INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact Factor: 6.078
(Volume 10, Issue 6 - V10I6-1399)
Available online at: https://www.ijariit.com

Skin Cancer Type Detection using Deep Learning

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ABSTRACT

The research "Detection of Skin Cancer Types Using Deep Learning" addresses the serious issue of skin cancer. There's an urgent need for early diagnosis to help patients get better treatment. Skin cancer, especially melanoma, can be hazardous and often leads to high death rates when not caught early. Traditionally, doctors mainly rely on visual checks, which can vary from person to person. This can lead to misdiagnoses and delayed treatments. So, we decided to use a technology called Convolutional Neural Networks (CNNs) to create a machine that recognizes different types of skin cancer using specialized images. We did a thorough review of current methods and identified their limitations. This will help us build our approach while also making it easier for places with fewer resources to access. By studying things like color, texture, shape, and size in dermoscopy images—and using fresh techniques like transfer learning—we hope to boost accuracy and efficiency in diagnosis. Ultimately, we look forward to helping improve skin cancer treatments.

Keywords: *CNN (Convolutional Neural Network), HAM (Human Against Machine), ReLU (Rectified Linear Unit), AI (Artificial Intelligence)*

1. INTRODUCTION

In recent years, skin cancer has seen a sharp rise in cases around the world, making it a big health concern! According to the World Health Organization (WHO), melanoma is particularly worrying due to its aggressive nature and high death rates if detected too late. Skin cancer is one of the more common cancers out there.

There are many reasons behind this increase. People are getting more exposure to ultraviolet (UV) rays from the sun and things like tanning beds. Also, many folks don't know the best ways to protect their skin properly.

Early detection is key for better treatment outcomes. Research shows that identifying skin cancer early gives patients a greater than 90% chance of surviving for at least five years! However, dermatologists' exams are still quite subjective and can vary greatly depending on experience levels. This raises concerns about misdiagnosis rates due to these differences.

That's where deep learning comes in! It's a part of artificial intelligence that has changed the game in analyzing medical images. CNNs are deep learning algorithms that work really well with complex visual data. The aim of our study is to automate skin cancer detection by processing dermoscopic images effectively.

Our primary goal is setting up a system that spots various kinds of skin lesions like melanocytic nevi or melanoma while also working efficiently with large datasets. We want this system to handle different image qualities as well!

In this study, we will explore how deep learning improves melanoma diagnoses and impacts patient outcomes positively by speeding things up! We'll discuss how we'll gather data, preprocess it, extract important features, & finally train our model.

2. METHODOLOGY & MATERIAL

This research focuses on building a deep learning model that identifies and classifies skin cancer types from dermoscopic images. Here's how we planned our work:

i. Data Collection

We used public databases filled with different skin lesion images.
These included:

a. Melanocytic nevi
b. Melanoma
c. Benign keratosis-like lesions
d. Basal cell carcinoma
e. Actinic keratosis
f. Vascular lesions
g. Dermatofibroma

ii. Pre-processing Techniques

Image Resizing: All images are resized so they're uniform (like 224x224 pixels).
Color Space Conversion: Images might get turned into different color setups based on what we need.
Normalization: We adjust pixel values between 0 & 1 for better training results.
Data Augmentation: Techniques like rotating or zooming help diversify our dataset.

iii. Architecture Model

We designed a specialized CNN just for identifying skin cancer.
Convolutional Layers: Different sizes extract features from pictures.
Pooling Layers: These helps reduce dimensionality while keeping essential info.
Fully Connected Layers: Combine everything to classify into various cancer groups.
Activation Functions: ReLU for hidden layers & softmax in output layers.

iv. Feature Extraction

From dermoscopic images, we pulled these features:
Color Features: Look at color distribution via histograms.
Texture Features: Local Binary Patterns & Gray-Level Cooccurrence Matrix evaluate texture.
Shape Features: Metrics like compactness measure shape characteristics.
Dimensions & Symmetry Features: Circumference & area also tell us more about lesions.

v. Training Process

We used labeled images for supervised learning:
Batch Size: Number of pictures processed together during training (like 32 or 64).
Epochs: Times going through training set (maybe 50 or 100 epochs).
Learning Rate & Dropout Rate helped optimize training.

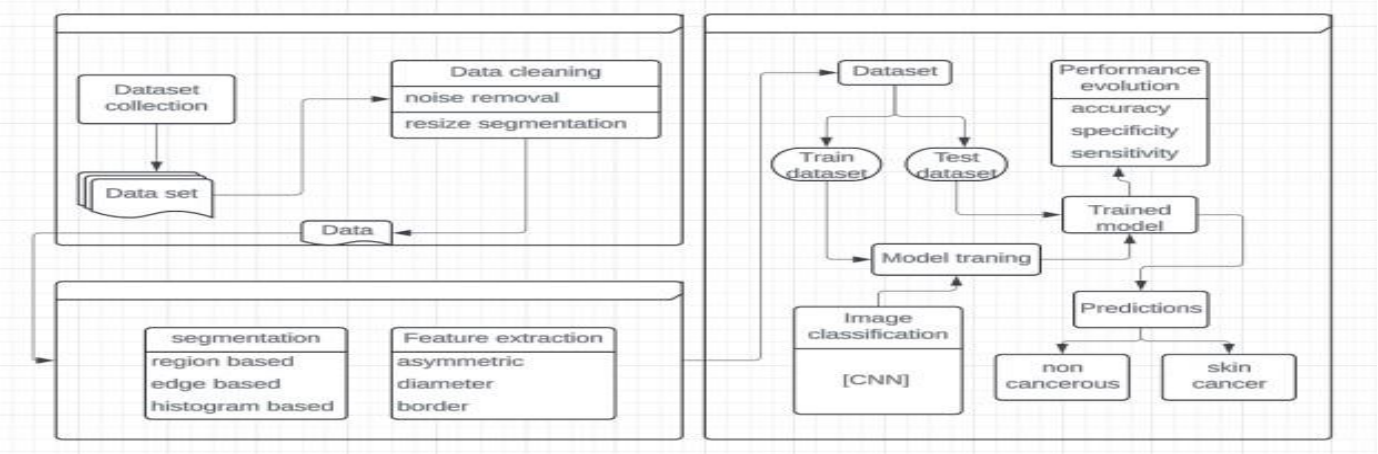
vi. Evaluation Matrices

Several criteria will check how well our trained model performs:
Accuracy: How many were classified correctly overall?
Precision: Ratio of predicted positives that were actually positive.
Recall: How many real positives were detected?
F1 Score: Balances precision with recall nicely!

vii. Tools & Technology

Common programming libraries used include:
Python as the main language.
TensorFlow & Keras built our deep learning models.
For image processing? We used OpenCV & PIL too!

Block Diagram



3. RESULT

With our Skin Cancer Type Detection research, users can expect accurate results based on their uploaded images! The user interface will be simple and friendly— First off, we enhance each image through resizing technology during pre-processing. Then comes classification where the model sorts lesions—like melanoma—while ensuring accuracy remains high!

4. ALGORITHM USED

In our CNN architecture:
Dermoscopy Images get normalized and resized first before entering.
Convolutional Layers identify textures and patterns with filters (kernels).
Activation Function uses ReLU adding non-linearity which helps!
Lastly, Pulling layers help downsample all those feature maps from convolutional layers.

5. LITERATURE SURVEY

1.M.Krishna Monika et al highlighted machine learning methods in July 2020! Their strategy involved Multi-Class Support Vector Machine (MSVM) achieving over 96% accuracy in classifying eight types!
2&3.Atosua Ghorbani's pieces in August 2023 detail AI's growing role both in diagnosis as well as patient care enhancement—Achieving around 93% accuracy too!
Overall? AI has a great potential for improving dermatology decisions!
This shows how crucial technology can be in helping with early diagnoses for better patient outcomes!

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