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**(Skin Guardian)**

**Skin Cancer Classification Using Deep Learning**

Egyptian E-Learning University

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# **Abstract**

Skin cancer is a highly dangerous disease, and early detection of skin lesions can significantly improve the chances of cure before it spreads. However, achieving automatic skin cancer classification is challenging due to imbalanced and limited datasets, as well as challenges in cross-domain adaptability and robustness. Deep learning-based methods have been widely used to address these issues, but reviews of these approaches are scarce.

The increasing prevalence of skin cancer and its importance for early detection make it crucial to develop an effective method for automatically classifying skin cancer. Melanoma, basal cell carcinoma (BCC), and squamous cell carcinoma (SCC) are the most common skin cancers globally, with over 1 million cases in 2018. Early detection can lead to improved cure rates, but diagnosing skin cancer with naked eyes is subjective and rarely generalizable. Therefore, developing an automatic classification method for skin cancer that is more accurate, less expensive, and quicker to diagnose is necessary.

However, achieving automatic classification of skin cancer is challenging due to the complexity and diversity of skin disease images. Different skin lesions have interclassed similarities, which could result in misdiagnosis. Handcrafted features from skin-disease images are often difficult to discriminate from their known imitators, and classification algorithms are sensitive to the types of camera devices used to capture images. Traditional machine learning approaches, such as ABCD Rule, Menzies Method, and 7-Point Checklist, are ineffective for complicated diagnostic demands in clinical practice.

Deep learning algorithms have been widely used for skin cancer classification without the need for domain expertise and feature extraction. They can analyze data from large-scale datasets faster and more accurately, extract relevant characteristics, and aid clinicians in thorough data analysis and examination of test results. However, there are still several challenges to overcome, such as data imbalance, lack of a large volume of labeled images, significant computing costs, and generation of different noises due to various conditions.

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**Chapter 1: Introduction**

## **1.1 Introduction**

High-quality images of skin diseases are crucial for dermatologists and automated diagnostic systems. Dermatologists use these images for diagnoses when direct observation is impossible, especially in telemedicine and medical consultations. Deep learning algorithms require large volumes of labeled data for better accuracy. This is especially important for clinical diagnosis and algorithm design. This section discusses three common types of images used in skin cancer diagnosis and public datasets.

A close-up of a skin with a large red spot

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fig 2 comparison between skin cancer image types

|  |  |  |
| --- | --- | --- |
| **A-Clinical Images** | **B-Dermoscopy Images** | **C- Histopathological Images** |
| • Acquired by directly photographing skin disease site.  • Used as medical records and provide insights for dermoscopy images.  • Limitations: Limited morphological information, inaccuracies due to imaging settings. | • Dermoscopy is an optical observation tool used to assess skin diseases.  • It's commonly used to diagnose benign nevi and malignant melanoma.  • Dermoscopy bridges clinical and pathological aspects, serving as a dermatologist's stethoscope.  • It provides clear visualization of skin's surface and analyzes color and microstructure of the epidermis.  • Diagnostic guidelines based on dermoscopy images include ABCD Rule Law, CASH Rule Law, and Menzies Method.  • Limitations include limited structure observation range and occasional influence of dermatologist experience. | • Histopathological images, obtained via microscopes, show vertical structure and internal characteristics of diseased tissue.  • Serve as the "gold standard" for diagnosing various cancer types and guiding treatment plans.  • Various histopathological images of skin cancer present unique morphologies, scales, textures, and color distributions, complicating diagnosis. |

## **1.** **1.1 Deep learning**

* Deep learning is a subset of machine learning, consisting of neural networks with multiple layers that simulate human brain behavior.
* It drives AI applications and services that improve automation, performing tasks without human intervention.
* Deep learning technology is found in everyday products and emerging technologies like self-driving cars.

## **1.2** Deep learning VS Machine learning**:**

Table 1.2: DL vs ML

|  |  |
| --- | --- |
| Deep learning | Machine learning |
| • Deep learning is a subset of machine learning that automates feature extraction and eliminates data pre-processing. | • Machine learning uses structured data for predictions, while deep learning uses gradient descent and back propagation for accuracy adjustment. |
| • Machine learning and deep learning models are supervised, unsupervised, and reinforcement learning. | |

Table 1.3: types of learning

|  |  |
| --- | --- |
| Supervised learning | Unsupervised learning |
| •In supervised learning, the algorithm is trained on a labeled dataset, which means that the input data is paired with corresponding output labels. | •Unsupervised learning involves working with unlabeled data where the algorithm is not provided with explicit output labels. |
| •The goal is for the algorithm to learn the mapping or relationship between the input features and the target labels. | •The goal is to identify patterns, structures, or relationships within the data without specific guidance. |

## **1.3 How deep learning works (Deep Learning Overview):**

1. Neural networks mimic the human brain using data inputs, weights, and bias.
2. Comprises visible layers for prediction refinement.
3. Back propagation calculates errors and adjusts weights and biases.
4. Different types of neural networks address specific problems or datasets.
5. CNNs detect features in images.
6. RNNs use sequential or times series data for natural language and speech recognition.
7. Requires high-performance GPUs for calculations.
8. Managing multiple GPUs on-premises can be costly and resource-intensive.

## **1.4 Deep learning applications in Healthcare:**

1. Deep learning applications integrated into daily products and services.
2. Healthcare field benefits from deep learning capabilities.
3. Image recognition software aids medical imaging professionals in analyzing and assessing more pictures.

## **1.5 What is Neural Network?**

* Neural networks, modeled after human brains, are a branch of machine learning.
* They consist of individual nodes forming layers influenced by multiple weights.
* Training data is passed through hidden layers, transforming values based on each node's weights.
* The output layer returns the resulting value.
* Proper tuning of a neural network requires time and balance between testing and training.
* "Deep" in deep learning refers to the depth of layers in a neural network.

A diagram of a network

Description automatically generatedFigure 1.2: DNN

## **1.6 Types of Neural Networks****:**

Table 1.4: Types of Neural Networks

|  |  |
| --- | --- |
| • Perceptrons: | The oldest and most common type of neural network. |
| • Multi-layer perceptrons (MLPs): | Composed of sigmoid neurons, used for training in computer vision and natural language processing. |
| • Neural networks: | A subset of machine learning, central to deep learning algorithms. |
| • Recurrent neural networks: | Used for natural language processing and speech recognition. |
| • Convolutional neural networks (CNNs): | Used for classification and computer vision tasks. |
| • CNNs: | Offer a scalable approach to image classification and object recognition, but can be computationally demanding, requiring GPUs for model training. |

## **1.7 Convolutional Neural Networks (CNNs):**

• CNNs are deep learning algorithms used for image, speech, or audio signal inputs. CNNs are commonly associated with image data

• They consist of three main layers: convolutional, pooling, and fully connected (FC), the convolutional layer is the first, followed by additional layers or pooling layers.

• As layers progress, the complexity increases, identifying larger elements or shapes of the image until it identifies the intended object.

• CNNs have been used in various fields like marketing, healthcare, retail, and automotive. And are used in various fields like computer vision, banking, and postal services.

• CNN’s output is a feature map, activation map, or convolved feature. The feature detector's weights remain fixed as it moves across an image, known as parameter sharing.

• After each convolution operation, a CNN applies a Rectified Linear Unit (ReLU) transformation to the feature map, introducing nonlinearity to the model.

• A CNN can become hierarchical by following an initial convolution layer.

• Pooling layers, also known as down sampling, reduce dimensionality by sweeping a filter across the input without weights.

•The full-connected layer is a classification layer that connects each node in the output layer to a node in the previous layer. Zip code recognition.

A diagram of a computer program

Description automatically generated with medium confidence

figure 1.3: CNN Layers

A diagram of a diagram of a network

Description automatically generated with medium confidence

Figure 1.4: CNN layers

## **1.8 Recurrent Neural Networks**

• Recurrent Neural Networks (RNNs) are artificial neural networks used for tasks like language translation, speech recognition, and image captioning.

• RNNs use training data and their "memory" to influence current input and output.

• RNNs account for future events in their predictions, unlike unidirectional CNNs.

• RNNs share parameters across each layer, allowing for reinforcement learning.

• They use the backpropagation through time (BPTT) algorithm to determine gradients.

• RNNs face problems like exploding gradients and vanishing gradients, which can be addressed by reducing hidden layers.

• Feedforward networks map one input to one output, unlike RNNs.

• Bidirectional recurrent neural networks (BRNN) improve prediction accuracy by incorporating future data.

• Long short-term memory (LSTM) addresses the vanishing gradient problem with "cells" in the hidden layers.

• Gated recurrent units (GRUs) address the short-term memory problem of RNN models using hidden states and two gates.

**A diagram of a mathematical equation

Description automatically generated**Figure 1.5: RNN

A diagram of a number of mathematical equations

Description automatically generated with medium confidence

Figure 1.6: RNN

## **Chapter 2: Database survey**

### **2.1** [**PH2 Dataset (PH2DERMOSCOPY Dataset)**](https://www.researchgate.net/publication/257602103_PH2_-_A_dermoscopic_image_database_for_research_and_benchmarking)

• A dermoscopic image database with 200 images of melanocytic lesions.

• Includes 80 common nevi, 80 atypical nevi, and 40 melanomas.

• TIFF format with resolution of 768 x 560 pixels and 24 bits color depth.

• Published in 2013 as part of a research paper.

• Aims for research and benchmarking on segmentation and classification algorithms of dermoscopic images.

• Provides clinical diagnosis, lesion segmentation, color segmentation, and other features.

• Aims to evaluate and compare different methods for skin lesion analysis.

### **2.2** [**MED-NODE Dataset**](https://www.researchgate.net/publication/276421885_MED-NODE_A_Computer-Assisted_Melanoma_Diagnosis_System_using_Non-Dermoscopic_Images)

• 170 JPEG images of melanocytic lesions, 70 melanomas and 100 naevi.

• Published in 2015 as part of a research paper.

• Aimed at research and benchmarking for comparative studies on segmentation and classification algorithms.

• Provides clinical diagnosis, lesion segmentation, color segmentation, and other features.

• Includes two types of lesions: melanomas and naevi.

• Aims to present a new dermoscopic image database for skin lesion analysis evaluation.

### **2.3** [**HAM10000 Dataset**](https://www.researchgate.net/publication/324078202_The_HAM10000_Dataset_A_Large_Collection_of_Multi-Source_Dermatoscopic_Images_of_Common_Pigmented_Skin_Lesions)

• Comprises 10,015 dermatoscopic images of pigmented skin lesions.

• Images are in JPEG format with a resolution of 600 x 450 pixels.

• Published in 2018 by Schendel et al.

• Includes images of seven types of skin cancer: melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, and vascular lesion.

• Collected from different populations and annotated by expert dermatologists.

• Can be used for machine learning and comparison with human experts.

• Aims to facilitate the development and evaluation of machine learning algorithms for skin cancer detection and diagnosis.

### **2.4** [**Derm7pt Dataset**](https://www.researchgate.net/publication/324381190_7-Point_Checklist_and_Skin_Lesion_Classification_using_Multi-Task_Multi-Modal_Neural_Nets)

• Contains 2000 clinical and dermoscopic color images of skin lesions.

• Published in 2015 by Giotis et al.

• Includes images of two types of skin cancer: melanoma and naevus.

• Annotated by expert dermatologists.

• Provides structured metadata for each image, including seven-point checklist criteria.

• Aims to train and evaluate computer-aided diagnosis systems for skin lesion analysis.

• Aims to compare different machine learning methods for predicting the seven-point checklist criteria and diagnosis

### **[2.5](https://www.isic-archive.com/)** **[ISIC Dataset](https://www.isic-archive.com/)**

• Comprises 23,906 images from various sources.

• Image type and format: JPEG format, 600 x 450 pixels resolution.

• Published in 2019 by Schendel et al.

• Includes images of seven types of skin cancer: melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, and vascular lesion.

• Collected from different populations, acquired, and stored by different modalities.

• Annotated by expert dermatologists.

• Can be used for machine learning and comparison with human experts.

• Aims to facilitate the development and evaluation of machine learning algorithms for skin cancer detection and diagnosis.

### **2.6** **[SIIM-ISIC Melanoma Classification](https://www.kaggle.com/c/siim-isic-melanoma-classification/discussion/155859)**

Melanoma Classification Dataset

• 33,126 dermoscopic training images of skin lesions from over 2,000 patients.

• Images are in DICOM or JPEG format.

• Published in 2020 for the SIIM-ISIC Melanoma Classification Challenge on Kaggle.

• Includes only melanoma, responsible for 75% of skin cancer deaths.

• Generated by the International Skin Imaging Collaboration (ISIC).

• Images from various sources including hospitals, universities, and cancer centers.

• Includes images of various skin lesions like nevi, seborrheic keratoses, lentigines, and dermatofibromas.

• Aims to develop image analysis tools to identify melanoma using patient-level contextual information.

### **2.7** [**Skin Lesion Analysis Towards Melanoma Detection (SLATMD) Dataset**](https://challenge2020.isic-archive.com/)

• Comprises 10,015 dermatoscopic images of pigmented skin lesions.

• Categorized into seven categories: Actinic Keratoses and Intraepithelial Carcinoma (AKIEC), Basel Cell Carcinoma (BCC), Benign Keratosis-like Lesions (BKL), Dermatofibroma (DF), Melanoma (MEL), Melanocytic Nevi (NV), and Vascular Lesions (VASC).

• Images in JPEG format, resolution of 600 x 450 pixels.

• Published in 2020 as part of the ISIC 2020 Challenge Dataset.

• Melanoma, responsible for 75% of skin cancer deaths, is included.

• Published by the International Skin Imaging Collaboration (ISIC).

• Aims to develop image analysis tools for melanoma detection using patient-level contextual information.

### **2.8** [**Dermofit Dataset**](https://licensing.edinburgh-innovations.ed.ac.uk/product/dermofit-image-library)

• Includes 1,300 dermatoscopic images of skin lesions in ten categories: Actinic Keratosis, Dermatofibroma, Haemangioma, Squamous Cell Carcinoma, Melanocytic Nevus, Seborrhoeic Keratosis, Intraepithelial Carcinoma, Pyogenic Granuloma, and Melanoma.

• Released by the DERMOFIT project, supported by the Wellcome Foundation, from August 1, 2008, to July 31, 2011.

• Includes various cancer types including Nevus melanocyticus, Squamous Cell Tumor, Internal Epithelial Cancer, Malignant Melanoma, and Intracellular Carcinoma.

• Melanoma accounts for 75% of skin cancer mortality.

• Created by the University of Edinburgh, aiming to create an interactive skin cancer picture database indexing tool.

### **2.9** [**MSK Dermatology Image**](https://paperswithcode.com/dataset/msk)

• Lesion recognition dataset used in ISIC lesion identification tasks.

• Comprises 1,000 photos of skin lesions classified into eight types: Melanoma, Melanocytic Nevus, Basal Cell Carcinoma, Actinic Keratosis, Benign Keratosis, Dermatofibroma, Vascular Lesion, and Squamous Cell Carcinoma.

• Photos are in JPEG format with 1024 × 1024-pixel resolution.

• Released as part of the ISIC 2017 Challenge Dataset in 2017.

• Aims to create image analysis techniques for identifying and categorizing skin lesions using patient-level contextual information.

### **2.10** [**Dermoscopedia Image Library**](https://dermoscopedia.org/Main_Page)

• Collection of nearly 2,000 dermoscopic images of skin lesions.

• Classified as melanoma, basal cell carcinoma, seborrheic keratosis, etc.

• JPEGs with resolution of 1024 × 768 pixels.

• Published by the International Dermoscopy Society in 2017.

• Melanoma, a major skin cancer, included.

• Contributed by dermatologists from various countries and sources.

• Aims to develop an online resource for dermoscopy and promote its use in clinical practice.

### **2.11** [**EDF (Edinburgh Dermofit Library)**](https://licensing.edinburgh-innovations.ed.ac.uk/product/dermofit-image-library)

• Contains 1,300 images of skin lesions.

• Captures normal RGB images with internal color standards.

• Published in 2012, covering 10 most observed skin lesions in primary care.

• Types of lesions include Actinic Keratosis, Basal Cell Carcinoma, Melanocytic Nevus / Mole, Seborrhoeic Keratosis, Squamous Cell Carcinoma, Intraepithelial Carcinoma, Pyogenic Granuloma, Haemangioma, Dermatofibroma, and Melanoma.

• Aims to provide a standardized set of skin lesion images for computer-aided diagnosis systems and facilitate comparison and reproducibility of different methods and algorithms.

### **2.12** [**PAD-UFES-20**](https://www.semanticscholar.org/paper/PAD-UFES-20%3A-A-skin-lesion-dataset-composed-of-data-Pacheco-Lima/6d7a6d578e9fa9b2e488ac98f14cc2bd610477ca)

• Gathers information from the UFES-Brazil Dermatological and Surgical Assistance Program.

• Consists of 2,298 skin lesion samples.

• Each sample contains a clinical picture as well as up to 22 clinical characteristics.

• Basal Cell Carcinoma (BCC), Squamous Cell Carcinoma (SCC), Actinic Keratosis (ACK), Seborrhoeic Keratosis (SEK), Bowen's disease (BOD), Melanoma (MEL), and Nevus (NEV) are all skin lesions.

• All BCC, SCC, and MEL samples have been biopsy-proven, with the remaining samples potentially having a clinical diagnosis. • Images were acquired using various smartphone devices and are accessible in.png format.

• Each skin lesion's metadata contains up to 26 characteristics.

• There were 1,373 patients, 1,641 skin lesions, and 2,298 pictures in total.

### [**2.13 BCN20000 Dataset**](https://paperswithcode.com/dataset/bcn-20000)

• A dermoscopic image database containing 19,424 images of skin lesions from 2010 to 2016.

• Images captured in JPEG format with a resolution of 600 x 450 pixels.

• Published in 2018 by Comb Alia et al.

• Includes images of seven types of skin cancer: melanoma, melanocytic nevus, basal cell carcinoma, actinic keratosis, benign keratosis, dermatofibroma, and vascular lesion.

• Useful for lesion recognition tasks, clinical diagnosis, lesion segmentation, color segmentation, and other features.

• Aims to facilitate the development and evaluation of machine learning algorithms for skin cancer detection and diagnosis.

### **2.14 Dataset comparison table**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Dataset | format | Number  Of images | types of lessions | published | goal of publication and brief description |
| PH2 Dataset | **TIFF resolution of 768 x 560 pixels and a color depth of 24 bits** | **200** | **3** | **2013** | **The publication aimed to introduce a new dermoscopic image database for scientific evaluation and comparison of various skin lesion analysis methods.** |
| MED-NODE Dataset | **JPEG resolution of 1024 x 768 pixels and a color depth of 24 bits.** | **170** | **2** | **2015** | **The publication aimed to introduce a new dermoscopic image database for scientific evaluation and comparison of various skin lesion analysis methods.** |
| HAM10000 Dataset | **JPEG resolution of 600 x 450 pixels** | **10,015** | **8** | **2018** | **The dataset, gathered from diverse populations and annotated by dermatologists, provides a comprehensive collection of pigmented skin lesions for research and evaluation of machine learning algorithms.** |
| Derm7pt Dataset | **JPEG** | **2000** | **2** | **2015** | **The publication presents a dermatology dataset for training and evaluating computer-aided skin lesion analysis systems, comparing machine learning methods for predicting seven-point checklist criteria.** |
| BCN20000 Dataset | **600 x 450 JPEG** | **19,424** | **7** | **2018** | **The publication aims to offer a comprehensive dataset of dermoscopic images of common pigmented skin lesions for research and education, and to aid in the development of machine learning algorithms for skin cancer detection.** |
| ISIC Dataset | **600 x 450 JPEG** | **23,906 (10,015 HAM+13,891 ISIC)** | **7** | **2019** | **The dataset, gathered from diverse populations and annotated by dermatologists, includes all diagnostic categories of pigmented lesions, enabling machine learning and expert comparison.** |
| SIIM-ISIC Melanoma | **DICOM or JPEG** | **33,126** | **1(melanoma)** | **2020** | **The publication aimed to create image analysis tools that can identify melanoma in lesion images, potentially improving dermatologists' diagnostic accuracy and potentially saving lives.** |
| Skin Lesion Analysis Towards Melanoma Detection (SLATMD) Dataset | **JPEG**  **600 x 450** | **10,015** | **1(melanoma)** | **2020** | **develop image analysis tools that can identify melanoma in lesion images, this could potentially improve the diagnostic accuracy of dermatologists and save lives** |
| Dermofit Dataset | **JPEG  resolution of 600 x 450  pixels** | **1,300** | **10** | **2008** | **The University of Edinburgh developed an interactive skin cancer image database indexing tool, comparing live skin lesions to selected images, potentially improving dermatologists' diagnostic accuracy and saving lives.** |
| MSK Dermatology Image | **JPEG**  **resolution of 1024 x 1024 pixels** | **1,000** | **8** | **2017** | **The Memorial Sloan-Kettering Cancer Center generated a dataset of Melanoma and Squamous Cell Carcinoma cancers, aiming to develop image analysis tools for improved dermatologist diagnostic accuracy.** |
| Dermoscopedia Image Library | **JPEG**  **resolution of 1024 x 768 pixels** | **2000** | **4** | **2017** | **Melanoma, a 75% skin cancer cause, was studied to create an online resource for dermoscopy, potentially improving diagnostic accuracy and saving lives.** |
| EDF (Edinburgh Dermofit Library) | **JPG** | **1,300** | **2** | **2012** | **The dataset aimed to facilitate the comparison and reproducibility of different. methods and algorithms.** |
| PAD-UFES-20 | **PNG** | **2,298** | **6** | **2020** | **The PAD-UFES-20 dataset, collected by the Dermatological and Surgical Assistance Program at UFES-Brazil, includes 2,298 samples of six skin lesions. The dataset includes 1,373 patients, 1,641 skin lesions, and 2,298 images, with 58% of samples being biopsy proven. The dataset includes clinical images and metadata for each skin lesion.** |

# **Chapter 3: Skin cancer algorithms survey**

Deep learning is a branch of artificial intelligence that uses multiple layers of neural networks to learn from large amounts of data and perform complex tasks. Deep learning has shown remarkable results in various domains, such as computer vision, natural language processing, speech recognition, and more. In recent years, deep learning has also been applied to medical image analysis, especially for skin cancer diagnosis.

In this paper, we review the state-of-the-art deep learning algorithms and methods for skin cancer classification and deduction. We focus on the challenges, opportunities, and limitations of using deep learning for this task. We also provide a comprehensive comparison of the performance, accuracy, and robustness of different deep learning models on various datasets of skin lesions. Finally, we discuss the future directions and open problems for further research in this field.

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| **[Application of Improved Chameleon Swarm Algorithm and Improved Convolution Neural Network in Diagnosis of Skin Cancer](https://www.igi-global.com/gateway/article/325059) 21 Jun 2023-International Journal of Data Warehousing and Mining (International Journal of Data Warehousing and Mining)** | |
| **Dataset used** | The paper uses the Kaggle dataset to classify skin cancer using a CNN-based feature extraction method and assesses the chameleon swarm algorithm for real-world skin cancer diagnosis. |
| **Abstract** | Skin cancer, a toxic form, is a major cause of mortality due to lack of awareness and prevention methods. A deep learning-based model using chameleon swarm algorithm and convolutional neural networks can aid in accurate diagnosis and classification. |
| **Model and architecture** | A diagram of a flowchart  Description automatically generatedICSA-CNN  fig 7 ICSA-CNN |
| **Methods used** | The paper proposes a method using a chameleon swarm algorithm and convolutional neural networks for skin cancer identification and classification, aiming to enhance accuracy, sensitivity, specificity, and F1 score. |
| **Limitations** | The paper evaluates a new skin cancer identification and classification method using chameleon swarm algorithm and convolutional neural networks, highlighting its limitations and suggesting further research for real-world application. |
| **Results** | The study presents an ICSA-CNN model for skin cancer prediction and classification, demonstrating improved accuracy, specificity, sensitivity, and F1 score, but requiring dermatologist training for intra-class variation. |

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| **[Skin Cancer Detection and Classification Using Deep Learning](https://www.ijraset.com/)** **31 May 2023-International Journal for Science Technology and Engineering** | |
| **Dataset used** | HAM10000 dataset |
| **Abstract** | Deep Learning for Skin Cancer Classification  • Utilizes Convolutional Neural Network (CNN) to classify skin lesions.  • CNN achieved 90% accuracy in skin rashes classification.  • Proposed model shows potential for skin cancer detection. |
| **Model and architecture** | Convolutional Neural Network (CNN) |
| **Methods used** | • Utilized Convolutional Neural Network (CNN) for skin cancer detection and classification.  • CNN trained skin lesion images to classify lesions as cancerous or noncancerous.  • Highlighted the use of computer-aided diagnosis systems for improved precision and effectiveness.  • Utilized HAM10000 dataset, consisting of 10015 skin cancer images, for deep learning algorithms training.  • Aimed to develop an automatic melanoma diagnosis system that supports photos of skin rashes taken using a conventional digital camera. |
| **Limitations** | - Lack of access to dermatologists and specialized healthcare facilities.  - Small dataset for machine learning training. |
| **Results** | - Accuracy of 90% in classifying skin rashes  - Potential as a tool for skin cancer detection |

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| **[A New Approach using Deep Learning and Reinforcement Learning in HealthCare](https://ijeces.ferit.hr/index.php/ijeces/article/view/2044)** **Dahdouh Yousra05 Jun 2023-International journal of electrical and computer engineering systems-** | |
| **Dataset used** | Researchers used the HAM10000 dataset, consisting of 10015 dermatoscopic images of seven skin lesions, resized to 28 x 28 pixels, and split it for training and testing. |
| **Abstract** | Researchers are using artificial intelligence tools like deep learning and deep reinforcement learning networks to develop innovative systems for early detection and prevention of skin cancer. |
| **Model and architecture** | CNN-DQN model - The Deep Q-Learning algorithm  A diagram of a deep learning model  Description automatically generated  A diagram of a deep q learning  Description automatically generated  fig 8 Deep Q-Learning algorithm |
| **Methods used** | The paper investigates the use of Deep Learning and Reinforcement Learning in skin cancer detection using the HAM10000 database, demonstrating the effectiveness of combining these techniques. |
| **Limitations** | The paper lacks comprehensive details on pre-processing techniques, CNN parameters, performance, limitations, challenges, and potential impact of false positives or false negatives on skin cancer classification. |
| **Results** | **Table 3.2 : Algorithm 3**  A grey and black text  Description automatically generatedThe proposed system for skin cancer detection and classification, combining deep learning and reinforcement learning, achieved 80% accuracy using the HAM10000 dataset. |

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| **[Automatically Diagnosing Skin Cancers from Multimodality Images Using Two-Stage Genetic Programming](https://ieeexplore.ieee.org/document/9819829)** **01 May 2023-IEEE transactions on cybernetics (IEEE transactions on cybernetics)** | |
| **Dataset used** | PH2 and Dermofit. |
| **Abstract** | Skin cancer, a global health concern, is rapidly increasing, with early detection crucial for survival. Dermatologists utilize visual properties and computer-aided diagnostic frameworks for early identification. |
| **Model and architecture** | A diagram of a person's hand  Description automatically generatedThe paper introduces a two-stage genetic programming method for automatically diagnosing skin cancers from multimodality images, incorporating local, global, texture, color, and multiscale image properties, and demonstrating improved machine-learning classification performance.A diagram of a diagram  Description automatically generated  fig 3 5-layer CNN |
| **Methods used** | The paper introduces a two-stage genetic programming method for automatically diagnosing skin cancers from multimodality images. The method uses genetic operators to select prominent features and constructs new ones to improve classification performance. It improves machine-learning classification algorithms and is interpretable, achieving good results without expert intervention or domain knowledge. |
| **Limitations** | The paper presents a two-stage genetic programming method for diagnosing skin cancers from multimodality images, but its effectiveness may vary due to dataset characteristics and computational complexity. |
| **Results** | A table of information  Description automatically generated with medium confidence  **Table 3.3 : Algorithm 4** |

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| **[Enhancing Skin Cancer Diagnosis with Deep Learning-Based Classification](https://ijritcc.org/index.php/ijritcc/article/view/6634)****17 May 2023-**[**International Journal on Recent and Innovation Trends in Computing and Communication**](https://typeset.io/journals/international-journal-on-recent-and-innovation-trends-in-85kjfkf9) | |
| **Dataset used** | (ISIC) dataset |
| **Abstract** | • Proposed automated system for skin cancer classification using ISIC dataset images.  • Deep learning techniques can accurately detect skin cancer.  • Addresses complex, costly, and subjective skin cancer diagnosis.  • Proposed automated methods for early diagnosis.  • Utilized ISIC dataset for developing and validating deep learning algorithms. |
| **Model and architecture** | consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers,  A diagram of a model  Description automatically generated with medium confidence  fig 9 Proposed automated system for skin cancer classification |
| **Methods used** | • Utilizes convolutional neural networks (CNNs) for skin cancer classification.  • CNNs are widely used in image classification tasks, including skin cancer classification.  • Aims to develop and validate deep learning algorithms using the International Skin Imaging Collaboration (ISIC) dataset.  • Use of deep learning and CNNs in skin cancer classification has shown advancements in AI research.  • Potential for accurate skin cancer detection at an early stage. |
| **Limitations** | - Complexity, cost, and subjective interpretation of skin cancer diagnosis  - Need for automated methods in early diagnosis |
| **Results** | - The paper proposes an automated technique for skin cancer classification using deep learning.  - The proposed technique could reduce the workload of medical personnel while providing accurate diagnoses. |

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| **[Deep Learning Model for Accurate Classification of Skin Cancer using Dermoscopic Images](https://typeset.io/papers/deep-learning-model-for-accurate-classification-of-skin-mxyepii4)26 Apr 2023-International Journal of Advanced Research in Science, Communication and Technology** | |
| **Dataset used** | HAM10000 dataset |
| **Abstract** | Deep learning model enhances skin cancer classification using convolution and neural layers, aiding in accurate diagnosis and treatment for common cancers. |
| **Model and architecture** | Convolutional Neural Network (CNN)  • Model designed with 7 convolution layers and 3 neural layers.  A diagram of a medical procedure  Description automatically generated  fig 10 Model designed with 7 convolution layers and 3 neural layers. |
| **Methods used** | A deep learning model with 7 convolution layers and 3 neural layers was designed to classify the HAM10000 dataset, which consists of 7 classes and includes dermoscopic images. |
| **Limitations** | N/A |
| **Results** | - Deep learning model achieved 99.01% accuracy in classifying skin cancer.  - Proposed model can assist experts in diagnosing skin cancer. |

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| **[MSDSC: A Multistage Deep Learning-based Skin Cancer Classifier](https://europepmc.org/article/ppr/ppr644281) 12 Apr 2023 Hassan AM, Mahar K, Fouad MM** | |
| **Dataset used** | the International Skin Imaging Collaboration dataset (ISIC) |
| **Abstract** | A multistage deep learning-based skin cancer classifier (MSDSC) is proposed for early detection, using GAN, U-Net, and EfficientNet types. The framework outperforms state-of-the-art studies using the International Skin Imaging Collaboration dataset, reducing mistakes in early diagnosis. |
| **Model and architecture** | The Generative Adversarial Networks (GAN) model  Mask generation stage: An attention-based U-Net model.  A diagram of a person's skin  Description automatically generatedEfficientNet model  fig 11 Generative Adversarial Networks (GAN) model |
| **Methods used** | • Pre-processing stage: Removes surrounding hair from samples.  • Synthetic image generation stage: Uses Generative Adversarial Networks (GAN) model for unbalanced datasets.  • Mask generation stage: Uses attention-based U-Net model to generate masks for regions of interest and eliminate background.  • Classification stage: Two types of EfficientNet models trained to classify skin lesions using segmented images. |
| **Limitations** | not mentioned |
| **Results** | The study presents a deep learning-based skin cancer classifier (MSDSC) for early detection of melanoma and non-melanoma skin lesions. The framework uses GAN, U-Net, and EfficientNet to classify images. Tested on the International Skin Imaging Collaboration dataset, it achieved impressive results with an accuracy of 0.96, F1-score of 0.91, recall of 0.95, and precision of 0.88. |

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| **[A novel approach toward skin cancer classification through fused deep features and neutrosophic environment](https://www.researchgate.net/publication/370089076_A_novel_approach_toward_skin_cancer_classification_through_fused_deep_features_and_neutrosophic_environment)** **Ahmed Abdelhafeez, Hoda K. Mohamed, Ali Maher, Nariman A. Khalil**  **17 Apr 2023-Frontiers in Public Health** | |
| **Dataset used** | ISIC 2019 |
| **Abstract** | Proposed research aims to develop a computer-aided diagnostic system using deep learning-based layer-fusion and neutrosophic-set techniques, using the International Skin Imaging Collaboration 2019 skin lesion dataset, for high accuracy in skin cancer classification. |
| **Model and architecture** | GoogleNet and DarkNet,  A diagram of a software testing process  Description automatically generated  fig 12 GoogleNet and DarkNet |
| **Methods used** | Hybrid deep learning for skin cancer classification uses layer-fusion and neutrosophic techniques. Utilizes GoogleNet and DarkNet for transfer learning on ISIC 2019 dataset. Enhances individual classification accuracy and combines networks for improvement. Performance metrics assess accuracy, sensitivity, precision, and F1 score. |
| **Limitations** | The focus of the paper is on introducing a novel methodology that combines deep learning-based layer-fusion and neutrosophic-set techniques to improve classification accuracy. |
| **Results** | The top two networks, GoogleNet and DarkNet, achieved accuracies of 77.41% and 82.42% respectively.  • Combines deep learning-based layer-fusion and neutrosophic-set techniques for improved accuracy.  • Uses feature fusion methodology for enhanced descriptive power.  **Table 3.4 : Algorithm 8**  • Employs EOC paradigm for well-trained SVM classifiers via fused DarkNet and GoogleNet feature maps.  A screenshot of a graph  Description automatically generated |

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| **[DSCC\_Net: Multi-Classification Deep Learning Models for Diagnosing of Skin Cancer Using Dermoscopic Images](https://www.mdpi.com/2072-6694/15/7/2179)** **Maryam Saba Tahir, Ahmad Naeem, Hassaan Malik, Jawad Tanveer, Rizwan Ali Naqvi, Seung-Won Lee 01 Apr 2023** | |
| **Dataset used** | ISIC 2020, HAM10000, and DermIS |
| **Abstract** | Deep learning algorithms are being used to detect skin cancer, with DSCC\_Net proposed as a classification network for four types using the SMOTE Tomek algorithm to address unequal distribution. |
| **Model and architecture** | DSCC\_Net  The paper also compares the performance of DSCC\_Net with six baseline deep CNN models, including ResNet-152, Vgg-16, Vgg-19, Inception-V3, EfficientNet-B0, and Mobile Net  A diagram of a model  fig 13 DSCC\_Net |
| **Methods used** | DSCC\_Net: Deep Learning-Based Skin Cancer Classification Network  • Implemented using a convolutional neural network (CNN) architecture.  • Evaluated on ISIC 2020, HAM10000, and DermIS datasets.  • Compared with six baseline deep CNN models.  • Used SMOTE Tomek algorithm for class distribution up-sampling.  • Implemented using Keras, Python programming.  • Experiment conducted on Windows 10 with 11 GB NVIDIA GPU and 32 GB RAM. |
| **Limitations** | The DSCC\_Net model, designed for fair-skinned individuals, is evaluated using publicly available datasets, but may have limitations in handling other skin conditions or infections, suggesting future work. |
| **Results** | • The model outperforms six baseline deep networks, achieving a high AUC of 99.43%.  • Achieved high accuracy, recall, precision, F1-score, and AUC in classifying four skin cancer diseases: melanoma, basal cell carcinoma, squamous cell carcinoma, and melanocytic nevi.  • Outperformed six baseline deep networks in various evaluation metrics.  • SMOTE Tomek algorithm addressed class imbalance in dataset.  • Can support early detection and diagnosis of skin cancer.  • Highlights importance of rapid and effective testing due to increasing prevalence and potential risks.  **Table 3.5 : Algorithm 9**  A table with numbers and symbols  Description automatically generated |

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| **[DeepSkin: A Deep Learning Approach for Skin Cancer Classification](https://www.researchgate.net/publication/370663908_DeepSkin_A_Deep_Learning_Approach_for_Skin_Cancer_Classification)** **01 Jan 2023-IEEE Access (IEEE Access)** | |
| **Dataset used** | HAM10000 |
| **Abstract** | The paper proposes a deep learning approach for early detection of skin cancer in dermoscopy images, outperforming other CNN models in terms of AUC score. |
| **Model and architecture** | A diagram of a data processing process  Description automatically generated  fig 14 CNN architectures used in the research are DenseNet169. |
| **Number of layers** | 169 layers |
| **Methods used** | • Utilizes Convolutional Neural Networks (CNN) for skin cancer classification.  • Experimentation used MNIST: HAM10000 dataset with seven skin lesions.  • Data pre-processing techniques: sampling, dull razor, segmentation using autoencoder and decoder.  • Transfer learning techniques: DenseNet169 and Resnet 50 used for model training.  • CNN aids in classification of seven skin cancer images. |
| **Limitations** | The specific limitations of this paper are not mentioned |
| **Results** | A close-up of a graph  Description automatically generated  **Table 3.6 : Algorithm 10** |

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| **[Optimization Detection of Skin Cancer using Deep Learning](https://fidelity.nusaputra.ac.id/article/view/139)**  **S. T. Tuba 31 Jan 2023** | |
| **Dataset used** | The dataset used in this study is called "Skin cancer: Malignant vs. Benign" and was downloaded from Kaggle.com |
| **Abstract** | A computer-based skin cancer screening method using TensorFlow and Keras has been developed for non-specialist users, allowing early detection and treatment of malignant melanoma. |
| **Model and architecture** | Convolutional 2-D |
| **Number of layers** | In the Results |
| **Methods used** | • Utilizes deep learning techniques like TensorFlow and Keras for skin cancer classification.  • Methodology includes importing packages like keras, NumPy, sklearn, itertools, and matplotlib.  • Dataset: "Skin cancer: Malignant vs. Benign" with 3609 images divided into benign and malignant groups.  • Uses image data generator, CNN, and Keras sequential model for training and classification.  • Classification system accuracy: 78% using Convolutional 2-D layer system. |
| **Limitations** | The study lacks specific information on CNN architecture, layers, methods for skin cancer classification, and performance compared to other methods or benchmarks. |
| **Results** | • The system achieved an accuracy of 78% in classifying skin cancer.  **Table 3.6 : Algorithm 10**  A table of numbers and layers  Description automatically generated |

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| **[Henry Gas Solubility Optimization Algorithm based Feature Extraction in Dermoscopic Images Analysis of Skin Cancer](https://www.mdpi.com/2072-6694/15/7/2146)** **M. Obayya, Adeeb Abdulwahab Alhebri, Mashael S. Maashi, Ahmed S. Salama 01 Apr 2023** | |
| **Dataset used** | The paper does not explicitly mention the specific dataset used for the research |
| **Abstract** | The article discusses the use of AI techniques, particularly Convolutional Neural Networks and Deep Learning, in early skin cancer diagnosis, highlighting the effectiveness of the MAFCNN-SCD technique in dermatology. |
| **Model and CNN architecture** | the Convolutional Neural Network (CNN) used in the proposed MAFCNN-SCD technique and MAFNet method is applied as a feature extractor.  A diagram of a diagram of a block  Description automatically generated  fig 15 MAFCNN-SCD |
| **Methods used** | Optimal Multi-Attention Fusion Convolutional Neural Network-based Skin Cancer Diagnosis  • Utilizes MAFNet method as feature extractor.  • HGSO algorithm used as hyperparameter optimizer in feature extraction.  • Deep Belief Network (DBN) used for skin cancer detection and classification.  • Proposed technique demonstrated superior performance in simulations. |
| **Limitations** | • Lacks specific details on CNN architecture and layers.  • Focuses on overall methodology and performance evaluation. |
| **Results** | MAFCNN-SCD Technique for Skin Cancer Detection and Classification  • Combines MAFNet feature extractor with HGSO algorithm.  • Shows superior performance in dermoscopic images.  • Conducted simulations for superior performance.  • Comprehensive comparative analysis confirms effectiveness.  **Table 3.8 : Algorithm 12**  A graph with numbers and text  Description automatically generated with medium confidence |

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| **[Skin Cancer Detection Using Deep Learning Technique](https://typeset.io/papers/skin-cancer-detection-using-deep-learning-technique-109m1h3c)**  **03 Mar 2023** | |
| **Dataset used** | not mentioned |
| **Abstract** | This study utilizes deep learning techniques and the Inception V3 method to improve early skin cancer detection, overcoming limitations in traditional machine learning and computer vision techniques. |
| **Model and architecture** | A table with numbers and symbols  Description automatically generated  Fig 16 comparison table between V3 model |
| **Number of layers** | not mentioned |
| **Methods used** | Skin Cancer Detection using Deep Learning and Image Processing  • Inception V3 method used for skin cancer detection.  • Data collection, augmentation, model construction, and prediction stages in model creation.  • Machine learning and computer vision methods used for automatic melanoma image classification.  • Differentiation between benign and malignant skin cancer based on lesions' characteristics.  • Segmentation of skin lesions and classification features crucial for performance.  • Emphasizes early diagnosis and automated approaches for diverse diagnoses. |
| **Limitations** | The study highlights the lack of a specific dataset for training and testing, potential biases and limitations of automated approaches, lack of comparison with existing methods, and difficulty in assessing novelty and effectiveness. |
| **Results** | • The Inception V3 method and image processing tools improve structure and accuracy to 85%. |

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| **[Classification of skin cancer from dermoscopic images using deep neural network architectures](https://link.springer.com/article/10.1007/s11042-022-13847-3)** **Jaisakthi S M, Mirunalini P, Chandrabose Aravindan, Rajagopal Appavu**  **12 Oct 2022** | |
| **Dataset used** | ISIC 2019 and ISIC 2020 |
| **Abstract** | Melanoma is a deadly skin cancer, requiring early diagnosis to reduce mortality rates. Traditional visual examinations are time-consuming and error-prone, while dermoscopy offers magnified images. Automated systems improve efficiency. |
| **Model and architecture** | A diagram of a computer network  Description automatically generated  fig 4 Deep Convolutional Neural Network (DCNN) EfficientNet architecture |
| **Methods used** | • Utilizes EfficientNet model for high accuracy in skin cancer classification.  • Employs transfer learning techniques for model enhancement.  • Analyzes performance of various deep learning architectures using AUC-ROC.  • Addresses class imbalance problem by augmenting data and utilizing metadata information.  • Uses ranger optimizer to improve EfficientNet model efficiency, reducing hyperparameter tuning. |
| **Limitations** | EfficientNet-B6 system execution time is high due to complexity, lack of explicit mention, transfer learning techniques, class imbalance problem, comprehensive performance analysis, and model generalizability. |
| **Results** | A white background with black text  Description automatically generated  **Table 3.10 : Algorithm 14**  • Ranger optimizer enhances EfficientNet model efficiency and reduces hyperparameter tuning.  • High AUC-ROC score of 0.9681 for EfficientNet-B6 with ranger optimizer.  • Comparative study shows better results in terms of AUC score. |

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| **[Skin Cancer Detection and Segmentation Using Convolutional Neural Network Models](https://ijeer.forexjournal.co.in/archive/volume-10/ijeer-100438.html)** **30 Dec 2022-International journal of electrical & electronics research (International journal of electrical & electronics research)** | |
| **Dataset used** | the ISIC and HAM dataset |
| **Abstract** | This paper explores the use of Convolutional Neural Networks (CNN) for detecting and segmenting melanoma skin cancer, employing VGG-16 classifier and data augmentation methods for improved accuracy. |
| **Model and architecture** | A diagram of a algorithm  Description automatically generated  fig 5 VGG-16 |
| **Number of layers** | The VGG-16 architecture is known for its deep structure, consisting of 16 layers |
| **Methods used** | "Data Augmentation Techniques for Skin Cancer Classification"  • Utilizes linear pixel shift operations to increase trained skin images.  • Classifies images using Convolutional Neural Networks (CNN).  • Utilizes VGG-16 architecture for melanoma skin cancer classification.  • CNN model includes 13 convolutional layers, 5 pooling layers, and 3 dense layers.  • Employs morphological segmentation methods to locate cancer pixels.  • Methods applied on ISIC and HAM dataset skin images for evaluation and analysis. |
| **Limitations** | The proposed CNN model lacks explicit layers, detailed data augmentation techniques, specific morphological segmentation methods, comprehensive computational complexity analysis, and comparison with existing skin cancer detection approaches. |
| **Results** | VGG-16 Classifier Improved Melanoma Cancer Detection  • Improved accuracy with 97.12% Precision, 98.17% Recall, 98.85% F1-Score on ISIC dataset.  • Enhanced accuracy with 99.11% Precision, 99.09% Recall, 99.28% F1-Score on HAM10000 dataset. |

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| **[Skin Cancer Detection Using Deep Learning](https://typeset.io/papers/skin-cancer-detection-using-deep-learning-v383njsvjt)** **Pradhumn Agrahari, Archit Agrawal, N. Subhashini VIT University 01 Jan 2022** | |
| **Dataset used** | HAM10000 ISIC dataset |
| **Abstract** | • Addresses skin cancer, a major health concern.  • Traditional diagnosis is ineffective due to inexperienced dermatologists.  • Deep learning outperforms human experts in computer vision tasks.  • Proposed multiclass skin cancer detection system uses pre-trained MobileNet model. |
| **Model and architecture** | MobileNet model |
| **Number of layers** | not mentioned |
| **Methods used** | The paper presents a skin cancer detection system using deep learning and a pre-trained MobileNet model, achieving high accuracy rates on the HAM10000 ISIC dataset, offering potential for clinical advancement. |
| **Limitations** | The text lacks detailed information on deep learning architecture, potential limitations, and challenges in skin cancer detection, including sensitivity, specificity, and computational requirements. |
| **Results** | • Model achieves high categorical accuracy of 80.81%, top-2 accuracy of 91.25%, and top-3 accuracy of 96.26%.  **Table 3.11 : Algorithm 16** |

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| [**Squeeze-MNet: Precise Skin Cancer Detection Model for Low Computing IoT Devices Using Transfer Learning**](https://www.mdpi.com/2072-6694/15/1/12) **Rupali Kiran Shinde, Md. Shahinur Alam, Md. Biddut Hossain, Shariar Md Imtiaz, J. Kim, Anuja Anil Padwal, Nam-Il Kim -20 Dec 2022** | |
| **Dataset used** | (ISIC) dataset |
| **Abstract** | Squeeze-MNet, a telemedicine device using Raspberry Pi and camera, aims to improve skin cancer detection through early diagnosis and improved outcomes. |
| **Model and architecture** | A diagram of a cell structure  Description automatically generated  fig 6 MobileNet model |
| **Methods used** | Squeeze-MNet Skin Cancer Detection Model  • Combines Squeeze algorithm and MobileNet deep learning model.  • Features flattened and dense layers with Leaky ReLU activation function.  • Tested on Raspberry Pi 4 IoT device with Neo pixel 8-bit LED ring.  • Validated by medical doctor.  • Calculates standard metrics like accuracy, specificity, sensitivity, precision, false alarm rate, and AUC-ROC. |
| **Limitations** | The paper lacks detailed analysis of computational resources, evaluation of the model on Raspberry Pi 4 IoT device, comparison with existing models, and generalizability to different datasets or skin cancer types. |
| **Results** | A table with numbers and symbols  Description automatically generated  **Table 3.12 : Algorithm 17** |

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| [**Dermatologist-Level Classification of Skin Cancer Using Cascaded Ensembling of Convolutional Neural Network and Handcrafted Features Based Deep Neural Network**](https://typeset.io/papers/dermatologist-level-classification-of-skin-cancer-using-18wfheib)  **01 Jan 2022-IEEE Access** | |
| **Dataset used** | the HAM10000 dataset |
| **Abstract** | This paper presents a computer-based melanoma lesion detection scheme that integrates a Convolutional Neural Network model with handcrafted features, achieving an accuracy of 98.3%. |
| **Model and architecture** | A diagram of a diagram of a number of rectangular objects  Description automatically generated  fig 7 ConvNet model |
| **Methods used** | "Improving Skin Cancer Classification Accuracy with Cascaded Ensemble Network"  • Integrates Convolutional Neural Network (ConvNet) model with handcrafted features.  • ConvNet model used for non-handcrafted feature extraction.  • Handcrafted features like color moments and texture incorporated.  • Methodology uses HAM10000 image dataset.  • Lacks detailed information on ConvNet model and handcrafted feature extraction process. |
| **Limitations** | The specific limitations of this paper are not mentioned in the provided sources. |
| **Results** | A table of numbers and symbols  Description automatically generated with medium confidence  fig 21 table of performance of ConvNet model |

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| [**On the Automatic Detection and Classification of Skin Cancer Using Deep Transfer Learning**](https://www.mdpi.com/1424-8220/22/13/4963) **30 Jun 2022 Authors: Mohammad Fraiwan, Esraa Faouri** | |
| **Dataset used** | The HAM1000 dataset |
| **Abstract** | The HAM1000 dataset classifies skin cancer types into seven, improving early diagnosis and reducing healthcare costs. Deep learning AI uses 13 models, but overall accuracy is reduced to 82.9%. |
| **Model and architecture** | * 13 deep learning models were customized, retrained,evaluated individually * SqueezeNet, GoogLeNet, Inceptionv3, DenseNet201, MobileNetv2, Resnet101, Resnet50, Resnet18 , Xception , Inception- , ResNet-v2 , ShuffleNet , DarkNet-53 , Efficient Netbo   A diagram of a training program  Description automatically generated  fig 22 Deep learning AI uses 13 models |
| **Number of layers** | Customize model: - Freeze initial layers - Replace final learnable layer: Fully connected layer or convolution 2d layer |
| **Methods used** | • Pre-processing includes resizing annotated input images and applying augmentation.  • The dataset is the HAM1000 dataset, divided into seven categories.  • 13 pre-trained models are used, with each model customized, retrained, and evaluated individually.  • Performance evaluation includes five metrics and common model parameters.  • Data splitting strategies are used for training and validation.  • Input images are augmented to increase variety.  • Training and evaluation are conducted with specified parameters and models compared based on classification ability. |
| **Limitations** | Imbalance of the dataset, small number of images in some categories, and large number of classes reduced the best overall accuracy to 82.9% |
| **Evaluation metrics** | A screenshot of a graph  Description automatically generated  fig 23 Evaluation metrics Deep learning AI uses 13 models. |
| **Results** | **Table 3.15 : Algorithm 21**  A table with numbers and text  Description automatically generated  best overall accuracy achieved by the system was 82.9%, some cancer types were correctly classified with high accuracy, indicating the effectiveness of the deep transfer learning approach for skin cancer classification |

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| [**SkinNet-16: A deep learning approach to identify benign and malignant skin lesions.**](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9395205/) **08 Aug 2022-Frontiers in Oncology** | |
| **Dataset used** | The initial dataset was obtained from Kaggle |
| **Abstract** | Skin cancer, a prevalent issue in Australia and New Zealand, is a serious health concern, necessitating early detection and treatment using advanced technologies like SkinNet-16. |
| **Model and CNN architecture** | The CNN architecture of SkinNet-16 is specifically designed to detect skin lesions with high accuracy  A diagram of a software algorithm  Description automatically generated  fig 24 SkinNet-16 |
| **Methods used** | • Initial dataset preprocessed with hair and background removal, image enhancement, region of interest selection, region-based segmentation, morphological gradient, and feature extraction.  • PCA-based feature extraction technique used to reduce data dimensionality.  • SkinNet-16 deep learning classifier used for early detection of cancerous skin lesions.  • Adamax optimizer used for training neural network-based model with 0.006 learning rate. |
| **Limitations** | • Focused on malignant and benign skin lesions.  • Limited scope due to diverse lesions in dataset.  • Limited image data for training model, potentially impacting model performance. |
| **Results** | SkinNet-16 Deep Learning Classifier: Detecting Cancerous Skin Lesions  • Achieved 99.19% accuracy in early detection of cancerous skin lesions.  • Utilized Adamax optimizer with a learning rate of 0.006 for highest accuracy.  • Underwent preprocessing steps like hair and background removal, image enhancement, and feature extraction.  • PCA-based feature extraction technique reduced data dimensionality, resulting in 10 input features.  • Applied filters and techniques like morphological operations and histogram equalization improved model accuracy. |

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| [**A Convolutional Neural Network Framework for Accurate Skin Cancer Detection**](https://link.springer.com/article/10.1007/s11063-020-10364-y) **Karl Thurnhofer-Hemsi1, Enrique Domínguez University of Málaga 01 Oct 2021** | |
| **Dataset used** | The HAM10000 dataset |
| **Abstract** | The study uses transfer learning and convolutional neural networks for accurate skin cancer detection, achieving high classification accuracies and lower false negatives on the HAM10000 dataset. |
| **Model and architecture** | DenseNet201 |
| **Number of layers** | 201 layers |
| **Methods used** | Skin Cancer Detection using Transfer Learning and Convolutional Neural Networks  • Transfer learning applied to five convolutional neural networks for skin cancer detection.  • HAM10000 dataset used for experiments.  • Data augmentation techniques used to enhance model performance. |
| **Limitations** | Skin Cancer Detection Models Limitations  • Lack of large datasets for training models, affecting reliability and generalizability.  • Focus on seven types of moles, potentially missing other skin cancer or skin diseases.  • Lack of detailed information on data augmentation techniques used complicating model performance assessment.  • Hierarchical classifier with two levels underperformed plain model, suggesting additional classification level may not be necessary.  • Lack of discussion on computational resources and time required for training and testing models. |
| **Results** | • DenseNet201 network achieved high classification accuracies and F-measures with lower false negatives.  • Binary classification between nevi and non-nevi yielded the best outcomes. |

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| **[A Convolutional Neural Network Framework for Accurate Skin Cancer Detection](https://link.springer.com/article/10.1007/s11063-020-10364-y) Karl Thurnhofer-Hemsi1, Enrique Domínguez University of Málaga 01 Oct 2021** | |
| **Dataset used** | The HAM10000 dataset |
| **Abstract** | The study uses transfer learning and five convolutional neural networks for accurate skin cancer detection, with the DenseNet201 network achieving high classification accuracy and lower false negatives. |
| **Model and architecture** | DenseNet201 |
| **Number of layers** | 201 layers |
| **Methods used** | Skin Cancer Detection using Transfer Learning and Convolutional Neural Networks  • Transfer learning applied to five convolutional neural networks for skin cancer detection.  • HAM10000 dataset used for experiments.  • Data augmentation techniques used to enhance model performance. |
| **Limitations** | Skin cancer detection models face limitations such as limited datasets, focus on seven mole types, lack of detailed data augmentation techniques, underperformance of hierarchical classifiers, and lack of discussion on computational resources and testing time. |
| **Results** | • DenseNet201 network achieved high classification accuracies and F-measures with lower false negatives.  • Binary classification between nevi and non-nevi yielded the best outcomes. |

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| [**Deep learning-based computer aided diagnosis model for skin cancer detection and classification**](https://link.springer.com/article/10.1007/s10619-021-07360-z) **Devakishan Adla1, G. Venkata Rami Reddy1, Padmalaya Nayak2, G. Karuna Jawaharlal Nehru Technological University, Hyderabad1, Gokaraju Rangaraju Institute of Engineering and Technology 23 Aug 2021** | |
| **Dataset used** | ISIC dataset |
| **Abstract** | Deep Learning-based CAD model for skin cancer detection, utilizing pre-processing techniques, feature extraction, class attention layer, and Swallow Swarm Optimization, achieves promising accuracy, sensitivity, and specificity. |
| **Model and CNN architecture** | • DLCAL-SLDC is a deep learning-based CAD model for skin lesion detection and classification.  A diagram of data processing  Description automatically generated  fig 25 DLCAL-SLDC |
| **Methods used** | • Utilized DLCAL-SLDC CAD model for skin lesion detection and classification.  • Utilized Dull razor approach and average median filtering for image pre-processing.  • Employed Tsallis entropy-based segmentation technique for lesion detection in dermoscopic images.  • Employed DLCAL-based feature extractor, CapsNet, CAL, and Adagrad optimizer for feature extraction.  • Classification used SSO-CSAE model based on CSAE.  • Validated using benchmark ISIC dataset. |
| **Limitations** | not mentioned |
| **Results** | DLCAL-SLDC Technique Promising Results  • 98.50% accuracy  • 94.5% sensitivity  • 99.1% specificity  • Outperforms other methods |

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| [**Multiclass skin cancer classification using EfficientNets – a first step towards preventing skin cancer.**](https://www.sciencedirect.com/science/article/pii/S2772528621000340?ref=pdf_download&fr=RR-2&rr=83d2a4b82dbc11a2)**Karar Ali, Zaffar Ahmed Shaikh, Abdullah Ayub Khan , Asif Ali Laghari 24/10/2021** | |
| **Dataset used** | HAM10000 dataset |
| **Abstract** | Skin cancer classification is challenging due to fine-grained variability in diagnostic categories. Convolutional neural networks (CNNs) outperform dermatologists. A preprocessing image pipeline was developed, fine-tuned using the HAM10000 dataset, and intermediate complexity models performed best. Successful transfer learning, data enhancement, resolution scaling, and noise removal contributed to high classification scores. |
| **Model and architecture** | EfficientNets B0-B7 (B4 was the best performing) |
| **Number of layers** | 8 layers |
| **Methods used** | Image preprocessing, EfficientNet model architecture, Transfer learning. |
| **Limitations** | lower number of dataset for the HAM10000 in comparison to ImageNet, high class imbalance in the HAM10000 |
| **Results** | The best model, EfficientNet B4, achieved an F1 Score of 87% and a Top-1 Accuracy of 87.91%.  **Table 3.16 : Algorithm 26**  A table with numbers and text  Description automatically generated |

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| **[Skin Cancer Diagnosis based on Improved Multiattention Convolutional Neural Network](https://ieeexplore.ieee.org/document/9390972)** **Huanqing Xu1, Li Jin, Tongping Shen, Fangliang Huang Anhui University of Chinese Medicine 12 Mar 2021** | |
| **Dataset used** | The paper uses medical image data for skin cancer diagnosis. |
| **Abstract** | The paper proposes an improved CNN for skin cancer diagnosis, incorporating a hybrid multi-attentive mechanism, demonstrating improved ROC, accuracy, and recall, indicating its effectiveness in medical image recognition. |
| **Model and architecture** | Eigenvalues of tumors are extracted using an improved VGG19 model, replacing the fully connected layer with extremely randomized trees. |
| **Number of layers** | 19 layers |
| **Methods used** | Improved Convolutional Neural Network for Skin Cancer Diagnosis  • Utilizes a hybrid multi-attentive mechanism to focus on tumor cells.  • Extracts tumor eigenvalues using an improved VGG19 model.  • Replaces fully connected CNN layer with extremely randomized trees for classification.  • Shows improvements in ROC, accuracy, and recall.  • Utilizes medical image data of malignant tumors on skin.  • Performance evaluated based on improvements in diagnostic metrics. |
| **Limitations** | The proposed CNN has limitations, including a lack of discussion on potential drawbacks, limitations of the improved VGG19 model for tumor eigenvalue extraction, and insufficient analysis of the generalizability of the methods to different skin cancer types or patient populations. |
| **Results** | • Improved Convolutional Neural Network (CNN) with hybrid multi-attentive mechanism for efficient eigenvalue extraction.  • VGG19 model used for extracting tumor eigenvalues.  • Replacement of fully connected layer with extremely randomized trees for classification.  • Study shows potential for accurate skin cancer diagnosis. |

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| **[Big transfer learning for automated skin cancer classification](https://ijeecs.iaescore.com/index.php/IJEECS/article/view/25756)****Zinah Mohsin Arkah, Dalya S. Al-Dulaimi, Ahlam R. Khekan 01 Sep 2021** | |
| **Dataset used** | ISIC Archive and SIIM-ISIC 2020 dataset, |
| **Abstract** | • Skin cancer is a rapidly growing disease with high mortality rates.  • Early diagnosis is crucial for effective treatment and cure.  • Dermoscopy, a noninvasive imaging technique, improves skin cancer diagnosis by providing high-quality visual images.  • Convolutional neural networks (CNNs) have shown potential in image classification tasks, including skin cancer classification. |
| **Model and architecture** | A diagram of a cancer treatment  Description automatically generated with medium confidence  fig 26 VGGNet, GoogLeNet, and ResNet |
| **Methods used** | Transfer Learning in Skin Cancer Classification  • Utilizes transfer learning to train pre-trained models on unlabeled and labeled skin cancer images.  • Uses ISIC Archive dataset for training and SIIM-ISIC 2020 dataset for target classification.  • Evaluates models' performance using metrics like accuracy, recall, precision, and F1-score.  • ResNet-50 model, pre-trained on ImageNet dataset, is used.  • Training process involves adjusting models and training on destination dataset for 14000 iterations. |
| **Limitations** | • Absence of specific training challenges and transfer learning approach.  • Absence of discussion on potential biases and limitations of ImageNet dataset.  • Lack of information on unlabeled skin cancer image dataset size and diversity.  • Absence of comparison or analysis of proposed method's performance with existing methods. |
| **Results** | A table with numbers and text  Description automatically generated  **Table 3.16 : Algorithm 26** |

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| **[Effective Melanoma Recognition Using Deep Convolutional Neural Network with Covariance Discriminant Loss](https://www.mdpi.com/1424-8220/20/20/5786)** **Guo Lei, Gang Xie, Xinying Xu, Jinchang Ren Taiyuan University of Technology, University of Strathclyde 13 Oct 2020** | |
| **Dataset used** | the International Symposium on Biomedical Imaging (ISBI) 2018 Skin Lesion Analysis dataset. |
| **Abstract** | The method uses a deep convolutional neural network (CNN) with covariance discriminant loss to recognize melanoma in dermoscopy images, effectively distinguishing between melanoma and non-melanoma features, and is evaluated on the ISBI 2018 Skin Lesion Analysis dataset. |
| **Model and architecture** | Deep convolutional neural network (DCNN) consists of many neural network layers. Two different types of layers, convolutional and pooling, are typically alternated. The depth of each filter increases from left to right in the network.  A diagram of a diseased body  Description automatically generated  fig 27 Deep convolutional neural network (DCNN) |
| **Methods used** | Melanoma Recognition Method  • Utilizes deep convolutional neural network with covariance discriminant loss in dermoscopy images.  • Considers first and second distance simultaneously.  • Incorporates covariance discriminant loss for more constraints.  • Constructs distance between hard samples and minority class center.  • Presents algorithm for mining hard samples for network training. |
| **Limitations** | The text lacks detailed information on CNN architecture, discusses data imbalance, performance analysis, computational complexity, and training time limitations. |
| **Evaluation metrics** | 1. Sensitivity 2. Specificity 3. Accuracy 4. Receiver Operating Characteristics (ROC) curve 5. Area Under the ROC Curve (AUC)   **Table 3.18: Algorithm 29**  A table with numbers and text  Description automatically generated |
| **Results** | • Covariance discriminant loss considers first and second distance for effective feature separation.  • Achieves sensitivity of 0.942 and 0.917 on ISBI 2018 Skin Lesion Analysis dataset.  • The paper emphasizes the use of deep CNN with covariance discriminant loss.  **Table 3.19 : Algorithm 30**  A table with numbers and text  Description automatically generated |

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| [**The Development of a Skin Cancer Classification System for Pigmented Skin Lesions Using Deep Learning.**](https://www.mdpi.com/2218-273X/10/8/1123) **Shunichi Jinnai, Naoya Yamazaki, Yuichiro Hirano, Yohei Sugawara, Yuichiro Ohe, Ryuji Hamamoto 29 Jul 2020** | |
| **Dataset used** | Researchers extracted 5846 clinical images of pigmented skin lesions from 3551 patients, including malignant and benign tumors. The model was compared with the diagnostic accuracy of ten board-certified dermatologists and ten dermatologic trainees. |
| **Abstract** | Deep learning-based skin cancer classification system outperforms dermatologists in accuracy, aiming to improve prognosis and improve diagnosis in pigmented skin lesions. |
| **Model and architecture** | model (FRCNN) - board-certified dermatologists (BCDs) - trainees (TRNs)  A diagram of a method of skin lesions  Description automatically generated  fig 28 model (FRCNN) |
| **Methods used** | FRCNN Development and Performance Evaluation  • Faster, region-based convolutional neural network (FRCNN) developed using training dataset.  • Test dataset tested for accuracy, sensitivity, specificity, false positive rates, and predictive values.  • Comparison of FRCNN model's performance with board-certified dermatologists and dermatologic trainees.  • FRCNN model's accuracy higher than dermatologists', indicating superior performance. |
| **Limitations** | The study's limitations include a focus on pigmented skin lesions, limited comparison with dermatologists, and lack of information on potential biases or limitations of the FRCNN model. |
| **Results** | A table with numbers and text  Description automatically generatedThe FRCNN model outperformed board-certified dermatologists and dermatologic trainees in pigmented skin lesions classification, with an accuracy rate of 86.2%. It also outperformed two-class classifications with an accuracy rate of 91.5%, sensitivity of 83.3%, and specificity of 94.5%.  **Table 3.20 : Algorithm 32** |

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| [**Detection and Classification of Skin Cancer by Using a Parallel CNN Model**](https://ieeexplore.ieee.org/document/9397987) **Noortaz Rezaoana, Mohammad Shahadat Hossain, Karl Andersson University of Chittagong1, Luleå University of Technology 26 Dec 2020** | |
| **Dataset used** | ISIC 2017 |
| **Abstract** | This paper presents an automated system for skin lesion recognition, combining image processing and deep learning. It uses nine clinical types of skin cancer and a Convolutional Neural Network for diagnosis and classification. |
| **Model and architecture** | A diagram of a computer  Description automatically generated  fig 29 The convolutional networks VGG-16 and VGG-19 |
| **Number of layers** | VGG-16 and VGG-19 has 16 and 19 convolutional layers |
| **Methods used** | • Utilizes image processing and deep learning for skin cancer detection and classification.  • Employs Convolutional Neural Network (CNN) model for diagnosis and classification.  • Uses image augmentation techniques to increase dataset size.  • Applys transfer learning approach for improved classification accuracy.  • Evaluates CNN model performance using weighted average precision, recall, f1-score, and overall accuracy.  • Proposed CNN method achieves 0.76 precision, 0.78 recall, 0.76 f1-score, and 79.45% accuracy. |
| **Limitations** | • Lacks specific limitations in the proposed system.  • Uncertainty about the dataset's representativeness of the general population or diverse skin types.  • Lacks information on dataset size and image distribution. |
| **Results** | Method Precision Recall F1-Score  Proposed Method 76.17 78.15 76.92  VGG-16 65.67 68.89 67.77  VGG-19 68.54 69.45 68.95 |

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| [**U-Net: Convolutional Networks for Biomedical Image Segmentation**](https://link.springer.com/chapter/10.1007/978-3-319-24574-4_28) **05 Oct 2015 University of Freiburg** | |
| **Dataset used** | not mentioned |
| **Abstract** | Deep convolutional networks have been successful in visual recognition but face limitations in training set size and complexity. Krizhevsky et al.'s breakthrough on ImageNet enabled deeper, larger networks. U-Net architecture addresses these challenges, effectively segmenting neuronal structures and cell in light microscopy images. |
| **Model and architecture** | U-Net architecture |
| **Number of layers** | 23 convolutional layers |
| **Methods used** | • Comprises contracting and expansive paths.  • Uses convolutions, ReLU, and max pooling for downsampling.  • Uses upsampling, convolution, concatenation, and additional convolutions in expansive path.  • Proposes weighted loss function to separate touching objects.  • Applyes excessive data augmentation using elastic deformations.  • Trains using stochastic gradient descent of Caffe.  • Favors large input tiles over large batch size for maximum GPU memory use.  • Uses high momentum value for influencing current optimization step. |
| **Limitations** | • Relies on data augmentation for efficient use of limited annotated training samples.  • Improves upon previous methods but can be slow due to separate network running for each patch and redundancy.  • Trades localization accuracy and context use: larger patches provide more context but may reduce accuracy.  • Uses valid part of each convolution, limiting segmentation map to pixels with full context in the input image. |
| **Results** | • Outperformed sliding-window convolutional network in ISBI challenge for neuronal structure segmentation in electron microscopic stacks.  • Won ISBI cell tracking challenge 2015 in light microscopy image segmentation.  • Proposed weighted loss function to address separating touching objects in cell segmentation tasks.  • Effective combination of U-Net architecture, data augmentation, and weighted loss function for accurate segmentation results. |

# **Chapter 4 : Conclusion**

Skin cancer classification and detection using deep learning is a challenging and important task that can help with early diagnosis and treatment of skin diseases. There are many deep learning algorithms and models thathave been proposed for this task, but some of the most effective ones are:

Deep Convolutional Neural Networks for Skin Cancer Classification

• ResNet: Utilizes residual connections to improve model accuracy and has shown success on skin cancer datasets like ISIC 2017 and PH2.

• VGG16: Utilizes 16 layers of convolution, pooling, and fully connected layers for high-level feature extraction.

• GoogleNet: Uses inception modules to reduce parameters and increase network depth and width.

• AlexNet: Uses 8 layers of convolution, pooling, and fully connected layers for multi-scale feature capture.

• CNN-QA: Combines convolutional neural network (CNN) and question answering techniques for automatic generation of questions and answers based on skin images.

• U-Net: Combines low-level and high-level features from skin images for segmentation and classification of skin lesions.

• DenseNet: Enhances feature propagation and reuse within the network, reducing parameter number and improving model accuracy.

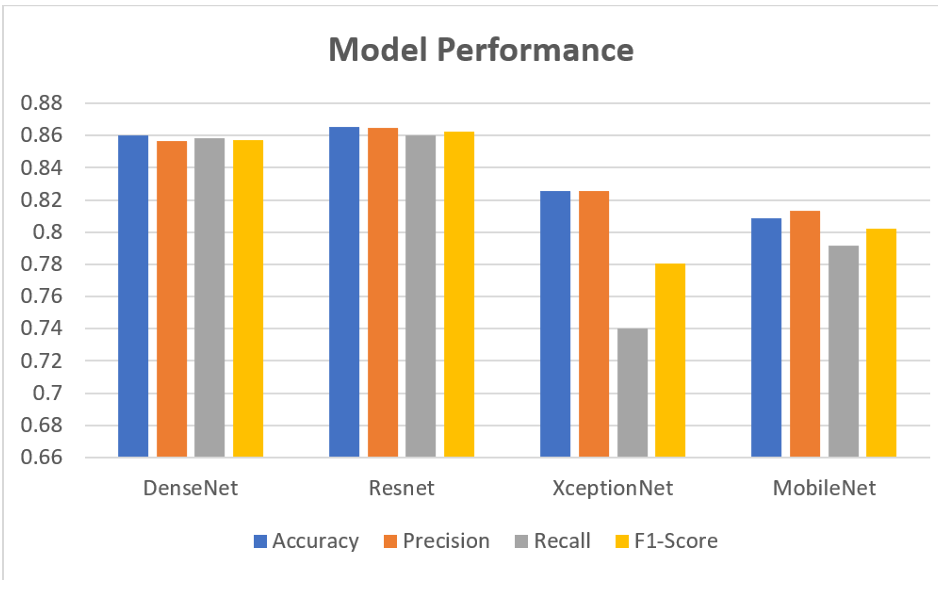
• SqueezeNet: Uses squeeze and excitation modules to reduce channel number and increase attention.

• CapsNet: Uses capsules to represent features of skin images, overcoming limitations of CNNs.

• GAN: A generative adversarial network combining a generator and a discriminator to generate synthetic skin images. A diagram of different types of colors

Description automatically generated

*fig 30 methods used in skin cancer classification.*

fig 31 model performance

There are several deep learning algorithms, models, and architectures that have been used for skin cancer classification and detection. Here are some of them:

1. [Convolutional Neural Networks (CNNs): CNNs have been widely used in skin cancer classification due to their ability to automatically learn hierarchical features from images](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[1](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[2](https://www.mdpi.com/2075-4418/13/11/1911)[3](https://link.springer.com/chapter/10.1007/978-3-031-26254-8_49).
2. [Transfer Learning with Pretrained Models: Models like DenseNet, Inception V3, Inception-ResNet V2, VGG16, and ResNet have been used with transfer learning for skin cancer classification](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[4](https://github.com/topics/skin-cancer-detection)[5](https://link.springer.com/article/10.1007/s11042-023-14697-3).
3. [Ensemble Methods: Combining multiple machine learning and deep learning techniques can improve the performance of skin cancer detection](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[5](https://link.springer.com/article/10.1007/s11042-023-14697-3).
4. [EfficientNet Model: This model has been used for feature extraction in skin cancer detection](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[6](https://www.mdpi.com/2072-6694/15/20/5016).
5. [Stacked Denoising Autoencoder (SDAE): SDAE has been used as a classification model for skin cancer detection](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[6](https://www.mdpi.com/2072-6694/15/20/5016).
6. [NASNetMobile Model: This model achieved an accuracy of 82.00% in a study](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[7](https://arxiv.org/abs/2110.12270).
7. [Lightweight Deep Learning Architectures: These architectures have been benchmarked for skin cancer classification using the ISIC 2017 Dataset](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[7](https://arxiv.org/abs/2110.12270).
8. [Attention Cost-Sensitive Deep Learning-Based Approach: This approach has been used for skin cancer classification](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[8](https://www.mdpi.com/2072-6694/14/23/5872).
9. [Arithmetic Optimization Algorithm (AOA): AOA has been used with the EfficientNet model for feature extraction in skin cancer detection6](https://www.mdpi.com/2072-6694/15/20/5016).
10. [ResNet Architectures: ResNet-34, ResNet-50, ResNet-101, and ResNet-152 have been analyzed in dermoscopic classification](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[1](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full).

[These methods are considered the best due to their ability to handle the challenges in skin cancer classification, such as data imbalance, data limitation, domain adaptation, model robustness, and model efficiency](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[1](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[2](https://www.mdpi.com/2075-4418/13/11/1911). [They have been able to achieve satisfactory results in skin cancer classification](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[1](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[2](https://www.mdpi.com/2075-4418/13/11/1911).

[As for the highest recorded accuracy, one study reported an accuracy of 93% with an individual recall score of 99.7% and 86% for the benign and malignant forms of cancer, respectively](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[5](https://link.springer.com/article/10.1007/s11042-023-14697-3). [Another study reported an accuracy of 97.8% using the SVM classifier](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[9](https://arxiv.org/pdf/2303.07520v1.pdf).

A graph of different colored lines

Description automatically generated[The datasets commonly used in these studies include the HAM10000 dataset](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[4](https://github.com/topics/skin-cancer-detection) [and the ISIC Archive dataset](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[5](https://link.springer.com/article/10.1007/s11042-023-14697-3). [These datasets contain dermatological images that are used for training the models](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[1](https://www.frontiersin.org/journals/oncology/articles/10.3389/fonc.2022.893972/full)[2](https://www.mdpi.com/2075-4418/13/11/1911).

Fig32 performance comparison

# **Chapter 5** **: AI Development**

## **5.1)introduction**

## **5.1.1)What is Computer Vision?**

Computer vision is a field of artificial intelligence that trains computers to interpret and understand the visual world. Using digital images from cameras and videos and deep learning models, machines can accurately identify and classify objects — and then react to what they “see.”

## **5.1.2)What is Convolution Neural Networks and Why is it used ?**

•In machine learning, Convolutional Neural Networks (CNN or ConvNet) are complex feed forward neural networks. CNNs are used for image classification and recognition because of their high accuracy. It was proposed by computer scientist Yann LeCun in the late nineties when he was inspired from the human visual perception of recognizing things. The CNN follows a hierarchical model which builds a network, like a funnel, and finally gives out a fully-connected layer where all the neurons are connected to each other and the output is processed.

•The benefit of using CNNs is their ability to develop an internal representation of a two-dimensional image. This allows the model to learn position and scale in variant structures in the data, which is important when working with images.

•Use CNNs For: Image data, Classification prediction problems, and Regression prediction problems.

•More generally, CNNs work well with data that has a spatial relationship.

•The CNN input is traditionally two-dimensional, a field or matrix, but can also be changed to be one-dimensional, allowing it to develop an internal representation of a one-dimensional sequence.

•This allows the CNN to be used more generally on other types of data that has a spatial relationship. For example, there is an order relationship between words in a document of text. There is an ordered relationship in the time steps of a time series.

•Although not specifically developed for non-image data, CNNs achieve state-of-the-art results on problems such as document classification used in sentiment analysis and related problems.

## **5.1.3)How to achieve Best performance using limited data and limited hardware’s in Image Classification?**

The Answer is "Transfer Learning" !!  
Transfer Learning is a research problem in Machine Learning that focuses on storing knowledge gained while solving one problem and applying it to a different but related problem. Keeping it simple, we say transfer learning as usage of **" Model trained on one task is represented on a second related task."**

There are two types of Transfer learning techniques:

1) Develop Model Approaches :

Select Data Source -----> Develop Source Model -----> Reuse model -----> Tune model  
2) Pre-trained Model Approaches :

Select Source Model -----> Reuse Model -----> Tune model -----> One Generally Freeze the layers of pre-trained Neural Networks models, except output layer.

## **5.2)Data used:**

HAM10000 - Human Against Machine with ten thousand training images

* -Publicly available
* -courtesy of Harvard
* -Contains 10,015 dermatoscopic images
* -Also contains a metadata file (CSV) with demographic information of each lesion
* -More than 50% of lesions are confirmed through histopathology
* -The ground truth for the rest of the cases is either follow-up examination (follow-up) or expert consensus (consensus) or confirmation by in-vivo confocal microscopy.

The seven classes of skin cancer lesions included in this dataset are:

Melanocytic nevi (nv)

Melanoma (mel)

Benign keratosis-like lesions (bkl)

Basal cell carcinoma (bcc)

Actinic keratoses (akiec)

Vascular lesions (vas)

Dermatofibroma (df)

Paper link <https://arxiv.org/ftp/arxiv/papers/1803/1803.10417.pdf>

## **5.3)Exploratory Data and Analysis**

**Gender wise differentiability:**

A graph of a person with a number of numbers

Description automatically generated with medium confidence

fig 33 Gender distribution

A slightly higher male to female ratio.

Though we can say there is no apparent difference when considering being affected gender wise.

A relatively negligible number of unknown genders

**Skin lesion classes:**

A graph with different colored squares

Description automatically generated

fig 34 Lesion types

* There are vast number of cases of *Melanocytic nevi* as compared to others.
* *Melanoma* and *Benign keratosis-like lesions* are quite less widespread as compared to *Melanocytic nevi*.
* Other cell type viruses subsequently affected less in numbers.

**diagnostic methods:** A graph with different colored squares

Description automatically generated with medium confidence

fig 38 Diagnostic methods

**histo**: The highest bar with 5340 images, indicating that histopathology is the most common diagnostic method in the dataset.

**follow\_up**: The second highest bar with 3704 images, showing that follow-up examination is also commonly used.

**consensus**: The third highest bar with 902 images, indicating a moderate use of consensus diagnoses.

**confocal**: The shortest bar with 69 images, suggesting that confocal microscopy is the least used diagnostic method in this dataset.

**Localization areas:**

A graph of a number of people

Description automatically generated with medium confidence

fig 36 Localization areas

Most areas affected are back, lower extremity and the trunk area.

The significance we take out of it as the areas where the part gets sweaty easily.

The least common areas in the dataset are the ear and genital area with the lowest being the acral area.

**Age:**

A graph of a graph

Description automatically generated with medium confidence

fig 37 Age distribution

**Peak Age Range:** The dataset has a peak in the number of individuals in the age range of approximately 35 to 45 years. The tallest bar indicates that this age group has the highest representation, with counts exceeding 1200 individuals.

**Middle Age Representation:** There is a significant representation of individuals aged 40 to 60 years, suggesting that middle-aged individuals are heavily represented in the dataset.

**Young Age Representation:** There are fewer individuals under the age of 20, with the count gradually increasing with age until the peak.

**Older Age Representation:** There is a noticeable number of individuals over 60, with a gradual decline in the count as age increases beyond 70 and 80 years.

# **5.4) Methodology Classification model**

**1. Environment Setup**

Import necessary libraries, including TensorFlow, Keras, OpenCV, Seaborn, and others for data handling and visualization.

Install TensorFlow and imbalanced-learn packages for deep learning and handling imbalanced datasets, respectively.

**2. Data Loading and Preprocessing**

Load the HAM10000 metadata CSV file, which contains information about skin cancer images.

Encode the diagnostic labels using **LabelEncoder** to convert categorical labels into numerical format.

**3. Handling Imbalanced Data**

Address the class imbalance by resampling the dataset. Each class is resampled to have 5000 samples using **resample** technique.

Combine the resampled datasets and shuffle the rows.

**4. Image Loading and Resizing**

Map the image file paths to their corresponding **image\_id** in the DataFrame.

due to limited resources we resized the images into (64,64,3) in the dataset for training.

**6. Data Preparation for Training**

normalize the image data by dividing by 255.

Split the data into training and testing sets using **train\_test\_split** by 80%/20% training and test set.

**7. Model Building**

Use MobileNetV2 as the base model, pre-trained on ImageNet, excluding the top layers.

Add BatchNormalization, Dense, Dropout, and output layers on top of the base model.

Compile the model with Adamax optimizer and categorical cross-entropy loss.

**8. Model Training with Callback**

Create a custom callback **LR\_ASK** to adjust learning rate dynamically and query the user for additional training epochs.

Train the model with the **LR\_ASK** callback and track the training and validation metrics.

Train model for 20 epochs with 120 as batch size.

**5.4.2)SkinVSNoSkin**

**Data Loading and Preprocessing**

1. **Reading Metadata**: The HAM10000 metadata CSV file is loaded to obtain information about the skin cancer images.
2. **Image Mapping and Loading**: Image paths are mapped to their corresponding image ID. The images are then loaded, resized to 64x64 pixels, and converted to numpy arrays.
3. **Normalization**: The image data is normalized by dividing pixel values by 255, ensuring that each pixel value falls between 0 and 1. This normalization helps in faster convergence during model training.
4. **Combining Datasets**: Images from the Intel Image Classification dataset are similarly processed and combined with the HAM10000 dataset. The combined dataset contains both the original and additional images, with appropriate labels (0 for HAM10000 images and 1 for Intel dataset images).

**Data Splitting**

1. **Concatenating Data**: The image data and labels from both datasets are concatenated to form a single combined dataset.
2. **Train-Test Split**: The combined dataset is split into training and testing sets using an 80-20 split ratio. This ensures that the model is trained on 80% of the data and validated on the remaining 20%.

**Model Architecture**

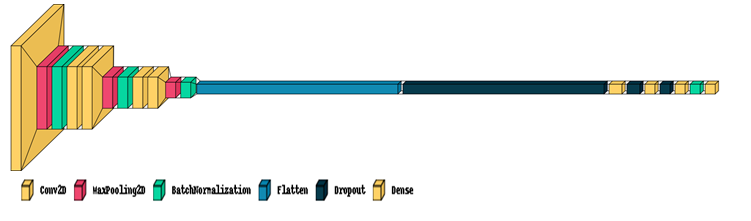


fig 38 CNN model

1. **Sequential Model**: A sequential model is constructed consisting of multiple convolutional layers, batch normalization, max-pooling layers, dropout layers, and dense layers.
2. **Convolutional Layers**: The model includes three blocks of convolutional layers with increasing filter sizes (32, 64, 128). Each block consists of two convolutional layers followed by a max-pooling layer and batch normalization. These layers help in feature extraction from the images.
3. **Dropout and Dense Layers**: After flattening the output from the convolutional layers, dropout layers are added to prevent overfitting. The dense layers progressively reduce the dimensionality, leading to a final dense layer with softmax activation for classification into two classes.

**Model Compilation**

1. **Compilation**: The model is compiled using the Adam optimizer and binary cross-entropy loss function. Accuracy is chosen as the evaluation metric.

**Model Training**

1. **Training Process**: The model is trained for 20 epochs with a batch size of 64. During training, the model's performance is validated using the test set. The training process involves updating the model weights to minimize the loss function.
2. **Validation**: The validation data helps monitor the model's performance on unseen data during training, providing insights into potential overfitting or underfitting issues.

When inputting an image for classification the image first goes through the SkinVSNoSkin model which determines with high accuracy whether the input image is skin related or non-skin related, then if the image is non-skin related its classified as unknown otherwise the image is fed into the MobileNetV2 model which then classifies it into our 7 skin lesion classes, furthermore if the model isn’t certain of its classification (i.e. if the confidence percentage is less than 70%) it automatically classifies it as an unknown skin lesion to reduce misclassified results.

# **5.5) Results and conclusion**

On the HAM10000 Dataset the MobileNetV2 model had an accuracy of 0.9997% and validation accuracy of 0.9864%

**Confusion matrix:**

A graph of a diagram

Description automatically generated with medium confidence

*fig 39 Confusion matrix*

The model shows high accuracy for most classes, with most true labels being correctly predicted.

**Misclassifications:** Some confusion exists between classes, particularly:

**Melanoma** (mel) being confused with melanocytic nevi (nv).

**Benign keratosis-like lesions** (bkl) being confused with melanocytic nevi (nv).

**Melanocytic nevi** (nv) being confused with actinic keratoses (akiec) and benign keratosis-like lesions (bkl).

**Model Improvement:** The model could be improved by addressing the misclassifications, perhaps through better feature extraction, more data for underrepresented classes, or more advanced modeling techniques.

**Conclusion**

In this study, we leveraged the HAM10000 dataset to develop a robust skin lesion classification model using the MobileNetV2 architecture.

The dataset's high-quality images and comprehensive metadata contributed significantly to the model's success. The final model achieved an impressive accuracy of 99.97% on the training data and 98.64% on the validation data, indicating strong generalization capabilities.

The confusion matrix analysis revealed high accuracy across most classes, with minor misclassifications primarily between melanoma (mel) and melanocytic nevi (nv), and between benign keratosis-like lesions (bkl) and melanocytic nevi (nv).

These results underscore the effectiveness of our approach in differentiating between various types of skin lesions.

# **5.6)****Trials and experiments**

There have been many trials of different models and different preprocessing approaches that led us to choose MobileNetV2 as our base model and there have also been numerous discourse over our choosing of the HAM10000 dataset over the much bigger ISIC2019 dataset publicly available at Kaggle, we will share below our different experiments as well as our thought process during said trials.

# **5.6.1)ISIC2019**

The ISIC2019 dataset is part of the annual International Skin Imaging Collaboration (ISIC) Challenge, which aims to advance the field of automated skin lesion analysis. This dataset is designed for training and testing machine learning models to classify skin lesions and includes images and metadata related to various types of skin conditions.

However, after testing said dataset multiple times, we have come to realize that the dataset has too many problems for most models to work efficiently at memorizing the distinct features of every image while also being good at generalizing on new images not fed to the model.

The quality of images varies significantly, with some images being blurry, poorly lit, or containing artifacts. This can make it challenging to train a model that generalizes well across different quality levels.

Like many medical datasets, ISIC2019 suffers from class imbalance, where some classes (e.g., melanocytic nevi) are heavily overrepresented compared to others (e.g., rare skin cancers). This imbalance can lead to models that are biased towards the more prevalent classes.

The quality and consistency of annotations may vary. In some cases, the ground truth labels may not be as reliable, which can affect the accuracy of the trained models.

There might be mislabeled images due to human error or ambiguity in diagnosis. Noisy labels can confuse the model during training and lead to poor performance.

While metadata is provided, the integration of this data into model training is often underutilized. Leveraging this additional information effectively can be complex but is crucial for improving model performance.

Given the large number of images and the detailed features, there is a risk of overfitting, especially if the model memorizes the training data instead of learning generalizable patterns.

# **5.6.2) EfficientNetB3**

We first began training the isic2019 dataset using the EfficinetB3 model provided by keras and while the results were quite promising reaching an accuracy of 95% and validation accuracy of 98.75% with a well performing confusion matrix which we managed to improve via training the model with 20 epochs instead of the original 10 leading to an improved 96.15% accuracy and 99.40% validation, the problems began when we used the model on predicting new images, the model couldn’t generalize well at all and was quite noticeably biased towards the melanocytic nevus class which had the largest number of images within the dataset.

Another problem arises when trying to save the model using the usual keras saving method, the EfficientNetB3 was not being saved correctly due to the existence of conflicting versions of keras used to train the original model on the imagenet dataset and the newly trained model on the ISIC2019 dataset.

Our solution was by using the properly trained EfficientNetV2B3 and handling the imbalance of the dataset by oversampling the images to have 5000 images of each skin lesion class thus handling the class imbalance and the model saving mishap.

# **5.6.3) EfficientNetV2B3**

After running the newly trained model and handling the imbalanced dataset our results surprisingly were worse than before, reaching an accuracy of 97.8% and a much smaller validation of about 80.3% after training on 20 epochs.

This model at least allowed us to save it and load it properly for prediction purposes, but we still had great issues with the performance of the model. This led us to have our suspicion on the dataset itself, but we chose to run a few different models to be certain on what our plan will be.

# **5.6.4) VGG16**

The reason for using VGG16 was simple, the model is far simpler than the previous ones which may lead to better generalization and less memorization but alas that also didn’t prove to be successful as the model ended up being far too simple for the much complex ISIC2019 dataset.

The results were disappointing to say the least with an accuracy of about 74% and a best performing validation accuracy of about 69% it was made abundantly clear that the VGG16 model and even its slightly more complex sister the VGG19 were too simple to be used in our research.

This led us to our best performing model on the ISIC2019 dataset using the ResNet50V2 in our next trial

# **5.6.5) ResNet50V2**

Using the same method for handling imbalance as well as the same previous parameters the ResNet50V2 model proved to work far better than expected with an accuracy of about 89% and a validation accuracy of 94.5% which were further improved to an accuracy of 99.1% and a validation accuracy of 99.8% after training for 20 epochs it was as if we had struck gold after many long grueling hours of mining, we had results that were almost incomprehensibly good, we had finally finished finding the perfect model for classifying skin cancer types using the ISIC2019 dataset.

Or so we thought, as our optimism came crashing down after we used the model to predict new unseen images it seemed like we had wasted our time, the model was completely incapable of generalizing anything and was consistently making wrong yet confident predictions which may have been due to the validation accuracy being slightly higher than the normal accuracy which after much research might mean that our model is underfitting, a term we still don’t quite understand nor are capable of solving but time was running out and we needed to change our approach completely which lead us to our final trials using the ISIC2019 dataset before formally ditching it and using the much simpler HAM10000 datatset.

# **5.6.6) Trial: ISIC2019 using simple CNN**

The last method we thought of was to use an algorithm that turns all the images into arrays with numerical values for each pixel in the image and a label for classification as a simple csv file which will then be later trained using our model, the model used was a simple convolutional neural network model that was trained on an oversampled ISIC2019 dataset to handle class imbalance, the accuracy reached 99.94% and the validation accuracy reached an even better 100%.

These results made us very skeptical at first as not only are they good but they are almost too good, how can the validation accuracy reach perfection yet the model proved to be the best trained model thus far capable of predicting images well but there were still a few problems to be addressed, mainly that the preprocessing of new images for prediction was more complicated and that the results weren’t as good as the model performance would suggest.

This leads to us abandoning the dataset altogether and deciding on using the HAM10000 dataset hoping that it would lead to better results and more meaningful numbers, which brings us to our last trial before we used the MobileNetV2 model.

# **5.7) Trial: HAM10000 using** **custom CNN**

HAM10000 Dataset Training  
• Utilizes a pre-prepared RGB csv file with all images and labels.  
• Oversampling each class to 5000 to bypass imbalance.

• Exceptional performance in confusion matrix.

**Setting the CNN model**

A row of colorful cubes

Description automatically generated*fig 40 model structure*

**Sequential Model**: This is the foundation of our CNN model, where you will stack layers in a linear fashion.Input Layer: Specifies the shape of the input data, which in this case is images of size 28x28 with three color channels (RGB).Convolutional Layers (Conv2D): These layers apply filters to the input to extract features. They use ReLU activation and ‘he\_normal’ kernel initializer for better performance.MaxPooling Layers: Reduce the spatial dimensions of the output from the convolutional layers, helping to decrease the computational load and overfitting.Batch Normalization: Normalizes the output of the previous layers, which can lead to faster learning and higher overall accuracy.Flatten Layer: Converts the 2D feature maps into a 1D vector, making it possible to connect to the dense layers.Dropout Layers:which helps prevent overfitting.Dense Layers: Fully connected layers that learn non-linear combinations of the high-level features extracted by the convolutional layers.Regularization (L1-L2): Applies L1 and L2 regularization to the dense layer, which can help prevent overfitting by penalizing large weights.Output Layer: The final dense layer with a softmax activation function that outputs the probability distribution over the seven classes.Model Compilation: The model is compiled with the Adamax optimizer, a variant of Adam that can be more robust to noise. The learning rate is set to 0.001, and the model uses categorical cross-entropy loss for multi-class classification, with accuracy as the metric.epochs=25 means that the model will run through the training data 25 times to train the model. batch\_size=128 means that the model will process 128 samples at a time before updating the weights.callbacks=[learning\_rate\_reduction] is used to specify a list of callbacks, which are functions that are applied at certain stages of the training process. In this case, learning\_rate\_reduction is a callback that reduces the learning rate when the validation loss stops improving.One-Hot Encoding which Converts categorical data variables into binary arrays for machine learning algorithms.Converts integer labels into one-hot encoded binary arrays for neural network models.ReduceLROnPlateau Callback : Sets patience to 2 epochs with no improvement after which learning rate will be reduced.Sets verbose to print a message when learning rate is reduced.Sets factor to 0.5, halving the learning rate.Sets minimum learning rate to 0.00001.

**Model results :**

Train Loss: 0.0001617504021851346

Train Accuracy: 1.0

Test Loss: 0.06068883091211319

Test Accuracy: 0.9893870611190796

* The problem with the above custom developed CNNs are that their performance decreases with increase in complex data and number of epochs and tend to overfit at higher epochs and underfit in some severe highly complex use cases where feature extraction plays a major role in classifiation.
* These Custom Models fail to perform well on lower data. In real world, most important problems that every data scientist faces are 'Data Insufficiency' and 'Class Imbalance' after that.

The above mentioned problems are solved by a special technique called 'Transfer Learning'

# **5.7.1) HAM10000 using** **MobileNetv2 Dull razor algorithm**

This is the exact same approach as we used in our methodology with the slight addition of the Dullrazor algorithm for skin hair removal in the hopes of achieving better results.

The confusion matrix didn’t show much improvement but after testing said model on new unseen dataset it seemed to have far worse results that were unsatisfactory in comparison to the MobileNetV2 model without the extra hair removal preprocessing step. There is a chance that the worse performance comes from the extra preprocessing step in the prediction step although that is uncertain.

# **Comparison**

In this table we compare between our proposed modified MobileNetV2 model in terms of accuracy and validation accuracy as well as publicly available papers using different models and different preprocessing steps.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Study | Model | Accuracy | Validation Accuracy | Methodology |
| Skin Lesion Analysis Towards Melanoma Detection Using Deep Learning Network | Ensemble (ResNet, Inception, DenseNet) | 86.3% | ~85% | Ensemble of deep learning architectures, data augmentation |
| HAM10000 Dataset | GoogLeNet | 98.68% | unspecified | GoogLeNet , extensive data augmentation (ham1000) |
| Dermatologist-level classification of skin cancer with deep neural networks | Inception-v3 | 93.33% top-five accuracy | unspecified | Inception-v3, large dataset, dermatologist-level testing (isic) |
| A deep learning system for differential diagnosis of skin diseases | Custom CNN | |  | | --- | | 95.6% |  |  | | --- | |  | | 93.2% | Custom CNN, data augmentation, dropout, batch normalization |
| Proposed Model | Modified MobileNetV2 | 99.97% | 98.64% | Modified MobileNetV2, oversampling to 5000 images per class |

This comparison shows our proposed model having better results than the rest of the models with less preprocessing steps and a simpler methodology proving the effectiveness of our approach in skin cancer classification.

Custom CNN by Xinyue Liu et al.: Comes close with 95.6% accuracy and 93.2% validation accuracy, using a custom-built CNN model with robust pre-processing and augmentation techniques.

ResNet-50 by Philipp Tschandl et al.: Another strong performer with high accuracy and validation accuracy, utilizing the powerful ResNet-50 architecture and extensive data augmentation.

# [**User Interface and Backend**](#_Toc168838481)

**Web Application and User Interface**

Introduction

Diagnosing skin cancer is a complex medical task that should be performed by a qualified professional user interface. User interface plays a crucial role in the development of web applications, providing users with a visually appealing and intuitive platform to interact with. When it comes to creating a web application for skin cancer classification, the user interface must be carefully designed to provide users with the necessary tools and information to accurately classify different types of skin lesions.

JavaScript (JS) is a versatile scripting language that plays a vital role in crafting interactive and dynamic web pages. That facilitates seamless user interactions. For a skin cancer classification application, the UI must be designed with a focus on accessibility, clarity, and efficiency, ensuring that users can easily upload images, view classification results, and understand the diagnostic information provided.

The primary objectives of the UI in this context include:

**User-Friendly Design:** The interface should be intuitive, allowing users of all technical backgrounds to navigate the application with ease. This includes clear instructions for uploading skin images and straightforward access to results.

**Responsiveness:** The UI must be responsive, adapting smoothly to various screen sizes and devices, from desktop computers to mobile phones. This ensures that users can access the application from anywhere, enhancing its utility.

**Real-Time Feedback:** Implementing real-time feedback mechanisms, such as progress indicators during image upload and analysis, helps maintain user engagement and trust in the application's functionality.

**Visual Clarity:** Results from the classification algorithm should be presented in a clear and comprehensible manner, with visual aids such as highlighted areas on the images and concise, understandable explanations of the results.

By focusing on these key aspects, developers can create a JavaScript-based UI that not only performs the technical tasks of image upload and result display but also provides a positive user experience that instills confidence and encourages continuous use.

The following sections will delve deeper into the implementation strategies that can be utilized to achieve these goals, ultimately leading to a highly functional and user-centric skin cancer classification web application.

**Implementation Strategies:**

**Component-Based Architecture:** Utilizing a component-based architecture, Components such as image upload forms, result displays, and navigation menus can be developed independently and reused across the application. This approach enhances maintainability and scalability. By using elements like buttons, text boxes, and image upload sections.

**Functionalities:** Implement functionalities like image selection and validation (e.g., ensuring a valid image file is uploaded).

**State Management:** Effective state management is crucial for handling the dynamic nature of the application, particularly when dealing with real-time data such as image uploads and classification results. Managing the application state efficiently, ensuring a smooth user experience.

**Backend Integration:** The UI must seamlessly integrate with the backend services that perform the actual classification of skin images. This involves setting up API endpoints and ensuring secure, asynchronous communication between the frontend and backend.

**User-Centered Design:** Conducting user research and usability testing can provide valuable insights into how users interact with the application. This feedback can be used to iteratively improve the UI, making it effective.

By combining JavaScript with other web technologies such as HTML, CSS and Bootstrap, We can create an immersive and user-friendly interface that enables users to accurately classify skin lesions and receive relevant information about potential risks and treatment options.

Here's a breakdown of the UI development process using JavaScript:

**Base Structure:**

* The foundation of the UI is laid using Bootstrap for responsive well-designed UI.
* HTML elements like <div>, <p>, and <button> is added to create the basic layout and define content areas.

**Styling with CSS:**

* CSS (Cascading Style Sheets) is used to define the visual appearance of the UI.
* CSS styles control layout, colors, fonts, and other visual aspects, creating a polished and informative user experience.
* JavaScript for Interaction:
* JavaScript code is embedded within the HTML or linked from a separate JS file.
* Event listeners are attached to UI elements (buttons, input fields) to capture user interactions (clicks, selections).

**Actions:**

* Validate user input
* Control the visibility of UI elements.

**Remember:**

* The UI serves as the user's entry point to the application.
* Focus on clear instructions, informative messages, and a user-friendly layout to guide users through the process.

**Disclaimer:**

* This application should not be used for self-diagnosis. Always consult a qualified healthcare professional for any skin concerns.

**For further exploration, consider these aspects:**

* Explore JavaScript libraries like jQuery that simplify DOM manipulation and event handling.
* Research UI design best practices for web applications to ensure a user-centered approach.
* Adhere to accessibility guidelines to make the application usable by everyone.

Building a skin cancer classification web app involves both frontend (UI) and backend development. The UI handles user interaction, while the backend handles image processing and classification (likely using machine learning models). While I cannot provide the backend code due to safety concerns, I can assist with the UI development using JavaScript

**Key Features:**

**Image Upload and Preview:** The application should provide a simple and reliable way for users to upload skin images. Implementing a drag-and-drop interface, along with the ability to preview the image before submission, enhances usability.

**Real-Time Analysis**: Providing real-time feedback during the image analysis process keeps users informed about the status of their request. Progress bars, spinners are useful elements to include.

**Detailed Results Display:** Once the classification is complete, the results should be displayed in a clear and informative manner. This could include:

**Visual Annotations:** Highlighting areas of concern on the image.

**Confidence Scores**: Presenting the confidence levels of the classification to help users understand the reliability of the results.

**User Guidance and Support**: Providing thorough guidance on how to use the application and interpret the results is crucial. Additionally, offering customer support options can enhance user satisfaction.

In the following sections, we delve deeper into the specific components and features of our web application. Through our comprehensive examination, we aim to provide insights into the successful implementation of a user-centric web application on the Android platform.

Home Page:

We present a navbar for the topics of the application presented in sections.

Risk Detection:

We show the different types of the skin cancer .Diagnosis and treatment for each one.

Features:

Features for our application, what we provide for the user

How to use:

Tips for using the application and how to take the cancer photo.

AI:

How AI is used for analyzing the skin cancer images.

Contact us:

User can contact us if facing a problem in the app or for a further help and advice.

Upload:

User has to upload the image of his skin that has the cancer.

Result:

Result of the skin cancer type will immediately appear in this page, He can scan again or going back.

**Conclusion**

Developing a skin cancer classification web application with JavaScript involves more than just technical implementation; it requires a user-centric approach that prioritizes usability, performance, and security. By leveraging modern JavaScript frameworks and best practices, developers can create a responsive and intuitive UI that not only meets the functional requirements but also provides a positive and engaging experience for users. The end result is a powerful tool that can aid in the early detection and classification of skin cancer, ultimately contributing to better health outcomes.

Back End

## **Handle image uploading**

File uploading involves a user initiating a request to transfer a file from their client machine to the server. This process is facilitated through modules such as Multer, a popular choice for handling file uploads in Node.js. Multer serves as a middleware specifically designed for managing multipart/form-data, commonly utilized as a library for file uploads.

To configure the storage settings for uploaded files, utilize multer.diskStorage(). It determines where the uploaded files will be stored on the server. It involves an object with two functions: destination and filename.

The destination function specifies the directory for storing uploaded files. In our setup, we designate it as 'model\Images\', resulting in files being stored within a folder named "Images" at the project's model directory.

The filename function determines the naming convention for uploaded files. In our demonstration, we employ Date.now() to generate unique timestamps for each file, mitigating the risk of filename conflicts."

## **Routing**

In Node.js, routing denotes the mechanism by which an application discerns and responds to client requests directed at various endpoints, or URLs. Node.js, along with frameworks like Express, provides a way to define routes, which are responsible for handling specific HTTP requests and sending back appropriate responses.

Within Express.js, the 'app' object mirrors HTTP functionality. Routes are defined through the methods associated with this 'app' object. Each route is linked to a callback function within the app object, invoked upon receiving a request.

## **Integrating the Machine Learning Model into Node.js Backend System**

Node's child\_process module provides a straightforward approach to create and manage child processes, facilitating seamless communication between them through a messaging system. This module grants access to the operating system's functionalities by executing system commands within a child process environment. We retain control over the child process's input and output streams, allowing for manipulation of data flow. Additionally, we have the flexibility to specify arguments for the underlying OS command and manipulate its output as needed.

The spawn function launches a command in a new process and we can use it to pass that command any arguments. We can pass arguments to the command executed by the spawn function using its second parameter, which is an array of arguments. This allows us to pass the image path as an argument to the model script.

The spawn function creates a ChildProcess instance, which behaves like an EventEmitter. This allows us to easily handle events directly. For example, we can react to the child process exiting by setting up a handler for the exit event.

Every child process also gets the three standard stdio streams, which we can access using child.stdin, child.stdout, and child.stderr. Since all streams are event emitters, we can listen to different events on those stdio streams that are attached to every child process. The stdout and stderr streams are readable, while the stdin stream is writable. We can use standard events with these streams. Importantly, on readable streams, we can listen for the data event, which contains the command's output or any errors encountered during execution.

When we execute the spawn function, the output of the model script is printed, and the child process exits with a code of 0, indicating that no errors occurred.

If an error occurs during command execution, the child.stderr data event handler will be triggered, and the the child process exits with a code of 1, indicating an error

After executing the command using the spawn function and processing the output, the extracted result is sent back to the client in a JSON response.

# **Chapter 6: future work**

**Future Work**

While our model demonstrated high performance, several areas offer potential for further improvement:

1. **Addressing Class Imbalance**:
   * The dataset's class imbalance was mitigated through resampling techniques. Future work could explore advanced methods such as Synthetic Minority Over-sampling Technique (SMOTE) or Adaptive Synthetic Sampling (ADASYN) to generate synthetic samples and enhance model training.
2. **Enhanced Feature Extraction**:
   * Misclassifications between certain classes suggest the need for better feature differentiation. Incorporating advanced feature extraction techniques or combining MobileNetV2 with other architectures (e.g., EfficientNet or ResNet) could improve performance.
3. **Augmenting Dataset Quality**:
   * Although HAM10000 provided high-quality images, integrating additional datasets like ISIC2019 could enrich the model's training data. Preprocessing steps to enhance image quality, such as noise reduction and contrast enhancement, might also prove beneficial.
4. **Real-World Application and Validation**:
   * Implementing the model in clinical settings for real-world validation is crucial. Collaborating with dermatologists to test the model on new, unseen data and gathering feedback will help refine the model further
5. **Dynamic Learning Rate Adjustment**:
   * The custom callback LR\_ASK for adjusting the learning rate dynamically showed promise. Further refinement of this callback and integrating other adaptive learning rate techniques like Cyclical Learning Rates (CLR) could enhance model training efficiency.

By addressing these areas, future research can build upon the strong foundation established in this study, leading to even more accurate and reliable skin lesion classification models.

The potential for integrating diverse datasets and advanced machine learning techniques promises significant advancements in the field of dermatological diagnostics.

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A black board with white text

Description automatically generated

fig 34

A screenshot of a computer screen

Description automatically generated

fig 35

A screenshot of a computer

Description automatically generated

fig 36

A screenshot of a computer

Description automatically generated

fig 3 7

A screenshot of a website

Description automatically generated

fig 38

A screenshot of a computer

Description automatically generated

fig 39

A screenshot of a contact us

Description automatically generated

fig 40

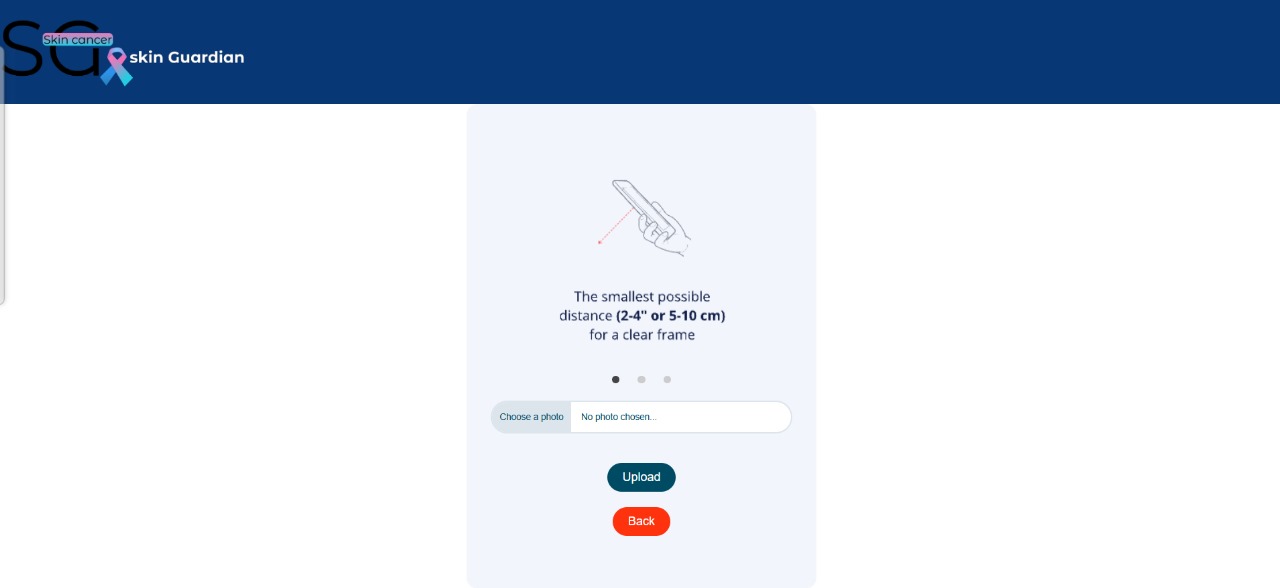


fig 41

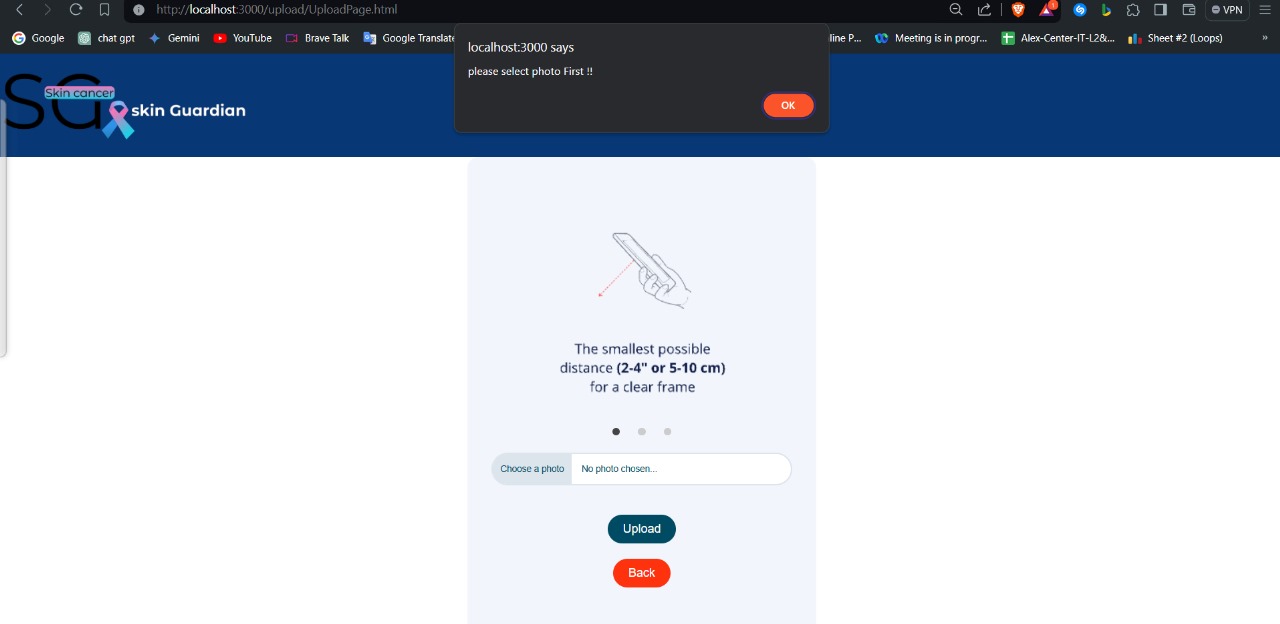


fig 42

A screenshot of a computer screen

Description automatically generated

fig 43

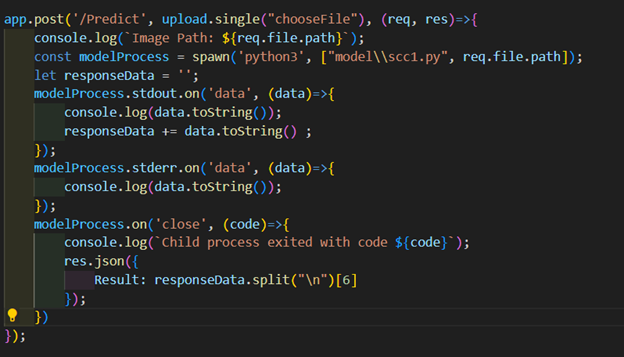


fig 44

A screen shot of a computer code

Description automatically generated

fig 45

A screen shot of a computer code

Description automatically generated

fig 46