (ML) and deep learning (DL) methods, which provide improved diagnostic capabilities, the issue of classification and detection of skin lesions has further established itself as an important problem in the medical industry. The advantages of distinguishing and classifying skin lesions, in particular melanoma and other skin diseases, which may become life-threatening without early diagnosis, are extremely beneficial when identifying skin lesions [29]. This literature review aims to investigate the various approaches, methods, and datasets for the classification and detection of skin lesions, and provide the efficacy, challenges, and progress of techniques in this field. Skin lesion classification refers to the process of identifying different lesions as benign or malignant lesions, or identifying specific types of skin disease (e.g., melanoma, basal cell carcinoma, etc.). Initially, skin lesion classification used conventional image processing methods, and then in recent years, deep learning has developed the capability to classify skin lesions more dependent on accuracy and generalization. In the last few years, convolutional neural networks (CNNs) have become the core of most skin lesion classification systems [30]. The strength of CNNs is that they can automatically ferret out features from image data without the pre-processes manual extraction of features. Various CNN architectures have been proposed in the literature for the classification of skin lesions, including ResNet, VGGNet, DenseNet, and EfficientNet. These CNN architectures have shown a high degree of accuracy in classifying skin lesions from images, as shown in Table 1.

- ResNet: A deep residual network that helps impede the degradation of performance in deep architectures by utilizing skip connections. Due to the capability of ResNet-based models to learn complex features in images, they have been widely utilized.
- DenseNet: A network that improves feature propagation and reduces the need for parameters by explicitly connecting every layer to every other layer. In skin lesion classification,
- DenseNet has greater accuracy than traditional CNN models.

TABLE 1. SUMMARY OF PREVIOUS STUDIES FOCUSED ON SKIN DISEASE CLASSIFICATION

References	Method	Objective
[31]	EfficientNet	Classification of melanoma and benign lesions
[32]	Genetic Algorithm Whale Optimization	Optimizing CNN architecture for classification
[33]	CNN	Melanoma detection and classification
[34]	Deep Learning + MobileNetV2 + LSTM	Classification and time-series prediction
[35]	ML + CNN	Skin lesion classification
[36]	DenseNet ConvNeXt	Comparing DenseNet and ConvNeXt for classification
[37]		Classifying skin lesions with a custom model

	Custom ResNet50	
[38]	Hierarchical Naive Bayes	Multi-class skin lesion classification
[39]	S2C-DeLeNet	A novel model for skin lesions classification
[40]	Hybrid CNN + LSTM	Combination of CNN with LSTM for classification

The outcomes demonstrating the powerful effect that complicated structures of the neural networks have on skin lesion classification, as shown in Table 10, are very recent, which speaks of the evolutionary changes that are coming into the picture. The major future research direction remains to increase the accuracy, efficiency, and interpretability of models. In support of this, hybrid architectures and ensemble models are becoming very common, since usually more than one model is better than the others in a classification project. One of the most important steps in this process is proper lesion detection, which should come before classification to guarantee good results. Detection deals with the process of finding and recognising the lesions in an image, whereas classification is directed towards providing the correct labels on the lesions that are identified. Some of the contemporary object detection methods have been successfully used here. Compared to traditional CNNs, Fast R-CNN is faster and more efficient at identifying objects because it incorporates Region Proposal Networks (RPNs) to localize objects at an incredible speed and accuracy level; therefore, the algorithm will be useful in tasks where time is critical. The U-Net was first proposed as a tool of biomedical image segmentation, but due to the symmetric nature of the model, which enables the model to precisely localize on small objects, U-Net has also been adopted in the task of skin lesion detection, where this property is essential. The other model is the much-admired YOLO (you only look once) model with the capability to identify and classify multiple objects in real time. This is not only because it is very fast and accurate, which makes it especially useful in clinical settings, but also because this diagnostic tool is very cheap. Collectively, these detection models led to a big step towards automated analysis of skin lesions, and this is where the success of reliable classification systems can be based.

TABLE 2. SUMMARY OF PREVIOUS STUDIES FOCUSED ON SKIN DISEASE DETECTION

References	Method	Objective
[41]	Fast R-CNN	Skin lesion detection and localization
[42]	DL + Image Processing	Hybrid model for skin lesion detection
[43]	Fusion Network	Hybrid model for skin lesion detection
[44]	U-Net + RPNet	Detecting melanoma from dermoscopic images
[45]	Hybrid CNN + Gradient Boost Classifier	Combining CNN with ensemble methods for lesion detection
[46]	VGG16 + ISR	Utilizing VGG16 for skin lesion detection

The papers in the table in Table 2 provide an overview of numerous approaches for identifying skin lesions. Hybrid methods that combine CNNs with other methods, such as gradient boosting, random forests, and evolutionary algorithms, have provided promising results, especially concerning improving the robustness of the detection process. Some research projects are looking to address the challenges of classifying, detecting, and segmenting skin lesions using a combined approach. Multi-task learning models present a comprehensive way to conduct this task, as the model achieves segmentation, localization, and classification at the same time. Multitask learning provides the advantage of utilizing information shared across tasks to help in accomplishing all the tasks.

- Multi-task CNN: This model performs the task of classification and segmentation simultaneously. The advantage of sharing weights across multiple components of the network allows the model to exploit large context features that assist with both lesion detection and classification.
- Segmentation Models (U-Net, Mask RCNN): Focus on pixel-level segmentation and

ensuring that lesions can be segmented away from background prior to classification. The segmentation step is a crucial step in regards to good classification results, especially for lesion with complex forms and varied in sizes.

TABLE 3. SUMMARY OF PREVIOUS STUDIES FOCUSED ON MULTIPLE OBJECTIVES (SEGMENTATION, CLASSIFICATION, AND DETECTION)

References	Method	Objective
[47]	GAWO	Segmentation, Classification, and Detection
[48]	ODNN +CADSCC	Combining segmentation, classification, and detection tasks
[49]	Hierarchical Naive Bayes	Segmentation, Classification, and Detection
[50]	S2C-DeLeNet	Unified model for segmentation and classification
[51]	MC-SVM	Multiclass SVM for skin lesion classification and detection
[52]	Ensemble Classifier	A model integrating segmentation, classification, and detection

Multitask techniques are now a developing trend in skin lesion detection, as can be seen in Table 4. Not only do multitask techniques achieve better classification and detection metrics, but they can also help solve the segmentation problem, which is key for more detailed analysis on skin lesions. Having access to high-resolution datasets is an important part of the classification and detection of skin lesions. Many available datasets, such as PH2, HAM10000, and ISIC (International Skin Imaging Collaboration), have been used extensively for training and validating algorithms for lesion identification. These datasets contain tagged images of skin lesions ranging from harmless moles to malignant melanoma, enabling researchers to train models that can generalize to real-world data. The ISIC dataset is one of the largest and most common datasets for melanoma detection. It provides high-quality dermoscopic images with detailed descriptions of each lesion. This dataset is currently used as a benchmark to evaluate skin lesion detection and classification models.

TABLE 4. SUMMARY OF POPULAR SKIN LESION DATASETS

Dataset Name	Source	Size	Number of classes	Common use
ISIC [53]	ISIC Archive	25,000+	2 (Malignant, Benign)	Classification ion, Detection
HAM10 000 [54]	HAM10 000 Dataset	10,000+	7(Various skin conditions)	Classification, Detection
PH2 [55]	PH2 Skin Cancer Database	200+	3 (Melano ma, Benign, Nonmelanoma ma)	Classification ion, Detection
Dement [56]	Dement NZ	20,000+	5(Various condition ns)	Classification ion, Diagnosis
SD-200 [57]	Skin Disease Dataset	200+	3 (Melano ma, Nonmelanoma ma, Benign)	Classification ion

There are some open ChallengeS in Skin Lesion Classification and Detection:

- Despite significant progress, several challenges remain in the field of skin lesion classification and detection.
- Data Heterogeneity and Bias: Many datasets have insufficient case diversity about skin types, geographies, and demographic attributes. This disparity may lead to biased models that underperform for certain groups of people.
- Interpretable AI: While deep learning models can be highly accurate, they are often considered "black-box" models, which are difficult to grasp. For models to be considered for therapeutic use, they must produce accurate predictions.
- Generalization: Models trained on specific datasets may not generalize well to other datasets or real-world scenarios. Ensuring that models can handle a wide range of skin

conditions and image qualities is a key challenge.

- Segmentation Accuracy: Accurate segmentation of lesions from the surrounding skin is still a challenging task, particularly for lesions that are small, irregularly shaped, or poorly contrasted against the background.

This comprehensive analysis provided an overview of the most recent methodological advances in classifying and detecting skin lesions. Improvements in skin lesion diagnostic systems' accuracy, efficiency, and equity will require the identification of sophisticated machine learning methods, datasets, and hybrid models. Although the progress made in automated skin lesion classification and detection with the help of AI is impressive, numerous issues are still being encountered, and these impede the spread of AI products to a large scale in the practical context. Bias and data heterogeneity are one of the most urgent concerns [58]. Most of the available datasets are not diverse and cannot represent a wide variety of skin types, demographics, and geography well, which leads to the conclusion that developed models might not be universal, and work better with one group of people than with the other. Such a data gap leads to unfair results and poses questions to the unbiased use of AI in dermatology. Moreover, although deep learning models have proved their extremely high accuracy, they cannot be interpreted, which is a barrier. The problem is that most of these black-box models do not offer any reasonable explanation of their predictions, and thus, clinicians are reluctant to use these models in making therapeutic decisions. Generalization of the AI models is another significant issue; models created using data on one type of set can be found worse off fitting with a new one or in a real-life scenario due to differences in imaging conditions, equipment, and demographics. The effectiveness of segmentation also remains controversial, particularly in the case of small lesions, irregular or low-contrast, which may have a devastating effect on further classification outcomes. Besides, the quality and availability of large, diversified, and labeled datasets persistently restrain improvements. Certain datasets are underrepresented, or not diverse enough regarding lesion anatomy and imaging conditions, and thus problematic class imbalance, where malignant lesions are underrepresented, occurs, or the models tend to be overfitted, as they do not have enough training samples. Regularization, dropout, and data augmentation are common techniques to ease such problems, although they are not a failsafe solution. Lastly, incorporating AI systems into clinical practice is currently not without difficulty, with its regulatory barriers, the necessity of acceptance by health workers, and the demand to be validated through clinical trials in large studies. To make AI-based diagnostic tools reliable, equitable, and practical, studies in the future should be aimed toward addressing these complex issues by improving data collecting practices, strong model design, hybrid methods, and transparent and interpretable AI.

METHODOLOGY

The study methodology is based on deep learning approaches, specifically Convolutional Neural Networks (CNNs), which provide a systematic and technical process for the classification and identification of skin lesions. Skin lesion investigation is important for the early diagnosis of many skin diseases like benign keratosis, basal cell carcinoma, and melanoma. To ensure reliable and precise classification, a deep learning pipeline was developed using CNN architectures with various kernel sizes, image preprocessing techniques, and training on the publicly available HAM10000 dataset, as shown in Figure 4 [59]. This method guarantees an end-to-end automated system that is capable of identifying benign and malignant lesions accurately.

CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE

CNNs' ability to learn spatial hierarchies of features using learnable filters makes them extremely suitable for image classification tasks. A custom CNN model was designed for this study, focusing on two sizes of Convolutional kernels: 3x3 and 5x5. The model learns both low-level and high-level features, as shown in Figure 3.

CONVOLUTIONAL LAYERS

The CNN model consists of multiple convolutional layers, where each layer performs the following operations:

- 3x3 Kernels: These small kernels are used in the first layers to register the edges of the skin lesions, local textures, and fine details.
- 5×5 Kernels: These are used in the deeper layers to learn contextual and abstract features such as border irregularity, asymmetry, and lesion shape.

To introduce more non-linearity into the model, the output of the convolution is passed through an activation function called the Rectified Linear Unit (ReLU).

POOLING LAYERS

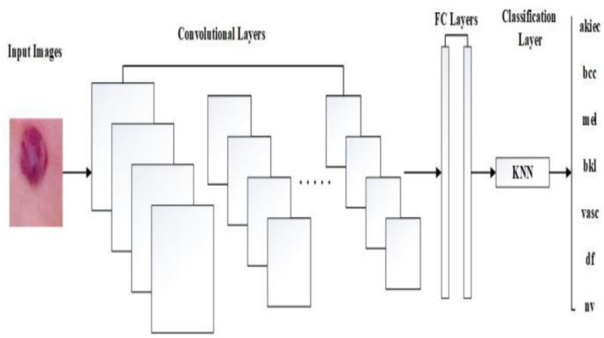
The max-pooling layer (usually 2x2) follows each convolutional block. Pooling reduces the spatial size of the feature maps used in the process, which reduces computation and is one way to avoid overfitting.

BATCH NORMALIZATION

The batch normalization is then applied after convolution but before activation. It speeds up training time and allows for stable gradients. It helps to accelerate the convergence of the network by standardizing the input to each layer. Dropout Layers

To further prevent overfitting, dropout layers with a dropout rate (e.g., 0.5) were used in fully connected layers. Dropout randomly disables a portion of neurons during training, forcing the model to learn redundant representations.

FIGURE 3. CONVOLUTIONAL NEURAL NETWORK ARCHITECTURE



FULLY CONNECTED LAYERS AND OUTPUT

After the last convolutional and pooling layers, the feature maps are flattened and run through fully connected (dense) layers. The last layer is a SoftMax classifier with seven output neurons, where each neuron represents one of the seven types of skin lesions. The outputs are converted as probabilities for each class using the SoftMax function.

LOSS FUNCTION AND OPTIMIZATION

This multiclass classification problem involved the use categorical cross-entropy loss function. This loss function works very well when we are estimating probabilities across many classes.

To train the model, we will use the Adam optimizer. The Adam optimzer is an adaptive optimizer that combines momentum and RMSprop optimizers. During the training, it will adjust the learning rate which speeds the convergence and produce better performance overall.

Hyperparameters:

- Learning Rate: 0.001
- Batch Size: 32
- Epochs: 20
- Optimizer: Adam

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- Loss: Categorical Cross-Entropy

DATASET: HAM10000

HAM10000 (Human Against Machine with 10,000 training images) is one of the most popular and publicly available datasets for dermatology research. It includes over 10,000 dermatoscopic images of seven different types of skin lesions. Actinic keratoses (AKIEC)

- Basal cell carcinoma (bcc)
- Benign keratosis-like lesions (bkl)
- Dermatofibroma (df)
- Melanoma (mel)
- Melanocytic nevi (nv)
- Vascular lesions (vasc)

On follow-up evaluation, dermatology experts discerned and labelled to consensus and determined via histology each of the images in the dataset.

The dataset includes the all the non-image factors including different light sources, resolutions, and image artifacts such as skin texture, hair and shadows. These differences replicate real life situations which is how you will develop an effective classification model.

To ensure the model receives quality inputs, extensive preprocessing was applied:

- Resizing: The images had been brought down to a uniform size (i.e., 224×224 pixels) so the CNN model would have a consistent size to input.
- Normalization: The pixel values had been normalized using min-max normalization to be in a [0,1] range to facilitate convergence during training.
- Data Augmentation: There were numerous data augmentation techniques to deal with class imbalance and improve overall model generalization:
- Rotation (±20 degrees)
- Horizontal and vertical flipping
- Zoom in and zoom out
- Random brightness and contrast adjustments

These techniques helped prevent overfitting and made the model more resilient to real-world input variability.

The HAM10000 dataset is inherently imbalanced because some classes possess significantly

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fewer images than others, as shown in Figure 4. As such, we used class weighting and resampling methods to tackle the class imbalance. Class weighting is an approach in which we place more emphasis on an underrepresented class during the model training, ensuring that when training the model, the learning has adequate attention for the minority class categories. This use of class weighting helps reduce model bias to the majority classes and helps the model learn to detect rare lesion types. Furthermore, due to the unbalanced distribution of images, both oversampling and undersampling methods were also used within the modelling process.

Oversampling techniques, such as image reuse and the Synthetic Minority Over-Sampling Technique (SMOTE), were used to create examples of the minority classes and undersampling techniques, thus reducing the number of images from the over-represented classes. This use of oversampling and undersampling will limit the negative impacts on the modelling and will hopefully fine-tune the training process with a more accurate representation of the data that the model is being trained to recognize. Again, this series of approaches is part of a modelling pipeline to mitigate bias from class imbalance of a deep learning model using Convolutional Neural Networks (CNN) for the classification and detection of various skin lesions. This modelling pipeline includes preparation and processing of the data, augmentations of data, deploying model training and optimisations, as well as testing and evaluations. By using both 3×3 and 5×5 convolution kernels, the spatial information was captured by the model from each of the fine and coarse features within the lesion. Lastly, the use of techniques for class balancing and robust data handling,

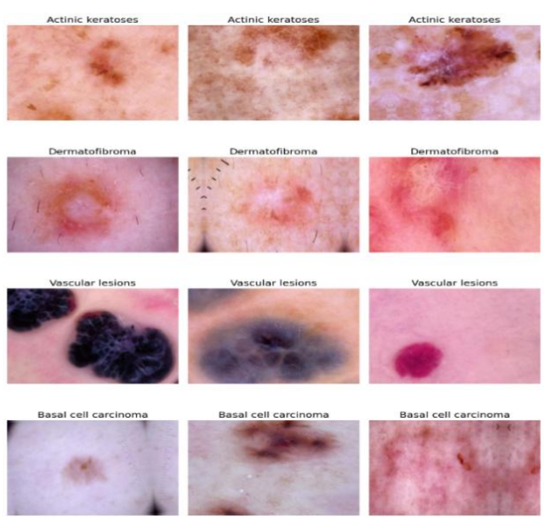

FIGURE 4. HAM10000 DATASET [60]

RESULTS AND DISCUSSION:

The model evaluation outcomes are highly favorable, and there has been positive performance on the test dataset. The model exhibited an accuracy of 97.86%; thus, the model accurately predicted the occurrence of the event for almost all of the test samples, as shown in Figures 5 and 6. The loss value is 0.0781, indicating that the differences from the values predicted from the model to the values of the target were quite small. It should be noted that the model's final test accuracy is 97.0%, which means the model generalizes well to new/unseen information. At this level, the model is well-trained, reliable, accurate, efficient, and capable of making precise predictions with small errors.

The dataset was split into Training, validation, and test sets. 70% dataset is divided into training and 20% into validation, and 10% data on testing. This separation prevents overfitting and ensures that the model is evaluated on data it has not seen before. Early stopping was used to halt training when there was no improvement in validation loss after a certain number of epochs, and the model was trained for 50 epochs in total. In addition, five-fold cross-validation was utilized to provide stability in the evaluation of performance. In this way, the dataset is divided into five subsets, and the model is trained five times, using a new subset to test the model each time, and the remaining subsets are used to train the model.

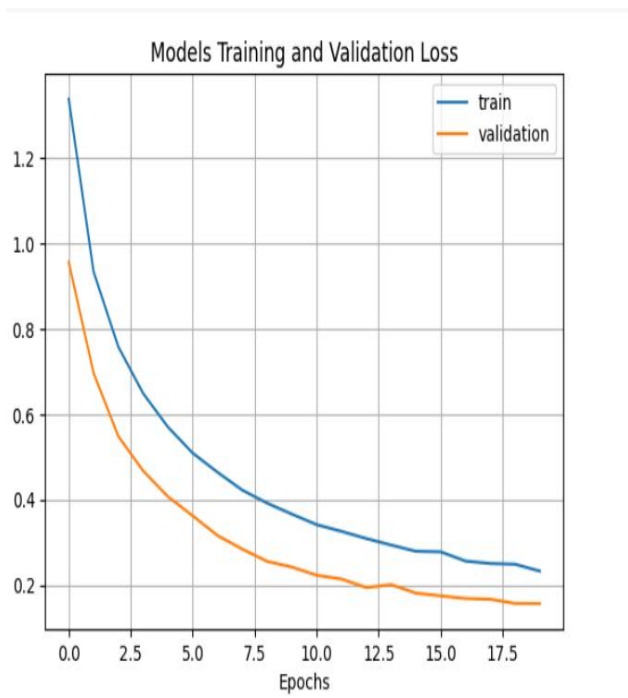

FIGURE 5. TRAINING AND VALIDATION LOSS

In the first plot, we observe the training and validation loss of the model throughout 20 epochs. The plot indicates that the training loss and the validation loss are decreasing steadily throughout the training epochs, which means that the model is learning correctly and the error on its predicted outputs is decreasing. The training loss starts relatively low and decreases over the epochs, and importantly, the validation loss never exceeds the training loss at any point across all epochs, which indicates there is no overfitting and that the model generalizes well. This behavior suggests that the model is not overfitting or underfitting, and that it appears to make sound predictions regardless of whether the data was used for model training or previously unseen validation data.

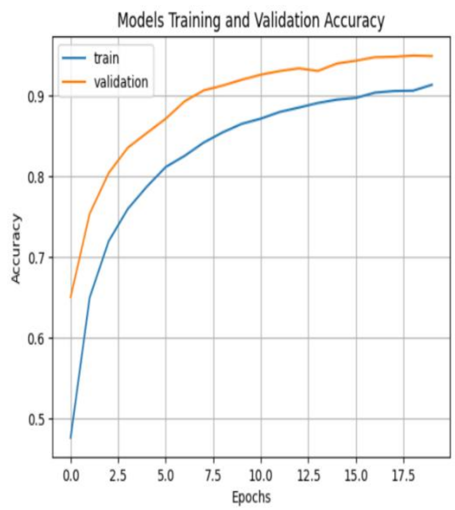

FIGURE 6. TRAINING AND VALIDATION ACCURACY

As shown in the second plot, training and validation accuracy continued to increase over the 20 epochs, demonstrating that the model is progressing. The model almost always exhibits higher validation accuracy compared to training accuracy; this may take place if the validation data is marginally easier or more representative. The validation accuracy peaked at approximately 96% while training accuracy increased distinctly past 91%, clearly demonstrating very good classification accuracy regardless of epoch. The upward trajectory of both forms of accuracy, with no sharp dips or noticeable gaps in accuracy between train and validation, indicates that the model is learning adequately with no evidence of overfitting or underfitting.

EVALUATION METRICS

After training the model, its performance was evaluated using a range of metrics:

- Accuracy: the fraction of correctly predicted labels out of all predicted labels.

- Precision: the fraction of actual positives to all predicted positives.
- Recall (Sensitivity): Ratio of true positives to all actual positives.
- F1-Score: a good metric when classes are unbalanced; it is the harmonic mean of precision and recall.
- A Confusion Matrix is a visual representation of actual and predicted labels.
- AUC and Receiver Operating Characteristic (ROC) Curve: to explore the trade-off between each class's true-positive rates and false-positive rates.

MODEL TUNING AND IMPROVEMENT

To optimize model performance, several techniques were applied:

- Hyperparameter Tuning: Grid search and random search were used to optimise the combination of batch size, learning rate, and dropout.
- Transfer Learning: Transfer Learning: VGG16 and ResNet50, both pre-trained CNN models, were also assessed. The last few layers were changed, and then these models were re-optimised on the HAM10000 dataset
- Ensemble Learning: Combining the predictions of several CNNs to increase classification accuracy (e.g., custom CNN + ResNet) through majority vote or average.

CONCLUSIONS

This research has been underlining the transformative capacity of AI in dermatology, especially during the diagnosis and management of skin conditions, including cancer. Machine learning-based models based on artificial intelligence algorithms have proved to be rather capable and can obtain an accuracy of reaching 97.86%, with some models beating human dermatologists in image-based diagnostics. These technologies can be of great assistance in resource-scarce environments to improve the clinical processes and patient outcomes. But there are still challenges like the quality of data sets, reasonable interpretation of the model, and integration, particularly, into clinical practice that are seen. In the future, researchers ought to target making robust, explainable AI via integration across disciplines. AI has a huge potential to make precision dermatology more successful and to provide better patient care with further advancements and innovations.

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