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Article

# Skin Lesions Diagnosis Using ML and DL Classification Models

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**Abstract***:* Skin cancer has been steadily growing for decades and is now the most prevalent form of cancer in humans. Recently, there has been a remarkable increase in the incidence of skin cancer. This presents a challenge as skin cancer lesions come in intricate and varied shapes and textures, making diagnosis difficult even for experts. To tackle this problem, the main objective of this paper is to utilize image classification techniques to diagnose skin cancer. Artificial neural networks, particularly convolutional networks, have shown great success in this field to distinguish between malignant and benign tumors. By leveraging the strengths of both Support Vector Machine and Convolutional Neural Network, we strive to improve the overall performance of skin cancer diagnosis. For experimentation, we used the ISIC dataset, which contains a collection of photos for melanoma skin cancer.

**Keywords:** skin cancer; classification; support vector machine; convolutional neural network; deep learning; machine learning

## 1. Introduction

The skin is the body's largest organ and serves to cover and protect muscles, bones, and other organs. Its function is vital, as even small changes in its functioning can have widespread effects on the rest of the body. The skin is exposed to the external environment, making it susceptible to diseases and infections. Skin lesions often serve as the first clinical sign of diseases such as varicella and melanoma [1].

As the largest organ of the human body, the skin plays a crucial role in maintaining balance and safeguarding the body against external aggressions, including mechanical shocks, ultraviolet rays, and temperature changes. To understand the mechanical behavior of the skin, it is necessary to differentiate its key structural elements that contribute to its mechanical properties. This is important for developing a comprehensive understanding of the skin's mechanical behavior. Fitzpatrick's skin type classification system was developed to describe how different skin types respond to sun exposure and their associated cancer risks. It is essential to consider skin type when addressing skin-related issues, as certain conditions may favor the development of specific skin types over others. However, many studies in the literature on computer-aided diagnostic systems do not specify the skin type used. It is worth noting that most of the samples identified in such studies appear to be type I and type II on the Fitzpatrick scale [2].

The rest of the paper is organized as follows: Section 2 presents the field of automated Skin Lesions Diagnosis. In Section 3, we present the related works of the skin cancer detection and classification. Section 4 describes the materials and methods used in this work. In Section 5, we present and analyze experimental results. Conclusions and future work are given in Section 6.

## 2. Automated Skin Lesions Diagnosis

Skin cancer is one of the most active types of cancer in the present decade [3]. It was the fourth most common cancer in 2020 [4]. In fact, abnormal skin cells grow spontaneously, invade nearby tissues, or spread throughout other parts of the body. There are both benign and malignant lesions on the skin. In this section, skin lesions imaging modalities and the used datasets in this field are presented.

### *2.1. Skin Lesions Imaging Modalities*

Medical imaging has become a formidable diagnostic tool for physicians. There are more and more ways of obtaining image information and the number of processed images is also increasing. A medical image is characterised essentially by its resolution, the clarity and fine detail that a monitor or printer achieves when producing an image. Since skin cancer detection in early stage of his development increases considerably the chances of obtaining a successful treatment prescription. Several skin cancer screening methods are proposed and among which we cite:

- Magnetic Resonance Imaging (MRI)
- Ultrasonography (US)
- Spectrophotometry (SP)
- Laser Doppler perfusion imaging (LDPI)
- Confocal Microscopy (CM)
- Optical Coherence Tomography (OCT)
- Dermoscopy (ELM)

Some advantages and drawbacks of each modality is presented in Table 1.

***Table 1.*** Skin cancer modalities.

| **Modality** | **Advantages** | **Drawbacks** | **Dataset Samples** |
|---|---|---|---|
| MRI | Offers detailed images.<br>Can assess tumor depth.<br>Images from various angles, enhancing diagnostic accuracy. | Limited resolution missing small or superficial lesions.<br>More expensive than other imaging techniques.<br>May not always distinguish benign from malignant lesions accurately. | Dermnet [5] |
| US | Non-invasive, making it suitable for regular monitoring.<br>Real-time imaging.<br>More cost-effective compared to other imaging modalities. | Limited depth penetration quality and interpretation<br>Depend on the skill and experience of the operator.<br>May have lower resolution compared to other imaging modalities. | Ultrasound Dataset [6] |
| SP | High Resolution.<br>Real-time Imaging.<br>Non-invasive.<br>accurate diagnosis of skin cancer by identifying specific cellular and morphological features associated with malignancy. | Operator Dependency.<br>Imaging equipment and software can be costly.<br>Limited Depth of Penetration.<br>May yield false-positive results, leading to unnecessary biopsies or treatments for benign lesions. | ISIC [7] |
| LDPI | Valuable information about the vascularization of skin lesions.<br>Non-invasive.<br>Real-time Imaging.<br>Enables quantitative analysis of blood flow parameters. | Limited Specificity.<br>Primarily assesses blood flow in superficial skin layers.<br>Interpretation may require specialized training and expertise. | American National Institutes of Health database [8] |

| | | | |
|---|---|---|---|
| CM | High-resolution images of cellular structures in the skin.<br>Real-time Imaging.<br>High sensitivity and specificity for the diagnosis of melanoma. | Limited Depth of Penetration.<br>Equipment and software can be costly.<br>False Positives. | ISIC [7] |
| OCT | Promise in detecting and characterizing skin cancer, particularly non-melanoma skin cancers.<br>High-resolution cross-sectional images of skin tissue. | False-positive results, leading to unnecessary biopsies or treatments for benign lesions.<br>limited accessibility for routine screening and clinical use in some healthcare settings. | HHS Provider Relief Fund database [9] |
| ELM | Magnified and enhanced visualization of skin lesions<br>Improved Diagnostic Accuracy.<br>Non-invasive and Cost-effective.<br>Photographs obtained through dermoscopy can be archived for documentation and comparison. | Variability in diagnostic accuracy among different practitioners.<br>Limited Depth of Penetration.<br>Some benign lesions may exhibit dermoscopic features that mimic those of malignant lesions. | ISIC [7] |

## *2.2. Dermoscopic Skin Lesions Image Datasets*

Dermoscopy is a technique used to examine the structure of the skin. Observation-based detection techniques can be used to detect cancerous spots using dermoscopy images. The accuracy of dermoscopy depends on the training of the dermatologist. Melanoma detection accuracy can reach 75–85%. Diagnostics performed by the system help increase the speed and accuracy of diagnosis. Computers can extract certain information, such as asymmetry, color variations, texture features, etc. An automated dermoscopy image analysis system involves three steps: pre-processing, segmentation and extraction, and feature selection.

In the realm of dermatology, datasets featuring skin lesion images are notably sparse, exacerbating the challenge of conducting reproducible research. Many existing datasets are either too small or inaccessible to the public, further hindering progress in the field. Notable examples of dermatology-related datasets utilized in recent studies include:

- Dermofit Image Library [10], developed by Edinburgh Innovations Ltd. at the University of Edinburgh, serves as the original dataset for training purposes. This comprehensive library comprises 1,300 high-quality dermofit images meticulously categorized into the ten most prevalent dermofit classifications: Malignant Melanoma, Basal Cell Carcinoma, Seborrheic Keratosis, Actinic Keratosis, Haemangioma, Dermatofibroma, Intraepithelial Carcinoma, Melanocytic Nevus, Pyogenic Granuloma, and Seborrheic Keratosis. Each image adheres to a standardized capture protocol and has undergone professional skin pathology detection.
- Dermnet [5], constructed in 1998. This database comprises over 23,000 dermoscopic images showcasing a wide array of 643 distinct skin diseases. These conditions are systematically categorized into a dual-level taxonomy: the lower tier encompasses over 600 fine-grained skin diseases, while the upper tier classifies them into 23 broader categories including benign tumors, nevi, eczema, moles and melanomas.
- ISIC archive [7], consolidates various databases and boasts a collection of 13,786 dermatoscopic images. Renowned for its permissive CC-0 licensing, meticulously structured availability, and expansive size, it has become the gold standard for research in dermatoscopic image analysis. Notably, the archive exhibits a bias towards melanocytic lesions, with 12,893 out of 13,786 images depicting nevi or melanomas.
- PH2 dataset comprises 200 images, with 160 images depicting naevi (including atypical and common naevi), and the remaining 40 images representing melanoma cases [11]. While pathology served as the definitive reference for melanoma diagnosis, such data was unavailable for most naevi. Due to its accessibility and rich metadata, the PH2 dataset has emerged as a pivotal benchmark dataset for research endeavors focusing on computer-aided melanoma diagnosis, maintaining its significance in the field up to the present day.
- Atlas dataset [12] serves as a comprehensive medical educational resource containing over 1,000 cases of pigmented skin lesions. Each case is meticulously documented with clinical and dermoscopic images, alongside rich clinical data such as lesion location, diameter, and elevation, as well as histopathological results, diagnosis, and the presence or absence of dermoscopic

attributes. These extensive metadata align with the educational objectives of the Atlas, aimed at facilitating teaching dermoscopy through reliable medical algorithms like the 7-point checklist.

- The HAM10000 dataset [13] addresses the issue of diversity scarcity within skin lesion datasets. Comprising 10,015 dermoscopic images, it draws from two primary sources: Cliff Rosendahl's skin cancer practice in Queensland, Australia, and the Dermatology Department of the Medical University of Vienna, Austria. Spanning a twenty-year period, this compilation process began before the widespread use of digital cameras. Initially, photographic prints of lesions were archived at the Dermatology Department of the Medical University of Vienna, Austria. Subsequently, these prints were digitized using a Nikon Coolscan 5,000 ED scanner, produced by Nikon Corporation Japan, and transformed into 8-bit color JPEG images with a 300 DPI resolution. Following digitization, each image was manually cropped and saved at a resolution of 800 by 600 pixels at 72 DPI.

### *2.3. Benign vs. Malignant Lesions*

Benign lesions are characterized as alterations that do not pose serious health risks to individuals. However, it is important to note that these lesions may occur in potentially dangerous areas of the body. One of the most prevalent benign lesions is melanocytic nevus, which often takes the form of round or oval structures on the skin's surface. These lesions can range in color from reddish pink to black and commonly develop during the first three decades of life. Types of melanocytic nevus include common moles, atypical moles, congenital moles, and Spitz nevus. Other examples of benign tumors include dermatomyomas, epidermal cysts, freckles, and moles. Conversely, in the context of this manuscript, the term "malignant" refers to cancerous pathologies that can persist until the death of the individual without appropriate professional intervention. Skin cancers are often the result of abnormal skin cell division or mutation, and the risk of death is primarily associated with the metastasis of the original tumor. Some skin cancers can be challenging to treat as they may recur without a sufficient margin of safety during resection. Additionally, these lesions can progress to advanced stages and may result in scarring and the loss of important body functions. Therefore, early detection and management of these lesions are crucial to limit the potential consequences and complications [14].

The term "malignant" in this manuscript refers to cancerous conditions that can persist until the person's death without appropriate professional intervention. These types of skin cancers occur due to an abnormal division or mutation of skin cells, and the risk of death is mainly due to the spread of the original tumor to other parts of the body. Some of these tumors can be challenging to treat as they may reoccur without a sufficient margin of safety during removal. Apart from the risk of death, these lesions may progress to advanced stages, depending on the type of tumor and the person's body genes, which can lead to scarring and other complications. Thus, it is crucial to detect and manage these lesions as soon as possible to limit their consequences and adverse effects.

## 3. Related Work

Skin cancer is a serious public health problem due to its increasing incidence and resulting high mortality rate. In this context, several researchers are working on this subject.

### *3.1. Machine Learning*

A subfield of artificial intelligence called "machine learning" enables computers to learn from data. This section provides an overview of recent studies focusing on handcrafted feature extraction techniques. Elgamal and Mahmoud [15] employed wavelet transformation for feature extraction. The extracted features underwent dimensionality reduction before being utilized for classification tasks. For the classification of skin cancer based on clinical findings and the correlation of specific characteristics in dermoscopic images and tumor depth, the authors applied the k-nearest neighbor (k-NN) and artificial neural network (ANN) algorithms. Approximately 81 descriptors, derived from parameters such as color, texture, shape, and pigment network features, were extracted. To achieve classification, a combination of logistic regression and neural networks was employed, resulting in an overall accuracy of 95%.

In [16], the authors presented a novel method that combines the characteristic bag approach with accelerated robustness features to extract entities and quadratic support vector machines for classification. Their proposed method achieved an accuracy of 85.7%, sensitivity of 100%, specificity of 60%, and a training time of 0.8507 seconds for lesion classification using the PH2 dataset for skin cancer. The authors also found that their method outperformed other advanced methods by 3%.

In [17], the authors used dermoscopic images in RGB format to detect skin cancer early using the support vector machine algorithm. The images were segmented using the De-segmentation method, and features were extracted using the GLCM methodology. The support vector machine achieved a precision

of 95%. In [18], the authors proposed an intelligent diagnosis of skin cancer based on dermoscopy images using several variants of the particle swarm optimisation algorithm for optimisation functionality. They used pre-treatment to remove noise, segmentation, and extraction of characteristics of both the skin and lesion regions. The proposed algorithms were used to optimise functionality to identify the most significant discriminating characteristics of benign and malignant skin lesions. The authors proposed four new PSO variant algorithms, including Hybrid Learning PSO, PSO Variant Model, Adaptive Coefficient PSO, and Random Coefficient PSO, for the selection of features. These models addressed premature convergence problems of the original PSO algorithm using various research strategies. Simple and set classifiers were used to classify benign and malignant lesions. The proposed PSO variants outperformed other advanced and classical research methods to identify discriminating characteristics that facilitate the classification of benign and malignant lesions. The authors obtained a precision of 92.11% with the combination of GA and SVM algorithms and a precision of 90.53% with the combination of PSO and SVM algorithms using the same database. The Wilcoxon Rank Sum test was used to test the statistical superiority of the proposed algorithms over other methods.

### *3.2. Deep Learning*

Deep artificial neural networks are used in the machine learning subfield known as deep learning to automatically learn hierarchical representations of data. It allows high-level feature extraction and better performance in complex tasks, often avoiding manual feature engineering. In [19], a novel approach to automatic skin lesion classification is introduced, leveraging the Ph2 dataset for training, which comprises 200 skin cancer images. To address the challenge of limited data, data augmentation techniques are implemented, expanding the dataset size to 6,600 images through image rotation. Transfer learning is then applied, utilizing the pretrained architecture of AlexNet. This involves updating the neural network's weights using the stochastic gradient descent (SGD) algorithm. Furthermore, the model's performance is assessed using key metrics including accuracy, precision, sensitivity, and specificity. Results demonstrate that the proposed model surpasses the performance of existing methods.

In [20], the authors achieved a precision of 75% using the ANN algorithm on the ISIC database which contains RGB images. In their current work, they improved the algorithm by using functions such as ReLU, Gradient Descend, and Optimizers. In [21], the authors used convolution neural networks (CNN) on a database of 1,680 clinical images in RGB form, achieving an accuracy of 86.67%. They found that CNN requires less repossession algorithm compared to previous methods. In [22], the authors used a 5-layer convolutionary neural network (CNN) to classify skin lesions, including melanoma, achieving 95% accuracy, 94% sensitivity, 97% specificity, and 100% AUC (area under the curve) on the PH² dataset of Dermoscopic images.

Zhang et al. [23] examined the limitations of deep convolutional neural networks (DCNN) in accurately classifying skin lesions, particularly emphasizing their incapacity to prioritize semantically significant areas. Consequently, they propose an attention residual learning CNN as a remedy. This network consists of several attention residual learning blocks that leverage residual learning to effectively distinguish between images. Through experimentation on the ISIC-skin 2017 dataset, the proposed network demonstrates superior performance compared to other cutting-edge methodologies.

In [24], the authors used the watershed method for segmentation, and KNN, Random Forest, and SVM classifiers on the ISIC database's RGB images to achieve precisions of 65.39%, 74.32%, and 85.72%, respectively. SVM provided better results for the classification of skin lesions. In [25], the authors used two methods of image recognition: ResNet 50 as a deep learning convolutional neural network (DLCNN) and Support Vector Machine (SVM) for skin cancer classification. The ResNet 50 DLCNN achieved a recognition rate of over 97% on the test images, while the SVM classifier reached an accuracy of 86.9%.

Overall, CNN and SVM appear to be the most effective algorithms for skin lesion detection and classification, as evidenced by their high accuracy and precision scores. Table 2 presents state-of-the art approaches to skin cancer detection and classification.

***Table 2.*** Summary of the main research on skin cancer detection.

| Author | Dataset | Image Type | Technique | Accuracy |
|---|---|---|---|---|
| [20] | (HAM 10000) ISIC. | RGB | ANN | 75% |
| [16] | PH2 dataset | Binary | SVM | 85.7% |
| [21] | 1680 clinical images | RGB | CNN | 86.67 % |
| [18] | Dermofit dataset (1300) | RGB | GA+SVM | 92.11% |
| | | | PSO+SVM | 90.53% |
| [24] | International Skin Imaging Collaboration (ISIC). | RGB | KNN | 65.39% |
| | | | SVM | 85.72% |
| | | | Random Forest | 74.32% |
| [25] | 320 clinical images | RGB | SVM | 86% |
| | | | CNN | 97.80% |
| [22] | PH2 dataset | RGB | CNN | 95% |
| [17] | Dermoscopic images | RGB | SVM | 95% |

## 4. Materials and Methods

The proposed approach consists of creating a cancer skin detector based on machine learning and deep learning. It involves many steps, starting with data normalization and feature extraction. Next, we create a CNN model and apply data augmentation techniques. We then compare this approach with a combination of CNN and SVM.

### *4.1. Data Augmentation*

The used dataset in this study was obtained from the International Skin Image Collaboration (ISIC) [7] archives and includes 1,800 images of benign moles and 1,497 images of malignant moles, all of which were resized to a low resolution RGB (224 × 224 × 3). The goal of this study was to develop a model capable of visually classifying moles as either benign or malignant. The dataset consists of two distinct classes of skin cancer: benign and malignant. Figure 1 displays some samples of the used dataset.

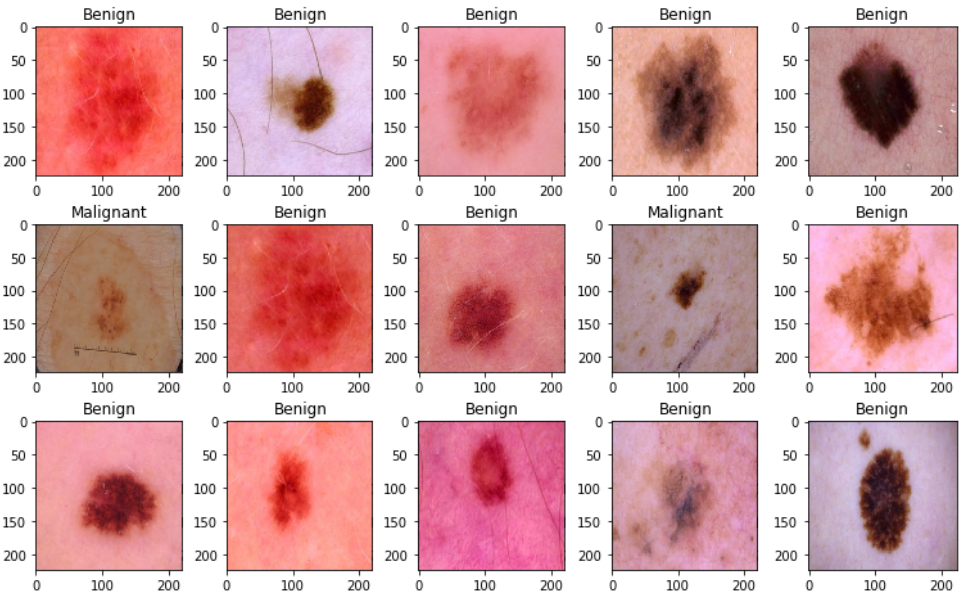
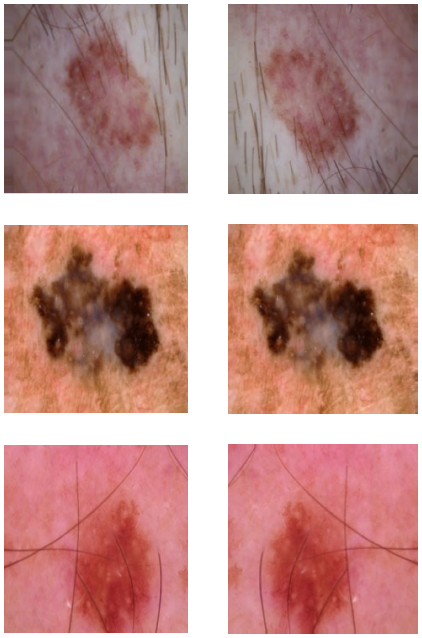



***Figure 1.*** Samples of ISIC images.

By increasing the amount of data available for training, data augmentation can improve the performance and robustness of machine learning models. Figure 2 displays some samples of the used dataset after application of data augmentation. This technique is used to artificially increase the amount of data available for training machine learning models. It involves creating new data by applying transformations to existing data, such as resizing, flipping, rotating, cropping, or padding. This technique is useful for addressing problems such as overfitting and data scarcity, as it allows for the creation of

more diverse and representative datasets. In this work, we applied these function to the dataset to optimize training precision, resulting in an increase in instances from 3,297 to 20,580 (11,435 images of benign moles and 9,145 images of malignant moles). This is a significant increase in data that can lead to improved model performance; the model becomes more robust to variation and noise in real data. There are several techniques commonly used for data augmentation in machine learning. Here are some of the popular techniques:

- Rotation: Rotating the image by a specific angle.
- Flip: Flip the image horizontally or vertically.
- Crop: Randomly crop part of the image.
- Zoom: Enlarge or reduce the image.
- Translate: Move the image horizontally or vertically.
- Add Noise: Add random noise to the image.



(**a**) (**b**)

***Figure 2.*** A slide of a skin lesions before (**a**) and after (**b**) data augmentation.

## *4.2. Convolutional Neural Network*

Convolution Neural Networks (CNNs) are like the rockstars of image processing in the AI world. CNNs are primarily employed to resolve challenging image-based pattern recognition tasks [26,27]. While more computationally intensive than simple machine learning methods, CNNs offer better performance. CNNs are widely used in recommender systems, natural language processing, and image and video recognition. To accomplish the classification task, the CNN architecture presented in Figure 3 was developed using Tensorflow Keras backend, and the results were analyzed to determine the model's potential usefulness in practical scenarios.

The first part of the CNN is the convolution part. It acts as an image feature extractor. The image is passed through a series of filters, or convolution kernels, creating a new image called a folded graph. Some intermediate filters reduce the resolution of the image through local filters. Finally, the convolution maps are flattened and concatenated into feature vectors called CNN codes.

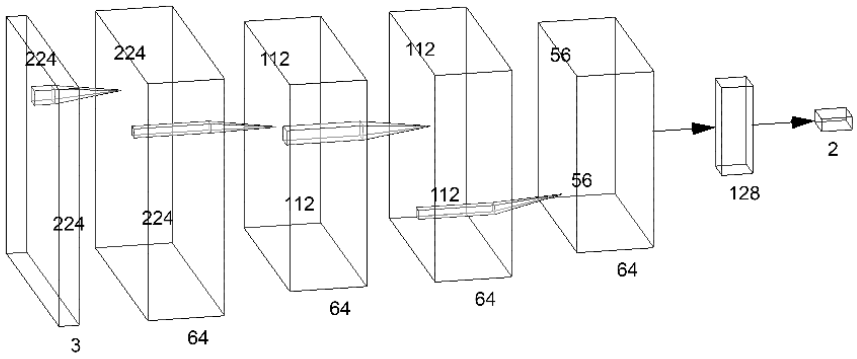



***Figure 3.*** Used Convolution Neural Networks architecture.

## *4.3 Support Vector Machines*

For skin cancer detection, machine learning models have been adopted due to their superior performance. Among these models is the Support Vector Machines (SVM), which is briefly discussed in this article for completeness. SVM is an algorithm mainly used to classify data into different categories, as described in [17,18]. Unlike most algorithms, SVM uses a hyper plane as the decision boundary between different classes. SVM can be used to create multiple splitting hyper planes to divide data into segments, with each segment containing only one type of data. SVM is also known as a "wide margin separator. They are part of supervised machine learning techniques that focus on classifying data sets into insightful groups. They are based on the concepts of decision plans and decision constraints. The objective of SVM is to find an ideal hyper plane that optimizes the distance between each data cluster's nearest points (See Figure 4).

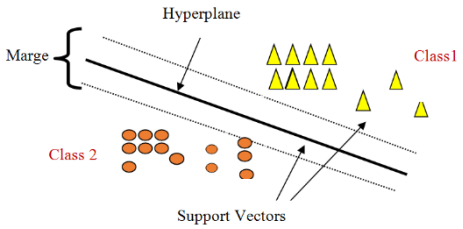



***Figure 4***. Support Vector Machine.

A "support vector" is a collection of instances that are near the ideal hyperplane. Through careful kernel selection, SVM offers a unifying framework for categorizing multiple types of data, allowing for the creation of various machine learning architectures. The linear SVM design is used when the data can be divided into linear categories. For nonlinear data, a different kernel function is used. Kernel functions transform low-dimensional data into a higher-dimensional space that allows separation for linear data [28]. To categorize novel data points, SVM assess their position relative to the hyperplane. Utilizing the acquired parameters from the training phase, SVM determines the side of the hyperplane the data point falls on, thereby assigning it to one of the classes (refer to Figure 5) [29].

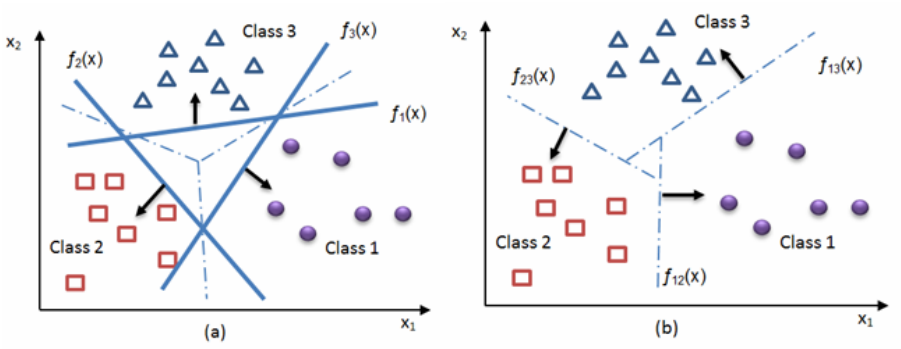



***Figure 5***. SVM approaches; (**a**) one-versus-all method, (**b**) one-versus-one method.

In medical image analysis, the SVM classifier widely used in research on skin cancer datasets has shown promising results. Protein function prediction, gene expression data classification, and cancer detection are some applications of massive SVMs [30].

In this paper, we used SVM to classify malignant tumors and benign tumors by passing the segmented and feature-extracted images into CNN where SVM establishes the hyperplane and categorizes individuals with similar features into separate classes. The performance of the SVM classifier was very accurate even for a small dataset [17], and its performance was compared to other classification algorithms such as CNN.

### *4.4. System Architecture*

The proposed CNN-based model [31] consists of three components, namely feature learning, image classification using SVM, and hybridization of CNN and SVM as depicted in Figure 6 We begin by feeding a 224 × 224 × 3 image to the model, followed by t wo identical blocks, each comprising three layers. The first convolution layer uses 64 filters of kernel size 3 × 3 with the RELU activation function, followed by a maxpooling layer of size 2 × 2 to reduce feature maps, and a dropout layer with a value of 0.25. We repeat the same process in the second block, using the output of the first block as input. Next, the model flattens the results of the two blocks and moves to the fully connected layer, which has 128 neurons and uses RELU as the activation function. We classify the images using the SVM classifier with Linear activation function. The training process involves using the Adam optimizer and Hinge as the loss parameter value.

## 5. Results and Discussion

This section discusses the results of the proposed method for classifying skin cancer, as well as performance measures of CNN, CNN with data augmentation, and CNN-SVM combination. The obtained results are then compared with state of the art results.

### *5.1 Experimental Results*

The initial step in our process involved loading the images and converting them into numpy arrays by considering their RGB value. It should be noted that the images have already been resized to 224 × 224. Subsequently, labels were created for each image, and finally, the images were added to a comprehensive training set and mixed together. The system was then able to analyze the images from the database and categorize them into two different classes, namely benign and malignant.

#### 5.1.1. CNN

To enhance the performance of our model, we experimented by training the model with a fixed number of epochs and noting down the achieved accuracy. It was observed that as the number of epochs increased, the accuracy of the model improved. For example, at 20 epochs, the accuracy was found to be 54%, while at 50 epochs, it increased to 91%. Finally, we trained our model with 100 epochs, which resulted in high accuracy of 97.27%, and hence, we stopped at this stage.

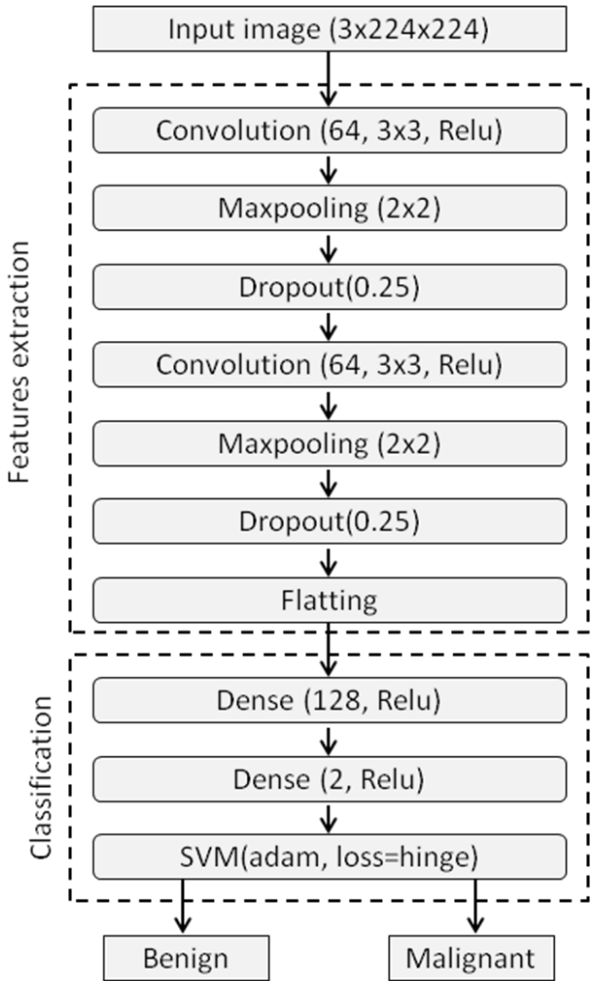



***Figure 6***. Global architecture of the model.

The proposed model was trained with 2,637 images, and achieved a validation accuracy of nearly 75%. Validation accuracy measures the accuracy of predictions on a randomly selected validation set after each epoch. Notably, the validation accuracy does not decrease and remains constant at around 75%, even as overall accuracy continues to improve (See Figure 7). The loss values follow a similar pattern, with the overall loss decreasing almost every epoch and approaching 0, while the validation loss remains stagnant like the validation accuracy. Loss values indicate how close the neural network is to its optimal performance.

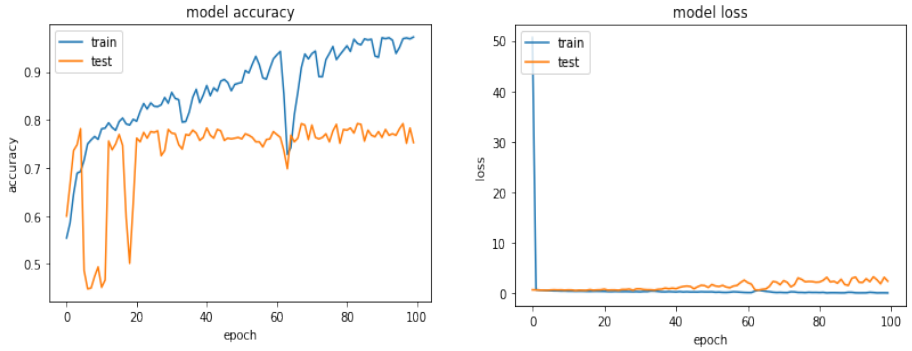



***Figure 7.*** Accuracy and loss Curves of CNN.

The size of the data set is a critical factor in determining the performance of a deep learning model. However, the model's accuracy can also be improved by expanding the existing data through data augmentation techniques. This approach also helps the model become more adaptable to diverse image types. Data augmentation involves adding variations to the existing data, such as applying random zoom-

ins or zoom-outs, rotating the image at random angles, blurring the image, and so on. Our model achieved 98.55% accuracy with 100 epochs while it had an accuracy of 97.27% without data augmentation. Therefore, we can conclude that data augmentation is an effective technique for enhancing the learning of a CNN model.

### 5.1.2. CNN-SVM Combination

The accuracy achieved after training the model without using data augmentation for 100 epochs with 2,637 training images and 660 testing images is about 94.72%. It is worth noting that the model's performance without using data augmentation is satisfactory. However, in the next section, we aim to enhance it further. During the training of our CNN+SVM model, the accuracy and loss values for the validation data may vary depending on the situation. Typically, as the number of epochs increases, we expect the loss to decrease and the accuracy to increase, which is what happened in our case.

Throughout this study, several results were obtained for the detection of malignant and benign images. This sheds light on the different methods used for skin cancer detection. The Table 3 presents the outcomes obtained using the different techniques: CNN, CNN+data augmentation, CNN+SVM, and CNN+SVM+data augmentation for both malignant and benign images.

***Table 3.*** Classification accuracy of the proposed systems.

| Data Augmentation | Technique | Training | Evaluation |
|---|---|---|---|
| Without | CNN | 97.27% | 75% |
| | CNN-SVM | 98% | 94.72% |
| With | CNN | 98.55% | 97.27% |
| | CNN-SVM | 99% | 98.71% |

To gauge the performance of the proposed binary classification model based on CNN-SVM combination on the testing data, we constructed a confusion matrix, as illustrated in Table 4. The results unequivocally showcase the remarkable discriminatory efficacy of our approach in skin cancer detection. In assessing these outcomes, we employed key metrics including Overall Accuracy (OA), Precision (P), Recall (R), and F1 score (F1), computed using Equations (1)–(4). In these equations, TP (True Positive), TN (True Negative), FN (False Negative), and FP (False Positive) represent the respective outcomes of the model's predictions. TP signifies correctly predicted positive outcomes, TN denotes correctly predicted negative outcomes, FP represents incorrectly predicted positive outcomes, and FN indicates incorrectly predicted negative outcomes.

***Table 4.*** Confusion matrix of CNN-SVM combination model (Class1: Malignant; Class2: Benign).

| | | Truth Data | | | |
|---|---|---|---|---|---|
| | | **Class 1** | **Class 2** | **Classification overall** | **User's accuracy (Precision)** |
| **Classifier results** | **Class 1** | 1,818 | 11 | 1,829 | 99.399% |
| | **Class 2** | 42 | 2,245 | 2,287 | 98.164% |
| | **Truth overall** | 1,860 | 2,256 | 4,116 | |
| | **Producer's accuracy (Recall)** | 97.742% | 99.512% | | |
| **Overall accuracy (OA)** | 98.712% | | | | |

$$OA = (TP + TN)/(P + N) \quad (1)$$

$$P = TP/(TP + FP) \quad (2)$$

$$R = TP/(TP + FP) \quad (3)$$

$$F1 = 2*TP/(2*TP + FP + FN) \quad (4)$$

In addition to the afore mentioned metrics, Table 4 provides the values of the Negative Predictive Value (NPV) and the False Positive Rate (FPR), which stand at 98.16% and 99.51%, respectively. Furthermore, the table presents supplementary performance measures derived from the confusion matrix of the CNN-SVM classifier. These include an accuracy (OA) of 98.71%, precision (P) of 99.4%, recall (R) of 97.74%, and an F1-score of 98.56%.

### *5.2. Comparison Study*

In this section, we have presented a comparison between our work and the recent studies that used the same database for skin cancer (See Table 5). We compared the highest mean results of our method with the mean results reported in other studies.

ML models, particularly deep learning models, can automatically learn complex patterns and nuances from data, allowing them to adapt to evolving forms of skin cancer. The benefit of the used machine learning models is to provide better generalization power for skin cancer classification problems. The use of deep learning networks has proven, as mentioned in [32,33], high performance. Consequently, through the power of ML and DL models, a detailed investigation of a hybrid architecture using CNN and SVM models was reported in this study.

From the reported results, it can be concluded that the proposed method outperforms comparative techniques. It uses a faster CNN with the SVM algorithm, which classifies a more efficient set of image features and can better deal with the model fitting problem. Therefore, we can say that our presented method is more effective and efficient for the detection and classification of skin lesions. However, it's important to note that bias in AI models is a critical concern that needs to be addressed in the development process. If the training data used to train a machine learning model is biased, the model is likely to inherit and perpetuate those biases. For example, if the training data contains imbalances in the representation of different groups, the model may not generalize well to underrepresented groups [32]. In this study, the used dataset is characterized by a diversity of data which is also guaranteed by data augmentation; therefore a major influence on the ability of the proposed methods can overcome biases.

***Table 5.*** Comparative study.

| Authors | Technique | Accuracy |
|---|---|---|
| [16] | SVM | 85.7% |
| [20] | ANN | 77% |
| [24] | KNN | 65.39% |
| | SVM | 85.72% |
| | Random Forest | 74.32% |
| [22] | CNN | 95% |
| [34] | CNN+SVM | 91.7% |
| Proposed system | CNN+SVM with data augmentation | 98.71% |

## 6. Conclusions

This paper describes a skin cancer detection system that combines a convolutional neural network and a support vector machine, using ISIC images for testing. Skin cancer is a serious and increasingly prevalent health problem, and early detection is crucial for a positive prognosis. Dermoscopy is a common imaging method for diagnosing skin lesions, but the interpretation of these images can be difficult and subjective. The proposed model aims to assist in the interpretation of these images, providing accurate information on the content of the image and the pathological aspects of the structures presented. The model can aid in improving different stages of medical image analysis and can provide better recognition performance. While the model will never replace the eye of the clinician, it can provide faster and more detailed interpretation tools, making it reliable for diagnosing and detecting diseases. The model uses a combination of machine learning and deep learning, with the CNN model being effective for detection problems and the SVM model being more effective for classifying cancer images. This study represents a significant advancement in the field of skin cancer detection by employing a combination of Convolution Neural Networks and Support Vector Machines for the precise categorization of skin lesions into benign and malignant forms. The proposed Model outperformed all existing models dedicated to skin cancer detection, thus showcasing its remarkable potential in improving diagnostic accuracy and potentially saving lives. This achievement underscores the importance of

harnessing machine learning techniques in the medical domain for more effective disease diagnosis and management.

**Author Contributions**
A.M. and S.S. carried out the bibliographic studies on skin lesions diagnosis, participated in the implementation of the system and drafted the manuscript. M.K. and A.M. participated in the design and coordination of the study. M.K. helped to draft the manuscript. All authors read and approved the final manuscript.

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**Conflict of Interest Statement**
The authors declare no conflicts of interest.

**Data Availability Statement**
Data supporting reported results are publicly available at *https://www.kaggle.com/datasets/fanconic/skin-cancer-malignant-vs-benign.*

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