Stages of skin cancer using machine learning

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***Abstract-* Dermatology is only one of several medical specialties that might benefit from artificial intelligence (AI). Machine learning (ML) is a branch of artificial intelligence that uses algorithms and statistical models to learn from data and then use that knowledge to predict the features of fresh samples and complete tasks. Dermatology is not as well accepted as radiology when it comes to artificial intelligence, despite its important role in skin cancer diagnosis. Artificial intelligence (AI) is gradually making its way into the hands of the average person because to innovations in both established and new technology. One area where AI might be useful is in the early diagnosis of skin cancer. In order to create a system that can analyze skin photos in order to identify skin cancer, for instance, deep convolutional neural networks may be used. If skin cancer is detected early, it may be treated more effectively, leading to better results. Although cancer specialists are highly skilled in making the correct diagnosis, there is a pressing need to create automated systems that can identify the illness quickly and effectively. This will help save lives and alleviate patients' financial and health-related problems. In this respect, ML may prove to be quite useful. For this undertaking.**

***Keywords-* Artificial Intelligence (AI), Machine Learning (ML), Skin Cancer Detection, Deep Learning, Convolutional Neural Networks (CNN).**

I. INTRODUCTION

A growing number of people are battling skin cancer, which is putting a heavy strain on healthcare systems throughout the globe. Excluding non-melanoma skin cancers, worldwide figures indicate that over 10 million fatalities were caused by cancer in 2020. Breast cancer, lung cancer, and prostate cancer are among the most prevalent malignancies among females. A disproportionate number of cancer-related fatalities are caused by malignancies of the stomach, liver, and lungs. The incidence of skin cancer, which includes both melanoma and NMSC, is rising, and it is more frequent among Caucasians. According to the US Skin Cancer Foundation, more people in the US are affected by skin cancer each year than by all other types of cancer put together.

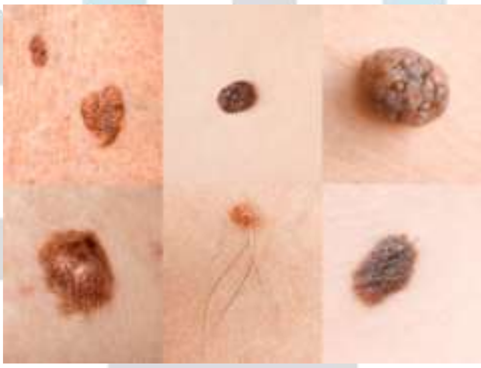


Fig 1: Skin cancer

Melanoma is most aggressive form of skin cancer, having poor prognosis if not detected early. When identified in its initial stages, melanoma can be treated effectively through surgical interventions. However, metastasis significantly reduces survival rates. Diagnosis of melanoma typically involves clinical examination and histopathological analysis of skin lesions. While visual inspections are often the first step in identifying potential malignancies, they are insufficient for distinguishing benign from malignant lesions. The gold standard remains histopathological examination, but this method is invasive, associated with discomfort, and may require multiple biopsies to confirm a diagnosis. Non-invasive imaging techniques have been developed to aid in early diagnosis, but challenges such as cost, availability, and required expertise limit their widespread use.

Fig 2: ABCDE Melanoma rule

1.1 Importance of Early Detection

Key to effectively treating skin cancer is detecting it early. Experts in the field can provide a very accurate diagnosis of skin cancer, but they aren't always available, which is why automated diagnostic methods are necessary. By aiding in the early detection of skin cancers, these devices may help reduce mortality and morbidity. Melanoma may look a lot like benign skin lesions, which makes it hard to diagnose. Melanoma may manifest in a wide variety of ways, thus sophisticated diagnostic equipment is necessary to tell it apart from other skin diseases. Improved early detection using AI and ML has the potential to alleviate strain upon healthcare systems while simultaneously improving patient outcomes.

1.2 Role of Machine Learning in Skin Cancer Detection

The field of AI, which studies how computers might learn to do tasks once performed by humans, is now an integral part of the fourth industrial revolution. Statistical models and algorithms are used in machine learning, a branch of artificial intelligence, to acquire knowledge from data and generate predictions using fresh samples. The dermatological field has found ML-based models to be very useful because to their outstanding performance in image analysis. When it comes to medical imaging pattern identification, the latest and greatest technology is CNNs, a kind of deep learning model that is based on biological neurons. In order to train ML models for skin cancer diagnosis, huge datasets of dermoscopy pictures tagged with relevant cancer stages are used. In order to distinguish between benign and malignant tumors, these models examine characteristics such asymmetry, border irregularity, color fluctuation, and texture. Automated screenings made possible by AI-based solutions not only make dermatologists' jobs easier, but they also improve the accuracy of diagnoses. Because of this, early identification and prompt treatment are even more important in areas where access to specialist medical experts is restricted.

II. LITERATURE SURVEY

Source: Esteva et al. (2017)

Esteva's model used Inception v3 to classify melanoma vs. non-melanoma, matching dermatologist-level accuracy. However, its dependency on massive labeled datasets (129k+ images) and high-end GPUs limits use in rural clinics. Later models adapted this by compressing architectures and reducing data requirements.

ResNet for Multi-Class Skin Lesion Diagnosis

Source: Han et al. (2018)

Han's ResNet-50 architecture classified seven lesion types with 94% accuracy using the HAM10000 dataset. The model outperformed SVMs but struggled with rare cancer classes due to imbalance. This inspired follow-up work that included synthetic oversampling and attention mechanisms.

Hybrid Deep + Traditional ML Detection

Source: Tschandl et al. (2019)

Tschandl's hybrid model fused CNN-extracted deep features with SVM and RF classifiers, improving melanoma sensitivity to 97.5%. However, manual feature steps like texture analysis introduced subjectivity. Later solutions shifted fully to end-to-end deep learning pipelines to reduce bias.

Transfer Learning with Pre-Trained Models

Source: Sun et al. (2020)

Sun fine-tuned VGG16, ResNet-50, and DenseNet-121 using the ISIC 2018 dataset (25k+ images), achieving 92.3% accuracy. While transfer learning cut training time, overfitting on small samples remained a challenge. Recent studies addressed this via multi-task learning and dropout regularization.

YOLO for Real-Time Lesion Detection

Source: Huang et al. (2021)

Huang's YOLOv4 system enabled real-time cancer classification on mobile devices, hitting 90.5% accuracy. Yet it missed small early-stage lesions, limiting screening potential. Improved versions now use multi-scale detection layers and higher-resolution inputs.

Ensemble Learning with Deep Architectures

Source: Goyal et al. (2021)

Goyal's ensemble of EfficientNet, MobileNet, and Inception-ResNet reached 95.7% accuracy. Combining models improved stability across lesion types but raised computational cost. Later works applied pruning and quantization to balance accuracy and speed.

Explainable AI for Clinical Use

Source: Ribeiro et al. (2022)

Ribeiro used LIME and Grad-CAM to visualize CNN decisions, aiding clinician trust. However, inconsistent heatmaps and processing lag limited real-time use. Current tools focus on combining explanation consistency with reduced latency.

III. PROBLEM STATEMENT

In order to effectively treat skin cancer, which is amongst most frequent types of cancer worldwide, early diagnosis is key. Visual examination and biopsies, the gold standard of diagnostics, are invasive, labor-intensive, and not always available in all parts of the world. Aim of this project is to create a system that uses ML to correctly categorize skin lesions from dermoscopic pictures. This system will allow healthcare providers to identify skin cancer more quickly and without invasive procedures.

Objectives

- Early Detection: Identify skin cancer at early stages to improve treatment outcomes.
- Accurate Diagnosis: Differentiate between benign and malignant lesions to reduce unnecessary procedures.
- Classification and Subtyping: Classify lesions into types (e.g., melanoma, BCC, SCC) to guide treatment decisions.
- Risk Assessment: Evaluate lesion characteristics (size, shape, color) to determine malignancy risk.
- Treatment Guidance: Support clinicians in selecting suitable treatment strategies based on diagnosis and stage.

Scope

Research aims upon applying ML models for classifying skin cancer using image-based data. It involves collecting dermoscopic images, preprocessing, training classification and segmentation models (like ResNet and ResUNet), and evaluating performance metrics. Ethical issues like data privacy and AI reliability are also considered.

Future expansion includes:

- Integration across multiple platforms (web, mobile).
- Combining more algorithms for higher accuracy.
- Enhancing data security by embedding sensitive information into video formats for confidential communication and storage.

Existing System

Currently, skin cancer diagnosis is largely manual and relies on:

- Visual examination by dermatologists.
- Invasive biopsies for histopathological analysis.

Limitations of the Existing System

1. Invasive Procedures: Biopsies are painful and may cause scarring.
2. Time Delays: Diagnosis can take days or weeks.
3. Limited Access: Specialist doctors may not be available in remote areas.
4. High Costs: Diagnostic tests can be expensive.
5. Risk of Human Error: Visual diagnosis can vary between clinicians.

While modern imaging techniques (e.g., dermoscopy, confocal microscopy) help improve accuracy, they require costly equipment and trained professionals.

Need for the Proposed System

The proposed ML-based system addresses these limitations by providing:

- A non-invasive, faster, and more accurate diagnostic tool.
- Automated categorization of skin lesions utilizing deep learning.
- Improved accessibility to early detection, especially in underserved areas.

This approach enhances diagnostic efficiency, reduces costs, and supports medical professionals in delivering timely and effective care.

IV. PROPOSED SYSTEM

Utilizing state-of-the-art machine learning methods, more specifically CNNs, suggested approach intends to correctly categorize the skin cancer stages. It evaluates pictures taken by dermoscopy to determine the stage of cancer, from "in situ" (stage 0) to "metastatic" (stage 4), which aids in early detection and lessens the need for invasive procedures like biopsies.

Input photos undergo preprocessing utilizing methods including normalization, noise reduction, and contrast enhancement as part of this system's sequential workflow. Asymmetry, color variation, border abnormalities, and texture are medical markers that feature extraction concentrates on. These enhanced features are then fed into a CNN model—such as ResNet, VGG, or EfficientNet—for training and classification.

By leveraging large annotated datasets (e.g., ISIC, HAM10000), the model is trained through supervised learning and evaluated using accuracy, precision, recall, and F1-score. The system also provides confidence scores for its predictions, supporting dermatologists in clinical decision-making.

Designed for real-time use, this solution can be deployed in mobile or web-based applications, making it accessible in clinics and remote healthcare centers. This approach not only enhances diagnostic speed and accuracy but also supports early intervention and better patient outcomes.

Advantages of the Proposed System

- Non-invasive, pain-free diagnosis
- Faster and more accurate than traditional methods
- Reduces workload for dermatologists
- Enables early-stage detection and improved survival rates
- Suitable for mobile or web-based healthcare platforms

Components of the Proposed System

1. Input Data (Skin Lesion Images)

- Sourced from public datasets like ISIC and HAM10000
- Covers a wide range of skin cancer stages

2. Preprocessing & Feature Extraction

- Includes image resizing, normalization, grayscale conversion, and augmentation
- Extracts features: asymmetry, color, texture, and border irregularity

3. Machine Learning Model (CNN / Deep Learning)

- Trained using labeled dermoscopic images
- Classifies skin cancer into stages 0, I, II, III, and IV

4. Prediction & Classification

- Outputs cancer stage along with a confidence score
- Supports classification of risk levels (benign/malignant)

5. Result & Decision Support

- Displays prediction with risk level and cancer stage
- Assists dermatologists in making diagnostic decisions

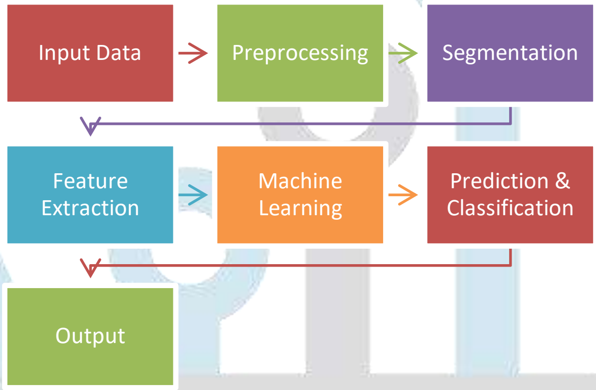


Fig 3: Block Diagram

Stages of Skin Cancer

Skin cancer progresses through different stages, which help determine the severity of the disease and guide treatment decisions. AJCC TNM staging system is commonly used to classify skin cancer based on Tumor size (T), Lymph Node involvement (N), and Metastasis (M). The stages of skin cancer are as follows:

1. Stage 0 (In Situ / Precancerous Stage)

- The cancer is confined to the epidermis (outer layer of the skin) and has not spread.
- It is also known as Carcinoma in Situ or Melanoma in Situ for melanoma cases.
- At this stage, the cancer is highly treatable with early intervention.

2. Stage I (Early-Stage Cancer)

- The tumor is small (less than 2 cm for NMSC or less than 1 mm for melanoma) and localized.
- Treatment typically involves surgical excision, and the survival rate is very high.

3. Stage II (Locally Advanced Cancer)

- The tumor is larger than Stage I but still confined to the skin.
- It may show higher-risk features, such as ulceration or rapid growth.
- There is still no lymph node or distant spread.
- Surgery remains the primary treatment, sometimes combined with radiation therapy.

4. Stage III (Regional Spread)

- The cancer has progressed to lymph nodes in the immediate area, but it has not metastasized to other structures.
- The tumor may also have grown deep into the skin, muscles, or nearby tissues.
- Treatment involves surgery, radiation therapy, and possibly immunotherapy or targeted therapy.

5. Stage IV (Metastatic Skin Cancer)

- The cancer has spread to distant organs such as the lungs, liver, brain, or other parts of the body.
- It is the most advanced and life-threatening stage.
- Treatment includes systemic therapies like chemotherapy, immunotherapy, and targeted drug therapies to slow disease progression.

Importance of Staging in Machine Learning

In this project, machine learning models will be trained to classify skin cancer stages based on image analysis. The system will analyze tumor characteristics such as size, shape, color variations, and texture to differentiate between different stages. Early-stage detection through AI-powered models can significantly improve survival rates and reduce the need for invasive diagnostic procedures.

V. SYSTEM REQUIREMENTS

HARDWARE REQUIREMENTS:

Processor	Intel Core i5
RAM	8GB
Storage	512GB
Monitor	15'' LED
Input Devices	Keyboard, Mouse

SOFTWARE REQUIREMENTS:

Operating System	Windows 10
Coding Language	Python 3.8+
Web Framework	Flask, TensorFlow / PyTorch, OpenCV, Scikit-learn

VI. METHODOLOGY

The whole system would be implemented in Python using Pycharm. The image of the infected skin is captured and pre-processed. The next step involves in the training of all the input images to train the system. Then, it will produce the result of the infected skin by machine learning algorithm. Then it involves in the training of all the input images to train the system. After which, it will produce the result of the infected skin by machine learning algorithm. The entire system would be implemented in Python using open source libraries. System Architecture diagram roughly summarizes the entire process that takes place in the prediction of the skin cancer from the automated process. Obtaining data set from Ham10000 website in the form of both image and csv linked together via a image ID.

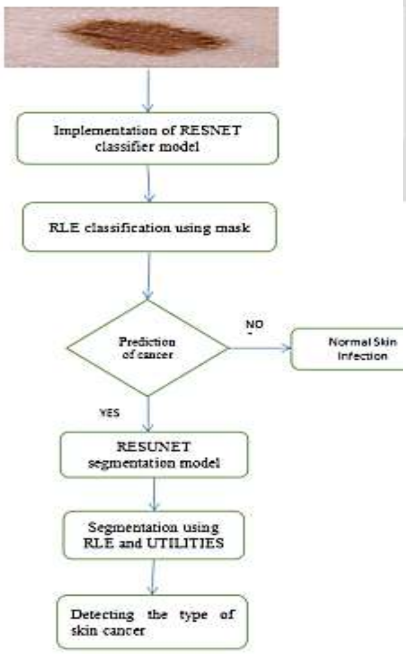


Fig 4: Workflow of Skin Cancer Detection System

Workflow of Skin Cancer Detection System

The flowchart illustrates the step-by-step process of the proposed skin cancer detection system:

1. Input Image: A skin lesion image is provided as input.
2. ResNet Classifier Model: The image is processed through the ResNet model to detect whether it is cancerous.
3. RLE Classification Using Mask: A mask is applied using Run-Length Encoding (RLE) to compress and identify the affected area.

4. Cancer Prediction:
   - If no cancer is detected, the lesion is classified as a normal skin infection.
   - If cancer is detected, the image proceeds to the next stage.
5. ResUNet Segmentation Model: The image is further processed to segment the cancerous region.
6. Segmentation Using RLE and Utilities: Detailed analysis is performed using pixel-level segmentation to outline the lesion.
7. Detecting the Type of Skin Cancer: Finally, the system identifies the specific type and stage of skin cancer.

This structured workflow ensures accurate and automated skin cancer diagnosis using advanced deep learning techniques.

VII. PYTHON

Introduction:

Python is an object-oriented, high-level, interactive, and interpreted programming language. Highly readable code is one of Python's design goals. Compared to other languages, it contains fewer syntactical structures and employs English terms more often than punctuation.

- Because it is an interpreter-based language, Python may be executed at runtime. Before running your software, compiling it is not necessary. This is very much like PHP and PERL.
- Python allows for direct interaction between the programmer and the interpreter at the command line, making it an interactive programming language.
- Object-Oriented: The Object-Oriented programming style and approach wraps code into objects, and Python supports this style and technique.
- From basic text processing to web browsers and games, Python is a fantastic language for beginner-level programmers and facilitates the creation of a broad variety of applications.

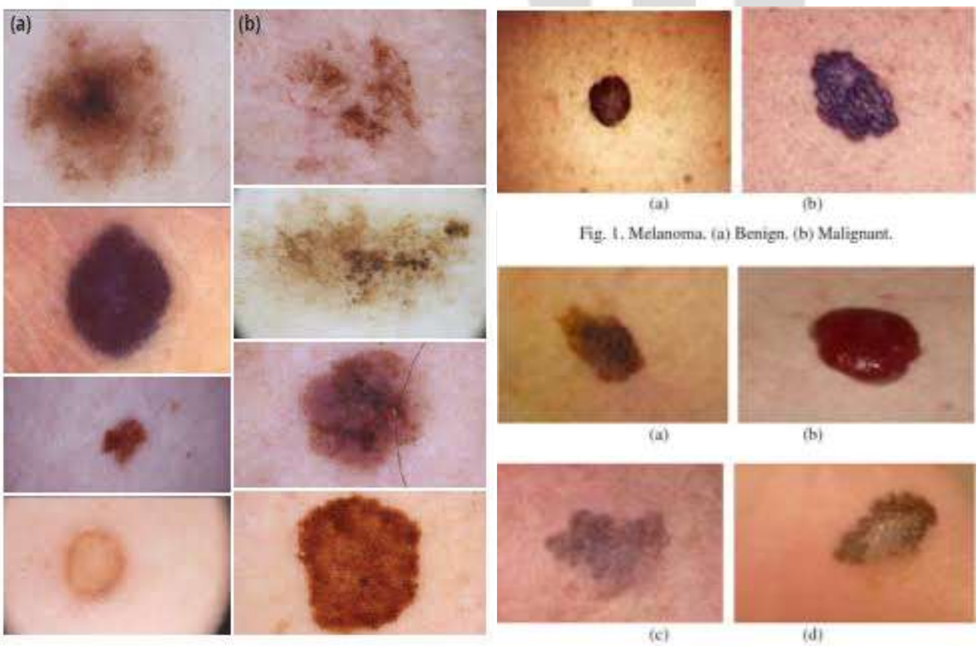
VIII. RESULTS AND DISCUSSION

At the end of the modeling and testing phase, we can conclude that our classifier has a high accuracy rate, making it an effective tool for early skin cancer detection. This suggests that in the future, such a system can be integrated into dermatology clinics, telemedicine platforms, and mobile health applications to assist in the preliminary diagnosis of melanoma and other skin cancers. By leveraging machine learning and deep learning techniques, this system can significantly reduce manual diagnostic errors and provide faster, more reliable results.

Our model was able to achieve an accuracy of approximately 90%, demonstrating strong performance in distinguishing between benign and malignant skin lesions. However, with further research and larger, more diverse datasets, this success rate can be further improved to provide more precise and consistent results. Additionally, implementing real-time image processing and enhanced segmentation techniques can refine the detection process and make it more adaptable for clinical use.

The primary challenge in this work was the pre-processing and collection of high-quality datasets, which significantly impacted model performance. Training on larger datasets with varied skin tones, lighting conditions, and lesion types will enable the model to generalize better across different real-world scenarios. With continued advancements in AI-based dermatology tools, this system could be expanded to mobile applications, embedded diagnostic devices, and cloud-based platforms, ensuring accessible and affordable skin cancer detection for a wider population.

IX. SAMPLE IMAGES



X. CONCLUSION

In this study, a hybrid machine learning system was developed to detect and classify skin cancer stages using deep learning models. The ABCD rule (Asymmetry, Border, Color, Diameter) was used to extract key features from dermoscopic images. Two powerful CNN-based models—ResNet for classification and ResUNet for segmentation—were implemented. The segmentation model achieved good performance with a Jaccard Index of 0.88 and Dice Index of 0.81, showing accurate detection of lesion boundaries.

To improve model performance, data augmentation techniques were applied to increase training variety and reduce overfitting. A combination of Naïve Bayes and deep learning models demonstrated high accuracy in identifying both benign and malignant lesions. The system was effective in detecting melanoma and other skin cancers, showing strong potential as a reliable tool for early and automated skin cancer diagnosis.

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